On the potential of AI based health assessment from photopletysmographic signals

Serena Zanelli[1], Mounim A. El Yacoubi[2], Magid Hallab[3], Mehdi Ammi[4]

[1] University of Sorbonne Nord Paris, Laga, Villetaneuse, France

[2] SAMOVAR Telecom SudParis, CNRS, Institut Polytechnique de Paris, Palaiseau, France.

[3] Clinique Bizet, Paris, France.

[4] University of Sorbonne Nord, Villetaneuse, France.

Correspondance: zanelli@math.univ-paris13.fr

Abstract

The necessity of implementing new options to improve telemedicine has gained much importance in recent years. Among all the available technologies, photoplethysmography is turning out to be a promising resource. Its cost effectiveness and its usability allow its embedding in several devices without the need of constraining requirements. In this paper, we explore how artificial intelligence-based approaches could improve the photoplethysmography use by leveraging its potential and minimizing its disadvantages.

Keywords — e-Health, biomedical devices, biosensors, signal processing

1 Introduction

With the increasing life expectancy and the impossibility for the healthcare system to be ensured for everyone, telemedicine and e-health will play a central role in the next years. Researchers and industries are more and more focusing on the development of systems to facilitate the patients' follow up from remote locations. Among them, the photoplethysmography (PPG) technology is attracting much interest thanks to its cost-effectiveness and usability. This technology can be easily embedded in wearable devices and it does not imply restrictive requirements. Currently, it is known to be used in clinical practice to assess blood oxygen levels (SpO2) through the utilisation of red and infrared LEDs. However, several studies have proven that PPG has a great potential and its use should not be limited to the SpO2 measure. It can be used to assess blood pressure [1], assess diabetes and the related microvascular complications [2] or to estimate vascular aging [3]. Yet, despite these promising results, the PPG has several limitations that makes its use challenging. In this article, we present a workframe to leverage its potential and limit its flaws. In particular, we focus on artificial intelligence based approaches to manage and detect anomalies in PPG recordings.

2 The potential of AI

Figure 1: Pictures of PPG devices. From the left to the right: wrist band (Huawei), pulse wave velocity sensor (Axelife), ring (Oura), oxymeter (Wellue), and smartphone (Xiaomi)

The PPG technology is composed of a light emitting diode (LED) and a photodetector (PD). The light emitted from the LED is transmitted or reflected according to the operating method, and then collected from the PD. This optical signal represents the blood volume changes in the microvascular network. Currently, the PPG technology can be implemented into wrist bands, pulse oximeters like sensors, smartphones and devices equipped with a video camera (remote PPG). A variety of PPG devices are shown in Figure 1. Although this technology has several advantages, it also has few but important limitations. The PPG signal is easily corrupted by noise artifacts [4]. External light, movement or electric noise can affect the PPG wave shape and make the related analysis unreliable. In addition to that, the photoplethysmographic waveform depends on the wavelength emitted light, on tissue reflectance, on blood volume, cardiac cycle phase, aging and presence of pathologies [5]. A strong influence on the PPG pulse waveform is given by the anatomical measurement site [6]. Finger, earlobe and wrist appear to be the best measurement sites with respectively 95%, 81% and 86% of analyzable waveforms due to rich arterial supply [7]. With the advent of machine learning, the processing of biomedical signals is becoming more and more accessible. The latter have been demonstrated to overcome the traditional approaches (non machine learning based) thanks to their capability of dealing with a large amount of data while being able to model more complex relations between input and output [8]. In particular, deep learning approaches, such as convolutional neural networks, are able to model the input directly without the need of handcrafted features. Dealing with real world PPG data, the feature extraction step can be challenging due to the presence of artifacts in the signals. The capability of these approaches would make the implementation of real life continuous monitoring systems a real possibility. In the next subsections, we go through the potential of using PPG to detect anomalies and diabetes and the current challenges that still need to be addressed.

2.1 Anomalies detection

In addition to the heart contraction related information such as systolic and diastolic contraction, the PPG contains information related to the status of the vascular system. For these reasons, the PPG can be used to assess a variety of anomalies related to the cardiovascular system. The PPG waves change their shape with aging due to the increase of arterial stiffness [9], with presence of pathologies such as diabetes, or even in presence of abnormal beats such as atrial fibrillation or extra systole [10]. An understanding of typical PPG wave shapes could contribute to the physiological interpretation of wave shapes, and could help in the development of robust PPG wave analysis algorithms. According to the literature [11], PPG waves can be classified into four main types considered as physiological based on the visibility of the dicrotic notch (class 1: dicrotic notch very visible - class4: dicrotic notch not visible). The main challenge in classifying the wave shapes is represented by the fact that real world data are difficult to label, since they show several shape variations (Figure 2). To overcome the labelling process issue, one possible strategy could be the employment of unsupervised learning [12]. To avoid the handcrafted features extraction, automated features can be used. Examples of automated features are those based on dynamic time warping [13], which were demonstrated to perform well in matching patterns [14], or automated features extracted using an encoder-decoder model [15] in which the model learns how to represent the data by minimising the Mean Squared Error (MSE) between the reconstructed input and the actual input. Thus, the combination of unsupervised learning with automated features would allow the identification of similar PPG waves overcoming some of the most challenging steps when dealing with large real-world datasets. Since the absence of labels does not make the validation process possible, related clinical data such as pulse wave velocity, pathologies, age or biological sex could be employed in order to assess the clinical relevance of the obtained wave prototype clusters. Such a workframe would resolve, or at least minimize, most of the typical PPG related burdens.

