A High-Fidelity Wearable System for Measuring Lower-Limb Kinetics and Kinematics

Mohamed Abdelhady, Antonie van den Bogert, Dan Simon

Abstract—There are many important challenges in gait analysis, which has many applications in healthcare, rehabilitation, therapy, and exercise training. However, gait analysis is typically performed in a gait laboratory, which is inaccessible to the general population and is not available in natural gait environments (e.g., outdoors). In this paper, we discuss the development of a high-fidelity, cost-effective, wireless sensor network to address the challenge of efficient gait monitoring in real-world walking scenarios. The sensor network is designed in a modular way to capture plantar forces and knee angle, angular velocity, and angular acceleration. A force module called a smart insole is designed to measure the plantar forces. The module is comprised of force sensitive resistors (FSRs) and a signal conditioning circuit. Various signal conditioning techniques, including a novel technique called transfrequency, are investigated to provide a linear mapping for FSR measurements and to provide data acquisition fidelity. The motion module includes a low-cost inertial measurement unit (IMU) augmented with a Kalman filter to provide filtered knee kinematics. A qualitative evaluation of the sensor network communication module is achieved by considering the internal communication protocols between the modules and the external wireless transmission protocol used to deliver data to an end-point terminal PC. Experiments are conducted to validate the motion and force modules. Then, the overall, integrated system is compared to gold standard laboratory results, demonstrating a successful application for gait identification. The results show that the sensor network accurately captures important gait parameters and features.

Index Terms—Motion capture, human gait, wearable sensors, smart insole, embedded system

I. INTRODUCTION

The human body is composed of many flexible segments, and the lower-body motion of the human is especially complicated in terms of force-motion relationships. The study of human motion requires precise monitoring of kinetics and kinematics. Recently, laboratories have relied on standard approaches to capture human motion parameters for medical purposes by utilizing optical motion analysis techniques based on high-speed cameras. High-speed motion capture systems include powerful computers to track human motion and to analyze human body segment behaviors with force plates. However, optical motion analysis requires a large workspace and high computational capability, such as powerful graphical signal processing units. Indeed, these devices are very costly. In addition to the cost problem, these laboratory systems have to adhere to strict calibration and maintenance procedures, and analyzing recorded photos includes complex off-line analysis [1]. Therefore, these types of standard systems, especially those using ultrasonic or magnetic technologies, are restricted to laboratory settings and are difficult to implement in daily living environments, such as walking on natural terrain.

Modern developments in microelectromechanical systems (MEMS) have facilitated the development and implementation of tiny sensors with powerful microcontroller units in single integrated packages such as system on a chip (SOC) and lab on a chip (LOC). This has inspired researchers to develop a new generation of wearable sensor systems (WSS).

Recent research on WSS for biomedical applications can be divided into two major areas. One area focuses on recognition of daily activities, such as walking feature recognition [2, 3], walking condition classification [1, 4-6] and gait phase detection [7-10], in which the kinematic data obtained from inertial sensors (accelerometers or gyroscopes) are directly used as inputs to inference techniques. The second area focuses on accurate measurement of human motion data such as joint angles, or 3D body segment positions and orientations. In this area of WSS, measurement calibration and data fusion are important to decrease the errors of the quantitative human motion analysis results [11].

The fundamental measurements required for analyzing human gait are forces, positions, velocities, and accelerations. As discussed below, the majority of WSS prototypes have been developed for either kinetic data or kinematic data, but not both.

A. Kinetic Data Acquisition

Plantar force is an example of a kinetic measurement. Plantar force measurement has important applications in medical diagnostics [12] and rehabilitation [13]. Plantar force measurements are usually conducted either via insole techniques or a stationary platform equipped with force plates [14]. However, the latter method is restricted to laboratory or clinical environments. Recent improvements in sensor miniaturization have led to drastic decreases in cost and power consumption [15-17]. The only obstacle to high-precision sensor networks is the sensor unit size.

Academic researchers have extensively explored the idea of embedding electronics in insoles or shoes. Bamberg et al. [18] developed a WSS called GaitShoe for gait data collection outside the confines of the traditional motion laboratory, which includes accelerometers, gyroscopes, force sensors, bidirectional bend sensors, pressure sensors, and electric field

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height sensors. Noshadi et al. [19] proposed a lightweight smart shoe called Hermes to monitor walking behavior and to assess instability with particular episodes of activity identified as important. Benocci et al. [20] used 24 hydro-cells, which are piezoresistive sensors contained in a fluid-filled cell, embedded in an insole to monitor gait. Sazonov et al. [21] utilized 5 force-sensitive resistors integrated with a flexible insole and a 3D accelerometer to identify common postures and activities using support vector machines (SVMs). All the aforementioned systems place the insole-like units inside the shoe, and the microcontrollers are mounted outside the shoe, which makes the system inconvenient to set up and uncomfortable to use in daily life. Shu et al. [22] developed an in-shoe monitoring system based on a textile fabric sensor array and introduced an early procedure for designing experimental smart insoles. Shu successfully extracted important parameters of human gait from simple walking test, such as foot center of pressure, the average of heel stick peaks, and center of pressure velocity.

