Challenges associated with sensors and data fusion for AGV-driven smart manufacturing

Adam Ziebinski[1], Dariusz Mrozek[1], Rafal Cupek[1], Damian Grzechca[1], Marcin Fojcik[2], Marek Drewniak[3], Erik Kyrkjebø[2], Jerry Chun-Wei Lin[2], Knut Øvsthus[2], Piotr Biernacki[1]

[1] Silesian University of Technology, Gliwice, Poland
[2] Western Norway University of Applied Sciences, Bergen, Norway
[3] AIUT Sp. z o.o. (Ltd.), Gliwice, Poland
{aziebinski@polsl.pl, dmrozek@polsl.pl,rcupek@polsl.pl, dgrzechca@polsl.pl, marcin.fojcik@hvl.no, mdrewniak@aiut.com.pl, erik.kyrkjebo@hvl.no, jerrylin@ieee.org, knut.ovsthus@hvl.no, pbiernacki@polsl.pl}

Abstract. Data fusion methods enable the precision of measurements based on information from individual systems as well as many different subsystems to be increased. Besides, the data obtained in this way enables additional conclusions drawn from their work, e.g., detecting degradation of the work of subsystems. The article focuses on the possibilities of using data fusion to create Autonomous Guided Vehicles solutions in increasing precise positioning, navigation, and co-operation with the production environment, including docking. For this purpose, it was proposed that information from other manufacturing subsystems be used. This paper aims to review the current implementation possibilities and to identify the relationship between various research sub-areas.

Keywords: Autonomous Guided Vehicles (AGV), Data fusion, Machine to Machine Communication (M2M), Sensor fusion.

1 Introduction

Contemporary production systems require that many stringent requirements be fulfilled, including flexibility, dynamic re-engineering processes, and production quality. Many changes enable the implementation of Industry 4.0 [1] functionalities to be made to meet these requirements. The production has to be adjusted to specific products, and the process organization must follow these changes. Avoiding non-productive time gaps reduces production losses [2]. The industrial environment consists of several Cyber-Physical Production Systems (CPPS) [3], IoT [4], and mobile subsystems. More and more efficient internal transport systems rely on solutions that use Autonomous Guided Vehicles (AGV) [5]. The logistics tasks must be performed in a distributed, dynamic, and autonomous manner, and therefore, they require the online information exchange between the AGVs and an industrial manufacturing environment. The new generation of the manufacturing ecosystems requires the regular supply and movement

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_45

of various components. To maintain the appropriate level of organization and quality of production, the precise execution of production orders is required. The currently used robotic systems enable the production of high-quality products. To work appropriately and above all efficiently [6], an AGV must be precisely docked to the assembly station (AS), and the loading and unloading operations have to be performed collaboratively. Integrating the information from an AGV and various sensors available from other production subsystems such as the IoT and CPPS [7] requires data fusion methods to be used [8] to achieve docking functionality to recalibrate an AGV to a specific AS if needed.

The aim of the article is to summarize the existing possibilities of using sensor and data fusion for the effective use of the AGVs that cooperate with the IoT subsystems and industrial manufacturing environments. The main contribution of this paper is the analysis of the challenges facing the implementation of internal logistics systems based on AGV, with a particular focus on the challenges related to data fusion:

(i) dynamic configuration of the data fusion methods - AGVs require a dynamic change in the way of cooperation with various ASs (chapter 2). Different sensors on each AS and AGV necessitate the usage of suited methods of data fusions.

(ii) wireless real-time communication – the specific docking example (section 2.2) requires real-time data exchange. Otherwise, data fusion will not support the accuracy of the docking procedure,

(iii) The integration of data streams produced by many IoT devices, AGVs, ASs, and extracted from other systems in a smart factory provides a broader view of the processed data and supports efficient and accurate data mining.

The main challenge is to find a way to prepare data fusion that depends on the available sensors on the AGV and AS, which could be recognized by the M2M communication methods and improved by the data analysis methods based on real-time information from data streams.

The paper is organized as follows: the second section presents the research challenges associated with the fusion between an AGV, the IoT subsystems, and the environment. The third section describes the ontology-based approach to implementing data fusion. The fourth section presents the methods of data fusion for AGV solutions. The conclusions are presented in the fifth section.

2 Research challenges related to the fusion between an AGV, the IoT subsystems, and the manufacturing environment

The internal transport systems for routing and supervising AGVs often use navigation systems. However, when an AGV reaches the specified production station, it usually has to dock there automatically. The industrial manufacturing environment uses many different types of sensors implemented in the IoT subsystems [9], CPPS [10], and AGV solutions. Although these sensors have different properties, some of them can be used to determine the position of an AGV and its distance to the objects in an industrial environment. Using data from several sensors can increase the precision of determining the position of an AGV. However, precise positioning is not required at all times, e.g.,

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_45

if an AGV is moving in relatively vast halls, the speed may increase, but the current position can be acquired using odometry. If the position accuracy is not high enough, then the Inertial Measurement Unit (IMU) can be switched on to support the less accurate odometry sensors in localizing it.

