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Enhanced Indoor Localization Scheme Based on Pedestrian Dead Reckoning and Kalman Filter Fusion with Smartphone Sensors

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스마트폰 센서를 이용한 PDR과 칼만필터 기반 개선된 실내 위치 측위 기법

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Abstract Indoor localization is a critical component for numerous applications, ranging from navigation in large buildings to emergency response. This paper presents an enhanced Pedestrian Dead Reckoning (PDR) scheme using smartphone sensors, integrating neural network-aided motion recognition, Kalman filter-based error correction, and multi-sensor data fusion. The proposed system leverages data from the accelerometer, magnetometer, gyroscope, and barometer to accurately estimate a user's position and orientation. A neural network processes sensor data to classify motion modes and provide real-time adjustments to stride length and heading calculations. The Kalman filter further refines these estimates, reducing cumulative errors and drift. Experimental results, collected using a smartphone across various floors of University, demonstrate the scheme's ability to accurately track vertical movements and changes in heading direction. Comparative analyses show that the proposed CNN-LSTM model outperforms conventional CNN and Deep CNN models in angle prediction. Additionally, the integration of barometric pressure data enables precise floor level detection, enhancing the system's robustness in multi-story environments. Proposed comprehensive approach significantly improves the accuracy and reliability of indoor localization, making it viable for real-world applications.

Key Words : IoT, Indoor localization, Pedestrian Dead Reckoning, Neural Network, motion recognition, and Smartphone Sensors

요 약 실내 위치 측위는 대형 건물에서 내비게이션부터 비상 대응까지 다양한 애플리케이션이다. 본 논문에서는 스마트폰 센서를 이용하고 신경망 기반 동작 인식, 칼만 필터 기반 오류 수정, 다중 센서 데이터 융합을 통합한 향상된 PDR(Pedestrian Dead Reckoning) 기반 보행자 실내 위치 측위 기법을 제시한다. 제안된 기법은 가속도계, 자력계, 자이로스코프, 기압계의 데이터를 활용하여 사용자의 위치와 방향을 정확하게 측위하며, 신경망은 센서 데이터를 처리하여 동작 모드를 분류하고 보폭과 방향 계산에 대한 실시간 조정을 제공한다. 칼만 필터는 이러한 추정치를 더욱 구체화하여 누적 오류와 드리프트를 줄이며, 대형 건물의 여러 층에서 스마트폰을 사용하여 수집한 실험 결과는 수직 이동과 진행 방향 변화를 정확하게 추적하는 능력을 보여준다. 성능 비교 분석 결과에서 제안된 CNN-LSTM 모델은 각도 예측에서 기존 CNN 및 Deep CNN 모델보다 성능이 뛰어난 것으로 나타났으며. 또한 기압 데이터를 통합하여 정확한 바닥 수준 감지가 가능해 다층 환경에서 시스템의 견고성을 향상시켰으며, 이 제안된 접근 방식은 실내 위치 파악의 정확성과 신뢰성을 크게 향상시켜 실제 응용 분야에서 활용 가능성이 높다고 판단된다.

주제어 : IoT, 실내 측위, 보행자 측위 항법, 신경망, 동작 인식 및 스마트폰 센서

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1. Introduction

Indoor navigation has become increasingly essential for various applications, requiring robust and accurate orientation, velocity, and position information. PDR(Pedestrian Dead Reckoning) using low-cost Inertial Measurement Units (IMUs) in smartphones, comprising magnetometers, accelerometers, gyroscopes, and barometers, has emerged as a widely used technique. PDR algorithms primarily focus on heading estimation, stride length calculation, and step detection [1]. However, traditional PDR systems face challenges in accurately maintaining orientation, especially with complex movements such as using elevators, walking backward, or sidestepping, which leads to increased localization errors over time [2].

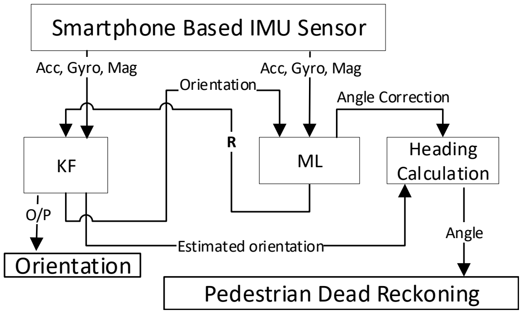
To address these issues, recent advancements integrate PDR with complementary localization technologies like computer vision-based systems (CVBS) and communication technology-based systems (CTBS), including Bluetooth, Wi-Fi, and RFID [3][4]. Despite these enhancements, PDR still suffers from drift due to cumulative errors in inertial sensor measurements [5][6]. Various techniques, including Kalman filters and optimization methods, have been proposed to mitigate these errors by combining data from multiple sensors [7][8].

