Design Considerations for a Brain-Controlled Wheelchair

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***Abstract*— In this project, a design for a non-invasive (EEG-based) brain-controlled wheelchair has been developed for use by completely paralyzed patients. The proposed design includes a novel approach for selection of optimal electrode positions, a series of signal processing algorithms and an interface to a powered wheelchair. In addition, a 3D virtual environment has been implemented for training, evaluating and testing the system prior to establishing the wheelchair interface. Simulation of a virtual scenario replicating the real world gives subjects an opportunity to become familiar with operating the device prior to engaging a wheelchair.**

Optimal electrode positions for largest differentiation between classes have been identified using an analysis of contribution to common spatial patterns. For the signal processing, common spatial patterns have further been identified as the best method for feature extraction of raw brain signals. Likewise, support vector machines with a radial basis function kernel have been shown to classify processed data most accurately. A modular wheelchair controller has been identified as a suitable interface device for connecting the classified brain signals to the four directions of forward, backward, left and right.

I. Introduction

In certain cases of Tetraplegia and with those experiencing Amyotrophic lateral sclerosis, muscle movement of any form has discontinued within the body, despite the subject being fully conscious and aware of his or her surroundings. Recent advancements in brain-computer interfacing (BCI) have presented new opportunities for development of a new wheelchair interface for such patients based on thought.

Some unique techniques for the adaption of BCI technology for a brain-controlled wheelchair (BCW) to assist a wide range of people in regaining the basics of mobility have been presented here.

Structurally, four stages exist in the design of the proposed wheelchair (Fig. 1). The first is a method for extracting the raw brain waves. The second deals with processing these signals and classifying them into different control thoughts/actions. The third stage deals with the connection of the action output to the wheelchair via an interface and the fourth concerns the powered wheelchair. In addition, testing and evaluating the performance of the constructed system, especially with regard to safety, is an essential part of the development process.

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II. Brain Signals

At times, the brain produces discriminable signal patterns from which control cues can be taken for appropriately moving the wheelchair. Beside frequency bandwidths often attributed to different levels of wakefulness, BCI research has examined uniquely identified voluntary features that emanate from the higher brain areas including slow cortical potentials, movement-related potentials and the P300 event-related potential, as well as effects from imagined movements and imagined actions.

In this research, we exploit sensorimotor rhythms (SMR) as control signals for wheelchair operation. These signals are generated in sensory and motor cortical regions in association with both real and imagined movement of the limbs and other body parts [1].

An appropriate BCW will need the ability to control each direction of movement and thus ideally requires at least 4 control signals (or classes). Although classification accuracy drops with an increase in number of selected classes [2], we have observed that use of 4 classes still provides sufficient accuracy and we present later some results illustrating this.

Increased discrimination of motor signals from the brain can be best achieved by maximizing the spatial separation of the cortical source for each signal. Thus the SMRs used in the current project are generated by imagined movement of left hand, right hand, either foot, and tongue.

III. EEG Equipment

There are various medical technologies that are either suited for or have been designed for monitoring or extracting brain signals. These include functional magnetic resonance imaging, near infrared spectroscopy or magnetoencephalography. There are also invasive methods that involve surgical risk. The electroencephalogram (EEG) is an ideal candidate for the BCW as it is small, non-invasive, safe, commercially available, comparatively inexpensive, and has superior temporal resolution.

The equipment available to this project is a 16-channel 24-bit portable EEG amplifier [3]. Previous work [4] has reported that performance correlates with the number of EEG channels used. However, high-resolution EEG (>32 channels) is impractical for a BCW device given constraints of size, cost, and user comfort. It is our experience that the performance loss incurred by a smaller EEG montage can be largely mitigated by applying high-performance signal processing and classification algorithms and by optimal electrode placement.

