Wearable Big Data Pertinence Learning with Deep Spatiotemporal co-Mining

Junhua Wong
Department of Electrical and Computer Engineering
Purdue School of Engineering and Technology
IN, USA

Qingxue Zhang, *Senior Member, IEEE*
Department of Electrical and Computer Engineering
Department of Biomedical Engineering
Purdue School of Engineering and Technology
IN, USA

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***Abstract*— Wearable Computers are greatly advancing big data practices, by levering their capabilities of ubiquitous big data capturing and streaming. However, one critical challenge is the amount of data to be transmitted, which consumes too much energy of the battery-constrained wearable devices. Targeting this obstacle, we propose a novel big data pertinence learning approach, which can learn and extract pertinent patterns in wearable big data for redundancy reduction. More specifically, a hybrid deep learning approach based on both Convolutional Autoencoder and Long Short-term Memory is proposed, which can mine both spatial and temporal patterns in the data for key pattern extraction. The achieved spatiotemporal co-mining ability when evaluated on a real-world motion dynamics big data application, demonstrates the attractive potential of pertinence extraction and redundancy minimization. This study is expected to greatly advance wearable big data practices.**

Keywords—Deep Learning, Spatiotemporal Learning, Wearable Computer, Big Data

I. INTRODUCTION

Big data [1, 2] is igniting many new practices, from smart home, smart health to smart world [3, 4]. Wearable computers, leveraging their ubiquitous big data capturing and streaming capabilities, are playing a more and more important role in big data innovations. The advancements of electronics, wireless communications, and miniaturization technologies make the wearable computers more capable of capturing biomedical dynamics, such as physical activities and cardiac conditions [5]. The long-term usage of wearable computers is essential for capturing time-varying and diverse biomedical dynamics, which, at the same time, poses new challenges to the wearable computer deployment.

Wearable computer is usually composed of sensing, wireless communication, processing, and power management units. The large amount of data usually requires a lot of communication energy and makes the long-term health monitoring highly challenging. Taking the physical activity monitoring as an example, the user may have different levels of fatigue and/or physical movement abilities, which usually makes the biomechanical dynamics fluctuate significantly over time. It is thus essential to continuously monitor the biomechanical dynamics for long-term analysis of the big data. This will contribute significantly to the prediction, diagnosis, and treatment of diseases, through leveraging big data-driven precision medicine.

Junhua Wong and Qingxue Zhang (qxzhang@purdue.edu) are with Department of Electrical and Computer Engineering, Purdue School of Engineering and Technology, Indiana, USA.

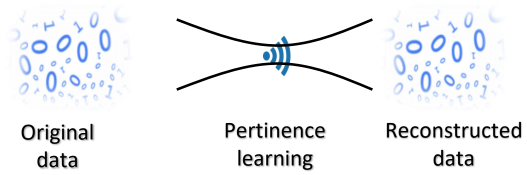

Fig. 1 Wearable big data pertinence learning and transmission.

Deep learning [6] has nowadays advanced many areas, such as smart health, computer vision, and natural language processing [7, 8]. Deep neural networks, inspired by human brain, analyze the patterns layer by layer, and gradually achieve high-level abstractions. Deep autoencoder [9], as one of the mainstream deep learning architectures, can gradually abstract the input into a compressed data representation, and then decode the representation to reconstruct the original data. Through this encoding and decoding process, deep autoencoder can be used to denoise the data. Another impressive application is pertinence extraction, meaning that the compressed data representation output by the encoder can be used to reflect the critical patterns of the original data. Motivated by this, we propose to leverage deep autoencoder to extract the pertinent patterns of the wearable data, and only transmit this compressed data to the big data center for minimizing the transmission requirements, as shown in Fig. 1. Compared with the traditional methods, such as wavelet transform and compressed sensing [10-13], deep learning can more intelligently learn the complex patterns in the data for critical information extraction. This is because the wavelet transform usually uses a predefined mother wavelet as a template to screen and compress the data, and compressed sensing uses a random transformation matrix to project the data to a low-dimension space, while deep learning leveraged data-driven learning abilities to find out highly non-linear patterns and relationships in the data for data compression.

