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# Optimization of Rao-Blackwellized Particle Filter in Activity Pedestrian Simultaneously Localization and Mapping (SLAM): An Initial Proposal

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### *Abstract*

*When Global Positioning Systems are obstructed, standalone pedestrian tracking can be very daunting. Users in such obstructed environments (especially in home environments) will find it difficult to perform on-site navigation. It is important to create a standalone pedestrian tracking system that provides better location determination services with less computational complexity and deployment cost. One promising way to implement this service is through the use of Inertial Measurement Unit (IMU) sensors. This tracking method provides the pinpointing of standalone tracking information but is handicapped by missing stance phase during pedestrian walking activities. A new pedestrian stance detection using simultaneously localization and mapping (SLAM) will be designed in this paper with a focus on robust indoor positioning systems. We will present our preliminary results to illustrate the performance of the system for an indoor environment set-up at the end of this paper.*

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

## 1. Introduction

Widespread advances of devices and technologies and the necessity for seamless solutions in location-based services have increased the relevance and necessities of Indoor Positioning Systems (IPS) [1]. The tracking of people or pedestrians (referred to as mobile nodes in the sequel) within a corridor or any enclosed structure is a salient part of IPS. Tracking tasks include emergency rescue locating, first-responder navigation, asset navigation and tracking or people movers [2]. A network of dedicated satellites offers a worldwide service coverage with the use of the widely diffused Global Navigation Satellite System (GNSS) [3]. GNSS is recognized as a legacy system for outdoor environments and, to a great extent, one of the most accurate sources of positioning information when available.

However, alternative systems need to be adopted for indoor environments, as GNSS is proving to be unfeasible in this area.

A large number of parameters need to be taken into account (for example: cost, accuracy, robustness, scalability, and coverage) to design and IPS with the latest and best technological equipment[4]. Obviously, there doesn't exist a single solution that works fine for all scenarios. It is vital then to consider and evaluate all available technological performance parameters and match them with specific user requirements which have to be analysed and articulated precisely for each application. Moreover, various factors and

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conditions affect and govern the performance parameters. A customized solution will only succeed if the right trade-off among performance parameters, user requirements and environmental are identified.

Bayesian tracking, distributed and cooperative tracking, fingerprinting, fusion method and pedestrian simultaneously localization and mapping (SLAM)were some of the many indoor positioning methods brought forward to track human pedestrians (PDR) [1]. Among these methods, the most capable method to determine pedestrian positions in unknown and changing environments was the SLAM method[5]. For many domestic environments where pedestrians were expected to enter all areas within a room or home, this approach had been proven to robust and successful [5]. It is more appropriate to utilize an existing map for pedestrians entering a large building in search of a specific destination. The initial map could be generated by Pedestrian SLAM and eventually updated to include changes in the environment and increase the navigational accuracy within the community. Yet, Pedestrian SLAM requires dedicated infrastructure and equipment [6] like Radio Frequency Identification (RFID) [7] or WLAN radio access points [8-11] which incur high costs. In additional, these infrastructures might be unavailable or are slow to deploy inexpensively thus making Pedestrian SLAM unsuitable for emergency, security and rescue applications. Other approaches do not require that high cost like Inertial Measurement Units (IMUs) [12-14], cameras [15] and laser scanners[16] because they do not require extensive deployment of infrastructure as they only rely on sensors. Among these methods, techniques based on IMU sensors are the only ones that can provide better mobility, privacy and are cheaper. Nevertheless, only [13, 14] can provide activity and location simultaneously (which fulfils the context awareness condition). A new technique that uses Rao-Blackwellized particle filters based on resampling analysis and KLD sampling in Pedestrian SLAM for efficient computational complexity will be discussed in this research. The suggested technique will be able to reduce the computational complexity and RMS errors in Pedestrian SLAM. It is hoped that the results of this research will assist in the modernisation of location determination systems as well as contribute to the current field of studies of Pedestrian SLAM. The outline of this paper is as follows: Section 2 will present the basic concepts related to robust indoor positioning, our problem formulation will be covered in Section 3, Section 4 will present our proposed methods, Section 5 will outline our experiment setup, followed by a discussion on our preliminary results in Section 6 and a discussion on the future direction of the project will be provided in Section 7.

