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Extracting Features for a Brain-Computer Interface by Self-Organising Fuzzy Neural Network-based Time Series Prediction

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Abstract— **This paper presents a novel feature extraction procedure (FEP) for extracting features from the electro-encephalogram (EEG) recorded from subjects producing right and left motor imagery. Four self-organizing fuzzy neural networks (SOFNNs) are coalesced to perform one-step-ahead predictions for the EEG time series data. Features are derived from the mean squared error (MSE) in prediction or the mean squared of the predicted signals (MSY). Classification is performed using linear discriminant analysis (LDA). This novel FEP is tested on three subjects offline and classification accuracy (CA) rates approach 94% with information transfer (IT) rates >10 bits/min. Minimum subject specific data analysis is required and the approach shows good potential for online feature extraction and autonomous system adaptation.**

Keywords—**augmentative communication, brain-computer interface, electroencephalogram, neural network, prediction**

I. Introduction

A person's ability to control their EEG may enable him/her to communicate without the prerequisite of being able to control their voluntary muscles. EEG-based communication does not require neuromuscular control therefore, people with neuromuscular disorders who may have no control over any of their conventional communication channels may still be able to communicate through a direct brain-computer interface (BCI). A BCI replaces the use of nerves and muscles and the movements they produce with electrophysiological signals, in conjunction with the hardware and software that translate those signals into actions [1].

An important component of most BCIs is the feature extraction procedure (FEP). This work demonstrates a novel FEP which carries out self-organizing fuzzy neural network (SOFNN)-based time series prediction, performing feature extraction in the time domain only. EEG is recorded from two electrodes attached to the scalp, over the motor cortex. The EEG time series data is configured so that data from each electrode (i.e. C3 or C4) is predicted by a single SOFNN. Features, derived from the mean squared error (MSE) of the predictions or the mean squared of the predictions (MSY), are extracted from EEG data within a sliding window. The unique coalescing of four SOFNNs for extraction of features through time series prediction makes it possible to extract features in a number of different ways. Also, utilization of SOFNNs [2] offers many advantages for BCI application, especially for ease of adaptability. Firstly, because each SOFNN can adapt its structure to each individuals EEG signals, very little subject specific knowledge or parameter selection is required. Secondly, the SOFNN has a self organizing structure and can perform online learning thus has potential for lifelong learning and continuous adaptation to the perpetually varying, multifarious dynamics of each individuals EEG. This paper illustrates how these potentials may be realized.

Quantification of BCI performance, by measuring the classification accuracy (CA) and information transfer (IT) rate [3], is very important for comparing different systems and measuring improvements in systems. The latter performance quantifier is based on the CA and the time required to perform classification of each mental task. A third and relatively new quantifier of performance for a BCI system is to quantify the mutual information (MI) [4] - a measure of the average amount of information a classifier output contains about the input signal when the classifier produces an output, D, which reflects the distance of the features from the separating hyperplane.

Results from this work show that the proposed FEP compares well to existing approaches. CA rates approaching 94% are achieved without using cross-validation. Results ranging from 70-95% are reported for experiments carried out on similar EEG recordings [5][6]. In some cases results are subject-specific and are based on a 10*10 cross-validation which provides a more general view of the classification ability [5] and may not accurately represent the abilities of the system for online data processing. Current BCIs have IT rates ranging between 5-25 bits/min [7]. The types of EEG signals utilized have a significant influence on the IT rates and the suitability of many signals for BCI use by impaired patients is speculative (see [8] for a review). For one particular parameter setup in this work IT rates are above 10 bits/min.

The paper is organized as follows. Section II describes the data acquisition procedure and the data configuration. The SOFNN, FEP and classification methods are also detailed. Section III provides a detailed description of the results and section IV is a discussion of the results and methods. Section V concludes the paper.

II. METHODOLOGY

A. Data Acquisition

The EEG data was recorded by the Graz BCI-research group [4][5][6] (see acknowledgement) who have developed a BCI which uses μ (8-12Hz) and central β (18-25Hz) EEG rhythms recorded over the motor cortex. The data is recorded from each subject in a timed experimental recording procedure where the subject is instructed to imagine moving the left and right hand in accordance to a directional cue displayed on a computer monitor. In each recording session a number of EEG patterns relating to the imagined right or left arm movement are produced by a subject, over a number of trials. All signals are sampled at 128Hz and filtered between 0.5 and 30Hz. Three bipolar EEG channels were measured over C3, Cz and C4. Details of similar experimental setups for recording these EEG signals are available in [4][5][6].

