Decentralized SLAM for Pedestrians without direct Communication

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***Abstract*— We consider the problem of Decentralized Simultaneous Localization And Mapping (DSLAM) for pedestrians in the context of Urban Search And Rescue (USAR). In this context, DSLAM is a challenging task. First, data exchange fails due to cut off communication links. Second, loop-closure is cumbersome due to the fact that fireman will intentionally try to avoid performing loops, when facing the reality of emergency response, e.g. while they are searching for victims.**

In this paper, we introduce a solution to this problem based on the non-selfish sharing of information between pedestrians for loop-closure. We introduce a novel DSLAM method which is based on data exchange and association via RFID technology, not requiring any radio communication. The approach has been evaluated within both outdoor and semi-indoor environments. The presented results show that sharing information between single pedestrians allows to optimize globally their individual paths, even if they are not able to communicate directly.

I. INTRODUCTION

Pedestrian navigation and localization is a growing field motivated from the context of Location Based Services (LBS) [14], navigation for the Blind [12], and emergency responder tracking [16]. Particularly in the field of emergency response, the efficiency of rescue teams, e.g. when performing the search for victims after a disaster, depends on their ability to coordinate and thus to be aware of their location. However, to be aware of locations during exploration within collapsed buildings is a challenging task. In urban environments GNSS (Global Navigation Satellite System) positioning is affected by the *multipath propagation* problem [6]. Buildings in the vicinity of the receiver reflect GNSS signals, resulting in secondary path propagations with longer propagation time, causing erroneous position estimates. Furthermore, communication might not be possible due to structures made of reinforced concrete, and the ability to re-observe landmarks might be affected by limited visibility due to smoke and fire.

One solution to this problem is to equip firemen with assistance systems, such as wearable devices [10], [16], performing Simultaneous Localization And Mapping (SLAM) without cognitive load, e.g. without requiring interactions by the user. SLAM methods work with the principle of map improvement through loop-closure, i.e. to improve the map globally each time places have been re-observed. However, when facing the reality of emergency response, fireman will try to intentionally avoid performing loops, e.g. while they are searching for victims.

In this paper, we introduce a solution to this problem based on non-selfish information sharing between pedestrians via the deployment of RFID technology. Hereby the pose of each pedestrian is automatically tracked by a PDR (Pedestrian Dead Reckoning) method, which recognizes human footsteps analytically from acceleration patterns. We introduce a centralized approach that improves the joint network of all trajectories by minimizing the Mahalanobis distance [15], while utilizing RFID transponders for data association [11]. Then, we extend this method towards a novel method for Decentralized SLAM (DSLAM) that allows to globally optimize the network in a decentralized manner by exchanging information via the memory of RFIDs. Hence, the method does not rely on direct radio communication.

We conducted extensive experiments within both outdoor and semi-indoor environments. Results from these experiments show that the introduced method allows to improve single trajectories significantly by exchanging data between the agents.

PDR methods have been extensively studied in the past. Human motion has been tracked by vision sensors [19], as well as based on the analysis of acceleration patterns [1], [4], [13], [7]. Furthermore, infrastructure-based localization has been studied, e.g. based on WLAN [5], and super-distributed RFID tag infrastructures [2], and also specifically in the context of emergency response [8], [16]. However, these methods are mainly designed from a single agent perspective, i.e. do not exploit the potential advantage of data sharing.

Efficient solutions for decentralized SLAM have been introduced in the past [18], [17], [9]. These approaches assume that at least low-bandwidth radio communication between the agents is possible. They solve the *double counting problem*, e.g. the multiple propagation of equal information via different paths, by probabilistic methods, such as Bounded Covariance Inflation (BCI) [18], and Covariance Intersection (CI) [17]. We show that this

problem can be solved also by managing estimates locally within the memory of RFIDs.

II. Pedestrian Dead reckoning (PDR)

Dead reckoning information from human walking is acquired after a method that has been introduced by Ladetto and his colleagues [13] [1]. Human walking generates a vertical acceleration with a maximum value if a foot is placed on the ground (see Figure 1). By detecting these maxima in the vertical acceleration curve within a fixed time interval, it is possible to detect and count the occurrence of footsteps. The method can be separated into three parts, which are step detection, step counting, and step direction detection.

