The background of the cover is a dark blue gradient. It features several overlapping circles of varying sizes and opacities in shades of blue and purple. A bright, glowing light source is positioned in the lower-left quadrant, creating a strong lens flare effect that illuminates the surrounding circles and the text below.

FROM TRADITIONAL TO INTERACTIVE PLAYSPACES

Automatic Analysis of Player Behavior in the
Interactive Tag Playground

Alejandro Moreno

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FROM TRADITIONAL TO INTERACTIVE PLAYSPACES

AUTOMATIC ANALYSIS OF PLAYER BEHAVIOR IN THE INTERACTIVE TAG PLAYGROUND

DISSERTATION

to obtain

the degree of doctor at the University of Twente,

on the authority of the rector magnificus

Prof. dr. H. Brinksma

on account of the decision of the graduation committee,

to be publicly defended

on Thursday, 21st of April 2016 at 16:45

by

Alejandro Moreno Céleri

born on July 09, 1984

in Guayaquil, Ecuador

This dissertation has been approved by:

Supervisor: Prof. dr. Dirk Heylen

Co-Supervisor: Dr. ir. Ronald Poppe

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And so it ends. After 4 years and a half of studying behavior in games, I get to write these lines to bring this chapter of my life to a close. It would be impossible to mention everyone who, in one way or another, helped me complete this thesis. For all of you: know that even if you are not present in these scarce few lines, I will be forever grateful.

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*Alejandro Moreno
Enschede, March 2016*

Abstract (EN)

Play is an essential activity for the physical, cognitive and social development of children. Studies have shown that, through play, children can learn what their bodies are capable of, or develop positive social relationships with their peers. With the emergence of digital games, the way in which games are played has changed significantly. Many digital games promote sedentary gaming habits, or are played in such a way that meaningful social interactions cannot occur. On the other hand, digital games can be more fun than traditional games, capable of keeping players engaged for prolonged periods of time.

Nowadays, new types of games are being developed that aim to promote the positive behavior associated with traditional play, as well as to retain the benefits of digital games. This is accomplished by employing sensors and actuators such as cameras, projection screens and accelerometers. Would it be possible to leverage these technological elements to design better games and provide enhanced game experiences? Could they be used to automate or improve the way in which we currently study how games are played? In this thesis, we answer these questions. We explore the use of technology to automatically and unobtrusively analyze player behavior in an interactive game installation.

We analyzed recordings of children playing traditional tag games to identify ways to improve or automate the process by which the behavior of players is studied. The information derived from the analysis was used to design an interactive playground that enhances the tag game experience while supporting the physical and social aspects of play that are exhibited by players during traditional tag. This installation, the Interactive Tag Playground (ITP), uses cameras to track players in the playing field and projectors to display game elements on the floor. This allows players to move freely during the game. Results from a user study showed that our interactive version of tag was more enjoyable and immersive than the traditional game of tag, while still allowing players to exhibit physically active, social behavior.

Besides being an entertainment installation, the ITP doubles as a game research platform. The ITP automatically logs the players' positions and roles. We used this information to automatically measure two aspects of play behavior that are important in the study of interactive playgrounds: physical activity and social interactions. We found that physical activity measured as speed from tracked players correlated well with exertion measurements from heart rate sensors. We also found that differences in social play behavior between children could be measured using social cues, such as the distance between players. Finally, we were interested in the automatic recognition

of roles during tag games, as this could be used to find anomalous behavior such as cheating or bullying. Our results showed that automatically estimating players' roles during tag games is possible. In conclusion, the ability to automatically track players makes it possible to derive useful play behavior information.

The work presented in this thesis showcases the potential benefits and applications of improving how play behavior is studied. Specifically, the use of automated, quantitative methods complements the qualitative methods currently used to study games. Furthermore, the automated analysis of player behavior can help the design of adaptive game installations and more engaging game experiences.

Abstract (NL)

Spelen is essentieel voor de lichamelijke, cognitieve en sociale ontwikkeling van kinderen. Studies hebben aangetoond dat door spel, kinderen kunnen leren waar hun lichaam allemaal toe in staat is en hoe ze positieve sociale banden aangaan met leeftijdsgenoten. Met de opkomst van digitale spellen is de manier waarop gespeeld wordt aanzienlijk veranderd. Veel digitale spellen leiden tot veel zittend gamen, of worden gespeeld op een manier dat zinvolle sociale interactie niet aan bod komt. Anderzijds kunnen digitale spellen soms veel meer plezier bieden dan traditionele spellen ... en kunnen ze spelers voor langere periodes bezighouden.

Nieuwe type spellen worden tegenwoordig ontwikkeld met het doel het positieve gedrag dat men associeert met traditionele spel te bevorderen en tegelijk de voordelen van digitale spellen te behouden. Dit wordt bereikt door het gebruik van sensoren en actuatoren zoals cameras, projectieschermen en versnellingsmeters. Zou het mogelijk zijn om deze technische elementen te gebruiken om betere spellen te ontwerpen en om speelgenot te verhogen? Zouden ze ingezet kunnen worden om de manier waarop wij nu spel onderzoeken te automatiseren of verbeteren? In dit proefschrift geven we antwoorden op deze vragen. We onderzoeken het gebruik van technologie om spelgedrag automatisch en onopvallend te analyseren in een interactieve opstelling.

We maakten video opnames van kinderen die traditioneel tikkertje speelden en analyseerden de opnames om er achter te komen hoe we het proces waarbij we het spelgedrag bestuderen kunnen verbeteren of automatiseren. De informatie die we hebben gewonnen uit de analyses hebben we gebruikt om een interactieve speelruimte te ontwerpen die de ervaring van tikkertje nog leuker maakt terwijl het de fysieke en sociale aspecten van traditioneel tikkertje ondersteunt. De installatie, de Interactive Tag Playground - ITP (een speelplaats om interactief tikkertje te spelen), gebruikt camera's om spelers te volgen op de speelplaats en projectoren om spel-elementen op te vloer te projecteren. Zodoende kunnen de spelers vrij bewegen tijdens het spel. Resultaten van een gebruikersstudie hebben aangetoond dat de spelers veel meer plezier hadden met onze interactieve versie van tikkertje en er veel meer in opgingen dan in een traditioneel potje tikkertje. Spelers vertoonden evengoed zowel lichamelijk actief gedrag als sociaal gedrag.

De ITP is zowel een entertainment installatie als een onderzoeksplatform. De ITP logt automatisch de positie van de spelers en hun rol. We hebben deze informatie gebruikt om twee aspecten van spelgedrag die belangrijk zijn in het bestuderen van interactieve speelruimtes automatisch te meten: lichamelijke activiteit en sociale interacties. We zagen dat lichamelijke activiteit (gemeten als de snelheid van gevolgde

spelers) goed overeenkomt met inspanning (gemeten met hartslagmeters). We zagen ook dat het variërende sociale spelgedrag van verschillende kinderen gemeten kon worden via sociale signalen zoals de afstand tussen spelers. Tenslotte waren we ook geïnteresseerd in de automatische herkenning van rollen tijdens een potje tikkertje omdat dat gebruikt kan worden om afwijkend gedrag zoals valsspelen of pesten op te sporen. Onze resultaten lieten zien dat het mogelijk is om de rol van de spelers automatisch in te schatten tijdens het spel. De optie om spelers automatisch te volgen maakt het mogelijk om informatie over belangrijk spelgedrag af te leiden.

Het werk hier gepresenteerd, laat zien wat de potentiële voordelen zijn van het verbeteren van de manier waarop spelgedrag wordt onderzocht en waar daarvoor de toepassingen liggen. Met name het gebruik van geautomatiseerde, kwantitatieve methoden complementeert de kwalitatieve methoden die op dit moment gebruikt worden om spel te onderzoeken. Bovendien kan geautomatiseerde analyse van spelgedrag ons helpen met het ontwerpen van adaptieve spelinstallaties en innemende spelervaringen.

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Part I

Theoretical Framework

1

Play: Present and Future

Play is an activity that is engaged in for enjoyment and recreation. It is also an important part of children's development. Consequently, the study of how players play games, the analysis of their behavior, is very important. By improving our current understanding of play, we could design games to better fit players' needs. This requires the quantitative analysis of play behavior during games.

The introduction of new types of games that combine elements from digital gaming and traditional play can make the analysis of in-game play behavior possible. These novel games aim to promote the type of positive behavior commonly elicited in traditional play, while adding interactive elements that support the benefits of digital gaming. This requires the deployment of different kinds of sensors to obtain input from players. This input is usually used to control game interactions. Would it be possible to use these sensors to analyze specific aspects of player behavior? Could the knowledge gained from such analyses help in the study and analysis of play? The research described in this thesis addresses these issues. More specifically, we address the automated, unobtrusive observation and analysis of player behavior during games.

In this chapter we will motivate the need to study play behavior. We will begin by introducing and describing what play is and discussing its benefits in Sections 1.1 and 1.2. In Section 1.3, we will discuss how technology has changed the way children play, the problems it has introduced, and how interactive games are being used to address these problems. Then, in Section 1.4, we will argue that the analysis of play behavior could aid in the evaluation of interactive games, and frame the scope of our research towards this goal. Finally, in Section 1.5, we will present the structure of this thesis.

1.1 Play and Games

Play has attracted the attention of researchers for a very long time. Studies have shown that play is essential for the development of children [1, 2], of their physical capabilities [3], cognitive processes [4], and social understanding [5]. But, *what is play?* Defining exactly what play means is a difficult task [6]. According to the

cultural theorist Huizinga, play is “... a free activity standing quite consciously outside ‘ordinary’ life as being ‘not serious,’ but at the same time absorbing the player intensely and utterly...” [7]. Caillois defines play as free, separate, uncertain, unproductive, regulated and make-believe [8]. To Rubin *et al.* play is intrinsically motivated, focused on means rather than ends, free from externally imposed rules and actively engaged in by the players [9].

Although the definitions of play differ, certain properties attributed to play are shared. First, play is “free” and not a “serious” endeavor. The main goal of play is entertainment; a person plays because it is fun, not because he is forced to. Second, play engages players mentally, physically and/or socially. Finally, play has some structure, but this structure is molded and adapted by the players as they see fit. This last point is very important, as it is the main difference between games and play [10]. Strictly speaking, games (game-playing) have rigid structures and rules that, when changed, lead to the game itself changing (or players cheating). However, in many game studies, play is seen as the activity of engaging in games, *i.e.* playing *games* is used interchangeably with *play* [10]. Therefore, in this thesis, we will also refer to play as both game-playing and play.

1.2 The Benefits of Play

Several studies on children’s play behavior have shown that play is essential for children’s proper development [1, 11]. While playing, children can explore what they are capable of in a safe environment, allowing them to experience and practice skills they have learned from their surroundings [12]. Problem solving, language development, social integration and convergent thinking have been shown to develop through play [1].

The benefits of play can be divided into three categories: physical, social/emotional and cognitive. Figure 1.1 shows these three categories and some of the benefits that we will describe in detail.

1.2.1 Physical Development

Physical development refers to the process by which children learn how to use their bodies and develop motor skills. Play presents children with the possibility to explore the potential of their own bodies. It is linked to both the development and refinement of fine and gross motor skills and hand-eye coordination. While playing, children also develop competences that will help them feel secure and confident in the future. Activities such as carrying, running and rough-and-tumble play help develop and maintain muscular fitness and flexibility [2, 3].

Besides developmental benefits, physical play has also been shown to have health benefits. Physical play has been shown to help regulate body weight, blood pressure and cholesterol [13, 14]. Considering the obesity problem the world is facing [15, 16], encouraging physical play in children is important.

Figure 1.1: The physical, social, emotional and cognitive benefits of play.

1.2.2 Social and Emotional Development

Social and emotional development refers to the learning of values, knowledge and skills that are needed to interact with others in a healthy and positive manner. Play presents children with the opportunity to interact with people in a comfortable environment, which has important developmental considerations. Social skills such as coping with anxiety and personal conflicts, role taking or managing control over information have been shown to develop through play [4]. Children learn how to work in groups with other children, and develop tolerance, acceptance and understanding. In general, through play, they learn how to build social relationships and maintain social bonds [17].

Erikson discussed the importance of social interactions during play in the development of character [18]. In what he defined as *macrosphere play*, children try to master social interactions by playing with peers and demonstrating their command of social conventions and elements. Bandura stated that directly interacting with peers during play is not the only way of learning social interactions, since children can also learn social conventions by observing their surroundings [19].

One specific type of play that has been studied extensively in relation to social development is pretend play (fantasy play, role-playing) [5]. Pretend play requires children to exhibit complex social skills such as turn-taking and role enactment [20]. Children assume the role of both actors and directors of their own play; they need to plan roles, themes and settings while accommodating for the opinion of others [21].

1.2.3 Cognitive Development

Cognitive development refers to the growth in the ability of children to process information, perceive and understand their surroundings or communicate with others. Studies have found a positive relation between play and learning readiness [22] and language development [23]. When free play is allowed, children practice their planning skills when determining what to do, decision-making skills when several options are presented, and foster their creativity by coming up with new games and rules [17].

Play also helps children to understand how the world works. According to Piaget, thanks to actions such as grasping or stepping, children learn that they are part of the world, but at the same time, independent of it [24]. They learn that they can influence other objects through their actions (*i.e.* cause-effect relationships), mostly in a repetitive, trial and error fashion. Moreover, play allows children to adapt to the environment by incorporating new information (ideas, concepts) from the world, and fitting it into their mental models (*i.e.* the assimilation process) [25]. New information may also modify existing mental structures (*i.e.* the accommodation process). Play allows children to assimilate the new concepts, and provides a space where they can rehearse until they master them.

While Piaget argued development is, for the most part, the result of a child's independent exploration of the world, Vygotsky believed that social factors and their context contributed greatly to cognitive development. He defined the *zone of proximal development* as “the distance between the actual developmental level as determined by independent problem solving and the level of potential development as determined through problem solving under adult guidance, or in collaboration with more capable peers” [26]. Older peers, caregivers, or skilled tutors can help children complete tasks that would have been impossible for the child to complete alone. During this process, children can understand and internalize the knowledge that is being passed on, furthering their development.

1.3 Play in the Digital Era

Play commonly takes place at traditional playgrounds. These playgrounds are leisure spaces designed specifically to allow children to play. They are usually equipped with recreational equipment such as swings, seesaws or slides. Playgrounds are spaces where children can freely develop their motor skills while creating and maintaining positive social bonds with their peers and/or family [27]. Playing in such spaces, having the opportunity to interact physically and socially with peers without the imposed constraints of adults, is of critical importance for children [28].

Nowadays, children spend a lot of time consuming online digital media, and a considerable amount of this time is dedicated to digital gaming [29]. Most young people play video games at least occasionally, and many, especially boys, play them on a daily basis [30, 31]. This has resulted in a major shift in children's lifestyles, and the consequences of this trend are increasingly becoming apparent. In regards to the social aspect of play, there is an alarming trend of children playing “together and apart”, playing games with others but not directly interacting with them [32].

Regarding the physical aspect, studies have shown increasing sedentary behavior of young children in western cultures, which is associated with digital games [33].

1.3.1 Interactive Games

Playing digital games provides certain benefits. For instance, digital games have been shown to improve players' reaction times, hand-eye coordination or attention allocation [34]. Digital games are also suitable for keeping players motivated and engaged. Therefore, novel types of games have been introduced that retain certain elements of digital gaming through the use of interactive technology. These games attempt to solve, or at least mitigate, the problems caused by digital gaming. These games are termed "interactive games", and aim to promote physical activity [35], encourage social interactions [36], or steer behavior in positive directions [37]. The technology employed in these games varies greatly, ranging from interactive toys [38] to full-blown interactive installations [39]. In general, players' body movements become an important element of the game experience.

The technological elements that are used in interactive games can be classified as sensors, actuators and logic processors. Sensors are used to obtain information from the environment and the players therein, and include cameras and touch-sensitive surfaces. Actuators are elements such as projectors, speakers or lights, that are used to provide feedback to the players. The logic processors are the "brains" behind the game that gather the information from the sensors, process it, and decide on the feedback to be given to the players via the actuators. Consequently, there is a feedback loop between these three elements in which the data is measured, processed, acted upon, and measured again.

Most of these interactive games are classified in the literature as one of three types: playware equipment, exertion games and interactive playgrounds. The distinction is given based on the goal of the game, the equipment used, and how players are meant/allowed to play in/with it. Nowadays, the boundaries between interactive games are blurred, as some games can have elements of multiple types. We describe each of the categories.

Playware refers to both hardware and software designed with the goal of producing playful experiences among its users [40]. This definition is very broad and includes almost anything designed purposefully to enable play (including video games). Therefore, for the scope of our thesis, we will refer to playware as gadgets or technologically enhanced toys aimed at enhancing the play experience of its users. These intelligent toys are usually small, and can be designed as armbands with radio-frequency identification (RFID) tags [41], interactive cylinders with LEDs and motion sensors [42], or swings with speakers and lights [43]. They can also be designed to communicate with each other, enabling the possibility to create a network of intelligent sensors [44]. Their complexity varies greatly, ranging from pressure sensors with LEDs to social robots that are capable of playing with people [45].

Interactive Playgrounds (IPs) are interactive installations that aim to combine traditional play with interactive elements to retain all the benefits of traditional

play, while enhancing the engagement, entertainment and immersion of the players [37, 46, 47]. IPs are, in general, room-sized installations where multiple players play co-located, using natural interactions as input for the system. Therefore, the body of the player becomes an integral part of the interaction. Some examples of IPs are interactive slides where children slide down to interact with game elements [48], or rooms with cameras and projectors where children can run freely and interact with elements projected on the floor [49]. Interactive playgrounds can be placed in various locations such as schools [38], public spaces such as streets or stairs [50] or sport facilities [51].

Exertion Games are games where the physical effort of the players is the core part of the experience [52]. They are designed to promote physical activity while providing a fun, engaging user experience. Many of these systems are designed to promote specific types of movement. For instance, heart rate measurements and audio feedback have been used to enhance jogging [53], projections to promote jumping and arm stretching [54], or augmented gloves and projections to encourage hitting [55]. Other systems try to enrich the experience of training sports [56, 57]. In general, games that promote full-body movement have been shown to generate higher levels of exertion [35], followed by those where lower-body movement was encouraged [58]. Similarly to IPs, the size of the installations can vary greatly, but are not necessarily co-located. Exertion games are also known as exergames or active video games (AVGs) [59].

1.3.2 Goals and Opportunities of Interactive Games

Interactive games are typically designed to provide a fun and engaging game experience but usually support other goals at the same time. These goals can be related to encouraging positive, healthy behavior or discouraging negative aspects of children's play. We discuss the most common goals as well as how they can be achieved.

1.3.2.1 Engagement and Fun

Interactive games commonly aim to elicit happiness in the players by providing a fun experience. In the case of children, this might be easier as they are more open to new technology, particularly when it includes novel means of interaction and visualizations [60].

One way of providing an engaging experience is to emulate an already fun game, using technological additions to enhance the experience. For instance, Mueller *et al.* augmented the game of table tennis to allow players to compete with two other players in different locations [61]. Avontuur *et al.* augmented the game of tag by using devices that vibrated and signaled that a player had the “buzz”.

Another method to keep the players engaged is to change how the game is played over time. This provides variety to the game, retaining the attention of players for longer periods time, since games that lack diverse interaction opportunities or adaptive gameplay mechanics can become boring over time [62]. For instance, Stockhausen *et al.* changed gameplay elements using heart rate measurements in the “Beats Down” mobile game [63]. This “whack-a-mole” type of game required players to tap

tiles that flashed randomly for brief moments. Heart rate affected how many points the player could get when tapping the tiles, and the duration of the tile flashing. Another game that used heart rate measurements to change gameplay was the “Webz of Wars” game by Navarro *et al.* [64]. In this game, a player’s upper body motion was tracked with a Microsoft Kinect, and the players used a Nintendo Wii Balance Board to move in the virtual environment. Using heart rate monitors, the game scaled a player’s attack power depending on his heart rate.

Sometimes, to keep players engaged, it is enough to present the “promise” of fun, the opportunity to have a good time and appeal to the creativity of the players. This is known as open-ended play. For instance, when colored shapes are projected on the floor, players may be drawn to chase and stomp them [65] or to swim on the floor amidst them [66] even when the shapes themselves are simply there, without a specific purpose. When given a slide, children will go up and down until they are exhausted [48]. When presented with interactive objects that support open-ended play, they will explore and find many different ways of using them [38].

1.3.2.2 Physical Activity

Encouraging physical activity can be achieved by adding elements that motivate players to explore and interact in a physically active way (e.g. running, jumping, climbing). Several studies have shown that interactive games help, sometimes only slightly, in improving the overall health of players, especially when compared to sedentary digital gaming [67, 68].

Physical activity can be encouraged in different ways. One method to promote it is to engage players in running. For instance, Soler and Parés designed the interactive slide: a big, inflatable slide that allowed children to slide down while a game was projected on its surface [48]. The children were observed by cameras and could interact with the projected elements. Within one game, the children had to slide down, climb, and slide down again several times in quick succession. Tetteroo *et al.* also used projections to steer players into running around in an interactive playground [65]. The installation used a top-down projector setup to display colored shapes on the floor of the playground. The colored shapes moved around the play area, and when children moved within the vicinity of one, it began to follow them.

Other game installations are not designed to allow players to run around, but still require full-body movements to interact with the game. For example, van Delden *et al.* designed a game that promoted body movements while trying to evoke the feeling of being suspended in mid-air in the “Hang in There” installation [69]. Players were suspended from a climbing harness and moved on a tilted platform while a game was projected in front of them. Besides lateral movement, the player also needed to flap to move vertically in the virtual world. Another example is the “Hanging off a Bar” game, where a flowing river with floating rafts was projected on the floor [54]. The game required players to hang from the bar most of the time. Sometimes, a raft floated by, allowing players to drop down and stand on the ground to rest. However, they had to hold onto the bar again once the raft had drifted down the river.

Some installations use the adaptation of game mechanics based on a player’s fitness level to promote physical activity. Derakhshan *et al.* presented an interac-

tive playground that consisted of tiles that children could step on and interact with through force sensors and LEDs [70]. They used neural networks to learn and model different types of game styles, such as fast, slow, or continuous. These styles were subsequently used as a basis to vary the amount of physical activity that the children had to engage in during the game. Stach *et al.* also showed how feedback could be adapted to promote a higher amount of activity in the “Heart Burn” racing game [71]. In this game, players needed to pedal on a stationary bicycle to speed their virtual vehicles, but instead of measuring their cycling speed, their heart rate was measured. Thus, the game did not evaluate how fast you could cycle, but how much effort you were putting in. This meant that players always needed to exert themselves, irrespective of their fitness levels.

1.3.2.3 Social Interactions

Interactive games can be designed to bring players closer together and trigger social interactions amongst them [72]. They should encourage positive behavior and discourage negative behavior. In traditional play settings, teachers or trainers supervise children and perform this task. In interactive games, it might be a functionality of the system.

A common type of interaction that people engage in is competition. Often, competition is achieved by striving for conflicting goals, such as competing for a limited number of resources [65]. For instance, the “TacTowers” training equipment set two athletes against each other by illuminating plastic balls that could only be interacted with by one person [51]. In this case, the first one to touch the ball scored a point. In a similar fashion, Toprak *et al.* designed “Bubble Popper”, a game where two players competed over colored bubbles projected on a wall [55].

Interactive games can also be designed to persuade children to cooperate, to work together towards a common goal. The augmented reality racing game “Scorpiodrome” encouraged cooperation by having the children assemble the track and landscape together [73]. Parés *et al.* designed an interactive installation that focused on cooperation by encouraging people to communicate and work towards a common goal [74]. “Water Games” consisted of several water fountains where each could be activated by forming a closed ring of people around it. Once the ring was formed and closed, players had to move in unison in one direction for the fountain to become active.

1.3.2.4 Education and Learning

Play can be used to enhance learning for people of all ages [75]. As such, interactive games can serve as mediums that support specific educational themes and goals like learning math or words. For example, Charoenying *et al.* developed an embodied game called the “Bar Graph Bouncer” [76]. They aimed at supporting children’s ability to conceptualize numbers and interpret graphs. Children were presented with an animated scene that responded to jumping. As children jumped, their corresponding bar grew in the animation, facilitating the understanding of correlation between the jumps and the bar.

Interactive games can also provide an environment where children can experience and practice skills they have learned before without stress or pressure. For example, Carreras and Parés created the “Connexions” playground for Barcelona’s Science Museum [77]. This interactive playground used floor projections to visualize concepts (represented as nodes) about a particular (hidden) object. When children stood on a node, the node started to glow if it was related to the hidden object. Children could activate the different nodes and connect them to each other, facilitating the abstract understanding of science being a network of knowledge. The “Wisdom Well” was another example of learning through interactive games [78]. This playground supported three types of applications for learning through kinesthetic interaction. The game allowed children to communicate and cooperate while interacting with simulations about geometry, physics and geography.

1.3.2.5 Rehabilitation

The possibility of addressing cognitive and emotional processes during the intervention duration [79] makes interactive games an attractive tool in the rehabilitation of disabilities. Rehabilitation programs are often long and cumbersome, leading to frustration, loss of motivation and even abandonment. Interactive games can maintain the motivation of patients for longer periods of time, promoting improved performance [80] and leading to better functional recovery [81]. For instance, Lange *et al.* showed that techniques to improve balance training could be implemented into a game that used the Nintendo Wii Fit Balance Board [82]. Friedman *et al.* designed a game that made use of a sensor-equipped glove to train functional hand movement for stroke victims [83]. The patients that tried the system scored higher in hand motor performance and also evaluated the game higher in training motivation when compared to traditional therapy.

1.4 The Study of Play

We can see that interactive games address problems that were introduced by digital gaming (Section 1.3). Digital gaming led children to adopt sedentary lifestyles, whereas interactive games try to promote physical activity. Digital gaming has encouraged solitary play habits, interactive games promote social interactions between players. To evaluate whether these games are actually able to achieve their set goals, the behavior of the players while playing these games needs to be studied.

