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Sub-Band-Power-Based Efficient Brain Computer Interface for Wheelchair Control

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Abstract An efficient Brain Computer Interface (BCI) is designed and implemented to allow disabled people to control the motion of wheelchairs. It uses a compact portable EEG sensor to capture 14 brain signals and wirelessly feed them to the PC. Four classes of motions are used: Forward, Backward, Left, and Right. The signals are obtained in a free-style manner without compelling users to perform pre-defined mental operations. This led to variations in the results that shed some light on the cognitive aspect of the problem. Principal Component Analysis (PCA) and Sub-Band Powers obtained from the Wavelet Transform are used to reduce the signal dimensionality from nearly 14000 to only 3. A Feed-Forward Neural Network with Back Propagation is used as a classifier. The average classification rate is 91 % on the overall and as high as 97.5 % for some users. The effect of mother wavelet type and user dependence are also investigated.

Keywords Brain Computer Interface, EEG, Wavelet Transform, PCA, Neural Network

1. Introduction

Recent advances in technology have made it possible for severely handicapped people to act on their surrounding environment without the normal muscle and nerves pathways. Brain Computer Interface (BCI) systems make it possible for such disabled people to activate devices such as wheelchairs merely by their thoughts. BCI systems rely on the weak Electroencephalogram (EEG) signals that were first recorded by Berger in 1924[1]. These are generated at the surface of the scull as a result of the neural activity and are picked up by appropriately placed non-invasive electrodes. Since its first introduction by Vidal in 1973[2], BCI has received considerable attention over the last two decades [3-8]. Numerous research efforts have been deployed in an attempt to translate intentions and thoughts into real actions.

Some of this work used the effect of facial gestures on EEG signals as a communication means with the outside world[9-11]. While such approaches may work with some users, they may not be acceptable for severely disabled people. In the context of our work, we are interested in BCI systems that rely on mere thoughts without any artifacts.

BCI systems have been used in several applications such as cursor control[12], spelling and teletyping[13], answering questions[14], and composing music[15]. An important application of BCI is to assist severely disabled people in controlling the motion of wheelchairs as this offers them valuable autonomous mobility[16-22]. In such systems, the users are usually required to perform one of several mental tasks such as movement imagination, geometric figure visualization, arithmetic operations, etc. These mental tasks are mapped into the various wheelchair motions directions. Classification is carried out in the usual way of extracting features form the EEG signals and then applying one of several classifiers to the feature vector. While some researchers used a time-series prediction approach and derived the features from the power of the predicted EEG signals[23], most others resorted to the wavelet transform [24-28]. The coefficients of the details resulting from the wavelet transform are used as features. The justification for using the wavelet transform is that it leads to a sub-band decomposition of the signal in hand. This naturally matches the fact that EEG signals are divided into five frequency bands that take on different power levels depending on the mental state. This is shown in Table 1.

Table 1. EEG Frequency Bands

Band	Frequency Range (Hz)	Voltage Level (μV)	Corresponding Brain Activity
Delta	0.5 – 4	20 – 200	Sleeping
Theta	4 – 7	< 20	Dreaming; Meditation
Alpha	8 – 13	30 – 50	Relaxation
Beta	13- 36	5 – 10	Problem solving
Gamma	above 36	5 – 10	Conscious Perception

Several classifiers were used by researchers such as Linear Discriminants (LD)[23], Bayesian[29], Hidden Markov Model (HMM)[30], Support Vector Machine (SVM)[31], and Neural Networks[19, 32,33].

The more recent work on BCI for wheelchair includes that

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of Lin and Yang[20]. The eye blinking artifact is not removed but utilized to control the motion of the wheelchair. Carlson and Millan[21] use motor imagery to feed a Gaussian classifier. Fattouh et. al.[22] use the Affectiv™ Suite of Emotiv to detect emotion changes in order to control the wheelchair.

The most related work to ours is that of Vijay Khare et. al.[19]. They reported a real time BCI system that uses 8 brain sensors from a medical stationary EEG sensor. They used the Wavelet Packet Transform along with a Radial Basis Function Neural Network (RBFNN). Their feature vector uses 21 detail coefficients. They reported a perfect classification rate[19].

