An Overview of Remote Photoplethysmography Methods for Vital Sign Monitoring

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Abstract Vital signs such as heart rate, respiratory rate, blood pressure, body temperature, and oxygen saturation are essential for early detection of any related significant illness. Many of the existing methods that are used to monitor the aforementioned vital signs are camera-based. In these methods, sensors are fixed to the body that are not sturdy to the motion of the subject. Another method to monitor vital signs is photoplethysmography (PPG), an emerging noncontact technique that maps, spatial blood volume variation in living tissue from the images captured through a video. Most of the camera-based methods are driven by three remote photoplethysmography algorithms. The camera-based methods are useful for detecting vital signs with an objective AAA, i.e., anyone, anywhere, and anytime. However, there exist few challenges in r-ppg methods and make it an open research problem. This paper presents an overview of the signal processing challenges faced by remote photoplethysmography for calculating the vital signs with a focus on heart rate estimation.

Keywords Heart rate · Remote photoplethysmography · Vital signs · Signal processing · Video processing

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1 Introduction

The human body has many integral signs such as heart rate, respiratory rate, blood pressure, body temperature, and oxygen saturation, to name a few that helps in deciding the fitness of the human body. Measurement of these vital signs needs a device, and therefore, it is not possible to measure them for the examination of body fitness at home. The heart rate is one of the important vital signs, as it plays a vital role in checking the fitness level of a human body. Monitoring of the heart rate even helps in detecting any growing heart problem. Heart rate is measured as beats per minute (bpm) that ranges from 60 to 100 bpm in healthy adults.

Respiratory rate (RR) is another vital sign, defined as the frequency of breaths per minute which ranges from 12 to 20 breaths per minute in a normal person. Monitoring respiration can give valuable information about neural and pulmonary conditions. Checking human RR regularly is an important task of examining the health of a person [1]. Measuring these mentioned vital signs needs some medical devices and a doctor to examine them. Generally, an individual has to visit the clinic and record the signs. For instance, medical professionals examine heart rate through ECG, which is the most commonly used contact-based or invasive method that induces skin irritation.

The noninvasive healthcare monitoring system involves either capturing the image or recording the video through a digital camera. One of the systems is photoplethysmography (PPG) that is used to detect blood volume variations in the microvascular tissue. PPG devices have been competent to monitor relevant signs that include pulse rate, respiration rate, and body temperature [2]. Verkruysse et al., in [3], described image photoplethysmography (i-PPG) technique. In this paper, the authors recorded the facial skin affected by the port-wine dye after laser therapy. The resulting data were used to obtain maps of the amplitude and phase of the spatially differing PPG signals. The main drawback of the proposed technique is that the PPG signals are sensitive to variations induced due to motion when camera-based phones are used. Many a time, the noninvasive vital sign monitoring is also termed as remote photoplethysmography (r-PPG). The name r-PPG has been coined due to the monitoring of remotely captured video through digital camera. Therefore, in the forthcoming paragraph, we present an overview of the work presented by various authors related to PPG vital sign monitoring.

Independent component analysis (ICA), a blind source separation method proposed by Poh et al., in [4] removed the noise from PPG signal face imaging. The measuring standards are recommended for the use of ECG sensors for measuring the heart rate variability (HRV) in [5]. However, it has been shown that PPG-derived heart rate variability can be a good substitute for HRV at rest [6]. In [7, 8], Sun et al. compared the performance of a low-cost web camera and a high-sensitivity camera to evaluate the variability of the heart rate and pulses. The authors stated that the 30 fps webcam function is similar to the 100 fps camera when signals are incorporated to improve the time-domain resolution [8]. HRV has been used to detect real-time changes in the workload to evaluate and index the autonomous nervous system [9]. Its spectral analysis can provide a sympathetic balance, a ratio that reflects mutual changes in sympathetic and vagal outflows [10]. HRV tends to be rhythmic and emotionally positive, followed by a phenomenon known as respiratory sinus arrhythmia. HRV, on the other hand, tends to chaotic, angry, anxiety, or sadness. These rhythmic variations create a condition of cardiac coherence [11, 12]. Detection of physiological signals using noncontact equipment is especially beneficial in emotional computing, where emotions like stress or fear are induced. Contact sensors can create a bias in these physiological experiments by interfering with the user, which results in an erroneous emotion classification [13]. Currently, published methods effectively recover spectral components of HR, BR, and HRV over a certain period. However, there have been a few attempts, instant HR measurement with a webcam, particularly considering artifacts of head motion [14].