It is surprising, then, that given how far back the study of play goes, the methods used to study behavior in interactive play settings are largely the same as those ones used in traditional play settings. These methods consist mostly of external evaluations such as direct observation of game sessions, proxy reports, offline annotation of recordings, or asking participants to assess their own experience through questionnaires [84, 85]. Many of these interactive systems are capable of analyzing information, interpreting signals and making smart inferences based on the data that is gathered. However, the information is mostly used to drive game interactions [85] rather than for the analysis of the exhibited play behavior.

We could significantly improve our understanding of play by harnessing the potential of new technology to analyze player behavior during games. This knowledge could help in the design of games that can, for instance, enhance the game experience, adapt the difficulty of games to aid less skillful players, recognize specific player behavior or objectively evaluate high-end goals such as physical activity. In this thesis, we will look into the use of technology to unobtrusively sense and analyze play behavior in interactive game installations (see Figure 1.2). To do this we developed an interactive playground in which we measure players' behavior unobtrusively. This playground is used to research how we can enhance the game experience, but also doubles as a tool to automatically analyze aspects of play behavior in an objective manner.

Figure 1.2: Behavior sensing, analysis and steering loop in an interactive game installation. This thesis focuses on the study of the right side of the cycle (sensing and analysis).

The topic of this thesis is the study of automated, unobtrusive observation and analysis of play in an interactive playground. To accomplish this, we will focus on three concrete tasks:

Enhancing the game experience Technology can be used to enhance the game experience of interactive games. During this process, key aspects of play, such as promoting physical activity or social interactions, can be lost. Enhancing the game experience can be achieved not only by making the game more engaging or immersive, but also by addressing players' (or the game's) limitations.

Goal 1 (G1) *Design an interactive installation that provides an engaging experience while still allowing players to exhibit physically active and social behavior.*

Facilitating the behavior analysis process Traditional player behavior analysis methods revolve around recording game sessions or subjective evaluations (e.g. questionnaires, interviews). These can provide personal and detailed information on the players, but not during the game session. In-game objective evaluation is possible when players wear sensors such as heart rate monitors, accelerometers or pedometers. These can sometimes be uncomfortable for the players, or require someone to hand out and retrieve the sensors. This is not the case for unobtrusive methods of behavior analysis.

Goal-2 (G2) *Design an interactive installation that simplifies the procedure by which play behavior is unobtrusively measured and analyzed.*

Analyzing player behavior Sensors in interactive installations are typically used to drive game interactions. In addition, the data could be used to understand how games are played, tailor or adapt game mechanics, or aid in the evaluation process of these installations. In this thesis, we focus on the following three goals.

Goal-3 (G3) *Measure physical activity automatically and unobtrusively in our interactive installation.*

Goal-4 (G4) *Analyze social behavior automatically in our interactive installation.*

Goal-5 (G5) *Automatically recognize a set of pre-defined player roles in our interactive installation.*

1.5 Structure of this Thesis

This thesis is divided into four parts (see Figure 1.3). The first part is an introduction to the different research fields related to our work. In this chapter, we have introduced play and motivated its importance in the development of children. We have also summarized what interactive games are currently capable of and presented our research goals. In Chapter 2, we will present ways in which technology could be used to measure, analyze and interpret behavior in games. We will discuss current research endeavors in this topic. Following this, we will discuss ways in which this could be used to improve current interactive installations.

In Part II of this thesis, we will describe the design, development and evaluation of the Interactive Tag Playground (ITP), the interactive installation used in our studies. In Chapter 3 we will look at the game of tag, a traditional playground game used as the basis for our installation. We will present a dataset of children playing different versions of tag, and analyze the behavior of the players to identify important traits in their play behavior. We will also discuss some challenges we encountered during the recording and analysis of the game sessions. In Chapter 4 we will describe in detail the design and development process of the ITP. We will motivate our design decisions, based both on insights of the analysis of tag behavior and characteristics that we envision for our installation. In Chapter 5 we will evaluate the ITP to find

out whether it provides an engaging and fun game experience while still allowing the players to exhibit physically active, social behavior.

Part III will contain our studies into the objective analysis of play behavior in the ITP. In Chapter 6 we will demonstrate the potential uses of the ITP as a research platform. We will use the Play corpus and two datasets of interactive tag sessions to compare player behavior in traditional tag games and interactive tag games. Chapter 7 will introduce our method to measure physical activity in the ITP. We conducted a user study with young adults and used the speed of the players to measure their amount of physical activity when changing a game element. In Chapter 8 we will present our user study on the analysis of children's social behavior in the ITP. Using the position of the players in relation to each other, we analyzed how social interactions change based on gender and age during interactive tag games. Chapter 9 will contain our models to recognize player roles in the ITP. We will present two models that determine pairwise interactions between the players, and then classify the role of the player. We tested our models using a dataset of interactive tag sessions.

Finally, Part IV (Chapter 10) will conclude this thesis. We will summarize our contributions, limitations and discuss avenues for future research.

Figure 1.3: Outline of this thesis.

2

Automated Behavior Analysis in Games

In this chapter, we will give an overview of current research endeavors in different fields that could help us to sense and analyze play behavior during games. Following this, we will discuss how the presented techniques could be used in interactive game installations. The structure of the chapter is as follows: Section 2.1 will present an overview of technologies used in the sensing and analysis of bodily behavior. We will focus on the visual analysis of behavior, but will also present studies that employ other commonly used sensors. We specifically cover how both approaches have been used to analyze behavior in games. In Section 2.2, we will discuss the requirements needed to apply the presented techniques in interactive playgrounds. We will also discuss their potential uses and limitations.

2.1 Sensing and Analysis of Behavior

The nonverbal behavior of a person represents both the way in which a person acts or conducts himself in a given situation, and how his body responds to stimuli in a particular context. In this chapter, we will focus specifically on the analysis of body motion as a means to study human behavior. The analysis of body motion encompasses the detection, tracking and interpretation of human behavior based on data derived from the human body [86]. Since the range of motions that the body can exhibit is very broad, many different cues can be analyzed from it [87]. Thus, we will focus on the analysis of two aspects: position/tracking and body movement. The former refers to the localization of a person over a period of time, whereas the latter refers to specific movements, or a sequence of movements, of body parts.

More specifically, the position of a person refers to the location of the person within a given reference frame. Being able to reliably determine the position of a specific individual in time is called “tracking” this individual. On the other hand, body movement is usually studied at three levels: action primitives, actions and activities [88]. Action primitives consist of atomic body movements such as “moving an arm”. Actions are composed of several coordinated action primitives such as moving the arm and clenching a fist. Lastly, activities are made up of several actions and are used

to describe high-level scenarios, such as punching and kicking someone may describe “fighting”.

Behavioral analyses can be carried out considering the behavior of individuals as isolated from their surroundings, but studies have shown that human behavior is affected by the behavior of people around us [89]. This means useful information is lost by ignoring a person’s movement in relation to others. Consequently, many studies nowadays focus on the analysis of group behavior, for instance to analyze pedestrian movement [90] or determine group activity [91]. By considering people as members of a group and taking into account social information (*i.e.* social cues), it becomes possible to investigate the influence that social cues have on human behavior. These studies focus on the sensing and interpretation of “social signals”, elements that humans use when communicating non-verbally. Many researchers refer to this approach as Social Signal Processing (SSP) [92, 93].

A social signal is defined as a “communicative or informative signal that, either directly or indirectly, conveys information about social actions, social interactions, social emotions, social attitudes and social relationships” [94]. Social signals are essential to function socially, conveying our attitudes in social contexts [95, 96]. Social signals are often ambiguous and their interpretation depends on the environment, inherent uncertainty of recognition algorithms or the joint analysis of cues exhibited at different time scales [97, 98]. Context has a big influence on the social signals people elicit, and this variation is one of the key challenges in SSP [99]. The most relevant social cues related to the analysis of bodily behavior in interactive playgrounds are kinesics [100], and proxemics [101]. We briefly discuss them below.

Kinesics refers to the study of body movements as a mode of communication, *i.e.* body language [100]. Important kinesic cues are postures and gestures. The former refers to static body configurations, while the latter are movements of the body over time, typically performed with the hands or arms. Both can have a communicative and/or affective meaning [92]. For instance, a thumbs up gesture is normally considered to be a show of appreciation [92]. Besides the conscious display of body language, body movements are also exhibited unconsciously. Recent studies demonstrate that affect can be estimated from body postures and movements to some extent [102]. This requires the numerical analysis of body postures, from video or depth sensors [87].

Proxemics refers to the study of how people utilize the space around them in social settings, that is, how they group together and arrange themselves [101]. This includes not only the distance between individuals, but also the physical arrangement of groups. The idea that personal space is negotiated between individuals during interaction dates back to Argyle and Dean [89] who observed that two people dynamically adapt their physical proximity, postures, gestures and gaze depending on the level of intimacy between them. Excessively close proximity results in the adoption of indirect body orientation, avoidance of eye contact, the use of objects (including the body) to create barriers and eventual flight from the invader [103]. Hall [101] also observed that people adjust their physical distance to others based on their social distance. He proposed four concentric circles that each person regulates when interacting. The inter-personal

distances range from personal to public relationships, and are maintained even when space constraints change [104]. Amaoka *et al.* observed that the space that people regulate around them depends also on the speed of movement and gaze direction [105]. This gives rise to a redefinition of the concentric circles to be more egg-shaped.

We present an overview of the techniques used for the automated analysis of social cues. Due to the pervasive and unobtrusive nature of camera measurements, we will focus on the visual analysis of behavior. We will also describe the analysis of behavior using other sensors. For both, we will explain how these cues are sensed and analyzed in games.

2.1.1 Vision-Based Behavior Analysis

Vision-based behavior analysis refers to the understanding of behavior using solely images, either recorded or from a live-video feed. It has proven to be a challenging and interesting problem in computer vision research. Its applications, such as pedestrian tracking or activity recognition (see [106, 107] for overviews) extend to diverse settings such as public spaces [108], political debates or conference rooms [109]. The benefit of using vision to track or analyze body movement is that no sensors need to be worn, allowing for a completely unobtrusive sensing of behavior. On the other hand, the analysis of behavior is complicated by variations in lighting conditions and movement. Dark environments, for instance, are difficult to process using standard cameras since the images do not have a lot of information to work with. Also, the way in which actions are performed may vary between people. For example, a person may greet someone by shaking hands, whereas someone else might just give a slight nod. Even the shaking of hands can be done at different speeds or with different intensities. In consequence, the algorithms used to analyze behavior are usually complex.

Most of the work that addresses the automatic visual processing of social cues is carried out in controlled environments such as meeting rooms, offices or debate stands [110]. Most of these studies analyze face-to-face or small group interactions since they represent the most common forms of interaction [111, 112]. More recently, researchers have started exploring the analysis of social cues in surveillance settings, where cameras are located at considerable distances from the subjects [110, 113]. For instance, a specific application of proxemics research is the analysis of a group structure known as ‘F-formation’, which “arises whenever two or more people sustain a spatial and orientational relationship in which the space between them is one to which they have equal, direct, and exclusive access” [114]. F-formations represent common patterns in which people arrange themselves when in social settings and which give all participants the possibility to maintain eye contact with the other group members. This information has been used recently to identify groups in social settings based solely on people’s positions and orientations [115, 116].

Being able to detect groups and analyze group behavior hinges on the ability to track the individuals that make up a group, and tracking these individuals has also benefited greatly from the modeling of social cues [110]. Chen *et al.* detected pairwise groups based on the fact that people that walk together tend to stay together

[117]. Then, they found optimal ways of coupling these elemental groups based on time, appearance and motion for multi-target tracking. Yamaguchi *et al.* also modeled social factors but took into account environmental cues such as potential destinations in a scene and collision avoidance to improve their tracking method [118]. Alahi *et al.* proposed the use of social affinity maps (SAM) to predict the destination of people in densely crowded spaces [108]. SAMs are derived from proximity analysis of pedestrians, following observations that social forces are mostly determined by proximity. In other words, the closer two individuals are, the more they affect each other. Similarly, Feng and Bhanu exploited the relationship between group members to improve the tracking accuracy of multiple people using tracking interaction networks [119]. Ge *et al.* also proposed a tracking method for small groups, but in crowded scenes and using clustering to find the groups [120].

Making use of social cues has not only aided in tracking people, but also in the recognition of individual, pairwise and group activities. This is done by looking at the relative movement direction or speed between individuals, or how close they are to each other in time. For instance, Bazzani *et al.* identified people who belonged to a group by regarding interactions as important cues [121]. They used an approximation of a person's visual field of view, along with interpersonal distances, to estimate interactions between individuals. In a related study, they also identified when groups were formed, maintained and dismissed [122]. These studies exploited the predictability of human movement, which has also been used in several studies to recognize group activities such as fighting, walking in groups and queueing [123, 124]. Choi and Savarese presented a framework to model some of such collective activities [125]. They estimated not only atomic activities but also pairwise relationships between individuals such as approaching or facing each other. Tran *et al.* also proposed an algorithm for group activity analysis that makes use of a grouping method based on social interactions [126]. They clustered people based on the amount of interaction to find relevant groups, and later classified activities based on their poses and motion within the group. Using a slightly different approach, Chang *et al.* proposed using proximity, not levels of interaction, to define groups in their probabilistic model for scenario recognition [127]. They used weighted connection graphs to define group memberships, and recognized scenarios such as flanking or loitering.

2.1.2 Non-Visual Behavior Analysis

Although vision is used extensively to study behavior, there are certain cues that are not easy to measure visually (e.g. heart rate or blood pressure). Consequently, in some circumstances, using sensors such as accelerometers, heart rate monitors, or capacitive sensors can prove more practical than using vision. Many of these sensors are small and portable. Nonetheless, certain sensors need to be worn, which can cause discomfort or unnatural behavior. Also, for certain activities, the sensor's output can change depending on where it is placed [128].

Tracking people and group behavior analysis can be accomplished using sensors that provide information about a person's location or his surroundings. For example, De la Guía *et al.* used RFID technology to locate people and improve the user interaction in smart environments [129]. They showed how, by embedding RFID tags

in art pieces and physical surfaces (*e.g.* walls, tables), people could be tracked and shown specific information. Hung *et al.* experimented with a single accelerometer to recognize F-formations by exploiting similar actions in social groups [130]. The accelerometer was worn around the neck, and was able to recognize social behavior such as drinking or laughing. By looking at the coordinated behavior of people, they identified who belonged to which group.

Although position is an important cue when analyzing behavior, the actions people perform are also relevant. Since sensors can be worn by people or equipped on certain items, they can be useful in recognizing actions. For instance, Cheng *et al.* explored how wearable textile capacitive sensors could be used to provide information on complex activities by wearing them on different parts of the body [131]. They attempted to recognize swallowing when the sensor was worn in the neck, heart rate measurement and breathing when worn on the wrist, and gait analysis when worn on the ankle. In contrast, Khan *et al.* tackled the recognition of daily activities using smartphones, but proposed a position-independent method that could work irrespective of where the phone was carried [132]. They were able to recognize activities such as resting, walking or running. Instead of equipping people with sensors, Möller *et al.* equipped fitness equipment with a smartphone for the monitoring and assessment of training [133]. The system was able to provide a quantitative analysis of the quality of training, identifying ways in which performance could be improved.

2.1.3 Behavior Analysis in Games

Game settings can vary greatly, from professional sport scenarios, where automatic behavior analysis has been used to aid in understanding team strategies [134, 135], to playground/children's games such as tag or peek-a-boo, where roles or actions have been automatically detected [136, 137]. For instance, Rehg *et al.* used Kinect sensors and microphones to analyze dyadic interactions between adults and 1-2 years old children during simple children games [138]. They employed face recognition to detect when children were smiling, and head tracking from the Kinect, along with information from regular cameras, to sense when the child made eye-contact with the adult. Tian *et al.* automatically labeled the type of play exhibited by children during simple group play [139]. They analyzed the interactions between the players, and the focus of their visual attention, to classify the type of play into solitary, parallel, and group play.

Following the scope of our research goals, we will focus on games that promote physical activity (*e.g.* running, jumping) and social interactions (*e.g.* team games).

2.1.3.1 Visual Behavior Analysis in Games

Tracking in sports and games requires a different approach than in related fields where motion can be more predictable, such as in pedestrian tracking. See [140, 141] for overviews in pedestrian and sports tracking, respectively. In many of these studies, it is assumed that proximity is a strong cue in both the identification of groups, as well as in the recognition of collective activities. In game settings, such assumptions are typically violated. For instance, in soccer games, two players in close proximity

are likely not from the same team. Moreover, the movement exhibited by players is much more varied. For example, players can have outbursts of speed or a sudden change of direction to perform specific actions such as dodging an opponent. Being unpredictable and able to change motion suddenly is often a desirable characteristic.

Tracking in games can be improved by taking into account the game's state. For instance, Lucey *et al.* showed that knowing the role of a player (defender, attacker) can aid the tracking process in field hockey matches [142]. Although teams can adopt many different formations, all are comprised of specific roles and their associated behaviors, which can reduce the potential number of locations where players can be located. Moreover, the opposing team players' locations can be used as well, since they need to guard their opponents and thus stay close to them. Liu *et al.* argued that simple, independent models are not powerful enough to track basketball players optimally [143]. They introduced context game features such as absolute or relative occupancy maps, to model player movements conditioned on the state of the game.

Once a player's track information is estimated, the player's behavior can be analyzed. Kim *et al.* predicted interesting moments in soccer matches based on how the flow of movement converged [144]. They assumed that the motion of every player is related to the motion of the surrounding players. Even though an individual player's behavior is complex, actions of nearby players can aid in recognizing it. Similarly, Lan *et al.* recognized activities in field hockey matches by analyzing low-level (*i.e.* actions) and high-level (*i.e.* events) information, based on player locations [145]. Sun and Chen used player tracking and knowledge of the players' attributes to suggest optimal defense formations in basketball matches [146]. By estimating attribute vectors for each player, they could infer how effective they were going to be depending on their position on the court (*e.g.* a high three-point shooting rating is useless inside the key).

Tracking players is not always required to understand games. Lucey *et al.* tracked the ball instead of the players in soccer matches [135]. They estimated the amount of ball possession a team has accumulated in any given part of the court to recognize home and away behavior for teams. Completely circumventing the need for tracking is also an option. Motivated by the inherent difficulties in tracking, Khokhar *et al.* used a spatiotemporal description of the events to classify activities [147]. They presented a method for multi-agent activity recognition that extracts motion patterns using optical flow, clusters them, and uses them to build a graph which describes the activity. They recognized activities in American football matches such as middle run and short pass.

2.1.3.2 Non-Visual Behavior Analysis in Games

Detecting and tracking players using sensors is a common method to analyze player behavior [148]. Outdoors, the easiest way of doing this is using GPS sensors (see [149] for a review). For instance, Brewer *et al.* used GPS to track elite and sub-elite Australian football players and compare their performance [150]. They found that physical demand was higher for elite players, and that certain roles/positions covered more distance than others. Similarly, Wisbey *et al.* used GPS to quantify movement of Australian football players, but compared recorded data from different years [151].

They discovered that physical demands had increased with time, evidenced by an increased player exertion index and distance covered. Indoors, the accuracy of GPS sensors drops, thus requiring the use of different sensors. Hedley and Zhang proposed a wireless ad-hoc system for positioning (WASP) to provide highly accurate detection of players in sports [152]. In the same vein of research, Michelsen *et al.* proposed using a sensor network to stream data for sport analysis in games [153].

Some studies do not rely on player detection and position tracking, but use cues related to body movement to analyze behavior. For example, Ghasemzadeh and Jafari used a body sensor network to analyze and correct baseball swings [154]. They used a swing model that evaluated whether different limbs moved at the correct time and in the correct sequence. Also related to baseball, Lapinski *et al.* used accelerometers, gyroscopes and a compass to analyze pitching and batting [155]. They presented valuable insight into the bio-mechanical information obtained during both tasks. Gageler *et al.* used inertial sensors to automatically recognize jumps in volleyball and measure the time of flight of players [156]. Their method performed well when compared to video analysis. Motion capture equipment is another option that can be explored to analyze behavior in games and sports [157].

2.2 Enhancing Interactive Playgrounds using Behavior Analysis

Using automated sensing techniques we can enhance what interactive games are currently able to do (see Section 1.3.2). Since the focus of our research is on interactive playgrounds, we will limit our discussion to how we could take advantage of the presented studies in IPs. We will first present different methods to improve IPs using sensor technology. Then, we will discuss what would be needed to implement these ideas.

2.2.1 Opportunities for Behavior Analysis in Interactive Playgrounds

Player behavior information can be used to improve certain methods or processes currently employed in interactive playgrounds. For instance, by recognizing the behavior of players, the way in which certain goals are achieved could be made more effective. Also, since information is gathered during the game rather than afterwards, new interaction possibilities are available. We first describe how behavior sensing could be used to adapt game mechanics. Afterwards, we propose ways in which player behavior analysis could aid in the evaluation of interactive playgrounds. Finally, we discuss how sensing behavior could be used to detect anomalous events during games.

2.2.1.1 Game Mechanics Adaptation

As seen in Figure 1.2, behavior steering results from changing the game mechanics. Through sensing, we obtain information about player behavior in-game, and upon its analysis, decisions on how to change the game mechanics can be taken during the game.

One strategy for gameplay adaptation is to change the game mechanics when specific events or behaviors are observed. This strategy is especially useful when behavior

is sensed that should be stimulated or discouraged. This might be the same behavior for all players, or different types of behavior depending on the specific player. For instance, we found that rough-and-tumble occurred often in an interactive playground because of gameplay that favored competition [66]. Sometimes, this behavior evolved into aggression, which should be discouraged. Upon the detection of rough-and-tumble, the game mechanics could be changed towards more passive or collaborative play to prevent further hostility. In this approach, thresholds for the detection of aggression might differ between players. For instance, boys engage in more rough-and-tumble play than girls [158], without this implying overt hostile behavior when boys play in comparison to girls.

Another strategy for gameplay adaptation is to create personal user profiles to adapt game mechanics to meet the player's expectations or style of play. The benefit of user modeling, personalization and consequent adaptation is that players can be kept immersed in the experience by balancing challenge and success [159]. This can be achieved by developing models that reflect the player's behavior or preferences. Derakhshan *et al.* used a platform that could recognize several player styles based on tempo, age and continuity of play [70]. The tempo of the game was adapted, along with other characteristics, to match what the player felt comfortable with to successfully promote physical activity. Shaker *et al.* organized a competition where participants had to use artificial intelligence methods to design levels for a given game [160]. One method chosen by a participant generated the levels based on a player profile created during the training period. If the player had performed well in the training phase, the level contained more enemies, whereas for those who performed badly, the number of enemies was decreased.

Lastly, both strategies could be combined to adapt gameplay. In this situation, the playground learns about players during the game and applies this information in later sessions while still reacting to certain events. If a play session is long enough, the playground could learn the player's profile and personalize the game during the same playthrough. This would be specially suitable for players that need special care, since the sensed behavior could be used to adapt the game when they are feeling discomfort.

2.2.1.2 Objective Evaluation of Goals

To determine whether interactive playgrounds have met their goal of providing the players with rich experiences, the interactions in the playground need to be evaluated quantitatively or qualitatively. In addition, other goals such as the promotion of specific behavior could be evaluated as well. Current playgrounds are usually evaluated using self/proxy-reports, group discussions or observational studies [85, 161, 162].

Promoting physical activity and social interactions are goals that are commonly sought after in interactive playgrounds. Annotation schemes [66, 84, 163] and questionnaires [164] are the typical tools used to evaluate these goals. The information derived from these methods is usually available after, but not during, the game session. For instance, the annotation procedure of the Play Observation Scale (POS) (Figure 2.1) [163] involves observing a child for ten seconds, and then selecting the predominant behavior within this time lapse from a list of predefined actions. The

Figure 2.1: Play Observation Scale composition.

Figure 2.2: Outdoor Play Observation Scheme composition

procedure prescribes that no child should be observed for more than five successive minutes to prevent a bias in the coding. In total at least 15 minutes should be analyzed, thus several sessions are needed to be able to evaluate a single child. In the Outdoor Play Observation Scheme (OPOS) (Figure 2.2), two different types of approach are considered: event coding (frequency-based approach) and state coding (duration-based approach) [84]. Event coding is related to event-sampling (*i.e.* registering specific point-events such as yelling). State coding refers to actions that are continuous in nature, or at least have a measurable duration such as running. The annotation is made on a per-child basis. We proposed an annotation scheme with a strong focus on social behavior during play based on previous schemes and observations of children playing [66]. Observations are carried out per child and, depending on the nature of the behavior being exhibited, time slots or event coding is used.

As can be seen, annotation schemes require observers to categorize specific actions during play, usually from game recordings since live annotation is difficult. Also, even though annotators undergo training to be able to agree on the items being annotated, differences in opinion can still be present and need to be accounted for. Questionnaires are filled in before or after game sessions, but their content needs to be processed before it can be used. Additionally, when dealing with children, questionnaire results are not entirely reliable [165, 166]. Interactive playgrounds could aid in evaluating whether goals have been achieved. For instance, the amount of body movement has been found to correlate positively with the players' perceived level of engagement [167]. Therefore, automatically measuring body movement could potentially be used to evaluate user experience.

2.2.1.3 Recognition of Deviant Behavior

In addition to the measurement of specific goals, the sensing capabilities of interactive playgrounds could also be used to identify when a player's behavior deviates from normal. For instance, IPs could be used to detect cheating or aggression during games by looking for deviations in expected player behavior. This would be especially suitable for games where roles are well defined. IPs could also be used to diagnose, at an early stage, certain behavioral disorders such as autism or mental retardation since they have been linked to children who fail to engage in social interaction during play, or show irregularities while doing so [168].

