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Optimisation of Emergency Rescue Location (ERL) using KLD-Resampling: An Initial Proposal

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Abstract

When an emergency occurs in a building, congestion avoidance becomes a very serious localisation issue, which is often ignored. If the emergency involves the outbreak of fire, the rescue team must establish the easiest and quickest exit route from the building. Any delay could be very dangerous, potentially even resulting in fatalities. To avoid congestion, an effective Emergency Rescue Localisation (ERL) system is essential to help rescue teams determine the easiest exit route from the building. This paper proposes an ERL methodology, based on the Inertial Measurement Unit (IMU).In this system, the IMU helps to determine and obtain positioning data from a building's interior. This study describes the application of the ERL system for an indoor situation in detail.

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

1. Introduction

With the rapid advancement in location technologies and tracking devices, andthe demand for flawless solutions to overcome the problems associated with current location-based techniques, there is wide-spread interest in Indoor Positioning Systems (IPS)[1-5]. One of the major components of IPS is indoor tracking, which facilitates the tracing of individuals (or mobile nodes) within corridors or other enclosed structures. Some examples of IPS include - asset navigation, first-responder navigation, emergency rescue search techniques, people movers and tracking [6-10]. The widely distributed Global Navigation Satellite System (GNSS), along with its network, which consists of many dedicated satellites, offers global service coverage [11]. GNSS is the primary system of choice for outdoor settings; where available, it has been recognised as the most accurate provider of location information. However, this system does not work well in unknown terrain,or in cases where the interior environment is constantly changing; hence, we need to adopt alternative systems.

While selecting the most ideal technology for IPS design, several factors need to be considered, for example robustness, accuracy, cost, coverage, and scalability, [12-14]. However, no technology currently exists that fulfils all the above-mentioned criteria. Thus, it is necessary to evaluate the parameters of all the available technologies and then compare them with the consumer's requirements, thereafter analysing and describing the utility of every application. However, the data values for these factors can vary, due to their dependence on several parameters and the different associated conditions. Hence, the ultimate customised IPS design would offer the best combination of implementing parameters to fulfil consumer needs, while also being applicable to the environmental set-

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up. Based on the IPS techniques available, several solutions [1] for Human Pedestrians (PDR) are propose. These include distributed and cooperative tracking, Bayesian tracking, pedestrian Simultaneously Localisation and Mapping (SLAM), fusion method, and fingerprinting. Of all these techniques, the pedestrian SLAM technique is the most helpful for locating the position of a pedestrian in a new and constantly changing environment[15-17]. It has been successfully used in domestic environments for this purpose[15,18].

An additional factor to consider for the purpose of a rescue operation is interior layout. In the case of an emergency, the rescue team might need to bypass or remove obstacles to reach a person under duress. A situation can suddenly become dangerous, and if the rescue operation is affected by a lengthy delay this could prove fatal [19-23]. On many occasions, rescues are delayed because, although they have arrived at the disaster site quickly, the rescue team must wait to determine the actual situation within the interior of the building. Before commencing a rescue, they require prior knowledge of the location in which the people are trapped, the areas that are congested, and the best access route(s) for the rescue operation. Certain technologies, for instance WSNs, can improve the efficiency of rescue operations, by providing information regarding the building’s internal environment.

Although WSN technology has several advantages, its application is limited. When a pedestrian enters a building to find a particular destination, the best way for them to identify congested areas to avoid is to refer to a map. For this purpose, a pedestrian SLAM system should prove useful, as it can be used for producing the preliminary map and subsequently for redesigning the map to represent further changes within interiors, or to improve its precision. However, improvements to the pedestrian SLAM system would incur huge costs if it were to rely on an installed infrastructure [24],like the Radio Frequency Identification (RFID) [25]or the WLAN radio access point [26-29]. In addition, these systems are not suitable in a crisis, or for security or rescue operations, where such systems would not be available, or where it could be impracticable to apply them rapidly and cost-effectively.

Alternative methods, such as Inertial Measurement Unit (IMU) [30-32], cameras [33], and laser scanners[34], can be used however, as they do not incur high costs and are based on an infrastructure-less methodology (the systems rely on sensors). Systems that are IMU sensor-based are beneficial, as they can provide increasing mobility, which makes them less intrusive and moderately cheap. However, few reports[31-32]have suggested methods that provide detailed information about activity and position simultaneously (satisfying the provision of context awareness). Hence, in this paper, we propose an Emergency Rescue Localisation (ERL) approach that considers both pedestrian obstruction and the rescuer’s activities. This paper is organised as follows: Section 2 reviews related papers. Section 3 explains the formulation of the problem. Section 4 outlines the important research hypotheses. Section 5 explains the major objectives of the study. Section 6 provides a detailed design for the IMU Pedestrian SLAM-based ERL. Finally, Section 7 offers a discussion based on the future prospect of the study.

