A PDR-based Map Matching Method for Estimating the Movement Path of Smartwatch Wearers

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***Abstract*—In emergency situations, accurate location information is essential for quickly securing the safety of the caller. Although GNSS (Global Navigation Satellite System) is widely used for outdoor positioning, its reliability decreases in environments where satellite signals cannot be consistently received. Therefore, to enhance both availability and accuracy, it is necessary to improve localization performance with alternative positioning infrastructures. In this study, we propose a PDR (Pedestrian Dead Reckoning)-based map matching method to continuously estimate the movement path of smartwatch wearers. The constant movement of the wrist, where the smartwatch is worn, makes it difficult to accurately determine walking segments. To address this issue, we utilize a HAR (Human Activity Recognition)-based deep learning classification model to identify whether the wearer is walking. For segments identified as walking, step detection, stride length estimation, and turn event detection are performed to generate PDR information. In the subsequent map matching stage, pedestrian road digital maps are edited into a node-edge structure, and the final movement trajectory is extracted based on the PDR information. The performance of the proposed method is validated through field experiments conducted in an urban environment.**

Keywords—Smartwatch, HAR, Deep Learning, PDR, Map Matching

I. INTRODUCTION

In emergency situations, quickly determining the location of a person under personal protection is important for reducing rescue times and ensuring safety. While GNSS (Global Navigation Satellite System) provides highly accurate location information, its performance degrades significantly in shadow areas, such as urban areas, due to signal blockage [1]. To address these limitations, various positioning technologies that utilize highly available mobile/wireless infrastructures such as LTE (Long Term Evolution) and Wi-Fi have been actively studied [2], [3]. Nevertheless, these technologies are sensitive to environmental changes, requiring constant data collection and frequent database updates.

Smartwatches are equipped with an IMU (Inertial Measurement Unit) capable of continuously acquiring 3-axis accelerometer and 3-axis gyroscope data regardless of the surrounding environment. This enables continuously estimating a pedestrian's location using inertial sensor-based positioning algorithms [4]. However, the wrist is one of the most active parts of the body, which can cause sensor signals to become irregular due to unpredictable movements [5]. This means that the signal patterns of inertial data constantly change depending on the user's actions, leading to a decrease in the accuracy of inertial sensor-based positioning algorithms.

PDR (Pedestrian Dead Reckoning) is a representative inertial sensor-based positioning technique that estimates relative position based on a pedestrian's step count, stride length, and heading information [6], [7], [8]. However, the positioning performance of PDR significantly declines when walking segments are not accurately identified. Applying inertial data from non-walking wrist movements to the PDR algorithm can result in false detections during the step detection phase or accumulated errors during the stride length estimation phase [9], [10]. Furthermore, irregular movements and arm swings make it difficult to reliably estimate the rotational direction [11]. To address this issue, this study designs a HAR (Human Activity Recognition)-based DNN (Deep Neural Network) classification model using 3-axis acceleration data to first determine whether a smartwatch wearer is walking. The HAR classification results directly prevent PDR algorithms from being affected by inertial signals originating from non-walking wrist movements.

Once walking segments are identified by the deep learning model, PDR information is generated through step detection, stride length estimation, and turn event detection. In the step detection phase, the pedestrian’s steps are counted using a peak detection method. Stride length is estimated using a parameter-based model derived from gait characteristics. Turn event detection utilizes a modified Z-score technique [12] applied to 3-axis gyroscope data to determine the pedestrian’s turning state at each step, such as straight, right turn, or left turn. Through this process, one-dimensional PDR information representing the pedestrian’s movement distance and turning state is generated.

In this study, we propose a PDR-based map matching method that integrates PDR information with a pedestrian road digital map to estimate the movement route of a smartwatch wearer. To achieve this, numerical data representing pedestrian roads are converted into a node–edge structure, and each node is connected bidirectionally to account for the various possible walking paths. Afterward, candidate starting points near the initial location are selected, and candidate paths are sequentially removed based on the movement distance and turning state derived from the PDR information. Finally, the movement trajectory of the smartwatch wearer is generated by selecting the route that satisfies all PDR conditions.

