Non-Contact Video Based Estimation for Heart Rate Variability Spectrogram using Ambient Light by Extracting Hemoglobin Information

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Abstract

Non-contact video based heart rate estimation has great various potential in areas such as medical, health care, and affective computing. Recently, the methods using a digital camera for remote heart rate (HR) measurement are widely spread. However, the accuracy of these methods are not sufficient enough to calculate heart rate variability (HRV) accurately. If HRV are measured with high accuracy, we can visualize the sympathetic nerve system by calculating heart rate variability spectrogram (HRVS).

In this paper, we propose a method of HR and HRV spectrogram estimation by analyzing extracted hemoglobin concentration from facial color images. Our method does not require any special camera. Furthermore, it is possible to have a stable presumption even under the ambient light sources. As a result, we could obtain 99% accuracy of HR and HRV spectrogram with the same accuracy electrocardiogram. Therefore we succeeded to identify whether participants were relaxed or stressed using conventional DSLR camera.

1. Introduction

In the recent progress of ubiquitous society, multi-functional smart phones are highly expected to be used for health care, medical diagnosis, stress monitoring and so on. Contact monitoring is not easily accepted by the user since the user may feel some discomfort to be touched. Therefore, remote detection of physiological information has great various potential for the above applications. Non-contact video based method is expected to be used easily by utilizing the inner-camera on the smart phone.

Since remote heart rate (HR) measurement has already become popular, there are various techniques for measuring blood volume pulse (BVP) exist now. Verkruysse *et al*. [1] has demonstrated the measurement of the BVP signal using ambient light. Furthermore, frontier work made it possible to measure cardio-pulmonary parameters (HR, breathing rate, and high and low frequency components of the HRV) [2]. HRV shows the sympathetic nervous system and is useful for stress monitoring. However, it was not shown whether detailed information about subtle changes over time could be measured using this approach.

Heart rate variability spectrograms (HRVS) are a useful non-invasive measurement of phenomena such as the modulation of sympathetic nervous system. McDuff *et al*. [3] proposed the method of remote HRV spectrogram measurement using a multi band camera. Most digital single-lens reflex (DSLR) cameras capture three color channels (RGB) with 16-bits/channel. They used a special DSLR sensor that has the capability to capture five color channels (16-bits/channel): red, green, blue, cyan and orange (RGBCO). The sensor they used has pixels for detecting light in the orange (O) and cyan (C) frequency bands as well as pixels for detecting light in the red, green and blue bands. According to this research, the set of channels including the orange band signals, especially the set of CGO channels, performed much better than the set of RGB signals. Therefore, they could obtain HRV spectrogram accurately.

However, high accuracy has not been realized yet in remote measurement of HRV spectrogram using a conventional RGB camera. The multi-band camera used by McDuff *et al*.[3] is a special camera and is not widely spread in the market. Due to this reason, it is expected to propose the new method of non-contact video based estimation for HRV spectrogram using a conventional RGB camera.

Tsumura *el al*. [4] proposed to extract hemoglobin information from facial color images, Hemoglobin pigments are flowing through the face via the bloodstream, and hemoglobin concentration of the face surface will temporarily increase. The technique of Tsumura *el al*. [4] may improve the accuracy of estimating BVP.

In this paper, therefore, we propose to use the extraction technique for hemoglobin information from conventional RGB camera to estimate the HRV spectrogram, and apply the proposed method to use for stress monitoring. In section 2, we present how to extract hemoglobin information from facial color images. In section 3, we describe the method of obtaining BVP. In section 4, we describe how to calculate HRV spectrogram from BVP and the relationship between HRVS and the sympathetic nervous system. In section 5 and 6, we described the experiment of stress monitoring using a conventional camera.

