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Comparison of Non-Contact Camera Based Methods to Measure the Pulse Rate for Awake Infants

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Abstract

Non-contact camera based methods to measure the pulse rate have been introduced in recent years. However, the previous research conducted experiments only for adults and/or sleeping infants, not for awake infants. In this paper, we compare the principal non-contact camera based methods and identify a suitable method for awake infants. We measured the pulse rate of five adults and three infants and obtained the success rate of setting the measurement region and RMSE of estimated pulse rates for several existing methods. The color based method and is the Independent component analysis are the most suitable methods for setting the measurement region and signal processing, respectively.

Introduction

Sudden Infant Death Syndrome (SIDS) is one of the fatal diseases for infants. SIDS causes serious brain damages or sudden death even if they are in good health [1]. Every infant is in a risk of SIDS. One of the counterplan of SIDS is an early detection of unusual conditions of infants. Once SIDS occurs, firstly an apnea occurs along with infrequent pulse, and then the infant's brain falls into the oxygen deficiency. As a result, the brain suffers serious damages such a cerebral palsy or death in the worst case.

It is important to protect infants from fatalities by detecting the incidence of the apnea or the infrequent pulse, to provide an emergency treatment. Therefore, infant monitoring is an important and desirable prevention mechanism for SIDS. Additionally, unhealthy infants also need monitoring to detect the change in their condition of the disease. However, it is a hard task for a caregiver to observe an infant constantly and carefully. To solve this problem, automatic vital sensing is available. In this study, we focus on a pulse rate as a parameter of vital signs.

Practically, a pulse oximeter is used in hospitals to measure the patient's pulse rate and oxygen saturation [2]. Pulse oximeter is one of the contact-type devices to measure the vital signs and can perform the noninvasive measurement instantly. Furthermore, it has a high accuracy for the patient who has no or slight body movement.

On the other hand, a standard pulse oximeter suffers from several weak points. First, it carries a risk of infectious diseases and the devices need regular decontamination and desinfection. Second, its application causes displeasure to infants. Third, limb's motion artifact causes a large error in a pulse rate measurement. To counteract this problem, a general pulse oximeter typically includes a function to detect the motion artifact. When the motion artifact is detected, the measured pulse rate value is rejected to avoid the false alarm. However, practically, a false alarm occurs frequently due to a failure of a motion detection or other factor, and consequently caregivers become desensitized or immune to the alarm [3]. Additionally, the attachment band of the pulse oximeter may be taken off by the movement of the limb. These weak points are common to- and typical faults of contact devices.

Many non-contact methods have been proposed in past. Although there are several types of devices to implement non-contact methods, in this paper, we focus on camera-based methods.

The pulse rate measurement with camera is implemented by the tracing of time-series change of the subject's facial features such as color [4]. This method can be divided into two steps: in step 1) Setting an appropriate Region of Interest (ROI) for an image captured by a camera; and in step 2) Processing a waveform extracted from the time-series change of the average pixel values in the ROI to obtain a pulse rate value. Many recent papers proposed the methods to implement both of the steps. [5-12].

The previous research have carried out experiments only for adults and/or sleeping infants, not for infants being awake. Infants, as subjects and patients, clearly, are a more difficult object of measurements, compared to cooperating adults. In addition, the amplitude of the heartbeat of infants is smaller than that of adults, and the movement of infants is more active and continuous than that of adults when they are not asleep.

In this paper, we compare the measurement results of pulse rate obtained by principal non-contact methods, with comparison between adults and infants. Then we discuss the most suitable method for infants. Additionally, we report on the detection of the motion error.

Method

As shown above, the method of pulse rate measurement with camera can be divided into two steps, "ROI Selection" and "Signal Processing". Here, we describe the overview of methods applicable to both of these steps.

Methods of ROI Selection

Verkruysse *et al.* confirmed that the pulse wave can be estimated from the time-series change of the skin color due to the slight flush caused by the heartbeat [4]. Based on this finding, most of the previous studies set ROI on a subject's face. Earlier works in this research field typically set ROI by manual operation [7]. However, recent studies proposed automated methods. This paper introduces three automated methods of ROI selection: Face Detection; Maximum SNR; Maximum Hemoglobin.