The possibility of powering some modules on and off leads to another big issue associated with the power management unit (PMU). It must be emphasized that a platform has a battery with a limited capacity – one of the goals is to increase the operating time for a platform. Having an up-to-date position and the platform, the IMU can be supplied by or disconnected from the battery. When connected, the dead reckoning algorithm should be used. It is assumed that there are some reference points for positioning in the local coordinate system in the working area of the platform. There is a wide range of positioning systems available for industrial use. They are starting from high-cost fast video systems and ending with ultrasound low-cost distance devices. Thus, the sensor selection is important from two aspects: one is the battery saving aspect, and the second is the positioning accuracy aspect. There are several advantages and disadvantages of both odometry and the dead reckoning algorithm [11]. The authors believe that the most crucial disadvantage is the lack of an absolute position. Therefore, other indoor positioning techniques [12] can be used for this purpose. Taking into consideration the navigation of a platform, wireless sensors based on RSSI (Radio Signal Strength Indicator) or ToF (Time of Flight) can be investigated [13]. Moreover, systems based on the methods mentioned above should also be assessed on their battery consumption. This can be achieved by selecting the most accurate sensor/system or combining the data obtained from several sensors when determining a position.

The main challenge is to support the optimal use of all available sources of information that can complement each other through sensor fusion. The goal is to integrate an AGV [14] and sensors in the manufacturing environment and to prepare a functionality to determine the position of an AGV, docking [15], and to provide support to Machine to Machine (M2M) communication [16], [17] with other subsystems.

2.1 Determining the position of an AGV

Precisely determining the position of an AGV enables the navigation system [18] to give orders correctly and increases the accuracy of the movement of an AGV in an industrial manufacturing environment [19]. It also leads to a reduction in costs in terms of battery consumption and human interference in the path correction of an AGV. The time required for human support reduces usability and increases the overall cost of implementing a system. Hence, the next challenge is to have a precise enough position and location of a platform. Therefore, one of the first steps in precise positioning is the kinematics of an AGV [5]. Next, other systems may be used to support any other assumptions or limitations caused by the AGV platform. For the dead reckoning algorithm, information obtained from the accelerometer, gyroscope, encoders, and sometimes a magnetometer is most often used in the navigation system [20]. Encoders or hall sensors enable the speed [21] of each wheel to be measured. If an AGV has a differential drive system, information about the speed of each wheel can be used to deter-

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_45

mine the overall speed of the AGV and its relative position and heading. An accelerometer can be used to measure the speed of an AGV, which can be obtained by integrating the AGV acceleration in time. To avoid a quantization error, it is recommended that an appropriate filtration method be used [22] (the method of filtration is another big issue with the system) as well as, e.g., Simpson's rule as the method for the numerical integration rather than simply multiplying the acceleration by the elapsed time. However, the speed of the vehicle that is determined by the accelerometers has a relatively large error relative to the accuracy of the encoders. Therefore, it is better to have some other system assumptions for positioning (or introducing higher-quality sensors). Theoretically, it is possible to calculate the distance based on the accelerometer data, but it is rarely used in practice due to its inaccuracy. The gyroscope can be used to measure the angular speed of an AGV to compensate for the yaw rate errors of an AGV caused by wheel slip. The measurements from the gyroscopes and magnetometers can be fused to estimate the accurate heading of an AGV and compensate for errors caused by the high electromagnetic pollution in an industrial manufacturing environment. Dead reckoning navigation tends to accumulate the errors such as inaccuracies in the encoder readings due to quantization, wheel slip, or IMU noise. Therefore, they need to be fused to estimate the AGV state better.

Each AGV is additionally equipped with a set of distance sensors, e.g., single-beam LiDAR and 2D LiDAR. To create the map and improve the position's determination, the SLAM technique [23], based on LiDAR technology, can be used. The information from other subsystems (the IoT, CPPS) can also be used to correct the calculated position. These subsystems are often equipped with sensors to determine the position, e.g., RFID tags, NFC modules, magnetic or color markers. The trilateration method [24] enables the position of the object to be calculated in a two-dimensional plane by referring to three specified points. The most advanced subsystems (e.g., AS) enable distance measurements by LiDARs or cameras. An AGV can obtain this additional information in a manufacturing environment, thus recognizing specific markers in space and receiving information about its position [13] (Fig. 1).

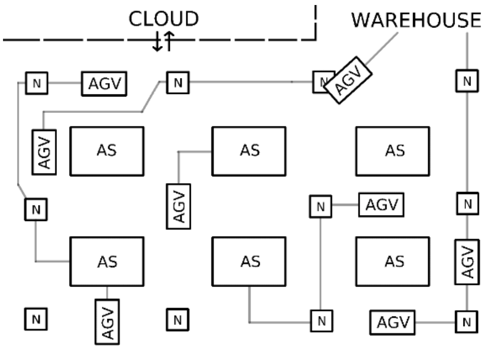

Fig. 1. Autonomous Guided Vehicles in manufacturing environment (N - NFC module).

