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Attempt of a Novel Calibration Method of Pulse Oximetry Using Support Vector Machines Regression

Mitsuhiro Ogawa, Yasuhiro Yamakoshi, Masamichi Nogawa, Takehiro Yamakoshi, Kosuke Motoi, Shinobu Tanaka and Ken-Ichi Yamakoshi

Abstract— **A novel calibration method using support vector machines regression (SVMsR) of pulse oximetry was proposed and attempted. Conventional calibration method of pulse oximetry that based on an optical density ratio of transmitted visible red light and infrared radiation whereas a proposed method here was not based on the optical density ratio directly. In theory, conventional calibrations using the ratio can be considered as a technique for nonlinear problem: nonlinear relation between two optical densities (red and IR) and oxygen saturation could be linearized by the ratio calculation. We thought, that nonlinear problem could be solved by using nonlinear analyses. Among them, the support vector machines regression method that has been studied well in this decade was attempted to be applied for pulse oximetry calibration. As an experiment, two photo plethysmograms (PPGs) by red and IR were measured on five subjects. Simultaneously, oxygen saturation (SpO_2) level was measured by a commercial pulse oxymeter. SpO_2 level was controlled by breathing 10% oxygen gas obtaining 98-75% SpO_2 level. Sequentially, feature points of two PPGs were extracted in beat by beat. Convex peaks and concave valleys on waveform and DC levels of PPGs were selected as feature points. Then, nonlinear regression using SVMs were attempted to obtain relationship between SpO2 by meter (regressand) and feature points of PPG (regressor). In result, a regression model was constructed from training data that is three fourths of measured cardiac data by using SVMsR. Finally, the constructed calibration model was evaluated by other one third data (validation data). The root mean squared error for the validation data is 1.90 [SpO_2 level %] and 89% of validation data fell within ± 2 % of SpO_2 level by the meter. In conclusion, SVMsR might be applicable on calibration for pulse oximetry.**

I. Introduction

A pulse oximeter is a medical device used for measuring the oxygen saturation (SpO_2) *in vivo* without any invasion [1-2]. As known, the pulse oximeter is widely used in medical and medical–related field. The principle is based on the difference of absorption of hemoglobin between oxygenated state and deoxygenated state. Oxygenated hemoglobin and deoxygenated hemoglobin should absorb different wavelengths of radiation. The pulse oximeter thus utilizes two photo plethysmograms (PPGs) signals: an infrared (IR) signal and a visible red signal.

As well known, the most basic calibration equations of pulse oxymeter are considered as following equations (eq. (1) and eq. (2)).

$$SpO_2 = \frac{\varepsilon_{Hb}(\lambda_R) - \varepsilon_{Hb}(\lambda_{IR})Ratio}{\varepsilon_{Hb}(\lambda_R) - \varepsilon_{HbO_2}(\lambda_R) + \left(\varepsilon_{HbO_2}(\lambda_{IR}) - \varepsilon_{Hb}(\lambda_{IR})\right)Ratio} \quad (1)$$

$$Ratio = \frac{\ln\left(\frac{I_{Peak}(\lambda_R)}{I_{Bottom}(\lambda_R)}\right)}{\ln\left(\frac{I_{Peak}(\lambda_{IR})}{I_{Bottom}(\lambda_{IR})}\right)} \quad (2)$$

$I_{Peak}(\lambda)$: transmittance intensity at peak on PPG waveform of one cardiac cycle at wavelength λ.
$I_{Bottom}(\lambda)$: transmittance intensity at peak on PPG waveform of one cardiac cycle at wavelength λ.
λ_R: wavelength of red visible light.
λ_{IR}: wavelength of infrared radiation.
ε_{Hb}: absorptivity of deoxygenated hemoglobin.
ε_{HbO2}: absorptivity of oxygenated hemoglobin.

The equation (1) clearly means that the *Ratio* (also called as *Ratio of Ratios* or Φ) defined by equation (2) can have almost liner relationship with SpO_2 level. At the same time, it also shows that measurable values $I_{Peak}(\lambda)$ and $I_{Bottom}(\lambda)$ themselves cannot have liner relationship with SpO_2 in any sense. The problem to obtain SpO_2 level from $I_{Peak}(\lambda)$ and $I_{Bottom}(\lambda)$ (and/or other information of PPG waveform) can be considered as a nonlinear problem. The equation (2) can also be considered as a linearization (at least, local linearization). In general, a linearization procedure for nonlinear problem is not easy and not enasured that it should be correct.