Face Detection [5,6,8,10]

Face detection algorithms implement an automated detection for human faces from an image. In this paper, we introduce Viola and Jones's method which is included in the OpenCV Library and is one of the most famous and frequently used algorithms for face detection [11]. Viola and Jones's method uses machine learning to distinguish face area from non-face area. OpenCV provides the learnt classifiers for a frontal face, profile, and so on.

This method runs in real-time, therefore it is easy to reset the position of ROI per every frame. This advantage enables the ROI to track human face even if the subject's head is moving.

Maximum SNR [11]

Signal to Noise Ratio (SNR) is a parameter which indicates the influence of the noise against the signal. An expression of general SNR is shown in Eq. (1).

$$\mathrm{SNR} = 10\log\frac{S}{N} \tag{1}$$

where S is a power of signal, N is a power of noise. In this research "signal" means a pulse wave. In the literature [11], the definition of a signal is the sum of the powers of the peak frequency and its neighbor frequencies of the frequency spectrum obtained by Fourier transform for the waveform extracted from time-series images. In contrast, the definition of a noise is the sum of the powers of the all frequencies except the frequencies used for signal.

In the first step of this method, time-series images were divided into several areas, then SNR was calculated for each area. Finally, the area which has maximum SNR value in this time-series images is taken as ROI for pulse rate measurement.

This method requires time-series images to contain around 12 or more seconds of images for the implementation of Fourier transform. This factor makes calculation time longer, therefore it is difficult to reset the position of ROI per every frame. The advantage of this method is robustness against the facial angle, expression, and color.

Maximum Hemoglobin

This method is a method proposed by us earlier and is based on the skin pigment separation [12] to estimate the hemoglobin pigment density from the RGB value. Figure 1 shows the overview of this technique.

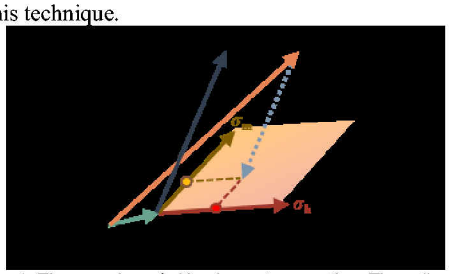

Figure 1. The overview of skin pigment separation. The yellow circle on the melanin vector $\boldsymbol{\sigma}_m$ and the red circle on the hemoglobin $\boldsymbol{\sigma}_h$ vector are estimated melanin and hemoglobin pigment densities, respectively

$\boldsymbol{v}$ indicates logarithmic / normalized RGB values which are generated by the conversion of sensor response in the RGB color space to the optimal density space. Modified RGB value $\boldsymbol{v}(x, y)$ indicates the value of $\boldsymbol{v}$ at the coordinates (x, y) on the skin and consists of the weighted linear combination of the three vectors $\boldsymbol{\sigma}_m$, $\boldsymbol{\sigma}_h$, and $\boldsymbol{1}$ biased vector $\boldsymbol{e}$. The melanin vector $\boldsymbol{\sigma}_m$ and the hemoglobin vector $\boldsymbol{\sigma}_h$ are pigment density vectors for these pigments. $\boldsymbol{1}$ is the vector for the shade. The melanin and hemoglobin pigment densities are calculated by projecting the modified RGB value $\boldsymbol{v}(x, y)$ onto the skin color plane with $\boldsymbol{1}$ and re- projecting it onto $\boldsymbol{\sigma}_m$, $\boldsymbol{\sigma}_h$, respectively.

In the first step of this method, we generate hemoglobin time-series images from RGB time-series images as showed in the upper part of Figure 2. Colored rectangles on the images are the ROI. The lower part of Figure 2 shows the waveform of the averaged hemoglobin density in the ROI for each frame. The color of each waveform corresponds to the color of ROI. The size of ROI is 160 px × 160 px uniformly. Every ROI is set onto the skin area, whereas the ROI whose hemoglobin pigment density is higher contains the response to the pulse. Specifically for the example, the red plot and the yellow plot have better response and higher value of hemoglobin than the green plot and the blue plot.

