


Volleyball Action Modelling for Behavior Analysis and Interactive Multi-modal Feedback

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Abstract—Quick and easy access to performance data during matches and training sessions is important for both players and coaches. While there are many video tagging systems available, these systems require manual efforts. In this project, we use Inertial Measurement Units (IMU) sensors strapped on the wrists of volleyball players to capture motion data and use Machine Learning techniques to model their actions and non-actions events during matches and training sessions.

Analysis of the results suggests that all sensors in the IMU (i.e. magnetometer, accelerometer, barometer and gyroscope) contribute unique information in the classification of volleyball-specific actions. We demonstrate that while the accelerometer feature set provides the best Unweighted Average Recall (UAR) overall, decision fusion of the accelerometer with the magnetometer improves UAR slightly from 85.86% to 86.9%. Interestingly, it is also demonstrated that the non-dominant hand provides better UAR than the dominant hand. These results are even more marked with decision fusion.

Apart from machine learning models, the project proposes a modular architecture for a system to automatically supplement video recording by detecting events of interests in volleyball matches and training sessions and to provide tailored and interactive multi-modal feedback by utilizing an html5/JavaScript application. A proof of concept prototype is also developed based on this architecture.

Index Terms—IEEE, IEEEtran, journal, L^AT_EX, paper, template.

I. INTRODUCTION

TOP performance in sports depends on training programs designed by team staff, with a regime of physical, technical, tactical and perceptual-cognitive exercises. Depending on how athletes perform, exercises are adapted, or the program may be redesigned. State of the art data science methods have led to ground breaking changes. Data is collected from sources such as tracking position and motion of athletes in basketball [1] and baseball and football match statistics [2].

Furthermore, new hardware platforms appear, such as LED displays integrated into a sports court [3] or custom tangible sports interfaces [4]. These offer possibilities for hybrid

training with a mix of technological and non-technological elements [3]. This has led to novel kinds of exercises [5], [4] including real-time feedback, that can be tailored to the specifics of athletes in a highly controlled way. Data science tools can then be used to precipitate tailored modifications to (the parameters of) such training.

These developments are not limited to elite sport. Interaction technologies are also used for youth sports (e.g., the widely used player development system of Dotcomsport.nl), and school sports and Physical Education [6].

This eNTERFACE project is a part of the Smart Sports Exercises (SSE) project which aims to extend the state of the art by combining sensor data, machine learning and interactive video to create new form of volleyball training and analysis.

For this particular project we focused on identifying volleyball actions performed by players by strapping IMUs (Inertial Measurement Unit) on their wrist(s) and using Machine Learning techniques to model and classify their actions. In addition to identifying the action, the second main aim of the project is to supplement the video recordings by automatically tagging (identify and provide a link to its timestamp) the identified action and events.

A. Motivation

Automatically identifying actions in sport activities is important for many reasons, therefore there have been numerous studies to identify actions in sports [7], [8], [9], [10]. Wearable devices such as Inertial Measurement Units (IMUs) [11], [12] are becoming increasingly popular for sports related action analysis because of their reasonable price as well as portability [10]. While researchers have proposed different configurations in terms of number and placement of sensors [13], it is ideal to keep the number of sensors to minimum due to issues related to cost, setup effort and player comfort [14], [15], [16], [13].

In addition to identification and analysis, access to performance data during sports matches and training sessions is

important for both players and coaches. Analysis of video recording showing different events of interest may help in getting insightful tactical play and engagement with players [17] and video edited game analysis is a common method for post-game performance evaluation [6].

Accessing events of interest in sports recording is of particular interest for both sports fans e.g. a baseball fan wishing to watch all home runs hit by their favorite player during the 2013 baseball season [7], or a coach searching for video recordings related to the intended learning focus for a player or the whole training session [6].

However, these examples require events to be manually tagged which not only requires time and effort but would also split a trainers attention from training to tagging the events for later viewing and analysis.

A system which could automatically tag such events would help trainers avoid manual effort has the potential to provide tailored and interactive multi-modal feedback to coaches and players.

