System for Evaluating Pathophysiology using Facial Image

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Abstract

Facial diagnosis is an important diagnostic method in Japanese-traditional (Kampo) medicine. Major disease states by facial diagnosis are blood stagnation, blood deficiency, and yin deficiency. These facial diagnoses are subjective and empirically obtained. To solve these problems, we proposed to construct a system to output the score (1 to 5) for evaluating pathophysiology of the patient by using facial image obtained by RGB camera. We evaluate this system by calculating mean squared error (MSE) between the score given by medical doctor and estimated by the system. Our method achieved to estimate the score accurately as the MSE is less than 1.0. From the results of construction of the system, we found the important regions of the face for diagnosing disease states by medical doctor using the method of significant feature selection.

1. Introduction

When we have an injury or get a disease, the medical care that we usually receive is the Western medicine in most of the Western countries. In the Western medicine, doctors find the cause of disease and remove it directly. On the other hand, in the Asia region, medical care called the Oriental medicine developed for many years. The Oriental medicine assumes that "heart (mind)" is inseparable from "body" and the disease is treated by correcting a body's strain. In addition, Kampo medicine that is Japanese medicine has developed and differ from the others Oriental medicine. The doctors in Japan with a national qualification give Kampo medicine and use it in combination with Western medicine [1].

Diagnoses in the Kampo medicine include diagnosis through visual observation, auscultation and olfactive examination, inquiry, and palpation. The diagnosis through visual observation is a diagnosis by observing the facial color, tong color and so on. The auscultation and olfactive examination is a diagnosis by listening sound emitted from a body and smelling body odor. The inquiry is a diagnosis by asking a question to a patient. The palpation is a diagnosis by touching a body.

The diagnosis through visual observation is important characteristic of the Kampo medicine. Facial diagnosis which is one kind of its diagnosis can diagnose a disease by observing the skin color and states of the skin. For instance, a patient whose skin color looks pale is possible to be diagnosed as the liver has a trouble because the depression of the generation function of the blood in the liver has an effect on the color skin.

Major disease states in Kampo medicine that is possible to be diagnosed by facial diagnosis include "blood stagnation", "blood deficiency", and "yin deficiency". Blood stagnation is developed due to the poor blood circulation. This disease state can be observed by redness by pigmentation. Blood deficiency is developed due to lack of the blood. The disease state can be observed by skin color which is plain and the state of skin which is dry by lowering generation function of the blood and not generating new blood. Yin deficiency is developed due to lack of the water in the face. This disease state can be observed from the luster and elasticity on the face.

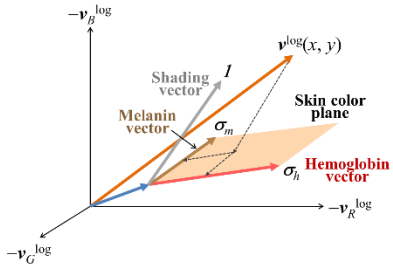


Figure.1 Overview of pigmentation component separation by ICA

There are two problems in diagnosing these disease states from facial diagnosis. First, these pathologic diagnoses need much experience and knowledge and are not diagnosed quantitatively because it is subjectively diagnosed. Second, in Kampo medicine, continuous observation of the pathologic diagnoses for the patient is important from view point of main approach of Oriental medicine. This is the problem since that the patient sometime does not go to the hospital continuously.

In this paper, to resolve these problems, we use general RGB camera to quantify the diagnosis from facial images. By extracting the feature values from RGB facial image, it comes to be possible to diagnosis a disease state quantitatively without going to the hospital. We ask Kampo doctor to evaluate disease states from facial image and construct an evaluating system by using quantified feature values obtained from RGB facial image and these evaluated scores. Finally, we assess the performance of our evaluating system by inspecting the precision of this system.

2. Generating Facial Image Database

In this section, we describe a method of generating database. In our research it was difficult to construct an evaluating system because the number of captured facial images isn't enough to construct it from the machine learning method. Therefore we increase the number of faces from a small number of captured facial image by the methods described in this section.

As previously mentioned, blood stagnation and blood deficiency have relation to blood and yin deficiency have relation to luster and elasticity. We assume that the blood has relation to hemoglobin and the luster and elasticity have relation to gloss. Therefore, the number of facial images is increased by modulating hemoglobin and gloss relevant to three kinds of disease state.

