

Intent Recognition in Gait Transition Using Muscle Volume Sensors with Deep Learning

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Abstract—Intention recognition is essential for wearable robotics and assistive systems. However, conventional approaches often suffer from cumbersome sensor setups or sensitivity to external disturbances. To address these limitations, this study proposes an LSTM-based intention recognition method using lower-limb Muscle-Volume (MV) sensors. An insole-type pressure sensor, an IMU sensor, and a cuff-type MV sensor were used to record a series of motions, including sitting, standing, walking, and running. Deep learning techniques were then applied for classification and transition detection. Accuracies of the predicted movement states based on data from the IMU, insole-type pressure, and cuff-type MV sensors were 93.04%, 97.65%, and 93.08%, respectively. The average transition detection latencies for the IMU, insole, and MV sensor model were 0.135 s, 0.377 s, and 0.455 s, respectively. Results show that the proposed MV sensor achieves performance comparable to insole pressure sensors, demonstrating its potential as a practical and robust alternative for intention recognition in wearable systems.

I. INTRODUCTION

Wearable assistive robots and gait assistance devices have been developed to improve human gait efficiency and to support rehabilitation for patients with mobility impairments. Accurate recognition of the user's intention is crucial for robots to provide proper assistance based on wearer's movement. Conventional intention recognition methods have utilized neural and muscular signals, such as electroencephalography (EEG) and electromyography (EMG), as well as wearable sensor signals, including inertial measurement units (IMUs) and insole sensors. However, EEG/EMG-based methods often suffer from user discomfort and are vulnerable to noise [1]. IMU-based methods can only measure motion after it occurs at the sensor, making them difficult to apply in environments where movement is constrained. Insole sensors also have limitations, as estimating the user's state is difficult when the user is stationary or when prior motion information is unavailable [3]. Muscle volume sensor (MVS) systems have emerged as a promising alternative for intention recognition. By directly measuring

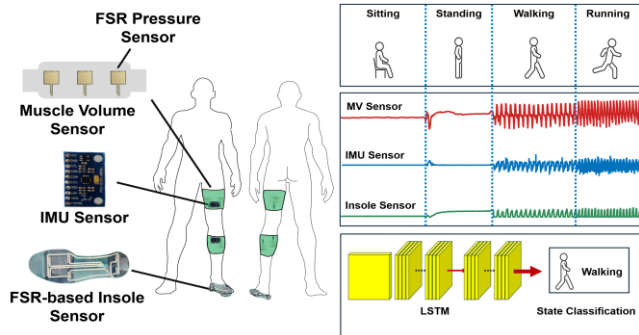


Fig. 1. Experimental setup for intention recognition using an MV sensor-based deep learning model, including comparison with insole and IMU-based methods

muscle volume changes using wearable pressure sensors, MVS systems offer robustness to noise and improved wearability. However, existing MVS-based systems still have limitations in capturing a wide range of human intentions in real-world environments [4]. To address these limitations, we propose an MVS-based intention recognition system that can operate in daily environments and recognize diverse activities.

II. METHODS

A. Gait experiment

A gait experiment was conducted with fourteen healthy adult male participants. Each participant was equipped with an MV sensor, an inertial measurement unit (IMU), and insole sensors. Participants performed a sequence of ten activities: standing (10s), sitting (10s), standing (10s), walking (10s), standing (10s), walking (10s), running (10s), standing (10s), running (10s), and standing (10s). Each session lasted 100 seconds. Each participant followed pre-recorded audio instructions and repeated the session 12 times. All sensor signals were collected at a sampling frequency of 100 Hz [2]. This study was approved by the Institutional Review Board of Kyungpook National University (IRB No. 2025-0247).

B. Data processing

We employed a deep learning model to classify state from the measured gait signals. Long Short-Term Memory (LSTM) network was selected for its ability to capture temporal dependencies in time-series data. The LSTM model consisted of a single LSTM layer with 400 hidden units, followed by a fully connected layer and a softmax layer for state classification. To train the model, activity data were labeled based on the transition points identified from the IMU sensor signals. For each participant, 12 datasets were collected, of which nine were used for training and three for evaluating classification accuracy and transition detection latency. State transition latency was calculated by comparing the predicted