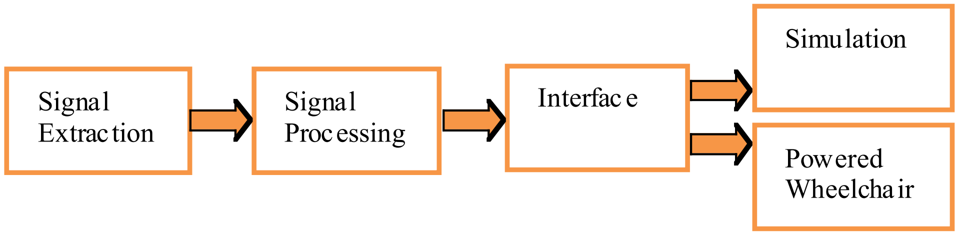

Fig. 1. Block diagram of a brain-controlled wheelchair

IV. OPTIMAL ELECTRODE SELECTION

In this project, the optimal number of electrodes with optimal locations was investigated to find a balance between classification accuracy and user comfort.

A. *Experimentation*

Optimal electrode locations were identified by considering the regions of the brain that contributed most significantly to control thoughts in previously obtained sensorimotor BCI data [5].

A comparison was made between the energy of the signals in each EEG channel by analyzing their contribution to common spatial patterns (CSP – refer to section 6).

The BCI source data was demeaned and normalized prior to being applied to the CSP algorithm for the outcome to be comparable. A weight matrix was obtained for each control thought (class) after applying the CSP algorithm. Each of these matrices showed the contribution of the channels for each class versus the rest. Using this method, we were able to identify the relative weight of each channel for the four class BCI data in consideration.

Performance of a linear SVM classifier (see section 6) was measured using 4, 8, 12, 16 and 32 most optimal electrodes in comparison to when all 60 electrodes were used (Fig.s 2 and 3). The optimum number of electrodes with optimum locations as identified using the CSP approach was further compared to the same number of electrodes used with non-optimum and uniform locations. In these comparisons, a Bonferroni-corrected Kruskal-Wallis one-way ANOVA was used to determine statistical significance across the results.

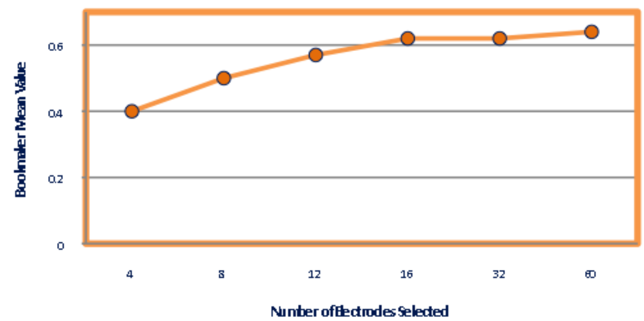

Fig. 3. Classification performance when different numbers of electrodes (with optimal locations as identified by Fig. 2) are used.

B. *Results*

Figure 3 shows that reducing the number of electrodes to four (one for each class) would give a bookmaker (see section 6) of 0.4 equating to a weighted average of about 55%. This finding is a big step in providing a comfortable, portable and user friendly EEG system for a BCW.

Use of 16 optimal electrodes (Fig. 4) was a good balance between number of electrodes used (simplicity of the system) and classification performance (accuracy of the system) and was therefore selected for further investigation.

Statistical experiments were performed between the 16 optimal electrodes (Optimal), all 60 electrodes (All), 16 uniformly selected electrodes and 16 electrodes selected uniformly from channels that contributed to less than 50% of classification (NonOptimal). The results show that there is no significant difference (within 3%) between the case with all electrodes used and the case with the 16 optimally selected electrodes (Fig. 5).