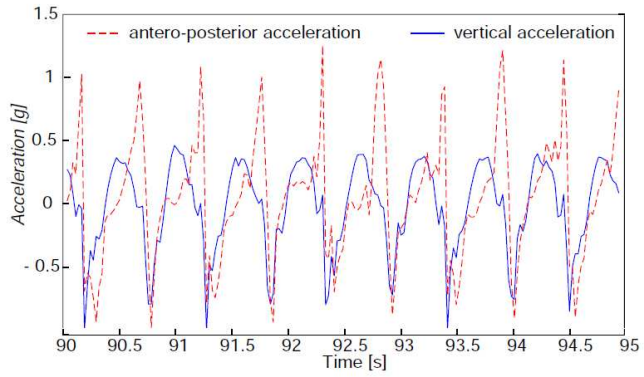

Fig. 1. Vertical (up-down), and antero-posterior (forward-backward) acceleration patterns recorded during human walking. Courtesy of Quentin Ladetto.

To detect the walking mode of a person, e.g. to distinguish between forward walking, lateral (sidewards) walking, and standing, is a challenging task due to the individual walking style of humans. Ladetto and his colleagues concluded that the mean variance over a short period of the vertical (up-down), and antero-posterior (forward-backward) acceleration correlates significantly with the walking mode and step frequency. The higher the frequency, the higher the variance. The occurrence of steps can thus be determined from the mean variance computed within a fixed time interval. Furthermore, a comparison between the mean variance of the antero-posterior acceleration and vertical acceleration allows to distinguish between lateral (sidewards) and forward movements. A lateral movement is detected, if the variance of the vertical acceleration is higher than the one of the antero-posterior, and vice versa.

To detect the frequency of steps, one has basically to count the maxima in the antero-posterior acceleration curve. Depending on the individual walking style of a person, a step might cause two peaks located closely to each other, originating from the impacts of the heel and the sole with the ground, respectively, whereas the heel impact normally shows the bigger amplitude.

[1]We utilized an implementation from Michael Dippold [3]

The traveled distance is computed by multiplying the frequency with the individual length of the person's steps. Since the step length greatly varies among different persons, we automatically calibrate this parameter from distances computed by GNSS positions, if they are available [13]. Furthermore, the direction of walking (forward-backward, left-right) is determined by computing the angles between the maxima and the two zero-crossings of the signal before and after the maxima, respectively. The direction estimate is coupled with an IMU (Inertial Measurement Unit) sensor, yielding the walking direction θ. Finally, we utilize an Extended Kalman Filter (EKF) for dead reckoning, yielding the pose estimate $(\hat{x}, \hat{y}, \hat{\theta})^T$ with covariance matrix Σ, from the successive integration of estimated distances $\hat{d}$ and orientations $\hat{\theta}$ with error variance $\sigma_{\hat{d}}^2$ and $\sigma_{\hat{\theta}}^2$, respectively.

III. CENTRALIZED RFID-SLAM

In centralized RIFD-SLAM we assume that pedestrians (e.g. firemen) are able to fully communicate with a central server (e.g. a command post). Furthermore, they track their pose by the PDR method described in Section II, while actively distributing and observing RFID tags in the environment. We assume that RFID detections are within a range of $< 1m$, which allows to cover corridors and doorways, while providing sufficient positioning accuracy. In the following, we will use the term "field agent", referring to the software agent executed on the pedestrian's mobile computer.