2. Related Work

Many earlier reports details the determination of emergency localisation and evacuation using WSNs [35-39]. In addition, in their paper,[39], the authors depicted the shortest path for evacuation and divided people into two separate groups depending on their location, as either those inside or those outside the emergency situation. To reduce the cost of communication, the study uses a small subset of sensors. According to the work described in [39], several other sensors have been added to WSNs. In a different report, the authors of [37], extended this technique to include 3D environments. Further, [39] also proposed distributed algorithms as guidance for the targets across the regions of a self-organised sensor network. It was noted, that in emergency cases, people usually follow the quickest and safest path as shown on a directed roadmap [35]. Using the medial axes of safe areas, a roadmap is constructed and directions assigned, thereby also decreasing the overhead packet. Unlike the road map in [35], a separate study,[36], used the skeleton graph to summarise the localisation field.

Several other reports have proposed different ways to help rescue teams, and these also provide valuable information[40-41]. In one study, [40], the authors presented a way to detect underground collapses using WSNs; whereas, in a different report, [41], the authors described a method for narrowing the search area in wild regions, to help rescue teams conduct their operations effectively. The authors relied on witness accounts provided by several hikers, which helped them to narrow down the probable locations of their victims. In their study, the authors [42] developed a novel network for a distributed mobile sensor system, to solve the problem of emergency response; wherein they used robots to detect people trapped by fires. However, none of these systems tackled pedestrian congestion problems. Hence, in several interior environments, a lack of space, and the presence of several evacuees, caused congestion (this problem could be exacerbated in emergencies that result in the failure of transport systems like elevators). Hence, the probability of congestion occurring should not be ignored when planning for emergencies. The ERL proposed in our study considers congestion and the likely activities of the rescue team to ensure a smooth evacuation in emergencies.

3. Problem Formulation

In the case of an emergency, there might be several danger zones within a building with the potential to endanger human life; for example, areas where there is fire or smoke, where there are obstacles [43-45]. It is imperative to keep people away from these areas and evacuate them as quickly as possible[46,47]. Sometimes, a safe exit path might be blocked or heavily congested. Additionally, if someone is trapped in a particular area, several of the systems available might not be able to generate output. Hence, any efficient system should be able to determine the position of individuals in different kinds of environments. Pedestrian SLAM-based IPS techniques can prove efficient in such circumstances, as they are able to determine position and generate maps in several types of environments. However, the chosen system should be both cost-effective and non-intrusive, respecting individuals' privacy. Due to its infrastructure, an IPS technology based on Wi-Fi, cameras, or RFID could prove very costly. A camera also invades the privacy of the individual; hence, this problem should be addressed. Our assumptions and the objectives for our design are as follows.

4. Assumption

We assume that in the case of an emergency, the areas concerned might contain several regions that could disappear, emerge, expand, or shrink at any time. We have also assumed that all fire personnel can contact the control centre.

5. Objective

The study aims to outline a credible new ERL, based on the integration of IMU-based Pedestrian SLAM. By implementing this system, it should be possible to ascertain a position in an interior environment in different contexts. Additionally, it might be possible to identify positions in illuminated environments when an individual is inside a building. The results of the study could also significantly contribute to modernising current location detection systems, and provide useful data for other Pedestrian SLAM-related studies.

6. System Design

Fig. 1 illustrates the complete framework, which contains two major blocks: the first includes the pre-processing stage and the SLAM update stage. In the initial pre-processing stage, the technique obtains a step estimate, $\hat{u}$, and then detects the location-related actions, $\hat{A}$, with the help of the wearable inertial sensors. Then the measurements are fused with the Rao-Blackwellised particle filter, as proposed by [48]. The proposed system then sections the path in the stance phases, t, wherein the pose is described as$s_t = \{x_t, y_{t,} h_t, \phi_t\}$, and the steps, u_t, connects_{t-1} and, s_t. In the notation, $= \{x_t, y_{t,} h_t\}$ represents the 3D location of the individual at the time, t, and ϕ_t refers to the foot's heading. The system outputs are a path, $s^{-t} = \{\overline{s}_0 \dots \dots \overline{s}_t\}$ containing the processes $\overline{s}_t = \{\overline{x}_t, \overline{y}_{t,} \overline{h}_t, \overline{\phi}_t\}$, and the map $\overline{\Theta}_t$ that comprises the $N_{l,t}$ landmarks $\overline{\theta}_{t,[i]}$. $[i] \in \{1 \dots N_{l,t}\}$ is the landmark index, and $N_{l,t}$ represents the number of landmarks available on the map.