B. Project Objectives

In summary, the project has the following objectives:

- To evaluate the potential of using sensor data from IMUs (3D acceleration, 3D angular velocity, 3D magnetometer and air pressure) in automatically identifying basic volleyball actions and non-action;
- to use Machine Learning techniques to identify individual player actions;
- to supplement the video recording by tagging the identified action and events, and
- to design a system to allow coaches and players to view tagged video footage to easily search for the information or event of interest (e.g. All the serves by a particular player)

II. RELATED WORK

Quick and easy access to performance data is important for both coaches and players, therefore it is important that video recordings related to the intended learning focus are immediately accessible [6]. In their work Koekoek et al. developed an application named Video Catch to manually tag events like sports actions during matches and training sessions [6]. Creating a system which can automatically tag such actions would be beneficial as it would save manual effort.

Inertial Measurement Units (IMUs) [11], [12] have been utilized to automatically detect sport activities in numerous sports e.g. soccer [18], [19], tennis [20], [21], table tennis [22], hockey [19], basketball [23], [24] and rugby [25].

Many approaches have been proposed for human activity recognition. They can be categorized into two main categories: sensor-based and vision-based.

Vision-based methods employ cameras to detect and recognize activities using several computer vision techniques. While sensor-based methods collect input signals from wearable sensors mounted on human bodies such as accelerometer and gyroscope. For example, In Liu et al. [26] identified temporal

patterns among actions and used those patterns to represent activities for the purpose of automated recognition. Kautz et al. [27] presented an automatic monitoring system for beach volleyball based on wearable sensor devices which are placed at wrist of dominant hand of players. Beach volleyball *serve* recognition from a wrist-worn gyroscope is proposed in Cuspinera et al. [28] which is placed on the forearm of players. Kos et al. [29] proposed a method for tennis stroke detection. They used a wearable IMU device which is located on the players wrists. A robust player segmentation algorithm and novel features are extracted from video frames, and finally, classification results for different classes of tennis strokes using Hidden Markov Model are reported [30]. Jarit et al. [31] studied with college baseball players. 88 subjects were studied in two groups. Jamar dynamometer was used to test maximum grip strength (kgf) for both hands. The recording was done for dominant and nondominant hands. The highest measurements were taken for the statistical analysis. Every subject put their maximal effort. 2-factor repeated measures to analyze the variance was used to compare both hands grip strength ratios of the experimental and control group. Results of the study showed that there is no significant differences of baseball players dominant and nondominant hands grip strength. Based on the above literature, we have concluded that the most studies take into account the role of dominant hand particularly for volleyball action modelling and the role of non-dominant hand is less explored.

III. METHODOLOGY

The project can be divided into following activities.

- Data Collection
- Prototype System
- Machine Learning (Feature Extraction and Modeling)

IV. DATA COLLECTION

A. Technical Setup

- Each player wears 2 IMUs (see Figure 1) on both wrists.
- Two video cameras on the side of team wearing the IMUs (see Figure 2).

B. Participants

Nine volleyball players wore IMU sensors [11] on both wrists during their regular training session. Players were encouraged to play normally as their routine training session. Due to some technical reasons IMUs wore by one player did not work, therefore the data used for the experimentation consists of 8 volleyball players.

C. Data Annotation

To obtain the ground truth for machine learning model training, the video recording was annotated using the Elan software (see Figure 3). 3 annotator annotated the video. Since volleyball actions performed by players are quite distinct there is no ambiguity in terms of inter-annotator agreement. The quality of the annotation is evaluated by a majority vote i.e. if



Fig. 1: Player wearing 2 IMUs on both wrists.

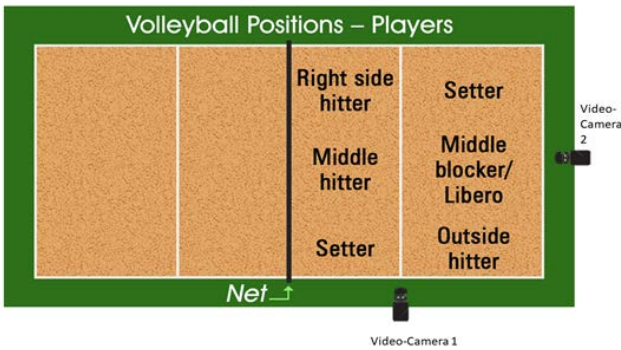


Fig. 2: Camera settings on court.

all annotator have annotated the same action or if an annotator might have missed or mislabelled an action.

As a result, for action case and non-action case there were 1453 and 24412 seconds of data, respectively. Table I shows the data (in seconds) information for each player. This data set is made available to research community. The annotators also annotated the type of volleyball actions such as under hand serve, overhead pass, serve, forearm pass, one hand pass, smash, underhand pass. Table I also details the number of volleyball actions performed by every player.

