腦波信號關聯式檢測之空間化頻譜分析軟體設計

Design of Topographic Spectral Analysis Software for Coherence Examination of EEG Signals

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一、中文摘要（關鍵詞：腦波棘波偵測、類神經網路、基底函數、關連矩陣）

本研究之目的為發展一多通道腦波圖之棘波辨識系統，利用基底函數訓練之類神經網路，配合波形簡化，以達成自動之即時線上棘波辨識。以操作者特性曲線決定最佳閥值、並經過神經內科醫師驗證結果，在十七位病患內的一百一十筆十六通道棘波共正確判斷出九十一筆，敏感度為百分之八十三。

英文摘要（Keywords : EEG spike detection, artificial neural network, radial basis function, incidence matrix）

An automatic spike detection algorithm for classification of multi-channel electroencephalographic (EEG) signals based on artificial neural network is presented. Radial basis function (RBF) neural network was chosen for single channel recognition, with model optimization using receiver operating characteristics analysis. Waveform simplification was employed for high noise immunity. Feature extraction with as few as three parameters was used as preparation for the inputs to the neural network. Identification of multi-channel geometric correlation was performed to further lower the false-positive rate by using an incidence matrix. Threshold value for spike classification was chosen for simultaneous maximization of detection sensitivity and selectivity. Evaluation with visual analysis in this preliminary study showed a 83% sensitivity using 16-channel continuous EEG records of four patients, while a high false positive rate was found, which was believed to arise from the extensive and exhaustive visual analysis process.

二、計畫緣由與目的

The EEG spikes are thought of as a cardinal medical sign of epilepsy [1], a detailed diagnosis of which usually demands a long-term continuous EEG monitoring. However, a long-term EEG recording generates a large amount of relatively normal but clinically useless data [2]. Consequently, there has been an increasing interest in the development of computer-based automatic spike detection algorithms which would be helpful in facilitating the objective evaluation of diagnostic information.

Spike detection algorithms based on computer automation have achieved various levels of success [3-6], but there leaves ample room for improvement in terms of sensitivity, specificity, and speed. Rule-based methods [3-4] for recognizing special features of spike waveforms have achieved a high true-positive rate but as well as a high false positive rate [5]. One of the major problems leading to false spike recognition in rule-based methods lies in the fact that there is no clear definition of a spike [2]. As a result, the artificial neural network (ANN) technique for spike detection, which simulates the human reasoning process, has demonstrated strong potential since it was presented [5-6].

In this work, an automatic multi-channel spike detection algorithm based on a modified radial basis function (RBF) ANN architecture is presented. Feature extraction with as few as three parameters was implemented for simplification in training of the neural network as well as for performance efficiency. Individual classification results obtained from separate channels were sent to an incidence matrix to include geometric consideration of location of the electrical discharging sources, which effectively avoided the disadvantages of possible low specificity in single-channel recognition.

三、研究方法

Figure 1 describes the block diagram of the entire system for multi-channel spike detection. Sixteen-channel unipolar EEG data were used with electrodes positioned according to the international 10/20 system. Note that the EEG signal from each individual channel was analyzed for presence of spikes through separate classification process. Waveform simplification [7] was first applied to the original EEG signals for noise immunity. Background activity was taken into account to highlight possible spike waveform [7]. Three parameters (peak angle, amplitude and velocity) [8] were consequently extracted from the cleaned waveform and were fed to the input of the neural network for single-channel spike detection. The classification results from individual channels were then sent to an incidence matrix for identification of multi-channel geometric correlation. The results of classification were shown on the screen graphically with spikes marked out using different colors than the nonepileptic background.

The architecture of the RBF neural network for single-channel spike detection is shown in Figure 2. The calculation of peak angle, amplitude, and velocity (i.e., slope) from the simplified EEG waveform was performed according to the definitions in Ref.[8] with voltage gain and chart speed properly adjusted. These parameters were then used as the inputs to the RBF neural network. The resulting structure thus had only five cells in the hidden layer, permitting very high speed operation and relatively little training needed for optimization of the network model. Ten EEG spikes and ten nonepileptic EEG waveforms were used as the training data of the RBF neural network. In this preliminary study, three different models were evaluated, with the optimal one chosen by using receiver operating characteristics (ROC) analysis.

