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Functional analysis of an Optical Real Time Locating System in production environments

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Abstract

Driven by the fourth industrial revolution (Industry 4.0), Real Time Location Systems (RTLS) are gaining importance. Holistic information about the position and movement of persons, vehicles and goods is an essential prerequisite for being able to efficiently automate entire process chains in the future with increasing machine autonomy. RTLS technologies enable the spatial and temporal localisation of objects within an environment. The current technological standard in the field of RTLS is based on anchors and transponders (e.g. Ultra Wide Band (UWB) systems), which use radio frequency (RF) signals to determine positions. However, the need for additional technical equipment is also a major weakness of these systems. In this paper, a new technological approach for real-time localisation of objects for industrial applications is presented. The proposed optical RTLS (ORTLS) is based on a decentralised sensor network, which enables the positioning of persons, vehicles and objects in industrial environments by means of artificial intelligence (AI) based object detection. In order to be able to use the system for safety-relevant applications in the future, certification must be obtained with regard to applicable regulations. A prerequisite for this is the validation and monitoring of the system performance with regard to the requirements of functional safety. For the analysis and evaluation of the system performance, this paper presents a methodology for the analysis of the AI-based detection under consideration of the environmental factors.

Keywords: Virtual, Digital, Smart Factories, Human centric Manufacturing, Systems, Machines and Operators' Digital Twins, Artificial Intelligence Methods and Big Data Analytics for Smart Production Systems, Human-Machine Intelligent Cooperation, Machine/Robot 4.0 and Operator 4.0

1. Introduction

The fourth industrial revolution (Industry 4.0) poses major challenges for companies, but also offers opportunities to maintain international competitiveness in the long term [1]. The core of this revolution lies in the horizontal and vertical integration of technical systems in real time [2]. Concepts of an Industry 5.0 are already being discussed today, which expand the existing paradigms with a human-centred view and focus on the well-being of industrial workers [3]. At the same time, humans are still given little consideration in the advancing digitalisation and automation of industrial processes and entire process chains. One example of this is autonomous transport systems in production environments. Due to the unpredictable behaviour of humans in the working area of autonomous vehicles, fleet efficiency is currently severely affected [4, 5]. The holistic integration of the uncertainty of human behaviour is a central building block for realising a true smart factory in the future. One technological approach to capture and integrate human actions are real-time locating systems (RTLS) [6]. Currently, these systems are based on the localisation of RF transponders [7]. However, the need for technical devices on

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the localised objects is a major weakness of these systems. By introducing an optical Real Time Location Systems (ORTLS) for industrial applications, the possibility of locating objects without technical devices on the objects is created. In this paper, an ORTLS for industrial applications is presented. By installing a decentralised optical sensor network in production environments, the ability of data privacy compliant object detection based on artificial intelligence is created. The intrinsic and extrinsic calibration of the sensor network allows the calculation of real world coordinates of the detected objects. The consolidation and filtering of position information on an application server makes it possible to create a digital twin of the production environment in real time. The information can be used for various applications, e.g. optimisation and operational extension of autonomous systems and occupational health and safety, in order to increase the safety and efficiency of production in the future.

To be able to use the system for safety-relevant areas of application in the future, however, the required functional requirements of the respective certifications must be satisfied. As a basis for certification, the system's function in accordance with the requirements within the respective environment must be validated and monitored during the system's operation. A major interference for optical real-time localisation is the environment itself. In order to be able to ensure localisation of objects at any time and at any relevant location in the environment, there must be a permanent and consistent detection of the objects. One problem can result from occlusions by the environmental features, as a line of sight from the sensors to the objects is needed for the detection. Multi-channel sensor coverage for critical areas can be used to solve this problem. To identify critical areas, this paper presents a methodology for the analysis and evaluation of AI-based object detection.

2. State of the art

Global Navigation Satellite Systems (GNSS) have become widely used to determine the position of objects and solve navigation tasks on Earth. However, due to signal attenuation by building structures, this technology cannot be used indoors. Today, the localisation of objects in buildings is often carried out by infrastructure localisation systems [8]. In industry, various applications can be realised with RTLS. In addition to the control and optimisation of production processes, challenges in the navigation of vehicles in intralogistics can be solved. Another example of current fields of application is the performance of efficiency analyses and the derivation of optimisation potential in operational processes [9, 10, 11]. The technology is also used particularly frequently to implement safety [12, 13], whereby persons are protected, for example, from a collision with a mobile working device.

