PEDESTRIAN LOCALIZATION IN MOVING PLATFORMS USING DEAD RECKONING, PARTICLE FILTERING AND MAP MATCHING

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ABSTRACT

Localization in global navigation satellite system denied environments using inertial sensors alone, or radio sensors alone or a combination of both are the currently active research topics. The current research works are primarily focused on static environments with earth fixed coordinate frames, having nonmoving maps. In this research work, we use micro electromechanical sensors based inertial sensors, band pass filtering, particle filtering, maps and map matching techniques for pedestrian localization with respect to on ground moving platforms such as train or bus. Since these platforms are moving, the maps of such platforms are moving maps with respect to earth centered, earth fixed coordinate frames. The techniques of this research work could further be extended and adapted to other moving platforms such as airplanes, boats and submarines.

***Index Terms*—** moving maps, particle filters, map matching, pedestrian dead reckoning, sensor fusion, indoor environments

1. INTRODUCTION

Knowing where we are located on a map is very useful information that helps us to find where our intended destination is, how far it is, and how quickly we can reach our destination. There exist several fields of interest such as pedestrian navigation, robotics, vehicular navigation, which needs a solution for localization. In this context, various solutions have been researched for decades. For example, global navigation satellite system (GNSS) provides localization solution to land based objects with respect to earth, with earth centered, earth fixed (ECEF) coordinate system [1]. Simultaneous localization and map matching (SLAM) is primarily adopted in robotic localization [2-5]. Different combinations of micro electromechanical sensors, vision sensors, radio sensors, dead reckoning, particle filtering, and map matching techniques are adopted in various fields of localization such as robotics, pedestrian and vehicular navigation [6-10]. In all these research works the localization is achieved with respect to ECEF system, considering map of the earth to be static with respect to earth itself.

In this paper, we propose novel concepts and techniques that could be applied for localizing objects in non-static environments, for example, airplanes, trains, boats, busses and different transportation vehicles. Maps of such environments are static but these environments are moving with respect to world map, hence the use the term moving for the maps of such environments. The moving maps can be either 2D or 3D maps, which layout the map of the moving objects mentioned above. The concept of moving maps was proposed in our earlier work in [11] but we have not shown any experiments to show the feasibility of the concept. In this paper, we introduce experiments where a bus is used as an experimental moving platform. Pedestrian localization experiments in this environment are carried out. The idea here is to obtain the accelerometer and gyro readings from a MEMS inertial unit carried by a person walking in the bus in real time. For example, a smart phone device contains such sensors and can be carried by a person. Such obtained data is processed to derive the attitude, and displacement information of the person walking in the bus, and apply the pedestrian dead reckoning and particle filter techniques [12] to localize the person in the bus.

2. THEORETICAL BACKGROUND

In pedestrian navigation solution, dead reckoning is a basic technique that has been used for several years now [13, 14]. Pedestrian navigation based on inertial measurements is popular nowadays [15] due to low cost MEMS sensors, and also with a combination of radio signal finger printing techniques [16]. In these types of localization techniques, the attitude information is primarily estimated using MEMS sensors namely gyroscope and accelerometer data. Dead reckoning is a method of deducing the current position utilizing the past known position and current displacement and attitude. For pedestrian dead reckoning (PDR) the information about the step count and step length is used in localizing a pedestrian. In its simplicity, a 2D position (E_n, N_n) at time instance n, where E, and N denote East, and North coordinates on the map, respectively, is as follows

$$(E_n, N_n) = \begin{bmatrix} E_{n-1} + \Delta S_n cos(H_n) \\ N_{n-1} + \Delta S_n sin(H_n) \end{bmatrix} \qquad (1)$$

where E_{n-1}, N_{n-1} is the past known position, ΔS_n and H_n are the displacement and heading from at time instance n. Using gyroscope data the heading is estimated, and the accelerometer data is used to estimate displacement. Because of the inherent errors [17] of these sensors the position estimated with (1) using these sensor data will also have errors, and these errors get accumulated over time to give a larger error in the overall position solution. To mitigate such errors, signal processing techniques are used, such as bandpass filters [18], Kalman filters (KF) [17], extended KF (EKF) [19], and particle filters with map matching [20].

Here we have used pedestrian dead reckoning (PDR) and PF for localization of a person walking in the bus. The new challenge here is to extract meaningful information from the sensor data obtained in the moving bus environment, and with dynamic walking nature of the person carrying the sensors. Due to this dynamic nature of the bus motion, the information contained in the walkers' inertial sensor data will be a superposition of the motions of the bus and the walker. Processing such data to extract walker motion is expected to be difficult. Other challenge would be to apply particle filtering (PF) with map matching in such dynamic moving maps, with such sensor data. In this paper, we assume that the entry point to such moving maps is fixed and known, and this known location will act as the initialization coordinate for the particles in the PF system.

