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Citation for published version (APA):

DOI:
10.1109/TBME.2014.2356291

Document status and date:
Published: 01/01/2015

Document Version:
Publisher’s PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:
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Exploiting Spatial Redundancy of Image Sensor for Motion Robust rPPG

Wenjin Wang*, Sander Stuijk, and Gerard de Haan

Abstract—Remote photoplethysmography (rPPG) techniques can measure cardiac activity by detecting pulse-induced color variations on human skin using an RGB camera. State-of-the-art rPPG methods are sensitive to subject body motions (e.g., motion-induced color distortions). This study proposes a novel framework to improve the motion robustness of rPPG. The basic idea of this paper originates from the observation that a camera can simultaneously sample multiple skin regions in parallel, and each of them can be treated as an independent sensor for pulse measurement. The spatial redundancy of an image sensor can thus be exploited to distinguish the pulse signal from motion-induced noise. To this end, the pixel-based rPPG sensors are constructed to estimate a robust pulse signal using motion-compensated pixel-to-pixel pulse extraction, spatial pruning, and temporal filtering. The evaluation of this strategy is not based on a full clinical trial, but on 36 challenging benchmark videos consisting of subjects that differ in gender, skin types, and performed motion categories. Experimental results show that the proposed method improves the SNR of the state-of-the-art rPPG technique from 3.34 to 6.76 dB, and the agreement (±1.96σ) with instantaneous reference pulse rate from 55% to 80% correct. ANOVA with post hoc comparison shows that the improvement on motion robustness is significant. The rPPG method developed in this study has a performance that is very close to that of the contact-based sensor under realistic situations, while its computational efficiency allows real-time processing on an off-the-shelf computer.

Index Terms—Biomedical monitoring, motion analysis, photoplethysmography, remote sensing.

I. INTRODUCTION

CARDIAC activity is measured by medical professionals to monitor patients’ health and assist clinical diagnosis. The conventional contact-based monitoring methods, i.e., electrocardiogram (ECG) and photoplethysmography (PPG), are somewhat obtrusive and may cause skin irritation in sensitive subjects (e.g., skin-damaged patients, neonates). In contrast, camera-based vital signs monitoring triggers a growing interest for noninvasive and nonobtrusive healthcare monitoring. Earlier progress made in camera-based vital signs monitoring can be categorized into two trends: 1) detecting the minute optical absorption variations of the human skin induced by blood volume changes during the cardiac cycle, i.e., remote-PPG (rPPG) [1]–[3]; 2) detecting the periodic head motions caused by the blood pulsing from heart to head via the abdominal aorta and carotid arteries [4]. However, both the color-based and motion-based approaches are sensitive to body motions, since these can dramatically change the light reflected from the skin surface and also corrupt the subtle head motion driven by the cardiovascular pulse. Although significant progress has been reported in the rPPG category for a fitness setting recently [3], the signal-to-noise ratio (SNR) of the pulse signals obtained by all existing methods are still reduced when the subject is moving relative to the camera.

The goal of this paper is to significantly improve the SNR of the rPPG pulse signal by better exploiting the spatial redundancy of the image sensor. To some extent, the spatial redundancy of the image sensor has already been exploited in previous rPPG methods [1]–[3] as they extract the pulse signal from the averaged pixel value in a skin region. Such averaging of independent sensors is optimal only if the (temporal) noise level in skin pixels is comparable and has a Gaussian distribution. However, the image-to-image variations in skin pixels from a face may be very strong in the mouth region of a talking subject, while relatively low on the stationary forehead. If the outliers (pixels near the mouth) could be removed from the average, the quality of the extracted pulse signal is expected to be improved significantly.

To this end, a motion robust rPPG method is proposed to treat each skin pixel in an image as an independent rPPG sensor and extract/combine multiple rPPG signals in a way that is immune to noise. The proposed method consists of three steps: 1) creating pixel-based rPPG sensors from motion-compensated image pixels, 2) rejecting motion-induced spatial noise, and 3) optimizing temporally extracted pulse-traces into a single robust rPPG signal. To demonstrate the effectiveness, it has been evaluated on 36 challenging videos with an equal number of male and female subjects in three skin-type categories and six motion-type categories.

The contributions of this paper are threefold: 1) a new strategy is proposed to track pixels in the region of interest (e.g., a subject’s face) for rPPG measurement using global and local motion compensation; 2) exploiting the spatial redundancy of an image sensor, i.e., pixel-based rPPG sensors, is proved to lead to a considerable gain in accuracy as compared to the common approach that takes a single-averaged color trace, and 3) a novel algorithm is introduced to optimize the pixel-based rPPG sensors in spatial and temporal domain.

Manuscript received April 25, 2014; revised August 18, 2014; accepted August 31, 2014. Date of publication September 8, 2014; date of current version January 16, 2015. Asterisk indicates corresponding author.

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Digital Object Identifier 10.1109/TBME.2014.2356291
The rest of this paper is organized as follows. Section I provides an overview of the related work. Section II analyzes the problem concerning this study and describes the proposed method. The experimental setup is discussed in Section I while the proposed method is evaluated and discussed in Section V. Finally, the conclusions are drawn in Section VI.