Each time a RFID has been observed, a message is generated that contains the ID of the previously visited RFID i and currently visited RFID j, as well as an estimate of the local displacement between both RFIDs. The noisy measurement of the local displacement between two nodes is denoted by $\hat{d}_{ij} = d_{ij} + \Delta d_{ij}$. It is assumed that the error Δd_{ij} is normally distributed and thus can be modeled by a Gaussian distribution with zero mean and 3×3 covariance matrix Σ_{ij}. The local displacement $\hat{d}_{ij}$ is defined by the vector $(\Delta\hat{x}_{ij}, \Delta\hat{y}_{ij}, \Delta\hat{\theta}_{ij})^T$, whereas $\Delta\hat{x}_{ij}$ and $\Delta\hat{y}_{ij}$ denote the relative spacial displacement, and $\hat{\theta}_{ij}$ the relative orientation change. Our goal is to compute a globally consistent map, i.e. to determine the true locations of the RFIDs from all observations communicated to the station. This map can then be communicated back to the field agents, allowing them to improve their individual trajectories.

We denote the true pose vectors of $n+1$ RFID nodes by $l_0, l_1, \ldots, l_n$, and the function calculating the true displacement $(\Delta x_{ij}, \Delta y_{ij}, \Delta\theta_{ij})^T$ between a pair of nodes (l_i, l_j) is denoted as measurement function d_{ij}. The central station incrementally builds a global graph from all displacement estimates communicated by the field agents, by utilizing the unique ID of RFIDs. The constructed graph $G = (V, E)$ consists of vertices V and edges E, where each vertex represents an RFID tag, and each edge $(V_i, V_j) \in E$ represents an estimate $\hat{d}_{ij}$ with covariance matrix Σ_{ij} between two RFID tags

associated with vertices V_i and V_j, respectively. The subgraphs from all field agents are unified in the following way: On the one hand, if the same vertex has been observed twice, a loop has been detected in the graph. A detected loop is modeled by a *pseudo* edge between the same RFID node with distance $\hat{d}_{ii}$ set to $(0, 0, \Delta\theta)^T$, whereas $\Delta\theta$ denotes the angle difference between the two pose estimates of the RFID. Furthermore, under the assumption that RFIDs are detected at 95% probability if they are within maximal reading range d_M, we model the according covariance matrix by:

$$\Sigma_{ii} = \begin{pmatrix} 36d_M^2 & 0 & 0 \\ 0 & 36d_M^2 & 0 \\ 0 & 0 & \sigma_\theta^2 \end{pmatrix}, \qquad (1)$$

whereas σ_θ^2 is the linearized variance of the angle, and $36d_M^2$ the variance of the normal distribution over the interval $[3d; 3d]$. On the other hand, if two or more field agents observe the same edge, i.e. their trajectory overlaps between two or more neighboring RFIDs, both observations are merged by an EKF.

Finally, the constructed graph, and thus the underlying map represented by RFID locations, is globally improved by minimizing the Mahalanobis distance [15]. Here, the goal is to find the true locations of the l_{ij} given the set of measurements $\hat{d}_{ij}$ and covariance matrices Σ_{ij}. This can be achieved after the maximum likelihood concept by minimizing the following Mahalanobis distance:

$$l = \arg\min_l \sum_{i,j} \left(d_{ij} - \hat{d}_{ij}\right)^T \Sigma_{ij}^{-1} \left(d_{ij} - \hat{d}_{ij}\right), \qquad (2)$$

where l denotes the concatenation of poses $l_0, l_1, \ldots, l_n$. Since measurements are taken relatively, it is assumed without loss of generality that $l_0 = 0$ and $l_1, \cdots, l_n$ are relative to l_0. Moreover, the graph is considered as fully connected, and if there does not exist a measurement between two nodes, the inverse covariance matrix Σ_{ij}^{-1} is set to zero. In order to solve the optimization problem analytically, Equation 2 can be transformed into matrix form [15]. Note that due to angle θ Equation 2 has to be linearized . The network of RFIDs can be optimized in $O\left(n^3\right)$, whereas n denotes the number of RFIDs.