B. Data Configuration

The EEG data recorded from each electrode is structured so that the measurements from time instants *t*-4 to *t*-1 are used to make a prediction of the measurement at time *t*. Each training data input exemplar contains four measurements from the data recorded from either the C3 or C4 electrode. The training data output contains every subsequent measurement *t* from each of the input data vectors. The extracted input-output data vector for the time series C3 and C4 are shown in (1) and (2). Each trial consists of approximately 5 seconds of task related data. The data was recorded from three subjects (S1, S2 and S3). There were 280 trials recorded for subject S1 and 320 trials recorded for subjects S2 and S3 (i.e. an equal number of trials for each type of movement imagery). Each trial consists of 640 samples ($5s/128^{-1}s = 640$) therefore, there are 636 training data pairs for each trial (i.e. samples 636 → 639 are used to predict 640).

$$[\ c3(t-4),\ c3(t-3),\ c3(t-2),\ c3(t-1)\ ;\ c3(t)\ ] \tag{1}$$

$$[\ c4(t-4), c4(t-3),\ c4(t-2),\ c4(t-1)\ ;\ c4(t)\ ] \tag{2}$$

C. SOFNNs – Architecture and Training Procedure

Four SOFNNs are used to perform prediction. Two SOFNNs are trained on the left EEG data and the other two on right EEG data. By using separate SOFNNs for each type of data, it is expected that each trained SOFNN has certain uniqueness, in that it is more apposite to each type of time-series data. The advantage of using a self-organizing structure, like that of the SOFNN [2], is that the problem of specifying the NN architecture does not have to be considered. For the well known Neural Networks (NNs), specifying the optimum architecture for a particular task can be problematic and does have a significant effect on the performance results. Fuzzy NNs are hybrid systems that combine the theories of fuzzy logic and NNs. In these hybrid systems, the fuzzy techniques are used to create or enhance certain aspects of the NNs performance. An important outcome of an SOFNN is the generation of a model(s) from observations of complex systems where little or insufficient expert knowledge is available to describe the underlying behavior, as in the case of EEG. The SOFNN can cope with characteristics of EEG such as large dimensions, non-stationarity and noise contamination to provide a model which can be used for interpretation of the complexities and nonlinearities in the EEG. This is another advantage of using an SOFNN for EEG analysis. The SOFNN is designed to approximate a fuzzy algorithm or a process of fuzzy inference through the structure of NNs and thus create a more interpretable hybrid NN model making effective use of the superior learning ability of NNs and easy interpretability of fuzzy systems. The dynamic adaptation of the structure of the hybrid network captures the underlying behavior of a nonlinear time-varying complex system more easily and accurately. The online learning algorithm, based on a hybrid recursive least squares estimator, and an autonomous neuron adding and pruning structure based on the optimal brain surgeon technique, provide a truly online learning algorithm for modeling/predicting the highly non-stationary EEG signal.

D. The System and Feature Extraction Procedure

Each SOFNN [2] is a multi-input-single-output (MISO) network so only EEG data recorded from a single electrode can be predicted by any one SOFNN. The system is configured in three stages. The first stage involves training four SOFNNs separately to perform one-step-ahead prediction, using four previous measurements of each time-series. Two SOFNNs are labeled ‘L3’ and ‘L4’ for ‘left data-electrode C3’ and ‘left data-electrode C4’, respectively and two SOFNNs are labeled ‘R3’ and ‘R4’ for ‘right data-electrode C3’ and ‘right data-electrode C4’, respectively, corresponding to the type of EEG data on which they are trained (i.e. either left or right motor imagery). The second stage involves entering each type of training data (i.e. the same data used to train the SOFNNs) into each SOFNN. All the ‘L3’ training data (i.e. left data recorded from electrode C3) is input to both the ‘L3’ and ‘R3’ SOFNNs. All the ‘L4’ training data is input both the ‘L4’ and ‘R4’ SOFNNs. The ‘R’ data is input to all SOFNNs in a similar way. Each SOFNN provides a one-step-ahead prediction for the data in each trial. When a trial is input to all SOFNNs, features can be extracted by calculating the MSE of the prediction for a segment of the trial. Alternatively the mean squared of the actual prediction (MSY) can be calculated. As these calculations deduce predictions over a segment to a scalar value, features based on the error for the first case, and on the predicted signal for the second case, can be obtained. Equations (3) or (4) are used for obtaining each feature.

