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Validation of a Novel Gait Analysis System

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***Abstract*—Many researches have proved the significance of gait analysis since it strongly relates to several urgent health issues. As a response, we develop an unobtrusive sensor device, named SennoGait, which provides comprehensive gait information. In this paper, we verify the robustness and reliability of the device's hardware components, including a 16 pressure sensors array and a 9-axis inertial measurement unit with state-of-the-art tools.**

I. Introduction

Gait analysis, a momentous study for recognizing patterns of normal or abnormal walking, has been applied to a wide range of health related applications. For instances, the gait analysis significantly improves the value of Timed-Up-and-Go, a well accepted test for the fall detection [1]. To this end, our team developed a novel insole-like wearable gait tracking device named SennoGait [2]–[9]. It can facilitate fine-grained gait analysis in both laboratory and real-world environments. In this paper, our first goal is to verify the accuracy of two important hardware components of the device, a 16 pressure sensors array and a 9-axis IMU. In addition, we present the validation of gait features extracted by the SennoGait.

II. SennoGait Overview

SennoGait can provide plantar pressure through a 16 pressure sensors array and foot orientation through a 9-axis IMU. The sensors array and the IMU are the foundation of recording gait data as they produce pressure, velocity, and acceleration values which are highly related to gait features such as step count, step pace, and step length.

Textile Pressure Array: Based on the advanced conductive eTextile fabric sensor technique, these embedded 16 pressure sensors in the SennoGait can provide the high-solution pressure map for the sole [10]. Each sensor has size 1 cm by 1 cm. The output pressure value is in unit Pascal.

Inertial Measurement Unit: This unit contains a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis magnetometer. The accelerometer provides linear acceleration values of movements, while the gyroscope is for recording the angular velocities. In order to establish the baseline of calibration for the first two subcomponents, the magnetometer is used [2].

III. SennoGait Validation

A. Pressure Sensor Verification

In order to apply precise amount of force onto each of the 16 pressure sensors, a Stable Micro System, TA.XTplus Texture Analyser, is used. The applied forces are set to be 5, 15, and

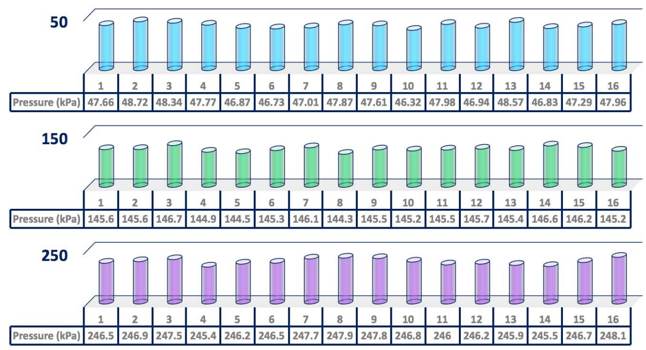

Fig. 1. The horizontal lines indicate the references of applied pressure value (50, 150, and 250 kPa). The index from 1 to 16 corresponds to different pressure sensors embedded in the SennoGait. The recorded pressure values with respect to each sensor are presented by colored columns.

TABLE I
The mean and standard deviation of accuracies of sensors

Applied Pressure	**50 kPa**	**150 kPa**	**250 kPa**
Mean of Accuracy	95.06%	97.01%	98.69%
Standard Deviation	0.0141	0.0045	0.0034

25 Newtons. The reference pressure values in unit Pascal for each sensor is computed as the applied force divided by the size of a single sensor. The results are 50, 150, and 250 kPa. We obtain the accuracies of our 16 pressure sensors through dividing each output pressure by the corresponding reference value (See in Fig. 1 and Table. I).

B. IMU Verification

For verifying SennoGait's IMU, a commercial IMU device, SparkFun 9DoF Razor IMU M0, is placed into the center of an insole-like sponge located under the SennoGait in the left shoe. Two male and three female testees ($50-76$ kg in weight and $157-178$ cm in height) participate in the experiment that each performs a 14-meter flat ground walking including a

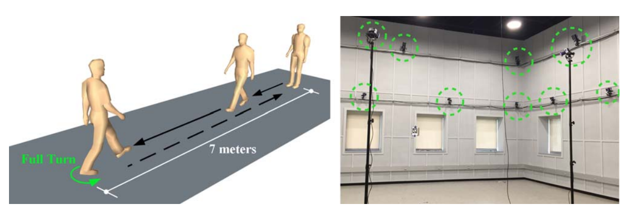

Fig. 2. (Left) The process of 14-meter flat ground walking. The testee first walks a 7-meter distance, turns, and then walks back. (Right) The established Vicon system for the validation of extracted gait features.