The r-PPG algorithms proposed in the literature have been developed on videos under constrained environments. However, there are many challenging issues faced during the development of algorithms under uncontrolled environment. Therefore, it is a potential field of research for researchers who are willing to work in the field of r-PPG for vital sign monitoring. These challenges have been described in Sect. 3.

This paper organization has three sections. The introductory section describes the vital signs and its importance. Section 2 discusses various r-PPG methods used for estimating the heart rate. Section 3 describes the different challenges faced in r-PPG. Finally, concluding section presents a summary of the review of techniques.

2 r-PPG Methods for Estimating Heart Rate

r-PPG is a remote photoplethysmography technique that measures, small changes in skin color caused by variations, in volume and oxygen saturation while heart pumping. All r-PPG techniques developed so far have used the videos captured from a digital camera for analyzing the pulse or heart rate. Recently, several r-PPG algorithms are developed for extracting the heart signal from videos. In this section, we present the study of each approach developed by researchers for estimating heart rate. Broad categories of the various approaches are blind source separation, model-based methods, and design-based methods. Each category and algorithm is further discussed in the forthcoming section.

2.1 Blind Source Separation (BSS)

The generalization of time series data as an alternative representation in the frequency domain is also important. This representation enables the understanding of the signals and the filtering or interpolation of the data. In particular, the singular value decomposition (SVD) [4] and independent component analysis (ICA) [15] techniques for the principal component analysis (PCA) have been examined. Both these PCA and ICA techniques use statistical data representation rather than time or frequency domain. In other words, data are projected on a new set of axes that fulfill certain statistical criteria, which implies independence, instead of a set of axes representing discrete frequencies such as the Fourier transformation, where independence is assumed. The criterion depends on the structure of the data and the axes on which the data is projected. The projection direction increases the signal-to-noise ratio, which allows us to observe the important structural signals. For example, the power spectrum of the data can be calculated to make the peaks of certain signals visible and to separate the noise from the signal. Such unwanted signals can be filtered using PCA and ICA. Most important, BSS techniques are analytical and computational for general problems of signal processing. It does not benefit from the unique characteristic of skin reflections used to solve the r-PPG problem. The ICA-based approach, in particular, normalizes the standard deviation of RGB signals, ignoring the fact that the PPG signal induces distant yet known relative amplitudes in the particular RGB channels.

2.2 Model-Based Method

The BSS method discussed above has limitations of assumption on the colors associated with source signals. In the blind source separation method, the colors are considered independently for the signal estimation. To overcome the limitations of BSS, model-based methods use different components of color vectors to control de-mixing. Therefore, model-based methods eliminate the dependency of colors on skin color reflection including light color. In addition, the model-based methods are also motion tolerance. Model-based method includes PBV and CHROM techniques proposed by De Haan in [15, 16], respectively. The PBV technique is based on blood volume pulse that retrieves the pulse directly from the pulsatile components restricting all color variations to possible direction. The PBV is also a motion robust improved method which uses blood volume pulse signature as mentioned. Further, the CHROM technique is robust to motion based on the standardized assumption of skin tone. The CHROM is different from PBV because it reduces sensitivity by eliminating the specular component and reducing the size. The CHROM algorithm assumes a standardized skin tone vector that allows white images to be balanced. From the literature, it has been observed that the CHROM is robust to mono-white illuminations and so it is categorized as best model-based algorithm. In addition, Wenjing Wang proposed a new method, the orthogonal skin plane (POS) [17]. This method resembles CHROM but alters the order in which the expected color distortions are reduced using different priors. In this new algorithm, authors developed a skin tone orthogonal plane in a temporarily normalized RGB environment.

Compared to multistep CHROM and POS, PBV is a one-step process and requires an accurate knowledge of the signature of the blood volume pulse. With regard to movement and stationary parameters, CHROM and POS perform well in stationary and motion situations when the alpha tuning is driven either by pulse or by large distortions, while PBV is specifically designed for movement. In addition, CHROM and POS are not as restrictive as PBV. In addition to all the above comparative analysis, one more similarity between CHROM and POS is that these two methods use soft priors to define a projection plane for alpha tuning in blood volume pulsation (i.e., channel ranking).

2.3 Design-Based Method

Model-based methods are good as they are robust to motion. They perform better than non-model-based methods. As discussed earlier, the limitation in CHROM is that it uses the vector for white skin reference, whereas PBV depends on the blood signals and diverts the signal to that side. However, apart from these limitations, the vital sign measurement is best for model-based methods as these methods are motion robust.