2.2 Precisely docking an AGV to an Assembly Station

Docking in the specified manner and site enables the orientation time of a robot or an automatic production loading station associated with the delivered parts to be shortened. This approach creates further challenges, the solution of which should enable increasing the precision of the orientation of the robot to be increased and any errors

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_45

that require handling by production staff to be eliminated. Because of the possible presence of surface irregularities, the location of an AGV relative to the AS in both the vertical and horizontal positions must be determined (Fig. 2).

The distance of an AGV from an AS can be measured using, e.g., single-beam LiDAR, 2D LiDAR, an optical ruler, or ultrasound. The angle of the deviation of an AGV to an AS can be additionally measured based on these measurements. However, these sensors have different properties regarding the measurement and accuracy of distance [25]. Therefore, methods that enable the data obtained from a sensor to be selected with the highest accuracy or using data fusion methods [26] to obtain the highest degree of accuracy from several sensors. Using these methods will determine the range of motion of an AGV, ensuring a more accurate docking. Determining the horizontal position of an AGV enables an inclinometer to be used. The information about position of an AGV can be made available to the AS, which will speed up the orientation of a robot or an automatic production loading station to the delivered parts.

Integrating sensors into manufacturing systems enables multisensor data fusion to be prepared [27]. An AS can also be equipped with several sensors that enable the working status of the production, machines, and the surrounding environment, including the docking of an AGV or loading process, to be verified. An AS is usually at ground level. A constant point of reference can be obtained by precisely leveling it, e.g., 3D LiDAR or camera sensors [28]. In fact, it is possible to obtain more accurate measurements of the angle of an AGV to an AS. In addition to measuring the distance, a camera also enables the orientation to be determined and the delivered parts to be recognized. Data fusion, which is based on information from both the AGV and AS systems can be used to increase the accuracy of positioning an AGV. Both enable distance and angle measurements to be obtained and enable the vertical and horizontal position of an AGV to an AS to be determined.

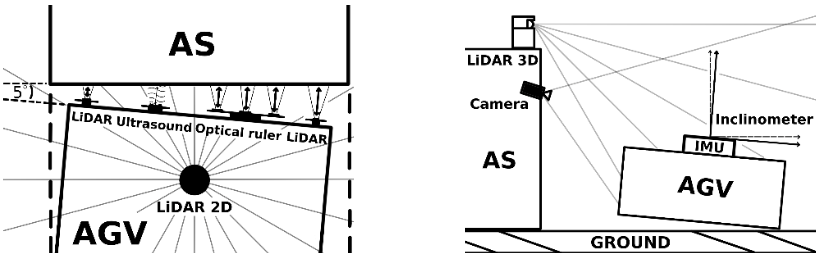

Fig. 2. Docking an AGV to an assembly station (top view on the left, side view on the right)

A mobile AGV can also be equipped with collaborative robot (CR) manipulators to perform different types of operations at an AS, e.g., picking up objects for transport or manipulating or placing new parts into the AS. These CRs can be used as additional sensor systems to aid in the precise docking of an AGV to an AS. A CR has very accurate proprioceptive sensors for determining the position and orientation of the different links and joints on a robot. By accurately positioning the robot tool-center-point (TCP)

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_45

on predefined points on an AS, the position and orientation of an AGV can be determined. This positioning does not necessarily have to be physical but can be performed using the camera systems on a robot [29].

Developing methods that enable changes in the area of production lines to be detected makes it possible to monitor the industrial process using data fusion techniques [30] and virtual sensing techniques [31]. This non-invasive method enables an operation or product quality in an industry to be optimized by measuring the parameters in dynamic systems in which stationary and mobile systems cooperate [32].

2.3 Properties of various sensors

To move in an industrial manufacturing environment with high precision, it is necessary to use a location engine based on the positioning system being used. On a fundamental level, the distance between some reference points and an AGV must be determined. Although the distance measurements can be investigated on several levels, the authors focused on the commonly used sensors in this paper. Positioning and localization systems can be used to map the environment and to navigate and avoid collisions. There are many different sensors for measuring distance, and each of them has various features (Fig. 3). Although that variety enables the suitable sensors for a specific task to be selected, on the other hand, there is a challenge when fusing many sensors with different specifications. Some of them (e.g., LiDARs) are very sensitive to ambient light or the color of the surface. They have different operating ranges, fields of view (FOV), measuring resolution, and accuracy, which can differ across the operating range. Ultrasound and radar sensors are not sensitive to ambient light or the color of any obstacles, but they have lower measurement and FOV resolutions.

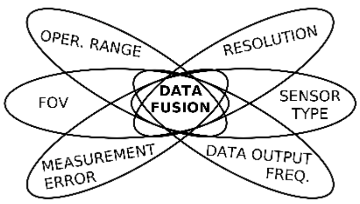

Fig. 3. Data fusion diagram – the problem of sensors' different specifications and features.

