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Brain Chess – Playing Chess using Brain Computer Interface

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ABSTRACT. The sole objective of this paper is to provide an opportunity for the physically challenged who have lost their limbs to play chess just by using their brain signals to inflict the movements in a chess game in a computer system which supports the Berlin Brain Computing Interface[1][2][3]. The user's brain signals are mapped and a distinction is made between the task related and non- task related signals using different mapping methodologies. Then these signals are stored as sample results taken from the user while they are undergoing a training period to ascertain the characteristics of his brain signals**.** During the entire game period the highly characteristic brain signals are obtained and correlated with the existing brain signal characteristics from the sample to inflict the chess moves thought by the user using the thought translation device (TTD)[5] as the connecting interface.

Keywords- BBCI, Chess, Brain Signal Mapping

1. Introduction

Brain Computer Interface (BCI) is an emerging field and a widely researched topic for several decades. The functions of the brain and the signals produced in a brain for every action which control movements of nerves and muscles originating from there, has been a major interest for scholars from variegated fields of science. Already several techniques for mapping the brain signals have been established which fall under two categories. We provide a mechanism by which we can use our brain signals to actually make moves in a computer aided chess game versus a human or a computer opponent.

2. Existing Brain Mapping Methodologies.

Present-day methodologies for mapping brain signals can be divided into five groups based on the electrophysiological signal patterns they use, rather than the terminology of dependence and independence. The types of patterns employed are as follows

2.1. Visual Evoked Potentials

The visual evoked potential (VEP) [9] is the electrical response of the brain's primary visual cortex to a visual stimulus. An example of this scheme used by a system based on VEP patterns is explained as follows.

In this system, the user faces a screen displaying 64 symbols in a 8X8 matrix and looks at the symbol he/she wants to select. Subgroups of these 64 symbols undergo a red/green check pattern alternation 40-70 times. Each symbol is included in several subgroups and the entire set of subgroups is presented several times. Each subgroup's VEP amplitude about 100 ms after the stimulus is computed and compared to a VEP template already established for the user.

2.2. Slow Cortical Potentials

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Negative or positive potential shifts in the EEG lasting over 0.5 – 10.0 s over the cortex are called slow cortical potentials (SCP's)[7]. SCP activity has been applied to control movement of an object on a computer screen and to choose a letter by using a series of two-choice selections in a word speller.

2.3. P300 Evoked Potentials

An event – related potential [5] (ERP) or (evoked response) is any electrophysiological response to an internal or external event. This event may be a sensory stimulus (visual flash or an auditory sound), a mental event (such as recognition of a specified target stimulus), or the omission of a stimulus (such as an increased time gap between stimuli).

2.4. Spontaneous Rhythmic Activity

An emerging BCI function is one which allows users to control the amplitude of their μ (8-12 Hz) or β (18-22 Hz) brain rhythmic activity over the sensor motor cortices. This is caused by Motor Imagery (i.e. imagining hand or foot movement). For MI, the users are instructed to imagine a specific motor action without any related motor output. The imagination of different movement is followed by the different power of the EEG or an effect known as event-related de/synchronization (ERD/ERS)[4] on the sensor motor cortex.

2.5. Cortical Neuron Activity

Unlike the previous patterns, the cortical neuron activity benefits from implanted electrodes. These devices are very small and are normally placed as an electrode array. By detecting the certain neural response evoked by imagined actions (imagined hand or distal arm actions), the firing patterns are transformed into a two-dimensional output signal displayed as a cursor position on a screen [6]. With these results one can use BCI to turn on lights, change TV channel, read E-mail and even draw something with a painting programme, all by moving the cursor through cognitive actions.

3. Existing Systems

3.1. Brain Pong

The simple game of Pong is revived in a new technological context. Imagination of the right hand moves the cursor to the right, imagination of the left hand pushes the cursor to the left. In this manner, the ball that is reflected from the sides of the game field can be hit by the brain racket. Thus the user can use his intentions to play "Brain Pong". [2][3]

3.2. Brain Tetris

An already existing game interface is the Tetris which is played by using the BBCI [1] (Berlin Brain Computer Interface) system. In this system the user thinks of a shape and it appears as the next move in building the blocks. It is a very intricate game where a small error can seriously spoil the course of the game.