In the other hand, a new method solving nonlinear problems named Support Vector Machines (SVMs) has been arisen in this decade [3-4]. This can be thought as a method to solve a nonlinear problem without any explicit linearization planned by a human *a priori*. Because the algorithm of SVMs can be considered having linearization procedures in itself, a human (researcher, engineer, student and so on) has no need to plan a linearization by himself/herself. We authors have

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Mitsuhiro Ogawa is with the yu.sys Corporation (phone: +81-(0)76-234-5771; fax: +81-(0)76-234-5772; e-mail: m_ogawa@y5.dion.ne.jp) and the Graduate School of Natural Science & Technology, Kanazawa University, Kamuma, Kanazawa, 920-1192, JAPAN (e-mail for mtsogawa@kenroku.kanazawa-u.ac.jp).

Yasuhiro Yamakoshi is with the yu.sys Corporation, Kanazawa, JAPAN (e-mail: yamakoshi@s4.dion.ne.).

Masamichi Nogawa, Takehiro Yamakoshi, Kosuke Motoi, Shinobu Tanaka and Ken-Ichi Yamakoshi are with are with The Graduate School of Natural Science & Technology, Kanazawa University, Kamuma, Kanazawa, 920-1192, JAPAN (e-mail for Proffesor Ken-Ichi Yamakoshi: yamakosi@t.kanazawa-u.ac.jp).

thought that the calibration of pulse oximeter without using Ratio (equation (2)) should be possible by combining with Support Vector Machines Regression (SVMsR), regression method of SVMs proposed by Vapnik [3].

II. Methods

A. PPG and SpO_2 Measurement

Two LEDs (visible red light and infrared emitting) operated with a time division of light (radiation) transmission and obtaining two photo plethysmograms (PPGs) on a left index fingertip (nondominant hand) from four healthy male subjects (aged 21-39 yrs). Simultaneously, transcutaneous oxygen saturation (SpO2) level was measured by a commercial pulse oxymeter with a commercial prove (Radical oximeter with LNOP DCI sensor, Mashimo) from another side index fingertip of subject.

To obtain wide range of SpO_2 level, SpO_2 level of subjects were controlled by breathing 10% oxygen gas (N_2 ballanced), then obtaining 98% to 75% SpO_2 level that is indicated by the pulse oxymeter.

Protocol of experiment was approved by a local ethics committee of Kanazawa University. All subject had agreed to participate the experiment in advance.

B. Calibration using SVMsR

In order to obtain the input information for making regression model, feature points of two PPGs (by red light and infrared radiation) were extracted in beat by beat. In this study, convex peaks and concave valleys on PPG waveforms and DC levels of PPGs were selected as feature points. Figure 1 shows the feature point extraction of PPGs. Sequentially, nonlinear regression using SVMs were attempted to obtain relationship between SpO2 by the meter (regressand) and feature points of PPG (regressor). As a kernel, ANOVA kernel was selected empirically. Parameters of SVMsR were searched and obtained by trial-and-error method. The procedure of SVMsR was done by the software *"R"* with the *kernlab* module [5-6].

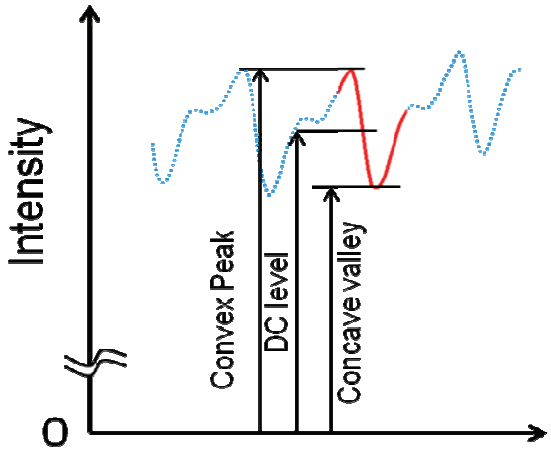

Fig. 1. Extraction of feature points. Convex peaks and concave valleys on waveform and DC levels of PPGs were selected as feature points as input of SVMsR learning and validation.