2.2.2 Requirements for Behavior Analysis in Interactive Playgrounds

To interpret a player's behavior we need sensors that can, at the very least, capture a player's location and body movement in sufficient detail. These sensors need to be embedded into the environment to prevent them from hindering or distracting the players. For instance, equipping players with microphones facilitates the measurement of vocal cues, but may restrict the movement of the players as they typically run, crouch and bump into each other during play. Instructing them to mind the microphones would prevent them from playing as they normally would, diminishing the levels of engagement and immersion. The same line of thought applies to equipping players with actuators. Players could become mindful of their movements, affecting the way they play.

2.2.2.1 Pervasive Sensing

Cameras can be used in interactive playgrounds to measure grouping, position and interpersonal distances in an unobtrusive manner. Several types of cameras are currently available, each suitable for particular settings or to achieve particular goals. Infrared cameras are useful in low-illumination conditions or with infrared markers [169]. Stereo vision and time-of-flight cameras are capable of estimating depth values, which facilitate the segmentation of foreground objects and therefore the recognition of players and their actions [69, 170].

Ambient microphones could be used to obtain the level and type of sound present in the whole playground, such as yelling or singing, as indicators of fun, immersion and engagement. In addition, they could be used to analyze patterns of imitation and synchrony. Another option is to embed microphones in toys such as stuffed animals to record specific sounds [171]. Multiple microphones could be employed to locate the source of a sound. This could be useful for the localization of players in environments where cameras cannot be used.

Sensors can also be embedded into the environment or the objects therein, providing information unobtrusively. Pressure sensors, for instance, have been embedded in many different kinds of objects such as stairs [50], building blocks [40], mats [172], walls [173] or floor tiles [174]. They can be used to track position, inform on grouping, physical arrangement and also to recognize subtle differences in actions such as stepping or stomping. They can even be used to identify people by creating walking profiles [174]. Accelerometers are small enough to be embedded in many of these objects as well, although the information they provide is specific. They can be embedded in toys [38], belts [175] or swings [43]. If the sensors need to be worn, they will hinder the possibility of the playground being a fully autonomous installation.

We should keep in mind the limitations of analyzing behavior from these sensors during play. Despite the advances in technology, many cues remain ambiguous or hard to identify, especially with coarse data. For example, tracking players is a difficult task since movement in games is usually fast and erratic, which might result in noisy measurements. Moreover, when players get too close to each other, cameras may not be able to distinguish them, making their detections ambiguous. When the cameras are distant, fine-grained information such as small or quick gestures may be difficult

to obtain.

2.2.2.2 Pervasive Actuation

Projectors are widely used actuators that can be placed in almost any location within interactive playgrounds [176]. They allow for the display of a wide variation of images, shapes or animations. They require a surface to project onto and, depending on the projector and lens, need to be at a considerable distance to maximize the projection surface. Players might be between the projector and the projection surface, casting shadows on the latter. This can be reduced by using multiple projectors to fill in the image. LEDs are other sources of light, and their limited size and low energy demands makes them suitable in building blocks or buttons to signal their presence and affordance [70, 173]. Grids of LEDs have been developed for outdoor use and as interactive floors. Furthermore, light fixtures, including spotlights and stage lighting, can be used for visual feedback. They are not only used to illuminate playgrounds, they can also be used when directed and precise feedback, or more subtle feedback, is needed.

Sound speakers can be located virtually anywhere, even outside the playground. They can provide sound effects in response to actions performed by the players [177], or they can provide music whilst the game is played [65]. Speakers might interfere with player communication, so careful control of the volume is recommended. Alternatively, directed speakers could be employed.

Haptic feedback refers to tactile feedback, technologies which take advantage of the sense of touch [178]. There are many devices that are able to provide haptic feedback, most of which are embedded in objects. For instance, chairs equipped with vibratory transducers on the backrest [179] or shoes with vibrotactile actuators in the soles [180].

Something that we need to account for is the possible interference between actuators and sensors. For instance, certain IPs require dark environments for projections to be visible, rendering the use of RGB cameras impossible. Another example is the use of loud auditory feedback in the way of music or sound effects, which would make it difficult to use ambient microphones. In general, sensors and actuators need to be combined in smart and responsible ways. In Chapter 4, we will elaborate on these requirements when describing the design of our interactive game installation.

Part II

From Traditional Tag to the Interactive Tag Playground

3

Analysis of Behavior in Traditional Tag Games

In this chapter, we will analyze player behavior in a traditional game to understand which behaviors can be automatically analyzed and how. We chose the game of tag for this task due to its simple rules and the widespread knowledge on how to play it. Specifically, we will introduce a corpus we recorded for the purpose of analyzing player behavior during traditional tag games, and present the results of its analysis.

The chapter is structured as follows: Section 3.1 will describe the game of tag, its rules and its variations. Section 3.2 will introduce the corpus we recorded to analyze behavior during tag games. We will also discuss the challenges we encountered while recording and processing it, such as the manual annotation of data and the chaotic play behavior of children. In Section 3.3, we will analyze in detail four different behavioral cues derived from the position of the players.

3.1 The Game of Tag

Tag is a popular and widely known game that children play in traditional playgrounds. In tag games, players assume one of two roles: tagger and runner. The tagger chases the runners around a playing area while trying to touch (tag) them. The runners, on the other hand, have to avoid being tagged by the taggers. In standard tag, if a runner is tagged, the roles of both players switch. Usually, the new tagger cannot tag the same player back immediately. This is known as the cool-down period.

The rules of the game are simple, allowing players to understand the game quickly and join others with ease. The game can be played almost anywhere, as long as there is enough space to run around. The game has no explicit end goal, and is usually played until the players are bored or tired. Due to this, the game's rules are very flexible in regards to how players join or exit the game. In general, players can come and go as they please, with new players joining as runners. There are also variations of the game that provide finish conditions, such as those where a tag “freezes” other players, or outright removes them from the game until there are no players left.

Figure 3.1: RGB image of a frame from the Play corpus.

Figure 3.2: Depth image of a frame from the Play corpus.

3.2 The Play Corpus

To analyze player behavior during tag games, we recorded the Play corpus, a dataset that contains nine sessions of children aged 8-12 playing standard tag in an open space¹. These nine sessions represent twelve and a half minutes of normal tag. This is equivalent to 15,008 frames (at 20 fps). During this time, 74 tag occurrences were registered, which amounts to an average of 10.14 seconds between consecutive tags. In each tag session, a maximum of eight players could play simultaneously. A referee supervised all sessions, and was responsible for instructing players to enter or exit the playing area, assigning the roles to the players, and for starting and stopping game sessions. Sessions with different numbers of taggers and runners were recorded.

The playing area was $7\text{m} \times 6\text{m}$. Sessions were recorded with three RGB cameras located on the corners of an equilateral triangle outside of the play area. In addition, four Microsoft Kinect sensors were placed in the ceiling of the playing area and set to capture top-down depth images. These images were manually stitched. Figures 3.1 and 3.2 show the RGB and depth images of a frame from the Play corpus.

Since we knew the distance from the floor to the Kinects, the depth information allowed us to separate background (floor) from foreground (players) and detect each player in the playing area. The detections for each player were fed to our offline, semi-supervised tracker. Usually, tracking results were propagated automatically by assigning the closest detected player to the closest track.

3.2.1 Manual Processing of Data

Although the position of the players was estimated automatically by our tracker, certain situations required manual input. For instance, whenever two players got very close, the tracker would only detect one person. Since each player had a unique label, the tracker was incapable of determining which label belonged to whom after the merge and assigned tentative labels to each player. In these cases, manual input was requested by the system. Missing detections were linearly interpolated if they were missing for less than three seconds, otherwise manual input of the location was

¹The Play corpus also contains variants of normal tag as well as sessions of another game, Pass-a-ball. The corpus is publicly available at <http://hmi.ewi.utwente.nl/playcorpus>

needed as well.

Using the RGB cameras' feeds, the roles of each player were manually annotated. The process involved one annotator going over the video, frame by frame, while writing down the role of each player. Specific problematic instances where players did not behave appropriately were reviewed several times to make sure the annotation was correct. For instance, if a player's tag went unnoticed by the tagged player, the original tagger would resume his role after some time had passed. In cases such as this, the initial tagger was assigned the tagger role for the entire duration. This meant going back and forth in the video to see how children reacted to certain tags. Moreover, on some occasions children just cheated and refused to become taggers. The same procedure as before was used in these cases.

3.2.2 Breakdown of Play

Due to the nature of tag as a playground game, there are several events that can disrupt the flow of the game, or outright cause the game to end before players intend to stop playing. We call this the breakdown of play. During the recording of the Play corpus, we saw several instances where this happened. For instance, several times players were not aware who was the tagger. This often happened when the number of simultaneous players was high (6-8). In many cases, players were running with their backs towards the other players, and when they turned, they had no way of knowing who was the actual tagger. This led to some people getting tagged because they did not know whom to run away from. The tagger sometimes even pretended not to be the tagger, walked close to someone, and then tagged them. Moreover, some taggers kept pretending they were not tagged and never tagged anyone. This led to confusion from the players as no one knew who exactly was the tagger, and since no one would take up the role, the game would end. Sometimes this was caused not by cheating, but by genuine belief that they had not been tagged, maybe because they did not feel the other player's touch.

Another issue that led to the breakdown of play was the difference in abilities between some players. During the recordings, a couple of times we witnessed noticeably slow taggers having difficulty while trying to tag others. These players tried to tag other players but, after a couple of unsuccessful attempts, they began slowing down, trying less earnestly. At some point, they just stopped trying and stood still in the center of the playground. This is expected, as frustration would build upon not being able to tag others for a prolonged period of time. This does not only affect the tagger though, as the runners would also eventually get bored of the game as their skills are not being challenged. Once the tagger stopped trying to tag, the game came to a halt and the referee had to instruct another player to come in and be an additional tagger. On other occasions, the runners started taunting the tagger by getting close to try to get him to resume the tagging behavior. This worked a couple of times, however when the tagger was unable to tag the taunting players, he would resume his disinterested behavior.

Figure 3.3: Occupancy map of (a) taggers and (b) runners. Darker values represent less presence at that specific location.

3.3 Behavior Analysis of Traditional Tag Games

We used the Play corpus to analyze the behavior of players during traditional tag game sessions. We wanted to understand how the game of tag is played, and also how player behavior differed between roles. Therefore, the cues that we focused on were those where we expected differences between roles. We looked at different cues that could be derived from the position and movement of the players. For each, we used the position data of the sessions in the Play corpus.

3.3.1 Absolute Position

We first analyzed the absolute position of the players in the playground, since we expected a difference in the occupancy patterns of taggers and runners. Runners, in an attempt to avoid being tagged, should try to maximize their distance to the tagger at all times. In contrast, taggers should aim to minimize the required moving distance to tag a runner. This implies that taggers would be looking to position themselves near the center of the playing area, whereas runners would favor moving along the boundary of the playing field.

Figures 3.3a and 3.3b show the average distribution of the absolute position of taggers and runners respectively over all sessions. We normalized the data to utilize the entire color range. We also applied a Gaussian filter to reduce peaks and make the image more clear. In the figure we can see that the position distributions differed between roles, and largely followed our intuition. Runners tended to move near the boundary of the playing area. In contrast, taggers tended to spend most of their time away from the borders, adopting a more central position. The average distance to the center of the field for runners was 2.262 meters, whereas for taggers it was 1.925 meters, which corroborated our assumptions.

3.3.2 Movement Speed

Next, we analyzed the movement speed per role to see if there were differences in how fast players ran. To measure the speed, we used the distance between a player's

position in consecutive frames. We expected that taggers would, on average, run faster than runners since taggers have to chase and tag other people constantly. In contrast, runners can rest when they are not being chased, or move slowly away from the tagger when not in direct danger of being tagged.

Figure 3.4: Frequency histograms of players' movement speed based on their role

In Figure 3.4 we can see the speed histograms for taggers and runners over all sessions. Although both histograms were very similar, differences existed especially at lower speeds. We can see that runners moved at lower speeds more often than taggers. This concurred with our reasoning that runners would move slowly or even stand still when not in danger. Interestingly, taggers also exhibited a high count for low speed bins, probably caused by moments where the tagger was deciding whom to tag, recovering from a failed tag attempt, or just when in need of rest. Regardless of the similarity in the speed profiles, taggers moved slightly faster at 1.06 m/s, in comparison to runners who moved at 0.91 m/s.

Another observation is that the speed of the players was very similar within sessions, even in sessions when the speed of the players was very low. This could imply that all players modulated their speed to match that of other players. This would be especially true for taggers, as the game requires the other players to run away from them. If a tagger is slow, runners do not need to move so fast to avoid being tagged.

3.3.3 Inter-Player Distance

The third feature that we analyzed was the distance between players based on their roles. Intuitively, we expected runners to be, on average, further away from taggers as they have to avoid them. Also, we have noticed that, during games, runners sometimes group together either to use other runners as bait (*i.e.* hoping the tagger focuses

their attention on them) or as protection (*i.e.* stand behind them and push them towards the tagger). This would result in runners being closer to other runners, making the difference in distance to taggers more evident.

Figure 3.5: Frequency histograms of inter-player distances based on their role.

We can see in Figure 3.5 that our expectations seemed mostly on point when considering all players and all sessions (the results are summarized in Table 3.1). Within short distances (less than two and a half meters), runners were closer to other runners by a small margin (3.91%). When looking at the bins around the 3-5 meters distance, we see that taggers had a higher count than runners (8.01%). Considering the size of the playing area, this coincided approximately with the distance from a corner to the center. This is consistent with our finding that runners moved around the boundary of the playing area while taggers moved mostly near the center. Similarly, when looking at distances greater than five meters, runners had a higher count again (3.78%). This is due to the fact that runners could be in opposite corners of the playing area to maximize their chances of not being tagged.

If we plot the inter-player distance, but only take into account the closest runner instead of all runners, we notice something interesting (Figure 3.6). The location of the peak for the tagger's distance distribution is much closer to zero than it was before. This is because when considering the distance to all players, when a tagger closes up on one particular runner, his distance to the other runners most likely increases. This causes the distribution to spread out. When only considering the closest runner to calculate the inter-player distance, we can see a clear difference in the distance taggers kept to the closest runner in comparison to the distance between runners and the closest runner (70.07% and 54.20% respectively, for distances between 0-2.5 m). The summary of the results can be found in Table 3.1.

Figure 3.6: Frequency histograms of distances of taggers and runners to the closest runner.

	0 - 2.5 m.	2.5 - 5 m.	5 - 7.5 m.
Taggers-Runners	26.43%	61.13%	12.43%
Runners-Runners	30.34%	53.12%	16.21%
Taggers-Closest Runner	70.07%	29.21%	0.72%
Runners-Closest Runner	54.20%	38.40%	7.39%

Table 3.1: Differences in inter-player distance distributions for taggers and runners

Even though the differences between inter-role distances exist, they are relatively small. As we can see in both of the previous figures, there is significant overlap between the peaks of the distributions.

3.3.4 Relative Movement Direction

The last feature we analyzed was the relative movement direction between players of different roles. The relative movement direction is defined as the angle that a focus player is moving at with respect to the position of another (see Figure 3.7). When the angle is close to zero degrees, the focus player is moving towards the other player.

Since tagging is about chasing after people, we expected angular differences between the tagger's movement direction and the direction of runners to be close to 0° . This feature only measures the relative direction and not the amount of movement.

Figure 3.8 shows the angular histogram for the relative movement direction between roles. Values are between 0° - 180° because we calculated the shortest relative

Figure 3.7: Relative movement direction of player i with respect to player j .

Figure 3.8: Angular histogram of the relative movement direction between roles. In blue from tagger to runner, in red from runner to tagger.

angle. This means positive or negative angular differences are overlooked. For instance, 10° and 350° (-10°) are considered the same. The blue and red bins correspond to the tagger-runner and runner-tagger relative movement direction respectively. As expected, the figure shows that the relative direction of taggers with respect to runners was most often close to 0° and fell off quickly. The variation in angle was caused by taggers predicting the movement of chased runners and moving ahead of their path to cut them off instead of moving directly towards them. Also, in the calculation of this feature, we considered the relative direction of the tagger with respect to all runners, which contributes to the spread of the values.

For the runner-tagger relative direction we also found what we were expecting. Runners tended to move away from taggers mostly at angles between 90° – 150° . This, together with the absolute position analysis of runners, leads us to conclude that runners moved in circles around the playground, since instead of running in the complete opposite direction (180°), they moved diagonally, keeping away from the center.

The analysis of these four behavioral cues allow us to better understand how player behavior changes between roles in tag games. This information, along with what we learned during the observation of the Play corpus recording, was used in the design of our interactive playground, which we will describe in the next chapter.

4

Development of the Interactive Tag Playground

In this chapter, we will describe the design and implementation of an interactive installation that facilitates the analysis of play behavior while enhancing the traditional game of tag. In other words, this installation, the Interactive Tag Playground (ITP), serves not only as an entertainment platform, but doubles as a research tool to analyze player behavior. We will describe in detail the different components that make up the ITP, motivate our design decisions, and present the player feedback that helped shape the final installation.

This chapter is structured as follows: Section 4.1 will present our design considerations for the playground based on the insights obtained from the Play corpus analysis and the reviewed literature. In Section 4.2 we will describe the two iterations of the ITP, detailing the improvements made on the second iteration and the different variants of the game of tag that we implemented and used in our studies. We will also describe in detail the tracking system of the ITP and its evaluation.

4.1 Designing the Interactive Tag Playground

Based on our research goals (Section 1.4), the literature on interactive playgrounds (Section 1.3.2), the requirements for behavior analysis in IPs (Section 2.2.2), and the analysis of the Play Corpus (Section 3.2), we identified several design considerations for our interactive tag game installation. First, the playground should provide a fun and engaging experience. Second, the installation should work autonomously and sense behavior unobtrusively. Third, our playground should be able to support key aspects of play such as social and active behavior. Fourth, the playground should be capable of automating the collection of data or, at the very least, facilitate its acquisition.

4.1.1 Fun and Engagement

Entertainment installations need to provide fun and engaging experiences. If children do not enjoy a game, they will not play it. If a provided experience is not engaging, players will lose interest quickly. The game of tag is already a fun and engaging game,

but during the recording of the Play corpus, we noticed events that diminished the overall game experience and could lead to the breakdown of play.

The breakdown of play in tag games can be caused by the (sometimes huge) disparity in skills between players. Part of playing is learning to deal with such differences, but when the differences are too big, and the affected player is not helped, players can become irritated or annoyed. To still be able to provide a fun experience when these differences in abilities are present, the playground should be capable of balancing the skills of the players to make the game more even. We could accomplish this by having the system mediate the interactions between players and the game.

Another situation that sometimes led to the breakdown of play was uncertainty in regards to the identity of the tagger. This happened several times when there were many players playing simultaneously, as players lost track of who was “it” amidst all the running. The system should try to prevent these situation from occurring. This could be achieved by giving feedback to the players about their role.

In both situations, the information that the players receive from the playground, and how they receive it, is important. If the system is mediating the interactions, then it should be clear to the players how this is happening. If the system gives feedback on who the tagger is, this information should be present at all times. This can be achieved by adding projections or screens to show the information that is needed. Sounds could be played when certain events occur, so that players are aware of them even if they do not see them happening. Likewise, if haptic actuators are equipped, vibrations could be used to signal that an event happened.

4.1.2 Unobtrusive and Autonomous Functioning

Interactive playgrounds are usually public installations, and as such, should be capable of working autonomously. This means that the game should start and stop on its own as soon as players enter or leave the area, that is to say, it should support an easy-in, easy-out style of play. This also follows from how tag games are played, where children can freely join or leave the game. Special care should be taken when the tagger leaves the playing area, as the game always requires a tagger. Also, because the game should run autonomously, the use of wearable sensors to gather data from the players appears to be difficult. Researchers would not be present to hand them out and retrieve them afterwards, so it would be up to the players to do this. The playground would need to assume that players will indeed wear the sensors, that they are properly fitted, and that they will be returned before leaving.

In the playground, behavior should be sensed unobtrusively to allow players to play tag as they normally would. There are different options to accomplish this. First, as mentioned above, equipping players with sensors is possible, as long as the sensors do not hinder how the game is played. The main challenge would be making sure the players fit the sensors properly. Second, embed sensors in the installation infrastructure. For instance, cameras or pressure tiles could be used to find the location of the players. In the case of cameras, they should be placed somewhere where they are not in the way of the players, for instance, on the ceiling. Third and last, equip toys that are needed to play the game with sensors, for example, a ball with RFID tags and an accelerometer. Since the game of tag does not require additional toys to be played,

they could be used to enable additional game interactions.

4.1.3 Physically Active, Social Behavior

Play serves as a powerful method by which children develop their physical and social skills. As such, our playground should be capable of promoting these important developmental aspects. Since the game of tag already promotes both physical and social play, our installation should focus on keeping the game elements or mechanics of the original game.

An essential characteristic of the game of tag is running. Players have to run in the playing area, either while chasing other players or running away from them. This makes the game especially effective at eliciting physical activity. To be able to retain this characteristic, players should be allowed to run freely inside our interactive playground. Also, since tagging is achieved by getting physically close to other players and touching them, our playground should be capable of detecting the position of each player in any given moment of the game. This information should be retrievable in real time.

Tag also allows players to exhibit a wide array of social behavior such as talking, joking, taunting, and so on. The playground should allow players to exhibit this type of behavior. This means players should be capable of communicating verbally and physically while playing.

4.1.4 Automation of Tasks

When analyzing the Play corpus, we noticed that a system that could provide information needed for the analysis of behavior would speed up the process significantly. Information such as the position of the players, their roles, or who they are interacting with, could be used to understand player behavior post-game, or even use this information in-game to react to specific events. Therefore, our playground should either facilitate the process by which this information is obtained, or directly obtain the information itself.

4.1.5 Design Choices

For our installation, we decided to use cameras for the behavior sensing and projections for the player feedback. One of our main goals was to have a playground that could, eventually, be placed in public locations. As such, we wanted to avoid the use of wearable sensors. Even if the wearable sensors could be fitted by the players themselves, and be designed in such a way that they do not interfere with how the game is played, there is no guarantee that players would wear them. Moreover, if the sensors are worn, there is the possibility that they will not be fitted properly. Also, we wanted players to be able to just walk in and start playing immediately, and leaving as soon as they felt like it. Cameras would support this, as well as the sensing of player behavior without hampering how the game is played.

To give feedback to the players, projectors seemed like the best option. Computer screens or monitors are capable of giving feedback continuously and supporting an

easy-in, easy-out style of play. However, placing screens on the sides of the playground would require players to divert their attention from the game, and from the other players, to the screen. This may affect the possibilities for running or interacting with other players. Floor projections are also capable of continuous feedback and supporting easy-in, easy-out play, and since the elements are projected on the playing area, they still allow players to move around and interact with each other. Additionally, the feedback can be projected directly onto the position of the players, enabling the association of the projected information to individual players. Finally, floor projections would allow us to introduce new interactive game elements easily.

4.2 The Interactive Tag Playground

Based on the design requirements, we set out to develop the Interactive Tag Playground, an interactive game installation that uses sound, sensor and projection technology to enhance the traditional game of tag. The ITP is able to detect and track players in the playing area, display visualizations on the floor, and guide player interactions by processing the game logic (Figure 4.1). It has been designed to retain the essence of the original game while making it possible to introduce novel gameplay elements easily. Since we can systematically change game mechanics, the ITP facilitates research on how game elements affect player behavior and game experience.

Figure 4.1: Interaction between the ITP elements.

We decided to implement game mechanics that resemble those used in the original game to retain the physical and social benefits of tag. The rules of the game are the same, as well as the roles that players can have. The most notable differences are the way in which players tag each other, and the use of visualizations to give feedback of the game state to the players. These visualizations can also be used to include novel game elements. Finally, sound feedback can also be triggered when certain events

occur, for example, tags.

The ITP tracks players and displays a colored circle on the ground underneath them. The color of the circle indicates the role of each player: red for taggers and blue for runners. To facilitate the tracking of the players, instead of physically touching other players to tag them, the tagger has to get his circle to overlap with a runner's circle. When a tagger manages to do this, the color of both circles switch to indicate that the roles have changed. If a player is tagged, he is not allowed to tag the previous tagger back for two seconds, enforcing a cool-down period. This is signaled by the circle of the runner becoming semitransparent. The cool-down period is designed to encourage players to look for other players to tag. When the game begins, a tagger is chosen randomly from the detected players. If a tagger leaves the playing area, the system randomly chooses one of the remaining players as the new tagger. As such, the installation is *de facto* a referee, capable of enforcing rules to prevent disagreements between players.

The ITP logs the position information of all players as well as their roles during the game. This information can be used during the game to drive certain game interactions (e.g. display a circle underneath a player's location), or after the game to analyze player behavior (e.g. analyze how players move during the game).

The ITP was designed in two iterations. We will describe the characteristics of both versions of the ITP, and highlight the changes it underwent between iterations. Given that the tracking component is of great importance to the functioning of the ITP, we will carefully describe its implementation and evaluation.

4.2.1 The Interactive Tag Playground 1.0

We designed the ITP in an iterative process. The first iteration of the ITP (1.0) was composed of four Microsoft Kinects located in the ceiling of the installation. The Kinects are input sensors that can capture both RGB and depth information. These Kinects were arranged in a grid-like setup, four meters apart from each other. Additionally, in the center of the grid, a wide-angle lens projector was placed (Figure 4.2). The Kinects and the projector were hung from trusses that could be moved to adjust their height, which was set to 5.3 meters. At this height, the installation was capable of tracking players in a $7\text{m} \times 6\text{m}$ area. However, because the projector could only display to a $6\text{m} \times 3.3\text{m}$ area, this defined the effective playing area (Figure 4.3). One computer was used to process the player tracking, game logic and game projections.

