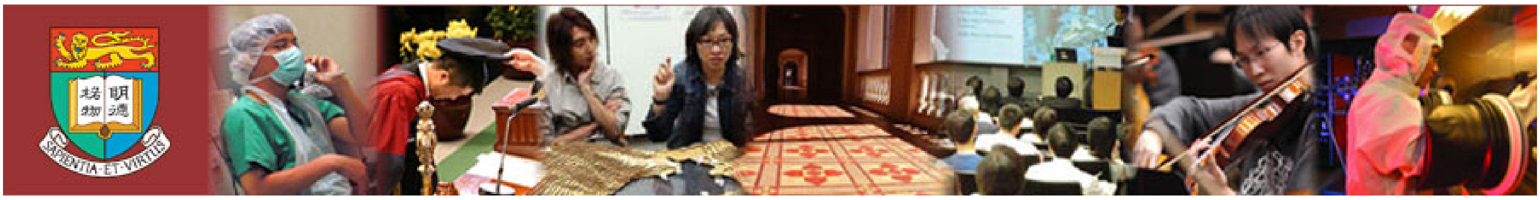

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A Dynamic Prediction Model for Intraoperative Somatosensory Evoked Potential Monitoring

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***Abstract*—This study proposed a support vector regression model applied in prediction of intraoperative somatosensory evoked potential changes associated with physiological and anesthetic changes. This model was developed from probability distribution and support vector machines. The predicted results showed that observed and predicted SEP has similar variation trend with different values, with acceptable errors. With this prediction model, changes of SEP in correlation with non-surgical factors were estimated. Not only the prediction accuracy of SEP has been improved, but also provides the reliability of the classification. It will be helpful to develop an intelligent monitor model based expert system that can make a reliable decision for the potential spinal injury.**

Keywords—support vector machine; probabilistic support vector regression; somatosensory evoked potential; prediction model

I. INTRODUCTION

Spinal surgery carries the risk of intraoperative trauma to the spinal cord[1]. It is crucial to ensure early detection of the damage to the spinal structures to prevent further pathogenic injury. Somatosensory evoked potentials (SEP) can reflect the integrity and function of sensory nerve pathways [2, 3], and SEP monitoring technique has been widely used to monitor the spinal cord function change during spinal surgery [4, 5]. The latency and peak-to-peak amplitude of the SEP waveform, which are associated with the neurological function of the spinal cord, were chosen to evaluate the performance of monitoring. Traditionally, a 10% increase in SEP latency or a 50% decrease in SEP amplitude according to the baseline recorded before the surgery were defined as the criteria of spinal cord deficit[6].

However, intraoperative SEP measurements are influenced by many surgical and non-surgical factors including blood pressure (BP), heart rate (HR), anesthesia dose (MAC) and body temperature (BT) [7,8], which all increase signal variability. The specialist whose knowledge is experience based and highly cost consuming is usually required on site. Moreover, the selection of the optimal baseline is very subjective and difficult for specialists to command. In addition, normal SEP and abnormal SEP are different based on the same environment when we assume the disturbances are the same. It also makes the traditional static SEP measurements is not reliable for the detection of the potential injury. In general, the medical process is under strong stochastic environment, and the effects of various factors on SEP have not been comprehensively and systematically studied [9-12], it makes hard to tell the variation in SEP caused by non-surgical factors. It is a challenge to develop an effective SEP measurements for SEP prediction with changes resulted from non-surgical factors, which is critical to the spinal operation, but is still unsolved in the clinic field up to now.

Support vector machine (SVM) is a new technology for data mining which solve machine learning problem by means of optimization methods. In recent years, SVM for intelligent prediction were studied [13]. Despite many benefits of SVMs, there is no mechanism for handling variations in the significance of data points, so that all the data points are treated identically in conventional SVMs. Probabilistic SVM, which can reflect the geometric significance in input data, combines the probability distribution and SVM, it improves the classification performance and provides more classification information [14]. Inspired by probabilistic distribution and regression model, this study will put forward a new combination of probability and SVM to construct a prediction model which will give the predictive values of intraoperative SEPs. And finally, evaluate its potential application in intraoperative monitoring.

