Application of Fuzzy ARTMAP Neural Networks for Epileptic spike detection Using Wavelet Feature Extraction

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Abstract: This paper aims to introduce two different classifier systems based on fuzzy ARTMAP neural network for the automatic detection of epileptic spikes in 19-channel human electroencephalogram these algorithm (EEG) are fast and delivers satisfactory results. EEG signals are decomposed into 4 sub-bands by means of Discrete Wavelet Transform (DWT). The inputs of the networks consist of two different features, which are extracted from the sub-bands 3 and 4. The performances of the classifiers introduced in this paper, are compared with each other's and other similar systems, according to the sensitivity, specificity and selectivity values.

Keywords: *ANN, EEG, Fuzzy ARTMAP, Wavelet.*

بکارگیری شبکه‌های عصبی Fuzzy ARTMAP برای تشخیص صعود ناگهانی سیگنال‌های EEG با استفاده از استخراج ویژگی توسط موجک

فاطمه صفری۱؛ علی فرخی۲؛ نعمت طالبی۳

چکیده: این مقاله در پی معرفی دو سیستم کلاس‌بندی مبتنی بر شبکه‌های عصبی Fuzzy Artmap برای تشخیص اتوماتیک حدودهای ناگهانی در امواج الکترد آلفا نوگرافی (EEG) ۱۹ کانال اشخاص می‌باشد. این الگوریتم سریع و نتایج قابل قبولی عرضه می‌نمایند. سیگنال‌های EEG به چهار زیر باند با استفاده از تبدیل ویولت گسسته تقسیم بندی شده‌اند. ورودی‌های شبکه شامل دو ویژگی متفاوت هستند که از زیرباندهای ۳ و ۴ استخراج می‌شوند. عملکرد این کلاس‌بندی کننده‌ها در این مقاله معرفی شده و باهم و دیگر سیستم‌ها مشابه مطابق با مقادیر حساسیت، ویژگی و انتخاب پذیری مقایسه گشته‌اند.

کلمات کلیدی: Fuzzy ARTMAP، موجک، شبکه عصبی مصنوعی، امواج الکتروآنسفالوگرافی.

1. Introduction

Epilepsy, the prevalence of which is approximately 1% of the world's population, may result in brief electrical of disturbances in brain that bring about changes in sensation, awareness and behavior. Since epilepsy is a condition related to the electrical activity of the brain, electroencephalogram (EEG) can be used for its detection. Between the seizures, epileptic transients are observed as spikes and sharp waves in the recorded EEGs, hence the importance of the detection of interictal spikes in diagnosing epilepsy. But detection and classification of spikes by means of the recorded EEGs is a difficult, time consuming, and error-prone process [1], [2]. There are many procedures for detection and classification of spikes and other transient signals in EEG, most of which are based on artificial neural network (ANN) structures [3]–[7].

In this paper efforts have been made to detect epileptic spikes in EEG, using two different classifier systems based on Fuzzy ARTMAP neural networks. EEG signals are decomposed into four sub-bands using Discrete Wavelet Transform (DWT). The inputs of the networks consist of two different features, which are extracted from the sub-bands 3 and 4. The results show that Fuzzy ARTMAP neural networks have satisfactory performances in detection of epileptic spikes. The next section contains dataset, data preprocessing, feature extraction and the structure of fuzzy ARTMAP neural network. The results of classifier systems introduced in this paper and the comparison of these two systems with each other and other similar systems are presented in section 3. Finally the conclusion of the paper is given in section 4.

2. Materials and methods

2.1. Data set

In this paper the EEG data discussed in [3] which is publicly available are used [8]. This data is recorded using the 10-20 international electrode placement system by means of 19 channels with the sampling frequency of 240 hertz.

2.2. Data Preprocessing

First, the existing events in EEG signal are divided into two groups:

1) Epileptic spikes (including single spikes, and spike and waves)

2) Any other mental process (non-epileptic spikes) including EEG background activities and muscular artifacts [1], [3].