## 2. Concept of Activity Pedestrian SLAM

The concept of Activity Pedestrian SLAM (see Figure 1) for fundamental system architecture) regards positioning determination and mapping across all environments [17-21]. It usually depends upon a multi-sensor setup while augmenting standalone positioning with other signals, motion sensors, and environmental features. Three dimensional (3D) mapping, context awareness and cooperation between users may enhance its capabilities. As indicated in Figure 1, three (3) subsystems make up the Activity Pedestrian SLAM: the field subsystem, the interface subsystem, and the database subsystem. The transmitters will always continuously broadcast their signal within coverage under normal circumstances. Devices equipped with special sensors within their coverage area will receive a signal. The central processing unit (where the algorithm is installed) will process the received signals before referring with the data in the database server. Finally, a device screen will display the mapping location sent by the system.

 

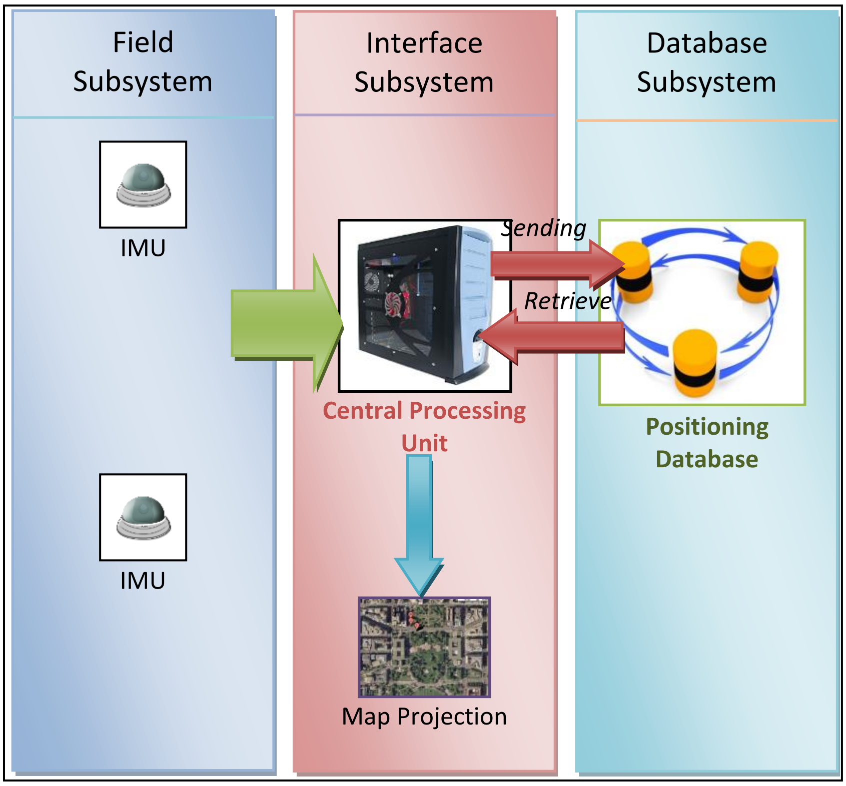


**Figure 1. General System Architecture of Pedestrian SLAM**

## 3. Problem Formulation

The concern in Pedestrian SLAM is the extensive computational resources needed by the engine framework during the resampling. This is because it involves iteration processes which are used to prevent weight degeneracy (by getting rid of particle if the weight is less).The reduction of computational complexity will affect the sampling quality in this research paper. The system will experience particle depletion if there is no reduction of computational complexity and eventually degrade the resampling quality.

## 4. System Design

Figure 2 depicts the two main phases in the Activity Pedestrian SLAM framework: the pre-processing phase and SLAM update phase. The system derives a step estimate,$\hat{u}$, during pre-processing and recognizes the location-related actions, $\hat{A}$, from wearable inertial sensors. A Rao-Blackwellized particle filter [22] then fuses these measurements. The system then segments the paths into stance phases$t$ with poses $s_t = \{x_t, y_{t,} h_t, \phi_t\}$ and steps $u_t$that connect $s_{t-1}$and $s_t$. In this notation, $= \{x_t, y_{t,} h_t\}$which denotes the 3D position of the user at time $t$and $\phi_t$, the foot's heading. The outputs of the system are a path of $s^{-t} = \{\bar{s}_0 \dots \dots \bar{s}_t\}$ composed of poses $\bar{s}_t = \{\bar{x}_t, \bar{y}_{t,} \bar{h}_t, \bar{\phi}_t\}$ and a map $\bar{\Theta}_t$made up of $N_{l,t}$landmarks $\bar{\theta}_{t,[i]}$. $[i] \in \{1 \dots N_{l,t}\}$is the index of the landmark, and $N_{l,t}$the number of landmarks in the map.

