Biometric Recognition of PPG Cardiac Signals Using Transformed Spectrogram Images

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Abstract. Nowadays, the number of mobile, wearable, and embedded devices integrating sensors for acquiring cardiac signals is constantly increasing. In particular, plethysmographic (PPG) sensors are widely diffused thanks to their small form factor and limited cost. For example, PPG sensors are used for monitoring cardiac activities in automotive applications and in wearable devices as smartwatches, activity trackers, and wristbands. Recent studies focused on using PPG signals to secure mobile devices by performing biometric recognitions. Although their results are promising, all of these methods process PPG acquisitions as one-dimensional signals. In the literature, feature extraction techniques based on transformations of the spectrogram have been successfully used to increase the accuracy of signal processing techniques designed for other application scenarios. This paper presents a preliminary study on a biometric recognition approach that extracts features from different transformations of the spectrogram of PPG signals and classifies the obtained feature representations using machine learning techniques. To the best of our knowledge, this is the first study in the literature on biometric systems that extracts features from the spectrogram of PPG signals. Furthermore, with respect to most of the state-of-the-art biometric recognition techniques, the proposed approach presents the advantage of not requiring the search of fiducial points, thus reducing the computational complexity and increasing the robustness of the signal preprocessing step. We performed tests using a dataset of samples collected from 42 individuals, obtaining an average classification accuracy of 99.16% for identity verification (FMR of 0.56% at FNMR of 13.50%), and a rank-1 identification error of 7.24% for identification. The results obtained for the considered dataset are better or comparable with respect to the ones of the best-performing methods in the literature.

Keywords: Biometrics · PPG · Spectrogram.

1 Introduction

The wide diffusion of mobile, wearable, and embedded systems introduced the need of novel mechanisms to protect the access to their data using user friendly recognition technologies. Therefore, biometrics are playing a primary role in this scenario thanks to their capability of recognizing people from physiological or behavioral characteristics. As an example, most of the current mobile devices and smartphones integrate biometric recognition sensors for face or fingerprint recognition. Anyway, the wide availability of heterogeneous sensors integrated in consumer technologies allowed the study of additional biometric recognition methods usable in conjunction or in different scenarios with respect to face and fingerprint recognition [27, 7]. In this context, cardiac signals present important advantages with respect to other biometric traits [8]: i) they are more difficult to counterfeit with respect to biometric characteristics that can be acquired using cameras; ii) they can be acquired only from living individuals; iii) they present additional information that can be used for supplementary applications (e.g., health monitoring [30] or stress level estimation [6]); they can be collected continuously for long periods of time without requiring any activity from the users since they can be acquired using wearable sensors.

Most of the studies on biometric recognition systems based on cardiac signals focus on electrocardiographic (ECG) sensors. This is due to the fact that ECG signals are widely used for clinical applications and to the availability of different public datasets of ECGs [28]. However, PPG sensors are nowadays more diffused in mobile, wearable and embedded systems with respect to ECG sensors thanks to their smaller size and inferior cost. Therefore, recent studies in the literature analyzed and proved the discriminability of PPG signals as biometric traits. Furthermore, empirical evaluations proved that PPG has sufficient stability for short periods of time [13].

The state-of-the-art methods for biometric recognition based on PPG signals can use algorithmic approaches [2, 32, 31, 35, 10], machine learning techniques based on hand-crafted features [37, 25, 22, 24, 33, 18, 19, 29, 5, 23, 14, 36], or DNNs [13, 1, 17, 26, 9]. To the best of our knowledge, all the methods in the literature process PPG signals using features directly extracted from one-dimensional representations of the signals. Furthermore, most of these methods need to extract fiducial points from the samples to compute distinctive features from PPG signals, thus performing an error-prone and computationally expensive task.