3. METHODS AND TECHNIQUES

In GNSS positioning solution, the motion of earth is modeled and taken in to account in the positioning equations to calculate the positioning solution in ECEF system [1]. Hence the map is assumed to be static by the end user, while the user is moving on the earth. In PDR, also localization solution is achieved in ECEF system. In PDR, gyroscope detects much higher rate of angular movements than compared to earth's rate of rotation, which is very slow. The errors inherent to the gyroscope are more significant compared to the error induced by neglecting the earth rotation rate [21] in localization solution. Since the maps used in PDR are fixed to the ECEF system, these maps can be assumed to be static similar to GNSS positioning.

Where as in this paper, a bus moving container movements such as vibrations due to motion, and rotations due to turnings of the bus, are significantly added to the walking motion sensor data. Since this data is a superposition of walker movements and bus movements, these movements cannot be ignored similar to neglecting the earth rotation rate in static PDR solution. Because of such movements of the bus platform with respect to ECEF system, the moving platform becomes a moving map in which localization is performed. For achieving a solution in such environments the movements of the platform needs to be separated from the superposed data in the walkers' inertial measurement unit (IMU) data. Thus separated data can then be used to extract the walkers' heading and step displacement information and apply PDR.

3.1. Step Detection and Heading Estimation

The raw signal data of accelerometer and gyroscope sensors, representing walking motion, cannot be directly used to detect steps and heading respectively. The sensors are very sensitive to motion, that they will also capture frequency components pertaining to other motions, such as high frequency vibrations induced by bus motion to the walking person. For this reason, we need to filter these signals. Here we are interested in human walking, and heading information, which happen at low frequency at about less than 6Hz. We pass the bus and walkers' time synchronized sensor data through band pass filter [18]. The 3-axis accelerometer norm signal of the walkers' IMU, after passing through the band pass filter is passed through the differentiator function to enhance the remaining high frequency components around 3-5Hz components, which corresponds to peaks during the foot fall. In our experiments, we have applied band pass filtering to both accelerometer and gyro data, as the vibrations of bus motion would have unwanted high frequency components.

The zero crossings are searched in the output accelerometer norm signal from the differentiator to mark the step start and the step end to count as one step. During this process we also evaluate the step frequency and the variance of the accelerometer data, which are used in adaptively evaluating the length of the step during a detected step [22]. We have implemented a heading estimation algorithm that uses band pass filtered 3-axis gyro and accelerometer data to project gyro data to the horizontal plane with respect to the ground, by using the gravity component from the accelerometer data [23]. The block diagram of the implemented system is shown in Fig. 1(a).

3.2. Particle Filtering

Particle filtering (e.g., [12]) is an approximation of the Bayesian filter where the posterior distribution $p(x_n|y_{1,\dots,n})$, with x_n denoting the state vector at time step n and $y_{1,\dots,n}$ being the measurements, is characterized by a cloud of random samples, called particles, instead of, for example, the moments of the distribution. The advantage of this representation is the ability to operate on arbitrary distributions, thus making it possible to estimate, for example, multimodal distributions which often cause divergence in Kalman-type and other filters that assume Gaussian distributions. PF is a Monte Carlo method and both its performance and computational complexity depend on the number of particles used. Here we used bootstrap variant of PF (BPF), where the importance distribution is chosen to be the transitional prior distribution. Suppose we

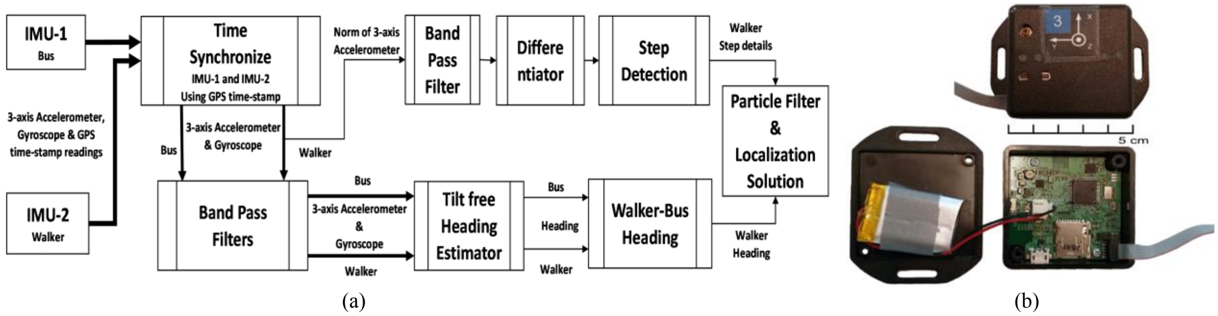

Fig 1 (a) Block diagram of the system and (b) IMU unit used to collect sensor data.

