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Global Localization and Position Tracking of an Automated Guided Vehicle ⋆

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Abstract: A swarm of Automated Guided Vehicles (AGVs) can be used in warehouses, distribution centers and manufacturing plants in order to automate the internal material flow. This swarm can overcome the disadvantages of roll conveyors and belts. The main problems of AGVs are global localization, position tracking, path planning and communication (especially within the swarm). Another technique which provides potential for logistic applications are Wireless Sensor Networks (WSNs). They can be used in warehouses to realize a decentralized stock database, monitoring a cold chain as well as for localization of an AGV and communication within the swarm. The paper presents a technique for global localization and position tracking of an omnidirectional AGV equipped with Mecanum wheels, which was designed to transport Euro-bins in a distribution center or warehouse. Global localization is realized through a technique based on range measurements obtained from an IEEE 802.15.4a WSN. The WSN is also used for communication within the swarm as well as for communication with the central warehouse computer. A developed sensor fusion of two safety laser range finders with the range measurements of a WSN solve the position tracking task. Laser range finders are used to detect pairs of landmarks to provide accurate positioning for docking maneuvers. The paper also presents a sensor model for IEEE 802.15.4a range measurements and experimental results. The latter show that the global localization technique guarantees accurate positioning and that the sensor fusion can be used for docking applications.

Keywords: Automated guided vehicles, Flexible manufacturing systems, Positioning systems, Sensor fusion, Warehouse automation

1. INTRODUCTION

Just-in-time inventory management and short production cycles require flexible material flow as well as usage of small transportation units (Furmans et al., 2008). These demands can be met by using small AGVs which act as a swarm of mobile robots. Several companies have introduced small AGVs for logistic applications. Examples are "The Kiva Mobile Fulfillment System (MFS)" (Kiva Systems, 2010) and "ADAM^{TM} (Autonomous Delivery and Manipulation)" (RMT Robotics Ltd., 2010). Inexpensive localization of small AGVs is an important issue for many logistic applications and object of current research activities. The Kiva MFS uses bar codes on the floor which can be detected with a camera by the AGVs (Guizzo, 2008). These bar codes specify the pathways and guarantee accurate localization. Drawbacks of this solution are the risk of polluting the bar codes and the need for predefined pathways which restrict the movements of the AGVs. Another approach in saving costs for localization is the usage of one technology for more than one function. The paper proposes the usage of an IEEE 802.15.4a WSN for communication as well as for global localization and laser range finders for safety as well as for detecting landmarks and local localization. A WSN consists of spatially distributed autonomous sensor nodes for data acquisition. Besides military applications and monitoring physical or environmental conditions, WSN can also be used for localization. To localize a mobile node, called *tag*, there have to be a couple of nodes with fixed and known positions. These nodes are called *anchors*. WSNs have the advantages that they can be used in a wide field of applications and that they are inexpensive and flexible. An overview of applications for WSNs in logistics is given by Evers et al. (2005). Disadvantage of using a WSN for localizing an AGV is the relative low accuracy which is insufficient for docking maneuvers.

Fig. 1 shows the AGV which was designed and built by the Intelligent Mobile Systems Lab of the University of Applied Sciences and Arts in Dortmund. It can transport bins with Euro footprint (600x400 mm) in manufacturing plants, distribution centers or warehouses. The robot is equipped with four Mecanum wheels in order to provide omnidirectional motion. This makes the robot applicable in environments with narrow passages and corners. The robot is equipped with two laser range finders (SICK S300 Professional) which provide operational safety. This paper extends the work presented by Röhrig and Spieker (2008), Röhrig and Müller (2009) and Kirsch and Röhrig (2010) in several ways. A Monte Carlo Particle Filter (MCP) is used

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Fig. 1. Omnidirectional transport robot

instead of an Extended Kalman Filter (EKF) in order to deal with non Gaussian motion and sensor models and to solve the global localization task. Furthermore laser range finders are used to detect pairs of landmarks to provide the accuracy which is necessary for docking maneuvers. To localize the AGV, the distances and angles to landmarks are fused with the range measurements of the nanoLOC WSN. Both measurements are used by a MCP together with dead reckoning information obtained from wheel encoders.