Cameras with depth-sensing can also be used for AGV navigation and docking. They can help to map the environment and take part in understanding it using image recognition techniques. IMUs (Inertial Measurement Unit) can be used to navigate and position an AGV system. IMUs and inclinometers can also be used to determine the orientation of an AGV, which is also crucial for the accuracy of an AGV performing specific processes. An off-balance AGV, in some situations, must be leveled. Otherwise, it can lead to errors when performing a task or even cause damage to other systems near an AGV. Like distance measuring sensors, IMUs and inclinometers have different operating ranges, measurement resolution, and accuracy. To obtain an accurate estimate of an orientation and position, sensor fusion should be used. Thus, one of the challenges is to develop a distributed computer system architecture [33] to integrate AGVs [14] and the required sensors, which will enable data fusion.

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_45

3 The ontology-based approach for implementing data fusion

To enable the data fusion proposed in section 2, it is necessary to collect and combine information from many different sensors. This information is available in various production subsystems, which means that it is represented in various formats with different communication capabilities and services. An ontological approach for information modeling can be used to exchange and merge information in heterogeneous distributed information systems, ensuring the unambiguous determination of the meaning of the available information and services and enables automatic communication between the individual system nodes. Such models can be used for flexible and dynamic communication between the system nodes according to the Machine to Machine (M2M) paradigm [34]. Ontology is how specific information such as a model of the entities and interactions in a specific area of knowledge is represented. Ontology enables the machine (independent of a human decision) interpretability of information containing the parameters and the relations between data [35]. Regarding the use case here, the ontology should describe the data and services used to navigate an AGV. The data and services must be selected according to the current position of the AGV and the tasks that are to be performed. The position of an AGV limits the list of available sources of information. The sensors must be selected based on their physical properties such as the detection method (1D, 2D, 3D), range, accuracy, scanning frequency, etc. [36]. On the other hand, the services must be adjusted to the operation to be performed by an AGV, e.g., avoiding an obstacle, preventing a collision with another AGV, or docking to a production station.

The ontology should be compatible with the contemporary models that are used in agile manufacturing, such as the Reference Architecture Model for Industry 4.0 (RAMI4.0), which defines the high-level schemas for manufacturing systems that are currently being developed [37] [38]. Moreover, the communication middleware should support a seamless connection between the entities and support the meta-information that enables the information to be interpreted correctly by considering the required presentation context. OPC UA is one of the communication solutions that has been widely accepted in the industry. It offers an object-based and service-oriented communication middleware that supports the exchange of information and organizes the information models [39]. OPC UA considers RAMI4.0 to be one of the key enabling technologies. The information and metainformation are organized in an object-oriented manner in which the relevant type definitions determine the structure and meaning of each data item. The basic OPC UA types are defined by the standard and are used to arrange the variables, objects, data, and references that show the relationships between the pieces of information. The model can easily be expanded according to the requirements of the application by using the inheritance mechanism [40].

3.1 M2M Communication

To navigate an AGV, the ontology should describe services (functions) that are offered, the available data, including any online measurements and sensor's properties, and pos-

DOI: 10.1007/978-3-030-77970-2_45

sible communication modes. Data from individual CPPS, the IoT, and AGV subsystems are often collected and processed in supervisory systems, data centers, or cloud platforms [41]. These systems also enable the required information to be exchanged between subsystems based on the M2M communication methods [42]. Additionally, individual subsystems, e.g., an AGV or AS, can exchange information directly based on reliable and time-determined M2M methods of communication [43].

Using 2D LiDAR enables information about the surroundings and objects in the nearest neighborhood to be obtained. On the other hand, a single-beam LiDAR enables the continuous observation of the road, often over a broader range than 2D LiDAR, and enables any objects that suddenly appear on the path of an AGV to be detected. There will always be cases where some of the measured areas are obscured by other objects, which means that the AGV will not be able to detect any other approaching objects or other AGVs. For this reason, the route of an AGV is mapped to the superordinate navigation system. Additionally, this system may take into account information about the movement of objects from other subsystems. For example, an AS and other IoT subsystems can also share information about moving objects detected in their environment using the IoT cloud solutions [44]. As a result, the navigation system will have information about moving AGVs and other objects. This information can reconcile the route, speed, and sequence of movement corrections and warn AGVs about the possibility of a collision because of other approaching objects or AGVs. AGVs can also communicate directly with other AGVs, AS, the IoT devices and share information about warnings or even moving objects based on M2M communication (Fig. 4). As a result, a local AGV navigation system will be able to combine data from other subsystems, map additional knowledge about the nearest surroundings, and use this information to predict possible collisions.

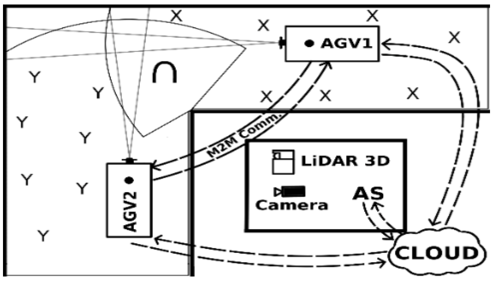

Fig. 4. M2M communication between AGVs and an industrial manufacturing environment

3.2 OPC UA-based communication for LiDAR

The use case of sensor fusion presented in Fig. 4 requires that information be exchanged between two AGVs and a production station. The M2M communication can be performed at a low level according to the communication services available for specific sensors or be changed into high-level services defined according to the ontological approach. In the first case, the LiDAR will provide information about a cloud of points that includes the angle of the LiDAR beam, the distance to the obstacle, and the reflectance factor. This information must be processed by the recipient, which will have to convert the data that describes the cloud of points into useful information about the location of the object. To use information from an external sensor, it is necessary to know the location of the remote LiDAR and the format in which the data is presented.