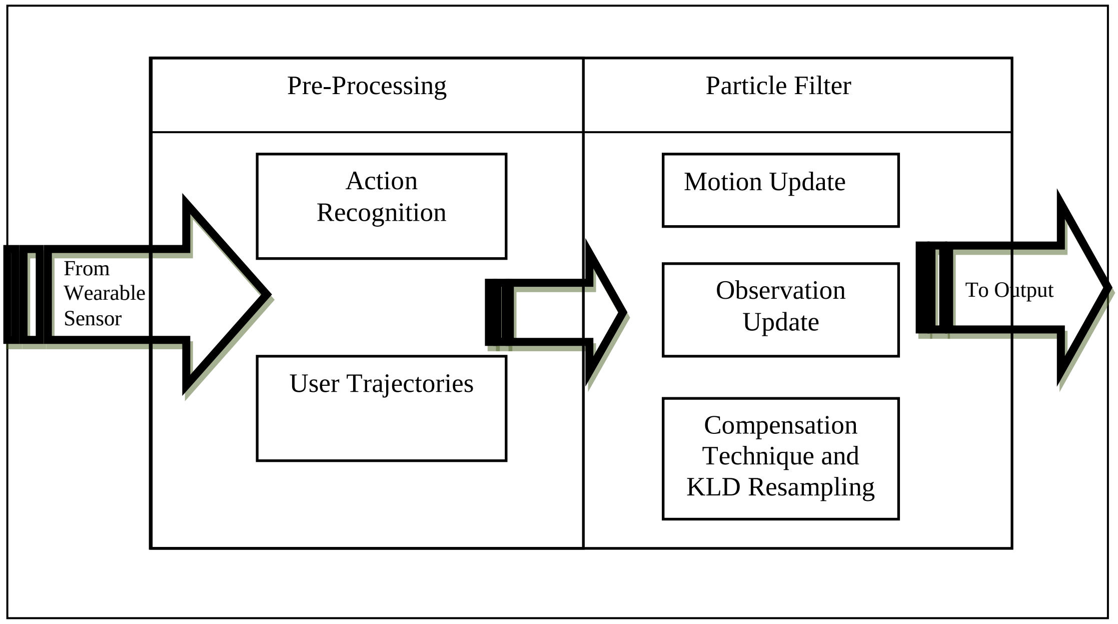

Figure1. System Architecture for the Activity Pedestrian SLAM

6.1. Pre-Processing

This section describes the pre-processing factor in two different subsections of the Pedestrian SLAM, i.e., action recognition and user trajectory, as depicted in Fig. 2.

