

Cognitive Tasks for Driving a Brain-Computer Interfacing System: A Pilot Study

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Abstract—Different cognitive tasks were investigated for use with a brain-computer interface (BCI). The main aim was to evaluate which two of several candidate tasks lead to patterns of electroencephalographic (EEG) activity that could be differentiated most reliably and, therefore, produce the highest communication rate. An optimal signal processing method was also sought to enhance differentiation of EEG profiles across tasks.

In ten normal subjects (five male), aged 29–54 years, EEG activity was recorded from four channels during cognitive tasks grouped in pairs, and performed alternately. Four imagery tasks were: spatial navigation around a familiar environment; auditory imagery of a familiar tune; and right and left motor imagery of opening and closing the hand. Signal processing methodology included autoregressive (AR) modeling and classification based on logistic regression and a nonlinear generative classifier.

The highest communication rate was found using the navigation and auditory imagery tasks. In terms of classification performance and, hence, possible communication rate, these results were significantly better ($p < 0.05$) than those obtained with the classical pairing of motor tasks involving imaginary movements of the left and right hands. In terms of EEG data analysis, a nonlinear classification model provided more robust results than a linear model ($p \ll 0.01$), and a lower AR model order than those used in previous work was found to be effective.

These findings have implications for establishing appropriate methods to operate BCI systems, particularly for disabled people who may experience difficulty with motor tasks, even motor imagery.

Index Terms—Brain-computer interface (BCI), cognitive task analysis, electroencephalographic (EEG) analysis, pattern classification.

I. INTRODUCTION

BRAIN-COMPUTER interface (BCI) technology is advancing rapidly toward enabling people with severe physical disabilities to operate computers by thought rather than

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by physical means. A number of groups around the world are developing BCI systems, in which surface electroencephalography (EEG) is used to record the brain signals that control cursor movements on a computer screen [1]–[6]. Implanted EEG electrodes can also be used [7], but the noninvasive method is proving to be viable and is obviously preferable. Typically, the generation and control of EEG signals to drive a BCI system require training of the user. Two approaches have been used to date, which can be broadly categorised as cognitive tasks and operant conditioning. The former trains subjects to perform specific thinking tasks, while the latter relies on biofeedback to allow the subject to acquire the automatic skill of controlling EEG signals in order to move the cursor.

The cognitive task most commonly used in BCI studies is motor imagery, as it produces changes in EEG that occur naturally in movement planning and are relatively straightforward to detect. The signals generated in the motor cortex can be recorded from electrodes over central head regions and studies have produced encouraging results [1], [8]–[10]. With the operant conditioning approach, the intention is to train subjects to control the cursor automatically [5], [9]. Unlike with cognitive tasks, the subjects may think about anything (or nothing) so long as they achieve control of the cursor. They are usually asked simply to try to move the cursor on the computer screen, the idea being that with the aid of feedback, the subject's brain learns to control EEG components in an appropriate way. Over many sessions, the subject acquires the skill of controlling the movement of the cursor without being consciously aware of how this is achieved. This approach may be compared to the skill of riding a bicycle or playing tennis, where employment of the skill is voluntary but automatic (the tennis player consciously decides to return the ball, but choice of muscles used, placement of the racket, timing of movements, how hard the ball is struck, etc., are achieved automatically).

Much BCI research has involved the development of powerful signal processing techniques to enable reliable and accurate cursor control. Little attention has been paid to the method of generating and controlling EEG activity [11]. No specific investigations have been conducted to explore appropriate tasks, with the reason for choice of method in many studies not being mentioned. While technological advances are essential, reliability of BCI systems will also be influenced by the performance of the user. Some tasks may be inappropriate for certain groups of subjects: Motor imagery may be difficult for a person who has been paralyzed for many years or, indeed, from birth.