For infrastructure-based localisation, a hardware system based on transmitting and receiving modules is installed in the environment. By communicating with mobile receiving and transmitting units, the position of the mobile unit can be estimated via electromagnetic signals. Geometric relationships of the hardware installation and information such as time of arrival (ToA) [14], time difference of arrival (TDOA) [15] or angle of arrival (AoA) [16] are used to estimate the exact position. As soon as the signals penetrate materials other than air or are deflected and reflected by object surfaces, the signals may be delayed. This makes the exact determination of the position considerably more difficult or can become very inaccurate. If the technology is used in interaction with persons, it must be ensured that they use the mobile unit correctly and permanently in an operational state, otherwise localisation is not possible.

Image-based localisation systems are another option for indoor localisation. These are already used, for example, in autonomous vehicles for self-location and navigation. By using cameras and a Vision Simultaneous Localisation and Mapping (VSLAM) algorithm, the vehicle's own position in the environment can be determined. In this process, point features are captured in the image and the change in the point features between the individual images is compared. From this, the camera position and thus the location of the mobile system can be determined by estimating the point projection [17]. In comparison to vehicles, this technology is not practical for the localisation of persons, as each person would have to carry a camera with sufficient field of view at all times.

In the state of research, it could be shown that persons in heavy industry can be tracked by camera images from cameras as part of the infrastructure. Several cameras were used, whose image data was analysed by artificial intelligence methods to determine where persons were present in the image. After persons had been detected in the image, the positions were determined by an extrinsic calibration of the cameras and a transformation of the coordinates into a global coordinate system. The focus of the investigations carried out is the deviation of the localised person to true position. However, no statement could be made about the reliability and functionality of the examined system. For an industrial use of such a system for safety-critical applications, however, this is a mandatory prerequisite [18, 19].

3. Optical Real Time Locating System

The system presented in this paper is able to classify and localise various objects on the basis of their optical properties. Initially, the system is able to localise any number of persons and transport vehicles such as forklift trucks. The knowledge of the positions of these object classes can be used, for instance, to prevent collisions between persons and transport vehicles.

The ORTLS consists of several AI-Sensors that are installed decentrally in the infrastructure. Fig. 1 shows a setup in a production environment where persons are localised. Here, several AI-Sensors are arranged in such a way that tracking of persons is possible even in narrow production environments. The AI-Sensors consist of an image sensor as well as an edge-computing unit and are thus able to process the optically captured information on an area of up to 1,000 m² directly on the AI-Sensor. For data protection reasons, the AI sensor is designed so that only the position information of the objects is transmitted from the sensor to a central server unit.

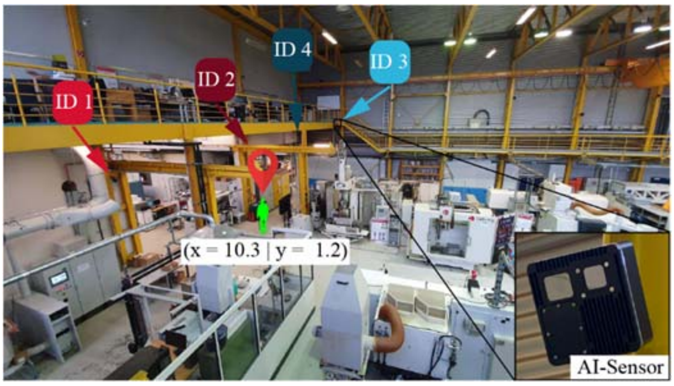

Fig. 1. Installed ORTLS system in production environment for localisation of persons with AI-Sensors

The system is able to detect, localise and track different object classes such as persons, manual vehicles or autonomous transport systems, depending on the detection model used. Fig. 2 shows a schematic representation of the individual system components and the process chain from data collection to determining of the position information on a central server. After the image data is captured by the AI sensor, a Convolution Neural Network (CNN) model is used to identify individual object classes and regress specific key features. For this, a pose detection algorithm is implemented, which is based on a Resnet18 backbone. Based on the individual detected features, the position of the object is determined initially in the image plane.

