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A Novel Non-contact Heart Rate Estimation Algorithm and System with User Identification

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***Abstract*:** In these days, the wearable devices have been developed for measuring biological data effectively. However, wearable devices have tissue allege and noise problem. Also, it is impossible for a remote center to identify the person whose data are measured by wearable devices, which could trigger a communication problem over treatment. To solve these problems, biometric measurement based on a non-contact method, such as face image sequencing is necessary. This makes it possible to measure biometric data without any operation and side effects. This system can monitor the biological signals of people in real time without allege and noise and simultaneously identify them. In this paper, we propose an authentication process while measuring biometric data, through a non-contact method.

***Keywords*:** Heart rate, Non-contact, Bio sensor, Mobile health

1. Introduction

In a patient-monitoring system, it is essential to monitor the state of the patient continuously and intensively. Patient monitors (bedside monitor) are currently used as a major medical equipment. A patient-monitoring system has the effect of reducing the manpower, effort and burden associated with monitoring patients. Through rapid understanding of the patient's medical data, the healthcare team can manage the patient's condition with the proper medical attention. The basic function of the patient monitors is to collect and process bio-signals from sensors attached to the patient [1, 2].

Since patient-monitoring systems are for inpatients, however, they are not suitable for the health management of discharged patients or for people who have never been to the hospital. The current medical system focuses on prevention rather than treatment of disease, so accurate biometric data measurement of patients and the rapid care based on those biometric data are needed in order to prevent diseases. By reflecting the changes in the medical system, medical devices have become more and more miniaturized and simplified, and more wearable or body-implantable devices have been developed for accurate measurement of a patient's biometric data. These devices have the advantage of measuring patient's data easily, without having them visit the hospital, and of measuring the data for nearly 24 hours a day. However, wearable or body-implantable devices also have to be improved.

Even though wearable devices are simplified and miniaturized, it is still difficult to wear them in everyday life, and they also have a disadvantage from the difficulty in accurately identifying the person whose data are measured by the device. It is difficult to select the materials for body-implantable devices owing to issues to be considered to ensure compatibility with the human body. In addition, there is the hassle of replacing batteries periodically if there are problems.

Due to these problems, research is currently being conducted into methods of measuring a bio-signal by making patients feel comfortable, rather than by attaching devices to the body or implanting them inside the body. A typical example is heart rate or oxygen saturation being measured by a smartphone camera. Using a video camera a patient's biometric data can be measured without any special operation. With this, the patients can be monitored in real time, and the health-care team is able to react immediately to an acute condition in the patient. This method makes continuous and steady biometric data measurement possible, which can identify the status of the patient more accurately, and it is very helpful for the prevention of diseases.

In this paper, a monitoring system is implemented to improve biometric data measurement methods using conventional medical devices because when using them it is difficult to identify the person the biometric data belong to, and difficult to collect and process biometric signals in an easy and simple way. This system is intended to overcome the limitations in preceding studies.

Earlier studies, mentioned that heart rate and respiratory rate can be measured with cameras and proper lighting, and the face is the best part of the body for extracting a photoplethysmography (PPG) signal [3]. In addition, if measured by an RGB camera, the green channel is more suitable than red or blue for measuring the heart rate and respiratory rate. The reason for this is that the light absorption wavelength of hemoglobin and oxyhemoglobin causing the color factor in the blood is 520~580 nm and this falls into the frequency band of the green filter in the camera [3].

Other studies, defined the face with a webcam using a face recognition system, which enabled measuring the heart rate and respiratory rate even with a large number of people [4, 5]. In one study, three independent factors from the RGB channels of the camera were extracted by using a blind source separation (BSS), and the independent component analysis (ICA) algorithm was used in this process. In this study, a PPG was extracted from one of three independent factors.

In addition, another recent study proved that using cyan, orange and green (COG) channels is more suitable than using RGB channels for measuring biometric data [6]. This is because the channels are 470 ~ 570nm (cyan), 520 ~ 620 nm (green) and 530 ~ 630 nm (orange) which results in more overlap of the hemoglobin and oxyhemoglobin in the light absorption wavelength.

In spite of several recent studies in progress, there are a number of problems in measuring biometric data. The most frequently occurring problem is that the measured value can be changed sensitively according to the lighting conditions and movement of the measurement target. In particular, in the case of rotation, difficulty occurs in continuous measurement since the coordinates that measure color can change significantly. Therefore, it is necessary to develop a system that is able to offset the illuminance variation and perform continuous measurement, regardless of any movement by the measurement target.

