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Abstract:

Background: Wearable technology has become a widely utilized method of objective data collection in healthcare. Several barriers currently exist that are limiting their clinical utility. 4-D Smart Wireless Motion Sensors (4-D SWMS) have been developed to offer a less obtrusive wireless sensor that can be used in a variety of settings. The addition of machine learning to captured motion sensor data has the ability to improve classification accuracy in the analysis of gait.

Purpose: The purpose of this pilot study is to determine whether the 4-D SWMS are sensitive enough to accurately differentiate normal gait parameters in healthy individuals.

Methods: Forty-three participants were recruited from The University of Texas at El Paso to participate in the study. Subjects were asked to fill out a health history survey prior to performing several tasks selected from the Functional Gait Assessment (FGA) while wearing 10 4-D SWMS along various landmarks on the body. Motion capture data from each sensor was continuously and wirelessly transmitted for analysis using different neural networks to identify and classify differences in normal gait.

Results: 4-D SWMS used in conjunction with a convolutional neural network (CNN) have the ability to differentiate between normal gait parameters with up to 90% accuracy.

Conclusion: This study demonstrates preliminary data to support the use of 4-D SWMS in conjunction with a CNN to accurately differentiate between gait patterns. The ultimate goal of future research is to detect the subtle abnormalities of patients with mild traumatic brain injury to determine need for earlier intervention.

Keywords: Wearable, Sensors, Gait, Analysis, Neural, Networks

Background

Over the last decade, wearable technology has become a widely researched and popular method of data collection in many applications including clinical, sports, military, and commercial fields [1]. These uses include gait analysis, balance, and range of motion [2]. Although other objective clinical measures are currently being used to measure changes in movement quality, there are several associated limitations that limit their clinical utility. Clinical outcome measures and observation are subject to bias and may not be sensitive enough to capture some of the more subtle changes in motion. Other, more objective methods of motion analysis such as high-speed motion capture systems have shown to be a reliable method of analyzing gait but may not be feasible in a small private clinic or a hospital setting. Their use is limited to the laboratory/indoor settings, which do not accurately simulate the daily physical demands of the patient [1,3]. Because of these limitations, larger laboratory technologies may fail to transfer the data obtained in the lab to real-life conditions experienced in the home and community. Clinically, wearable sensors have given clinicians the opportunity to supplement their mostly subjective methods of collecting motion data to monitor progress with more quantifiable and reliable measures [4]. In addition to cutting cost and time in the clinic, the use of wearable technology helps provide clinicians with quantitative data from the home and community to address the patient's most immediate and specific needs to ensure a safe living environment [4-5].

Among the most clinically relevant uses for wearable sensors in the physical therapy field is the analysis of gait for the diagnosis of neuromusculoskeletal dysfunction. Many different orthopedic and neurological pathologies seen every day in the clinical setting are associated with gait deficits, therefore gait analysis is an essential component in any physical therapist's examination. An in-depth and comprehensive gait analysis is essential for a physical therapist to identify specific gait impairments and for creating the most effective plan of care specific to the patient's needs. However, not even the most experienced clinician will have a trained eye sensitive enough to identify some of the subtle gait deviations through observation alone. The recent trend in the use of technology to objectively assess gait parameters has led to extensive research to address the safety and functional limitations in many different clinical populations. Development of wearable technologies have addressed some of these issues, but the research suggests that wearable sensors still have many barriers to overcome. Some of the current issues faced with wearable technologies for real time data collection are wearing discomfort due to awkward designing, mobility impediment, and poor sensing accuracy [6]. Bulky rigid designs and wires may impede normal gait and can cause inaccurate and unreliable data collection.

The 4-D Smart Wireless Motion Sensor (SWMS) are small, lightweight, wireless, unobtrusive, and may be able to succeed where other technologies falter [7]. Motion analysis using 10 4-D SWMS strapped on to various anatomical landmarks allows the user to continuously capture data in real time. Wireless transmission of data is made possible through the use of 10 Xbee trace antennas using the ZigBee communication protocol and programmed using XCTU (6.4.4) software [7]. This program allows for continuous, real-time motion capture of the subject while simultaneously capturing the angular and linear displacement of the limbs and trunk in four dimensions using accelerometers, magnetometers, and gyroscopes.