V. AUTO-TAGGING SYSTEM PROTOTYPE

The auto-tagging system has the following components.

A. Sensors on Player Wrist(s)

During a training session or a match, players wear a wireless sensor such as an IMU (Inertial Measurement Unit) [11], [12] on one or both wrists (see section IV for details). Features are extracted from the IMU signals to train machine learning models to recognize volleyball actions and non-actions. The machine learning is performed in two steps as shown in Figure 4, first we recognize if a frame of sensor data belongs

to a volley ball action or not. If it belongs to an action then we further classify it into types of actions (see VI for machine learning modelling and experimentation). Once the actions are identified, its information along with the timestamp is stored in a repository for indexing purposes.

B. Repository

Information related to the video, players and actions performed by the players are indexed and stored as documents in a tables or cores in Solr search platform [32]. An example of a Smash indexed by Solr is shown in table II.

C. Web Application

The interactive system is developed as web application. The server-side is written using asp.net MVC framework. While the front-end is developed using HTML5/Javascript.

Figure 5 shows a screen shot of the front-end of the developed system. The player list and actions list are dynamically populated by querying the repository. The viewer can filter the actions by player and action-type (e.g. over head pass by player 3). Once a particular action item is clicked or taped, the video is automatically jumped to the time interval where the action is being performed.

VI. EXPERIMENTAL SETUP

For classification, a two level task classification is planned. In the first step a binary classification scheme is adopted where the given frame (as described in section VI-A) is classified as Action or Non-Action. In the second step (future plan), the action in the window will be classified as Forearm Pass, One Hand Pass, Overhead Pass, Serve, Smash, Underhand Pass, Underhand Serve or Block. In this study, we have only trained machine learning models for action and non-action events (i.e. first step only). This section describes the process of machine learning models training for action and non-action events.

A. Feature Extraction

In this study, we have used time domain features such as mean, standard deviation, median, mode, skewness and kurtosis which are extracted over a frame length of 0.5 seconds of sensor data with an overlap of 50% with the neighbouring frame. As a results we have six features for each dimension of sensor data per frame. For action case and non-action case there were 5812 and 97648 frames, respectively.

B. Classification Methods

The classification is performed using five different methods namely Decision Tree (DT, with leaf size of 5), Nearest Neighbour (KNN with K=5), Naive Bayes (NB with kernel distribution assumption), Linear Discrimination Analysis (LDA) and Support Vector Machines (SVM with a linear kernel with box constraint of 0.5 and SMO solver). The classification methods are employed in both Python and MATLAB¹ using the statistics and machine learning toolbox in the Leave-One-Subject-Out (LOSO) cross-validation setting, where the

¹<http://uk.mathworks.com/products/matlab/> (December 2018)