The paper is organized as follows: Sec. 2 presents related work about global localization and WSN techniques. An introduction to the sensor fusion using MCP and the global positioning technique is presented in Sec. 3. A probabilistic model of measurement errors in ranging obtained from IEEE 802.15.4a is developed in Sec. 3.1. Experimental results of global localization are presented in Section 4. Finally, the conclusions are given in Section 5.

2. RELATED WORK

Global localization is a necessary process for every mobile robot, especially for AGVs in warehouses or distribution plants. Global localization is the process of determining the position without any a priori position information. Up to now there exist a few techniques and products which use laser range measurements and landmarks to solve the global localization problem. The company Götting KG and SICK AG produce such *laser navigation systems*. The laser navigation system "HG43600ZA" (Götting, 2005) by Götting uses artificial distinguishable landmarks and an algorithm to compute the position. The product "NAV200" (SICK, 2004) by SICK, uses artificial landmarks which are distinguishable through the distance between themselves. Both laser navigation systems guarantee a very accurate positioning but have the disadvantage that further laser range finders are needed to provide operational safety. Another possibility to solve the global localization problem is to use undistinguishable landmarks and to solve the *data association problem*. To localize a robot without any a priori position information the robot has to estimate which landmarks it has detected. Bailey et al. (2000) used a graph representation and a *maximum clique* search-algorithm to solve the data association problem.
Another sensor type which can be used for localization and especially global localization are wireless networks. A review of existing techniques is given by Vossiek et al. (2003).
These techniques can be classified by the information they use. These information are: Received Signal Strength (RSS), Angle of Arrival (AoA), Time of Arrival (ToA), Round-trip Time of Flight (RToF) and Time Difference of Arrival (TDoA). All of these techniques can be used for global localization but the best accuracy with a relative low effort offer range-based techniques. The range-based methods use distances to known anchors to localize a tag. To estimate the position of a mobile device with trilateration, the distances to at least three anchors have to be measured. Ultra Wide Band (UWB) offers a high potential for range measurement using ToA, because the large bandwidth ($> 500\,\mathrm{MHz}$) provides a high ranging accuracy (Gezici et al., 2005). Fernández-Madrigal et al. (2007) used UWB range measurements for tracking a vehicle in a warehouse. IEEE 802.15.4a specifies two optional signaling formats based on UWB and Chirp Spread Spectrum (CSS) with a precision ranging capability. Nanotron Technologies distributes a WSN with ranging capabilities using CSS as signaling format. A modification of RToF utilize the nanoLOC WSN from Nanotron Technologies. The features and modifications of the nanoLOC WSN are described in (Nanotron, 2007). For the experiments in this work a nanoLOC network is used.
In order to increase the accuracy of wireless localization techniques, sensor fusion with complementary sensors can be used. Park and Song (2008) proposed a sensor fusion of RSSI obtained from a WSN with computer vision. Sensor fusion of RSSI obtained from a Wireless LAN and laser range finders is presented by Lam et al. (2008). In that paper the authors propose a hierarchical method which uses the Ekahau location engine for room level localization in the first step and a laser range finder for local localization in the second step.

