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Tracking of Transport Vehicles for Warehouse Management using a Wireless Sensor Network

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Abstract— **A warehouse management system is a key part of the supply chain and controls the movement of goods within a warehouse. Usually the state of a warehouse is managed in a central database, which must be updated for every storage and retrieval activity. The entire process is prone to errors, because it relies on manual activities performed by employees. This paper presents a technique to monitor the manual transportation processes of goods in a warehouse, in order to update the database automatically. In the proposed scenario, transport vehicles such as forklift trucks or pallet jacks are equipped with wireless sensor nodes and every storage and retrieval activity is reported to the warehouse management system. Tracking of transport vehicles is performed with nanoLOC sensor nodes, which offer range measurement capabilities. This radio positioning system determines the range between two devices by measuring the signal propagation delay. The paper describes the tracking of transport vehicles with range measurements and trilateration using the Extended Kalman Filter. It presents experimental results of tracking a forklift truck in a warehouse.**

I. Introduction

Research on warehouse management focuses on optimal development and efficient retrieval according to the fundamentals of Supply Chain Management (SCM). Warehouse Management Systems (WMS) are employed to manage all relevant information in a central database and to automatize the information transfer. Among other things, the location of load carriers, e.g. a pallet, is of particular interest. The process of database updates is prone to errors, because it relies on manual activities performed by employees. We propose tracking of manual transportation activities in a warehouse using a Wireless Sensor Network (WSN), in order to update the database automatically. A WSN consist of spatially distributed autonomous sensor nodes for data acquisition. Via such a network the location of nodes can be identified, so that the whole material flow process within a warehouse can be monitored. Transport vehicles such as forklift trucks or pallet jacks can be equipped with wireless sensor nodes in order to report every storage and retrieval activity to the WMS. Tracking of transport vehicles is performed with nanoLOC sensor nodes as part of the WSN, which offer range measurement capabilities. For database updates of storage and retrieval activities, load carriers have to be identified automatically. In former times, load carriers were equipped and identified over bar code. Nowadays with the growing requirements for mobility and reliability increasingly Radio Frequency Identification (RFID) tags are employed to request information. When a wireless node at the transport vehicle detects that a load carrier is lifted up, it identifies the carrier by means of a barcode or RFID scanner and reports the retrieval to the WMS. After the load carrier is put down, the wireless node reports the storage of the load carrier along with the new bin location. The proposed technique is evaluated in a demonstration warehouse of the Fraunhofer-Institute for Material Flow and Logistics.

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II. Related Work

Localization of load carriers such as pallets or containers is a strong demand in many logistics applications [1]. In [2] automated tracking of pallets using WSN with ultrasound range measurement is proposed. Up to now several kinds of localization techniques are developed for the use in wireless networks. A review of existing techniques is given in [3]. This techniques can be classified by the information they use:

- Connectivity information,
- Received Signal Strength (RSS),
- Angle of Arrival (AoA),
- Time of Arrival (ToA),
- Round-trip Time of Flight (RToF),
- Time Difference of Arrival (TDoA).

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 infrastructure mode of a Wireless LAN (WLAN), the access point (AP) to which the mobile device is currently connected, can be determined since mobile devices know the MAC hardware address of the AP, which they are connected to. In a WSN with short radio range, connectivity information can be used to estimate the position of a sensor node without range measurement [4]. Bluetooth is another technology, which allows a relatively accurate localization because of its low radio range [5]. Besides the deployment of RFID in SCM, the RFID technology is also suitable for position estimation. RFID tags can be deployed at known positions in the environment, in order to obtain position information when they are in range. This information can be be fused with data from other sensors (e.g. odometers) for the purpose of improving the accuracy of localization [6], [7]. The high effort and costs for placing RFID tags in a high density makes this technique unfavorable for the target application.

