Artificial Intelligence and Human-Computer Interaction
Y. Ye and P. Siarry (Eds.)

doi:10.3233/FAIA240155

Physiological Signal-Based Biometric Identification for Discovering and Identifying a New User

Xinxin MU [a], Hongyu JIANG [a], Fan LI [b], Tongjie PAN [a], Guocheng XIONG [a] and Yalan YE [a,1]

[a] *University of Electronic Science and Technology of China*

[b] *Civil Aviation Flight University of China*

Abstract. Using physiological signals acquisition from wearable devices makes biometric identification more convenient and secure. Yet most of existing studies focus on Physiological signal-based biometric technology in a verification application rather than an identification application. Actually, identification application is a more general senior and there is an inevitable problem in discovering and identifying a new user. Existing approaches can only identify trained users and fail to join a new user into model conveniently, which limits identification application in human-computer interaction. In this work, we propose a physiological signal-based method for identifying both older users and new users. A deep network combining Transform and LSTM is introduced to extract user-specific features. Then, one-vs-all classifier is used to identify old users and discover a new user, and the classifier is updated to identify the new user without retraining whole model. Based on electrocardiogram (ECG) and photoplethysmography (PPG) signals in BIDMC dataset, our method achieved an accuracy of 99.52% and 99.30% for old users, as well as 93.18% and 91.23% for a new user. Extensive experiments demonstrate the performance in identifying old users and the effectiveness in discovering and identifying a new user via physiological signals.

Keywords. Biometrics, physiological signal, authentication, new user

1. Introduction

Traditional biometric identification as fingerprints [1], iris [2] and face biometric [3] recognition technologies have been employed in identification application, but these technologies have low recognition security and accuracy in some uncontrolled environments (such as non-frontal view face recognition). Physiological signals have high security due to its advantages of good confidentially and inability to copy and forge. As well as some physiological signals such as electrocardiogram (ECG) signal, photoplethysmography (PPG) signal, can be continuously acquired via small low-cost sensors. Therefore, physiological signals acquisition from wearable devices provides a more secure and efficient ways of biometric identification.

There are usually two applications for physiological signal-based biometric identification: (1) one-to-one matching: the verification is used to prove someone's identity by

[1] Corresponding Author: Yalan Ye, College of Computer Science and Engineering, University of Electronic Science and Technology of China, China. E-mail: yalanye@uestc.edu.cn.

matching the acquired features only by the person's stored template; (2) one-to-many matching: the identification is used to identify a user by comparing the acquired features with all stored templates [4].

For biometric authentication based on physiological signals in real workplace, we focus on ECG-based and PPG-based technology. For ECG biometric technique, S. I. Safie et al.[5] proposed pulse active ratio as a feature extraction and I. Khalil et al.[6] used Legendre polynomials based on QRS of ECG. PPG-based technology is also proposed as a way for biometric identification. Fuzzy logic analysis [7] and linear discriminant analysis [8] were used to prove the feasibility of PPG-based authentication although the accuracy is not actually well. To better identify, three features were obtained via the autocorrelation coefficients of PPG and its derivatives in [9]. Polat K et al. [10] had even extracted up to 40 features. Above all, template matching methods were adopted for authentication by extracting designed features of these signals. However, the handcrafted feature extraction process is complicated and tedious.

Table 1. A comprehensive comparison of some existing works. We denote the complexity of the method in the tables as High(H), Middle(M) and Low(L). " Available Signal" denotes signals can use the method.

Ref	Application	Feature Extraction		Expanding		Available Signal
		Method	Complex	Method	Complex	
[7]	Verification	Handcrafted Features	H	Retrain	M	PPG
[8]	Verification	Handcrafted Features	H	Retrain	M	PPG
[10]	Verification	Handcrafted Features	H	Retrain	M	PPG
[11]	Verification	Handcrafted Features	H	Retrain	M	ECG
[12][13]	Verification	Deep Features	M	Retrain	H	PPG
[14]	Verification	Deep Features	H	Retrain	H	PPG
[9]	Identification	Handcrafted Features	H	Retrain	M	PPG
[15]	Identification	Deep Features	M	Retrain	M	ECG
[16]	Identification	Deep Features	M	Retrain	H	ECG
Ours	Identification	Deep Features	M	Part Retrain	M	ECG, PPG