2. Extraction of Hemoglobin Information from Facial Color Image[4]

The human skin is roughly fall into two principal layers composed of the epidermis and dermis. The epidermis has melanin pigments and the dermis has hemoglobin pigments. Incident light into the skin and passes the epidermis and dermis. After that it is emitted to outside from the skin surface. The modified Lambert-Beer's law is satisfied in the skin layer for incident light presumptively. It is conceivable that incident light is absorbed by the melanin pigments and hemoglobin pigments. This skin color is depending on the pigmentation distribution of these two pigments. We extract melanin pigments, hemoglobin pigments and shading from skin color images by using independent component analysis (ICA) based on this assumption. In Figure 1, $\mathbf{v}^{\log}$ is the obtained density distribution signal by converted logarithm and represented

by the weighted linear combination of the three vectors $\boldsymbol{\sigma}_m, \boldsymbol{\sigma}_l$, $\boldsymbol{1}$with the bias vector $\boldsymbol{e}^{\log}$. The vectors $\boldsymbol{\sigma}_m$, $\boldsymbol{\sigma}_l$ are relative absorbance vectors for the melanin and hemoglobin components, respectively.$\boldsymbol{1}$isshading vector. Figure 2 (a) and (b) are the extracted melanin and hemoglobin pigments and (c) is shading in whole facial images shown in Figure 3 (a) by independent component analysis. We can recognize moles and pigmented spots from the melanin component images in Figure 2 (a) and pimples from the hemoglobin component images in Figure 2 (b). The shading is considered as pseudo facial structures and can be recognized face shape in Figure 2 (c).

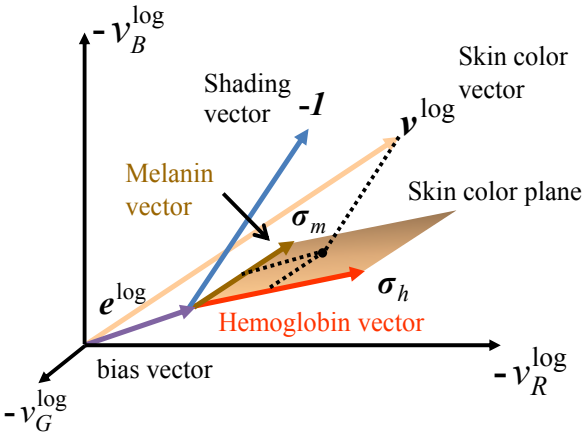
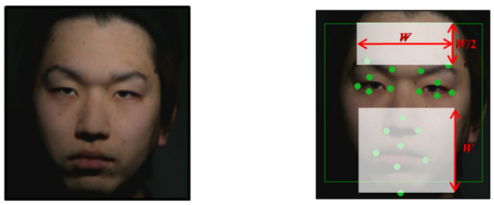


Figure 1. *Overview of independent component analysis*

(a) (b) (c)

Figure 2. *The results of independent component analysis extracted pigment components: (a)melanin, (b) hemoglobin, (c) shading*



(a) (b)

Figure 3. *Sample of captured image; (a) Original image, (b) Detected feature points and ROI*

3. Extracting BVP Signal from Video Images

For the method described in the section 2 all of the video images taken by a DSLR camera, and we generate the hemoglobin component images shown in Figure 2 (b). These numerous number of hemoglobin images represent temporal fluctuation of hemoglobin concentration of the facial surface. We obtain the BVP from these hemoglobin images. However, these images include the artifacts of blinking and eye movements. Therefore we determine region of interest (ROI) using detected feature points. The LEAR [5] facial feature points detector was used to find the x- and y- coordinates of facial feature points of the participant's face. We defined the width between the outer eye corners as W. The one side of ROI is a square with side lengths of W and is set around the mouth. The center point of bottom of the square has a same position with the feature point of chin. Another side of ROI interested in forehead and separated W/2 from lower ROI. This width is W and height is W/2. [3]

We calculated the mean of pixel value from hemoglobin component images limited by ROI. Figure 4 shows the result of lining up these values. We can find the component of HR in this signal. We applied detrending [6] and band pass filter to this signal to detect peaks easily. We used a technique based on a smoothness priors approach to detrend the signals. This signal was band-pass filtered using a Hamming window filter with low- and high- frequency cut-offs at 45 beats-per-minute (bpm) (0.75Hz) and 180 bmp (3Hz) respectively. These cut-off frequency were decided from approximate lower and higher limits in heart rate. Figure 5 shows the BVP signal obtained by these processes. This signal was interpolated with a cubic spline function at a sampling frequency of 50 Hz same as electrocardiogram's measurement resolution.

