Photoplethysmography Imaging – Future Prospects and Challenges

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Abstract

Photoplethysmography Imaging (PPGI) is a rather novel technique to unobtrusively acquire vital information with a camera. PPGI allows contactless and spatial assessment of peripheral perfusion. Due to its unobtrusive spatiotemporal characteristics, PPGI offers great potential and new possibilities for diagnostics and monitoring. Measurement of heart rate, breathing rate, heart rate variability, oxygen saturation, perfusion strength, and blood pressure correlates, among others, have been reported. Recent works have demonstrated novel clinical applications. In contrast to contact-based photoplethysmography, the spatiotemporal resolution of PPGI provides access to additional information. However, despite a wide range of possibilities, PPGI has barely realized its potential in practical use to date. The technology holds many pitfalls as it relies on complex processing pipelines including not only signal processing but also image and video processing. At the same time, algorithms and datasets are rarely made public. While the design principles of PPGI measurements are complex, the application of PPGI is as simple as recording a video. This renders PPGI ideal for multi-parameter monitoring in telemedicine, for scenarios that require spatial resolution, and for vulnerable patients in which contact-based measurements are unsuitable.

1. Introduction

Photoplethysmography Imaging (PPGI) was first described by the German research group of Blazek in 2000 [1]. Over time, PPGI has been given many other names, including remote, camera-based, video, and imaging photoplethysmography [2]. The technique depends on the interaction of light with superficial skin that contains vasculature [3]. More precisely, the measurement principle of PPGI is *the modulation of optical properties of the skin by changes in blood volume that are sensed by intensity measurement on the basis of the photoelectric effect*.

This work aims to provide an overview over essential design principles and potential applications of PPGI to outline future prospects and challenges of the technique.

2. Design Principles

The pipeline of PPGI measurement is complex and generally covers recording, image processing, channel combination, signal processing, and analysis [3].

Recording: Most works utilize industrial-grade RGB cameras with ambient illumination [4]. Near-infrared cameras and monochromatic cameras with narrow-band filters allow for PPGI in other spectral regions [3, 4]. Consumer-grade cameras (e.g. webcams) have also been used but provide lower signal-to-noise ratio [4]. Particular attention should be paid to the setup design, especially to motion reduction and uniform illumination while avoiding saturation and interference. Recordings in which the region of interest (ROI) only makes up a small part of the image are inefficient, but some reserve is essential to capture the ROI also during movement. Recordings often feature a frame rate smaller or equal to $30\,\mathrm{fps}$ and an amplitude resolution of $8\,\mathrm{bit}$ [3]. While this is sufficient for pulse rate and breath rate measurement, other types of analysis require higher resolutions (e.g. pulse rate variability, pulse wave morphology) [3]. Video compression reduces data size but distorts the subtle intensity changes relevant for PPGI. Therefore, video compression should be used with careful selection of an appropriate codec. Regarding the studied populations, most works on PPGI include only a few participants, typically young and healthy volunteers [4].

Image Processing: To extract physiological information from the recorded video, a ROI must be defined and updated over time to account for movement. There are three approaches to solve this task: (1) static selection, (2) skin detection, and (3) anatomical markers. (1) Approaches of static selection cover the manual annotation of image regions, which fails in case of movement, and the division of the frame into static subregions. To account for movement, the contribution of the subregions to the final PPGI signal may be updated over time by evaluation of functional criteria. (2) There are many algorithms for skin detection that are typically applied to every n^{th} frame. Earlier works utilized thresholding of color channels in color spaces such as L*a*b* or YCbCr. These have recently been outperformed by convolution neural networks [5]. One of the few

ROI algorithms developed specifically for PPGI is called Level Set Segmentation [6]. Level Set Segmentation refines and tracks an initial Bayesian skin detection mask under consideration of homogeneity criteria [6]. Accurate skin detection across all skin tones may be challenging [7], but skin detection can be applied to all skin regions of the body [6]. (3) The most simple case for anatomical markers is face detection and tracking. However, eyes and teeth hold no perfusion information and strongly distort PPGI signals. This may be addressed by clustering the detected face into subregions whose contribution to the PPGI signal is then evaluated by functional criteria (similar to the static subregions) [8]. More refined facial feature markers (e.g. eyebrows, nose) allow for ROIs on anatomically motivated regions, for example forehead, glabella and cheeks, which are suitable for PPGI due to high capillary density and thin skin. However, in contrast to skin detection, anatomical marker detection depends on frontal face recordings and may fail if the face is even just partly obstructed.

