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A Proposal of Emergency Rescue Location (ERL) using Optimization of Inertial Measurement Unit (IMU) based Pedestrian Simultaneously Localization and Mapping (SLAM)

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Abstract

Congestion avoidance in emergencies is one of many overlooked localization issues. During an emergency (such as a fire), it is difficult for rescuers to determine the best exit route when inside a building. Any time delay during decision making can risk loss of life. Therefore, an efficient Emergency Rescue Localization (ERL) system is essential to assist rescuers to identify the best route for reaching the outside when inside a building. Thus, we propose a new ERL based on an Inertial Measurement Unit (IMU). In the proposed ERL, an IMU is used to retrieve location information from inside the building. To conclude, we illustrate out proposed solution for indoor environmental set-up.

Keywords*: Simultaneously Localization and Mapping, Global Positioning System, Inertial Measurement Unit, Wi-Fi*

1. Introduction

Interest in indoor positioning systems (IPS) has been rising in tandem with the many widespread advances in devices and technologies and the necessity for seamless solutions to overcome the limitations of existing location-based services [1]. An important component of IPS is indoor tracking, in which pedestrians (referred to as mobile nodes) are tracked within a corridor or any enclosed structure. Examples include emergency rescue locating technologies, first-responder navigation, asset navigation and tracking, and people movers [2]. The widely diffused Global Navigation Satellite System (GNSS) offers worldwide service coverage, due to its network of dedicated satellites [3]. GNSS is recognized as the legacy system in outdoor environments, and where available it is one of the most accurate sources of positioning information However, it is unfeasible in the unknown and changeable indoor environment; thus, alternative systems must be adopted. When choosing the best technology for designing an IPS, a large number of parameters must be taken into account (for example: cost, accuracy, robustness, scalability, and coverage) [4]. To date, a single solution that fits any scenario does not exist. Therefore, it is important to consider the performance parameters of all technologies, and match them to user requirements, which then have to be precisely analyzed and described for each application. Moreover, the values of performance parameters vary, as they are dependent on multiple factors and conditions. Therefore, it is essential to discover the right trade-off for performance parameters, user requirements and environmental conditions, in order to design a customized solution. A number of solutions based on indoor positioning methods for human pedestrians (PDR) have been offered [1]; these include: Bayesian tracking, distributed and cooperative tracking, fingerprinting, fusion method, pedestrian simultaneously localization and mapping (SLAM), among others. Of these methods,

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pedestrian SLAM is apparently the most capable of determining a pedestrian's position in an unknown and changeable environment [5]. This is a robust and successful approach employed in a majority of domestic environments where it is beneficial to track the position of a person [5]. In emergencies, rescuers might also need to remove obstacles swiftly to reach an individual. As any position within the indoor environment may become dangerous over time, a longer waiting time reduces the probability of survival [6] [7] affecting the efficacy of rescuers [8-10]. Although rescuers can arrive at an emergency site very quickly, they might be delayed by the need to determine the situation within a building. For example, where people are trapped, knowledge of areas of congestion, and which paths can be safely used might be unknown to the rescuers. Using WSNs to attain more information about the interior environment to aid rescuers can greatly improve the efficiency of an emergency rescue.

Despite the clear advantages of such technology, its usefulness is limited. For a pedestrian entering a large building in search of a specific destination it is most appropriate to relate areas of congestion to existing maps. To achieve this, pedestrian SLAM might be used to generate the initial map and then to update the map to account for future changes in the environment or to refine its accuracy for the purpose of navigation. However, augmenting pedestrian SLAM will result in high costs if using installed infrastructure [11], such as Radio Frequency Identification (RFID) [12] or WLAN radio access point [13-16]. Moreover, these approaches are often unsuitable for emergency, security, and rescue applications, where such infrastructures might be unavailable, or where it might be unfeasible to deploy them quickly and inexpensively. Other approaches do not exact high costs; inertial measurement units (IMUs) [17-19], cameras [20], and laser scanners [21], since they are based on infrastructure-less technology (the technique relies on sensor). Techniques based on IMU sensors are the only means necessary to provide additional mobility, while being less invasive of privacy and relatively cheap. Nevertheless, only [18,19] provide details of activity and location simultaneously (fulfilling conditions associated with context awareness). Therefore, we propose a new Emergency Rescue Localization (ERL) system that accounts for both pedestrian congestion and rescuer's actions. The remainder of the paper is organized as follows. Section 2 summarizes related works. Section 3 describes the problem formulation. Section 4 presents the main research assumptions. Section 5 describes the main research objectives. Section 6 presents the design details for ERL based on IMU Pedestrian SLAM. Finally, Section 7 provides a discussion regarding the future direction of the project.