The purpose of this study was to examine cognitive tasks other than just motor imagery, in terms of being able to differen-

tiate between their EEG signals reliably. Specifically, the aims were:

- 1) to test two new cognitive tasks; an auditory and a spatial task used in brain imaging studies, for suitability with BCI systems;
- 2) to compare the reliability of the new tasks against right/left motor imagery tasks commonly used in BCI research;
- 3) to determine the most appropriate signal classification paradigm.

II. METHODS

A. Subjects

Ten normal volunteers were studied: five males aged 29–54 and five females aged 24–44. Exclusion criteria were: any neurological disorders or history of head injury; skin conditions contraindicating the use of surface electrodes on the scalp; previous BCI training. Subjects were asked not to consume alcohol within 24 h prior to testing and not to take coffee within 4 h. Subjects gave their written, informed consent and the study was approved by the Riverside Research Ethics Committee.

B. Equipment

All channels of EEG were recorded using silver-silver chloride electrodes. Skin impedance was checked at regular intervals throughout the experiment and was maintained below $5\text{ k}\Omega$. All signals were amplified using “ISO-DAM” [12] isolation amplifiers with gain 10^4 and bandpass filtered using fourth-order analogue filters with cutoff points set at 0.1 and 100 Hz. The signals were subsequently digitized at 384 Hz to 12-b resolution. All data were stored in real-time using a Pentium 266-MHz PC.

C. Cognitive Tasks

Four cognitive tasks were studied and standardized instructions were given to subjects for conducting each task.

- 1) *Spatial navigation (around subject’s home)*: The subject was asked to imagine being in familiar surroundings, moving from room to room and around rooms in their home. They were asked to scan the rooms and notice what they saw as they looked around, rather than think about actually walking around (to avoid motor activity). This task was inspired by work discussed in [13].
- 2) *Auditory imagery (of a familiar tune)*: The subject was asked to think of a favorite song or a familiar tune that they enjoyed [14]. They were instructed to “listen” to it in their head, without mouthing the words or moving any part of their body.
- 3) *Right Motor imagery*: This involved imagining opening and closing the right hand. This was demonstrated to the subject, who was then asked to practice actually opening and closing their right hand and notice how this felt. They were then asked to imagine doing this, while making sure that their hand did not actually move and trying to remember the feeling of opening and closing their hand.
- 4) *Left Motor Imagery*: The same procedure used for the right hand was also used for the left hand.

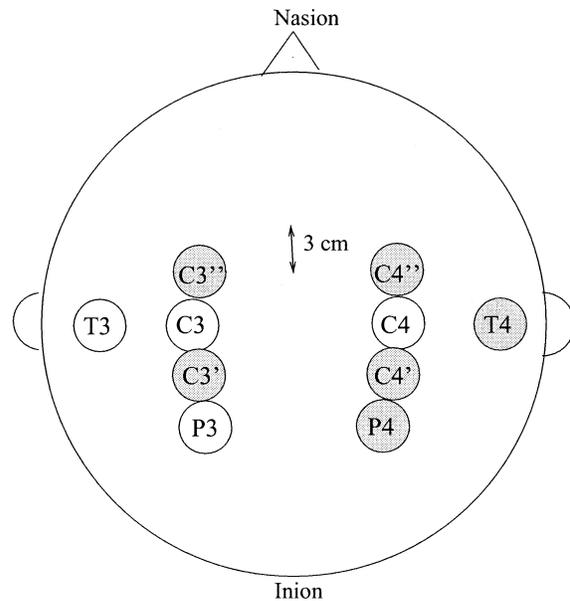


Fig. 1. Electrode positions used in the study are shown shaded, other electrodes are shown for reference. In the augmented 10–20 system, electrodes at C3', C3'', for example, are placed 3-cm posterior and anterior, respectively, to C3.