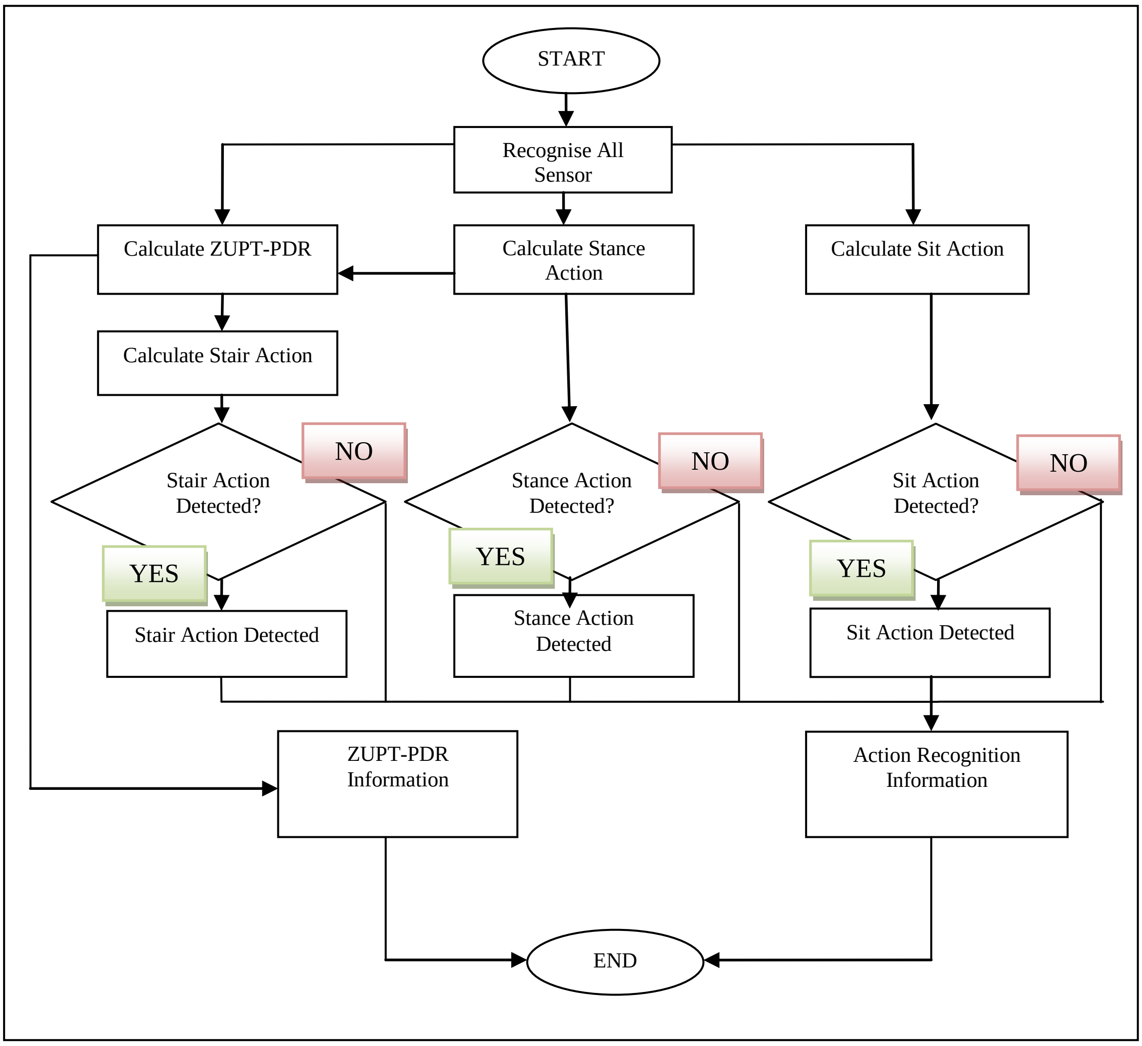

Figure 2. Action Recognition and User Trajectory in the Activity Pedestrian SLAM

6.1.1. Action Recognition

Four fundamental actions are detected, which include: sitting, standing erect, stair low (i.e., arriving at the lower stair end) and the stair high (i.e., arriving at the upper stair level). The inclusion of action recognition constituents allows detection of these actions. This section describes the recognition of actions like sit detection, stand detection and stair detection. Sit detection detects actions while sitting using a threshold to the upper leg sensor orientation. Whereas, Stance detection (usually, detects standing still action), comprises of two different sub-components, e.g., standing still detection, and adaptive stance detection (walking path segmentation). Standing still actions are highly complex and are detected only if the individual wears a special sock. The walking path segmentation is initially divided into steps, after which adaptive stance detection is used to mediate the detection criterion on the stepwise rise in the stance detection threshold, as depicted in Fig. 2. Meanwhile, the standing still detection gauges an action while standing still, by recognising that a stance phase with a duration of less than 0.75s occurs while interrupting gait. Finally, stair detection detects actions involving the stair low and the stair high criteria, after calculating the variance, $var(h(t))$, of the ZUPT-PDR altitude output, $h(t)$, within a sliding window with a length, ΔT. If $var(h(t))$ remains for a minimum τ_0 above threshold, h_0, this phase is recognised as a stair ascent or descent. With respect to the final output results, the system's action recognition block presents action observations {sitting, standing still, stair low, stair high}, as related to the stance phases, t.

6.1.2. User Trajectories

The pre-processing of the data, involves an open-loop estimate, $\hat{s}^t$, for an individual's trajectory, which consists of the steps,$\hat{u}_t$. 3D-foot coordinates are assessed using ZUPT-PDR [].ZUPT-PDR stance detection divides the walking pathway into steps, $\hat{u}_t$, explained by horizontal step length, $\hat{l}_t$, change in altitude, $\delta\hat{h}_t$, and change in heading, $\delta\hat{\phi}_t = \hat{\phi}_t - \hat{\phi}_{t-1}$.

