An Efficient Smartphone Assisted Indoor Localization with Tracking Approach using Glowworm Swarm Optimization Algorithm

Mohammad Alshehri[1]

[1]Visiting Professor, University of Technology Sydney, Sydney, Australia

Emails: Mohammad.Alshehri@uts.edu.au

Abstract

Presently, a precise localization and tracking process becomes significant to enable smartphone-assisted navigation to maximize accuracy in the real-time environment. Fingerprint-based localization is the commonly available model for accomplishing effective outcomes. With this motivation, this study focuses on designing efficient smartphone-assisted indoor localization and tracking models using the glowworm swarm optimization (ILT-GSO) algorithm. The ILT-GSO algorithm involves creating a GSO algorithm based on the light-emissive characteristics of glowworms to determine the location. In addition, the Kalman filter is applied to mitigate the estimation process and update the initial position of the glowworms. A wide range of experiments was carried out, and the results are investigated in terms of distinct evaluation metrics. The simulation outcome demonstrated considerable enhancement in the real-time environment and reduced the computational complexity. The ILT-GSO algorithm has resulted in an increased localization performance with minimal error over the recent techniques.

Keywords: Indoor localization, Smartphones, Tracking model, GSO algorithm, Kalman filter, Estimation error.

1. Introduction

In previous years, precise indoor tracking and positioning have gained more interest in the field of indoor platforms like hospitals, airports, and supermarkets [1, 2]. When precise position data is accessible in Realtime, several position based services can be offered namely location information push, advertising market services, indoor navigation services, and so on. Unfortunately, related to the frequently employed GPS technique in outdoor environment, still, there is a lack of typical localization systems that are extensively used in indoor environments [3]. As the GPS signal doesn't operate in indoor environment, several radio based approaches employ signal strengths/frequencies like Wi-Fi, Bluetooth, WLAN [3], RFID/UWB are broadly studied for realizing indoor localization. But, as a result of variation of radio signal in complex indoor environment, each localization method tends to have huge fluctuation, results in poorer precision. Furthermore, additional structure should be placed in advance for indoor environment, and extra receiving signals devices were required at the user end [4-6].

Since the indoor environments are complicated, shadowing effect and multipath propagation on radio signals are more popular [7, 8]. Henceforth, the receiving signals could have LOS and NLOS signals components. It leads to lesser propagation time measurement and synchronization that possess problems on IPS which is based on signal measuring standards such as AOA, TOA, and TDOA. Furthermore, the RSS isn't stable, because of the superimposing of multi-path signals of differing stages [9-11]. While the magnetic signals have a constrained perceptibility as well as the necessity of appropriate standardization of the magnetometers in smartphones. As the indoor environments are very complicated and lesser

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considered compared to the outdoor environments, it isn't easier for modelling the indoor radio signal propagations. The indoor signal propagation models are typically depending upon propagation paths and the recognized obstacle in which slight indoor modifications could reduce the signal propagations.

The positioning approaches such as WC and trilateration localization [12] are based upon the signal propagations for estimating the distance from the RSS. Furthermore, this method requires accurate standardization of path loss exponents per indoor environment. Fingerprint positioning is one of common IPS methods which is based upon the radio fingerprints for producing localizations outcome. But, these method training phases are time-consuming and labor-intensive, and the time difficulty of the implementation stage grows using the size of positioning region. Furthermore, the unpredictability of RSS in indoor environments enforces common updating of the radio map databases. Alternatively, by the exponential growth of smartphones, mobile devices are currently armed with many types of strong on-board sensor nodes, involving gyroscopes, accelerometers, proximity sensors, compasses, cameras, depth sensors, and so on [13]. The well-known Pedestrian dead reckoning (PDR) technique aim is to trace a user's existing location according to the motion direction, former position, and step length. Alongside, visual sensor nodes, the VIO techniques [14] could attain more accuracy on signal tracing, because of the corresponding features of these 2 sensing modules. But, the main drawback of these kinds of methods is the growing drift errors. For long term and long distance tracing, further global mapping as well as another physical limitation are needed for eliminating the increasing errors.