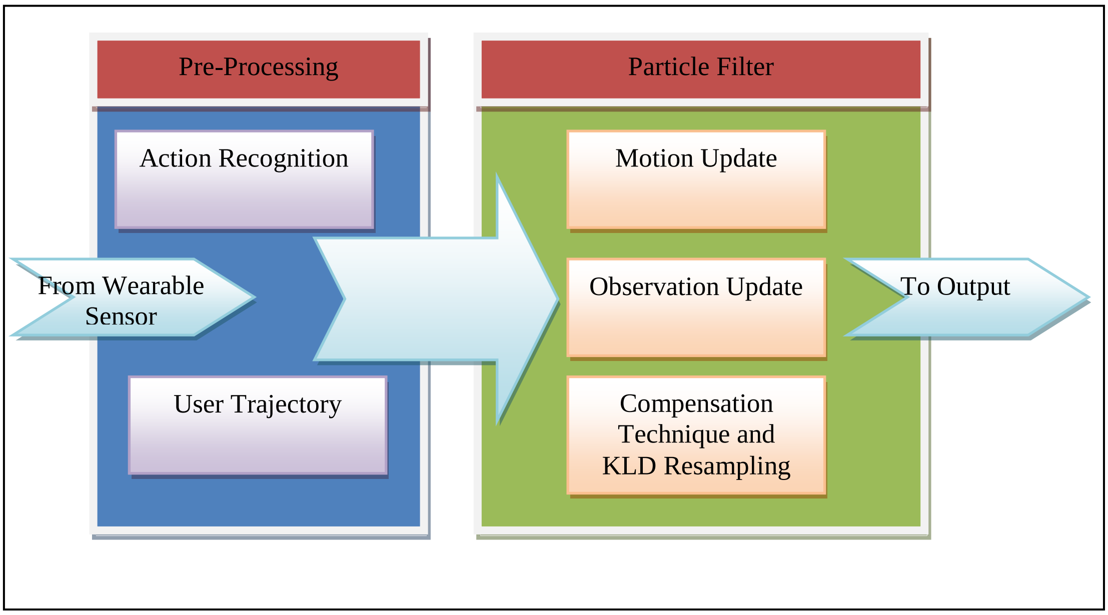


**Figure 2. System Architecture of Activity Pedestrian SLAM**

### 4.1. Pre-Processing

In this section, the pre-processing [22] (see Figure 3) phase will be discussed in two (2) subsections: action recognition and user trajectory. Figure 3 shows the action recognition and user trajectory phases within Pedestrian SLAM. In action recognition, the standing still, stair low (reaching the lower end of a stair) and stair high (reaching the upper end of a stair) are the four (4) basic detectable actions. The action recognition phase is needed to detect these kinds of actions. Action recognition basically comprises of sit, stance and stair detection. Sit detection is used to detect sitting actions by setting a limit to the upper leg sensor's orientation. There are two subcomponents for stance detection (generally used to detect standing still action). They are the standing still detection and adaptive stance detection with walking path segmentation. An example of a standing still detection that needs to be measured or captured is the action of a user putting on a pair of socks. Initially, walking path segmentation will be broken down to steps followed by applying adaptive stance detection. Concurrently, standing still detection is implemented to identify standing still actions by identifying stance phases with duration < 0.75s that happen during gait interruptions. Stair detection is used to detect stair low and stair high actions by computing the variance of the ZUPT-PDR altitude,$var(h(t))$, as an output of$h(t)$in a sliding window of$\Delta T$ length. The phase is identified either as a stair ascent or descent depending if $var(h(t))$ stays for at least $\tau_0$ above a $h_0$ threshold. The action recognition block of the system then provides observations{sitting, standing still, stair high, stair low} associated to the $t$stance phasesin the final output.