Recently, deep neural network has been used in classification applications since its ability to feature self-extraction [12-13]. Dae Yon Hwang et al. [14] proposed PPSNet for PPG-based biometric authentication. D. Jyotishi et al. [17] used HLSTM model to the biometric representation based on ECG signal. Although these works benefit to move away from the complexity and instability of extracting handcrafted feature, few approaches have been employed in the identification application. Distance similarity [18] was used to discover new user, but it required setting the threshold manually. Consequently, the model of most works must be retrained completely when a new user joins. Comparison between our work and existing work is given in Table 1. Our method can accurately identify old users and discover a new user both on ECG and PPG.

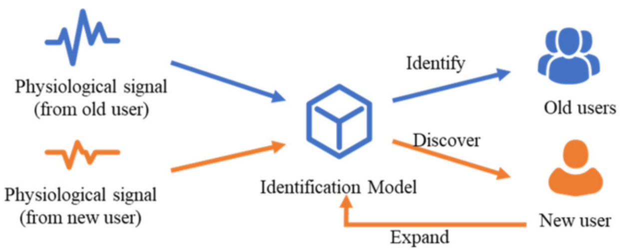

Figure 1. Identification scenario for discovering a new user.

Therefore, this work focused on developing a method that can discover and identify a new user without manual feature design and complete retaining for the identification application. Figure 1 shows the scenario of identification application. In this paper, we propose to use Transformer-LSTM network as a feature extractor, combined with one-vs-all classifier to discover and identify a new user, which reduce time cost of complete retaining via updating classifier. The main contribution of this study is summarized as follows.

- We investigate identification application, in which discovering and identifying a new user is taken into consideration. The problem setting is more general than prior work and is more practical for human-computer interaction application.
- For identification application with a new user, we introduce a deep network as feature extractor that combine Transformer with LSTM and a one-vs-all classifier identifying old users and discovering a new user. Besides, the new user can be identified via updating classifier without retraining whole model.
- We conduct extensive experiments using both ECG and PPG signals, and the results demonstrate the effectiveness in identification. Discovering and identifying a new user is also verified with well performance.

2. Method

The overview of our proposed approach is given in Figure 2. Physiological signals are preprocessed to eliminated noises. Then a deep network is trained based on k users' signal data, and a one-vs-all classifier is used to identify. At the testing stage, features of the remaining new user are extracted through feature extractor. They can be discovered by one-vs-all classifier after inputting features. Finally, the classifier is updated by features from a new user. More details are introduced below.

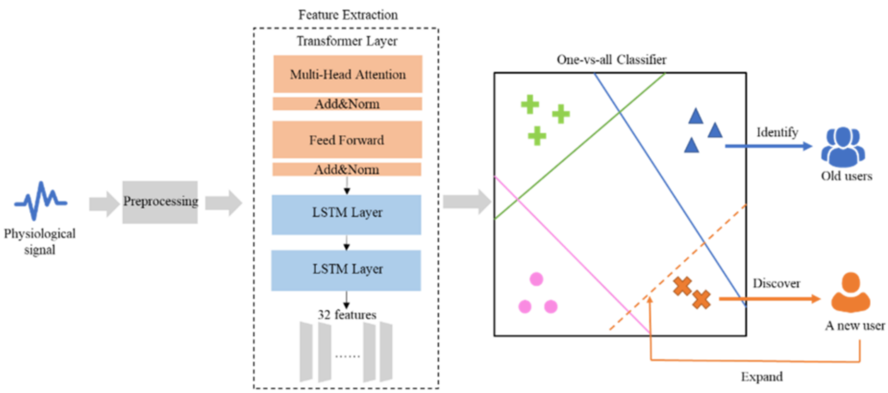

Figure 2. Overview of our method for physiological signal-based identification. At training stage, physiological signals are preprocessed and the feature extractor is trained. One-vs-all classifier is used to identify old users and discover a new user. At testing stage, classifier is updated to identify the new user.