D. Electrode Placement

Three recording sites were used, with a total of seven electrodes, which were placed according to the augmented 10–20 positions at T4, P4 (right temporo-parietal for spatial and auditory tasks), C3', C3'' (left motor area for right motor imagery) and C4', C4'' (right motor area for left motor imagery), and the ground electrode was placed just lateral to the left mastoid process (Fig. 1). Two recording channels were used during each task. So that pairing of tasks could be analyzed under standardized conditions, the same electrode placement was required for specific pairing. The right motor imagery task was to be compared with the two new cognitive tasks, as well as the left motor imagery task. It was, therefore, necessary to repeat the right motor imagery task under two conditions: For one set of tasks (right motor imagery, spatial and auditory, performed randomly), the two recording channels used electrodes at C3'–C3'' and T4–P4. For the other set, in which left and right motor imagery tasks were to be compared (again in random order), electrodes were placed at C3'–C3'' and C4'–C4''.

E. Performance of Cognitive Tasks

Standardized instructions were given to each subject. They were asked to remain as still as possible while performing the tasks. Within each pair, each task was performed for 10 s and repeated ten times, with 5 s rest between each one. Sufficient time was also given between each task pairing to allow the subject to rest. Each task began in the subject’s own time, initiated by pressing a key on the computer with recording starting 5 s later. Instructions appeared on the computer screen, counting down to the start of the task. A stationary cursor was present on the screen during the 10-s recording period. The order of cognitive tasks, within each of the two sets, was randomised to minimize the effects of fatigue. Between the two sets of tasks tested,

the electrode input to one ‘‘ISO-DAM’’ channel was changed (i.e., T4–P4 exchanged with C4’–C4,’’ as explained previously).

After the recording session, subjects were asked to provide feedback about performing the different tasks. They were asked to rate the navigation, auditory, and right motor tasks in terms of difficulty with concentration on a scale of 0–5 (with 5 being difficult and 0 being easy). They were also given the opportunity to make comments about why they found any particular tasks relatively easy or difficult to perform.

III. DATA ANALYSIS

In order to ensure that the conclusions drawn from the experiments were meaningful, we first aimed to find the most appropriate processing technique. The approach was classical in the sense that the analysis was separated into a preprocessing and a classification stage, the latter being conditioned on the results from preprocessing. The overall structure of the BCI consists of a preprocessing method, a classification stage, and final sensor fusion based on a naïve Bayes assumption. These constituent parts of the BCI are described in detail in the following.

A. Signal Parameterization and Preprocessing

All EEG data were recorded at a sample rate of 384 Hz and subsampled to 192 Hz. Subsequent analysis investigated the use of low-pass finite impulse response (FIR) filters at 45 and 96 Hz (see Section IV), the coefficients of which were obtained using the method of least-squares [15]. The EEG signals were parameterized using a lattice filter representation of an autoregressive (AR) process that models each EEG channel separately. The model parameters of the lattice filter AR process are the so-called reflection coefficients. The theory behind our approach to estimating the reflection coefficients is detailed in the following subsection.

1) *Reflection Coefficients*: Autoregressive (AR) models may be regarded as signal models in which the signal sequence, in discrete time $y[t]$, is modeled as the output of an all-pole filter driven by a white noise sequence (i.e., Gaussian random numbers). Denoting the white noise sequence as $\epsilon[t]$, we may consider the observation model of for $y[t]$ as a linear combination of past observations (the allpole filter) and an additive noise term, i.e.,

$$y[t] = - \sum_{m=1}^p a_m y[t-m] + \epsilon[t]$$

in which p represents the order of the AR process and a_m the AR model coefficients which parameterize the all-pole filter. While these coefficients themselves are often used as features to represent the signal characteristics they do not have desirable properties, being highly dependent upon one another. Alternative representations may be found by linear transformation of these coefficients, the most useful of which is to a set of so-called *reflection coefficients* [16]. The m th reflection coefficient ρ_p defines the reduction in residual signal-model error E when the AR model increases its order from $m-1$ to m

$$E_m = (1 - \rho_m^2) E_{m-1}.$$

These have the advantage that an increase in model order does not effect the reflection coefficients from previous orders, and hence, there is little interdependency between the coefficients, thus making them more suitable for pattern analysis techniques.