II. RELATED WORK

In the cardiovascular system, the blood pulse propagating throughout the body changes the blood volume in the vessels. Given the fact that the optical absorption of hemoglobin varies across the light spectrum, a specific cardiovascular event can be revealed by measuring the color variations of skin reflections [1]. In 2008, Verkruysse et al. found that in an ambient light condition, the PPG signal has different relative strength in three color channels of an RGB camera that senses the human skin [5]. Based on this finding, Poh et al. proposed a linear combination of RGB channels defining three independent signals with independent component analysis using non-Gaussianity as the criterion for separating independent resource signals [1]. As an alternative, Lewandowska et al. suggested a principal component analysis (PCA)-based solution to define three independent linear combinations of RGB channels [2]. In 2012, MIT developed a method called “Eulerian video magnification” to amplify the subtle color changes through band-pass filtering the temporal pyramidal image differences [6]. However, any motion-induced color distortions within the same frequency band as that of the pulse are unfortunately amplified. More recently, de Haan et al. introduced the chrominance-based rPPG method (CHROM) to consider the pulse as a linear combination of three color channels under a standardized skin-tone assumption [3]. This method demonstrates the highest accuracy of all existing rPPG methods. Based on a comparison of the state-of-art rPPG methods, this study relies on the CHROM method as the baseline to develop a motion robust rPPG method.

III. METHOD

The overview of the proposed motion robust rPPG framework is shown in Fig. 1, which takes a video sequence containing a subject’s face as the input and returns the extracted pulse signal as its output. There are three main steps in the processing chain: motion-compensated pixel-to-pixel pulse extraction, spatial pruning, and temporal filtering. Each step is discussed in detail in the following sections.

A. Motion-Compensated Pixel-to-Pixel Pulse Extraction

To extract parallel pulse signals from spatial-redundant pixels, the pixels belonging to the same part of skin should be concatenated temporally. So this method compensates for the subject motion and relates temporally corresponding pixels.

1) Global Motion Compensation: In previous rPPG methods [1]–[3], the subject’s face is typically used as the region of interest (RoI) for pulse measurement. The motion of the face can be interpreted as a linear combination of global rigid motion (head translation and rotation) and local nonrigid motion (e.g., eye blinking and mouth talking). The common approach to compensate for the global motion of a face is using the Viola–Jones face detector to locate the face in consecutive frames with a rectangular bounding-box [7]. However, a classifier that has, for example, been trained with only the frontal-face samples cannot detect the side-view faces. This fundamental limitation may lead to a discontinuous face localization across subsequent video frames.

As an alternative, a “tracking-by-detection” approach, which enables the online updating of the target appearance model while tracking the object, demonstrates the capability of adapting to occasional appearance changes of the target as well as handling the challenging environmental noise (e.g., partial occlusions and background clutter). According to the latest benchmark results of online object tracking presented in 2013 [8], the circulant structure of tracking-by-detection with kernels (CSK) developed by Henriques et al. [9] has the highest tracking speed among the top ten accurate trackers, which can achieve hundreds of frames per second [8]. Considering that no significant accuracy difference can be observed among the state-of-the-art trackers in the setting of this study, the fastest CSK method is chosen to compensate for the global motion of the subject’s face instead of a Viola–Jones face detector.

2) Local Motion Compensation: Based on the globally tracked face, the pixels’ displacements can be more precisely
estimated in this step. The implementation of the Farneback dense optical flow algorithm [10] in OpenCV 2.4 [11] is utilized to measure the translational displacement of each image pixel between adjacent frames. In addition, the idea of forward-backward flow tracking proposed by Kalal et al. [12] is adopted to detect the pixel-based tracking failures: in a bidirectional tracking procedure, the motion vectors with larger spatial errors yielded by abrupt motion are removed as noise, whereas the consistent motion vectors are retained to associate the temporal corresponding pixels via spatial bilinear interpolation.

3) Pixel-to-Pixel Pulse Extraction: After global and local motion compensation, the pixels between adjacent frames have been aligned into pairs. By concatenating them in a longer frame interval, multiple pixel trajectories can be generated. However, there is a problem in creating such longer pixel trajectories: pixels belonging to the same trajectory may disappear due to occlusions (e.g., face rotation).

In fact, under a constant lighting environment, the pixels in different locations of the skin show the same relative PPG amplitude. It implies that if the pulse-induced color changes in each aligned pixel pair are temporally normalized, they can be concatenated in an arbitrary order to derive a long-term signal. Since the pixel-based motion vectors only need to be estimated between two frames (the smallest possible interval), it minimizes the occlusion problem and also prevents the propagation of errors in local motion estimation.

The temporally normalized RGB differences of the \( t \)th pixel between frame \( t \) and \( t+1 \) is denoted by a vector \( \mathbf{C}_i^{-t+1} \), which is defined as

\[
\mathbf{C}_i^{-t+1} = \mathbf{C}_i^{t+1} - \mathbf{C}_i^t = \begin{pmatrix}
R_i^{t+1} - R_i^t \\
G_i^{t+1} - G_i^t \\
B_i^{t+1} - B_i^t
\end{pmatrix}.
\]

Assuming the spatial displacement of the \( i \)th pixel from frame \( t \) to \( t+1 \) is \( \mathbf{d} = (d_x, d_y) \), (1) can be written as

\[
\mathbf{C}_i^{-t+1} = \begin{pmatrix}
R_i^{t+1}(x+d_x, y+d_y) - R_i^t(x, y) \\
G_i^{t+1}(x+d_x, y+d_y) - G_i^t(x, y) \\
B_i^{t+1}(x+d_x, y+d_y) - B_i^t(x, y)
\end{pmatrix}.
\]

Fig. 2 shows the histogram distribution of \( \mathbf{C}_i^{-t+1} \) on three different skin tones: the Gaussian-shaped distribution of \( R_i^{t+1} \), \( G_i^{t+1} \), and \( B_i^{t+1} \) on different skin tones are all within the range \([-0.02, 0.02]\), which is very concentrated compared to its theoretical variation range \([-1, 1]\). Thus, it can be concluded that in all skin pixels, pulse-induced color variations roughly exhibit the same strengths in temporally normalized color channels.