6.3. Adaptive Rao-Blackwellised Particle Filter

The regular SLAM problem, $p(s_t, \Theta|\hat{u}^t, \hat{z}^t, \hat{n}^t$, of assessing system landmarks is not identified by$\hat{n}_t$; it can identify only action type, $\hat{A}_t$. Moreover, the evaluated position for a landmark that is observed at time, t, is similar to the individual's position at that time. Thus, $\hat{z}^t$ is derivable using the values s and Θ alone; hence, it reduces the SLAM problem by the approximation of: $(s^t, \Theta_t|\hat{u}^t, \hat{A}^t)$. The system also uses the Rao-Blackwell factorisation [48] for fusing motion and observational measurements (Figure 3):

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

This factorisation technique decreases the SLAM problem by evaluating path, s^t, in a formerly strange environment, Θ_t, based on the different estimators of the individual's path, s, and every $N_{l,t}$landmark, $\Theta_{[i],t}$. This system also assesses the path's probability, $p(s^t|\hat{u}^t)$, in the particle filter with N_p particles; therefore, it can approximate non-Gaussian distributions, and perform nonlinear filtering. The $N_{l,t}$ individual filters are also used for the estimation of landmark probability distributions, $p\left(\theta_{[i],t} \middle| s^t, \hat{A}^t\right)$. Since landmark qualities $\theta_{[i],t}$ are inured depending on the individual's path, every particle, $[m]$, should retain its individual map, $\Theta^{[m]}$, along with the pose $s_t^{[m]}$.The system calculates, $s_t^{[m]}$ during a motion update, whereas any map update, $\Theta^{[m]}$ requires an observational update; however, this is only in response to action data.

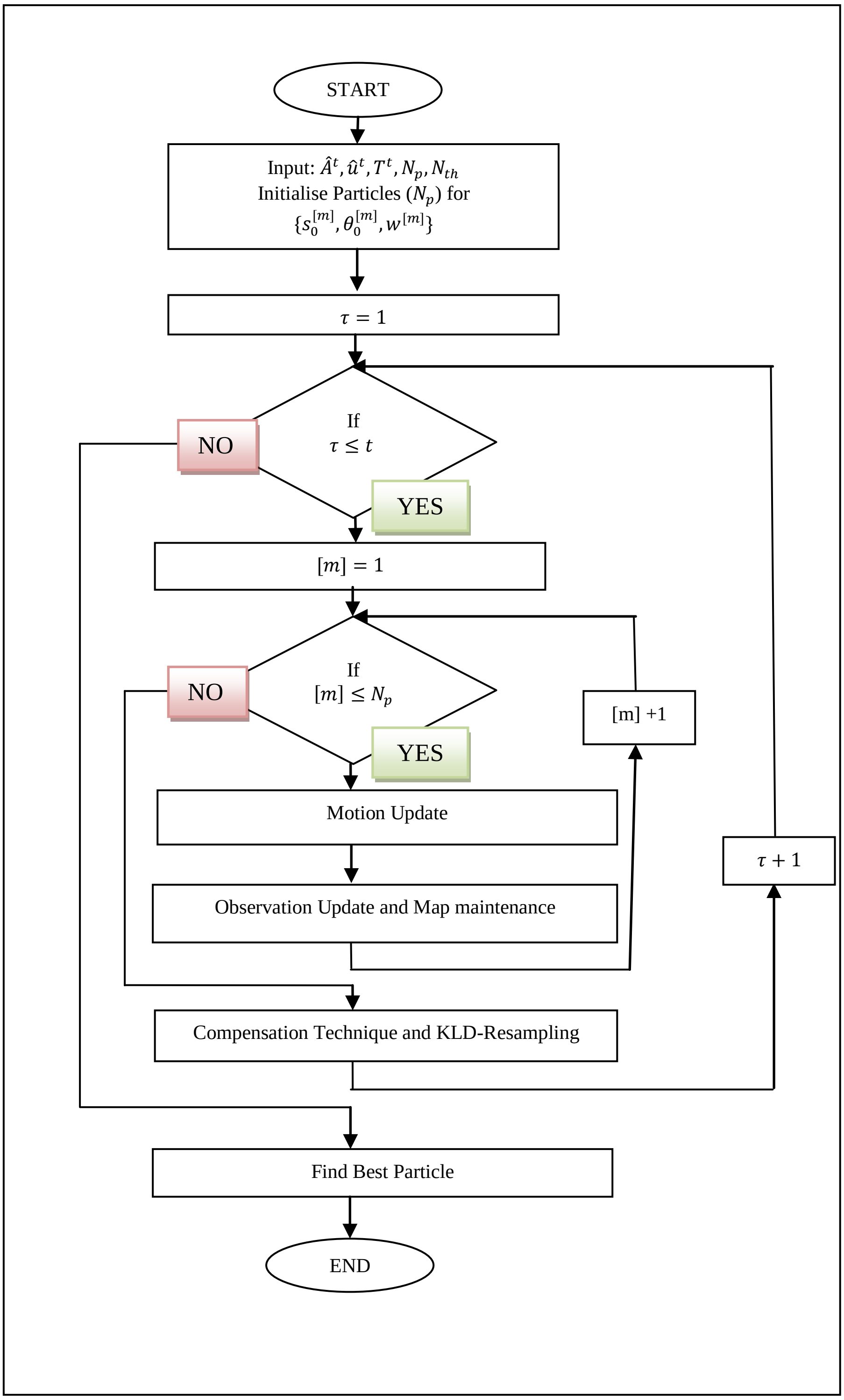

Figure 3. Algorithm Flow of the Rao-Blackwellised Particle Filter in the Activity Pedestrian SLAM