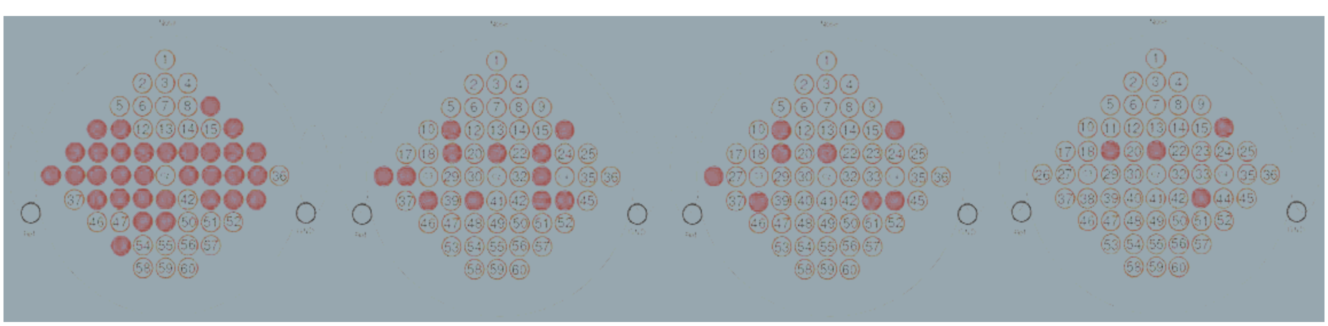

Fig. 2. Position of the 32, 12, 8 and 4 most optimal electrodes for classifying 4-class BCI data [5] identified by using analysis of contribution to common spatial patterns.

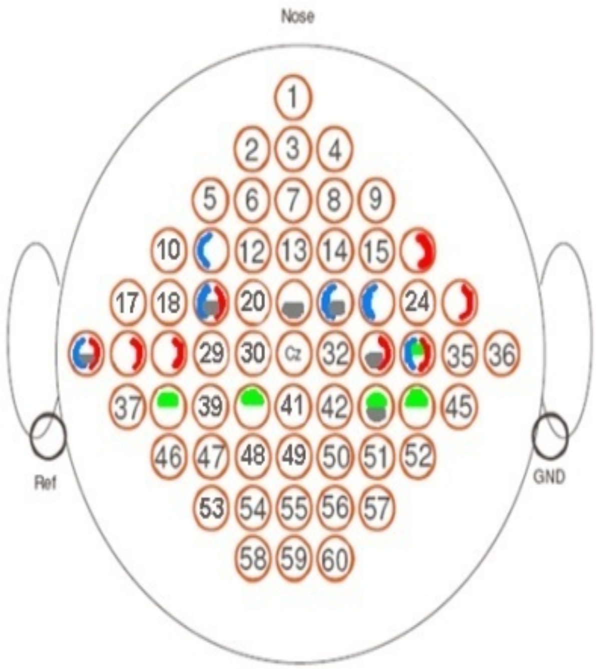

Fig. 4. 16 optimal channels selected on a 60-electrode cap for data in [5]. The colors identify the usefulness of the selected electrode for each of the classes. Red electrode locations are useful for classifying right hand imagination, blue for left hand, green for tongue and grey for foot.

These 16 channels identified here may not necessarily be the most effective electrodes for other types of brain signals. However, the same technique may be applied in order to find the most effective electrodes for the purpose of another project such that the number of electrodes may be reduced to a practicable amount that could be used comfortably by the user.

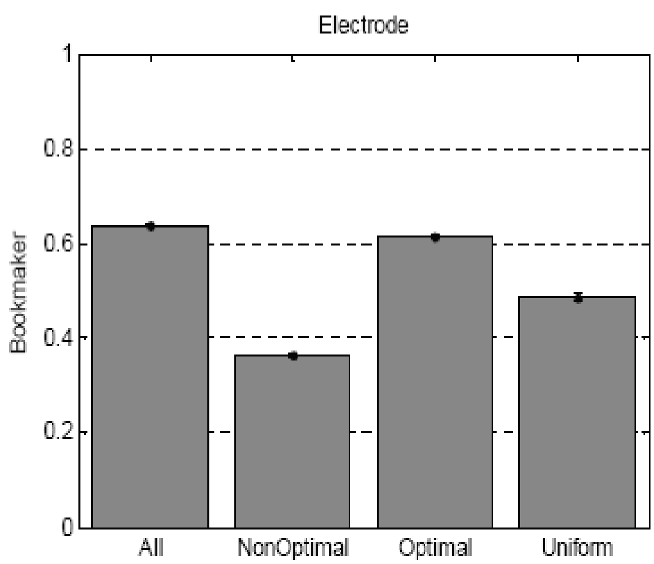

Fig. 5. Main effect plots for performance comparisons between all 60 electrodes (All) and 16 electrodes selected with different techniques. Error bars indicate standard error of the mean.

