

High-dimensional Time-series Gait Analysis using a Full-body Wireless Wearable Motion Sensing System and Convolutional Neural Network

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Abstract—This paper reports high-dimensional time-series data processing for gait analysis using data from a full-body wireless wearable motion sensing system with machine learning models. The wearable sensing system consists of ten sensors deployed on limb landmarks, which record quaternion data at 59 sample/Second. Two pilot clinical studies have been designed to investigate the capability of the sensors for accurately differentiating normal gait parameters in healthy individuals. The two studies are interlimb coordination correlation and gait task classification. The interlimb coordination study calculates the correlation coefficient between the left and the right joints to evaluate interlimb coordination. The gait task classification uses a five-layer convolutional neural network to test the classification accuracy of four tasks selected from the Functional Gait Assessment. Clinical experiments show that the system is able to identify the correlation coefficient between normal and synthesized abnormal gaits. The convolutional neural networks have the ability to differentiate functional gait tasks with up to 90% accuracy.

Index Terms—Gait Analysis, Wearable Sensor, Motion Sensor, Convolutional Neural Network, High Dimensional Data, Time Series Data

I. INTRODUCTION

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 challenges that limit their clinical utility. Clinical outcome measures and observations are subject to bias and may not be sensitive enough to capture some of the more subtle changes in motion. Moreover, 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 data obtained from the lab to real-life conditions experienced.

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.

Data from full-body wearable motion sensors also have the potential for evaluating the prognosis of Mild Traumatic Brain Injury (mTBI). mTBI is a time-evolving injury featuring a neurometabolic cascade, self-reported symptoms, cognitive dysfunction, and physical signs such as poor static balance and gait [6]. These problems seem to recover over several days and weeks. However, consistent results across studies have shown that for some patients, some subtle, cognitive, and gait abnormalities, especially assessed concurrently using multimodal tasks, are present for 90 or more days, critically interfering with function [7], [8]. Therefore, objective assessment of various complex gait tasks may be particularly helpful in identifying high-level mobility deficits and offer great clinical utility for the clinical management of mTBI during post-acute timeframes. Progressing gait assessment beyond subjective

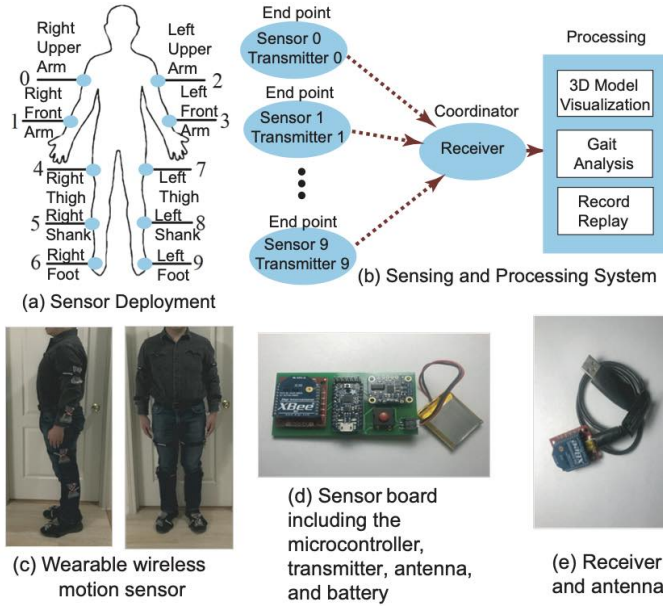


Fig. 1. Full-body wireless wearable motion sensing system.

evaluations toward clinically feasible objective quantifications should be a primary goal that requires full-body motion data.

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. The development of wearable technologies has 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 impediments, and poor sensing accuracy [9]. Bulky rigid designs and wires may impede normal gait and can cause inaccurate and unreliable data collection.