II. MATERIALS AND METHODS

A. SEP Monitoring System with Dynamic SEPs

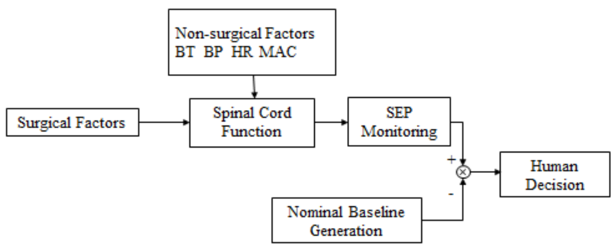

Fig. 1. SEP monitoring system with static SEPs.

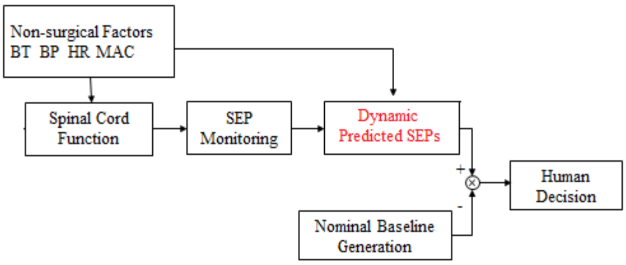

Fig. 2. SEP monitoring system with dynamic SEPs.

The sketch of traditional human assisted SEP monitoring under normal surgical situation presented in Fig.1. In this figure, the non-surgical factors that effecting SEP variations include BP (blood pressure), BT(body temperature), HR (heart rate), and MAC (anesthesia dose), the SEPs are static value recorded before surgery process, and finally the monitor specialist will make a judgment by comparing the observed SEP and baseline. Here, SEP monitoring is performed during surgery going on; it will not tell the SEP values in the coming time, which may be an abnormal SEP. In Fig.2, the prediction model will provide accurate predicted dynamic SEPs according to non-spinal factors based the former SEPs monitoring.

B. Prediction Model of Dynamic SEPs Changes

The dynamic prediction model for SEPs is achieved by probabilistic support vector regression. (PSVR) (Fig.3) [13, 14]. Given a training sample set $T=(X,y), X\in R^n, y\in R$, and assume that the training set is independent and identically distributed sample points selected based on an unknown probability distribution $P(x,y)$ on $X\times Y$, the objective is to find optimal hyperplanes in SVM by maximizing the minimum possibilistic distance from a hyperplane $(\mathbf{w},b)$ when y is in a certain neighborhood with a maximal probability. Thus, the goal of regression is to seek the following regression function:

$$f(x)=<w\cdot x>+b \tag{1}$$

Where $<w\cdot x>$ is the inner product of w and x. Taking into account the stability, b can be computed using the average of support vector.

According to the Duality Theory, the above optimization problem can be translated to its corresponding dual problem. By using Lagrange multipliers, the w_i can be obtained for each SVR by solving the following optimization problem:

$$\begin{aligned}&\underset{\mathbf{w},b,\xi_i,\xi_i^*}{\text{minimize}} \quad =\frac{1}{2}\|\mathbf{w}\|^2+C\sum_{i=1}^{N}(\xi_i+\xi_i^*)\\ &\text{subject to} \quad \begin{cases} y_i-<\mathbf{w},\mathbf{x}_i>+b\le\varepsilon+\xi_i\\ <\mathbf{w},\mathbf{x}_i>+b-y_i\le\varepsilon+\xi_i^*\\ \xi_i,\xi_i^*\ge 0, i=1,\dots,N\end{cases}\end{aligned} \tag{2}$$

Where $\mathbf{w}=[x_1,x_2,\dots,x_N]$ is an N-vector, $b\in R$. We choose the loss function as ε - insensitive loss function:

$$\begin{aligned}c(x,y,f(x))&=|y-f(x)|_\varepsilon\\ &=\max\{0,|y-f(x)|-\varepsilon\}\end{aligned} \tag{3}$$

Where ε is a positive number given in advance. By increasing or decreasing the value of ε, it can control the number of support vectors.

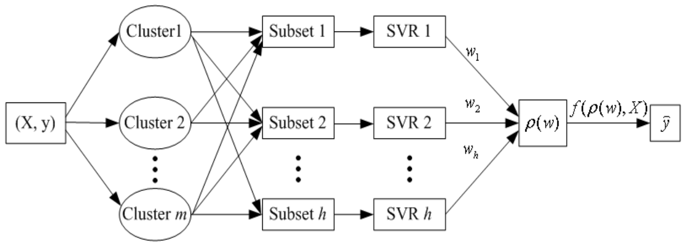

Fig. 3. A conceptual structure of PSVR.

