Deep Mining of Wearable Spatial Variability for Efficient Edge Computing

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***Abstract*—Wearable biomechanical sensors can be placed on different body locations and each sensor may have multiple channels. Deep mining of the spatial variability in these sensor locations and channels, is essential for not only optimal system configuration towards energy efficient edge computing, but also comprehensive musculoskeletal dynamics understanding. Targeting these needs, we propose to leverage deep learning to investigate seven body locations and six channels for each location, thereby demonstrating the spatial variability among 42 combinations. The research findings indicate that the thigh location and the accelerometer axis-Y is the best configuration. Further, experimental results also indicate the diverse spatial variability among different sensor locations and sensor channels, which provide interesting and rich information about the biomechanical dynamics. This study will thus greatly advance our understanding of the spatial variability in wearable biomechanical sensors and channels, thereby minimizing the data analytics load and facilitating energy efficient edge computing for big biomechanical data mining.**

Keywords—Deep Learning, Edge Computing, Spatial Variability, Wearable Computer, Big Data

I. INTRODUCTION

With the advancement in smart sensors, more and more emerging applications are paving the way toward big data-driven precision medicine [1]. Wearable biomechanical big data provides promising means for medical decision support and lifestyle management. The motion sensors like the accelerometer and gyroscope, can continuously monitor the physical movements of humans. The signals can be wirelessly streamed to the cloud for further data analytics and long-term big data management.

We in this study take a special interest in wearable biomechanical monitoring applications. Previous studies have reported different algorithms for signal processing of sensor data from some specific location. For instance, the wrist sensor was used for motion data acquisition and the support vector machine was designed for motion detection in [2]. In [3], the phone sensor and the decision tree were used. There are also other studies which used methods like the frame difference method [4], and random forest [5]. Recently, deep learning methods have also been used in motion detection, such as the convolutional neural network and long short-term memory. However, the understanding of the spatial variability among different sensor locations and sensor channels, is still limited. Filling this gap is essential to determine the optimal sensor configuration for minimum data analytics load and maximum power efficiency in real-time edge computing.

Targeting this challenge, we in this study propose to leverage a customized deep neural network for deep mining of the spatial variability. This study is essential for not only optimal system configuration but also comprehensive musculoskeletal dynamics understanding. We have leveraged the convolutional neural network (CNN) to investigate seven body locations and six channels for each location, thereby demonstrating the spatial variability among 42 combinations.

Our research findings indicate that the thigh location and the accelerometer axis-Y is the best configuration, for minimizing the data analytics load and maximize energy efficiency on the edge. Further, experimental results also indicate the diverse spatial variability among different sensor locations and sensor channels, which provide interesting and rich information about the biomechanical dynamics. This study will thus greatly advance our understanding of the spatial variability in wearable biomechanical sensors and channels, and also facilitate energy efficient big biomechanical data mining.

II. METHODS

A. The Spatial Variability Mining Algorithm

To maximize the energy efficiency, we have developed a convolution neural network with shared pattern filters. It is well known that convolutional operations are highly efficient with these shared connections. However, no previous study on using it on wearable spatial variability mining has been conducted, to the best of our knowledge. We here leverage it to thoroughly evaluate 42 different combinations of sensor locations and sensor channels.

The selected optimal sensor location and sensor channel will be set as the final recommendation, meaning that in the real-world use, we only need to execute the deep learning algorithm on this minimized amount of data. To further illustrate the variability of the wearable biomechanical dynamics, in Fig. 1a), the selected biomechanical signals are visualized, which indicate the diverse behaviors for different channels. The dynamics will be automatically learned with the proposed deep learning algorithm, to determine the optimal channel among six dimensions. And the process will be executed for each sensor location among seven.

