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Photoplethysmographic Biometrics: a Comprehensive Survey

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ABSTRACT

The wide diffusion of wearable sensors and mobile devices encouraged the study of biometric recognition techniques that require a low level of cooperation from users. Among them, the analysis of cardiac information extracted from plethysmographic (PPG) signals is attracting the research community due to the possibility of performing continuous authentications using low-cost devices that can acquire signals without any action required from the users. Although PPG-based biometric systems are relatively recent technologies, machine learning techniques and deep learning strategies have shown accuracy in heterogeneous application scenarios. This paper presents the first literature review of PPG-based biometric recognition approaches. First, we describe the application contexts suitable for PPG-based biometrics. Second, we analyze the systems in the literature, describe the acquisition sensors, and present a classification of the processing methods. Third, we summarize the available public datasets and the results achieved by recent state-of-the-art approaches. Finally, we analyze the open problems in this research field.

1. INTRODUCTION

The wide availability of heterogeneous sensors integrated in wearable and mobile devices encouraged the study of additional biometric recognition methods with respect to the best-known methods (e.g., face, fingerprint, and iris) [1, 2]. These recent recognition modalities can be used in conjunction with other biometric technologies to increase the robustness of the recognition system [3] or can be designed for specific application scenarios [4].

In this context, the interest of the research community in heart biometrics (also referred to as cardiac biometrics) is constantly increasing. Heart biometric systems aim to recognize individuals from the analysis of cardiac signals noninvasively measured through the surface of the human body. These signals consist of waveforms providing information on heart activity and can be acquired using heterogeneous technologies based on different physical measurements [5]. Examples of cardiac signals suitable for biometric recognition are the electrocardiogram (ECG), photoplethysmogram (PPG), seismocardiogram (SCG), and phonocardiogram (PCG).

With respect to other biometric characteristics widely used in current identity recognition systems, cardiac signals present relevant advantages [6] because they:

- are more difficult to counterfeit with respect to physiological characteristics acquired using digital cameras since physiological signals can only be acquired using dedicated technologies;
- can be acquired only from living individuals, thus reducing the need to include vitality check strategies in biometric recognition systems;
- present additional information related to physiological, behavioral, and emotional conditions, which can be used for complementary applications;
- can be acquired for long periods of time without requiring any form of collaboration from the users, and are thus particularly suitable for continuous authentication systems.

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This paper focuses on PPG signals. PPG is a noninvasive technique for measuring blood perfusion through tissues by the emission of light rays [7]. PPG-based biometric recognition systems present relevant advantages with respect to other heart biometrics since the acquisition sensors are usually smaller, less expensive, and frequently integrated in wearable and mobile consumer devices.

PPG-based biometric systems are suitable for a wide set of applications including those in which the signals are already acquired and processed for different purposes, such as health monitoring and fitness. PPG-based biometric systems can acquire PPG signals using heterogeneous sensors in devices such as medical instruments, wearables, smartphones, and digital cameras. The biometric recognition process can be based on algorithmic approaches or computational intelligence techniques. The results reported in the literature proved that PPG has sufficient discriminability and stability for a great variety of biometric applications.

This paper presents the first literature review of PPG-based biometric systems. Most of the literature reviews on heart biometrics only treat ECG signals [8, 9, 10]. Furthermore, general surveys on heart biometrics [5, 11] do not describe the characteristics and processing schemas of PPG-based biometric systems.

This paper is organized as follows. Section 2 discusses application scenarios suitable for PPG-based biometric recognition. Section 3 describes the techniques usable to acquire PPG signals. Section 4 presents the processing methods used by PPG-based biometric systems in the literature. Section 5 analyzes the results of state-of-the-art techniques. Section 6 discusses open problems. Section 7 concludes the work.

2. Application scenarios

Biometric systems based on PPG signals can be suitable for access control applications in physical and digital contexts. As an example, a PPG-based biometric system based on a wearable bracelet could be used to open a car as well as log in with a smartphone without requiring any cooperation from the user. Furthermore, biometric recognition systems based on PPG signals can adopt sensors already used for other applications and thus have limited economic impact for a great variety of applications. As an example, PPG acquisition sensors integrated in wearable devices are frequently used for health monitoring [12] or for fitness purposes [13]. PPG acquisition sensors can also be integrated in the steering wheel of a car to evaluate the attention level of the driver [14]. Furthermore, cameras integrated in smartphones can be used to infer PPG signals to obtain health-related information [15]. In the context of mobile devices, PPG signals can be used to perform multimodal biometric recognition, for example, by combining PPG and face characteristics [16]. Biometric systems based on signlas inferred from videos could also be integrated into assistive robots such as Nao Robot [17] and Pepper Robot [18]. This creates possibilities in healthcare and elderly assistance, other than playing an essential role in social engineering.