In order to solve the two quadratic programming problems equation (2), introducing the Lagrange function [13].

$$\begin{aligned}L(\mathbf{w},b,a,a^*)=&\frac{1}{2}\|\mathbf{w}\|^2+C\sum_{i=1}^{N}(\xi_i+\xi_i^*)\\ &-\sum_{i=1}^{N}a_i(\xi_i+\varepsilon-y_i+<\mathbf{w}\cdot\varphi(\mathbf{x}_i)>+b)\\ &-\sum_{i=1}^{N}a_i^*(\xi_i^*+\varepsilon-y_i-<\mathbf{w}\cdot\varphi(\mathbf{x}_i)>-b)\\ &-\sum_{i=1}^{N}\eta_i^*(\xi+\xi_i^*)\end{aligned} \tag{4}$$

Where $a,a^*\ge 0, i=1,\dots,N$. C is the trade-off parameter that controlling the horizontal between the complexity of the model and the variance, and reference [15] illustrated how to choose the value of C. Considering the complexity and error of the model, C should generally be small but cannot be too small , usually ranged from 1 to 1000. ε is used to control the regression approximation error so as to control the number of support vectors and generalization ability, the greater its value, the less the number of support vectors, and accuracy will be lower. In order to balance between fitting accuracy and generalization ability, ε generally ranged from 0.000 1 to 0.01. ξ_i,ξ_i^* are the slack variables related to the penalty for misclassification.

In order to solve the equation (4), the partial derivative of the Lagrange function for the parameters is equal to zero[13]. In addition, the Karush-Kuhn-Tucker (KKT) conditions play a central role in both the theory and practice of constrained optimization. For the primal problem above by KKT conditions, can be chosen as a_i or a_i^* in $[0,C)$ [13]:

If a_i is chosen then

$$b = y_j - \sum_{i=1}^{N}(a_i^* - a_i)K(x_i, x_j) + \varepsilon \qquad a_i \in [0, C) \tag{5}$$

If a_i^* is chosen then

$$b = y_j - \sum_{i=1}^{N}(a_i^* - a_i)K(x_i, x_j) + \varepsilon \qquad a_i^* \in [0, C) \tag{6}$$

As an immediate application, note that, while w is explicitly determined by the training procedure, the threshold b is not, although it is implicitly determined. However b is easily ound by using the KKT "complementarity" condition by choosing any i for which $a_i = 0$ and computing b (note that it is numerically safer to take the mean value of b resulting from all such equations).

Then, the Lagrange dual problem of the original optimization problem is below:

$$\begin{aligned} \underset{a_i, a_i^*}{\text{minimize}} \quad &= \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(a_i - a_i^*)(a_j - a_j^*)K(x_i, x_j) \\ &\sum_{i}^{N} y_i(a_i - a_i^*) + \varepsilon \sum_{i}^{N} y_i(a_j - a_j^*) \\ \text{subject to} \quad &\sum_{i}^{N} y_i(a_j - a_j^*) = 0, 0 \le a_j, a_j^* \le C \\ &i = 1, \ldots, N \end{aligned} \tag{7}$$

Finally, the Parzen-window method is used to estimate the probability density function (PDF) $\rho(w_i)$ of w [16]. Thus, we can kernelize the PSVR, and so the decision function is as follows:

$$f(X) = \sum_{h}^{i=1} \rho(w_i) g(w_i, X) \tag{8}$$

We assume the disturbance of predicted SEP is the same as the normal SEP, Fig.3 presents different SEPs under disturbance X. Here, the predicted SEP is ajusted with the non-surgical factors.

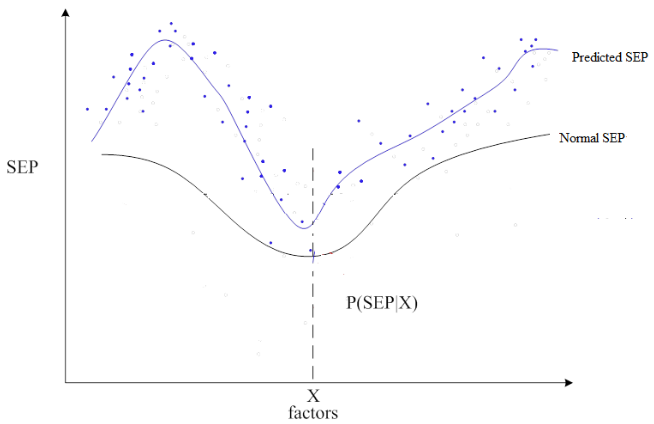

Fig. 4. Different SEPs under same disturbance X.