V. Signal Extraction

Using the electrode positions identified, an experiment was conducted by which motor imagery signals relating to imagination of left hand, right hand, foot and tongue were recorded for training and evaluation.

Fig. 6. Photographs of data collection experiment with G.Tec portable EEG amplifier [3].

VI. Signal Processing

Once the motor signals have been measured they go through a series of signal processing stages that determine the class identity of the signals. This procedure typically includes a feature extraction (FE) stage for expressing the spatial or frequency content of each signal and a classification (CL) stage for determining the class identity of each block (or epoch) of signal (Fig. 7). Following Fitzgibbon [4], we define a stage between FE and CL in which dimension reduction (DR) is applied to reduce the volume of the data whilst maximizing information content. Singular value decomposition (SVD) is used for DR and is applied to both the spatial and feature dimensions of the data. It has been empirically investigated that the application of spatial and feature DR makes a negligible difference to the classification accuracy, however it results in dramatically faster training times [4]. Note that DR is only necessary when the amount of data aggravates classification time.

Fitzgibbon [4] conducted a systematic examination to determine the performance of a range of different FE (frequency, phase, entropy, cepstrum, and autoregressive models) and CL (random forests and neural networks) algorithms. In this paper we extend this work by examining new FE and CL algorithms using the same framework.

A. Experimentation

Two additional algorithms are introduced to our systematic exploration of the BCI chain: support vector machines (SVM) and common spatial patterns (CSP). Both algorithms have been used successfully in other BCI systems [6].

SVM is in essence a linear discriminator similar to a perceptron or single layer feedforward network, however, it seeks to separate class instances by the widest channel possible (as defined by at least three support vectors for each pair of classes, one from one class and two from the other, that bind or support the channel). Further modifications of this basic idea include the use of mappings to a higher dimensional space (HDS) where separation may be easier, then mapping back to the original space, composing these transformations with the comparison metric performed in the HDS as a 'kernel' function.

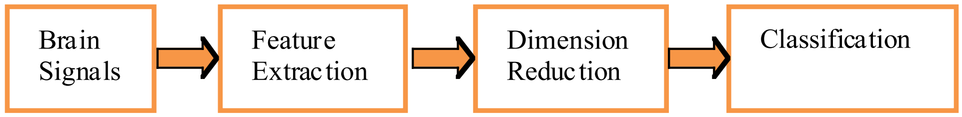

Fig. 7. Block diagram showing the general stages of signal processing in BCI.

CSP uses simultaneous diagonalization of two covariance matrices relating to any two given control signals [7]. The algorithm outputs a series of eigenvectors relating to the direction of maximum variance between these two control signals. In this way, difference between two control signals is expressed for the classifier.

The signal processing environment used in this project for training and evaluation is coded on Matlab but will be shifted to a multithreaded language such as Python once the best method for signal processing is identified. In this project, SVM has been implemented into the environment using an open source library called 'LIBSVM' [8] with a wrapper code unique to this project which simplifies parameter grid search and selection. Also, the algorithm for CSP has been based on [7] and [9] and extended to multiclass using the one-versus-rest approach investigated in [10].

Two particular SVM kernels have been investigated in this project, namely linear and radial basis function (RBF). Selection of the RBF kernel was based on findings from [11] and experimentation with the linear kernel was for comparison. The RBF kernel requires two parameters (cost and gamma) to be inserted by the user and the performance of the classifier is heavily dependent on these two values, which are in turn dependent on the features for the classifier. For this reason, as per [11] a grid search was performed for each set of features every time an RBF SVM was used as a classifier.

Performance of the SVM algorithm was compared against a backpropagation feed-forward artificial neural network (ANN) that had been shown to perform well in previous work [4]. This performance was compared across both spatial and frequency FE methods (CSP and absolute DFT). Likewise, the CSP was compared against an absolute discrete Fourier transform (DFT) that had similarly performed well with this dataset in previous work. The performance was examined across two different classifiers (ANN and linear SVM). Note that for these experimental comparisons, dimension reduction was not applied to the data. A Lillifors test indicated that the data was not normally distributed and as such statistical comparisons were made using the Kruskal-Wallis one-way ANOVA.