Channel Combination: Spatial averaging of the intensities in the ROI of every frame yields a red, a green, and a blue channel signal from the RGB video. Many methods for the combination of these channels have been proposed that can be grouped into: (1) model-based, (2) source separation, and (3) data-driven channel combinations. (1) Model-based methods set the channel combination on the basis of *a priori* knowledge. For example, the dichromatic reflection model has been used in CHROM [9] and POS [10] to extract the pulse rate, and blood absorption models have been used to infer functional oxygen saturation [11]. The green channel is directly linked to blood volume absorption but prone to artifacts [3]. Color space transformations decouple chromatic information from light intensity, which increases artifact robustness for example in the Hue color channel [3, 10]. (2) Source separation methods such as independent component analysis or principal component analysis aim to reconstruct a set of source signals from the set of measured signals (red, green, and blue channel) by optimization of statistical parameters [3]. However, the order of the reconstructed source signals is not determined and the selection of a signal for evaluation is error-prone [3]. (3) Data-driven methods determine the color channel combination empirically and directly output the signal of interest [10]. This includes convolution operations in deep learning methods. Comprehensible linear combination grid search optimization has revealed that there is monotonic progression towards a single optimal color channel combination (O3C) [7]. Also, it was shown empirically that color channel combinations can be designed independent of skin tone with O3C [7]. It is important to understand that different color channel combinations lead to different PPGI signal components. CHROM and POS, for example, remove low-frequent information required to investigate vasoconstriction and vasodilation to focus on the cardiac pulsatile signal component [12]. In O3C and in the green channel, for example, such low-frequent information remains [12].

Signal Processing: Signal processing typically covers digital filtering. The filter specifications depend on the PPGI signal component of interest. The most low-frequent information originates from Traube-Hering-Mayer waves (0.1 Hz oscillations) and vasomotion. Baseline modulation due to respiration is found in the frequency range of breathing (0.1 Hz – 0.5 Hz). The cardiac pulsatile component (typical photoplethysmogram) is found in the frequency range of heart rate and its first harmonic (0.5 Hz – 6 Hz). The analysis of pulse wave morphology requires an even higher upper cut-off frequency to maintain signal characteristics originating from reflections in the vascular system (0.5 Hz – 12 Hz). It should be avoided to use cut-off frequencies that interfere with the physiological range of the PPGI signal component of interest.

Analysis: Most works on PPGI focus on the extraction of a pulse rate [3,4]. However, similar to conventional contact-based photoplethysmography, other vital signs can be derived [11, 13, 14], including parameters of pulse rate variability, breath rate, pulse strength, perfusion index, pulse arrival time, pulse transit time, and correlates of functional oxygen saturation and blood pressure. Novel to PPGI are spatiotemporal investigations, for example with regard to two-dimensional perfusion maps [12, 15]. Although the feasibility of such analyses has been shown, prospective studies with diverse (and diseased) populations that allow for the generalization of findings are still missing.