PPG-based biometric systems in the literature can perform different biometric recognition tasks.

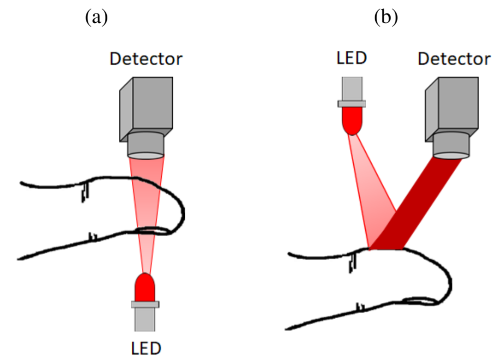

Fig. 1. Schematic of functioning principles of photoplethysmography sensors: a) light transmission and b) light reflection.

- **Verification**: two samples are compared to confirm or deny the claimed identity. All algorithmic matchers for PPG-based biometric recognition [19, 20, 21, 22, 23] and a limited number of systems based on computational intelligence [24, 25, 26, 27] are designed for identity verification.
- **Closed-set identification**: the identity corresponding to a sample is searched in a biometric database. Most of the computational intelligence approaches in the literature [28, 29, 30, 31, 4, 32, 33] are designed for closed-set identification.
- **Continuous authentication**: the system periodically verifies the identity of the subject. Since wearable sensors can acquire PPG signals continuously over time without requiring any action from the user, PPG signals are particularly suitable for designing user-friendly continuous authentication techniques.

3. Acquisition

PPG signals are usually acquired by using sensors placed in contact with the skin surface. These sensors measure the amount of infrared light absorbed or reflected by blood. The acquired signals represent the volume changes of blood vessels, which occur throughout the cardiac cycle [34]. PPG sensors can be classified according to their functioning principles into two categories: sensors based on light transmission and sensors based on light reflection [7]. For the first class of sensors, the LED light that passes through absorbent substances (the skin, bone, arterial blood, and venous blood) is received by the detector and quantified by filters and converters. For the second class of sensors, the light reflected over the skin is received by the detector and quantified by filters and converters. A sensor based on light reflection can therefore be used for a wide set of body parts. Regardless of the functioning principle, PPG sensors are designed to be portable, lightweight, low cost, and comfortable for users. Fig. 1 shows a schema of the two classes of photoplethysmography sensors.

PPG signals can be measured from several sites that have a rich arterial source. Examples of possible placements of

PPG sensors are the fingers [35], forehead [36], wrist [37] and ear [38]. The consumer market is therefore taking advantage of this characteristic, integrating PPG sensors in wearable devices such as smart bracelets, smart watches, wristbands, headphones, and earphones.

There are also techniques aiming at inferring signals similar to those acquired using touch-based PPG sensors from videos captured by using commercial cameras [39]. These techniques are called remote optical PPG imaging methods, and the obtained signals are commonly called remote PPGs (R-PPGs). The videos can be collected from body parts such as the face [40, 41] or fingertips [42].

4. Biometric recognition methods

Most biometric recognition systems that use PPG signals are based on acquisitions performed using medical sensors or wearable devices. There have been preliminary studies on techniques based on R-PPG signals [40, 41, 42]. Since R-PPG signals present relevant differences with respect to PPG signals acquired using contact-based sensors, we separately describe biometric systems based on PPG and R-PPG signals.

4.1. Biometric recognition based on PPG signals

The computational chain of biometric recognition systems based on PPG signals usually consists of the following steps: preprocessing, feature extraction, and matching. The preprocessing techniques are similar in most of the studies in the literature, while the feature extraction and matching steps present relevant differences. According to the feature extraction and matching methods, state-of-the-art biometric recognition systems can be classified into algorithmic-based approaches and approaches based on computational intelligence techniques.