All experiments were performed on 4-class imagined motor imagery data from subject 'k3b' of dataset IIIa relating to BCI Competition III [5]. The EEG was re-sampled to 250 Hz, re-referenced to a common average reference, and segmented in non-overlapping 0.5s epochs.

Training and testing of all algorithms was conducted using a 10-fold cross validation technique repeated 10 times. Performance was measured using the bookmaker [12], with the value of '1' representing perfectly correct, '0' being chance and '-1' being perfectly incorrect. The magnitude of the bookmaker score represents the probability that an informed decision is being made versus a random guess. In the direction of prediction this 'informedness' is also known as 'DeltaP' in Psychology, whilst the reverse direction shows how probable marking of the predicting condition is, and this 'markedness' is known as DeltaP in Psychology. However, DeltaP is only defined in the dichotomous case, whilst informedness (and markedness) can be calculated even for the multiclass situation we have here using the bookmaker formula.

In addition to using a single classifier, limited experiments with ensembles of classifiers in parallel were also conducted. This was largely to confirm that fusion of results from multiple classifiers in parallel increases overall classification accuracy. The reported experiment conducted was with two RBF SVM classifiers running in parallel with a product combination rule. Although both classifiers were trained on the full portion of the training dataset, diversity among them was obtained based on the different FE algorithms used, which were CSP and absolute DFT. The latter also underwent dimension reduction with SVD.

B. Results

The number of CSP eigenvectors to include for best classification performance was investigated empirically. It was observed that classification performance increased logarithmically with the number of eigenvectors included (Fig. 8). Thus all eigenvectors were included in subsequent CSP analyses. The CSP essentially achieves a dimension reduction in both the spatial and feature domain, therefore no dimension reduction is required.

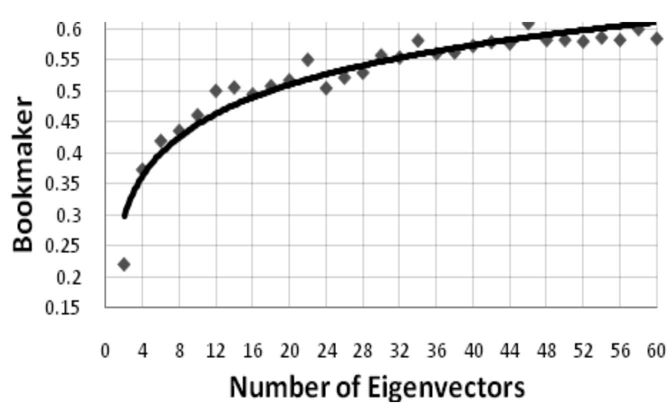

Fig. 8. Classification performance using different numbers of CSP eigenvectors

From the sequence of systematic experiments conducted, the best classification performance was 0.66 bookmaker for the CSP algorithm combined with SVM with an RBF kernel. This corresponds to a weighted average of 75%. Note that the CSP set up determined in this analysis for the full set of electrodes (Table I) was used for the reduction of electrodes discussed above, and the analysis repeated.

The experiments showed that there was a main effect for FE characterized by CSP performing significantly better than absolute DFT ($p<0.01$). There was also a main effect for CL with SVM (RBF) performing significantly better than both SVM (Linear) and ANN ($p<0.01$). SVM (Linear) was also significantly better than ANN.

The ensemble classifier approach earlier referred to resulted in a significant improvement on the data with the bookmaker reaching 0.68. This suggests that further testing with multiple parallel classifier fusion techniques is worthy of more-detailed future examination.

The results for all the different combinations tested are summarized in Table 1, with the main effects being illustrated in Fig. 9.

TABLE I
COMPARATIVE EXPERIMENTS BETWEEN CSP VS ABSOLUTE DFT AND ANN VS SVM.

FE	***CL***	***Mean Bookmaker***	***Standard Deviation***
CSP	ANN	0.60	0.04
CSP	SVM (Linear)	0.64	0.01
CSP	SVM (RBF)	**0.66**	0.01
Absolute DFT	ANN	0.53	0.03
Absolute DFT	SVM (Linear)	0.62	0.01
Absolute DFT	SVM (RBF)	0.65	0.01

VII. TRAINING AND EVALUATION

Asynchronous evaluation of the system after signal processing is necessary prior to establishing the wheelchair interface, predominantly as a safety measure.