Based on player feedback and observations of game sessions in the ITP 1.0, our interactive game managed to successfully recreate the experience of tag (Figure 4.4). However, players suggested several ways in which the game could be improved. One of the main issues we had with the original setup was the size. Every player that participated in a game session said the space was too small to play comfortably. With only one projector, it was impossible for us to address this. Also, the graphics used in the game were very simple, and many players suggested making them more engaging and flashy. The idea of the circles was deemed good, but something had to be done to make them more interesting. The ITP 1.0 also had no sounds, and players suggested adding auditory feedback when certain events happened. Lastly, many players mentioned it would be great to have more digital game elements, like being able to shoot

Figure 4.2: Location of the Kinects and projector on the ceiling of the ITP 1.0.

Figure 4.3: Playing area of the ITP 1.0

other players or being able to pick up power-ups.

Figure 4.4: Players playing tag in the ITP 1.0

4.2.2 The Interactive Tag Playground 2.0

Taking the most relevant suggestions to heart, we developed the second version of the ITP. The ITP 2.0 (from here on out just ITP) consists of the same four Kinects on the ceiling of the installation, but with an additional projector. The projectors are located in between the Kinects, four meters apart from each other (Figure 4.5). This allows us to make use of the entire tracking area, which remains $7\text{m} \times 6\text{m}$ (Figure 4.6). The height of the ceiling is also kept the same at 5.3 meters. Additionally, four speakers are located on one side of the playground.

In regards to the game, the plain circle shapes have been replaced by pulsating, neon-colored circles that leave bright trails upon movement (Figure 4.7). Instead of using red for the tagger's circle color, we use orange to allow color-blind people to identify it. Tagging mechanics remain the same, but a sound effect now accompanies each tag occurrence.

We also added one computer to the setup to separate the processing of the game logic from the player tracking. This is done to facilitate the design and implementation of future games as well as to diminish the burden on the computers, allowing

Figure 4.5: Location of the Kinects and projector on the ceiling of the ITP.

Figure 4.6: Playing area of the ITP.

Figure 4.7: Young adults playing tag in the ITP.

for faster execution of processing tasks. The computer that deals solely with the tracking transmits the location information of the players over the network using the User Datagram Protocol (UDP) in combination with the Transmission Control Protocol/Internet Protocol (TCP/IP). The second computer receives the information and uses it to drive the game interactions and logic using the Unity Game Engine. Thanks to this modular structure, additional computers could be used to process or control other tasks. Figure 4.8 shows an overview of the ITP components.

We have implemented several variants of the game of tag for the ITP. Each of these variants is aimed at promoting specific behavior [181]. The variants that are currently developed are: interactive tag with no interventions (base game), tag with dynamic

Figure 4.8: Component overview of the ITP.

circle size, tag with arrows pointing to certain runners, and tag with power-ups. In this thesis, we will only present studies that use the variant without interventions and the adaptive circle size variant. As its name implies, the variant without any intervention is the basic interactive tag game. The variant with adaptive circle size intervention balances players' skills by changing the size of their circles depending on the time a player has been a tagger (Figure 4.9). When a player is a tagger, his circle will slowly grow (up to a maximum size) as long as he remains the tagger, making it easier to tag other players as time goes by. On the other hand, a player that has been the tagger for long periods of time will have his circle's size reduced when he is a runner. The variant used will be mentioned when explaining a particular study.

Figure 4.9: An instance of the tagger's circle having grown in size

Besides the different game variants, the ITP was also placed in different locations for some of the studies. Some locations had restrictions on the size of the area that

could be used, and therefore have a smaller playing field. In total, the ITP was placed in two different locations. The different playing fields that were used are: $7\text{m} \times 6\text{m}$ and $6\text{m} \times 5\text{m}$. The size of the playing field will be mentioned when describing each study.

4.2.3 Player Tracking Component

The ITP features an online, top-down, multi-person tracker that uses the depth images from the Kinects as input to detect the players. We only use depth images because the game projections are better appreciated in dark environments, which would make the use of RGB images difficult due to the uneven and low illumination conditions. An overview of the algorithm can be seen in Figure 4.10.

Figure 4.10: Overview of the tracking algorithm

It is important to mention that player identity cannot be estimated from the low resolution, top-down depth images. Even then, by default, depth images are not stored by the system to protect the privacy of the players. This, however, can be changed if player consent is obtained.

4.2.3.1 Player Detection

To detect the locations of players in the playground, we first apply a threshold to the depth images to remove the floor and any small object that might be present. Since we know the exact height at which the Kinects are located, the threshold can be set simply by taking into account the players' heights. The thresholded images contain depth values predominantly of the head and shoulders region, but typically also contain the

arms. To accentuate the head region, we filter the images with an approximation of the Mexican Hat filter, a Difference of Gaussians (DoG) kernel. This filter gives higher weight to Gaussian-like objects such as the head-shoulder region, while non-Gaussian objects such as stretched arms will be filtered out. This is important because players stretch their arms to make physical contact with other players when playing tag, which would normally lead a vision system to treat them as one object because of the merged outlines (Figure 4.11). After having filtered the images, we find the contour of the areas with filter responses above a selected threshold. The center of mass of these areas typically corresponds to the location of the players.

Figure 4.11: Sequence of unprocessed images of children playing in the ITP. The yellow squares show how outlines can merge when players get too close or try to tag using their arms.

Afterwards, the locations of the players are mapped from Kinect-specific coordinates (pixels) onto real-world coordinates (meters, measured from the center of the sensor). We apply this procedure for each Kinect individually. Since we know the physical location of each Kinect and their distances to each other, we can map the Kinect-based real-world coordinates to the playground-based real-world coordinates (meters, measured from a specified Kinect). Since the Kinects' fields of view partly overlap, we check for detections that originate from different Kinects but are within 0.5 meters of each other, measured from the center of the detection. When this occurs, we assume that they belong to the same person and set the player's location as the average between the detections' positions.

4.2.3.2 Player Tracking

We decided to use Kalman filters [182] to track players in the ITP because they are straightforward and capable of tracking running players appropriately. The algorithm behind this filter works recursively in two steps: a prediction and an update step. During the prediction step, a Kalman filter tries to predict state variables (*i.e.* position) based on their history (*i.e.* past position) and the estimated system model (*i.e.* laws of motion). During the update step, newly measured values are used to correct the prediction and update the system model.

At each time step, each Kalman filter is assigned one detection from the pool of

available detections. This assignment is based on the Euclidean distance between each detection and the prediction of all the Kalman filters. We use the Kuhn-Munkres algorithm, also known as the Hungarian method [183, 184]. This algorithm finds a solution that minimizes the cost of assigning detections to tracks, that is to say, it minimizes the sum of the Euclidean distance between a detection and its assigned track, for all tracks.

Usually, each detection corresponds to one of the players in the ITP and, therefore, each player gets assigned to one track. However, sometimes noise from the Kinects can be detected as well, which leads to having more detections than players. To prevent creating tracks for these noisy detections, whenever a new detection is located (*e.g.* a new player enters the playing area), the system creates a candidate track for this detection. After five frames (approximately 0.25 seconds), we evaluate the track's stability by counting how many frames the detection has been missing. Out of the five frames, if the detection was present in at least three frames, the track is maintained. Since noisy detections are usually sporadic and unstable, candidate tracks of these detections are safely deleted.

When the number of detections is lower than the number of tracks, it is usually due to players going outside the playing area, going below the height threshold (*e.g.* falling down), or getting too close to other players. In most of these cases, the player is detected again after a short time. To prevent deleting a track (with its associated motion model and history) for temporary miss-detections, we use a similar approach as when creating tracks. If a track does not have an assigned detection, we keep the track alive for fifteen frames (approximately 0.75 seconds). After this time, if the track is not assigned any detection, it is deleted. Using this approach, we can handle occasional missed detections, while still preserving tracking accuracy.

4.2.3.3 Optional Component: Gyroscopes

When two players get too close to each other and their detections merge, one of the tracks disappears. When the players move apart from each other, the merged detection splits, and the tracker assigns a label to each player based on their motion model prior to the merge if the “hidden” track has not been deleted. To make a more informed label assignment, players can be equipped with YEI 3-space wireless gyroscopes in a strap around their chest before the game begins. Gyroscopes are devices capable of measuring rotation and, thus, the orientation they are facing in regards to a coordinate reference system. Figure 4.12 shows the wireless gyroscope and dongle that can be used in the ITP.

If the gyroscopes are used, we can compare the movement direction obtained from the tracker to the one sensed by the gyroscopes. This procedure is applied in each frame, and if the difference between both estimates exceeds a certain threshold, we assume the labels have not been properly assigned. When this happens, we check for another player that shows the same inconsistencies between the sensor and the tracker estimated movement direction. If found, the labels of the two players are switched if the inconsistencies have lasted more than 45 frames (2.25 seconds). Even though gyroscopes allow the system to recover automatically from errors in track assignment, the setup of the game becomes more complex due to the need of equipping

Figure 4.12: Wireless gyroscope and dongle used in the ITP

the sensors and calibrating them. Also, guidelines of movement-based games suggest that ambiguity of movement can add to the player experience [185]. Therefore, we only use the gyroscopes in our role recognition study (Chapter 9).

4.2.4 Tracker Performance

The tracker is a core component of the ITP because a) it allows players to run freely and still interact with the game properly, and b) position is an important behavioral cue that is logged by the ITP and used in the analysis of behavior. To evaluate the performance of the tracker, we manually corrected thirteen interactive tag game sessions of one and a half minutes. In each session, four children played simultaneously in the $6\text{m} \times 5\text{m}$ version of the ITP. The game that was played was the standard interactive game of tag with no interventions.

The manual correction was carried out by saving unprocessed depth images from the game sessions. These images were observed next to a visual representation of the ITP's tracker output on a frame-by-frame basis (Figure 4.13). Players could not be identified from the depth images, but their contours provided sufficient information to distinguish them from each other when in close proximity. Whenever labels were incorrectly assigned, they were corrected. When players were lost by the tracker, their position was annotated. When a player went out of bounds, the frame was logged.

The evaluation consists of two metrics. The first metric evaluates the frequency with which a player's track switches with that of another player after a tag (T-Sw). T-Sw is calculated by dividing the total number of label assignment errors by the total number of tags. The second metric evaluates how frequently a player is lost by the tracker. This includes both when the player is inside the playing area (LT-In), or out of bounds (LT-Oob). LT-In is calculated by dividing the number of frames a track was manually corrected by the total number of frames. Similarly, LT-Oob is calculated by

Figure 4.13: Software used for the manual correction of the tag game sessions.

dividing the number of frames a player went out of bounds by the total number of frames. Losing track of players that go out of bounds is not really a tracker error, but we still report it for the sake of completeness. The results can be seen in Table 4.1.

#Frames	#Tags	T-Sw	LT-Oob	LT-In
21877	265	9.81%	1.41%	2.63%

Table 4.1: Evaluation of the employed tracker.

Overall, the performance of the tracker is good. We can see that 9.81% of the times a tag occurs, the track of the players change. This means that, out of ten tag occurrences, only one would result in a track change between players (T-Sw). The number of track switches per session will naturally depend on the length of the session and the number of tags. In the game sessions that we used for the tracker evaluation, one track switch happened approximately every 45 seconds of play. This means that, on average, there were two track switches per game session.

It is important to note that we also consider label assignment errors from runners bumping into each other towards the calculation of T-Sw. This event does not happen often and, strictly speaking, runners colliding with other runners are not tag occurrences. Nonetheless, taking into account every error in the assignment of player labels provides a better overview of the actual performance of the tracker.

Label assignment errors do not have a big impact on gameplay. When the tracks of a tagger and a runner switch during tags, players usually assume their circles did not collide. When two runners run into each other, since both have blue circles, the track switch is not noticeable to the players. When looking at the ITP as a research tool, errors in the assignment of labels are important. If the label of any player is incorrectly assigned, the data can no longer be used for individual behavior analysis.

Finally, we can see that losing track of a player that is in the playing field rarely

happens (2.63%). In general, the tracker is capable of locating and tracking players inside the playing area with relatively few mistakes.

5

Evaluation of the Interactive Tag Playground

In this chapter, we will describe our evaluation of the ITP to validate its use as an entertainment installation. This is important because if the ITP fails to entertain players, analyzing their behavior is meaningless as it would not represent natural play behavior. We evaluated four different dimensions of the ITP: enjoyment, immersion, gameplay and game elements. Additionally, we asked users about the balance and fairness of the installation, as well as their skill level. Finally, we will discuss our observations of the game sessions, and the feedback that we received from the players.

This chapter is structured as follows: Section 5.1 will briefly present some risks that are associated with using technology to augment games, and why it should be done carefully. In Section 5.2 we will present a subjective evaluation of the ITP to check whether it enhances the game experience by augmenting the traditional game of tag. We will also describe the observations we made during the game sessions, and the most important feedback we received from the players. Finally, in Section 5.3, we will discuss the results of our evaluation and the use of the ITP as a game installation.

5.1 Risks of Technology-Augmented Games

Exploiting technological advances in games can help promote positive, healthy, physical and social behavior (see Section 1.3.2). To accomplish this, games need to be designed carefully, as the use of technology itself can prove detrimental in certain cases [186]. Concerned about this, Isbister discusses how technology could be used to gracefully augment game experiences while allowing important characteristics of play to be displayed [36]. She argues that, in real life, people connect to each other through physical experiences, and that games should not be any different. When introducing technology into games, social interactions can be easily lost. For instance, the heavy use of screens or projections can lead to people focusing on these elements rather than interacting with other players. This means that the amount of extraneous cognitive load caused by the additional information being presented to the players needs to be accounted for when designing interactive games [187].

Besides the social aspect of play, physical exertion can also be lost by introducing

technology. In [164], Berthouze studied in detail how body movement can be related to engagement in games. One of the points she covered is the difference in strategies with which players approach a game: “hard-fun” and “easy-fun”. In the easy-fun strategy, players are interested in enjoying the game. In the hard-fun strategy, players are solely concerned with winning and will exploit technology to their advantage. During the analysis of several physical games, they observed that hard-fun players limited their movements to the bare minimum since, in many cases, winning was easier when moving less [188]. This shows that not planning carefully how technology is introduced can harm important social and physical aspects of play.

There are also more specific issues that can be introduced when augmenting games. For instance, Altimira *et al.* showed that skill balancing in games can lead to feelings of unfairness [186]. They attempted to balance the skills of players in a Wii table tennis game and a normal table tennis game. Players were asked to assess their own skills, and the best player was given different handicaps during the game sessions (play with non-dominant hand, start with a six point disadvantage). They observed that in real life scenarios, the handicaps helped the less skilled player, but in the Wii game, it was nearly impossible for the skilled player to win under the test conditions. This shows that considering which game interactions are, and will be, available to players is important when introducing technological interventions.

5.2 Evaluating User Experience in the ITP

To evaluate the ITP, we conducted a user study where players compared their experience between playing a traditional game of tag and playing an interactive game of tag. Specifically, players were asked to compare their enjoyment and immersion between both conditions. Additionally, we asked them to rate the game elements of the ITP, and to evaluate whether they thought the system was fair to skilled and non-skilled players alike. Since the ITP is designed to retain the physical and social aspects of traditional tag, we observed the game sessions to find out if the ITP allows players to exhibit physically active and social behavior.

5.2.1 Setup and Experimental Procedure

We recorded seven groups of people playing both traditional and interactive tag (our two conditions). All sessions were played by four players simultaneously, except one session which was played by five. All players were young adults. The duration of each game session was three minutes, resulting in a total of six minutes of tag gameplay for the entire experimental session. The size of the playing area was $7\text{m} \times 6\text{m}$. The traditional game of tag was played in the same installation, but no sounds, game projections or Kinects were used during this condition (Figure 5.1). Also, players played the dynamic circle size variation (skill balancing) when playing the interactive condition, which meant a player’s circle grew or shrank depending on how long the player had been the tagger. Figure 5.2 shows some players playing interactive tag in the ITP. In future chapters, the interactive tag sessions described in this chapter will be referred to as the ITag2 dataset.

Figure 5.1: Four young adults playing traditional tag in the ITP.

Figure 5.2: Four young adults playing interactive tag in the ITP. We can see that the size of the circle is different for all players due to the dynamic circle size intervention.

Before starting the experiment, players were asked to fill in a consent form that briefly explained the procedure. After filling it in, players were informed in detail that they were going to play two different versions of tag: a traditional version and an interactive version. The order of the conditions was alternated between groups. Players were not informed that we were using the dynamic circle size intervention during the interactive tag condition. In between sessions, players were given a short break of around one minute. After both conditions were played, participants were asked to fill in a questionnaire and invited to engage in a short feedback and discussion session. It is important to note that in one session, only two participants filled in

the questionnaire. As a result of this, we only obtained feedback from 27 participants.

We will first present the questionnaire used for the evaluation, how it was constructed, and the results obtained. Afterwards, we will describe our observations of the game as well as the feedback that we received from the players.

5.2.2 Questionnaire

To evaluate whether the ITP enhances the traditional game of tag, we designed a questionnaire (see Table 5.1) based on the Revised Gaming Engagement Questionnaire (GEQR) of Berthouze [164]. Our questionnaire consisted of four dimensions that we were interested in evaluating. The first two dimensions compared the game experiences of the interactive tag and normal tag (A-Enjoyment, B-Immersion). The last two dimensions evaluated elements of the ITP independently (C-Gameplay, D-Enjoyment of Game Elements). The questionnaire had two additional categories (Balance/Fairness, Skill Level) that did not necessarily measure the same construct, but evaluated related issues interesting for our study.

Sixteen of the 24 questions in the GEQR fit our four dimensions and were manually assigned to one of them (we left out the GEQR questions 4, 6, 8, 12-14, 18 and 22). We also added eleven questions of our own, which belonged mostly to the two categories Balance/Fairness and Skill Level. This means that questions 3-18 in our questionnaire were derived from the GEQR, and questions 1-2 and 19-27 were of our own formulation. We used a Likert scale which ranged from 1 (Disagree) to 7 (Agree), and therefore had to rephrase the GEQR questions into the form of statements for which the participants had to specify their level of agreement/disagreement (e.g. “How enjoyable did you find the graphics in this game?” to “I enjoyed the graphics of the game”). Furthermore, the GEQR questions used for the dimensions Enjoyment and Immersion had to be rephrased to accommodate the comparison of the tag conditions (e.g. “How interested are you in playing this game again?” to “I am more interested in playing the interactive tag game again than normal tag”).

In the printed questionnaire, all the questions were put in a constant randomized order. Our modified version of the questionnaire was not validated, but we did calculate the Cronbach’s alpha for each dimension. It must be noted that Q14 and Q22 are reversed (r) when calculating the dimension statistics because of their direction with respect to the other questions, and Table 5.1 shows the reversed scores. We will now discuss the findings per dimension.

5.2.2.1 Enjoyment (A)

The Enjoyment dimension contained five questions (Q1-5) related to whether the players had more fun playing interactive tag compared to normal tag. We first checked the answers for consistency by calculating the Cronbach’s alpha, which yielded a value of 0.88. This means that the questions did indeed measure a single construct. The mean of the answers for the enjoyment dimension was 5.37, indicating an effect towards interactive tag. To find out if this effect was statistically significant, we conducted a two-tailed one-sample t-test against the center of the scale (4). This showed a significant effect ($t(26) = 6.7, p < 0.001$) in the direction of more enjoyment dur-

Question	Item mean	Item SD	Dim. mean
A - Enjoyment			
1) The interactive tag game made me laugh (more) than the normal tag game	5.22	1.37	5.37
2) I would recommend the interactive tag game over the normal tag game	5.22	1.45	
3) I liked playing the interactive tag game more than the normal tag game	5.33	1.36	
4) I am more interested in further exploring the interactive tag games environment than playing normal tag	5.56	1.05	
5) I am more interested in playing the interactive tag game again than normal tag	5.52	1.19	
B - Immersion			
6) I felt more involved in the game when playing the interactive tag than when playing normal tag	4.81	1.10	4.92
7) I was more engaged in the game when playing interactive tag than when playing normal tag	4.81	1.30	
8) I felt I lost track of time more when playing interactive tag than when playing normal tag	5.27	1.40	
9) I felt I was inside the game while playing interactive tag more than during normal tag	4.77	1.37	
C - Gameplay			
10) I was able to anticipate what would happen next in response to the actions I initiated	4.69	1.44	4.87
11) The controls for the game were appropriate	5.40	0.91	
12) The controls for the game felt natural	5.65	1.02	
13) I was able to clearly identify what game pieces/objects/models represented	5.77	1.03	
14) I experienced delay between my actions and the expected outcomes within the game	1.81(r)	0.90	
15) I understood the graphics of the game	5.92	0.80	
D - Enjoyment of Game Elements			
16) I enjoyed the graphics of the game	5.73	0.87	5.31
17) I enjoyed the sound effects in the game	4.69	1.52	
18) I enjoyed the context and theme of the game	5.50	0.99	
Balance / Fairness			
19) The game allowed me to demonstrate my ability of playing tag	4.11	1.40	4.30
20) I think the game helps less skilled players	4.63	1.47	
21) I think the game aids skilled players	4.04	1.26	
22) The game interferes with my ability to play tag	4.41(r)	1.50	
Skill level			
23) I am physically active	4.70	1.77	4.83
24) I consider myself to be in good shape	4.59	1.47	
25) I exercise regularly	4.26	1.91	
26) I enjoy physical activity	5.78	1.15	
27) I consider myself a good tag player	4.81	1.14	

Table 5.1: Questionnaire used in the evaluation of the ITP, with means and SD for each question, and the mean for each dimension. Scale 1 stands for disagree and scale 7 for agree.

ing the interactive sessions. The test allows us to confidently state that the players enjoyed the interactive game more than playing traditional tag.

5.2.2.2 Immersion (B)

The Immersion dimension contained four questions (Q6-9). With these questions we wanted to find out whether people lost themselves while playing in the ITP more than they did during traditional tag. Just like the previous dimension, a value close to four would imply players did not get immersed more in one condition than the other. Cronbach's alpha was 0.71, implying that there was a fair correlation between the items. The mean for the answers was 4.92. Q8, which looked into whether players felt they lost track of time in the interactive tag more than during normal tag, had a slightly higher rating than the other questions. Again, we used a two-tailed one-sample t-test against the center of the scale to check for statistical significance, and the result again showed a significant effect ($t(26) = 5.2, p < 0.001$) in the direction of more immersion during the interactive session. From this follows that players were more immersed during the game of tag played interactively compared to playing normal tag.

5.2.2.3 Gameplay (C)

We used six questions for the Gameplay dimension (Q10-15). This dimension evaluated how effective the controls, graphics and mechanics of the game were. When we calculated the Cronbach's alpha for this dimension, the value was quite low, at 0.48. Due to the various components and some network issues during the user study, there was a lag of about half a second in the movement of the circles. We presumed the low alpha was related to this lag as gameplay is positively affected when delays between a player's actions and the system's response are small. Indeed, upon closer examination of the individual questions, we noticed that by removing the questions affected by the delay (Q10 and Q14), the value of alpha increased to 0.74.

The mean for this dimension, if we take into account all questions, was 4.87. If we remove the two questions mentioned above, the mean was 5.69. We saw that Gameplay scored rather high if we did not take the lag into account. However, even when including the questions affected by the lag, the mean was still leaning towards the positive scale of Gameplay. Players felt good about how the game played out. However, we feel it would be beneficial if the lag problem were mitigated.

5.2.2.4 Enjoyment of Game Elements (D)

The Enjoyment of Game Elements dimension was composed of three questions dealing with players' rating of the graphics, sound and theme of the game (Q16-18). The Cronbach's alpha for this dimension was 0.35. The low alpha value was due to Q17, which asked about the audio effects of the game. When talking to the players, some of them mentioned they did not notice there were any sounds being played while playing. This explains the relatively high SD for this question.

If we take into account all questions, the mean for the dimension was 5.31. If we leave out the question about sound, the mean was 5.62 and the alpha 0.63. Even without Q17, the alpha was still not very high, which may indicate that these questions would fit better in different dimensions. For instance, sound and graphics are very different aspects of a game, and their evaluation might be better carried out separately. Regardless, even if the questions did not measure a single construct, we could still see that the items were rated positively in general. Nonetheless, we need to address the sound not being noticed.

5.2.2.5 Balance/Fairness

We included four questions to cover the category of Balance and Fairness (Q19-22). These questions informed us whether players felt the ITP allowed them to play tag, and whether they felt the game was helping skilled or unskilled players. Q19 and Q22, which dealt with how the ITP allowed players to play tag, had a mean of 4.11 and 4.41(r), respectively. This shows that players felt the game neither interfered with their ability to play, nor did it allow them to show all their skills. Although ideally players would have felt the game allowed them to demonstrate all their tagging skills, it is still important that they did not think the game limits their ability to do so.

Q20 and Q21 dealt with the issue of Balance, and whether players felt anyone was receiving help from the ITP when playing. A high value for the mean would signify

players felt the game helped a particular type of player, depending on the question. The mean for Q20 was 4.63 and for Q21 4.04. It seems that players had a feeling that the ITP was helping less skilled players, but overall were not very pronounced in their judgment. The reason for this could be that we increased the speed at which the circles normally grow because the sessions were quite short. For longer sessions, the growth's speed would be set to a lower value, making the change in circle size less noticeable. For skilled players, the mean was effectively four, which implies they did not feel it helped or hurt skilled players. This ties in with our findings in the feedback sessions, where players were unable to pinpoint the reason of the circle size change. The results suggest the game was able to modify the circle size based on tagger time, in an effort to balance out skill levels, and still feel fair to the players.

