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Method of collaborative detection of autonomous transport vehicles based on laser rangefinder data

Verfahren zur kooperativen Erkennung autonomer Transportfahrzeuge basierend auf Laserscanner-Daten

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To master changing performance demands, autonomous transport vehicles are deployed to make in-house material flow applications more flexible. The so-called cellular transport system consists of a multitude of small scale transport vehicles which shall be able to form a swarm. Therefore the vehicles need to detect each other, exchange information amongst each other and sense their environment. By provision of peripherally acquired information of other transport entities, more convenient decisions can be made in terms of navigation and collision avoidance. This paper is a contribution to collective utilization of sensor data in the swarm of cellular transport vehicles.

[Keywords: Cellular Transport Vehicles, Internet-of-Things, Logistics, Computer Vision, Wireless Sensor Network, Synchronization, Sensor Models]

Kurzbeschreibung: Für die Flexibilisierung des innerbetrieblichen Materialflusses werden autonome Transportfahrzeuge eingesetzt, um wechselnden Leistungsanforderungen gerecht zu werden. In diesem sogenannten Zellularen Transportsystem, bestehend aus einer Vielzahl kleinskaliger Transportfahrzeuge, sollen Fahrzeuge in der Lage sein, untereinander zu kommunizieren, sich gegenseitig zu erkennen und die Umwelt wahrzunehmen. Durch die Bereitstellung von dezentral akquirierten Informationen anderer Transportentitäten können bessere Entscheidungen zur Wegfindung und Kollisionsvermeidung getroffen werden. Dieses Paper ist ein Beitrag für die gemeinsame Nutzung von Sensordaten innerhalb eines Fahrzeugschwarms.

[Schlüsselwörter: Zellulare Transportfahrzeuge, Internet der Dinge, Bildverarbeitung, Computer Vision, Wireless Sensor Network, Synchronisierung, Sensormodelle]

1 Introduction and Motivation

To master changing performance demands in facility logistics, autonomous transport vehicles are deployed to make in-house material flow applications more flexible. The so-called cellular transport system consists of a multitude of small scale transport vehicles which shall be able to form as a swarm. Therefore the vehicles need to detect each other, exchange information amongst each other and sense their environment. By provision of peripherally acquired information of other transport entities, more convenient decisions can be made in terms of navigation and collision avoidance. This contribution to collective utilization of sensor data in the swarm of cellular transport vehicles is based upon three founding pillars: synchronization of sensor data, modeling of distance sensors, probabilistic computer vision algorithms for vehicle detection and network based sensor fusion. Finally, this detection methodology was empirically evaluated at the LivingLab Cellular Transport Systems at the Fraunhofer Institute for Material Flow and Logistics in Dortmund.

Methodically, this work follows the visualized approach in figure 1. Fundamentally information about the visible cellular transport vehicles of a sensor network is extracted from a set of data, in this case sensor data of a laser scanner. During the processing along the toolchain in figure 1 the information content increases steadily whereas the amount of data reduces. The pipeline starts with the synchronization of sensor data which is reflected in chapter 2.1. This step is the basis of the data processing. For the interaction of the vehicles and the collective utilization of the acquired sensor data a common time base is needed. In the second step of the toolchain the sensor data acquisition takes place which is explained in the context of sensor models in chapter 2.2. Besides the utilization of the vehicles own sensors, data from other vehicles can be acquired. During the next step the acquired data have to be transformed into the coordinate system of the vehicle. In the next process of the toolchain, the clustering, the amount of data reduces drastically. The acquired and transformed sensor data are segmented and clusters can be build. Those are important for the object extraction. Based on geometric probabilities of the clusters objects can be extracted. In the object extraction step some clusters like noise are rejected so that the amount of data decreases whereas the information content increases. During the classification process the extracted objects are classified into a list of vehicle candidates and a list of other objects. Chapter 3 deals with the methods of segmentation, object extraction and classification. Finally, the vehicle detection

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is described in chapter 4. The list of candidates is used to verify the real vehicles and to calculate their poses.