This study focuses on the design of efficient smartphone assisted indoor localization and tracking model using glowworm swarm optimization (ILT-GSO) algorithm. The ILT-GSO algorithm involves the design of GSO algorithm based on the light emissive characteristics of glowworms to determine the location. In addition, the Kalman filter is applied to mitigate the estimation process and update the initial position of the glowworms. A wide range of experimentations was carried out and the results are investigated interms of distinct evaluation metrics.

2. Related works

Li et al. [15] proposed an incorporated CSMS technique which attains submeter accurateness for smartphones. CSMS constructs combined fingerprinting maps of CSI and MFS as well as propose LDTW algorithms for geomagnetic tracing and the MultiModule KNN approach for merging fingerprinting active weight assessment. del Horno [16] presented a multisensor tracing scheme based on incremental incorporating advanced model of WiFi interfaces and gyroscope, magnetometer, and accelerometer sensor of smartphones. The method includes calibrative stage of tracing scheme that involves assisting concurrent collecting information from each 3 sensor nodes and WiFi interface. Vy et al. [17] provide hybrid approaches among WiFi and PDR for iPhone in indoor environment, also address the succeeding 2 challenges. Firstly, Apple Inc. anymore provides public data regarding presently linked WiFi (viz., receiving signal channel and strength, service set identifier), WiFi-based pedestrian tracing app running on the iPhone is limited than another one on Android platform. Next, the PDR method provides a manner for self positioning, it suffers from collected error of inertial sensor embedded in the smartphone. They proposed an adaptation purpose from WiFi status values to closeness for positioning purposes.

Roy et al. [18] proposed a weighted ensemble classifiers dependent on Dempster Shafer's beliefs concept for powerfully manage contexts heterogeneity. Now, the contexts are determined based on distinct smartphones configuration employed to train and test the systems and sequential variations of signal. This technique uses the Dempster Shafer concept of beliefs function for calculating the weight of base learner. In [19], general NNELILS is aimed in this study for addressing the problem of heterogeneity devices. NNELILS contain a heterogeneous group of base classifiers and NN dependent Meta classifiers combine a decision of base classifier. Consequently, algorithm is implemented and proposed over realtime dataset. Salimibeni [20] introduces consistent datasets, represented as the IoTTD, leverage certain group of 4 visual cameras for providing traffic management with accuracy. The presented IoTTD datasets consist of RSSIs values gathered from 5 BLE sensor nodes and corresponding IMU signals from the targeted mobile devices. Alternatively, the study presents a multimodel dynamic approximation architecture link RSSI based particle filtering by IMU built PDR.

3. The Proposed Indoor Localization Scheme

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The fingerprinting localized approach needs altering fingerprint at given RPs for creating the respective fingerprint datasets or radio maps from the offline phase. At this point, the design of fingerprint datasets is described. Assuming the testing condition against the testing part was primarily divided to grid with same size dependent upon floor design. Afterward, the mobile node collects RSS values in all AP at each RP to certain time period and transfers the samples to server. The server accordingly arranges the samples as to necessary fingerprint design and collects the dataset.

The xth fingerprints r_x from the dataset has been expressed as:

$$r_x = \begin{matrix} \left(s_{xy}^a, l_x, P\left(l_x \middle| s_{xy}^a\right)\right), a = 1,2, \dots, A_x, \\ x = 1, \dots, L, y = 1, \dots, M, \end{matrix} \tag{1}$$

Where N_x implies the sum of numerous values from T samples composed at RP_x in AP_y. s_{xy}^a is the a^{th} value, and the amount of s_{xy}^a during the sample group, represent the $num_{s_{xy}^a}$, fulfills the formula that $\sum_{a=1}^{N_x} num_{s_{xy}^a} = F$. M implies the amount of noticeable AP from the testing part, l_x indicates the coordinate of RP_x, and L defines the RPcount.

