Knowledge Transferring in Deep Learning of Wearable Dynamics

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***Abstract*— Wearable dynamics learning is attracting intensive interests now in the era of smart health. One challenge is how the learning model can be effective trained with limited amounts of data. Targeting this, we in this study propose a deep transfer learning framework, to leverage the knowledge obtained from non-target users and boost the performance on the target-user. More specifically, we have designed and pre-trained a convolutional neural network on the non-target database, and then fine-tuned the model on a small portion of the target database. The framework has been evaluated on a wearable biomechanical learning application for physical activity detection. Compared with direct target-data-based learning, the proposed deep transfer learning approach great boosts the detection accuracy. This study will advance the wearable dynamics learning applications through deep knowledge transferring.**

Keywords*— *Transfer Learning, Wearable Computer, Deep Learning, Biomechanical Big Data

I. Introduction

Wearable dynamics learning has been attracting intensive interests in the era of smart health. For instance, wearable cardiac monitoring has been sued for heart disease monitoring [1]. Wearable motion sensor has been equipped on smart watches and bands for step counting and lifestyle management [2]. Wearable glucose monitor has been used for real-time glucose level tracking. These advancements have brought promising possibilities for smart health and big data practices. In this study, we take a special interest in biomechanical mining, which is essential for rehabilitation, lifestyle management and fall detection applications.

Previous studies on biomechanical data analytics include machine learning and deep learning approaches. For the former one, support vector machine, decision tree, random forest and other methods have been reported [3-6]. For the latter one, convolutional and recurrent networks have been studied [7-9]. One challenge is how the learning model can be effective trained with limited amounts of data, and currently the study of knowledge transferring for wearable data analytics is still a gap to be filled [3, 4].

Transfer learning has been successful applied in areas such as computer vision and natural language processing [10]. The pre-trained models on related databases usually significantly improve the performance on the target problem. The abstracted patterns on the non-target databases can encode some common knowledge that, if applied on the target data, will facilitate information abstraction and contribute to the performance increase. As mentioned-above, it is still unclear how transfer learning can be applied on the wearable data analytics.

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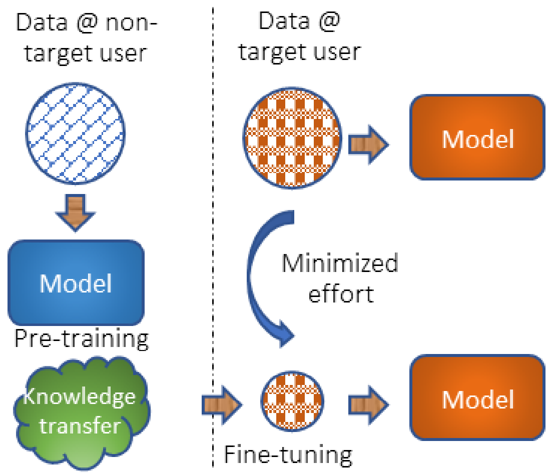

Fig. 1. Transfer learning in biomechanical big data mining.

Targeting this, we in this study propose a deep transfer learning framework, as shown in Fig. 1, to leverage the knowledge obtained from non-target users and boost the performance on the target-user.

More specifically, we have designed and pre-trained a convolutional neural network on the non-target database, and then fine-tuned the model on a small portion of the target database. The framework has been evaluated on a wearable biomechanical learning application for physical activity detection. Compared with direct target-data-based learning, the proposed deep transfer learning approach great boosts the detection accuracy. This study will advance the wearable dynamics learning applications through deep knowledge transferring.

We will then detail the methods and results in section 2 and 3, respectively. Finally, we will conclude the study in section 3.

II. Methods

A. System Diagram

The system diagram of the deep transfer learning approach is given in Fig. 2, and an example of the biomechanical dynamics is given Fig. 3. Compared with the direct learning that may require a large amount of data, the transfer learning approach can leverage the knowledge from non-target users and minimize the data need on the target user. Furthermore, with the same percentage of the target data, transfer learning is expected to bring performance boosting, by leveraging the