In this work, we designed, implemented, and tested an efficient BCI system for wheelchair control. Even though our work carries some similarities with that of Khare et. al., it differs with the following contributions:

- We allow users to record their thoughts in a free-style manner without having to perform any given mental exercises that not all may be able to go through. Instead, each user is given the freedom to imagine the four motions of the wheel chair in an independent way. Even though this has made the recorded EEG signals less clustered hence harder to classify, it simplified the system use. In addition, it led to interesting variations in the results that shed some light on people's perception of directions amongst other things.
- A considerable simulation and testing effort was deployed to investigate the issue of feature selection. Inspired by the effect of mental state on the EEG sub-frequency bands powers, we used the average power of the details coefficients (corresponding to sub-band powers in the EEG signal), as features. We were able to reduce the signal dimensionality to only 3, resulting in a considerable speed-up of the BCI system training and testing time.
- Our BCI system is compact and portable thanks to its wireless light weight headset. This allows maximum mobility for the users.

The remainder of this paper is organized as follows. In section 2, we summarize the details of the signal measurement and data collection. In section 3, we provide the details of the overall BCI system, including the signal processing, feature selection, and input classification. In section 4, we summarize the performance assessment of our BCI system. A brief discussion of the mother wavelet effect, user dependence, and some cognitive aspects of the problem are also provided. Finally, in Section 5, we summarize and conclude our work.

2. Data Collection

The BCI implemented in this work uses the portable wireless headset from *Emotiv*[34]. It has a total of 16 sensors, 2 reference signals and 14 channels: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. The sensors are applied to the scull surface using a saline solution and follow the 10-20 international standard. Nick-named "EPOC", the headset uses a 128 Hz sampling rate with a 14 bit A/D resolution. It has a built-in fifth order sinc filter that cuts frequencies above 64 Hz. In addition, two notch filters suppress the 50/60 Hz interferences caused by the power lines. The EPOC has a 12-hr battery life and weighs around 7 Ounces. It comes in different packages including the Cognitiv™ Suite and Affectiv™ Suite that provide ready packages for EEG analysis without direct access to the EEG signals. In our work, we used the more expensive Development Kit that allowed us to store and handle the EEG signals. Figs. 1-3 respectively show the headset, its sensor locations, and a sample of the picked-up signals. All channels are wirelessly transmitted to a USB module in the PC via a proprietary encoding/modulation on a 2.4GHz carrier.

Figure 1. Emotiv Headset[35]

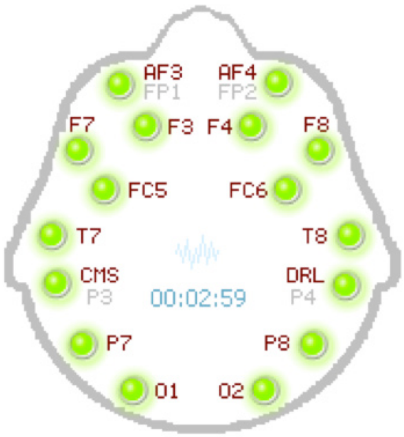

Figure 2. Emotiv Headset sensor location[36]

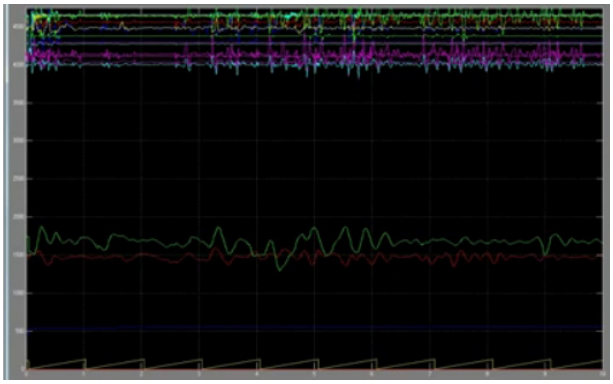

Figure 3. Sample of measured EEG signals

It is known that various artifacts such as facial movements and eye blinks result in large spikes in the EEG signals. For example, Fig 4 shows the picked-up EEG signals with three eye blinks at the end.