2.1. *Modulation Method of Hemoglobin*

We use pigmentation component separation from human skin by independent component analysis (ICA) proposed by Tsumura *et al* [2]. We generate the facial images by modulating hemoglobin. The overview of this technique is shown in Fig.1. The signal $\boldsymbol{v}^{\log}$ is obtained by converting sensor response of digital camera in RGB

color space to the optimal density space. The $\boldsymbol{v}^{\log}$ is expressed by the weighted linear combination of the three vectors $\boldsymbol{\sigma_m}$, $\boldsymbol{\sigma_h}$, and $\boldsymbol{1}$ with the bias vector $\boldsymbol{e}^{\log}$. The vectors $\boldsymbol{\sigma_m}$, $\boldsymbol{\sigma_h}$ are relative absorbance vectors for the melanin and hemoglobin components, respectively. $\boldsymbol{1}$ is shading vector. The hemoglobin and melanin pigmentation densities is obtained by re-projecting onto pigmentation density vectors of $\boldsymbol{\sigma_m}$ and $\boldsymbol{\sigma_h}$ after projecting the $\boldsymbol{v}^{\log}$ on the skin color plane in parallel with shading vector of $\boldsymbol{1}$. We can separate the RGB facial image to three components that are hemoglobin, melanin, and shadow component. We only modulate hemoglobin components multiplied by the coefficient α_h (α_h = 0.4, 0.7, 1.0, 1.3, 1.6). We reconstruct the facial images using the modified hemoglobin densities and the other components. Fig.2 shows facial images reconstructed by modulating quantity of hemoglobin. The facial image of α_h = 1.0 shown in Fig.2(c) is equivalent to original facial image.

2.2. *Modulation Method of Gloss*

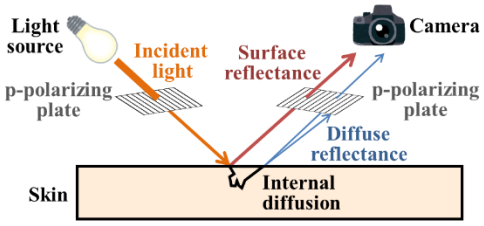
We use extraction of surface reflection from facial image [3]. We generate facial images by modulating gloss. The surface reflection expresses the facial gloss and is obtained by subtracting the facial image including only diffuse reflection from the facial image including both of surface and diffuse reflections. The surface reflection keeps the same polarizability as the incident light. The diffuse reflection loses polarizability by scattering inside the skin. The extraction of surface reflection method using these polarizability is shown in Fig.3. We capture a face with setting the polarizing plates in front of camera and light source. The incident light through the *p*-polarizing plate passes only *p*-polarized light. The surface reflection keeps polarizability, while the diffuse reflection loses polarizability. Therefore, both of the surface and diffuse reflection in the *p*-polarized lights pass thorough the p-polarizing plate in Fig.3(a), while the only *s*-polarized light of diffuse reflection pass through the *s*-polarizing plate shown in Fig.3(b). We obtain a gloss only image based on this theory. We use gloss only components multiplied by the coefficient α_g (α_g = 0.6, 0.8, 1.0, 1.2, 1.4) to synthesize the various facial images under modulating gloss that are obtained by the combination of modulated gloss only image and diffuse only facial images. Fig.4 shows the facial images with modulating gloss. The facial image of α_g = 1.0 shown in Fig.4(c) is equivalent to original facial image including both of surface and diffuse reflections.

2.3. *Constructing Facial Image Database by Modulating Hemoglobin and Gloss Components*

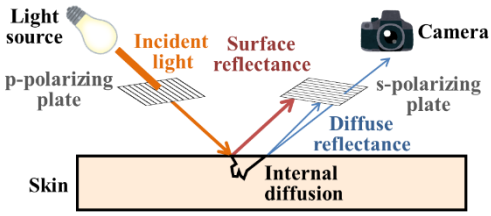
We generate the facial images by synthesizing the gloss images with the modulation of gloss quantity and hemoglobin quantity. Figure 5 shows environment to capture the facial images. The facial images are taken by a RGB camera in the dark room with polarized LED light. The polarized light source is made by setting polarizing plates in front of the light source. The polarizing plate remove the surface reflection to extract its reflection and estimate facial skin color vector such as hemoglobin and melanin vector [1]. We captured facial images of 7 patients in Kanazawa university hospital. They are 6 females from 20s to 40s years old and a male 50s years old. As shown in Fig.6, we generated 25 facial images by modulating hemoglobin in 5 levels (α_h = 0.4, 0.7, 1.0, 1.3, 1.6) and gloss in 5 levels (α_g = 0.6, 0.8, 1.0, 1.2, 1.4) for each image of patient. As a result, we constructed a database of 175 facial images by performing the modulation for 7 patients.