After that, the temporally normalized RGB differences are projected onto the chrominance plane using the CHROM method [3], which defines the pulse signal as a linear combination of RGB channels as

\[
\begin{align*}
\hat{X}_i^{-t+1} &= 3\mathbf{C}_i^{t+1} - 2G_i^{t+1} \\
\hat{Y}_i^{-t+1} &= 1.5R_i^{t+1} + G_i^{t+1} - 1.5B_i^{t+1} - \mathbf{C}_i^{t+1}.
\end{align*}
\]

By temporally concatenating \((\hat{X}_i^{-t+1}, \hat{Y}_i^{-t+1})\) estimated from pixel pairs between adjacent frames and integrating them, multiple chrominance traces can be derived as

\[
\begin{align*}
\hat{X}_i^{-t+l} &= 1 + \sum_{0}^{l} \hat{X}_i^{-t+1} \\
\hat{Y}_i^{-t+l} &= 1 + \sum_{0}^{l} \hat{Y}_i^{-t+1},
\end{align*}
\]

where \( l \) is the interval length of the chrominance trace defined by a temporal sliding window. In line with [3], \( l \) is specified as 64 frames in case of a 20 FPS video recording rate. The pulse trace in the temporal window can be calculated as

\[
\hat{P}_i^{-t+l} = \hat{X}_i^{-t+l} - \alpha \hat{Y}_i^{-t+l}
\]

with \( \alpha = \frac{\sigma(\hat{X}_i^{-t+l})}{\sigma(\hat{Y}_i^{-t+l})} \)

where \( \sigma(\cdot) \) corresponds to the standard deviation operator. In order to avoid the signal drifting/explosion in a long-term accumulation, the pulse traces estimated from the sliding window are overlap—added together with a Hann window [3].

Note that the spatial averaging of local pixels can reduce quantization errors during the temporal color normalization. The face RoI is downsamples starting from the local motion compensation step, which not only reduces the noise sensitivity of pixel-based PPG sensors, but also increases the processing speed of the dense optical flow. There is a tradeoff in selecting the optimal downsampling size considering the accuracy and efficiency. Since the size of all subjects’ face used in this study are approximately \( 200 \times 250 \) pixels, the RoI is uniformly downsampled to \( 36 \times 36 \) pixels.
B. Spatial Pruning

Since the temporal noise level in pixel-based rPPG sensors is not Gaussian distributed, the next step is to optimally select the inliers (reliable sensors) from a set of spatially redundant sensors for a robust PPG-signal measurement. In practice, there are mainly two kinds of noise degrading the quality of PPG sensors: 1) nonskin pixels (e.g., eyebrow, beard, and nostril) that do not present pulse signals; 2) skin pixels that contain motion-induced color distortions. Based on this observation, a spatial pruning method including skin/nonskin pixel classification and color space pruning is designed to preselect the reliable sensors.

1) Skin/Nonskin Pixel Classification: Most skin segmentation methods use predefined thresholds of skin color composition or model a binary boundary between foreground and background. However, these approaches suffer from dilemmas in choosing suitable thresholds or defining foreground/background. As a matter of fact, most of the pixels inside a well-track region represent the skin while only a small number of them are not skin. Since the skin pixels that share some similarities are bound in one cluster, a clustered feature-space can be constructed to detect the pixels that are further away from the cluster center as novels (nonskin pixels). In this method, the one class support vector machine (OC-SVM) [13] is employed to estimate such a hyperplane, which encircles most of the pixel samples as a single class (skin class) without any prior skin color information.

In order to train an OC-SVM, a list of feature descriptors 
\[ x_1, x_2, x_3, \ldots, x_n \] should be created to represent the skin pixels. Inspired by [14] that using the intensity-normalized RGB and YCrCb to discriminate skin and nonskin regions, this method represents each vector \( x_i \) with four components: \( r - g \), \( r - b \), \( Y - Cr \), and \( Y - Cb \). The OC-SVM is only trained with the first few frames to adapt to the subject skin tone; then, it is used to predict the skin pixels in the subsequent frames, i.e., the pixels with the positive and negative responses for \( f(x) \) are classified as skin and nonskin pixels, respectively. This step significantly removes the pixel-based rPPG sensors that are not pointing at the subject’s skin, and its performance is invariant to different skin tones, as shown in Fig. 3.