5.2.2.6 Skill Level

The last five questions belonged to the category of Skill Level (Q23-27). These questions were included to obtain background information on the physical abilities of players and their self-assessed ability to play tag. The mean for this category was 4.83 and its Cronbach's alpha was 0.78. The high value of the alpha suggests that this category could be considered a dimension on its own. We added this category to explore how the self-assessed ability of the players correlated with the Enjoyment and Immersion dimensions. In this regard, we did not find any significant correlation between each question related to a player's physical abilities (Q23-26) and either the Enjoyment or Immersion dimensions when using a 2-tailed bi-variate Pearson correlation test. Considering that the physical fitness of the participants varied greatly (SD for Q23 and Q25 was relatively high), this means the game was enjoyable for people who reported being physically active as well as for those who did not. We also hypothesized that players who considered themselves in good shape (Q24) would usually think they make good tag players (Q27). However, there was no correlation between the two questions. Interestingly, there was no correlation between Q27 and any dimension, which shows that players found the game enjoyable independent of whether they thought they were good at tag.

5.2.3 Observations and Feedback

Besides asking players to fill in the questionnaire, we also invited them to a short discussion session. This discussion included elaborating on their impressions of the game and setup, as well as commenting on things that were not asked in the questionnaire, such as suggestions for improvements or problems they encountered. Below we discuss the most important points that players brought up in the discussion, as well as our own remarks derived from observations of the game sessions. This information complements the evaluation done using the questionnaires, and provides further insights on the functioning of the ITP.

The space available for the game was regarded differently based on which type of tag was being played and the number of simultaneous players. For traditional tag, players said they felt the space was too small with both four and five players. For interactive tag, when played with four players, the space was considered adequate,

but when played with five, it was regarded as rather small. This difference in opinion is related to how the game is played and how players tag each other in each version of the game. In interactive tag, players need to make their circle come into contact with that of other players, and because of this, they have to look down from time to time to check the position of the circle. Due to the circles lagging behind the players, this behavior was seen often, and, although it did not prevent players from running, it did slow them down a little. In traditional tag, players have no need of verifying the position of their circles, and can run at full speed towards other players. Moreover, they can use their arms to extend their tagging reach. Although this could be simulated in the ITP by changing the size of the circles to approximate an arm's reach, more important is the fact that the size of the circle can be modified depending on what goals are being sought. Changing the tagging reach is one possible goal, but others could include changing the game's difficulty or attempting to modify how much people move.

When playing the interactive version of the game, a sound was played to signal the occurrence of a tag but many players mentioned they did not notice it. Some of them said that if you were not running, then the sound was easier to hear. This is reflected in the score of Q17. Something all players did notice was the changing circle size. When asked for the reason of the size change, most players were not able to guess the correct reason. Many players thought the circle size changed according to their movement speed, stating that moving slowly made the circle grow. Moving slowly does lead to prolonged periods of being a tagger, which means that indirectly, they are related. Nonetheless, speed was not taken into account at all when calculating the size change rate. This is important because it conveys it is possible to carefully design game interventions that can change the course of the game without players being aware of what is happening or affecting how they perceive the game. This further corroborates our analysis of the Balance/Fairness category, where the scores indicate that players did not feel the game favored players based on skill.

In both the normal and interactive game sessions, besides tag game behavior, we could also witness an abundance of social interaction between the players. Although we did not conduct a formal study on these game aspects, players were observed yelling at each other, making jokes, making fun of each other, and seeking revenge when tagged (e.g. see Figure 5.3). This is very important because it means the game, in its interactive version, supports social elements of play. Players are not only playing with the system, but actually with each other, and the system acts as a moderator. Also for physical exertion, we could witness significant investment from players in both normal and interactive tag sessions, although to a lesser degree in the interactive version of the game.

In general, all participants agreed that the interactive tag game was very enjoyable and exhausting. Due to some problems with the network setup when carrying out the experiments, there was a lag of about half a second in the movement of the circles. During the feedback session, some players were unsure whether this was a feature of the game or if the tracking was not working properly. Players said that at the beginning of the session, the circle seemed a bit hard to control because it was slightly behind them, but they got used to it as the game went on. Some players said they

Figure 5.3: Player performing a short dance when tagging another player in the ITP

liked it because it forced them to be more strategic, thinking on what to do and trying to predict other players' movements instead of just chasing them. Consequently, body feints became incredibly useful as they allowed runners to escape more easily given the delay in the tagger's circle response.

5.3 The ITP as a Game Installation

The results of the questionnaire show that the ITP was able to positively enhance tag games while providing a fun experience, which was one of our main design considerations. The two dimensions used to compare the experience, Enjoyment and Immersion, showed a statistically significant preference towards the interactive tag game. The questions that were used in the Gameplay and Enjoyment of Game Elements dimensions also scored positively, which means that tracking players using cameras is an appropriate way to locate players and interact with the game. Also, the game elements were designed appropriately, although the sound was not heard very well. The results of the Skill Level category demonstrate that the enjoyment of the game did not depend on whether the players were good at tag or were physically active, which is promising for a potential deployment of the ITP as a public installation.

The results of the study also show that the ITP, through its digital elements, was capable of adapting the gameplay and game mechanics subtly. Players did not feel the game favored skilled or unskilled players. On a general level, this means that there

are opportunities for balancing skill levels using player information, which can lead to potential improvements in game enjoyment and prevent play from breaking down. The Balance category showed a) that players did not feel the game interfered with their ability to play tag games, but b) that the ITP did not allow them to show all their skills, either. The former indicates that the visual tracking of players allows them to run freely during the game. The latter, we believe, is due to the lag preventing them from exhibiting the full extent of their capabilities and the inability to use their arms to tag.

Finally, the observations made during the interactive tag game sessions demonstrate that the ITP is able to retain the social and physical aspects of the traditional game of tag. This was one of our goals when we decided to use as many of the original game mechanics as we could in the ITP. We observed people running around, attempting to jump circles, pushing people to use them as shields or yelling at each other. The size of the playground was considered big enough for only four players, which is a limitation of the current implementation of the ITP. Also, players could not run as fast as they wanted due to some technical difficulties that caused the circles to lag behind the players. This, however, should be solved quickly once the network problem is fixed. In general, the ITP elicits physical exertion by allowing players to move freely while playing, mediates the interactions between players, and still allows them to interact amongst themselves while doing so.

Part III

Objective Analysis of Tag Behavior in the ITP

6

Analysis of Behavior in Interactive Tag Games

In Part III of this thesis, we will describe how the collected player data can be used to analyze different behavioral aspects of play in the ITP. In this chapter in particular, we will take a first look at the data that can be automatically gathered by the ITP, and derive information on basic behavioral cues that allow us to understand how the game is played. We will compare this to the analysis we carried out on the Play corpus, which provided insights into how traditional tag is played. This comparison provides an objective analysis of how the ITP changes the way players approach the game of tag. We will also look into how the playing space available to the ITP can affect player behavior.

The chapter is structured as follows: In Section 6.1 we will briefly describe why it is important for the ITP to be able to automatically measure player data during games, and how this can be used to analyze behavior more easily. In Section 6.2 we will analyze the behavior exhibited by players in three different datasets and compare how or if the exhibited behavior changes between different settings. These analyses use data that is collected automatically by the ITP. Finally, in Section 6.3, we will sum up our findings, discuss how the ITP can facilitate the process by which behavior is analyzed in games, and present some possible applications for the data.

6.1 Facilitating Behavior Analysis with the ITP

Behavior in interactive playgrounds is normally evaluated through observational studies or by annotating game recordings. In Chapter 5, by observing players play in the ITP, we could state that physically active and playful, social behavior was being exhibited. Observations are good in providing an overall picture of the exhibited behavior, but a quantitative analysis of player data could provide further insights into how games are played. In Chapter 3, we showed how objective measurements can be derived from the annotation of game sessions, but the process by which they are obtained can be time-consuming and error-prone.

One of the main goals of the ITP is to change this. In the ITP, we are able to gather position-related in-game data that can be used for many purposes. When used

online, for instance, the data could be used to adapt game mechanics to make the game more fun, or to steer player behavior to promote positive outcomes. When used post-hoc, it could be used to evaluate or analyze certain aspects of the game to design better game interactions, reveal differences between individuals, or “debug” interactions or games. Importantly, these analyses or conclusions would be based on objectively measured data gathered automatically by the system.

We will present the analysis of the behavior exhibited by players when playing interactive tag, derived solely from automatically collected data by the ITP. We use the same four behavioral cues that were used to analyze behavior in the Play corpus. We compare the behavior shown by the players during the interactive tag game sessions to the behavior shown in the Play corpus to see how much of it is translatable not only across settings (interactive versus traditional), but also across target groups (children versus young adults). We will also look into how the playing space might affect how players play the game.

There are three goals we want to achieve with the analysis presented in this chapter. First, showcase how the system can help researchers speed up the behavior analysis process of games played in the ITP. Second, although we managed to confirm that the positive aspects of traditional tag were still present in the ITP (Section 5.2.3), we want to evaluate whether this is a consequence of play behavior being similar in both settings. Third, since the ITP is designed to be a public installation, we want to identify early on if there are differences in play behavior between people of different age groups, or when playing with different space restrictions.

6.2 Automated Analysis of Behavior in the ITP

We compared the behavior of the players using three datasets. The first one is the Play corpus, introduced in Section 3.2. The Play corpus consists of children playing traditional tag in a $7\text{m} \times 6\text{m}$ area. We used four cues to analyze this corpus: absolute position, movement speed, inter-player distance and relative movement direction (Section 3.3). These four cues will be used to analyze the other two datasets as well. In the Play corpus, obtaining this information required the manual annotation of position and role information for each player, however, in the ITP, they are entirely derived from the automatically collected position and role data.

The second dataset is the one we used in the previous chapter, the ITag2 (Section 5.2.1) dataset. This dataset consists of seven sessions of young adults playing tag in the ITP in a $7\text{m} \times 6\text{m}$ area. In six of these seven sessions four players played simultaneously. In the seventh session, five players played at the same time, and it is therefore not considered in this analysis. The last dataset, the ITag1, also consists of young adults playing tag, but in the ITP 1.0. Although there are differences between iterations of the ITP, the core game mechanics and tracking algorithm did not change between ITP iterations. This dataset contains 14 sessions of young adults, aged 20-30, playing interactive tag in a $6\text{m} \times 3.3\text{m}$ playing space. In each session, three players played simultaneously for approximately four minutes.

Figure 6.1: Occupancy map of (a) taggers and (b) runners in the ITP. Darker values represent less presence at that specific location.

6.2.1 Absolute Position

In the analysis of the Play corpus, we noticed that both taggers and runners exhibited distinct patterns while playing. Runners tended to stay around the edges of the playground, noticeably avoiding the center of the playing area. Taggers, in contrast, spent most of their time near the center of the playground, with no other specific preference. As we can see in Figures 6.1a and 6.1b, the patterns exhibited by players in the ITP are largely the same. Taggers remained close to the center, whereas runners stayed close to the boundary of the playing area.

When comparing the behavior to the one exhibited in the ITP 1.0 (approximately half the playing area), we can see that it did not change. Figures 6.2a and 6.2b show that even with only half the space to run around, runners still spent most of the time near the edges of the area. Taggers also had the same tendencies as in the other settings.

In the three different datasets we have analyzed, the behavior is largely generalizable. Since testing against every possible combination of age and available space would not be practical, we feel that these results show that, in general, players occupied approximately the same locations of the playground even when certain conditions changed. We must note that in extreme circumstances this might not be the case. For instance, we have witnessed that players that are too young (approximately five years old) sometimes do not understand how the game is played and therefore move differently. Also, in a separate study, we have seen that interventions can be used to alter how players move during the game.

Figure 6.2: Occupancy map of (a) taggers and (b) runners in the ITP 1.0. Darker values represent less presence at that specific location.

6.2.2 Movement Speed

The speed of both roles was found to be very similar in the Play corpus. Runners showed a slightly higher likelihood than taggers to move at slow speeds, whereas taggers showed the same tendency but for faster speeds. In general, however, the differences were marginal. As seen in Figure 6.3a, the same could be said for player speeds in the ITP. Runners tended to move more at lower speeds, and taggers tended to move more at higher speeds. One difference between the exhibited behavior is the distribution of speed values. In the Play corpus, the speed range was broader and the peak was located near the 0 m/s value. In the ITP, the peak of the speed distribution is more centered, located around the 1-1.5 m/s value.

When analyzing the speed of players in the ITP 1.0 (Figure 6.3b), we can see that runners also adopted slower speeds more often than taggers, and the peak of the distribution is also rather centered. One notable difference is that players were moving most of the time in the ITP 1.0 in comparison to the ITP, as evidenced by the difference in the 0 m/s occurrences. This may be due to the space being smaller, which did not allow players to rest in a corner since the tagger was always nearby. Additionally, the fact that there were fewer players also meant runners had a higher chance of being chased, leading to less time to rest.

Speed values were similar for the different age groups, type of tag, and playing spaces. We notice that certain tendencies also appear in all settings; namely that runners usually moved at lower speeds more often than not, and that taggers moved faster than runners. We believe the specific speed values can change depending on

Figure 6.3: Frequency of player speeds during the (a) ITP game sessions and (b) ITP 1.0 game sessions.

the players and setting, but these tendencies will most likely remain the same. At least from our recordings, we can say that movement speed remained similar across age differences, playing space variations, and interactive or traditional tag environments.

6.2.3 Inter-Player Distance

Inter-player distance in the Play corpus did not show big differences based on the roles when considering all runners in the calculation. As we can see in Figure 6.4a, the same happened in the ITP. There was a small decrease in the occurrence of runner-runner distances near the 2m-3m distance, which conveys that runners were actively avoiding being at this distance from other runners. Besides this, both distributions were very similar. On the other hand, in the ITP 1.0, we can see that the tagger-runners distance distribution was slightly different than the runner-runners one, with the peak noticeably closer to zero (Figure 6.4b). This was probably due to the limited playing space, which made it impossible for runners to stay far away from taggers.

Figure 6.4: Frequency histograms of inter-player distances based on their roles in the (a) ITP and (b) ITP 1.0.

When looking solely at the closest runner to a particular player, as in the Play corpus, the difference in inter-player distance based on role was more evident. Figure 6.5 shows that taggers were very often close to a runner (1m-2m), and the behavior

was the same in all settings.

Figure 6.5: Frequency histograms of inter-player distances to the closest runner in the (a) ITP and (b) ITP 1.0.

The distance between players is a measurement that is largely dependent on the available playing space. We assumed we were going to see big differences in distance between players, but as we can see, this is not entirely the case. Especially for the tagger, in all settings, the distance at which the closest runner was located more often was consistently found around the 1m-2m mark. Of course, the smaller the playing area, the closer all players are to each other. This is the reason why the distance distribution in the ITP 1.0 was narrower than in the other settings. Nonetheless, there are no notable differences between how children and young adults positioned themselves, and neither on how players in traditional tag and interactive tag do so.

6.2.4 Relative Movement Direction

The last feature that we analyzed in the Play corpus was the relative movement direction between roles. This feature was highly discriminating between roles. We found that taggers were mostly running directly towards the runners. In contrast, runners moved away from taggers, but not in the completely opposite direction (180°), but at around 90° - 150° . When looking at the relative movement direction of players in the ITP, we noticed that the behavior was almost identical (Figure 6.6a). The number of times taggers moved at relative angles close to 0° (*i.e.* chasing runners) was very high. On the other hand, runners often ran at relative angles between 90° and 140° . The behavior was the same when considering the smaller playing space, as seen in Figure 6.6b.

Relative movement direction remains one of the most role-discriminant features, even when the game is played by people of different age groups, with different amounts of space, or when playing interactive tag. Since the goal of the game is the same, (*i.e.* avoid being tagged) unless an intervention changes the goal of the game, we believe the behavior will be the same under any condition.

Figure 6.6: Angular histogram of the relative movement direction between roles in the (a) ITP and (b) ITP 1.0. In blue from tagger to runner, in red from runner to tagger.

6.3 The ITP as a Research Platform

The features used in the previous analysis (position, speed, inter-player distance, and relative movement direction) provide insights into how the game of tag is played, and show that player behavior does not vary significantly between the three different conditions: type of tag, available playing space, and age group. Therefore, not only does the ITP make the game of tag more engaging (Section 5.2), but it does so without affecting how the game is played normally. Moreover, it also showcases how the automatic logging of player data can be useful when analyzing player behavior. Regarding the players' position, we have found consistent player location trends based on their roles: runners tend to stay on the boundary of the playground, taggers tend to stay near the center. We also found that, in general, taggers move faster than runners. Lastly, taggers consistently move towards runners, whereas runners move away from taggers at around 90° to 150° .

An important consideration is that when the analysis of the same features was carried out on the Play corpus, we had to manually annotate the position of all players and their roles. When using the ITP, the data was collected automatically, speeding up the process considerably. Besides using this information for post-hoc analysis of behavior, it can also be used to design novel ways to change or steer behavior during gameplay. One could, for instance, define temporary safe zones in the playground where players are invulnerable to being tagged, and place these areas near the center of the playground to see if players are willing to take risks in exchange for advantages. As such, players could be steered towards demonstrating more risk-seeking behavior.

It is also important to mention that even though in this study we analyzed the behavior of players during an interactive tag game, the analysis could be performed on other types of games without complications. Since the data logging and measurement do not depend on the game logic module, the data gathering would not be affected by implementing other types of games. This would be very helpful in games implemented through iterative design paradigms, as the in-game data could help speed up the analysis of each prototype.

7

Automatic Measurement of Physical Activity in the ITP

In this chapter, we will show that players' physical activity can be automatically measured in the ITP. To do this, we estimated the speed at which players moved during interactive tag games, and showed it was correlated to the players' physical effort as measured by their heart rate. The players played different versions of the interactive game of tag where the size of the circles had been modified, and these differences were shown to elicit different amounts of physical activity. To evaluate our proposed approach, we will compare it to other physical activity measurement methods.

This chapter is structured as follows: Section 7.1 will present an overview of how physical activity is currently measured or evaluated in active video games. In Section 7.2 we will describe our experimental setup. We will start by presenting the physical setup as well as the experimental design. We will then explain the different methods that we used to measure physical activity, followed by our hypotheses and explanations of how these hypotheses were evaluated. Lastly, in Section 7.3, we will present the results of our study, detailing the outcome of each hypothesis, the comparison of our proposed method to other evaluation methods, and the in-depth analysis of the obtained data.

7.1 Physical Activity in Interactive Installations

In Section 1.3 we discussed that digital gaming has brought many unforeseen problems with its adoption, such as an increase in children's sedentary behavior and consequent health complications. To address this issue, games that encourage players to be physically active while playing, games known as active video games (AVGs) or exergames (Section 1.3.1), have been introduced. One problem with AVGs is that promoting physical activity does not necessarily mean that players actually engage in appropriate levels of activity during play [35]. Players could, for example, move very little during the game and exercise only briefly. In contrast, players might move too much and burn out before a game session is over.

This could be prevented if the game were able to adapt automatically based on a

player's levels of physical activity. This, in turn, would only be possible if the game could measure and assess a player's physical activity level during the game. AVGs are typically evaluated through the direct observation of game sessions, proxy reports, annotation of recordings, or asking participants to assess their own experience through questionnaires [85]. The results obtained by these methods cannot be used in-game. Annotating requires observers to categorize specific actions during play using annotation schemes, but most of the times it is performed using game recordings since live annotation is difficult [66, 84]. Questionnaires that evaluate physical activity are filled in after the game sessions since they ask players about their experience. Likewise, the results of observational studies of game sessions are only available after the study has been concluded and, therefore, after the game sessions have concluded as well.

A potentially more useful method of assessing exertion is using in-game data. In-game measurements provide a continuous stream of data in real time via sensors that players usually have to wear, such as accelerometers, pedometers, or heart rate monitors. They provide researchers fine-grained data, allowing them to understand the causes and effects of certain actions. Typically, these sensors are used as input for controlling games rather than measuring physical activity. For instance, body-mounted trackers have been used to sense upper body motion in games [189], or gloves equipped with sensors to interact with projections on walls [55]. With the advent of more affordable and accurate sensors, in-game measurements in AVGs are becoming more common. Rather than only evaluating exertion goals/levels after the game session has ended, they allow the system to react to certain scenarios on-the-fly and adapt gameplay to steer behavior in positive directions [37, 181]. This is only possible with real time measurements.

In regards to the in-game measurement of exertion, many studies rely on heart rate monitors (HRMs) for this task. Due to the relationship between heart rate (HR) and oxygen consumption [190], their increasing accessibility and portability, HRMs are considered a standard method to assess exertion in games. In-game heart rate measurements can be used, for instance, to balance skill differences based on fitness levels [71], to create the illusion of presence in distributed activities [53], or to modify game mechanics based on the amount of effort being put into the game [64]. Other studies prefer disregarding wearable sensors in lieu of pervasive sensing methods. These studies use the automatic measurement of body position or location to analyze and evaluate the amount of player movement [69, 191].

We also propose using a pervasive approach for the measurement of player activity in the ITP. In the following section, we will present our method to obtain in-game measurements of physical activity using a completely unobtrusive method, namely computer vision. Furthermore, we will also demonstrate how the level of activity can be influenced by adapting a single gameplay element in the ITP. Both contributions together demonstrate the potential of automatically and unobtrusively measuring physical activity for active video games.

7.2 Measuring Physical Activity in the ITP

To investigate whether we could measure physical exertion in the ITP, we designed three scenarios with different circle sizes. We expected that changing the size of the circles would affect the amount of physical activity that is required to play the game. We measured the amount of physical activity in each condition in a completely unobtrusive manner through computer vision. We tracked players during the game and calculated their speeds. Using this information, we estimated their physical activity levels. We compared our estimates with HR measurements obtained from heart rate monitors, which we considered as ground truth for physical activity in this study. Additionally, we also compared the measured physical activity to the players' self-reported exertion levels, obtained from questionnaires. Finally, we compared our approach to two previously used ways of measuring physical activity: using accelerometers and using pixel-differences.

The tag game played was the basic game of interactive tag (Fig. 7.1). This means that no interventions were employed by the ITP, and the circle size was set to a constant radius during each sub-session (instead of pulsating as they normally do). The playing area was set to $6\text{m} \times 5\text{m}$.

Figure 7.1: People playing tag in the ITP

7.2.1 Experimental Design

There were two distinct goals in this study. First, to modulate physical activity in the ITP by changing players' circle size. The purpose of changing the size of the circle was to manipulate the amount of effort it takes to tag other players. With smaller circle sizes, we expected an increase in effort. Our second goal was to demonstrate that a player's speed could be used as a reliable measurement of general physical activity

in interactive playgrounds. The experiment we designed to achieve these goals was approved by our university's ethical committee.

We recorded 12 sessions, each with four participants. The first four sessions were planned as pilot runs. Each session consisted of three tag game sub-sessions with breaks in between. In each sub-session, players played different versions of the game in which the size of the circles differed (see Figure 7.2). The first sub-session was always played with the standard circle size and was meant for players to familiarize themselves with the game and its mechanics. In the other two sub-sessions, we wanted to find out if the size of the circles affected players' activity levels, and if so, if we could measure the difference. In one condition, the circle size was smaller than the standard size (High Exertion Condition - HEC), and in the other, the circle was bigger than the standard size (Low Exertion Condition - LEC). Experimental conditions were balanced by alternating the order in which they were carried out.

All participants were BSc, MSc and PhD students from our faculty. They were approached at the university and asked if they wanted to voluntarily participate in a 30-minute study in which they were going to play tag. After this, they were taken to the playing area.

7.2.1.1 Pilot Study

The goal of the pilot sessions was to test the game and determine a suitable duration for each sub-session and the breaks in between. The size of the circles was empirically determined. After each game session, players took part in a semi-structured interview where we asked whether they noticed differences between sub-sessions, what was the difference, and which session they liked the most.

In general, all players noticed the difference in circle size. Most players stated that the sessions were a bit too long for their liking. Some players were noticeably tired or flat out exhausted. We also noticed that the duration of the break was not enough for several participants to regain their breath for another sub-session. Based on these remarks and observations, we fixed the parameters for the final study.

7.2.1.2 Final Study

For the final study, the duration of the first sub-session was set to one minute and the duration of the two condition sub-sessions was set to four minutes. The duration of the breaks between sub-sessions was set to four minutes. The diameter of the circles was set to: 102 cm in the standard condition, 66 cm in the HEC, and 149 cm in the LEC. The size of the circle in the HEC was set to resemble the average shoulder width of young adults, whereas the size in the LEC was set to approximate an arm's reach.

7.2.2 Measurements

We measured physical activity using several methods to compare to our proposed approach. The first method for measuring physical activity was to obtain the HR of the players using HRMs. HRMs are widely used to determine exercise intensity [192], which is why we used them as our ground truth measurement. We used Scosche Rhythm Plus HRMs, which were strapped to the forearm of each player. We measured

Figure 7.2: Difference between circle sizes in the HEC(t) and LEC(b)

HR every second for the entire duration (four minutes) of the condition sub-sessions. The unit used for the HR measurements is beats per minute (bpm).

The second method for activity measurement was using accelerometers. Accelerometers measure the amount of acceleration to which the sensor is subjected, a measurement directly related to the amount of movement of the user. Accelerometers have been shown to measure exertion reliably in previous studies [162, 190]. We used YEI 3-Space wireless accelerometers for this study, which were placed in the pocket of each player. These sensors allow us to collect acceleration data 15 times per second.

We applied a median filter with a window size of one third of a second to remove noise and interpolated missing values. The unit used for the acceleration values is g , where $1g$ represents the standard acceleration of gravity ($9.8m/s^2$).

The third method used to measure physical activity was pixel difference. Pixel difference is a computer vision method by which the similarity of two consecutive images is calculated by subtracting one from the other. If two images are exactly the same, no pixel differs between them and thus the subtraction yields zero. In the case of a video feed of people moving, subtracting consecutive frames yields an approximate measurement of how much movement is present in the sequence since the background does not change and is thus ignored in the subtraction. To obtain the pixel difference value, we subtracted consecutive depth images obtained from the Kinects every one fifteenth of a second. We took into account the entire playing area. We applied basic morphological operations (dilation, erosion) to diminish the effect of noise on the input side, and a median filter (window size = one third of a second) on the actual pixel difference values to clean the obtained data. We used depth instead of RGB images because the projections that we use are animated, which would result in differing pixels in consecutive frames irrespective of whether players had moved.