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 [8]. 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 this disturbances make the use of a propagation model for accurate localization in an indoor environment almost impossible [9]. A method to overcome this disadvantage is fingerprinting, which is introduced in [10] 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. A metric to compare the measured RSS values with the radio map is Euclidean distance proposed in [10]. Other approaches use a Bayesian algorithm [11] or Delaunay triangulation with lines of constant signal strength [12]. 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 [9]. 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 [13] 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, RToF and TDoA estimate the range to a sender by measuring the signal propagation delay. The Cricket localization system [14] developed at MIT utilizes a radio signal and a 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 [15] or to track the position of a mobile robot [16]. Ultra-Wideband (UWB) offers a high potential for range measurement using ToA, because the large bandwidth (> 500 MHz) provides a high ranging accuracy [17]. In [18] UWB range measurements are proposed for tracking a vehicle in a warehouse. The Ubisense system, developed at the University of Cambridge, is a commercial UWB based localization system [19]. Position estimation is performed using both TDoA and AoA measurements. The anchor nodes are equipped with antenna arrays in order to provide AoA measurements. The TDoA information is determined between pairs of anchor nodes connected with a timing cable. The combination of AoA and TDoA measurement allows a reliable position estimation of a mobile tag with an guaranteed accuracy of 15 cm, even if only two anchor nodes receive the signal. Owing to the complex technology, the Ubisense location system is very expensive.

Nanotron Technologies distributes a WSN with ranging capabilities, which avoids complex technology. This WSN meets the requirements of the target application and is described in the next section.

III. The nanoLOC Localization System

Nanotron Technologies has developed a WSN which can work as a Real-Time Location Systems (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 [20]. 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 [21]. 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 draft standard IEEE 802.15.4a. Data rates are selectable from 2 Mbit/s to 125 kbit/s.

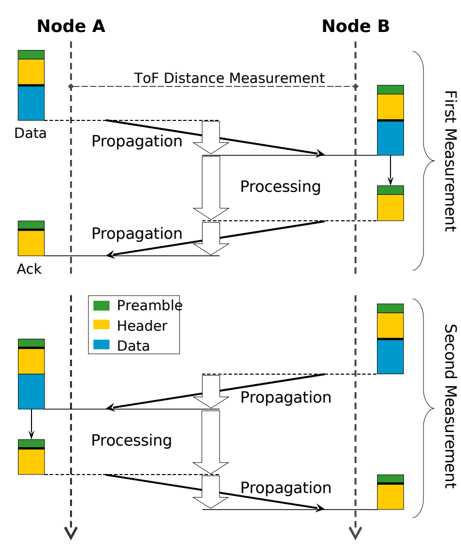

Fig. 1. Symmetrical Double-Sided Two Way Ranging [21]

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 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. 1). 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. This double-sided measurement zeros out the errors of the first order due to clock drift [20].

Based on the nanoLOC TRX transceiver and the micro-controller ATmega 128L, the nanoLOC WSN can be used for developing location-aware and distance ranging wireless applications [22]. A mobile tag localizes itself by measuring the distances to a set of anchors as reference points. The anchors are located to predefined positions within a Cartesian coordinate system (Fig. 2). The tag position can be calculated by trilateration.

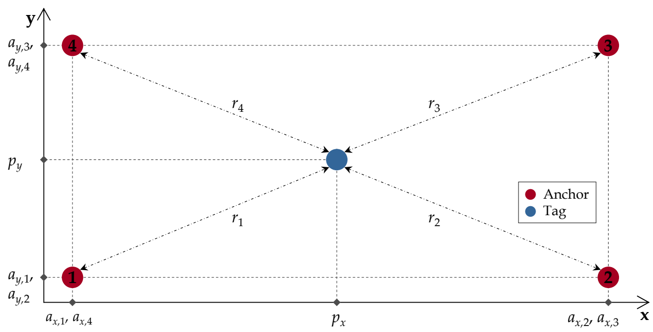

Fig. 2. Localization of a mobile tag based upon the distances to the four anchors

In the Fig. 2, (p_x, p_y) represents the x- and y-position of the mobile tag to be located. The positions $(a_{x,i}, a_{y,i})$ with $i \in \{1, 2, 3, 4\}$ are the x- and y-positions of the four anchors. The variables r_i incorporate the four distances between the tag and the anchor nodes. At least three distances are required to calculate the position of the tag.

IV. Using the Extende Kalman Filter for Tracking of Transport Vehicles

By monitoring a dynamic system, the interior process state such as position and velocity of transport vehicles are not direct accessible. The distance measurements are subject to errors and noise. The Kalman Filter (KF) 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.

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.