There are also several commercial off-the-shelf (COTS) insole devices. The pedar in-shoe system [23] embeds single or multiple piezoelectric sensors into the shoe for real-time monitoring. However, the sensors are easy to damage under pressure because of long-term application of body weight. The most recent insole product, F-Scan from Tekscan [24], provides similar function and accuracy as our proposed system. However, due to the lack of a wireless transmission module, the collected data cannot be transmitted to an end-point computational unit for visualization in real time or uploaded to a data server for post-processing. Moreover, most of these systems have problems with high nonlinearity, hysteresis, and temperature dependence if they use electric capacitive sensors. Finally, most of these systems are lacking in functionality or sophistication in fundamental ways and are therefore not suitable for sophisticated tasks like real-time gait analysis.

B. Kinematic Data Acquisition

Motion tracking based on inertial measurement unit (IMU) data has been applied in navigation for many decades, and was originally developed for estimating the attitude of aerial vehicles [25, 26]. Lower limb orientation angle estimation using inertial sensors, consisting of accelerometers and gyroscopes, has been extensively studied by many authors. In fact, both an accelerometer and a gyroscope can measure the orientation angle of a body segment. However, an accelerometer is low-bandwidth and sensitive to linear accelerations, and a gyroscope suffers from drift and unknown initial inclination [27, 28]. Many solutions have been proposed to solve these problems [29]. Some of these solutions have been realized commercially with hardware implementations of filtering algorithms (e.g., anti-drift and adaptive filtering) to provide high-accuracy data [30]. Examples of commercial wearable motion sensors based on accelerometers and gyroscopes are the Ossur patient activity monitor (PAM), ActiVPal, Dynaport and Xsens MT9 [31]. Recently, many companies rise to sell motion capturing IMU-based system e.g., Invensense (Invensense, San Jose, CA, USA), Trivisio (Trivisio, Trier, Germany), Microstrain (Lord Microstrain, Williston, VT, USA), BTS GaitLab and G-WALK (BTS Bioengineering, Quincy, MA, USA) and a number of start-ups which target IMU-based systems. The products that they sell often include motion attitude reconstruction, which is provided as output to the user, or even full body motion reconstruction.

However, these types of systems are unable to provide the foot planter force and ground reaction force. Current state-of-the-art gait analysis systems for free-living contexts are costly and have been designed primarily to be used in a clinical research setting for short recording sessions [31]. Therefore, there is a market opportunity to offer a high-quality device at a low cost. Finally, current body worn systems are bulky and have awkward interconnecting wires between components, which hinders everyday usability.

We summarize the main features of some current WSS in Table 1. An inexpensive but capable WSS must offer several capabilities: a simple structure with no extraneous components outside the shoes or insoles, continuous perception, and remote transmission of information to a terminal PC or cell phone for further analysis.

Table 1 shows the basic features for wearable lower limb kinetic and kinematic measurement systems. As we can see from Table 1, only a few devices are able to provide force and angle data acquisition, and those are only partially able to provide this functionality. Also, the IMUs in [18], [32] provide only foot orientation. Finally, the noise characteristics of the IMU data were not considered or filtered.

<table>
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<tr>
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<td>100</td>
<td>100</td>
<td>50</td>
<td>118</td>
<td>750</td>
</tr>
</tbody>
</table>

C. Paper Contribution

This paper develops a high-fidelity wireless sensor network with off-the-shelf components to capture lower-limb joint kinematics and plantar foot pressure. The main motivation for this research is to develop a measurement framework to evaluate, analyze and control the gait parameters of amputees and able-bodied individuals. We are motivated to develop a system that combines all the features depicted in Table I and that avoids the shortcomings of current state-of-the-art devices. The system is easy to use, easy to replicate, and inexpensive to manufacture. It is well-suited for monitoring rehabilitation, evaluating prosthesis or orthosis performance, or other activities in a wide variety of scenarios, both outdoors and indoors. The key contributions of this paper are as follows.

1. In order to deal with force sensitive resistor (FSR) nonlinearity, a smart insole is developed and different signal conditioning techniques are investigated.
2. IMUs are implemented to measure knee angle, and a Kalman filter was implemented to reduce signal noise.
3. A wired internal network and a wireless end-point communication connection were designed to increase network speed and provide high-fidelity communication.
4. Customizable communication packets were designed to facilitate data transmission.
5. Case studies were conducted based on the data gathered by our sensor network.