Field agents improve their own trajectories by constructing a graph from their poses augmented with pseudo poses, which are generated from the positions of corrected RFIDs communicated by the station. A pseudo pose is added for each RFID that has been observed by the field agent. Furthermore, each pseudo pose k is connected with those poses i and j that were directly recorded before and after the RFID observation. Therefore, the angle of the pseudo pose is interpolated between θ_i and θ_j. The connecting pseudo edges $\hat{d}_{ik}$ and $\hat{d}_{jk}$ are modeled by $(0, 0, \Delta\hat{\theta}_{ik})^T$, and $(0, 0, \Delta\hat{\theta}_{jk})^T$, respectively, and covariances Σ_{ik} and Σ_{jk} are modeled after Equation 1, reflecting the position uncertainty in RFID detection. Finally, the augment graph is corrected with the same procedure as described above, whereas the pseudo poses force an adjustment of the trajectory towards the added constraints.

IV. DECENTRALIZED RFID-SLAM (DRFID-SLAM)

In the context of emergency response it might happen that communication to a central station or between the agents is not possible at all. One obvious reason is that within building structures radio waves might not be able to penetrate walls made of reinforced concrete. Otherwise, it might also be likely that first responders, which search for victims on a large terrain, are simply out of communication range. Moreover, they might visit the same locations at different times, and thus also not be able to communicate. Therefore, we assume in Decentralized RIFD-SLAM (DRFID-SLAM) that communication is not possible at all. Note that this assumption is hard, compared to other approaches that require at least low-bandwidth communication channels between the agents [18], [17], [9]. Furthermore, we assume that RFIDs have sufficient memory for storing RFID graph structures as described in Section III.

The basic idea is to utilize the memory of RFID tags for learning the topology of the RFID graph. When agents pass a tag, they update their knowledge on the graph by reading data from the tag, as well as synchronize the tag by writing data they have collected so far. By this, agents are able to learn a subgraph larger than their own trajectory, i.e. extended by trajectories of other agents. The union with other trajectories might lead to subgraphs that contain loops, hence, allowing agents to correct their own trajectories.

The procedure can be considered as a step wise information propagation through the network of RFIDs, whereas each RFID that has been visited, learns about nearby RFID nodes from the trajectory of the visitor, as well as from trajectories that were previously stored by other agents in those nodes. Therefore, after a sufficient amount of trajectories has been traveled, a single RFID node memorizes the complete infrastructure of RFIDs. Note that also a subgraph of RFIDs, particularly if it contains cycles, might support the improvement of a trajectory.

One problem arising in the context of distributed SLAM is the double counting of information propagated via different paths, i.e. rumor propagation. While this problem typically requires to apply probabilistic methods, such as Bounded Covariance Inflation (BCI) [18], and Covariance Intersection (CI) [17], it can be solved rather trivially with RFIDs. Here the basic idea is to manage displacement estimates locally within their memory.

We distinguish edges as *managed* and *propagated* within the memory of RFIDs and introduce a counter C_i attached to each RFID, which is locally updated each time an agent writes information concerning a managed edge. Edges that are managed by node i are all the

adjacent edges that have i in common, i.e. those edges that directly connect to i. Consider the case that an agent travels from RFID i to RFID j and generates thereby a new estimate $\hat{d}_{ij}, \Sigma_{ij}$. Then, RFID j is the managing node, i.e. manages the edge between i and j. Consequently, the agent stores in RFID j a new entry $e_{ij} = \left\langle i, j, \hat{d}_{ij}, \Sigma_{ij}, C_i \right\rangle$, consisting of the IDs of the two visited RFIDs i and j, their displacement estimate, and the current count value of the RFID, which is incremented after writing. Obviously, there can be two nodes managing the same edge since agents can either travel from i to j or from j to i. Therefore, we have to distinguish both cases during propagation, which is carried out by defining that $\langle i, j, \cdots \rangle \neq \langle j, i, \cdots \rangle$, i.e. the managing mode corresponds to the second node in the sequence.

Propagated edges are managed edges after they have been copied by agents. If visiting a node, the agent performs a union operation between all entries stored in the memory of the RFID, denoted by subgraph R_i, and its own subgraph, denoted by A_i, and propagates them further to other RFIDs. The double counting of identical estimates is prevented by ensuring that there always exists only one unique entry for each combination of i, j, and c and unique sequence $< i, j >$ within each RFID. The complete procedure for updating RFID nodes is shown by Algorithm 1. Note that the agent updates its own subgraph A_i by the same procedure, while considering propagated edges only.