In order to limit the operation of our BCI system to brain thoughts only, we recorded all data without any such artifacts by asking the users not to make any facial gestures including eye blinks. Three volunteers participated in the data collection: User1 is a female student (age 23, left-handed), User2 is another female student (age 23, right-handed), and User3 is a male adult (age 50, right-handed). All subjects were normal in the sense they had no disability. The intent was to collect data from some handicapped people, but this was not possible at the time of preparation of this initial work. Each subject recorded a total of 100 samples for each of the four motions: Forward, Backward, Right, and Left. The recording was carried out at different time intervals and mental conditions. Each recording was about eight-seconds-long during which the user is asked to relax with eyes open and think of one of the four directions. Ten of the 100 recordings were used for testing purposes and the remaining 90 for training the classifier.

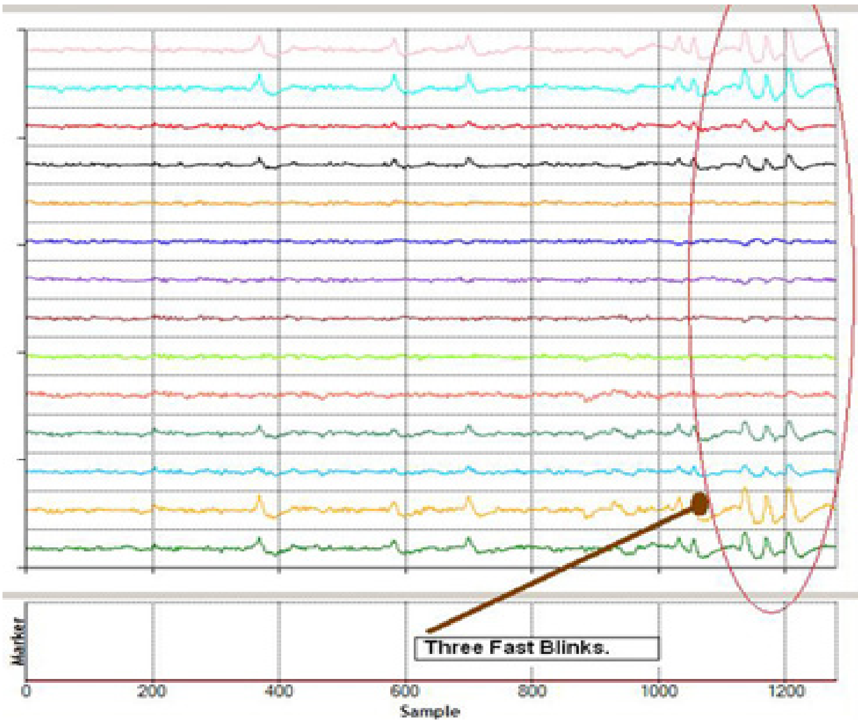

Figure 4. EEG signal with three fast eye blinks[37]

3. BCI System

The proposed BCI system is shown in Fig. 5.