3. MONTE CARLO PARTICLEFILTER

The usage of raw distance measurements of a WSN has two crucially drawbacks: Firstly, because of noisy distance measurements there is always a position uncertainty, even if the tag is not moving. The noisy distance measurements result from None-line-of-sight (NLOS) measurements and multipath fading. Secondly the orientation of the tag can not be estimated. The last disadvantage can be relaxed for position tracking by combining the distance measurements of the WSN with odometry data. Through this combination the position and orientation – called *pose* – of the AGV can be estimated. However, the estimated pose can be erroneous because both information are noisy. To estimate the AGV pose accurately by using noisy measurements, methods based on the Bayesian filter are used. The Bayesian filter estimates the pose by using probability density functions which model the measurement uncertainty. An introduction into the Bayesian filter is given by Fox et al. (2003). One method which is based on the Bayesian filter is the Kalman Filter (KF). The KF has approved itself in mobile robots for position tracking. In (Röhrig and Spieker, 2008) the Extended Kalman Filter (EKF) is used to track the position of a forklift truck. The EKF is an extension of the KF for non-linear systems. The EKF by Röhrig and Spieker (2008) is enhanced by Röhrig and Müller (2009) to use distance measurements in NLOS

environments. In both papers the distance measurements from a tag to anchors of a nanoLOC WSN are used. The KF and EKF rely on the assumption, that motion and sensor errors are Gaussian and that the estimated position can be modeled by using a Gaussian distribution. Because of this fact, KF and EKF can not handle position ambiguities.

Another method which is based on the Bayesian filter is a Particle Filter (PF). A PF can handle position ambiguities and does not rely on the assumption that motion and sensor errors are Gaussian. Also PF can cope with multimodal distributions. In a PF, a set S of N samples is distributed in the environment or at known places. A sample s is defined by cartesian coordinates and an orientation. A widely used PF for mobile robot localization is the MCP, which is described by Dellaert et al. (1999), Fox et al. (1999) and Thrun et al. (2000). The estimated pose of a mobile robot and its uncertainty about the correctness is represented by the samples. MCP consists of two phases: The *prediction* phase and the *update* phase. Inside the prediction phase the motion information u_t are applied on each sample s^i_{t-1} $(1 \leq i \leq N)$. The prediction phase is also called *motion model*. The result of the motion model is a new set of samples $\overline{S}_t$ which represents the positions, where the mobile robot could be after executing the movement u_t.
Inside the update phase, the set of distance measurements D_t is used to assign each sample with an importance factor w. The importance factor complies the probability $p(D_t \mid s^i_t, m)$, i.e. the probability of the distance measurements D_t at a point in the environment defined by sample s^i_t and by using the information from the map m. In m the positions of anchors and landmarks are stored. The result of the update phase – also called *measurement update* – is the set of samples $\overline{S}_t$ of the prediction phase with the corresponding set of N importance weights w_t. Both sets together represent the current position likelihood of the mobile robot. After the update phase, the resampling step follows. Inside the resampling step, samples with a low importance weight are removed and samples with a high importance factor are duplicated. The result of the resampling is the set S_t of N samples which represents the current position of the mobile robot. In the next time step, the set S_t is used as S_{t-1}. There are two possibilities to extract the pose of the mobile robot out of the sample set S_t: The first method is to use the weighted mean of all samples and the second method is to use the sample with the highest importance factor. MCPs flow chart is drafted in Fig. 2. The MCP has the advantages that it copes with global localization (no a priori information) and position tracking (given a priori information). The sensor fusion with some dependencies and special cases can be implemented easily. Generally the combination of sensor specific advantages and the compensation of sensor specific disadvantages is called sensor fusion.

In this paper the MCP uses distance measurements from the nanoLOC WSN for global localization. The global localization task, which has to be done before the MCP starts, is shown as a red block in Fig. 2. The probability density function of the nanoLOC measurement error which

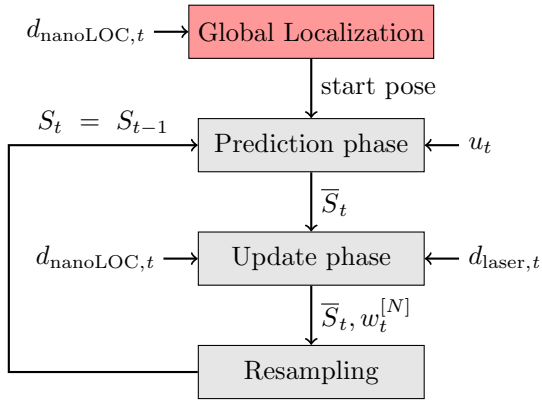

Fig. 2. MCP flow chart.

is used to compute the importance factor, is presented in the next section.