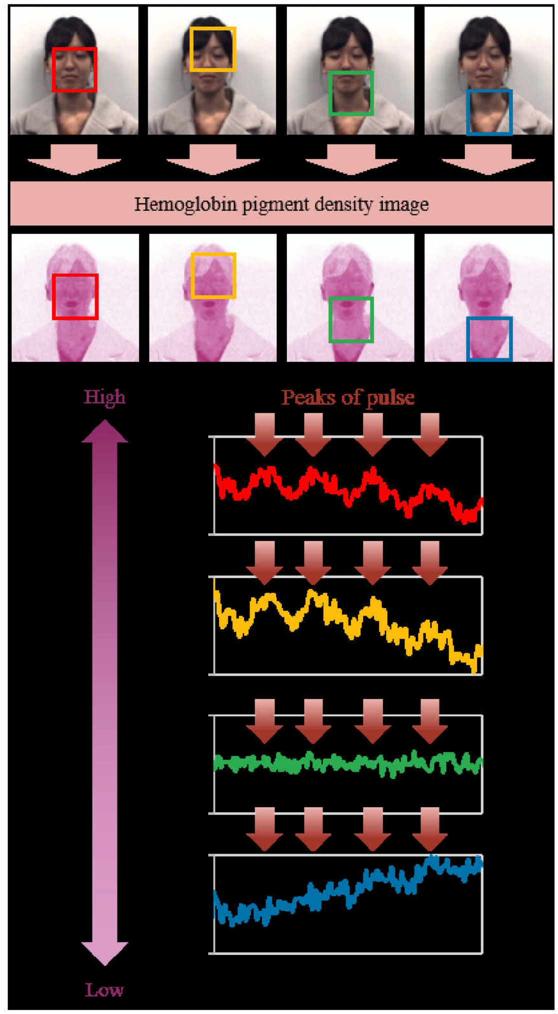

Figure 2. Waveforms of hemoglobin pigment density for various ROIs on the skin. The color of each waveform corresponds to the color of ROI. Four arrows above each waveform indicate peaks of pulse.

Figure 3 shows the plot of the SNRs for the waveforms in many positions of ROIs and its average amplitude values of hemoglobin density for motionless two subjects. For the result, the ROI which has highest hemoglobin density has high SNR for pulse measurement. Therefore, the area which has the maximum hemoglobin density value in each frame is taken as ROI for pulse rate measurement.

The advantage of this method is robustness against the facial angle and expression. Even though the face color of subjects are different, especially between adults and infants[13], however this method is not affected by the redness of the face. In addition, it is easy to reset the position of ROI per every frame.

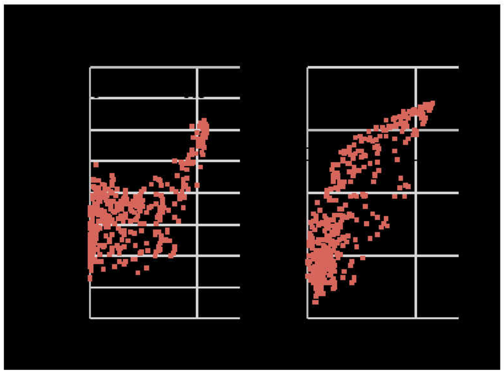

Figure 3. The relationship between SNR and hemoglobin pigment density in many ROIs in the captured image. Each red point is the result of each ROI. The left graph is the data of subject.1(adult), the right one is the data of subject.2(adult).

Methods of Signal Processing

The waveform extracted from the time-series change of the average pixel values in the ROI contains not only the component of the pulse wave, but also the component of the position change of the skin due to the body movement, the change of illumination, and noise. Therefore, one must reduce the influence of the nuisance components except the pulse wave. This paper introduces four automated methods of signal processing suitable for this task: G Channel separation from RGB Image; Independent Component Analysis (3-dimentional and 1-dimentional); and Skin Pigment Separation.

G Channel separation from RGB Image [5,7,11]

Verkruysse *et al.* confirmed that G channel reflects pulse wave stronger than R channel and B channel because of the spectral characteristics of the skin. As a pre- processing step, we set the ROI by using one of the methods introduced in the section of "Methods of ROI Selection".

First, the waveform is extracted by aligning the average pixel values of G channel in the ROI of the time-series images. Second, the waveform is detrended and run through a bandpass filter and/or other processes in order to reduce the influence except the pulse wave. Figure 4 shows the example of the waveform obtained from G channel and Figure 5 shows the results of detrending and bandpass filtering. In this paper, the frequency band for the bandpass filter is chosen to be 0.7Hz ~ 3.0Hz for adults and 1.0 Hz ~ 3.3 Hz for infants as the suitable bands for pulse rate. We empirically deduced the bandpass levels. Figure 6 shows the frequency spectrum obtained by Fourier transform of the waveform shown in Figure 5. The pulse rate is calculated by taking a peak frequency or counting peaks in waveform shown in Figure 5.