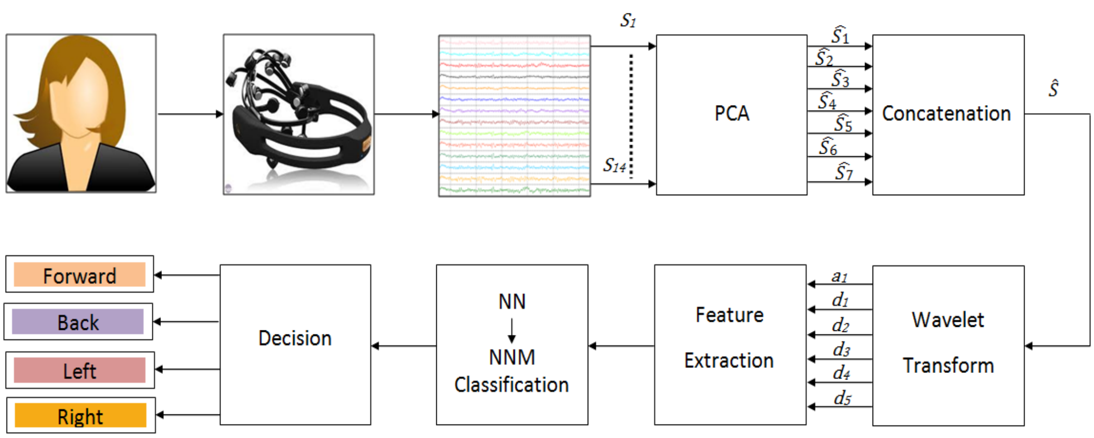

Figure 5. Overall BCI System

Based on previous reports[19], it was clear that 14 sensors were more than needed for this problem. Hence, the first intent was to reduce the redundancy in the EEG signals. PCA was used for this purpose. Each measurement was organized in a matrix of size 14 by 999. Let $\mathbf{X_{ik}}$ be such a matrix corresponding to measurement "i" (i = 1,…90) of class "k" (k = 1,…4). After making $\mathbf{X_{ik}}$ zero mean, The 14 by 14 covariance matrix $\mathbf{C_k}$ of class "k" is obtained by

$$\boldsymbol{C}_k = \boldsymbol{E}\{\boldsymbol{X}_{ik}\, \boldsymbol{X}_{ik}^T\} \tag{1}$$

Where "T" denotes the transpose operations and the expected value is carried out by averaging over the 90 measurements. Next, an Eigen analysis is performed on $\mathbf{C_k}$ to yield

$$\boldsymbol{C}_k = \boldsymbol{P}_k^T \boldsymbol{\Lambda}_k \boldsymbol{P}_k \tag{2}$$

Where the 14 by 14 unitarian matrix $\boldsymbol{P}_k$ is made up of the fourteen eigenvectors as its rows, and $\boldsymbol{\Lambda}_k$ is a diagonal matrix made up of the 14 eigenvalues (all non negative) arranged in descending order of magnitude.

The data redundancy is removed by keeping only the "m" largest eigenvalues and neglecting the smaller ones along with their eigenvectors. Let $\boldsymbol{P}_k^m$ denote the "m" by 14 reduced eigenvector matrix obtained by keeping the "m" eigenvectors (rows) corresponding to the largest "m" eignvalues. The reduced data matrix $\boldsymbol{X}_{ik}^m$ of size "m" by 999 is obtained by

$$\boldsymbol{X}_{ik}^m = \boldsymbol{P}_k^m \boldsymbol{X}_{ik} \tag{3}$$

The choice of "m" is rather subjective. Fig. 6 shows the mean squared error between $\boldsymbol{X}_{\mathbf{ik}}$ and $\boldsymbol{X}_{ik}^m$ averaged over all classes and measurements for various values of m.

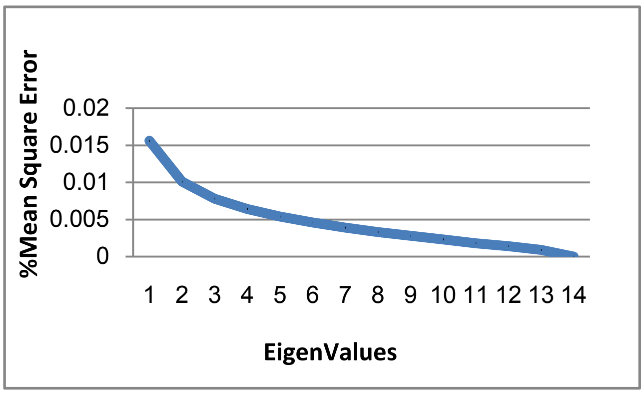

Figure 6. Mean squared error between $\mathbf{X_{ik}}$ and $\boldsymbol{X}_{ik}^m$ versus the number of "m" largest eigenvalues taken

It can be seen from Fig. 6 that keeping the 6 or 7 largest eigenvalues is a good compromise between reducing the problem dimensionality and loss of data. A rough initial classification using the K Nearest Neighbours (KNN) showed that after the 7th eigenvlue, little effect on the performance is obtained. Hence, it was decided to reduce the problem dimensionality to 999 by 7 only. This is equivalent to saying that 7 of the 14 signals picked-up may be omitted without considerable loss of performance. This is in agreement with the previous results that use only an eight-signal EEG system[19].