III. Results and Discussion

As a result, a regression model was constructed from training data and evaluated by validation data. The 3/4 of data sets was used as training data and other 1/4 data was applied as validation data. The best parameters were obtained as follows; the ANOVA kernel parameter sigma = 3.2 and epsilon = 0.4. By the resultant parameters, the root mean squared regression error for the validation data is 1.90 [SpO_2 %] and 89% of validation data fell within ±2 % of SpO_2 level by the commercial pulse oxymeter. Figure 2

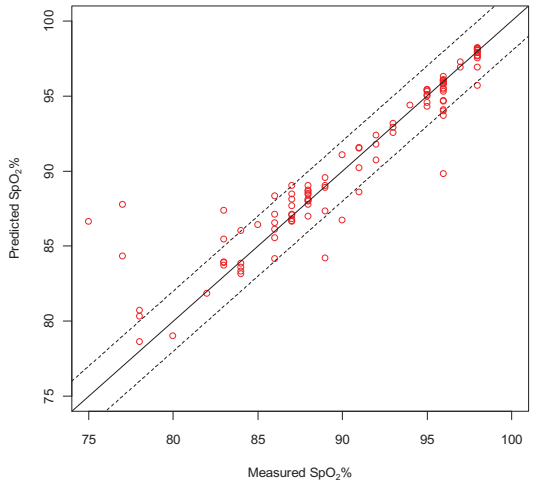

Fig. 2. Scatter plot of estimated SpO2 level by two PPGs and SVMsR versus a commercial pulse oximeter (from a subject aged 22). Dashed lines show range within ±2 % of SpO2 level by the meter

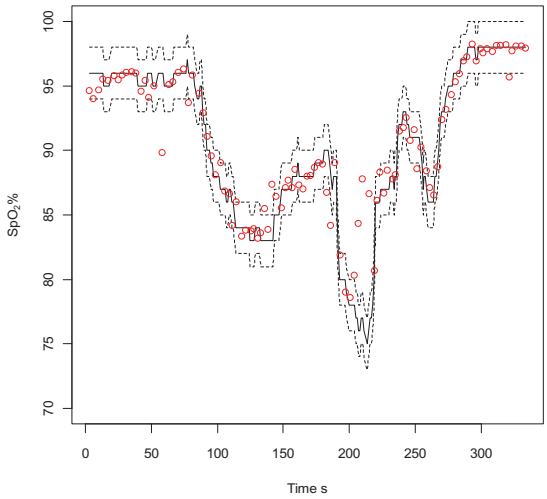

Fig. 3. Time series plot of estimated SpO2 level by two PPGs and SVMsR (red circles, from a subject aged 22). Solid line shows measured SpO2 level by a commercial meter and its linear interpolation. Dashed lines show range within ±2 % of SpO2 level by the meter and its linear interpolation.

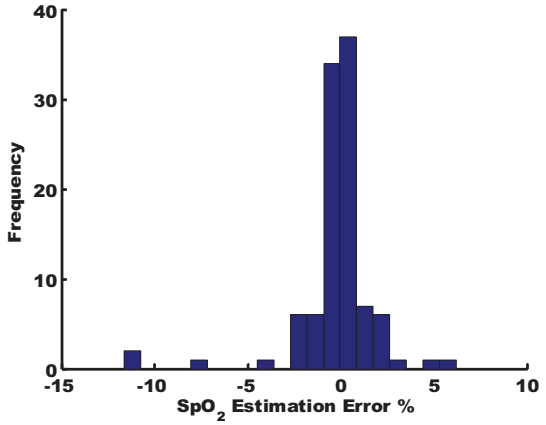

Fig. 4. A histogram of estimation error (from a subject aged 22). The 84% of errors is distributed within the range of the accuracy of the pulse oximeter (±2% of SpO_2 level).

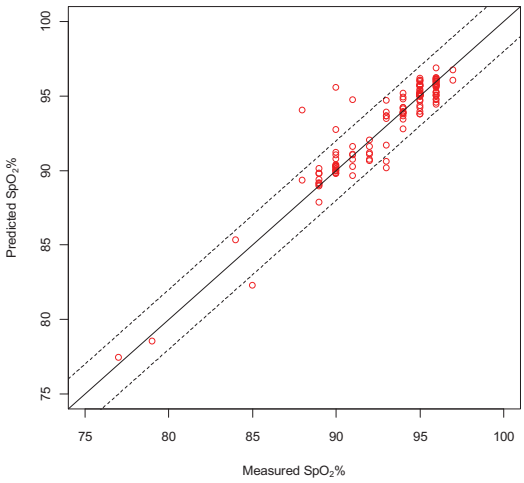

Fig. 5. Scatter plot of estimated SpO2 level by two PPGs and SVMsR versus a commercial pulse oximeter (from a subject aged 39). Dashed lines show range within ±2 % of SpO2 level by the meter