Detection results from a single-channel RBF network contained a number ranging mostly from -1.0 to 1.0 for each data segment 330 msec in length. A threshold classifier was then applied for decision of the classification process. The optimal threshold value was chosen to simultaneously maximize the detection sensitivity and selectivity [9]. For each time segment, the waveform with a number from the RBF network output larger than the threshold value was regarded as a spike. A "1" was hence assigned for such a waveform, otherwise a "0" was assigned. The single-channel classification is thus accomplished.

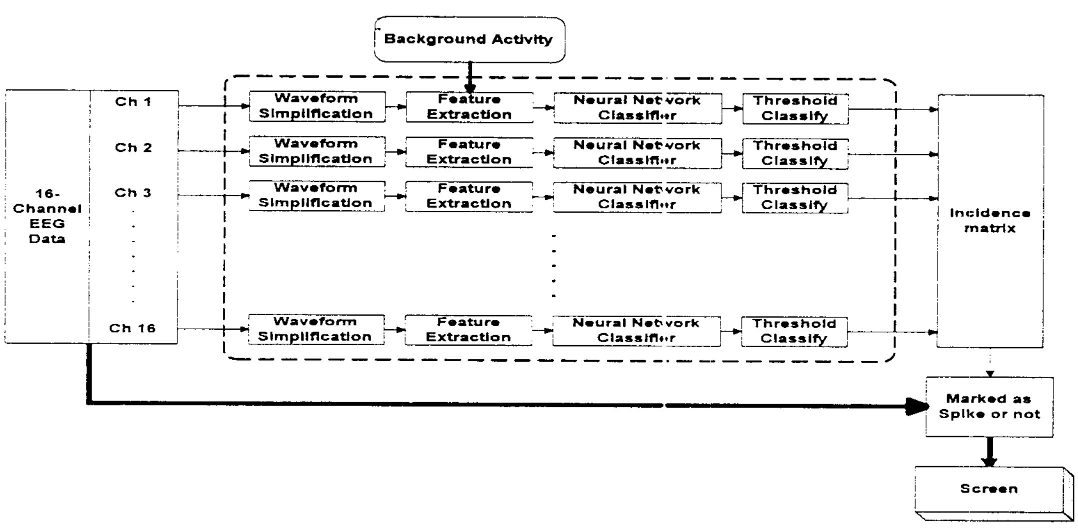

Fig. 1. Block diagram of the spike detection system.

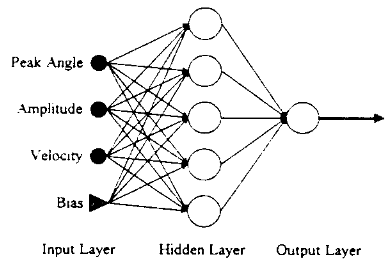

Fig. 2. The architecture of the RBF neural network with three parameters as the input.

Finally, the concept of the incidence matrix was employed to include identification of multi-channel geometric correlation. Assuming the epileptic spikes are from a discharging source at a specific location in the cortex, the appearance of spikes in unipolar recordings should possess geometrical correlation in that spikes tend to be grouped in neighboring channels. The identification of such a correlation was achieved by feeding the single-channel classification results as a 1x16 row vector to a 16x12 incidence matrix given below:

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix}$$

where each column of the matrix represents each of the twelve geometrical adjacency as shown in Figure 3. It is to be noted that each adjacency contains its neighboring channels in which spikes are expected if a discharging source is located within that certain region. Therefore, a multiplication of the 1x16 row vector obtained from the 16 RBF networks by the incidence matrix yielded a 1x12 row vector, in which each element is a number representing the likelihood of the discharging location for the spikes. If any one of the 12 elements yielded a number equal to the number of channels belonging to the corresponding column, spikes were found in all channels geometrically close to the source location. A real spike was thus declared to be found. Through such an operation, false detection of eye-blinks as single-channel spikes would be eliminated, thereby reducing false-positive identification rate.