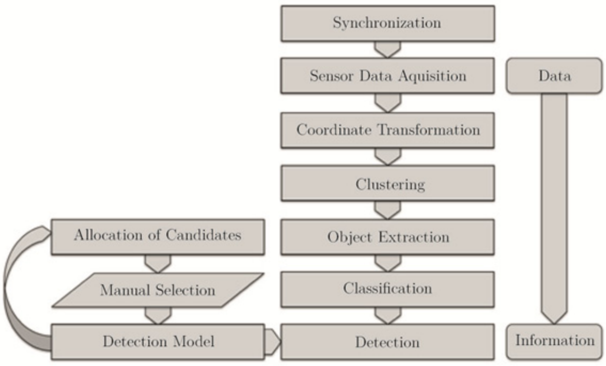

Figure 1. Toolchain for collaborative detection of autonomous transport vehicles

2 KEY TECHNOLOGIES

This chapter deals with the key technologies which shall be considered for an optimal detection of the used vehicles by the utilization of laser scanners.

2.1 WIRELESS SENSOR NETWORK SYNCHRONIZATION

The topic of sensor data synchronization plays a major role and represents a challenge in the interaction of the used technologies. Without a common time base, sensor data cannot be assigned to a defined point time. Due to the use of WLAN as a communication medium, no time deterministic transmission behavior can be mapped. On that account it is necessary to determine the point of time of the data acquisition as precise as possible. Otherwise, no reliable data analysis of merged data is possible.

Therefore, the clocks of all cellular transport vehicles have to be synchronized in order to get a common time base. A synchronization accuracy of at least 10 ms was aimed at. During the next two paragraphs two standards for synchronization are introduced.

Precision Time Protocol Synchronization

The Precision Time Protocol (PTP) is a time synchronization protocol based on the IEEE-1588-Standard [IEEE08] with which, according to the master-slave principle, different clocks can be synchronized throughout a wired (Ethernet) network. Figure 2 provides an overview of the process. Theoretically, the PTP protocol is able to completely eliminate the delay times of a deterministic transport medium with symmetric connections. In case of asynchronous connections, for example different routes on a round-trip of a package, the synchronization accuracy is decreased. In Ethernet networks with conventional topologies the deviation is usually in the range of nanoseconds. As a part of the Cellular Transport System the radio protocol IEEE 802.11 (WLAN) is used. Due to the non-deterministic characteristics of this transport medium a larger loss of synchronization accuracy, which will be examined in the following, has to be expected. For this purpose the following experiment has been implemented:

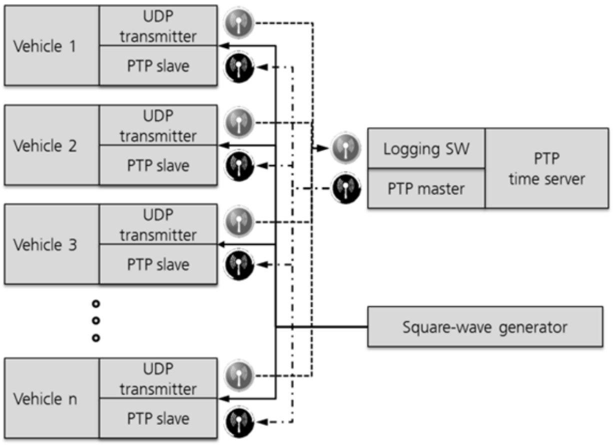

Figure 2. Setup for PTP series of measurements

The cellular transport vehicles of the Fraunhofer IML were physically supplied with a square wave with 4 Hz resp. 10 Hz. The edge change of the square-wave signal acted as a trigger for the recording time of the local vehicle clock.

Table 1. Synchronization accuracy with PTP-measurement in a busy network with and without filtering

measurement	E	E filtered	F	F filtered
filter	-	exp. smoothing	-	exp. smoothing
smoothing factor	-	$\gamma = 0.1$	-	$\gamma = 0.01$
max. error	81.799 ms	21.266 ms	111.101 ms	7.945 ms
min. error	0 ms	0 ms	0 ms	0 ms
arithm. average	0.756 ms	0.501 ms	0.596 ms	0.284 ms
standard average	4.215 ms	1.219 ms	4.336 ms	0.542 ms
3σ	12.647 ms	3.659 ms	13.009 ms	1.628 ms
median	0.200 ms	0.168 ms	0.199 ms	0.105 ms