Section II introduces the methodology used to develop the
sensor network. Section III introduces the smart insole design and the candidate FSR calibration procedures. Section IV discusses the design of the motion measurement module and noise filtration with a Kalman filter. Section V discusses the communication protocols and packet customization to meet the network needs. Section VI provides results and discussion of some simple case studies. Finally, we present a conclusion and discussion of future work.

II. METHODOLOGY

The system can be divided into three main parts: force sensing module, motion sensing module, and the communication protocol between components. This functional classification facilitates modularity and helps with the tracking and debugging of errors during development. The modules can be replicated to measure the gait parameters of both legs as depicted in Fig. 1.

The microcontroller units used in this work are based on the ATmega2560. Equipped with 16 MHz crystal oscillator, 8KB of static RAM and 4 KB of EEPROM, and 54 digital input/output pins, 16 analog inputs, and 4 universal asynchronous receiver/transmitter (UART) ports.

Two types of sensors were considered in this work: FSR sensors (Interlink Electronics, Camarillo, CA, US) and IMUs form Invensense® IMU-6050, each with dimensions 49.53 × 27.94 × 1.5 mm. Each IMU consists of a triple axis accelerometer with 13-bit resolution, a three degree-of-freedom gyroscope and a magnetometer. 3D-printed enclosures were designed to house the electronics. The first one is on the shank and is responsible for scanning the smart insole and reading the shank IMU. The second enclosure is on the thigh, houses the thigh IMU, and reads the thigh IMU and transfers all data to the coordinator unit. IMU data was calibrated and filtered to provide acceptable noise levels for joint angle, velocity and acceleration. We used a Raspberry Pi board as the coordinator node. Figure 1(b) shows the complete wearable system.

Our methodology included calibrating the FSR sensors and placing them in a 3D printed insole. The insole was 3D printed with a soft malleable material called Ninja Flex, which is ideal for use as a material meant to be constantly walked on [37-39]. A custom protocol was designed to transfer sensor data to the coordinator node. To achieve high fidelity data transmission, we tested the customized protocol against different standard communication protocol topologies.

III. SMART INSOLE MODULE

The force measurement module is an insole equipped with FSRs [40]. FSRs are a polymer thick film device that exhibit a decrease in resistance with an increase in the force applied to the active surface. FSRs can provide a suitable alternative to bulky load cells. However, FSRs exhibit many nonlinear behaviors. Their force sensitivity is optimized for human touch control of electronic devices. FSRs are not load cells or strain gauges, though they have similar properties. In general, the FSR response approximately follows an inverse power-law characteristic (roughly 1/R).

Due to increased demand for force measurement and wearable applications, much research has been conducted to calibrate FSR sensors [41-43]. In this section, we discuss some signal conditioning approaches to compensate the nonlinear characteristic of FSRs, including a new and effective technique.

A. Force Sensor Calibration

In this section, different signal conditioning techniques are investigated to achieve a linear operating region. FSR signal conditioning generally needs to account for hysteresis, but in our application, human gait dynamics are slow enough that hysteresis can safely be ignored.

1) Coating method

First, we tested a naïve method to increase the linear operating range of the FSR sensor. We found that coating the sensor with thermoplastic polyurethane (TPU) gives a more elastic surface. That moves the sensor’s force threshold and restricts the operating range to the linear range. We found that a coating layer of 0.4 mm gives a good operating range (about

Fig. 1 (a) Full hierarchical functional diagram of sensor network with homogenous intercommunication protocol; (b) System realization of right leg modules housed in 3D-printed enclosures and connected to smart insole.
4 kg–10 kg) as depicted in Fig. 2.

2) **Wheatstone Bridge**

A well-known signal conditioning technique that relies on a Wheatstone bridge is extensively used with load cells and strain gauges as a basic interface to data acquisition systems. The Wheatstone bridge is a divided bridge circuit used for the measurement of static or dynamic electrical resistance. The output voltage of the Wheatstone bridge is expressed in millivolts output per volt input. The bridge is simply adjusted by selecting $R$ values to make the bridge balanced (no current flow between nodes). Although this method is very easy to implement, it adds resistive load to the power supply, which can be significant with a large number of FSRs. Also, isolating bridges to draw a constant current demands multiple voltage regulation units. Moreover, this method is highly sensitive to voltage variations, which leads to unpredictable performance, especially if we consider a regulator-free design.

3) **Transfrequency approach**

Here we introduce a new transfrequency approach for interfacing FSR sensors. Interfacing FSR outputs to a microcontroller includes two stages, as shown in Fig. 3(a). In the first stage, we use a voltage-to-frequency circuit (VF) to convert the voltage across the FSR to a fixed-amplitude alternating signal with a frequency value proportional to the FSR resistance. In the second stage, the frequency of the previous-stage signal is measured with a frequency-to-voltage (FV) circuit whose output is sent to an analog input of a microcontroller. The mathematical representation of the VF stage can be represented as

$$f_{VF} = \frac{K_1}{V_{fsr}}$$

where $V_{fsr} \propto R_{fsr}$ and $K_1$ is the circuit gain. The mathematical representation of the FV stage is

$$V_{out} = K_2 f_{out}$$

where $K_2$ is the circuit gain and an auxiliary RC circuit is used to tune the VF circuit.