Motivated by the successful application of feature extraction techniques based on transformations of the spectrogram of other types of cardiac signals [4, 3], in this paper, we propose a preliminary study on a biometric recognition approach able to extract features from transformed spectrograms of PPG signals. The main advantage of using the proposed representation of one-dimensional signals consists of obtaining pseudo-images analyzable by a human observer, who can easily understand similitudes between genuine comparisons and differences between impostor comparisons. Another advantage of the proposed feature represention consists of the simple preprocessing method, which is more computationally ef-

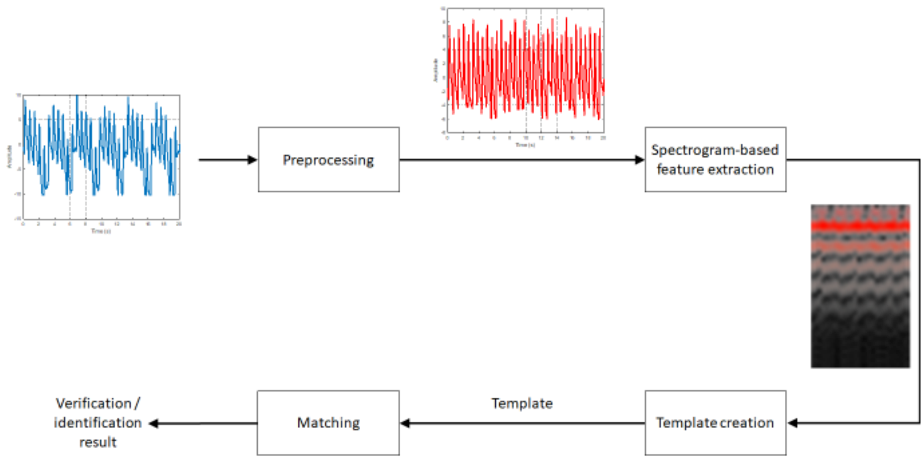

Fig. 1. Schema of the proposed approach for biometric recognition based on PPG signals. The approach uses a simpler preprocessing with respect to most of the state-of-the-art techniques, which need to detect fiducial points.

ficient and less prone to errors with respect to the algorithms commonly used to detect fiducials points.

Our proposed approach first performs a simple signal preprocessing to normalize the PPG signal. Second, it computes a specific pseudo image from the signal. Third, it extracts a template using a dimensionality reduction strategy based on the Principal Component Analysis (PCA). Finally, our approach performs an identity verification or identification using dedicated matching strategies, which are based on k-Nearest Neighbors (k-NN) and ensembles of Support Vector Machines (SVM). Fig. 1 shows the schema of the proposed approach.

We validated the proposed approach using the publicly available dataset CapnoBase PRRB [20, 21], including signals collected from 42 individuals. We achieved an average classification accuracy of 9.169% (FMR of 0.56% at FNMR of 13.50%) for identity verification, and a rank-1 identification error of 7.24% for identification. The results obtained for this dataset are better or comparable with respect to the ones of the best performing methods in the literature.

The paper is organized as follows. Section 2 reviews the related works on PPG-based biometric recognition. Section 3 describes the proposed approach. Section 4 presents the performed experiments and the achieved results. Section 5 concludes the work and discusses future research directions.

2 Related Works

Most of the studies in the literature on biometric recognition techniques based on PPG signals consider data acquired for clinical purposes. With the increasing diffusion of mobile devices, the number of studies on PPG biometrics using signals captured from mobile devices is also increasing. For example, the method described in [25] considers the finger placed on top of the smartphone camera to capture PPG signals. Similarly, the method proposed in [37] exploits wristbands to perform continuous biometric authentications. In the context of mobile devices, the combination of PPG signals with different biometric traits has also been investigated. As an example, the approach described in [33] combines PPG with face biometrics to ensure a more accurate liveness detection for smartphones.

It is possible to divide the methods for PPG-based biometric recognition into three categories [13]: i) methods based on algoritmic approaches [2, 32, 31, 35, 10]; ii) methods based on handcrafted features and machine learning classifiers [14, 29, 5, 18, 19, 36, 33, 37, 25, 22]; iii) methods based on DNNs [17, 26, 9, 1, 24, 13].

Methods based on algoritmic approaches usually perform a preprocessing step to enhance the PPG signal, compute a template by extracting a set of features corresponding to the distinctive characteristics of the signal, and use a correlation-based matcher to compare the templates [2]. There are also algorithmic approaches applicable to PPGs in conjunction to other cardiac signals [10]. To investigate the stability of PPG signals for biometric recognition applications, the approaches presented in [32, 31] use a correlation-based methodology to compare the performance of several feature extractors and matchers for PPG signals acquired after several days. Other methods in the literature consider correlation-based algorithms as a feature extractors, such as the method presented in [35], which uses auto-correlation and derivatives to extract a feature vector, then apply a distance-based classifier to compare templates.