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Because of the equal length of each cable the vehicles were supplied simultaneously with the signal. Each of the vehicles was equipped with a separate in hardware implemented time server (PTP slave) with an own WLAN connection as well as a separate WLAN to communicate (UDP sender). The time emitter server has also been connected via WLAN to the network for synchronization (PTP master) and communication (logging-software). As part of the system implementation of the PTP based syn-

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chronization the timeserver solution of the project PTPd -- Precision Time Protocol daemon [CBB06] was utilized. On the vehicle side the EL6688 EtherCAT Terminal of the Beckhoff Automation GmbH was used. After several trials an exponential smoothing filter has been implemented which yielded the best results. Figure 3 illustrates the accomplished synchronization accuracy with and without a filter. In table 1 more information about the measurement is given.

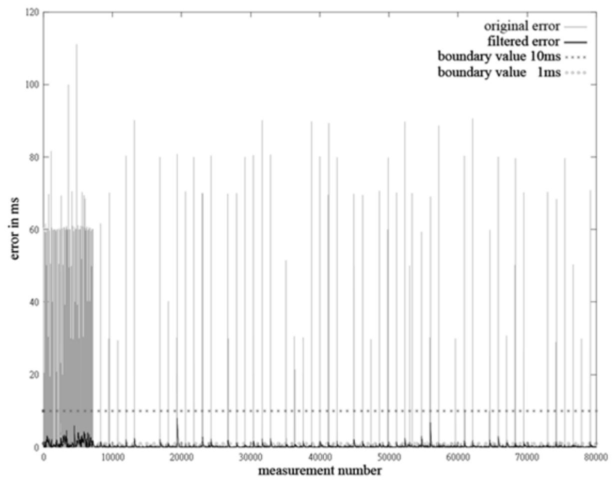

Figure 3. Synchronization accuracy with PTP-measurement in a busy network with and without filtering

Network Time Protocol Synchronization

Because of the importance of the synchronization step during the toolchain and the huge maximum error, which is achieved with PTP without filtering another standard for synchronization, will be introduced. Network Time Protocol (NTP) is a standard (RFC-5905) for clock synchronization between computer systems which is currently available in version 4 [Mil10], [Mil10a]. NTP is designed for a package based communication within a network resp. internet and uses the UDP protocol. Objective of NTP is a fault-tolerant clock synchronization within a network. The packages of the network have a variable time period.

Theoretically, NTP is able to calculate the weighted and averaged time delay of a non-deterministic transport medium depending on the number of subscribers. Asymmetric connections, for example different routes on a round-trip of a package, play a minor role in the standard. In Ethernet networks with conventional topologies the deviation is usually in the range of microseconds. As part of the LivingLab the radio protocol IEEE 802.11 (WLAN) is used. Because NTP is also designed for asymmetric connections similar synchronization accuracies as in normal networks can be expected.

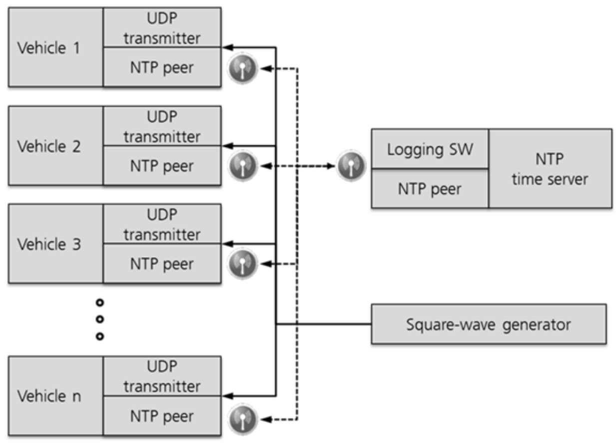

Figure 4. Setup for NTP-measurements

To examine the synchronization accuracy an experiment similar to the PTP-experiment has been set up with the exception that no additional hardware was used for synchronization on the vehicle. Furthermore, the same WLAN connection is utilized for communication and synchronization.