In this study, we propose a novel deep spatiotemporal co-mining approach for wearable big data pertinence learning, by leveraging both Convolutional Autoencoder (CAE) [9] and Long Short-term Memory (LSTM) [1] that are capable of spatial and temporal learning, respectively. More specifically, the fully-connected autoencoder, when equipped with the convolutional operators, can more effectively capture the spatial patterns and save number of operations. Moreover, we further introduce LSTM – a typical architecture of recurrent neural networks, to mine the temporal relationships in the data. The achieved LSTM-CAE deep learning architecture, called LSCAE, is then evaluated on a real-world physical activity monitoring application, to demonstrate its effectiveness of data pertinence learning. To the best of our knowledge, it is the first time to leverage spatiotemporal learning for wearable big data compression.

Our major contributions are summarized as below:

- Proposing a novel deep spatiotemporal co-mining approach for wearable big data pertinence learning;
- Leveraging a hybrid deep autoencoder architecture based on both CAE and LSTM, for spatial and temporal pattern mining, respectively;
- Evaluating the achieved LSCAE architecture on a real-world physical activity monitoring application, and demonstrating its effectiveness on data pertinence learning.

II. METHODS

In this section, we detail the proposed spatiotemporal co-mining architecture, LSCAE, for wearable big data pertinence learning.

A. System Diagram

A system diagram is given in Fig. 2, where the wearable data is firstly fed into the LSCAE encoder for big data pertinence extraction, and then into the decoder for original data reconstruction on the data center. In such a way, the data to be transmitted is only the extracted low-dimension representation.

B. Spatiotemporal Learning

The proposed LSCAE architecture is composed by an encoder and an decoder, each of which is then composed by the LSTM and CAE components. Here let's detail the encoder of the LSCAE architecture. As shown in Fig. 2, the wearable data goes through LSTM and then CAE for spatial and temporal pattern extraction.

The LSTM module aims to extract the temporal relationships in the input data segment, as defined in (1-6), where f_t, i_t, and o_t correspond to the weighting factor of the memory gate, input gate, and output gate, respectively, $\tilde{c}$, c_t and h_t correspond to the pre-gated input, gated input, and gated output, respectively, σ, W, U and b correspond to the activation function, neural weights for input, neural weights for gated output at last moment, and bias respectively, and x_t is the input at the current moment. W, U, and b are learnable parameters during the training phase, and h_t is the hidden state generated by the LSTM neurons.

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \tag{1}$$

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \tag{2}$$

$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \tag{3}$$

$$\tilde{c} = \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \tag{4}$$

$$c_t = f_t c_{t-1} + i_t \tilde{c} \tag{5}$$

$$h_t = o_t \sigma_h(c_t) \tag{6}$$

In such a way, the LSTM module learns to capture the relationships in the temporal data, by controlling the input, memory and output intelligently. The output is then fed into CAE, where, as shown in Fig. 2, the patterns are gradually compressed into a short vector.

The overall LSCAE can be summarized as (7-8), where the input signal segment X is encoded as $\bar{\bar{X}}$ – a compressed data representation that reflects critical patterns, and afterwards, $\bar{\bar{X}}$ is decoded as the estimate of the input, $\hat{X}$. $\hat{X}$ is expected to maintain the critical patterns of the original signal segment. Therefore, the LSCAE architecture, through learning spatiotemporal patterns for pertinence extraction, and reconstructing the original signal on the receiver side, can effectively compress the wearable big data for transmission effort minimization.

$$\bar{\bar{X}} = LSCAE\_encoder(X) \tag{7}$$

$$\hat{X} = LSCAE\_decoder(\bar{\bar{X}}) \tag{8}$$

C. Deep Learning Architectures

Multiple deep learning architectures have been designed and evaluated in this study. The depth of CAE in the encoder has been selected as 2 and 4, respectively. For each depth, the number of feature maps is chosen as 2 and 6, respectively (except last stage, which has one feature map). The max