Independent Component Analysis (3-dimentional) [8]

Independent Component Analysis (ICA) is a method to estimate the original signals from observed signals which were generated by mixed original signals. This method implements original signals estimation by taking the advantage of the non-Gaussianity of an independent signal.

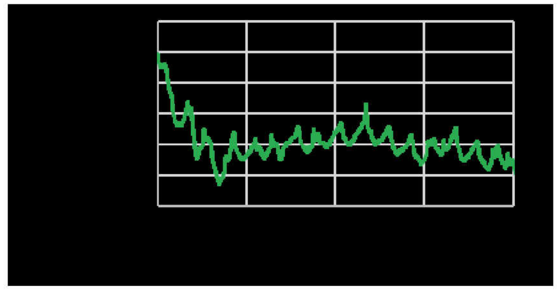

Figure 4. The waveform for averaged pixel value of G channel in ROIs of the time-series images.

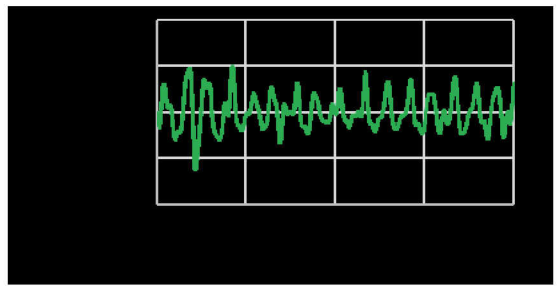

Figure 5. The result of detrend and bandpass filter for the waveform shown in Figure 4.

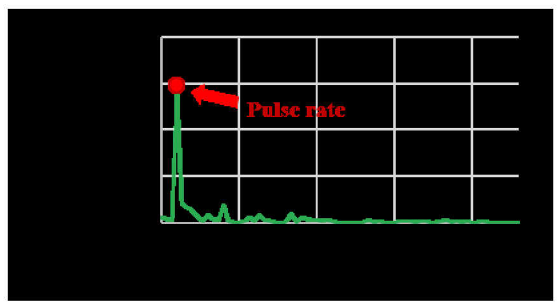

Figure 6. The frequency spectrum obtained by Fourier transform of the waveform shown in Figure.5. The red circle is the peak frequency which corresponds to the pulse rate.

For image-based pulse rate measurement, observed signals are the waveforms of R channel, G channel, and B channel. For the result of ICA, three waveforms of independent components are obtained. Poe *et al.* confirmed that the one of the three independent components indicates the pulse wave. After the pulse wave is obtained, the pulse rate is calculated from the component which has highest SNR in the three components the same way as G channel shown in previous section.

Independent Component Analysis (1-dimentional) [10]

Previous section's ICA is 3-dimentional approach because it takes 3-dimentional signals (R channel, G channel, and B channel) as observed signals. However, previous research [10] utilizes the monochromatic near-infrared camera under the night condition, that means, only one channel is available. For this reason, 1-dimentional ICA is applied on a single observed signal. As a pre-processing step for ICA, Zhao *et al.* prepared the 3-dimentional signals from the single observed signal by the embedding matrix $\boldsymbol{X}$ which consists of delayed waveforms as shown in Eq. (2),

$$\boldsymbol{X} = \begin{bmatrix} x_t & x_{t+\tau} & \cdots & x_{t+n\tau} \\ x_{t+\tau} & x_{t+2\tau} & \cdots & x_{t+(n+1)\tau} \\ x_{t+2\tau} & x_{t+3\tau} & \cdots & x_{t+(n+2)\tau} \end{bmatrix} \tag{2}$$

where x_t is the amplitude of the single observed signal at time t, τ is the delay time, n is appropriate number for the length of the observed signal. In this paper, we choose G channel for the single observed signal due to the better response to the pulse. In the literature, monochromatic infrared camera is used under the night condition [9] .

After the construction of the embedding matrix, each row of Eq. (2) is taken as an observed signal, then ICA and pulse rate calculation are executed in the same way as in the case of 3-dimentional method.

