Signals for a spherical robot control based on EEG recordings

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Abstract: The brain is coordinating all actions of our whole body. It is a complex system, but its fundamental structure and functional characteristics are not yet wellknown. We can only do a scanning of the brain to pick up some information about brain events. One scanning method it could be the use of Electroencephalograms (EEGs). The functional brain generates electromagnetic fields. The recorded field variations could inform us about a fact, that something is happening inside a very-complex system. We want to interpret what we have measured. The variation in time and space of an electrical potential, as difference measured between two points of the scalp is an EEG signal. This signal could give us a glimpse into an unknown system. Brain Computer Interface (BCI) systems have been developed to capture, as accurate as possible, EEG signals to have a chance to think about the supposed transmitted information. One waycould be to capture event related potentials (ERP), to learn their variance with an ANN (Artificial Neural Network) and then to use this knowledge to localize control signals.

BCI systems are interconnecting the signal acquisition sub-systems (electrodes) and a sub-system for signal processing, pattern recognition and classification logic (usually a computer). If there is a success in pattern (information) recognition carried by the recorded signals, then the information can be translated into a control signal set. This paper gives a practical solution to show the methods starting from capturing ERP type EEG signals ending with real time control of a spherical robot. The control signal transfer between the BCI system and spherical robot is realized through a wireless communication system.

Keywords: BCI system, Spherical robot, ANN in signal classification.

1. Introduction

The starting idea for this paper was to get EEG signals andto elaborate and test software algorithms to extract brain information able to control a spherical robot movement on a horizontal plane. We have an original project of a spherical robot but its presentation is not the aim of this paper. We are considering only the way to get the control signals for this robot, on-line, in real time from our measured EEG multichannel recordings[1][9]. This realization is convincing, considering the utility of such kind of interface, able to translate EEG signals into a set of control signals for equipments to facilitate the everyday existence of disabled persons. It is obvious that, based on today's technologies in electronics and signal processing, it was possible to analyze and realize methods to measure EEG signals with more then two channels, to amplify the signals after increasing the value of signal to noise ratio[2]. If we have the signals with usable power level, proper signal processing methods can be experimented to extract information. We call these information as patterns, then information extraction is a pattern identification (classification) procedure. In case of spherical robot control, the patterns to be identified are the elements of signal pairs from the pattern set (PS) as {Left,Right, Up, Down} and in the same time are representing'directions code' of the robot displacement vector. The used EEG signal recordings are from double channel or multiple channel recordings. Basically, we have used patterns extracted from two channels. The two channels were properly selected from multichannel recordings[7]. The recognition and extraction of patterns is a theoretical, and in the same time an algorithmic problem. It was necessary to find a conceptual way to define a pattern (as the correlation of two 'shapes' of event related potentials (ERP) type respond of brain (motor cortex area)) and then to create the methods for an accurate enough recognition of them. To recognize shapes (a consecutive sequence as samples) within signals is a classification procedure. To classify time series (EEG signals) is not all the time an easy task [4][5][6].

1. About the recorded EEG signals

We have started with the concept that electrical signals generated by the synchronized activity of neurons from the cortical regions of the brain (layer 1 and sometimes layer 2 of the left and right hemisphere) can be recorded[3]. The cortical regions generate the EEG signals usable to control some external systems. Steps to achieve our goal are: multichannel EEG signal recordings, automatic pattern identification as components of the recorded signal, tracing the co-appearance of the patterns in at least, two different channels, the identification of correlation type between the coexistent (shapes) patterns and

finally, the identification of an event as an element of the previously mentioned PS. In our project, the classification based on PS, is realized with a trained artificial neural network. The set up of the training set of this neural network was possible using a very large number from our EEG recordings (some samples arerepresented on Figure 3), event controlled recordings. The appearance of events within EEG signals were the result of planned (ERP) presence of stimulus.

As we know, a wide broad noise events are affecting the recorded signals. There are internal (physiologic) and external (external electromagnetic field effects, 50Hz disturbing power supply effect) noises. Using the standard methodologies during the recordings, we have created such an environment to minimize noise contamination. Different noise reduction algorithms have been tested. Methods based on time-frequency algorithms (continuous wavelet transform (CWT), Hilbert-Huang transform(HHT)) are very efficient in noise reduction. The methods are proper for non-stationary signals. These methods don't alter the correlation and coherence of the shape signals. The PS shape signals have the characteristics of ERP events responds (as it is visible onFigure 4).