Currently, there are some challenges in performing comprehensive gait analysis using wearable motion-sensing systems. Firstly, most commercially available sensing systems are limited to only lower extremities [10] or upper extremities [11]. Some of the available full-body solutions also have a limited number of sensors such as 4 or 6 sensors [12]–[16], which are not able to report angles of each joint and detailed gaits of each limb for complicate gait analysis or classification. Moreover, the commercial solutions only record limb movement data without a real-time reconstruction and playback functions for clinicians. Furthermore, the cost of such systems is usually very expensive for small clinics or at-home usage. Power consumption and battery lifetime are also design challenges for fully wireless sensors [17]–[19]. In our prior

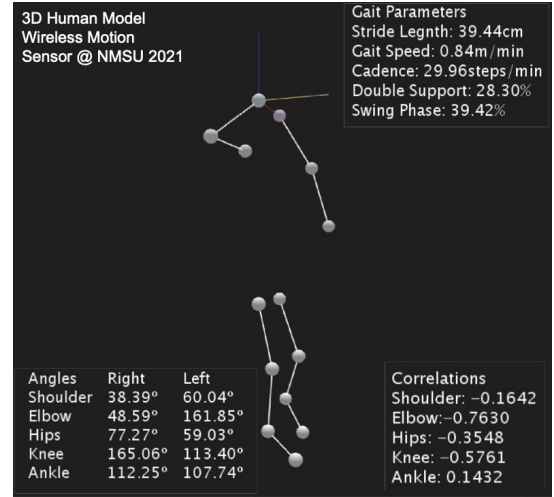


Fig. 2. 3D Human Model tracking gait parameters and interlimb coordination.

work [20], we reported a full-body wireless motion-sensing system based on the hardware sensor and data collection system. In this work, we extend the data processing and applied machine learning models to evaluate the performance of gait classification using high-dimensional real-time data obtained from clinical recordings.

The primary contribution of this paper includes (1) collecting clinical data from a full-body wearable wireless motion-sensing system for gait analysis, (2) performing an interlimb coordination correlation study that demonstrated the capability of the sensing system's ability to evaluate interlimb coordination using correlation coefficient, and (3) conducting gait classification of four tasks selected from the Functional Gait Assessment (FGA) and evaluated the classification accuracy of high-dimensional time-series gait data using convolutional neural network. The results show that the quality of data from the full-body wearable motion sensors is adequate for complicated gait analysis using machine learning models that achieve acceptable accuracy for detecting normal gait parameters in healthy individuals.

II. FULL-BODY WIRELESS WEARABLE MOTION SENSORS

The full-body wireless wearable motion-sensing system applied in this study is based on our prior work [20]. The overall system consists of the hardware sensing and communication subsystem, and the software processing and control subsystem as shown in Fig. 1. The hardware includes ten sensors and one receiver. Each sensor contains a BNO055 inertial measurement unit (IMU), an XBee Explorer transmitter with an XBee trace antenna, a PRO Trinket microcontroller, and a battery. The ten wireless sensors sample at 59 sample/second form a star network with the receiver with Carrier-sense multiple access with collision avoidance (CSMA/CA) mechanism [21]. The sensor data are processed in a laptop computer which reconstructs a 3D human model and calculates the gait parameters and correlation coefficients between limbs. The real-time processing of interlimb coordination and abnormal limb

classification in a graphical user interface (GUI) is illustrated in Fig. 2.

The ten sensors are strapped onto various anatomical landmarks that allow the medical practitioners to continuously capture data in real-time. The system records angular and linear displacement of limbs and trunk in four dimensions using accelerometers, magnetometers, and gyroscopes. The XBee antennas were set up using XCTU (6.4.4) software [20] and are displayed in Fig. 1 (a). 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 real-time 3D model to simulate the subject's motion profile.

III. HIGH-DIMENSIONAL TIME-SERIES GAIT ANALYSIS

Each wearable motion sensor generates four-dimension quaternion data at a sampling rate of 59 Samples/Second. Data from ten sensors collect a 40-dimension time-series data for gait analysis. In this work, we focus on interlimb coordination correlation and machine-learning-based gait classification. In the study of interlimb coordination, the collected quaternion vector data from wearable motion sensors are processed in real-time to obtain the interlimb coordination coefficient. The sensor data are converted into Cartesian coordinate systems to reassemble and animate the limbs of the human model and obtain the angles of the shoulder, elbow, hip, knee, and ankles. Second, the angle minimums and maximums in the time domain are located to calculate the gait parameters. Third, correlation coefficients between angles are computed to determine interlimb coordination using analytical cross-correlation equations. The correlation coefficients are only calculated between the left and right sides of the joints.

