# Localization of Autonomous Mobile Robots in a Cellular Transport System

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***Abstract*—The paper presents global localization for a swarm of autonomous mobile robots which transport Euro-bins in a distribution center or warehouse. Localization is realized by sensor fusion of range measurements obtained from an IEEE 802.15.4a network and laser range finders. The IEEE 802.15.4a network is used for communication as well as for global localization. Laser range finders are used to detect landmarks and to provide accurate positioning for docking maneuvers. Range measurements are fused in a Monte Carlo Particle Filter. The paper presents the design of the network including the communication protocol together with the design of the localization algorithm. In order to support a large number of robots, the whole working area is divided into cells which use different frequencies. The network protocol provides handover between the cells and routing capabilities in real-time. Experimental results are given to prove the effectiveness of the proposed methods.**

***Index Terms*—Localization, IEEE 802.15.4a CSS, Autonomous Transport Vehicle, Swarm Intelligence**

## I. Introduction

SHORT production cycles and just-in-time inventory management require flexible material flow as well as usage of small transportation units. These demands can be met by using small autonomous mobile robots which act as a swarm. Several companies have introduced small mobile robots for logistic applications. Examples are "The Kiva Mobile Fulfillment System (MFS)" [1], the "Self-Driving Courier" from Adept Technology [2], "RoboCourier™" from swisslog and "ADAM™ (Autonomous Delivery and Manipulation)" [3]. Inexpensive localization of mobile robots is an important issue for many logistic applications and object of current research activities. The Kiva MFS uses bar codes on the floor that can be detected with a camera by the robots [4]. 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 robots. The "Self-Driving Courier", RoboCourier™ and ADAM™ are based on the same technology, which was developed by MobileRobots in Amherst USA. These mobile robots use open path navigation with laser range finders to travel to their destination. Laser range finders can be used to track the position of an autonomous vehicle within a known environment using a predefined map, if the initial position is given, but it is difficult to find the initial position in a complex or dynamically changing environment without apriori information.

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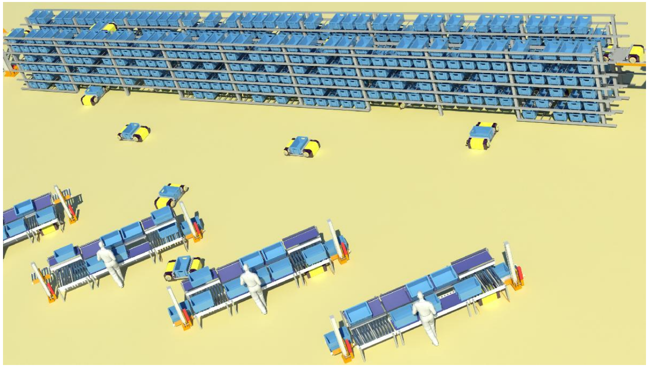

Fig. 1. Swarm of mobile robots in a distribution center © Fraunhofer IML

The paper proposes an open path navigation, which is based on sensor fusion of range measurements using an IEEE 802.15.4a wireless network, measurements of laser range finders and dead-reckoning (odometry). The IEEE 802.15.4a wireless network is used for communication and global localization (without apriori information), the laser range finders and odometry are used for position tracking and improved local accuracy.

Fig. 1 shows the target application of the proposed communication and localization system. In this distribution center, mobile robots transport bins with Euro footprint (600x400 mm) from a high bay racking to order picking stations and back to the racking. Order pickers collect the orders from Euro-bins and pack them into custom bins. This so called *Cellular Transport System* is based on the Multishuttle Move (MSM) technology [5]. MSM is a fusion of a conventional rack shuttle and a mobile robot developed by Fraunhofer-Institute for Material Flow and Logistics (FhG IML). The vehicles are rail-guided while they are located in the racking system or the lift. The vehicles are able to leave the rail-system and to operate as mobile robots with open path navigation. This scalable and flexible vehicle swarm concept is a compact, adaptable solution for high storage capacity and covers the entire performance spectrum of facility logistics with the maximum possible flexibility [5]. Since the robots navigate autonomously and act as a swarm, real-time communication and global localization is needed.

The paper proposes the usage of an IEEE 802.15.4a Wireless Sensor Network (WSN) for communication as well as for global localization. A WSN consists of spatially distributed autonomous sensor nodes for data acquisition. A new communication protocol for WSN is developed which is based on IEEE 802.15.4a and provides global localization, communication and routing in real-time. Since the data size in an IEEE 802.15.4 frame is limited to 127 Bytes, low overhead of the protocol is one key requirement. Instead of using the superframe structure of IEEE 802.15.4, a new superframe

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structure is developed, because IEEE 802.15.4 supports only superframes with 16 equally sized time slots. Furthermore the paper describes location tracking of mobile robots using an Extended Kalman Filter and global localization using a Monte Carlo Particle Filter. Experimental results are given to prove the effectiveness of the proposed methods. This paper extends the work presented in [6] to global localization using a Monte Carlo Particle Filter.

## II. Related Work

Up to now several kinds of localization techniques have been developed for the use in wireless networks. A review of existing techniques is given in [7]. These techniques can be classified by: Connectivity, Received Signal Strength (RSS), Angle of Arrival (AoA), Time of Arrival (ToA) and Round-trip Time of Flight (RToF).

Connectivity information is available in all kinds of wireless networks. The accuracy of localization depends on the range of the used technology and the density of the beacons. In cellular networks Cell-ID is a simple localization method based on cell sector information. In a WSN with short radio range, connectivity information can be used to estimate the position of a sensor node without range measurement [8].

RSS information can be used in most wireless technologies, since mobile devices are able to monitor the RSS as part of their standard operation. The distance between sender and receiver can be obtained with the Log Distance Path Loss Model described in [9]. Unfortunately, the propagation model is sensitive to disturbances such as reflection, diffraction and multi-path effects. The signal propagation depends on building dimensions, obstructions, partitioning materials and surrounding moving objects. Own measurements show, that these disturbances make the use of a propagation model for accurate localization in an indoor environment almost impossible [10]. A method to overcome this disadvantage is fingerprinting which is introduced in [11] and uses a radio map. Fingerprinting is divided in two phases: In the initial calibration phase, the radio map is built by moving around and storing RSS values at various predefined points of the environment. In the localization phase, the mobile device moves in the same environment and the position is estimated by comparing the current RSS values with the radio map. Other approaches use a Bayesian algorithm [12] or Delaunay triangulation with lines of constant signal strength [13]. The main disadvantage of radio map based methods is the high manual effort to build the map in the calibration phase. The use of Delaunay triangulation and interpolation allows a radio map with a low density of calibration points and reduces the time for manual generation of the map [10]. However, the accuracy of RSS based methods is insufficient for the target application.

