Successive Collaborative SLAM for Professional Use Cases: Map Learning Aspects

Susanna Kaiser[1] [0000-0003-3210-6259]

[1] Institute for Communications and Navigation, German Aerospace Center (DLR), Oberpfaffenhofen, Germany
susanna.kaiser@dlr.de

Abstract. Pedestrian navigation solely based on inertial measurement units in indoor environments is challenging if there is no signal of opportunity that can be exploited. In collaborative simultaneous localization and mapping (collaborative SLAM) the learned maps of several users can be combined in order to help indoor positioning. In this paper, we investigate the combination of the maps of several pedestrians and analyze the resulting position accuracy and the map. Depending on the number of users, on the sensor drifts, and on the amount of revisited area the degree of convergence of the maps varies. This paper provides a discussion about the map learning aspects and the advantages of successive collaborative mapping when there is no loop closure. The results show that even without loop closures the position error can be reduced to ~ 0.5m when applying successive collaborative mapping.

Keywords: pedestrian navigation, indoor navigation, simultaneous localization and mapping (SLAM), collaborative mapping, collaborative SLAM.

1 Introduction

For professional use cases like firefighter rescuing and policemen supervision, which are mainly addressed in this paper without excluding other scenarios, it is desirable to know the positions of the emergency personnel. For instance, in the case of a hostage-taken, an amok act, or a terror attack it would be very helpful for the head of the police personnel to know the exact positions of the team members. In such scenarios an infrastructure-less, ad-hoc applicable indoor navigation solution is preferable due to the fact that infrastructure might be disturbed or even not available.

In an indoor pedestrian navigation scenario, where no signals of opportunity like Wireless Fidelity (WiFi), radio frequency identification (RFID), iBeacons or ultra-wideband (UWB) are available and cannot quickly be installed, pedestrian navigation solely based on inertial sensors is still challenging due to the remaining drift inherently resulting from the integration of the inertial sensor measurement errors. For professional use cases like fire fighter rescuing and policemen supervision it is demanded to obtain a unique solution based on techniques that are not dependent on any infrastructure and which are able to provide accurate positioning in any case. For this reason we propose to apply collaborative mapping.

In emergency situations inside buildings, usually the rescue personnel arrive by professional vehicles and several emergency forces enter the building. In addition, for instance in the special case of a serious crime, special police forces enter the building in groups of 6-8 persons in a star or triangle formation. Here, collaborative mapping comes into play. The aim of this paper is to investigate collaborative mapping solely based on inertial data resulting from pedestrians (or rescue personnel) that are entering an unknown building. The main focus of the paper is the map learning process: When entering a building usually long paths are followed before a loop closure occurs or area is revisited. Without loop-closures, the position accuracy is usually poor. We investigate methods based on collaborative mapping to ensure good position accuracy when pedestrians commonly enter a building.

The paper is organized as follows: A review of the state of the art of collaborative mapping is given in Section 2. The overall system is shortly introduced in Section 3, where the collaborative, multi-user SLAM and the new option for successive collaborative mapping are described. Different experiments are conducted in Section 4. Finally, Section 5 is devoted to conclusions and provides an overview of future work.

2 Collaborative Mapping: State of the Art

Different solutions for collaborative SLAM can be found in the literature. Depending on the sensors used and on the application these techniques vary. With the development of SLAM [1], the possibility of merging the maps from multi-robots/agents is a straightforward continuation but it is not yet fully investigated. Five different multi-robot SLAM solutions are presented and partly compared in [2]. A more comprehensive review on multi-robot SLAM can be found in [3], where different SLAM solutions are presented and the problems of multiple-robot SLAM are worked out including communication, map representation and map merging. In the area of localization based on visual sensors a first collaborative SLAM with multiple cameras moving independently in a dynamic environment was developed in [4]. In [5] the visual SLAM is extended with inertial data and the author investigated a client-server structure for collaborative SLAM with monocular data as well as with visual-inertial data.

