Spatial Variability Learning of Biomechanical Dynamics

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***Abstract*—With the rapid development of modern electronics and computation capability, biomechanical mining is attracting more and more attentions. Due to the complexity and inter-person variance among the biomechanical dynamics, it is important to study the spatial variability to not only optimize the activity recognition performance but also deepen the understanding of inter-sensor-location and inter-subject differences. We here propose a system with both wearable motion sensing and deep learning, for comprehensive biomechanical dynamics understanding. More specifically, the system allows collection of motion data from diverse body locations. Further, the deep learning algorithm then learns the signals and yields the physical activity types. The experiments have promisingly indicated the spatial variability of biomechanical dynamics capturing and analysis. This study will benefit the understanding of biomechanical dynamics.**

Keywords—Biomechanical dynamics, gait, deep learning, spatial variability, motion sensor

I. INTRODUCTION

Biomechanical dynamics of human motion is a critical and long-lasting area in kinematic and locomotion areas [1]. By studying the biomechanical dynamics of human motion, people could analyze the gait patterns, muscle and joint functions, balance and stability, foot biomechanics, foot biomechanics, footwear, and orthotics, among many. To make a quantitative analysis of motion, there are many ways to acquire the motion data of the human body, such as the video camera, Electromyography (EMG), force plate, 3D Imaging, wearable sensors, and others. [2-5]. Force plate is the most straight forward way to analyze the human motion. It can get the load of the body directly, especially the lower body with other sensors [6]. But with the limitation of the plate area, the subject can only move in a small area which means not all the activities can be captured. Video cameras are a popular way to gather motion data in many research areas. Recently, a system containing the video and motion sensor is widely used to record ground-truth motion [7]. While the video camera and 3D image system can gather the motion data effectively, there are still some constraints [8, 9]. The video method usually costs much resources and time to set up the system. Same as the force plate, the data acquisition will be usually used in the lab and most of the motions of a subject in daily lives cannot be easily captured.

Recently, with the rapid development of electronics, MEMS technology has experienced a significant growth over the years [10]. Based on inertia devices' performance boosting and price drops, the inertia chip which can detect and record the motion of the human body has been integrated into smart phones, smart watches, and other wearable devices with a low cost [11]. The high precision and the portable ability of smart devices enable various studies based on the inertia data. D. Micucci *et al.* also set up a human activity dataset UniMiB SHAR which includes seventeen kinds of activities. They also studied the data with different classifiers such as Support Vector Machine (SVM) and Random Forest (RF) [12]. In 2019, Q. Zhang also proposed deep learning algorithms for motion data analysis [13]. To get more accurate motion data, H. Leutheuser *et al.* developed a four-sensor classification system gathering the inertia data. More and more sensors are added on the human body to get more dynamics [15]. It's therefore promising to gather the motion data of different body locations.

Due to the complexity and inter-person variance among the biomechanical dynamics, it is important to study the spatial variability to not only optimize the activity recognition performance but also deepen the understanding of inter-sensor-location and inter-subject differences. We here propose a system with both wearable motion sensing and deep learning, for comprehensive biomechanical dynamics understanding. More specifically, the system allows collection of motion data from diverse body locations. Further, the deep learning algorithm then learns the signals and yields the physical activity types. The experiments have promisingly indicated the spatial variability of biomechanical dynamics capturing and analysis. This study will benefit the understanding of biomechanical dynamics.

II. METHODS

A. Experiment Setup for Biomechanical Bynamics Sensing

In this study, we've built the experiment in our laboratory based on daily activity facilities, such as the treadmill, the excise bike, the bed and the sofa. The motion we have studied includes sleeping, sitting, walking, running, climbing, and biking.

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A multi motion data capturing system is crucial for biomechanical dynamics study based on human movement. We here put motion sensors on twenty different body locations, which gathering the biomechanical data on different locations of the human body as TABLE I, with the IRB approval. The sensor is based on the nRF52840 which is an MCU produced by Nordic Semiconductor. The nRF52840 is built with the 32-bit ARM Cortex-M4 processor and the motion sensor is a 6-axis MEMS Motion Tracking device that combines a 3-axis gyroscope and a 3-axis accelerometer. To the best of our knowledge, it is the first time to have such as rich dataset with diverse biomechanical dynamics of different body locations.