Background and Problem Definition

PPG measurement with a camera extracts PPG signal $p(t)$ by analyzing the recording of the person's face by the camera. The recorded video image is shown in the form $V(x,y,t)$ for each frame, in accordance with the strength of the signal. Each video frame saves the light reflected from the face as the pixel value on each of the x, y coordinates, and if the camera sensor takes a measurement of many colors (e.g. red, green, blue), it can obtain a number of data values separated by color channels in a single frame (e.g. $V_r(x,y,t)$, $V_g(x,y,t)$, $V_b(x,y,t)$).

The video image, $V(x,y,t)$, also consists of two elements: illumination intensity $I(x,y,t)$ and skin reflectivity $R(x,y,t)$.

$$V(x,y,t) = I(x,y,t)R(x,y,t) \tag{1}$$

The intensity of the illumination indicates all the lighting that shines on the face. When measuring PPG, certain illumination intensity is needed for the measurement area. The reflectivity of the skin indicates the intensity of illumination reflected from the skin, and there are two types of reflection: from the surface of the skin and from subcutaneous tissue.

Camera-based PPG Signal Acquisition Model

Divide the blood flow evenly in the region of interest (ROI) from the intensity of the extracted signal $V(x,y,t)$ and show it as R. Here, $y_i(t)$ is the mean value of the pixel values of ROI R_i, according to time t, and $i \in \{1,2...,n\}$ is the index value of R.

In addition, if the intensity of illumination, $I(x,y)$ of ROI R_i is constant, and it is shown as I_i, $y_i(t)$ can be defined as follows:

$$y_i(t) = I_i\left(a_i \bullet p(t) + b_i\right) + q_i(t) \tag{2}$$

In the formula above, I_i represents the intensity of illumination of ROI R_i, and a_i indicates the intensity of blood flow. In addition, b_i is the reflectivity rate from the surface of facial skin and $q_i(t)$ represents camera quantization noise. When the light of I_i shines on ROI R_i, a large amount of reflection (b_i) takes place at the surface of the skin. However, this value is not at all affected by the changes in blood flow. Some of the light enters through the skin surface, and reflectivity depends on the changes in blood flow, represented by $p(t)$. Furthermore, a_i seems to change depending on the absorption of the light and the wavelength of the irradiating light of hemoglobin and oxyhemoglobin. Thus, subcutaneous reflectivity can be calculated with two elements a_i and $p(t)$, which contribute to the reflection of the light under the surface of the skin. In this paper, we use the green channel which has the highest wavelength in the light absorption rate of two color factors, hemoglobin and oxyhemoglobin.

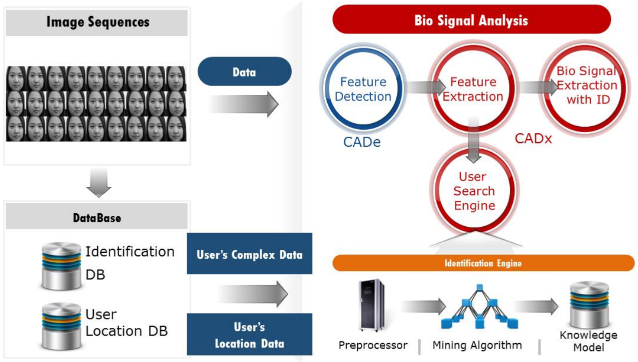

Fig. 1. Diagram of vision pulse.

2. Method

The proposed system is based on biometric data measurement using a camera. First, it recognizes the face of the patient by using a camera, compares the face with image in a database, and then subjects it to a process to confirm the identity of the patient. In this process, the system aims to track many people's faces at the same time, not to track the face of just one person. This is intended to verify the individual's identity by recognizing everyone, not just one person, when more than one person is within the camera image. Only the heartbeat of the person in the image whose identity is verified by face recognition can be measured. Heart rate is measured by tracking the face of the target person, and by continuously extracting the color of the same coordinates through the color change of the pixel. With this system, the identity and the heart rate of the person in the image can be measured by using only the camera image. The system proceeds in the following order.

2.1 Face Position Detection using PCA

Form an eigen face (common information of the facial types) using principal component analysis (PCA), then specify the part that has a form similar to the input image of the person's face, and track it. PCA is a secondary statistical method using the statistical nature of mean and variance. For input data, PCA finds a set of orthogonal normalized axes, which point in each direction of the maximum normalized covariance with respect to the input data. This has the advantage of efficiently reducing the dimensions of the material by finding the most important axes of the input data. However, with PCA, it is difficult to show the most basic features in the video because it only utilizes secondary statistics.