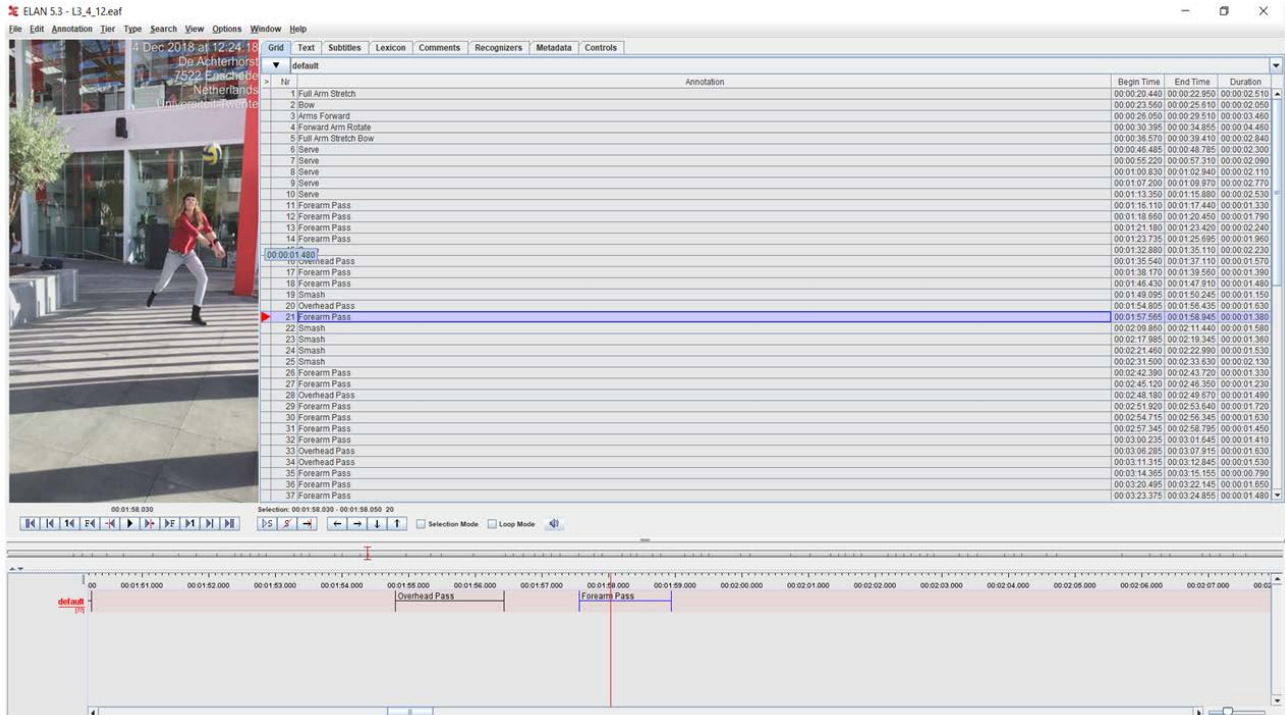


Fig. 3: Annotation example with Elan annotation tool.

TABLE I: Data Set Description: Time taken by each player for performing actions, non actions and number and type of actions performed by each player

ID	DH	Action(sec)	Non-Action(sec)	# Actions	Forearm Pass	Onehand Pass	Overhead Pass	Serve	Smash	Underhand Serve	Block
1	R	198	3055.25	120	40	3	16	0	29	28	4
2	L	193.75	3061	125	36	2	14	32	15	0	6
3	R	191	3030	116	50	3	3	34	25	0	1
5	R	176.75	3054.5	124	46	2	19	21	28	4	4
6	R	228.5	3009	150	30	1	70	0	12	30	7
7	R	135.5	3080.25	106	39	4	13	0	14	34	2
8	R	146.25	3077.5	105	34	4	16	34	17	0	0
9	R	183.25	3044.5	144	42	1	58	33	4	1	5
total		1453	24412	990	317	20	209	154	144	97	49

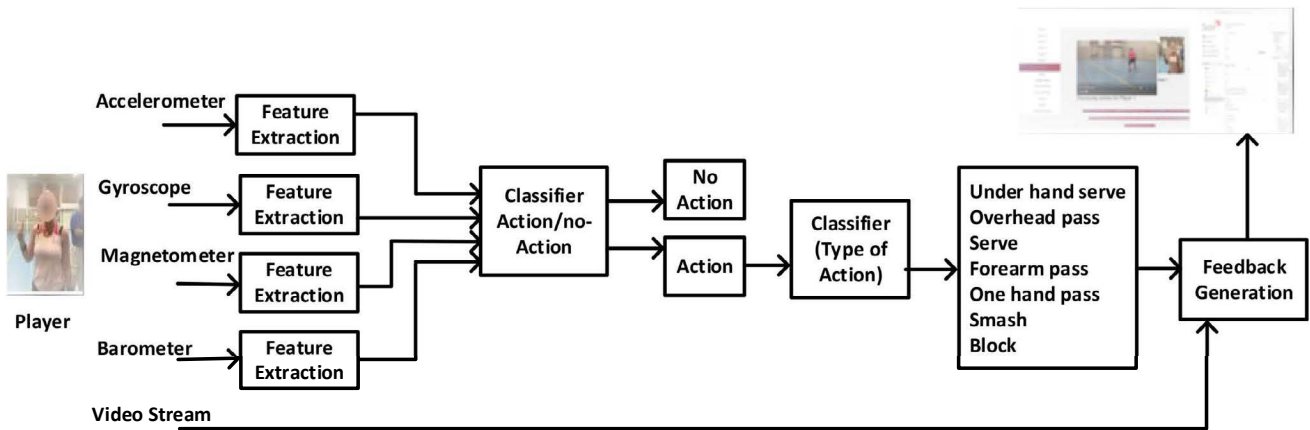


Fig. 4: Prototype System Architecture

training data do not contain any information of validation subjects. To assess the classification results, we used the unweighted average recall as the dataset is not balanced. The unweighted average recall is the arithmetic average of recall

of both classes.

