HEADSLAM - HEAD-MOUNTED SIMULTANEOUS LOCALIZATION AND MAPPING FOR WEARABLE COMPUTING APPLICATIONS

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Abstract
In this paper, we demonstrate how simultaneous localization and mapping techniques (SLAM) from robotics can be used in wearable computing to automatically create floor maps from sensor data recorded by a pedestrian. We give preliminary results based on different self-localization and motion models.

1. Introduction

Self-localization of users is one of the most important sources of context information in wearable computing and other pervasive computing applications. There are many systems described that use pre-deployed infrastructure for localization, ranging from global systems such as GPS to various indoor localization systems [11], e.g. based on existing or special-purpose hardware. The latter systems have in common that they use *a priori* information such as site survey data. In situations where the environment is previously unknown, localization infrastructure can be deployed by users [12]. Systems based on inertial navigation [7, 1] can track the motions of pedestrians in buildings. We present an approach for indoor localization and mapping that does not require *a priori* information and user-deployed markings or beacons. The approach is especially suited for time-critical applications such as Urban Search and Rescue.

In mobile robotics, sensors measuring the distance to obstacles such as 2D laser-range scanners can be used to create current local maps of the environment. Matching current scans of the environment with previous scans or *a priori* map data (so-called scan matching) can be used to improve wheel-rotation odometry based position estimates of the robot.

The incremental acquisition of maps during exploration of previously unknown environments constitutes a fundamental problem in mobile robotics. It is referred to as the *simultaneous localization and mapping (SLAM) problem* . There are multiple approaches to solve the SLAM problem (see [9] for a survey). The two main directions are Kalman filtering [13] and particle filtering [4, 10]. SLAM-based approaches have been used for pedestrian localization [12].

Doucet et al. [2] introduced in their work Rao-Blackwellized particle filters (RBPF) as a solution approach for the SLAM problem. Each particle in RBPF has its own map of the environment and represents a possible trajectory of the robot. Each map is computed based on the potential trajectory of the corresponding particle and the one with the highest likelihood survives. The first application of this technique was FastSLAM by Montemerlo et al. [8] for landmark based maps. They used Rao-Blackwellized particle filters to estimate the robot path where each individual map is represented by a set of features. In contrast to FastSLAM, in DP-Slam [3] there is no need of existing landmarks in the environment since the map is represented by evidence grids. The challenge of GridSlam [6] by Hähnel et al. was to decrease the number of particles by combining scan matching with Rao-Blackwellized

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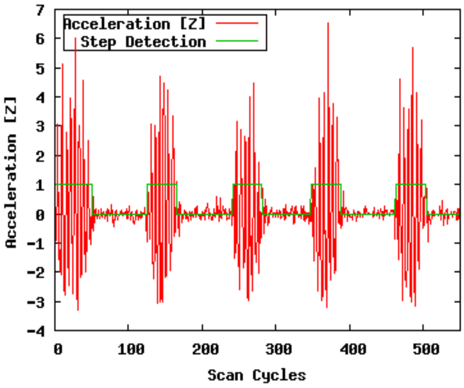
(a) The test person with *Hokuyo* laser scanner and *XSens* sensor mounted onto her helmet.



(b) Classification of motion state of the person as "walking" or "standing" in different intervals.

Figure 1. Our setup and step detection

particle filtering. This also provides a more accurate estimation of the robot pose since not only the odometry information but also the most recent observation is used in the generation of next particles. Grisetti et al. [5] extended this idea and presented an improved proposal distribution in their work GMapping which generates particles more effectively than GridSlam.

2. Methods

We used the GMapping implementation from Grisetti et al. [5] which is available on OpenSlam[3] as the basis for our implementation. This implementation uses (wheel-)odometry and laser range readings from a 2D long-range laser scanner as input. In the wearable scenario, we mounted a 2D short-range laser scanner[4] and an inertial measurement unit (IMU)[5] on the helmet of a person (cf. Figure 1(a)).

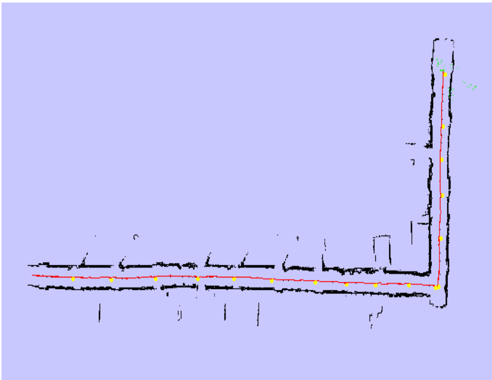
The original implementation assumes that there is a bound error on the odometry information and that the laser range scanner is mounted parallel to the floor the robot is moving on. With the sensor mounted on the human head, resulting in tilting motions and the absence of odometry, these assumptions do not hold.

In our implementation, we therefore use additional sensor data provided by the IMU to estimate the motion and to correct the distance information in the laser range scans. The IMU output consists of pitch, roll and yaw angles that indicate the orientation of the sensor relative to the direction of gravity and the earth magnetic field and three acceleration values in the frame of reference of the sensor.