The transfrequency approach is similar to the transimpedance technique [44]. However, in addition to linearizing the relationship between input force and output voltage, it also facilitates force rate measurements because of the VF and FV circuits. Also, when using FSRs in a sensor network, the transfrequency circuit does not need external isolation hardware to guarantee robust behavior.

A dual function integrated circuit (IC) from Texas

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**Fig. 2** FSR interface voltage versus effective weight

**Fig. 3** (a) Transfrequency cascade signal conditioning between the Arduino and the FSR, with the (b) VF and (c) FV stages
4) Assessment of Results

We test the three techniques from 0.1 kg to 10 kg. For each approach, we measure the voltage input to the microcontroller, which represents the variation in FSR resistance. As shown in Fig. 2, coating the sensor with a rubbery material like TPU shifts the force sensing threshold. Increasing the coating layer thickness leads to a greater shift; that is, it increases the threshold. That reduces sensor sensitivity and restricts operation to the linear region. The Wheatstone bridge reduces nonlinearity, but the voltage variation at the upper range of the resistive load tends to be very small if we increase the input resistive load. We found that the transfrequency approach provides a good characteristic regarding both linearity and sensitivity, as shown in Fig. 2.

![Fig. 4 Illustration of insole layers designed in SolidWorks (left) and the 3D-printed implementation (right)](image)

Finally, a 3D-printed insole was designed with approximately optimal FSR sensor placement. Sensors placed at high pressure point, with assuming interfacial pressure for every 31.2 mm² foot plantar area approximate 90 N/m and even distribution of half of body weight over one foot. That is make FSRs with 10 Kg maximum load fits design need [34, 46, 47]. The design uses a malleable material called Ninja-Flex filament, which offers flexibility, elasticity, and high strength. Also, the insole design is provided with a channel to facilitate the routing of FSR wires. Each FSR sensor location is capped with 0.4 mm of the same material (see the Coating section above) to protect the sensors, as depicted in Fig. 4.

Motion Measurement Module

The motion sensing module is comprised of two IMUs to measure angular position and velocity, and linear acceleration of the thigh and the shank. We use two IMUs, each of which consists of a three-axis accelerometer, a three-axis gyroscope, a digital motion processor and a peripheral controller. The IMU sensing element has a programmable accelerometer range between ±2 and ±16 g, a programmable gyroscope range between ±250 and ±2000 deg/sec, a maximum output data rate of 1 kHz, and an internal digital motion processing engine.

These sensors, however, need to be calibrated before use. Default operation ranges (2g - 16g for accelerometer and 250 deg/sec - 2000 deg/sec for gyro) were selected for conducting all experiments in this paper.

B. Motion Processing

Evaluation of the relative angle between the thigh and shank is possible by using a pair of accelerometers, one on the thigh and one on the shanks. The accelerometers are mounted such that given accelerometer axes are coincident when the relative angle is zero. Give the two acceleration vectors $A_x$ and $A_y$ of the shank and thigh respectively (including gravity), the relative angle of the segments can be obtained as

$$A_x \cdot A_y = \left(\begin{array}{c} a_{x_1} \\ a_{y_1} \\ a_{z_1} \end{array}\right) \cdot \left(\begin{array}{c} a_{x_2} \\ a_{y_2} \\ a_{z_2} \end{array}\right) = |A_x| \cdot |A_y| \cos \theta_{knee}$$

$$\theta_{knee} = \arccos \frac{a_x a_{x_1} + a_y a_{y_1} + a_z a_{z_1}}{\sqrt{a_{x_1}^2 + a_{y_1}^2 + a_{z_1}^2} \cdot \sqrt{a_{x_2}^2 + a_{y_2}^2 + a_{z_2}^2}}$$

In order to reduce high frequency noise components, a filter stage is necessary. Each IMU unit provides data to a microcontroller in which the filtering algorithm is embedded. The filtered signal is wirelessly transmitted via the coordinator to the terminal PC. Some frequently used procedures for IMU data filtering include the Kalman filter, and the simple low pass/high pass complementary filter, which combines accelerometer and gyroscope data to attain the filtered angle. However, It is hard to tune this filter, especially if the IMU unit doesn’t have antidrift embedded hardware.

In this work we consider the Kalman filter, which produces a statistically optimal estimate of the system state based on the state dynamics and the measurements. This process of predicting and correcting the state estimates repeats for successive values of the time index. Implementation of the Kalman filter assumes white process noise and white measurement noise, which are uncorrelated with each other [48-49].