Algorithm 1: Updating the subgraph R_k of visited RFID k

Input: New entry e_{ik}, a set of subgraphs $S = \{R_j : j \in P\}$, whereas P denotes the RFID trajectory of the agent
Output: Updated subgraph R_k

Update managed edges:
$R_k \leftarrow R_k \cup \left\langle i, k, \hat{d}_{ik}, \Sigma_{ik}, C_k \right\rangle$;
$C_k \leftarrow C_k + 1$;

Update propagated edges:
foreach $R_j \in S$ **do**
  foreach $e \in R_j$ **do**
    if $e \in R_k$ **then**
      continue ;
    $R_k \leftarrow R_k \cup e$;
  end
end

V. EXPERIMENTAL RESULTS

We conducted extensive experiments within both semi-indoor and outdoor scenarios, while obtaining ground truth data from a GNSS (Global Navigation Satellite System) device for each RFID location. For this purpose, we utilized the *GPSlim236* GPS receiver from *Holux*, which is equipped with *SiRF Star III* technology. The receiver allows to track up to 20 satellites at an update rate of $1Hz$ and has a position accuracy of $5 - 25$ meters without DGPS. Furthermore, the receiver is able to process data from the *EGNOS* system [2], improving the horizontal position accuracy towards < 2.2 meters and vertical position accuracy towards < 5 meters at 95% of the time. Note that we were able to also obtain ground truth within semi-indoor scenarios since RFIDs where intentionally placed outdoors.

For the purpose of pedestrian dead-reckoning we utilized the *MTi* IMU (Inertial Measurement Unit) from *Xsens*, which combines a tri-axial accelerometer and a tri-axial gyroscope with a tri-axial magnetometer. Due to the simultaneous integration of gyro and compass data, the device provides a drift-free orientation vector that is stable towards minor perturbations caused by external magnetic sources. The device has been attached to a test person for measuring the vertical and lateral acceleration, as well as the azimuth orientation (see the orange box in Figure 2). Based on an empirical evaluation, we modeled pose tracking uncertainty with $\sigma^2_{\hat{d}} = (0.05m)^2 d$, and $\sigma^2_{\hat{\theta}} = (15^\circ)^2$.

Fig. 2. Experimental setup: Test person (the second author) with *Xsens MTi* and *Holux* GPS device for obtaining ground truth data.

Without loss of generality we simulated the RFID sensor by manually marking places with numbered labels that are re-observable by the test person. Each time the test person deployed a new label, or was within range of a label that has been deployed before, the RFID observation has been logged to a data base, whereas each entry in the data base consisted of a time stamp and the identification of the observed RFID. We measured that re-observations take place within an error of maximally ± 1.0 meter. Hence, the covariance matrix in Equation 1 has been modeled with $d = 1$.

A. Semi-Indoor Experiment

The semi-indoor experiment has been carried out on the campus of the University of Freiburg, including many accessible buildings which have been entered by the test person. We measured that some of these buildings contain magnetic fields disturbing the angle estimate of the

[2]EGNOS stands for European Geostationary Navigation Overlay Service and provides Differential GPS (DGPS) vi satellites that broadcast correction signals on the same frequency as GNSS satellites.

PDR method, as for example, metal stairs or metal doors, such as shown in Figure 2. Figure 3 provides an overview of the area, which has been generated by *GoogleEarth*. During this experiment, the test person traveled six trajectories with different starting and ending locations, while performing pose tracking with the PDR method previously described, and while distributing and re-observing RFIDs. In order to visualize the PDR trajectories, we utilized the accurate starting locations taken from the ground truth data and projected each PDR trajectory with respect to its starting location on the map. In Figure 3 each trajectory is shown with a different color. As can be seen, position accuracy decreases with increasing length of the traveled trajectory.