ERP signals are small in amplitude (1–30μV) relative to the background noise activity. The amplitude provides a characteristic of the extent of neural activity. For this reason, the amplification factor must be the same for each channel's signals.

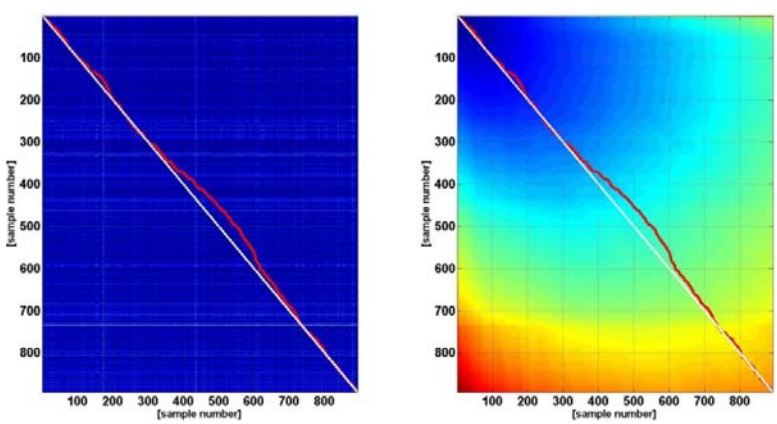

*Figure 1:*The panel on the left we can see the local match scores distance of magnitudes. On the right we can see the dynamic time warping distances of the two signals. The red line (minimum path, similarity) signify the lowest cost path. The white diagonal line is about the complete similarity. We have used synchronized sequence of ERP from two channels from our EEG recordings.

As it was also mentioned, clustering (classifying) the extracted patterns from EEG signals is very important. In clustering events from time series, algorithm of Dynamic Time Warping (DTW) distance measure is often used. For our time series data, we have used DTW due to its shape-based similarity concept and this is not the one-to-one mapping of Euclidean distance, the well-known distance metric. It is often used as a distance measure in averaging the shape of time series[9][10][11].

DTW supports non-equal-length time series comparison. It uses dynamic optimization technique to find all possible paths in a distance matrix, and selects the one that yields a minimum distance between the two time series (Figure 1.). (Each of the following representations of the executed procedures are based on our EEG recordings made by the members of the NSRG research group.)

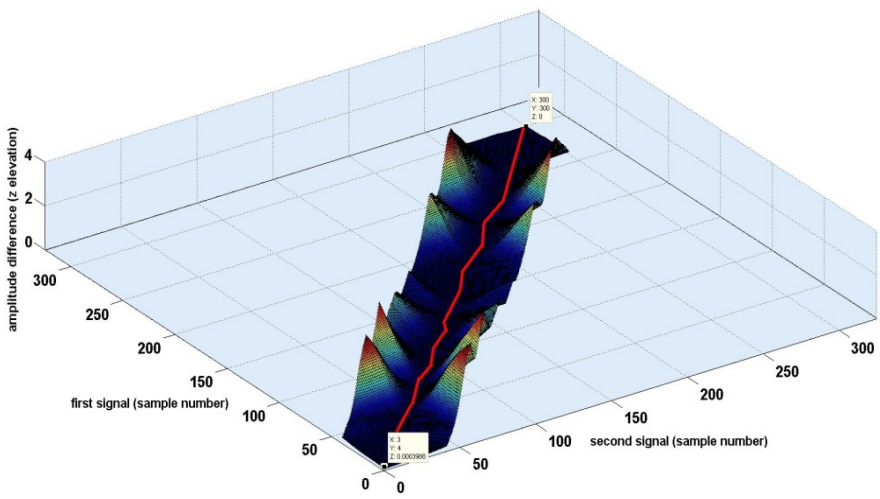

Figure 2:.Representation of the DTW signal matching matrix as a three dimensional surface. The two signals are identical (first signal, second signal) if the red line is positioned as diagonal line of the distance matrix.