4. Proposed System"BRAIN CHESS"

Our thought process while making a chess move consists of 4 parts

Which particular chess piece should we move?
How that particular chess piece will move? (all possible ways)
Where should we move it to? (The target)
What will happen after we move? (Consequences)

The 4th part is related more to the cognitive thinking and analytical ability of the brain. We do not focus on this part at the moment. After this we make our particular move or rather imagine that move in our brain and then move that particular chess piece. This is what we utilize to move our chess piece using BCI by the BBCI system[2][3].

4.1. Which Particular Chess Piece Should We Move?

A user in a chess game has maximum 16 chess pieces i.e. a whole set. Now what we do is that we take the user to the BCI system. The user is first sent to play a memory game.

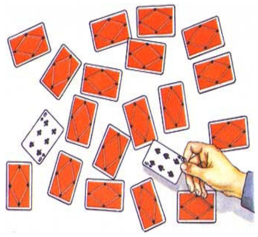

Fig. 1: Memory Game

Here all the 16 pieces are hidden. A chess piece is given from the set. All the 16 set pieces are hidden and arranged in a random order. The user is needed to remember which set piece it was and click every card to check if it was that particular set piece. Otherwise he closes the card and searches for another one. This process is repeated continuously until the final matching card with the set piece initially shown is found. During the whole process the brain signal is observed. After the initial high & low values intermittently, the average signal value is obtained. This signal value is the value assigned to the user's brain signal value for that particular chess piece. This process is repeated until the whole set piece values for every single chess piece is accounted for. This is done in the training process.

The dark curve is for the standard value during the average card viewed by the user. The lighter curve is for the card when viewed during the phase when the target card is viewed.

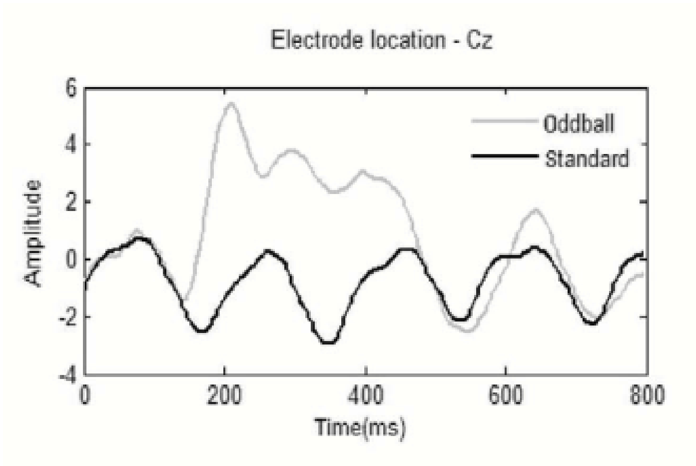

Fig. 2: Mapped Brain Signals

This average value is the signal of the brain for the set piece queen in this example.

There is a fluctuation in the value when we click on other cards and we have a visual perception of those set pieces. After that we return to our visual perception of the queen chess piece. Here, at the initial stage, when the queen is shown and the final value when the queen card is found, the signals of these time intervals are recorded to find the average value of the user's brain signal for the queen's visual evoked potential.

We use the P300[5] visually invoked potential as an input to the BCI [1] to detect the deflection in the EEG signal.

We can use this positive deflection to compute the difference in deflection. The positive deflection is observed when the target is found and the deviation from the standard average signal value is recorded. We can assign this deflection value to that particular chess piece as an additional training input value where there is a discrepancy in the initial value which we have already assigned to that chess piece. This acts as a secondary chess piece recognition value. The same process is carried out for all the 16 different chess pieces and their respective primary and secondary recognition brain signal amplitude values are recorded in the database.

4.2. How that Particular Chess Piece will Move?

Here we take examples of a few chess pieces and record the input of brain signals as to how the user imagines the sensory movement using his hand to move a chess piece from one place to another.

4.2.1. Sensorimotor Rhythms

Sensorimotor rhythms [10] include an arch shaped μ-rhythm, with a frequency of 10 Hz (range 8-11 Hz), often mixed with a β (around 20 Hz) and a □ component (around 40 Hz) recorded over somatosensory cortices most preferably over C3 and C4 electrodes in the BBCI interface cortical electrodes.