Collaborative SLAM can also be realized as a decentralized system. In [6] a decentralized system was proposed where an EKF-SLAM algorithm using different kinds of sensors such as inertial, GPS, vision and radar/laser sensors is applied for unmanned flight vehicles. In [7] a decentralized SLAM for pedestrians using PDR and RFID techniques is proposed, where the RFID memory is exploited for exchanging information.

A general survey on the current state and different aspects of SLAM techniques including collaborative SLAM and the future directions of SLAM is given in [8]. In this paper, we investigate a collaborative SLAM technique called FeetSLAM [9] [10] that is especially designed for pedestrians in a GNSS denied, infrastructure-less area and that is additionally very useful for emergency forces. It is capable to determine the pedestrian’s position inside buildings solely based on body worn IMU data leaving open the possibility for applying other sensor data.

3 Overview of the System

3.1 Collaborative Mapping: FeetSLAM

In the collaborative FeetSLAM algorithm, the individual trajectories/positions of several pedestrians/forces are combined [9] [10], where the inputs to the SLAM are the delta step and heading outputs from a previous PDR [11]. The collaborative FeetSLAM algorithm is based on the so called FootSLAM algorithm [12], where a map of walkable areas is estimated during the walk. The estimated map of the FootSLAM algorithm is based on a hexagonal grid, where each edge of a hexagon represents a transition counter. In collaborative FeetSLAM several FootSLAM maps of different pedestrians are combined iteratively.

In the first iteration FeetSLAM calculates the individual maps of each data set representing a trajectory of a pedestrian. They can be combined with either a geometric transformation [9] [10] or a Hugh transform [13]. The merged posterior maps are then used for the next iteration as prior maps. The starting conditions are transformed in the same way as the respective posterior map. This process is repeated until a good estimation is found (in [10] it has been shown that the crossed wall ratio doesn't change much after 10 iterations). It should be noted that the merged map for a specific data set, which is used in the next iteration as prior map for this data set, is the combination of the resulting posterior maps of every data set except the specific data set. This is done because the prior maps contain then the information of the rest of the data sets excluding intentionally the map of the specific data set.

3.2 Successive Collaborative Mapping

In an emergency scenario, the map of the environment is usually unknown. The emergency forces will enter the building either separately or in groups as it is the case with special police forces and there will be no loop closures at the beginning. In order to reduce the drift when there are no loop closures, FeetSLAM is performed in a successive way. In contrast to previous work on FeetSLAM, where the converged maps of whole datasets are combined, we apply FeetSLAM successively after short times or distances and investigate the map learning process. The advantage of this procedure is that the drift can directly be corrected because the information of several sensors is used from the beginning on and it can be exploited that the drift after a short distance is less than the drift after a long distance. In a similar way a single pedestrian could be equipped with several sensors and the trajectories of the sensors could be combined applying successive FeetSLAM in order to obtain a better positioning.

Fig. 1 shows the schematic illustration of successive collaborative FeetSLAM. The inputs to the FeetSLAM algorithm are the n data sets, the FootSLAM specific input parameters like starting conditions, and a prior map, if available. FeetSLAM is repeated for data sets ending at predefined times of a set of m end times $\{t_1, \dots, t_m\}$, where $t_j > t_{j-1}$. The last member of the set is the maximum duration of the data sets t_{max}. FeetSLAM itself is performed iteratively, where at each iteration i FootSLAM is applied on each of the n data sets ending at t_j and the resulting posterior maps $(M^i_{1_{t_j}}, \dots, M^i_{n_{t_j}})$ are combined to prior maps $M^i_{p_{k_{t_j}}}, k = 1 \dots n$ (excluding the map of the respective specific data set in the combination process) for the next iteration. The maximum number of iterations in FeetSLAM is i_{max}.