Although these sensors allow for the capture of limb movement in real time, the vast quantity of data points makes it difficult to interpret without the use of machine learning. Artificial neural networks help bring clinical relevance to these data by recognizing patterns that help classify and interpret different gait parameters [8]. When comparing different artificial neural networks, there is evidence to support that the precision of Convolutional Neural

Networks (CNN) is superior to other artificial neural networks in its ability to recognize different gait patterns in three-dimensions [8]. However, there are no current studies in the literature that investigate the use of multiple artificial neural networks in conjunction with one another for a four-dimensional system.

Purpose

The purpose of this pilot-study is to determine whether 4-D SWMS are sensitive enough to accurately detect normal gait parameters in healthy individuals. Additionally, the study aims to compare the accuracy of a CNN alone to a CNN plus a Long Short-Term Memory (LSTM) system. Data collected in this study will be compared to data obtained in future studies using clinical populations in order to determine the clinical utility of the 4-D SWMS going forward.

Methods/Materials

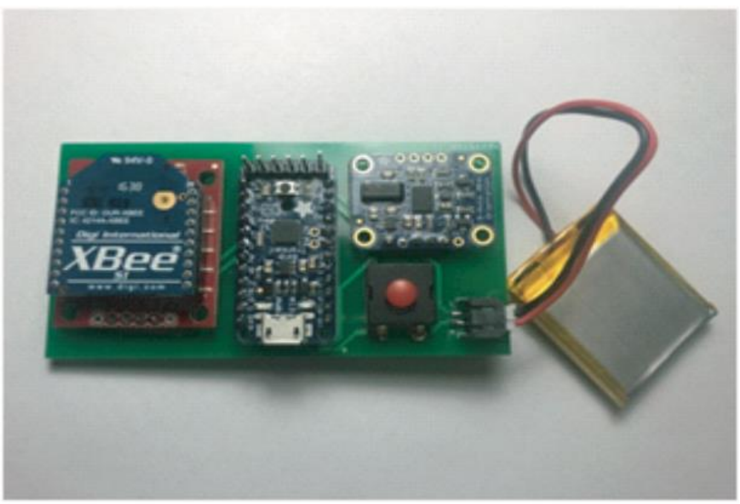
Participants

Forty-three participants were recruited from the Campbell building of The University of Texas at El Paso. Recruitment was limited to the students, faculty, and staff of the Doctor of Physical Therapy program who are following the safety protocols set forth by The University of Texas at El Paso in order to limit COVID-19 exposure. Prior to data collection, subjects were asked to fill out a physical health survey in order to establish a baseline for our normative data. These questions served the purpose of excluding participants that may not be able to perform the different gait tasks and provided us with different groups for which to perform statistical analyses. The requirements of the study were explained to each participant who then voluntarily signed an informed consent form. Participants were assigned a number in order to protect personal health information and reduce any risk of bias. The study was approved by the institutional review board of The University of Texas at El Paso. In addition to IRB approval, a safety plan was also approved by The University of Texas at El Paso to ensure that all COVID-19 precautions are in place.

System Design

The motion capture system used in this pilot study consisted of 10 4-D SWMS, a central processor, and a laptop for display of captured data. The sensors consisted of an Adafruit Pro Trinket microcontroller, BNO055 accelerometers/gyroscopes, and XBee trace antennas and are displayed in figure 1 below.

