Model-based Region of Interest Segmentation for Remote Photoplethysmography

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Abstract: Remote photoplethysmography (rPPG) is a non-contact technique for measuring vital physiological signs, such as heart rate (HR) and respiratory rate (RR). HR is a medical index which is widely used in health monitoring and emotion detection applications. Therefore, HR measurement with rPPG methods offers a convenient and non-invasive method for these applications. The selection of Region Of Interest (ROI) is a critical first step of many rPPG techniques to obtain reliable pulse signals. The ROI should contain as many skin pixels as possible with a minimum of non-skin pixels. Moreover, it has been shown that rPPG signal is not distributed homogeneously on skin. Some skin regions contain more rPPG signal than others, mainly for physiological reasons. In this paper, we propose to explicitly favor areas where the information is more predominant using a spatially weighted average of skin pixels based on a trained model. The proposed method has been compared to several state of the art ROI segmentation methods using a public database, namely the UBFC-RPPG dataset (Bobbia et al., 2017). We have shown that this modification in how the spatial averaging of the ROI pixels is calculated can significantly increase the final performance of heart rate estimate.

1 INTRODUCTION

The photoplethysmography (PPG) is an optical technique to non invasively detect the blood volume pulse (BVP). PPG sensors have two basic components, a LED light source and a photodetector. The light source illuminates the human tissue and the photodetector detects the light variation. Since the amount of light variation is proportional to blood intensity variation, the BVP can be obtained and the HR is calculated based on BVP.

The PPG is a low-cost and non-invasive technique, however it cannot work when motion and long-term monitoring are required. Therefore, remote PPG (rPPG) has been recently developed to address these drawbacks. The principle of rPPG is very similar with contact PPG. However, instead of using a LED light source and a specified photodetector, the rPPG can simply makes use of a web camera and ambient light. By detecting the variation of the light reflected by the face, the BVP and HR can be measured.

According to many previous studies (Sun and Thakor, 2016; Mcduff et al., 2015), the rPPG methods for HR measurement share a common pipeline-based framework: ROI selection for each frame, RGB signals selection and combination to get the pulse signal, and finally HR extraction from the filtered pulse signal. The ROI selection is the first step of the whole framework. The state of the art methods for ROI selection includes manual selection (Verkruysse et al., 2008), skin pixel classification (Wang et al., 2015) and conventional face detection and tracking (Poh et al., 2011).

Lots of research work has indicated that the ROI detection has significant effect on the HR measurement (Bousefsaf et al., 2013). This is because the numerical error of the signals will increase if the number of the effective pixels, i.e. skin pixels, is too small. Conversely, the number of non-skin pixels also has a significant negative influence on signal quality. Moreover, it has been shown that rPPG signal is not distributed homogeneously on the face. Some skin regions contain more rPPG signal than others. For example, it has been shown that the cheeks and forehead contain much more information than other areas of the face (Tur et al., 1983). From this premise, some studies have suggested to simply select the cheeks and/or forehead as ROI (Scalise et al., 2012; Lewandowska et al., 2011). This selection has the undeniable advantage of simplicity but it is also possible to weight

the skin pixels by their relative importance. In doing so, we explicitly favor areas of the face where there is more information.

In this paper, we propose a model-based ROI segmentation that explicitly favors the most important facial regions. The model describing the spatial distribution of rPPG information on the face was trained with ten videos. This model is then used to weight the pixels during spatial averaging. This approach has been validated using our in-house publicly available video dataset (Bobbia et al., 2017), called UBFC-RPPG specifically geared towards research on rPPG techniques. We have shown that this modification in how the spatial averaging of the ROI pixels is calculated can significantly increase the final performance of heart rate estimate compared with other state of the art methods such as face detection, skin classification and landmarks detection.

In section 2, the state of the art methods are briefly introduced. The proposed ROI segmentation method is explained in details in section 3. The experiment is described in section 4. The conclusion is presented in section 5.

2 STATE OF THE ART OF ROI SEGMENTATION METHODS

Most ROI segmentation techniques are based on the result of classical face detection and tracking algorithms. The ROI is then possibly refined with skin pixel classification or more precise ROI definition based on a set of landmarks. In this section we present several state of the art ROI segmentation techniques.

Since all of the video dataset are the recordings of heads and faces, the most straightforward method to detect the ROI is to use face detector and tracker (later called *face*). For this algorithm, the classical Viola-Jones face detector (Viola and Jones, 2001) and Kanade-Lucas-Tomasi tracking (Lucas et al.,) algorithm (cf. Fig 1(a)) can be used for implementation.