An experimental environment based on simulation provides this opportunity and enables training. For this reason, we created a virtual environment, which was presented on a computer screen.

The virtual environment simulated the same features of the real wheelchair driving environment. In the real world, a powered wheelchair moves forward by a certain increment with each forward movement of the joystick and then stops. Holding the joystick forward causes continual movement forward. Moreover, powered wheelchairs generally have four directional controls (forward, backward, left and right) and no emergency stop.

This virtual world was created using Java3D with the camera perspective of a first-person viewpoint (Fig. 10) as would be the viewpoint of the person sitting on a wheelchair. In this environment, there were four different movement commands similar to that of a real wheelchair driving controller. With each command received via TCP/IP, there was either a certain incremental movement forward or backward or a turn to either left or right. There was also an alarm triggered if the wheelchair hits the walls.

VIII. INTERFACE TO WHEELCHAIR

Generally, there are two types of controllers, namely, integral and modular/remote. The integral controller has both the user control device and the output functions integrated into a single box whereas modular controllers have the control device remotely from the output section.

A comparison of the two types of controllers resulted in selecting the modular as the more appropriate option for the purpose of the BCW due to its flexibility and expandability in interfacing with other controllers or systems such as chin control and head arrays. One disadvantage, however, is the greater expense.

The interfaces to the modular controller are designed for a large variety of input mechanisms corresponding to the large range of specific disabilities and degrees of incapacity. Different variants consider features of the input to a user interface controller or the degree and mechanisms of its safe control options for example, should a control be held or an action repeated, or whether speed/direction are locked until another command is received.

In terms of the BCW, repeated commands and ongoing directional thought are required for the system to maintain its direction and motion. If the user stops thinking appropriately, the interfacing system is required to slow down and stop the wheelchair. This is similar to driving the wheelchair using joystick.

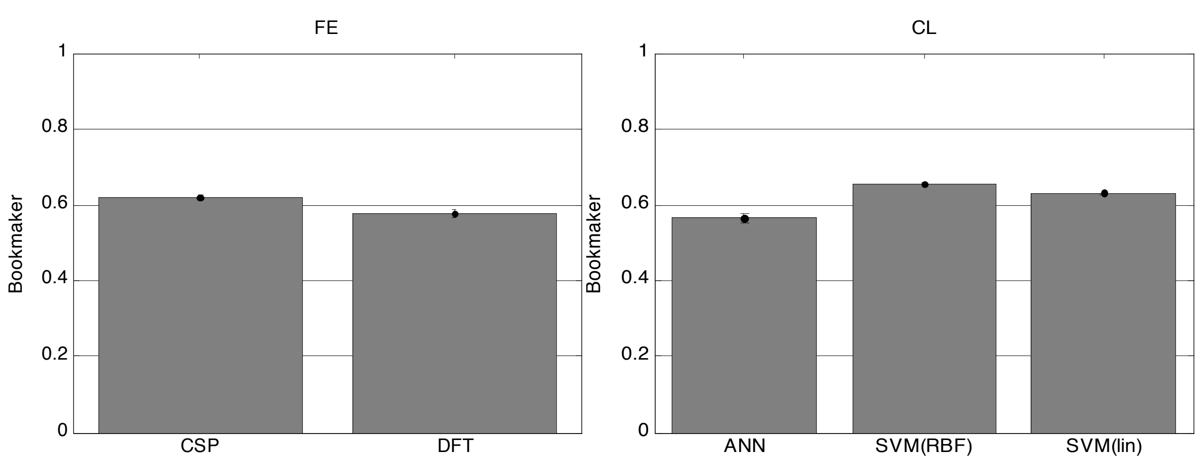

Fig. 9. Statistical results of comparison in CSP versus absolute DFT and SVM (Linear) versus SVM (RBF) and ANN. Error bars indicate the standard error of the mean.