2. Related Work

Emergency localization determination and guidance for evacuation using WSNs are addressed in several works, such as [22-26]. In [26], a shortest path to exit is offered to evacuees, and people are divided into two groups according to their positions, either inside or outside dangerous regions. Only a subset of sensors is used to reduce communication costs. Based on the work of [26], additional kinds of sensors are added into WSNs and [24] extends the protocol to 3D environments. Distributed algorithms are proposed in [26] to guide a target across a region for self-organized sensor networks. In addition, research proposes people navigate following the safest and shortest path using a directed road map [22]. The medial axis of safe regions is used to build a road map and assign directions, also helping to lower the packet overhead. In [23], the authors utilize the skeleton graph to abstract the localization field, which differs from the road map mentioned in [22]. Additionally, some other works aimed to offer help to rescue forces. Methods proposed in [27,28] provide useful information to rescuers. In [27], underground collapses can be detected by regulating the deployment of WSNs. In [28], a method is proposed to help rescuers work more effectively, by narrowing down the searching region in wild areas. The authors use witness information, offered by other hikers to identify the possible locations of victims. In addition, the researcher [29] developed a network of distributed mobile sensor systems to resolve the emergency response problem; whereby robots are used to look for immobile people trapped by fire. Nevertheless, these systems do not consider pedestrian congestion. Meanwhile, in most scenarios, such as indoor environments, limited space and multiple evacuees results in congestion (some emergencies might cause some transportation systems to fail, for example elevators). Thus, the possibility of congestion should not be ignored in emergency situations. The proposed ERL takes both congestion and rescuer team actions into account, in order to evacuate people more efficiently in emergencies.

3. Problem Formulation

There might be several danger areas in a building in an emergency, in the form of threats to human safety; for example: fire, smoke, obstacles, and etc. [30-32]. Therefore, it is essential that evacuation take place as quickly as possible, and that people are kept away from dangerous areas [33,34]. In some instances the safest path to an exit might be obstructed, or become congested. In addition, once someone has been trapped in a dangerous area, the system will be unable to output any path. Thus, the system should have the capability to determine positioning in various environments. Offering a solution in the form of an IPS method based on Pedestrian SLAM might be helpful in this case, since it is capable of determining positioning and generating a map in various environments. For practical reasons, any solution should also be inexpensive and not invade privacy. The usage of IPS technology based on WiFi, RFID, or a camera can be costly for the developer, since it is necessary to build an infrastructure. Use of a camera will invade privacy so this also needs to be addressed. The assumptions and objectives of the design are presented below.

4. Assumption

We assume that in an emergency state, regions of interest may include several dangerous areas, each of which might emerge, disappear, expand or shrink at any time. We also assume that all firemen can keep in touch with the control center.

5. Objective

This research aimed to outline a possible new ERL, based on the integration of IMU-based Pedestrian SLAM. By implementing it, it will be possible to determine a location in an indoor environment in various contexts. The location also can be determined in an illuminated environment when the user is inside the building. The outcome of this study is expected to contribute significantly to the modernization of location determination systems. It will also contribute to current studies in the field of Pedestrian SLAM.

6. System Design

Figure 1 depicts the overall framework for Activity Pedestrian SLAM, with two main blocks: The pre-processing phase, and the SLAM update phase. In the pre-processing phase, the system derives a step estimate $\hat{u}$, and recognized location-related actions $\hat{A}$ using wearable inertial sensors. A Rao-Blackwellized particle filter then fuses the measurements, as proposed in [35]. The system then segments paths into stance phases t, in which pose is given as $s_t = \{x_t, y_{t,} h_t, \phi_t\}$, and steps u_t connecting s_{t-1} and s_t. In this notation, $= \{x_t, y_{t,} h_t\}$ denotes the 3D position of the user at time t, and ϕ_t the foot's heading. The outputs of the system are a path $s^{-t} = \{\overline{s}_0 \dots \dots \overline{s}_t\}$ comprised of poses

$\overline{s}_t = \{\overline{x}_t, \overline{y}_t, \overline{h}_t, \overline{\phi}_t\}$ and a map $\overline{\Theta}_t$ comprised of $N_{l,t}$ landmarks $\overline{\theta}_{t,[i]}$. $[i] \in \{1 \ldots N_{l,t}\}$ is the index for the landmark, and $N_{l,t}$ denoted the number of landmarks on the map.