shows an example of scatter plot of estimated SpO_2 levels by SVMsR from validation data versus SpO_2 levels by the commercial meter from a subject (aged 22). Figure 3 shows time series of estimated data and actual data. From Figure 3, it is clearly found that almost of estimation plots by SVMsR tend to follow measured SpO2 level. Figure 4 is a histogram of estimation error in the case of Figure 2 and 3. Figure 4 also shows almost of errors are distributed in the range of the accuracy of the commercial pulse oximeter (±2% of SpO_2 level). Figure 5, 6 and 7 show another example that is from a subject aged 39.

It is seemed that there are several plots with big error by observation of scatter plot and time series plot (for example, plot at about 200-250 sec in the Figure 3, about 450-500 sec in Figure 6). However, histograms (Figure 7) inform that almost plots have small errors. Estimated errors by SVMsR should depend on the number of data in a data region. In the case of Figure 3, the number of data in the range of around 75-85 % SpO_2 should be considered as relatively small for

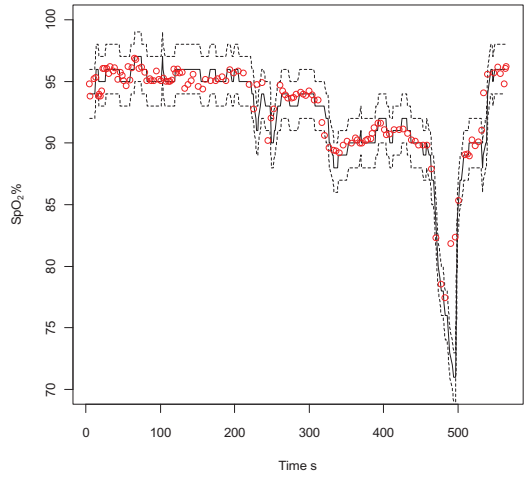

Fig. 6. Time series plot of estimated SpO2 level by two PPGs and SVMsR (red circles, from a subject aged 22). Solid line shows measured SpO2 level by a commercial meter and its linear interpolation. Dashed lines show range within ±2 % of SpO2 level by the meter and its linear interpolation.

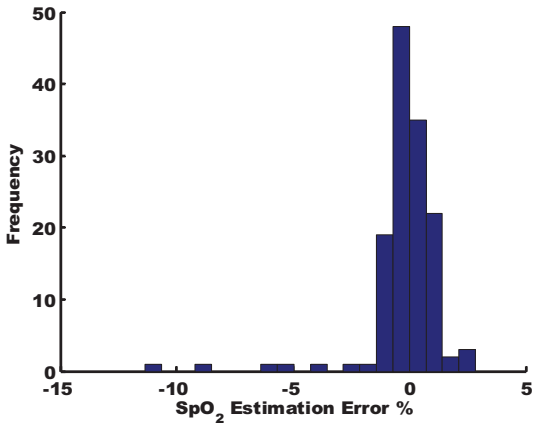

Fig. 7. A histogram of estimation error (from a subject aged 39). The 93% of errors is distributed within the range of the accuracy of the pulse oximeter (±2% of SpO_2 level).

getting good regression. Performance of SVMs should be depended by the support vectors (samples on the maximum margin). In this case, samples may be too small to find good support vectors in the range of 74-85%. If additional data within that region could be accumulated, errors could become smaller.

In this study, feature point (as the input information to the system) selection rule was planned *a priori* by the human, the authors. If we could skip the planning of feature point extraction procedure (if we can input two PPG waveforms directly to SVMsR system), this should be ideal and provide a novel powerful tool for calibrating a pulse oximeter.

The standard ratio method of pulse oximeter calibration purposefully ignores higher order nonlinear considerations of optical measurement such as the details of boundary conditions pertaining to source-detector geometry and effects of scattering. By using SVMsR and other nonlinear analyses,

those problems might be overcome.

IV. Conclusion

A new calibration method of pulse oximetry using a non-linear multivariate regression method, support vector machines regression (SVMsR) was proposed and attempted. Calibration using SVMsR can provide good relationship between SpO2 from a pulse oximeter (regressand) and beat-by-beat feature points extracted from red and infrared PPGs (regressor). This result suggests that SVMsR might be applicable for calibration of pulse oximetry. This approach should give a new perspective on *in vivo* oximetry.

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