3.1 Kalman Filter based tracking modelling

The advantage of GSO has been ability for exploring to global optimum immediately, it can be expectable for creating a massive evaluation error when there are no glowworms that localization in Ω_0 this GSO depends fingerprinting localized technique. For removing the inference bias, a primary method of glowworms is changed to recovering the GSO outcomes and consider the Kalman Filter (KF) for enhancing the localized accuracy moreover. In the online phase, the mobile node drives at specific velocity $v = [v_i, v_j]^F$, and retains collecting the real-world fingerprints $\tilde{r}$ at the unidentified place $\theta = [i, j]^F$. The upgraded places were set in the tracking technique to an optimum $\left\lfloor \frac{z}{2} \right\rfloor$applicants glowworm at time $f-1$ $\left(represented\ as\ \theta_{pz}^{f-1}, z = 1,2 \dots, \left\lfloor \frac{z}{2} \right\rfloor\right)$ an initial place of $\left\lfloor \frac{z}{2} \right\rfloor$ glowworms from the swarm under the commencement of GSO approach at time t. Concurrently, another $K - \left\lfloor \frac{z}{2} \right\rfloor$ glowworms were frequently circulating under the testing part. $\lfloor \cdot \rfloor$ refers the rounding up procedure. To another variable of GSO and place of glowworms at time $f = 0$ $(\theta_{pz}^{f=0})$, the initialized is similar [21].

3.2 GSO based location estimation:

GSO is considered a smart swarm optimized technique utilized for accelerating the luminescent feature of firefly. During the GSO approach, the glowworm swarms were distributing from solution spaces and Fitness Function (FF) of all glowworm's places [22]. The robust glowworms are higher brightness and better place that they can be collected for maximal FF rate. The glowworms were composed of vigorous line of sight which is termed as decision domain that is the kind of density to adjacent node. However, the decision radius has been restricted but glowworms travel nearby same kind of strong fluorescence in decision domain. Obtaining the superior values of iterations, all glowworms are located from the optimum places.

The fluorescence in the focus on upgrading technique was simplified in Eq. (1).

$$l_i(t) = (1-\alpha)l_i(r-1) + \beta f(x_i(t)), \tag{1}$$

where $l_i(f)$ implies the fluorescence under the focus of i th glowworm at time f, α defines the fluorescence in volatilization coefficients, β indicates the fluoresce from enhancement factor, f(x) refers the FF and $x_i(r)$ stands for the place of glowworm i at f time that was executed by Eq. (2).

$$N_i(t) = \{j: \|x_j(r) - x_i(t)\| < r_d^i; l_i(t) < l_j(t)\}, \tag{2}$$

where $N_i(f)$ indicates the neighbor group of ith glowworm at time r and $r_d^i(r)$ refers the radius of decision domain of i th glowworm at moment f as written by Eq. (3).

$$r_d^i(t+1) = \min\{r_s, \max\{r_d^i(t) + \gamma(n_i - |N_i(t)|)\}\}, \tag{3}$$

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where r_s signifies the reached radius of glowworm, γ refers the value of decision domain, and n_i depicts the neighbor thresholds. The moving possibilities of upgraded manner were illustrated in Eq. (4).

$$p_{ij}(r) = \frac{l_j(t) - l_i(t)}{\sum_{k \in N_t} l_k(t) - l_i(r)}, \tag{4}$$

where $p_{ij}(t)$ depicts the probabilities where glowworm i travels to glowworm j at t time as demonstrated in Eq. (5).

$$x_i(t+1) = x_i(t) + s(\frac{x_j(t) - x_i(t)}{\|x_j(t) - x_i(t)\|}), \tag{5}$$

The measure $\tilde{r}$ reliant place estimation occurs in same technique as GSO. The situation of evaluation result is referred to at period $f\ as\ \hat{X}_f = [\hat{x}, \hat{y}, v_i, v_j]^F$, where $\hat{\theta} = [\hat{x}, \hat{y}]^F$ implies the comparative place evaluation result.