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_45

Moreover, the head of a LiDAR rotates several times per second, and during this time, several hundred to several thousand measurements are taken. In the case of low-level M2M communication, some high throughput, real-time transmission channels have to be built on wireless communication.

The second approach replaces the data exchange of the raw data measured by sensors with ontology-defined location services. In the first step, the AGV interested in the location data sends a location request using the Locate service provided by LiDAR's communication middleware. If it is possible to locate the AGV, the Locate service creates a new variable containing the AGV's position and this is identified by the ID used in the service request. Otherwise, the LiDAR returns an error code. In this case, no new measurement is created.

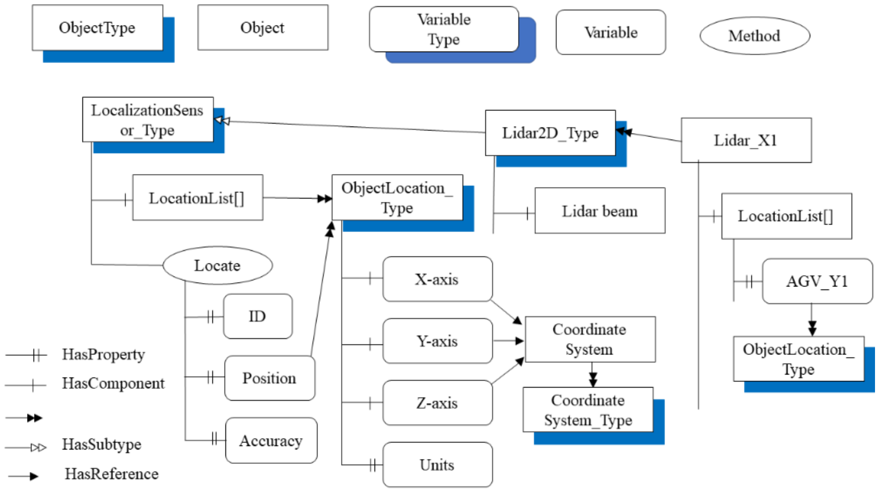

Fig. 5 Use case of OPC UA based ontology – localization sensor.

4 Data Fusion Methods

The sensors located on AGVs, ASs, and other IoT devices generate a series of events that form continuous data streams. Various sensor systems provide separate data streams. One of the challenges identified for AGVs logistics is the integration of the data streams. This integration can be performed within the data fusion process [45] to produce a complete set of data for further analysis within data mining processes. Data fusion can be achieved by joining events from the individual data streams that are produced directly by AGVs, ASs, and the IoT devices, and also those that are collected in a CPPS, a Distributed Control System (DCS), and Supervisory Control And Data Acquisition (SCADA) systems by using a stream joining operation. This operation can be implemented in various ways and in many places, i.e., (1) on the IoT device that are located on the AGV, (2) another IoT device that aggregates the data streams or plays a role in the Edge/fog gateway for transmitting the data to a data center, or (3) in the data center itself.

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_45

In all of these cases, the joined data streams should include a common attribute that can be used in the join operation. Frequently, the fusion of data streams is performed in the time domain, and therefore the timestamp that accompanies all of the collected events is used as a common attribute to assess the proximity of the events. Based on the timestamp, the real-time fusion of specific events can be performed. If the events are generated in close synchrony, it is enough to pair them (in the case of two data streams) with any new events that appear.

Asynchronous data streams raise another challenge and require more sophisticated methods that rely on timestamps, but the fusion of events is performed in time windows. One of the approaches for solving this problem proposed in the scientific literature is to use various variants of the sliding window algorithm [46], [47]. The window-based algorithms group sensor events along the timeline, which simplifies operating on these events. Once the events are collected, it is possible to use some set-based computations on them. Aggregating specific sensor readings (e.g., finding the maximum or minimum) is one of the frequently performed operations in time windows. For example, Gomes et al. [48] used the sliding window algorithm to calculate the maximum and average values of the collected sensor readings to reduce the amount of data needed to be processed. There can be different types of sliding windows, including count-based and time-based windows. A sliding count-based window retains a fixed number of events. Once the window is complete, each new event of the data stream that appears in the window displaces the oldest event, which is then removed from the window. A time-based window retains a variable number of events that had arrived within the specified time interval. As time passes, the IoT events that have been in the window longer than the specified interval are removed from the window. The expiration of events happens regardless of whether new events arrive in the window or not. Windows can be updated continuously with every incoming event or cyclically with a specified or dynamically assigned cycle time [49].