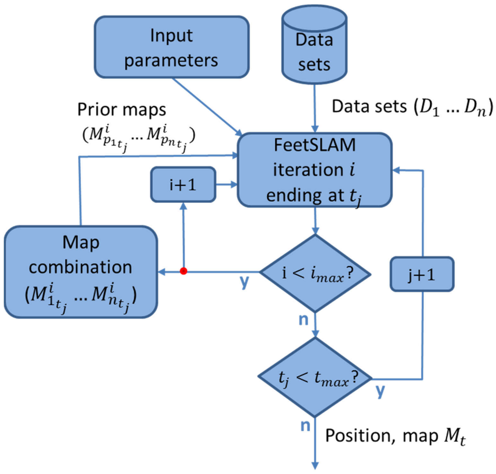

Fig. 1. Schematic illustration of successive collaborative FeetSLAM

In contrast to the original FeetSLAM procedure, we omit the transformation part and apply the combined estimated maps directly as prior maps without any map transformation. Despite the assumption that the maps are rotational invariant in FootSLAM, in this paper we assume that the initial directions are known from the starting conditions and that the PDR actually provides an estimation of the following directions. The variance of the starting angle is set to a relative small value (1°) for assuming a high confidence on the starting direction, but leaving space for diversity. The main advantage of this approach is the reduced complexity due to the omitted map transformation computation which facilitates real time operation more probably.

4 FeetSLAM Experiments

Experimental Settings. Inside our office building at DLR, Oberpfaffenhofen, second floor, two pedestrians collected a total of 6 data sets $\{D_1, \dots, D_6\}$, respectively. In $\{D_1, \dots, D_4\}$ the pedestrian mounted the IMU XSENS MTx strapped to the instep of their right foot whereas in $\{D_5, D_6\}$ the XSENS MTw instead of the MTX was mounted at the same location. The numbers of particles used in the Particle Filter of the FootSLAM algorithm is $N_p = 10000$. The hexagon radius is r=0.5m. The output of FootSLAM are the best particles positions and the estimated posterior maps denoted as $\{M_1, \dots, M_6\}$. In data sets $\{D_1, \dots, D_4\}$ the pedestrian started from the starting point (green dot, $(x, y) = (0,0)$, see Fig. 2). After that the pedestrian went to GTP2 (orange dot) and through the corridor of the 2nd floor until he reached the end of the floor (blue dot, GTP3). In data sets $\{\mathrm{D}_1, \ldots, \mathrm{D}_4\}$ he entered additionally a room. At every GTP he stopped about 3 seconds for getting the time of the GTP crosses. In data sets $\{\mathrm{D}_1, \ldots, \mathrm{D}_4\}$ additionally to the mentioned GTPs several GTPs between them are crossed. These 6 data sets together can be viewed as the trajectories of a group of 6 persons (or emergency forces) starting from the same position optionally at the same time, and walking straight along a corridor without any loop closure. The walks are comparable to walks starting outdoors and entering the building.

Experiment 1: FeetSLAM and no Loop Closures. In Experiment 1 we used the data of the six walks until the pedestrian reached GTP3 (see Fig. 2.). In this experiment we want to examine FeetSLAM on data sets containing a straight walk of a certain distance (walking a distance of about 4m in negative y-direction and about 38 m in positive x-direction) without having any loop closure (except a small one when entering the room in $\{\mathrm{D}_1, \ldots, \mathrm{D}_4\}$). The PDR results of the six different data sets ending at GTP3 are depicted in Fig. 2. One can see that the drift of the trajectories varies depending on the sensor, the sensor temperature and the calibration.