The technique proposed in this paper was verified through field tests conducted in urban environment. In the experiment,

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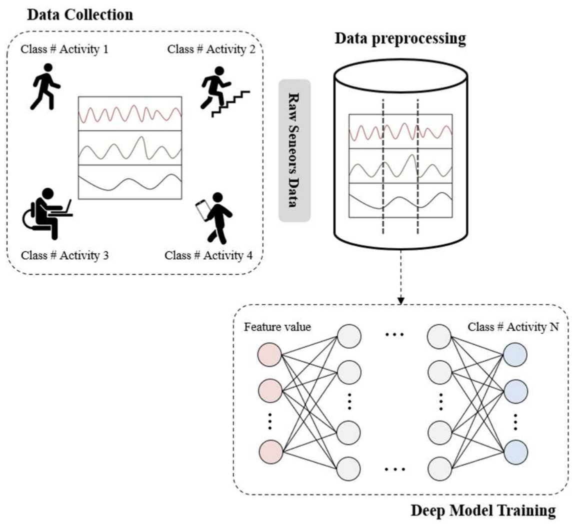

Fig. 1. Framework of the HAR-based deep learning model.

we designed a predefined scenario that included various walking patterns and comprehensively evaluated the HAR classification performance, and map matching results. The experimental results show that the proposed technique successfully matches the true trajectories, demonstrating its feasibility and potential for smartwatch-based pedestrian navigation.

II. Methodology

This section describes the methodology used to estimate the movement trajectory of smartwatch wearers. The proposed approach identifies walking segments using a HAR-based deep learning model and then generates PDR information from the walking segments. The estimated PDR data are subsequently matched with a pedestrian road digital map to determine the final movement route. For clarity, key terms used in this section are defined as follows. A pedestrian road digital map is a numerical representation of walkable pedestrian paths. The node-edge structure models this map as a graph, where nodes represent intersections or discretized path points and edges represent walkable segments with associated distance and directional information. PDR information refers to pedestrian movement data, including distance and turning state, which are used as constraints in the map-matching process.

A. HAR-based Classification Model

Fig. 1 shows the framework of the HAR-based deep learning model. This model is used to identify walking segments from the inertial sensor data of a smartwatch. First, 3-axis accelerometer data are collected for various activities, including walking and non-walking. The walking types are defined as Swing (walking with arms swinging), Handheld (walking while using a smartphone), and Pocket (walking with hands in pockets). Non-walking data are obtained by maintaining a static state for each walking type.

The collected inertial sensor data undergo a series of preprocessing procedures prior to model training. First, a low-pass filter is applied to the raw accelerometer signals to reduce noise caused by continuous and irregular wrist movements. This filtering process removes unexpected outliers and smooths the signal, improving the accuracy of the learning model. Next, a sliding window technique with overlapping windows is used to segment the time-series data, which increases the flexibility of the training samples [13]. From each segmented window, representative statistical features are extracted to characterize motion patterns. Considering the variability and asymmetry of activity data, features such as mean, variance, standard deviation, and median can be calculated. Finally, min-max normalization is applied to scale all features into a range between 0 and 1, to reduce dependence on a specific scale in the learning model.

The preprocessed data are used to train an FCL (Fully Connected Layer)-based deep learning classification model. The network consists of three hidden layers with 128, 64, and 32 nodes, respectively, and uses the ReLU activation function. Batch normalization is applied to improve training stability and convergence. The output layer consists of six nodes corresponding to three walking activities and three non-walking activities. The model is trained using the Adam optimization algorithm [14]. The dataset is divided into training and validation sets at a ratio of 9:1, with early stopping applied based on validation performance. After training, the model outputs an activity class for each input window, and only the segments identified as walking are passed to the subsequent PDR information generation process.

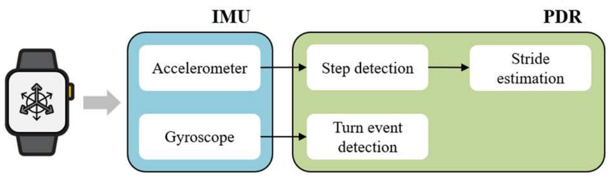

Fig. 2. PDR information generation process using smartwatch IMU data.