6.3.1. Motion Update:

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

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

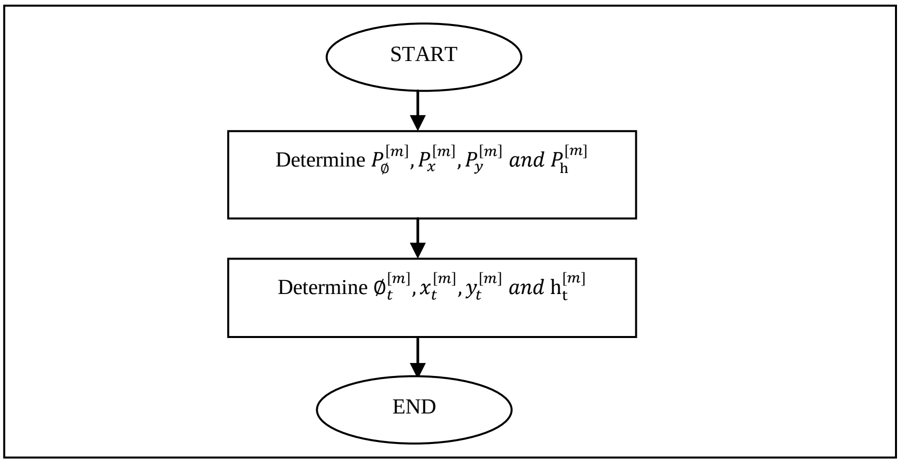

Figure 4. Algorithm Flow for a Motion Update in the Activity Pedestrian SLAM

The motion model [48] update describes the probability density function, $p\left(s_t^{[m]}\middle|s_{t-1}^{[m]}, \hat{u}_t\right)$. As described in [48], we have defined T_t as the time interval that occurs between two subsequent stance stages: $t-1$ and t. The error in the position is introduced with the help of an accurately calibrated accelerometer, which follows the second-order random walk: with a standard deviation, $\sigma_{x,acc}(T_t) = k_{x,acc}.\, T_1^{\frac{3}{2}}$, where, $k_{x,acc}$ describes the accelerometer. An impartial calibrated gyroscope introduces a heading error, i.e., a random walk position error of $\sigma_{x,gyro}(T_t) \approx k_{x,gyro}$, with $k_{\phi,gyro}$ as a gyroscope property. The resultant motion equations are as follows

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

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

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

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

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

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

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

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

6.3.2 Observation Update

The system also conducts observation updates [48] subsequent to the motion update related to stance phase, t. However, if more than one action occurs during one stance phase, then the action recognition activates several consequent observation updates. In an observation update, the methodology modifies the maps, $\Theta_{t-1}^{[m]}$, for every particle depending on its existing pose, $s_i^{[m]}$, and observation, $\hat{A}_t$. Initially, the algorithm determines if the observation matches a landmark depicted on a map, and if it does, it enquires which landmark it matches. The algorithm can then add the new landmark, $\theta_{N_{l,t},t}^{[m]}$ with$N_{l,t} = N_{l,t} + 1$, or alter the associated$\theta_{[i],}^{[m]}$. Fig. 6 describes this decision-making process. If we consider sitting as an example: while sitting, the individual's foot can move in an area with a diameter$\sim 0.5m$, without any significant movement in the upper body. Hence, the factors used in the methodology for describing a landmark indicate its centroid location, $\{x_{[i],t}, y_{[i],t}\}$, ellipse shape factors, $\{a_{[i],t}, b_{[i],t,}\alpha_{[i],t}\}$, and landmark altitude, $h_{[i],t}$. Additionally, every landmark also has a related action type, $A_{[i]}$ ∈{sitting, standing still, stair low, stair high}, that remains fixed.

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

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

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

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

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

Here, η is the normalisation factor; hence, the summation of all $p_{[i]}$ with $[i] = 1 \ldots N_{l,t-1} + 1$ equals 1. The observation covariance matrix, $Q_{[i]}$, can be described as the sum of the landmark position covariance, $\sum_{[i],t-1}$, and measurement covariance, R_t.