End-to-End Deep Learning Approaches: Driven by recent advantages in deep learning, end-to-end approaches have become a popular field of research in PPGI. These approaches cover the whole processing pipeline from image processing to analysis in a single model to directly evaluate video recordings. However, robust design of such methods is challenging and many of the works recently published exhibit major design flaws. Key obstacles include:

1. The extraction of target variables is not comprehensible ("black box" systems). Some networks provide attention masks similar to a ROI [16], but mechanisms of signal construction or vital sign measurement remain inexplicable.
2. The ground truth significantly differs from PPGI [17]. The ground truth is usually provided by a conventional near-infrared finger PPG clip. Penetration depth and optical properties of skin and blood components differ in the near-infrared spectral region. In addition, skin anatomy and vascular regulation vary between face and finger.
3. Evaluation structure and data basis differ considerably between studies. There are still works being published that do not rule out data leakage between training, test, and val-

idation sets. Reviewers should insist on transparent descriptions and cross-database evaluation in this regard.
4. Architectures often cannot be reproduced due to incomplete or diffuse descriptions. Models are rarely shared.
5. The performance comparison of end-to-end approaches is merely focused on color channel combinations. Often, the ROI is derived with a simple skin detection algorithm and standard filters are applied. This leads to unfair comparisons to the advantage of end-to-end approaches [16]. Proper ROI detection algorithms that have been validated for PPGI (e.g. [5, 6]) and visual verification of the ROIs are essential prerequisites for fair comparisons. End-to-end approaches typically produce heavily smoothed PPGI signals, which is beneficial for evaluation metrics such as signal-to-noise ratio. To reduce distortions in the comparison, filter design should be oriented towards the same data basis that was used for the end-to-end approach.

3. Applications

Autonomic Function Assessment: PPGI allows for the unobtrusive and parallel measurement of vital signs related to the cardiac, respiratory, and vascular systems. This results in a wide range of possibilities for autonomic function assessment, for example, to investigate systemic or local reactions to mental [14, 18] and physical [19, 20] stressors. Apart from stress, human states such as vigilance, fatigue, and sleep may be of interest. The analysis of spatiotemporal patterns opens up new possibilities for quantitative assessment of areal perfusion, for example with the Allen Test [21] or negative-pressure therapy (vacuum assisted closure) [12].

Out-of-Hospital Monitoring: PPGI is not only unobtrusive but easy to apply, which renders it suitable for home monitoring and telemedical applications. Such systems have large potential to improve adherence in longitudinal monitoring of at-risk groups [22]. However, easy to apply PPGI requires fully integrated, user-centered systems [22] that must be adaptive to different environments and illumination. Also driver monitoring with PPGI has been reported, with the dynamics of ambient light and head movement as the main challenges [23].

Clinical Patient Monitoring: In clinical settings, the low disinfection effort and rapid preparation of PPGI are further advantages. PPGI allows to measure skin areas that are not available for sensor application (e.g. sensitive, burned, or wounded skin). PPGI has, for example, been used for unobtrusive clinical monitoring of neonates [24, 25] and geriatric patients [8] and for control of recovery after cardiac surgery in the intensive care unit [26]. The characteristics of PPGI render it a useful technique for sleep monitoring (polysomnography) and control after treatment (e.g. drug delivery).

Intra-Operative Assessment of Tissue Perfusion: Few works investigate intra-operative settings such as perfusion monitoring during fasciocutaneous flap transplantation [27], intestinal tumor resection [28], and cerebral anastomosis [29]. It is apparent that spatial characteristics of PPGI hold large potential for perfusion-related surgery.

Differentiation from Smart Watch PPG: Smart watches are used to capture wrist PPG. They are mobile, but deliver PPG signals without an environmental context, which often hampers interpretation. PPGI, on the other hand, is mostly used in the same environment. Both technologies are susceptible to relative movements between light source, sensor and tissue, which, during free movement, is likely to occur more often in the non-contact settings of PPGI. However, PPGI enables the spatial measurement of perfusion, which is not possible with smart watches. The camera recordings of PPGI can also be used for further analysis (e.g. emotion or fall detection).

4. Summary and Outlook

PPGI offers unique benefits due to its non-contact and spatiotemporal characteristics. While the application of PPGI is simple, the design principles are complex and feature many degrees of freedom. Nevertheless, the feasibility of novel applications inside and outside the clinical environment has been shown. Yet, to reach clinical practice, the reliability of PPGI, generalization of findings (e.g. across patient groups and diseases), and standardization require more attention.

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