For complex gait analysis, high-dimensional machine learning models are applied to classify different gaits. In this study, Gait analysis required participants to complete several tasks selected from the Functional Gait Assessment (FGA), which include (1) gait on a level surface (LS); (2) gait with head turns (HT); (3) gait with stepping over an obstacle (OB); (4) and tandem stance walking (TD). These tasks were selected due to their ability to simulate everyday tasks associated with a 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.

Given the data generated from our motion tracking system, there are rich details on each gait task, and the data is in the manner of high dimension (40 dimensions) and high

frequency (59 sample/second), which is difficult to explore the temporal-spatial dependence structures by classic statistical models. Deep Neural Networks (DNNs), using hierarchical architectures of multiple nonlinear transformations, is a powerful tool for gait recognition problems. In this study, we build a Convolutional neural network (CNN) classifier to recognize different gait tasks. Based on our input size (40-dimension) and referring some successful CNNs for gait recognition [22]–[24], we defined a 5-layer CNN model, which are three temporal convolution layers (*Conv1D*), one pooling layer (*GlobalAveragePooling1D*) with drop-off rate 0.3 to prevent over-fit, and a dense layer with softmax for classification. Detailed parameters of the CNN model are listed in Table I.

TABLE I
CNN STRUCTURE: LAYERS, OUTPUT SHAPE AND PARAMETER #

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 125, 128)	41088
batch_normalization (BatchNormalization)	(None, 125, 128)	512
activation (Activation)	(None, 125, 128)	0
conv1d_1 (Conv1D)	(None, 125, 256)	164096
batch_normalization_1 (BatchNormalization)	(None, 125, 256)	1024
activation_1 (Activation)	(None, 125, 256)	0
conv1d_2 (Conv1D)	(None, 125, 128)	98432
batch_normalization_2 (BatchNormalization)	(None, 125, 128)	512
activation_2 (Activation)	(None, 125, 128)	0
global_average_pooling1d (GlobalAveragePooling1D)	(None, 128)	0
dropout (Dropout)	(None, 128)	0
dense (Dense)	(None, 2)	258

IV. EXPERIMENTAL SETUP AND RESULTS

The experiment on interlimb coordination was conducted at New Mexico State University while the experiment on gait classification was performed at the University of Texas at El Paso. The ethical approvals for the experiments were granted by the internal review boards (IRBs) of the two universities. For the interlimb coordination experiment, Fig. 3 shows the normal and abnormal interlimb correlation coefficients for the five joints (shoulder, elbow, hip, knee, and ankle), where the abnormal data was constructed by mixing limb data between samples from different subjects. From the experimental results, a threshold of correlation coefficient has been identified. If the correlation coefficient is under 0.1, the angles are determined uncorrelated and the limbs are not coordinating as normal.

For the study of the FGA analysis experiment, forty-three subjects were recruited to participate in the pilot study. A majority of subjects were students currently enrolled in the UTEP Physical Therapy program falling in the 22-27 age range. Demographic information is included in Table II. During the experiments, motion data collected from each of the mounted antennas were continuously and wirelessly