Given data X, and if there are n pieces of observed samples, then X can be defined as $X = [x1, x2, ..., xn]$. Here, each sample x_i of X, consists of m pieces of data, where $x_i = [x_i(1), x_i(2), ..., x_i(m)]^T$ constitutes the sample. Here, T denotes the transposition of a matrix, and with a face image, the m value becomes the number of pixels in the image of the face and can be expressed as a one-dimensional vector.

The method for representing data by PCA is as follows. R represents data by PCA, and at this time, each row is matched to the sample of the original data. Called V when a matrix containing eigenvectors is arranged in columns, R can be obtained by $R = XTV$. So, it has the properties $VVT = 1$, since eigenvector V is symmetrical and orthogonally normalized. The conversion of the data in the reverse can be obtained with $XT = RVT$.

The feature vector space obtained by applying PCA results in a recognition rate that falls, because it includes features like changes in illumination of the image and changes in facial expression. Considering this, it only takes the approximate location of the face through PCA and extracts the feature points in that location. We intend to improve the recognition rate by recognizing the face using a comparison of the feature points.

2.2 Feature Point Extraction in the Detected Face Position

Since a face recognition method usually uses the information of entire pixels, a localized area of a face image can be affected by small lights, position, and any change in facial expression, which can affect the recognition algorithm. This makes a face recognition method easily influenced by lighting, posture, and facial expression changes. On the other hand, since the model-based face recognition method can be configured in consideration of the model, lighting, posture, and facial expression change, it can reduce the influence of these factors at the time of recognition. Gabor feature vectors (coefficients obtained by the convolution of a Gabor wavelet kernel from the face image feature points), are feature vectors used when configuring the model. They are widely selected for face recognition because they are somewhat robust for lighting, posture, and facial expression changes [7]. Elastic bunch graph matching (EBGM) is the leading face recognition method using Gabor feature vectors [8, 9]. A face recognition method based on EBGM finds feature points from the face by using Gabor coefficients.

Image-based face recognition techniques have the disadvantage of not being able to respond to a changing environment, because they use information from the entire image. EBGM, a feature vector based technique that uses local information was developed in order to offset this disadvantage. EBGM is done by obtaining the Gabor coefficients from the feature points (facial geometric information of the eyes, nose, and mouth) and then verifying the person who has the highest similarity when comparing the similarities between Gabor coefficients.

EBGM extracts only the local frequency characteristics of the image through the Gabor wavelet function. It is then divided it into a real part and an imaginary part using the Gabor wavelet filter, which discretizes each of them and then creates a Gabor wavelet mask. After that, coefficients are obtained via rising integral with the pixel values of the feature points from the face area image.

Gabor jets are the coefficients obtained from each feature point, and "*bunch*" is a group of Gabor jets. The bunch graph is a collection of facial feature points. The model bunch graph is made by creating a specific training image of M and manually putting dots on these bunch graphs.

A model bunch graph is used to obtain the feature points of the face. Feature point extraction used in EBGM is influenced largely by the number and type of models bunch graphs. Therefore, the model bunch graph must be created with consideration to a variety of factors, including gender, age, lighting, posture, and facial expression.

2.3 Verification of the Identity of the Face Detected by Comparing Feature Points

The point matching method is the most widely used comparison method in the area of computer vision and pattern recognition. The two types of point matching are divided into rigid matching and non-rigid matching, depending on the strain of the target object extracted from the image sequence. Non-rigid matching is much more complicated, compared with rigid matching. In non-rigid matching, it is difficult to make comparisons because the relationship between each feature point has a severe degree of variation, depending on the strain of the target object. Facial features correspond to very severe non-rigid matching because the variation is severe, depending on the facial expression and angle. An effective non-rigid matching algorithm is needed in order to solve this.

In this paper, for effective verification of identity, we perform point matching using the topology preserving relaxation labeling (TPRL) algorithm, a modified version of the robust point matching-preserving local neighborhood structure (RPM- LNS) algorithm, for comparison of feature points.

2.4 Measurement of Heart Rate Value

The heart rate variability (HRV) measurement method using a camera in the detected face area is basically the same as the PPG measuring principle. PPG measurement is a method for estimating the heart rate by measuring a blood flow in the blood vessels by using the optical properties of biological tissue. The diastolic and systolic blood flow slows when the blood flows through the peripheral vascular region, causing transparency changes in the blood vessels. PPG is basically sensing that transparency change.