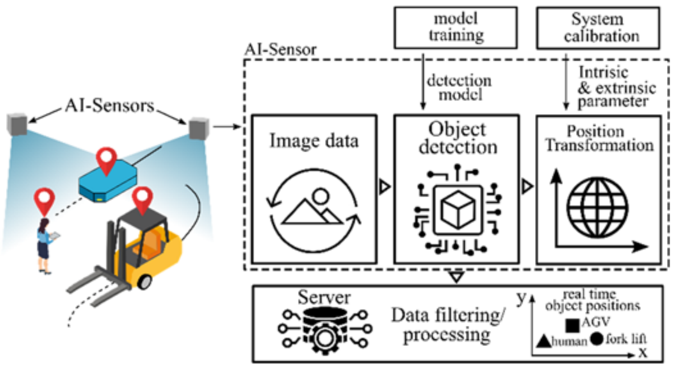

Fig. 2. Optical Real Time Locating System functional principle.

By means of sensor calibration, in which intrinsic and extrinsic calibration takes place, the individual AI-Sensors are combined to form a sensor network. To determine the extrinsic calibration parameters, spatially measured markers are used, which are detected by the sensors in the environment. The previously determined positions of detected objects in the image plane are then converted into real-world coordinates via a perspective transformation. In order to evaluate the detected object positions of the individual AI-Sensors, data filtering takes place on a central server. In this way, the individual information are merged into an overall location map. By using multiple AI-Sensors, multi-channel coverage is achieved, which can also localise objects that are temporarily obscured from one perspective.

4. Multi-channel detection and approach for analysing and evaluating system functionality

For reliable detection and localisation of objects, a line of sight to the objects is required. This is a major challenge, especially in production environments, where persons and vehicles often move between large machines and equipment and are obscured from different perspectives by the infrastructure installed. In order to achieve reliable real-time localisation despite this, the ORTLS presented is based on multi-channel coverage by multiple AI sensors. However, prior design and planning of the different sensor positions does not guarantee complete and reliable coverage of the entire area. Although an area is covered by multiple sensors, objects may be occluded simultaneously from all perspectives through everyday operating situations. A visual analysis and evaluation of the system coverage based on image data by a person is not reliably possible due to the high complexity of the environments as well as the large number of sensors.

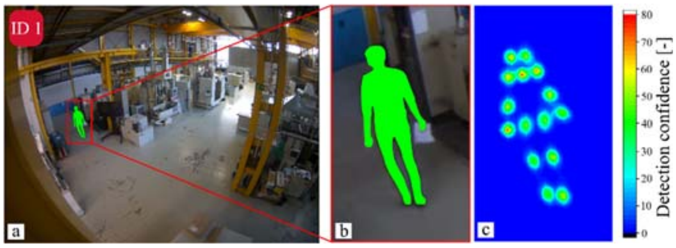

Fig. 3. (a) Example frame AI-Sensor ID1; (b) detected Person; c) confidence map of detected key features.

Since reliable and holistic sensor coverage is critical for future safety-relevant applications, e.g. collision prevention, this paper presents a methodology for an analysis and evaluation of system functionality. The number of simultaneous detections of different AI-Sensors and the confidence of the detection are used as evaluation criteria. As shown in Fig. 3, a person is detected by several key features.

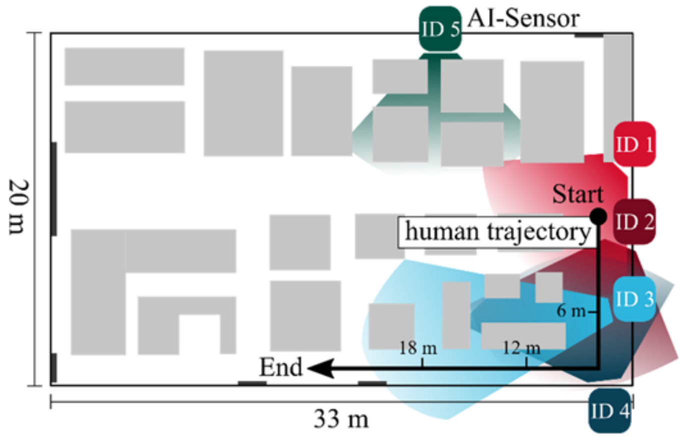

Fig. 4. Test environment with position and orientation of the 5 AI-Sensors and human trajectory for the experimental investigation.