(a) α_h = 0.4 (b) α_h = 0.7 (c) α_h = 1.0 (d) α_h = 1.3 (e) α_h = 1.6

Figure.2 Facial images obtained by modulating hemoglobin component



(a) Both of p-polarizing plates



(b) One is p-polarizing plate while another is s-polarizing plate

Figure.3 Overview of the extraction of surface reflection by setting polarizing plate in front of camera and light source

(a) α_g = 0.6 (b) α_g = 0.8 (c) α_g = 1.0 (d) α_g = 1.2 (e) α_g = 1.4

Figure.4 Facial images obtained by modulating gloss component

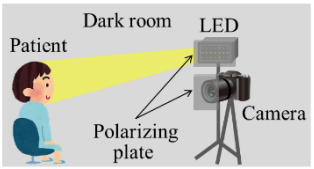


Figure.5 Photographic environment of facial images

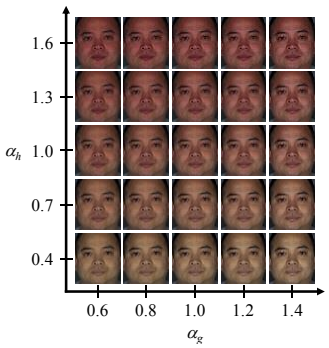


Figure.6 Facial images obtained by changing hemoglobin and gloss components in each five level

3. Evaluating Disease States of Facial Images by Kampo Medical Doctor

In this Section, we describe the method and the result of evaluating disease states of facial images by Kampo medical doctor. Figure 7 shows the experimental environment. Evaluations of disease states are conducted in the dark room. The display is 20 inch and the viewing distance was approximately 90 cm that corresponded with three times of the height of the display. The evaluator is a Kampo medical doctor. The Kampo medical doctor utilized the method of absolute evaluation and evaluated three disease states which are "blood stagnation", "blood deficiency" and "yin deficiency" for a facial image. The evaluated scores are from 1 indicating no disease state to 5 indicating severe disease state with increments of 1. The duration of evaluation for disease states is not limited in this evaluation. The interval of the evaluations is 5 seconds in order to eliminate the influence on the next evaluation by showing black screen.

The results of evaluated disease states of facial images is shown in Fig.8. The results of averaged evaluated scores with changing hemoglobin are shown in Fig.8 (a), (c), and (e). The results of average evaluated scores with modulating gloss are shown Fig.8 (b), (d), and (f). Blood stagnation tends to worsen as the skin color become redness by increasing hemoglobin in Fig.8 (a), while it is constant for modulation of gloss in Fig.8 (b). Blood deficiency tends to worsen as the complexion become plain by decreasing hemoglobin in Fig.8(c), and marginally tends to worsen as the skin become dry by decreasing gloss in Fig.8 (d). Yin deficiency tends to worsen as the luster and elasticity on the face is lost by decreasing gloss in Fig.8 (f), while it is constant for modulation of hemoglobin in Fig.8 (e). These results are corresponding with the consideration by Kampo medical doctor.

4. Constructing Pathophysiology Estimating System by Support Vector Regression

In this chapter, we construct pathology evaluating system by support vector regression (SVR) and evaluate its system by estimated error.

4.1 Support Vector Regression

In late years, SVR which is expanded method based on the Support Vector Machine (SVM) attracts attention in the issue of classification for the form of regression [4]. We explain the SVR in detail. In this research, we use a ε-SVR. The overview of the ε-SVR is shown in Fig.9. In ε-SVR, the goal is to find a regression function $f(x)$ that deviates from observed response variables y_n by the value no greater than ε for each training point x. In the beginning, we explain a linear SVR. Suppose we have a set of training data where x_n is a multivariate set of N observations with observed response variables y_n. We define the linear regression function as follows.

$$f(x) = x^t \beta + b \,, \tag{1}$$

where $\beta \in R^n$ and b is a real number. We ensure that it is as flat as possible, find $f(x)$ with the minimal norm value ($\beta^t \beta$). In addition, we introduce slack variables ξ_i and ξ^*_i, for each points. The slack variables allow regression errors to exist up to the value of ξ_i and ξ^*_i, yet still satisfy the required conditions. This leads to an optimization problem as follows.