The extraction of reflection coefficients was performed using a Bayesian method, which is described in [17]. This section summarizes the results of a Bayesian analysis of a lattice filter representation of an AR Gaussian process. The coefficients of this model are the reflection coefficients, henceforth denoted by ρ . A review of AR lattice filters can be found in [18]. As we want to model real EEG, we know with certainty that the underlying AR-process must be stable. As the reflection coefficients of a stable model have to be within the interval $[-1, 1]$, we may use a flat prior within this range and set $p(\rho) = 1/2$. Another parameter of the lattice filter model is the precision of the noise model for $\epsilon[t]$, which we denote by β . Since the noise level is a scale parameter, we may follow [19] and use the Jeffrey’s prior $p(\beta) = 1/\beta$.

In order to arrive at an expression for the posterior distribution over the m th reflection coefficient ρ_m , we treat both the $(m-1)$ th stage and the noise level as nuisance parameters and integrate them out. Using ϵ_m as forward prediction errors and \mathbf{r}_m as backward prediction errors at the m th stage, we obtain

$$p(\rho_m | \mathcal{Y}) = \frac{1}{\sqrt{2\pi}s} \exp\left(-\frac{1}{2s^2}(\rho_m - \hat{\rho}_m)^2\right)$$

for the *a posteriori* distribution of the m th-order reflection coefficient, in which

$$\hat{\rho}_m = -\frac{\mathbf{r}_m^\top \boldsymbol{\epsilon}_m}{\mathbf{r}_m^\top \mathbf{r}_m} \quad (1)$$

represents the most probable value of the reflection coefficient, and

$$s^2 = \frac{1 - (\hat{\rho}_m)^2}{(N-1)} \quad (2)$$

is the corresponding variance. The Bayesian model evidence of the m th reflection coefficient is

$$p(\mathcal{Y} | I_m) = \frac{1}{2} \pi^{-\frac{N}{2}} \Gamma\left(\frac{N}{2}\right) \times ((\boldsymbol{\epsilon}_m + \hat{\rho}_m \mathbf{r}_m)^\top (\boldsymbol{\epsilon}_m + \hat{\rho}_m \mathbf{r}_m))^{-\frac{N}{2}} \sqrt{2\pi}s \quad (3)$$

in which I_m represents the hypothesis that signal (i.e., non-noise) information may be extracted from the observations set \mathcal{Y} by the lattice AR model.

Comparing the m th lattice filter stage with the Bayesian evidence of *not* using the m th reflection coefficient allows model selection and measures model uncertainty. We obtain the evidence of *not* using the m th reflection coefficient by integrating out the m th-order AR coefficients and the noise level β . We indicate the corresponding model by I_m^c and obtain

$$p(\mathcal{Y} | I_m^c) = \pi^{-\frac{N}{2}} \Gamma\left(\frac{N}{2}\right) \boldsymbol{\epsilon}_m^\top \boldsymbol{\epsilon}_m. \quad (4)$$

Taking equal priors for both models, the *a posteriori* probability of the m th reflection coefficient compared to a white noise explanation is

$$P(I_m|\mathcal{Y}) = \frac{p(\mathcal{Y}|I_m)}{p(\mathcal{Y}|I_m) + p(\mathcal{Y}|I_m^c)}. \quad (5)$$

The probability $P(I_m|\mathcal{Y})$ has also the interpretation that it estimates how likely a particular segment of a time series is to contain information that can be extracted with a lattice filter AR-model. Thus, with probability $P(I_m|\mathcal{Y})$ the time series \mathcal{Y} contains information about ρ_m .