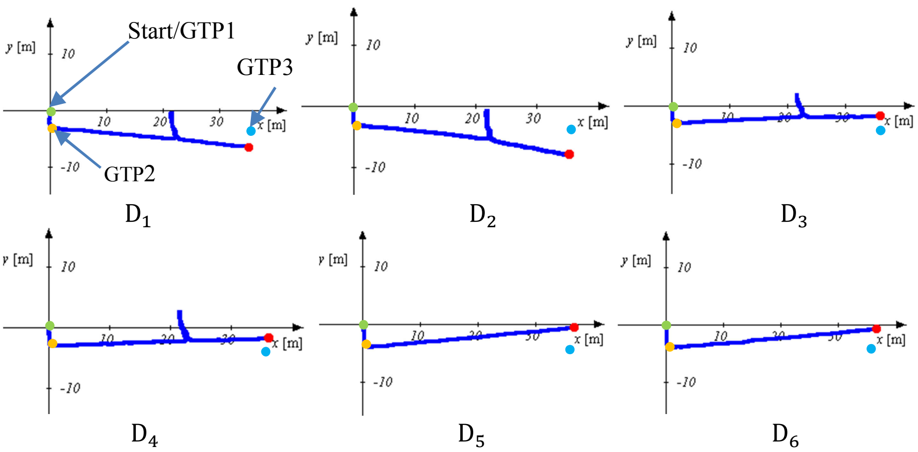

Fig. 2. PDR results of data sets $\{\mathrm{D}_1, \ldots, \mathrm{D}_6\}$ ending at GTP3. Depending on the sensor and the calibration, the drift in the different data sets differs for each data set.

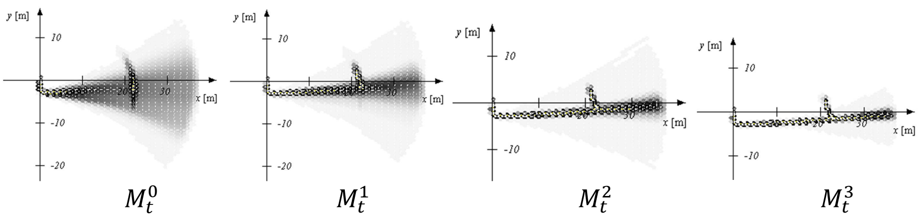

Fig. 3. Total combined posterior maps of data sets $\{\mathrm{D}_1, \ldots, \mathrm{D}_6\}$ ending at GTP3 performing iteration 0-3 of FeetSLAM. Because FeetSLAM introduces a drift in positive y-direction at GTP3 the resulting positioning errors will be comparable.

After performing FeetSLAM at iteration 0 – which can be seen as performing Foot-SLAM -, we obtain 6 different maps that reflect the drifts of the PDR because there was no loop closure to correct the drift. From Fig. 2 it is observable that two walks show a drift leading to a trajectory with an error in the negative y-direction at GTP3, two walks show a very small drift in positive y-direction at GTP3 and two walks show a higher drift in positive y-direction at GTP3. The total combined posterior maps $\mathrm{M}_{\mathrm{t}}^{\mathrm{i}}$ of the 6 walks after iteration $\mathrm{i} = 0 \dots 3$ of FeetSLAM are depicted in Fig. 3. From this Figure one can see that the map refines after each iteration, but it is relatively uncertain and results in a combined map that is drifted to the positive y-direction at GTP3. The problem is that the drifts especially for $\{\mathrm{D}_5, \mathrm{D}_6\}$ in positive y-direction are higher that the drifts for $\{\mathrm{D}_1, \mathrm{D}_2\}$. In addition $\{\mathrm{D}_3, \mathrm{D}_4\}$ show small drifts in positive y-direction so that the effect is reinforced.

The position error curves for the data sets ending at GTP3 are depicted in Fig. 3. The position error is the 2D Euclidean distance at the GTPs. One can observe that the error grows due to the drift in the estimated map (see Fig. 3). The mean error for $\{\mathrm{D}_5, \mathrm{D}_6\}$ should be considered carefully because we crossed only 3 GTPs .

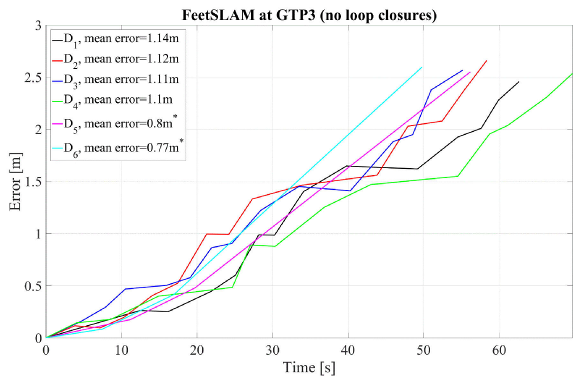

Fig. 4. Position error curves for data sets $\{\mathrm{D}_1, \dots, \mathrm{D}_6\}$ after performing FeetSLAM at GTP3. Due to the drifted combined posterior map the error increases until GTP3 is reached.