As mentioned in the experimental examination of PTP the systematic requirements engineering methods were also applied to the following examination. Aim of the examination is to achieve the required synchronization accuracy of 1 ms resp. 10 ms without any additional hardware in the vehicle control. Therefore, several measurements with different NTP system implementations as well as filters were taken. The results are illustrated in figure 5 and table 2.

Table 2. Synchronization accuracy with NTP-measurement in a busy network with and without filtering

measurement	I	I, filtered a	I, filtered b
filter	-	exp. smoothing	exp. smoothing
smoothing factor	-	$\gamma = 0.01$	$\gamma = 0.001$
max. error	18.000 ms	15.879 ms	9.756 ms
min. error	0 ms	0.001 ms	0.002 ms
arithm. average	5.697 ms	5.480 ms	3.669 ms
standard average	3.675 ms	3.501 ms	2.567 ms
3σ	11.025 ms	10.504 ms	7.701 ms
median	6.000 ms	5.618 ms	3.348 ms

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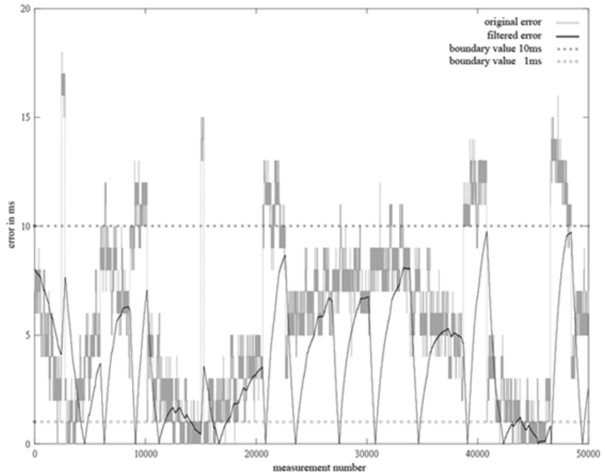

Figure 5. Synchronization accuracy with NTP-measurement in a busy network with and without filtering

Benchmark

Table 3 summarizes relevant results of the measurements and shows a comparison between both synchronization variants. The maximal permitted jitter of 10 ms can be achieved with the Precision Time Protocol as well as with the Network Time Protocol. Neither of the two synchronization variants can reach the lower jitter boundary of 1 ms in the reference industrial environment, Cellular Transport System.

Table 3. NTP-measurements compared to PTP-measurements with and without filtering

measurement	F (PTP)	F filtered	I (NTP)	I filtered
filter	-	exp. smoothing	-	exp. smoothing
smoothing factor	-	$\gamma = 0.01$	-	$\gamma = 0.001$
max. error	111.101 ms	7.945 ms	18.000 ms	9.756 ms
min. error	0 ms	0 ms	0 ms	0.002 ms
arithm. average	0.596 ms	0.284 ms	5.697 ms	3.669 ms
standard average	4.336 ms	0.542 ms	3.675 ms	2.567 ms
3σ	13.009 ms	1.628 ms	11.025 ms	7.701 ms
median	0.199 ms	0.105 ms	6.000 ms	3.348 ms

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2.2 SENSOR MODELS

After the synchronization step the sensor data will be acquired to detect objects. The sensory detection of objects contains measurement errors. Depending on the environment and the quality of the sensor the errors can have a vital impact on later data analysis. Therefore, the knowledge about the sensor behavior in an application is essential and constitutes one of the founding pillars of this publication. If the measurement behavior of a sensor is well known, the recent measurement can be evaluated by using predictive algorithms and can possibly be corrected. Measurement errors can be taken into consideration in the following process, for example during classification, likewise in the applied method. Probabilistic based sensor models are the basis of many research works particularly in the field of predictive algorithms, navigation, localization as well as mapping. For example, by use of sensor models the function principle of a range finder sensor with a part of its stochastic error can be modeled. Due to missing apriori knowledge certain errors cannot be modeled by use of sensor models. The so called beam model which is particularly suited for range finder sensors (e.g. laser scanners) is used as basis for this work. For each beam a model is built up incorporating

- uniform distributed random measurements,
- maximal sensor range measurement,
- unexpected obstacles,
- measurement noise around the mean

and all models are merged to a combination model [TBF05].

As part of this research work a beam model of the SICK S300 Professional CMS was developed and has been exemplary tested for objects, which surfaces have different remission characteristics.

