Optimizing indoor PDR performance with self-deployed position markers

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Abstract. Infrastructureless positioning systems such as pedestrian dead reckoning suffer from error accumulation. This paper describes the application of a technique using self-deployed localization tokens and simultaneous localization and mapping to overcome this limitation. We successfully applied the technique known from mobile robotics to pedestrian self-localization based on pedestrian dead reckoning and present some preliminary findings.

1 Introduction

Self-localization of wearable computers and their wearers is a difficult problem that has been extensively studied in the past. Reliable self-localization is often a requirement for context-awareness but may also be an application requirement, e.g., in urban search and rescue applications.

In general, two approaches to localization can be distinguished: localization based on external infrastructure and localization purely based on local sensors. Infrastructure-based systems range from systems covering tabletops such as optical[1] to systems like GPS that span the globe. Infrastructure-based systems rely on the fact that the infrastructure can observe the location of the system to be localized or the system can observe the locations of infrastructure devices, e.g., a GPS receiver can observe the distances to the satellites of the GPS infrastructure and with the known positions of these satellites, it can calculate its own position. Inaccuracies in the observation lead to inaccuracies in the position calculated, but as every observation is independent of other observations, errors do not accumulate, e.g. over time. In contrast to this, systems based on local sensors estimate the current position based on previous positions and the observation of the sensor values, e.g., by sensing the relative motion of the system through acceleration sensors, wheel encoders or cameras. Inaccuracies in these observations thus lead to the accumulation of a positioning error.

1.1 Pedestrian Dead Reckoning for localization

Dead reckoning is a relative navigation technique that is based on the observation of the ego-motion of an object. By recording direction and distance of movement, one can estimate the current position by adding these motion vectors to a given start position. The observation of the displacement is implemented by using sensors such as odometers and compass sensors and dead reckoning is a standard technique for ships, planes and land vehicles including wheeled mobile robots. One class of sensors that is often used for dead reckoning are IMUs, i.e., Inertial Measurement Units. These devices can measure linear and angular acceleration and are often combined with a compass sensor. For instance, by applying double integration to the linear acceleration measured, one can infer a displacement distance. However, the mobile low-power IMUs that can be used on mobile devices give quite noisy signals, so a simple approach using pure double integration leads to insufficient results for localization. PDR is a dead reckoning method that tracks the motion of a pedestrian by observing the length and direction of each step. This can be implemented using several techniques, such as time-of-flight distance measurement [2]. By considering the biomechanical properties of the human body, one can also use the sensors of an IMU to detect steps and infer length and distance. There are several existing implementations of this technique and these mostly differ in the way the step length is inferred. Ladetto derives the step length from the step frequency by observing biomechanical energy optimizations of the human gait [3]. Dippold also derives the the step length from the step frequency but uses a table of observed step length/frequency pairs during the presence of good GPS fixes and constant walking speeds [4]. Beauregard uses an artificial neural network for step length prediction based on features of the IMU sensor signals [5].

Common to all these solutions is a compass that is used in conjunction with the angular acceleration sensors to obtain a global orientation reference and to avoid the accumulation of orientation errors. But in an indoor environment, a compass is affected by local magnetic fields that cause a perturbation of the earth magnetic field, for example produced by ferromagnetic building materials such as steel.

The navigation accuracy of PDR can be optimized, but as with every technique based on dead reckoning, the general problem of the accumulation of position errors remains unsolved. The problem has been intensively studied in robotics, a good overview over the state of the art can be found in the paper by Thrun [6]. One proposed solution for this is the use infrastructure independent external references, i.e., landmarks to compensate for the errors accumulated between landmarks, thus simultaneously localizing the robot and producing a map of the landmarks (Simultaneous Localization and Mapping or SLAM). One possible implementation are self-deployed reference points. An example of using self-deployed reference points for robot self-localization can be found in [7].

As it has been demonstrated in robotics, it is feasible to improve the dead-reckoning-based self-localization by using self-deployed reference points, provided that the robot revisits a sufficient amount of these points and that the errors accumulated by the dead-reckoning system of the robot are small enough. In our experiments, we want to verify if a similar approach can be used to improve pedestrian dead-reckoning. The following section illustrates this approach.