AoA determines the position with the angle of arrival from fixed anchor nodes using triangulation. In [14] a method is proposed, where a sensor node localizes itself by measuring the angle to three or more beacon signals. Each signal consists of a continuous narrow directional beam, that rotates with a constant angular speed. Drawback of AoA based methods is the need for a special and expensive antenna configuration e.g. antenna arrays or rotating beam antennas.

ToA and RToF estimate the range to a sender by measuring the signal propagation delay. The Cricket localization system [15] developed at MIT utilizes a radio signal and an ultrasound signal for position estimation based on trilateration. TDoA of these two signals are measured in order to estimate the distance between two nodes. This technique can be used to estimate the position of a node in a WSN [16] or to track the position of a mobile robot [17]. Ultra-Wideband (UWB) offers a high potential for range measurement using ToA, because the large bandwidth (> 500 MHz) provides a high ranging accuracy [18]. In [19] UWB range measurements are proposed for tracking a vehicle in a warehouse. The new WSN standard IEEE 802.15.4a specifies two optional signaling formats based on UWB and Chirp Spread Spectrum (CSS) with a precision ranging capability [20], [21]. Nanotron Technologies distributes the nanoLOC TRX Transceiver with ranging capabilities using CSS as signaling format.

Compared to the large number of published research focused on localization, there is less research on protocols combining localization and communication. In [22] a MAC protocol with positioning support is described. This work is mainly focused on energy efficient medium-access. A MAC protocol combining localization and communication based on IEEE 802.15.4a is described in [23] and [24]. The protocol is contention-based and did not support real-time localization. WirelessHART is based on IEEE 802.15.4 and offers real-time communication using TDMA, but it did not support ranging [25], [26].

In order to increase the accuracy of wireless localization techniques, sensor fusion with complementary sensors can be used. In [27] a sensor fusion of RSSI obtained from a WSN with computer vision is proposed. Sensor fusion of RSSI obtained from a Wireless LAN and laser range finders is presented by [28]. 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.

## III. The nanoLOC Localization System

Nanotron Technologies has developed a wireless technology which can work as a Real-Time Location System (RTLS). The distance between two wireless nodes is determined by Symmetrical Double-Sided Two Way Ranging (SDS-TWR). SDS-TWR allows a distance measurement by means of the signal propagation delay as described in [29]. It estimates the distance between two nodes by measuring the RToF symmetrically from both sides.

The wireless communication as well as the ranging methodology SDS-TWR are integrated in a single chip, the nanoLOC TRX Transceiver [30]. The transceiver operates in the ISM band of 2.4 GHz and supports location-aware applications including Location Based Services (LBS) and asset tracking applications. The wireless communication is based on Nanotron's patented modulation technique Chirp Spread Spectrum (CSS) according to the wireless standard IEEE 802.15.4a. Data rates are selectable from 2 Mbit/s to 125 kbit/s.

SDS-TWR is a technique that uses two delays which occur in signal transmission to determine the range between two nodes. This technique measures the round trip time and avoids the need to synchronize the clocks. Time measurement starts in Node A by sending a package. Node B starts its

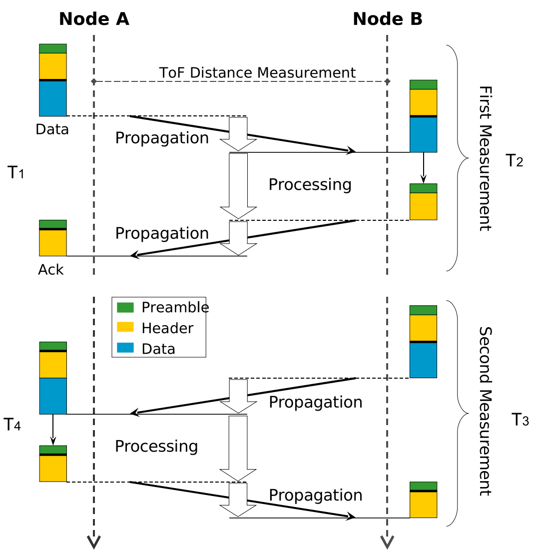


Fig. 2. Symmetrical Double-Sided Two Way Ranging [30]

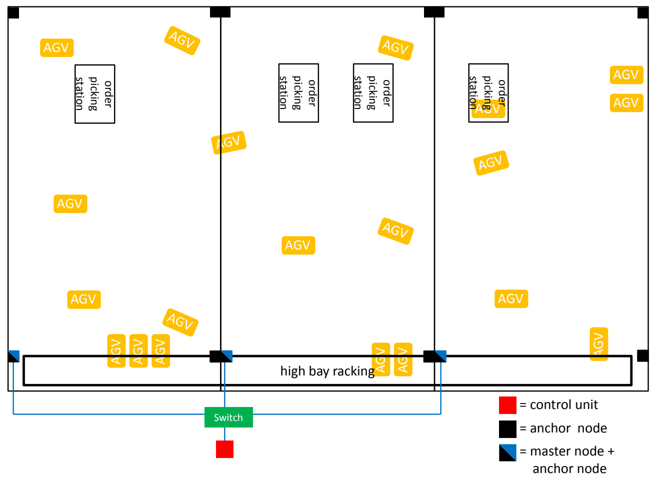


Fig. 3. Wireless network with three cells and router

measurement when it receives this packet from Node A and stops, when it sends it back to the former transmitter. When Node A receives the acknowledgment from Node B, the accumulated time values in the received packet are used to calculate the distance between the two stations (Fig. 2). The difference between the time measured by Node A minus the time measured by Node B is twice the time of the signal propagation. To avoid the drawback of clock drift the range measurement is preformed twice and symmetrically. The signal propagation time $t_\mathrm{d}$ can be calculated as

$$t_\mathrm{d} = \frac{(T_1 - T_2) + (T_3 - T_4)}{4}, \tag{1}$$

where $T_1$ and $T_4$ are the delay times measured in node A in the first and second round trip respectively and $T_2$ and $T_3$ are the delay times measured in node B in the first and second round trip respectively (see Fig. 2). This double-sided measurement zeros out the errors of the first order due to clock drift [29].