$$fy_k = \frac{1}{M}\sum_{t=1}^{M}(y(t) - \hat{y}_k(t))^2 \quad \text{for } MSE \tag{3}$$

or

$$fy_k = \frac{1}{M}\sum_{t=1}^{M}(\hat{y}_k(t))^2 \quad \text{for } MSY \tag{4}$$

where $y(t)$ and $\hat{y}_k(t)$ are the values of actual signal and predicted signals (i.e. C3 or C4) at time *t,* respectively. The *k* index indicates whether the signal is the output from a left or right SOFNN (i.e. *k* can be *l* or *r*). *M* is the number of prediction samples used for the MSE or MSY calculation. Equation (3) is used for calculating the MSE-type features and (4) is used for calculating the MSY type features. The feature vector, *fv*, is shown in Figure 1. For each trial a four element feature vector is obtained and classes of features for right and left data can be obtained by entering all trials of training data into the SOFNNs, as illustrated in Figure 1. Normalizing the features (i.e. dividing each feature vector by the sum of the components within the vector) can reduce the intra class variance – a fundamental goal of any FEP. Features can be extracted for every time point in a trial using a sliding window approach. To extract a new set of features for every time point in a trial using the sliding window approach, *t* in (3) and (4) ranges from *t*=s to *M* where *s* and *M* are incremented before the next set of features is extracted (initially *s*=1 and *M*=window size). This means that data at the beginning of a trial is forgotten as the window slides away from the start of the trial. The advantage of using the sliding window for feature extraction is that the FEP does not require knowledge about the point at which communication is initiated by the user and thus online feature extraction can be realized.

E. Classification

The third stage is classification, performed using Linear Discriminant Analysis (LDA), a classifier that works on the assumption that different classes of features can be separated linearly. Linear classifiers are generally more robust than their nonlinear counterparts, since they have only limited flexibility (less free parameters to tune) and are less prone to over fitting. Experimentation involved extraction and classification of features at every time point in a trial, allowing selection of the optimum time point(s) to perform feature extraction and classification for more effective deployment of the system. This approach allows features to be extracted at the rate of the sampling interval very easily, as described in the previous section. The full system is illustrated in Figure 1.

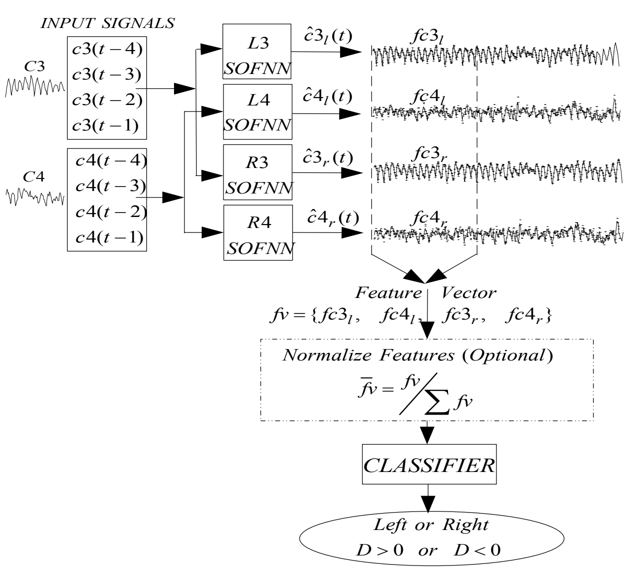

Fig. 1. Illustration of FEP and the complete system.

TABLE I
A COMPARATIVE ANALYSIS OF THE FEATURE TYPES BASED ON RESULTS FROM THREE PERFORMANCE MEASURES.

Subject	Feature Type	Win. size	CA %	Time [s]	IT [bpm]	MI [bits]	Best
S1	MSE	315	82.85	3.46	5.88	0.27	
	MSY	393	**89.28**	4.07	**7.5**	0.33	X
	MSE n	328	84.28	3.56	6.27	0.37	
	MSY n	351	87.86	3.74	7.48	**0.55**	
S2	MSE	100	68.75	1.63	3.82	0.04	
	MSY	300	71.88	2.69	3.2	0.13	
	MSE n	360	85	3.82	2.96	0.38	
	MSY n	300	**88.13**	3.87	**7.36**	**0.45**	X
S3	MSE	295	**93.13**	3.56	**10.76**	**0.46**	X
	MSY	167	75.63	2.09	5.78	0.24	
	MSE n	285	78.13	4.13	3.56	0.17	
	MSY n	187	81.25	2.55	7.14	0.28	

