Maximizing Energy Efficiency of Mobile Biomechanical Decoding with Spatial Variability Mining

Kiirthanaa Gangadharan
Electrical and Computing Engineering
Purdue University School of
Engineering and Technology
Indiana, USA

Cody Daniel
Electrical and Computing Engineering
Purdue University School of
Engineering and Technology
Indiana, USA

Qingxue Zhang
Electrical and Computing Engineering
Biomedical Engineering
Purdue University School of
Engineering and Technology
Indiana, USA

***Abstract*—Mobile sensing and data analytics usually take a substantial amount of energy, which limits the durability of the wearable devices. Especially, when deep learning is applied for data mining, the energy need is even more hungry. In this study, we take a special interest in wearable biomechanical data analytics, and propose to leverage data mining to tackle this challenge. More specifically, we leverage deep learning to mine the spatial variability of motion sensors embedded in mobile devices placed on the forearm and upper arm. In addition to compare the sensor locations, we further compare six different channels of each sensor location, thereby making twelve different configurations. Ultimately, we determine the optimal sensor location and the optimal sensor channel, which indicates the minimized data processing need in the real-world applications. The results indicate that the upper arm location and Y-axis of the accelerometer is the optimal configuration. This study will advance the field of maximizing energy efficiency of mobile biomechanical monitors, towards continuous data-driven precision medicine.**

Keywords— Mobile Devices, Deep Learning, Spatial Variability, Big Data

I. Introduction

Many devices like the smart phones, watches, and wrist bands are now supporting the biomechanical data tracking [1]. The applications span a variety of possibilities, such as the daily activity detection, the step counting, and physical movement difficulties. In the studied on physical movement detection, the sensors were usually placed placed on the arm or the chest, or other locations [2]. It is obvious that different sensor locations may have diverse impacts on the data acquired. Especially, considering the different moving patterns of each body location, the obtained data may be highly diverse. Besides, the accelerometer and gyroscope both have three channels, which reflect acceleration in three directions and angular rate in three directions, respectively.

In addition to select out optimal and minimum system configuration for energy efficiency maximization, understanding the difference among different sensor locations and further the difference among different signal channels, is also very promising for high physical activity detection performance and for physician to get insights on how biomechanical dynamics differ under different system configurations [3].

Therefore, to fill this gap, we leverage deep learning to mine the spatial variability of motion sensors placed on the forearm and upper arm. In addition to compare the sensor locations, we further compare six different channels of each sensor location, thereby making twelve different configurations. Ultimately, we will determine the optimal sensor location and the optimal sensor channel, which indicates the minimized data processing need and maximized energy efficiency.

We next in section II provide the technical details, and in section III demonstrate the experimental results. In section IV, the conclusion is finally made.

II. Methods

A. System Diagram

As shown in Fig. 1, the deep learning algorithm based on CNN has been designed and developed for mining the spatial variability. Each combination of the sensor location and sensor channel is evaluated independently with the algorithm, and the final detection accuracy is used for optimal configuration determination.

B. Spatial Variability Mining

To the best of our knowledge, this is the first study to thoroughly study, evaluate, and quantize the biomechanical spatial variability.

The proposed convolution neural network in Fig. 1 consists of several convolutional layers for pattern abstraction. The maxpooling layers reduce the dimension for further pattern abstraction. The fully connected layers, or called dense layers, yield the final detection results. There are six activity types evaluated in this study, so the output layer has six neurons, and each corresponds to one category.

C. Experimental Setup

The really-world biomechanical data [4] has been used for the evaluation, with two- to ten-minute recordings from fifteen subjects who performed six activities including climbing down/upstairs, lying, running, walking, and jumping.

III. Results

The results are given in this section, and the optimal sensor and channel configuration is determined by the comprehensive study.