This form can be clearly measured in peripheral tissues from areas like the face, fingers, or earlobe, and the general PPG measurement is performed using a finger. If the same principle is applied to the face, the blood flow in the facial skin will also be changed depending on the heart rate, and this can be measured and analyzed through the camera, so the heartrate can be estimated.

2.5 Selection of the Regions to Extract Heart Rate

In the face, the area in which the capillaries are most dense is the forehead and cheeks [10]. Because of this, the body temperature of a person is usually measured from the forehead or cheeks. Similar to measuring body temperature, when measuring PPG from the face, it is appropriate to measure the area that has a big change in hemoglobin concentration in accordance with the heart rate, owing to the dense capillaries. Thus, this system uses the forehead and cheeks as measuring sites, but the cheeks were ultimately chosen for the measurement because hair could cover the forehead, depending on the person.

When the feature points of the face are extracted, the following placeholders are used: $n(t)$ for the ala of the nose, $e(t)$ for the ears, $m(t)$ for the corners of the mouth. The center of gravity ($G(x, y)$) of the triangle is formed by these three points $n(t)$, $e(t)$, and $m(t)$, and 10 x 10 pixels are extracted from this center point. The values from the 10 x 10 pixels are then taken to come up with an average.

$$G(x, y) = \left(\frac{x_n + x_e + x_m}{3}, \frac{y_n + y_e + y_m}{3}\right) \tag{3}$$

2.6 Blood Pressure Measurement

The cuff-based blood pressure measurement method is the most commonly used non-invasive method of measuring blood pressure. However, the disadvantage to this method is that continuous blood pressure require an interval of one to two minutes between measurements in order to reduce error. Therefore, this method cannot be used to measure a change in blood pressure over a short period of time, resulting in not being able to obtain an immediate response to blood pressure changes. In order to resolve this problem, a method of measuring blood pressure had to be developed by using time difference between the pulse rate at the fingertips and the heart [11].

In this paper, like the conventional method, blood pressure was measured by using the pulse time difference between the heart and fingertips, and the pulse time difference between the heart and face.

2.7 SpO_2 Measurement

Generally, the oxygen saturation rate can be obtained by calculating the ratio of oxy-hemoglobin and hemoglobin:

$$SpO_2[\%] = \frac{HbO_2}{HbO_2 + Hb} \times 100 \tag{4}$$

Here, HbO_2 represents oxy-hemoglobin, and Hb represents normal hemoglobin that does not contain oxygen. HbO_2 absorbs the 880nm wavelength and, Hb absorbs 765 nm. Using these principles, the 765nm and 880nm wavelengths were used as a light source system for alternately emitting light to measure oxygen saturation from the image.

In the system, we create light wavelengths of 765 nm and 880 nm to emit light alternately in a half sampling rate of the camera by positioning 6×6 light emitting diodes (LEDs) with alternate wavelengths of 765nm and 880nm.

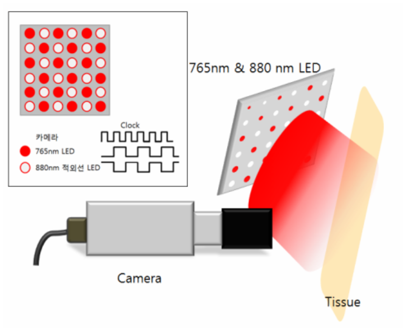

Fig. 2. Non-contact pulse oximetry system consisting of a camera, 765nm light emitting diode (LED), and 880nm LED.

When you shoot an image matching the start of the image and the LED pulse, the image taken by 765nm becomes an even-numbered image, and the image taken by 880nm becomes the odd-numbered image. These images are separated into odd-numbered and even-numbered, and then the mean value is calculated from 40 × 40 pixels of the image. After this, the wavelength is passed through 0.5~3Hz of a Butterworth band-pass filter to the value of the G channel, to obtain the value R_{os} using Eq. (5).

$$R_{OS} = \frac{\ln(\frac{R_V}{R_P})}{\ln(\frac{IR_V}{IR_P})} \tag{5}$$

R_V is the minimum point for 765nm, and R_P is the maximum point for 765nm. IR_V is the minimum point for an 880nm infrared ray, and IR_P is the maximum point of an 880nm infrared ray. The blood oxygen saturation will be shown in real-time by mapping R_{OS} calculated using Eq. (5) on the actual SpO_2.

