Deep Learning of Biomechanical Dynamics With Spatial Variability for Lifestyle Management

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***Abstract*—Human Physical Activity Detection (PAD) is essential for advanced lifestyle management. Nowadays, many devices like smartwatches and phones have motion sensors. And the placement of devices, especially phones, is diverse. Understanding the optimal sensor location is important for robust PAD applications. However, the biomechanical dynamics are highly complex, making signal processing very challenging. In this study, we propose to leverage deep learning to perform intelligent PAD, and comprehensively compare seven different body locations for optimal sensor placement recommendation. Multi-stage deep learning has been proposed and developed, which firstly leverages convolutional layers to abstract spatial features from the motion data, and then generates the physical activity type prediction with fully connected layers. Evaluated on the real-world database, the proposed deep learning model is very effective on PAD tasks, and successfully determines the thigh location as the optimal sensor placement method. This study will greatly advance deep learning-driven biomechanical dynamics mining for advanced lifestyle management.**

Keywords—Wearable Computer; Deep Learning; Smart Health

I. INTRODUCTION

The field of Human Physical Activity Detection (PAD) has a wide range of applications such as in lifestyle management, health analysis, mobility tracking and security systems [1, 2]. The advancement of electronics enables affordable devices, like the smart phone that performs data collection from their inbuilt inertial sensors.

The placement of devices, especially phones, is diverse. Understanding the optimal sensor location is important for robust PAD applications. However, the biomechanical dynamics are highly complex, making signal processing very challenging. In this study, we propose to leverage deep learning [3, 4] to perform intelligent PAD, and comprehensively compare seven different body locations for optimal sensor placement recommendation.

A multi-stage deep learning has been proposed and developed, which firstly leverages convolutional layers to abstract spatial features from the motion data, and then generates the physical activity type prediction with fully connected layers.

II. METHODS

As shown in Fig. 1, the proposed multi-stage deep learning model consists of four stages of convolutional operations (and corresponding max-pooling operations), and also fully connected layers. The former can extract the signal patterns as shown in Fig. 2, by leveraging the convolutional filters. The latter one combines the learned features to generate the final PAD results, i.e., the physical activity type prediction. Besides, DO in the figure means the dropout regulation for the learning process. The architecture details are shown in Table I.

Table I. The architecture details of the deep learning model.

Activation	LAYERS	Parameters	VALUES
ReLu	Convolution 1	Kernel size	(1,2)
		Filters	16
	Maxpooling		(1,2)
	Dropout		0.15
ReLu	Convolution 2	Kernel size	(1,2)
		Filters	32
	Maxpooling		(1,2)
	Dropout		0.15
ReLu	Convolution 3	Kernel size	(1,2)
		Filters	32
	Maxpooling		(1,2)
	Dropout		0.15
ReLu	Convolution 4	Kernel size	(1,2)
		Filters	64
	Maxpooling		(1,2)
	Dropout		0.15
ReLu	Dense 1		512
	Dropout		0.2
ReLu	Dense 2		256
	Dropout		0.2
Softmax	Dense		num_classes
TRAINING	Loss function		Cross entropy
	Optimizer		Adam
	No. of epochs		80

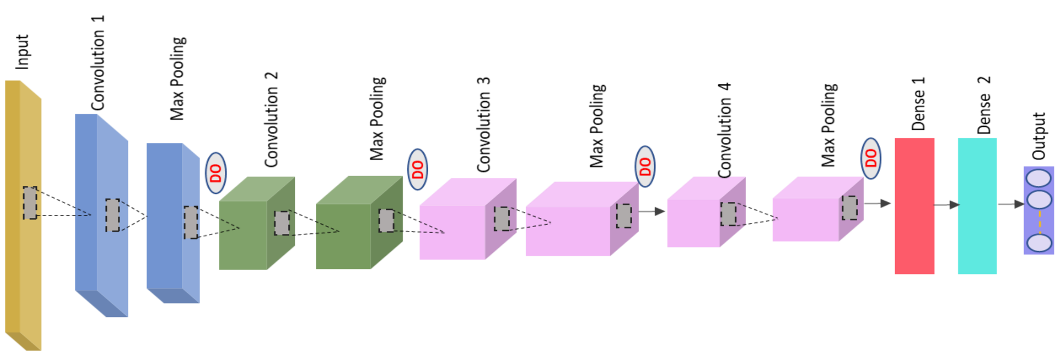

Figure 1. The proposed deep learning architecture for optimal sensor location investigation.