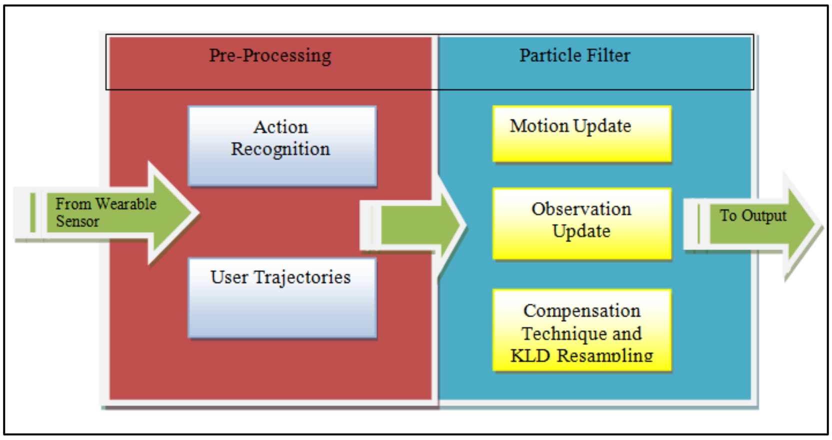

Figure 1. System Architecture for Activity Pedestrian SLAM

6.1. Pre-Processing

In this section, the pre-processing component will be described in two (2) subsections: action recognition and user trajectory. Figure 2 will depict the action recognition and user trajectory within Pedestrian SLAM.

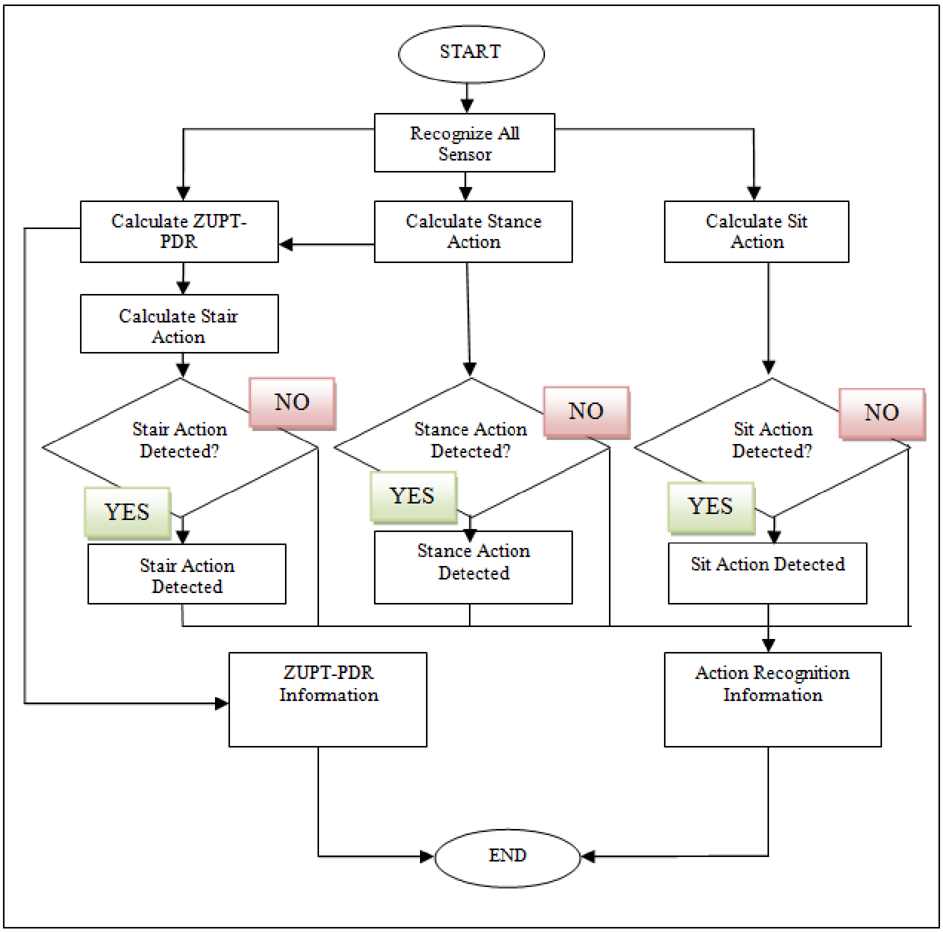

Figure 2. Action Recognition and User Trajectory in Activity Pedestrian SLAM

6.1.1. Action Recognition

Four (4) basic actions can be detected: sitting, standing still, stair low (reaching the lower end of a stair) and stair high (reaching the upper end of a stair). To detect these actions, action recognition components must be included. In this section, the action recognition consists of sit detection, stance detection and stair detection. Sit detection is used to detect a sitting action by applying a threshold to the orientation of the upper leg sensor. Stance detection (generally used to detect standing still), consists of two (2) sub components, which are: standing still detection, adaptive stance detection walking path segmentation. Complex standing still actions can only be measured when the user is wearing a sock. Walking path segmentation will first be segmented into steps, then adaptive stance detection will be used to soften the stance detection criterion based on a stepwise increase in the stance detection threshold as shown in Figure 2. Meanwhile standing still detection is used to detect standing still action by recognizing the stance phase with a duration < 0.75s, which occurs during gait interruption. Stair detection is used to detect stair low and stair high actions by calculating the variance $var(h(t))$ of the ZUPT-PDR altitude output $h(t)$in a sliding window of length ΔT. If $var(h(t))$ stays for at least τ_0 above the threshold h_0, the phase is identified as stair ascent or descent. In terms of final output, the action recognition block for the system provides observations $\{$sitting, standing still, stair high, stair low$\}$ associated with stance phases t.