2) Color Space Pruning: As explained before, the pulse-induced color variations exhibit similar changes in \( C_{i-t+1} \) under a homogeneous lighting environment, i.e., in temporally normalized color space, the transformation between \( (\overline{R_i}, \overline{G_i}, \overline{B_i}) \) and \( (\overline{R_i+1}, \overline{G_i+1}, \overline{B_i+1}) \) should ideally be the translation. However, motion-induced color distortions enter this translation by adding additional residual transformations, such as rotation. Therefore, by checking the geometric transformation of pixel-based rPPG sensors in the temporally normalized color space, a number of unreliable sensors distorted during the transformation can be found and pruned. To realize this step, the inner product \( \phi \) of the unit color vectors between frame \( t \) and \( t+1 \) is simply calculated as

\[
\phi_{i-t+1} = \left\langle \frac{\overline{C_i}}{||\overline{C_i}||}, \frac{\overline{C_{i+1}}}{||\overline{C_{i+1}}||} \right\rangle
\]

where \( \langle \cdot, \cdot \rangle \) denotes the inner product operation, \( || \cdot || \) corresponds to the L2-normalization. When \( \phi_{i-t+1} \) is more deviated from 1, the angle between \( \overline{C_i} \) and \( \overline{C_{i+1}} \) is larger, which implies that the color transformation is more likely to be motion induced. In this manner, all the rPPG sensors are sorted based on their inner products and a fraction \( \beta \) (e.g., \( \beta = \frac{1}{2} \)) of them ranking closest to 0 (orthogonal) are pruned as outliers. Fig. 4 shows an example of spatially pruned results in this space: subject motion yields a more sparse distribution of rPPG sensors in the spatial domain as compared to the stationary scenario.

Furthermore, the remaining rPPG sensors are pruned in the temporally normalized XY space. On the projected chrominance plane using (3), it can be observed that when the subject is perfectly stationary, \( X - \alpha Y \) (pulse direction) is the principal direction while the projections are densely distributed as an ellipse; when motion appears, the direction orthogonal to \( X - \alpha Y \) starts to dominate the space and the projections are sparsely distributed like a stripe, as shown in Fig. 5. The direction orthogonal to the pulse direction on this chrominance plane is named as the “motion direction,” which can be expressed as

\[
\overline{M_{i-t+1}} = \overline{X_{i-t+1}} + \alpha \overline{Y_{i-t+1}}
\]

where \( \alpha \) is identical to the one calculated in (6). The criterion to prune sensors on the chrominance plane is: selecting the sensors containing the least motion signals but the most likely pulse signals. Therefore in the first round, all sensors are sorted...
To derive a robust rPPG signal from adaptive union of pulse traces whose frequency-peak position are temporally normalized, they can be randomly concatenated generating parallel pulse traces. This step removes the sensors containing implicit motion-induced distortion residues, but retains the sensors with the most likely pulse signal.

C. Temporal Filtering

Till this step, there are two alternatives to use the spatially pruned rPPG sensors: 1) averaging the inliers for subsequent pulse estimation that is further identical to previous rPPG methods; 2) first extracting independent pulse signals from the inliers in parallel, and then combining them into a single robust pulse signal after postprocessing. Due to the residual errors in motion estimation, the noise in spatial inliers still shows no Gaussian distribution and is not zero mean. Furthermore, concatenating the local rPPG sensors separately allows the local optimization of $\alpha$ in (5) when deriving the pulse signals. Consequently, option (2) is adopted to separate the pulse signal and noise by generating parallel pulse traces.

Given the fact that the pulse derivatives in local rPPG sensors are temporally normalized, they can be randomly concatenated for creating long-term traces. But generating all possible concatenations is an impossible task (e.g., $(600!)^{64}$ different ways of concatenation in case of 600 skin pixels over 64 frames), so a simple solution is proposed to find favorable concatenations: first, sort all the pulse derivatives (sensors) based on their distance to the mean and concatenate them in the sorted order. The signal-traces ranking at the top are expected to be fairly reliable pulse signals, whereas the ones ranking at the bottom are likely to be suboptimal. Afterward, the adaptive band-pass filtering and PCA decomposition steps are designed to further enhance and combine the multiple pulse traces into a single robust rPPG signal.

1) Adaptive Band-Pass Filtering: Essentially, the pulse rate of a healthy subject falls within the frequency range $[40, 240]$ beats per minute (bpm), so the parts of signal that are not in this frequency band can be safely blocked, i.e., in a temporal sliding window with 64 frames length, the in-band frequency range corresponds to $[2, 12]$. For a given moment, the instant pulse frequency should be even more concentrated in a smaller range such as $[80, 90]$ bpm. So using the real-time pulse-rate statistics, an adaptive band-pass filtering method is developed to better limit the band-pass filter range.

An example is shown in Fig. 6: the mean frequency-peak position of all pulse traces in the current temporal window is found as the most probable instantaneous pulse frequency of the subject, then a fraction $\beta$ of pulse traces whose frequency-peak position has a large distance to the most probable instantaneous pulse frequency are pruned. After that, the original pulse-frequency band is adapted to the first two harmonics derived from the mean frequency peak position, i.e., if the most probable peak position is at 4, the pulse-frequency range is reduced from original $[2, 12]$ to $[3, 5] \cup [6, 10]$ (first two harmonics). Similarly, if the most probable peak position is at 5, the pulse-frequency band is narrowed down to $[4, 6] \cup [8, 12]$.

Note that the proposed adaptive band-pass filtering method adjusts the pulse-frequency bandwidth based on instantaneous statistics in the current sliding window, which does not rely on any prior assumptions or previous observations (e.g., Kalman filter) of a specific subject’s pulse rate.

2) PCA Decomposition: To derive a robust rPPG signal from multiple band-passed pulse traces, the robust pulse signal is defined as a periodic signal with the highest variance. The reasons are 1) the subject motions are often occasional and unintentional in a hospital/clinical use case, i.e., nonperiodic motions, 2) the motion-induced variance has been reduced by motion compensation, so the pulse-induced periodicity is more obvious in a cleaner signal trace.