Skin Pigment Separation [6]

Kurita *et al.* proposed a method to measure the pulse rate by estimating the change of the hemoglobin pigment density from the change of skin color. Kurita's method is based on the skin pigment separation introduced in the section of "Maximum Hemoglobin".

Kurita *et al.* applied skin pigment separation to each frame obtained by a camera. After the Hemoglobin component of each frame is extracted to make the waveform, the pulse rate is calculated in the same way as G channel.

Results

In this chapter, we describe the experimental results for adult subjects and infant subjects.

Ethical considerations

All parents of infant subjects provided their written informed consent. This study was approved by the ethics committee of Kanazawa University (No. 2017-102).

Experimental setup

The RGB camera used in this experiment is Imaging Source DFK23UP031. The frame rate is 30 fps, the resolution is 480 px × 640 px. The distance between a subject and the camera is 1.8m, enough length to keep subject from being hit by the tripod when it falls down. This experiment carried out under the fluorescent light without any limitation. The measurement time is 30 second per one data. While capturing time-series images with the camera, a pulse oximeter measured subject's pulse rate simultaneously for a reference method. The pulse oximeter was attached to a finger-tip or an ankle.

The adult subjects consisted of 2men and 3 women, with a mean age of 22.8±0.8 years(mean±s.d.). And, the infants subjects consisted of 2 men and a woman, with a mean age of 4.7 ±5.5months(mean±s.d.). Three trials were captured per one subject. The provided data were grouped into "without motion" and "with motion" according to the degree of their body motion. Table 1 shows the data quantity of each condition.

Table 1. The data quantity of each condition

	Without Motion	With Motion
Adult	5 trial	10 trial
Infant	3 trial	6 trial

ROI Selection

Figure 7 shows the one of the result of ROI selection with "Face Detection", "Maximum SNR", and "Maximum Hemoglobin".

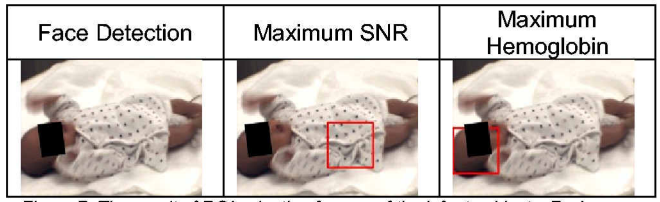

Figure 7. The result of ROI selection for one of the infant subjects. Red rectangles are the selected ROI. The imege without a red rectangle fails in the ROI selection.

To compare the ability of the three ROI-selection methods, we extracted the "success rate" of the face tracking. The definition of "success" is "ROI is being set on the subject's face from the start to the end of time-series images". The "success rate" is the ratio of the number of the success trials to the number of all trials. Figure 8 shows the success rates of the three methods in comparison with the kind of subject and the state of motion.

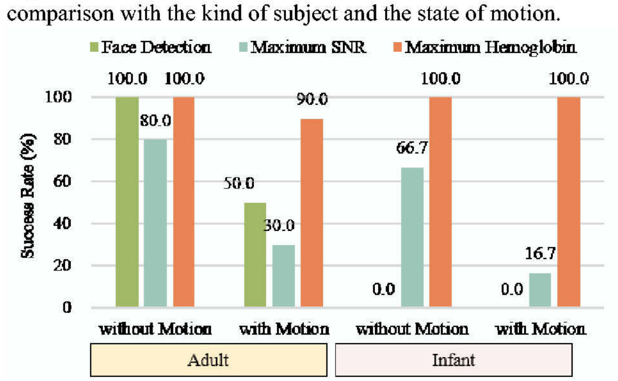

Figure 8. The success rates of three methods for ROI selection. The color of bars shows the type of method. The sets of three methods' bars show the result of Adult without motion, Adult with motion, Infant without motion, and Infant with motion, from left to right.

Signal Processing

We compare the four methods with the RMSE of the measured pulse rate. The signals used to obtain RMSE are extracted from successful ROIs selected by "Maximum Hemoglobin" because of its high success rate. The estimated value is the pulse rate obtained by the RGB camera, the reference value is the pluse rate obtained by the pulse oximeter. Figure 9 shows shows the RMSEs of four methods in comparison with the type of sbjects and the state of motion.