Machine learning models, particularly convolutional neural networks (CNNs) and long short-term memory networks (LSTMs), have shown promise in improving PDR by accurately classifying motion patterns and reducing heading errors. These models outperform traditional heuristic methods and provide more reliable estimates by leveraging time-series data from IMUs [9][10]. Recent studies have demonstrated the effectiveness of integrating CNNs and bidirectional LSTMs (BDLSTMs) for recognizing complex motion patterns, significantly enhancing PDR accuracy [11].

This paper introduces a robust PDR system that integrates CNN and LSTM for improved motion mode recognition. By employing a Kalman filter for continuous error correction and fusing data from accelerometers, magnetometers, gyroscopes, and barometers, the system significantly enhances position and orientation estimates. It effectively handles complex motion patterns and accurately tracks vertical movements using barometric pressure data. Experimental validation on a Galaxy S8 smartphone demonstrates the system's superior performance in diverse scenarios, with comparative analysis showing that the CNN-LSTM model outperforms conventional models in angle and position estimation accuracy.

2. Methodology

The block diagram as shown in Fig. 1 denotes the information flow in enhanced indoor localization system. The localization system using smartphone sensors, including the accelerometer, magnetometer, and gyroscope. It employs a neural network-aided PDR(Pedestrian Dead Reckoning) system, augmented by a Kalman filter for error correction and data fusion. The system improves the accuracy and reliability of indoor positioning by integrating and processing data from multiple sources: the accelerometer (measuring linear acceleration for step detection and stride length), magnetometer (measuring magnetic fields for heading direction), gyroscope (measuring rotational rates for orientation tracking), neural network outputs (providing motion mode recognition and angle correction), PDR outputs (estimating continuous position updates based on movement), and the Kalman filter (fusing and refining data to predict and correct errors). By combining these diverse data sources, the system achieves a comprehensive and precise estimate of the user's indoor position and orientation.



[Fig. 1] Information flow in enhanced indoor localization based on machine learning for the pedestrian dead reckoning system.

The architecture depicted in Fig. 2 has several primary objectives. First, it aims to achieve accurate motion mode recognition using a neural network to classify different motion modes, which is crucial for real-time stride length and heading adjustments. Second, it seeks to minimize errors through a Kalman filter, which continuously predicts and corrects orientation and position estimation errors, thereby reducing inertial navigation drift. Third, it enhances the robustness of the PDR system by incorporating Zero Velocity Update (ZUPT) and Zero Angular Rate Update (ZARU) techniques, ensuring accurate positioning during stationary periods. Fourth, it facilitates real-time data fusion by integrating data from multiple sensors to provide a precise estimate of the user's position and orientation. Lastly, it aims for adaptive learning and correction through a learning module that adjusts angle estimations and stride length, improving overall system reliability.