III. RESULTS

The system was tested on 140 trials for subject S1 and 160 trials for each of the subjects S2 and S3. Table 1 shows the results obtained. The time course of all performance measures were calculated and the results at optimum performance are presented. The first column specifies the subject. The second column specifies the feature type; an *n* indicates normalized features. Column three specifies the sliding window size. The CA rates, the corresponding classification times, the IT rates and the maximum MI are specified in columns 4-7, respectively. The last column specifies the best choice of feature type based on making a trade off between the results from all three performance measures. All results in bold specify the best results obtained for each type of performance quantifier.

IV. DISCUSSION

All IT rates were calculated using the time interval between communication initiation (i.e. second 3 of timing scheme [5]) and the point that maximum CA was obtained. This provides good indication about the maximum IT rate a system can achieve whilst system accuracy is optimal. IT rates can be much higher if calculated in the first second of a trial, even if CA is lower although, a system which has higher error rates (low CA) could be frustrating or exhausting to use, especially by patients with severe neuromuscular disorders.

The maximum MI usually occurs around the point where CA is maximized. The maximum MI for all subjects is relatively low, indicating that the SNR is not very high and that an increase in MI is required to facilitate using the classifier output to perform, for example, modulated control of a cursor. An increase in MI would also indicate a more reliable FEP and classifier. Irregular transients in the signals, caused by noise or artifacts, resulted in an increase in the value of an MSE type feature due to larger prediction errors. This did not have as much affect on the MSY features because the SOFNNs did not predict irregular transients in the signal, indicating that the SOFNNs helped to aid the removal of artifacts and noise for subjects S1 and S2 although, for subject S3 the MSE type feature provided the best results. The CA and MI show significant improvements on most tests using the MSY features, although, these results were obtained at the expense of requiring increased classification time which can cause a reduction in the IT rate (depends on CA). Normalizing the features reduces the intra-class variability although, CA and IT rates are only improved in some cases and degraded in others. For subject S1 and S2 the MI is increased, indicating that normalizing the features helped to increase the signal-to-noise (SNR).

A frequency analysis and visual inspection of subject S2's EEG data shows increased noise levels and perhaps a badly attached C3 electrode producing large spikes in some trials. This resulted in the SOFNN architecture growing very large (the number neurons increasing). The windowed FEP and the normalized MSY type features helped to remove the effects of the noise and provide satisfactory results (approx. 88% CA). The number of neurons in each SOFNN was significantly different to it's counterparts due to variations in the types of signals on which each SOFNN was trained. Neurons are added and pruned based on a number of criteria and a number of preset parameters therefore; specification of these parameters affected the overall SOFNN architecture and thus the extracted features. During training, as the number of neurons and training exemplars increased, the memory requirements increased, placing limitations on the amount of training data and the number of neurons which may prevent this approach achieving its optimum performance. However, the potential applicability of this approach is demonstrated through the results.

V. Conclusion

The proposed SOFNN-based time series prediction approach shows good potential and compares well to existing approaches. This method meets the requirements for the first level adaptation; outlined in [1], being easily adapted to each individual subjects and does not require a subject-specific frequency analysis or any form of EEG analysis. No artifact removal or noise reduction was carried out on the raw EEG data which suggests that this approach is fairly robust. The overall structure and concept provide plenty of options for further development. It has been shown that the approach can be used for online feature extraction through the windowing technique. Whilst a system is being used continuously by a person, features can be extracted from the ongoing EEG. When the user attempts to provide a communication signal the features should evolve and become similar to those on which the classifier was trained. The classifier should recognize this and act accordingly. Also, as features can be based on the predicted signals (MSY), increased IT rates may be realizable by performing multiple-step-ahead predictions and thus extracting features much faster - a significant prospective of this approach.

The advantage of using a SOFNN, that can self organize the network architecture, adding and pruning neurons as required, is that the network architecture does not have to be adjusted manually for each individual user and the structure can be optimized online. A system that can autonomously add neurons to accommodate variations in the EEG, as the user learns to control his/her EEG better and/or prune neurons if older EEG characteristics are not used by the person any longer, would have advantages for continual online adaptation. This approach is being developed further to allow continuous feature extraction and online autonomous adaptation to the feature extraction procedure thus confronting the second level of adaptation requirements, outlined in [1].

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