A. EKF Design

The Extended Kalman Filter is suitable to determine the x- and y-position of the mobile tag with the measured distances to the four anchors. Using the trilateration method the anchor distances r_i with $i \in \{1, 2, 3, 4\}$ are calculated as follow:

$$r_i = \sqrt{(p_x - a_{x,i})^2 + (p_y - a_{y,i})^2}. \tag{1}$$

To gain the unknown tag position, the equations in (1) are solved for p_x and p_y, and are transformed in matrices:

$$\boldsymbol{H} \cdot \begin{pmatrix} p_x \\ p_y \end{pmatrix} = z \text{ with } \boldsymbol{H} = \begin{pmatrix} 2 \cdot a_{x,1} - 2 \cdot a_{x,2} & 2 \cdot a_{y,1} - 2 \cdot a_{y,2} \\ 2 \cdot a_{x,1} - 2 \cdot a_{x,3} & 2 \cdot a_{y,1} - 2 \cdot a_{y,3} \\ 2 \cdot a_{x,1} - 2 \cdot a_{x,4} & 2 \cdot a_{y,1} - 2 \cdot a_{y,4} \end{pmatrix},$$
$$\text{and } \boldsymbol{z} = \begin{pmatrix} {r_2}^2 - {r_1}^2 + {a_{x,1}}^2 - {a_{x,2}}^2 + {a_{y,1}}^2 - {a_{y,2}}^2 \\ {r_3}^2 - {r_1}^2 + {a_{x,1}}^2 - {a_{x,3}}^2 + {a_{y,1}}^2 - {a_{y,3}}^2 \\ {r_4}^2 - {r_1}^2 + {a_{x,1}}^2 - {a_{x,4}}^2 + {a_{y,1}}^2 - {a_{y,4}}^2 \end{pmatrix}. \tag{2}$$

Eqn. 2 can be solved using the method of least squares:

$$\begin{pmatrix} \hat{p}_x \\ \hat{p}_y \end{pmatrix} = (\boldsymbol{H}^{\mathrm{T}}\boldsymbol{H})^{-1}\boldsymbol{H}^{\mathrm{T}} \cdot z \tag{3}$$

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:

$$\begin{aligned} \tilde{\boldsymbol{x}}_{k+1} &= \boldsymbol{f}(\hat{\boldsymbol{x}}_k, \boldsymbol{u}_k, \boldsymbol{w}_k) \\ \tilde{\boldsymbol{y}}_k &= \boldsymbol{h}(\tilde{\boldsymbol{x}}_k, \boldsymbol{v}_k). \end{aligned} \tag{4}$$

In the target application, the state vector $\boldsymbol{x}_k$ contains the tag position to be estimated as well as the first and second derivatives. The optional input control vector $\boldsymbol{u}_k$ is set to zero. 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 (4) must be linearized as follow:

$$\begin{aligned} \boldsymbol{x}_{k+1} &\approx \tilde{\boldsymbol{x}}_{k+1} + \boldsymbol{A}_k \cdot (\boldsymbol{x}_k - \hat{\boldsymbol{x}}_k) + \boldsymbol{W}_k \cdot \boldsymbol{w}_k \\ \boldsymbol{y}_k &\approx \tilde{\boldsymbol{y}}_k + \boldsymbol{C}_k \cdot (\boldsymbol{x}_k - \tilde{\boldsymbol{x}}_k) + \boldsymbol{V}_k \cdot \boldsymbol{v}_k, \end{aligned} \tag{5}$$

where $\boldsymbol{A}_k, \boldsymbol{W}_k, \boldsymbol{C}_k$ and $\boldsymbol{V}_k$ are Jacobian matrices with the partial derivatives:

$$\begin{aligned} \boldsymbol{A}_k &= \tfrac{\partial \boldsymbol{f}}{\partial x}(\hat{\boldsymbol{x}}_k, \boldsymbol{u}_k, 0) & \boldsymbol{W}_k &= \tfrac{\partial \boldsymbol{f}}{\partial w}(\hat{\boldsymbol{x}}_k, \boldsymbol{u}_k, 0) \\ \boldsymbol{C}_k &= \tfrac{\partial \boldsymbol{h}}{\partial x}(\tilde{\boldsymbol{x}}_k, 0) & \boldsymbol{V}_k &= \tfrac{\partial \boldsymbol{h}}{\partial v}(\tilde{\boldsymbol{x}}_k, 0). \end{aligned} \tag{6}$$