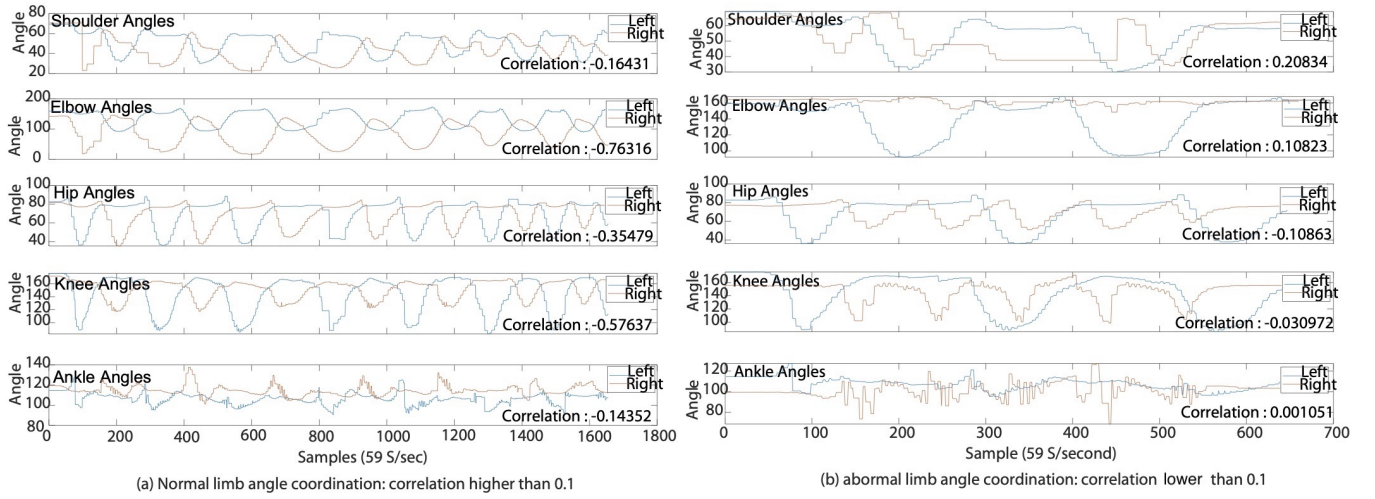


Fig. 3. Recorded joint angles of normal and abnormal limb coordination between left and right joints. Normal correlation coefficient is higher than 0.1.

transmitted to the central processor where it is stored for further analysis. Input data were 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 [25]. 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 a 95% confidence interval) and compared for each neural network system.

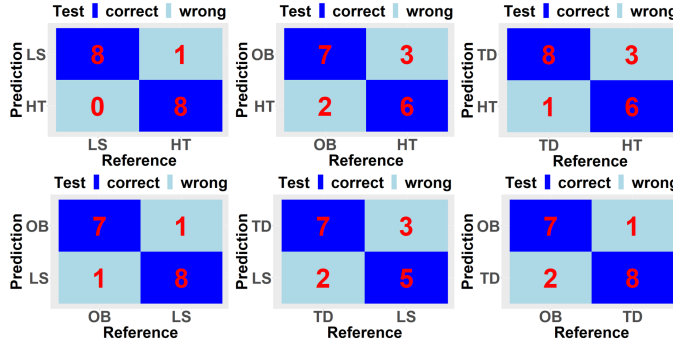


Fig. 4. Confusion matrices of binary classifications for HT vs. LS, HT vs. OB, HT vs. TD (the first row from left to right) and LS vs. OB, LS vs. TD and OB vs. TD (the second row from left to right)

In this study, we have 43 subjects who had completed 4 different gait tasks with tracking systems (HT: 41, LS: 40, OB: 42, and TD:43). So the total number is 166. We split the data into training data (80%) and testing data (20%). The confusion matrix and evaluation metrics for testing data are presented in Fig. 4 and Table III. The classification results show that the motion tracking system can capture sufficient information on distinguishing the gait type with acceptable accuracy.

TABLE II
DEMOGRAPHICS SUMMARY

Demographics $N = 43$		
Gender		
	Male	Female
	18	25
Age		
18-26	27-37	50+
36	6	1
Race		
White	Asian	Black
36	6	1
Ethnicity		
Hispanic	Non-Hispanic	Decline to Answer
22	20	1

TABLE III
TESTING RESULTS AND EVALUATION METRICS

	Accuracy	Sensitivity	Specificity	F_1 Score
HT vs. LS	94.2 (71.3,99.9)	.8889	1.000	.9412
HT vs. OB	72.2 (46.5,90.3)	.6667	.7778	.7059
HT vs. TD	77.8 (52.4,93.4)	.6667	.8889	.7500
LS vs. OB	88.2 (63.4,98.5)	.8889	.8750	.8889
LS vs. TD	70.6 (44.0,89.7)	.6250	.7778	.6667
OB vs. TD	83.0 (58.6,96.4)	.8889	.7778	.8421

V. CONCLUSION

This paper reported a high-dimensional time-series data analysis for a real-time full-body wearable motion-sensing system in conjunction with a convolutional neural network to classify gait patterns. The results show that the combination of hardware and algorithm is able to accurately classify different gait tasks and evaluate the interlimb coordination through correlation coefficient between left and right joint angles. The ultimate goal of future research is to detect the subtle abnormalities of patients with mild traumatic brain injury to determine the need for earlier intervention.

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