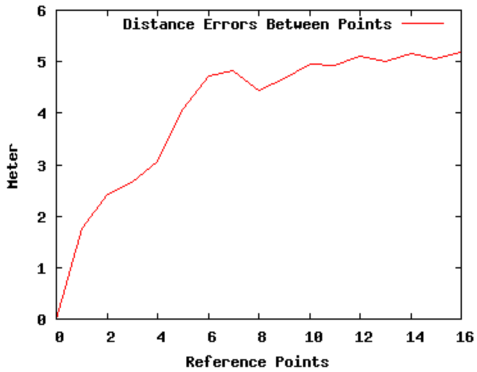
We assume that walls are vertical, that the sensor is mounted at a certain height above ground. We ignore distance readings that we assume to be generated from the ground or the ceiling. We then project the range scan data into a horizontal plane in the global coordinate system, generating virtual scan data in that plane. However, the projection of distance measurements to a horizontal plane combined with errors on distance and attitude measurements can lead to accumulated errors. One of the research challenges is therefore to explore the effect of these errors on the map quality.

Our initial test was performed with the odometry information set to zero, i.e. we assumed that the scan matching implemented in the original algorithm could generate updated position information. However, the scan matching in GMapping could not give us reliable position updates to acquire a

[3]OpenSLAM: http://www.openslam.org/
[4]Hukuyo URG http://www.hokuyo-aut.jp/02sensor/07scanner/urg.html
[5]XSens MTi http://www.xsens.com/



(a) Acquired map with simulated data with 16 reference positions on the floor.



(b) Error plot of distance differences between estimated and manually measured positions.

Figure 2. Outputs from simulated odometry data

usable map. To overcome this problem, we integrated a simple motion model which detects a step occurrence by observing the vertical acceleration, similar to the approach used by Ladetto et al. [7]. If the vertical acceleration exceeds a threshold value in a defined time interval, we assume the pedestrian to be walking forward in the direction of view with a fixed speed, otherwise, we assume the pedestrian to be standing. With this very simple motion model, scan matching can be used to correct the position estimate (cf. Figure 1(b)).

3. Results

In our first experiment, we surveyed 16 positions in the corridor of our office. When conducting the experiment, while continuously recording sensor data, we associated the data to the 16 positions by hand, creating a timestamp whenever we passed a position.

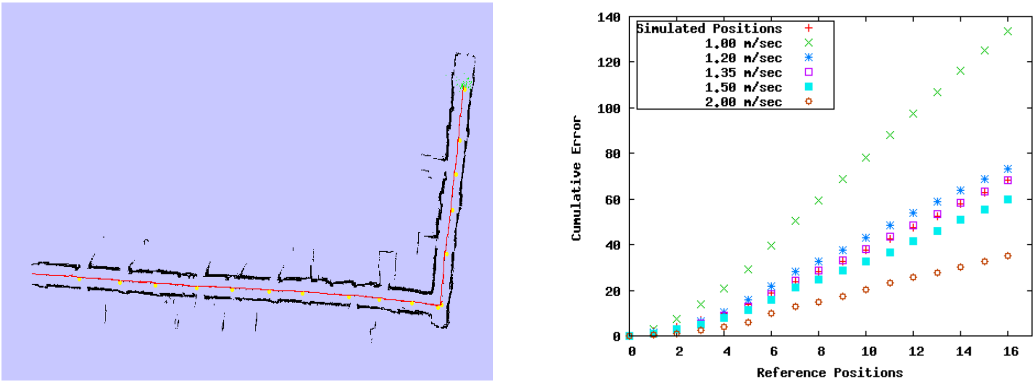
From this data, we created an artificial odometry, interpolating the trajectory between the surveyed positions. We then ran the algorithm with real sensor data and artificial odometry, creating the map in Figure 2(a). Even though we provided accurate position data as input, a displacement error of about 5 meters appeared between the positions surveyed and estimated by the algorithm. The accumulating error for each of the surveyed points is shown in Figure 2(b).

In the second evaluation of the same experimental data, we used the yaw angle from the IMU as heading and created artificial odometry data from our simple motion model. According to Ladetto et al. [7] the most natural step frequency for an average person is around 110 steps/min ($\sim$1.8Hz) and the mean step length is 75 cm. In our model, we therefore used an average linear speed of 1.35 m/sec. The map, based on this simple motion model, is shown in Figure 3(a). Testing other speed values between 1.00 m/sec and 2.00 m/sec, we found different cumulative errors, shown in Figure 3(b).

4. Discussion

We have demonstrated that head-mounted laser range and inertial sensors can be used for simultaneous localization and mapping of previously unknown environments, creating a method for indoor localization for wearable computing applications that does not rely upon pre-deployed localization infrastructure or *a priori* map data.

In our experiment, we found that our algorithm is capable of creating visually correct map data of our office environment. However, when looking at the position data, we found that the algorithm is under-estimating the distance travelled. Even setting motion speeds in the simple motion model to



(a) Acquired map with our motion model.

(b) Cumulative errors of different motion model variables.

Figure 3. Outputs from real data

unrealistically high values compared to the actual speed of motion determined by using the surveyed points as reference, we still see this under-estimation. We conclude that a part of the problem may be the lack of laser-detectable features in the corridor. An improved motion model that includes confidence values for the current position and a re-parameterization of the particle filter algorithm based on these confidence values may lead to the reduction of the position error observed. Another open question is the ability of our algorithm to perform loop-closing, i.e., to recognize that perceived sensor data matches to already seen parts of the map.

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