A Survey on continuous cardiac authentication using Photoplethysmography (PPG)

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***Abstract*—In this paper, we made a systematic literature review of the authentication systems based on PPG. We collected and filtered more than 700 papers, giving us 45 relevant papers. For each of these papers, we analyzed the employed methodology developed by authors to authenticate persons from their PPG records. Here we present the main evolution of this research community from 2003 to 2022. We also present our future works.**

***Index Terms*—Human authentication; PPG recognition; Deep Learning, Review, Biometric Continuous Authentication**

I. Introduction

In the past few years, researchers showed the need to develop continuous authentication [1]. The main problem with static authentication is the impossibility to remedy a hijacked session. Continuous Authentication aims to re-authenticate the user multiple times during the session while keeping the process transparent for the user [2]. Many methods have been explored during the last decade, such as behavioral biometrics (keystroke, mouse movement, etc) [3]. Recently the usage of IoT to enforce continuous authentication has been studied [4]. The two main advantages of wearable systems are the possibility to wear them discretely, without causing any discomfort to the user, and the possibility to continuously measure a physical signal.

In this survey, we focused on the usage of plethysmography [5] (or PPG) sensors, also called PulseOxymeter sensors for the authentication of individuals in a computer system. PPG can be defined as a cardiac signal, measured with a LED and photo-optical sensors [6]. PPG is a method for measuring the amount of light that is absorbed or reflected by blood vessels in living tissues. Since the amount of optical absorption or reflection depends on the amount of blood that is present in the optical path, the PPG signal represents the changes in the volume of the blood. The PPG signal varies with heart beat, showing the systolic peak (when the heart pump) and the diastolic peak (when the heart relax). The APG is the second derivative of the PPG signal and is often used to segment signal in single heart beat. Figure 1 shows a raw PPG signal and the major fiducial points, such as systolic peak (contraction of the heart), dicrotic notch (the transient increase in aortic pressure upon closure of the aortic valve) and diastolic peak (when the heart fills with blood).

In this work, we describe our methodology to make a systematic literature review of this topic. We briefly describe the main results of this study and our future works.

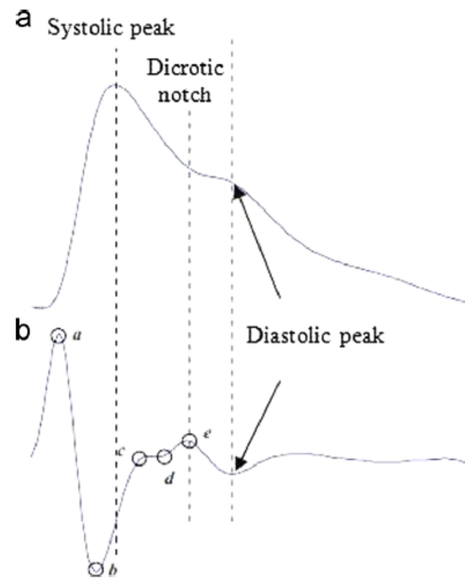

Fig. 1: An example of fiducial points from PPG raw signal and Accelarated-PG (APG). Figure from Kavsaoglu et al. [7]

II. Related works

The main advantages of the PPG technology are its cost (a few dollars for a PPG sensor), its difficulty to counterfeit, and the possibility to add this sensor inside wearable devices (watches, T-shirts, etc). This led to the ability to provide a new ergonomic, simple, and non-invasive form of continuous authentication. This system can be used with commercial smart watches to provide continuous and ergonomic authentication. This is why we focus only on the PPG technology and not ECG.

The technology description, its advantages, and disadvantages are described in most of the papers that we studied. However, the authors from [8] made a full description of the use case scenario. To the best of our knowledge, they are the only ones to provide a survey on this problem. But they study only 14 papers, mainly between 2016 and 2021, and their study lack of a methodology section. This is why we have made this study, gathering 45 papers over 20 years and providing a full dataset of all the experiences realized for this topic.

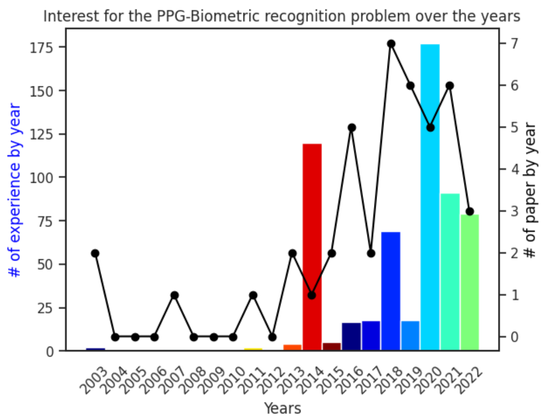

Fig. 2: Representations of the evolution of the research interest for the PPG biometric recognition from 2003 to 2022, with the number of experiences and papers published each year

III. Methodology

In this section, we present the methodology we used to gather, filter and analyze papers about human authentication with PPG. Then we present the common methodology used by researchers to achieve PPG biometric recognition.

A. Papers collection

To make a good systematic literature review, we followed the guidelines provided by Wohlin [9]. Thus, we defined requests for two search engines: Google Scholar and PubMed. All of our requests were made on these two search engines, for two time periods: one with no limits and the second considered only papers from 2017 to 2021. This step was done in April 2021. We took the 10 first results. The first step of this systematic review collected papers up to the end of January 2021. The 9 requests are the following: "Personal Identification with PPG"; "Personal recognition with PPG"; "Signature with PPG"; "biometric identification with photoplethysmography"; "Personal Identification with photoplethysmography"; "Personal recognition with photoplethysmography"; "Signature with photoplethysmography"; "ppg signal for biometric personal identification system"; "photoplethysmography signal for biometric personal identification system".