To find the covariance matrix for the Arduino implementation, we estimated the variance of the accelerometer and gyroscope measurements by keeping the IMU immobile and collecting many measurements. From these samples, we calculated the variances for the three components of the gyroscope and the accelerometer. Then we used these six values as the diagonal entries of the $R$ matrix. It’s observed that $\sigma^2 = 0.07251$ for all six components of $R$ (rad/sec for the gyroscope, and m/sec² for the accelerometer). These numbers were obtained with 1000 samples recorded at 500 Hz. Changing the sampling rate results in different values.

C. IMU Calibration

In order to calibrate motion module sampling rate, a commercial Consensys Shimmer3 IMU (Shimmer, Dublin, Ireland) is considered as a pre-calibrated IMU and a gold standard reference. The aim of calibration is to justify motion module sampling rate in a way that reduce the measurement error between motion module and the gold standard IMU. A free hanging oscillation experiment was conducted in the x-y plane. Normalized data were collected at nominal sampling rate of 200 Hz.

A slight phase difference was found between the IMUs due to variation in hardware processing. To compensate for this phase difference, the motion module sampling rate was changed
to 177 Hz. Figure 5 demonstrates the fidelity of the motion module after calibration. To depict the effect of the Kalman filter, 10 gait cycles were captured at 500 Hz with a single subject. Shank and thigh IMU data were used to compute the knee angular position, velocity, and acceleration without filtering. Embedded numerical integration using Euler method was applied to obtain angular position, which it has a small residual error at small discrete time step. Then the Kalman filter was applied to compute filtered knee angular position, velocity, and acceleration.

Both filtered and unfiltered results were simultaneously sent to the terminal PC in real time via the coordinator node and results are shown in Section VI.

Since sensor alignment is very important, a static calibration procedure was performed to ensure that the IMUs were aligned in the sagittal plane. Initially, the subject must stand in a neutral pose so that the rotation from the sensor coordinate frame to the body coordinate frame can be determined. If the sensors are misaligned, calibration will be incorrect, and the output joint angles will have errors. In a similar manner, if the subject does not assume the correct neutral pose during calibration, the sensors will be calibrated incorrectly, resulting in output joint angle biases.

### IV. Communication Protocol and Software Interface

In this section, we address the problem of establishing high-fidelity communication between the sensors and their respective microcontroller units; between the microcontroller units and the coordinate note; and finally, between the coordinator node and the terminal PC. It is easy to evaluate the performance of embedded system communication theoretically; however, it is more difficult experimentally due to practical issues such as configuration options. Rapid prototyped electronics can often support multiple communication protocols (e.g., SPI, serial, CAN, and I2C). This can lead to a nonhomogeneous communication environment in which the performance of the sensor network could be negatively affected. Nonhomogeneous data transfer can lead to drawbacks such as overall transmission rate reduction and data loss due to asynchronicity.

#### A. Protocol and Data Structure

High-fidelity communication implies that the received data is identical to the transmitted data. A combination of hardware and software is used to achieve this goal. One important component in this effort is an effective protocol. This implicitly includes the definition of specific design elements such as the receiver characteristics (e.g., slow communication rate with or without memory, fast rate with or without memory), the transmission medium (i.e., wired or wireless), synchronization, etc.

The next step after building each sensor module is to design a communication protocol to transfer data from the signal conditioning and acquisition level to the coordinator node level (see Fig. 1). As mentioned in Section II, electronics manufacturers provide components with different communication protocols to provide interface compatibility for a wide spectrum of needs.

Data transmission starts from the sensor microcontroller unit and ultimately ends at the terminal PC. Since a centralized buffer in the terminal PC is not considered here, and data could be transmitted with different standard protocols, we consider an effective procedure to receive sensor data. First, we evaluate the computational load of each sensor microcontroller. We find that the FSR microcontroller has more computational load than the IMU microcontrollers. Second, we plan a data transmission path that provides a computational load balance between the sensor microcontroller units. We start the acquisition process by obtaining data from the force module; then we pass the force data to the motion module microcontroller, where the force data and motion data are combined to form a complete packet.

The motivation for this technique is the characteristics of the standard protocols that are used to transfer data, especially protocols that can connect multiple devices. For example, the inter-integrated circuit (I2C) protocol communicates through two wires (serial data (SDA) and serial clock (SCL)) and is thus slower than the serial peripheral interface (SPI) protocol, which provides full duplex communication via four wires (serial clock (SCLK), Master out slave in (MOSI), master in slave out (MISO), and slave select (SS)). Additionally, I2C is less susceptible to noise than SPI. Also, SPI only supports one master device on the local bus while I2C supports multiple master devices. In order to determine the effect of the community topology between the microcontrollers and their associated sensors, different topologies were tested and acquisition time was recorded.

