Using a Chain of LVQ Neural Networks for Pattern Recognition of EEG Signals Related to Intermittent Photic-Stimulation

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Abstract

This work reports the use of neural networks for pattern recognition in electroencephalographic signals related to intermittent photic-stimulation. Due to the low signal/noise ratio of this kind of signal, it was necessary the use of a spectrogram as a predictor and a chain of LVQ neural networks. The efficiency of this pattern recognition structure was tested for many different configurations of the neural networks parameters and different volunteers. A direct relationship between the dimension of the neural networks and their performance was observed. Results so far encourage new experiments and demonstrate the feasibility of the proposed system for real-time pattern recognition of complex signals.

1. Introduction

The identification of patterns in electroencephalographic (EEG) signals related to evoked potentials by intermittent photic-stimulation is a method for building a prosthetic keyboard. A prosthetic keyboard is a kind of brain-computer interface (BCI) that permits seriously handicapped people to interact with the world using the few movements that he/she still has, sometimes only the eyes movement [6][10].

The use of intermittent photic-stimulation as the modulation factor of a BCI system [8] is possible thanks to a special characteristic of the retina: it concentrates the light sensitive cones in its central part (fovea). Also, the response of the visual cortex is larger for stimuli with spatial angle less than 2° from the fovea. It is not possible to determine the color or the geometry of visual stimuli only by analysis of the EEG signal, but the presence of a dynamic stimulus is observable [10]. The problem is the automatic identification of such patterns in real-time.

In the pattern classification of EEG signals, one of the factors that most influence the performance of the recognition system is the quality of the acquired signals. For complex signals with low signal/noise rate, like those from intermittent photic-stimulation, the recognition cannot be accomplished only with simple signal processing techniques. It is necessary to use more sophisticated non-linear techniques, such as neural networks.

Techniques like averaging increases the signal/noise rate [7], evidencing the patterns to be recognized. However, these techniques usually cannot be applied to build real-time classification systems. In this paper it is shown the use of a spectrogram as a predictor and a chain of learning vector quantization (LVQ) artificial neural networks for recognition of the underlying patterns.

Artificial neural networks have been widely used in pattern recognition of EEG signals [9]. However, the parameters to be used in training the neural networks are dependent of the nature and quality of these signals, as well as the purpose of the neural networks. For the determination of these parameters, an experimental procedure was conducted, training/validating the neural networks with several different configurations.

2. Methodology

A dedicated software for signal analysis, neural networks training and validation was developed using the Borland C++ Builder environment. This software is able to analyze EEG signals of any length and sample rate, and allows the use of a chain of LVQ neural networks of any size with any frequency associated to each neural network. It also includes four different clustering methods. These features automate the project of a classification system for real-time operation. In the following, it will be presented the methodology for EEG signals processing and analysis.

2.1. EEG Signal Acquisition

The EEG signals were acquired from electrodes placed on volunteer's scalp. The electrodes positioning were according to 10-20 electrodes system, recommended by the EEG International Federation [4]. Signals were acquired in differential mode using electrodes O2 and OZ with right ear lobe as reference.

The data acquisition system used was composed by a signal amplifier and filter, a 10 bits, 16 channel data acquisition digital board model AT-MIO-16E-10 (National Instruments, Austin), and a Windows-based synchronization and management acquisition software, developed in C++ language. Sampling rate was 512Hz.

2.2. Spectrogram Computation

A spectrogram represents the variation of the frequency spectrum of a signal along time. The spectrogram is computed using the Fast Fourier Transform (FFT) module of a rectangular window of 2^N samples. This window is slid along time in s samples. A new FFT is calculated each time the window slides, compounding the spectrogram. For a signal of L samples with sample rate F_S, the number I_T of intervals presented in the spectrogram is given by equation 1, as well as the smallest frequency interval R_F, given by equation 2.

$$I_T = \frac{L - 2^N}{s} \quad [1]$$

$$R_F = \frac{F_S}{2^N} \quad [2]$$

Equations 1 and 2 show that there is a tradeoff between the time domain and the frequency domain accuracies. The bigger the FFT window size, the greater the accuracy in frequency domain, but the spectrogram will be divided in less time intervals. Conversely, if the number of points of the FFT decrease, the accuracy in the frequency domain will decrease, however, the spectrogram will have a greater number of smaller time intervals.

2.3. LVQ Neural Network Organization

Initially, the spectrogram of the EEG signal related to the intermittent photic-stimulation session is calculated. For each frequency component, a LVQ neural network is built to recognize the neurological activity present in the spectrogram, as shown in Figure 1.