## IV. Network Architecture and Protocol Design

The protocol supports communication and localization in real-time. Owing to this requirement, the medium-access is divided into different time slots (TDMA). In order to provide real-time communication for a large number of mobile robots the whole working area is divided into three cells which use different frequencies (FDMA).

### A. *Network Architecture*

Fig. 3 shows the architecture of the whole system. Mobile robots transport Euro-bins containing one sort of goods from a high bay racking to order picking stations and back to the racking. Order pickers collect the orders from Euro-bins and pack them into custom bins. In order to navigate from high bay racking to order picking stations the robots localize itself using IEEE 802.15.4a ranging to at least three anchor nodes. IEEE 802.15.4a range measurements are not precise enough to allow docking maneuvers at order picking stations. For docking maneuvers the range measurements can be fused with measurements obtained from a safety laser range finder.

Every cell consists of a master node and three anchor nodes. The master node controls the medium-access in its cell and acts also as anchor node. Master nodes are connected to a distributed system (Ethernet) for routing purposes. Routing is executed by a central control unit which is connected to the warehouse management system. The control unit stores a routing table with all robots connected to a cell. The warehouse management system sends transport orders to the robots and monitors their state.

### B. *Protocol Design*

The network protocol supports different services:

- *Ranging*: Every mobile node in a cell (mobile robot) uses this service to obtain range measurements to any other node in the cell. Usually a mobile node executes ranging to the master node and three anchor nodes during its time slot. To optimize localization accuracy mobile nodes can execute ranging to robots at fixed positions e.g. docking stations.
- *Data Transmission*: Nodes are addressed with 16 Bit addresses (8 Bit type, 8 Bit ID), where mobile nodes own the same type. Every node can send messages to other nodes during its time slot. Messages to nodes in a different cell are routed through the master node of the source cell via the control unit and the master node of the destination cell to the target node.
- *Time Slot Request, Release*: Before executing other services, a mobile node has to assign to a cell and request a time slot. After service, a mobile node releases its time slot.
- *Handover*: During their way from the racking to the picking stations, robots can travel through different cells. The mobile nodes execute a handover to change a cell, after their position has moved to another cell. Handover is triggered through the position of a mobile node and requested by the mobile node.

The master node controls the medium-access in its cell and send a time slot table in regular intervals as a broadcast. The time slot table contains a time slot for any connected node together with free time slots for concurrent medium-access (CSMA/CA). Fig. 4 shows the format of the superframe as well as a time slot table. Every node that is in range of a

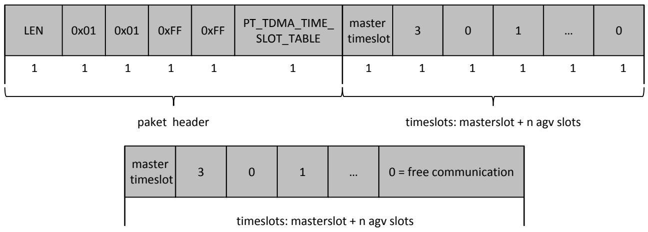


Fig. 4. Time slot table and superframe design

cell receives the time slot table and synchronized its real-time clock. The time slot table includes occupied slots and slots for free communication (CSMA/CA). The first time slot in a superframe is always occupied by the master node. The time slots are marked with the address of the nodes (8 Bit ID), free slots are marked with 0. Since all nodes receive the time slot table, they know every node connected to the cell and can transmit data during their time slot directly.

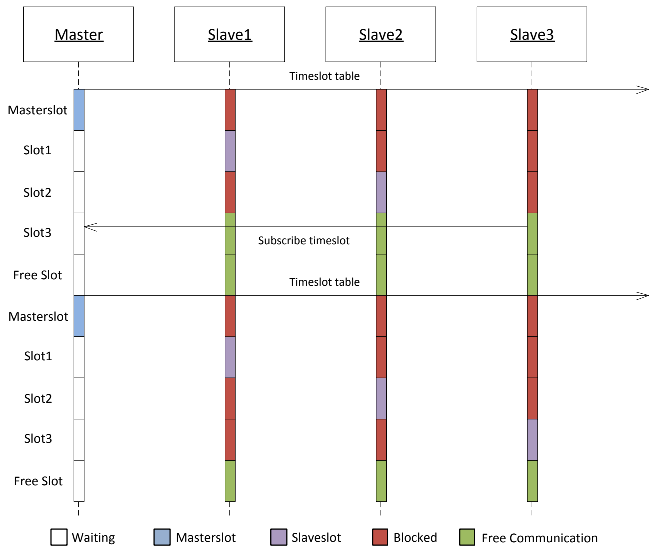


Fig. 5. Allocation of time slot

When a mobile node needs to connect to a cell, it waits for the master slot table and sends a request in the first free slot. Media access in free slots are controlled by CSMA/CA. The last slot at the end of the superframe is never allocated by the master node and therefore always free. Fig. 5 shows a sequence chart with a time slot allocation. At the beginning of the first superframe, the master node broadcasts a time slot table, in which mobile node Slave1 occupies the first time slot and Slave2 occupies the second time slot. Slave3 sends a time slot request in the first free slot (Slot3). At the beginning of the next superframe, the master node broadcasts a new time slot table, in which Slave3 occupies Slot3.