C. Assessment of performance

In order to evaluate the performance of the predict model, we assessed the mean squared error (MSE) and mean absolute percentage error (MAPE) based on prediction error, which is defined by the following equation:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{9}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100\% \tag{10}$$

where $\hat{y}_i$ and y_i are the predicted and observed values respectively.

D. Data recording

This study employed a dataset from scoliosis patients undergoing surgical correction to evaluate efficiencies of dynamic baseline based intelligent decision system for SEP monitoring. Intraoperative SEPs were monitored using the electrophysiological monitoring system Nicolet Viking IV (Nicolet Biomedical Inc., Madison, WI, USA), a constant current of 10 to 30mA was applied with a frequency between 5.1 and 5.7 Hz and a duration of 0.3 ms. The SEP signals were recorded 2 cm posterior to Cz (according to the international 10-20 electrode placement system) and over Cv (on the cervical spine over the C2 spinous process), and the reference electrode was placed at Fz. Cortical SEP signals were recorded from Cz-Fz (Cz-SEP) and subcortical signals from Cv-Fz (Cv-SEP). The signal was amplified 100,000 times, band-pass filtered at 20-3000Hz [17].

SEPs were monitored continuously during surgery, SEP signals recorded after the spine was exposed, but before instrumentation loading and deformity correction, were used as the static baseline. The data conclude non-surgical factors that effecting SEP variations include BP (blood pressure), BT(body temperature), HR (heart rate), and MAC (anesthesia dose), and the recorded SEPs. The 23 features which are the records of heart rate, blood pressure, body temperature, anesthetic does and types, SEP, etc., were monitored at the same time.

III. RESULTS AND DISCUSSION

We use the proposed model predict the dynamic SEPs. In this study, we select the Gauss Radial basis Function as the kernel function, $C = 20, \varepsilon = 0.1$. The data were collected from 9 surgeries. Due to various technical problems, the data is incomplete. After eliminating the samples without SEP record, 158 samples can be used for training (more than 125 samples) and testing the model (the rest samples). Each sample has 23 features which are the records of heart rate, blood pressure, body temperature, anesthetic does and types, SEP, etc.

After samples training, test samples were used to test the learning efficiency of the model. The errors between predicted results and observed values were analyzed. The amplitude of SEP signal (CSEPLA1) is the output.

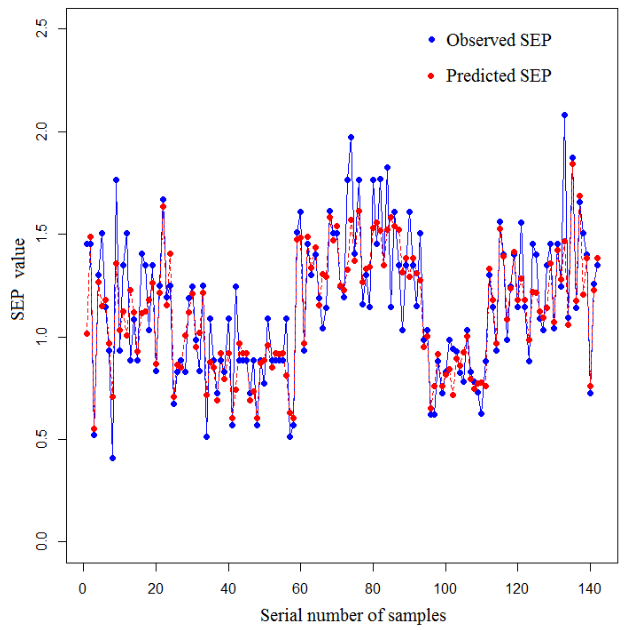

Fig. 5. Taining results of SEP baseline on one patient.