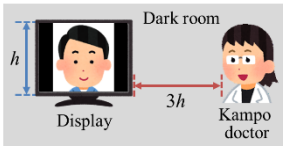
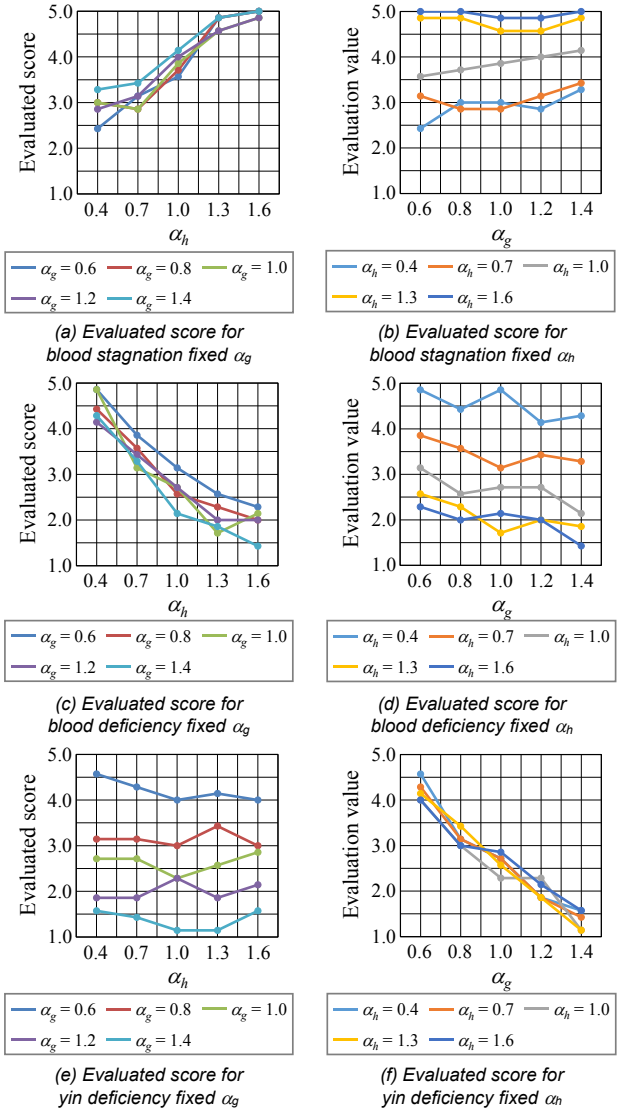


Figure.7 Experimental environment in evaluating disease states by Kampo medical doctor



(a) Evaluated score for blood stagnation fixed α_g

(b) Evaluated score for blood stagnation fixed α_h

(c) Evaluated score for blood deficiency fixed α_g

(d) Evaluated score for blood deficiency fixed α_h

(e) Evaluated score for yin deficiency fixed α_g

(f) Evaluated score for yin deficiency fixed α_h

Figure.8 Fluctuations of evaluated scores by modulating hemoglobin or gloss components

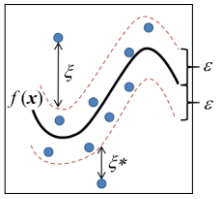


Figure.9 Overview of ε-Support Vector Regression

$$\underset{\beta,\xi,\xi^*}{Minimize}\ J(\beta)=\frac{1}{2}\beta^t\beta+C\sum_{i=1}^{n}\xi_i+\xi^*{}_i \tag{2}$$

$$\text{s.t.}\quad \begin{aligned}(\beta^t x_i+b)-y_i &\le \varepsilon+\xi_i\\ y_i-(\beta^t x_i+b) &\le \varepsilon+\xi^*{}_i\\ \xi_i,\xi^*{}_i &\ge 0\end{aligned} \tag{3}$$

The constant C is the box constraint, a positive value that controls the penalty imposed on observations that exist outside the epsilon margin. The optimization problem in Eq.2 is computationally simpler to solve by Lagrange multiplier method. By finding β using this method, we obtain the function $f(x)$ as follows.

$$f(x)=\sum_{i=1}^{n}(\lambda_i-\lambda^*{}_i)x_i{}^t x+b, \tag{4}$$

where λ_n and $\lambda^*{}_n$ are Lagrange multipliers for each observation x_n.