Next, the reduced EEG signal is concatenated into a 999*7 vector onto which a wavelet transform is applied. In an effort to find a closer matching wavelet to the EEG signal in hand, different types of mother wavelets have been tested. A five-level decomposition is used leading to details d1-d5 and approximation a5. These five levels conveniently map to the 5 frequency sub-bands of EEG signals shown in Table 1. Taking into account the sampling rate of 128 Hz, this important mapping is shown in Table 2 below.

It is known that the Beta band is the most dominant during problem solving. Hence, we expect that "d2" to be the focus of the feature vector as it contains the most discriminatory information for this current application. Since the users record the data in a meditation-like session, we also expect the Alpha and Theta (corresponding to d3 and d4 respectively) to be of importance. This observation shall be validated by the experimental testing in the next section.

Table 2. EEG sub-bands and corresponding wavelet coefficients

Wavelet Coefficients	Frequency Range (Hz)	Corresponding EEG Band
d1	32 –64	Gamma
d2	16 – 32	Beta
d3	8 – 16	Alpha
d4	4 – 8	Theta
d5	2 – 4	Upper Delta
a5	0 – 2	Lower Delta

Previous approaches use the coefficients of the wavelet transform as features. For example Vijay Khare et. al. use 21 of the wavelet coefficients as input to the NN classifier. In our work, the average power in each sub-band (the mean of the squared terms of a1 and d1-d5) is calculated and used as a feature candidate. This is motivated by the argument stated above related to the variations of the power in the EEG sub-bands due to various mental states. As shall be shown in the next section, extensive testing narrowed down the feature vector to size 3, resulting in a considerable speedup of the BCI system's training and testing. Finally, using National Instrument's data card, the decision of the classifier is output as one of four bits (using the USB as a virtual parallel port of the laptop PC). Hence, our BCI system provides direct switching to the wheelchair motors via relays. For testing purposes, we connect the four bits to four LEDs.

4. Results

In order to find an optimum feature vector, we performed an extensive testing using the average powers of the details and approximation of the wavelet transform. In this we were guided by the a-priori expectations that d2 should be our focus. Table 3 shows the overall classification results for different feature vector sizes using dB5 as mother wavelet.

The three-point vector made up of the average powers of d2, d3, and d4 led to the best overall classification rate, hence shall be used in what follows. This corresponds to the average powers of the beta, alpha, and delta bands.

Table 3. Feature Vector Size Effect on Classification Rate

Feature Vector Size	Features	Classification Rate (%)
6	a5; d1-d5	86
4	d2-d5	82.5
3	d2-d4	91
3	d1-d3	85
2	d1-d2	82.5
2	d2-d3	81
1	d2	66.7

It is a fact that the degree of correlation between the wavelet and the signal in hand has an effect on the decomposition coefficients. Hence, our BCI system was tested using different types of mother wavelets. The results are summarized in Fig. 7. Even though the effect of the wavelet type was not very pronounced, dB5 seemed to lead to the best results hence was adopted in all the subsequent testing. Fig. 8 summarizes the overall classification rate for the four directions. It can be observed that the Forward direction is the most favorable. This observation was consistent in all the testing we performed. With the human senses naturally geared forward, it is expected that people tend to perceive the forward direction easiest. In addition, it may be favored because it is generally related to an optimistic and progressive perception of life events.