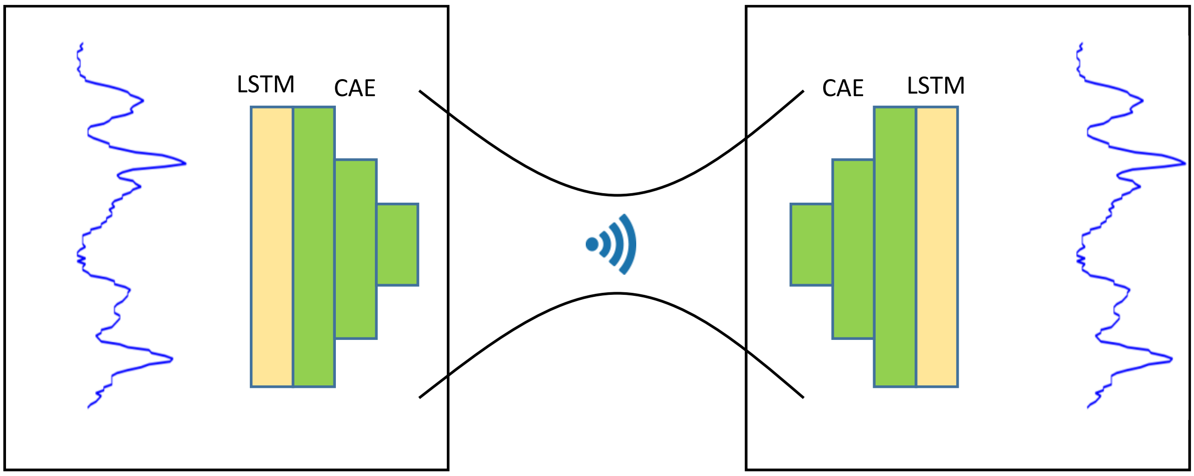

Fig. 2 The proposed novel deep LSTM-CAE spatiotemporal co-mining architecture, named as LSCAE, for wearable big data pertinence learning.
Notes. LSTM: long short-term memory; CAE: convolutional autoencoder.

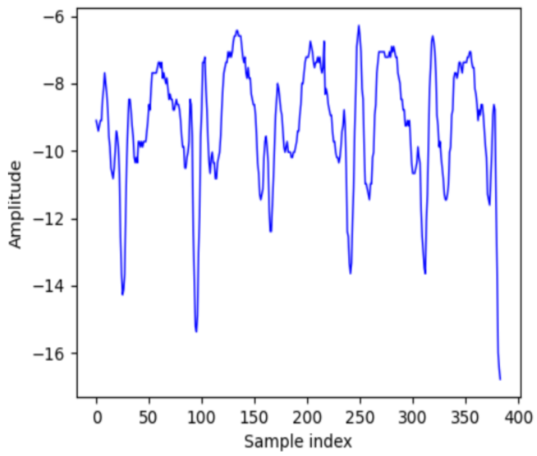

Fig. 3 The biomechanical dynamics during physical movements. X-axis of the accelerometer signal is visualized.

pooling size is set as 2, and the convolutional size is 5. The output dimension of LSTM in the encoder is set to be 1 to minimize the computation requirement. The decoder is the reversed encoder, to gradually increase the dimension and reconstruct the original data.

III. RESULTS

We here detail the experimental design, evaluation results and analysis, to demonstrate the effectiveness of the proposed LSCAE architecture.

A. *Experimental Design*

A real-world physical activity monitoring database [14] is used for the evaluation of LSCAE. Five subjects with complete data are chosen, and the Treadmill-Slop-Walking activity is used in the evaluation. The X-axis of the accelerometer signal is used for minimizing the power of the wearable application. Each recording has 78080 samples with a sampling rate of 128 Hz, and the segmentation length is 128 that results in 610 instances (seconds) per subject. The data is split into 90% and 10%, for training and testing, respectively. One thing is note is that we have selected one activity type that was repeated performed by the subjects, to demonstrate the effectiveness of LACAE, but at the same time, the proposed framework can also be generalized to other physical activities types, and other signal modalities. A signal segment is given in Fig. 3, which indicates that the biomechanical dynamics are time-varying.

B. *Learning Process*

To demonstrate the learning process, Fig. 4 gives the training process of the proposed LSCAE. The curve converges effectively after 100 epochs, indicating that the network has well learned the patterns in the data. Deep learning, although it has complex computation process, owns a good landscape of solutions. It means that the optimization algorithm usually can find good solutions in the searching process [15]. The advantage of this learning process is data-driven, and no manual feature engineering is required, as compared to the traditional signal processing algorithms.

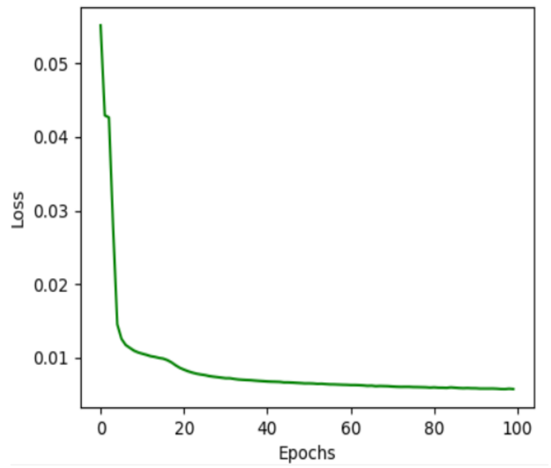

Fig. 4 The learning curve showing a good converges trend.