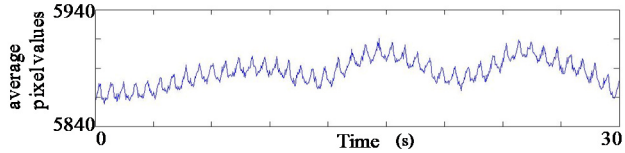


Figure 4. *Average pixel values of hemoglobin component images*

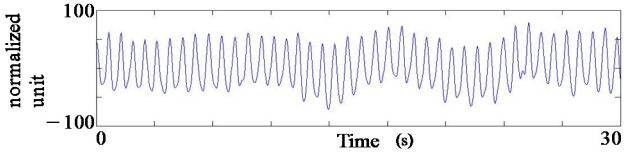


Figure 5. *Normalized, detrended, and filtered signal*

4. Heart Rate Variability Spectrogram

The peaks of BVP signal were detected by hill climbing method. The peaks of electro cardiogram(ECG) waveform is called R wave and corresponding with the peaks of BVP signal. Interval of R wave to R wave is called R-R interval. R-R interval is always fluctuating and this is called HRV. Therefore we constructed the HRV spectrograms by calculating the power spectral density from R-R intervals using a Lomb periodogram [7]. In this analysis, we used a moving window of one minute and the step size was one second. Figure 6 shows the examples of HRV

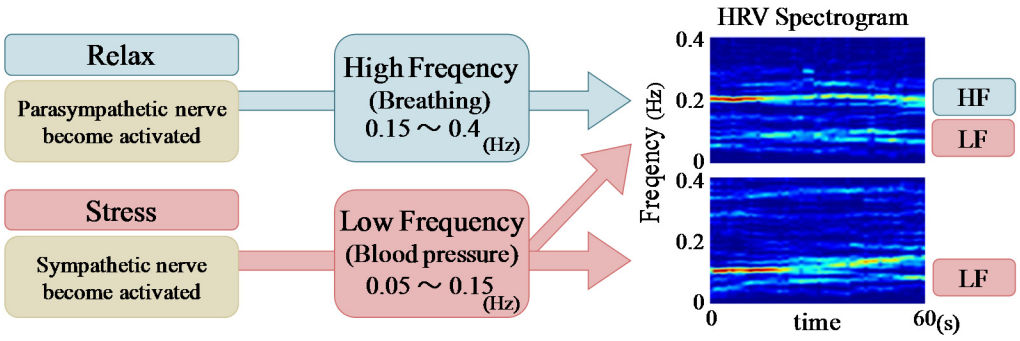


***Figure 6**. Relationship between the sympathetic nervous system and HRV spectrogram*

spectrograms obtained by above method, and the relationship between HRV spectrogram and the sympathetic nervous system.

The high frequency (HF :0.15-0.4Hz) powers reflects parasympathetic influence on the heart and is connected to respiratory sinus arrhythmia (RSA). Contrary, the low frequency (LF : 0.04-0.15Hz) powers were modulated by blood pressure fluctuation and contains both sympathetic and parasympathetic activity [8]

For example, when we are relaxed, parasympathetic nerve become activated. Parasympathetic nerve influences on HF. Therefore, if we pay attention to above HRV spectrogram in Figure 6, we can find high spectrum appear at the range of HF. In this case we can estimate that he was relaxed. Contrary, when we are under stress, sympathetic nerve become activated. Sympathetic nerve makes the heart less likely to be affected by RSA. Therefore spectrum in the range of HF become less compared with the case of being relaxed. The spectrum at lower HRV spectrogram in Figure 6 appear only in the range of LF. In this case we can estimate that he was under stress.