2) *Data Detrending*: Differencing is usually applied to remove linear and higher order trends from time series. This is necessary because trends violate the assumptions underlying the AR-process model. In order to obtain further insight into this approach, we consider the application of the first-order difference operator q to a time series with a zero-order trend (nonzero mean) we write [18]

$$y[t] = \frac{1}{A[q]}\epsilon[t] + \alpha \frac{\delta[t]}{1 - q^{-1}} \quad (6)$$

in which $\alpha \in \mathbb{R}^+$ is an arbitrary constant, $\epsilon[t]$ is the white-noise driving term, and $1/A[q]$ is the impulse response function of the AR filter. The first term is simply the AR model and the second term represents a model for the nonzero offset. We may rewrite (6) to give

$$y[t] = \frac{\epsilon[t](1 - q^{-1}) + \alpha\delta[t]}{A[q](1 - q^{-1})}. \quad (7)$$

Hence, differencing the time series leads to another time series which fulfills the assumptions underlying AR-processes. The resulting time series

$$z[t] = y[t](1 - q^{-1}) = \frac{w[t]}{A[q]} \quad (8)$$

has the same filter coefficients as the original time series; however, the noise model has changed from $\epsilon[t]$ to $w[t] = \epsilon[t](1 - q^{-1}) + \delta[t]$. The contribution of $\delta[t]$ is only of mathematical interest since this term exists only at time $t = 0$. We now consider the influence of the first-order difference operation on the driving white noise sequence $\epsilon[t]$. According to our AR assumptions, all $\epsilon[t]$ are independent and identically distributed (i.i.d.) samples of Gaussian random numbers. Hence, the first order difference of the sequence $\epsilon[t]$ is equivalent to taking the difference of two Gaussian random numbers with zero mean and identical standard deviation σ_ϵ . The resulting sequence is still i.i.d. zero mean Gaussian, however, with doubled variance, i.e., $w(t) \sim \mathcal{N}(0, \sqrt{2}\sigma_\epsilon)$. Hence, extracting the AR coefficients from the differenced time series should reveal the true underlying filter coefficients. The only difference is that the estimates of the driving noise variance are doubled.

B. Data Classification

Classification was based on logistic regression and on a nonlinear generative classifier. Logistic regression is a standard technique in pattern recognition and can, for example, be found in [20]. It is also the method of choice in previous BCI

work such as [10]. The generative classifier is inferred using a variational learning framework, for which details of the method are found in [17].

Compared with nonprobabilistic models, the chosen approach has two advantages.

- 1) Generative models provide the possibility to solve missing data problems. We may infer the conditional probability density over missing inputs during both training and prediction and the conditional probability of missing target labels during training.
- 2) Probabilistic learning provides means to determine an appropriate model structure. It not only provides probabilities for classes, but probabilities over the complexity of the model as well. With appropriate inference procedures, such as the variational Bayesian scheme used in this work, we can guarantee that the model complexity is chosen appropriately. We avoid the precarious requirement of assessing many models of different complexity using more traditional methods, such as cross-validation.

Of course, we have to pay a price for these advantages: As is pointed out in [20], modeling class conditional densities is much more difficult than modeling posterior probabilities directly.¹

We consider a set of K classes whose posterior probabilities we wish to infer given an input, or feature, vector \mathbf{x} which is given by the vector of reflection coefficients, i.e., $\mathbf{x} \stackrel{\text{def}}{=} \{\rho\}$. Denoting the class priors as P_k , we may write

$$p(\mathbf{x}) = \sum_{k=1}^K P_k p(\mathbf{x}|k) \quad (9)$$

in which the class-conditional probabilities are modeled via a mixture model with D components, i.e.,

$$p(\mathbf{x}|k) = \sum_{d=1}^D w_{d,k} p(\mathbf{x}|\Theta_d) \quad (10)$$

in which Θ_d are the parameters of the component densities. In this form, the approach we take is similar to that of a *mixture density network* and a *radial basis function* (RBF) classifier. We may use Bayes' theorem to easily express the posterior probabilities for classes as $P(k|\mathbf{x}) = P_k p(\mathbf{x}|k)/p(\mathbf{x})$. The D component densities $p(\mathbf{x}|\Theta_d)$ can be any parameterized density function. For the sake of convenience we will use normal densities with diagonal covariance matrices; hence, Θ_d corresponds to a parameter vector whose components are the mean and diagonal covariance elements. The problem then becomes one of inferring the unknown model parameters given a training data set. The BCI classifier is inferred using a variational Bayesian approach which has been developed in [17] and was used previously for sleep analysis [22].