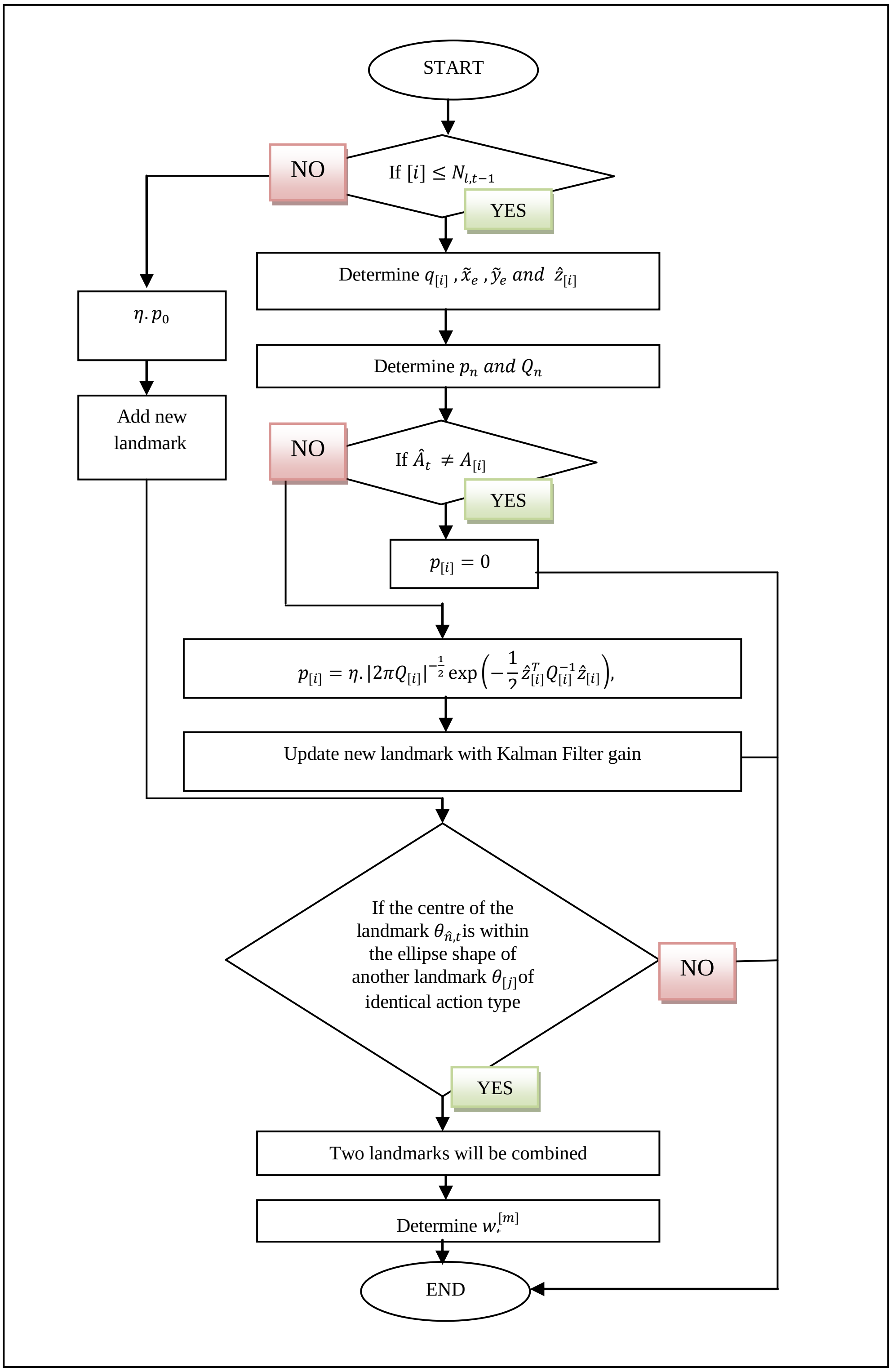

Figure 5. Algorithm Flow of the Observation Update in the Activity Pedestrian SLAM

$$Q_{[i]} = \Sigma_{[i],t-1} + R_t with R_t = \begin{pmatrix} r_0^2 & 0 & 0 \\ 0 & r_0^2 & 0 \\ 0 & 0 & r_0^2 \end{pmatrix} \tag{18}$$

The system tests the data association outcome, $\hat{n} \in \{1, \dots, N_{l,t-1} + 1\}$ for the probabilities, $p_{[i]}$. If the resultant outcome is, $\hat{n} = N_{l,t-1}$+1, then the system adds a new landmark with the corresponding features to the particle map, Θ_{t-1}:

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

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

$$A_{\hat{n}} = \hat{A}_t \tag{21}$$

$$\textstyle\sum_{\hat{n},t} = R_t \tag{22}$$

If, $\hat{n} \leq N_{l,t-1}$, then the system updates the related landmark position with a Kalman filter showing a gain, K:

$$K = \textstyle\sum_{\hat{n},t-1} Q_{\hat{n}}^{-1} \tag{23}$$

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

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

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

If the landmark centre ,$\theta_{\hat{n},t}$ lies within the elliptical shape of a different landmark $\theta_{[j]}$denotinga similar type of action, then both ellipses are merged to form one ellipse at that landmark, $\theta'_{\hat{n},t}$. In this system, an ellipse is formed around all the observed locations noted for landmarks $\theta_{[j]}$ and$\theta_{\hat{n},t}$, with a semi-major axis length restricted to$\leq 0.8\, m$. Thereafter, the system carries out an observation update for every particle independently, and then finally calculates the new weights, $w_t^{[m]}$, as described in [49], $w_t^{[m]} = w_{t-1}^{[m]}. p_{\hat{n}}^{[m]}$.

6.3.3.Compensation Technique and KLD-Resampling

After each observation update (as shown in Fig. 6), the algorithm estimates the effective particle number, $N_{eff} = \frac{1}{\sum_{m=1}^{N_p}(w_t^{[m]})}$ and then carries out the compensation technique [50] and the KLD resampling technique [51],if$N_{eff} = N_{th}$. Thus, the filter abandons particles with very low weights, and improved approximates$p(s^t, \Theta_t | \hat{A}^t, \hat{u}^t)$ in regions not near to zero.

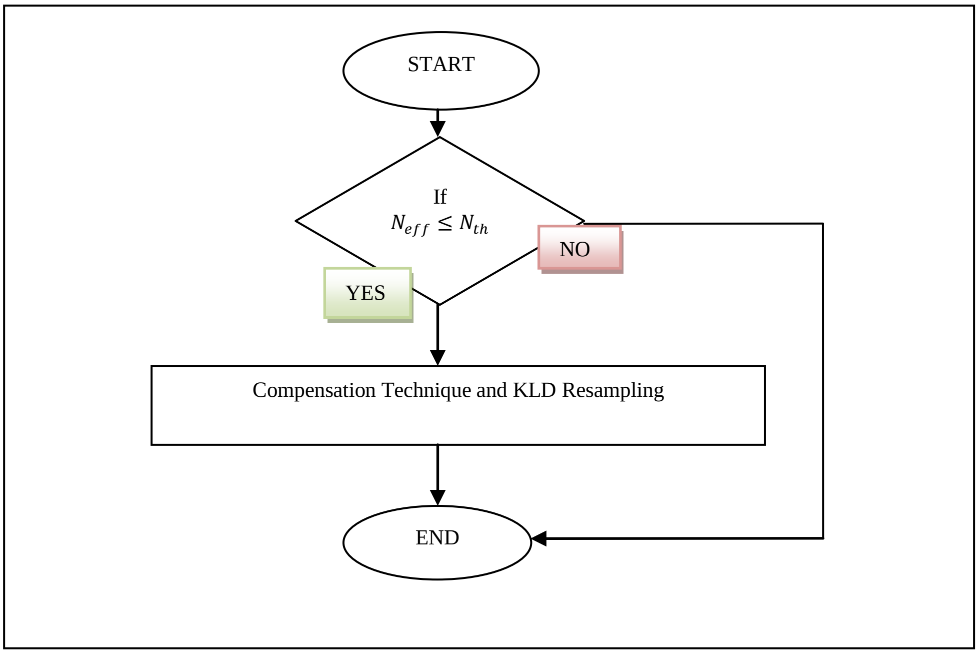

Figure 6. Algorithm Flow of the Compensation Technique and the KLD-Resampling In Activity Pedestrian SLAM

7. Conclusions and Future Directions

In obstructed areas (mainly local environments), the user can find it very difficult to traverse a path, especially if there are emergencies and rescue teams need to reach the trapped individuals quickly. This study proposed an ERL system based on IMU Pedestrian SLAM, which can be applied in congested areas. Such as system is very useful when Global Positioning Systems are blocked. This system provides a better position determining method, one that is less computationally complex and incurs fewer deployment costs. The study described a standalone pedestrian tracking system, based on IMU technology designed to provide standalone-tracking data. However, this approach lacks the stance phase that arises when an individual is walking. Therefore, to overcome this limitation, a novel stance detection stage was proposed for pedestrian SLAM, to improve the robustness of the IPS. In our future works, we will present some preliminary data that demonstrates the system's performance in an enclosed arrangement.

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