When a mobile robots travels from one cell to another cell, it must change the frequency and request a time slot in the new cell. The protocol supports this procedure with a handover service. The handover service is requested by the mobile node and triggered by its position. Fig. 6 shows a sequence chart of the handover procedure. The robot requests a handover from Cell1 to Cell2. It sends a handover request to the master node of Cell1. The master node of Cell1 sends a handover time slot request via distributed system and control unit (router) to the master node of Cell2. The master node of Cell2 confirms the handover time slot request with a message to master node of Cell1 which confirms it to the robot. The mobile node on the robot changes its frequency and waits for the start of the superframe in Cell2 and the time slot table. In its time slot it sends a handover done message to the master node of Cell2, which sends a handover delete message to the master node of Cell1. The master node of Cell1 releases the time slot of the robots. Master node of Cell2 send a message to the control unit (router), to update the routing table. After this last update the handover procedure is completed.

Since the assignment to a cell depends on the position of the mobile node, a mobile node has to localize itself, before requesting a time slot in a cell. During initialization of a mobile node its position is unknown. Fig. 7 shows a sequence chart of the initialization procedure of a mobile node and the assignment to the correct cell. In the first step a mobile node changes its frequency to the Cell1. It waits for a free time slot and executes ranging to the master node of Cell1. If the obtained range to this master node is smaller than the width of Cell1 it determines Cell1 as the correct cell. If not, the mobile node changes its frequency to the Cell2 and executes ranging to the master node of Cell2. After that step, the mobile node can localize itself with bilateration and consequently assign to the correct cell.

## V. Location Tracking Using the Extended Kalman Filter

The Kalman Filter is an efficient recursive filter, which estimates the state of a dynamic system out of a series of incomplete and noisy measurements by minimizing the mean of the squared error. It is also shown to be an effective tool in applications for sensor fusion and localization [31].

The basic filter is well-established, if the state transition and the observation models are linear distributions. In the case, if the process to be estimated and/or the measurement relationship to the process is specified by a non-linear stochastic difference equation, the Extended Kalman Filter (EKF) can be applied. This filtering is based on linearizing a non-linear system model around the previous estimate using partial derivatives of the process and measurement function.

The Extended Kalman Filter is suitable to track the x- and y-position of a mobile system using measured distances to artificial landmarks (anchors). To estimate the initial position of a mobile system, at least three distances are necessary. Using trilateration the anchor distances $r_i$ are calculated as follow:

$$r_i = \sqrt{(p_x - a_{x,i})^2 + (p_y - a_{y,i})^2}, \qquad (2)$$

where $(a_{x,i}, a_{y,i})$ are the x- and y-positions of anchor $i$ and $(p_x, p_y)$ represents the x- and y-position of the mobile system to be located.

To gain the unknown initial position, equations (2) are solved for $p_x$ and $p_y$, and are transformed in matrices:

$$\boldsymbol{H} \cdot \begin{pmatrix} p_x \\ p_y \end{pmatrix} = z \text{ with } \boldsymbol{H} = \begin{pmatrix} 2 \cdot a_{x,1} - 2 \cdot a_{x,2} & 2 \cdot a_{y,1} - 2 \cdot a_{y,2} \\ \vdots & \vdots \\ 2 \cdot a_{x,1} - 2 \cdot a_{x,n} & 2 \cdot a_{y,1} - 2 \cdot a_{y,n} \end{pmatrix},$$

$$\text{and } z = \begin{pmatrix} {r_2}^2 - {r_1}^2 + {a_{x,1}}^2 - {a_{x,2}}^2 + {a_{y,1}}^2 - {a_{y,2}}^2 \\ \vdots \\ {r_n}^2 - {r_1}^2 + {a_{x,1}}^2 - {a_{x,n}}^2 + {a_{y,1}}^2 - {a_{y,n}}^2 \end{pmatrix}, \qquad (3)$$