In this way we can estimate if participants were relaxed or under stress. We apply this method to stress monitoring.

5. Experiment

Our experiment featured 4 participants. All of them are male 20s or 40s years old. They were Japanese students or professor of Chiba University. All participants had normal hearing, normal vision. Our experiments was conducted twice time to each participants. First experiment, they were captured at rest, and another experiment they were under cognitive stress. Mental arithmetic tasks can increase low frequency components power spectral analysis of the HRV [9]. In this experiment, participants were asked to perform a mental arithmetic test silently. While the recording time, they were required to keep on subtracting 7 from 4000, as quickly as possible. The participants started the task immediately after the recordings were started.

The video images of the face is taken by a RGB DSLR camera from 3 meters distance. The videos were recorded with a frame rate of 30 frames per second (fps) and a resolution of 960 x 720. The recording were 2 min, as 16-bit RGB color image. All experiments were conducted in darkroom and with polarized artificial sun light. The polarized light source was made by the polarizing plate attached to the light source and the camera lens. Polarization was carried out to remove the surface reflection to estimating facial skin color vector such as melanin and hemoglobin vector. The picture shown in Figure 7 presents the over view of experimental system.

We measured correct value of electrocardiogram by the polygraph system [RMT-1000 : NIHON KOHDEN. Inc]. We set the measurement resolution at50hz, and applied low-pass filter. Cut-off frequency was set at 15Hz.It is enough to get the peak of R-wave. From these signals, we obtained the R-R intervals and calculated HR and HRV spectrogram by the method used to hemoglobin component signal.

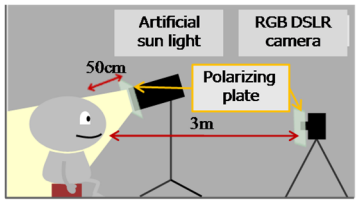


***Figure 7**. Experiment environment*

6. Results

Table 1 shows high correlation between HR by proposed method and HR by polygraph system in relax condition.HR was calculated as60 / $\overline{R-R\ intervals}$, where $\overline{R-R\ intervals}$ is the mean of the R-R intervals. Table 2 shows the results under cognitive stress. These results also represent high accuracy.

Table 1. Comparison HR between detected value and correct value at rest. P1(Participant 1), P2(Participant 2), P3(Participant 3), and P4(Participant 4)

	P1	P2	P3	P4
Proposed method (bpm)	83.50	63.87	60.08	72.81
Electrocardiogram (bpm)	83.63	64.40	60.78	72.75
Accuracy (%)	99.84	99.16	98.84	99.92

Table2. Comparison between detected value and correct value under cognitive stress, P1(Participant 1), P2(Participant 2), P3(Participant 3), and P4(Participant 4)

	P1	P2	P3	P4
Proposed method (bpm)	85.14	72.06	61.30	72.15
Electrocardiogram (bpm)	84.61	71.82	60.97	72.19
Accuracy (%)	99.37	99.66	99.46	99.94