C. *Reconstruction Performance*

To demonstrate the performance of LSCAE, Fig. 5 illustrates the reconstructed signals for different compression ratios. In Fig. 5(a), the LSCAE depth is 2 (compression ratio is 4), and increasing the number of feature maps has non-significant impacts of the reconstruction performance. With deeper LSCAE, higher compression ratio is obtained with some drop of the reconstruction performance. When increasing the depth to 4 (compression ratio is 16) in Fig. 5(b), 6 feature maps (FM6) is better than 2(FM2), in terms of signal reconstruction. This is due to the fact that FM6 can capture more patterns from the original data and thus generate better data pertinence in the compressed representation. This

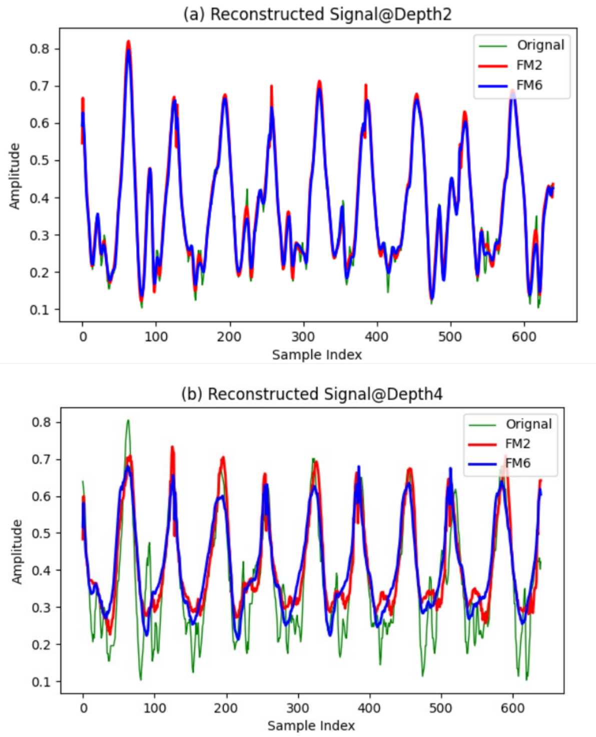

Fig. 5 The reconstructed signals at LSCAE depth 2 (a) and 4 (b), respectively, indicating that more feature maps (FM6) improve the performance compared than less feature maps (FM2). Overall, the signals are well reconstructed.

Notes. FM: feature map.

indicates that, when choosing a higher compression ratio, the number of features can contribute to the reconstruction performance.

D. Performance Summary

TABLE I. PERFORMANCE SUMMARY

Depth	*#FM*	*RMSE*
2	**2**	**0.079**
	6	**0.041**
4	**2**	**0.163**
	6	**0.149**

Further performance summary is given Table I. When LSCAE depth is 2 and #FM is 6, the root mean square error (RMSE) is 0.041, better than that of FM2. Similarly, more feature maps also improve the performance when depth is 4. The systematic design of the deep LSCAE architecture is thus needing the co-consideration of all these crucial design parameters.

E. Future Studies

Future studies may include further optimization of the LSCAE architecture, as well more evaluations using the real-world applications. Besides, multiple design parameters, including depth, feature map, convolutional size, and LSTM dimensions, are also of interest, and the comprehensive design principles will facilitate the performance improvement. It is also interesting to compare with other methods like wavelet transform and compressed sensing [16-18], to further evaluate the intelligent compression ability of the proposed LSCAE framework.

IV. CONCLUSION

We have proposed and evaluated a novel deep spatiotemporal co-learning architecture, for wearable big data pertinence learning. The proposed LSCAE architecture owns an encoder for data pertinence extraction and a decoder for original data reconstruction. More specifically, the encoder firstly abstracts the temporal patterns using LSTM and then abstracts spatial patterns using CAE. The achieved LSTM-CAE encoder can thus learn both temporal and spatial patterns. The CAE-LSTM decoder on the data center can then reconstruct the data from the compressed data representation. The LSCAE architecture has been evaluated on the real-world physical activity monitoring application, and demonstrated its effectiveness on critical pattern extraction. It will be interesting to further investigate lightweight LACAE architectures for easy deployment on the wearable devices. This study will greatly advance wearable and other related big data applications.

V. ACKNOWLEDGEMENT

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