Location prediction:

During the stage, this approach expects a previous place with upgrading the time as provided in Eq. (6).

$$\begin{cases} \tilde{X}_f^- = FS\tilde{X}_{f-1}^- + w_{f-1} \\ P_f^- = FSP_{f-1}FS^F + Q \end{cases} \tag{6}$$

Where $\tilde{X}_f^- \epsilon \mathbb{R}^4$ represents the previous place estimation at time t, $FS = \begin{bmatrix} X_2 & \Delta t \cdot X_2 \\ 0 & X_2 \end{bmatrix}$, X_a refers to the $a \times a$ identity matrix. w_t indicates the zero-mean Gaussian noise with covariance Q, and $Q = diag(q)$ has been supposed that invariable. $\Delta f = 2s$ defines the sampling interval amongst successive fingerprints collected from the localization technique. $P_f, P_f^- \epsilon \mathbb{R}^{4\times4}$ represents the posterior as well as prior estimation fault covariance are explained in $P_f = E(X_f - \hat{X}_f)(X_f - \hat{X}_f)^F$, $P_f^- = E(X_f - \tilde{X}_f)(X_f - \tilde{X}_f)^F$ respectively.

Location updating:

The final place estimation $\tilde{X}_f$ is upgraded by measurement updated formulas are described in Eq. (7)

$$\begin{cases} K_f = P_f^- H^F (HP_f^- H^F + \delta) \\ \tilde{X}_f = \tilde{X}_{f-1} + K_f(\hat{X}_f - H\tilde{X}_{f-1}) \\ P_f = (X_4 - K_f H)P_f^- \end{cases} \tag{7}$$

Where K_f refers the Kalman gain, $\tilde{X}_f = HX_f + \epsilon_f$, and $H = [X_2\ 0]$. The measures sound ϵ_f is assumed that zero-mean Gaussian distribution with stable covariance $\delta = diag(\gamma)$. Generally, q and γ are experimental calculated for getting an optimum tracking outcome. Here, $q = 1$ and $\gamma = 90$ have been utilized for experimentation. At this time, there are 3 advantages from these techniques of reaching maximal localization accuracy. Primarily, the set of initial place of glowworm is afforded a privilege possibilities to the glowworm that located from Ω_0. Secondly, the initialized technique feasibly improves the speed of end condition, rising the real world result of place evaluation. Eventually, the ability of KF has been utilized for diminishing the estimation faults.

4. Performance Analysis

Fig. 1 investigates the computational time (CT) analysis of the ILT-GSO technique with existing techniques [21] in Table 1 and Fig. 1. The results portrayed that the kernel model has resulted in worse outcomes with the higher CT of 2.7. At the same time, the WKNN technique has offered a slightly enhanced performance with a CT of 1.6. moreover, the cRBF technique has obtained moderately closer performance with the CT of 1.4. Furthermore, the PSO algorithm has achieved reasonable CT of 0.7. However, the ILT-GSO technique has outperformed the existing techniques with a lower CT of 0.4.

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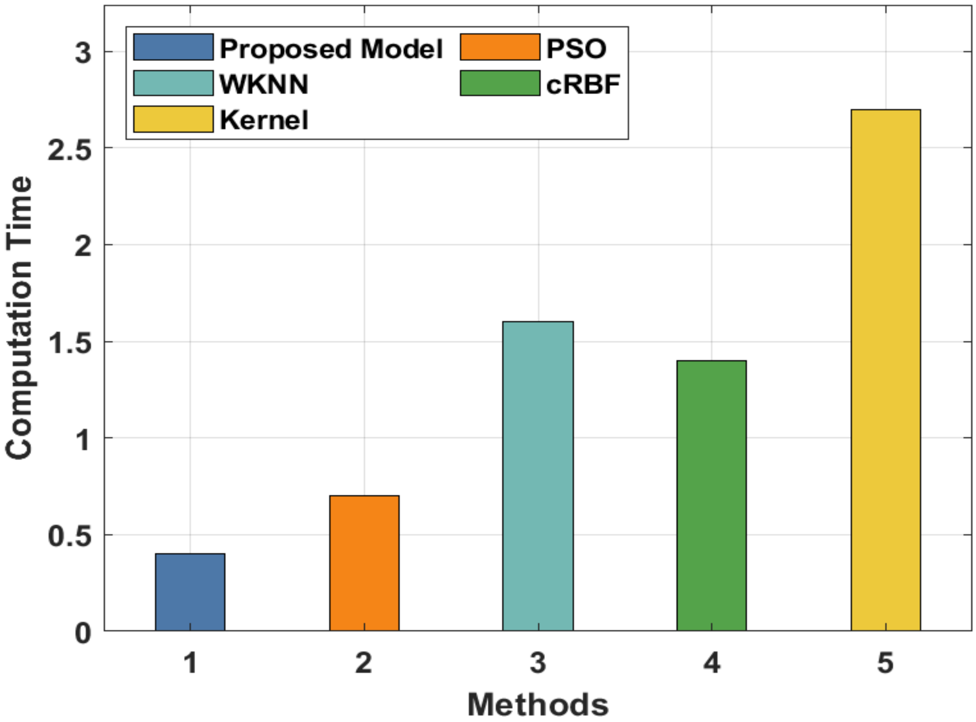