B. PDR Information Generation

Once walking segments are identified through the HAR-based classification model, PDR information is generated using the IMU data corresponding to those segments. Fig. 2 shows the overall process of generating PDR information from the inertial sensors embedded in the smartwatch. The PDR process consists of step detection, stride estimation, and turn event detection. In the step detection stage, the acceleration power is calculated to convert the 3-axis accelerometer signals into a single magnitude value, as follows:

$$Acc_{P,t} = \sqrt{Acc_{x,t}^2 + Acc_{y,t}^2 + Acc_{z,t}^2} - G \quad (1)$$

where $Acc_{p,t}$ is the acceleration power, $Acc_{i,t}$ is the acceleration output in the i-axis acquired at time t, and G is gravity, which is equal to 9.81 m/s^2. A Butterworth low-pass filter with a cutoff frequency of 2 Hz is applied to transform the acceleration power into a sinusoidal form. The filtered power signal is then used to count the pedestrian's steps through peak detection.

Stride length represents the distance traveled per step. To estimate stride length, a parameter-based approach is used, which is related to the correlation between walking speed and step frequency, as follows [15]:

$$Stride_k = \alpha \cdot F_k + \beta \cdot V_k + \gamma \quad (2)$$

where F_k and V_k are the step frequency and variance of acceleration power at the k-th step, respectively, and α, β, γ are model parameters. The model parameters can be estimated

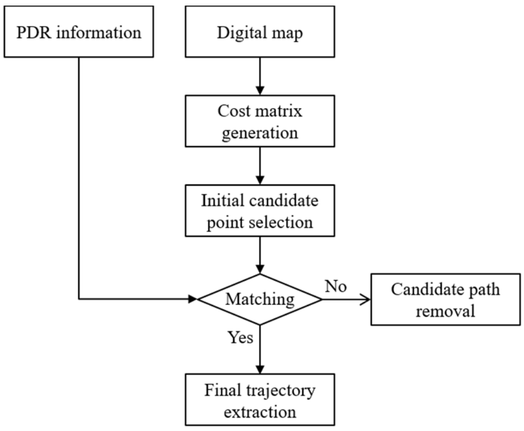

Fig. 3. Flowchart of the proposed PDR-based map matching algorithm.

using the least squares method based on pre-experimental data.

Due to various walking patterns and irregular wrist movements, it is difficult to accurately estimate heading. Therefore, this study utilizes a 3-axis gyroscope to determine the pedestrian's turning state. To do this, gyroscope signal power is calculated using Eq. (1), excluding the gravity component. The calculated power signal is then applied to the modified Z-score technique, as follows:

$$Z_t = 0.6745 \cdot \frac{Gyro_{P,t} - Median}{MAD} \tag{3}$$

where $gyro_{P,t}$ is the gyroscope signal power at time t, and *Median* and *MAD* are the median and median absolute deviation, respectively. A score is extracted for each step, and a threshold is applied to determine turn events. A positive value exceeding the threshold indicates a right turn, whereas a negative value exceeding the threshold indicates a left turn. This turn event detection technique is applicable to all walking patterns. Finally, PDR information is generated by combining the turning state according to the movement distance.

C. Map Matching

In the map matching stage, the PDR information is combined with a pedestrian road digital map to estimate the movement trajectory of the smartwatch wearer. Fig. 3 shows the overall flow of the proposed map matching algorithm, which consists of four steps: pedestrian map construction, initial candidate point selection, candidate path removal, and final trajectory determination.

First, pedestrian road network data are constructed using the QGIS tool. Pedestrian road layers are created on walkable paths, and node points are generated at intersections where turning can occur. Subsequently, vertex points are extracted at intervals of approximately 10 m between adjacent nodes to construct detailed numerical data along walkable paths. The constructed map is then converted into a bidirectional node-edge structure. Each point is assigned a unique ID, FromNodeID, ToNodeID, angle, distance, and geographic coordinates. This node-edge map structure provides the geometric constraints used for comparison with the PDR information.