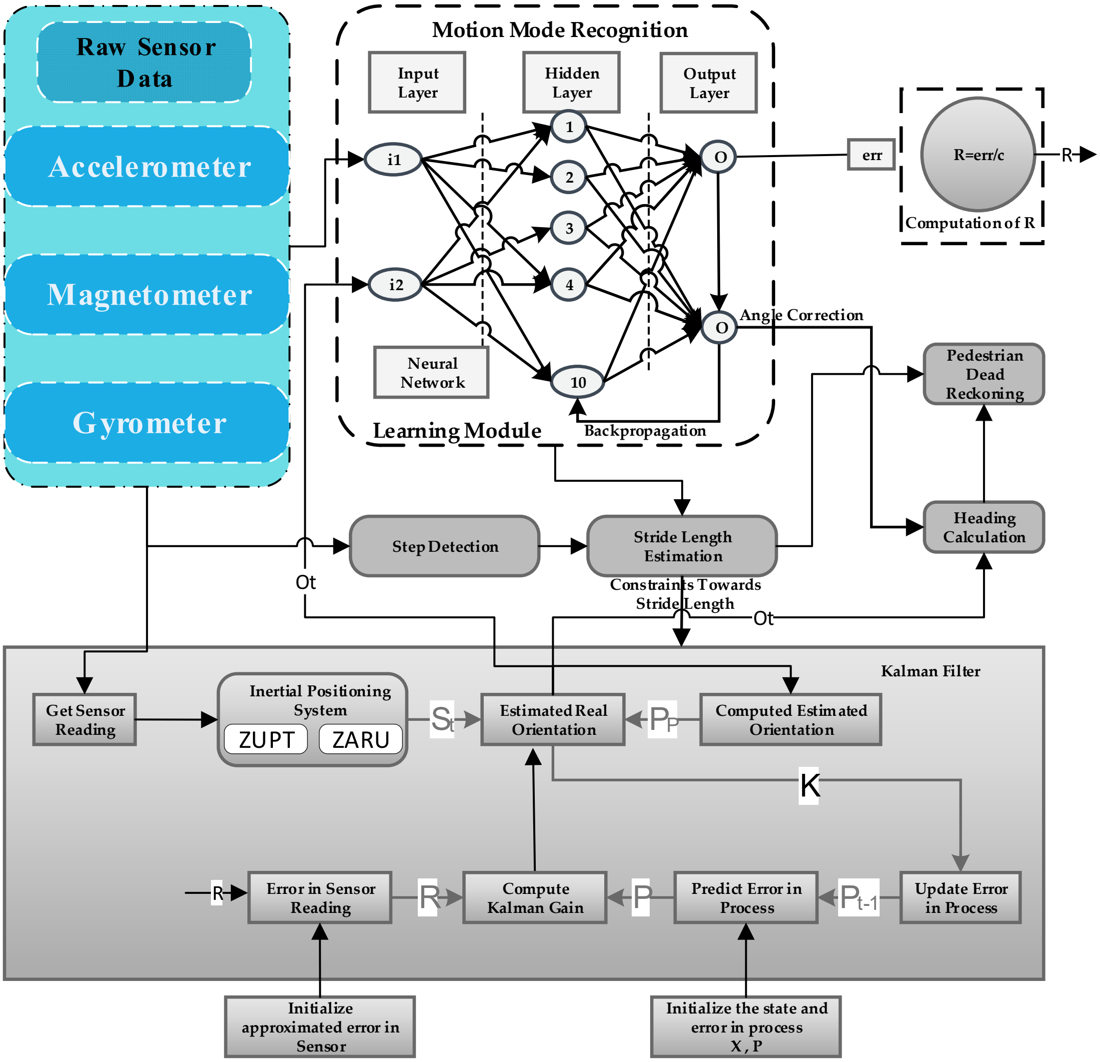
This improves the PDR system by enhancing step detection and stride length estimation, dynamically correcting heading direction, and reducing cumulative errors through neural network outputs. The Kalman filter integration reduces noise and corrects errors, while ZUPT and ZARU minimize drift and improve long-term accuracy. Leveraging data from multiple sensors offers a holistic approach to movement tracking, and the neural network's continuous learning capabilities make the PDR system robust and adaptive to various movements.

2.1 Neural Network-Aided Pedestrian Dead Reckoning

The PDR system begins by collecting data from multiple smartphone sensors. The accelerometer measures linear acceleration along the x, y, and z axes, which is crucial for detecting steps and changes in speed. The magnetometer measures the strength and direction of the magnetic field, helping determine the heading or direction of movement. Meanwhile, the gyroscope measures the rate of rotation around the x, y, and z axes, providing information on changes in orientation. Once the raw sensor data is collected, it undergoes preprocessing to make it suitable for analysis. Filtering techniques are applied to reduce noise and smooth the data. Key features are then extracted from the sensor data, such as acceleration magnitude, orientation changes, and frequency components of the movement. These features serve as the input to the neural network.

The neural network designed for the PDR system has a specific architecture tailored to process sensor data. The input layer receives the preprocessed sensor data features. Several hidden layers then process this input data, learning to recognize patterns associated with different types of pedestrian movements by adjusting their weights during training. The output layer produces the classification of the current motion mode, such as walking, running, or standing.