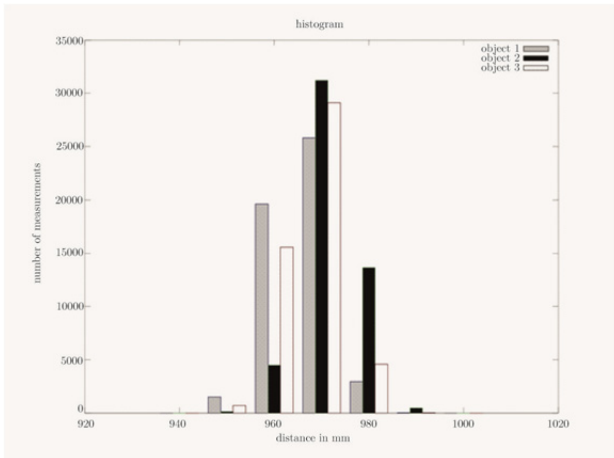

Figure 6. Histogram of distance measurements to different test objects with a distance of 1000 mm

The results of the experiment clearly show that the systematic errors, which depend on the remission characteristic of the examinee, cannot be mapped onto the SICK S300 Professional CMS without any prior knowledge because of the lack of knowledge about the detected object in an unknown environment. For this reason the systematic error has not been considered in the modeling. Not considering the systematic error is one of the weaknesses of

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probabilistic sensor models. After the analysis of the experiments the measurement noise around the mean was in the measurement with the smallest standard variation σ at 0.58 and was in the measurement with the largest standard variation σ at 0.63. The average noise of all experiments amounts to approx. σ = 0.61. According to the probabilistic model this value will be used in further experiments for the SICK S300 Professional CMS.

3 Computer Vision

In the penultimate step of cooperative vehicle detection the algorithmic basis of the recognition has to be created. With the help of a laser scanner a scene is recorded. Subsequently, information about the detected object is generated and evaluated out of the data resp. points. First of all the acquired point sets are transformed into a global coordinate system and then segmented. Afterward the extraction of the detected objects and the classification of these through the developed methods take place. During the next paragraphs the different processing steps will be explained in detail.

3.1 Segmentation and Line Extraction

Distance values of the laser scanner emerge from diffuse reflections of the laser spot at objects. Each point of the captured environment can be matched to an object.

The segmentation aims at the collection of single measuring points to segments so that the segments can be matched to an object [SFS03], [DSS01], [SCM05]. After the segmentation each segment corresponds ideally to one object [GCB10], [FD04]. The arranging into disjoint sets can be denoted as clustering [MBN04], [MN05] and is shown in figure 7. Subsequently, the line extraction according to the *Iterative End Point Fit* procedure which is illustrated in figure 8 is applied.

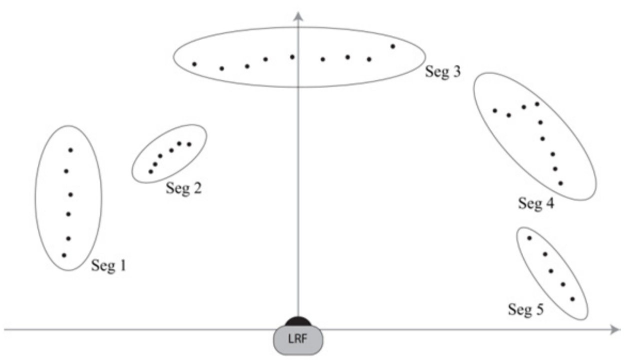

Figure 7. Clustering of a laser scanner point cloud

Figure 8. Iterative End Point Fit

3.2 Object Extraction

For a successful object extraction a list of candidates with segments, which are qualified based on their geometric properties for a later classification of cellular transport vehicles, has to be generated. Therefore the form of the segment and its alignment has to be extracted. This procedure has to be as time optimal as possible and shall include all of the possible candidates for a later classification.

From the point of view of a laser scanner the cellular transport system consists in rough approximation of blocks. Each block, which ideally consists of one segment or one pair of segments, has to be detected. Subsequently, the geometric properties of these segments have to be verified. In figure 9 possible pairs of segments which represent two unloaded vehicles and one rectangular object are exemplarily visualized. It has to be mentioned that the orientation of the vehicle cannot always be distinguished by one scan because of the similar shape of the front side and back side of the vehicle. In the next step the extracted objects have to be classified.