Since the rPPG information is only present on skin pixels, skin/non-skin classification (later called *skin*) is a popular improvement over the classical face detection and tracking. For instance, some researchers (Macwan et al., 2017) used this algorithm (Conaire et al., 2007) in their rPPG research work. The skin detection algorithm is achieved by thresholding of a non-parametric histogram which is trained by manually classified skin/non-skin pixels. The significant advantage of this algorithm is that it works very fast since it is based on a Look-Up-Table (LUT). Fig. 1(b) is an example of this method.

The ROI detection can also be segmented by defining a facial contour with a set of landmarks (later called *landmarks*). For this algorithm the method proposed by Kazemi can be used for implementation (Kazemi and Sullivan, 2014). One example is shown in Fig. 1(c).

The rPPG signal is not distributed homogeneously on skin. Some skin regions contain more rPPG signal than others. For example, it has been shown that SNR of rPPG signals extracted from forehead or cheekbones are significantly higher than other face regions. This assertion has already been used by different ROI segmentation techniques. For example, in some work only the cheeks and forehead were selected (Lewandowska et al., 2011). In a previous study, ROI segmentation, based on temporal superpixels, implicitly favors regions of interest where the pulse trace is more prominent (Bobbia et al., 2017). However, this data-driven method is very sensitive to motion and errors in superpixel tracking induce incorrect segmentation.

3 MODEL BASED ROI SEGMENTATION

In this paper, we propose an effective technique for explicitly favoring certain areas of the face during the spatial averaging step of RGB pixels. The model that encapsulates the spatial distribution of rPPG information was trained using an in-house database of 10 videos recorded under very favorable conditions. For this experiment, we used a EO-23121C camera recording 1024×768 uncompressed images at 30 fps. The average length of each video is about one minute. Subjects sat on an chair with back support. To make sure that the face is fixed in a specified position, we used a shelf and asked the volunteers to put the heads onto the shelf. Fig. 2 shows two sample images from the dataset.

Then, the face sequence is aligned based on the location of the eyes. The video frames were filtered by a 25×25 averaging filter to decrease quantization noise. The rPPG signal is extracted using the chrominance-based method (De Haan and Jeanne, 2013). This method is very fast and the computational complexity is very low. It linearly combined the RGB channels by projecting them onto two orthogonal chrominance vectors:

$$\begin{aligned} X(t) &= 3y^R(t) - 2y^G(t), \\ Y(t) &= 1.5y^R(t) + y^G(t) - 1.5y^B(t). \end{aligned} \tag{1}$$

Where $y^c(t)$ is the RGB signal after filtering, $c \in \{R, G, B\}$ are the color channels, and X and Y are



(a) (b) (c)

Figure 1: The State of Art ROI segmentation examples: (a) *face* (b) *skin* and (c) *landmarks*.

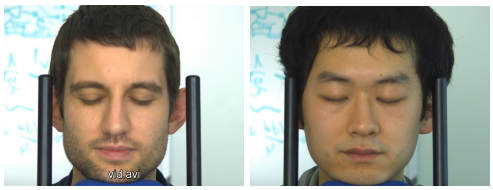


Figure 2: The subjects for the model.

two orthogonal chrominance vectors. The pulse signal S is obtained by $S(t) = X(t) - \alpha Y(t)$ where $\alpha = \sigma(X)/\sigma(Y)$. This σ is the standard deviation calculated over time.

The SNR for each pixel is then estimated as the ratio of the area under the power spectrum curve in a region surrounding the maximum peak in the frequency spectrum, divided by the area under the curve in the rest of the frequency spectrum:

$$SNR_{(x,y)} = 10 \times log_{10}(\frac{P_{signal}}{P_{noise}}) \quad (2)$$

Fig. 3 presents the spatial distribution of the SNR values averaged for all the videos of this dataset. As expected, we can observe that cheeks and forehead have in average, higher SNR (about 6 dB) than other face locations (e.g. 0 dB for the chin).

This spatial map is then used during the spatial averaging of the pixels of the ROI. Instead of using equal weights for all pixels in the ROI, we use a weighted average where weights are defined based on our model.

The weights are calculated as:

$$\omega_{(x,y)} = \frac{a^{SNR_{(x,y)}}}{\sum_{(x,y)} a^{SNR_{(x,y)}}} \quad (3)$$

where a is a constant. With higher a, the weights of the region of higher SNR are higher.