Some regression problem can't be described using a linear model. In such a case, the Lagrange multiplier method allows the previously described technique to be extended to nonlinear functions. We obtain a nonlinear SVR by replacing the inner product $x_1{}^t\ x_2$ with a nonlinear kernel function $K(x_1, x_2) = <\varphi(x_1), \varphi(x_2)>$, where $\varphi(x)$ is a transformation that maps x to a high-dimensional space. We don't need to know φ, because we can use the kernel function to generate $K(x_1, x_2)$ directly. Using this method, nonlinear SVR finds the regression function $f(x)$ as follows.

$$f(\boldsymbol{x})=\sum_{i=1}^{n}(\lambda_i-\lambda^*{}_i)K(x_i,x)+b \tag{5}$$

4.2 Extracting Feature Values from Facial Images

We extract feature values from facial images to construct a pathophysiology evaluating system. As shown in Fig.10, we obtain a hemoglobin density image and a gloss image by using pigmentation component separation and extraction of surface reflection respectively. We extract five regions including forehead (100×100px), left and right eye below (100×50px), and left and right cheek (100×100px) from these images and use an entire region (all) that sum these 5 regions as shown in Fig10. We use 6 kinds of region in total. We calculate 5 values which consist of average, standard deviation, maximum, minimum, and range for these six regions from each hemoglobin density and gloss image. Finally, we use 60 feature values to construct an evaluating system.

4.3 Accuracy Verification for the Evaluation System

We perform accuracy verification of a pathologic evaluating system. At first, we normalize 60 feature values from 0 to 1 because SVR needs normalized feature values. Thereafter, we construct SVR model to diagnose disease states using these feature values extracted from facial image and evaluated scores by Kampo medical doctor. We use the 60 feature values as explanatory variables and the evaluated scores as objective variables. In this research, we use kernel functions including linear, gaussian, 2-dimentional, and 3-dimentional kernel.

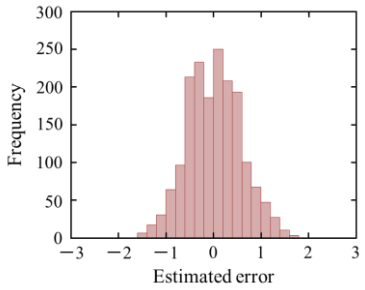
We calculate *mean squared error* (*MSE*) that describe difference of estimated values by SVR and evaluated scores by a Kampo medical doctor. *MSE* is an indicator of the predictive accuracy. It has high accuracy as the value is close to 0.

(a) hemoglobin density image (b) gloss image

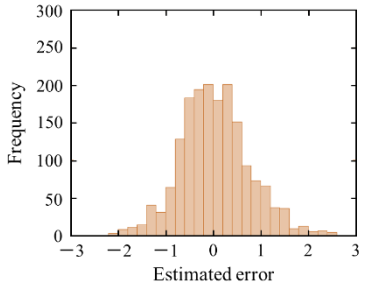
Figure.10 Regions (red rectangles) where feature values are extracted.

Table.1 The result of average of MSE for each disease states

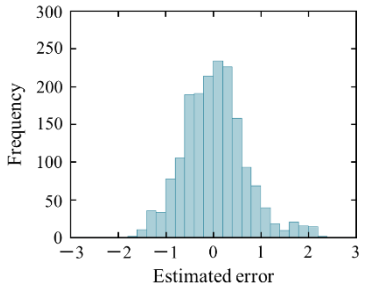
		Disease state		
		Blood stagnation	Blood deficiency	Yin deficiency
Kernel	linear	0.34	0.52	0.44
	gaussian	0.42	0.66	0.62
	2-dimentional	0.32	0.52	0.42
	3-dimentional	0.37	0.66	0.48



(a) Blood stagnation



(b) Blood deficiency



(c) Yin deficiency

Figure.11 Histogram of estimated error for each disease state

We calculate accuracy of the evaluating system by *k*-fold cross validation. Table.1 shows the result of average of *MSE* for each kernel functions by performing 10 times of 5-fold cross validation. The accuracy of blood stagnation and yin deficiency are the best in the case of 2-dimentional kernel. The accuracy of blood deficiency is the best in the case of linear kernel.

We obtain an estimated error by subtracting estimating values from evaluated scores. Histograms of estimating error for each disease states are shown in Fig.11.

4.4 Feature Selection

In this section, we select effective feature values in pathophysiology evaluating system. If there are much feature values for estimating classes or samples, the accuracy may be increased by removing a feature value which show weak correlation. Therefore we select effective feature values to increase the accuracy.