have N particles x^i with nonnegative weights w^i, $i = 1, \dots, N$. Each particle is a state vector containing the quantities that are to be estimated

$$x^i = \begin{bmatrix} E^i \\ N^i \end{bmatrix}. \tag{2}$$

In the importance sampling phase of BPF, we draw particles from the transitional distribution specified by contextual dynamic model at each n^{th} time step

$$x_n^i | x_{n-1}^i = \begin{cases} \begin{bmatrix} E_{n-1}^i + \Delta S_n + q_n \\ C + \upsilon_n \end{bmatrix} if\ \Delta H_n \le T_H \\ \begin{bmatrix} E_{n-1}^i + \Delta S_n cos(H_n) + q_n \\ N_{n-1}^i + \Delta S_n sin(H_n) + r_n \end{bmatrix} if\ \Delta H_n > T_H \end{cases} \tag{3}$$

where ΔS_n is the estimated distance travelled by pedestrian during a single step, and C is a constant value representing the north coordinate component of the center pathway of the bus. Here υ_n, q_n, r_n are normally distributed noises. ΔH_n is the total heading change during the step taken by the pedestrian and T_H is the threshold of pedestrian turn angle during a step to indicate if a person is either walking straight in path way of the bus or about to settle at some place in the bus.

In the reweighting step, the weights of the particles are modified according to the likelihood of a measurement given the state vector. In the case of the bootstrap filter, the update is done according to the simple proportion

$$w_n^i \propto p(y_n | x_n^i) w_{n-1}^i. \tag{4}$$

The weights are normalized to sum to unity after updating, which enables to estimate the mean of the posterior distribution as the weighted average of the particles.

In this study, map update likelihood is computed by modeling each particle as a freely moving point mass. While the particles are propagated, the posterior distribution would have only a subset of the particles that were propagated in the previous step. A partial set of particles would be cut-off from the distribution if that particle crosses the boundaries or partitions of the bus map. The partitions represent the seating arrangement and the boundaries represent the bus body. We use the 2D map as a source of measurement updates from the pseudo-measurement model

$$p(y_n^i | x_n^i) = \begin{cases} 0 & if\ x_n^i\ crosses\ partition \\ & or\ boundary\ of\ bus\ map \\ 1 & otherwise. \end{cases} \tag{5}$$

It means that the particles, which cross the partition or the boundary of the bus are discarded. At any instance of time step of propagation, if the number of particles in the posterior distribution falls below a threshold, a resampling is performed. A particle is said to be crossing a partition or the boundary, for example, when the line formed by the particles previous coordinate and the current coordinate intersects with any of the lines representing the boundary or a partition [7]. It is obvious that discarding collided particles leads to a situation where only a small fraction of the N particles are actually used for the state estimation. Such a cloud of particles is not a good approximation of a probability distribution. Additionally it would unnecessarily consume computational resources if zero-weighted particles are propagated. This problem can be avoided by resampling. It is a procedure, in which a new set of N particles is drawn from the discrete probability distribution defined by the old particles and their respective weights. The newly obtained set of particles then represent the same distribution as the old one, but with a full number of "alive" particles. This process of prediction and update is performed as long as the localization is needed and the sensor data is available.

4. EXPERIMENTS

As a simple case scenario of localizing in moving maps, we choose bus to be our moving map environment. We have