Methods based on handcrafted features and machine learning usually process the PPG signal to extract a set of discriminant features, then apply a classifier based on machine learning to perform the biometric recognition. In the literature, there are several methods which differ one to each other according to the extracted features and to the used classifier. For example, the method described in [14] considers acceleration-based features computed using the derivative of the PPG signal, then applies a Bayes Network and a k-NN classifier. Similarly, the method proposed in [5] extracts features related to the derivative and frequency of the PPG signal, then applies a Linear Discriminant Analysis for classification. To investigate which features and classifiers could improve the recognition accuracy using PPG signals, the method described in [29] performs statistical analyses to extract a redundant set of features, then applies a forward feature selection algorithm. The classification is performed by comparing several methods such as k-NN, Fuzzy k-NN, and Gaussian Mixture Model. Similarly, a comparison with k-NN and other classifiers such as decision trees and SVM is also presented in [22].

Methods based on DNNs can take advantage of the capability of Convolutional Neural Networks (CNN) to automatically learn data representations. As an example, the method described in [26] proposes an end-to-end architecture for biometric recognition based on PPG signals, which uses a CNN to directly extract a discriminant representation from the raw signals and to perform

Table 1. State-of-the-art methods based on deep neural networks

Work	Method	Datasets	Performance
[13]	CNN + LSTM + individual classifiers	Biosec 1 (2 sessions for 15 individuals)	AVG ACC = 87.0%
		Biosec 2 (3 signals for 100 individuals)	AVG ACC = 87.1%
		PRRB (single session, 24 individuals)	1 ch.: AVG ACC = 99% 2 ch.: AVG ACC = 100%
[9, 1]	CNN + LSTM	TROIKA (22 signals, 12 individuals, sport)	AVG ACC = 96%
[17]	DBN + RBM	TROIKA (22 signals, 12 individuals, sport)	ACC = 96.1%
[26]	CNN with end-to-end biomarker learning	PulseID (5 signals for 43 individuals)	AUC = 78.2%
		TROIKA (22 signals, 12 individuals, sport)	AUC = 83,2%
[24]	GAN for cross-domain adaption	in-house (multiple sessions, 10 individuals)	ACC = 95.68%
		TROIKA (22 signals, 12 individuals, sport)	ACC = 89.35%

Notes: AVG ACC = avarage accuracy, ACC = accuracy, AUC = area under the curve, ch. = channel.

the classification. Similarly, a combination of CNNs with DNNs based on Long Short-Term Memory (LSTM) is proposed in [9, 1] to process and classify PPG signals captured from wrist sensors. The same CNN and LSTM combination is used in [13] to analyze the stability of PPG-based biometric information over time. Different DNNs models can also be succesfully used. As an example, the method presented in [17] is based on Deep Belief Networks (DBN) and Restricted Boltzman Machines (RBM). To address the accuracy reduction due to different acquisition sources, the method presented in [24] uses a Generative Adversarial Network (GAN).

Currently, methods based on DNNs and machine learning classifiers are achieving the best performance in terms of biometric recognition accuracy. To provide examples of the achieved accuracy, Table 1 summarizes the results achieved by recent methods based on DNNs.

While the majority of the methods in the literature use fiducial points to extract features, the approach described in [18, 19] propose non-fiducial features based on wavelet transforms, then applies FeedForward Neural Networks and SVM for classification. With a similar computational strategy, the method proposed in [36] investigates the accuracy of wavelet-based non-fiducial features in the case of PPG signals captured in different mental states.

3 Proposed Approach

Our proposed approach can be applied for identity verification as well as for identification. It takes in input a PPG signal s of fixed time duration of t seconds. Our method extracts features from different transformations of the spectrogram of PPG signals, performs biometric recognitions without needing to extract fiducial points, and computes the matching phase by using machine learning classiers. Fig. 1 shows the schema of the method, which can be divided into the following steps:

1. signal preprocessing,
2. spectrogram-based feature extraction,
3. template creation,
4. matching.

3.1 Signal preprocessing

The proposed approach uses a simple preprocessing technique, by only applying a bandpass filter to the signal s, as performed by most of the state-of-the-art algorithms for processing PPG signals. Specifically, it applies a second order high-pass Butterworth filter and a sixth order low-pass Butterworth filter, with cutoff frequencies f_h and f_l, respectively.