Based on the edited map, a cost matrix is generated, containing movement distance and turning information between adjacent nodes. This matrix represents the distance and directional transitions required to move from one node to another and is used to determine whether each candidate path is consistent with the movement distance and turn events of the PDR information. In the initial step, all points located within a certain radius of the GNSS-based initial position are selected as candidate starting points. These candidates represent all possible locations where the pedestrian may have actually started.

Fig. 4. Confusion matrix of the HAR-based classification model.

The matching procedure is performed by comparing the PDR movement distance and turning state with the candidate paths on the map. If the distance or turning direction between two nodes does not match the PDR information, the path is immediately removed from the candidate set. This candidate path removal process is performed sequentially according to the PDR sequence, and the number of possible paths is gradually reduced as turns progress. Ultimately, the route that satisfies all PDR conditions is selected as the final trajectory of the smartwatch wearer.

III. Results

To evaluate the performance of the proposed method, field experiments were conducted. The smartwatch used was a Galaxy Watch 5 Pro, and inertial data were acquired at a sampling rate of approximately 8 Hz. The experiments were conducted based on a predefined scenario in a field environment, and both the HAR classification accuracy and the PDR-based map matching performance were analyzed. The results validate the effectiveness of the proposed method.

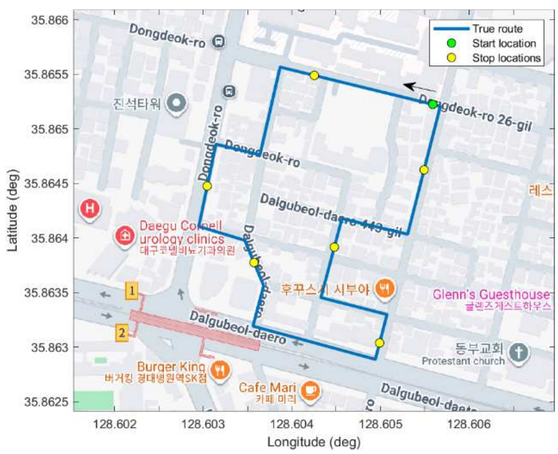

Fig. 5. True route defined for the experiment.

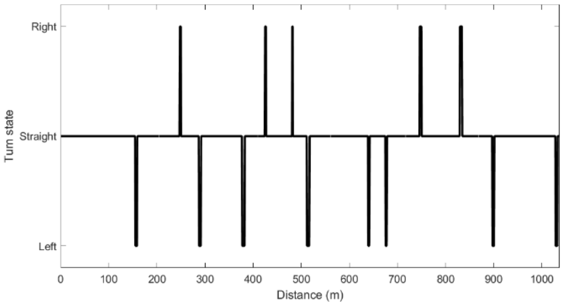

Fig. 6. PDR information represented by movement distance and turning states.

A. Classification Results

We evaluated the performance of a HAR classification model designed to identify walking signals from the inertial sensors of the smartwatch. The entire dataset was divided into training and validation sets to prevent overfitting. During the training process, early stopping was applied when no improvement in the validation accuracy was observed for a set period. The test data, collected individually over approximately 7 minutes for each activity type, were used to verify the generalization performance of the model. Fig. 4 shows the confusion matrix representing the classification results for six activity classes. All walking classes (Swing, Handheld, Pocket) were accurately classified, and the non-walking classes Standing (stop) and Handheld (stop) were also identified without misclassifications. While a small number of misclassifications occurred in the Pocket (stop) class, the overall classification accuracy remained above 99%. Overall, the experimental results confirm that the HAR classification model can distinguish between walking and non-walking activities with high accuracy. This capability plays a crucial role in the subsequent PDR information generation process by effectively filtering out non-walking signals.

B. PDR-based Map Matching Results

To validate the performance of the PDR-based map matching method, experiments were conducted based on a predefined scenario. The experiments were conducted in an urban area in Jung-gu, Daegu, South Korea. Fig. 5 shows the true walking trajectory of the participant, which includes multiple turns. At each stop point, marked by yellow circles, the participant remained stationary for approximately 2 minutes while including slight micro-movements. This complex walking pattern provides crucial testing conditions for evaluating the robustness of PDR-based turn detection and map matching.