Based on this observation, the periodicity of a pulse signal is defined as a ratio between the maximum power and total power of the signal spectrum in the pulse-frequency band. When the signal is more periodic, this ratio is larger. Similarly, the pulse traces are sorted based on their periodicity, and a fraction $\beta$ of traces with low periodicity are pruned.

Finally, PCA is performed on the periodic pulse traces to obtain the eigenvectors, which has two benefits: 1) the decomposed eigenvectors are orthogonal to each other in the subspace, which clearly separates the pulse signal and noises, 2) the eigenvectors are ordered in term of variance, which simplifies the procedure of selecting the most variant trace. In the temporal sliding window, the eigenvector (among the top five eigenvectors) that
has the best correlation with the mean pulse trace is selected to be the rPPG signal after correcting the arbitrary sign of the eigenvector as

$$\tilde{P}_{t-l}^{\text{selected}} = \frac{\langle \tilde{P}_{t-l}^{\text{eigen}}, \tilde{P}_{t-l}^{\text{mean}} \rangle}{\langle \tilde{P}_{t-l}^{\text{eigen}}, \tilde{P}_{t-l}^{\text{mean}} \rangle} \times \tilde{P}_{t-l}^{\text{eigen}}$$

where $\tilde{P}_{t-l}^{\text{eigen}}$ and $\tilde{P}_{t-l}^{\text{mean}}$ represent the eigenvector and mean pulse trace, respectively; $\langle \cdot, \cdot \rangle$ corresponds to the inner product (correlation) between two vectors; and $| \cdot |$ denotes the absolute value operator.

### IV. EXPERIMENT

This section presents the experimental setup for evaluating the proposed rPPG method. First, it shows the way of creating the benchmark video dataset. Next, it introduces two metrics for evaluating the performance of rPPG methods. Finally, it includes five (r)PPG methods for performance comparison.

#### A. Benchmark Dataset

To evaluate the proposed rPPG method, six healthy subjects (students) are recruited from Eindhoven University of Technology. The study is approved by the Internal Committee Biomedical Experiments of Philips Research, and the informed consent is obtained from each subject. The video sequences are recorded with a global shutter RGB CCD camera (type USB UI-2230E-C of IDS) in an uncompressed data format, at a frame rate of 20 Hz, 768 × 576 pixels, 8 bit depth, and has a duration of 90 s per motion category. During the video recording, the subject wears a finger-based transmissive pulse oximetry (model CMS50E from Contec Medical) for obtaining the reference pulse signal, which is synchronized with the recorded video frames using the USB protocol available on the device. The subjects sit in front of the light source (type: Philips HF3319—EnergyLight White).

Fig. 7 shows a snapshot of the recorded subjects from three skin-type categories according to the Fitzpatrick skin scale [15]: Skin-category I with “Skin-type II” male/female; Skin-category II with “Skin-type III” male/female; and Skin-category III with “Skin-type V” male/female. All subjects are instructed to perform six different types of head motion: stationary, translation, scaling, rotation, talking, and mixed motion (mixed motion is the mixture of all motions). For each recording, the subject remains stationary in the first 15 s and then performs a specific motion till the end by repeating it. There is no guidance to restrict the amount of motion, so it leads to displacements up to the maximum 35 pixels per picture-period in practice. This is intended to better mimic the practical use cases and make the videos sufficiently challenging for rPPG.

Fig. 8 shows some uniformly sampled frames in the rotation video sequence of skin-category II male.

The goal of this study is aimed to improve the “motion robustness” of rPPG, “motion” is considered the key variable that is varied in the dataset. (As mentioned before, the gender and skin type are also varied.) So when recording each video sequence, the subject is asked to perform a specific type of motion repeatedly. Each motion is repeated approximately 15 times in each video sequence. Since motion is the most important variable affecting the rPPG performance in a single constant luminance environment, the measurement of the whole video sequence with repeated subject motion can be considered as a composition of multiple repeated short-term measurements. Hence, the video sequences allow studying the measurement repeatability. The Bland–Altman plots in Fig. 10 shows, for example, the within-measurement repeatability comparison between rPPG and PPG, in which each scatter point represent the measurement of one complete pulse. To prevent an explosion of test data, the subjects selected for recording are representative/typical in each skin category. There are no subjects at all intermediate skin types, which makes it impossible for us to draw thorough conclusions on skin-tone invariance of the rPPG methods.

#### B. Evaluation Metrics

This study adopts the same SNR metric as used in [3] to measure the signal quality for comparing the strength and weakness of rPPG methods. In this SNR metric, a temporal sliding window is utilized to segment the whole pulse signal into intervals for deriving the SNR trace, i.e., the temporal window has a 300 frames stride and a one frame sliding step. In the sliding window, the signal interval is transformed to the frequency domain using FFT. The SNR is measured as the ratio between the energy around the first two harmonics (pulse in-band frequency) and the remaining energy (noises out-of-band frequency) of the spectrum, which is defined as

$$\text{SNR} = 10 \log_{10} \left( \frac{\sum_{f=40}^{220} |U_t(f)|^2 \hat{S}(f)^2}{\sum_{f=40}^{220} (1 - |U_t(f)| \hat{S}(f))^2} \right)$$

where $f$ is the pulse frequency in bpm, $\hat{S}(f)$ is the spectrum of the pulse signal, $U_t(f)$ is a defined binary window to pass...
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Fig. 9. In each category, the color bar is the averaged SNRa while the black bar is the standard deviation. (a) Motion SNRa: it compares the SNRas obtained by the (r)PPG methods in different motion types (averaged over genders and skin categories). (b) Skin SNRa: it compares the SNRas obtained by the (r)PPG methods in different skin categories (averaged over genders and motion types).