Then, EEG signal is divided up using Hamming time windows with the length of 50 samples and 50% overlap. EEG signal division was done in a way that there was an epileptic spike in each section. After finishing the processes mentioned above, 198 spike waves were extracted from the EEG data.

2.3. Discrete wavelet transform (DWT)

In order to extract the individual EEG sub-bands, a wavelet filter is employed. Wavelet transform has the advantages of time-frequency localization, multi-rate filtering, and scale-space analysis [9]. Wavelet transform uses a variable window size over the length of the signal, which allows the wavelet to be stretched or compressed depending on the frequency of the signal. This results in excellent feature extraction from non-stationary signals such as EEG signals. In this research, the discrete wavelet transform (DWT) , based on dyadic (powers of 2) scales and positions, is used to make the algorithm computationally very efficient without compromising accuracy. The EEG signal is decomposed into progressively finer details by means of multi-resolution analysis using complementary low-pass and high-pass filters. After a first level decomposition, two sequences representing the high (details) and low (approximations) resolution components of the signal are obtained. The low-resolution components are further decomposed into low and high resolution components after a second level decomposition and so on. Four level wavelet decompositions are shown in Fig. 1. The multi-resolution analysis, using four levels of decomposition, yields five separate EEG sub-bands.

2.4. Feature Extraction

In the process of this paper each segment of the EEG data is decomposed into 4 sub-bands, using the Daubechies order 3 (Db3) wavelet transform. Then two methods were used for fea-

ture extraction.

In the first method, for sub-bands 3 and 4 of each segment of EEG signal, the energy of frequency spectrums of sub-bands 3 and 4 (cd3 and cd4), the energy of the 4th, 5th and 6th frequency bank of sub-band 4 (cd4) and the energy of the 5th frequency bank of sub-band 3 (cd3) are all calculated as follows:

By using Fourier transform, the frequency spectrum of sub-bands 3 and 4 is calculated and the absolute value of the actual part is computed. Then, the energy of frequency spectrum for each sub-band is calculated by using (1):

$$E_j = \sum_{n=0}^{N} x_j^2(n) \qquad (1)$$

where x_j (n) is the nth sample in the jth segment, the value of N equals to the total number of samples in the jth segment. For each segment, the frequency spectrum of sub-bands 3 and 4 is then divided into 6 identical sections. Each of these sections is considered as a frequency bank. In the next step, the energy of the 4th frequency bank of cd4, the energy of the 5th frequency bank of cd3 and cd4, and the energy of the 6th frequency bank of cd4 are all calculated.

In the second method, for each segment of EEG signal, the energy, the mean of absolute value, and the standard deviation of the wavelet coefficient of sub-bands 3 ad 4 are calculated. Features are extracted for all epileptic and non-epileptic spikes by means of the mentioned methods.

2.5. Fuzzy ARTMAP neural networks

Fuzzy ARTMAP network is a supervised training neural network which is able to classify analog and binary patterns. It has an evolutionary
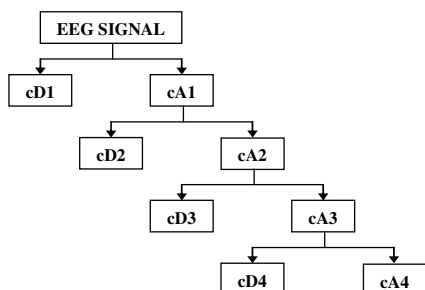
linked to each other by a series of connections architecture and consists of two fuzzy ART network: ART_a and ART_b. These two networks are which are located between the F_2 layers of the two networks and are called Map Field (F^{ab}). The input vectors to ART_a and ART_b are exerted utilizing complementary coding of A= (a, a^c) and B= (b, b^c) [10]–[12].