The confidence score for each feature can be determined from the local maxima of the confidence map shown. In order to be able to make a conclusion about the detection accuracy of an entire frame, all the individual confidences are added up to a total confidence. As an example for the presented approach, the experiment shown in Fig. 4 is carried out. A person moves 25 m from point start to point end through the production environment. On the route, the person is detected and localised by 5 AI-Sensors with IDs 1 - 5. For the analysis, 20 data points per AI-Sensor and second are recorded, each consisting of the number of sensors detecting at the same time and the confidences of the individual sensors. The experiment aims to show how an analysis can identify areas with insufficient sensory coverage.

5. Experimental investigation of system coverage

For an evaluation of the experimentally recorded data, the determined confidences as well as the detections are plotted over the examined trajectory as shown in Fig.5. In summary, the ORTLS detects and locates the person over the entire distance and from different perspectives.

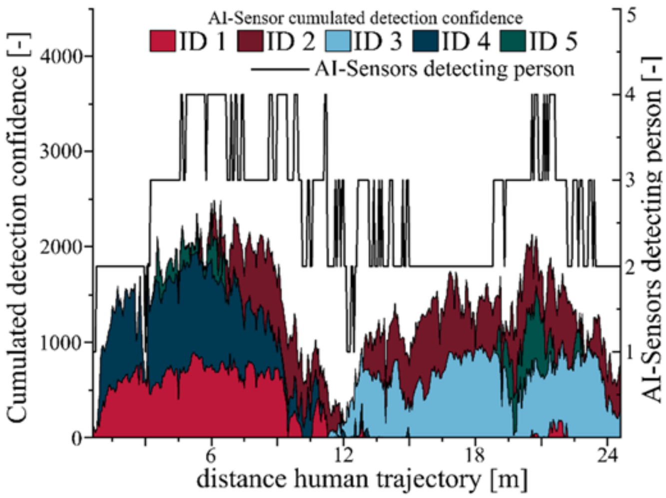

Fig. 5. Total number of AI-Sensors detecting the person as well as the cumulative detection confidence of the examined human trajectory

Furthermore, a decrease in detection as well as cumulative confidence is observed at approximately 12 m of the human trajectory, suggesting a limitation in sensor coverage. Although in some areas coverage by more than 2 sensors is given, the determined confidence is nevertheless at a low level. From the experiment it can therefore be concluded that a sole investigation of parallel detection by several sensors is not sufficient for an evaluation of the system reliability. However, a quantification of the results can only be done in the context of a concrete application domain. The necessary system requirements in terms of functionality and reliability are determined by the respective applications and can vary widely. In Fig. 6, the confidence values are additionally projected as a heat map onto the examined trajectory. As shown, the impairment of the system reliability can also be determined here. In addition, the critical area can also be identified spatially. To check the analysis results, the individual frames in this area were evaluated. As shown in Fig. 6, the person is partially obscured from the perspectives of AI-Sensors ID 2, ID 3 and ID 4. From the perspective of ID 1 and ID 5, the person is completely covered by the infrastructure of the test environment. The evaluation shows that even with multi-channel coverage, an impairment of the system function can occur due to occlusions. Furthermore, it is shown that an identification of these areas is made possible by the presented analysis approach.

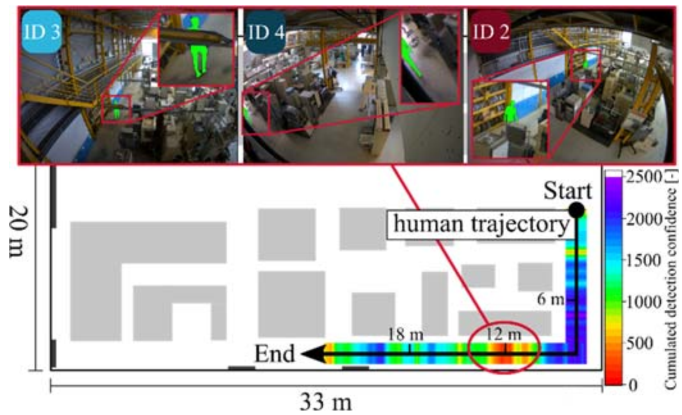

Fig. 6. Experimentally determined cumulative confidence of the trajectory as projected heat map