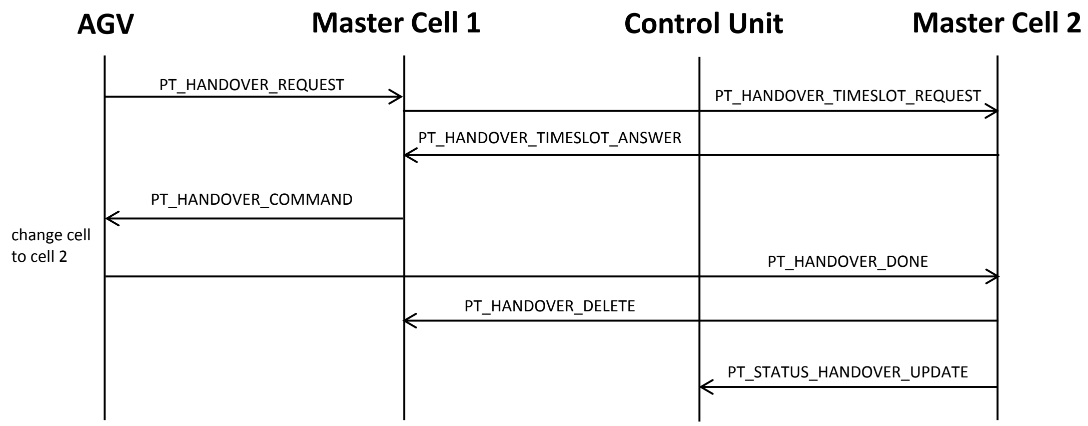


Fig. 6. Sequence chart of handover procedure

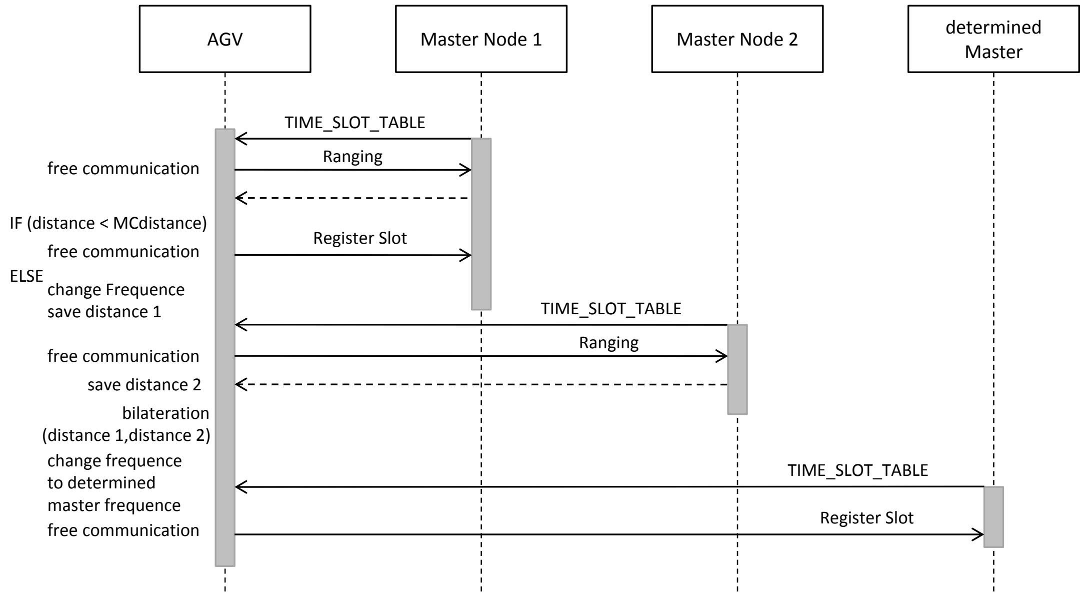


Fig. 7. Initialization and cell assignment

where $n$ is the overall number of anchor nodes. Eqn. 3 can be solved using the method of least squares:

$$\begin{pmatrix} \hat{p}_x \\ \hat{p}_y \end{pmatrix} = (\boldsymbol{H}^{\mathrm{T}}\boldsymbol{H})^{-1}\boldsymbol{H}^{\mathrm{T}} \cdot z \tag{4}$$

For location tracking using EKF, Eqn. (3) needs only to be solved for the initial position estimate $\hat{\boldsymbol{x}}_0$. The EKF addresses the general problem of estimating the interior process state of a time-discrete controlled process, that is governed by non-linear difference equations:

$$\begin{aligned} \tilde{\boldsymbol{x}}_{k+1} &= \boldsymbol{f}(\hat{\boldsymbol{x}}_k, \boldsymbol{u}_k, \boldsymbol{w}_k), \\ \tilde{\boldsymbol{y}}_{k+1} &= \boldsymbol{h}(\tilde{\boldsymbol{x}}_{k+1}, \boldsymbol{v}_{k+1}). \end{aligned} \tag{5}$$

The state vector contains the position of the mobile robor $\boldsymbol{x}_k = (p_x, p_y)^{\mathrm{T}}$. The optional input control vector $\boldsymbol{u}_k = (v_x, v_y)^{\mathrm{T}}$ contains the desired velocity of the robot. These values are set to zero, if the input is unknown. The observation vector $\boldsymbol{y}_k$ represents the observations at the given system and defines the entry parameters of the filter, in this case the results of the range measurements. The process function $\boldsymbol{f}$ relates the state at the previous time step $k$ to the state at the next step $k+1$. The measurement function $\boldsymbol{h}$ acts as a connector between $\boldsymbol{x}_k$ and $\boldsymbol{y}_k$. The notation $\tilde{\boldsymbol{x}}_k$ and $\tilde{\boldsymbol{y}}_k$ denotes the approximated *a priori* state and observation, $\hat{\boldsymbol{x}}_k$ typifies the *a posteriori* estimate of the previous step. Referring to the state estimation, the process is characterized with the stochastic random variables $\boldsymbol{w}_k$ and $\boldsymbol{v}_k$ representing the process and measurement noise. They are assumed to be independent, white and normal probably distributed with given covariance matrices $\boldsymbol{Q}_k$ and $\boldsymbol{R}_k$. To estimate a process with non-linear relationships the equations in (5) must be linearized as follow:

$$\begin{aligned} \boldsymbol{x}_{k+1} &\approx \tilde{\boldsymbol{x}}_{k+1} + \boldsymbol{F}_{k+1} \cdot (\boldsymbol{x}_k - \hat{\boldsymbol{x}}_k) + \boldsymbol{W}_{k+1} \cdot \boldsymbol{w}_k \\ \boldsymbol{y}_{k+1} &\approx \tilde{\boldsymbol{y}}_{k+1} + \boldsymbol{C}_{k+1} \cdot (\boldsymbol{x}_{k+1} - \tilde{\boldsymbol{x}}_{k+1}) + \boldsymbol{V}_{k+1} \cdot \boldsymbol{v}_{k+1}, \end{aligned} \tag{6}$$

where $\boldsymbol{F}_{k+1}, \boldsymbol{W}_{k+1}, \boldsymbol{C}_{k+1}$ and $\boldsymbol{V}_{k+1}$ are Jacobian matrices with the partial derivatives:

$$\begin{aligned} \boldsymbol{F}_{k+1} &= \tfrac{\partial \boldsymbol{f}}{\partial \boldsymbol{x}}(\hat{\boldsymbol{x}}_k, \boldsymbol{u}_k, 0) \quad & \boldsymbol{W}_{k+1} &= \tfrac{\partial \boldsymbol{f}}{\partial \boldsymbol{w}}(\hat{\boldsymbol{x}}_k, \boldsymbol{u}_k, 0) \\ \boldsymbol{C}_{k+1} &= \tfrac{\partial \boldsymbol{h}}{\partial \boldsymbol{x}}(\tilde{\boldsymbol{x}}_{k+1}, 0) \quad & \boldsymbol{V}_{k+1} &= \tfrac{\partial \boldsymbol{h}}{\partial \boldsymbol{v}}(\tilde{\boldsymbol{x}}_{k+1}, 0). \end{aligned} \tag{7}$$

Because in the analyzed system the predictor equation contains a linear relationship, the process function $\boldsymbol{f}$ can be expressed as a linear equation:

$$\boldsymbol{x}_{k+1} = \boldsymbol{F}\boldsymbol{x}_k + \boldsymbol{B}\boldsymbol{u}_k + \boldsymbol{w}_k, \tag{8}$$

where the transition matrix $\boldsymbol{F}$ and $\boldsymbol{B}$ are defined as:

$$\boldsymbol{F} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \quad \boldsymbol{B} = \begin{pmatrix} T & 0 \\ 0 & T \end{pmatrix}, \tag{9}$$

where $T$ is the constant sampling time.