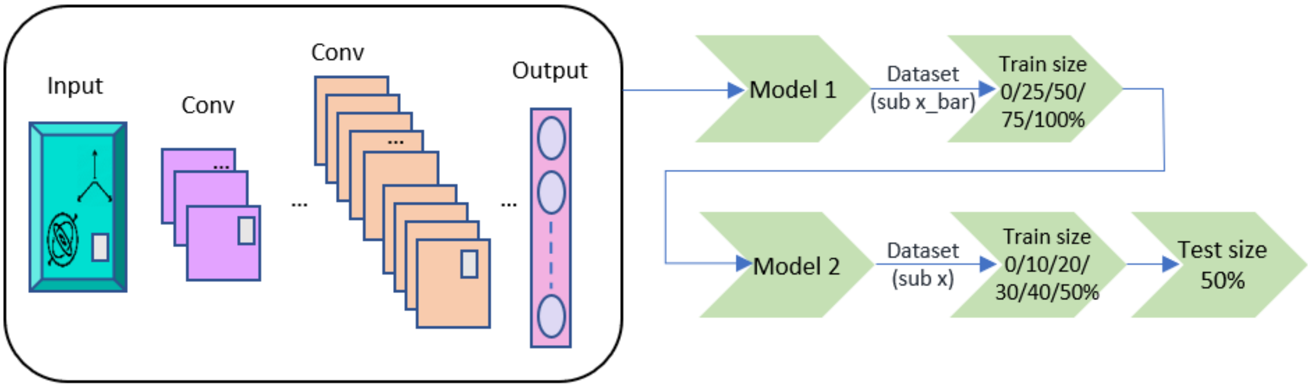

Fig. 2. The proposed deep transfer learning strategies, which leverage pre-training on the non-target data and fine-tuning on the target data to boost the detection performance.
Notes. Conv: convolution; sub: subject; sub x_bar: non-target dataset; sub x: target dataset.

knowledge captured from the non-target data during the pre-training process.

B. *Knowledge Transferring*

The knowledge transferring between non-target users and the target user is through the model pre-training. We have designed a convolutional neural network which has multiple convolutional layers and dense layers. The model will firstly learn the patterns from the non-target users. Although inter-subject variabilities exist, there are significant amounts of patterns also when the subjects are performing the same activities. For example, in the walking activity, the movements of hands and legs are more or less similar among different subjects. The deep learning model can therefore learn these patterns.

Afterwards, we apply the target data to fine-tune the pre-trained model. It allows the model to further adjust its neural weights to accommodate the inter-subject variability. This process is expected to improve the detection accuracy. One thing is note is that we want to minimize the fine-tuning effort, so we only adopt a small portion of the d ata from the target user.

The process is further given in (1-3). In (1), the initial deep model M_0 is pre-trained on the dataset $D_\tau^{\bar{x}}$ that is constructed from non-target users $\bar{x}$ with a percentage of τ. Then in (2), the pre-trained model M is further fine-tuned on the dataset D_σ^x that is constructed from the target user x with a percentage of σ. Finally, in (3), the fine-tuned model M' is tested on the dataset D_{50}^x that is selected from the target user with a percentage of 50%.

$$M = T(M_0, D_\tau^{\bar{x}}) \quad (1)$$

$$M' = T(M, D_\sigma^x) \quad (2)$$

$$\rho = \Omega(M', D_{50}^x) \quad (3)$$

C. *Training and Testing Strategies*

We have evaluated different training and testing strategies. More specifically, different percentages of data from non-target users as given in (4) have been used for model pre-training. Afterwards, different percentages of data from the

Fig. 3. Inter-activity biomechanical dynamics, indicating the diverse behaviors in the signals.
Note. A-x/y/z: accelerometer x/y/z axis.

target user as given in (5) have been applied in the model fine-tuning process. In such a way, we will have a comprehensive understanding of how pre-training and fine-tuning should be applied. To provide fair comparison, the testing is performed on 50% of the data from the target user.

$$\tau\epsilon[0\%, 25\%, 50\%, 75\%, 100\%] \quad (4)$$

$$\sigma\epsilon[0\%, 10\%, 20\%, 30\%, 40\%, 50\%] \quad (5)$$

D. Framework Evaluation

A physical activity database [11] that includes six activity types and fifteen subjects will be used for evaluation. We will demonstrate both subject-level and database-level performance, to evaluate the framework. The six activities are climbing downstairs, climbing upstairs, jumping, lying, running/jogging, and walking. The signal segmentation size is two seconds, with a sampling rate of 50Hz.

III. Results

We will firstly illustrate selected wearable signals to show the similarity and variability among different users. Then we will demonstrate the knowledge transferring results, followed by the performance summary and future research directions.

A. Selected Wearabel Signals

In Fig. 3, the selected signals from two different activities are visualized. We can observe that the variabilities between them are significant. This is reasonable because different activities have diverse biomechanical diversities.

Meanwhile, there are also consistencies between these two users. These are what we will leveraging through deep transfer learning and what we want to share among the users.