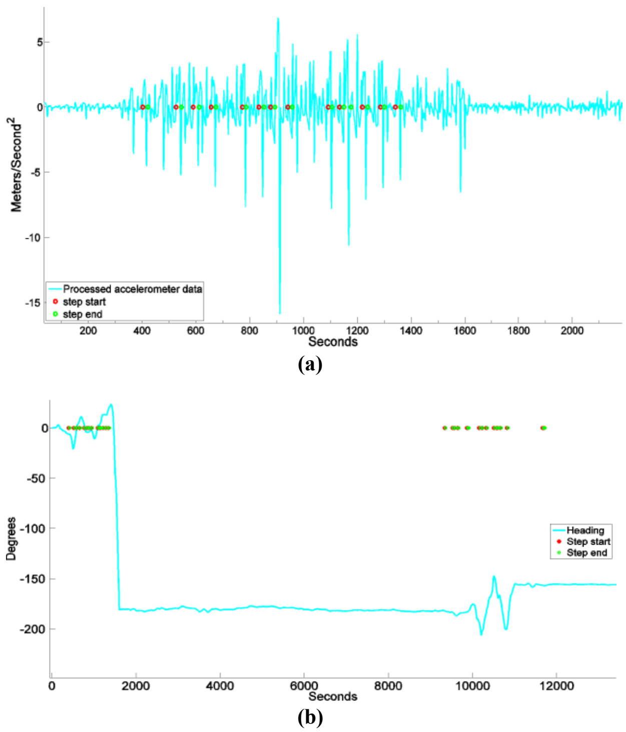

Fig 2 (a) Processed accelerometer data representing walker motion and (b) processed gyroscope data representing walker's heading estimate. Detected steps are plotted with start and end markings for each step on both (a) and (b) plots.

conducted data collection trials in this environment using two custom built IMU shown in Fig. 1(b), with 3-axis accelerometer, gyroscope, and a GPS based timestamp logger. Data sampling was done with gyro sensor at 100Hz, and accelerometer at 500Hz. The timestamp data from GPS logger was used for synchronizing the logged data between the two IMUs. In this field test, two persons were used to collect the data. The first person boarded the bus at the first bus stop and attached the inertial sensor unit to the body of the bus, thus collecting the accelerometer and gyro data corresponding to the bus. The second person boarded the bus in the next stop, while another sensor is attached to his waist belt. Both the IMU data is synchronized with the help of GPS timestamps.

As a reference for verifying our localization results, walking motion data was collected by walking in a bus on a certain path. From the front of the bus, the person walked to the last middle seat while the bus is moving and sat in the bus at that location. After a while the person walked back to the front of the bus. The collected sensor data was processed offline in MATLAB according to the methods mentioned section 3.1. The steps detected using the accelerometer data, along with the accelerometer data from the differentiator output are shown in Fig. 2(a). The final projected heading data can be seen in Fig 2(b). Adaptive step length estimation is an essential requirement because of dynamic nature of the bus and walking movements where the step lengths are not fixed. Using thus obtained heading and step length information, dead reckoning is applied in prediction step according to (3) and as the measurement update step the posterior distribution is obtained using (4) & (5). We have used 150 particles for the PF simulations. The experimental localization results are shown in Fig 3. From these results it can be seen that the pedestrian in the bus can be localized to three different sections of the bus, such as front, last or middle sections and closer to the expected seat. In this experiment, the localization solution is within 1.5 meters and it is comparable in general, to localization solutions in static platforms.

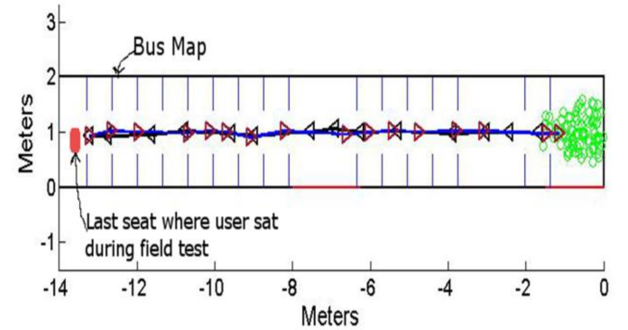

Fig 3 Localization solution in the bus map in meters. Left arrows indicate step locations forward direction walking to last seat and right arrow back to front of the bus.

5. CONCLUSIONS

The feasibility of localizing in moving containers such as trains, busses, or ships was evaluated by conducting experiments in a bus as a simple use case. The experimental results show that the localization of a walking person in the bus is feasible. The dynamic nature of the bus and the walking person movements poses a challenging task working with the sensor data in such environments. At this stage we realize that, the knowledge of heading information of the moving containers would help to offset the heading sensed by the sensors attached to the walking person, and enable to provide better localization solution. Our proposed contextual dynamic model (3) for bootstrap PF is expected to reduce the degeneracy problem of particle filter, and it is a specific model to be used with the bus container moving map model specific to our experiment. Such dynamic models should be chosen, by taking the map information in to account, for example information such as pathways, turns, obstacles, ramps and stairs. In the future, we plan to do more tests in the bus container with complex use case scenarios, and later plan to work with train containers. The localization solution in such moving containers helps the users of the system for example to quickly locate their friend inside the bus, a coffee kiosk inside a train, and helps to navigate between compartments and to another place of interest in the train or a ship.

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