B. Potential System Configurations

We will consider seven different body locations, including locations, chest, forearm, head, shin, thigh, upper-arm, and waist. For each location, we will consider both the accelerometer and gyroscope sensors, each with tri-axis signals. So, in total there are 42 combinations. We will

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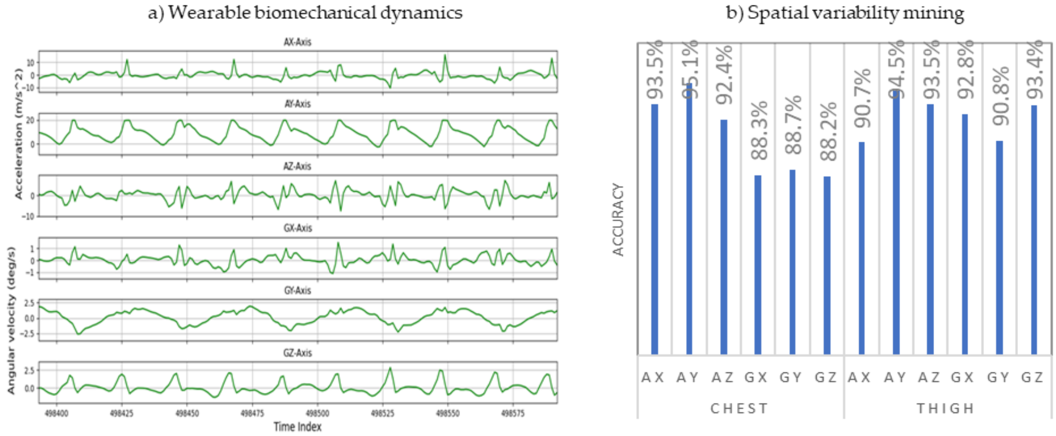

Fig. 1. The illustration of (a) the selected biomechanical signals from a subject during running, with six dimensions (3-axis accelerometer and 3-axis gyroscope), and (b) the selected detection accuracy under different configurations (chest, thigh) that indicates the accelerometer-Y axis is optimal.
Notes. A/G: accelerometer/gyroscope; X/Y/Z: 3 different axis.

therefore be able to comprehensively investigate the biomechanical dynamics and determine the optimal configuration with deep learning.

Mathematically, the optimal system configuration is determined by (1), where μ is the optimal combination of the sensor location l, sensor type s, and sensor channel c.

$$\mu = \underset{l,s,c}{argmax}\, \Phi(D_{l,s,c})$$

And Φ is the deep learning model, and $D_{l,s,c}$ is the corresponding dataset with the configuration l, s, and c.

C. Experimental Evaluation

The real-world motion database [6] is used. Fifteen participants performed six different activities, including climbing downstairs, climbing upstairs, jumping, lying, running/jogging, and walking. Each activity is from two to ten minutes, and the signal is segmented with a size of 100.

III. Results

A. Comprehensive Study of 42 Configurations

We have compared all 42 configurations in terms of the physical activity detection accuracy. As shown in Fig. 1b), we have highlighted the chest and thigh locations, and their corresponding channels, which have better performance compared with the forearm, head, thin, upper-arm and waist locations and channels. Especially, for the forearm, head, and upper-arm locations, the performance is relatively low, considering there are more diversity during the movements.

We finally determine the chest location and the accelerometer axis-Y channel as the optimal combination, with an accuracy around 95.1%. One thing worth noting is that, the thigh location and accelerometer axis-Y is also a possible candidate solution, considering the chest location may need a strap that lowers the wearability.

B. Further Investigations

In future, we will further enhance the motion detection accuracy though model improvements. We will also evaluate the power consumption of the model on the edge based on the optimal configuration, considering this study mainly minimizes the data needed through determining the optimal and minimum sensor configuration.

IV. Conclusion

In this study, we have systematically investigated the spatial variability among different sensor locations and sensor channels, for biomechanical energy efficient big data-driven precision medicine. More specifically, we have designed and developed a deep neural network to compare seven sensor locations and six signal channels per location, in terms of physical activity detection accuracy. We have then evaluated the algorithm on a real-world database and determined the optimal combination. This study will significantly advance the biomechanical big data mining and relevant smart health applications, by minimizing the data need while maintaining effective edge inference.

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