Fig. 1. Comparative results analysis of ILT-GSO technique interms of CT

Fig. 2 investigates the accuracy analysis of the ILT-GSO technique with existing techniques. The results represented that the kernel model has occasioned to worse outcome with the reduced accuracy of 76.40%. In line with that, the WKNN technique has offered a somewhat improved performance with an accuracy of 80.40%. Additionally, the cRBF technique has attained moderately closer performance with an accuracy of 81.30%. Furthermore, the PSO algorithm has achieved reasonable accuracy of 86.20%. However, the ILT-GSO technique has outperformed the existing techniques with a higher accuracy of 90.65%.

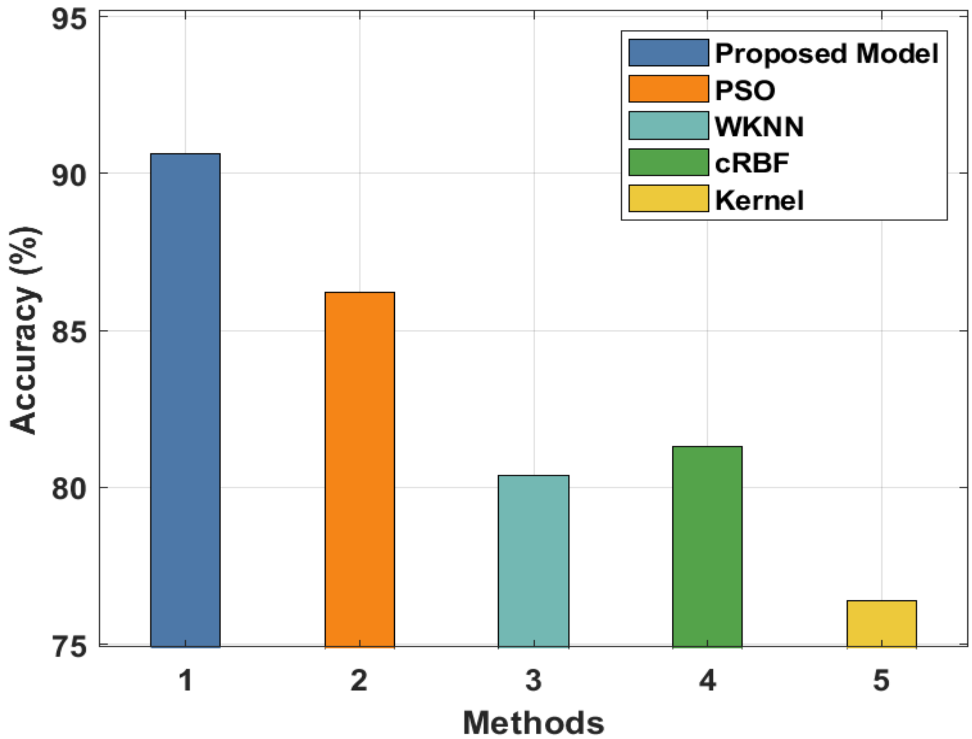

Fig. 2. Comparative results analysis of ILT-GSO technique interms of localization accuracy