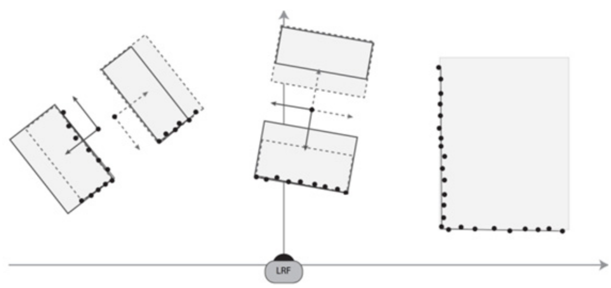

Figure 9. Recognition of geometrical forms; possible vehicle positions are highlighted gray

3.3 Classification

Within the developed classifier a disposition into two classes takes place:

- The class *vehicle* contains all possible extracted objects which may represent a vehicle.
- The class *no vehicle* contains all extracted objects which may for sure represent no vehicle.

Figure 10 shows three different kinds of classification. The ideal classification is visualized in figure 10a. This classification cannot be realized because of measurement noise and the lack of knowledge about the vehicle orientation. In figure 10b an incomplete classification

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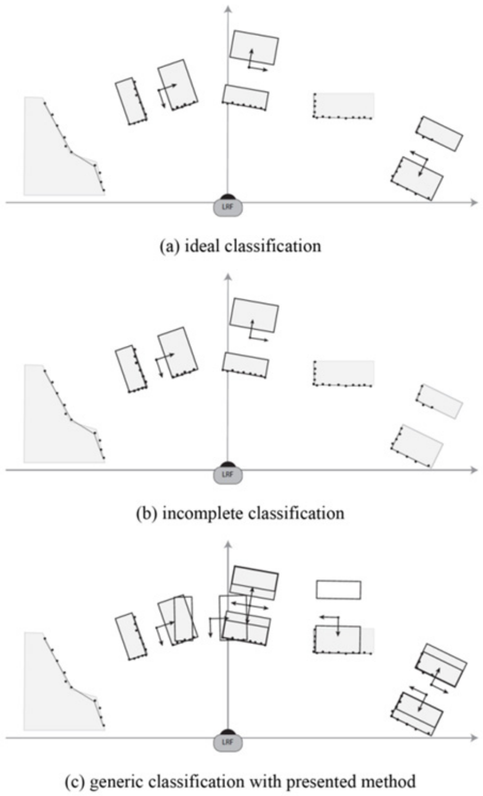
is shown. This classification would not classify the right vehicle in figure 10b correctly. Therefore, the vehicle will no longer be used in further processing steps. Figure 10c visualizes the result of the classification method which has been implemented in this work. It consists of all possible vehicle candidates and this means that the ideal vehicle candidates and the false vehicle candidates are included. The advantage of this method is that in further processing steps all vehicle candidates are considered.



(a) ideal classification

(b) incomplete classification

(c) generic classification with presented method

Figure 10. Classification

3.4 Vehicle Detection

From the vehicle candidates, who are produced during the classification, the real vehicles as well as their exact pose have to be calculated. This chapter has a focus on the set of candidates which shall be verified by the use of a probabilistic approach. Based on the developed sensor models in chapter 2.2, the acquired data in a synchronous network (s. chapter 2.1) and the methods of computer vision in chapter 2.3, a new method with an approach of an occupancy grid will be introduced. This method assigns identity features to the extracted set of candidates and scores them.

To modulate the environment which is captured by a sensor the so called occupancy grids can be used. Thereby the environment will be divided into uniform, often rectangular cells of the same size. Those cells contain information about the state of occupancy in the environment. Occupancy grids can be updated online and therefore allow an immediate integration of new measurement data. Additionally, occupancy grids provide the opportunity to integrate several spatially divided measurement data sets, for example from a synchronized heterogenic sensor data network. For example, sensors like laser scanners, radar sensors, PMD-cameras or a merged data set of these sensors can be used [BH08], [ME85], [ME88]. In the LivingLab the sensor data of other vehicles can be integrated in the occupancy grid of one vehicle. It has to be mentioned that the merging of data is only possible if the vehicles have a common time base which can be achieved through synchronization methods (s. chapter 2.1).