The distance between signals in the surface model can be deduced using the position of the valley (red track), being close to the main axes of the matrix. As the matching matrix shows, the start and end point of the valley can have an elevation (in z value), if this is null value then it is the low cost path. Based on this path cost definition, we have a distance metric value between the two signals. This idea is represented on Figure 1.

3. Control sample sequences

What is visible on Figure3 are the result of planned event triggered potentials. It is obvious that it is possible to reproduce ERP events and in this way we can associate control signals to them. This is the first step toward a brain computer interface. In our case, the relative position of signals within an event (highlighted by red squares) can stipulate moving directions code for the spherical robot. Identified events are within pairs of time series, previously recorded in 10-20 standard electrodes position. The recordings have different lengths, are recorded at different, well documented time moments and have been used in creating the training set for the ANN (Artificial Neural Network) based event classification methods. The highlighted events are very similar for different test persons (patients) when they are executing the same planned actions. During the different recordings, each test person's event turnout time moment have been registered. After comparing the registered physical action timing and the timing of the turnout event signals, it can be concluded that the same action (in relative phase of the two signals) has produced the very similar ERP. For this reason, the events can be associated with control signals in a BCI system. The events must be classified with a very fast (real time) algorithm. Three different algorithms were tested. The first is based on dynamic time warping logic (DTW), the second is based on training of an artificial neural network (ANN) with identified events and finally a method based on amplitude position identification (Amplitude method).

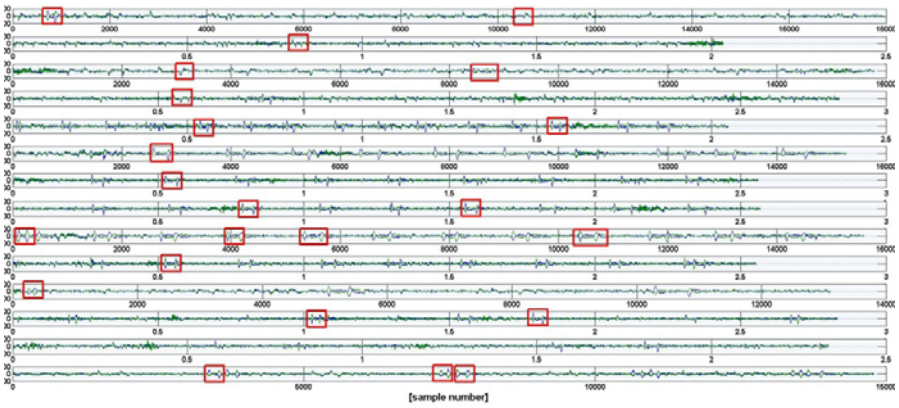

*Figure 3:*Fourteen different EEG signals where recorded from four different persons. The red squares highlight the sequences of EEG signals witch contain useful information. These are identified on all of the signal sequences (red squares) and we call them events. Each track (row) contains two superimposed time series recorded by two electrodes in almost the same scalp position.

Considering the events highlighted in Figure 4, there are four different relative positions of two shapes recorded on two different EEG channels. The two channel recordings have a very special shape and a very special phase relationship of them. After comprehensive testing, it was determined that each directional eye movement type stimulation is constantly producing the same EEG signal peak sequence. Each of them has a maximum point lag, a minimum point (red dot, time coordinate) and they are in phase or in anti-phase position. (see Figure 4). The three methods to get control signals for a BCI interface are based on approaches to consider these four relative positions of two channel recordings. We have considered the PS for the set of control signals for up, down, left and right direction as the robot displacement vectors. The four control signals were associated with the four relative possible position of two shapes. Each of the shape segments of an event has a minimum and a maximum value. Using the facts that the two signals are in phase and which of extreme point occurs first, we have the four possible combination of them. This is the Amplitude algorithm. Figure 4-A is representing an event associated with the 'up' rotating direction. Figure 4-B is associated with 'down' direction. Figure 4-C is associated with 'left' and Figure 4-D with 'right' rotating direction of the spherical robot.