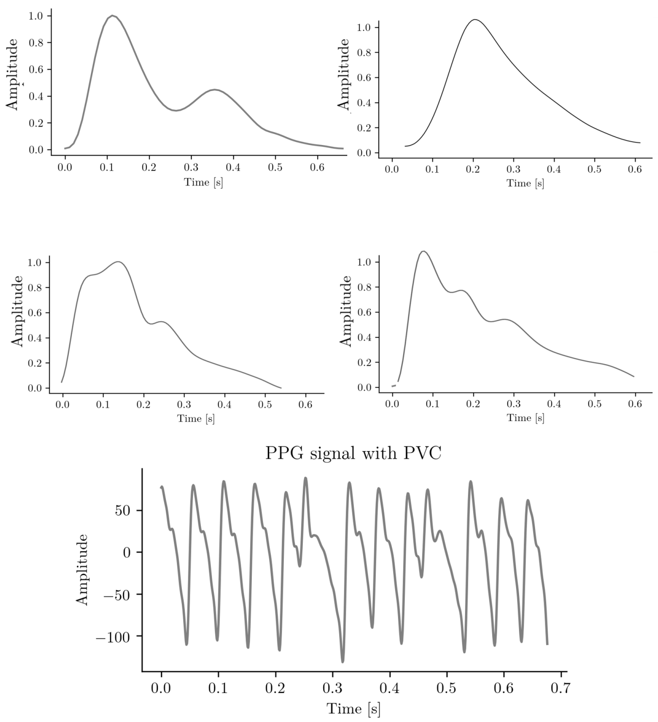

Figure 2: Example of real world PPG shapes. From the top to the bottom, from the left to the right: standard PPG wave in which systolic and diastolic peak are observable; PPG wave in which the diastolic peak is not visible probably due to an elevate arterial stiffness; PPG wave in which a peak is visible before the systolic peak; PPG wave in which a peak is present between the systolic and diastolic peak. Bottom figure: PPG signal with premature ventricular contraction events.

2.2 Diabetes

Diabetes mellitus (DM) is a group of endocrine diseases characterized by sustained high blood sugar levels. High blood sugar levels lead to arterial stiffness [16] and modifications in the pulse wave shape. As stated by the World Health Organization, about

422 million people have diabetes and 1.5 million deaths are directly attributed to diabetes each year [17]. As of today, the reference to identify the presence of this pathology is the glycated hemoglobin exam (HbA1c) which involves a blood test. In some cases, testing the blood sugar levels in specific conditions (fasting or after a meal) can also lead to diabetes diagnosis. In the first case, the exams require a sanitary structure and specialized personnel. In the second one, the required devices need to be specifically bought and this usually becomes the case when there is a suspicion of diabetes. By contrast, the PPG signal is accessible through several devices that are already used in everyday life such as smartphones and wristbands. The implementation of these solutions would make large scale prevention plans possible and it would ensure the remote follow up of several patients with reduced medical expenses. There is, therefore, a real interest and added-value in managing and assessing the risk of diabetes using the PPG signals. Several studies already presented different approaches in this respect. Among them, Moreno et al. [18] proposed a machine learning algorithm to detect diabetes through PPG relevant features. Avram et al.[19], proposed a deep learning approach which predicts diabetes using raw PPG signals and Srinivasan et al. [20] proposed a 2 dimensional approach which assesses the diabetes risk based on the PPG spectrogram. Although the obtained results, in terms of specificity and sensitivity, are promising, they do not overcome the gold standard performances. To fully exploit the PPG potential, larger and more stratified databases are needed. Since the PPG signal contains information about the cardiovascular state of a subject, lack of information such as drug treatments, pathologies, previous surgeries and biological sex transitions may result in biased results.

2.3 Current challenges

The PPG signal is strongly affected by noise artifacts such as movements, external light and electronic noise. However, other factors can change the wave shape without necessarily being considered as noise. For example, if the relative position of the measurement point from the heart changes during the recording, the wave shape will be affected since the volume changes in the microvascular bed will be altered. Similarly, if the subject moves from a standing position to a lying position, the pressure changes will affect the wave shape. The implementation of AI based models could help in detecting changes in the wave shape that are not related to a cardiovascular status modification [21].

In addition to the subject related modifications, it is possible to identify also some acquisition related challenges. The lack of standardisation in best practices in signal acquisition and processing make the results reproducibility and comparison very challenging [22]. Variables such as temperature of the skin, external light, wavelength, signal processing chain and measurement protocol should follow some guidelines or at least be clearly stated in the experiment description.

3 Conclusion

The implementation of systems that facilitate telemedicine is of fundamental utility in order to keep up with the healthcare system necessities. The photoplethysmography technology has a strong potential in assessing the cardiovascular status and its related complications. However, this technology also has some limitations that make its use challenging. The implementation of AI-based approaches could solve some of these challenges such as quality assessment, lack of labelled data and non-physiological related variation in the signal. Nonetheless, important progresses are still needed in order to validate these approaches to allow the transition from the research to the market of the PPG technology.

Conflict of interest: S. Zanelli collaborates with Axelife, a company that designs and develops PPG-based medical devices. M. Hallab is the founder of Axelife and has authored patents used by Axelife.

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