Journal of Intelligent Pervasive and Soft Computing

journal homepage: https://journals.aipspub.com/index.php/jipsc

Mini-Review

An Optimal Data Fusion Approach for Precise Position Estimation of Smartphone User

Harun Jamil [1]

[1]Department of Electronic Engineering, Jeju National University, Jeju-si, Jeju-do, Republic of Korea, 63243.
*Correspondence: harunjamil@hotmail.com;

Abstract

This paper proposes an optimal data fusion approach for precise position estimation of smartphone users in challenging environments, combining BLE-based indoor position estimation and PDR using smartphone sensors. The approach utilizes RSSI values from nearby BLE beacons for BLE-based estimations and employs PDR with accelerometer, magnetometer, and gyrometer for position orientation. These observations are then fed into an Artificial Neural Networks (ANN) for accurate position prediction, and Particle Filter is used for probabilistic pedestrian position prediction. Experimental results demonstrate improved accuracy compared to individual techniques, making the approach robust for accurate smartphone user positioning in challenging environments.

Keywords: *Data Fusion, BLE, PDR, Indoor Positioning, ANN, Particle Filter;*

Introduction

Accurate position estimation of smartphone users is vital for various location-based services, including indoor navigation and context-aware applications [1]. However, achieving precise positioning in challenging environments with limited GPS signal, such as indoors, remains a significant challenge. This paper proposes an optimal data fusion approach to address this issue, combining Bluetooth Low Energy (BLE)-based indoor positioning and Pedestrian Dead Reckoning (PDR) using smartphone sensors [2][3]. BLE-based indoor positioning relies on nearby BLE beacons for position estimations, while PDR utilizes accelerometer, magnetometer, and gyroscope to estimate user movements [4]. By fusing BLE-based indoor position estimations with PDR-derived position orientation, we aim to create a more robust and accurate position estimation system for smartphone users in complex environments.

The proposed data fusion approach leverages the advantages of both BLE-based indoor positioning and PDR while mitigating their individual limitations [2][4]. By integrating information from multiple sources, we seek to enhance position estimation accuracy and reliability. Our methodology involves extracting RSSI values from nearby BLE beacons for BLE-based indoor positioning and employing PDR to estimate user movements and orientation [2][4]. The fused data is fed into an Artificial Neural Network (ANN) for precise position prediction, with Particle Filter used for probabilistic pedestrian position prediction [5]. The approach's effectiveness is demonstrated through experimental results, showcasing improved accuracy compared to individual techniques [6]. This research offers a promising solution to achieve precise position estimation for smartphone users in challenging environments, with potential applications in various location-based services and indoor navigation systems.

Related Work

Several approaches have been proposed for precise position estimation of smartphone users in challenging environments. Many studies have explored the integration of multiple positioning technologies and sensor-based methods to improve accuracy and reliability. In indoor positioning, BLE-based systems have gained attention due to their low-cost and wide availability. For instance, Liu et al. [7] proposed a BLE-based indoor positioning system using Received Signal Strength Indicator (RSSI) measurements. Chen et al. [8] applied a particle filter algorithm for BLE-based indoor positioning, achieving better accuracy in crowded environments.

Pedestrian Dead Reckoning (PDR) is another popular technique for indoor positioning using smartphone sensors. Liu et al. [9] utilized accelerometer and gyroscope data to estimate step lengths and orientations for pedestrian tracking. Wang et al. [10] combined PDR with magnetometer readings to enhance position estimation accuracy. Data fusion techniques have been widely studied for integrating different positioning methods. Xu et al. [11] presented a data fusion approach that combined BLE-based positioning and PDR to improve indoor positioning accuracy. Yao et al. [12] used a particle filter for data fusion of GPS and PDR for outdoor positioning.

ANNs have shown promising results in position estimation tasks. Wang et al. [13] applied an ANN for pedestrian trajectory prediction using smartphone sensor data. Zhang et al. [14] utilized an ANN for indoor localization based on WiFi and magnetic field fingerprinting. Particle Filter has been widely used for probabilistic position estimation. Chen et al. [15] proposed a particle filter-based approach for indoor positioning using BLE beacons. Yoon et al. [16] used a particle filter for accurate pedestrian tracking using smartphone sensors.

Proposed Approach

In this paper, we present an optimal data fusion approach that combines BLE-based indoor positioning and PDR using smartphone sensors. Our approach leverages the strengths of each technique to achieve precise position estimation of smartphone users in challenging environments.