6.1.2. User Trajectories

The pre-processing concerns the open-loop estimate $\hat{s}^t$ for the person's trajectory, comprised of steps $\hat{u}_t$. The ZUPT-PDR [] is used to estimate 3D foot coordinates. The stance detection for ZUPT-PDR segments the walking path into steps $\hat{u}_t$, as described by horizontal step length $\hat{l}_t$, altitude change $\delta\hat{h}_t$ and heading change $\delta\hat{\phi}_t = \hat{\phi}_t - \hat{\phi}_{t-1}$.

6.3. Adaptive Rao-Blackwellized Particle Filter

The standard SLAM problem of estimating$p(s_t, \Theta|\hat{u}^t, \hat{z}^t, \hat{n}^t)$, the landmarks for the system are not uniquely identifiable by $\hat{n}_t$; this only identifies action type $\hat{A}_t$. Furthermore, the estimated position for the landmark observed at time t is always equal to the person's position at that time. Therefore, $\hat{z}^t$can be derived from s and Θ alone, which reduces the SLAM problem by approximating $(s^t, \Theta_t|\hat{u}^t, \hat{A}^t)$. To fuse motion and observation measurements, the system uses Rao-Blackwell factorization, as proposed in [35] (see Figure 3):

$$p\left(s^t, \Theta_t \middle| \hat{u}^t, \hat{A}^t\right) = \; p(s^t|\hat{u}^t) \prod_{[i]=1}^{N_{l,t}} p\left(\theta_{[i],t} \middle| s^t, \hat{A}^t\right) \tag{1}$$

This factorization decomposes the SLAM problem by estimating a path s^t, in a previously unknown environment Θ_t according to the separate estimators for a person's path s and each of the $N_{l,t}$ landmarks $\Theta_{[i],t}$. The system also estimates the path probability $p(s^t|\hat{u}^t)$ in a particle filter containing N_p particles, thus it is capable of approximating non-Gaussian distributions and performing nonlinear filtering. Meanwhile, $N_{l,t}$ individual filters can be used to estimate the landmark probability distributions $p\left(\theta_{[i],t} \middle| s^t, \hat{A}^t\right)$. As the landmark characteristics $\theta_{[i],t}$ are conditioned based on a person's path, each particle $[m]$ must maintain its own map $\Theta^{[m]}$, together with pose $s_t^{[m]}$. The system estimates $s_t^{[m]}$ in the motion update, while any updating of the map $\Theta^{[m]}$ involves an observation update, but only in response to action observations.