2.1. Preprocessing

To better extractor signal feature, we first preprocess physiological signals to remove noises. For ECG signal, it is passed through a bandpass filter with a cutoff frequency 0.5Hz-40Hz to remove high frequency noise, baseline wander and power line interference [17]. Then we follow the method in [15] to remove the noises that are present within

0.5 Hz to 40 Hz frequency range. For PPG signal, we use the method in [19] to eliminate noise. The training and testing sequences are extracted using a rectangular window. We utilized cubic spline interpolation to scale it to 128 samples and form a unified input format for deep neural networks.

2.2. Feature extraction

Inspired by works in [12-13,15], a completely data-driven approach based on Transformer in conjunction with LSTM was adopted to extract features from physiological signals. Our idea is to train it as a feature extractor for identification which can be used on multi physiological signals. The implementation details are introduced below:

1) Model Design: A signal with 128 samples is served as the input of the deep net. Transformer layer consists of multi-head self-attention, feedforward network and skip connecting. It is used to learn the important signal complexes for person identification. Two LSTM layers are then used to capture the temporal features since they can address sequential time series data and consider both the new input at the current time and the output of the neural network in the previous time. Finally, a dense layer with 32 neurons is used to retain the most discriminate features.

2) Optimization: We use the loss function $L = L_s + \lambda L_c$ to train the model, where L_c is center loss with parameter λ [20]. And traditional softmax loss L_s is defined as:

$$L_s = -\sum_{i=1}^{m} \log \frac{e^{W_{y_i}^T x_i + b_{y_i}}}{\sum_{j=1}^{n} e^{W_{y_i}^T x_i + b_j}}, \tag{1}$$

where $x_i \in \mathbb{R}^d$ is the i th feature, belonging to the y_i th subject. d is dimension of feature. $W_j \in \mathbb{R}^d$ denotes the j th column of the weights $W \in \mathbb{R}^{d \times n}$ in the last fully connected layer and $b \in \mathbb{R}^n$ is the bias term. The size of minibatch and the number of class is m and n . The center loss L_c is given as:

$$L_c = \frac{1}{2} \sum_{i=1}^{m} \| x_i - c_{y_i} \|_2^2, \tag{2}$$

where c_{y_i} denotes the y_i th subject's center of features.

2.3. Identification

We adopted one-vs-all classifier to transform the classification problem of multiple users into multiple independent binary classification problems. Meanwhile, this also allows new users to be discovered. After extracting deep feature from network, we create an independent binary classifier for each user, where the identity label of that user is treated as the positive category, while the labels of other users are treated as the negative category. Sklearn [21] is used to implement one-vs-all classifier.

When a new user joins the identification system, a new classifier is created and trained based on the features of a new user and old users. Finally, this approach allows us to do identification efficiently while being adaptive and able to cope with the joining of new users.

3. Experiment and results

Two different physiological signals are discussed in experiments. The datasets used in this work, which is called BIDMC [22-23]. BIDMC is a public dataset which was acquired from critically-ill patients during hospital care at the Beth Israel Deaconess Medical Centre (Boston, MA, USA). It contains 53 recording of ECG and PPG. For each user, 80% was randomly selected for training and the remaining 20% was used for testing. We conducted the following experiments in Python using Pytorch.

Table 2. Compare identification results of old users based on ECG signals in BIDMC.

Method	Subjects	Application	Average Accuracy (%)
[11]	12	verification	97.2
[17]	40	identification	97.4
[16]	15	identification	98.66
Ours	12	identification	**99.52**

Table 3. Compare identification results of old users based on PPG signals in BIDMC.

Method	Subjects	Application	Average Accuracy (%)
[12]	12	verification	98
[9]	38	identification	89.48
[24]	50	identification	98.88
Ours	12	identification	**99.30**

Table 2 and Table 3 compares the results in old users among our method and other works based on ECG and PPG signals. We trained the network to get the feature extractor in the case of 12 subjects. We achieved the average accuracy of 99.52% based on ECG and accuracy of 99.3% based on PPG. We also test the method on a new user's discovering and identification. Table 4 shows the average accuracy of discovering and identifying a new user based on old users. In summary, our method achieves good results on ECG and PPG signals.