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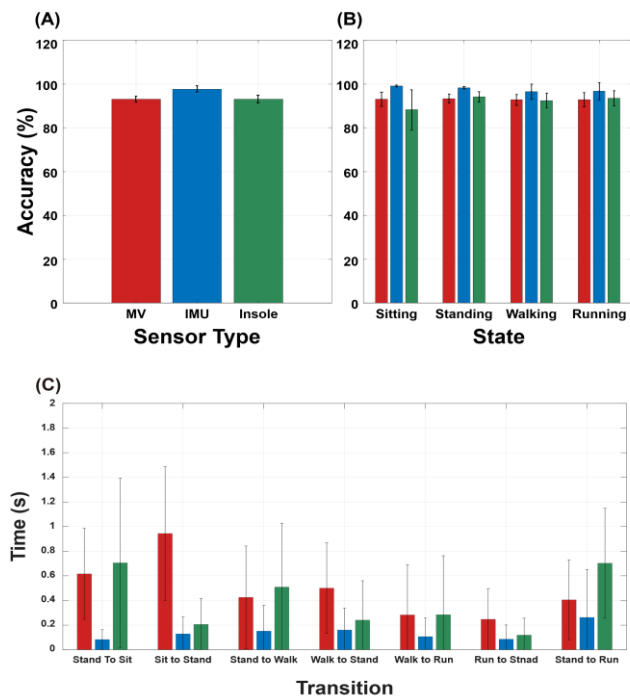


Fig. 2. (A) Overall classification accuracy for each sensor modality, (B) Per-state classification accuracy for each sensor modality, (C) Analysis of transition detection latency during state transitions for each sensor modality

states from the LSTM model with reference states obtained from IMU-based labeling and defined as the time difference between the reference transition point and the corresponding change in the predicted state.

III. RESULT

A. Classification Accuracy

Preliminary results from nine participants data show that the IMU-based model achieved the highest overall state classification accuracy of 97.65%. The insole-based and MVS-based models achieved overall accuracies of 93.08% and 93.04%, respectively.

- For sitting, the IMU-based model achieved 99.03% accuracy, followed by the MVS-based model (93.04%) and the insole-based model (88.2%). For standing, the MVS, IMU, and Insole-based models achieved accuracies of 93.27%, 98.28%, and 94.17%, respectively. For walking, the respective accuracies were 92.72%, 96.51%, and 92.46%, while for running, they were 92.81%, 96.68%, and 93.52%.

B. Transition latency

The transition detection latency was also evaluated for three sensor modalities. IMU-based model detected state transitions the fastest, with an average latency of 0.135 s. Insole-based model showed an average transition latency of 0.377 s, while MVS-based model required 0.455 s on average to detect state transitions.

- For the transition from walking to running, the IMU-based model detected the transition fastest (0.107 s), followed by the MVS-based model (0.283 s) and the insole-based model (0.285 s).

- For transitions from sitting to standing, walking to standing, and running to standing, the IMU-based model achieved the shortest latencies (0.129 s, 0.160 s, and 0.086 s, respectively), followed by the insole-based model (0.206 s, 0.241 s, and 0.119 s, respectively) and the MVS-based model (0.944 s, 0.500 s, and 0.248 s, respectively).
- For transitions from standing to sitting, standing to walking, and standing to running, the IMU-based model again showed the fastest detection (0.083 s, 0.152 s, and 0.262 s, respectively), followed by the MVS-based model (0.616 s, 0.426 s, and 0.406 s, respectively) and the insole-based model (0.705 s, 0.509 s, and 0.703 s, respectively).

IV. CONCLUSION

The IMU-based intention recognition method achieved the best overall classification performance, with more than 95% accuracy across all activities. The MVS-based model showed relatively lower classification accuracy compared to the IMU-based model, but detected transitions from static to dynamic activities, such as standing to running, faster than the insole-based model. Similarly, while the insole-based model achieved relatively lower classification accuracy than the IMU-based model, it detected transitions from dynamic to static activities, such as running to standing, faster than the MVS-based model. Future work includes analyzing additional data from five participants and statistically evaluating performance differences among the models. When applied to gait assistance devices and wearable robots, the proposed method enables real-time recognition of the user's intention, allowing the robot to provide appropriate assistance and improve user adaptation and walking efficiency.

ACKNOWLEDGMENT

This research was conducted with the support of the Korea Institute for Advancement of Technology (KIAT) grant funded by the Korean government (Ministry of Trade, Industry and Energy, MOTIE) (P0020616, The Competency Development Program for Industry Specialist).

This research, undertaken at Kyungpook National University, was supported by the Regional Innovation System & Education (RISE) program through the Daegu RISE Center, funded by the Ministry of Education (MOE) and the Daegu Metropolitan City, Republic of Korea.

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