TABLE I. GENERATED PDR RESULTS

Distance (m)	Turning state
156.9581	Left
89.5077	Right
43.8353	Left
91.5947	Left
45.4585	Right
56.6730	Right
32.2713	Left
130.0506	Left
39.9334	Left
70.4294	Right
77.8786	Right
68.7104	Left
129.8740	Left
7.0823	Straight

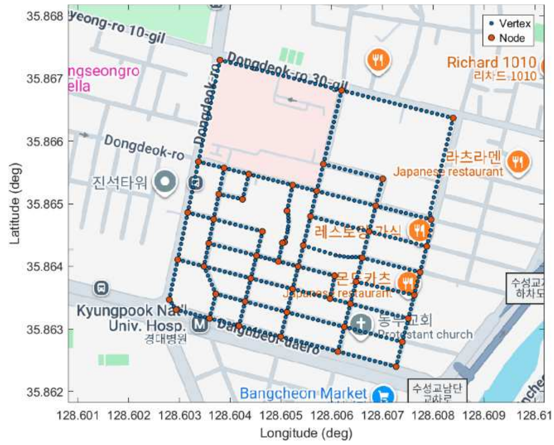

Fig. 7. Constructed pedestrian road digital map with nodes and vertices.

Fig. 6 shows the PDR information generated from the smartwatch IMU data, expressed in terms of movement distance and turning state. Each spike represents a left or right turn occurring during walking, while segments without peaks correspond to "Straight." The results confirm that the PDR algorithm successfully detects all turning events that occurred along the true route. The detected turning states function as key criteria for eliminating candidate paths during the map matching process, and the distance information is used to compare the true distance between adjacent nodes. Table I sequentially organizes the PDR information generated in Fig. 6 and is used as quantitative input data for the map matching procedure.

The pedestrian road map used in the experiment was constructed using the QGIS tool, as shown in Fig. 7. Vertex points were extracted at approximately 10 m intervals along the centerline of walkable paths, while node points, marked by orange circles, were placed at locations where turning could occur. This structure was then converted into a bidirectional node-edge graph, enabling direct comparison with the PDR information. The combination of vertices and nodes provides a map representation capable of modeling both directionality and connectivity, making it suitable for the candidate path elimination process based on turn events and distance constraints.

Fig. 8 shows the result of applying the map matching algorithm using the generated PDR information. In the initial

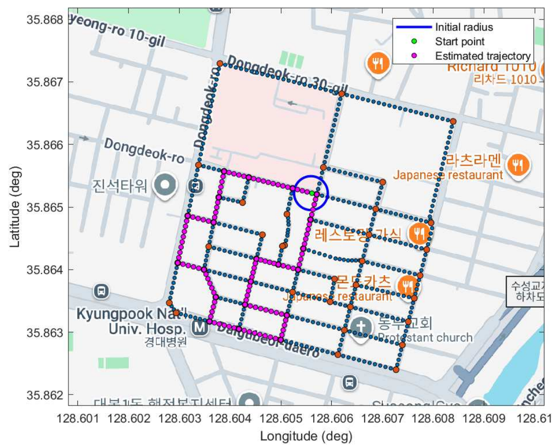

Fig. 8. Final route estimated through PDR-based map matching.

stage, a certain radius, shown as a blue circle, is set around the GNSS-based initial position, and all points within this radius are selected as candidate starting points. Subsequently, the movement distances and turning events listed in Table I were applied sequentially to remove inconsistent candidate paths. This iterative candidate path elimination process becomes even more decisive when a turn event occurs. In fact, because the experimental route contained multiple turns, the number of feasible candidate paths decreased rapidly as matching progressed. Once matching is complete, only a single route satisfying all PDR conditions remains. The final route estimated is shown as a purple trajectory in Fig. 8, and it can be confirmed that the route matches the true route in Fig. 5.