3.2 Spectrogram-based feature extraction

In this subsection, we describe the proposed algorithm for extracting features from different transformations of the spectrogram of PPG signals. Our approach computes the spectrogram of the filtered signal x to obtain a specific single-channel image I showing distinctive characteristics of the individuals in the frequency and time domain.

A spectrogram is a visual representation of the spectrum of frequencies of a signal as it varies with time. The spectrogram can be defined as an intensity plot of the squared magnitude of the Short-Time Fourier Transform (STFT) magnitude [34]. The STFT is a sequence of FFTs of windowed data segments, where the windows are usually allowed to overlap in time. More formally, given a signal x of duration N, consecutive segments of x of length m (where $m \ll N$). Let $X \in \mathbb{R}^{m \times (N-m+1)}$. As an example, $[x(0), x(1), \ldots, x(m-1)]^T$ is the first column, while $[x(1), x(2), \ldots, x(m)]^T$ is the second column. The rows as well as the columns of X are indexed by time. Hence, the STFT of the input signal $\hat{X}$ is defined as:

$$\hat{X} = \bar{F}X, \tag{1}$$

$$X = (1/m)F\hat{X}, \tag{2}$$

where $\bar{F}$ is the complex conjugate of F, and F is the Fourier matrix. In our case, we use slinding windows of size m and overlap o_m.

The STFT of the input signal x is composed of complex numbers. Therefore, a common way to obtain a two dimensional image to be further processed consists of computing a gray-scale representation as the logarithm of the power spectral density. However, this representation of PPG signals is not producing the highest accuracy if directly applied for biometric recognition approaches. In the proposed approach, taking as example specific methods used to plot spectrograms using pseudo images in audio processing applications, we create three different channels from the spectrogram. In order to improve the final accuracy, we compute a pseudo image I_p composed of three channels (A, B, C) as follows.

For each row r of $\hat{X}$, we compute $A(i)$ as follows:

$$A(i) = f/f_{max}, \tag{3}$$

where f represents the cyclical frequencies, and f_{max} is the maximum value of f.

We compute the chanel B as follows:

$$B = L/L_{max}, \tag{4}$$

$$L = \log_{10}\left(1 + 10 \times (P'_s)\right), \tag{5}$$

$$P' = (P - P_{min})/(P_{max} - P_{min}), \tag{6}$$

where P is power spectral density or the power spectrum of each segment, P_{min} is the minimum value of P, P_{max} is the maximum value of P, and L_{max} is the maximum value of L.

We compute the chanel C as follows:

$$C = \left[(P - P_{min})/(P_{max} - P_{min})\right]^{0.2}. \tag{7}$$

To further improve the final accuracy, a second transformation can be profitable. Therefore, we evaluated different channel transformations, obtaining the best results by computing a pseudo image I_s representing I_p after converting it from the HSV color space to the RGB color space. Figure 2 shows examples of images I_s obtained from samples acquired from two individuals. It is possible to observe that the patterns of the images obtained from samples of the same individual are similar one to each other, while images computed from samples of different individuals present local differences one to each other.

With the aims of improving the final recognition accuracy and of reducing the dimensionality of the final feature vectors, we explored the possibility of reducing the number of channels. We obtained the best results using the first channel of I_s. Therefore, in the following, we will refer to the first channel of I_s as the single channel image I, and we use this image as the input of the subsequent step of the proposed method.

3.3 Template creation

Our approach computes a vector V composed of n_f floating point numbers representing the biometric template. In particular, from the image I, the proposed

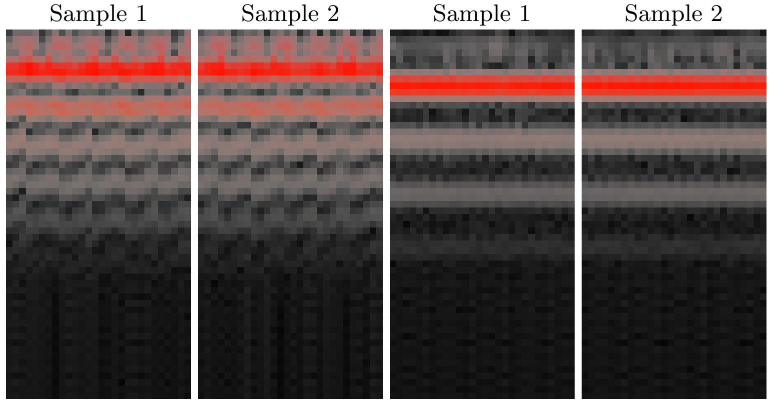

Fig. 2. Examples of images I_s obtained from samples acquired from two individuals. It is possible to observe that the patterns of the images obtained from samples of the same individual are similar one to each other, while images computed from samples of different individuals present local differences one to each other.