Because in the analyzed system the predictor equation contains a linear relationship, no process function $\boldsymbol{f}$ is required and the interior process state is a vector:

$$\boldsymbol{x}_k = \begin{pmatrix} p_x & v_x & a_x & p_y & v_y & a_y \end{pmatrix}^{\mathrm{T}}, \tag{7}$$

where p_x, p_y define the position, v_x, v_y represent the velocity and a_x, a_y define the acceleration. The transition matrix $\boldsymbol{A}_k$ is defined as:

$$\boldsymbol{A} = \begin{pmatrix} 1 & T & T^2/2 & 0 & 0 & 0 \\ 0 & 1 & T & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & T & T^2/2 \\ 0 & 0 & 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}, \tag{8}$$

where T is the constant sampling time. The observation vector $\boldsymbol{y}_k$ contains for each cycle the current measured distances to four anchors:

$$\boldsymbol{y}_k = (r_1 \quad r_2 \quad r_3 \quad r_4)^{\mathrm{T}}. \tag{9}$$

The initial state estimate $\hat{\boldsymbol{x}}_0$ is calculated based on (2). For the subsequent estimation of the tag position (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 (1) and calculates the approximated measurement $\tilde{\boldsymbol{y}}_k$ to correct the present estimation $\tilde{\boldsymbol{x}}_k$. The equation $\tilde{\boldsymbol{y}}_k = \boldsymbol{h}(\tilde{\boldsymbol{x}}_k)$ is given as:

$$\begin{pmatrix} r_1 \\ r_2 \\ r_3 \\ r_4 \end{pmatrix} = \begin{pmatrix} \sqrt{(p_x - a_{x,1})^2 + (p_y - a_{y,1})^2} \\ \sqrt{(p_x - a_{x,2})^2 + (p_y - a_{y,2})^2} \\ \sqrt{(p_x - a_{x,3})^2 + (p_y - a_{y,3})^2} \\ \sqrt{(p_x - a_{x,4})^2 + (p_y - a_{y,4})^2} \end{pmatrix}. \tag{10}$$

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

$$\boldsymbol{C}_k = \begin{pmatrix} \frac{\partial r_1}{\partial p_x} & \frac{\partial r_1}{\partial p_y} \\ \frac{\partial r_2}{\partial p_x} & \frac{\partial r_2}{\partial p_y} \\ \frac{\partial r_3}{\partial p_x} & \frac{\partial r_3}{\partial p_y} \\ \frac{\partial r_4}{\partial p_x} & \frac{\partial r_4}{\partial p_y} \end{pmatrix} \text{ with } \begin{aligned} \frac{\partial r_i}{\partial p_x} &= \frac{p_x - a_{x,i}}{\sqrt{(p_x - a_{x,i})^2 + (p_y - a_{y,i})^2}} \\ \frac{\partial r_i}{\partial p_y} &= \frac{p_y - a_{y,i}}{\sqrt{(p_x - a_{x,i})^2 + (p_y - a_{y,i})^2}} \end{aligned}. \tag{11}$$

Given that $\boldsymbol{h}$ contains non-linear difference equations the parameter r_1, r_2, r_3 and r_4 as well as the Jacobian matrix $\boldsymbol{C}_k$ must be calculated newly for each estimation.
The Jacobian matrices $\boldsymbol{W}_k$ and $\boldsymbol{V}_k$ depend on the process and measurement noise $\boldsymbol{w}_k$ and $\boldsymbol{v}_k$ and are defined as identity matrices.

Fig. 3 shows a complete picture of the operations of the EKF by presenting the specific predictor and corrector equations. The time update projects the *a priori* state and covariance estimates forward from time step to step. The first task during the measurement update is to compute the Kalman gain $\boldsymbol{K}_k$. The next step is to generate an *a posteriori* state estimate $\hat{\boldsymbol{x}}_{k+1}$ as the result of the filter, in this case. The final step is to obtain the corresponding error covariance estimate $\boldsymbol{P}_{k+1}$ for the next iteration.

B. Parameter Tuning

The effect of the Kalman estimation depends significantly on the parameters of the covariance matrices. To preferably gain an exact estimation, appropriate values for the process noise covariance $\boldsymbol{Q}_k$ and the measurement noise covariance $\boldsymbol{R}_k$ must be detected. The process noise covariance represents