3.1 Nanoloc Measurement Model

In the update phase, the measurement model is used to calculate the importance factor w for each sample s. The measurement model is the probability density function $p(d_{\text{nanoLOC},k} \mid s^i_k, m)$ which characterizes the measurement properties and error. The measurement set $d_{\text{nanoLOC},k}$ contains distance measurements to A anchors. The density function depends on sensors and environment. To estimate the density function for nanoLOC distance measurements, LOS-measurements to four anchors are taken while a mobile robot moves a straight path between them. While the robot moves, an accurate position was estimated by laser measurements to two walls. In Fig. 3, error histograms of measurements to four anchors are shown. The error is the difference between measured distance d^a_k and the Euclidean distance from robot position to anchor a.

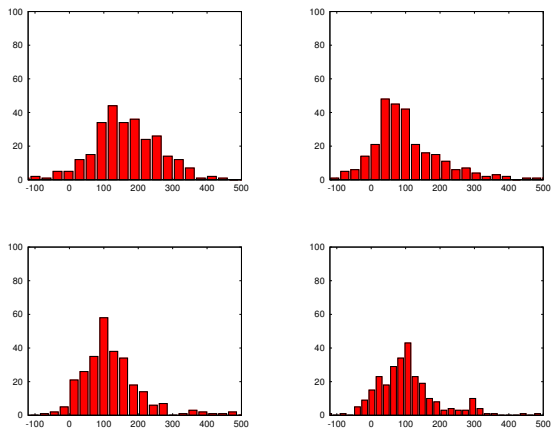

Fig. 3. Error histograms of nanoLOC distance measurements to four anchors. The x-axis is the error in centimeter and the y-axis show their frequency.

The histograms show, that all measured distances are too large, the average error is 107 cm. The error depends on the position of the anchor and on the environment. The median and standard deviation of the error distributions are different but they all have a Gaussian structure. Owing

to that fact, it is possible, to use a Gaussian distribution as nanoLOC probability density function:

$$\mathcal{N}\left(x,\mu,\sigma^2\right) = \frac{1}{\sqrt{2\pi}\sigma^2}\exp\left(\frac{-1}{2}\frac{(x-\mu)^2}{\sigma^2}\right) \quad (1)$$

To calculate the importance weight of sample s_k^i, the Euclidean distance $d_k^{a,i*}$ between this sample and the anchor a is calculated as

$$d_k^{a,i*} = \sqrt{(x_i - x_a)^2 + (y_i - y_a)^2}, \quad (2)$$

where (x_a, y_a) is the position of Anchor a and (x_i, y_i) are the Cartesian coordinates of sample s_k^i. The Euclidean distance and the measured distance d_k^a are used with an anchor specific constant d_c^a in a fixed Gaussian distribution:

$$p\left(d^a_{\text{nanoLOC},k} \mid s_k^i, m\right) = \mathcal{N}\left(d^{a,i*} - (d_k^a - d_c^a), 0, \sigma^2\right) \quad (3)$$

where d_c^a is the median of the distance errors shown in the histograms. The advantages of this fixed Gaussian distribution are, that a normalization during the localization, to guarantee $\sum p = 1$, is not needed and that the domain can be restricted. This last advantage can be used to detect estimation failure. If a lot of samples are out of range, new samples can be drawn in the environment. This fact enables the MCP to re-localize the mobile robot.