The last method used to measure physical activity, the one we propose in this study, was tracking players in the playing area and calculating their speed. Since the system is able to track players, the speed information can be obtained automatically by calculating the track displacement every one fifteenth of a second. To eliminate the noise inherent to data collection, we applied a median filter with a window size of one third of a second on the position data, and interpolated position values when tracks went missing.

For all data analysis, we discarded the first two minutes of data since during this period the HR is rising (see Figure 7.4). During the last two minutes, HR has stabilized and more accurately represents exertion levels. For all methods, we averaged the measurements per group for two reasons. First, even though the tracker works well, player tracks occasionally switch during tagging. This means that, without manual supervision, there is no guarantee that measurements related to a given player belong only to this player. This is a limitation of our proposed approach. Second, pixel difference is a group/global measurement, thus we use group measurements for the other methods as well to be able to compare between them. The drawback is that we average over inter-personal differences. Also, this effectively reduces the number of observations, which makes statistical analyses conservative.

7.2.3 Experimental Procedure

Before the session, all players were asked to read and sign a consent form with a brief description of the game. After signing, players were taken to the playing area, explained the game in detail and left to play for 1 minute. Afterwards, they were asked to sit down for 4 minutes. During this time, the HRMs and accelerometers were fitted. The accelerometers were put in the players' pockets, and the HRMs were secured to the upper part of the players' forearms (see Figure 7.3). Once the break was over, players were asked to return to the playing area and play the second sub-session for 4 minutes. After this, they were asked to fill in a short questionnaire while

they rested. After the break, they were asked to play the last sub-session. Afterwards, they were asked to sit down again, fill in the last part of the questionnaire, and to engage in a short debriefing/feedback session.

Figure 7.3: Sensors used in this study.

7.2.4 Questionnaire

The questionnaire served two purposes. The first was to evaluate the perceived exertion of the players after a given condition session. The second goal was to keep players occupied during the break so they would rest. Perceived exertion was measured using Borg's Rating of Perceived Exertion (RPE) Scale [193]. The Borg scale is a linear scale from 6-20. The range of the scale was designed to broadly represent the HR of healthy adults. Using this scale, a perceived exertion of 10 would be expected to coincide with a HR of 100 bpm. We also asked additional questions in regards to their estimated fitness level, physical characteristics (height, weight), preference of game elements, among other information. None of this information was used for this particular study.

7.2.5 Hypotheses and Operationalization

Below, we will describe our hypotheses, the rationale behind them and the data that was used to validate them.

7.2.5.1 Physical Activity and Circle Size

HR is likely to change depending on the size of the circles. With larger circles, less effort should be required to tag others, resulting in lower HR. Therefore, it should be possible to influence the amount of physical activity of players in the ITP by varying circle sizes.

H1: The HR of players is higher in the HEC than in the LEC.

This hypothesis is a manipulation check to validate whether changing the size of the circles indeed affects players' physical activity. The hypothesis is validated by comparing the average HR of all players in a group for the last two minutes of the LEC and HEC sub-sessions, respectively. This leads to one HR value, per group, for each condition.

7.2.5.2 Player Speed and Circle Size

The speed needed to tag other players is affected by the size of the circles. With larger circles, players should be able to run slower and still tag other players. Therefore, players' speed measurements through tracking should be lower in the LEC than in the HEC.

H2: The speed of the players is higher in the HEC than in the LEC.

This hypothesis checks whether we can use a player's speed to measure physical activity. To validate it, we use the average speed of all players in a group for the last two minutes of the LEC and HEC sub-sessions, respectively. This results in one speed value for each group, for each condition.

7.2.5.3 Heart Rate and Player Speed

Exertion measurements not only depend on the amount of physical activity a player is undertaking, but also on his fitness level and body properties. However, the speed at which players move should still directly affect the amount of effort players are putting in when playing. If the amount of effort needed to tag others is changed, exertion should change as well. Therefore, the speed at which players move should be directly related to HR, our ground truth measurement for exertion.

H3: The speed and HR of the players are positively correlated.

This hypothesis checks whether we can replace HR measurements (exertion) with players' speed measurements (general physical activity). To validate it, we use the average speed and HR of all players in a group for the last two minutes of the LEC and HEC sub-sessions, respectively. We pair the HR and speed measurements for each group, for each condition.

7.3 Experimental Results

The analysis is based on the questionnaire data and the measurements of the HRMs, accelerometers and the tracker. We carried out eight sessions with four participants each. In total there were 32 participants: 23 male, 9 female. Their age ranged from 19 to 28 years, with a mean of 21.9 and a standard deviation of 2.36.

7.3.1 Measuring Physical Activity using Tracking

First, we needed to verify whether our two conditions elicited different amounts of physical activity. Therefore, we checked whether the HR measurements using the HRMs changed between conditions. In Figure 7.4 we can see that the difference between conditions was noticeable almost from the beginning. To check whether the difference between conditions was significant, we conducted a 2-tailed paired samples t-test. The test showed a statistically significant increase in HR of 9.6 bpm in the HEC ($t(7) = 3.2, p < 0.05$). This confirmed hypothesis **H1** that the HEC promoted more exertion than the LEC and that circle size could be used to influence the amount of activity.

Figure 7.4: Average HR measurements of all players in the LEC and HEC. Only the last two minutes of play are used for the data analysis.

With **H1** validated, our next step was to investigate whether it was possible to use the speed of the players to measure physical activity. Since each condition elicited different amounts of physical activity, we expected the speed to be different in each condition as well. The speed of the players in both conditions can be seen in Figure 7.5. We ran a 2-tailed paired samples t-test to evaluate whether speed changes were significant between conditions. The test showed a statistically significant increase of 0.06 m/s in the HEC ($t(7) = 2.5, p < 0.05$). This confirmed hypothesis **H2** that the players moved faster in the HEC than in the LEC. This means that by changing the

size of the circles in the ITP we cannot only achieve a higher HR, but also encourage players to run faster during the game. We note though that the difference in speed was not very large for some groups, such as in session 3. In session 5, we can even see that the measurement is the opposite to what we expected. This is discussed in more detail in Section 7.3.4.

Figure 7.5: Average group speed per condition, per group.

Lastly, given that both HR and speed were significantly different in both conditions, we needed to check whether they were correlated. We used a 2-tailed bi-variate Pearson correlation test and obtained a statistically significant correlation for both variables ($r = 0.72, p < 0.01$). Pearson's r measures the degree of linear relationship between two variables, the strength of their relationship. An r value of 0.72 is considered a strong relationship, which means both HR and speed were strongly correlated, confirming hypothesis **H3**. This shows that it could be possible to use tracking and measure speed to measure physical activity when HRMs are not appropriate or possible. We also fitted a linear equation using linear regression on the data for each group ($f(x) = 0.0045x - 0.142$), which showed the positive correlation between the variables (see Figure 7.6).

7.3.2 Comparison to Other Activity Measurement Methods

We compared our proposed approach to two other physical activity measurement methods. First, to the one discussed in [191], where computer vision was used to measure exertion in an interactive installation. Second, to the use of accelerometers.

Figure 7.6: Scatter plot of the average speed vs. the HR of all groups and both conditions.

7.3.2.1 Pixel Difference

Pixel difference has been used in IPs to measure the physical activity of groups of children with success [191]. A problem with this approach is that it can be affected by elements not related to movement per se. Having more people in the playground can lead to more pixels changing, although this could be solved by dividing by the number of people. Body size, clothing, viewpoint, occlusion, and other characteristics can also affect the pixel count, but none of these are related to exertion. Another problem is that pixel difference is a global feature, which means it considers the entire image for a single measurement. This prevents the analysis of individual players.

We found a statistically significant increase in the pixel difference count of 0.97% in the HEC ($t(7) = 2.7, p < 0.05$), and a statistically significant correlation between HR and pixel difference ($r = 0.78, p < 0.01$). As we can see in Figure 7.7, session three did not show a higher value of changed pixels in the HEC (speed values only showed a small increase in the HEC for this session). Sessions one and five also showed a very small increase.

7.3.2.2 Accelerometer

Compared to tracking people and counting pixel differences, using accelerometers does not require having a computer vision system in place. This makes the deployment of accelerometers significantly easier in comparison to the other two methods. However, since accelerometers (or sensors in general) need to be fit before playing, they cannot be used in autonomous public installations as additional personnel would be required to hand out and collect them. Since accelerometers measure changes in speed, the measurements depend on where on the body they are fitted [128]. Moreover, sometimes it is just not possible for players to wear sensors. Also, when phones are used, these need to be paired to other devices in advance.

Figure 7.7: Average group pixel difference per condition, per group.

We found a statistically significant increase of 0.07g in acceleration in the HEC ($t(7) = 2.5, p < 0.05$), and a modest correlation between HR and acceleration ($r = 0.52, p < 0.05$). We can see in Figure 7.8 that acceleration also exhibited behavior opposite to what we were expecting in session five (speed measurements showed higher speeds in the LEC), and only showed a small increase in session three.

7.3.3 Perceived Exertion Analysis

Perceived exertion can inform us whether the players were aware they were exerting differently in the two conditions. This can prove to be valuable information in the design of future game interventions. For instance, in some cases, it would be beneficial to promote high levels of exertion without players being aware of it (could result in longer play sessions). For this study, players rated their perceived exertion after each condition, which led to two ratings per player.

To analyze the difference in perceived exertion, we conducted a 2-tailed paired samples t-test on the RPE questionnaire answers. This showed a statistically significant increase of perceived exertion in the HEC of 1.88 in the Borg scale (corresponding to a 18.8 bpm difference) ($t(31) = 6.2, p < 0.01$). This difference is roughly twice the difference measured using HRM (9.6 bpm). This implies players were not only exerting more in the HEC, but they also perceived this as such. If we look at the measured and perceived HR for all sessions, we see that in both conditions players underestimated their amount of exertion, more so in the LEC than in the HEC (Table 7.1). This actually conveys that players thought they were exerting less than they were, and perceived the difference between conditions bigger than it actually was.

Figure 7.8: Average group acceleration per condition, per group.

Condition	RPE	HR (bpm)	
		Perceived	Measured
LEC	12.75	127.50	157.53
HEC	14.63	146.30	167.08

Table 7.1: Perceived and measured exertion (HR) for both conditions.

7.3.4 Discussion

The findings reported in this paper are important for a number of reasons. First, we have shown that completely unobtrusive measurements of physical activity are possible. This can alleviate the workload required to evaluate whether certain IPs indeed promote physical activity. In cases where the use of questionnaires or observational studies is not possible, our method could be used to get an estimation of how much physical activity is being promoted by the installation. Moreover, physical activity measurements could be used in-game to adapt gameplay and steer behavior.

Specifically in the ITP, we have shown that by changing the size of the circles we can manipulate the speed at which players run. Therefore, the system could sense when players are not playing at intended levels, and grow or shrink the circles slowly to reach an acceptable level. Considering that taggers run faster than runners in tag games (Section 6.2), it would be interesting to test whether changing the circle sizes can be used to balance the amount of physical activity between roles. For instance, when calculating the speed of the players based on their roles (Table 7.2), we find that taggers were not affected much by the size of the circles. There was a statistically

Role	Condition	Speed (m/s)	
		Mean	SD
Runner	LEC	0.52	0.10
	HEC	0.59	0.06
Tagger	LEC	0.66	0.07
	HEC	0.68	0.07

Table 7.2: Speed values of players per role and condition.

significant increase in speed of 0.07 m/s in the HEC for runners ($t(7) = 3.1, p < 0.05$), but for the taggers this was not the case ($t(7) = 0.8, p = ns$). The difference in the effect hints at the possibility of balancing physical activity between roles in the ITP.

Table 7.3 shows a comparison between the investigated methods and how good they can measure physical activity. We can see that tracking players and measuring their speed is a good approach to measuring physical activity. It is a completely unobtrusive method, has a high correlation to HR, and could potentially be used to assess physical activity individually. Currently, our tracker can only measure physical activity at group level without the manual correction of players' tracks. Pixel difference can also be regarded as a good method to measure physical activity. Its correlation to HR is high and it is also a completely unobtrusive method. Additionally, it does not require tracking, which simplifies the implementation. However, counting pixels can lead to different values based on reasons not related to physical effort, such as player size and clothing. Also, it can only measure physical activity at a group level, since it is impossible to distinguish individual players using this method. Lastly, accelerometers also proved to be able to measure physical activity differences between conditions, but their correlation to HR is mediocre, which hints at it not being an appropriate method to measure exertion. Even though accelerometers also allow measurement on both group and individual levels, they are not unobtrusive.

	HRM	Tracking	Pix. Diff.	Accel.
r -HR	1	0.720	0.777	0.521
Tracking		✓		
Contactless		✓	✓	
Individual	✓	?		✓

Table 7.3: Comparison of physical activity measurement methods.

When looking at individual differences between sessions, we can see that in sessions one, three and five, measurements sometime exhibit effects contrary to what we expected. At least one of the methods shows a decrease in its corresponding measurements for one of these sessions, or shows a very small increase. Since all odd-numbered sessions (one, three, five, seven) started with the HEC, we looked at the speed of the players in each condition, based on whether they were played first or last, to see if there were any order effects (Table 7.4). We can see that, surprisingly, for a given condition, the speed at which players ran is higher when it was played last. We thought that due to exhaustion, it is more likely for players to run slower in

conditions played last, however the opposite was true. This might be because players were more willing to exert themselves in the last sub-session, having already invested significant effort in the previous one. It could also be that they were “warmed up”. This would explain why the expected difference in conditions was very small or sometimes even reversed in sessions one, three and five considering that, on average, the speed of the HEC when played first was only slightly higher than the LEC when played last. Also worth noticing is the fact that the effect was not very visible in the HEC, probably due to players already running fast due to the intervention.

		Speed (m/s) (2 minutes)		Speed (m/s) (4 minutes)	
	Playing Order	Mean	SD	Mean	SD
LEC	First	0.52	0.09	0.56	0.10
	Last	0.60	0.12	0.60	0.12
HEC	First	0.61	0.12	0.64	0.12
	Last	0.62	0.11	0.65	0.11

Table 7.4: Speed values of players per condition and playing order using different time-windows.

Since players ran faster in the sub-sessions that were played last, we also looked at the speed of the players over time during each sub-session to see if the behavior was similar. In Figure 7.9 we can see that player speed diminished over time within a session, probably due to exhaustion. It is interesting to see that the decrease in speed was not linear, but actually followed a sinusoidal-like pattern, with consecutive peaks and valleys of speed. This conveys that players had short outbursts of high speed, followed by short recovery periods, and that all players adapted to this pattern.

Figure 7.9: Average player speed during a sub-session over all sessions.

This also sheds some further insight as to why player speeds in the LEC and HEC condition were very similar when the LEC was played last. Since we only took into

account measurements obtained during the last two minutes of play of each sub-session, we only looked at the segments of play where exhaustion was kicking in. Since the HEC condition required a higher level of effort, the onset of exhaustion should have been faster and more pronounced than in the LEC. Indeed, Table 7.4 shows that when calculating the speed of each condition based on the playing order, and taking into account the whole session, the difference between both conditions is more evident. When we calculate the average group speed in both conditions using the whole session (Figure 7.10), the speed in the HEC is higher in all sessions.

Figure 7.10: Average group speed in both conditions for each group using the measurements of the entire session.

In regards to perceived exertion, it is important for the design of future game interventions that players perceived they were exerting less than they actually were. In some cases, it would be best if people are not too aware of their amount of exertion, since they can choose not to play if the game is too physically intensive.

7.3.4.1 Limitations

The results obtained from our analysis show that the proposed approach has many merits, but in its current state, it also has several shortcomings. First of all, because the scope of our work is interactive playgrounds, our approach is designed to work in playing spaces of limited size. Increasing the playing area would require additional equipment to be procured, some of which can be expensive. Also, while it is true that the installation can be set up at different locations, this can easily take an entire day. Lastly, because the tracking software relies on the correct positioning of the cameras, the installation has to be stationary, and, in our case, indoors due to sunlight interfering with the Kinect sensors.

Other limitations stem from the fact that we use a camera system to sense behavior. Although vision has the advantage of being able to gather data unobtrusively, there is information that cannot be (easily) measured visually, such as the age or the fitness level of the players. In these cases, the use of questionnaires or interviews is necessary, as they are the only means of acquiring such personal information. Likewise, not every behavioral cue can be measured visually due to their complexity or duration. In these cases, observational approaches such as manually annotating specific behavior are needed.

8

Social Behavior Analysis in the ITP

Promoting social behavior is a goal that is often sought after in interactive playgrounds. In this chapter, we will show how player social behavior can be objectively measured and analyzed automatically in the ITP. We do so by measuring specific social cues, such as the distance between players or the number of times a player is tagged, that can aid in the analysis of social behavior. We use these cues to study how social behavior differs between genders and age groups when playing tag.

This chapter is structured as follows: In Section 8.1 we will present literature related to gender-typed behavior, typical behavior exhibited specifically by boys and girls, and how it affects the way children play together. In Section 8.2 we will describe our experimental setup and the user study that we conducted to analyze gender-typed behavior. We will also introduce two constructs to evaluate the changes in children's play behavior: physical play and social engagement. Lastly, in Section 8.3, we will present the results of our social behavior analysis, discuss our findings, and examine the limitations of our study.

8.1 Age and Gender Effects on Children Social Play Behavior

Children's friendships and relationships are largely composed of children of the same gender due to their preference to interact with them [194, 195, 196, 197]. This tendency starts very early in childhood, and lasts well until children reach puberty. For instance, a study of children between one and twelve years old showed that although this behavior is already shown at an early age, it is more evident as children grow older [198]. This is due to the fact that they become more conscious of, and grow into, their own gender as time goes by. Moreover, the behavioral patterns exhibited by these groups differ between genders. Boys, for instance, prefer to interact in larger groups, leading to many "shallow" relationships, whereas girls prefer smaller groups, typically of only a couple of "best" friends [194, 199]. Differences in behavior that are typically attributed to gender are called gender-typed behavior.

Gender-typed behavior is not only limited to everyday social interactions, but it can also be found during play. Boys, for instance, often prefer to play in public spaces

such as streets, whereas girls usually get together in private homes or yards [200]. Maccoby and Jacklin showed that boys usually play in groups, whereas girls play mostly with one or two best female friends [201]. Although children most often play with children of their same gender, cross-sex play is seen in children's play, however, many times it is due to external factors such as limited availability in playing partners [202].

Preference towards certain play activities that children engage in, and the manner in which the activities are carried out, also changes based on gender. Pellegrini observed that rough-and-tumble play is not only seen more often in boys than in girls, but it is also related to their social standing amongst boys [158]. Archer also presented several studies where boys engaged in more active play than girls [203]. Eccles and Harold found that gender plays a big part in the attitude of children towards certain sports [204]. Interestingly, they mentioned that the preference was not so much about their aptitude towards the sport itself, but more related to gender-role socialization. In other words, the more they saw sports as being appropriate for their gender, the higher they rated their abilities in sports. Cherney and London looked not only at sports, but also toys, computer games, TV shows and outdoor activities differences for kids between five and thirteen years old and found gender to be a significant factor [205]. Boys preferred to spend more time doing sports, playing video games and watching television, whereas girls preferred only to watch television. Also, the activities they preferred became more gender-typed as they grew older.

The methods commonly used to assess gender-typed social behavior are observations, preference tests or interviews [206]. In this chapter, we will propose the automated analysis of social behavior in the ITP. We will specifically analyze how gender and age change the way in which players behave during interactive tag games. In the next section, we will present how the data obtained by tracking players in the ITP can be used to analyze social behavior automatically during games.

8.2 Objective Analysis of Gender-Typed Social Behavior in the ITP

To test whether we can measure differences in gender-typed social behavior in the ITP, we conducted a user study with children of different ages and gender playing interactive tag. The only thing that changed between game sessions was which players played together. Children were placed in either a mixed gender group, or a group with players of the same gender. They were also grouped according to their age. The different arrangements were designed to bring forth differences in play behavior, as observed in the literature.

The cues that we collected are related to players' social behavior as well as their physical activity, and were automatically collected by the ITP. Our hypotheses and the cues that we measured are explained in detail in Sections 8.2.1 and 8.2.2 respectively.

For this study, children played the basic interactive game of tag with no interventions. The size of the playing field was set to 6m × 5m. No additional sensors were used by the players. The user study we designed has been approved by the ethical committee of the university.

8.2.1 Hypotheses and Operationalization

Based on the related literature, we defined two constructs to analyze how children's play behavior differs between genders and age groups: physical play and social engagement. The first construct, physical play, refers to how physically active players are during the game. The second construct, social engagement, refers to how socially active players are during the game, that is, how much they interact with other players.

8.2.1.1 Gender-Typed Physical Play

The literature suggests that boys are in general more physically active, show more active aggression, and employ more physical contact during play than girls [158, 207]. Based on this, we believe that boys will also be more physically active than girls when playing interactive tag. This should manifest itself in boys tagging more and running faster than girls.

Hypothesis 1a (H1-Tg) The number of tags is greater for boys than girls.

Hypothesis 1b (H1-Sp) The speed at which boys run is greater than the speed at which girls run.

Both the number of tags and a player's speed can be instrumental in measuring physical play. To tag a player, the tagger needs to chase them around the playing field. Therefore, players that have a high number of tags must have chased many players. This means that by analyzing which players tag the most, we should be able to measure which players are the most active. Speed, on the other hand, is more straightforward. Players that move at higher speeds are more active, since they cover more space during the game session. It is important to note that a low number of tags does not guarantee that a player is not active, since he might be fast enough to avoid being tagged. Speed can then aid in the recognition of such players.

Hypothesis H1-Tg is measured by comparing the average number of tags per player and per session, based on their gender. H1-Sp is measured by comparing the average speed per player and per session, based also on their gender.

8.2.1.2 Gender-Typed Social Engagement

From the related literature we identify two avenues of research that are normally followed when studying gender-typed social engagement:

SE-A The analysis of how children of the same gender interact with each other and how this differs between genders (*i.e.* boy-boy versus girl-girl).

SE-B The analysis of how children of opposite genders interact with each other in comparison to their interaction with children of the same gender (*i.e.* boy-girl and girl-boy versus boy-boy and girl-girl).

In regards to SE-A, it has been observed in several studies that boys play in larger groups than girls [201], which leads to many, but superficial, relationships [194, 199]. On the other hand, girls play in smaller groups, which leads to fewer, but more

intense, relationships. We believe this will be reflected in the ITP by girls choosing to tag girls more often than boys choosing to tag boys and girls staying closer to other girls than boys staying closer to other boys.

Hypothesis 2a (H2-Tg) The number of tags between girls is higher than between boys.

Hypothesis 2b (H2-Dt) The distance between boys is bigger than the distance between girls.

In regards to SE-B, researchers have suggested that children usually form groups made up of children of the same gender [195, 197], or that children mostly play with children of the same gender [202]. We believe this will lead to players preferring to tag players of the same gender over those of the opposite gender and players staying closer to players of the same gender than those of the opposite gender in the ITP.

Hypothesis 3a (H3-Tg) The tagging ratio for players of the same gender is greater than the tagging ratio for players of the opposite gender.

Hypothesis 3b (H3-Dt) The distance between pairs of the same gender is smaller than the distance between pairs of opposite genders.

We also found studies that described differences in gender-typed social engagement depending on the age of the children. It is commonly believed that this type of behavior is exhibited from a very young age up until the teen years. Studies have shown that gender-typed behavior is even more evident when children are older [198]. We believe that this will manifest itself in the ITP in the form of greater differences between the measurements of our behavioral cues for young and older children.

Hypothesis 4a (H4-Tg) The number of tags between players of the same gender will be higher for the older children.

Hypothesis 4b (H4-Dt) The distance between pairs of the same gender will be smaller for the older children.

We believe the number of tags between players and the distance between players can help us measure social engagement. By analyzing whom a player tags the most, we should be able to find if there is a preference to interact (tag) with players based on their gender. Likewise, by calculating the distance to other players, we expect to find preferences related to whom they want to be close to, and therefore interact with more.

Hypothesis H2-Tg is measured by comparing the average number of tags per player and per session, based on their gender. H3-Tg is evaluated by comparing the tagging ratio of players depending on their gender. H2-Dt and H3-Dt are evaluated by comparing the average distance between pairs of players per session, based also on their gender. H4-Tg and H4-Dt are measured by looking at the gender differences in both the number of tags between players and the distance between players for the younger and older children.

8.2.2 Behavioral Cues

Based on the hypotheses that we set for our two constructs, we used three behavioral cues derived solely from the position and role information of each player. The first cue, T_g , is the average number of tags per player. The ITP keeps track of the roles of the players, and, by counting the number of times the tagger role switches, we can measure the number of times a player has tagged someone. We analyzed this cue at individual and pairwise levels. This means that, respectively, we counted the number of tags per player and per pair of players, per session. We also considered the gender of a player when counting the number of tags.

The second cue, D_t , is the average distance between players. Since the ITP tracks players and logs their position during the game, we calculated D_t by averaging, over the entire game duration, the distance between any two given players. This means that, inherently, D_t is a pairwise cue. When analyzing this cue, we specifically looked at pairs of players, taking into consideration their gender. As such, we analyzed the distance between pairs of male players, female players, and players of the opposite gender. D_t is measured in meters.

The last cue we measured, S_p , is a player's average speed. To estimate S_p , we calculated the players' track displacement every frame. We measured the speed for every player individually. We again focused on differences between genders, and as such, we measured the speed of boys and girls per session. Since the ITP tracks the position of the players at fifteen frames per second, we converted the speed from meters/frame to meters/second by dividing it by fifteen.

For all data analysis, we first preprocessed the data by running a median filter of one third of a second on the position data to remove noisy detections. We also interpolated position values when tracks were missing.