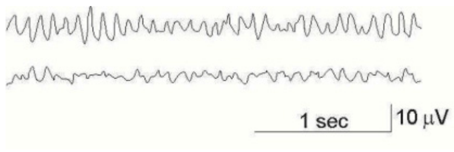

Fig.3: Upper trace: μ-rhythm over sensory motor areas.

Lower trace: de-synchronization of μ-rhythm through movement imagery

The upper trace is the signal while a sensorimotor is used for a thought process. The lower trace is when de-synchronization of that signal takes place when the thought goes away and the brain thinks of another thought or is at rest.

4.2.2. Using SMR as input for BCI

After obtaining the brain amplitude, we shortlist the one which is selected from the positive deflection of the EEG signal using the visual evoked potentials described earlier.

Now let us look at some sample chess pieces and the results of the amplitude of the user's brain signals during the training period for the data set using the 1-D and 2-D variations in the amplitude signals obtained in the Sensory Motor Rhythm Signals(SMR)[6] .

4.2.3. PAWN

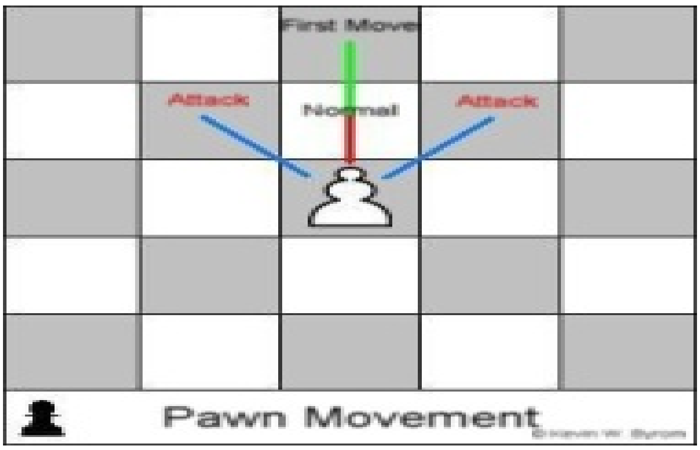

Fig. 4: Moves for a Pawn

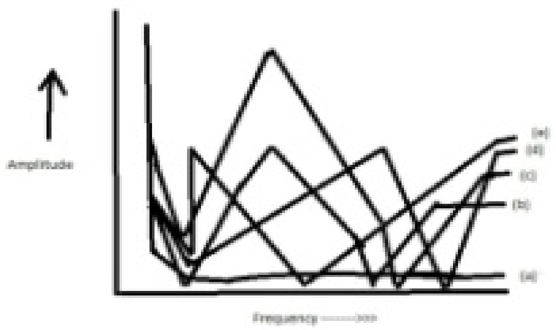

Fig. 5: Mapped Amplitudes

These 5 signals **a,b,c,d,e** are the ones observed when the users on an average think about

a) initially when pawn is at rest
b) pawn moves one position in the front to the next block
c) pawn moves two steps front
d) pawn goes diagonally right 1 block, cutting existing opponent chess piece
e) similar move but in the left

4.3. Where should we move it to? (The target location)

4.3.1. The Queen

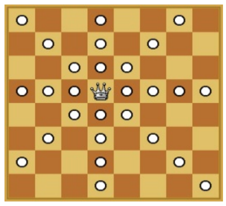

Fig. 6: Moves for Queen on the Board

These are the possible moving locations for a queen. But a queen need not necessarily move only one box at a time. It could move several boxes. At this point we take another sample test for calculating the target box from the chessboard. It is similar to the target alphabet identifier game[9].