In the recently developed spatial subspace rotation (2SR) method [18], the RGB values are quantified as spatial representation. In the temporal domain, pulsatile blood causes variation in RGB channels, thus changing subspace of skin pixels. The algorithm creates a subject-dependent skin color space and tracks the tone change over time to measure the pulse in which the instant tone is determined on the basis of the statistical distribution of the skin pixels in the image. The idea of using the hue as a basic pulse extraction parameter is supported by the analysis of the use of different color spaces to measure the pulse [19]. Since then, the tone drives measurement, the method at an early stage eliminates all variations in intensity. In this sense, 2SR is a skin approach that defines a temporarily normalized orthogonal projection plane in the RGB pulse extraction space. The subspace axes built by 2SR are, however, completely data-driven without physiological consideration. This presents performance problems in practice when spatial measurements are not reliable, i.e., when the skin mask is noisy or poorly selected. A new lock-in technique is proposed in [20] for extracting pulse rate which when compared with gold standards differed only by four beats [20].

In this section, we presented different approaches proposed by various researchers in last few decades. From the detailed literature, it has been observed that estimation of heart rate using r-PPG from captured video still struggles with many challenges. These challenges are further discussed in the next forthcoming section.

3 Challenges in r-PPG

From the literature, it is evident that r-PPG focuses on extracting the pulse signal from video to estimate the heart rate of a person. However, r-PPG has many challenges due to various factors like subject motion, ambient light illumination, image optimization, spectrum analysis, etc. These factors present challenges to the researcher for recovering the accurate physiological data for different r-PPG methods. The men-

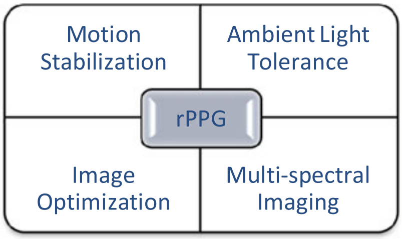

Fig. 1 Factors related to challenges in r-PPG

tioned four factors related to the main challenges in r-PPG are shown in Fig. 1. In subsequent sections, we present each of these factors for better understanding.

3.1 Motion Stabilization

The subject motion has been studied in most of the r-PPG algorithms to analyze its effects. The subject motion is an important and a great challenge that is faced by r-PPG algorithms. The subject motion changes the region of interest in the video when the subject is in motion. Early investigations of r-PPG focused on rigid and stationary regions of interest as used in researches [3, 14, 16, 21–23]. Ideally, when subjects are stationary, the ROI must also be constant in subsequent frames used by r-PPG algorithms. However, this might not be the practical scenario of the application of r-PPG algorithms. Therefore, there is a need of motion stabilization that is to be achieved in the video. Thus, the tracking of ROI can be proposed as a solution to this problem.

On the other hand, few of the studies introduced later focus on face imaging of the subjects that allowed limited naturalistic motion [19, 21]. The work proposed in [19, 21] used the emotion factor in unconditional environment while recording the videos for the study.

Further studies investigated the algorithm's performance under translational motion which limited the use of techniques as simple region of interest (ROI). These ROIs focused on object tracking [15], color difference, and chrominance-based signals from RGB color space [19]. Later, approaches for estimating the motion artifacts and correcting the obtained r-PPG signal using adaptive filtering have also been explored [24]. As stated earlier, this motion artifact is a challenge for r-PPG, with specific advancements in three big areas: (1) the development of an algorithm for image processing, (2) spatial redundancy, and (3) the use of integrated multiband techniques in visible and invisible wavelengths. While it is important to explore systematically varying motion artifacts, use cases in applied environments are included but not limited to exercise [25, 26], cognitive states [27, 28], and clinical care [29, 30], with a view to transition from the laboratory environment. Finally, the effects of movement artifacts have been extended beyond the pulse rate alone to cardiopulmonary measures. The authors in [31] proposed a new technology sub-band r-PPG for HR measurement in fitness by increasing the pulse extraction signal dimensionality. During fitness exercise, they tested the algorithm on the subjects. The proposed pre-filtering method improved r-PPG performance. The approach of selective amplitude filtering filtered the r-PPG signal based on the RGB color band. The authors in [32, 33] designed a filtering method that filters the RGB signals before the pulse is extracted.