C. Experiments

The overall action frames for eight players were 5812 frames while in Non-Action case there were 97648 frames.

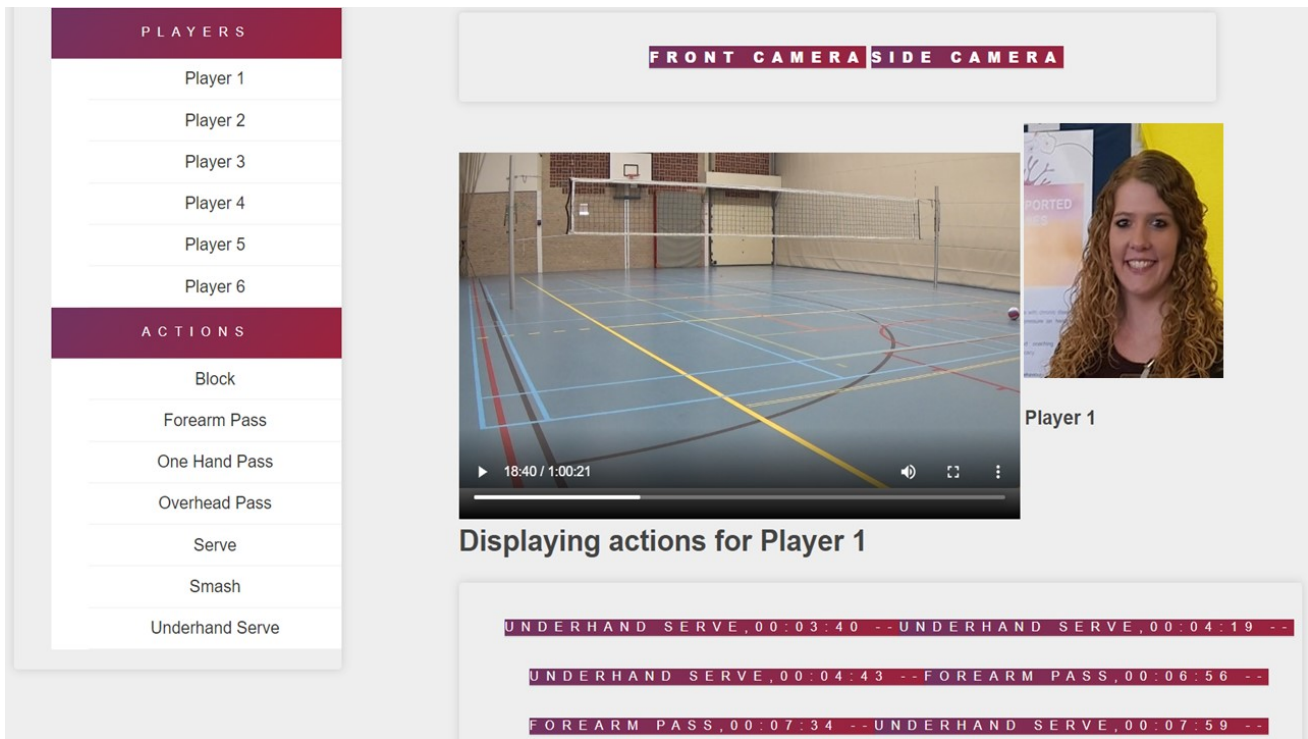


Fig. 5: Interactive front-end system

TABLE II: Sample Solr structure

```
"id":"25_06_Player_1_action_2"
"player_id":["25_06_Player_1"],
"action_name":["Smash"],
"timestamp":["00:02:15"],
"_version_":1638860511128846336
```

One can understand from the samples that the data set is imbalanced. In order to evaluate the performance of IMU sensor, we train machine learning models using balanced and imbalanced data set for the recognition of Action and non Action frames, we have conducted two experiments as follow:

- **Experiment 1:** training is performed on balanced data sets in terms of actions and non actions, where the same number of non-actions events (selected randomly) and action events for each player are used. The validation is performed on imbalanced (full) dataset in leave-one-subject out settings.
- **Experiment 2:** training is performed on imbalanced data sets in terms of action and non actions and validation is performed on imbalanced dataset in leave-one-subject out settings.

VII. EXPERIMENTAL RESULTS

This section describes the results of machine learning models for action and non-action events and demonstrate the discriminate power of different IMU sensors placed on dominant and non-dominant hand.