The optimal selection of a is done empirically. Experiments and details are given in Section 4.

Eventually, RGB triplet is obtained for each frame with the following weighted average:

$$S(t) = \sum_{x,y} I_t(x,y) \times \omega_{(x,y)} \quad (4)$$

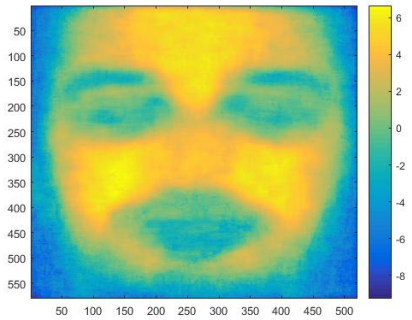


Figure 3: Different SNR in different locations.

Where $I_t(x,y)$ is the RGB value at time t of a pixel at location (x,y) and $\omega_{(x,y)}$ is the corresponding weight of the pixel.

It is interesting to note that this technique can be advantageously combined with all the rPPG methods that perform a spatial average of the ROI pixels.

4 EXPERIMENTS

The proposed model-based ROI segmentation (later called *model*) is experimentally compared with the state of the art methods, namely face detection (*face*), skin detection (*skin*) and landmarks detection (*landmarks*). This section presents the details of the experiments. First, we describe the video dataset and experimental setup. Then, we present the system framework. Evaluation metrics and experimental results are finally presented.

4.1 Video Dataset

All of the ROI selection methods were assessed by the performance of remote HR measurement. For the experiments, we used our in-house video datasets *UBFC-rPPG* (Bobbia et al., 2017) which have 46 videos. The volunteers were asked to sit at the distance of one meter from the web camera and were asked to play a time sensitive video game. Ambient light was

used in the experiment to create diffuse reflections. The experimental set up is shown in Fig. 4.

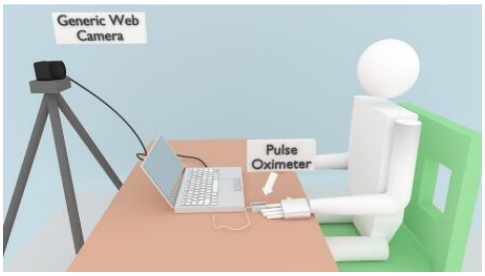


Figure 4: Experimental Setup.

A C++ program was used to record the videos and synchronize the videos with the signals of the contact PPG sensor which was used as the ground truth. The web camera is a Logitech C920. The resolution of the video frame is 640x480 and the frame rate is 30/second. The format is 8-bit uncompressed RGB. The contact PPG sensor is a CMS50E transmissive pulse oximeter. The experimental dataset with the ground truth can be downloaded from our project webpage [1]. Some sample images are shown in Fig. 5.



Figure 5: Experimental sample images from the *UBFC-RPPG* database.

4.2 System Framework

As explained previously, most methods share a common pipeline-based framework where ROI are first detected and tracked over frames, RGB channels are then combined to estimate the pulse signal, which is filtered and analyzed to extract heart rates. In this study, we used the same procedure to compare our ROI segmentation method with other segmentation techniques. First, RGB signals are normalized, detrended by smoothness priors approach and filtered by band-pass Butterworth filter. Then the RGB signal is selected and combined by chrominance based method (De Haan and Jeanne, 2013).

[1]https://sites.google.com/view/ybenezeth/ubfcrppg

With this pulse signal, we used Welch's method to obtain the periodogram with a sliding window of 20 seconds, and step size is one second. Identically, this process was used on the PPG signal of the contact sensor, which was utilized as the ground truth. The system framework is briefly shown in Fig. 6.

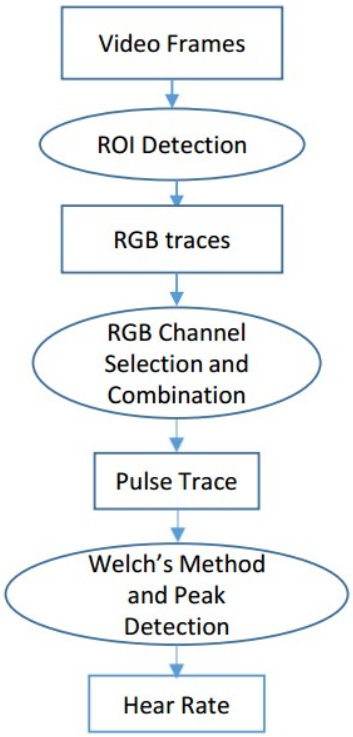


Figure 6: System Framework.