Error detection

The experimental results indicate that each method is affected the body motion (details are in the below chapter "Discussion"). Therefore, the measured data should to be cancelled when the body movement of the subject is large enough to cause a non-acceptable and insolvable error. In this paper, we obtained the SNR of processed waveform to taken as the threshold for the error detection. The data whose SNR is lower than the threshold SNR is canceled to avoid the false alarm. We applied the -7.5 dB to the threshold SNR. As a result, RMSE for all data decreased by 2.00

bpm from 35.8 bpm. The improved result is comparable with the the pulse oximeter. Figure 11 shows the bland altman-plot of the ICA (3-dimentional).

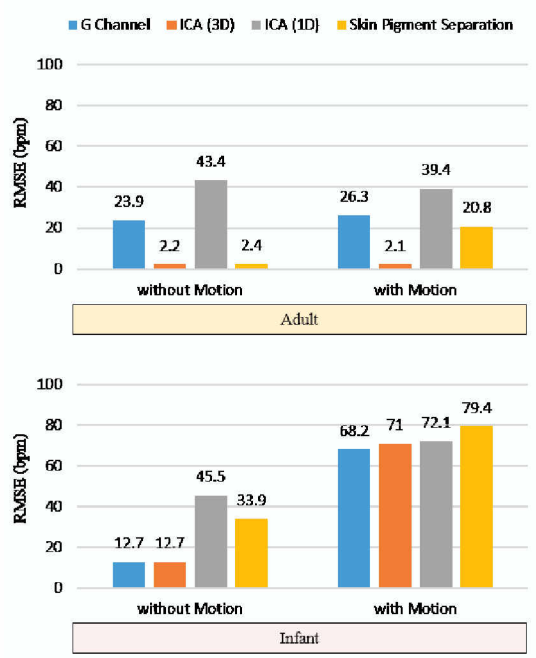

Figure 9. The RMSE of four methods for signal processing. The color of bars shows the type of method. The sets of four methods' bars show the result of Adult without motion, Adult with motion, Infant without motion, and Infant with motion, from upper left to lower right.

Figure 10 shows the bland altman-plot of the ICA (3-dimentional) to reveal the trend of error.

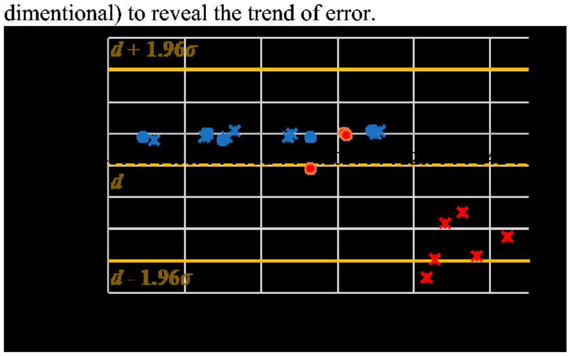

Figure 10. The bland altman-plot of the ICA(3D). Vertical axis is the subtraction of reference value from estimated value. Blue markers and red markers represent the adult data and the infant data, respectively. Circle markers and asterisk markers represent the "with motion" data and the "without motion" data. The broken yellow line represents the bias. The solid yellow lines represent limits of agreement.

Discussion

We discuss the most suitable method for infant based on the experimental results.

Comparison of ROI Selection Methods

As seen from Figure 8, results of ROI selection method vary greatly, depending on the type of subject and the type of motion.

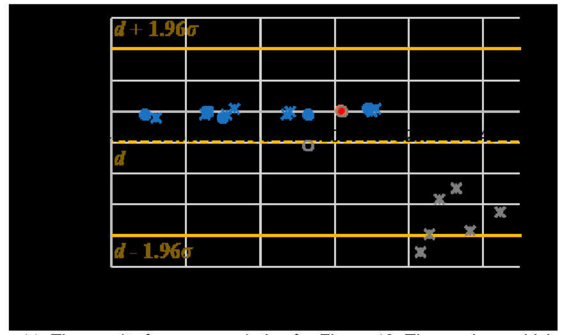

Figure 11. The result of error cancelation for Figure 10. The markers which turns into gray compared with Figure 10 represent canceled data.