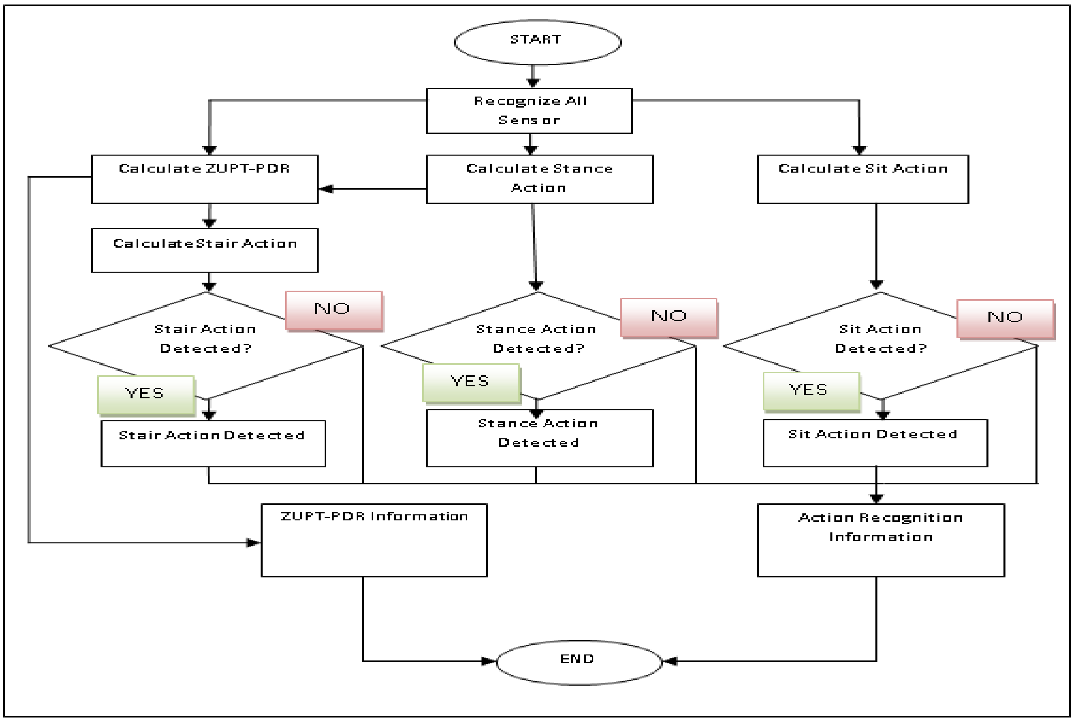


**Figure 3. Action Recognition and User Trajectory in Activity Pedestrian SLAM**

In user-trajectories [22], the pre-processing's first output is the open-loop estimate, $\hat{s}^t$, of the person's trajectory which is made up of $\hat{u}_t$ steps. ZUPT-PDR is used to estimate 3D foot coordinates. The walking path is segmented by ZUPT-PDR stance detection into $\hat{u}_t$ steps described by the horizontal step length, $\hat{l}_t$, altitude change, $\delta\hat{h}_t$, and heading change where $\delta\hat{\phi}_t = \hat{\phi}_t - \hat{\phi}_{t-1}$.

### 4.2. Proposed Rao-Blackwellized Particle Filter

As compared to standard SLAM problem of estimating $p(s_t, \Theta|\hat{u}^t, \hat{z}^t, \hat{n}^t)$ , the highlights of the system are not immediately identifiable with $\hat{n}_t$ , but only with their $\hat{A}_t$ action types. Moreover, the estimated landmark position observed at time $t$ is always equal to the person's position of similar time. Therefore, $s$ and $\Theta$ alone are enough to derive $\hat{z}^t$ and this reduces SLAM's problem in approximating $p(s^t, \Theta_t|\hat{u}^t, \hat{A}^t)$. The system uses Rao-Blackwell factorization [22] (see Figure 4) for motion fusion and observational measurements.

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

This factorization decomposes the SLAM problem of estimating a path, $s^t$, in a previously unknown environment, $\Theta_t$, into separate estimators for the person's path, s, and each of the $N_{l,t}$ landmarks, $\Theta_{[i],t}$. The system is capable of approximating non-Gaussian distributions and performing nonlinear filtering by estimating the path probability, $p(s^t|\hat{u}^t)$, in a particle filter with $N_p$ particles. Meanwhile, the landmark probability distributions $p\left(\theta_{[i],t}\middle|s^t, \hat{A}^t\right)$ are estimated by the $N_{l,t}$ individual filters. Each

 