Table 4. The test accuracies on discovering and identifying a new user. "Discover a New User" denotes the percentage of an untrained user discovered as a new user. "Identify a New User" denotes the average accuracy of reidentifying a new user after retrain classifier.

Signals	Discover a New User	Identify a New User
ECG	97.14	93.18
PPG	95.37	91.23

4. Conclusions

In this paper, we propose a physiological signal-based method to discover and identify a new user. The Transformer-LSTM network is trained as the feature extractor, and one-vs-all classifier is used to identify old users and discover a new user. Besides, we can update one-vs-all classifier by features of the new user to identify. We evaluated the performance of discovering and identifying based on ECG signal and PPG signal. The results demonstrate that our proposed method is applicable for multiple physiological signals from wearable devices.

Acknowledgment

This work is supported in part by the National Natural Science Foundation of China (No. 61976047), in part by the Science & Technology Department of Sichuan Province of China (No. 2022YFG0184, No. 2023YFG0055, 2023YFG0270 and 2023NSFSC0518), in part by Open Fund of Key Laboratory of Flight Techniques and Flight Safety, CAAC (No. FZ2022KF14), in part by Sichuan University West China Nursing Discipline Development Special Fund Project (No. HXHL21004), and in part by the Health Department of Sichuan Province of China (No. GBKT23030).

References

[1] Valdes-Ramirez D, Medina-Pérez MA, Monroy R, Loyola-Gonzalez O, Rodriguez J, Morales A, Herrera F. A review of fingerprint feature representations and their applications for latent fingerprint identification: Trends and evaluation. IEEE Access. 2019; 7(1): 48484-48499, doi: 10.1109/ACCESS.2019.2909497.

[2] Garagad VG, Iyer NC. A novel technique of iris identification for biometric systems. 2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI): IEEE; c2014. p.973-978. doi: 10.1109/ICACCI.2014.6968623.

[3] Osadchy M, Pinkas B, Jarrous A, Moskovich B. Scifi-a system for secure face identification. 2010 IEEE Symposium on Security and Privacy: IEEE; c2010. p. 239-254. doi: 10.1109/SP.2010.39.

[4] Jain AK, Ross A, Prabhakar S. An introduction to biometric recognition. IEEE Transactions on Circuits and Systems for Video Technology. 2004;14(1): 4-20, doi: 10.1109/TCSVT.2003.818349.

[5] Safie SI, Soraghan JJ, Petropoulakis L. Electrocardiogram (ECG) biometric authentication using pulse active ratio (PAR). IEEE Transactions on Information Forensics and Security. 2011 Dec; 6(4): 1315-1322, doi: 10.1109/TIFS.2011.2162408.

[6] Khalil I, Sufi F. Legendre polynomials based biometric authentication using QRS complex of ECG. 2008 International Conference on Intelligent Sensors, Sensor Networks and Information Processing: IEEE; c2008. p. 297-302. doi: 10.1109/ISSNIP.2008.4762003.

[7] Gu YY, Zhang Y, Zhang YT. A novel biometric approach in human verification by photoplethysmographic signals. 4th International IEEE EMBS Special Topic Conference on Information Technology Applications in Biomedicine: IEEE; c2003. p. 13-14. doi: 10.1109/ITAB.2003.1222403.

[8] Spachos P, Gao J, Hatzinakos D. Feasibility study of photoplethysmographic signals for biometric identification. 2011 17th International Conference on Digital Signal Processing (DSP): IEEE; c2011. p. 1-5. doi: 10.1109/ICDSP.2011.6004938.

[9] Walia A, Kaul A. Human recognition via PPG signal using temporal correlation. 2019 5th International Conference on Signal Processing, Computing and Control (ISPCC): IEEE; c2019. p. 144-147. doi: 10.1109/ISPCC48220.2019.8988419.

[10] Kavsaoğlu AR, Polat K, Bozkurt MR. A novel feature ranking algorithm for biometric recognition with PPG signals. Comput Biol Med. 2014 Jun; 49:1-14, doi: 10.1016/j.compbiomed.2014.03.005.