The observation vector $\boldsymbol{y}_k$ contains the current measured distances:

$$\boldsymbol{y}_k = (r_1 \quad \cdots \quad r_n)^{\mathrm{T}}. \tag{10}$$

The initial state estimate $\hat{\boldsymbol{x}}_0$ is calculated based on (3). For the subsequent estimation of the position $\boldsymbol{x} = (p_x, p_y)$ the functional values of the non-linear measurement function $\boldsymbol{h}$ must be approached to the real position. The function $\boldsymbol{h}$ comprises the trilateration equations (2) and calculates the approximated measurement $\tilde{\boldsymbol{y}}_{k+1}$ to correct the present estimation $\tilde{\boldsymbol{x}}_{k+1}$. The equation $\tilde{\boldsymbol{y}}_{k+1} = \boldsymbol{h}(\tilde{\boldsymbol{x}}_{k+1}, \boldsymbol{v}_{k+1})$ is given as:

$$\begin{pmatrix} \hat{r}_1 \\ \vdots \\ \hat{r}_n \end{pmatrix} = \begin{pmatrix} \sqrt{(\tilde{p}_x - a_{x,1})^2 + (\tilde{p}_y - a_{y,1})^2} \\ \vdots \\ \sqrt{(\tilde{p}_x - a_{x,n})^2 + (\tilde{p}_y - a_{y,n})^2} \end{pmatrix} + \boldsymbol{v}_{k+1}\,. \tag{11}$$

The related Jacobian matrix $\boldsymbol{C}_{k+1} = \frac{\partial \boldsymbol{h}}{\partial \boldsymbol{x}}(\tilde{\boldsymbol{x}}_k, 0)$ describes the partial derivatives of $\boldsymbol{h}$ with respect to $\boldsymbol{x}$:

$$\boldsymbol{C}_{k+1} = \begin{pmatrix} \frac{\partial \hat{r}_1}{\partial \tilde{p}_x} & \frac{\partial \hat{r}_1}{\partial \tilde{p}_y} \\ \vdots & \vdots \\ \frac{\partial \hat{r}_n}{\partial \tilde{p}_x} & \frac{\partial \hat{r}_n}{\partial \tilde{p}_y} \end{pmatrix} \text{ with } \begin{array}{l} \frac{\partial \hat{r}_i}{\partial \tilde{p}_x} = \frac{\tilde{p}_x - a_{x,i}}{\sqrt{(\tilde{p}_x - a_{x,i})^2 + (\tilde{p}_y - a_{y,i})^2}} \\ \frac{\partial \hat{r}_i}{\partial \tilde{p}_y} = \frac{\tilde{p}_y - a_{y,i}}{\sqrt{(\tilde{p}_x - a_{x,i})^2 + (\tilde{p}_y - a_{y,i})^2}}. \end{array} \tag{12}$$

Given that $\boldsymbol{h}$ contains non-linear difference equations the parameters $r_i$ as well as the Jacobian matrix $\boldsymbol{C}_{k+1}$ must be calculated newly for each estimation.

## VI. Global Localization Using the Monte Carlo Particle Filter

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 Monte Carlo Particle Filter (MCPF), which is described in [32]. The estimated pose of a mobile robot and its uncertainty about the correctness is represented by the samples. MCPF 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 t he 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. MCPFs flow chart is drafted in Fig. 8. The MCPF has the advantages

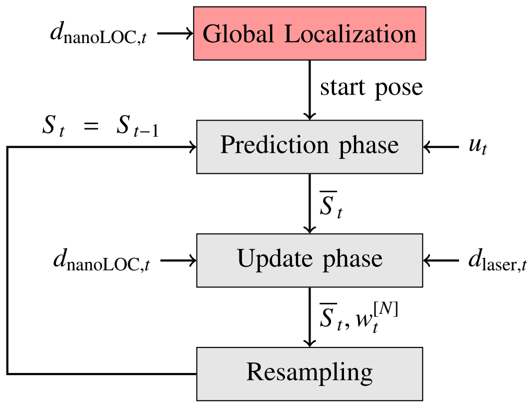


Fig. 8. MCPF flow chart.

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 work the MCPF uses distance measurements from the IEEE 802.15.4a WSN for global localization. The global localization task, which has to be done before the MCPF starts, is shown as a red block in Fig. 8. The probability density function of the IEEE 802.15.4a measurement error which is used to compute the importance factor, is presented in the next section.

### A. IEEE 802.15.4a 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 IEEE 802.15.4a distance measurements, line of sight 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. 9, 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 $a$.

The histograms show, that all measured distances are too large, the average error is 107 cm. The error depends on the

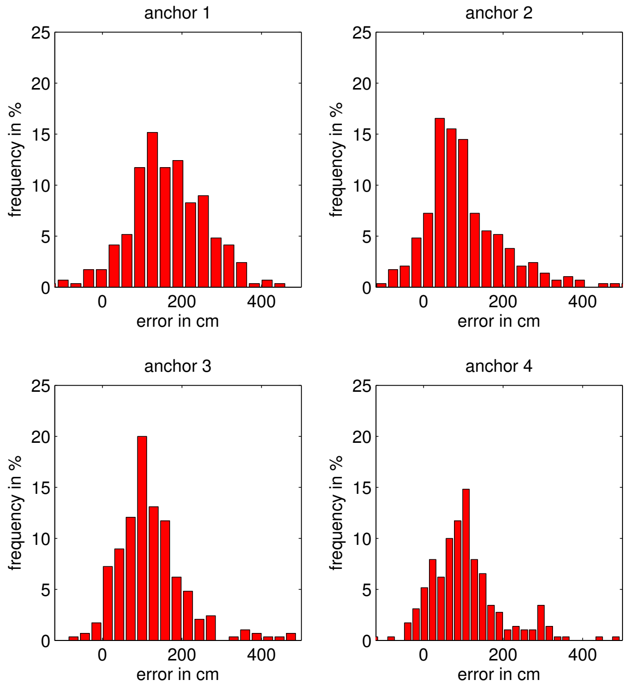


Fig. 9. Error histograms of IEEE 802.15.4a distance measurements to four anchors. The x-axis is the error in centimeter and the y-axis show their frequency in %.