By the help of new measurement data the occupancy grid can be created. These measurement data generate occupancy probabilities for the grids. To integrate those probabilities at the right position into the existing occupancy grid the existing probabilities have to be merged with the new probabilities [CLH05]. Figure 11 shows the training process for detecting by the use of occupancy grids. If one can assume that the occupancy probabilities of the cells are independent of each other, those can independently be updated [Elf89].

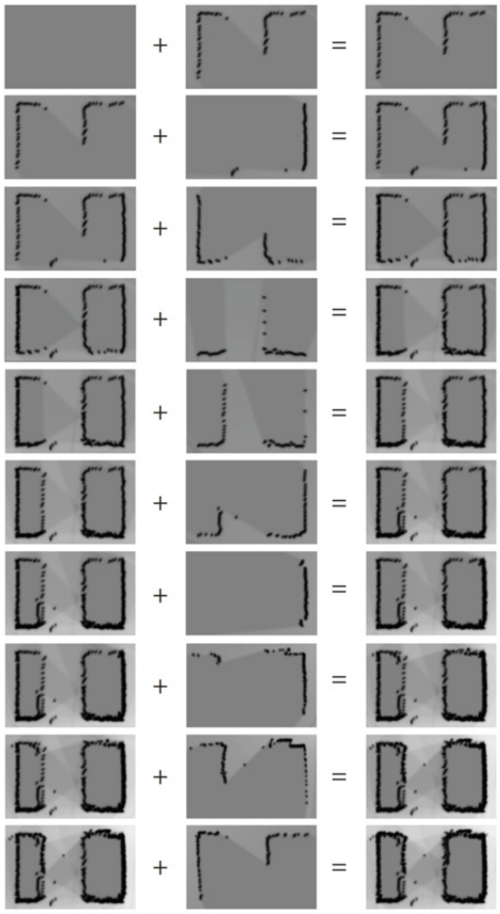


Figure 11. Vehicle detection training model

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4 EVALUATION

The goals of the empirical evaluation are the qualitative and quantitative valuation of the developed algorithms as well as to analyze the methods for real-time capability in application-related, logistical scenarios. Initially, the individual methods of the vehicle recognition are qualitatively and quantitatively evaluated in several test set-ups. Therefore, the data of the individual vehicles as well as the merged data set are taken as a basis. The reference scenario illustrates a circulation between storage rack and a picking station:

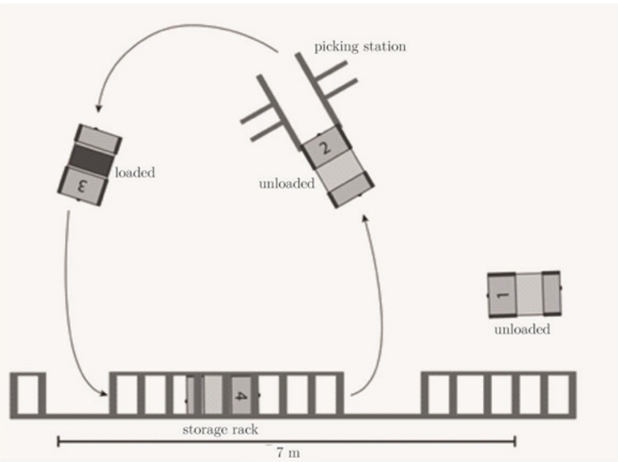

Figure 12. Logistical setup of the interconnected cellular transport vehicles

The recordings of the defined test set-ups are evaluated. Thereby, the quantitative as well as the qualitative appraisal of the detection take place on the basis of the classifier and the detection model. During the evaluation the poses of the vehicles are manually determined through consideration of the individual recordings and are compared to the results of the detection procedure. The following notation is used throughout the evaluation:

- *Correct candidate* is used for vehicle candidates if they correspond according to the manual verification to a real vehicle.
- *Incorrect candidate* is used if at the position of the vehicle candidate no vehicle is located.