We kept the relevant papers and extract all their references. For each one, we analyze the title, abstract, introduction, and conclusion and only keep the relevant papers. We continue this process until we could not add a new paper. This leads us to analyze more than 700 papers and keep 45 relevant.

B. General statistics on the collected papers

Figure 2 represent the distribution of the experiences over the years combined with the number of relevant papers published each year. We can see very few experiences done each year before 2014. Less than 5 experiences by year where made during this period. Before 2013 only three papers were published, one in 2007 and two in 2003. After 2013, at least one paper was published each year. We can observe a big increase in the relevant publication starting in 2016 with at least 5 papers per year from 2016 to 2021 (except in 2017).

For example, in 2014 [7] was the only published paper that references 120 different experiences, which represent 19.9% of the total experiences conducted from 2003 to 2022.

IV. Works summary

In this section, we present some of the main contributions of the PPG recognition methods.

The first paper published about PPG biometric recognition was the one made by Gu et al. [10] where the authors made the first experience recognizing people with PPG. They collected data from 17 people. To recognize people they extract four fiducial features from the raw PPG signal, and stored them as a template. They compute a ratio for each variable to maximize inter-class variation and minimize intra-class variation. Then they use a classical distance metric to recognize people.

In 2014 Kavsaoglu et al. [7] provide 120 different experiments on this topic. They extracted 40 different time domain features on the raw PPG, first and second derivatives. Next, they rank from the most important to the less using a Z-score. Finally, they use a subset of the extracted features to compute a template and a KNN (K-Nearest Neighbors) and major voting with Euclidean distance to identify a subject. They test multiple values for K and for the number of extracted features. They collect data on 30 healthy subjects, 15 cycles in two sessions (no precision on the time between the two sessions). They test their methods in three different subsets, Thus leading to 120 different experiences to test one single architecture. They compute accuracy, recall, specificity, and F-measure for each subject and in mean for all experiences. This allows them to find the better parameter combination for the KNN algorithm. The results show that the ranking process increases significantly the accuracy. However the optimal number of extracted feature change from one dataset to another. They achieve good accuracy, over 90%.

In 2022 Wang et al [11] made 24 experiences. In that paper, the authors try to create a new authentication system based on PPG. They use 3 public databases to test their model: Vital DB [12] Capnobase [13] & BIDMC [14]. Their first step is to pre-process the signal with a complex pipeline involving re-sampling wavelet decomposition and recomposition, segmentation quality assessment with Skewness, and zero mean normalization. This step reduces the noise and filters the non-usable signals. Then they compute the first and second derivatives of the PPG signal (Velocity-PG and Acceleration-PG). These signals are used as input in a 1-D Covolutional Neural Network (CNN) which will produce a template for authentication. They test 8 different models. For the Capnobase and BIDMC datasets, the ROCKET [11] (new algorithm made by the team) extraction feature gives the best result, but for the VITAL DB, SK-NET and SNL, two algorithms developed by Wang et al. [11] give the best results (algorithms described in the paper). However, the difference between the two algorithms is only 0.05% in accuracy and EER (Equal Error Rate). Next, they evaluate the computational performances for the algorithms using the number of train Epochs, the train time, run time, FLOPs number, and total parameters. From their results, it seems that the ROCKET algorithms provide the best performances in all criteria. Finally, they show why they took 3 channels PPG and not only one. They show that the performances of all their algorithms can decrease a lot (it can be halved for some).

V. Conclusion and future works

From 2003 to 2022, we observe different methodologies to create an authentication system based on PPG. From our analysis of the 45 papers we find that the main methodology to build such a system is to first, pre-process the signal (reduce noise and segment the signal), then extract and select features to reduce dimensionality, and finally class the signal with the identity. For each of these phases, we study the evolution of the techniques used over the years. To filter the signal, the Butterworth filters are the most used. Most studies segment their signal into a single beat, by finding the systolic peak. Next many techniques are used to extract features: fiducial (physiological landmarks such as systolic peak), statistical (min, max, power, skewness, etc.), or features extracted with signals transformation (FFT, DWT, etc.). Then most of the studies keep all the extracted features, but the best ones reduce dimensionality with statistical techniques such as PCA or feature ranking. Finally, the classification is made using the most common classification algorithm: distance matching, KNN, SVM, and lately deep learning (CNN and LSTM). However many studies do not provide enough details on the used techniques. For example, the cut-off frequencies of the filters are not always mentioned, the depth of the decision tree or the exact number of extracted features are not given. Furthermore, we observe a big lack of common methodology, mainly in the data set segmentation, training, and testing phases. The details of the data set splitting are often lacking. Moreover, the most used metric is accuracy which did not reflect the security of a biometric system and this metric is influenced by the dataset splitting for training and testing.

Finally some problems such as the long-term stability of the PPG lack of exploration. For this problem of long-term stability, only 4 papers work on it.

Some biases remain in the data set, learning, testing, noise suppression, etc. Hence, we want to provide tracks for the community in order to increase the quality of studies. In our future works, we will provide a full benchmark for the community. Our goal is to provide one unique methodology with one common dataset to compare the models. This benchmark will have to show metrics to represent the time stability of the system, the security level, the ergonomic level, and the usability level (using the Failure to Enroll problem) [15]. Moreover, the lack of open-source code does not allow the community to reproduce the experiences. This is why we need to provide one unique platform where each team can upload its code and compute all the relevant associated metrics.

In our future works, we will implement some of the proposed algorithms in this literature review and benchmark them with the proposed method. We will also provide one platform where all teams can test their algorithms.

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