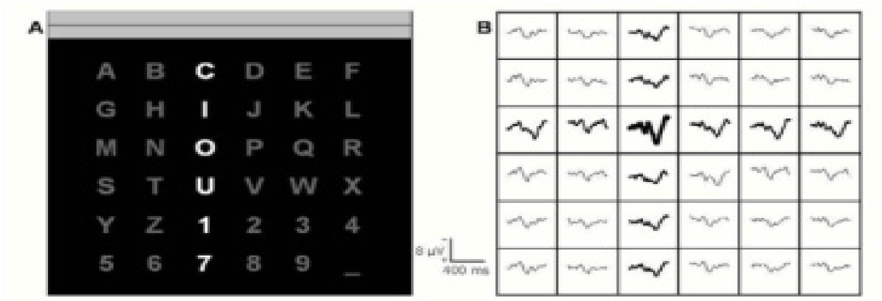

Fig. 7: Target Alphabet Identifier Game

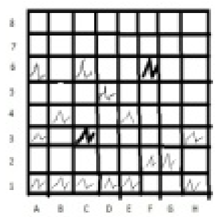

Fig. 8: Wave Patterns Observed

From this wave pattern we know which block does the user want to move his chess piece to and the BCI system makes the move. Here initially the chess piece is at position at the C3 electrode and the user is planning to move it to the position F6 (a particular chess move). The other smaller signals are for the rest of the positions in the chess board.

5. BCI Software

The Thought – Translation Device (TTD) [7] was first designed to train completely paralysed patients to self-regulate their SCPs to enable verbal communication. The hardware of the device consists of an EEG amplifier, which is connected to a PC equipped with two monitors, one for the operator to supervise the BCI training by giving inputs and the other for receiving outputs. We dwelve on the same TTD for utilization of the ‘Brain Chess Interface’.

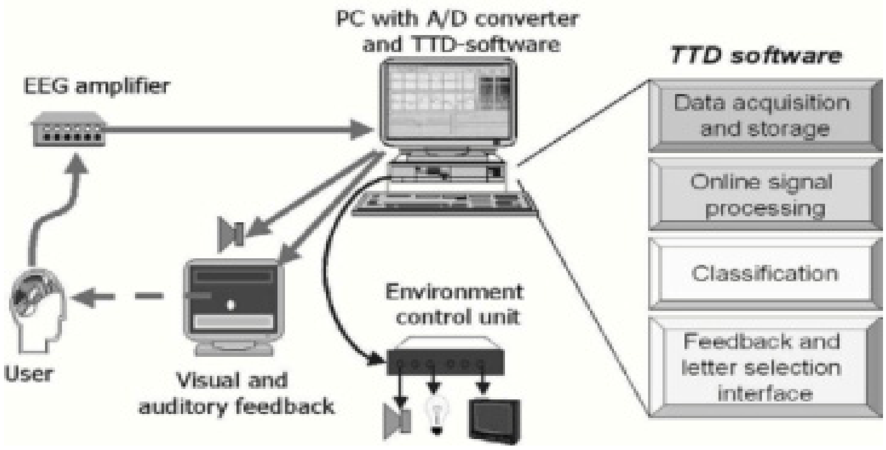

Fig. 9: Thought Translation Device

Signal Detection

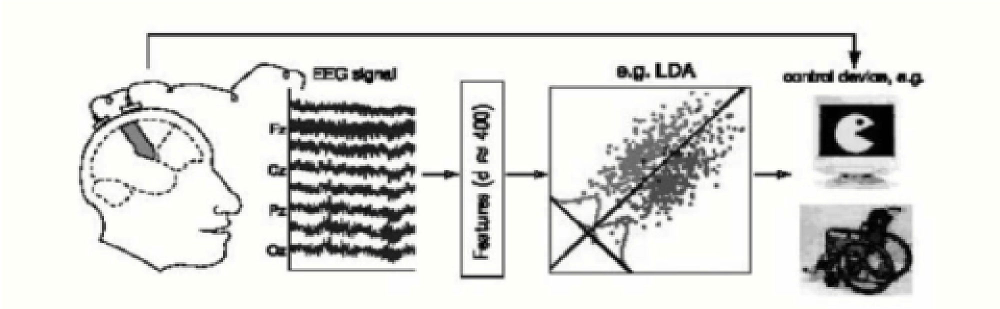

Fig. 10: Signal Detection

We have to differentiate our brain’s signals and detect the useful task related signals and non-task related signals. The following method was employed to find out the same.