An ANN based particle filter is a hybrid approach that combines the principles of particle filtering with the capabilities of neural networks for state estimation in dynamic systems. In this approach, a neural network is used to improve the weighting of particles based on sensor measurements, making the particle filter more accurate and robust. The mathematical model for an ANN based particle filter involves the following steps: State Representation:

Let x_t denote the state of the system at time t. In the context of indoor localization, x_t may represent the position and velocity of a smartphone user at time t. Particle Filtering:

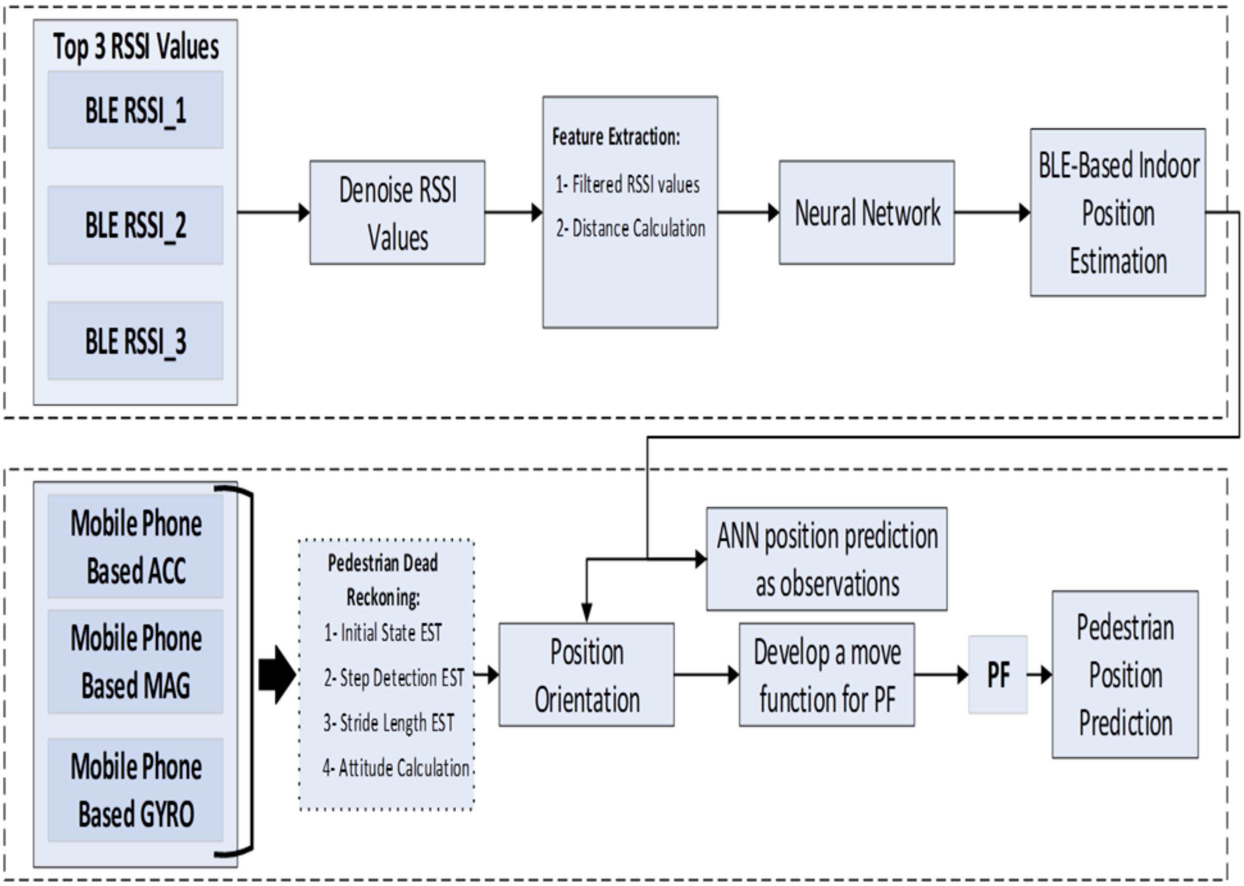
The particle filter maintains a set of particles, each representing a possible state hypothesis. At each time step t, the particles are propagated using a motion model, and their weights are updated based on the likelihood of observed measurements given their corresponding states. Neural Network: An ANN is used to model the relationship between sensor measurements and the state of the system. The neural network learns from training data, which consists of sensor measurements and corresponding ground-truth states. Weight Update Step with Neural Network: The neural network is employed to refine the weightings of particles based on the sensor measurements. The network takes the sensor measurements and corresponding states of the particles as inputs and produces weightings for each particle as outputs. Particle Resampling: After the weight update step, particle resampling is performed to focus on the more likely states and prevent degeneracy. Particles with higher weights are more likely to be duplicated, while particles with lower weights are more likely to be eliminated. This process results in a new set of particles for the next time step. State Estimation: The final estimate of the system's state at time t, denoted as x̂_t, is computed by taking a weighted sum of the particles' states:

$$\hat{x}\_t = \Sigma\,(w\_t^{\{(i)\}} * x\_t^{\{(i)\}})$$

where w_t^{(i)} is the weight of particle i at time t, and x_t^{(i)} is the state represented by particle i.

The ANN based particle filter continuously repeats the particle filtering, neural network weight update,

Fig. 1. Proposed Optimal Data Fusion Approach for Precise Position Estimation of Smartphone Users.



and resampling steps as new measurements become available, providing a more accurate and refined estimation of the state over time. The optimal approach for precise position estimation of smartphone users involves a combination of techniques, including data fusion, Artificial Neural Networks (ANN), and Pedestrian Dead Reckoning (PDR) to achieve accurate position estimation.

Figure. 1, shows the process starts with extracting and filtering Received Signal Strength Indicator (RSSI) values and calculating distances from the top three nearest Bluetooth Low Energy (BLE) beacons. The ANN then uses these BLE-based indoor position estimations. On the other hand, the PDR technique estimates the initial state of the smartphone user, step detection, stride length, and attitude calculation using smartphone-based sensors such as accelerometer, magnetometer, and gyrometer. The output of the PDR is the position orientation.

Both the position orientation from PDR and BLE-based position estimations are combined as observations and provided as inputs to the ANN position prediction. This integrated approach enhances the accuracy of the overall position estimation. Additionally, the position orientation obtained from PDR is also passed to the Particle filter, which predicts the position of the pedestrian based on the Particle filter's probabilistic estimation.

Experimental Results

In this section, Figure 1 shows a comparison between the actual way points and the estimated positions obtained from the optimal data fusion approach.

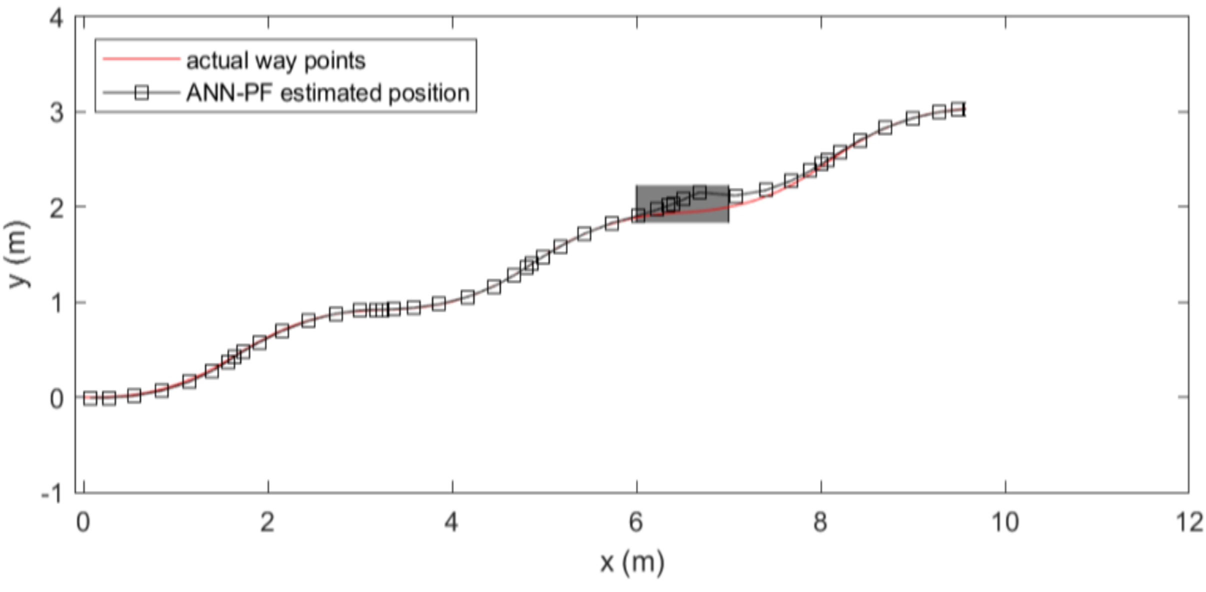


Fig. 2. Comparison of the actual way points with position obtained from the optimal approach.