Events from various data streams can be joined in these sliding windows. Gomes et al. [48] proposed the XGreedyJoin algorithm, which operates on the sensors and joins data streams. To do this, the algorithm uses a join tree with a count-based sliding window for every stream. The algorithm can run in a single data stream processing unit (e.g., in a data center) or in a distributed sensor network. However, stream fusion can be computationally demanding in distributed sensor networks, which was observed and reported by Zhuang et al. [50]. The challenge especially appears when joining more than two data streams for a sensor network. Multiple data streams may increase the pressure on the IoT devices and field gateways, which usually have limited computational resources (CPU and memory). Therefore, Zhuang et al. proposed two approaches for solving the problem, i.e., the All In One (AIO) and Step By Step (SBS) approach. The AIO approach assumes that all data streams are processed and combined in a single stream processing job. The SBS approach distributes the joining operation into many steps that combine pairs of data streams in each step. Both approaches are implemented in the Apache Samza framework.

Recent works in the area of fusing asynchronous sensor events show that using fuzzy sets could bring several benefits. For example, Malysiak et al. [51] proposed using a fuzzy umbrella join algorithm to combine the sensor data from separate IoT data lakes

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_45

for Cyber-Physical Systems. Wachowicz et al. [52] proposed a fuzzy join algorithm for merging readings from various sensors while monitoring the performance of sports workouts and studying the correlations between the performance and weather conditions. The authors applied the concept of the fuzzy umbrella to join the sensor data that had been obtained from the smartwatches worn by sports amateurs with the atmospheric parameters that had been obtained from the weather services. The umbrella was spread out in overlapping time windows. However, in both solutions, the sensor events were processed after all of the collected data (i.e., not in real-time). These methods can be used, e.g., for fusing sensor data from SCADA and DCS systems in an AGV-equipped factory. An alternative solution was proposed for data in motion, i.e., for joining data streams [8], where the authors proposed a hopping umbrella to join asynchronous data streams. The hopping umbrella-based join enables the importance of specific events in the data streams to be assessed based on defined membership functions, sensor readings of higher importance to be selected in a specific case and reducing the size of the output stream. It is essential that the algorithm be used on the Edge (i.e., on an IoT device) or in a data center (the authors tested it in the cloud). Implementing the algorithm on an IoT device enables the data that is transmitted in the merged data stream to be reduced, which reduces the network traffic and the storage space consumed in a data center. These properties make the joining method suitable for the real-time fusing of data streams in the IoT devices mounted on an AGV and the events produced by the sensors located in a smart factory environment. However, the number of data streams that must be merged in such a way is challenging and requires dedicated approaches to the process implementation. Furthermore, the variety of integrated data coming from different sensors, systems, and IoT devices and the volume of data provided by these sources raise challenges of Big Data. The methods mentioned above address these challenges only partially, so there is still space for developing new techniques in the view of the Big Data problems.

5 Conclusions

Today's production ecosystems use many active subsystems that enable data about the operation of production systems and their environment to be obtained from CPPSs and IoT devices. The AGV systems used in this environment should actively participate in the exchange of data between these systems. Sharing additional information may be used by an AGV to increase the quality of its service. Such a solution can be obtained using data fusion methods based on information from multiple subsystems. However, achieving such solutions poses many challenges and related research. In this article, we presented some considerations on the issues associated with the data fusion methods for integrating an AGV and an AS with the required sensors and determining the position, docking, and communication methods of an AGV with other subsystems a smart industry environment. These challenges lead to reorganizing the methods used and adjustments of particular algorithms to be implemented in real-time industrial environments.

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_45

Acknowledgments

The research leading to these results received funding from the Norway Grants 2014-2021, which is operated by the National Centre for Research and Development under the project "Automated Guided Vehicles integrated with Collaborative Robots for Smart Industry Perspective" (Project Contract no.: NOR/POLNOR/CoBotAGV/0027/2019 -00) and partially by the Polish Ministry of Science and Higher Education Funds for Statutory Research.