B. Knowledge Transferring

We have shown the examples of how transfer learning contributes to the performance improvement in Fig. 4, where when increasing the percentage of the pre-training data, the model performance basically improves. There are also some interesting findings on other subjects. Sometimes more data for pre-training may not have obvious contributions to the performance improvement, which could be because of the

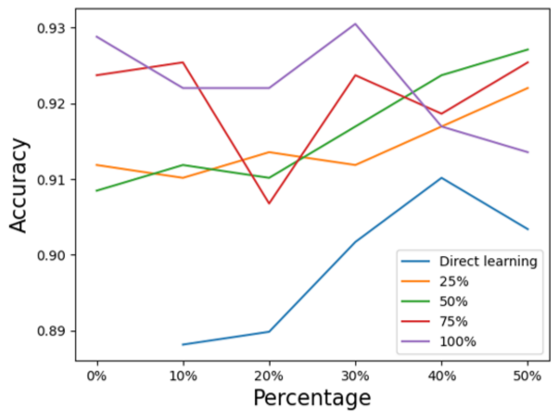

Fig. 4. Knowledge transferring performance on a selected subject.
(1) Notes of the legend. Direct learning: no transfer learning; 25/50/75/100%: transfer learning with different percentage of the non-target data.
(2) Notes of the horizontal axis. 0/10/20/30/40/50%: the percentage of the target data used for fine-tuning (or training @ Direct learning).

inter-subject variabilities. But overall, it is appropriate to use more data for pre-training.

C. Performance Summary

The performance summary on the whole database is given in Fig. 5, where the contribution of the pre-training step is obvious. The direct learning without model pre-training has a low accuracy, because of limited data for training. When the percentage of target data small is small, the contribution from pre-training is high. When increasing the percentage of target data, the direct learning has increasing performance, but the pre-training still brings significant performance boosting. Therefore, the proposed deep transfer learning is effective in enhancing the model performance.

D. Future Efforts

It will be interesting to further investigate more data to further evaluate the framework. Also, it is possible to apply the proposed algorithm to other smart health applications, considering that the wearable data usually scarce and the training can introduce lots of inconvenience.

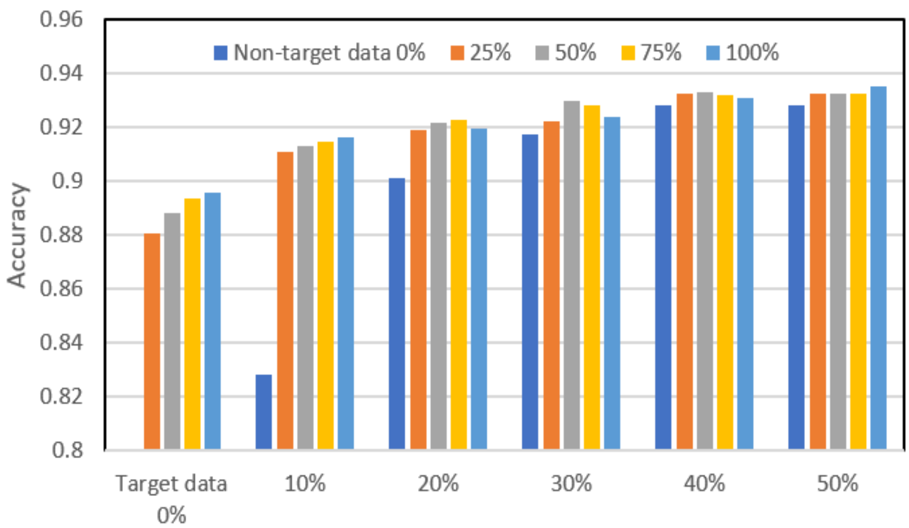

Fig. 5. Performance summary under different combinations of pre-training and fine-tuning strategies. Overall, the transfer learning based on both pre-training and fine-tuning has boosted the performance significantly. For example, when target data = 10%, the transfer learning has an accuracy of 92%, compared with 83% without transfer learning.

IV. CONCLUSION

In this research we have targeted the wearable big data learning problem and proposed a deep transfer learning framework to minimize the training effort on the target user. More specifically, the deep learning model is firstly pre-trained on the non-target data and then fine-tuned on the target data, thereby sharing the similar knowledge and patterns among different subjects. The validated framework has demonstrated very promising performance and boosted the biomechanical data analysis accuracy compared with direct learning without knowledge transferring. Thus, this study will significantly benefit the wearable dynamics learning applications.

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