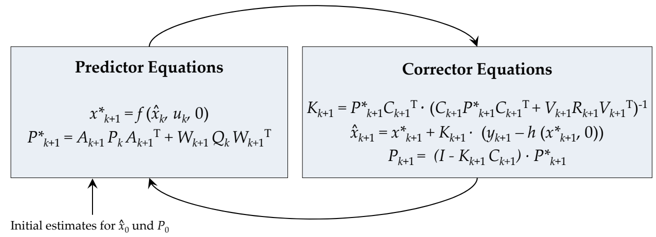

Fig. 3. Time update and measurement update equations of the Extended Kalman Filter

the accuracy of the estimates for the interior process state. We assume that $\boldsymbol{Q}_k$ is the zero matrix. The measurement noise covariance depends directly on the environment of the range measurements. Several experiments with different anchors show covariances in a range between 0.0216 and 0.354. The measurement noise covariance is chosen with $\boldsymbol{R}_k = 0.1328 \cdot \boldsymbol{I}$ as mean variance of all experiments.

V. Tracking of Transport Vehicles

A. Experimental Setup

Experiments are carried out at a demonstration storage of the Fraunhofer-Institute for Material Flow and Logistics. The standard NanoLOC development kit which contains five sensor boards with sleeve dipole omnidirectional antennas is utilized for the experiments. In a first test series, the positions of europallets in a high bay warehouse are estimated with the nanoLOC system. With this experiments estimation of a bin location in a rack is evaluated. Due to the size of the rack, the anchors compose a measuring field with the dimension 9.48×3.25 m. In total 21 measurements, allocated above three levels, are accomplished in order to find out, if the metering precision of the individual racking compartments diverge. For a distinct position determination of a storage place, the metering precision must be under half wide of the europallets (< 0.40 m).

Fig. 4. Forklift Truck with Wireless Sensor Network

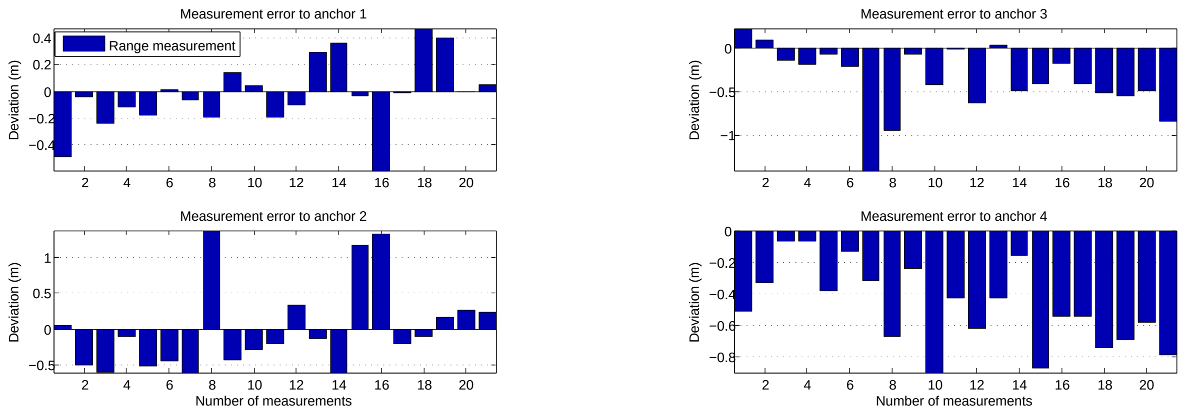

Fig. 5. Measurement error in the distances to the anchor

In a second test series, the position of a forklift truck is tracked using the Extended Kalman Filter. The forklift truck shown in Fig. 4 can be operated in automatic and manual mode. For the experiments the forklift truck moves in automatic mode along a straight line to the target position and than back to the start position.

B. Experiment Results

By the data interpretation of the range measurement the allocation of the metering precisions above the individual storage positions is of particular interest. In this context it must be evaluated at which positions extreme deviations of range errors occur.

At first the anchor distances toward the tag are examined. In order to notice random or systematic errors of measurement, the median over the measurement results is related to the real anchor distances, as demonstrated in the bar charts of Fig. 5. Using these anchor distances, the positions of the tag are estimated with the method of the EKF. The mean deviations within the EKF-estimation related to the real x- and y-positions are presented in Fig. 6.