The training data for each LVQ neural network is obtained by a sliding window along time over the spectrogram, with a configurable size of m samples (for reference, $10 < m < 100$). For each frequency component, in each instant of time, the m samples obtained with this window will compose an m-dimensional input vector to the corresponding neural network. These m-dimensional vectors, with their associated class (“with pattern” class or “without pattern” class) are used for training the neural network corresponding to the input frequency.

Thus, the output of the neural networks can be combined so that the system gives a single information of which frequency component of the signal presents relevant neurological activity in each instant of time.

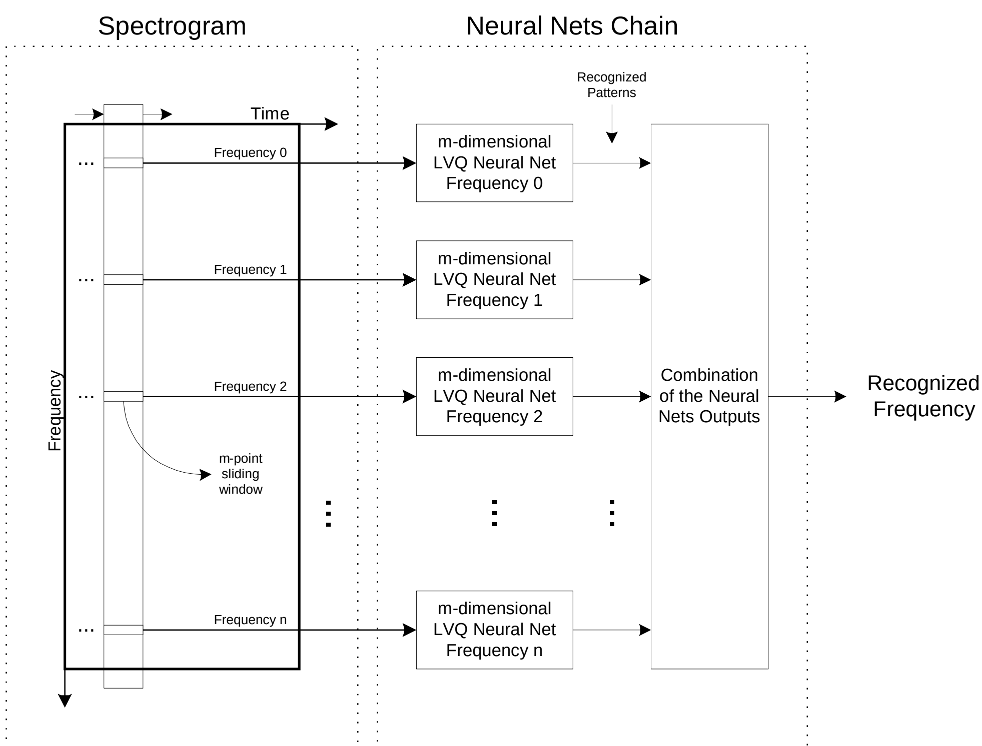


Figure 1 –Classifier structure

2.4. Subclustering

Clustering algorithms cannot be applied when the input samples were already classified. This is the case of EEG signals related to intermittent photic-stimulation where each segment of the training vectors is previously classified into two classes: “with pattern” and “without pattern”. If a clustering algorithm were applied directly, this initial classification would be lost. Thus, it is necessary to cluster each class one by one. This method we call subclustering.