Fig. 10. Instantaneous pulse-rate plot (first row) and Bland–Altman plot (second row) for six motion types of the male subject in skin-category II. The subject’s appearance is shown in Fig. 8. The Bland–Altman agreements are calculated between rPPG signals and reference signals (REF), where the reference signals are the smoothed signals recorded by CBS. To visually compare the agreements between rPPG methods and reference, the Bland–Altman plots of four rPPG methods are put in one graph and $\sigma$ of $\pm 1.96\sigma$ obtained between PTC and the reference to denote the variance range.

The pulse in-band frequency and block the noisy out-of-band frequencies. Consequently, the SNRa, an averaged value of the SNR-trace, is used to summarize the quality of the pulse signal.

Additionally, Bland–Altman plots are included to show the agreements of the instantaneous pulse rate between the rPPG and reference PPG sensor. The instantaneous pulse rate, defined as the inverse of the peak-to-peak interval of the pulse signal, is derived by a simple peak detector in the time domain. The reasons of using it for signal comparison are twofold: 1) the primitive pulse signals obtained by rPPG and PPG have good alignment with each other, thus their instantaneous rates are comparable, 2) it captures the instantaneous changes of the pulse signal and reflects the occasional differences between compared signals, as an example shown in Fig. 10. In the standard Bland–Altman plot, the Cartesian coordinate of a pulse rate’s sample $s_i$ is calculated as

$$s_i(x, y) = \left( \frac{PR_i + RR_i}{2}, PR_i - RR_i \right)$$

where $PR_i$ and $RR_i$ are $i$th instantaneous pulse rates obtained by rPPG and PPG, respectively. $RR_i$ is smoothed by a five-point mean filter for suppressing the noise effect. Furthermore, the Bland–Altman agreement $A$ between $PR_i$ and $RR_i$ is calculated as

$$A = \sum_{i=1}^{n} \frac{a_i}{n}$$

with

$$a_i = \begin{cases} 1 & \text{if } |PR_i - RR_i| < 1.96\sigma \\ 0 & \text{if } |PR_i - RR_i| \geq 1.96\sigma \end{cases}$$

where $n$ is the total number of samples in a pulse rate; $\sigma$ denotes the standard deviation of the difference between $PR_i$ and $RR_i$.

Finally, the analysis of variance (ANOVA) is applied on SNRas values to analyze the significance of difference between (r)PPG methods under certain categories (e.g., skin or motion), i.e., to show whether the main variation in SNRas is “between” groups (rPPG methods) or “within” groups (video sequences). Based on the results of ANOVA, the post-hoc comparison is used to further evaluate the posteriori pairwise comparisons between individual methods to see which one is significantly better than the other. The ANOVA with post-hoc comparison gives a clear overview of statistical comparison between investigated (r)PPG methods.
TABLE I
SNR  R  E  ULTS  A  I  G  NA  I  E  D  BY  (r)PPG  M  EOTH  O  ODS  O  N  B  E  N  C  H  M  A  N  K  V  I  D  O  S  (AV  E  R  AGED  O  V  E  R  G EN  D  E  R  S)

<table>
<thead>
<tr>
<th>Videos</th>
<th>FDM</th>
<th>FTM</th>
<th>PTC</th>
<th>PTC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skin-category I stationary</td>
<td>6.54</td>
<td>6.65</td>
<td>6.73</td>
<td>7.18</td>
</tr>
<tr>
<td>Skin-category I translation</td>
<td>6.20</td>
<td>6.75</td>
<td>6.33</td>
<td>8.40</td>
</tr>
<tr>
<td>Skin-category I scaling</td>
<td>3.90</td>
<td>5.48</td>
<td>5.44</td>
<td>8.26</td>
</tr>
<tr>
<td>Skin-category I rotation</td>
<td>1.53</td>
<td>6.83</td>
<td>6.78</td>
<td>7.91</td>
</tr>
<tr>
<td>Skin-category I talking</td>
<td>5.69</td>
<td>5.94</td>
<td>1.34</td>
<td>7.25</td>
</tr>
<tr>
<td>Skin-category I mixed motion</td>
<td>1.86</td>
<td>4.24</td>
<td>4.30</td>
<td>7.18</td>
</tr>
<tr>
<td>Skin-category II stationary</td>
<td>8.26</td>
<td>8.24</td>
<td>7.93</td>
<td>8.80</td>
</tr>
<tr>
<td>Skin-category II translation</td>
<td>6.13</td>
<td>6.95</td>
<td>6.52</td>
<td>6.91</td>
</tr>
<tr>
<td>Skin-category II scaling</td>
<td>7.43</td>
<td>7.39</td>
<td>7.20</td>
<td>8.11</td>
</tr>
<tr>
<td>Skin-category II rotation</td>
<td>−0.20</td>
<td>4.29</td>
<td>4.30</td>
<td>5.90</td>
</tr>
<tr>
<td>Skin-category II talking</td>
<td>2.49</td>
<td>2.42</td>
<td>1.39</td>
<td>3.60</td>
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<tr>
<td>Skin-category II mixed motion</td>
<td>1.18</td>
<td>2.97</td>
<td>1.53</td>
<td>3.97</td>
</tr>
<tr>
<td>Skin-category III stationary</td>
<td>5.87</td>
<td>6.55</td>
<td>7.24</td>
<td>8.93</td>
</tr>
<tr>
<td>Skin-category III translation</td>
<td>2.81</td>
<td>3.89</td>
<td>3.90</td>
<td>5.97</td>
</tr>
<tr>
<td>Skin-category III scaling</td>
<td>2.16</td>
<td>2.29</td>
<td>2.55</td>
<td>7.37</td>
</tr>
<tr>
<td>Skin-category III rotation</td>
<td>−1.80</td>
<td>−0.70</td>
<td>0.83</td>
<td>6.09</td>
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<tr>
<td>Skin-category III talking</td>
<td>0.30</td>
<td>1.24</td>
<td>−0.32</td>
<td>5.00</td>
</tr>
<tr>
<td>Skin-category III mixed motion</td>
<td>−0.24</td>
<td>0.94</td>
<td>−0.21</td>
<td>4.93</td>
</tr>
<tr>
<td>Average</td>
<td>3.34</td>
<td>4.58</td>
<td>4.10</td>
<td>6.76</td>
</tr>
</tbody>
</table>