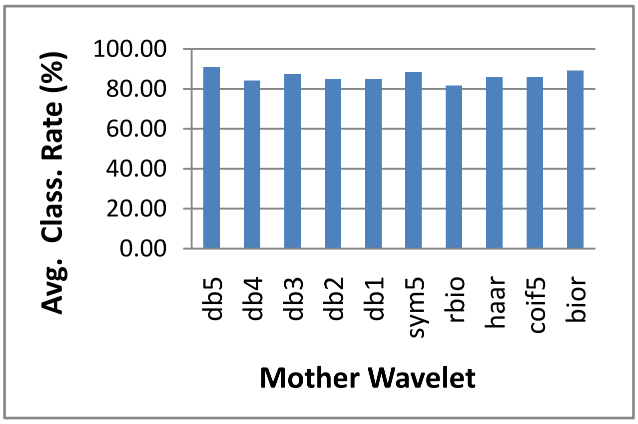

Figure 7. Effect of the Wavelet type on the classification rate

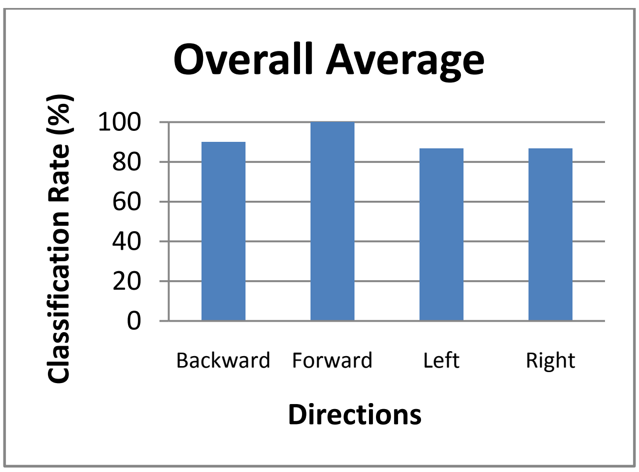

Figure 8. Overall Classification Rate Using dB5

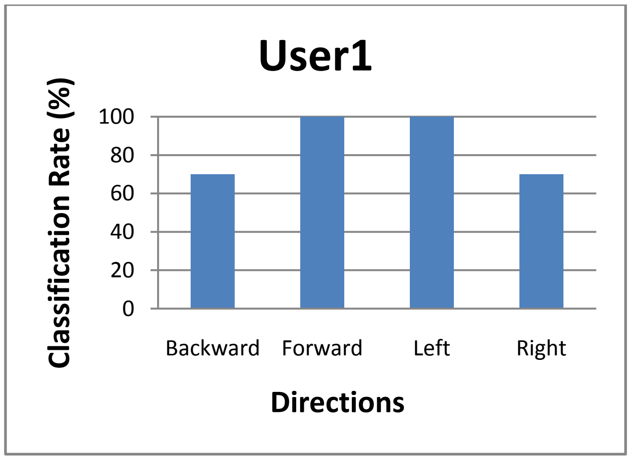

Figure 9. Classification Rate Using dB5 Wavelet for User1

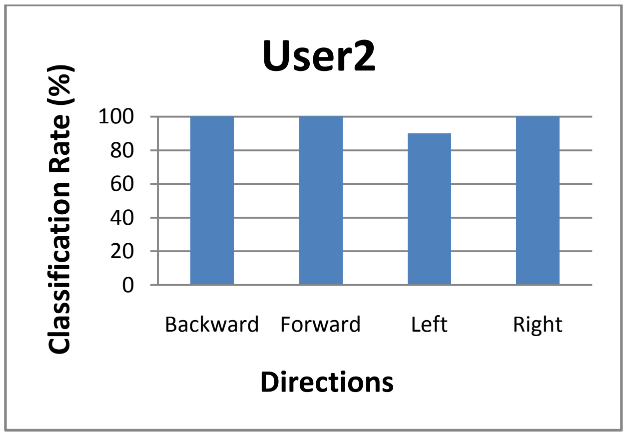

Figure 10. Classification Rate Using dB5 Wavelet for User2

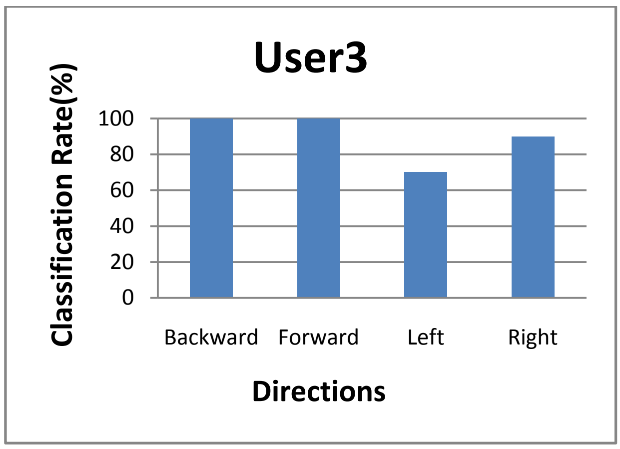

Figure 11. Classification Rate Using dB5 Wavelet for User3

Due to the free-style data collection in our work, we left the users with the freedom to perceive the four directions in their own ways. This had two implications. First, we expected the performance to vary from one user to another. Figs. 9-11 depict the classification rate for each user. As can be seen, user 2 seems to have the most "consistent" way of perceiving the four directions and led to the highest classification rate of 97.5%, while it is 85% and 90% for users 2 and 3 respectively. User1 (left-handed) perfectly classified the “Left” class but made some errors with “Right”, while Users 2&3 (right-handed) showed an opposite behavior. Again, this observation was consistent throughout all the tests we performed (with different mother wavelets and different feature vector size).

Second, we expected the system to be heavily user-dependent. To verify this, we used the data of user2 as training and tested the system with data from users 1&2. The classification rate results are shown in Table 4. Except for the Forward direction, all other directions performed quite poorly. Interestingly, this also seems to indicate that the Forward direction is not only the most favorable amongst people, but also that they tend to perceive it in a simlar manner.

Table 4. Classification rate (in %) when the system is trained on User2 and tested with Users 1&3

	Backward	Forward	Left	Right
User1	0	99	37	11
User2	0	68	2	7

5. Conclusions

An efficient and portable Brain Computer Interface (BCI) was designed, built, and tested to assist disabled people in controlling wheelchairs. The *Emotiv*[31] portable wireless headset was used to pickup 14 EEG signals off users’ scalps. Three volunteers (User1 a left-handed female of age 23, User2 a right-handed female of age 23, and User3 a right-handed male of age 50) helped to collect the needed EEG data. Four classes were used: Forward, Backward, Left, and Right. The EEG data was recorded in a free-style manner without compelling the users to perform various mental operations that are mapped to the motion directions. This has caused the signals to be less clustered hence harder to classify. On the other hand, it simplified the system use and resulted in anticipated variations that shed light on some cognitive aspects of the problem. It also allowed us to more genuinely test the user dependence of our BCI system.