To conclude which topology is more effective, we test different combinations of the I2C and SPI protocols (see Table II). For example, topology 1 is formed by using an I2C adapter interface chip (MC3008) to establish an I2C communication bus between the force sensors and their associated microcontroller, and motion data is sent to the IMU microcontroller with the I2C protocol.

<table>
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<tr>
<th>Topology</th>
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<td>SPI</td>
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<td>SPI</td>
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<td>Motion Module</td>
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<td>8.4</td>
<td>6.3</td>
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</table>
A dummy packet with 144 bits was used to test the time needed to scan all sensors (acquisition time) for each topology. From the results Table II, we can see that the best performance is provided by connecting the FSR sensors with their microcontroller using I2C and connecting the IMU sensors with their microcontroller using SPI (topology 3). Since I2C is slower than SPI, it was expected that the I2C:I2C combination (topology 1) would be slower than the SPI-SPI connection (topology 4). The delay observed with the SPI-SPI connection is due to the time required to multiplex signals over the SPI four-line bus. We can infer from Table II that force data acquisition takes 6 msec using I2C and 5 msec using SPI, while IMU data acquisition takes 3 msec with I2C and 1 msec with SPI. Any of the topologies in Table II can synchronize both modules, even if one of the modules periodically enters sleep mode.

Next, we evaluate the connection between the coordinator node (Raspberry Pi) and the terminal PC. The coordinator node operating system is Linux Debian with built-in support for Bluetooth, Wifi, and radio frequency (RF) communication through a serial port interface. The serial RF module is the nRF2401 from Nordic with a 2.4 GHz carrier, which is similar to Bluetooth and Wifi. Each of those wireless options has its own advantages and disadvantages; here we conduct a test to find out which one provides high speed and high fidelity.

Our test transmits 100 MB of dummy data from the coordinator node to the terminal PC with baud rates of 115200 bps. The terminal PC received the data and compared it with a prerecorded copy of the transmitted data to calculate the total percentage transmission error (TPTE), which is defined as the number of bytes incorrectly received divided by the total number of bytes transmitted. The experiment is repeated 10 times, and the average TPTE and transmission time are recorded for each wireless communication method.

The transmission test results show that serial RF, Bluetooth and Wifi have latency time 240 μsec, 410 μsec and 520 μsec respectively; and 1.7%, 0.2% and 0.5% TPTE respectively. It is observed that the serial RF has the fastest transmission time and highest TPTE due to the low processing overhead. By repeating the experiment with different baud rates (57600, 74880, 115200, and 320400 bps), it is clear that TPTE increases proportionally with baud rate. When considering both TPTE and transmission time, baud rate 115200 bps with the RF protocol was found to provide a good tradeoff for our sensor network. That translates to a maximum transmission speed for wireless RF at around 600 samples per second; sample size will be discussed in the next section.

B. Packet Structure

The packet structure is designed to contain the sensor data between a start and stop byte. The packet starts with a sequence composed of two characters: “@” to indicate the packet start byte, and “L” or “R” to indicate left or right leg. Then the sensor values are included in the order shown in Fig. 6. Finally, the end of each packet is indicated by the character “#”. This format is used to enhance data transmission fidelity.

The force packet includes 70 bits, and the motion packet includes 144 bits. Asynchronous transmission is used to check and troubleshoot the motion and force modules individually. However, in the normal operating mode, the force packets are sent to the motion microcontroller, where the force and motion data are combined in a single packet as illustrated in Fig. 6. Then the combined packet is transmitted to the coordinator node, which wirelessly transmits it to the terminal PC.

V. RESULTS AND DISCUSSION

This paper investigates the sensor system integrity that able to assemble high fidelity data. The application of this sensory system is varied from collecting kinetic and kinematic data for offline analysis as investigated in [35, 36], however use this system for prosthesis feedback control purposes requires data fusion form to generate control signals. For example, using knee displacement and velocity, beside vertical GRF (vGRF) as an input for neural network to obtain a good prediction of horizontal component of GRF, which is practically hard to measure. Another example of fusion data application is estimate lower limb weight using vGRF and acceleration without consider anthropomorphic features. In this paper we will focus more on how the sensory system is able to provide walking data accurately compared to gold standard reference.

A. Motion modules

This section reports the verification of our proposed data acquisition system. A subject with weight 110 kg and height 170 cm used the motion and force module as shown in Fig. 1. The first 5 seconds of data recording is used for initialization while the subject stands in an upright position. The thigh and shank angular position during this time period is used to calibrate the recorded angles as zero. Then the subject starts walking with normal gait for 10 steps. This experiment was repeated 10 times while force and motion data were recorded.

The coordinator transmitted data at 115200 baud to a laptop (i7 core, 2.4 GHz) via RF modules with a range of 20 m indoor and 100 m outdoor. Matlab 2017a was utilized to read the serial RF transmission and record the incoming data.