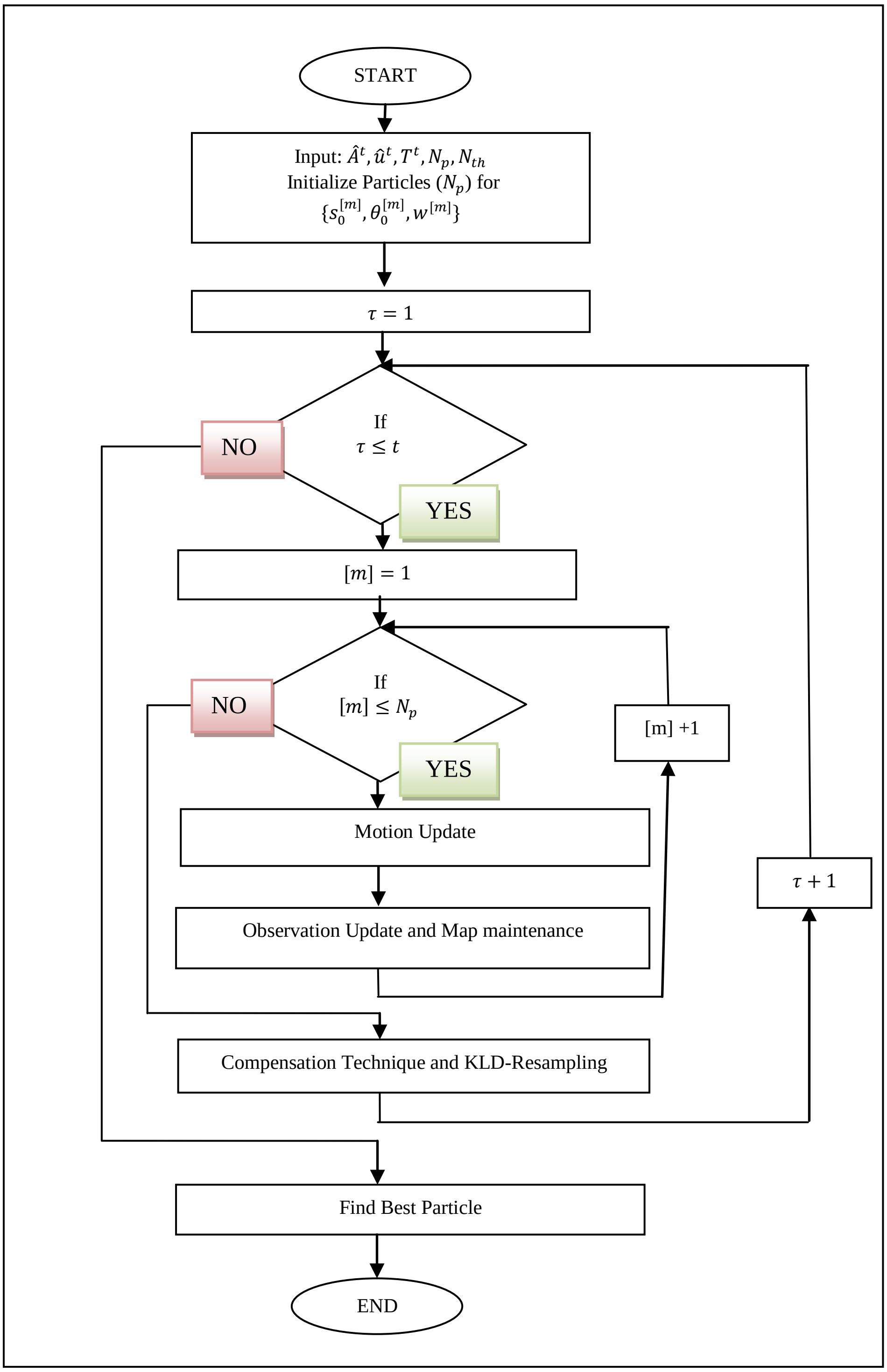

Figure 3. Algorithm Flow of Rao-Blackwellized Particle Filter in Activity Pedestrian SLAM

6.3.1. Motion Update

At the beginning of a stance phase, t, the system performs a motion update and sequentially calculates $p(s^t|\hat{u}_t)$ by sampling particle poses from:

$$s_t^{[m]} \sim p(s_t^{[m]}|s_{t-1}^{[m]}, \hat{u}_t) \tag{2}$$

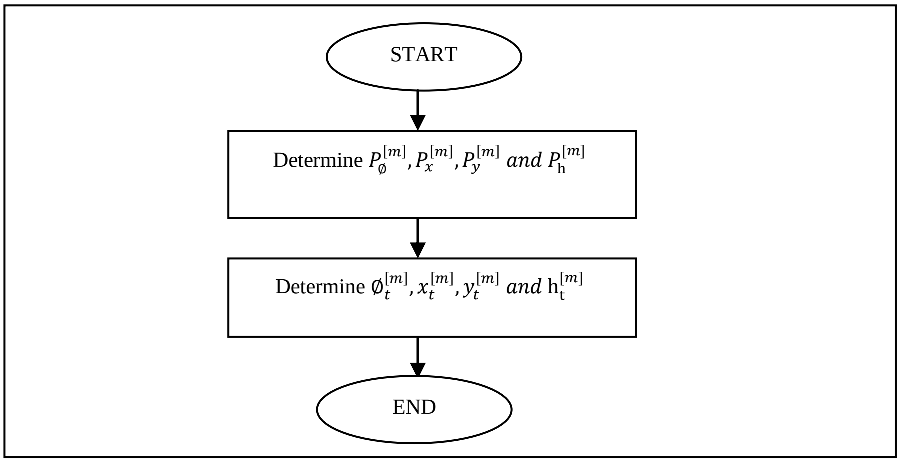

Figure 4. Algorithm Flow for a Motion Update in Activity Pedestrian SLAM

The motion model [35] update describes the probability density function $p\left(s_t^{[m]}\middle|s_{t-1}^{[m]}, \hat{u}_t\right)$. Based on [35], we define T_t as the time between two subsequent stance phases: $t-1$ and t. The position error is introduced by a perfectly calibrated accelerometer, which in this phase follows a second-order random walk: with standard deviation $\sigma_{x,acc}(T_t) = k_{x,acc} \,.\, T_1^{\frac{3}{2}}$, where $k_{x,acc}$ characterizes the accelerometer. The heading error introduced by an unbiased, calibrated gyroscope follows a random walk with $k_{\phi,gyro}$ being the gyroscope property. The gyroscope adds a random walk position error, of $\sigma_{x,gyro}(T_t) \approx k_{x,gyro}$. The resulting motion equations are:

$$p_\phi^{[m]} \sim \mathcal{N}(0, \sigma_{\phi,0} + k_{\phi,gyro}.\sqrt{T_t}) \tag{3}$$