Fuzzy ARTMAP employs a match-based learning process in which the learning is based on the similarity between the input pattern and the weights of the category neurons. This process is distinct from on error-based learning approach as employed in neural networks such as MLP in which the learning process is based on the error between the output of the network and the desired output [13]. In this paper, neural network of Fuzzy ARTMAP was applied because of its high learning speed, no catastrophic forgetting, stability, and strong yields in classification of the patterns. Fig. 2 shows the structure of this network.

2.6. Suggested Approach for Detection of Epileptic Spikes

Two different fuzzy ARTMAP neural networks are created, each of which is trained and tested by two different data sets. Data sets consist of the features extracted using the two mentioned methods and are exerted into the network after being normalized between 0 and 1. Each fuzzy ARTMAP neural network has 12 inputs and 2 outputs (because of the complementary coding, the number of inputs is twice the number of features). Training set consists of 247 data (148 epileptic spike and 99 non-epileptic spike data), and testing set consists of 98 data (50 epileptic spike and 48 non-epileptic spike data).
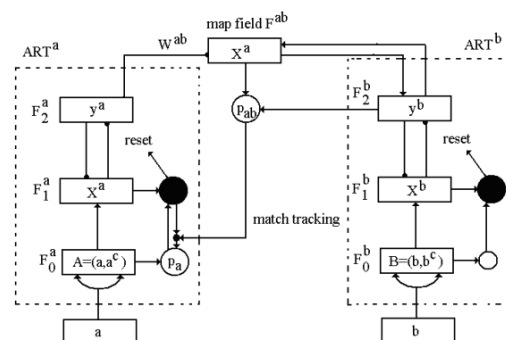

Fig. 1. Four level wavelet decompositions. D and A denote detailed and approximation coefficients, respectively

Fig. 2. Structure of Fuzzy ARTMAP neural network

Table 1. Performance of the system

System	TP	FN	TN	FP	sensitivity	specificity	selectivity
First	45	5	43	5	90%	89.58%	90%
second	46	4	39	9	92%	81.25%	83.64%

3. Results and Discussion

The performance of each of the classifier systems is evaluated through the three criteria of sensitivity, specificity, and selectivity. These three criteria are defined as [14]:

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100\% \qquad (2)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100\% \qquad (3)$$

$$\text{Selectivity} = \frac{TP}{TP+FP} \times 100\% \qquad (4)$$

where TP (true positives) is the number of epileptic spikes which are correctly detected by the system; TN (true negatives) is the number of non-epileptic spikes which are correctly detected by the system; FP (false positives) is the number of non-epileptic spikes which are incorrectly classified as the epileptic spike by the system; FN (false negatives) is the number of epileptic spikes which are incorrectly classified as the non-epileptic spike by the system.

The obtained results from both of the mentioned classifier systems are shown in Table I. The values attributed to sensitivity, specificity, and selectivity for the first system was calculated as 90%, 89.58%, and 90% respectively. The same values for the second system were 92%, 81.25%, and 83.64% respectively. The first system turned out to have better performances in comparison to other epileptic spikes detection systems. Ganesan *et al.* [3], for instance, using the wavelet transform method based on artificial neural networks and the same EEG data set, calculated the values of sensitivity and specificity as 86% and 80% respectively. Indiradevi *et al.* [9], using a multi-level wavelet transform approach, have reported 91.7% for sensitivity, 89.3% for specificity, and 78.1% for selectivity. Acir and Güzeliş [15] using a two layer system based on SVM, came up with 90.3% for sensitivity and 88.1% for selectivity.

4. Conclusion

Detection of Epileptiform discharges in EEG is an important component in the diagnosis of epilepsy. In this study, two different classifier systems based on fuzzy ARTMAP neural network were used for detection of epileptic spikes in recorded EEG. Each of these classifiers use different input data. As is presented in the results, the system using the first data set has the best performance in detecting non-epileptic patterns and the system using the second data set has the best performance in detecting epileptic patterns. But by comparing these two systems to each other and to other similar systems for detecting epileptic spikes, it is clear that the system using the first data set as input has the best accuracy. The advantages of the two classifier systems presented in this paper are fast learning, no catastrophic forgetting, and stability.

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