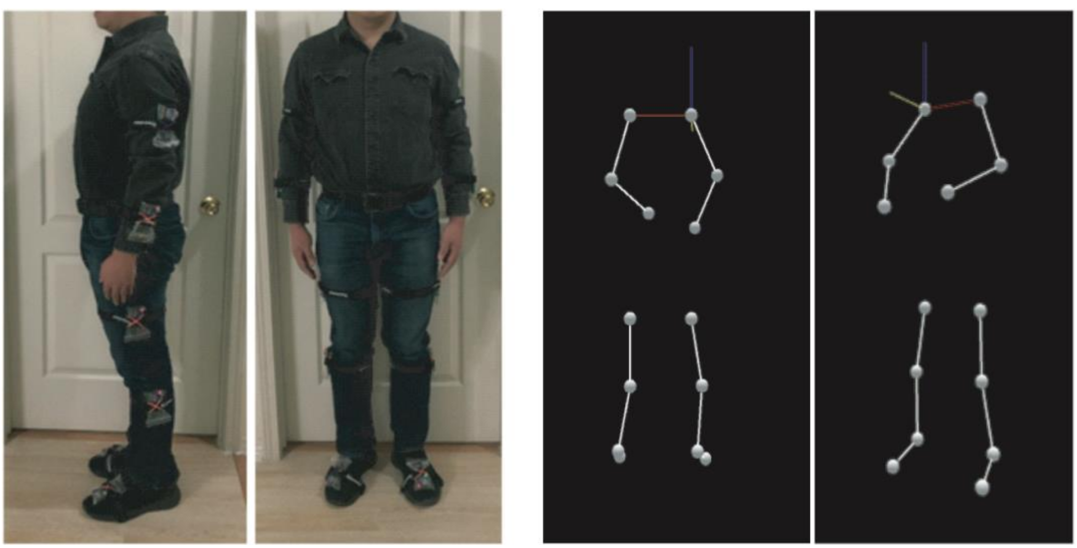
Fig. 1: Individual 4-D SWMS with microcontroller, antenna, and battery



The XBee antennas were set up using XCTU (6.4.4) software and are displayed in figure 2. Sensors were fastened using Velcro straps to (1) right upper arm; (2) left upper arm; (3) right forearm; (4) left forearm; (5) right thigh; (6) left thigh; (7) right shank; (8) left shank; (9) right dorsal foot; (10) left dorsal foot. Dycem was used to protect the limbs, provide a supportive adhesive for the sensors, and to provide an antimicrobial surface that could be cleaned before and after each use. The capture of real time motion data from the sensor set can be controlled from the laptop as it is wirelessly streamed to the central processor for storage and interpretation. The central processor is able to organize the captured data and reconstruct a 4-dimensional model to simulate the subject's motion profile in real time as seen in figure 3.

Fig. 2: XBee Retriever Antenna

Fig. 3: Wireless motion sensors with 4D reconstructed image



Neural Networks

Convolutional Neural Networks (CNN) have shown to be very effective at image recognition and classification [7]. A six-layer CNN was defined for this study for the analysis of normal gait and compared to a CNN combined with a Long-Short Term Memory (LSTM) system.

The LSTM neural network is known for its ability to learn order dependence and sequence prediction. The structure of the LSTM network is made up of a chain of four neural networks and several different cells with gates that manipulate the information that is run through the system. The three different gates found in a LSTM neural network are Forget Gate, Input Gate, and Output Gate [9].

Combination of a CNN with a LSTM will provide an additional layer of machine learning that may enhance the overall power of the system and yield stronger relationships between the data captured.

Study Protocol

Gait analysis required participants to complete several tasks selected from the Functional Gait Assessment (FGA). Once the sensors were on and calibrated, the researcher read the instructions from the FGA and demonstrated each respective task prior to collecting the subject's data. Tasks included (1) gait on a level surface; (2) gait with head turns;(3) gait with stepping over an obstacle; (4) and tandem stance walking. These tasks were selected due to their ability to simulate every-day tasks associated with normal gait. All tasks were performed within a 20 foot long and 1-foot-wide area that was taped off for the participants. The obstacle used for task 3 was a wooden box measuring 9 inches in height. Participants were only given 1 opportunity to complete each task successfully. Failure to do so resulted in failure of the task and omission of the corresponding data.

Data Collection

Motion capture data collected from each of the mounted antennas was continuously and wirelessly transmitted to the central processor where it is stored for further analysis. Input data was then sorted using a binary classification to classify each task against one another based on predefined categories. Once the binary classifier is trained, it is able to make predictions using input data to classify into one of two groups [10]. Each gait task used in this study was predefined and classified using the prediction model of the binary classification system. The accuracy for which the neural networks were able to correctly classify each gait task against one another was recorded (with 95% confidence interval) and compared for each neural network system.