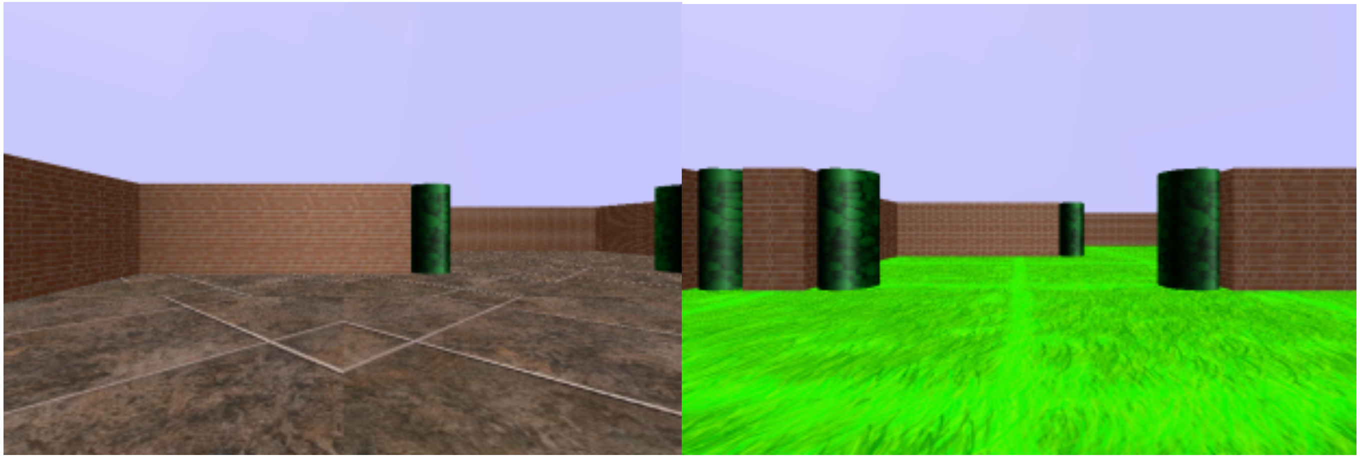

Fig. 10. Screen captures of the virtual environment designed for testing and evaluating the system prior to the wheelchair interface.

Human factor evaluation is a requirement for finalizing the type of commands and for determining the necessity of having an emergency stop. Currently four commands (left, right, forward, back) exist in the system; therefore, a remote which can take at least four momentary switches would be a suitable option. This remote is required to be programmable so that the safe speed for each user could be set. It also needs to have programmable features for increasing/decreasing the speed using only four inputs.

Analyzing available remote products and performing product selection resulted in finding DX-5SW as the most suitable option for processing inputs from the Flinders processing environment. The DX-5SW is compatible with the needs and requirements of BCW considered earlier [13].

However, the Ruby Plus wheelchair [14] we have purchased for the project is conFig.d with a VSI 50A controller [15], and we are also investigating the suitability of using this controller as well as options to bypass the controller.

IX. Future Directions

The next phase of this project is to connect all of the separate components together with an interface to the virtual simulation. This will require establishing an asynchronous link between the data from the EEG output and the rest of the BCW components, hard coding the signal processing algorithms to process EEG data real-time and connecting the classified results to the TCP/IP of the simulation interface.

We are also fielding a semifinalist entry in the MultiAutonomous Ground Vehicle International Challenge (MAGIC) [16], and are exploring use of multiple wheelchair bases as a base for Autonomous Unmanned Ground Vehicles (UGVs), whilst our Brain Computer Interface technologies are being adapted as part of the Ground Control System, allowing users to control the interface and information flow, rather than UGVs *per se*.

Despite progress in the BCW design reaching relative maturation, certain challenges still exist which must be considered and thoroughly dealt with prior to the commercial use of this device. These problems are mainly concerned with the accuracy and precision of movement controls acquired from the brain signals.

The accuracy reported in the experimental results meets approximately 25% error, which though relatively small for 4-class BCI, could result in significant consequences if not dealt with appropriately. One suggested approach is to trigger each movement after reception of multiple sequential epochs for that movement. This reduces the error to $(0.25)^n$, where n is the number of sequential epochs that must be received for each movement. By making each epoch period small and enabling overlapping epochs, the device can increase both accuracy and time of response. This approach also fits well with the idea of repeating commands to maintain a particular motion – those that contributed to the last movement will also contribute to the next if consistent, but otherwise will trigger slowing/stopping.