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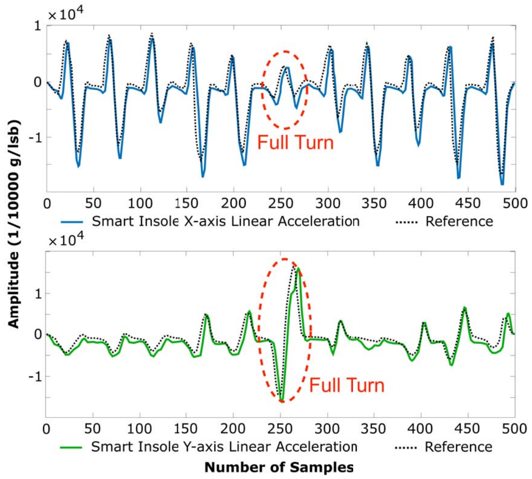

Fig. 3. The linear accelerations in X-axis (Upper) and Y-axis (Lower) of left feet recorded by the SennoGait's and SparkFun's IMUs. A moving-average filter is applied for the clearness.

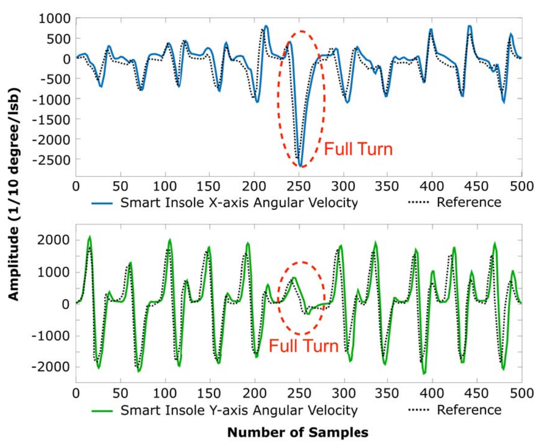

Fig. 4. The angular velocities in X-axis (Upper) and Y-axis (Lower) of left feet recorded by the SennoGait's and SparkFun's IMUs. A moving-average filter is applied for the clearness.

full turn (see in Fig. 2 Left). By comparing the experimental output of two IMUs both sampling at 100 Hz, we obtain the reliability of SennoGait in collecting linear accelerations and angular velocities.

The Pearson correlation coefficients of data, recorded by the SennoGait's and the SparkFun's IMUs, are presented in Table. II. A very strong correlation exists between the two data sets as $|r| > 0.70$, where r stands for each computed coefficients. Normally, r ranges from -1 to 1. If $|r| = 1$, a linear equation describes the relationship between two variables. If $|r| = 0$, no linear correlation exists between the two. In addition, the experimental results of one male testee are plotted in Fig. 3 and Fig. 4. The pair of graphs in a plot have similar patterns proving the strong correlation. We select the linear accelerations and the angular velocities in only X-, Y-axes since they are more representative in the case of flat ground walking and turning. As the reliability of accelerometer and gyroscope is proved, the correctness of magnetometer is verified as well because it sets the baseline of IMU calibration.

TABLE II
THE PEARSON CORRELATION COEFFICIENTS OF THE DATA PROVIDED BY THE SENNOGAIT'S AND THE SPARKFUN'S IMUS

Linear Acceleration	X-axis	Y-axis	Z-axis
Pearson Coefficient	0.824	0.819	0.816
Angular Velocity	X-axis	Y-axis	Z-axis
Pearson Coefficient	0.820	0.827	0.818

TABLE III
THE MEAN AND STANDARD DEVIATION OF ACCURACIES OF EXTRACTED GAIT FEATURES IN DIFFERENT TRIALS

Gait Feature	Step Count	Step Pace	Step Length
Mean of Accuracy	97.33%	97.42%	91.24%
Standard Deviation	0.0072	0.0056	0.0194

C. Gait Feature Verification

Each participant as mentioned in III-B performed another 14-meter flat ground walking with the SennoGait in shoes for the purpose of validating the device's capability in gait feature extraction. To obtain the reference data, a motion capture system (see in Fig. 2 Right), named Vicon, was monitoring the experiment using eight Vantage cameras [11], ten Vero cameras [12], and five $14mm$ pearl retro-reflective markers [13] attached around each shoe. We verified three basic gait features including step count, step pace, and step length. The results of verification is presented in Table. III.

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