$[m]$ particle must maintain its own map, $\Theta^{[m]}$, together with the pose,$s_t^{[m]}$, because the landmark characteristics,$\theta_{[i],t}$, are conditioned on the person's path. The system estimates $s_t^{[m]}$during motion update while the $\Theta^{[m]}$map update is done in the observation update

and only in response to action observations.
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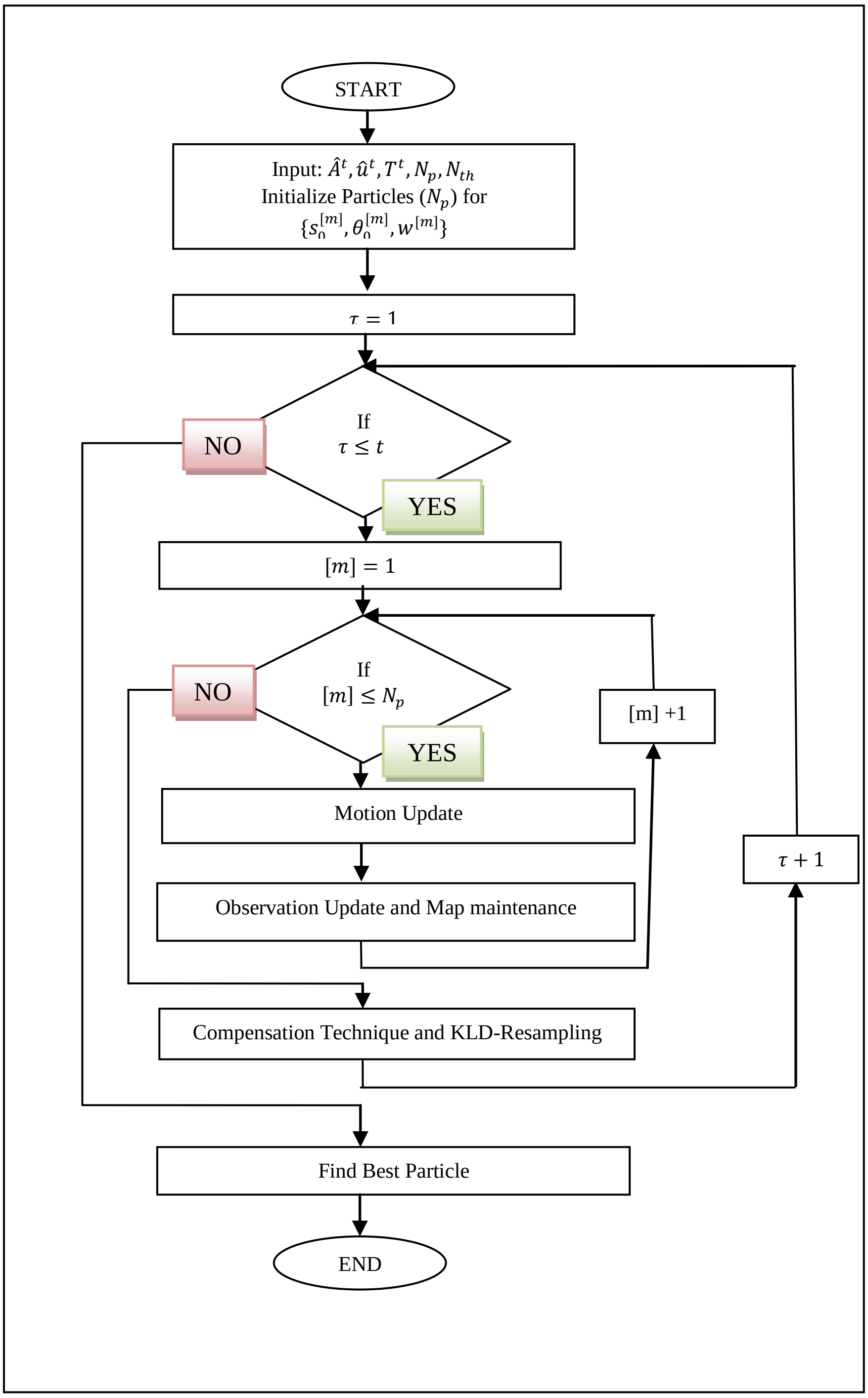


**Figure 4. Algorithm Flow of Proposed Rao-Blackwellized Particle Filter in Activity Pedestrian SLAM**

 

### 4.2.1. Motion Update

A motion update (see Figure 5) [22] and sequential calculation of $p(s^t|\hat{u}_t)$s performed by the system at the start of each *t* phase stance by sampling particle poses from:

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

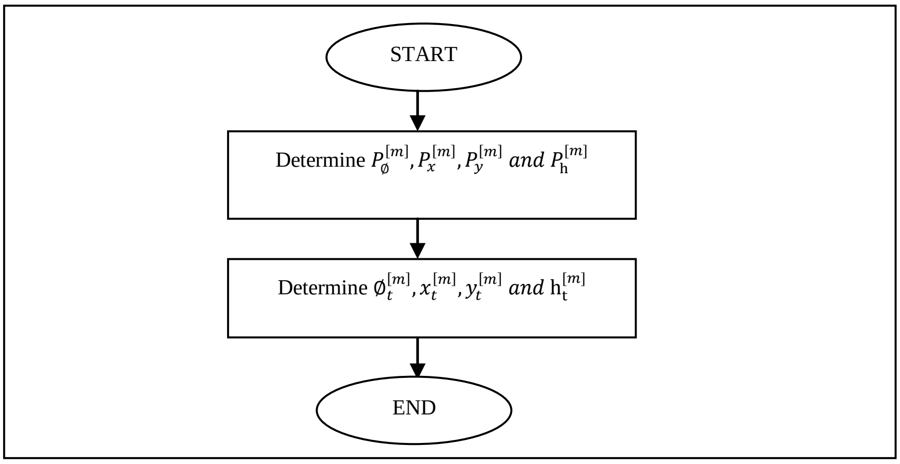


**Figure 5. Algorithm Flow of Motion Update in Activity Pedestrian SLAM**

The probability density function,$p\left(s_t^{[m]}\middle|s_{t-1}^{[m]}, \hat{u}_t\right)$, is described by the motion model. Exponential error growths in long phases without stance detections were not taken into account in the model. The time that passed between the two subsequent stance phases $t-1$ and $t$ is now defined as $T_t$. An unbiased and calibrated gyroscope gives a heading error that follows a random walk with $k_{\phi,gyro}$ being a property of the gyroscope. The gyroscope further added a random walk position error with $\sigma_{x,gyro}(T_t) \approx k_{x,gyro}$when foot swings were assumed to have constant forward velocity. Apart from sensor errors, the ZUPT-PDR position and heading estimates were also affected by inaccuracies in stance detection. These errors were modelled as additive Gaussian noise with standard deviations $\sigma_{x,0}$for position and $\sigma_{\phi,0}$forheading and both were independent of $T_t$. The sum of the previous $s_{t-1}^{[m]}$pose, the ZUPT-PDR estimate,$\hat{u}_t$, and a sampled error, $p^{[m]}$, equalled the new pose,$s_t^{[m]}$,of a particle after a $u_t$step. The resulting motion equations are:

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

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

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

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

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

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

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

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

### 4.2.2. Observation Update

The system performs observation updates (see Figure 6) [22] after the motion update, associated to stance phase $t$, for non-empty $\hat{A}_t$. The action recognition triggers multiple subsequent observation updates if more than one action occurs during a single stance phase (*e.g.*, stairs high and standing still). As compared to the previous [22], there are no changes to the observation update itself except that we now assign an additional coordinate, $h$, for vertical displacement to landmarks. The system modifies the maps $\Theta_{t-1}^{[m]}$ of each particle, given its current pose, $s_i^{[m]}$, and the observation, $\hat{A}_t$, during the observation update. Initially, the algorithm determines whether the observation corresponds to a landmark already in the map. If the algorithm successfully locates the corresponding landmark, it then identifies the landmark. The algorithm 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 6describes the decision procedure. Since different foot placements in a plane can correspond to the same location-related action, landmarks in the system have aplanar elliptic shape. Consider for example the act of sitting. There may not be any changes in upper-body posture with foot movements in an area of $\sim 0.5m$ diameter. 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 $h_{[i],t}$ were the parameters used in the system to describe a landmark. On top of that, each landmark had an accompanying action type $A_{[i]} \in$ {sitting, standings till, stair high, stair low} that stayed stationary. For the sake of better readability, we set aside the particle index, $[m]$. The system first calculates the probability of linking the current observation to each of the previously inserted landmarks in the particle's map. The probability of association, $p_{[i],t}$, equals 0 if $\hat{A}_t \neq A_{[i]}$. The difference vector, $\hat{z}_{[i]}$, between the current location of the foot and the landmark's shape in all other cases is calculated, using the formulas for ellipse intersection (with $q_{[i]}$ as intersection angle):