[11] Wübbeler G, Stavridis M, Kreiseler D, Bousseljot RD, Elster C. Verification of humans using the electrocardiogram. Pattern Recognition Letters. 2007; 28(10):1172-1175, doi: 10.1016/j.patrec.2007.01.014.

[12] Everson L, Biswas D, Panwar M, Rodopoulos D, Acharyya A, Kim CH, Van Hoof C, Konijnenburg M, Van Helleputte N. Biometricnet: Deep learning based biometric identification using wrist-worn ppg. 2018 IEEE International Symposium on Circuits and Systems (ISCAS: IEEE; c2018. p. 1–5. doi: 10.1109/ISCAS.2018.8350983.

[13] Biswas D, Everson L, Liu M, Panwar M, Verhoef BE, Patki S, Kim CH, Acharyya A, Van Hoof C, Konijnenburg M, Van Helleputte N. CorNET: Deep learning framework for ppg-based heart rate estimation and biometric identification in ambulant environment. IEEE Trans Biomed Circuits Syst. 2019

Apr;13(2):282-291, doi: 10.1109/TBCAS.2019.2892297.
[14] Hwang DY, Hatzinakos D. PPG-based personalized verification system. 2019 IEEE Canadian Conference of Electrical and Computer Engineering (CCECE): IEEE; c2019. p. 1-4. doi: 10.1109/CCECE43985.2019.9052394.
[15] Sharma LN, Dandapat S, Mahanta A. ECG signal denoising using higher order statistics in wavelet subbands. Biomedical Signal Processing and Control. 2010; 5(3):214-222, doi: 10.1016/j.bspc.2010.03.003.
[16] Ammour N, Jomaa RM, Islam MS, Bazi Y, Alhichri H, Alajlan N. Deep contrastive learning-based model for ecg biometrics. Applied Sciences. 2023;13: 3070, doi: 10.3390/app13053070.
[17] Jyotishi D, Dandapat S. An ECG biometric system using hierarchical lstm with attention mechanism. IEEE Sensors Journal. 2022 March; 22(6): 6052-6061, doi: 10.1109/JSEN.2021.3139135.
[18] Ye Y, Xiong G, Wan Z, Pan T, Huang Z. PPG-based biometric identification: discovering and identifying a new user. 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC):IEEE; c2021. p. 1145-1148. doi: 10.1109/EMBC46164.2021.9630883.
[19] Xiong G, Ye Y, Lu L, Dong Q, Zhang B. A stable PPG-based biometric method using dynamic time warping and deep learning. 2021 3rd International Academic Exchange Conference on Science and Technology Innovation (IAECST): IEEE; c2021. p. 517-520. doi: 10.1109/IAECST54258.2021.9695870.
[20] Wen Y, Zhang K, Li Z, Qiao Y. A discriminative feature learning approach for deep face recognition. Computer Vision–ECCV 2016: 14th European Conference: Springer International Publishing; c2016. p. 499–515. doi: 10.1007/978-3-319-46478-731.
[21] Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, Blondel M, Prettenhofer P, Weiss R, Dubourg V, Vanderplas J, Passos A, Cournapeau D, Brucher M, Perrot M, Duchesnay É. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research. 2011; 12: 2825–2830, doi:10.48550/arXiv.1201.0490.
[22] Pimentel MAF, Johnson AEW, Charlton PH, et al. Toward a robust estimation of respiratory rate from pulse oximeters. IEEE Transactions on Biomedical Engineering. 2017 Aug;64(8):1914-1923, doi: 10.1109/TBME.2016.2613124.
[23] Goldberger A, Amaral L, Glass L, et al. PhysioNet: Components of a new research resource for complex physiologic signals. Circulation. 2000 Jun;101(23): E215-20, doi: 10.1161/01.cir.101.23. e215.
[24] Wang K, Chen X. PPG signal identification method based on CSASVM. 2019 IEEE 10th International Conference on Software Engineering and Service Science (ICSESS): IEEE; c2019. p. 1-4. doi: 10.1109/ICSESS47205.2019.9040765.