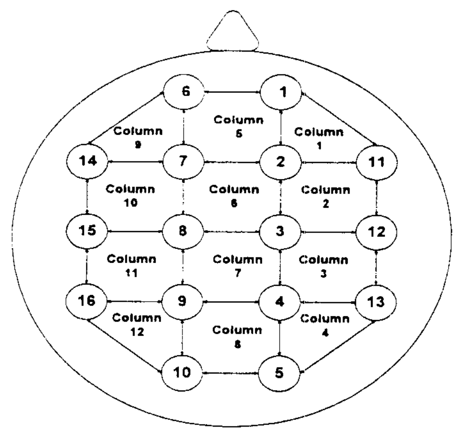

Fig. 3. The twelve adjacency used for identification of geometrical correlation. Each column in the incidence matrix represents the channels in which spikes are expected if a discharging source is located within that region.

四、結論與成果

On choice of neural network models

The choice of neural network parameters were evaluated by comparing the ROC curves of three models of the RBF network. The models differed in the fact that the spikes used for training the neural network were different. In our first model, spikes with typical (within mean +/- one standard deviation) peak angle, amplitude, and velocity values were selected as the training data. This has the advantage of minimizing the number of false detection, while with drawback of missing spikes with less representative feature parameters. Figure 4 shows the ROC curves plotted as detection sensitivity versus (1-specificity) varied as a function of threshold values. Model 1 was shown to exhibit high specificity but relatively low sensitivity, as expected. For comparison purpose, a second model using training data with feature parameters falling outside (mean +/- std) was constructed. The ROC curve of model 2 as shown in Figure 4 demonstrated the opposite trend with low specificity, as the RBF network tended to give false identification. Model 3, obtained using training data consisting of wide spread of but centered at mean values of feature parameters, was therefore chosen. The ROC curve in Figure 4 clearly showed that model 3 had the best performance. It was thus chosen as the model for single-channel spike detection.

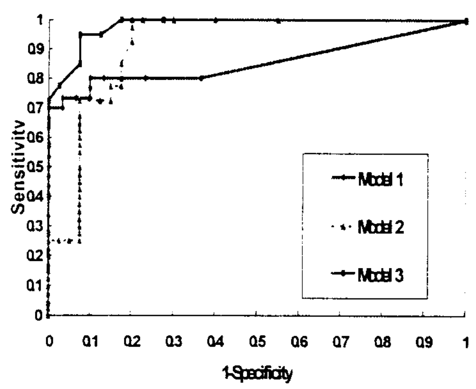

Fig. 4. ROC curves for the choice of optimal RBF neural network model.

On choice of the threshold value

Figure 5 shows the crossover curve for model 3 of the RBF network. A threshold of 0.5 was found to be the crossover point which yields high sensitivity and specificity simultaneously [9]. In our study, a threshold of 0.4 was chosen because of higher sensitivity with no loss in specificity compared with the threshold of 0.5.

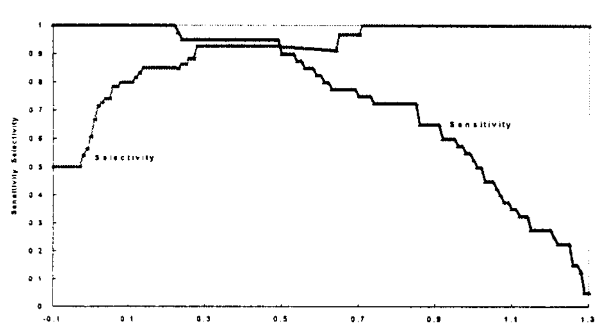

Fig. 5. Crossover curve for choosing the threshold value using model 3 of Figure 4.

On the performance of the proposed algorithm

Sixteen-channel continuous EEG records from four patients were used in the preliminary study for evaluation of the spike detection algorithm. Each record was about two minutes in length. The algorithm analyzed the EEG signals in 330 msec time segments, following which an increment of 150 msec was added and the new time segment analyzed. On a PC system the computation time for spike detection was found to be significantly lower than that required for online display of the EEG signals. With validation by visual analysis by one experienced neural physician, 91 out of 110 spikes were detected, yielding a sensitivity of 83%.

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