A. Experiment 1

The results of dominant hand and non-dominant hand for all sensors are shown in Table III and Table IV respectively. The best results indicate that the dominant hand (82.50%) provides better UAR than non-dominant hand (81.71%) using the accelerometer. The average of results indicated that the accelerometer provides the best averaged UAR of 81.92% (dominant hand) and 80.41% (non-dominate hand). SVM classifier provides the best averaged UAR of 74.36% (dominant hand) and 72.30% (non-dominant hand). All sensors provide better results (i.e. UAR) on dominant hand than on non-dominant hand.

TABLE III: Dominant Hand: Unweighted Average Recall (%)

Sensor	DT	KNN	NB	SVM	LDA	avg.
Acc.	81.99	82.50	82.19	82.35	80.52	81.91
Mag.	77.47	74.86	79.25	79.50	79.08	78.03
Gyr.	73.72	75.48	75.94	74.17	72.78	74.42
Baro.	57.19	56.80	59.30	61.45	61.01	59.15
avg.	72.59	72.41	74.17	74.36	73.34	-

TABLE IV: Non-Dominant Hand: Unweighted Average Recall (%)

Sensor	DT	KNN	NB	SVM	LDA	avg.
Acc.	78.90	80.33	81.71	81.28	79.84	80.41
Mag.	74.80	69.59	75.31	76.69	75.90	74.46
Gyr.	72.84	73.42	74.74	75.35	75.10	74.29
Baro.	51.57	50.22	49.46	55.88	56.07	52.64
avg.	69.52	68.39	70.30	72.30	71.72	-

B. Experiment 2

The UAR of dominant hand and non-dominant hand for all sensors are shown in Table V and Table VI respectively. These results indicate that the non-dominant hand (83.99%) provides better UAR than dominant hand (79.83%), with NB being the best classifier for action detection. The results indicated that the accelerometer provides the best averaged UAR of 69.76% (dominant hand) and 74.17% (non-dominant hand). NB classifier provides the best results of 71.47% (dominant hand) and 68.01% (non-dominant hand). The averaged UAR also indicates that the accelerometer (74.14%) and magnetometer (73.52%) provide better UAR on non-dominant hand than on dominant hand.

TABLE V: Dominant Hand: Unweighted Average Recall

Sensor	DT	KNN	NB	SVM	LDA	avg.
Acc.	70.83	68.83	79.83	59.77	69.56	69.76
Mag.	63.10	57.12	74.16	50.00	67.71	62.41
Gyr.	64.07	60.78	74.58	53.35	64.86	63.53
Baro.	59.22	56.53	57.24	53.01	56.78	56.56
avg.	<i>64.30</i>	60.81	<i>71.45</i>	54.03	64.72	-

TABLE VI: Non-Dominant Hand: Unweighted Average Recall

Sensor	DT	KNN	NB	SVM	LDA	avg.
Acc.	71.53	72.98	83.99	66.47	75.90	74.17
Mag.	76.61	67.67	80.83	66.75	75.74	73.52
Gyr.	61.42	58.85	75.71	50.00	64.70	62.14
Baro.	40.86	38.56	31.53	50.00	50.53	42.30
avg.	<i>62.60</i>	59.51	68.01	57.80	66.71	-

C. Sensor Fusion

We implemented a simple decision fusion strategy by taking a vote among all feature sets i.e fusing the output of the best classifiers for each sensor, breaking ties by considering them as implying a non-action label. The ‘fusion results’ of experiment 1 and experiment 2 are shown in Table VII and Table VIII respectively. The reported results are quite promising, indicating that the sensors placed on the wrist of players could be used to detect whether a player is performing a volleyball action or not. It also suggests that fusion of accelerometer and magnitude sensors provides the best results when placed on both hands. However placing magnitude and accelerometer on one hand provides slightly less accurate results than placing them on both hands. It is also observed that the fusion for Experiment 2 provides better results than fusion of Experiment 1. It could be due to the reason of training setup, as lesser data is used in experiment 1 than experiment 2. The average UAR of sensor fusion indicated that the fusion improves the UAR and the confusion matrix of best UAR for experiment 1 and experiment 2 are shown in Figure 6 and 7 respectively. This study will also help in lowering the number of sensors for the players which could result in cost reduction of system and making the system less intrusive.