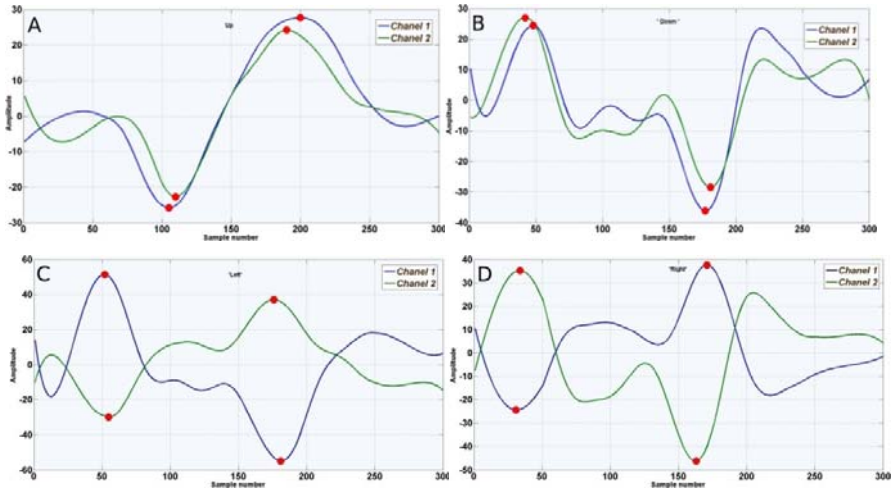

Figure 4: The code of control signals. (A) signals in relative position for 'up'-control, (B) signals in relative position for 'down'-control (C) signals in relative position for 'left' and (D) is 'right' control code. The minimum and maximum points of the channel-1 and channel-2 (300 sample length segments) are marked with red dots.

4. Implementation

These events must be automatically selected for on line algorithms. The first step was to generate a database (DB) for further proceedings. After creating the database, the three mentioned methods were analyzed. For this reason a graphical interface was created (see Figure5). The 'Patient' is defined as the person involved in EEG signal recordings. It is very important to conclude, these control signals were extracted in real time. The recognized 'Up', 'Down', 'Left' and 'Right' (from pattern set) events code have been sent, on-line, to the spherical robot controller for further processing.

The DTW based algorithm is identifying the components of an event using the DB. The component signals must be in the same time window and must be DTW similar with a database sequence. The Amplitude method is taking a decision about the control signal type using a procedure of identification and classification of maximum and minimum point legs of an recognized events in a time-window. The ANN based method has a training sequence and a use in real-time.

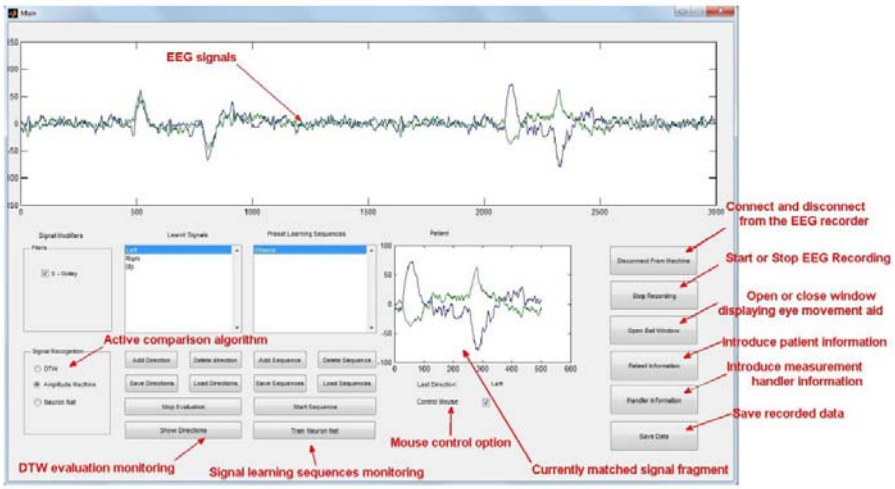

*Figure 5:*The main graphical interface of the evaluation program. It has a real-time EEG signal presenting surface. In a smaller sub-panel, the currently evaluated EEG signal fragment is visible (a detected event). It is possible to switch between the three evaluations algorithms. Patient and measurement handler information can be introduced and saved as well. The evaluation algorithms are also linked to patient for further identification.