3. Result

We verified the difference between the actual heart rate and the measured data value taken by the camera, which was obtained by comparing the HRV value measured by using the value change of the green channel data in a specific face with the value obtained with SpO_2 and PPG measurement using a Biopac MP150.

3.1 Recognition Rate

In the face recognition experiment, we conducted face recognition from the front, and right and left sides of the face, and under irregular lighting. This experiment was conducted on only 50 people. Recognition rate with this system was 96.0% with the front of the face, and 86.0% from the sides of the face. In addition, the recognition rate under irregular lighting was 94.0%.

The experiment measuring the heart rate was performed in bright light and dark light, and the first to fifth experiments were done under bright fluorescent lights, while the sixth to tenth experiments were conducted in dark incandescent lighting.

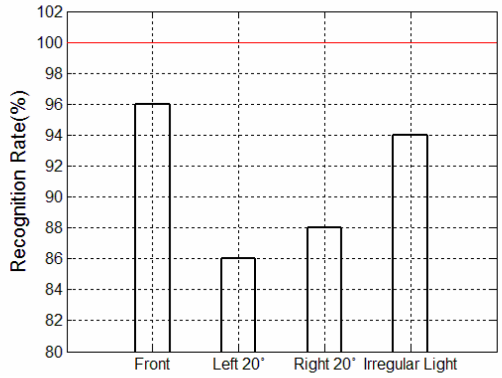

Fig. 3. Identity recognition rate.

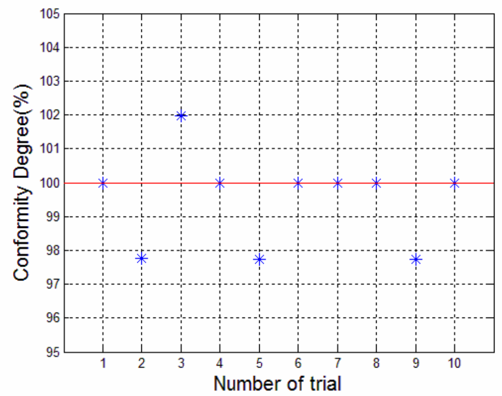

Fig. 4. HR measurement conformity rate.

We processed measurement of the heart rate with a photographed image under bright fluorescent light (the exact value of ambient light was measured after) at a peak value of 30 to 35 seconds, and this showed differences where the value of the heart rate was the same (or one less) when measured by each RGB channel. The G-channel filtered the same in comparison to the other channels, but showed a uniform shape.

For data measured under incandescent light, since the measured data is processed by measuring the change in complexion, filtering was done under a low light, but a relatively irregular pattern was observed compared to bright fluorescent light.

The experiment was conducted 10 times in total and the accuracy of the average heart rate was 99.1%.

3.2 Non-contact Method to Measure Pulse Oximetry

In this study, to measure pulse oximetry with a non-contact method, we used an image sequence, and 40 × 40 pixels had enough photons from the acquired image sequence for selection. After the selected area signal was divided into R, G, and B channels, we calculated the mean

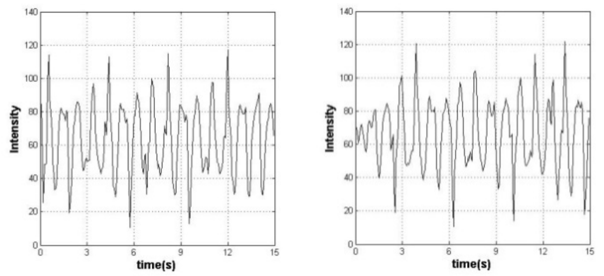

Fig. 5. Signals after bandpass filter (a) 765nm, (b) 880nm.

of the G channel. Then, odd frames and even frames were divided, and a 0.5 ~ 3.0 Hz bandpass filter, which is the general pulse rate, was applied to the divided signals. After filtering the signals, the offset value vanished. Therefore, for the data reconstruction, the minimum value obtained was shifted to match the minimum value of the original signal.

To get R_{OS} , we substituted the maximum point and minimum points of an odd frame which captured 765nm photons, and even frames, which captured 880nm photons into Eq. (5). The mean of R_{OS} was 1.61. As a common SpO_2 value is about 96, we could calculate $k = \frac{96}{1.61} = 69.63$.

A non-contact method for pulse rate was available with a average error of 3.66 % and 0.72% for each case. And R_{OS} in the non-contact method for pulse oximetry was proportional, in relation to common SpO_2 values.