4.1.1. Preprocessing

The preprocessing step consists of two main tasks: sample extraction and signal enhancement.

Since most of the feature extraction techniques in the literature require an input of fixed length, the sample extraction task aims at obtaining vectors of a predetermined number of values from the PPG signals. Most of the methods in the literature compute samples consisting of signals of known time duration [19] or composed of a defined number of heartbeats [27]. To segment heartbeats from PPG signals, the majority of the state-of-the-art techniques analyze the second derivative of the input signal for estimating fiducial points as the systolic peaks [43]. Fig. 2 shows the fiducial points commonly extracted from PPG signals. Systems that estimate fiducial points are usually called fiducial-based approaches, while systems that do not need any fiducial point are called non-fiducial-based approaches.

The signal enhancement frequently consists of a bandpass filter [25] applied with the aims of normalizing the signal baseline and reducing artifacts introduced by the acquisition sensor. Fig. 3 shows an example of a bandpass filter applied to a PPG sample. Some systems can apply additional techniques for heartbeat selection and optimized resampling algorithms [27].

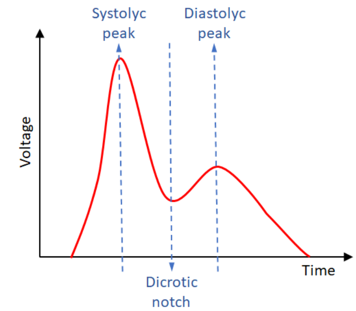

Fig. 2. Fiducial points commonly extracted from PPG signals.

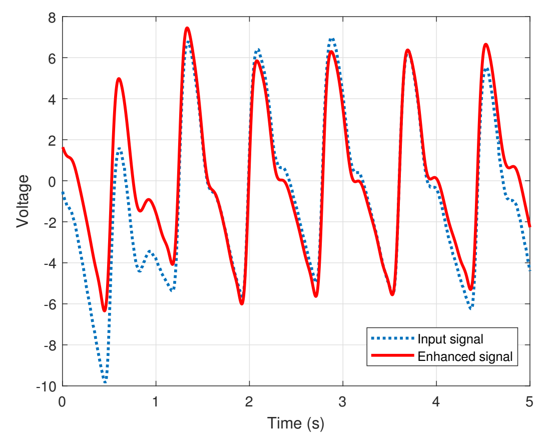

Fig. 3. Example of preprocessing consisting of a bandpass filter.

4.1.2. Feature extraction and matching

Considering the feature extraction and matching approaches used, PPG-based biometric technologies can be divided into systems based on algorithmic approaches and systems based on computational intelligence techniques. It is also possible to further divide the second class of systems into methods based on handcrafted features and methods based on deep learning (DL) strategies. Fig. 4 shows a schema describing the proposed classification.

Algorithmic approaches can use feature vectors consisting of signals or numerical descriptors inferred from PPG signals.

An example of a method using signals as feature vectors is presented in [19]. The method computes templates composed of a fixed number of signal portions extracted in time slots centered in the systolic peak to obtain a representation robust to changes of the signal due to physical or emotional activities. Every portion of the PPG signal, in fact, roughly corresponds to the QRS region of ECG signals, which is the most stable portion of the cardiac signal [44]. The matcher computes the best cross-correlation value between the signals composing the templates. The method presented in [23] does not need to compute any fiducial point and compares PPG signals by using a cross-correlation algorithm.

Methods that extract numerical descriptors from PPG signals use more complex feature extraction algorithms but require less complex matchers. The method presented in [45] computes features related to the fiducial points and signal slopes, which are