The extraction of a candidate set out of a data set was described in chapter 2.3. The goal of the candidate extraction is to add as soon as possible all visible vehicles to the extracted candidate set. Due to the fact that candidates who do not correspond to a real vehicle are filtered out in the following steps, the extraction of incorrect candidates plays a minor role as long as the number of those incorrect candidates is limited. Therefore the detection rate shown in figure 13 is examined in the context of the quantitative appraisal. The extracted candidates were individually, manually examined and evaluated.

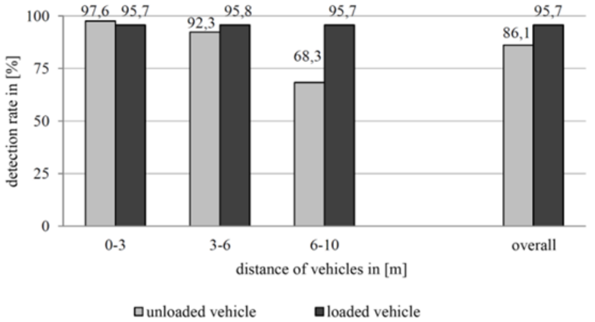

Figure 13. Diagram of the detection rate of extracted vehicle candidates with different loading

Based on the scenarios the average detection rate in figure 14 was examined. As appraisal benchmark the average identity criteria of loaded and unloaded vehicles in different distances was compared. This means that the average identity criteria *correct candidate* was calculated in all scenarios.

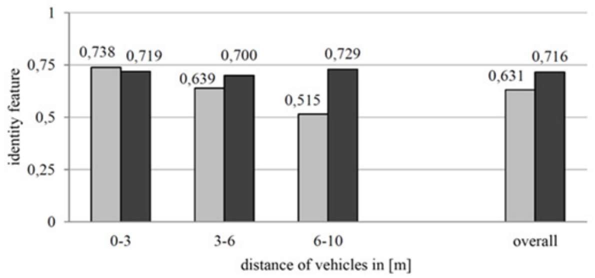

Figure 14. Average identity feature of correct vehicle candidates

5 DISCUSSION AND OUTLOOK

With these developed methods a contribution to the enhancement of the cognitive abilities of cellular transport vehicles was achieved. By the help of a synchronized network, sensor data can be evaluated decentralized or centralized and they can be processed without a fallback onto proprietary solutions with additional hardware. In chapter 2.1 the proof was given that through standard WLAN components a high precision time synchronization of the individual transport identities with standard protocols and an intelligent parameterization and filtering can be conducted. Developing novel sensor models in chapter 2.2 which are based on a probabilistic approach provides a basis for further evaluations with pattern processing procedures which were developed in chapter 2.3. Those methods in cooperation with the new vehicle detection method can be used in real-time in cellular transport vehicles with low computational power. The evaluation of the detection methods and performance which occurred in chapter 4 emphasizes the adaptability of the developed processes because the system could be integrated into the LivingLab cellular transport systems at the Fraunhofer

IML and the capability for real-time tasks could be proved.

The detection procedure which has been developed as a part of this work is currently extended to different tracking procedures and one resultant collision avoidance method. This one enables sustainable collision avoidance in the vehicle swarm with heterogenic sensors through dynamic, topographic environment models which are provided to all transport identities.

Distinct trends show that novel 3D-sensors will be largely deployed in cellular intralogistics and in the field of automated guided vehicles so that bounding volume of a vehicle and not only the area can be considered. Therefor one can better react to exterior influences. Furthermore, by the use of methods which has been developed in this work novel and inexpensive 3D-sensors, e.g. the Microsoft Kinect, can be used in the future. Currently, at the Fraunhofer IML research work to detect environment features, transport vehicles and persons by the use of 3D-sensors as well as native gesture controls take place. These sensors can be arbitrarily distributed to transport identities in a synchronized sensor data network. In the field of small-scaled autonomous transport systems a basis for a distribute collision avoidance system can be provided. This leads to considerable saving of system costs because just a fraction of the nowadays used sensors is necessary. Besides, a synchronized network for knowledge management of multi-agents-systems for time critical tasks can be utilized so that the partly existing disadvantages in the field of reactivity of multi-agents-systems can be compensated through deterministic information flow.

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