The importance factor of a sample i is calculated with:

$$w_k^i = \prod_{a=1}^{A} p\left(d^a_{\text{nanoLOC},k} \mid s_k^i\right) \cdot \prod_{l=1}^{2} p\left(d^l_{\text{laser},k} \mid s_k^i\right) \quad (4)$$

The importance factor w is the product of the probability of measurements to A anchors and to two landmarks. The probability $p(d^l_{\text{laser},k} \mid s_k^i, m)$ is a fixed Gaussian with σ = 28 mm. The landmarks are equipped with reflectors, in order to allow easy detection by the laser range finders. If no landmarks are detected, the importance factor is equal to the probability of the distance measurements to A anchors.
The next section presents the global localization approach which uses distance measurements of the nanoLOC WSN.

3.2 Anchorbox

For global localization range measurements of the nanoLOC WSN are used to reduce the area in which particles are distributed. This method is based on a technique which was presented by Baggio and Langendeon (2006). Fig. 4 shows an example of an Anchorbox which is computed by using range measurements to four anchors. The red dot is a robot which is equipped with a node.
In the first step of the MCP the particles are distributed in the area defined through calculation specifications 5 and 6, where (x_i, y_i) is the position of anchor i and $\overline{d}_i$ is the average of I range measurements.

$$x_{\min} = \max_{i=1}^{I}\left(x_i - \overline{d}_i\right) \qquad x_{\max} = \min_{i=1}^{I}\left(x_i + \overline{d}_i\right) \quad (5)$$

$$y_{\min} = \max_{i=1}^{I}\left(y_i - \overline{d}_i\right) \qquad y_{\max} = \min_{i=1}^{I}\left(y_i + \overline{d}_i\right) \quad (6)$$

One disadvantage of the Anchorbox approach is that the orientation can not be estimated by nanoLOC range measurements. To overcome this disadvantage more particles with an random orientation are distributed at the beginning of the algorithm. After the particles are distributed

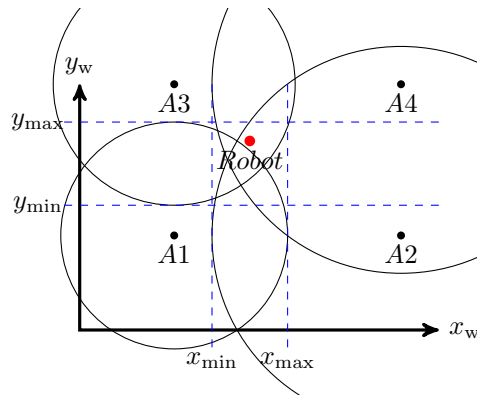

Fig. 4. Anchorbox example by using range measurements to four anchor nodes with known positions.

the robot drives 1 m in positive x robot direction. Because of this technique, the adapted MCP is an active localization technique. Thereby, particles with an incorrect orientation remove themselves from the correct position and are getting a lower importance factor during the first measurement update. Another possibility to overcome this disadvantage is to compute the position through trilateration during the robot drives the path. The orientation can be estimated by computing the average orientation between these trilateration points. This approach is not used because these points vary significantly and the estimated orientation will be erroneous.

The advantage of the developed technique is a smaller particle cloud at the beginning of the algorithm. Because of this, the first position can be estimated faster. Another advantage is that this technique can also be used to solve the *kidnapped-robot problem*. To solve this problem, the Anchorbox can be computed in every MCP cycle. Inside this computed Anchorbox a sample subset can be distributed to represent a much larger area where the robot can be. The advantage of this approach is, that it does not rely on the odometry data, which is necessary to solve the kidnapped robot problem.
The process of global localization is shown in the next section through experimental results with an robot equipped with Mecanum wheels.