In order to investigate the effect of the Kalman filter, the unfiltered data was stored in the coordinator node memory. Filtered and unfiltered data collected from a single walking trial are used to illustrate the effect of Kalman filtering. Figure 7 depicts the results for knee angle, angular velocity.

As stated earlier, the covariance matrix values used in the Kalman filter are diag(0.07251, 0.07251), which are provided in the IMU data sheet (see Section IV). The Kalman filter code used to produce this result is posted in GitHub [48] and was based on [49]. A graphical user interface (GUI) software developed for online acquisition using C# is posted in GitHub [50] with the basic microcontroller firmware.
From consecutive strides, it is easy to extract important information such as step count, average swing time, average stance time, average stride length and walking speed. In addition, we extract some indirect quantities such as center of pressure during stance phase and velocity of COP.

The Matlab signal processing toolbox can save development effort by helping to build powerful signal analysis algorithms. For example, to get the average walking speed, the Matlab command pulseperiod provides a temporal analysis by analyzing the knee angle signal and extracting a vector containing the time difference between the rising midpoint crossings of consecutive strides. The estimated average stride speed can easily be evaluated by extracting cycle period from knee angle signal as depicted in Fig. 8.

We can also extract transition information in other ways; for example, we can extract stance phase duration using the Matlab function raisetime, which uses a histogram to detect the time duration required to transition from 10% to 90% of the maximum knee angle value.

B. Force module

Next, we consider the force module and its normalized voltage values. Figure 9 depicts the normalized voltage value for each sensor, averaged over 10 trials, according to the sensor distribution shown on the right side of the figure. The shaded regions indicate the two-sigma (95%) regions, which are calculated using means and standard deviations. The small distance between sensors S1 and S2 resulted in very similar signals for those two sensors, which were averaged and considered as a single sensor.

The center of pressure trajectory can be calculated from the force data by taking the moment around a virtual point, which is depicted as the origin of the insole coordinate system in Fig. 9, then the velocity of COP can be estimated as

\[
x_{\text{cop}} = \frac{\sum_{i=1}^{7} S_i x_i}{\sum_{i=1}^{7} S_i}, \quad y_{\text{cop}} = \frac{\sum_{i=1}^{7} S_i y_i}{\sum_{i=1}^{7} S_i}
\]

(14)

Fig. 7 The effect of the Kalman filter for smoothing the knee angle, velocity, and acceleration

Fig. 8 Temporal analysis using Matlab signal processing toolbox to evaluate average stride time (pulse period) from knee angle signal.

Fig. 9 (a) The map of sensor distribution on the insole surface. (b) The normalized voltages and two-sigma (95%) regions of the force sensor data, averaged over 10 walking trials (c) Trajectory of the center of pressure for right leg
\[ v_{cap} = \sqrt{[x_{cap}(t + \Delta t) - x_{cap}(t)]^2 + [y_{cap}(t + \Delta t) - y_{cap}(t)]^2} \]  

(15)

where the \( s_i \) values are the seven force sensor data, and the \( L_x \) and \( L_y \) values are measured such as \( L_{x1}=L_{x2}=L_{x6}=5 \text{ cm} \), \( L_{x3}=L_{x4}=L_{x5}=7 \text{ cm} \), \( L_{y1}=1 \text{ cm} \), \( L_{y2}=9 \text{ cm} \), \( L_{y3}=14 \text{ cm} \), \( L_{y4}=18 \text{ cm} \), \( L_{y5}=22 \text{ cm} \), \( L_{y6}=24 \text{ cm} \) and \( L_{y7}=26 \text{ cm} \). The average COP loci are plotted on the insole map in Fig. 9.

Vertical ground reaction force can be easily calculated by summing the force sensor values as illustrated in Fig. 10. The GRF values are obtained according to the transfrequency calibration interface which reflects different foot phases. The confidence zone near heal strike (HS) is narrow, since the foot impact is momentary and sudden in each trial. During the midstance (MS) phase, the confidence zone tends to be wider, since the exerted force changes around the average sensor values from trial to trial. Like the HS phase, the toe-off (TO) phase is associated with a narrow confidence zone because of the sudden decrease in GRF before swing phase. The figure shows the expected shape for ground reaction force, thus providing confirmation of the force module functionality.