8.2.3 Experimental Design

In this study, we specifically looked at how children's physical play and social engagement are affected by gender and age. For the first variable, *gender*, we designed three scenarios: a mixed gender scenario where the same number of players from each gender played together (G-X), a scenario where only female players played together (G-F) and one where only male players played together (G-M). For our second variable, *age*, two scenarios were designed: players of 6-8 years old playing together (A-Y), and players of 9-10 years old playing together (A-O). We will refer to these two groups as younger and older children, respectively. For every game session, a combination of both variables was needed to define the condition being tested. For instance, a group of old girls playing tag would be labeled as (G-F+A-O).

Seventy two children from two different schools were invited to the university over the span of two days. The children took part in many activities during their visit, including playing tag in the ITP. The children were separated into groups of four players, which led to a total of eighteen groups. From these eighteen groups, only the data of thirteen groups was used in the analysis. This is due to, first, technical difficulties encountered when one group was playing and, second, four groups not having brought signed consent forms from their parents. From the 52 children that

	6-8 years old (A-Y)	9-10 years old (A-O)
Mixed gender (G-X)	4	5
Female-Female (G-F)	0	3
Male-Male (G-M)	0	1

Table 8.1: Group arrangement based on age and gender.

did bring consent forms, 29 were girls and 23 were boys. In regards to their age, 16 children were 6-8 years old, whereas 36 were 9-10 years old. It must be noted that the consent form only asked whether we could record and analyze the data of the children. Therefore, there are no pictures or videos of the game sessions.

Since we did not know beforehand how many children were bringing signed consent forms, it was impossible to arrange them into groups based on their gender before the experiment. Therefore, the groups were arranged ad-hoc. This led to not having a balanced number of groups for different conditions. Table 8.1 summarizes the group arrangements.

As it can be seen, there are no same-gender groups for the 6-8 year old children. This was due to the fact that almost half of the younger children did not have signed consent forms. We decided to only record mixed gender sessions because we expected richer social behavior in this condition. Also, by doing this, we could at least ensure that the comparison between the mixed gender sessions of both age groups was possible.

8.2.4 Experimental Procedure

Once the children arrived at the university, those that had a signed consent form were given a green colored tag to differentiate them from those that were not given consent. Once they were shown all the possible activities they could partake in, they were allowed to move around and participate in any activity they wished. Due to how the event was structured, it was difficult for us to balance out our different conditions. Children could move between different stations at will, and the pool of available children was limited to the children that were at the ITP at any given moment. Sometimes we had to go to other stations to ask players if they wanted to play a game of tag. This is how the event was programmed, and as such, it was impossible for us to structure our experiment in a different way.

For each game session, four players were chosen randomly from the available pool of children based on the scenario to be played out (G-X, G-F, G-M). Of course, this also depended on whether it was possible to arrange them in such way. If only boys were available, then the G-M was chosen. We managed to arrange almost all the G-X sessions in such a way that two boys played with two girls. Nonetheless, one mixed gender group consisted of three boys and one girl since there were no more players to choose from.

Once the children were selected, the game was explained to them. Afterwards, depending on the condition to be played out, the players were asked to stand on specific colored stars located in the corners of the playground (Figure 8.1). For the G-X sessions, girls were asked to stand on the red stars, whereas boys were asked to

stand on the yellow ones. For the G-F and G-M sessions, players were instructed to stand on any of the colored stars. Using this method, we could know which players were male and which females at the start of each mixed gender session. Each group played the game for one minute and a half. After each session, players were asked to participate in a very brief discussion and feedback session.

Figure 8.1: Projected image before every tag game session in the ITP.

8.2.4.1 Manual Annotation

In a previous study we showed that, occasionally, the label assigned to each player by the ITP changes when players run too close to each other or bump into each other (Section 4.2.3). For this particular study, we had to ensure that the labels assigned to the players at the beginning of the game were maintained throughout the entire session, as their starting position and assigned label was used to distinguish their gender in the G-X condition. Due to this, the track information provided by the ITP was manually revised to correct any missing detections and label miss-assignments. The annotation process and the accuracy of the tracker were described in Section 4.2.4. The manual correction of tracks significantly increases the time needed to analyze behavior. Consequently, it is impossible to use the results of the analysis in-game.

Based on the starting position of each player, we can know which labels belonged

to males and females. This information was saved for the data analysis process. By manually correcting the label assignment process, we made sure that the analysis of behavior could be carried at both group and individual levels.

8.3 Experimental Results

Normally, we would have had six experimental conditions: three for gender $\times$ two for age. However, as discussed previously, we were unable to conduct sessions with players of the same gender in the A-Y condition (Table 8.1). To overcome this problem, we took two measures. First, when evaluating physical play, we analyzed our behavioral cues by considering the data of the players for all the game sessions. In other words, we ignored the composition of the group and treated each player individually. Second, when evaluating social engagement, we only used the sessions where players of both genders played together (G-X condition). It must be noted that one G-X session was unbalanced (three boys, one girl), and thus it was not used in the analysis of social engagement, which meant only eight G-X sessions were used.

8.3.1 Analysis of Physical Play

Measuring how active a child is when playing interactive tag without considering others does not require analyzing who it played with or who it interacted with. Therefore, we analyzed the behavior of every player from all sessions together. To evaluate the two hypotheses that we defined for physical play, H1-Tg and H1-Sp, we need to look at how Tg and Sp are affected by a player's gender.

A total of thirteen play sessions were analyzed. From the 52 children, 23 were boys, 29 were girls, 16 were young children and 36 were older children. We did not take into account which condition each child played in.

8.3.1.1 Average Number of Tags per Player

We can see in Table 8.2 that when considering players from both age groups, the average number of tags per session for the male players was 5.17, whereas for female players it was 5.03. We found that in both age groups boys had a higher number of tags per player than girls. In the A-O condition, boys averaged 5.07 tags whereas girls averaged 4.95. In the A-Y condition, the values were higher at 5.38 and 5.25 for boys and girls respectively. When we break down the analysis by both age and gender, it is worth noticing that the change in behavior is consistent irrespective of age. In both the A-O and A-Y conditions, the average number of tags for the boys was higher than the average number of tags for the girls by almost the same amount.

To evaluate H1-Tg, we ran a 2-tailed independent samples t-test on the results. As expected from the small differences in the measurements, the difference in Tg between boys and girls was not significant ($t(50) = 0.37, p = ns$).

8.3.1.2 Average Player Speed

It can be seen in Table 8.3 that the speed at which players ran during the game sessions was very similar irrespective of their age or gender. When considering only

Average Number of Tags per Player			
	Male	Female	Average
A-Y	5.38	5.25	5.31
A-O	5.07	4.95	5
Average	5.17	5.03	

Table 8.2: Average number of tags per player considering gender and age for all sessions.

Average Player Speed (m/s)			
	Male	Female	Average
A-Y	0.99	0.93	0.96
A-O	0.99	0.99	0.99
Average	0.99	0.97	

Table 8.3: Average player speed considering gender and age for all sessions.

the gender of the players, boys ran slightly faster at an average speed of 0.99 m/s in comparison to the girls' 0.97 m/s. When considering only the players' age, the older children ran at an average speed of 0.99 m/s, just slightly faster than the younger children, who ran at 0.96 m/s. The biggest difference in speed was shown by the girls in A-Y condition, who ran at an average speed of 0.93 m/s.

We used a 2-tailed independent samples t-test to measure H1-Sp. The test did not show a statistically significant difference in player speed between genders ($t(50) = 0.39, p = ns$).

8.3.1.3 Discussion of Physical Play Results

The results show that both boys and girls were almost equally active during the interactive tag game sessions. Both the number of tags and the speed of the players were slightly higher for boys. For both gender and age, we found no statistically significant difference between the two groups. As a result, we reject H1-Tg and H1-Sp.

One possible explanation for these results is the way in which our interactive tag game is played. Traditional tag games inherently promote physical contact between players since tagging involves physically touching other players. This can lead to more physical and aggressive play. By removing this touch component, the ITP is perhaps reducing the opportunity for rough-and-tumble play, which is exhibited primarily by boys. Also, the size of the playground may be limiting the speed at which children can run, reducing the differences in running speeds between the fast and slow players.

8.3.2 Analysis of Social Engagement

In the analysis of physical play, we did not analyze who the players were playing with, or with whom they interacted. In contrast, to evaluate social engagement, we need to be able to study in detail the pairwise interactions between the players. In other words, we need to analyze the way in which players interact with those they are playing with. We specifically focused on how gender affects the way in which children behave towards each other. To evaluate the hypotheses we proposed for this

Tagging Ratio				
	Male-Male	Male-Female	Female-Female	Female-Male
A-Y	0.33	0.67	0.30	0.70
A-O	0.37	0.63	0.44	0.56
Average	0.35	0.65	0.37	0.63

Table 8.4: Tagging ratio based on a player's gender and age for the mixed gender sessions.

Normalized Average Number of Tags Between Players per Session				
	Male-Male	Male-Female	Female-Female	Female-Male
A-Y	1.75	1.81	1.63	1.81
A-O	1.88	1.50	2.25	1.56
Average	1.81	1.66	1.94	1.69

Table 8.5: Average number of tags between players based on their gender and age for the mixed gender sessions. The number of tags between players of opposite genders has been normalized.

metric (H2a-b, H3a-b, H4a-b), we needed to look at how Tg and Dt differ between genders. We will also need to analyze how these cues change depending on the age of the players.

A total of eight play sessions were analyzed, four mixed gender play sessions in the A-Y condition, and four in the A-O condition. Each session consisted of two boys playing with two girls of the same age group.

8.3.2.1 Average Number of Tags per Player

We first calculate the tagging ratio of the players based on their gender. To do this, we count the times a player tagged children of a specific gender, and divide this value by the player's total number of tags. The results are summarized in Table 8.4.

Considering that every game session consisted of two boys and two girls, for any given player, the baseline ratio of tagging a player of the same gender was 0.33, and 0.67 for a player of the opposite gender. We can see that only the older children showed a preference to tag other players of their same gender. In the A-Y condition, we can see that the tagging ratio between boys was 0.33, which means there was no preference. For the girls, this value was 0.30, which was also close to the baseline value. However, when we look at the A-O condition, we can see that the tagging ratio for boys increased to 0.37, and the ratio of girls tagging other girls increased to 0.44.

To get a better picture of how the tagging behavior changes between the conditions, we also calculate the number of tags between players. Importantly, when calculating the number of tags between players of opposite genders, for any given player, there are always two players of the opposite gender. In this case, the number of tags needs to be averaged. The results are shown in Table 8.5.

The average number of tags between girls (1.63) was lower than for boys (1.75) when considering the A-Y condition, but in the A-O condition the average tags per player for girls (2.25) was higher than for boys (1.88). This means that, apparently, the age of the children had an influence on tagging preferences between players of

the same gender. Also, it seems girls tagged players of the same gender more often than boys did, at least for the older group of children.

We can also see that the average number of tags between players of the same gender increased in the A-O condition when compared to the A-Y condition. The difference in the number of tags between players of the same gender and those of the opposite gender is interesting as well. It changed from -0.06 to 0.38 for boys, and -0.18 to 0.69 for girls, when going from the A-Y to the A-O condition.

The interaction between Tg , gender and age can be seen in Figure 8.2. We can see in the graph an important increase in the number of tags between girls when going from the A-Y to the A-O condition. There is also an increase in the number of tags between boys, but it is considerably smaller than the one seen for the girls. The number of tags between players of opposite genders decreased in the A-O condition. It is interesting to notice that the younger girls had the least number of tags between players of the same gender, but the older girls had the most.

Figure 8.2: Average number of tags between players depending on their age and gender in the mixed play sessions.

To evaluate H2-Tg and H4-Tg, we ran a 2-way factorial ANOVA to find the effect of gender and age on the number of tags between players. There was no statistically significant interaction between the effects of gender and age on the number of tags per player ($F(1, 28) = 0.415, p = ns$). To assess H3-Tg, we ran a set of 1-sample t-tests

Average Distance to other Players (m)			
	Male-Male	Female-Female	Opposite Gender
A-Y	2.86	2.60	2.89
A-O	2.47	2.37	2.63
Average	2.67	2.49	2.76

Table 8.6: Average distance to other players based on their gender and age for the mixed gender sessions.

against the baseline tagging ratio for players of the same gender (0.33). We found no statistically significant differences in any of the four tests (number of tags between males and number of tags between females for the younger and older children).

8.3.2.2 Average Distance to Other Players

In Table 8.6 we can see that for both the A-Y and A-O conditions, the distance that girls kept between them is shorter than the distance boys kept. When looking at A-Y, we can see that the distance between boys (2.86 m) was bigger than the distance between girls (2.6 m), but was almost the same as the distance between players of opposite genders (2.89 m). This means that boys did not show a marked preference in staying close to players of the same gender. Girls, on the other hand, already showed gender-typed behavior in the young group.

When looking at the A-O sessions, the distances between all the players shrank, and boys started to exhibit a preference to stay close to other boys. This can be seen in the 2.47 m they kept from each other, in comparison to the 2.63 m that players kept to players of the opposite gender. Girls did not really change their behavior, and preferred to stay even closer to other girls (2.37 m). The interaction graph between the variables can be seen in Figure 8.3.

To test H2-Dt, H3-Dt and H4-Dt, we conducted a 2-way factorial ANOVA to measure the effect of gender and age on the distance between players. The test showed a statistically significant decrease in *Dt* for the older children ($F(1, 42) = 11.78, p < 0.05$). We also found that gender had a statistically significant effect on *Dt* ($F(2, 42) = 4.215, p < 0.05$). After running a post-hoc test on gender, we found that the distance between girls was significantly shorter than the distance between players of different gender ($p < 0.05$). However, there was no statistical difference in *Dt* between boys and girls, nor boys and opposite gender pairs. Finally, the interaction between age and gender did not show a statistically significant effect on *Dt* ($F(2, 42) = 0.275, p = ns$).

8.3.2.3 Discussion of Social Engagement Results

The results show that there were some differences in social engagement with respect to gender and age in the ITP. For the number of tags between players, *Tg*, we only found small differences. From these differences, the most noticeable one was found for girls in A-O condition, which had the highest number of tags between them when compared to tags between boys or between mixed gender pairs. Also, the difference in tagging behavior between the girls in the younger group and the older group was the

Figure 8.3: Average distance between players based on age and gender in the mixed play sessions.

most pronounced. Nonetheless, neither the 2-way factorial ANOVA nor the 1-sample t-tests we ran found statistically significant differences in tagging ratios or number of tags per player. In consequence, we reject H2-Tg, H3-Tg and H4-Tg.

When looking at the distance between players, D_t , we again found the biggest differences for girls in the A-O condition. In this case, the older girls kept the shortest distance between them when compared to the distance between boys or players of opposite genders. For this cue, though, the biggest difference between age groups was seen for the boys. We found a statistically significant difference in the distance between girls in comparison to the distance between players of different genders. However, since there was no significant difference between girls and boys, or boys and pairs of opposite gender, we reject H2-Dt and H3-Dt. In regards to H4-Dt, we found a statistically significant decrease in the distance between players when going from A-Y to A-O, which confirms this hypothesis.

8.3.3 Limitations

We identified several limitations in our current study. The first one is that, by explicitly telling boys and girls to stand on specific corners to start the game, we may have been priming them into thinking about their gender and enhancing their awareness of it.

Moreover, studies suggest that gender segregation is more evident when situations have not been structured by adults [200], which could mean that by forcibly arranging mixed gender play groups, children may feel pressured to adapt their play style to fit the situation. We have no evidence to suggest that either happened, but still it would have been better if the children themselves had chosen who they wanted to play with.

This directly relates to another limitation in our experiment: the number of children that took part in the experiment. From the 72 children that played the game, only the data of 52 could be used. This, considering we had six experimental conditions we wanted to carry out, is on the low side. Especially for the analysis of social engagement, where we only had eight mixed gender sessions, the number of children is quite low. This could be one of the reasons why some of our statistical tests did not find significant differences. With a larger sample size, the variance of the measurements may diminish.

9

Automatic Role Recognition in the ITP

In this chapter, we will shift our focus towards the automatic and unobtrusive recognition of player roles in tag games. We will present two different models to accomplish this. The first one, the Game Observation (GO) Model, is derived from tag game observations, and uses the location and motion information of each player to recognize three pairwise interactions (approach, chase, avoid) discriminant to each role. The second one, the Behavior Analysis (BA) Model, is derived from the objective analysis of tag games, and extends the first one by including individual cues as well as global ones.

This chapter is structured as follows: In Section 9.1 we will briefly review some techniques used to recognize behavior in interactive games. In Section 9.2 we will describe in detail our two different models to recognize roles in tag games, the GO-Model and the BA-Model. In Section 9.3 we will show the results of both role recognition models on the ITag1 dataset. Lastly, Section 9.4 will contain a brief discussion on the outcome of the model testing, as well as limitations and future work.

9.1 Recognition of Behavior in Interactive Games

The behavior that players exhibit during games can be interesting to detect or recognize for many different purposes (Section 2.1.3). In interactive environments, many sensors that are used to gather the necessary player and environmental data to recognize behavior, be it cameras, touch surfaces or toys, are already in place and are integral to the game [85]. Usually, the sensed data is used to interact with the game by controlling certain game elements [38], or with other players in the game [208]. However, this data can also be used to recognize actions [69] or steer behavior [181].

The manner in which the players interact with the system can vary. Sometimes, the player needs to physically interact with the system in order for actions to be recognized. For instance, children used a rope with an accelerometer-equipped handle to play different games like tug-of-war or kite-flying over a distance in the “Rope-Plus” gaming environment [209]. The system was able to recognize different ways in which players used the rope, like pulling, releasing or rotating. In [65], players

had to shake a ball to interact with projected shapes on the floor of a playground. In both examples, players needed to use the sensors for their behavior to be sensed. However, as Landry *et al.* stated in [210], it would be very helpful if actions could be recognized automatically in an unobtrusive manner. For instance, Höysniemi *et al.* used a webcam to recognize flapping and leaning movements that children performed when trying to control a virtual flying dragon which made the game feel very intuitive [211]. In a similar fashion, Van Delden *et al.* used the Kinect skeleton tracking to recognize flapping and diving actions to make a flying virtual avatar increase or lower its altitude [69].

In tag games, recognizing certain actions could prove incredibly beneficial for gameplay. For instance, by recognizing when a player is cheating continuously or not following the established conventions for his role, the system would be capable of intervening to solve the problem. By recognizing how long specific players assume certain roles, the system could infer their tagging skills and adapt the game appropriately. In the following section, we will present two models to automatically recognize player roles based on their location, movement and relative behavior to other players.

9.2 Role Recognition in Tag Games

We developed two models for the recognition of player roles in tag games. The first model is based on the observation of children playing tag games (see Section 3.2) and common knowledge of how the game is played. The second model is based on the objective analysis of player behavior during tag games that we carried out in Section 3.3. We will explain both models in detail below.

9.2.1 Role Recognition based on Game Observations (GO-Model)

The first model starts by describing the location and motion of individual players. From these, we determine pairwise interactions between players. Specifically, we consider chasing, avoiding and approaching behavior. Finally, from the full set of pairwise interactions, we determine the role of each player. The GO-Model applies to any number of players, with arbitrary roles.

9.2.1.1 Individual Motion Analysis

The first step in the recognition of the players' interactions is the analysis of their motion. Consider a player i with speed v_i and direction ϕ_i , measured in meters per second and degrees, respectively. Based on the individual movement information, we can classify the player's type of motion (m^t) into one of two states, where $m^t \in \{stand, run\}$. Other motion types could also be recognized, such as walking or jumping, however they are not informative in our current context. We use sigmoid functions to model the probability of each motion type. A sigmoid function is defined as:

$$1/(1 + e^{-a(x-c)}) \quad (9.1)$$

where parameter a determines how severe the threshold is (*i.e.* fall-off rate) and the direction of the sigmoid (*i.e.* open to the right or left), and c controls the function's displacement from the origin (*i.e.* its center). The value assigned to c can be based on facts or common knowledge, for instance, the average running speed of children to decide the speed threshold for running. On the other hand, a is assigned based on how quick the probability should change when approaching the threshold, and choosing a value for it is not trivial. Based on what we saw during the tag games, we set c to 0.5 m/s as the threshold between the run and stand states for m^t . The sigmoid response function that models m^t with $c = 0.5$ and $a = 150$ can be seen in Fig. 9.1.

Figure 9.1: Response function for m^t .

9.2.1.2 Probabilistic Recognition of Pairwise Interactions

Next, we recognize important pairwise interactions present in tag games. Given players i and j , we denote a pairwise interaction executed by player i towards player j as $a_{ij} \in \{\text{chase}, \text{approach}, \text{avoid}, \text{none}\}$. Each interaction is defined by several terms which can include a relative direction term, a motion type term and a distance term. These definitions are based on the observation of game sessions and common knowledge of tag games. The advantage of defining the pairwise interactions this way is that restrictions, limitations and other terms can be added easily without the need to retrain the model. The modular representation of the pairwise actions also makes the system easily extendable in the future. Ad hoc actions or rules could be defined for specific types of tag games. Moreover, these relationships are also appropriate for games other than tag.

To recognize the pairwise interactions, we first need to compute the distance vector (d_{ij}) between i and j , and its angle (ϕ_{ij}). Afterwards, we calculate the angle difference between ϕ_i and vector d_{ij} . This value informs whether i is moving towards j and is defined as $\phi_{i,j} = |(\phi_i - \phi_{ij})|$. We also calculate the angle difference between

the movement direction of both j and i , defined as $\phi_{j,i} = |(\phi_j - \phi_i)|$. A graphical description of these variables can be seen in Fig. 9.2.

Figure 9.2: Graphical description of the motion analysis variables.

Based on the relative movement information, we classify relative directions, defined as $m^\phi \in \{\text{same}, \text{opposite}\}$. We use sigmoid functions to model the probability of the relative directions. Based on our game observations, we chose 55° and 110° as the thresholds for the states of m^ϕ . The probability distribution for m^ϕ using these values and $a = 0.25$ (empirically determined) can be seen in Fig. 9.3.

Figure 9.3: Response function for m^ϕ .

The informal definition for each pairwise interaction is the following. Player i approaches player j when i runs in the same direction of j , and j is standing. When i is running in the direction of j and j is running away from him, i is chasing j . Player i avoids player j when i runs in the opposite direction of where j is, and j is running in the direction of i . Formally, the interactions are defined as:

$$P(a_{ij} = approach) = P(m_{i,ij}^\phi = same) \cdot P(m_j^t = stand) \cdot P(m_i^t = run) \cdot prx(i, j) \quad (9.2)$$

$$P(a_{ij} = chase) = P(m_{i,ij}^\phi = same) \cdot P(m_{j,i}^\phi = same) \cdot P(m_i^t = run) \cdot P(m_j^t = run) \cdot prx(i, j) \quad (9.3)$$

$$P(a_{ij} = avoid) = P(m_{i,ij}^\phi = opposite) \cdot P(m_{j,ji}^\phi = same) \cdot P(m_i^t = run) \cdot P(m_j^t = run) \cdot prx(i, j) \quad (9.4)$$

where $prx(i, j)$ is a 2-D Gaussian function. This function gives more importance to the interactions of players that are nearby. Given the location of two players (x_i, y_i) and (x_j, y_j) , and the standard deviation σ (function's distance fall-off rate), $prx(i, j)$ is defined as:

$$prx(i, j) = \exp\left(-\left(\frac{(x_i - x_j)^2}{2\sigma_x^2} + \frac{(y_i - y_j)^2}{2\sigma_y^2}\right)\right) \quad (9.5)$$

9.2.1.3 Temporal Correlation / Filtering

The scores of the pairwise interactions are stored in a matrix $A \in \mathbb{R} : T + 2N + C$, where C is the number of possible interactions, N is the number of players, and T is the number of frames in the video. Since we have three interactions, C is set to three. The data that is stored in A is filtered and processed taking into account the temporal correlation between interactions. If an interaction is performed consecutively, but the recognition score is low, the confidence that the recognition is correct should increase. This leads to better recognition when an interaction is not recognized accurately, for instance, as a result of tracking inaccuracies.

At each frame f , if no interaction was recognized with a score above the recognition threshold δ , we compare the interaction with the highest recognition score, $\hat{a}_{i,j}^f$, with the one in the previous frame $\hat{a}_{i,j}^{f-1}$. If the interaction is the same, we re-evaluate the score of that interaction in frame f . The new value is calculated as follows:

$$\begin{aligned} \max P &= \max(\hat{a}_{i,j}^f, \hat{a}_{i,j}^{f-1}) \\ \min P &= \min(\hat{a}_{i,j}^f, \hat{a}_{i,j}^{f-1}) \\ \text{new } P &= \max P \cdot 0.75 + \min P \cdot 0.25 \end{aligned} \quad (9.6)$$

This calculation is biased towards the highest recognition score between adjacent values, but only when the same interaction is recognized in subsequent frames. If the subsequent interactions are not the same, no new estimation is performed since there is no temporal correlation, which means no interaction is classified confidently at frame f .

9.2.1.4 Role Estimation

After the pairwise interaction values have been calculated, we estimate the roles of the players. In tag games, a player can only be assigned one of two roles, thus we define a player's role as $r \in \{tagger, runner\}$. As the interactions are closely related to the roles, the assignment becomes trivial. We estimate each player's role as:

$$r_i = \begin{cases} tagger & \text{if } \exists j | A_{i,j} = approach \vee chase, \\ runner & \text{Otherwise.} \end{cases} \quad (9.7)$$

This rule represents each role's specific type of behavior: a tagger's goal is to chase and tag runners, whereas runners have to avoid being tagged. In the particular case of tag games, if a player is not chasing anyone, he has to be either avoiding someone who is chasing him, or just moving away from the taggers to maximize his escape possibilities.