We use a rapper method as feature selection methods [5]. In the rapper method, the model is practically constructed using a subset of feature values, and decide an optimal combination of feature values by performing accuracy verification using this model. The rapper method uses lots of calculation amount, however the accuracy is better than the others method. We select feature values using an individual optimization method included in the rapper method. The individual optimization method evaluate the feature values individually and select the feature values based on the evaluation. In this research, as shown in Fig.12, we evaluate the feature values individually by removing each feature values one by one. We assume that a feature value that the estimated error is low in the case of removing it has high influence. We rank feature values by this technique using *MSE*. The top 5 Feature values selected for each disease state are shown in Table 2, 3 and 4. The result of *MSE* calculated by using the top 15 feature values is shown in Table.5. The resultant accuracy of feature selection is improved in comparison with the original accuracy before the feature selection.

5. Discussion

As is shown in Table 1, *MSE* of blood stagnation which equals to 0.32 and yin deficiency which equals to 0.42 are the best in the case of 2-dimentional kernel. *MSE* of blood deficiency which equals to 0.52 is the best in the case of linear and 2-dimentional kernel. We find that the 2-dimentional kernel works quite well for all three disease states.

In this research, evaluation criterions is from 1 indicating no disease state to 5 indicating severe disease state with the increments of 1. We assume that adjacent values in the estimated score give enough accuracy of the estimation. As explained above, we assume that evaluated scores can be accurately estimated because *MSE* is less than 1.0 and most estimated error fall within the range of ± 1 as shown in Fig.11.

We rank feature values and select effective feature values by individual optimization method. We calculate *MSE* using the top 15 feature values. The resultant accuracy of feature selection is improved in comparison with the original accuracy before the feature selection. The feature values of hemoglobin is mainly selected for blood stagnation and blood deficiency and the feature values of gloss is mainly selected for yin deficiency. The most effective feature value is the range of hemoglobin in forehead for blood stagnation and yin deficiency and the standard deviation of gloss in right eye below for yin deficiency. A Kampo medical doctor gave us the comments that the forehead is an attracted point when diagnosis of disease states including blood stagnation and blood deficiency. The region where gloss is easy to appear is selected for yin deficiency. As stated above, our experimental results are corresponding with the knowledge of the Kampo medical doctor.

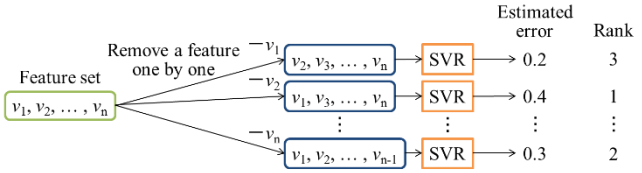


Figure. 12 Overview of individual optimization method

Table.2 Rank of features for blood stagnation

rank	hem/gloss	values	region
1	hemoglobin	range	forehead
2	hemoglobin	standard deviation	left eye below
3	hemoglobin	range	right cheek
4	hemoglobin	range	right eye below
5	hemoglobin	minimum	all

Table.3 Rank of features for blood deficiency

rank	hem/gloss	values	region
1	hemoglobin	range	forehead
2	gloss	range	left cheek
3	hemoglobin	minimum	forehead
4	hemoglobin	average	left cheek
5	hemoglobin	average	right cheek

Table.4 Rank of features for yin deficiency

rank	hem/gloss	values	region
1	gloss	standard deviation	right eye below
2	gloss	range	right eye below
3	gloss	average	right cheek
4	gloss	range	right cheek
5	gloss	maximum	right eye below

Table.5 The result which perform SVR using the top 15 features

	Disease state		
	Blood stagnation	Blood deficiency	Yin deficiency
Before feature selection	0.38	0.52	0.42
After feature selection	0.32	0.51	0.40

6. Conclusion and Future works

In this research, we constructed pathophysiology evaluating system using facial image captured by RGB camera. We assumed that evaluated scores can be accurately estimated by the system with the accuracy that *MSE* is less than 1.0. We see that effective feature values to construct this system can be selected by feature selection. In this research, we asked a Kampo medical doctor to evaluate images generated from only 7 facial images, and facial images were

taken under strictly controlled lighting conditions. In the future works, we will increase the original facial images of patients to verify how many original faces are enough in constructing the system, and construct the system we can use under more common lighting conditions. Furthermore, we would like to automate the process in capturing facial images to diagnosing disease states.

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