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

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

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

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

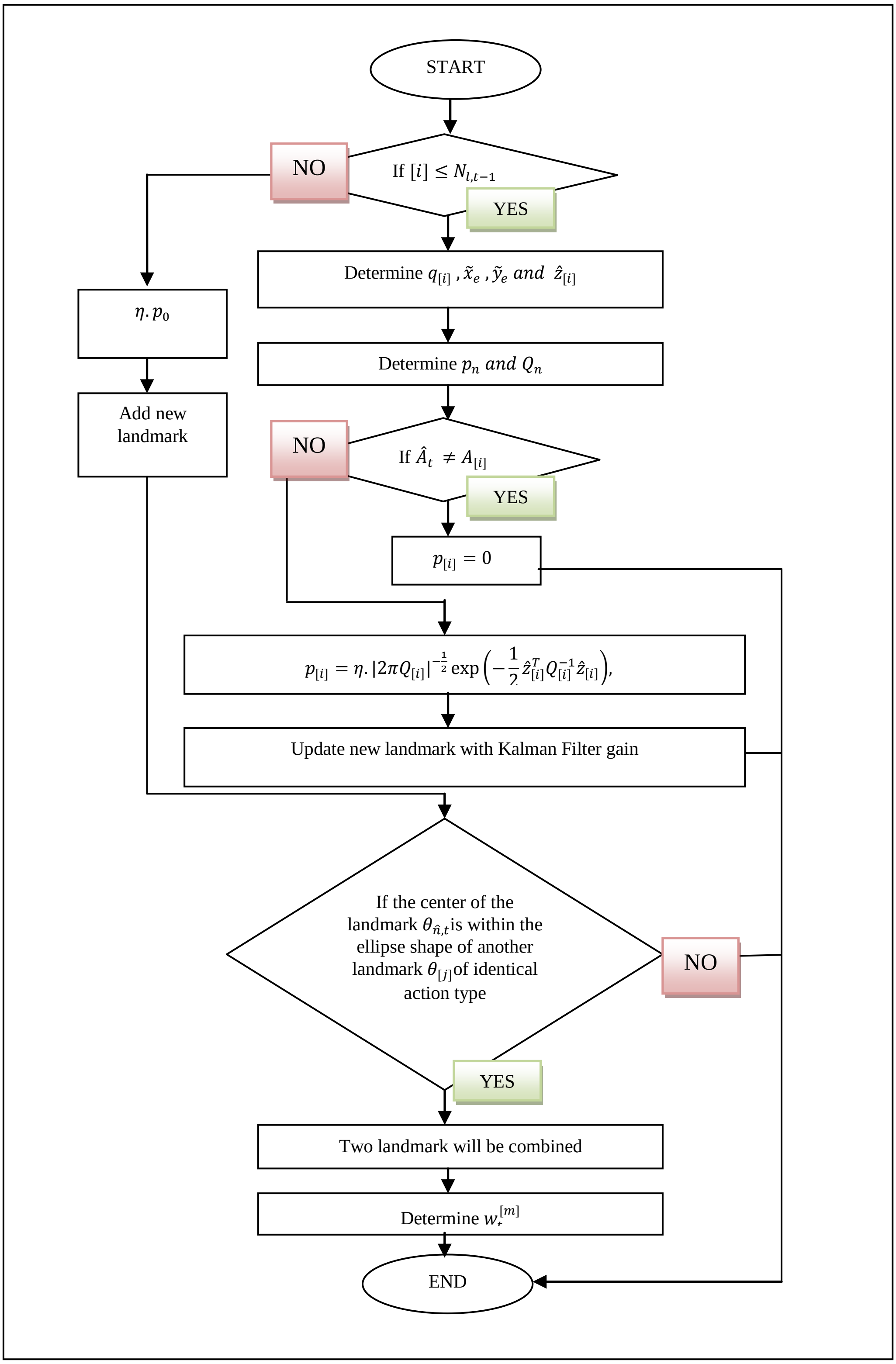


**Figure 6. Algorithm Flow of Observation Update in Activity Pedestrian SLAM**

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

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

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

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 map $\Theta_{t-1}$of the particle:

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

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

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

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

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

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

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

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

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

The two ellipses are combined into a single ellipse landmark,$\theta'_{\hat{n},t}$,if the centre of the $\theta_{\hat{n},t}$landmark is within the ellipse shape of another landmark $\theta_{[j]}$of identical action type. An ellipse is set by the system around all observation locations of landmarks $\theta_{[j]}$ and $\theta_{\hat{n},t}$with the semi-major axis lengths constrained to $\leq 0.8\ m$.