Using the data from one patient as an example, Fig.5 and Fig.6 are the training and testing results of SEP baseline respectively, in which the blue ones are the observed SEP and the red ones are the predicted SEP dynamic baseline by PSVR. It can be seen that the observed and predicted SEP has similar variation trends with different values. The errors between the predicted and observed SEPs of nine surgeries are displayed in TABLE I, the MSE of the training results is no more than 0.05 with a mean value about 0.04, and the testing one is no more than 0.25 with a mean value about 0.15. In addition, the MAPE of training results is no more than 40% with a mean value about 8.07, and the testing one is no more than 40% with a mean value about 20.96.

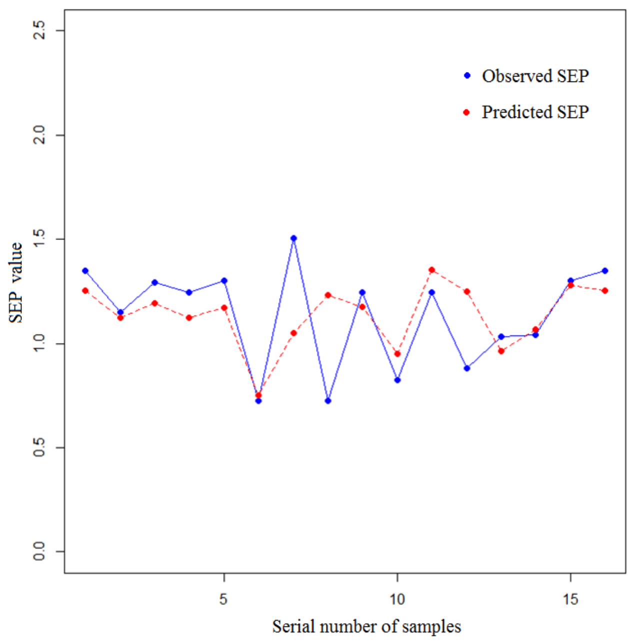

Fig. 6. Testing results of SEP dynamic baseline on one patient.

TABLE I. THE ERRORS BETWEEN THE PREDICTED AND OBSERVED SEP

Surgery Number	**MSE**		**MAPE (%)**	
	Training	***Testing***	***Training***	***Testing***
1	0.03545269	0.17057931	13.029900	29.06152
2	0.04189505	0.06002790	11.073410	16.73524
3	0.04663822	0.19722274	4.531748	39.53710
4	0.04129597	0.04744948	37.69891	12.32971
5	0.03112592	0.22814107	18.218174	20.08646
6	0.04411074	0.05100731	9.964643	14.38063
7	0.04506636	0.21955787	3.619238	21.28673
8	0.04307397	0.09986727	3.275755	15.09381
9	0.03833042	0.23523224	5.145017	20.09362
Mean	0.04077659	0.14545391	8.069753	20.956090

In fact, many non-surgery-factors may influence the evoked potentials, including temperature, blood pressure, anesthesia under a given surgery-factors, the SEP has been found to change during different stages of surgery, even before the spinal cord is put at risk, it reduces the reliability of monitoring results. In the current study, we were concerned about these non-surgical to predict dynamic SEPs within the whole operation process.

Here, we induced probability distribution to support vector machine model for regression analysis. Fig.5 and Fig.6 showed that SEP values were better fitted by the prediction model based PSVR, although some values are not entirely consistent with the observed values, the predicted curve clearly indicates the main trend, and the predicted results is ideal with acceptable errors. In addition, this model was concerned about the non-surgical factors, and the surgical factors which have been reported increased SEP changes were not considered, this may be one reason resulting in some values not entirely consistent with the observed values.

Moreover, as an effective support vector regression model, it can not only achieve a good fit of the existing data, but has good generalization ability. After the establishment of an effective support vector regression model to predict the unknown point, it can not just be satisfied with the predicted value, and it is important to be able to predict the point at a given confidence level confidence interval, which will Improve the generalization ability of the model, this will be the further study.

IV. CONCLUSION

This study constructed a probabilistic modeling according to the actual situation, and developed a probabilistic learning method that could predict dynamic SEP changes from limited samples under uncertainties which combining the advantages of SVM and probability modeling to improve the classification performance of support vector machine. Not only the prediction accuracy of monitoring SEPs has been improved, also provides the reliability of the classification. It will be helpful to develop an intelligent monitor model based expert system that can make a reliable decision for the potential spinal injury.

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