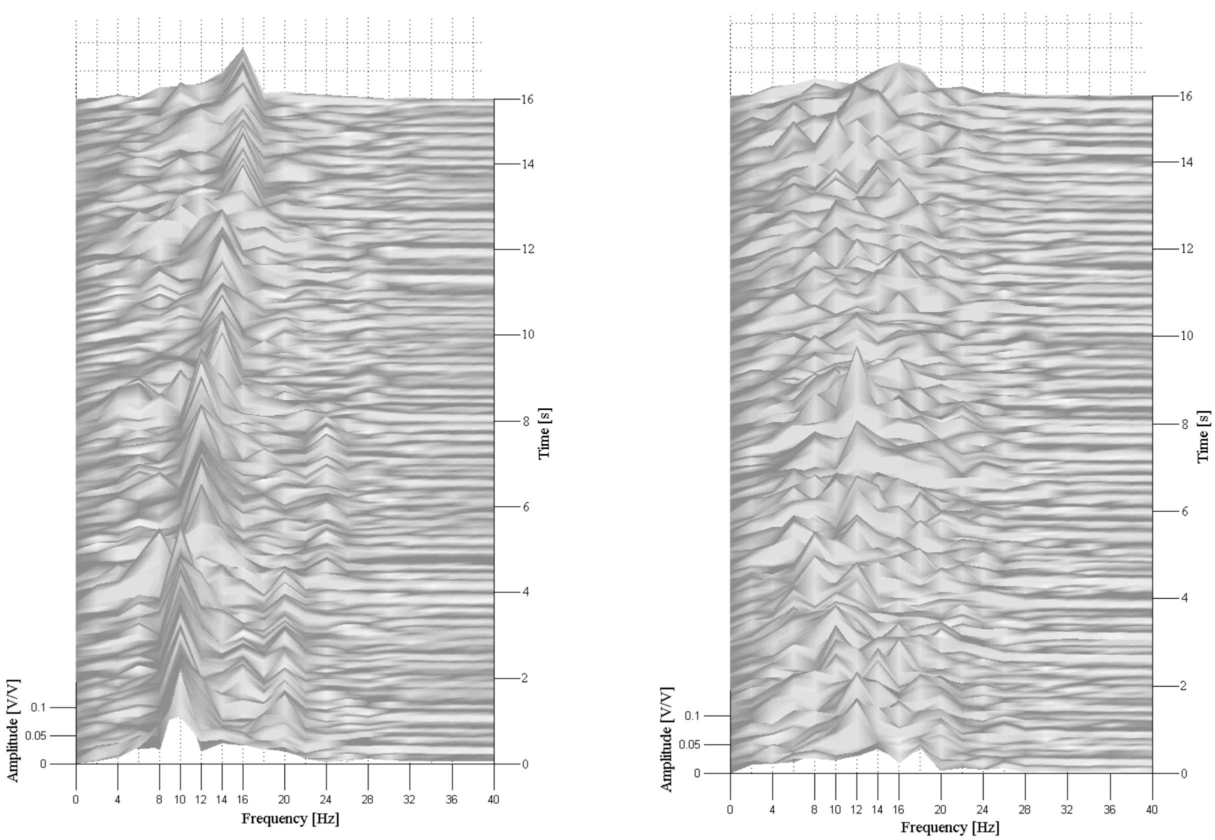
The subclustering method consists in isolating the samples of a class in a new space, where they will be normally clustered with any regular algorithm. The software developed includes four different clustering algorithms: Threshold Order Dependent, Max-Min Distance Method, c-Means Iterative and ISODATA [2] [11]. For each cluster created in this new space it is given an attribute related to the class to which the samples belong. In the training process of the LVQ neural networks, each subcluster is considered an independent cluster. However, in the classification and performance evaluation phase, the cluster attribute is used to evaluate the neural networks efficiency.

Therefore, it is possible to create a better decision surface for the classes, while using the same clustering and training algorithms for the neural networks.

2.5. Experiments

The intermittent photic-stimulation sessions related to the signals used in these experiments were composed by four different frequencies, all of then generated at the same time. To generate these stimuli an 8x8 LED matrix was used. This matrix was divided in 4 quadrants (one for each frequency), connected to a host computer, which generate appropriate time intervals to the matrix. Volunteers were instructed to stare at each quadrant for 4 seconds, following a given order, composing a 16 second session. This procedure was repeated 20 times for each volunteer so as to have a large amount of data for training the neural networks.

Figure 2 shows typical spectrograms of a signal to be analyzed, where axes *x*, *y* and *z* are, respectively, frequency, time and amplitude (of the FFT module). In this example, the volunteer was submitted to the following frequencies: 10Hz, 12Hz, 14Hz and 16Hz.



(a) (b)

Figure 2 – Spectrograms of a volunteer submitted to four windows (4 second each) of intermittent photic-stimulation: (a) average of 20 signals and (b) a single signal.

The spectrogram showed in Figure 2a represents the average of 20 signals in the time domain. As can be seen, it presents well-defined peaks in the stimulation frequencies. However, for implementing a real-time system, it is not possible to use such averaging, but a single signal at a time. However, for a single signal as shown in Figure 2b (it corresponds to the same stimulation session of Figure 2a), it is not possible to distinguish the peaks using a simple threshold analysis. Considering that the signals to be analyzed in a real-time system are usually like that of Figure 2b, it is necessary to use a more efficient method to recognize the frequency patterns, such as the method presented here.

Signals acquired in a session are divided into small files, each one containing data of only one stimulation frequency at a time, so as to form the training vector of the neural networks. To load these data into the software, each file is associated to its stimulation frequency, composing a table. According to this table, the data are then applied in the neural networks as described before.

A subclustering algorithm is then applied (see section 2.4) to compose the reference vector for each neural network. In our experiments, the c-Means method was used because it allows the prior determination of the desired number of clusters and also due to the performance attained in previous experiments.

Finally, the neural networks are ready to be trained. The algorithm used to train the nets is the well-known LVQ1 method [1] [3] [5]. The learning factor was not decremented during epochs. Instead, it was set to a fixed low value (0.001). Previous experiments demonstrated that large number of epochs just caused an oscillation in the performance of the system. Therefore, the number of training epochs was limited to 50. The final result of the training is the subclusters set that gave the best performance throughout the training process (instead of the last subclusters set).