2 RFID Technology-based SLAM

RFID tags have a world-wide unique number encoded and thus provide an elegant way to mark places with bounded uncertainty in perception. The basic idea of the proposed approach is to actively distributing these tags in the environment, i.e. placing them on a door frame and to measure the relative distances between them. From the correspondences of recognized RFID tags and the measured distances from the Pedestrian's trajectory, a globally consistent map is calculated according to the method introduced by Lu and Milios [8]. This method can be illustrated by considering the analogy to a spring-mass system (see Figure 1. Consider the locations of RFIDs as masses and the measured distances between them as springs, whereas the uncertainty of a measurement corresponds to the hardness of the spring. Then, finding a globally consistent map is equivalent to finding an arrangement of the masses that requires minimal energy.

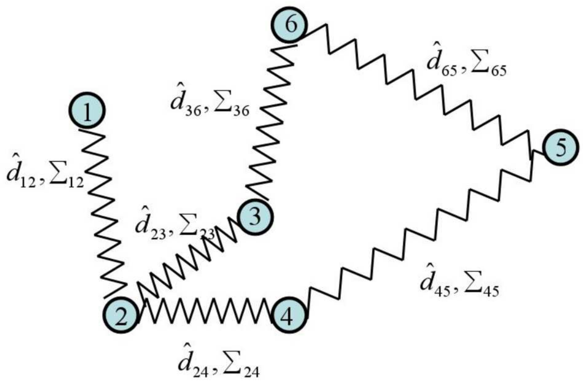

Fig. 1. RFID technology-based SLAM: A graph generated from RFID detections (vertices) and measured distance and covariance (edges) between them.

The proposed method builds successively a graph $G = (V, E)$ consisting of vertices V and edges E, where each vertex represents an RFID tag, and each edge $(V_i, V_j) \in E$ represents a measurement $\hat{d}_{ij}$ of the relative displacement $(\Delta x, \Delta y, \Delta\theta)^T$ with covariance matrix $\Sigma_{(\Delta x, \Delta y, \Delta\theta)}$ between the two RFID tags associated with the two vertices V_i and V_j, respectively. The relative displacement between two tags is estimated by a Kalman filter. If the pedestrian passes a tag, the Kalman Filter is reseted in order to estimate the *relative* distance $\hat{d}_{ij}$ to the subsequent tag on the pedestrian's trajectory.

We denote the true pose vectors of $n + 1$ RFID nodes with $x_0, x_1, \ldots, x_n$, and the function calculating the true distance between a pair of nodes (x_i, x_j) as measurement function d_{ij}. The noisy measurement of the distance between two nodes (x_i, x_j) is denoted by $\hat{d}_{ij} = d_{ij} + \Delta d_{ij}$. We assume that the error Δd_{ij} is normally distributed and thus can be modeled by a Gaussian distribution with zero mean and covariance matrix Σ_{ij}.

Our goal is to find the true locations of the x_{ij} given the set of measurements $\hat{d}_{ij}$ and covariance matrices Σ_{ij}. This can be achieved with the maximum likelihood concept by minimizing the following Mahalanobis-distance:

$$\mathbf{x} = \arg\min_{\mathbf{x}} \sum_{i,j} (d_{ij} - \hat{d}_{ij})^T \Sigma_{ij}^{-1} (d_{ij} - \hat{d}_{ij}), \tag{1}$$

where $\mathbf{x}$ denotes the concatenation of poses $x_0, x_1, \ldots, x_n$. Moreover, we consider the graph as fully connected and if there is exists no measurement between two nodes, the inverse covariance matrix Σ_{ij}^{-1} is set to zero.