Results

Of the forty-three subjects recruited to participate in the pilot-study, a majority of subjects were students currently enrolled in UTEP DPT program falling in the 22-27 age range. Demographic information is included in Table 1 below:

Table 1: Demographics

Gender	***n***	**Race**	***n***
Male	18	White	36
Female	25	Asian	6
		Black	1
Age		**Ethnicity**	

22-27	36	Hispanic	22
28-37	6	Non-Hispanic	20
50+	1	Declined to answer	1

Table 2 displays the amount of total data points taken throughout the entire study with both the CNN and CNN+LSTM. You can also see from the table how many of the parameters were able to be utilized through the artificial neural networks and how many were deemed untrainable.

Table 2: Neural Network Parameters

Neural network parameters	**Convolutional Neural Network**	**Convolutional Neural Network + Long-Short Term Memory**
Trainable Parameters	292,610	307,804
Non-Trainable Parameters	1,024	1,024
Total Parameters	293,634	308,828

Table 3 shows the accuracy of each neural network's ability to differentiate between tasks from the experiment using binary classification. From the table, we can see that the CNN was able to accurately differentiate between walking with head turns and walking on level surface with 90.3% accuracy compared to the CNN + LSTM which was only 70.1% accurate for the same task comparison. The same is true for all other task comparisons to varying extents with the exception of one. The CNN + LSTM was more accurate than CNN for differentiating between walking with head turns versus walking with tandem stance, but only by a small margin.

Table 3: Accuracy of Different Neural Networks using Binary Classification

Full Model Binary Classification	**CNN Accuracy (95% CI)**	**CNN + LSTM (95% CI)**
HT vs LS	90.3%(87.3-96.9)	70.1%(59.9-80.3)
HT vs OB	71.9%(62-81.8)	62.5%(51.8-73.2)
HT vs TD	78.1%(67.8-88.4)	78.2%(67.9-88.5)
LS vs OB	90.3%(83.6-97)	87.1%(79.6-94.6)
LS vs TD	70.8%(59.2-82.4)	70.8%(59.2-82.4)

OB vs TD	84%(74.8-93.2)	76%(65.3-86.7)

Discussion

The purpose of this pilot study was to determine how accurately the 4-D SWMS could identify subtle differences in normal gait. Data from similar studies suggests that a CNN is the most effective neural network for classification accuracy of gait, which was supported by our study's findings. To our understanding, the addition of a LSTM system would add another layer of machine learning to the system and would only strengthen the classification potential when added to the already effective CNN. Although the addition of the LSTM system to the CNN yielded more learnable parameters, the addition of these learnable parameters hindered the accuracy of the system for most normal gait tasks as demonstrated by our results in Table 3. The CNN alone demonstrated the strongest accuracy and should be used in future studies using the 4-D SWMS for the classification of gait.

There are several limitations to the summary that are worth noting. Only 20 subjects of the 43 recruited completed the tandem gait task, which could explain why tasks involving tandem gait were more difficult to accurately identify using the binary classification. Additionally, the tandem gait task required 10 tandem steps followed by normal gait for the remainder of the 20-foot walkway. The data extracted for analysis was made up of the middle 50% of each task, meaning that the tandem gait may have included normal gait within the extracted data. This could be a possible explanation as to why the neural network was less accurate in determining the difference between normal gait on level surface versus tandem stance. Since this pilot study was looking at preliminary data on normal subjects, a gold standard or reference system was not used for comparison of accuracy. The addition of data from a control group using similar products currently on the market would have allowed for relative comparison of the system's accuracy to better determine clinical utility.

In future studies, 4-D SWMS will be used to capture data on pathological gait utilizing a CNN in order to determine how effective the system is at identifying different pathological gait parameters. Eventually, we would like to be able to apply our findings to clinical populations to identify even the subtlest deviation from normal gait in order to identify needs for early intervention.

Ethical Standards

This study was approved by the institutional review board of The University of Texas at El Paso. In addition to IRB approval, a safety plan was also approved by The University of Texas at El Paso to ensure that all COVID-19 precautions are in place.

Conflict of Interest

The authors of this study declare that they have no conflict of interest to disclose.

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