Bold entries indicate the best performance of rPPG methods in each category.

C. Compared Methods

Based on the benchmark dataset and evaluation metrics, three comparisons have been performed for the evaluation: 1) comparing the proposed method to the state-of-the-art rPPG method CHROM [3], 2) comparing the separate steps in the developed framework to show their independent improvements and contributions to the complete solution, since these separate steps involve innovations that are not addressed in previous rPPG studies, and 3) comparing the rPPG methods to the PPG method to show the disparity between camera-based and contact-based approaches. The details of the compared (r)PPG methods are described below:

1) Face-Detect-Mean (FDM) is a reimplementation of the CHROM method. It uses the Viola–Jones face detector to locate the face, and applies the OC-SVM method to select the skin pixels to derive the averaged RGB traces for pulse-signal estimation.

2) Face-Track-Mean (FTM) is the included substep of the proposed method. It replaces the Viola–Jones face detector in FDM with the CSK tracker for the better face localization.

3) Pixel-Track-Mean (PTM) is the included substep of the proposed method. It extends FTM with spatial redundancy by creating pixel-based rPPG sensors, but takes the averaged values of the temporally normalized color differences to derive the pulse signal.

4) Pixel-Track-Complete (PTC) is the complete version of the proposed method, which adds the spatiotemporal optimization procedure (spatial pruning and temporal filtering) to the PTM.

5) Contact-Based-Sensor (CBS) is a finger-based pulse oximetry. It is used to record the reference pulse signal for comparison.

V. RESULTS AND DISCUSSION

The proposed method is implemented in Java using the OpenCV 2.4 library [11] and run on a laptop with an Intel Core i7 2.70 GHZ processor and 8 GB RAM. All five methods are evaluated on 36 video sequences from the benchmark dataset. For fair comparison, only the RoI (e.g., subject’s face) needs to be manually initialized, while the other parameters remained identical when processing different videos.

The results show that the gender is not the key factor that needs to be investigated in this dataset, i.e., the differences between stationary male and female from the same skin-category are rather small. Thus, the results obtained by the different genders in the same skin category and motion type are averaged. Tables I and II summarize the gender-averaged SNRa and Bland–Altman agreements, respectively. Moreover, the SNRa values in Table I are further averaged over 1) the three skin categories for comparing the motion robustness, 2) the six motion types for comparing the skin-tone invariance, as shown in Fig. 9 (the standard deviation of SNRa is also calculated to show the methods’ variability in each category).

1) Stationary Scenario

Fig. 9(a) shows that all (r)PPG methods gain similar performance on stationary subjects, i.e., the standard deviations of their SNRa are below 1.0 dB. The reason is that these methods are all using the chrominance-based method [3] for pulse extraction. Their main difference is in motion estimation and outlier rejection. No significant improvements can be expected for static subjects.

2) Motion Scenarios

In videos, where the subjects’ frontal face can be detected by the Viola–Jones method (e.g., translation, scaling, and talking),
FDM still works properly, whereas FTM that relies on the online object tracker is approximately 1.0 dB better. The improvement is due to the object tracker, which leads to a smoother face localization between consecutive frames compared to the face detector by exploiting the target’s appearance consistency and position coherence.

However, the comparison between FTM and PTM implies that only exploiting the spatial redundancy cannot consistently improve the signal quality, i.e., in talking videos that contain local nonrigid mouth/lips motions, PTM increases the noise sensitivity in local pixel-based rPPG sensors and thus exhibits more quantization errors (even 2.4 dB less than FTM). This problem is solved in PTC that incorporates an outliers pruning procedure to remove the motion-distorted sensors.

In videos with vigorous motions (e.g., rotation and mixed motion), PTC including its substeps (FTM and PTM) shows superior performance against FDM in Fig. 9(a). The failure of FDM in these two types of motion (~0.15 and 0.93 dB, respectively) is mainly caused by the face detector, which cannot locate the side-view faces in some frames. Another significant challenge is from the large motion-induced color distortions on the skin surface, i.e., both the magnitude and orientation of skin-reflected light are dramatically changed during the rotation. In such a case, PTC achieves the largest improvement over FDM compared to other motion types (~6.79 and 4.43 dB more, respectively), which indicates that the proposed method can better deal with the subject motions in challenging use cases. Comparing the subject variability (standard deviation) between the videos with and without motion, FDM, FTM, and PTM increase around ±2.0 dB while PTC increases around ±0.7 dB, which is fairly stable.