method computes V as the vector of scores obtained from the first n_c coefficients of a PCA processed from the vector of intensity values of the image I. The PCA coefficients are computed using all the samples of a training set. The samples of every enrolled individual are therefore used to compute PCA coefficients to be used for every fresh sample. In this preliminary study, the PCA coefficients should therefore be updated for each new user enrollment.

3.4 Matching

Our approach use different strategies for identity verification and identification.

Identity verification The identity verification strategy aims at confirming or denying the identity declared by the user from the analysis of a template V. To this purpose, we use a binary classifier for each individual enrolled in the gallery. The output of every classifier is equal to 0 and 1 for impostor and genuine comparisons, respectively. Then, for each identity verification attempt, the user declares that her identity corresponds to the enrolled individual i and then only the classifier c_i is used to check if the template V corresponds to the declared identity. We use SVMs since they can provide relatively robust classification results when applied to imbalanced data sets [12]. The proposed approach can perform open set identity verifications since it does not assume that fresh samples correspond to any identity enrolled in the gallery database. However, in this preliminary study, a classifier should be created and trained for each new user enrollment.

Identification The identification strategy aims at searching the enrolled identity corresponding to the template V using only the knowledge-base of the biometric system. Therefore, having a set of n_i identities enrolled in the gallery, we consider the identification task as a classification problem with n_i classes. From the wide set of machine learning classifiers in the literature, we chose to adopt kNN and ensembles of SVMs due to their capability of dealing with problems characterized by high numbers of classes. In particular, we use ensembles of binary SVM classifiers with a voting strategy based on the error-correcting output codes model [11]. In this preliminary study, the SVM classifiers should be created and trained for each new user enrollment.

4 Experimental Results

We experimentally evaluated the performance of the proposed approach for identity verification as well for identity verification scenarios, comparing the obtained results with that of recent state-of-the-art biometric recognition techniques.

We evaluated the performance of the proposed approach using a publicly available dataset, CapnoBase PRRB [20, 21]. This dataset has been collected in a single session and is composed of PPG signals acquired from 42 subjects (29 children and 13 adults). The acquisitions have been performed by physicians in monitored conditions. The sampling rate is equal to 300 Hz and the duration of every acquisition is 8 minutes. We considered only the first PPG channel.

Our approach uses fixed length signals of t seconds as input. We estimated that $t = 20$ is a good tradeoff between the system usability and the amount of information usable to compute discriminative features. Therefore, we divided the CapnoBase PRRB dataset into non-overlapping samples of 20 seconds, obtaining 24 signals per individual, for a total of 1008 samples.

We used different figures of merit to evaluate the accuracy of the proposed method for identity verification and identification. Specifically, for the identity verification scenario we used figures of merit typically adopted to evaluated the performance of biometric recognition systems, as False Match Rate (FMR), and False Non Match Rate (FNMR) [15]. Width the aim of simplifying the comparison of the achieved performance with that of recent methods in the literate based on DNNs [13, 9, 1, 17, 24], we also computed the average classification accuracy. For the identification scenario, we used the rank-1 error [16].

For identity verification, as well as for identification, we validated the performance of the proposed approach using a k-fold cross-validation technique performing the selection of the test set by considering samples contiguous in time. Having a dataset composed of n_i samples per individual, for each iteration i, we create a testing set composed of n_i/k samples contiguous in time by starting from the $(i - 1) \times (n_i/k) + 1$ th sample. For each fold i, we computed the PCA coefficients and trained the proposed matchers by using the i th training set. We considered $k = 2$ and $k = 8$.

We implemented all the methods using Matlab 2020b. The operating system was Windows 10 professional 64 bit.

We set the parameters of the Butterworth pass-band filter used for the signal preprocessing as $f_h = 50$ Hz and $f_l = 90$ Hz. This configuration is used by many state-of-the-art methods for processing PPG signals.