If the pedestrian's orientation is sufficiently accurate measured, we do not need to consider the orientation θ within the d_{ij} and the optimization problem can be solved linearly by inserting $d_{ij} = x_i - x_j$ in Equation 1:

$$\mathbf{x} = \arg\min_{\mathbf{x}} \sum_{i,j} (x_i - x_j - \hat{d}_{ij})^T \Sigma_{ij}^{-1} (x_i - x_j - \hat{d}_{ij}), \tag{2}$$

Since measurements are taken relatively, we assume without loss of generality that $x_0 = 0$ and $x_1, \cdots, x_n$ are relative to x_0. In order to solve the minimization problem analytically, Equation 2 can be rewritten in matrix form:

$$\mathbf{x} = \arg\min_{\mathbf{x}} (\hat{\mathbf{d}} - \mathbf{hx})^T \mathbf{\Sigma}^{-1} (\hat{\mathbf{d}} - \mathbf{hx}), \tag{3}$$

where $\mathbf{hx}$ denotes the measurement function in matrix form with $\mathbf{h}$ as an index function whose elements are $\{1, -1, 0\}$ and $\mathbf{x}$ as the concatenation of pose vectors. Furthermore, $\hat{\mathbf{d}}$ denotes the concatenation of observations $\hat{d}_{ij}$, and $\mathbf{\Sigma}^{-1}$ the inverse covariance matrix of $\hat{d}_{ij}$, consisting of the inverse sub-matrices Σ_{ij}. Finally, the minimization problem can be solved by:

$$\mathbf{x} = (\mathbf{h}^T \mathbf{\Sigma}^{-1} \mathbf{h})^{-1} \mathbf{h}^T \mathbf{\Sigma}^{-1} \hat{\mathbf{d}} \,. \tag{4}$$

and covariance of $\mathbf{x}$ be calculated by:

$$\mathbf{c_x} = (\mathbf{h}^T \mathbf{\Sigma}^{-1} \mathbf{h})^{-1} \tag{5}$$

Equation 4 can be solved in $O\left(n^3\right)$ if the covariances Σ_{ij} are invertible. In practice, we assume that measurements are independent from each other, consequently the Σ_{ij} are given as diagonal matrices. Moreover, since many nodes in the graph are unconnected, most Σ_{ij}^{-1} are set to zero. Therefore, $\mathbf{\Sigma}$ is a sparse matrix and can generally be efficiently inverted.

Lu and Milios show that Equation 4 can also be utilized for the correction of angles by linearizing the measurement equation d_{ij} with a Taylor expansion [8]. Since the linearization leads to errors, the procedure has to be applied iteratively. However, we noticed during our practical experiments that five to six iterations are sufficient.

3 Experimental Setup

In order to verify the general feasibility of our approach, we conducted a preliminary experiment.

For this, we equipped a test person with a PDR-based localization system, a GPS-based localization system and a RFID reader device.

The PDR-based localization system was the one implemented by Dippold [9]. The system was previously trained to the test person with activated GPS and the resulting step-speed step-length table was saved. For the experiment, the GPS support was then deactivated so that the system acted as a pure PDR system, but used the learned data to calculate the step length. The IMU sensor used was an XSENS MTi.

The GPS-based localization system used a commodity SIRFstar III GPS receiver with bluetooth connection to the host. The RFID reader device is a GestureWrist, a wearable input device based on the SCIPIO Platform [10]. In order to scan a tag, the reader has to be in about 5cm range to the tag.

The experiment was conducted outdoors in order to use the GPS-based localization as ground truth information. The person walked a test parcours. During the walk, the person deployed and then scanned RFID tags, approximately every 10 meters of way in no particular order. Whenever the person passed the site of an already-deployed RFID tag, he scanned the tag. The parcours was chosen so that it contained a number of "‘loops"’, i.e., parts of the parcours were visited several times. The result of the experiment were three files containing data timestamped with the system clock of the wearable computer used. The first file contains the timestamped localization information based on PDR, the second file contains timestamped localization information based on GPS fixes, the third one timestamped RFID scans. Figure2 shows a google earth view of the parcours with an overlay of the GPS localization data. Figure3 shows a plot of the recorded PDR localization, clearly showing the accumulation of localization errors.