Experiment 2: FeetSLAM at Consecutive Time Instances and no Loop Closures. In Experiment 2 we performed FeetSLAM under the assumption that prior maps resulting from the data sets will be used at an earlier stage. We assumed that the prior maps are calculated after different distances of walking in x-direction: 10m, 20m, 30m, and GTP3, respectively, and performed FeetSLAM (10 iterations) successively as described in Section 3.2. We define the times of reaching the distances as $t_{1,} \dots, t_4$.

The results for the different total combined maps at $t_{1,} \dots, t_4$ are given in Fig. 5. One can see that the use of prior maps at earlier time instances reduces the drift. After calculating FeetSLAM for data sets ending at t_1 the drift of the combined map is very small. Therefore, due to the map combination at t_1 the drift can be compensated after performing FeetSLAM at t_1. Using the resulting posterior maps as prior maps for data sets ending at t_2, the resulting maps contain again less drift, because the drift is compensated from the beginning on. Continuing this process for t_3, the drift is compensated further on and this helps also to compensate the drift at GTP3.

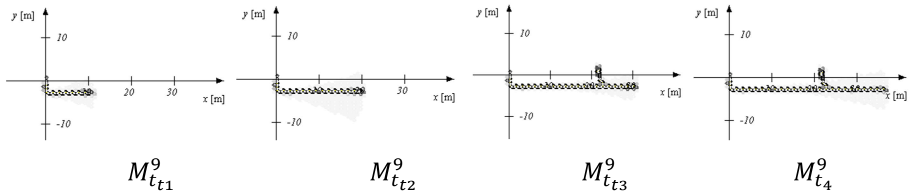

Fig. 5. Total combined posterior maps after 10 iterations performing successive FeetSLAM at different times $t_1 - t_4$.

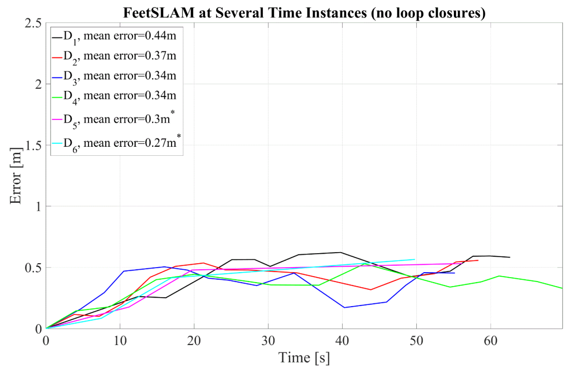

Fig. 6. Position error curves for data sets $\{D_1, \ldots, D_6\}$ after performing FeetSLAM at different time $t_1 - t_4$. Without any loop closure the results are very good for all data sets.

The position error curves for the data sets ending at GTP3 performing FeetSLAM successively at different time instances until GTP3 is reached are depicted in Fig. 6. One can observe that the error is very small (~0.5m) due to the drift correction in the estimated map (see Fig. 5). The general improvements compared to Fig. 4 result from the fact that the drift is small for short distances. It will be corrected because we used the combined map of 6 data sets over short distances as prior map at iteration 0 for the next FeetSLAM run. This correction will be continued when applying FeetSLAM successively over short periods of time.

5 Conclusions and Outlook

In this paper, a successive collaborative SLAM algorithm called FeetSLAM is investigated for the case of several pedestrians (or emergency forces) entering a building simultaneously and assuming that there are no loop closures. In emergency situations, walking an area twice is usually avoided, so that the assumption of having loop closures does not necessarily hold. In the experiments it has been shown that the drift of the inertial sensors can be reduced by applying FeetSLAM successively. With it the error reduces to ~0.5m also when having no loop closures. This is additionally a promising option for reliable positioning of one person wearing multiple sensors.

Future work will focus on the communication part and the starting condition estimation for FeetSLAM. In addition, wearing several sensors and applying FeetSLAM in real time in a common estimation procedure is foreseen for future work.

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