3. Results

The analyses were made in sessions with stimulation frequencies of 10Hz, 12Hz, 14Hz and 16Hz (similar to Figure 2) for 5 different volunteers. For one of the volunteers, two more different sessions were made, one with frequencies of 11Hz, 13Hz, 15Hz and 12Hz, and other with 11Hz and 15Hz alternately. Each session contains 20 files for each frequency. These files were randomly partitioned in two sets: 12 for training and 8 for validation.

For each file, the spectrogram was computed for 1s windows (512 points), with sliding of 8 samples (with overlapping) and averaging a number of samples along time to eliminate noise (for reference, 0, 10, 20 and 50 samples). This averaging causes a delay in the system, but can be easily accomplished in real-time.

Several different configurations of neural networks were tested, changing each of the parameters individually for all signals of all volunteers. The ranges of parameters used were:

- Dimension (input vector size): 10, 20, 50 and 100;
- Subclusters per class: 5, 10, 20 and 40;
- Averaged points in the spectrogram: 0, 10, 20 and 50.

The combination of these parameters gives 64 different possibilities. All these possibilities were tested in each of the 7 sessions of the 5 volunteers (recall that one volunteer had 3 sessions). Therefore, a total of 448 neural networks chains were trained. As explained before, each neural network chain has 4 neural networks, corresponding to the 4 frequencies present in each session (except for that volunteer that had 3 sessions, which had one session with only two frequencies). This gives a total of 1664 neural networks. All trainings were made by 50 epochs with learning factor of 0.001. In the valuating procedures, the spectrograms were calculated with the same parameters of window size and averaging.

For all volunteers, the results were analyzed plotting performance versus the variation of one of the three parameters described at a time, resulting in one graphic for each neural net of each chain. These results were averaged so as to evaluate the general performance of the system.

Figure 3 shows the behavior of the average performance of the neural networks for one of the volunteers, related to frequencies 10Hz, 12Hz and 14Hz of a session similar to that in Figure 2. The same behavior of the curve is present in the analysis of results of almost all signals of all volunteers.

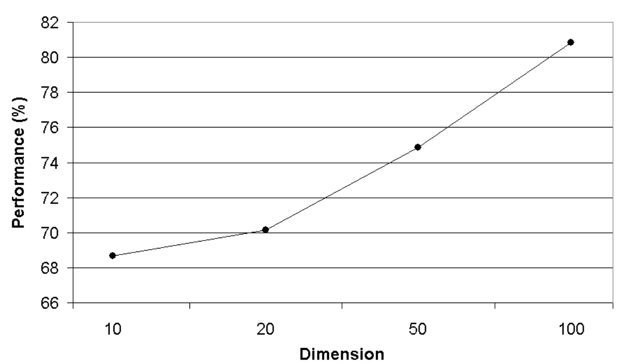


Figure 3 - Variation of average performance against the dimension of the neural networks

The other parameters analyzed in this work (number of subclusters per class and averaged samples on the spectrogram) did not present any significant change on the performance of the neural network chain.

The increment in the dimension of the neural networks seems to decrement the influence of the number of subclusters per class in their performance, as the standard deviation of the performances decreases as the dimension increases. However, this behavior, reported in the majority of the neural networks, was not observed in neural networks associated with noisy components of the analyzed signals.

4. Conclusions

The EEG signals used in the experiments reported here were not acquired specifically for this purpose. In particular, the filter used in the EEG signals amplifier had a very irregular frequency response. As a consequence, the amplitude of the signal is not even for each frequency component. Possibly, this effect can explain the fact that some neural networks reported quite different performances for testing vectors (ranging from 50% to 100%), when it was expected a much shorter variation. Therefore, it was difficult to observe a behavior pattern in the performance analysis of the neural networks with the variation of different parameters. Overall, this situation stresses the necessity of a data acquisition system having the same frequency response for all stimulating frequencies of interest (flat transfer curve).

Notwithstanding, it was possible to have preliminary results. The dimension of the neural networks turns out to be a very important parameter for the performance, showing that it is necessary to analyze a window with hundreds of milliseconds for a good performance. The number of subclusters per class had influence in neural networks of small dimensions, but has no effect in larger ones (50 or more dimensions).

The neural network chains have demonstrated to be a good structure for the analysis of EEG signals related to intermittent photic-stimulation.

As soon as more high quality data will be available, more experiments will be conducted mainly to investigate the influence of the other parameters in order to determine the best configuration of the LVQ neural networks. In the sequence, the next functional block that combines the result of all neural networks will be implemented.

5. References

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