$$p_x^{[m]} \sim \mathcal{N}(0, \sigma_{x,0} + k_{x,gyro}.T_t^{\frac{3}{2}}) \tag{4}$$

$$p_y^{[m]} \sim \mathcal{N}(0, \sigma_{x,0} + k_{x,gyro}.T_t^{\frac{3}{2}}) \tag{5}$$

$$p_h^{[m]} \sim \mathcal{N}(0, \sigma_{h,0} + k_{h,gyro}.T_t^{\frac{3}{2}}) \tag{6}$$

$$\phi_t^{[m]} = \phi_{t-1}^{[m]} + \delta\hat{\phi}_t + p_\phi^{[m]} \tag{7}$$

$$x_t^{[m]} = x_{t-1}^{[m]} + \hat{l}cos\phi_t^{[m]} + p_x^{[m]} \tag{8}$$

$$y_t^{[m]} = y_{t-1}^{[m]} + \hat{l}sin\phi_t^{[m]} + p_y^{[m]} \tag{9}$$

$$h_t^{[m]} = h_{t-1}^{[m]} + \delta h + p_h^{[m]} \tag{10}$$

6.3.2 Observation Update

The system performs observation updates [35] following a motion update associated with stance phase t. If more than one action occurs during a single stance phase, action recognition function triggers multiple subsequent observation updates. During an observation update, the system modifies the maps $\Theta_{t-1}^{[m]}$ for each particle according to its current pose $s_i^{[m]}$ and observation $\hat{A}_t$. First, the algorithm determines whether the observation corresponds with a landmark already present on the map, and if so, it asks which of the landmarks it corresponds with. It then either adds a new landmark $\theta_{N_{l,t},t}^{[m]}$ with $N_{l,t} = N_{l,t} + 1$, or modifies the associated $\theta_{[i],}^{[m]}$. Figure 6 depicts the decision making procedure. Consider sitting for example: The foot may move within an area of $\sim 0.5m$ diameter, without any change in upper-body posture. The parameters used in the system to describe a landmark are therefore its centroid location $\{x_{[i],t}, y_{[i],t}\}$, the ellipse shape parameters $\{a_{[i],t}, b_{[i],t,}\alpha_{[i],t}\}$, and the altitude of the landmark $h_{[i],t}$. In addition, each landmark has an associated action type $A_{[i]} \in$ {sitting, standing still, stair high, stair low}, which remains fixed.

$$q_{[i]} = \operatorname{atan}\left(\frac{a_{[i]},t-1}{b_{[i]},t-1} \cdot \frac{x_t - x_{[i],t}}{y_t - y_{[i],t}}\right) \tag{11}$$

$$\tilde{x}_e = a_{[i],t-1} \cos\left(q_{[i],t}\right) \cos\left(\alpha_{[i],t-1}\right) - b_{[i],t-1} \sin\left(q_{[i]}\right) \sin\left(\alpha_{[i],t-1}\right) \tag{12}$$

$$\tilde{y}_e = a_{[i],t-1} \cos\left(q_{[i],t}\right) \sin\left(\alpha_{[i],t-1}\right) + b_{[i],t-1} \sin\left(q_{[i]}\right) \cos\left(\alpha_{[i],t-1}\right) \tag{13}$$

$$\tilde{z}_{[i]} = \begin{pmatrix} \max(0, x_{[i],t-1} - \tilde{x}_e) \\ \max(0, y_{[i],t-1} - \tilde{y}_e) \\ h_{[i],t-1} - h_t \end{pmatrix} \tag{16}$$

$$P_{[i]} = \begin{cases} 0, & if\ \hat{A}_t \neq A_{[i]}, [i] \leq N_{l,t-1} \\ \eta . \left|2\pi Q_{[i]}\right|^{-\frac{1}{2}} \exp\left(-\frac{1}{2} \hat{z}_{[i]}^T Q_{[i]}^{-1} \hat{z}_{[i]}\right), & if\ \hat{A}_t = A_{[i]}, [i] \leq N_{l,t-1} \\ \eta . p_{0,} & if [i] = N_{l,t-1} + 1 \end{cases} \tag{17}$$

η is a normalization factor, so that the sum of all $p_{[i]}$ with $[i] = 1 \dots N_{l,t-1} + 1$is 1. The observation covariance matrix $Q_{[i]}$, is the sum of the landmark position covariance $\sum_{[i],t-1}$, and the measurement covariance R_t.