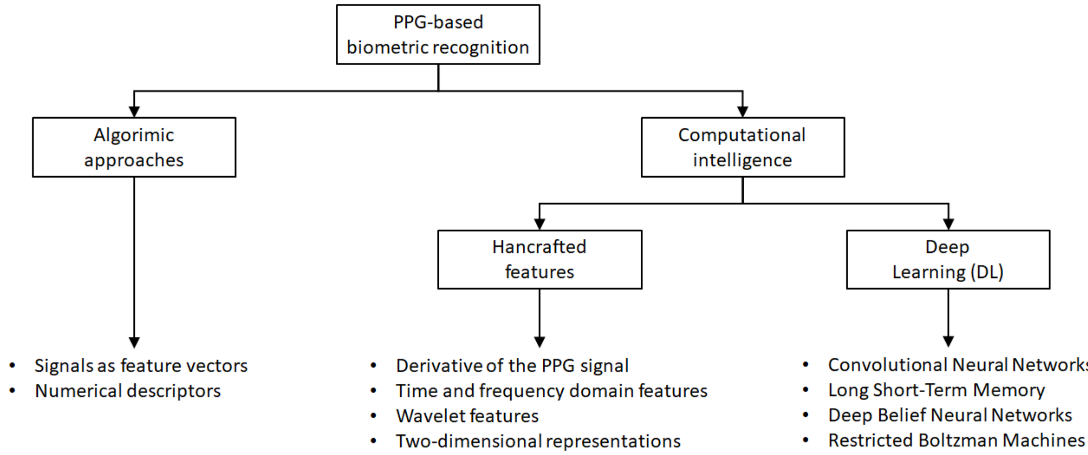

Fig. 4. Classification of PPG-based biometric recognition methods.

then compared by computing the Euclidean distance between templates. The method proposed in [21] uses features extracted from the Karhunen-Loève transform and compares the templates by computing the Euclidean distance. The study presented in [20] evaluates a set of feature extractors (based on the time domain and the Karhunen-Loève transform) and matching metrics (Manhattan and Euclidean distances). The approach described in [22] extracts three types of feature vectors by computing the autocorrelation of the PPG signal and its first and second derivatives. The matching function consists of the Euclidean distance between templates.

Computational intelligence approaches based on handcrafted features present relevant differences in the feature set and classification approach used. According to the feature set used, it is possible to distinguish methods that extract numerical features from the derivative of the PPG signals, methods using time and frequency domain features, methods based on wavelet features, and methods based on two-dimensional representations of PPG signals.

The derivative of PPG signals can be used to extract a set of statistical features. As an example, the method proposed in [28] computes acceleration-based features from the derivative of the PPG signal and performs closed-set identification by using a Bayesian Network and a k-Nearest Neighbor (k-NN) classifier. The method described in [29] extracts features in a similar way from the derivative of the PPG signal but performs the identification task by using a classifier based on Linear Discriminant Analysis.

Time- and frequency-domain features can also be sufficiently discriminative to achieve accurate biometric recognition. As an example, the method presented in [30] processes PPG signals using Empirical Mode Decomposition, computes a template composed of a set time and frequency domain features, and uses a Support Vector Machine (SVM) to identify the users. The method presented in [31] searches a set of discriminative features by performing statistical analyses to extract a redundant set of characteristics and by applying a Forward Feature Selection algorithm. This approach also compares different classifiers for closed-set identification such as k-NN, Fuzzy k-NN, and the Gaussian Mixture Model. The method presented in [46] compares feature sets by using a matcher based on fuzzy logic.

In contrast to the majority of the previously described approaches, methods based on wavelet features do not require the computation of fiducial points. As an example, the method described in [47, 24] extracts nonfiducial features and then applies Feedforward Neural Networks and SVMs to perform identity verifications. The study presented in [48] uses a similar approach to investigate the biometric recognition accuracy for PPG signals acquired in different mental and physical states.

Two-dimensional representations of PPG signals can also be used to extract discriminative features, providing the advantage of a simple visual inspection of the data from human operators. The method presented in [25] extracts a set of distinctive features by applying Principal Component Analysis to a two-dimensional representation obtained by processing the spectrogram of the PPG signal without computing any fiducial point. The method can perform closed-set identifications by using a k-NN or SVM, and it can perform identity verifications by using an ensemble of SVMs.

Computational intelligence approaches based on DL strategies automatically learn data representations from training samples. Furthermore, DL techniques can achieve impressive performance for heterogeneous applications including the biometric recognition of cardiac signals [8, 6].

In particular, Convolutional Neural Networks (CNNs) are widely adopted by biometric recognition systems and have achieved satisfactory results [49]. The method described in [26] represents an example of a deep CNN designed for PPG-based biometric recognition. It consists of an end-to-end deep CNN designed to perform identity verifications for samples with a time duration of one second. Similarly, the method presented in [4] uses a one-dimensional CNN and a specially designed filtering algorithm to perform closed-set identifications for signals acquired using a sensor embedded in the steering wheel of a car. The method proposed in [32, 33] overcomes the limitation of requiring samples of fixed time duration by mixing CNNs and Long Short-Term Memory (LSTM) layers. The network is trained for closed-set identification. Similarly, the method presented in [27] uses CNNs combined with an LSTM layer. This method improves the recognition performance by using selection and data augmentation strategies. Furthermore, the network is trained for identity verification.