TABLE I The sensor location on the body

Sensor number	Location	Sensor number	Location
1	Left foot	11	Left elbow
2	Left ankle	12	Left up arm
3	Left knee	13	Right hand
4	Left thigh	14	Right hand
5	Right foot	15	Right elbow
6	Right ankle	16	Right up arm
7	Right knee	17	Belt
8	Right thigh	18	Down chest
9	Left hand	19	Up chest
10	Left wrist	20	Head

B. *Motion Data Analysis and Processing*

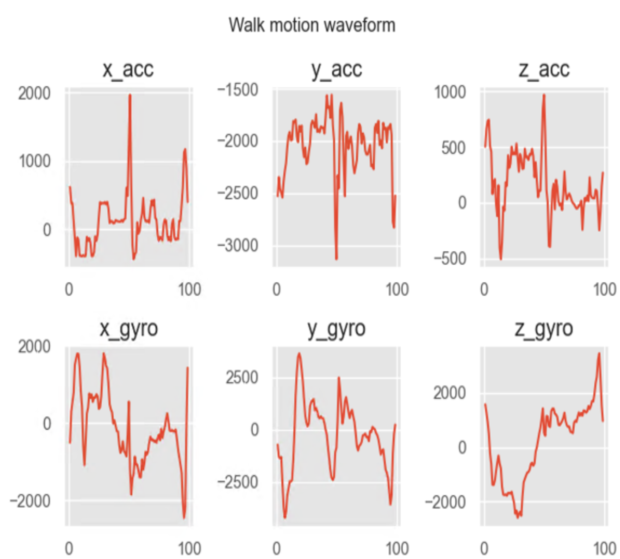

Fig. 1 The waveform of the 6-axis walking data. Notes, the data is normalized.

There are six kinds of motion types during the experiment: lying, sitting, walking, running, climbing, and biking in one session. Each activity is 3-min long. The whole experiment contains seven sessions for each subject. The raw data includes the 3-axis accelerometer and 3-axis gyroscope, waveform during walking is shown in Fig. 1. As demonstrated, the figures have successfully reflected different dynamics in different directions and with different sensing modalities.

To capture the details of the activities in experiments, the sampling rate of the motion sensor is set as 50Hz and a bit resolution of 16 has been configured. A two-second window is applied for activity data segmentation.

C. *Deep Learning of Biomechanical Dynamics Data*

After capturing and processing the data, we have developed a Convolutional Neural Network (CNN), as Fig. 2, to analyze the patterns of different activities, different sensing locations, and different subjects.

The dimension of the input data for the CNN model is 100x6. There are multiple Convolutional layers to capture the spatial motifs in the data. To accelerate the training process, the 'Relu' activation function is applied to each 1D Convolution layer. To deal with potential overfitting, the Dropout layer is also applied after the Convolution layer. To classify the input instances to six categories of activities, in the final layer, the 'Softmax' activation function is applied to generate the category probability.

Fig. 2 The CNN Model architecture.

D. *Spatial Variability Learning for Biomechanical Dynamics*

To analyze the spatial variability, we have applied the same CNN to process the motion data for all the sensors, and then compare the performance accordingly. That means, we have obtained the sensor-location-specific performance, which allows us to comprehensively compare different body locations in terms of sensor placement.

III. Results

The results of our study are given and discussed in this section.

A. *Learning Patterns of the Biomechanical Dynamics*

Fig. 3 shows the learning accuracy and learning loss of the CNN model based on the data acquired in the experiment. From the figure, we can see the accuracy of the learning model is approximately to 100% and the loss is almost 0 after around 100 epochs. The results clearly indicate the success of the CNN model training.

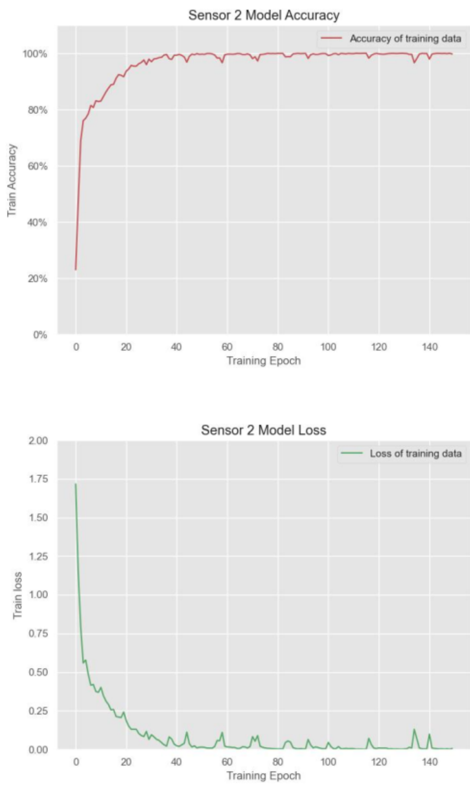

Fig. 3 Learning accuracy and loss curve of the deep learning model. Note: sensor 2 is corresponding to the left ankle location.