9.2.2 Role Recognition based on Objective Player Behavior Analysis (BA-Model)

From the objective analysis of tag player behavior carried out in Section 3.3, we know that both a player's position and relative movement direction are useful in determining a player's role. We therefore used both cues to design our second model. More specifically, these cues are used to define the *boundary response* and the *tagging intention*. The former is a function that estimates the role of a player based on his location in the playground. The latter is a function that evaluates how likely it is that one player is trying to tag another. We developed a probabilistic formulation to determine each player's role individually by considering these two concepts. We only look into tagger-runner interactions because runner-runner interactions are not apparent. The BA-Model applies to any number of players and, for this study, we consider the case of only one tagger.

9.2.2.1 Model Description

Formally, we consider a set of N players, each with $R \in \{tagger, runner\}$ a random variable indicating their role. We omit the index on the player for clarity. Given a set of observations O , the probability of a player being a tagger follows from Bayes' rule:

$$P(R = tagger|O) = \frac{P(R = tagger) \cdot P(O|R = tagger)}{\sum_{i \in \{runner, tagger\}} P(R = i) \cdot P(O|R = i)} \quad (9.8)$$

Given that we consider only a single tagger, the prior probability of a player having the tagger role depends on the number of players in the game: $P(R = tagger) = 1/N$. The likelihood function $P(O|R = tagger)$ is calculated by the boundary response B and tagging intention I . The normalization term is the sum over all hypotheses, specifically the player being a tagger or a runner. Below we describe the likelihood function in detail.

9.2.2.2 Likelihood Function

The likelihood function is estimated using two different functions, B and I . We assume both are independent from each other, so the likelihood function is formulated as follows:

$$P(O|R) = P(B, I|R) = P(B|R) \cdot P(I|R) \quad (9.9)$$

Boundary Response

Taggers have a tendency to stay in the center of the playground, and avoid the borders. On the other hand, runners have a preference to run around in circles near the borders of the playground. Consequently, the boundary response B is defined as a normalized distance function that takes as input the location of a player and the size of the playground, and outputs a response like the one seen in Figure 9.4. As such, $P(B|R = \text{tagger}) = 1$ when the player is in the center, and $P(B|R = \text{tagger}) = 0$ when he is at the border. Given that we only have two roles, the probability for the runner role is reversed, i.e. $P(B|R = \text{runner}) = 1 - P(B|R = \text{tagger})$.

Figure 9.4: The boundary response function outputs high values near the center of the playground, and lower ones as we move towards the boundary.

Tagging Intention

To define the tagging intention of one player towards another, I , we use the movement direction of player i in relation to player j . We use a similar approach to that in Section 9.2.1.2 when calculating a player's relative movement direction. First, we calculate the angular difference between the movement direction of i and the vector between players i and j . This angle is defined as $\phi_{i,ij}$. We then obtain $\theta_{i,j}$ by applying a sigmoid function (see Equation 9.1) to $\phi_{i,ij}$.

$$\theta_{i,j} = 1/(1 + e^{-a(\phi_{i,ij}-c)}) \quad (9.10)$$

When $\phi_{i,j}$ is small, player i is moving in the general direction of player j , in which case the probability that i is a tagger increases. In contrast, larger angles increase the probability of i being a runner. Figure 9.5 shows $\theta_{i,j}$ for $c = 80^\circ$ (based on our analysis in Section 3.3.4) and $a = -0.1$.

Figure 9.5: Output of function $\theta_{i,j}$ for $c = 80^\circ$ and $a = -0.1$.

When player i is not, or barely, moving we cannot accurately calculate $\theta_{i,j}$. In this case, we set the tagging intention I to 0.5 as we cannot distinguish between a tagger and a runner. We use a conservative speed threshold of 0.2 m/s. Below this threshold, we assign equal probabilities for the tagger and runner roles. When the speed is above the threshold, we set $I = \theta_{i,j}$.

A tagger is typically chasing one out of a number of runners. As $\theta_{i,j}$ considers only a single player, we calculate the probability of a player being a tagger based on the tagging intention as $P(I|R_i = \text{tagger}) = \max_{j \in 1 \dots N, i \neq j} \theta_{i,j}$.

9.2.2.3 Role Classification

Recall that we assume a single tagger and an arbitrary number of runners. We classify the roles of the players by estimating their probability of being a tagger using Equation 9.8, and select the player with the highest probability as the tagger. The other players are assigned the runner role.

9.3 Experimental Results

We tested both role recognition models on the iTag1 dataset introduced in Section 6.2. As the iTag1 dataset consists of interactive tag game sessions, the ground truth for the position and roles was obtained automatically by the ITP. It must be noted that while both the GO-Model and BA-Model were respectively developed by observing and analyzing children play tag games, the iTag1 dataset is composed of young adults playing interactive tag. Nonetheless, as we showed in the same chapter, the behavior

of children playing traditional tag is very similar to that one exhibited by young adults in the ITP despite the differences in age and size of the playing area.

9.3.1 GO-Model

When using the GO-Model, the parameters used in the pairwise interaction estimation need to be set beforehand. These three parameters are c , a and the recognition threshold δ . As mentioned in Section 9.2.1.2, we set c to a value that seems natural and was derived from previous game observations (0.5 m/s). Likewise, for a player's type of motion m^t , a is set to a high value so that the transition from standing to running is very quick since walking is considered running in the current GO-Model formulation. For the relative direction of a player (m^ϕ), however, a cannot be set in such a straightforward manner. Hence, we tested how the model fares with different values of a and different values of δ . The results can be seen in Fig. 9.6

Figure 9.6: Accuracy matrix for parameters δ and a in the GO-Model.

The highest values for accuracy (defined as the proportion of correctly classified results amongst the total number of cases examined) were obtained when using a low δ value. On the other hand, accuracy did not change drastically for different a values. If we only visualize the area with highest accuracy values ($0.15 \leq \delta \leq 0.35$, $0.05 \leq a \leq 0.8$), we obtain Figure 9.7. In general, the differences between parameters settings were small, but it is clear that the best combination of values for both parameters is $a = 0.05$ and $\delta = 0.25$. This means that the model performed better when the state transition for a player's relative direction of movement was smooth, and when the recognition threshold was not very strict. In regards to a , a smooth transition between states makes sense because taggers did not follow runners in straight lines, but actually tried to predict where they were going to move. This added a lot of variability to their movement. A steep slope for the state transition would not allow the model to cope well with this variability. In regards to δ , the low threshold also makes sense because we are calculating the product of several terms. For each pairwise interaction's score estimation, the end result will be equal to (best case scenario) or lower than (most likely scenario) the term with the lowest probability. Naturally, the more

	Precision	Recall	Accuracy
Tagger	61.97%	40.50%	71.94%
Runner	74.71%	87.61%	

Table 9.1: Results on the iTag1 dataset with the GO-Model.

	GT Tagger	GT Runner
Guessed Tagger	27,614	16,946
Guessed Runner	40,561	119,830

Table 9.2: Confusion matrix over all tag sessions in the iTag1 dataset using the GO-Model. GT stands for ground truth.

terms a pairwise interaction's definition has, the higher the chance that the product will yield a lower score.

Figure 9.7: Accuracy matrix for the best values of α and δ in the GO-Model.

The results for the accuracy, precision and recall when using the best parameters are summarized in Table 9.1, and the confusion matrix can be seen in Table 9.2. Although the accuracy of the GO-Model is 71.94%, the recall for taggers is particularly low at 40.5%. The results for the runner role are higher than those for the tagger, but this is due to the inherent higher baseline for runners. Since there are always two runners and one tagger, the baseline accuracy for runners is 66.67%, whereas for taggers it is 33.33%.

9.3.1.1 Analysis of m^t , m^ϕ and $prox$

We also analyzed the different terms that make up the pairwise interactions definition to find out which ones contribute more to the model (see Table 9.3). It is evident that the most important cue for the GO-Model is the relative direction term m^ϕ . When we removed this term from the pairwise interaction estimation, accuracy dropped considerably. The tagger precision, for instance, was almost at chance level (33.33%). The recall for runners was extremely low, pointing at the fact that without this term,

	No proxemic	No motion type	No relative direction
Precision Tagger	56.25%	49.82%	35.17%
Recall Tagger	51.88%	72.44%	89.59%
Precision Runner	76.91%	82.24%	77.31%
Recall Runner	79.88%	63.63%	17.67%
Accuracy	70.57%	66.56%	41.60%

Table 9.3: Contribution of the pairwise interaction terms to the GO-Model's performance.

the model was biased towards taggers (whose recall was very high). On the other hand, the motion type m^t and proxemics term prx do contribute to the model, but not to the same extent, as evidenced by the small accuracy drop (especially without prx).

9.3.2 BA-Model

The BA-Model uses two parameters for the calculation of the tagging intention: fall-off rate a and center c . We set c to 80° , following our observations in Section 3.3.4. We evaluated different values for a and measured the overall accuracy. Since the results of Equation 9.8 can be somewhat noisy, we ran a median filter with a window size of seven frames at twenty frames per second on these probabilities. After this temporal smoothing, we selected at each frame the player with the highest probability of being the tagger.

The results for different values of a are visualized in Figure 9.8. These numbers are calculated over all frames in the iTag1 dataset. As can be seen, the differences between settings were generally small. Values of a closer to zero resulted in a more gradual decrease in tagger probability (see Equation 9.10). In the figure, we observe that the best accuracy was obtained for $a = -0.1$. In the analyses in the remainder of the paper, we used this value.

Figure 9.8: Variation of the BA-Model's accuracy with respect to parameter a .

	Precision	Recall	Accuracy
Tagger	67.14%	66.41%	78.02%
Runner	83.35%	83.80%	

Table 9.4: Results of the BA-Model over all sessions in the iTag1 corpus.

	GT Tagger	GT Runner
Guessed Tagger	45,277	22,157
Guessed Runner	22,898	114,619

Table 9.5: Confusion matrix over all tag sessions in the iTag1 corpus using the BA-Model. GT stands for ground truth.

We summarize the results for the tagger and runner roles in Table 9.4. The confusion matrix appears in Table 9.5. Given that there is one tagger at each moment, guessing the tagger in these three-player sessions would give a baseline accuracy of 33.33%. On the other hand, guessing that each player is a runner would lead to a baseline accuracy of 66.67% but without any tagger identified. Since one third of the players are taggers, and two thirds are runners, the combined label baseline accuracy is $(1 * 1/3 + 2 * 2/3)/3 \approx 55\%$. Our role recognition model was able to determine the roles with a 78.02% accuracy. The differences in baselines for the individual labels were also reflected in the results, which showed better performance, both in precision and recall, for runners.

To understand the relative importance of the boundary response and the tagging intention, we also tested the model with a modified likelihood function. When using only boundary response B , the accuracy of the role classification was 69.60%. For tagging intention I only, this increased to 76.66%. This shows that the interactions between players were more informative than their locations for recognizing their roles. This was not surprising since the interactions are directly related to the expected role behavior, while location only gives a coarse approximation of the role. Nonetheless, the location did add useful information as shown by the slightly higher accuracy when using both features.

9.3.2.1 Analysis of Different Sessions

When looking at the individual sessions, the precision, recall and accuracy remain relatively stable as seen in Figure 9.9. Session 5 scored the lowest accuracy of all sessions. Closer analysis of the videos revealed that the players initially did not rely on the automatically assigned roles, but rather used physical tag despite the prior explanation of the game. Halfway through the session, they started using the assigned roles. Although the role classification model uses only behavioral cues to classify the roles, the role information provided by the ITP was used as ground truth for the classification. This means that the ground truth for the first half of the session was essentially incorrect, which affected the model's performance. Overall, the results between sessions are not too different even though there were notable differences in skill level, roughness and enthusiasm between the different groups of players. We

therefore believe that the approach is general enough to suit a broad audience.

Figure 9.9: Role recognition results for all sessions in the iTag1 corpus using the BA-Model.

9.3.2.2 Temporal Analysis

Tag games are dynamic and there are several phases to be identified. Taggers chase runners, go for a tag, the roles switch and the process starts again. The behavioral cues that we identified are most pronounced when a tagger chases a runner. Once the tag has been made, the behavior is somewhat less pronounced. Taggers have to switch from chasing to running and the opposite is true for the runners. We hypothesize that our recognition accuracy around tags is therefore lower. To this end, we have calculated the average accuracy around a tag, which we identified from the automatic annotations as a change in roles.

Figure 9.10: Average probability (BA-Model) over a 2 second window around a tag of the former (blue) and new (red) tagger.

Figure 9.10 shows the average probability variation for the two seconds before and two seconds after a tag. The figure shows both the probability values of being

a tagger for the old tagger (the one that becomes a runner) and for the new tagger. Directly before the tag, the probability for the old tagger starts to decrease, which is probably due to the player reducing his speed and trying to avoid a full-on collision with the other player. We see that this probability further decreases after the tag, which makes sense as the roles are then switched and the old tagger needs to flee from the new tagger. For the new tagger, we see the probability increase, but only after a second. The new tagger first needs to realize he is tagged and then localize a target.

Since we selected the player with the highest probability of being a tagger as the guessed tagger, it becomes clear that this delay of over a second lowers the overall accuracy of our recognition model. In the iTag1 dataset, there is a tag on average every 5.4 seconds. A delay of over a second therefore has a significant effect on the performance. These observations therefore motivate the introduction of a model that takes into account the different phases of a tag game. Still, given that the behavior is less pronounced, it will be more difficult to make correct guesses on who the tagger is. Alternatively, we could rely more on the estimated tagger probabilities. Apparently, a drop in probability for the current tagger occurs before the increase in probability for the next tagger.

Currently, the BA model assumes that there is a single tagger. If we drop this assumption, in line with the GO-Model, we can identify all players with values for Equation 9.8 over 50% as taggers. This leads to a 68.85% accuracy. It should be noted that the recall for taggers is higher (73.11%) because the precision drops (52.27%). Instead of having the threshold at 50%, we evaluated a range of thresholds. Figure 9.11 shows that the best accuracy is obtained when the threshold is very high (95%-100%). This means that a player is only classified as tagger if the probability of being a tagger is at least 95% or 100%. Obviously, the recall for taggers is even lower in this case. This comparison shows that the knowledge that there is a single tagger in the playground helps in the classification of the players. Notably, the recall for taggers is much higher.

Figure 9.11: Variation of the BA-Model's accuracy with respect to the tagger probability threshold.

9.4 Discussion

We have presented two models that were developed through very different approaches. The GO-Model was developed based solely on game observations of tag play behavior, whereas the BA-Model was developed through computer analysis of the same game sessions to identify discriminant cues. The results obtained show that the BA-Model is better at recognizing player roles during tag games (71.94% versus 78.02%).

One of the most important cues for the correct recognition of roles in tag games is the direction of movement of a player in relation to the other players. In the GO-Model, we showed that from the three different terms that compose the pairwise interactions (m^t , m^ϕ , prx), the relative movement direction term was the most important one. When removed from the pairwise interaction estimation, the accuracy of this model dropped by 30.34%. In comparison, m^t and prx cause 5.38% and 1.37% drops, respectively. Since this model does not consider game information, the strong dependence on a player's movement direction to classify roles can harm the model in certain scenarios. For instance, when the tagger is not actively chasing someone, this model does not have additional information to make a correct decision and this ends up harming the tagger's recall. Also, we consider pairwise interactions between runners, which are not specified.

In the BA-Model, the tagging intention term I takes into consideration the movement direction of a player in relation to the others. When this term is not used to calculate the probability of being a tagger, this model's accuracy drops by 8.42%, in comparison to 1.36% when not using the boundary response term B . The difference in accuracy drop when not using relative direction information is due to the additional information that this model uses in the classification. In contrast to the GO-Model, the BA-Model takes into account information not related to a player's movement that can help in the classification when a tagger is not actively pursuing a runner.

Since the ITP is in charge of assigning roles, the models could serve as validation tools to check whether players are following the expected behavior for their assigned role. When the assigned and recognized roles differ, the system could infer that the game is not taking its normal course, such as when players are cheating or bored.

9.4.1 Limitations

An important aspect that neither of the models currently consider is the temporal dynamics of role classification. We showed for the BA-Model that during a tag event, the probability of being a tagger does not change at the exact occurrence of the tag, but approximately one second later. The reason is clear: it takes time after being tagged to adjust to the new role. It would be interesting to see the effect that modeling this delay could have in the performance of the model. Also, other discriminant features could be identified after thoroughly examining play behavior in more recorded game sessions. Lastly, the models were tested with tag game sessions where only three players played simultaneously in the smaller version of the ITP. This may not be an issue since player behavior did not change much between the different settings where the ITP was placed (Section 6.2). Nonetheless, we would like to run the models on game sessions where more players play together in a bigger area.

Part IV

Conclusion

10

Conclusions and Future Work

In our research, we aimed to automate the process by which behavior is studied and analyzed during games. We built the Interactive Tag Playground (ITP), an interactive installation that facilitates the analysis of behavior during tag games. It also enhances the traditional game of tag by introducing interactive game elements. We used this installation to analyze several aspects of player behavior using data that was collected automatically and unobtrusively. We showed that this information can be used in interactive playgrounds to measure physical activity, analyze social behavior or recognize player roles.

In this chapter, we will summarize our contributions, discuss the limitations of our work and present possibilities for future research.

10.1 Contributions of this Thesis

Analysis of player behavior in traditional tag games To understand how the game of tag is played, what behavioral cues are important to measure, and how the acquisition of these cues could be automated, we recorded children playing tag games in an uninstrumented environment. This data has been made publicly available as the Play corpus. These recordings were analyzed in terms of players' position, speed, distance and orientation (Section 3.3). Special attention was given to how these cues change based on the role of the player. The analyses show that position and orientation contain discriminant information about a player's role (G-5). Observations made during the recordings indicate that players are both socially and physically active. Shortcomings of the game of tag were identified, the most important ones being the lack of game state information, such as the roles of the players, and the difference in skills. Both of these can lead to the breakdown of play. These insights were used in the design of our interactive game installation (G-1).

A game installation that enhances the traditional game of tag (G-1) We designed the Interactive Tag Playground, an interactive installation that introduces interactive elements to the traditional game of tag to enhance the player experience

(Section 4.2). Owing to the understanding of player behavior (analysis of the Play corpus) and the capabilities of the ITP, we were able to design the game in such a way that players are able to exhibit physically active and social behavior during play (Section 5.2.3). We conducted a user study that shows players are more engaged and immersed when playing tag in the ITP than when playing traditional tag (Section 5.2.2). Due to the ITP's capability of collecting data online (G-2), the game can make use of this information to address shortcomings of the original game or steer behavior in certain directions. We presented some ways in which this can be done, for instance, by giving feedback to players about their role (Section 4.2) or changing the size of the circles (Section 7.2). It is important to note that our work is applicable beyond tag games, which was only chosen as a testbed case for our research. Also, since the ITP was set up, several interactive games have been implemented for the ITP by students.

A game installation that facilitates the analysis of player behavior (G-2) Besides being an entertainment installation, the ITP doubles as a tool to record player behavior. The installation is equipped with four Kinects placed on the ceiling, which are used to track players in the playing area. This enables the completely unobtrusive sensing of the players, preventing any type of disruption in play behavior (G-1). We tested the performance of the tracker, and obtained reasonably good results (Section 4.2.4). The system is able to automatically log important information about the players, such as their position and their role. This speeds up the analysis process since annotation is not needed. We analyzed players' position, speed, distance and orientation during interactive tag sessions, using only data that was obtained automatically by the ITP (Section 6.2).

Automatic analysis and evaluation of play behavior (G-3,4,5) We showed that it is possible to measure and analyze physical activity (G-3), social behavior (G-4), and player roles (G-5) using automatically collected data from the ITP. We demonstrated that a player's speed has a good correlation with the player's heart rate. We also showed that the speed of the players, and their heart rates, could be manipulated by changing the sizes of the circles in the ITP (Section 7.3). We analyzed how age and gender affect social behavior in the ITP using two constructs: physical play and social engagement. The former refers to how physically active players are, and the latter refers to how socially active players are. We used three different cues to evaluate these constructs: number of tags, distance between players and the speed at which players move. Our results showed that there is no difference in the players' activity levels during interactive tag. Also, age and gender had a significant effect on the distance that players kept between them (Section 8.3). Finally, we proposed two probabilistic models to automatically recognize player roles in tag games. The first model, which was designed based on tag game observations, relies on identifying pairwise interactions between the players such as chasing or avoidance. The second model, which was designed based on the objective analysis of player behavior in tag games, uses pairwise interactions as well as individual and global cues. We showed that the model based on the objective analysis of tag games performs

better in recognizing roles (Section 9.3).

10.2 Final Considerations

In this section, we will discuss several issues that we encountered while conducting our studies. We will also introduce potential avenues for future research.

Users Since our target audience is composed primarily of children, user studies where children participate have high ecological validity. On the other hand, getting children to participate in studies complicates experimental control for two reasons. First, children are a sensitive user group and are not always accessible. Second, their participation is dependent on getting consent from their parents. Besides the Play corpus analysis, only one of our studies was conducted with children. The other studies were carried out with young adults. Although we demonstrated that the behavior of children playing tag is similar to the behavior of young adults playing interactive tag (Section 6.2), the two user groups are fundamentally different. Children are still developing physically, cognitively and socially. The way children approach games and play is different from how young adults do it. It would be interesting to see whether our findings would change, and if so, how, if children had been the participants in the studies in which young adults took part. This would present interesting challenges with regards to the lack of experimental control mentioned before.

Number of participants In most of our studies we showed that there are differences in play behavior based on our experimental conditions. However, in some cases, the differences in measurements were small. Furthermore, in some studies, even though we could notice some differences in the measurements, these did not prove to be statistically significant. This may be due to the variation in behavior between people. Some people might be more social than others, and some people might be more fit. Given that our sample sizes were small, the variance of the measurements had an important effect on our statistical tests. It would be useful to perform tests with more participants to see if this indeed affects the results we obtained.

Size of the playground The size of the playground limits the number of players that can play simultaneously. We were able to accommodate comfortably a maximum number of four players in each interactive tag play session. Although four players seemed like an adequate number, having more players would be beneficial. This is especially true since the number of interactions between players is affected by the number of simultaneous players. Since the distributed nature of the ITP components allows for the addition of cameras to the tracker PC and projectors to the game PC, it should be possible in the future to increase the size of the playground to accommodate more players. More interesting, even, would be the implementation of another ITP setup in a different location. This would allow us to look into how distributed play affects the behavior of the players, or their attitude towards the system.

Tracker One aspect of the ITP that could be improved is the tracker. We have shown that it is able to locate and track players in real time, but it occasionally switches tracks when players bump into each other or get too close to each other. In general, it works reasonably well (Section 4.2.4), but it cannot be used to analyze behavior at the level of the individual players without manual correction of the tracks. This problem can be mitigated by using group measurements, which can still provide insight into how players behave, but information is lost when averaging over the players. Manually correcting the data is another option, but it would defeat the purpose of having an installation that facilitates automatic behavior analysis. We could also look into the use of better sensors, or exploit information that we are currently discarding. For instance, if we were to track (upper body) poses, we could do a better job at predicting locations of the players and even estimate the location of their shoulders and perhaps elbows and hands. It is important to mention that, from a game installation perspective, players did not complain about not being tracked and could play the game as it was supposed to be played. The shortcomings that we have identified are mostly important when looking at the ITP as a behavioral analysis tool, where the acquisition of more data, or more accurate data, is important.

Tag game The ITP was planned from its inception to be both a game installation and a tool for the analysis of behavior. Consequently, every study described in this thesis was conducted in the ITP and with our interactive game of tag. Although the game has been evaluated to show it is engaging and fun, no other game was tested to see if our findings carry over to different types of games. The game of tag has many characteristics that are inherent to the game, for instance, the number of roles, the need to chase other players, or the lack of winning conditions. It would be interesting to see which findings carry over to other types of games. Are the cues that we selected for the evaluation of physical activity or social behavior suitable for other games? How much would the platform aid in the behavior analysis process in games where movement is not very important? We expect that some of our findings translate to similar types of games, especially those in which moving around is a key game mechanic.

Online game adaptation Ultimately, one of the biggest upsides of the ideas and techniques that we have presented in this thesis is using the automatically collected behavior data during the game itself. We showed that we can measure and evaluate player behavior, but we have not really looked into how this could be used, for example, for the in-game adaptation of game elements or mechanics. For instance, if the players are not very active, we could add power-ups to kindle players' curiosity and encourage movement. If a particular player is playing separately and is not socially active, the system could display elements that draw the other players to him in an attempt to promote social interactions. If a player has not been tagged for some time, his circle could start glowing to try to draw the attention of the tagger. These particular interventions are aimed at steering how players behave during games based on sensed player behavior, which would also be an interesting avenue for future research.

All in all, we have looked into several aspects of play in this thesis: traditional play, interactive play, subjective evaluation of behavior, automated measurement of behavior, evaluation of goals, amongst others. Our studies on traditional and interactive play demonstrated that it is possible to improve the overall player experience in interactive playgrounds by better understanding how games are played. Our studies on the automated measurement of behavior and the evaluation of goals shed some light on the potential benefits of analyzing player behavior in interactive playgrounds. We hope that this thesis can help kindle new ideas and perspectives on how to design adaptive game installations, and engaging, fun game experiences.

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About the Author

Alejandro Moreno obtained his B.Sc. degree in Computer Engineering from the ESPOL University in Guayaquil, Ecuador in 2008. From 2007 to 2009, he worked at the Information Technologies Center (CTI-ESPOL) as a research assistant in the Human Computer Interaction group where he carried out research in the field of natural user interfaces using Computer Vision. In 2011, he received a joint Masters degree in Computer Science from the University of Jean Monnet in Saint-Étienne, France and Gjøvik University, Norway after winning a full scholarship from the European Union to enroll in the Erasmus Mundus Color in Informatics and Media Technologies (CIMET) master program.

In 2011, he joined the Human Media Interaction (HMI) group of the University of Twente as a Ph.D. student working in the fields of Entertainment Computing, Human-Computer Interaction and Computer Vision. His research interests include the analysis, understanding and modeling of human behavior from video to develop innovative, engaging and interesting ways to interact with games and systems.

A list of publications that resulted from his Ph.D. research can be found below.

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