3.3 Error Rate Comparison of the Algorithm

We conducted an experiment on the error rate for each algorithm to prove the effectiveness of the algorithms used for the comparison of feature points. In these experimental methods, we did a comparison by calculating distance error for each feature point occurring when matching the feature points of the database and the feature points of the image sequences.

As a comparison target, we chose an iterated closet point (ICP) algorithm, the thin plate spline robust point matching (TPS-RPM) algorithm and the shape context (SC) method, which are commonly used in point matching.

In order to minimize the strain, this experiment was conducted by adjusting the image sequence in a state similar to the database, and then by comparing the extracted feature points in a state looking towards the front. Each algorithm was compared based on the same feature points and the mean error values are as follows.

In addition, an experiment was conducted on the error rate under rotation, in noisy situations, and with occlusion of the target object. In a strain due to the rotation, we conducted the experiment into error value under duress by modifying the change value from 5° to 20° in intervals of 5°. For noise, we generated random noise in all feature points, and it was tested by adjusting the ratio at 10% intervals. Also, in the case of occlusion, we generated an obstacle in an arbitrary position, then calculated the error value after comparing the extracted feature points by disturbing the feature point extraction from the corresponding location.

In the rotation transformation experiment, the results were as seen below on the left and right respectively.

Fig. 7 shows the results for these experiments. We note that without occlusion in Fig. 7(a), the four algorithms achieve similar matching performance until rotation. However, as the rotation degree increases, we see that TPRL shows robustness, compared to other algorithms. The increased mean RMS error from 5° to 20° is 0.015 mm compared to 0.027 mm in TPS-RPM, 0.047 mm in ICP, and 0.020 mm in SC. In Fig. 7(c), all four algorithms

Table 1. Mean error of each algorithm.

	TPRL	TPS-RPM	ICP	SC
Mean Err	0.04771	0.04854	0.04872	0.068448
Min Err	0.03002	0.02190	0.02169	0.038251
Max Err	0.075103	0.091851	0.08873	0.135526

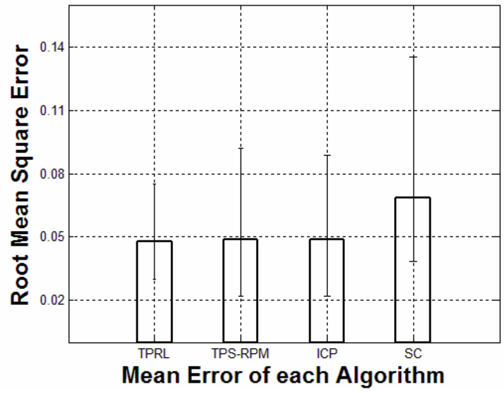

Fig. 6. Mean error of algorithms.

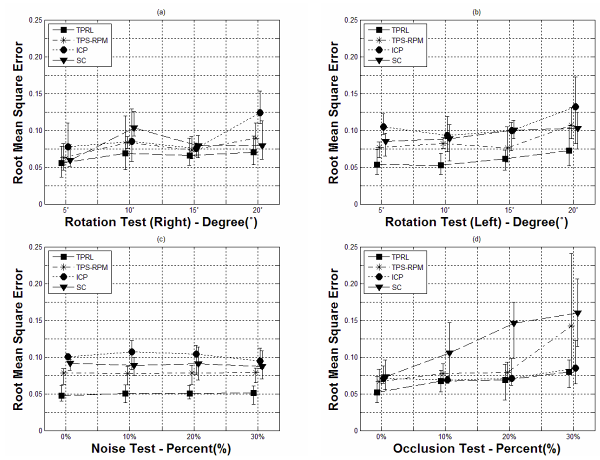

Fig. 7. Comparison of the matching performance of TPRL, TPS-RPM, ICP, and SC. Error bars correspond to the standard error for the mean of each pair's RMS error.

show similar mean RMS error differences with noise. Fig. 7(d) shows the results with occlusion. With a 0.3 occlusion ratio, the mean RMS error is 0.08 mm, compared to 0.085 mm in ICP, the second smallest error among the algorithms.

4. Conclusion

This study proposes an authentication process, implemented at the same time as measuring biometric data, through a non-contact method. In the face recognition experiment, we conducted face recognition in various situations. The recognition rate of this system exhibited 96.0% accuracy when trying to recognize the front, and exhibited 86.0% accuracy from the sides of the face. The average heart rate estimation accuracy was 99.1%, compared to the gold standard method.

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