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Electrical evoked potentials prediction model in visual prostheses based on support vector regression with multiple weights

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ABSTRACT

Electrical evoked potentials (EEPs) elicited by electrical stimuli to the optical nerve are an important study object in optical nerve visual prostheses to investigate the temporal property of responses of the visual cortex. Concentrating on reducing the cost of the visual prostheses research, this paper proposes an intelligent EEPs prediction model based on the support vector regression with multiple weights (SVR–MW) method in substitution of numerous biological experiments. In SVR–MW, to improve the predictive performance of traditional SVR, more temporal weights and similarity-based weights are given to the recent training data extracted from similar experimental cases for new electrical stimulus parameters than the distant data from less similar cases during regression estimation. For temporal weight (TW), we propose two TW functions *i.e.*, linear temporal weight (LTW) function and exponential temporal weight (ETW) function to calculate the temporal weight of training sample at different time nodes. For similarity-based weight (SW), the similarity measurement (SM) is the key issue, and we adopt the multi-algorithm-oriented hybrid SM methods *i.e.*, textual SM, numerical SM, interval SM and fuzzy SM to solve the SW computation for training data derived from different experimental cases. The proposed method was empirically tested with data collected from actual EEPs eliciting experiments. Empirical comparison shows that SVR–MW is feasible and validated for EEPs prediction in visual prostheses research.

1. Introduction

Visual prostheses research to restore vision offers a promising approach for the blind and has become a rapidly growing scientific field in neuro-rehabilitation engineering [1]. In recent years, the optic nerve visual prostheses based on optic nerve stimulation with a penetrating electrode array have been focused upon by many researchers [2–4]. One of the key issues in optic nerve visual prosthesis is the research of responses of the visual cortex after the electrical stimulation to the optic nerve. To investigate the temporal property of responses, the electrical evoked cortical potentials (EEPs) are elicited over the rabbit skull when the optic nerve was stimulated using different electrical stimulation parameters, *e.g.*, intensity, frequency, and charge density, et al. However, subjected to experiment cost and material restriction, the experimental EEPs recorded data with different stimulation parameters are too sparse and inadequate to be analyzed in optic nerve visual prosthesis research.

Concentrating on reducing the cost of the visual prostheses research, this paper tries to explore an innovative intelligent model with machine learning technique to predict the new EEPs results in view of new electrical stimulation based on existing EEPs experimental cases rather than doing numerous biological experiments, in which target stimulation parameters are considered as the inputs, and the corresponding output result is the special EEP value at the given time node. But, the characteristics of EEPs training data in experimental cases are time series, non-linear, inherently noisy, non-stationary, and deterministically chaotic [5]. This means that not only is a single data series non-stationary in the sense of the mean and variance of the series, but the relationship of the data series to other related data series may also be changing [6]. Thus, modeling such non-stationary data is expected to be a challenging task.

Time series prediction (TSP) is an important issue that has served as the impetus for many academic studies, range from stock indexes forecasting [7–11], price analysis [12,13], due-date assignment [14,15] to sales forecasting [16,17]. Recently, support vector machines (SVMs), proposed by Vapnik [18,19], have been successfully employed in solving classification and regression problems [6,20–24]. TSP can attribute to regression problems, so SVMs such as support vector regression (SVR), least-squares SVM (LS–SVM)

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and robust support vector regression networks (RSVRN) are applied to deal with TSP issue [10,25–29]. Classic SVM approaches for regression problems use some arbitrarily chosen loss functions which equally penalize errors on all training samples, therefore all training examples are considered equally significant. However, in TSP, the relationship between input variables and output variable gradually changes over time, and recent past data could usually provide more important information than the distant past data [30,31]. On the other hand, the regression functions achieved by SVMs are less robust, namely, sensitive to noises [32]. Therefore, it is advantageous to give high weights on the information provided by "useful" sample. For EEPs prediction, the EEPs experimental case with higher similarity for new stimulation input could be more significant than dissimilar cases, in terms of the case-based prediction principle. Enlightened by these facts, we intend to research a EEPs time series forecasting model based on SVR with multiple weights (SVR–MW) to predict the EEP values responses to new stimulation inputs, in which more temporal weights and similarity-based weights are given to the recent training data from similar experimental cases than the distant data from less similar cases.

The breakdown of this paper is organized as follows: Section 2 provides a brief description of the literature surveys for the related areas. Section 3 discusses the SVM–MW for regression estimation in detail. Section 4 gives an example to illustrate the implementation of the proposed method. Section 5 focuses on the performance comparisons with other predictive methods. In the final section, the conclusions and future work are presented.