The reported study is part of the Smart Sports Exercises project in which we aim to develop new forms of volleyball training using wearable sensors data and pressure sensitive in-floor displays to provide analysis and feedback in an interactive manner. While we are interested not only in action and

TABLE VII: Sensor Fusion: Unweighted Average Recall

Sensor	DH	NDH	Both Hands
acc	82.50	81.71	82.52
Mag	79.50	76.69	77.65
Gyr	75.94	75.35	76.42
Baro.	61.45	56.07	60.14
Acc + Mag	81.87	80.03	83.84
Acc + Gyr.	80.60	79.21	81.88
Gyr + Mag	78.64	76.97	81.08
Acc + Mag + Gyr	79.73	80.30	83.52
All	82.25	79.73	83.51
Avg.	78.05	76.82	78.95

TABLE VIII: Sensor Fusion: Unweighted Average Recall

Sensor	DH	NDH	Both Hands
acc	79.83	83.99	85.86
Mag	74.16	80.83	86.38
Gyr	74.58	75.71	81.25
Baro.	59.22	50.53	59.34
Acc + Mag	81.84	86.42	86.87
Acc + Gyr.	79.40	83.09	85.02
Gyr + Mag	78.34	82.91	86.08
Acc + Mag + Gyr	80.73	84.58	85.80
All	72.91	84.53	85.32
Avg.	75.66	79.17	82.43

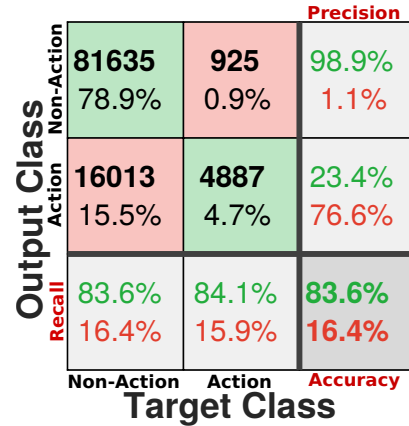


Fig. 6: Experiment 1 (Confusion matrix): best sensor fusion results obtained using fusion of accelerometer and magnetometer sensors from both hands.

non-action but also the type of action such as serve, forearm pass. It may be the case that dominant hand plays a crucially important role in determining the type of action. However, in many applications such as fatigue and stamina estimation [8], researchers are only interested in determining the amount of actions performed regardless of their type. In such cases, the reported results show an interesting case of using non-dominant hand compared to the common practice of using sensor(s) on the dominant hand [33], [34].

VIII. CONCLUSION

The overall aim of this project was to design an automatic video tagging system for sports related events using Machine Learning techniques and IMU sensors. In terms of contribution, this project proposed an architecture to automatically supplement video recordings, to this end; apart from the architecture, a prototype was developed based on that architecture

		Precision		
		82433	621	99.3%
Output Class	Non-Action	79.7%	0.6%	0.7%
	Action	15215	5191	25.4%
		Recall		
		14.7%	5.0%	74.6%
Target Class	Non-Action	84.4%	89.3%	84.7%
	Action	15.6%	10.7%	15.3%
		Accuracy		

Fig. 7: Experiment 2 (Confusion matrix): best sensor fusion results obtained using fusion of accelerometer and magnetometer sensors from both hands.

as proof of concept. Secondly the project developed and tested machine learning models trained on IMU data.

The experimentation performed during the project provided interesting results not only in terms of UAR but also in terms of sensor configuration. The analysis of using non-dominant hand for sensor placement opened up interesting opportunities for sports research.

IX. FUTURE DIRECTIONS

The outcome of this eNTERFACE project has the potential to be extended in multiple ways. In terms of machine learning models, we aim to train models to not only classify action vs non-action but also type of volleyball actions such as under hand serve, overhead pass, serve, forearm pass, one hand pass, smash, underhand pass. Additionally we plan to use frequency domain features such as Scalogram and Spectrogram instead of time domain features currently used to train the models.

Apart from extending the machine learning models the aim is to further develop the video tagging system from a proof of concept prototype to a more functional and integrated system.

The following list summarises possible ways to extend the project.

- Further classify actions
- Using frequency domain approaches for feature extraction
- Scalogram, spectrogram
- ResNet, AlexNet, VGGNet
- Classification based on the above feature set.
- Further integration of Demo system and models.

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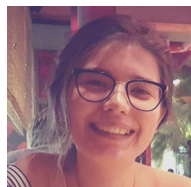
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