IV. CONCLUSION

In this study, we proposed a PDR-based map matching method that estimates the movement route of a pedestrian using the inertial sensors of a smartwatch. First, we distinguish between walking and non-walking activities using a HAR classification model, filtering out non-walking signals that could affect PDR performance. The classification results achieved an accuracy of over 99%. In the identified walking segments, PDR data including movement distance and turning information were generated through step detection, stride estimation, and turn event detection. In addition, a pedestrian road digital map was constructed using a combined structure of nodes and vertices to enable comparison with PDR information. The proposed map matching algorithm successfully estimated the walking trajectory in the urban field tests, showing full consistency with the predefined true route. Even in scenarios involving multiple turns, turn events were accurately reflected, and the candidate paths were consistently reduced until a single correct route remained.

In the future, we plan to conduct additional experiments across various walking environments to further enhance the generalization capability of the algorithm. We also intend to expand the coverage of the pedestrian road map and involve a larger number of participants to strengthen the robustness and applicability of the proposed method.

REFERENCES

[1] G. Ciattaglia, L. Senigagliesi, A. De Santis, M. Raimondi, A. Nocera, S. Spinsante, and E. Gambi, "Position uncertainty of consumer GNSS smart devices: a GUM-based analysis," IEEE Consumer Electronics Magazine, vol. 14, pp. 86–93, 2025.

[2] N. Singh, S. Choe, and R. Punmiya, "Analysis machine learning based indoor localization using Wi-Fi RSSI fingerprints: an overview," IEEE Access, vol. 9, pp. 127150–127174, 2021.

[3] Y. S. Cho, J. I. Jeon, J. H. Lee, S. S. Chun, and J. A. Kang, "A noble probabilistic RF fingerprinting method by using multiple MNO's cellular signals on smart watch," in Proceedings of 2025 15th International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–9, 2025.

[4] Y. Wu, H.-B. Zhu, and S.-M. Tang, "A survey of the research status of pedestrian dead reckoning systems based on inertial sensors," International Journal of Automation and Computing, vol. 16, pp. 65–83, 2018.

[5] A. I. Alexan, A. R. Alexan, and S. Oniga, "Real-time machine learning for human activities recognition based on wrist-worn wearable devices," Applied Sciences, vol. 14, pp. 1–20, 2024.

[6] S. Y. Cho, and C. G. Park, "MEMS based pedestrian navigation system," Journal of Navigation, vol. 59, pp. 135–153, 2006.

[7] S. Y. Cho, J. H. Lee, and C. G. Park, "A zero-velocity detection algorithm robust to various gait types for pedestrian inertial navigation," IEEE Sensors Journal, vol. 22, no. 6, pp. 14916–14931, 2022.

[8] X. Hou, and J. Bergmann, "Pedestrian dead reckoning with wearable sensors: a systematic review," IEEE Sensors Journal, vol. 21, pp. 143–152, 2021.

[9] Y. H. Cho, H. T. Cho, and C. M. Kyung, "Design and implementation of practical step detection algorithm for wrist-worn devices," IEEE Sensors Journal, vol. 16, pp. 7720–7730, 2016.

[10] Y. Jiang, Z. Li, and J. Wang, "PTrack: enhancing the applicability of pedestrian tracking with wearables," IEEE Transactions on Mobile Computing, vol. 18, pp. 431–443, 2019.

[11] L. Xu, Z. Xiong, J. Liu, Z. Wang, and Y. Ding, "A novel pedestrian dead reckoning algorithm for multi-mode recognition based on smartphones," Remote Sensing, vol. 11, pp. 1–19, 2019.

[12] B. Iglewicz and D. C. Hoaglin, How to Detect and Handle Outliers, vol. 16. USA: ASQ Press, 1993.

[13] G. Wang, Q. Li, L. Wang, W. Wang, M. Wu, and T. Liu, "Impact of sliding window length in indoor human motion modes and pose pattern recognition based on smartphone sensors," Sensors, vol. 18, pp. 1–20, 2018.

[14] D. P. Kingma, and J. Ba, "ADAM: A method for stochastic optimization," in Proceedings of International Conference on Learning Representation (ICLR), 2015.

[15] Z. Jin, X. Zhang, G. Liu, M. Guo, Y. Su, and M. Lu, "Flexible gaits-adaptive pedestrian dead reckoning system: precision positioning across diverse gaits," IEEE Sensors Journal, vol. 25, pp. 15431–15441, 2025.