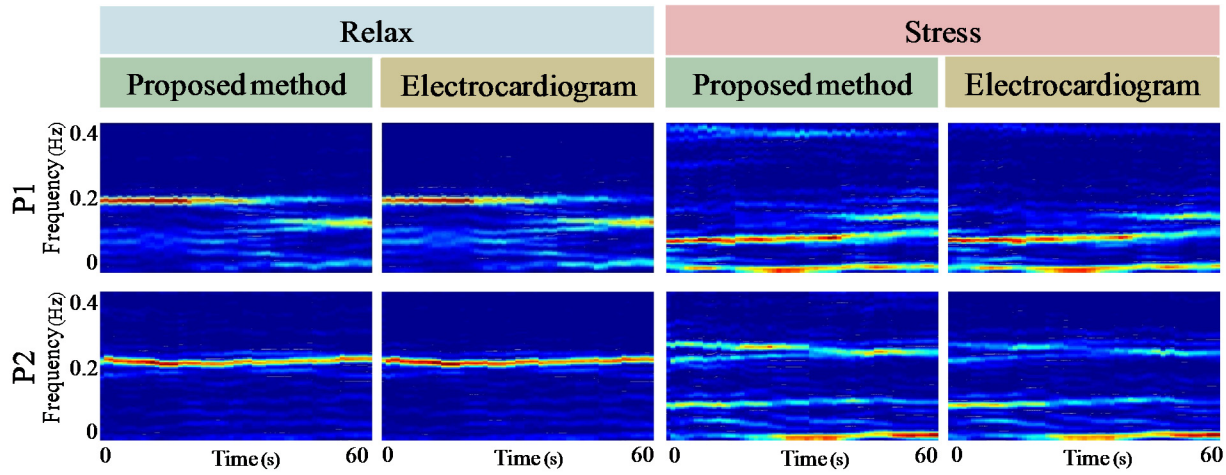


***Figure 8**. Heart rate variability spectrogram under the polarized light source*

We calculated HRV spectrogram from R-R intervals and compared between the proposed method and correct measurement. Figure 8 shows HRV spectrogram of participant 1 (P1) and participant 2 (P2) they were relaxed and stressed respectively.

In the HRV spectrograms measured at rest, high power of spectrum appears in HF. Therefore we can recognize that they were relaxed and parasympathetic nerve were more active than sympathetic nerve. Under cognitive stress, high power of spectrum appears in LF. Therefore we can recognize that they were stressed and sympathetic nerve are more active.

These results are very similar between the proposed method and electrocardiogram-based method. Therefore we understood that we could get HRV spectrogram accurately by RGB camera. However, the method limited only using a polarized artificial sun light. Our purpose is making possible to measure HRV accurately using a conventional RGB camera under ambient light source.

Therefore we conducted experiment and measure the HRV spectrogram under fluorescent light. However, under non-polarized light sources, it is difficult to estimate the hemoglobin vector, because we considered only incident light without surface reflection. Due to hemoglobin vector's property that is not affected by light source, we used the vector estimated under a polarized artificial sun light. In this way we get hemoglobin component images under fluorescent light. Examples of these images shown in Figure 9 (a) and (b). In these figures, color appears in background accidently. In this case background has similar color vector with skin. It does not affect any results because ROI doesn't include background. Figure 10, and Figure 11 shows the signals measured under fluorescent light source using the same method under the polarized light source. Table 3 shows the calculated HR and Figure 12 shows the HRV spectrograms. These results represent high accuracy as well as polarized light source.

Table 3 Comparison between detected value and collect value at rest under fluorescent light

	P1	P2
Hemoglobin (bpm)	66.318	64.152
Electrocardiogram (bpm)	66.422	64.160
Accuracy (%)	99.843	99.988