2. Literature review

2.1. Time series prediction (TSP) model research

In the early development of prediction approaches, most commonly used methods were statistical methods such as trend analysis and extrapolation. It is easy to apply this kind of methods due to simple calculation but with lower predictive accuracy. After that alternative approaches with soft computing were developed, often called time series prediction (TSP) [33] or time series analysis (TSA) [34]. In TSP, the historical observation values are collected and analyzed to predict the possible values of future time point. Due to its high predictive accuracy, TSP has become a popular research subject. So far TSP model can be separated into two categories, *i.e.*, linear models and non-linear models [35]. The linear models, such as moving average model [34] and auto-regressive integrated moving average model (ARIMA) [36], have been extensively investigated and are quite advanced, but they only work well when the data dependency is linear.

In the 1990s, the non-linear models used for time series forecasting were chiefly the neural network (NN) [37–41], and Chang et al. [34,42] pointed out that the multi-layer perceptron (MLP) model is the most commonly used NN model for TSP. Although NNs works well, they have some inherent drawbacks, such as the problem of multiple local minima, the choice of number of hidden units and the danger of overfitting [10,22,35,43]. Different from the NN, SVM implements the structural risk minimization principle and tries to minimize an upper bound of generalization error instead of minimizing the misclassification error or deviation from correct solution of the training data. Under this principle, SVM could achieve an optimum network structure, and eventually resulting in better generalization performance than other NNs [29,44,45]. In addition, the solution of SVM may be a global optimum while other NN models may tend to fall into a local optimal solution. Thus, over-fitting is unlikely to occur with SVM [10]. Originally, SVM was developed for the pattern recognition problems. Lately, with the introduction of Vapnik's ε-insensitive loss function, SVM has been extended to solve the nonlinear regression estimation problems, called as SVR, and SVR model exhibits the excellent performances in TSP field [23,31].

2.2. Weight-setting strategies in SVM

In the conventional SVM methods for regression problem (SVR, LS–SVM), the insensitive error of every training sample is equally penalized, which means every sample affects the generalization ability equally. In TSP, better results can be achieved when some examples are considered more significant then others, correspondingly, the insensitive error of the sample which could provide more important information should be penalized more heavily [31]. Right now, researchers have developed many weight-setting algorithms. Suykens et al. [46] proposed a weighted LS–SVM (WLS–SVM), which trained input variables using unweighted LS–SVM firstly to get some useful statistical information and then calculated the weights for each sample. However, the weights in WLS–SVM, which largely depend on the original regression errors from LS–SVM, might be unreliable for correcting the regression results, especially when it is seriously bent towards the samples having large deviations. In order to overcome the drawbacks of the WLS–SVM, Wen et al. [32] proposed a heuristic weight-setting algorithm to exploit the prior knowledge of the noisy characteristics of the samples via computing the abnormal sample's distance from other samples, so the original result of LS–SVM is not need. But this algorithm focused on the method to find the outliers in noisy data and the weight was determined by a simple linear interpolation.

For weight-setting research in SVR model, refer to Wen's study, Wang et al. [47] also adopted a linear interpolation to calculate the weight coefficients of samples to remove the redundant samples. Chuang et al. [23], Tay and Cao [30], and Mao et al. [31] proposed the non-linear tangent function, exponential function and arc tangent function, respectively to represent every sample's importance, Zhang and Guo [48] presented a recursive weight-setting strategy based on exponential weighting function, nevertheless, all these non-linear functions' parameter values mainly rely on the prior knowledge. Moreover, Lin and Wang [49] held that the importance of first sample in data with time property is lowest while that of most recent sample is highest, and assigned a fuzzy membership to each sample.

In general, most of these mentioned algorithms are concentrated on the weight-setting procedure for single weight but rare are about considering the multiple weights from different aspects. Furthermore, in the situation of lacking enough prior knowledge, the best regression model cannot be obtained if the fixed weight function is used for all applications directly [31]. In this paper, the SVR with multiple weights (SVR–MW) for EEPs forecasting are concerned, in which two weight-setting approaches are proposed, then a global weight of each training sample combined with temporal weight and similarity-based weight is calculated and put on the error penalty parameter. Because the proposed weight calculation method explores the temporality and closeness of training data for different time nodes and inputs, the weights in SVR–MW can be optimized automatically and conveniently.

3. Specification on SVR–MW for EEPs prediction

3.1. Framework of SVR–MW

The frame of SVR–MW is displayed in Fig. 1. Temporal weight (TW) and similarity-based weight (SW) are computed, respectively