We analyzed the performance of the proposed approach by varying the parameters m and o_m used to compute the spectrograms. The values considered for m are 150, 300, 450, 600, 750, and 900. The values considered for o_m are 50, 100, 150, 200, 250, 300, 350, 400, 450, and 500. We achieved the best results using $m = 600$ and $o_m = 400$. Similarly, we evaluated the performance of the proposed approach by varying the number of PCA coefficients used to compute the templates, achieving the best results with $n_c = 10$.

4.1 Identity verification accuracy

We computed the accuracy of the proposed identity verification strategy for the CapnoBase PRRB dataset by performing a 2-fold cross-validation and a 8-fold cross-validation. Table 2 resumes the achieved results.

Table 2 shows that the obtained FMR is particularly low, thus showing a great robustness of the biometric recognition method to impostor attacks. The achieved FNMR, however could imply multiple authentication attempts from the users, but can be considered as satisfactory for a wide set of applications. Furthermore, the results show that the performance achieved using the 2-fold cross-validation and 8-fold cross-validation are comparable, thus proving the capability of the proposed identity verification approach of learning from a limited number of training samples.

As a reference, we computed the performance of the correlation-based method presented in [2] for the same dataset and by using the same time partitioning strategy. The method presented in [2] obtaining an Equal Error Rate [15] of 14.7% and FMR at FNMR = 1% equal to 93.62%. Our proposed method clearly outperforms the compared algorithm.

As a further comparison, the method based on deep learning presented in [13] reports an average classification accuracy of 99% for the CapnoBase PRRB dataset. It should be considered that the method proposed in [13] used a different time division of the signals and a different validation protocol with respect to the ones adopted in this work. Anyway, the obtained results prove that the proposed approach can achieve better or comparable accuracy with respect to the best performing state-of-the-art methods for the considered dataset.

4.2 Identification accuracy

We computed the accuracy of the proposed identity verification strategy for the CapnoBase PRRB dataset by performing a 2-fold cross-validation and a 8-fold cross-validation. Table 3 resumes the achieved results.

Table 3 shows that the identification accuracy of the proposed approach can be sufficient for heterogenous applications, with the best rank-1 error equal to 7.24%. Furthermore, the ensembles of SVMs achieved better performance

Table 2. Identity verification accuracy

Validation strategy	Average Accuracy (%)	FMR (%)	FNMR (%)
2-fold cross-validation	99.03	0,73	12.87
8-fold cross-validation	99.16	0.56	13.50

Table 3. Identification accuracy

Validation strategy	Classifier	Rank-1 Error (%)
2-fold cross-validation	k-NN (1-NN)	11.11
2-fold cross-validation	SVM	10.32
8-fold cross-validation	k-NN (1-NN)	8.93
8-fold cross-validation	SVM	7.24

with respect to k-NN classifiers. However, the performance achieved for the 8-fold cross-validation test are better than the ones achieved for the 2-fold cross-validation test, proving the need for a greater number of samples for training the proposed identification method to further improve its accuracy.

5 Conclusions

This paper presented a preliminary study on extracting features from different transformations of the spectrogram of PPG signals for biometric recognition. The proposed biometric recognition method classifies the obtained feature representations using machine learning techniques. To the best of our knowledge, this is the first study in the literature proposing the use of two-dimensional representations for biometric recognition systems based on PPG signals. Furthermore, with respect to most of the state-of-the-art techniques, the proposed approach presents the advantage of not needing to extract fiducial points. We validated our method for a dataset of 42 individuals acquired for 8 minutes, and tested it in k-fold cross-validation. Our approach achieved average classification accuracy of 99.16% for identity verification (FMR of 0.56% at FNMR of 13.50%), and rank-1 error of 7.24%. The results achieved for the considered dataset are better or comparable with respect to the ones of the best performing state-of-the-art techniques. Further studies should consist of designing more robust classification strategies and evaluating the performance in heterogeneous conditions. Since in this preliminary study we only considered a single session dataset acquired in controlled physical conditions, future work should also consider bigger datasets acquired in challenging and less-constrained conditions.