References

1. Wang S, Wan J, Li D, Zhang C (2016) Implementing Smart Factory of Industrie 4.0: An Outlook. Int J Distrib Sens Netw 12:3159805
2. European Commission (2013) A Manufacturing Industry Vision 2025, European Commission (Joint Research Centre) Foresight study.
3. Shafiq SI, Sanin C, Szczerbicki E, Toro C (2015) Virtual Engineering Object / Virtual Engineering Process: A specialized form of Cyber Physical System for Industrie 4.0. Procedia Comput Sci 60:1146–1155
4. Botta A, de Donato W, Persico V, Pescapé A (2016) Integration of Cloud computing and Internet of Things: A survey. Future Gener Comput Syst 56:684–700
5. Shi D, Mi H, Collins EG, Wu J (2020) An Indoor Low-Cost and High-Accuracy Localization Approach for AGVs. IEEE Access 8:50085–50090
6. Realyvásquez-Vargas A, et al. (2019) Introduction and configuration of a collaborative robot in an assembly task as a means to decrease occupational risks and increase efficiency in a manufacturing company. Robot Comput-Integr Manuf 57:315–328
7. Kuc M, Sułek W, Kania D (2020) FPGA-Oriented LDPC Decoder for Cyber-Physical Systems. Mathematics 8:723
8. Mrozek D, Tokarz K, Pankowski D, Małysiak-Mrozek B (2019) A Hopping Umbrella for Fuzzy Joining Data Streams from IoT Devices in the cloud and on the Edge. IEEE Trans Fuzzy Syst 28:916–928
9. Ji Z, Ganchev I, O'Droma M, Zhao L, Zhang X (2014) A Cloud-Based Car Parking Middleware for IoT-Based Smart Cities: Design and Implementation. Sensors 14:22372–22393
10. Opara A, Kubica M, Kania D (2019) Methods of Improving Time Efficiency of Decomposition Dedicated at FPGA Structures and Using BDD in the Process of Cyber-Physical Synthesis. IEEE Access 7:20619–20631
11. Grzechca D, Ziębiński A, Paszek K, Hanzel K, Giel A, Czerny M, Becker A (2020) How Accurate Can UWB and Dead Reckoning Positioning Systems Be? Comparison to SLAM Using the RPLidar System. Sensors 20:3761
12. Paszek K, Grzechca D, Tomczyk M, Marciniak A (2020) UWB Positioning System with the Support of MEMS Sensors for Indoor and Outdoor Environment. J. Commun. 15:
13. Grzechca DE, Pelczar P, Chruszczyk L (2016) Analysis of Object Location Accuracy for iBeacon Technology based on the RSSI Path Loss Model and Fingerprint Map. Int J Electron Telecommun. https://doi.org/10.1515/eletel-2016-0051
14. Grzechca D, Paszek K (2019) Short-term positioning accuracy based on mems sensors for smart city solutions. https://doi.org/10.24425/MMS.2019.126325

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_45

15. Roth H, Schilling K (1998) Navigation and docking manoeuvres of mobile robots in industrial environments. In: IECON 98 Proc. 24th Annu. Conf. IEEE Ind. Electron. Soc. Cat No98CH36200. IEEE, Aachen, Germany, pp 2458–2462
16. Thota P, Kim Y (2016) Implementation and Comparison of M2M Protocols for Internet of Things. In: 2016 Intl Conf ACIT-CSII-BCD. IEEE, Las Vegas, NV, USA, pp 43–48
17. Hanzel K, Paszek K, Grzechca D (2020) The influence of the data packet size on positioning parameters of UWB system for the purpose of tagging smart city infrastructure. Bull. Pol. Acad. Sci. Tech. Sci. 68:
18. Tokarz K, Czekalski P, Sieczkowski W (2015) Integration of ultrasonic and inertial methods in indoor navigation system. Theor Appl Inform 26:107–117
19. Ziebinski A, Cupek R, Nalepa M (2017) Obstacle Avoidance by a Mobile Platform Using an Ultrasound Sensor. In: Nguyen NT, all (eds) Comput. Collect. Intell. 9th ICCCI Nicos. Cyprus 2017 Proc Part II. Springer Int. Pub., pp 238–248
20. Han Y, Wei C, Li R, Wang J, Yu H (2020) A Novel Cooperative Localization Method Based on IMU and UWB. Sensors 20:467
21. Ziebinski A, Bregulla M, Fojcik M, Klak S (2017) Monitoring and Controlling Speed for an Autonomous Mobile Platform Based on the Hall Sensor. In: Nguyen NT, all (eds) Comput. Collect. Intell. 9th ICCCI Nicos. Cyprus 2017 Proc. Part II. Springer Int. Pub., pp 249–259
22. Guan H, Li L, Jia X (2013) Multisensor fusion vehicle positioning based on Kalman Filter. IEEE, pp 296–299
23. Wen S, Othman K, Rad A, Zhang Y, Zhao Y (2014) Indoor SLAM Using Laser and Camera with Closed-Loop Controller for NAO Humanoid Robot. Abstr Appl Anal 2014:1–8
24. Fang BT (1986) Trilateration and extension to Global Positioning System navigation. J Guid Control Dyn 9:715–717
25. Grzechca D, Hanzel K, Paszek K (2018) Accuracy analysis for object positioning on a circular trajectory based on the UWB location system. In: 2018 14th Int. Conf. Adv. Trends Radioelecrtronics Telecommun. Comput. Eng. TCSET. IEEE, Lviv, Ukraine, pp 69–74
26. Sidek O, Quadri SA (2012) A review of data fusion models and systems. Int J Image Data Fusion 3:3–21
27. Liggins II M, Hall D, Llinas J (2017) Handbook of multisensor data fusion: theory and practice. CRC press
28. Budzan S, Kasprzyk J (2016) Fusion of 3D laser scanner and depth images for obstacle recognition in mobile applications. Opt Lasers Eng 77:230–240
29. Bjerkeng M, Pettersen KY, Kyrkjebø E (2011) Stereographic projection for industrial manipulator tasks: Theory and experiments. IEEE, pp 4676–4683
30. Błachuta M, Czyba R, Janusz W, Szafrański G (2014) Data Fusion Algorithm for the Altitude and Vertical Speed Estimation of the VTOL Platform. J Intell Robot Syst 74:413–420
31. Lichuan Liu, Kuo SM, Zhou M (2009) Virtual sensing techniques and their applications. In: 2009 Int. Conf. Netw. Sens. Control. IEEE, Okayama, Japan, pp 31–36
32. Min Cheol Lee, Min Gyu Park (2003) Artificial potential field based path planning for mobile robots using a virtual obstacle concept. In: Proc. 2003 IEEEASME Int. Conf. Adv. Intell. Mechatron. AIM 2003. IEEE, Kobe, Japan, pp 735–740
33. Ziebinski A, Cupek R, Piech A (2018) Distributed control architecture for the autonomous mobile platform. Thessaloniki, Greece, p 080012
34. Weyrich M, Schmidt J-P, Ebert C (2014) Machine-to-Machine Communication. IEEE Softw 31:19–23
35. Cupek R, Ziebinski A, Fojcik M (2017) An Ontology Model for Communicating with an Autonomous Mobile Platform. In: Kozielski S, all (eds) Databases Archit. Struct. Effic. Solut. Data Anal. Knowl. Represent. Springer, pp 480–493