On the basis of the error bars it is observable, that the required precision better than 0.40 m can be achieved with some exceptions. 15 of 21 measurements (71%) meet the requirements. Extreme errors appear in the measurements 7, 8 and 16. By the mentioned measurements the distances are imprecise to anchor 2 with extreme deviations about 1.38 m and 1.33 m as well as to anchor 3 with deviations about −1.40 m and −0.94 m. Positive deviation occurs because the LOS propagation on the transmission path between the tag and anchor nodes is blocked. So the signal propagation is conducted through reflection and scattering. This phenomenon is the main source for the observed errors in the location estimation. A negative derivation in the range measurement of more than 1 m is observed in position 7 to anchor 3 only. Anchors 3 and 4 produce range measurements with a negative bias in nearly all measurements. Since the EKF requires a zero mean error distribution of the measurements, biased range measurements lead to errors in position estimation. The cause for large negative errors or biased measurements is unknown and has to be addressed in future investigations. Since trilateration requires three range measurements only, one can detect large measurement errors by using the redundancy of more than three measurements. After detecting an outlier, this measurement can be except from EKF.

The second test series evaluates the tracking accuracy of the EKF. The forklift truck moves in automatic mode along

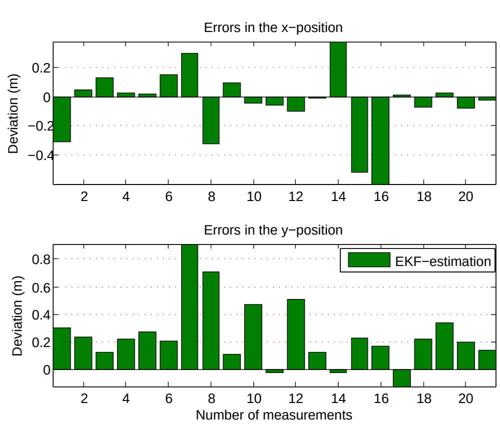

Fig. 6. Errors in the EKF-estimation

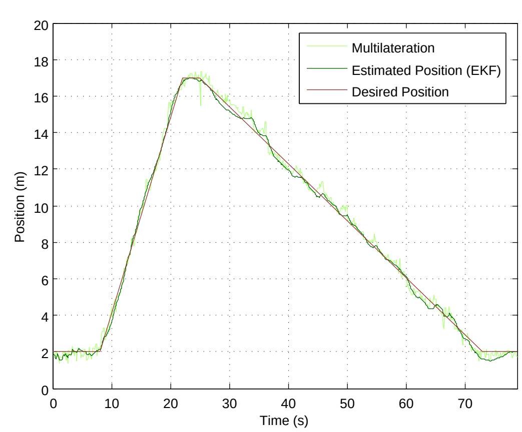

Fig. 7. Results of the Extended Kalman Filtering

a straight line with $v_x = 1\,\mathrm{m/s}$ to the target position ($p_x = 17\,\mathrm{m}$) and than back to the start position ($p_x = 2\,\mathrm{m}$) with $v_x = 0.3\,\mathrm{m/s}$. The y-position is constant ($p_y = 2\,\mathrm{m}$) during this experiment. The line plot in Fig. 7 presents the result of this experiment. The red line shows the desired x-position of the truck. The raw trilateration (light green line) shows large peak errors of up to 2 m. The estimated x-position of the EKF (dark green line) removes the measurement noise and shows an accuracy better than 0.4 m in most cases. The largest errors are generated at points of acceleration. In this points, the estimated velocity has to be changed by the EKF, which needs some time and leads to estimation errors. In future work, the desired velocity of the transport vehicle can be included in the output vector $\boldsymbol{y}$ to solve this problem.

VI. Conclucions and future works

Tracking of transport vehicles can solve the problem of warehouse management with manual storage and retrieval of load carriers. WSNs establish a basis for radio linked location positioning. Concerning the localization of pallets within a high bay warehouse a metering precision better than 0.4 m is required. The analyzed sensor network meets the mentioned requirements in most cases. In some estimations the position error is larger than 0.4 m. This problem has to be addressed in future work by detecting range measurements with large errors. As already mentioned, the trilateration method just requires three ranging information. An approach is to measure the distance to more than three anchor nodes and to use this redundancy to detect measurement errors. This measurements have to be disregarded in order to improve the accuracy and reliability. Another technique to mitigate non-line-of-sight (NLOS) and multi-path errors is the Biased Kalman Filter presented in [23]. This filtering uses the estimated standard deviation to mitigate the NLOS error through increasing parameters of the measurement noise covariance matrix.

The tracking performance of transport vehicles can be improved by including additional sensor data in the measurement vector of the EKF. Possible sensors are dead reckoning sensors (wheel encoders) or inertial sensors (accelerometer, gyroscop).

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