4.3 The Evaluation Metrics

Seven metrics were used to assess the performance of the ROI selection algorithms in the framework of HR measurements:

- **Pearson Correlation Coefficient** (R) is used to evaluate the correlation between the RPPG measurement and contact PPG measurement (ground truth).
- **Mean Absolute Error** (MAE) in beats per minute (bpm) is calculated as the absolute differences between HR measured from RPPG and HR measured from contact PPG signals which can be represented as $|HR_{rPPG} - HR_{PPG}|$.
- **MAE5** is the MAE which discards all the outliers with an error larger than 5 bpm.
- **Precision5** and **Precision2.5** represent the percentage of estimations where the absolute errors is under a threshold (2.5 or 5 bpm).

Table 1: The evaluation values for different weight calculation methods.

	Correlation R	**Precision 2.5**	**Precision 5**	**MAE**	**MAE5**	**RMSE**	**SNR**
a = 10	0.737	0.757	0.874	3.60	1.27	4.84	2.82
a = 5	0.732	0.755	0.873	3.68	1.27	4.93	3.08
a = e	0.728	0.755	0.876	3.68	1.29	4.92	3.31
a = 2	0.695	0.750	0.872	3.99	1.29	5.55	3.35
a =1.5	0.676	0.740	0.862	4.54	1.27	6.23	3.14
a = 1	0.674	0.737	0.861	4.56	1.28	6.25	3.09

Table 2: The average evaluation values for ROI detection.

	Correlation R	**Precision 2.5**	**Precision 5**	**MAE**	**MAE5**	**RMSE**	**SNR**
face	0.531	0.612	0.766	8.72	1.50	12.4	0.570
skin	0.683	0.716	0.851	5.10	1.36	6.78	3.21
landmarks	0.649	0.714	0.842	5.24	1.32	7.08	2.83
model	0.695	0.750	0.872	3.99	1.29	5.55	3.35

- **Root mean square error** (RMSE) is the square root of the average of squared differences between HR measured from RPPG and ground truth.
- **Signal-to-Noise Ratio** (SNR) is calculated as the ratio of the power of the main pulsatile component and the power of background noise, computed in dB due to the wide dynamic range.

4.4 Results

First, we present an experiment to empirically select the optimal scalar a of equation (3). To do this, several values for a were tested in the system framework. The result is shown in table 1. It can be observed that the ranking is different according to the different metrics. $a = 2$ provides a higher SNR while a larger value of a provides a better HR estimation (given by Correlation R, MAE and RMSE). For the rest of the experiments, we chose to favor the quality of the signal (given by the SNR) and will use $a = 2$.

Second, the proposed model-based ROI segmentation method is compare with other state of the art methods. The average results are shown in table 2. It is obvious that the ROI segmentation algorithms have significant effects on the results. All the metrics are very different with different ROI selection methods. It is also very clear that the proposed algorithm performs much better than all the other algorithms. It has the lowest MAE5 and RMSE. It has the highest correlation R, which means the RPPG method matches the ground truth better than other methods. SNR metric is also the highest which indicates that the method offers the best quality of the signal. The *skin* method is actually very good, although it is slightly worse than the proposed algorithm.

5 CONCLUSION

A good ROI is very important for rPPG algorithms to work properly. The ROI must contain as much critically useful information as possible. Most of the state of the art methods focus on the improvement of the face and skin detection, and their objectives are mostly to get as many skin pixels as possible and to discard as many non-skin pixels as possible. However, the rPPG signals are not distributed homogeneously on the human face, so it is reasonable to consider putting weights on the pixels before other processing. In this paper, we presented a supervised model based on SNR weights to improve the ROI segmentation. This algorithm is compared with other algorithms by evaluating the performance of HR measurement. The experiments were done with a low-cost web camera and a contact PPG sensor as the ground truth. 56 videos were used in the experiments and 10 of them were used to create the SNR weight map and the other 46 were tested with this map. The results showed that the ROI segmentation affects the HR measurement significantly and our new algorithm performed better than all the other state of the art methods.

Since the algorithm is based on a supervised model, it is important to generate a reliable SNR weight map. The model may be different in different environmental conditions. It may fail if the registration of the model is imprecise due to the low accuracy of the landmarks detection. The ROI may have different ways to be resized or reshaped to fit the model. For instance, an elliptical model can be generated with the contour provided by the landmarks detection. These offer good opportunities to improve this algorithm.

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