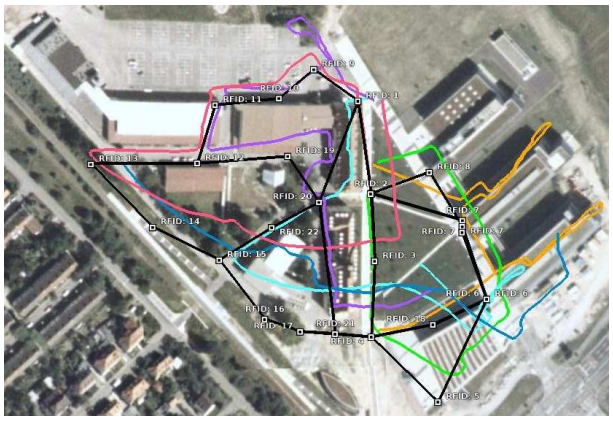

Fig. 3. Result from the semi-indoor experiment: Each line indicates the pose tracking of the trajectory of a single pedestrian. Black lines and squares show the corrected graph of RFIDs.

All trajectories have been collected and merged into a single graph for applying the centralized method described in Section III. The corrected edges between RFIDs are shown by the black lines in Figure 3, as well as the corrected locations of the RFIDs (small squares). Furthermore, we computed the average Cartesian error with respect to ground truth. Figure 4 depicts these errors according to each pedestrian. It shows the uncorrected trajectory, the single trajectory corrected on its own, and the trajectory corrected from the unified graph. As can be seen, the correction based on the unified graph yields best results for each pedestrian.

B. Outdoor Experiment

The outdoor experiment has been carried out within a larger area of approximately $1000m^2$ around a lake. This area contained both residential buildings and wide open spaces. Analogous to the semi-indoor experiment, Figure 5 provides an overview of the surroundings, showing eight independent trajectories, as well as the corrected graph of RFIDs, which has also been computed from the centrally merged trajectories. We also computed the average Cartesian error with respect to ground truth, shown in Figure 6. As can be also seen here, the correction based on the unified graph yields best results for each pedestrian.

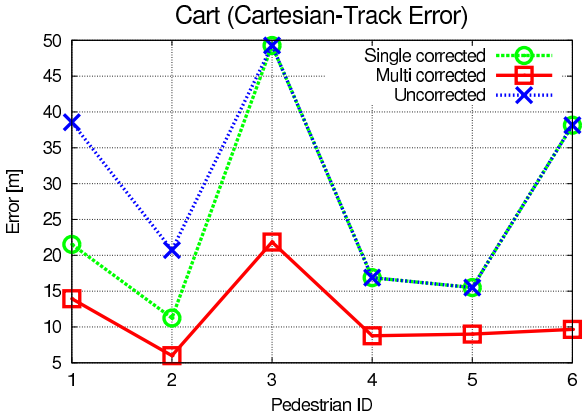

Fig. 4. Result from the semi-indoor experiment: the average Cartesian error.

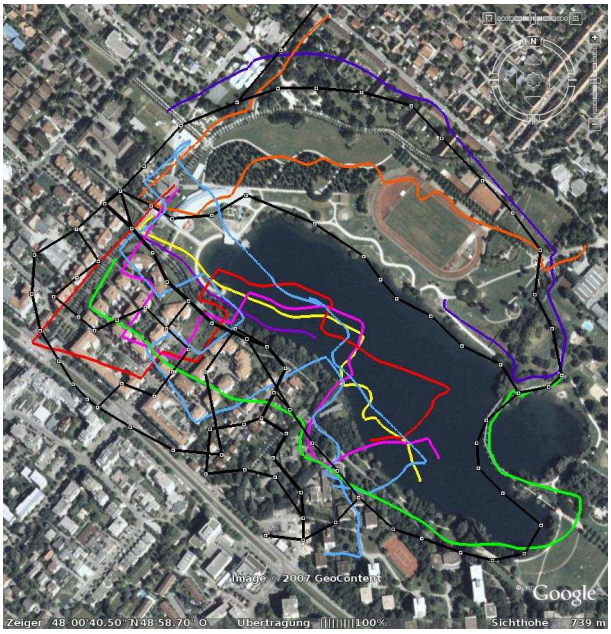

Fig. 5. Result from the outdoor experiment: Each line indicates the pose tracking of the trajectory of a single pedestrian. Black lines and squares show the corrected graph of RFIDs.