Fig. 10 shows the instantaneous pulse rate and Bland–Altman agreement of the stationary male subjects in three skin categories. It is apparent that only PTC shows consistently high agreements with the reference signal.

3) Different Skin Categories

In addition to the motion robustness comparison, the skin-tone invariance of rPPG methods is analyzed. Fig. 9(b) shows that FDM, FTM, and PTM have difficulties in dealing with the darker skin type (Skin-category III) as compared to the brighter skin types [(Skin-category I and II)] (around 3 dB less). The performance degradation is caused by using the skin-chromaticity-based method for pulse extraction: the higher melanin contents in darker skin absorb part of the diffuse light reflections that carry the pulse signal, whereas the specular reflection is not reduced [3]. In contrast, PTC obtains a relatively consistent performance across the different skin categories, since the skin pixels with specular reflections caused by either the subject motion or skin absorption are all pruned as outliers. Besides, its temporal filtering suppresses the out-of-band frequency noise and strengthens the pulse frequency. Fig. 12 shows the instantaneous pulse rate and the Bland–Altman agreement of the stationary male subjects in three skin categories. It is apparent that only PTC shows consistently high agreements with the reference signal.

4) ANOVA With Post-Hoc Comparison

To analyze the significance of differences in motion and skin-tone robustness between methods, the SNRa values in Table I are grouped into five categories: the skin categories (I, II, and III), the stationary category, and the overall category. In each of the skin categories, the significance of differences between methods on motion robustness is measured (results on moving videos). In
the stationary category, the significance of differences between methods on skin-tone robustness is investigated. Finally, in the overall category, the overall significance of difference between methods is shown using the entire dataset. This paper applied the balanced one-way ANOVA on these five categories, and posthoc comparison using Tukey’s honestly significant difference criterion. In each category, a common significance threshold (\(p < 0.05\)) is used. Fig. 11 shows the results, while Table III lists the main ANOVA statistics.

In skin-categories I and III, the compared methods have significant differences (both \(p < 0.05\)). In skin-category II, the differences are not significant \((p = 0.6466)\). This high \(p\)-value reflects a limited variation between groups \((3.71)\) as compared to that within groups \((5.89)\). Indeed, the subjects in this group caused rather large motion variations as compared to subjects in the other groups. This could happen as limited instructions for the precise movements to be made were given to the subjects. In Fig. 11, the ANOVA plots show that PTC achieves the best performance in all three skin categories with respect to the subject motion. The post-hoc plots show that PTC is the only method that is significantly different from the baseline method (FDM) for skin-categories I and III. CBS, the contact-based reference method, only has significant difference with FDM in skin-category I. FTM and PTM have no significant pairwise differences with FDM in any skin-category, i.e., their possible motion-robustness improvement is very limited.

In the stationary-category, the \(p\)-value is 0.4398 (> 0.05) and, thus, the differences between methods are not significant in terms of the skin-tone robustness. Fig. 11 shows that on average PTC does score best.

Also in the overall category, the differences between methods in the complete benchmark dataset are significant 0.0003 \(< 0.05\). Fig. 11 shows that PTC again yields the largest improvement over the baseline method (FDM) and has a performance that is similar to the contact-based method (CBS), i.e., PTC and CBS have significant pairwise differences with FDM in the posthoc comparison.

It can be concluded that the proposed method, PTC, leads to significantly improved motion robustness, while for stationary videos the skin-tone robustness on average is the best though the differences with other methods are not significant.

VI. CONCLUSION

This study introduces a motion robust rPPG method that enables the remote detection of a pulse signal from subjects using an RGB camera. This paper integrates the latest methods in motion estimation and pulse extraction, and proposes novel algorithms to create and optimize pixel-based rPPG sensors in the spatial and temporal domain for robust pulse measurement. Experimental results on 36 challenging benchmark video sequences show that the proposed method significantly improves the SNR of the state-of-the-art rPPG method from 3.34 dB \(( \pm 2.91)\) to 6.76 dB \(( \pm 1.56)\), and improves the Bland–Altman agreement \((1.96\sigma)\) with instantaneous reference pulse rate from 55% to 80% correct, i.e., a performance that is very close to the contact-based sensor. ANOVA with post-hoc comparison shows that the proposed method, PTC, leads to significantly improved motion robustness, while on stationary videos with skin-tone variance it is also the best on average though the difference with the baseline method is not significant.

ACKNOWLEDGMENT

The authors would like to thank I. Kirenko, E. Bresch, J. Westerink, B. den Brinker, W. Verkruysse, and V. Jeanne at Philips Research for their support. Also, we are grateful for the help of volunteers from Eindhoven University of Technology in creating the benchmark video dataset.

REFERENCES


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Dr. de Haan received five Best Paper Awards, the Gilles Holst Award, the IEEE Chester Sall Award, bronze, silver, and gold patent medals, while his work on motion received the EISA European Video Innovation Award, and the Wall Street Journal Business Innovation Award. He serves in the program committees of various international conferences on image/video processing and analysis, and has been a Guest Editor for special issues of Elsevier, IEEE, and Springer.