3.2 Ambient Light Tolerance

Ambient light is the light already present in a video without any manipulation. There is no additional light added in the video. Such ambient lighting conditions might be considered proportionately consistent in most of the applications; nevertheless, there are some probable use cases like a computer simulation, virtual reality, mobile screen brightness, etc, where there can be variations in lighting conditions. The difference in illumination intensity many a time influences the intensity of the PPG waveform [23]. At the same time, the effects of ambient light on any other currently available PPG methods are unknown. In a limited, uncontrolled study in [32], Li et al. used an adaptive filtering approach, with more background region of interest. The ROI served as the input noise reference signal which compensates for background illumination. The results in [34] depicted improvement for varying illumination on a publicly available video database [35]. The detailed experiments presented in [34] derived modest reduction in heart rate error when compared to ECG recorded.

To estimate the vital signs, it is very important to deal with the ambient light tolerance in the background of the video. This is because the background or the region of interest, if it is either under-illuminated or over-illuminated, might result in incorrect signal extraction. This incorrect signal extraction will further lead to an incorrect estimate from the video. Consequently, it is very important to keep the illumination of a region of interest constant throughout the video acquisition process. The background illumination might be canceled using the technique developed in [34] as one of the illumination cancelation techniques. However, identification and removal of the effect of illumination on the region of interest still remains a challenging issue to be explored that further bring complexity in analyzing the heart rate from the region of interest.

3.3 Image Optimization

Image optimization specifically emphasizes on capturing the images or videos through different sources. The varieties of image sensors or video cameras that allow fostering of r-PPG also bring variations in a different level. For instance, a variation in the image sensor (e.g., digital camera, mobile phone cameras, etc,) brings variations in features that are to be examined, which additionally induces variations in further analyses. These features could be a basic sensor type, color separation sensors, special sensors, aspect ratio, image sizes, and the number of pixels, to name a few.

However, from the literature, it can be seen that the image quality does not rely only on the quality of an image sensor being used. The other factors that affect the image quality are a type of lens (CCD and CMOS), spectral properties as an illumination source, and image shutter speed. Thus, image quality directly or indirectly changes the feature of an image or video under consideration. Apart from this, although the frame rate is not directly related to image sensor properties, it is also considered as one of the vital components for variations in features under consideration for estimating vital signs. An image can be optimized with the use of automatic ROI selection from the image. Recently, Wang et al. performed supervised living skin detection using r-PPG by transforming the video into signal shape descriptor called multiresolution iterative spectrum [36].

Thus, an image optimization deals with capturing video in different formats. One such format for video is 'mp4' format that stores the frames in compressed form. The compression of an image or a video might lose information resulting in an inaccurate vital sign estimation from the recorded video. In this context, the image optimization is, therefore, a challenge and is to be dealt with before measuring the vital sign from the optimized video.

3.4 Multispectral Imaging

Multispectral imaging captures images with a specific wavelength and multiband spectrum. There are different spectral bands used for satellite images, such as Blue, Green, Red, near-infrared, mid-infrared, and thermal. Many contemporary r-PPG studies focus on three spectral bands in the visible light spectrum, i.e., red, green, and blue. While green/orange visible bands are the most pervasive of common oxygen and de-oxyhemoglobin derivatives [37], multispectral imagery from a single image sensor has often been used for r-PPG methods involving linear decomposition using multiple data channels. As shown by Martinez et al., in [38] with front spectrophotometry, some wavebands are better for measuring r-PPG pulse rate and respiration rate. The different spectrums have a different effect on the signal estimation. Thus, the r-PPG is still an open challenge because the different bands lead to the creation of different estimates for vital signs. This shows that it is difficult to identify good signal for estimation of vital signs.

4 Conclusion

Photoplethysmography technique maps the blood volume pulsating signals into the vital signs. The vital signs can be measured by heart rate, respiratory rate, or saturation per oxygen level (SPO2) from images or videos. In this paper, we have presented three r-PPG methods, namely, BSS, model-based, and design-based, based on digital video signals. Each method has its own advantages and limitations in various contexts of r-PPG as discussed in the paper. Among all the three described methods, BSS is a widely used r-PPG method in the literature. Further, we presented different factors, like subject motion, ambient light illumination, image optimization, and spectrum analysis, that make r-PPG an open research issue to be explored. Among all the factors listed above, motion stabilization is an important factor to be dealt with as it brings an uncontrolled environment and makes r-PPG a challenging task.

From the discussions presented in this paper, it has been observed that many research challenges are still open for solutions in the field of r-PPG. The researchers can initiate to pursue research and contribute to social technology.

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