References

1. Biswas, D., Everson, L., Liu, M., Panwar, M., Verhoef, B., Patki, S., Kim, C.H., 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. on Biomedical Circuits and Systems **13**(2), 282–291 (2019)
2. Bonissi, A., Donida Labati, R., Perico, L., Sassi, R., Scotti, F., Sparagino, L.: A preliminary study on continuous authentication methods for photoplethysmographic biometrics. In: Proc. of the 2013 IEEE Workshop on Biometric Measurements and Systems for Security and Medical Applications (BioMS). pp. 28–33 (2013)
3. Byeon, Y., Pan, S., Kwak, K.: Ensemble deep learning models for ECG-based biometrics. In: Proc. of the 2020 Cybernetics Informatics (K I). pp. 1–5 (2020)
4. Byeon, Y.H., Kwak, K.C.: Pre-configured deep convolutional neural networks with various time-frequency representations for biometrics from ECG signals (2019)
5. Chakraborty, S., Pal, S.: Photoplethysmogram signal based biometric recognition using linear discriminant classifier. In: Proc. of the 2016 2nd Int. Conf. on Control, Instrumentation, Energy Communication (CIEC). pp. 183–187 (2016)
6. Chauhan, U., Reithinger, N., Mackey, J.R.: Real-time stress assessment through PPG sensor for VR biofeedback. In: Proc. of the 20th Int. Conf. on Multimodal Interaction: Adjunct (2018)
7. Donida Labati, R., Genovese, A., Piuri, V., Scotti, F.: A Scheme for Fingerphoto Recognition in Smartphones, pp. 49–66. Springer International Publishing, Cham (2019)
8. Donida Labati, R., Muñoz, E., Piuri, V., Sassi, R., Scotti, F.: Deep-ECG: Convolutional neural networks for ECG biometric recognition. Pattern Recognition Letters **126**, 78–85 (2019)
9. Everson, L., Biswas, D., Panwar, M., Rodopoulos, D., Acharyya, A., Kim, C.H., Van Hoof, C., Konijnenburg, M., Van Helleputte, N.: BiometricNet: Deep learning based biometric identification using wrist-worn PPG. In: Proc. of the 2018 IEEE Int. Symp. on Circuits and Systems (ISCAS). pp. 1–5 (2018)
10. Faragó, P., Groza, R., Ivanciu, L., Hintea, S.: A correlation-based biometric identification technique for ECG, PPG and EMG. In: Proc. of the 2019 42nd Int. Conf. on Telecommunications and Signal Processing (TSP). pp. 716–719 (2019)
11. Fürnkranz, J.: Round robin classification. J. Mach. Learn. Res. **2** (March, pages = 721–747, 2002)
12. He, H., Garcia, E.A.: Learning from imbalanced data. IEEE Transactions on Knowledge and Data Engineering **21**(9), 1263–1284 (2009)
13. Hwang, D.Y., Taha, B., Lee, D.S., Hatzinakos, D.: Evaluation of the time stability and uniqueness in PPG-based biometric system. IEEE Trans. on Information Forensics and Security **16**, 116–130 (2021)
14. Jaafar, N.A.L., Sidek, K.A., Mohd Azam, S.N.A.: Acceleration plethysmogram based biometric identification. In: Proc. of the 2015 Int. Conf. on BioSignal Analysis, Processing and Systems (ICBAPS). pp. 16–21 (2015)
15. Jain, A.K., Flynn, P., Ross, A.A.: Handbook of Biometrics. Springer Publishing Company, Incorporated, 1st edn. (2010)
16. Jang, J., Kim, H.: Performance Measures, pp. 1062–1068. Springer US, Boston, MA (2009)
17. Jindal, V., Birjandtalab, J., Pouyan, M.B., Nourani, M.: An adaptive deep learning approach for PPG-based identification. In: Proc. of the 2016 38th Annual Int. Conf.