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_45

36. Kohlbrecher S, von Stryk O, Meyer J, Klingauf U (2011) A flexible and scalable SLAM system with full 3D motion estimation. In: 2011 IEEE Int. Symp. Saf. Secur. Rescue Robot. IEEE, Kyoto, Japan, pp 155–160
37. Hankel M, Rexroth B (2015) The reference architectural model industrie 4.0 (rami 4.0). ZVEI
38. Cupek R, Drewniak M, Ziebinski A (2019) Information Models for a New Generation of Manufacturing Systems - a Case Study of Automated Guided Vehicle. In: 2019 IEEE Int. Conf. Syst. Man Cybern. SMC. IEEE, Bari, Italy, pp 858–864
39. Lange J, Iwanitz F, Burke T OPC from Data Access to Unified Architecture. 2010. OPC Found. Softing
40. Cupek R, Drewniak M, Ziebinski A, Fojcik M (2019) "Digital Twins" for Highly Customized Electronic Devices – Case Study on a Rework Operation. IEEE Access 7:164127–164143
41. Varghese A, Tandur D (2014) Wireless requirements and challenges in Industry 4.0. In: 2014 Int. Conf. Contemp. Comput. Inform. IC3I. IEEE, Mysore, India, pp 634–638
42. Elgazzar MH (2015) Perspectives on M2M protocols. In: 2015 IEEE Seventh Int. Conf. Intell. Comput. Inf. Syst. ICICIS. IEEE, Cairo, Abbassia, Egypt, pp 501–505
43. Fadlullah ZM, Fouda MM, Kato N, Takeuchi A, Iwasaki N, Nozaki Y (2011) Toward intelligent machine-to-machine communications in smart grid. IEEE Commun Mag 49:60–65
44. Cheng Y, Tao F, Xu L, Zhao D (2016) Advanced manufacturing systems: supply–demand matching of manufacturing resource based on complex networks and Internet of Things. Enterp Inf Syst 1–18
45. Trawiński B, Smętek M, Lasota T, Trawiński G (2014) Evaluation of Fuzzy System Ensemble Approach to Predict from a Data Stream. In: Nguyen NT, Attachoo B, Trawiński B, Somboonviwat K (eds) Intell. Inf. Database Syst. Springer, Cham, pp 137–146
46. Golab L, Özsu MT (2003) Processing sliding window multi-joins in continuous queries over data streams. Elsevier, pp 500–511
47. Hammad MA, Aref WG, Elmagarmid AK (2003) Stream window join: tracking moving objects in sensor-network databases. In: 15th Int. Conf. Sci. Stat. Database Manag. 2003. IEEE Comput. Soc, Cambridge, MA, USA, pp 75–84
48. Gomes J, Choi H-A (2008) Adaptive optimization of join trees for multi-join queries over sensor streams. Inf Fusion 9:412–424
49. Ji Y, Liu S, Lu L, Lang X, Yao H, Wang R (2018) VC-TWJoin: A Stream Join Algorithm Based on Variable Update Cycle Time Window. In: 2018 IEEE 22nd Int. Conf. Comput. Support. Coop. Work Des. CSCWD. IEEE, Nanjing, China, pp 178–183
50. Zhuang Z, Feng T, Pan Y, Ramachandra H, Sridharan B (2016) Effective Multi-stream Joining in Apache Samza Framework. In: 2016 IEEE Int. Congr. Big Data BigData Congr. IEEE, San Francisco, CA, USA, pp 267–274
51. Malysiak-Mrozek B, Lipinska A, Mrozek D (2018) Fuzzy Join for Flexible Combining Big Data Lakes in Cyber-Physical Systems. IEEE Access 6:69545–69558
52. Wachowicz A, Małysiak-Mrozek B, Mrozek D (2019) Combining Data from Fitness Trackers with Meteorological Sensor Measurements for Enhanced Monitoring of Sports Performance. In: Rodrigues J, et al. (eds) Comput. Sci. – ICCS 2019. Springer, pp 692–705

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_45