6. Cross-Correlation Template Matching

Initially, a cross-correlation template matching (CCTM)[11] method for signal detection is used. For CCTM, we compute an ERP template using triggered averaging of the training data. Normalized cross-correlation between an ERP [4] template with the ECoG[6] of the test data forms the decision feature. A significant portion of the ERP template energy occurs after the trigger, the CCTM method typically uses templates that extend well after the trigger. The CCTM approach is equivalent to a likelihood ratio test under a simple two-hypothesis statistical detection model. Let x denote one block of say 2 s of ECoG data and suppose that x arises from one of the following pair of hypothesis.

H_0 : x ~ Normal $(0,\sigma^2 I)$ “rest”

H_1 : x ~ Normal $(\mu,\sigma^2 I)$ “task/event”

Where μ denotes the ERP template, σ^2 is the noise variance assuming white noise and I denotes the identity matrix. For this model, the Neyman- Pearson optimal detector[8], formed from the likelihood ratio, is the inner product $x'\mu$. In practice, we must choose between rest & task not just once, but at each time point, so we slide the signal block x along the ECoG data, applying the template to each block. The resulting decision feature is the output of the CCTM method.

6.1. The Two – Covariance Signal Model

6.1.1. Quadratic Detector

The "White Noise" signal model[3] underlying CCTM ignores event-related changes in the signal power spectrum. As an alternative to the one that accounts for power spectrum changes, we have developed a quadratic detector based on a two-covariance signal model. We assume that each ECoG signal block x arises from one of the following two classes.

$$H_0 : x \sim \text{Normal } (0,K_0) \text{ "rest"} \quad [1.1]$$

$$H_1 : x \sim \text{Normal } (0,K_1) \text{ "task/event"} \quad [1.2]$$

Where k_0 and k_1 are signal covariance matrices in the rest state and task state. We ignore the ERP component μ for simplicity. By the Neyman-Pearson lemma the most powerful test for such a detection problem is given by the likelihood ratio. The likelihood ratio for the following quadratic form- $\hat{}\,(x) = x'(k_0^{-1} - k_1^{-1})\,x$

6.2. Training Period

The covariance matrices k_0 and k_1 are unknown a priori, so one must estimate them from training data. If the length of the signal block is say, 100 samples, corresponding to 0.55 of ECoG (ElectroCorticalography) data[7] , then each covariance matrix is 100x100 – too many parameters to estimate from limited training data. Therefore we assume a p^{th} order autoregressive (AR) parametric model [8] for the signal power spectrum as follows-

$$X[n] = - \Sigma^{p}_{m=1} a_q\ [m]x[n-m]+\mu[n] \quad [1.3]$$

Where n is the sample index, the square brackets [n] denote discrete time signals and n>p,q=0,1(each hypo) and

$$\mu[n] \sim \text{Normal } (0,\sigma^2{}_q) \quad [1.4]$$

We assume that the $\mu[n]$ are independent and identically distributed. Based on the past work, we use p=6, although this has not been optimized. Thus for a 6^{th} order AR model, we must estimate 6 AR coefficients (a_q [m]) and a driving noise variance $\sigma^2{}_q$ for each of the two signal states and for a total of 14 unknown parameters. If each ECoG training data sample point were labelled as coming from a 'rest' or 'task' state, then it would be straightforward to find the maximum- likelihood (ML) estimates of the AR coefficients and driving noise variances using the Yule-Walker equations. However, our ECoG experiments are unprompted with subjects performing self-paced tasks and our data is labelled by EMG[1] (Electromyography) onset at only a single time instant per event. This incomplete labelling complicates the training process. To label our training data for the purposes of estimating the AR model parameters, we must estimate which ECoG samples correspond to which state. We assume that the brain is in the 'task state' before and after each EMG signal trigger. We parameterize these task–state intervals using a variable ω that describes the width of the task interval around each EMG trigger and a variable c that describes the location of centre of each task-state interval relative to each EMG trigger time point. We assume that the remainder of the training data belongs to the "rest" state. With this model we construct a joint probability density function for training data by adopting the procedure in Kay(1988)