The training set is built from a certainly identified event sequence. If the length of an event is 300 samples (at 256Hz sampling frequency), then an input element of the neural network has a length of 600 samples (The two signals from an event in sequence). In this way, the neural network has 600 input neurons (with 2 hidden layers with 60 neurons, as a result of optimality experiments). The network has 4 outputs (for the 4 possible command signal's code). The accepted error of neural network training accuracy was 5.10^{-5}, a very significant minimal error level. The neural network learning error was reached after twenty-nine training epochs.

The performance of the three methods was compared. The results are represented on the Figure6 bar diagram.

The DTW and the Amplitude methods are taking less time to be executed. The computation time of the neural network based algorithm could be dropped but would be followed by a drop in identification accuracy. The DTW algorithm based evaluation is not precise enough, but the precision can be raised at the cost of speed.

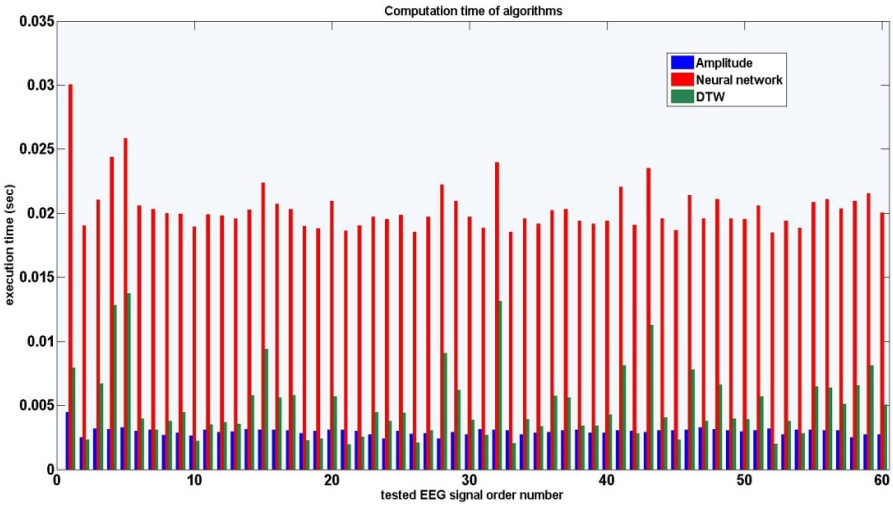

*Figure 6:*The bar diagram of computation speeds of the utilized algorithm. Sixty EEG signals have been evaluated for the useful information they contain. The height of the bars is proportional with the computation time

The Amplitude method based evaluation needs a multitude of samples to be calibrated, and is useful only for a small variety of control signals. Table 1. contains the average values relative to the execution time of the algorithms. The fastest algorithm it look likes to be the Amplitude method, the slowest the ANN method.

Table 1:

Algorithm	Amplitude	ANN	DTW
Mean-time of processing	3.0ms	20.6ms	5.1ms

Table 2:

Algorithm	Amplitude	ANN	DTW
Efficiency	41.67%	53.33%	21.67%

In real time testing, the most efficient method is the ANN (Table 2). The efficiency is goes to show that which of the methods can identify more accurately in real time, the control signal (Table 2.). Used after an adequate training session, the ANN is more accurate in identification of events of PS then the other methods. This was tested with success in real time processing of EEG signals in driving a spherical robot to follow a trajectory.

5. Conclusions

Starting from real-time analyzed EEG signals, we have realized the control of a spherical robot in its trajectory following process. The subject of this paper was only to present the control signals extraction methodology, in real time from EEG signals. Such kind of project includes a signal recording, signal processing, pattern recognition and pattern classification proceedings. Within each of this methods, different algorithms have been tested. Our main goal was to create and optimize the speed and efficiency of the procedures at each execution step. It is obvious that almost all of the procedures can be improved. One of the conclusions is that not the fastest algorithm is the most efficient. The real time control systems must be based on real time measured signals. It is necessary to find an optimal balance between speed and efficiency. This depend also on the parameters of the controlled systems (an important parameter is about slow/fast systems). Next step in this domain must be to use only hardware signal processing units in each step of the real-time based control technology [9].

Acknowledgements

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