(a) *(b)*

***Figure 9**. Hemoglobin component images under fluorescent light; (a) P1,(b) P2*

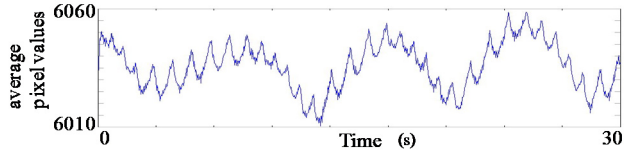


***Figure 10**. Average pixel values of hemoglobin component images*

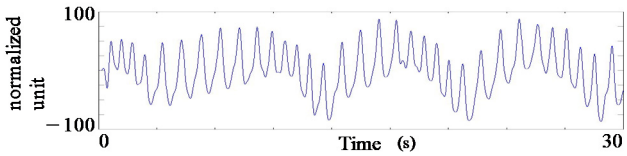


***Figure 11**. Normalized, detrended, and filtered signal*

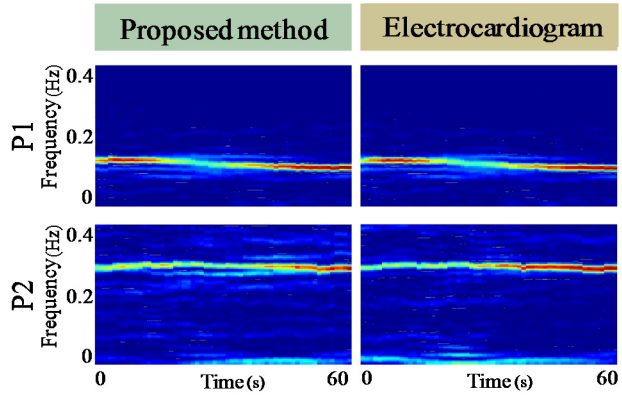


***Figure 12**. Heart rate variability spectrograms under fluorescent light sources.*

7. Discussion

We achieved to obtain the HR with almost over 99% of accuracy by using a conventional camera under the ambient light sources. HRV spectrograms also represent very high accuracy. In addition to this, the signals in Fig 4 and 10 include large wave which is about 0.1Hz besides the HR signal. Because the frequency corresponds to the frequency appearing in the LF of HRV spectrogram, we consider that the wave shows the blood pressure modulation. There is a modulation called Mayer wave and its frequency is 0.1Hz in ECG [10]. It has possibility to be applied to affect computing as HRV.

In this experiment, all the participants did not move, nor say anything. In their mouth, there are many hemoglobin pigments as you can see in Figure 8. If the participants move or talk, hemoglobin component changes larger than the factor from BVP. To this problem, we consider that it is effective to determine smaller ROI excepting around their mouth.

Some people might say there is no proof that this signal shows the changing hemoglobin pigment concentration. However, BVP signals appear only in hemoglobin component signal as you can see in Figure 13, 14, and 15. This are unmistakable signs that we could separate hemoglobin component accurately. In addition to this, moving factor and light source factor might affect only shading components or bias vector. This means that our method have strong robustness for change of lighting conditions.

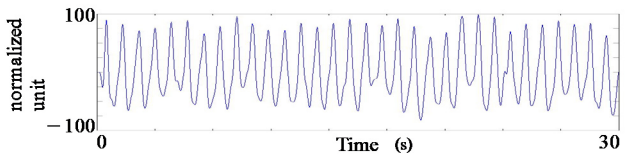


***Figure 13**. Average pixel values of hemoglobin component images*

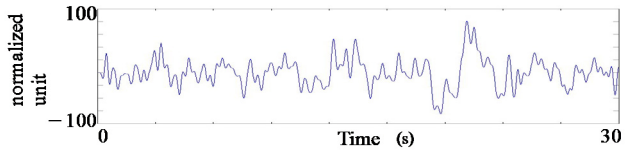


***Figure 14**. Average pixel values of melanin component images*

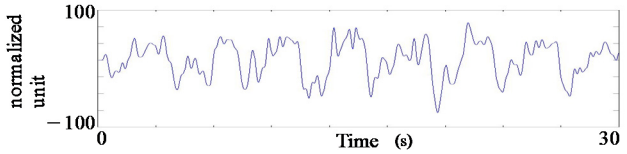


***Figure 15**. Average pixel values of shade component images*

8. Conclusion and Feature work

We succeeded in measuring HRV accurately using a conventional camera under ambient light source by extracting hemoglobin concentration of facial color images. This is the first examples of HRV spectrograms calculated from video images captured by conventional DSLR camera.

However, in this experiment, all the participants were Japanese. Therefore in the future work, we would like to experiment with people from other countries having different skin colors. Furthermore, we would like to improve the method that is corresponding to the movement and the voice of the participants, as we asked participants not to move or say anything during the experiment this time.

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