Other ways of improving the accuracy of classification are by bettering the signal processing aspect through further research. As earlier mentioned, experimentation with some late fusion techniques has successfully shown improvement on accuracy of classification [4]. Based on these findings and the limited work performed as part of this project, it is expected that classification accuracy can still largely increase from reports made here using the newly implemented algorithms. Although use of support vector machines as base classifiers for late fusion has been tested to a degree as a part of this project, the experiments performed have been very limited and carried out only as proof of concept. Systematic experimentation with late fusion techniques is among the future work necessary for strengthening the signal processing aspect of the brain-controlled wheelchair. In particular, late fusion algorithms which train base classifiers on different subsets of the training data are likely to enhance classification most [4].

Integration of the basic wheelchair design with safety infrared lasers could also improve wheelchair movement in narrow walkways and tight spaces like an elevator. The laser system could be linked to the classified brain signals and could respond to the surroundings contextually. For example, the speed of the wheelchair in a particular direction could decrease if brain signals are pointed towards that direction and a wall facing the wheelchair is also sensed by the lasers. In this way, entrance of the wheelchair into tight spaces such as an elevator is eased by downscaling the speed assumptions built into the command sequences.

A fifth emergency stop class may also need future investigation. Although classification performance drops with increasing number of classes, inclusion of this class may become necessary for the working prototype. Various signal processing 'tricks' may be used in this instance to increase likelihood of correct classification for the emergency stop control [4].

Abrupt movements of the wheelchair may be eliminated by a gradual transition from each state of movement. For example, the maximum speed in the forward direction can be utilized only if classified signals periodically point forward after some time. Likewise, a sharp turn to left or right may be avoided by reducing the speed of the wheelchair to a safe threshold.

As earlier mentioned, utilization of task-relevant control thoughts would also be of interest in this project. This is another branch which requires further research. Therefore, evaluation of classification accuracy using abstract thoughts related to direction of movement (such as 'thinking left' or 'thinking right') is another topic for future study.

Based on the accuracy of classification for command signals from the brain, the wheelchair interface could be developed to rely solely on the driver or it may have to require other assistive technology in conjunction with the brain signals. Further work for this section would be to perform a human factor evaluation and find the accuracy and safety of a user driving the wheelchair purely on thought. As earlier mentioned, this accuracy could be improved by including other technological devices to the system such as infra red sensors in order to provide more control options for the user.

Although we have undertaken thorough investigation and development in each of the BCW design aspects, we are yet to unite these stages into a complete working prototype. This is the ultimate goal of this ongoing research programme. This paper presents a snapshot of progress to date.

X. Conclusion

The brain-controlled wheelchair system proposed in this project identifies the early challenges and successes in realizing a mobility device for completely paralyzed, yet fully conscious patients, solely based on brain-computer interaction. Implementation of the discussed considerations is expected to significantly raise the final accuracy of the device to the point of being commercially viable.

In this project, advances have been made in the design aspect of the brain-controlled wheelchair components. Such advances were that two new algorithms were introduced to an existing BCI signal processing environment and evaluated with respect to the existing algorithms in the environment. Both algorithms were found to be superior to the previously existing algorithms in the environment with support vector machines outperforming artificial neural networks and common spatial patterns outperforming absolute discrete Fourier transforms.

Other advances have been made in the optimization of electrode placement on the scalp. A novel approach has been identified for reducing the total number of electrodes required for classifying brain signals in order to provide practicality for the system. The reduction in the number of electrodes has been tested to show insignificant difference in the performance of the classifier.

Furthermore, a 3D virtual environment has been developed to provide a live feedback presentation for wheelchair users as well as enabling training and testing of signal processing algorithms. The virtual environment provides a safe method for allowing wheelchair users to practice operating the controls before engaging the real wheelchair.

Finally, recommendations have been made for a suitable and compatible wheelchair interfacing device. Future work has also been considered which directs future participants in this project toward achieving the overall goals of the project.

Acknowledgment

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