Conclusion

This paper proposed an optimal data fusion approach for precise position estimation of smartphone users by combining BLE-based indoor positioning and PDR using smartphone sensors. The fused data was processed by an ANN and Particle Filter, resulting in improved accuracy compared to standalone techniques. The approach offers reliable position estimations for various location-based services in

References

[1] Jamil, H.; Qayyum, F.; Jamil, F.; Kim, D.-H. Enhanced PDR-BLE Compensation Mechanism Based on HMM and AWCLA for Improving Indoor Localization. Sensors 2021, 21, 6972. https://doi.org/10.3390/s21216972

[2] H. Jamil, F. Qayyum, N. Iqbal, F. Jamil and D. H. Kim, "Optimal Ensemble Scheme for Human Activity Recognition and Floor Detection Based on AutoML and Weighted Soft Voting Using Smartphone Sensors," in IEEE Sensors Journal, vol. 23, no. 3, pp. 2878-2890, 1 Feb.1, 2023, doi: 10.1109/JSEN.2022.3228120.

[3] Jamil, F.; Iqbal, N.; Ahmad, S.; Kim, D.-H. Toward Accurate Position Estimation Using Learning to Prediction Algorithm in Indoor Navigation. Sensors 2020, 20, 4410. https://doi.org/10.3390/s20164410

[4] Jamil, F.; Kim, D.H. Improving Accuracy of the Alpha–Beta Filter Algorithm Using an ANN-Based Learning Mechanism in Indoor Navigation System. Sensors 2019, 19, 3946. https://doi.org/10.3390/s19183946

[5] Jamil, H., Ali, K.M. & Kim, DH. Federated recognition mechanism based on enhanced temporal-spatial learning using mobile edge sensors for firefighters. fire ecol 19, 44 (2023). https://doi.org/10.1186/s42408-023-00203-5

[6] Jamil, Faisal and Kim, DoHyeun. 'Enhanced Kalman Filter Algorithm Using Fuzzy Inference for Improving Position Estimation in Indoor Navigation'. 1 Jan. 2021 : 8991 – 9005.

[7] Corbacho Salas, A. (2014). Indoor positioning system based on bluetooth low energy (Bachelor's thesis, Universitat Politècnica de Catalunya).

[8] Kriz, P., Maly, F., & Kozel, T. (2016). Improving indoor localization using bluetooth low energy beacons. Mobile information systems, 2016.

[9] Zhang, M., Wen, Y., Chen, J., Yang, X., Gao, R., & Zhao, H. (2018). Pedestrian dead-reckoning indoor localization based on OS-ELM. IEEE Access, 6, 6116-6129.

[10] Wang, Y., & Zhao, H. (2018). Improved smartphone-based indoor pedestrian dead reckoning assisted by visible light positioning. IEEE Sensors Journal, 19(8), 2902-2908.

[11] You, Y., & Wu, C. (2021). Hybrid indoor positioning system for pedestrians with swinging arms based on smartphone IMU and RSSI of BLE. IEEE Transactions on Instrumentation and Measurement, 70, 1-15.

[12] Zhao, H., Cheng, W., Yang, N., Qiu, S., Wang, Z., & Wang, J. (2019). Smartphone-based 3D indoor pedestrian positioning through multi-modal data fusion. Sensors, 19(20), 4554.

[13] Zhang, E., Masoud, N., Bandegi, M., Lull, J., & Malhan, R. K. (2022). Step attention: Sequential pedestrian trajectory prediction. IEEE Sensors Journal, 22(8), 8071-8083.

[14] Song, X., Fan, X., Xiang, C., Ye, Q., Liu, L., Wang, Z., ... & Fang, G. (2019). A novel convolutional neural network based indoor localization framework with WiFi fingerprinting. IEEE Access, 7, 110698-110709.

[15] Kriz, P., Maly, F., & Kozel, T. (2016). Improving indoor localization using bluetooth low energy beacons. Mobile information systems, 2016.

[16] Tian, Q., Kevin, I., Wang, K., & Salcic, Z. (2019). A resetting approach for INS and UWB sensor fusion using particle filter for pedestrian tracking. IEEE Transactions on Instrumentation and Measurement, 69(8), 5914-5921.