B. Confusion Matrices

To demonstrate the performance of the CNN model, we a confusion matrix is given in Fig. 4, based on the motion data on the sensor 1 of the subject 1. As shown, most of motions are accurately predicted. The average motion prediction accuracy for this sensor is also calculated as 92.2%.

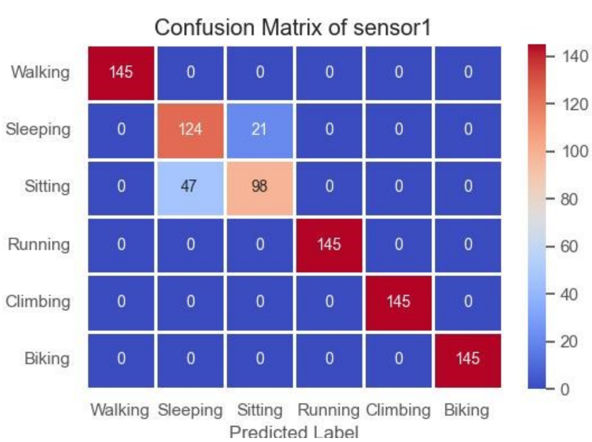

Fig. 4 Confusion matrix of the deep learning model for motion data on the sensor 1 of the subject 1. Note: sensor 1 is corresponding to the left foot location.

C. Spatial Varability of the Biomechanical Dynamics on Different Sensor Locations

To study the spatial variability of the motion of the human body, we analyzed accuracy of all the sensors on the body. Fig. 5 shows the comparison of the accuracy of all the sensors on the subject 1. From the figure, the accuracy of the sensor on different parts of the body is from 66.8% to 92.2%. The highest accuracy of the sensor is the sensor 1 which is located on the left foot.

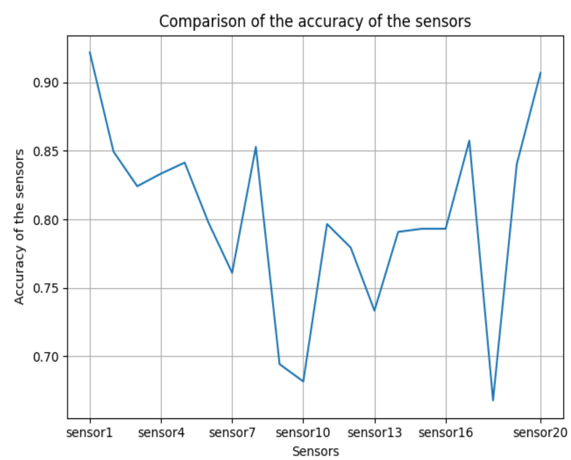

Fig. 5 Comparation of all sensor accuracy on the subject 1.

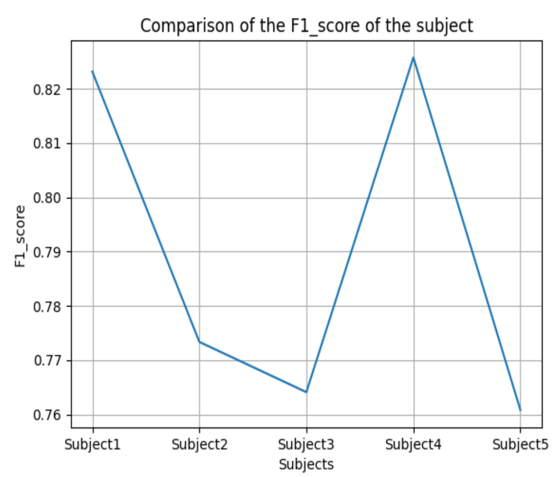

Fig. 6 F1-score of different subjects

D. Spatial Varability Learning pattern of the biomechanical dynamics on different subjects

To get the performance of the system on different subjects, we used the F1-score as shown in Fig. 6. For all the subjects, the F1-score is calculated by the average F1-score of all the motions on all the sensors. As shown, the F1-scores of five subjects vary from 76.1% to 82.6%.

IV. Conclusion

In this study, to comprehensively understand the spatial variability of the subject in human movement experiments, a system with biomechanical dynamics sensing and deep learning has been developed. In specific six normal activity types, we have captured the 3-axis accelerometer and 3-axis gyroscope data, and afterwards fed the data into a customized CNN model for motion pattern recognition. In our experiments, we tested five subjects and the results clearly show that the data has been successfully captured from and the CNN model has also effectively detected different activity types. The prediction accuracy of the sensors is above 90% for the sensors on the feet and head. This research is expected to further our understanding of the spatial variability of biomechanical dynamics and also suggest the optimal configuration to boost the performance. In future, we will advance the study on more subjects and enhance the deep learning algorithms.

V. Acknowledgement

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