DL strategies based on models different from CNNs can also be used with satisfactory results for PPG-based biometric recognition. As an example, the method presented in [50] is based on Deep Belief Networks and Restricted Boltzman Machines.

DL approaches can also be used to increase the number of available samples and perform data normalizations. As an example, the method presented in [51] uses a Generative Adversarial Network to limit the negative effect of different acquisition sources on the biometric recognition accuracy.

4.2. Biometric recognition based on R-PPG signals

In the literature, there are only a few works on biometric recognition approaches based on R-PPG signals. There is a study on signals computed from videos of the finger skin acquired using a smartphone camera [42], and there are two studies on R-PPG signals extracted from videos of the face [40, 41].

To extract R-PPG signals from videos of the finger skin, the method presented in [42] analyzes the mean of the pixelwise luma component from the pixels in each video frame. The method performs identity verifications by applying a classifier based on an Isolation Forest or on a one-class SVM. It uses a set of features related to different characteristics of the signal (statistical, curve widths, frequency domain, and fiducial points).

The first study on biometric recognition of R-PPG signals computed from face videos was presented in [40]. This method extracts the R-PPG signal using the algorithm described in [52]. The method performs closed-set identification by using Radon-based features and a Decision Tree classifier. To obtain more accurate results, the method presented in [41] extracts R-PPG signals using a technique consisting of Laplacian pyramid-based video amplification and performs identity verifications by using a DL strategy based on Stacked Autoencoders.

5. Performance and datasets

This section describes the figures of merit used to evaluate the accuracy of PPG-based biometric recognition systems, presents publicly available datasets, and summarizes the performance achieved by recent methods for public data.

The figures of merit used in the literature are different for identity verification and closed-set identification. For identity verification, studies in the literature use figures of merit typically adopted to evaluate the performance of biometric recognition systems such as the false match rate (FMR), false non-match rate (FNMR), equal error rate (EER), and area under the curve (AUC) [53]. Since many PPG-based biometric recognition techniques are based on binary classifiers, another commonly used figure of merit is the average classification accuracy. For closed-set identification, the most commonly used figure of merit is the classification accuracy, corresponding to the rank-1 error [54].

Since the use of PPG signals as biometric traits is a recent research topic, many studies in the literature on PPG-based biometric systems are based on private datasets collected by the authors using sensors with different characteristics. Researchers recently started reporting results achieved for public datasets. One of the most commonly used datasets in the literature is CapnoBase PRRB [55, 56], which permits evaluation of the performance of biometric recognition algorithms in ideal conditions. This dataset is composed of samples acquired by physicians in controlled conditions. However, this dataset has been acquired in a single session and includes signals acquired from 42 individuals. PulseID [26] is another dataset acquired in controlled conditions but includes 5 distinct acquisitions for each of the 43 volunteers. The widest collection of PPG signals acquired in controlled conditions is used to evaluate the accuracy of biometric systems in MIMIC-II [57]. However, this dataset includes acquisitions performed in an intensive care unit. Another widely used dataset acquired in controlled conditions is Biosec 1 [27], which includes signals acquired with a time difference of 14 days from 43 individuals. To study the discriminability of PPG signals for wider sets of people, Biosec 2 [27] provides samples acquired from 100 individuals in controlled conditions. In contrast to the previously described datasets acquired in controlled conditions, TROIKA [58] was acquired using a wristband during physical activities. However, the signals were acquired from a set of 12 users. Biosec exercise [48] was collected from a wider set of users after they performed physical activities and by using a finger plethysmograph. Studies in the literature also considered datasets of samples acquired in heterogeneous emotional states, such as DEAP [59]. Table 1 summarizes the characteristics of the most commonly used public datasets in the literature. For completeness, Table 1 reports on studies in the literature that presented results achieved for each public dataset, including works that used a subset of the available data.

Since methods based on DL strategies achieve the best performance in terms of biometric recognition accuracy, we summarize the results obtained by these methods for public datasets in Table 2. The reported results can be considered satisfactory for a wide set of applications.