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Finally, an extensive tracking rate analysis of the ILT-GSO technique with PSO and WKNN techniques under varying estimation error in and Fig. 3. The experimental results reported that the ILT-GSO technique has resulted in an optimum performance with a higher tracking rate under all ranges of estimation errors. For instance, with the estimation error of 0.5, the ILT-GSO technique has accomplished superior performance with a higher tracking rate of 0.74 whereas the PSO and WKNN techniques have obtained an inferior performance with the tracking rate of 0.45 and 0.15. Moreover, with an estimation error of 1.0, the ILT-GSO technique has accomplished superior performance with a higher tracking rate of 0.80 whereas the PSO and WKNN techniques have obtained an inferior performance with the tracking rate of 0.74 and 0.62. Furthermore, with the estimation error of 1.5, the ILT-GSO technique has offered an effectual outcome with a higher tracking rate of 0.89 whereas the PSO and WKNN techniques have resulted in a reduced performance with the tracking rate of 0.86 and 0.79. Additionally, with the estimation error of 2.0, the ILT-GSO technique has accomplished improved outcomes with the increased tracking rate of 0.92 whereas the PSO and WKNN techniques have offered reduced outcomes with the tracking rate of 0.93 and 0.84.

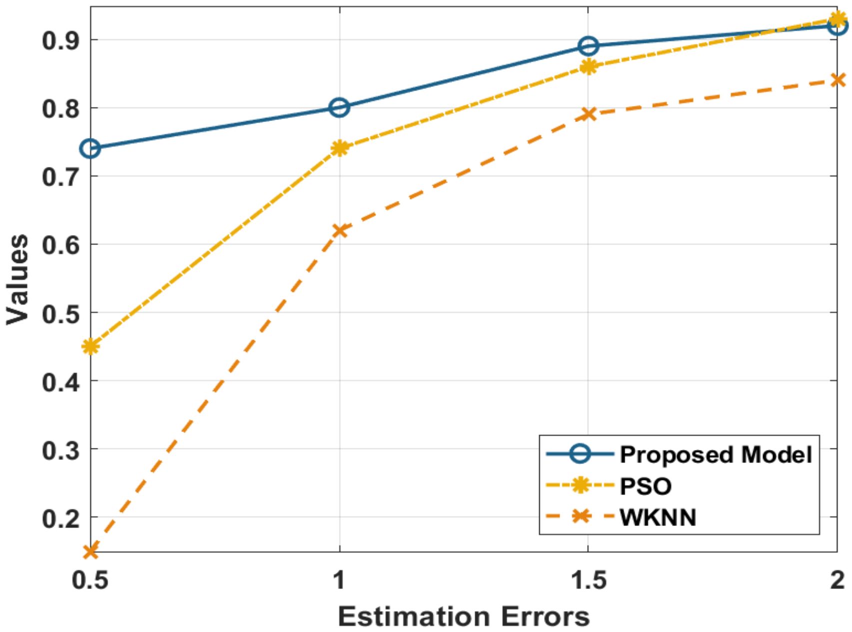

Fig. 3. Comparative tracking results analysis of ILT-GSO technique

5. Conclusion

This study focuses on the design of efficient smartphone assisted indoor localization and tracking model ILT-GSO algorithm. The ILT-GSO algorithm involves the design of GSO algorithm based on the light emissive characteristics of glowworms to determine the location. In addition, the Kalman filter is applied to mitigate the estimation process and update the initial position of the glowworms. A wide range of experimentations was carried out and the results are investigated interms of distinct evaluation metrics. The simulation outcome demonstrated considerable enhancement in the real time environment and reduce the computational complexity. The ILT-GSO algorithm has resulted in an increased localization performance with minimal error over the recent techniques. In future, the presented model can be extended to the outdoor real time environment to enable precise localization process.

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