The results can also be used to derive possible measures to eliminate the obscuration caused by the infrastructure and thus the impairment of system functionality. For this purpose, the orientation of an existing sensor can be adjusted. An example of this is the perspective of AI-Sensor ID 4 in Fig. 6. The detection of the person is limited here, as the person is only partially visible at the outermost edge of the image. By rotating the sensor, this area may be better covered and the system reliability in this area could be increased. Another possibility is to install an additional sensor. In addition to insufficient coverage, depending on the area of application, there may also be over-coverage, which may be undesirable from an economic point of view. To enable an evaluation of the system coverage taking into account application-specific evaluation criteria, the recorded test results are evaluated in a portfolio analysis. Here, again, the boundaries of the individual fields are determined by the specific requirements of the application area. For the portfolio analysis shown in Fig. 7, a cumulative confidence of 700 and a multi-channel coverage at each data point of more than 2 AI-Sensors are assumed as limit values.

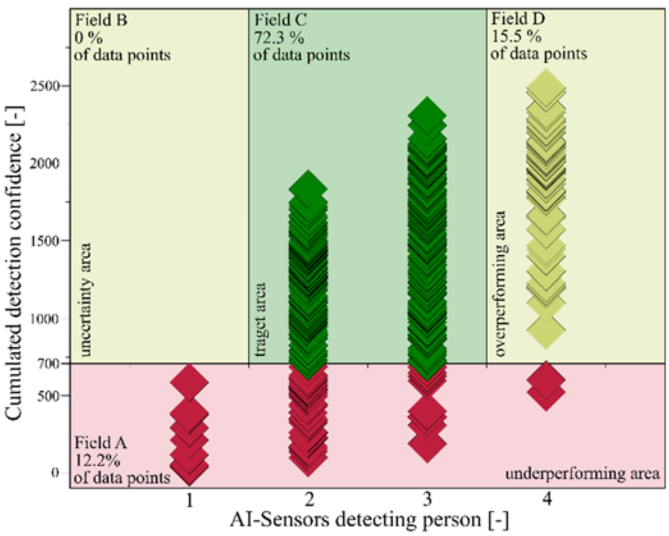

Fig. 7. Portfolio analysis of the collected data points

Corresponding measures can now be derived for the data points in the respective fields. Areas for which data points are located in field A show an underperformance in relation to the respective application due to an insufficient cumulative detection confidence. For these areas, measures must be taken to achieve the system requirements for the respective application. For the investigation carried out, approx. 12.2 % of the recorded data are located in field A.

Field B describes an area of uncertainty. In contrast to field A, the required detection confidence is achieved, but with insufficient redundancy of the sensory coverage. For these areas, it can be examined whether this limitation can be justified for the respective application and the specific area of the environment or whether measures must also be implemented to improve the system performance. In the investigation carried out, there is no data point in field B.

Field C describes the target range of the system performance with regard to the requirements from the respective application. Here, the functional minimum requirements are fulfilled without disproportionately exceeding them. For the examined area, approx. 72.3 % of the values fall into field C and thus represent by far the largest share.

Data points that fall into field D are characterised by overperformance, which is not a problem from a technical point of view, but may not be desirable from an economic point of view. For these areas, it can be examined whether a reduction of the sensory redundancy makes sense in order to reduce the costs for the system. A total of 15.5 % of the determined data points of the investigation are classified in field D.

The portfolio analysis shown in Fig. 7 thus represents an effective strategy for evaluating the system performance of the ORTLS with regard to the specific requirements of an application. Furthermore, the analysis can be used to derive specific measures to ensure that the functionality of the system meets the requirements.

6. Summary

In this paper, the optical, AI-based RTLS was presented and this technological approach was distinguished from the current state of the art of established technologies. It was shown that multi-channel AI-Sensor coverage can continuously detect and localise objects even in complex industrial environments. However, the design and verification of the AI-Sensor coverage is associated with high challenges, since a manual verification based on individual sensor positions is not reliably possible. Through the experimental collection of parallel multiple detections as well as the respective confidences, it could be shown through an analysis that impairments of the system performance due to occlusions of the environment can be identified. The presented approach makes it possible to evaluate the system performance with regard to the requirements of the respective application area as well as to derive specific measures for optimising the system functionality.

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