$$w_t^{[m]} = w_{t-1}^{[m]}.\, p_{\hat{n}}^{[m]} \quad (25)$$

### 4.2.3. Compensation Technique and KLD-Resampling

The algorithm (see Figure 7) will calculate the effective particle number $N_{eff} = \frac{1}{\sum_{m=1}^{N_p}(w_t^{[m]})}$, which performs compensation technique [23] and systematic resampling [24], if $N_{eff} = N_{th}$ after each observation update.In this way, the filter better approximates $p(s^t, \Theta_t|\hat{A}^t, \hat{u}^t)$ in areas which arenot close to zero and gets rid of particles with very low weight. The observation update phase sometimes adds landmarks due to non-location related actions, for example when a person stops in the middle of a room to answer a phone call. Such landmarks should be eliminated because they may lead to erroneous data association in later observation updates. An observation time, $L_{[i]}$, is stored by the system for each landmark and is reset to the current time whenever $\hat{n} = [i]$. $L_{[i]}$ measured walking distance within the indoor area. The system's particle filter estimates the probability density, $p(s^t, \Theta_t|\hat{A}^t, \hat{u}^t)$ , but we are actuallykeen on $s^t$ and $\Theta_t$ . The system approximates $s^{-t}$ and $\overline{\Theta}_t$ of $s^t$ while $\Theta_t$ are the paths on the map of the best particle, $[\overline{m}]$. This is the particle which best reflects the current belief of the filter according to the following heuristically defined rules: 1) $[\overline{m}]$ candidates are all particles with $N_l^{[\widetilde{m}]} \leq N_l^{[m]}$ minimum number of landmarks and 2) $[\overline{m}]$ is the particle with the highest weight, $w_t^{\overline{m}}$, among these candidates.

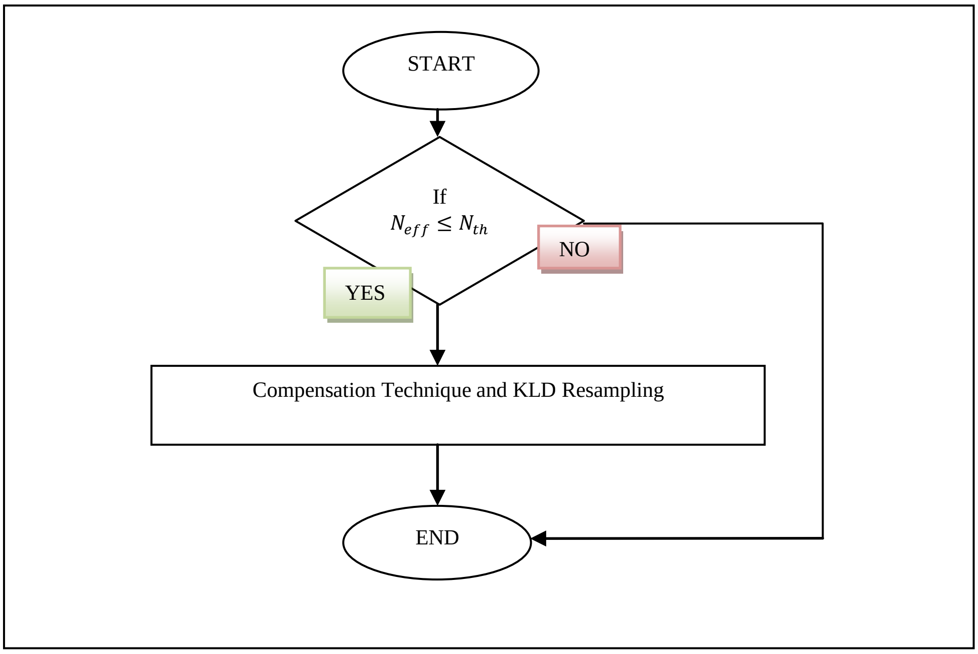


**Figure 7. Algorithm Flow of Compensation Technique and KLD-Resampling in Activity Pedestrian SLAM**

## 5. Conclusions and Future Directions

This paper discussed solutions on developing a standalone pedestrian tracking in obstructed areas that is block Global Positioning System signals. Users usually find it hard to move around on-site in such conditions, especially in obstructed environments like the inside of homes. The establishment of a standalone pedestrian tracking method is needed to provide better location determination services with less computational complexity and deployment cost. Based on IMU technology, this tracking technique allows for the determination of standalone tracking information but suffers from missing stance phase during human walking activities. In order to overcome this shortcoming, a new stance detection in pedestrian simultaneously localization and mapping (SLAM) needs to be designed for robust indoor positioning systems. To illustrate the performance of the system in an indoor environment set-up, we will present our preliminary results in the future.

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