![Fig. 10 Vertical ground reaction force calculated by summing the averages of the FSR sensor signals.](image)

VI. EXPERIMENTAL RESULTS

In order to verify force and motion module performance, a comparative study was conducted to validate the estimated knee angle data and vGRF. Three subjects were recruited to participate in this experiment. The Institutional Review Board at Cleveland State University approved the study protocol (IRB-FY2019-126). Subject information can be seen in Table III.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Age (years)</th>
<th>Gender</th>
<th>Height (cm)</th>
<th>Weight (kg)</th>
<th>Foot size (U.S.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sub 1</td>
<td>21</td>
<td>Male</td>
<td>173</td>
<td>88</td>
<td>10</td>
</tr>
<tr>
<td>Sub 2</td>
<td>20</td>
<td>Male</td>
<td>165</td>
<td>62</td>
<td>10</td>
</tr>
<tr>
<td>Sub 3</td>
<td>22</td>
<td>Female</td>
<td>170</td>
<td>83</td>
<td>9</td>
</tr>
</tbody>
</table>

This study was conducted in the Human Motion Laboratory at Cleveland State University, which is equipped with a 10-camera motion capture system (Motion Analysis Corp.), a V-Gait instrumented treadmill with software-controlled pitch and sway actuators (Motek Medical), and D-Flow software (Motek Medical) for real-time control of experiments and real-time data processing.

A. Experimental description

As stated in Section I, this research is preparatory for our prosthesis control studies, but in this section, we strictly focus on system validation at normal walking speeds and gait patterns, which comprises the major proportion of everyday activity for amputees. Since kinematic and kinetic information are important for transfemoral amputees, special attention has been given here to the fidelity of the sensory system.

The participants were asked to wear the force and motion modules, and passive reflective markers were attached to the subjects for the Vicon cameras. Then participants were asked to stand still on the treadmill for 5 seconds before walking. During walking, knee angle and vGRF were recorded by the wearable modules, the Vicon system, and the instrumented treadmill.

Knee angle and vGRF were captured for different walking speeds (0.6, 0.8, 1.0, and 1.2 m/s). Also, each participant conducted a single trial at 1 m/s with the treadmill inclined at 5 degrees (handicap standard). The wearable sensor modules, instrumented treadmill and Vicon cameras recorded at 302 Hz, 100 Hz and 100 Hz respectively.

![Fig. 11 (a) Filtered knee angle compared with Vicon knee data. (b) Normalized vGRF results from the force module compared with the instrumented treadmill.](image)

The force module was compared with the treadmill as depicted in Table IV. It is seen that the difference between the force module and the treadmill measurement is approximately independent of gait speed and incline, which is about 22.35±1.16 N. Figure 11 shows that the peak of the treadmill measurement signal is always more than that of the force module. This is due to the sample aggregation of the FSR signals, which can be addressed in better signal processing in future work.

| TABLE IV. NORMALIZED RMSE (N) BETWEEN FORCE MODULE MEASUREMENTS AND TREADMILL MEASUREMENTS FOR 20 SEC OF WALKING |
|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| 0.6 m/s | 0.8 m/s | 1.0 m/s | 1.2 m/s | 1 m/s Incline |
| Sub 1   | 24.3   | 25.2   | 24.4   | 24.7   | 25.1   |
| Sub 2   | 17.4   | 18.7   | 17.2   | 18.6   | 19.3   |
| Sub 3   | 20.3   | 25.2   | 24.3   | 25.8   | 24.7   |

Similarly, the RMSE between the motion module and the Vicon measurements is approximately independent of gait speed and incline, and is about 11.9 ± 0.45 deg.

| TABLE V. NORMALIZED RMSE (deg) BETWEEN MOTION MODULE MEASUREMENTS AND VICON MEASUREMENTS FOR 20 SEC OF WALKING |
|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| 0.6 m/s | 0.8 m/s | 1 m/s | 1.2 m/s | 1 m/s Incline |
| Sub 1   | 11.4   | 12.1   | 12.4   | 11.8   | 12.7   |
| Sub 2   | 10.8   | 10.6   | 11.7   | 12     | 11.2   |
| Sub 3   | 12.1   | 12.4   | 12.6   | 12.8   | 12.5   |
A sensor network comprised of a motion sensing module and a force sensing module was developed with a priority on data accuracy and fidelity. Methods using physical coating, Wheatstone bridge, and transfrequency were explored for signal conditioning and FSR calibration. The transfrequency approach outperformed the other two methods by providing the best linearization result. The FSRs sensors were housed in a 3D-printed insole layer.

The motion sensing module was comprised of two IMUs, one on the shank and the other on the thigh. IMU calibration was performed along with signal conditioning using a Kalman filter to enhance signal quality. The internal communication protocol was studied with a given packet structure to recommend a connection topology. Different wireless transmission options were studied and the serial RF protocol was recommended for endpoint transmission. Finally, an experiment was conducted to collect walking force-motion data under normal gait. The sensor network was able to successfully collect synchronous data. Some analyses were performed on the collected data, and it was shown that the system can assist in providing data such as force and kinetic knee information, in addition to the indirect estimation of quantities like vertical GFR and COP loci.

Gait analysis can be either use kinetic data or kinematic data. Moreover, sensor fusion technique uses both type of data to provide a sophisticated gait analysis and more accurate estimates. For example, person identification has been studied and the serial RF protocol was performed along with other two methods to enhance signal quality.

VII. CONCLUSION AND FUTURE WORK

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