Principle Component Analysis (PCA) was used to reduce the signal redundancy and keep only seven of the fourteen EEG signals. The wavelet transform with a five-level decomposition was applied to the concatenated 7 signals. Several types of mother wavelet were tested. The dB5 wavelet led to best classification rates. The average powers of the details d1-d5 and approximation a5 (corresponding to the average powers of the EEG sub-frequency bands) were investigated as possible feature vector components. This is justified by the fact EEG sub-frequency bands exhibit different power levels under different mental states. The beta band is known to be most prominent during problem solving. Extensive testing showed that, as expected, d2 (corresponding to the Beta EEG band) is the most important detail level along with the alpha and delta bands. This may be explained by the fact that data recording was done in a meditation-type manner. Hence, the dimension of our problem was considerably reduced from nearly 14000 to only, leading to a much efficient training and testing of the BCI system. The overall average classification rate is 91% and ranges between 85 and 97.5%.

The free-style data collection in our work resulted in variations in the results as well as a heavy user-dependency. Despite the different consistency levels in perceiving the four directions, all users systematically performed best with the “Forward” direction. With the human senses naturally geared forward, it is expected that people tend to perceive the forward direction easiest. In addition, it may be favored because it is generally related to an optimistic and progressive perception of life events. In another expected variation, User1 (left-handed) perfectly classified the “Left” class but made some errors with “Right”, while Users 2&3 (right-handed) showed an opposite behavior.

The user dependency of our BCI system was demonstrated when it was cross tested with inputs from other non-training users. All directions were very poorly classified except for the “Forward” . Interestingly, this also seems to suggest that the forward direction is not only the most favorable amongst people, but also that they tend to perceive it in a very close manner.

The results of the classifier are output as four bits through the USB port of a laptop PC (emulated as a virtual parallel port) using National Instrument’s data card. Hence, our BCI system provides direct switching to the wheelchair motors via relays. For a quick testing, we connected the four bits to four LEDs.

We are currently working to extend the initial results of this work by testing other classifiers, enabling the system to operate in real-time, and using data from disabled people.

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