4. EXPERIMENTAL RESULTS

To evaluate the proposed MCP localization, some experiments are conducted at the University of Applied Sciences and Arts in Dortmund. The AGV is equipped with two SICK S300 Professional laser range finders with a scanning angle of 270°. With both laser range finders, the robot gets a full 360° scan of the environment. The laser range finders provide a resolution $\Delta\alpha$ of 0.5°. A docking station for handing over bins serves as landmark. Two pillars of the docking station are equipped with reflectors, in order to allow easy detection by the laser range finders. The AGV is also equipped with a nanoLOC tag for ranging and communication purposes. At the margins of the environments six nanoLOC anchors are placed. The figures 5(a) – (b) show the first steps of the global localization and the estimated positions with a comparison to the driven path and the odometry data (dimensions in millimeter).
The AGV is moved in manual mode from a starting point

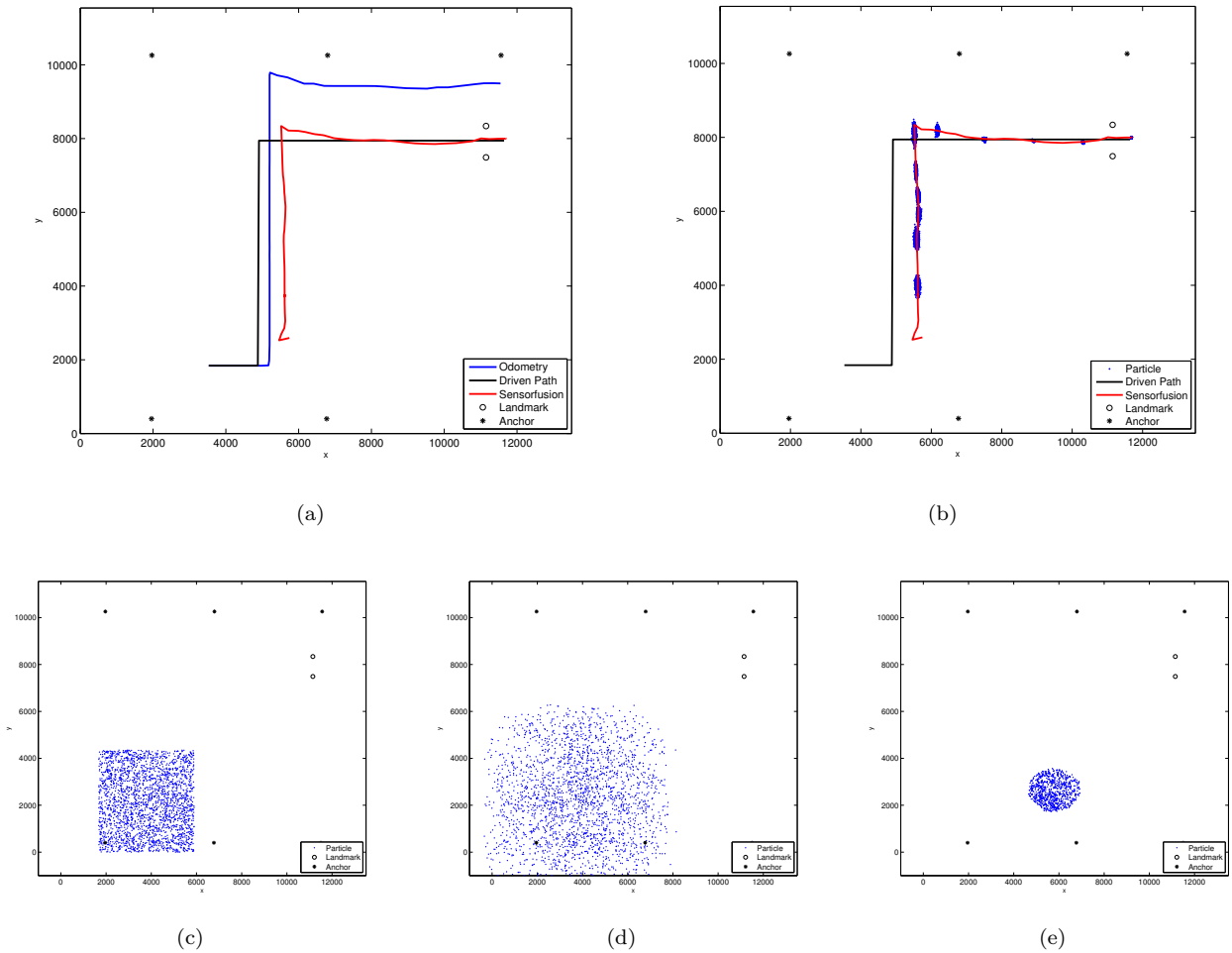

Fig. 5. Experimental results: (a) and (b) show results of global localization. (c) - (e) show the process of global localization with the Anchorbox approach.

into the docking station which is shown by the black path in Fig. 5(a) and (b). The AGV is moved forwards first, then sidewards and finally forwards into the docking station in the upper right corner, always with the same orientation $\theta = 0°$. During the movement of the robot, all necessary sensor data for MCP are stored. These values are odometry data, distance measurements to six nanoLOC anchors and the laser range data. The first movement should simulate the first step of global localization if the AGV acts in automatic mode with no a priori position information. The second and third movement represent the estimated path into the docking station, which guarantees a precise localization.

To perform the global localization first of all the Anchorbox is computed by using distance measurements to six anchors. Then 10000 samples with random orientation are distributed inside the Anchorbox. Fig. 5(c) shows the Anchorbox with the distributed sample set. The sample set after the first movement part is shown in Fig. 5(d). It can be seen, that samples with an incorrect orientation have moved away from the real position. Subsequently the first importance factor is computed by using range measurements of the WSN. The resulting sample cloud of the resampling step is shown in Fig. 5(e). The start pose is set to the weighted mean of the sample cloud.

After estimating the start position the MCP segue from global positioning into position tracking and the sample set is reduced to 2000 samples. The estimated start position depends on the nanoLOC measurements and on the set of samples with random orientation.