Kiirthanaa Gangadharan and Cody Daniel are with Electrical and Computing Engineering, Purdue University School of Engineering and Technology, USA. Qingxue Zhang is with Electrical and Computing Engineering, and Biomedical Engineering, Purdue University School of Engineering and Technology, USA. Email: qxzhang@purdue.edu

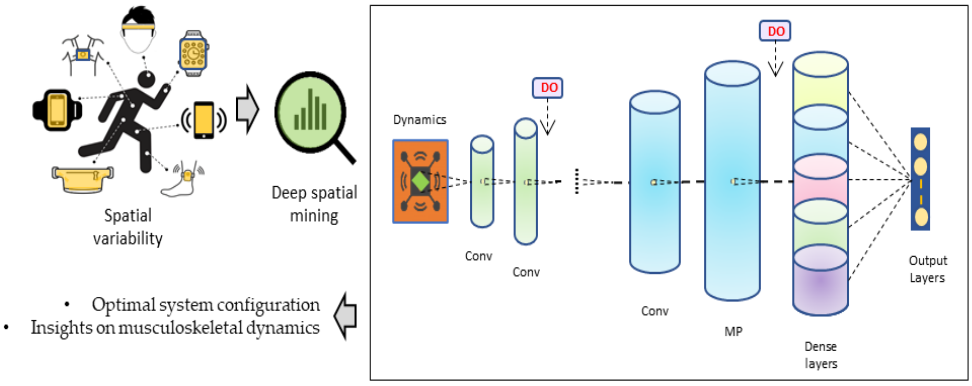

Fig. 1. Spatial variability mining among diverse combinations (different locations, sensors, and sensor channels), with the deep convolutional neural network.
Notes. Conv: convolution; MP: max-pooling; DO: drop-out.

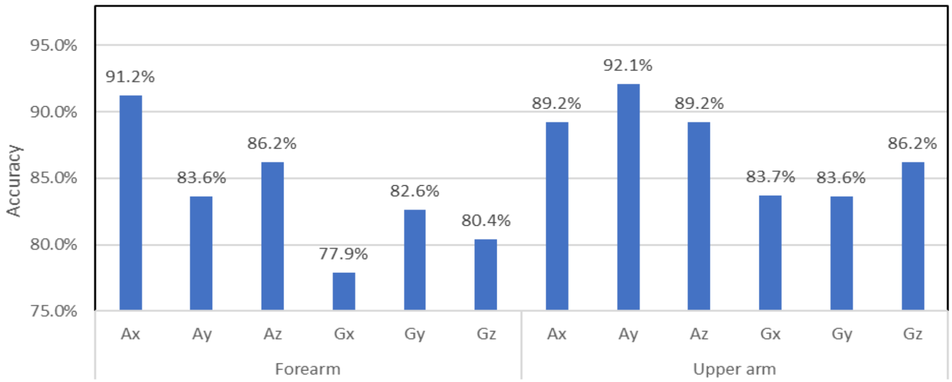

Fig. 2. The illustration of the mined spatial variability in terms of the detection accuracy. Different configurations (forearm, upper arm) bring the diversity of arm movements, which have important impact on the performance.
Notes. A/G: accelerometer/gyroscope; X/Y/Z: 3 different axis.

A. *Maximizing Energy Efficiency*

Fig. 2 shows the thorough comparison of the forearm and upper arm locations, and the six channels of signals for each location, acquired by the accelerometer and gyroscope.

We can observe that the upper arm location and the Y-axis of the accelerometer is the optimal configuration, with the highest activity type detection accuracy. Further, generally, the signal channels of the accelerometer have higher accuracy than those of the gyroscope, indicating that more informative dynamics are encoded in the former one.

We therefore have demonstrated that it is promising to only use a single chancel for robust activity type detection. The accuracy is up to 92.1%, with maximized energy efficiency.

B. *Further Investigations*

In future, we will further study more spatial locations, and more combinations of the different sensor channels or sensors for required tradeoffs between performance and energy consumption.

IV. Conclusion

In this study, we have thoroughly studied the spatial variability of biomechanical mobile devices, thereby determining the optimal sensor and channel configuration with minimum data processing load and maximum energy efficiency. We have demonstrated that the upper arm location and Y-axis of the accelerometer is the optimal configuration. This study will advance the field of maximizing energy efficiency of mobile biomechanical monitors, towards continuous data-driven precision medicine.

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