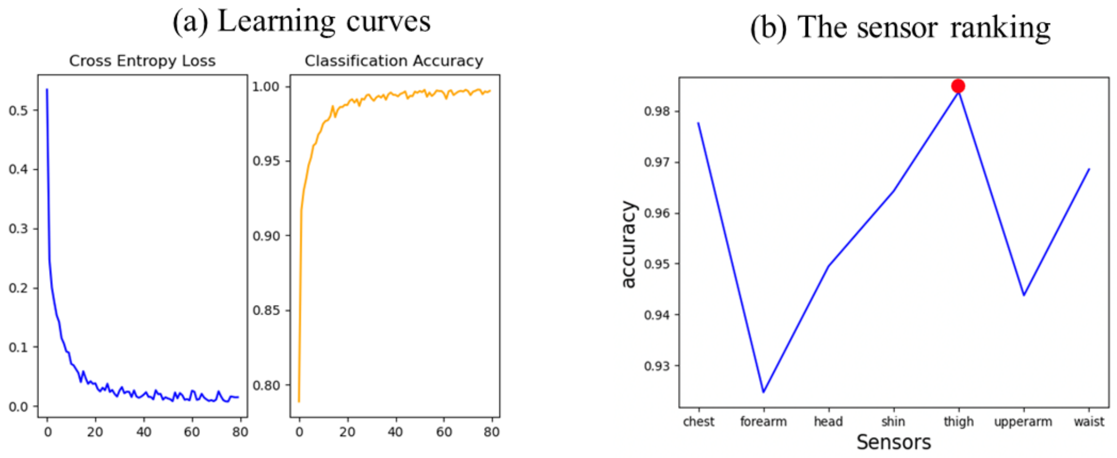

Figure 3. The selected learning curves for the waist sensor showing good convergence (a), and the ranking of all seven sensors with averaged accuracy across the whole database (b).

Seven sensor locations are investigated in this study, including the chest, forearm, head, shin, thigh, upper arm, and waist. The motion sensor on the smart phone has been used, and the sensor includes a 3-axis accelerometer and a 3-axis gyroscope.

III. Results

The experiment has been conducted on a motion database [5], which has data collected with the smart phone from seven body locations and 15 subjects. Eight activity types are included. The total number of instances are split into 80% training data and 20% test data for model classification. The selected signal segments are shown in Fig. 2, indicating the diverse dynamics in the signals.

Fig. 3 (a) shows the selected learning curves for the waist sensor, which had good convergence. Fig. 3 (b) gives the comparison of seven sensor locations. All seven sensors have promising performance on the PAD task.

More specifically, the chest, thigh and waist locations show better performance, compared with other locations. Further, the thigh location shows the best performance, which is over 98%.

IV. Conclusion

In this study, we have proposed a deep learning model that can intelligently analyze the biomechanical dynamics for physical activity detection. The convolutional layers extract the spatial patterns in the data, and then the fully connected layers generate the activity type prediction. We afterwards investigated different sensor placement locations, to determine the optimal one. The evaluation on a real-world database indicates the thigh location provides the best performance. This research is expected to provide recommendations for placing the motion onto the optimal locations for robust physical activity detection. It will greatly advance smart lifestyle management and other relevant smart health applications.

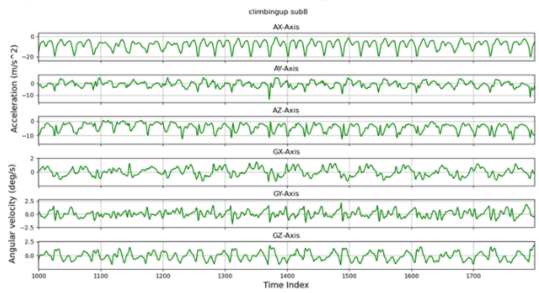

Figure 2. Selected signal segments for the thigh sensor location.

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