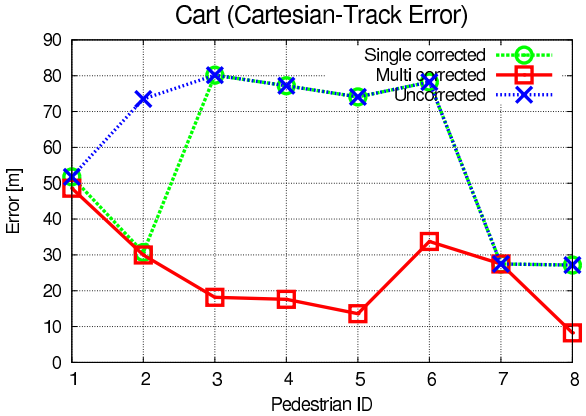

Fig. 6. Result from the outdoor experiment: the average Cartesian error.

C. Decentralized SLAM Experiment

The last experiment has been conducted in order to evaluate the DRFID SLAM approach. This has been carried out by simulating the incremental execution of three trajectories taken from the outdoor experiment previously described. After the execution of each trajectory, the according subgraph collected by the agent and the subgraphs learned by the RFIDs has been computed. Therefore, the first pedestrian had no advantage at all, the second pedestrian benefited from data propagated into RFIDs by the first, and the third benefited from data propagated by the first and the second. Note that subgraphs stored in RFIDs do not necessarily consist of the complete trajectories from all visiting agents. They contain information from all nodes that the visiting agent has seen before synchronizing the data. Figure 7 depicts the average Cartesian error after correcting the trajectory of each pedestrian based on the subgraph generated from the union of data from all visited RFIDs. As can be seen from the figure, the more pedestrians have traveled through the environment beforehand, the better the pose estimate of a single pedestrian can be improved. Hence, the third pedestrian achieved a 2.96 times higher pose accuracy by exploiting loops that have been closed due to joining subgraphs from other pedestrians.

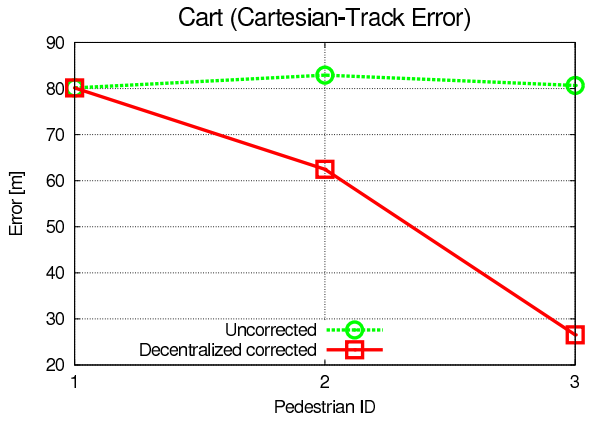

Fig. 7. Result from the decentralized experiment: The average Cartesian error.

VI. CONCLUSIONS AND FUTURE WORKS

We introduced a novel method for distributed SLAM by exploiting the advantages of RFID technology. The result shows that sharing information between single pedestrians allows to optimize globally their individual paths, even if they are not able to communicate directly. Obviously, this can be accelerated if subgraphs are additionally communicated via radio between agents directly. Moreover, the introduced method allows to apply SLAM without requiring pedestrians to intentionally loop, which is a necessary requirement if applying SLAM in the real-world, particularly when humans are involved.

In future work we will investigate the approach within purely indoor environments while utilizing real RFIDs. Furthermore, we will aim on reducing the number of required RFIDs by utilizing active transponders that can be detected within distances of up to 5 meters, while allowing to estimate their distance and bearing.

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