Training the neural network involves using a labeled dataset containing sensor data and corresponding motion modes. This dataset cover various types of movements and environmental conditions to ensure comprehensive learning. The neural network is trained using supervised learning, where it learns to map input features to the correct motion mode by minimizing the error between its predictions and the actual labels. The backpropagation algorithm adjusts the weights of the neural network based on the error gradient, improving its accuracy over time. In real-time, the trained neural network continuously receives



[Fig. 2] Enhanced Indoor Localization Architecture.

live sensor data from the smartphone. It processes the incoming data to classify the current motion mode. The identified motion mode is then used to adjust the PDR calculations. For instance, if the neural network detects walking, the system applies walking-specific stride length and step frequency to update the position.

The classified motion mode informs the system about the type of movement, allowing it to apply the appropriate stride length estimation algorithm. The neural network's output helps dynamically adjust the heading based on detected turns and changes in direction. Additionally, the continuous and adaptive nature of the neural network helps reduce cumulative errors in position and orientation estimates, ensuring more accurate tracking over time. By incorporating a neural network, the PDR system achieves enhanced accuracy through precise detection of motion modes, leading to accurate stride length and heading calculations. The system becomes more robust, with an improved ability to handle various movement patterns. Continuous correction and dynamic adjustments minimize cumulative errors, reducing drift.

2.2 Integration of Inertial Positioning and Kalman Filter

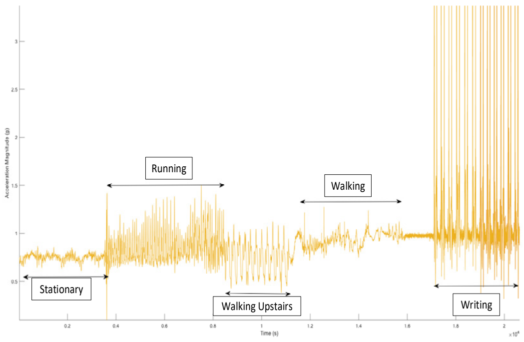
The inertial positioning system and Kalman filter play crucial roles in the overall architecture by enhancing the accuracy and reliability of the Pedestrian Dead Reckoning (PDR) system. The inertial positioning system uses data from accelerometers and gyroscopes to estimate the user's position and orientation by tracking movements such as steps and rotations. However, this system is prone to accumulating errors over time, known as drift. To mitigate this, the Kalman filter is employed. The Kalman filter continuously predicts and corrects these errors by integrating sensor data with real-time updates, refining position and orientation estimates. The inertial positioning system and Kalman filter work together to ensure that the estimates remain accurate and stable. The neural network aids this process by providing precise motion mode classification and real-time adjustments to stride length and heading direction, which are fed into the inertial positioning system. The Kalman filter uses these refined inputs to further reduce errors, resulting in a more robust and adaptive PDR system. This combined approach leverages the strengths of each component: the neural network for accurate motion recognition, the inertial positioning system for continuous tracking, and the Kalman filter for error correction, collectively enhancing the overall performance of the indoor localization system.

2.3 Experimental Setup and Data Collection

All experiments and data collection were conducted at Jeju National University (JNU) using a Galaxy S8 smartphone to gather human activity data across various floors of the university. The accelerometer data was sampled at a rate of 333.33 Hz, while the barometer data was sampled at 20 Hz. The comprehensive smartphone-based dataset encompasses approximately 2.75 hours of Human Motion Recognition (HMR) data collected on different floors of JNU. Four participants were involved in the data collection process, each carrying a smartphone in their right hand to record six daily human activities across different floors. To facilitate the labeling of the raw smartphone-based sensor (SBS) data, participants paused for 2-3 seconds when changing activities and floor levels. This approach made it easier to label the data accurately. Additionally, we performed time-series analysis on all motion data, identifying distinct activity signal patterns in each segment based on the amplitude of the accelerometer and relative changes in pressure data corresponding to altitude variations.