The resulting path of the global localization and position tracking is shown in Fig. 5(a) and (b). Owing to an unequal floor contact, the robot has a large slippage when it moves sideways. Fig. 5(a) shows odometry in blue and MCP estimation using all sensor data in red. The sample clouds resulting from position tracking (after the global localization) are presented in Fig. 5(b). Until the robot detects the landmark pair, the importance factors were computed by using the range measurements of the WSN. This results in bigger sample clouds and a higher position uncertainty, which can be seen in Fig. 5(b). During the last movement the robot detects the landmark pair with the two laser range finders. Because of this, the resulting sample clouds are compressed and the uncertainty of the estimated position is reduced. The position estimated by using nanoLOC measurements is good enough for planning the path and through using the sensor fusion a successful docking maneuver can be guaranteed.

5. CONCLUSION AND FURTHER WORK

In this paper global localization and position tracking of an omnidirectional AGV which was designed to transport Euro-bins in a distribution center or warehouse is presented. Localization is realized by sensor fusion of range measurements obtained from an IEEE 802.15.4a WSN and two laser range finders. The range measurements are fused in a MCP. The IEEE 802.15.4a network is used for communication as well as for global localization. The two laser range finders are used for safety and can measure distance and bearing to landmarks equipped with reflector tape. The paper presented an approach for global localization, a sensor model for IEEE 802.15.4a range measurements and experimental results. The latter show, that the MCP with the Anchorbox approach is able to estimate the position of an AGV without any a priori position information. The laser range data improves the position accuracy, especially the robots orientation, and allows docking maneuvers.

The next steps will be experiments with an accurate positioning system to estimate the position uncertainty of the MCP at global localization. Thereby we can compute the position uncertainty in every MCP cycle and we can compare results from different sensor models and parameters. Results in (Kirsch and Röhrig, 2010) show the position uncertainty at position tracking with a related MCP.
Another step will be a comparison of map-based localization techniques with the presented MCP and an improvement of the global localization. The improvement will be based on a combination of the presented Anchorbox and a new landmark-matching algorithm for global localization.

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