The face detection method has the second highest success rate for adults as shown in Figure 8. The cause of the failure in the result of "with motion" is the complexity of the angle of the face. All other ROIs are set appropriately. However the success rates of this method for infants fall to zero in the both case of "without motion" and "with motion". Infants' face are not recognized even if the camera captures the infant's frontal face vertically. We consider that the learnt classifier is not suitable for infants.

Maximum SNR has the highest success rate for adults and the second highest success rate for infants. Maximum SNR decreased in the case of "with movement". The change of pixel value caused by the body movement affects the waveform, then the contribution to a frequency spectrum of the pulse wave is disturbed. On the other hand, success rates for infants are lower than success rates for adults because the amplitude of the pulse wave in infants tends to be lower than that in adults.

Maximum Hemoglobin has the highest success rate in each condition shown in Figure 8. The skin color based methods such as this Maximum Hemoglobin method is effective and overcome the difference of the facial feature between adults and infants as well as the difference of the amplitude of the pulse.

The method using skin color as in the method of maximum hemoglobin value can be measured more stably than a method using a shape such as face detection. However, if a face detection algorithm specialized for infants is developed, it should be reconsidered.

Comparison of Signal Processing Methods

In this experiment, all measurements for infants with motion failed as shown in Figure 9 and 10 because their body movement is consecutive and too large compared to the amplitude of their pulse wave. This problem is caused by lower sensitivity against to the infant's pulse, therefore the proposed solution is to use a high sensitivity camera and reconstitution of the photographic conditions such as the resolusion of camera or the focal length of the lens. One of the other important factors is subjects' frequency of pulse. The errors in Figure 10 tend to be large as frequency becomes higher. Another factor is that the estimated values tend to smaller than reference values. This tendency is caused by the affection of the body motion which has the lower frequency than the pluse rate.

G channel has the third smallest RMSE for the adults and the smallest RMSE for the infants. The waveform of G channel is affected by several artifact such as a body movement or the relocation of ROI which means the skin potision in the face of interest. Bandpassfilter reduce the influence of the compornent which has the lower or higher frequency than the passband for pulse. However, the artifact which has the frequency included in the passband (i.e. quick motion) occurs occasionally. Particularly, the infants tend to shake their body periodically. Therefore, the methods which can reduce noise without depending on frequency.

ICA (3-dimentional) has the smallest RMSE for the adults and the first or second smallest RMSE for the infants. ICA is able to reduce the contribute of other compornents by separating the pulse compornent from the RGB signals. As shown in the adult's result in Figure 9, the feature of ICA compared with other methods is robustness of the body motion because this method is based on the statistical independency of compornents.

ICA (1-dimentional) has the worst RMSE for the both of adults and the infants. This method requires us to set the several parameters for implemention, then the best parameter changes depending on the conditions of data. This method need more consideration to the setting of these parameters.

Skin Pigment Separation has the second smallest RMSE for the adults and the third or fourth smallest RMSE for the infants. The extracted waveform for Hemoglobin has less affection of Melanin and shading. This factor means that the method using skin pigment separation is robust against to the change of the skin potision in the face of interest. However this method has no solution against to the body movement. The result of adult shown in Figure 9 reflects this tendency.

The most important factor for awake infants is the robustness against to the body motion because they shake their body or limbs actively. Therefore, the most suitable method according to our results is 3-dimentional ICA.

Conclusion

In this paper, we compared the accuracy of pulse rate detection obtained by principal non-contact methods. We measured the pulse rate of five adults and three infants by using several previous methods in ROI selection and signal processing. For the ROI selection, the skin color based method is the most suitable for infants due to the robustness against to the difference of the facial feature between adults and infants as well as the difference of the amplitude of the pulse. For the signal processing, 3-dimentional ICA is the most suitable for infants due to the robustness against to the body motion. Additionally, error detection function with SNR improve the accuracy by canceling the data with body motion.

Our future work is the increase of the number of the subjects and the range of age which has relation to the height of the pulse rate. In this paper, we dealt with the data affected the body motion by canceling it. Our goal of this study is the construction of the improved method which is able to implement the accurate measurement against to the body motion. Finally, some recent research proposed the two steps ROI selection [5]. Our future work is three steps consideration: Step1) Global ROI Selection; Step2) Local ROI selection; Step3) Signal Processing. Local ROI selection implements to select the valuable ROI carefully. This procedure is expected to be suitable for infant's weak heartbeats.

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