of the IEEE Engineering in Medicine and Biology Society (EMBC). pp. 6401–6404 (2016)
18. Karimian, N., Guo, Z., Tehranipoor, M., Forte, D.: Human recognition from photoplethysmography (PPG) based on non-fiducial features. In: Proc. of the 2017 IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP). pp. 4636–4640 (2017)
19. Karimian, N., Tehranipoor, M., Forte, D.: Non-fiducial PPG-based authentication for healthcare application. In: Proc. of the 2017 IEEE EMBS Int. Conf. on Biomedical Health Informatics (BHI). pp. 429–432 (2017)
20. Karlen, W., Raman, S., Ansermino, J.M., Dumont, G.A.: Multiparameter respiratory rate estimation from the photoplethysmogram. IEEE Trans. on Bio-Medical Engineering **60**(7), 1946–53 (2013)
21. Karlen, W., Turner, M., Cooke, E., Dumont, G., Ansermino, J.M.: CapnoBase: Signal database and tools to collect, share and annotate respiratory signals. In: Annual Meeting of the Society for Technology in Anesthesia (STA). West Palm Beach (2010)
22. Khan, M.U., Aziz, S., Hassan Naqvi, S.Z., Zaib, A., Maqsood, A.: Pattern analysis towards human verification using photoplethysmograph signals. In: Proc. of the 2020 Int. Conf. on Emerging Trends in Smart Technologies (ICETST). pp. 1–6 (2020)
23. Lee, A., Kim, Y.: Photoplethysmography as a form of biometric authentication. In: Proc. of the 2015 IEEE SENSORS. pp. 1–2 (2015)
24. Lee, E., Ho, A., Wang, Y., Huang, C., Lee, C.: Cross-domain adaptation for biometric identification using photoplethysmogram. In: Proc. of the 2020 IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP). pp. 1289–1293 (2020)
25. Lovisotto, G., Turner, H., Eberz, S., Martinovic, I.: Seeing red: PPG biometrics using smartphone cameras. In: Proc. of the 2020 IEEE/CVF Conf. on Computer Vision and Pattern Recognition Workshops (CVPRW). pp. 3565–3574 (2020)
26. Luque, J., Cortès, G., Segura, C., Maravilla, A., Esteban, J., Fabregat, J.: END-to-END Photopleth YsmographY (PPG) based biometric authentication by using Convolutional Neural Networks. In: Proc. of the 2018 26th European Signal Processing Conf. (EUSIPCO). pp. 538–542 (2018)
27. Maiorana, E., Campisi, P., Gonzalez-Carballo, N., Neri, A.: Keystroke dynamics authentication for mobile phones. In: Proc. of the 2011 ACM Symp. on Applied Computing. p. 21–26 (2011)
28. Merone, M., Soda, P., Sansone, M., Sansone, C.: ECG databases for biometric systems: A systematic review. Expert Systems with Applications **67**, 189 – 202 (2017)
29. Namini, S.P.M., Rashidi, S.: Implementation of artificial features in improvement of biometrics based PPG. In: Proc. of the 2016 6th Int. Conf. on Computer and Knowledge Engineering (ICCKE). pp. 342–346 (2016)
30. Rundo, F., Conoci, S., Ortis, A., Battiato, S.: An advanced bio-inspired photoplethysmography (PPG) and ECG pattern recognition system for medical assessment. Sensors **18**(2) (2018)
31. Sancho, J., Alesanco, A., Garca, J.: Photoplethysmographic authentication in long-term scenarios: a preliminary assessment. In: Eskola, H., Väisänen, O., Viik, J., Hyttinen, J. (eds.) EMBEC & NBC 2017. pp. 1085–1088 (2018)
32. Sancho, J., Iglesias, Á.A., García, J.: Biometric authentication using the PPG: A long-term feasibility study. Sensors **18**(5), 1525 (2018)

33. Spooren, J., Preuveneers, D., Joosen, W.: PPG2Live: Using dual PPG for active authentication and liveness detection. In: Proc. of the 2019 Int. Conf. on Biometrics (ICB). pp. 1–6 (2019)
34. Tan, L., Jiang, J.: Digital Signal Processing: Fundamentals and Applications. Elsevier Science (2018)
35. Walia, A., Kaul, A.: Human recognition via PPG signal using temporal correlation. In: Proc. of the 2019 5th Int. Conf. on Signal Processing, Computing and Control (ISPCC). pp. 144–147 (2019)
36. Yadav, U., Abbas, S.N., Hatzinakos, D.: Evaluation of PPG biometrics for authentication in different states. In: Proc. of the 2018 Int. Conf. on Biometrics (ICB). pp. 277–282 (2018)
37. Zhao, T., Wang, Y., Liu, J., Chen, Y., Cheng, J., Yu, J.: TrueHeart: Continuous authentication on wrist-worn wearables using PPG-based biometrics. In: Proc. of the IEEE Conf. on Computer Communications (INFOCOM). pp. 30–39 (2020)