6. Open problems

Although PPG-based biometric systems in the literature achieved remarkable accuracy, this kind of biometric recognition technique is relatively novel and thus requires further studies from the research community to obtain accurate and robust recognition approaches applicable in uncontrolled and unconstrained conditions. In the following, we discuss some of the main open problems in the field of PPG-based biometrics.

- **Stability over long periods of time**: Although there are promising studies on multiple session datasets [27], the considered time interval between the acquisitions is limited. The stability of PPG signals over long periods of time (years or decades) has not yet been studied.

- **Discriminability of PPG samples for datasets composed of relevant numbers of users**: Studies in the literature considered datasets composed of samples acquired from a maximum of approximately 100 users [27]. The discriminability of PPG signals as biometric has not yet been studied for wider sets of users.

Table 1. Public datasets for PPG-based biometric recognition

Dataset	Samples	Signal duration	Sampling frequency	Acquisition conditions	Studies using the dataset
CapnoBase PRRB [55, 56]	Single session for 42 subjects	8 minutes	300 Hz	Acquisitions performed by physicians in monitored conditions	[27, 25, 60, 20, 48, 47, 24]
TROIKA [58]	22 signals, 12 individuals	5 minutes	125 Hz	Acquisitions performed using a wirstband during fast running	[51, 33, 26, 32, 50]
PulseID [26]	5 signals for 43 individuals	30 seconds	200 Hz	Acquisitions performed using a medical device	[26]
MIMIC-II [57]	25,328 patient records	variable	125 Hz	Acquisitions performed in an intensive care unit	[20, 28]
Biosec 1 [27]	2 sessions for 31 individuals	3 minutes	100 Hz	Two sessions with at least 14 days gap in between	[27, 48, 61]
Biosec 2 [27]	3 signals for 100 individuals	1.5 minutes	100 Hz	After each acquisition, the sensor was detached	[27]
Biosec exercise [48]	41 subjects for session 1 34 subjects for session 2	3 minutes	100 Hz	The second session has been acquired after physical activity	[48]
DEAP [59]	40 signals for 32 indviduals	1 minute	128 Hz	Acquisitions performed in different emotional states	[48]

- **Uncontrolled acquisitions**: Although there are methods designed to cope with challenging acquisition conditions (e.g., during sport activities [50]), there are no studies considering datasets acquired in completely uncontrolled conditions, performing daily life activities.
- **Cross-domain recognition**: Apart from a few specific studies [51], most of the works in the literature present recognition methods trained and tuned for specific datasets. To obtain methods applicable in heterogeneous contexts, it is necessary to study cross-domanain and cross-sensor approaches.
- **Continuous authentication**: In the literature, there are only preliminary studies on continuous authentication methods [19] because there are no publicly available datasets of samples collected continuously for long periods of time.

Table 2. State-of-the-art methods based on deep neural networks

Work	Year	Method	Datasets	Performance
[27]	2021	CNN + LSTM	Biosec 1 Biosec 2 PRRB	AVG ACC = 87.0% AVG ACC = 87.1% 1 ch.: AVG ACC = 99%
[51]	2020	GAN for domain adaption	In-house TROIKA	ACC = 95.68% ACC = 89.35%
[33] [32]	2019 2018	CNN + LSTM	TROIKA	AVG ACC = 96%
[26]	2018	End-to-end CNN	PulseID TROIKA	AUC = 78.2% AUC = 83,2%
[50]	2016	DBN + RBM	TROIKA	ACC = 96.1%

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

7. Conclusion

This paper presented the first literature survey on biometric systems based on photoplethysmographic (PPG) signals, describing application scenarios, acquisition techniques, processing methods, state-of-the-art performance, and open problems.

PPG-based sensors are broadly diffused in wearable and mobile devices, thus enabling the use of PPG-based biometric recognition techniques in a wide set of applications. An analysis of the performance obtained by recent PPG-based biometrics revealed that the accuracy of the approaches based on computational intelligence techniques is satisfactory for a great number of contexts. However, PPG-based biometric systems are relatively recent technologies, and there are still problems to be addressed to obtain robust and accurate biometric technologies. The research community is therefore working on collecting large sets of samples under challenging conditions and on designing innovative and more robust recognition methods mainly based on deep learning approaches.

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