$\log p\ (x_1,k,x_0,k,\ ;\ a_1,\sigma_1{}^2,\ a_0,\ \sigma_0{}^2,\ c,\ \omega)$

$$= - 1/2\sigma_1{}^2\ \Sigma_{k=1}{}^{k-1}\ \Sigma_{n=p+1}{}^{\mu}{}_{1,k}{}^{(c,\omega)} - 1/2\sigma_0{}^2\ \Sigma_{k=1}{}^{k}\ \Sigma_{n=p+1}{}^{\mu}{}_{0,k}{}^{(c,\omega)}$$

$$\mu_0{}^2,\ k[n+c,\omega] - 1/2\sigma_1{}^2\ \Sigma_{k=1}{}^{k-1}\ \Sigma_{n=p+1}{}^{\mu}{}_{1,k}{}^{(c,\omega)}\ . \quad [1.5]$$

Where μ_q , k (c,ω) denotes the no of samples in the k^{th} block under the hypothesis q and x_q,k[n;c,ω] indicates the n^{th} data sample in the k^{th} data block under hypothesis q. By construction $N_{1,}k\ (c,\omega) = \omega$ for q=0,1.

$$\mu_{\ q,k}\,[n,c,w] = x_{\ q,k}\,[n;c,w] + \Sigma_{m=1}{}^{p}\ a_q\ [m]\ x_q\,,\ k[n-m;\ c,w] \quad [1.6]$$

The approximation in the above equation is reasonable when $\mu_{q,k}\,(c,\omega)$ is large relative to p. Based on this model, we use a joint μ_L estimation procedure to estimate simultaneously the AR parameters and the centre c and width ω of the task-state interval as follows.

$$e(c,w) = \arg\max\max c, w\ a1,\sigma_1{}^2, a_0, \sigma_0{}^2 \log Pv(x_1,k,x_0,k,a_1,\sigma_1{}^2,a_0,\sigma_0{}^2, c, w) \quad [1.7]$$

This joint labelling and training procedure requires an iterative search over the centre c and width ω parameters (outer maximization). This inner maximization has a simple analytical solution based on modified Yule – Walker equations to find the AR parameters.

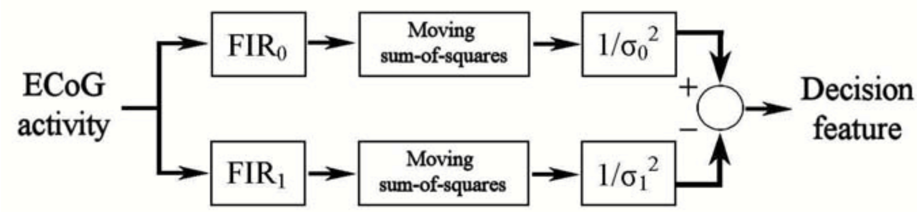

Fig. 11: Quadratic Detector Implementation

The figure above indicates the model for the Quadratic Detector implementation [12] where FIR indicates the finite impulse response filter for each model.

6.3. Quadratic Detector Implementation

Implementing the quadratic detector directly would be inefficient due to the large matrix sizes. Fortunately for AR signal models, one can implement [1.7] using simple FIR filters.

$\hat{}(x) = \hat{}_0 (x) - \hat{}_1 (x)$ Where

$$\hat{}q(x) = 1/\sigma_q{}^2\, \Sigma_{n=p+1}{}^N\, \mu_q [n]^2 , q=0,1 \quad [1.8]$$

Where N denotes the no of samples in a signal block and the innovation signals are defined by

$$\mu_q [n] = x[n] + \Sigma_{m=1}{}^p\, a_q [m]\, x [n-m] \quad [1.9]$$

The block diagram summarizes the implementation of the quadratic detector. The ECoG signal is passed through two FIR filters, each the inverse of the corresponding AR model. Then a moving sum-of-squares computes the power of the innovation signal, which is normalized by the ML estimates of the driving variances.It illustrates how the variances of the innovations process work as a decision feature by plotting individually the normalized innovation variances. $\hat{}_0(x)$ (“rest class”) and $\hat{}_1 (x)$ (“event class”). The signal power spectrum becomes that of the event class near the trigger point. So the event-class innovations variance decreases whereas the rest-class innovations variance increases leading to a large decision feature value.

7. Conclusion

We have theorized a possible way of mapping the brain signals and identifying the useful task related signals and then utilizing those signals to inflict a move on the chess board. As illustrated, chess moves are executed with accuracy through the Berlin Brain Computer interface by employing the process explained in the paper.

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