3. Performance Results and Analysis

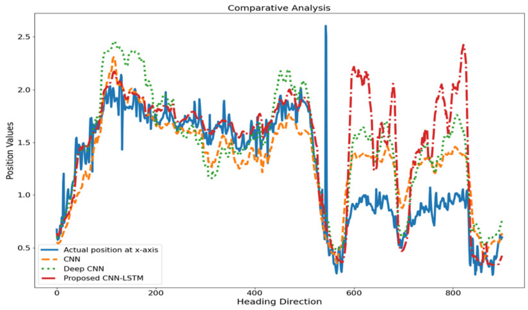
Fig. 3 illustrates different motion activities captured by the accelerometer, each characterized by distinct acceleration magnitude patterns. The variations in these patterns, such as the high-frequency spikes during running and the more stable signals during stationary activities like working on a computer, provide essential features for the ML model within the main architecture.



[Fig. 3] Activity detection based on varyiyg acceleration magnitude measurements.

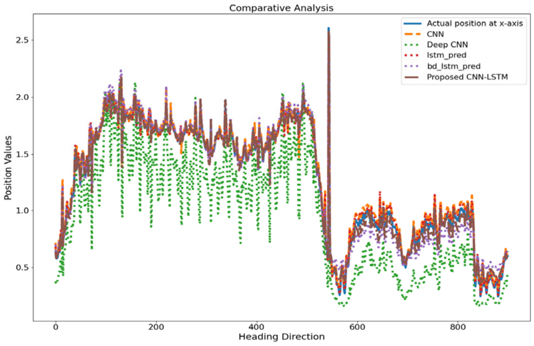
The neural network utilizes these distinct amplitude patterns to classify various motion activities accurately. By learning these patterns during training, the neural network can recognize and differentiate activities in real-time, thereby enhancing the overall Pedestrian Dead Reckoning (PDR) system by providing precise motion mode classifications for accurate stride length and heading adjustments.

Fig. 4 presents a comparative analysis of angle estimation accuracy using different neural network architectures—CNN, Deep CNN, and the proposed CNN-LSTM—against the actual angle, without explicit feature computation. The actual angle is shown by the solid blue line, while the CNN, Deep CNN, and CNN-LSTM predictions are represented by the orange, green, and red dashed lines, respectively. The proposed CNN-LSTM model closely aligns with the actual angle, demonstrating its superior ability to predict angles directly from raw sensor data by capturing spatial and temporal dependencies. This analysis underscores the effectiveness of advanced neural networks in enhancing the PDR based localization system, improving angle estimation accuracy without manual feature computation.



[Fig. 4] Comparative analysis of angle estimation methods without feature computation.

Fig. 5 presents a comparative analysis of angle estimation accuracy using different neural network architectures—CNN, Deep CNN, LSTM, bidirectional LSTM, and the proposed CNN-LSTM—against the actual angle, with explicit feature computation involving the rotation matrix. The actual angle is shown by the solid blue line, while the predictions from CNN, Deep CNN, LSTM, bidirectional LSTM, and the proposed CNN-LSTM are represented by the orange, green, red, purple, and brown lines, respectively.



[Fig. 5] Comparative Analysis of Angle Estimation Methods with Feature Computation (Rotation Matrix).

The proposed CNN-LSTM model shows a high degree of alignment with the actual angle, demonstrating its superior ability to predict angles accurately by leveraging both raw sensor data and computed features like the rotation matrix. This analysis highlights the effectiveness of combining advanced neural network models with feature computation to enhance the PDR system, resulting in more accurate and reliable angle estimation for indoor localization.

4. Conclusion

This paper presents an advanced PDR system that significantly enhances indoor localization accuracy by integrating CNN and LSTM models. The system employs a Kalman filter for continuous error correction and fuses data from multiple smartphone sensors, including accelerometers, magnetometers, gyroscopes, and barometers. This multi-sensor data fusion enables precise estimation of position and orientation, effectively mitigating drift and cumulative errors. The system addresses complex motion patterns, such as elevator usage, walking, running, sidestepping, and climbing stairs, which are often challenging for conventional PDR methods. Experimental validation using a Galaxy S8 smartphone across various floors demonstrates the system's superior performance in accurately tracking vertical movements and heading direction changes. Comparative analysis reveals that the proposed CNN-LSTM model outperforms traditional CNN and deep CNN models in angle and position estimation accuracy. This work highlights the potential of combining advanced neural networks with traditional PDR components to develop robust and reliable indoor navigation systems, providing a foundation for future enhancements in this field.

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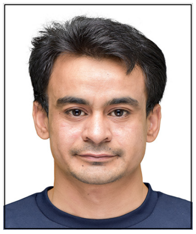

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