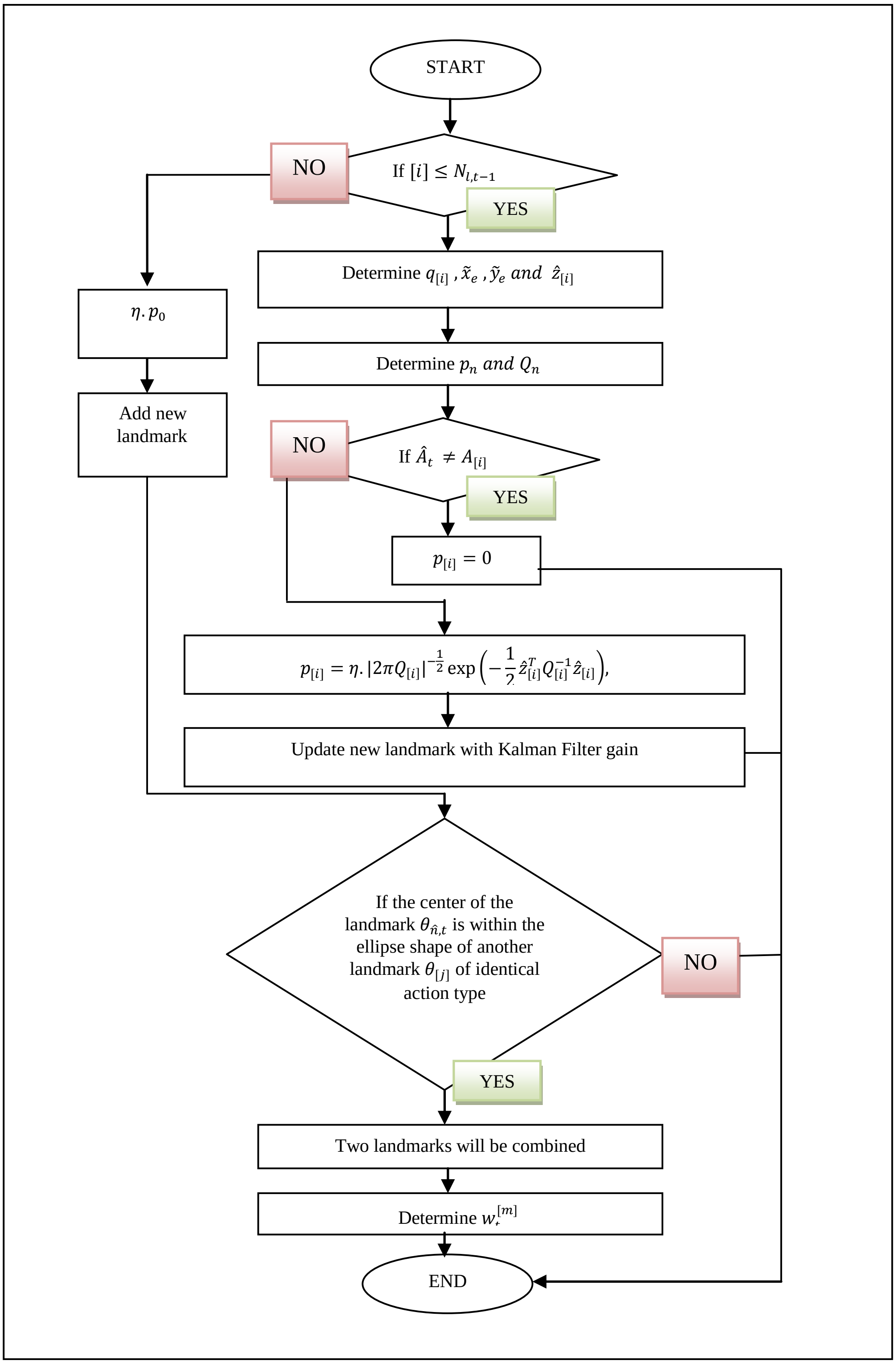

Figure 6. Algorithm Flow of Observation Update in Activity Pedestrian SLAM

$$Q_{[i]} = \sum_{[i],t-1} + R_t \; with \; R_t = \begin{pmatrix} r_0^2 & 0 & 0 \\ 0 & r_0^2 & 0 \\ 0 & 0 & r_0^2 \end{pmatrix} \quad (18)$$

Given the probabilities $p_{[i]}$, the system samples the data association decision $\hat{n} \in \{1, \ldots, N_{l,t-1} + 1\}$. If the outcome is $\hat{n} = N_{l,t-1}$+1, the system adds a new landmark with the following characteristics to the particle map Θ_{t-1}:

$$x_{\hat{n},t} = x_t, y_{\hat{n},t} = y_t, h_{\hat{n},t} = h_t \quad (19)$$

$$a_{\hat{n},t} = b_{\hat{n},t} = r_1, \alpha_{\hat{n},t} = 0o \quad (20)$$

$$A_{\hat{n}} = \hat{A}_t \quad (21)$$

$$\sum_{\hat{n},t} = R_t \quad (22)$$

If $\hat{n} \leq \; N_{l,t-1}$, the system updates the associated landmark's position in a Kalman filter with gain K:

$$K = \sum_{\hat{n},t-1} Q_{\hat{n}}^{-1} \quad (23)$$

The new position for landmark $\theta_{\hat{n},t}$ and the updated position covariance $\sum_{\hat{n},t}$ are:

$$\begin{pmatrix} x_{\hat{n},t} \\ y_{\hat{n},t} \\ h_{\hat{n},t} \end{pmatrix} = \begin{pmatrix} x_{\hat{n},t-1} \\ y_{\hat{n},t-1} \\ h_{\hat{n},t-1} \end{pmatrix} - K\hat{z}_{\hat{n}}^T \quad (24)$$

$$\sum_{\hat{n},t} = (I - K) \sum_{\hat{n},t-1} \quad (25)$$

If the center of landmark $\theta_{\hat{n},t}$ is within the ellipse shape for another landmark $\theta_{[j]}$ of an identical action type following this step, the two ellipses are combined into a single ellipse at landmark $\theta'_{\hat{n},t}$. The system fits an ellipse around all the observation locations for landmarks $\theta_{[j]}$ and $\theta_{\hat{n},t}$, with the semi-major axis lengths constrained to $\leq 0.8\,m$. The system executes an observation update for each particle individually, and concludes by calculating the new weights $w_t^{[m]}$. according to Montemerlo et al.[36]. $w_t^{[m]} = w_{t-1}^{[m]} . p_{\hat{n}}^{[m]}$

6.3.3. Compensation Technique and KLD-Resampling

After each observation update (see Figure 7), the algorithm calculates the effective particle number as $N_{eff} = \frac{1}{\sum_{m=1}^{N_p} (w_t^{[m]})}$ and performs compensation technique [37] and KLD resampling [38]. If $N_{eff} = N_{th}$. In this way, the filter relinquishes particles with a very low weight, and better approximates $p(s^t, \Theta_t | \hat{A}^t, \hat{u}^t)$ in areas not close to zero.

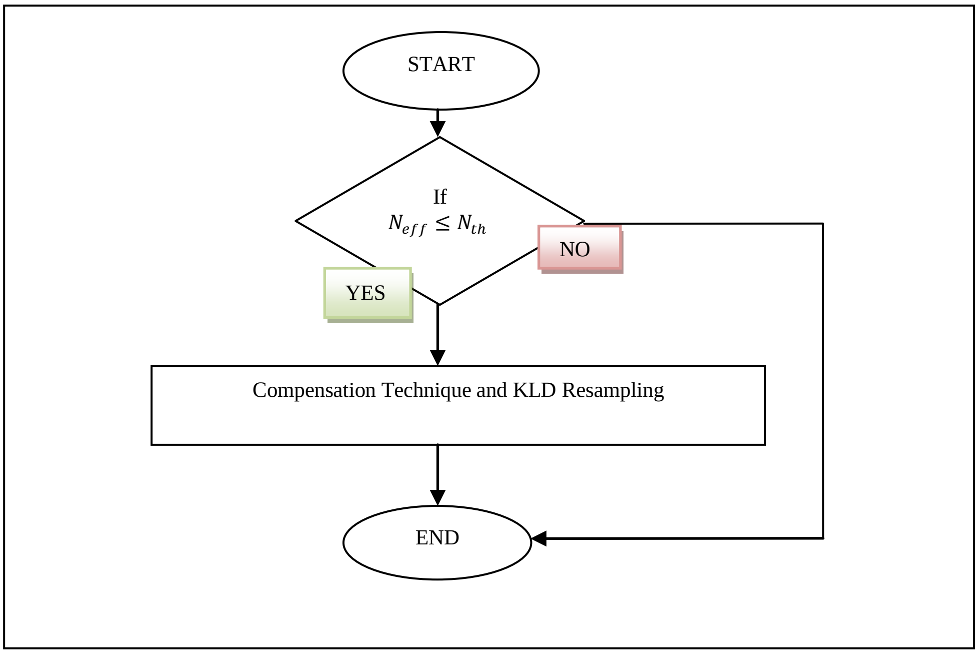

Figure 7. Algorithm Flow of Compensation Technique and KLD-Resampling in Activity Pedestrian SLAM

7. Conclusions and Future Directions

This paper has discussed problem solving, by explaining how to develop a ERL system based on IMU Pedestrian SLAM in obstructed area, especially when traditional Global Positioning Systems are blocked. The user will find it difficult to navigate directly on-site in such conditions; particularly in obstructed environments (especially in home environment). To provide a better location determination service with less computational complexity and deployment costs, the establishment of a standalone pedestrian tracking method is necessary. This tracking technique will be based on IMU technology, which allows determination of standalone tracking information. However, the approach suffers from the lack of a stance phase during human walking activity. In order to resolve this, a new stance detection phase will be designed for pedestrian simultaneously localization and mapping (SLAM) to improve the robustness of the indoor positioning system. In future work, we will present our preliminary results to illustrate the performance of the system for an indoor environmental set-up.

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