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 IEEE 802.15.4a probability density function:

$$\mathcal{N}\left(x,\mu,\sigma^2\right) = \frac{1}{\sqrt{2\pi\sigma^2}}\exp\left(\frac{-1}{2}\frac{(x-\mu)^2}{\sigma^2}\right) \tag{13}$$

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

$$d_k^{a,i*} = \sqrt{(x_i - x_a)^2 + (y_i - y_a)^2}, \tag{14}$$

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:

$$p\left(d^a_{\text{nanoLOC},k} \mid s_k^i, m\right) = \mathcal{N}\left(d^{a,i*} - (d_k^a - d_c^a), 0, \sigma^2\right) \tag{15}$$

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 MCPF to re-localize the mobile robot.

The importance factor of a sample $i$ is calculated with:

$$w_k^i = \prod_{a=1}^{A} p\left(d^a_{\text{nanoLOC},k} \mid s_k^i\right) \cdot \prod_{l=1}^{2} p\left(d^l_{\text{laser},k} \mid s_k^i\right) \tag{16}$$

The importance factor $w$ is the product of the probability of measurements to $A$ anchors and to two landmarks. The probability $p(d^l_{\text{laser},k} | s_k^i, m)$ is a fixed Gaussian with $\sigma$ = 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 IEEE 802.15.4a WSN.

### B. Anchorbox

For global localization range measurements of the IEEE 802.15.4a WSN are used to reduce the area in which particles are distributed. This method is based on a technique which was presented in [33]. Fig. 10 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.

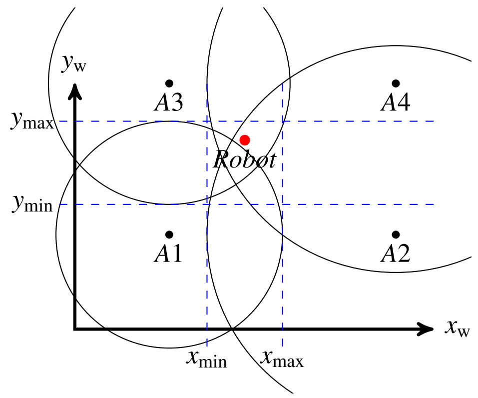


Fig. 10. Anchorbox example by using range measurements to four anchor nodes with known positions.

In the first step of the MCPF the particles are distributed in the area defined through calculation specifications 17 and 18, where $(x_i, y_i)$ is the position of anchor $i$ and $\overline{d}_i$ is the average of $I$ range measurements.

$$x_{\min} = \max_{i=1}^{I}\left(x_i - \overline{d}_i\right) \qquad x_{\max} = \min_{i=1}^{I}\left(x_i + \overline{d}_i\right) \tag{17}$$

$$y_{\min} = \max_{i=1}^{I}\left(y_i - \overline{d}_i\right) \qquad y_{\max} = \min_{i=1}^{I}\left(y_i + \overline{d}_i\right) \tag{18}$$

One disadvantage of the Anchorbox approach is that the orientation can not be estimated by IEEE 802.15.4a range measurements. To overcome this disadvantage more particles with a random orientation are distributed at the beginning of the algorithm. After the particles are distributed the robot drives 1 m in positive $x$ robot direction. Because of this technique, the adapted MCPF 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 MCPF 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.

## VII. Implementation and Experimental Results

The protocol is designed for a distribution center with 50 mobile robots and three cells.

### A. Hardware

Fig. 11. Wireless sensor node for anchors and mobile tags

In order to fulfill the requirements of the target application, a wireless sensor board was developed that can be used as:

- Mobile node (tag) on a mobile robot,
- Fixed anchor node,
- Master node with connection to the distributed system.

The board is designed around a STM32 micro-controller which includes an ARM Cortex-M3 core. The STM32 micro-controller provides interfaces and enough RAM and computational power to perform communication and location tracking using EKF in real-time. IEEE 802.15.4a radio is built with a nanoPAN 5375 module which supports up to 20 dBm output power and three frequency channels with 22 MHz bandwidth.

The architecture of the wireless sensor board is modular, only necessary components are assembled. Master nodes are equipped with a Xport to connect to an Ethernet. Mobile nodes are equipped with an IMU (inertial measurement unit) which increases localization accuracy of the robots. Mobile nodes are connected via CAN-bus to the robot's PLC (programmable logic controller). Communication to the PLC is performed with CANopen protocol. As a fall back, the boards are equipped with a serial interface (RS-232).

### B. Communication and location tracking using EKF

Several experiments have been conducted, to prove the implementation of the protocol and the localization accuracy. Fig. 12 shows the result of a roaming experiment. The robot moves from Cell1 to Cell2 and performs a handover while crossing the boundary between the cells. The position tracking of the mobile robot is estimated using the EKF as described in section V, the initial position is calculated with trilateration (Eqn. (3)). The blue dots in Fig. 12 show the position tracked in Cell1, the black circles show the position in Cell2. The position error near the border of the cells are caused by bad radio conditions in this area due to the directional antennas of the anchors. In this experiment, only range measurement using four anchors of each cell are used for tracking. The tracking error can be decreased, if odometry and laser range finders are included in the tracking algorithm [34].

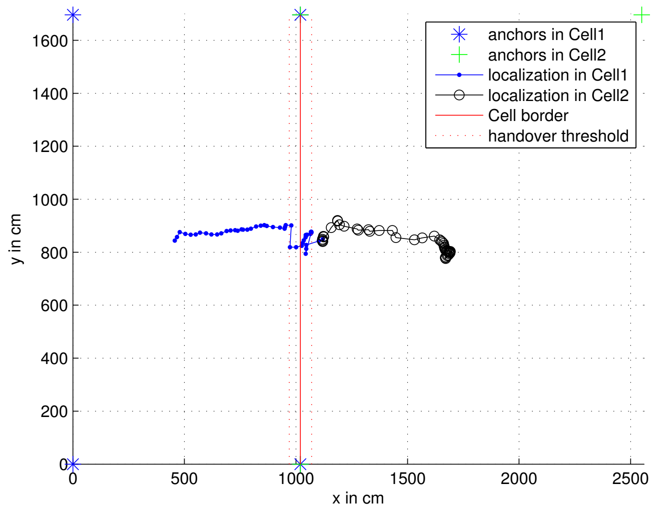


Fig. 12. Wireless synchronisation

### C. Global localization Using MCPF

To evaluate the proposed MCPF global localization, some experiments are conducted at the University of Applied Sciences and Arts in Dortmund with an omnidirectional mobile robot, that is equipped with Mecanum wheels. The robot and it's motion model is described in [34]. It 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 mobile robot is also equipped with a IEEE 802.15.4a tag for ranging and communication purposes. At the margins of the environments six IEEE 802.15.4a anchors are placed. The figures 13(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 mobile robot is moved in manual mode from a starting point into the docking station which is shown by the black path in Fig. 13(a) and (b). The mobile robot 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 MCPF are stored. These values are odometry data, distance measurements to