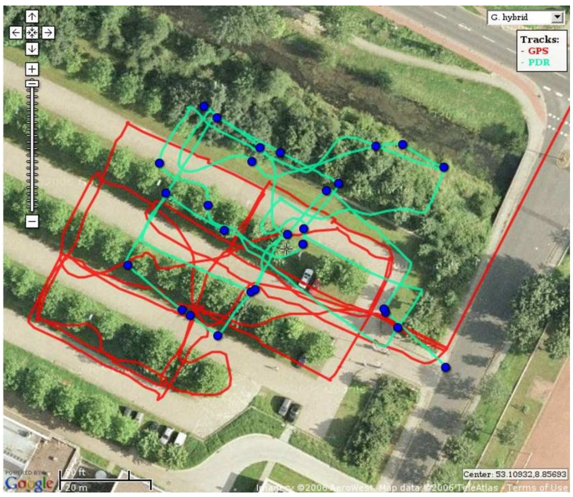

Fig. 2. Google Earth view of the parcours with an overlay of the GPS localization data (red), the PDR track (green) and the RFID tags (blue)

In further processing, the timestamped RFID file and the timestamped PDR position file were used to create the input for the RFID-based SLAM algorithm by identifying the PDR position corresponding to a RFID tag scan. The PDR trajectory section between two RFID scans was then converted into a displacement as input for the algorithm. The algorithm calculates a new optimized displacement that produces an affine transformation when related to the original displacement calculated. This transformation is then applied to the original PDR trajectory section, producing a new optimized trajectory.

4 Results and Analysis

In the experiment, start and end point of the analyzed trajectory were the same. Figure 3 shows a comparison between the original and the optimized trajectory. In the original trajectory, the start and end points are far apart, indicating the accumulated error.In the optimized trajectory, the start and end points overlap. In the original trajectory, parts of the parcours that are close and parallel in reality show up turned and displaced. In the optimized trajectory, these parts of the parcours are parallel and close to each other.

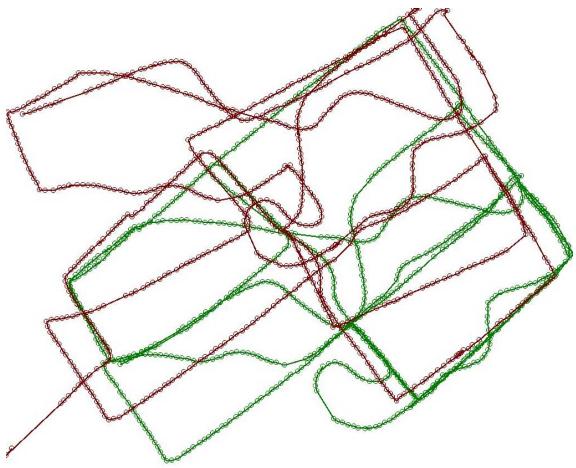

Fig. 3. A plot of the original PDR trajectory (red) and the optimized one (green) produced by our approach.

The data presented in this paper are the results of a single experiment with a single test person, therefore we will not present a numerical evaluation of our results but discuss them in a qualitative manner. The results are an indication that the RFID-based SLAM approach can indeed be applied to pedestrian dead reckoning. The quality of the localization observed in our experiment is comparable to the one obtainable by consumer-grade GPS receivers. Provided that there is sufficient trajectory data with re-visited RFID tags, the algorithm proposed can produce an optimized trajectory.

The task of deploying and scanning the RFID tags was left to the user in our experiment. The deployment of an RFID tag took about 10 seconds each and consisted of placing the tag and then scanning it with the wrist-mounted scanner. In our experiment, the tags were put on the ground. Scanning an already deployed tag also took about 10 seconds as the test person hat to visually locate the tag and then scan it. Altough the deployment and re-scanning is a rather simple task, it slowed down the test person considerably which might limit the manual deployment of tags to non time-critical applications. Finding the tags on the ground also was considered tedious by the test person and required some concentration on the task, so it might have an impact on the primary task of the user.

5 Discussion and future work

We have demonstrated that RFID-based simultaneous localization and mapping can be applied to trajectory data produced by pedestrian dead reckoning. Our preliminary results indicate that the quality of the localization produced is a significant improvement to the localization quality produced by pure PDR approaches. However, a number of important questions remain open. First, the single experiment conducted so far has not produced sufficient data to evaluate the approach quantitatively, thus more experiments are needed. Second, it is necessary to vary a number of parameters in the setup, especially the number of re-visited tags, the length of the trajectory between tags and the experiment has to be conducted with a number of different persons. Third, it remains to be seen if the deployment and scanning of RFID tags can be successfully integrated into the application environment without impeding the user's primary tasks.

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