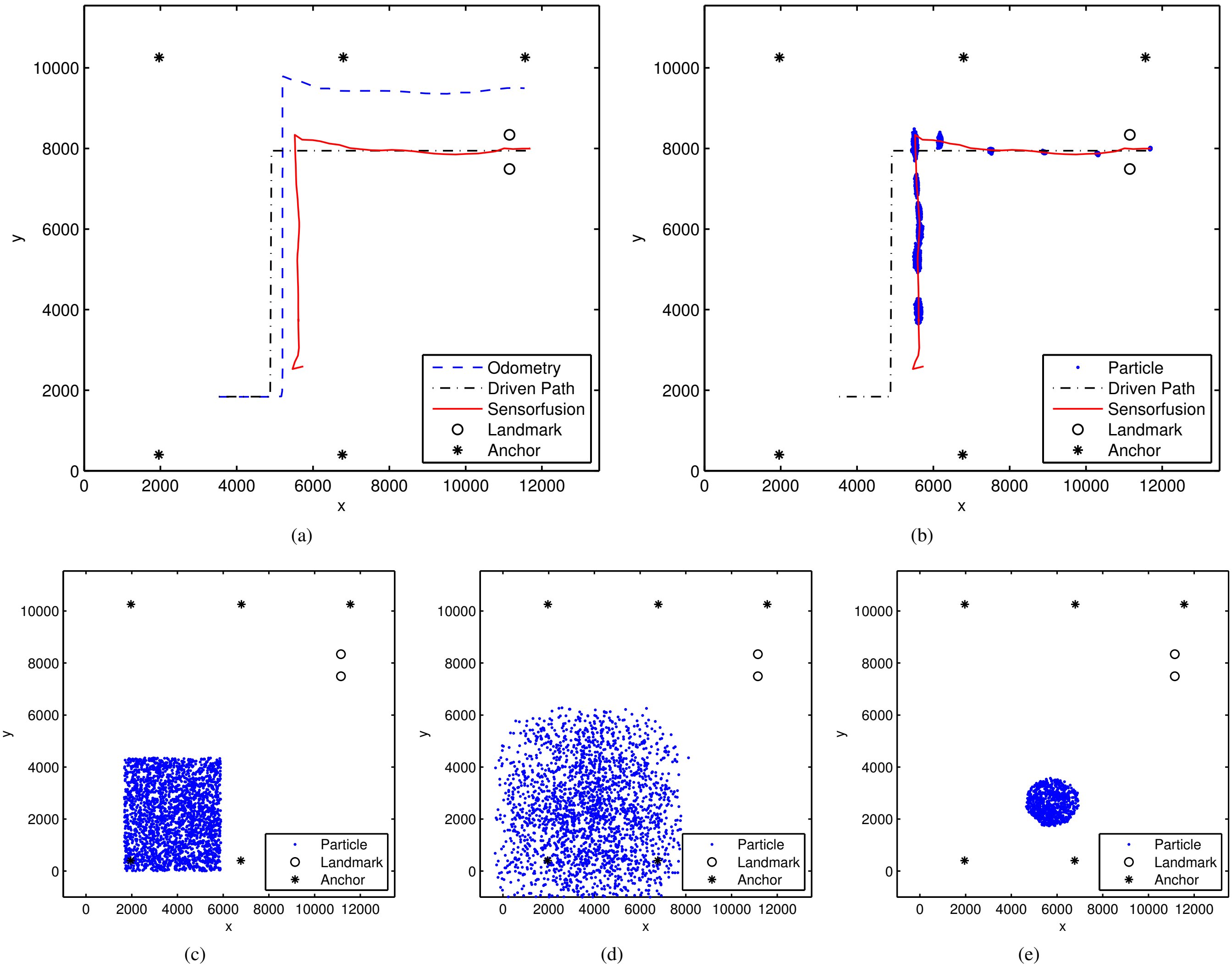


Fig. 13. Experimental results: (a) and (b) show results of global localization. (c) - (e) show the process of global localization with the Anchorbox approach.

six IEEE 802.15.4a anchors and the laser range data. The first movement should simulate the first step of global localization if the mobile robot 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. 13(c) shows the Anchorbox with the distributed sample set. The sample set after the first movement part is shown in Fig. 13(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. 13(e). The start pose is set to the weighted mean of the sample cloud.

After estimating the start position the MCPF segue from global positioning into position tracking and the sample set is reduced to 2000 samples. The estimated start position depends on the IEEE 802.15.4a measurements and on the set of samples with random orientation.

The resulting path of the global localization and position tracking is shown in Fig. 13(a) and (b). Owing to an unequal floor contact, the robot has a large slippage when it moves sideways. Fig. 13(a) shows odometry in blue and MCPF estimation using all sensor data in red. The sample clouds resulting from position tracking (after the global localization) are presented in Fig. 13(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. 13(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 IEEE 802.15.4a measurements is good enough for planning the path and through using the sensor fusion a successful docking maneuver can be guaranteed.

## VIII. Conclusions and Future Works

In this paper global localization of autonomous mobile robots using IEEE 802.15.4a CSS and laser range finders was proposed. A new communication protocol for a wireless network and a localization method using EKF and PCPF was developed, implemented and tested. The network uses

FDMA to divide the area into cells, TDMA for real-time communication and global localization within a cell and CSMA/CA for cell assignment and management services. A sensor node was developed which provides all functions to act as a mobile node as well as as an anchor or a master node. In the next step, the system will be implemented in a demonstration center with 50 mobile robots and three cells.

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