C. Sensor Fusion

Sensor fusion was performed using 1-s sliding windows with 0.5-s overlap and assuming that the observations in the window were class conditionally independent. In this case, we obtain the

¹As is, for example, mentioned in [21], modeling *a posteriori* probabilities is, in turn, more complex than modeling class labels. However, having the class labels only, we do not know how reliable they are.

TABLE I
TASK PAIRINGS

task pairing	electrode position
auditory - navigation	C3'-C3" and T4-P4
auditory - right motor	C3'-C3" and T4-P4
navigation - right motor	C3'-C3" and T4-P4
left motor - right motor	C3'-C3" and C4'-C4"

total probability of the events as the normalized product of the individual probabilities for each observation in the window, i.e.,

$$p(t|\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_T) = \frac{\prod_i P(t|\mathbf{x}_i)}{\sum_k \prod_i P(k|\mathbf{x}_i)}. \quad (11)$$

It should be noted that this approach neglects the uncertainty present in the modeling process, per se, and that this idea of sensor fusion is identical to the "latent space smoothing" as is advocated in [23] and applied to BCI data in [10].

D. Comparison of Classifiers

For results of the form generated by our experiments, we need to count the number of errors n_a and n_b made by one classifier and not by the other [20]. The numbers n_a and n_b are from a binomial distribution \mathcal{B} and the exact null hypothesis, to be rejected, is that (n_a, n_b) is a probable outcome from $\mathcal{B}((n_a+n_b), 0.5)$. This is achieved by summing the probabilities of the outcome (n_a, n_b) along with all less probable outcomes under the null hypothesis, then rejecting using an appropriate significance level.

IV. RESULTS

Based on the cognitive tasks described earlier, four different pairings were considered, which are shown in Table I, together with the corresponding electrode positions.

A. Evaluation of Signal Processing Methods

Our initial experiments were designed to determine a plausible combination of methods. This evaluation was performed sequentially due to combinatorial explosion, which otherwise would make it difficult to obtain any significant results.

Three reflection coefficients from both EEG channels were extracted from one second sliding windows with a 0.5-s overlap. All results presented in this paper were obtained by fusing the predictions for two successive 0.5-s segments using a naïve fusion method. The performance figures reported are, hence, obtained via decisions for every 0.5-s block of data. We note that there was no application of doubt thresholds as is sometimes done [10]. It is quite common in BCI systems to use AR model orders up to eight (see, e.g., [10]), obtained by considering a model of the EEG. There is, however, a difference between the optimal model order for such *modeling* of the EEG and the optimal number of model coefficients needed to *classify* EEG in a given situation. We note that no performance gain was obtained when successively adding reflection coefficients. For computational brevity, therefore, we retained only three coefficients.

We also confirmed empirically that nonlinear classification is indeed required for optimal BCI performance and showed that filtering has a negative effect on the classification performance.

TABLE II
NONLINEAR VERSUS LINEAR CLASSIFICATION

correct non-linear	correct linear	p-value
71 %	69 %	$\ll 0.01$

TABLE III
LOWPASS FILTER CUTOFF FREQUENCY AT 96 VERSUS 45 Hz

correct 96 Hz	correct 45 Hz	p-value
71 %	62 %	$\ll 0.01$

Since our data were manually checked for artifact contamination, this can only be explained by undesired side-effects of filtering on the signal in the passband.

1) *Linear versus Nonlinear Classification:* This comparison was performed by combining two separate models: one obtained from each electrode site. For this experiment, the results of all four task pairings were combined. The outcome of the experiment is summarized in Table II. In this, as in all subsequent tables of results, "correct" represents the percentage of correct classifications for each method. The p -values are obtained via the null-hypothesis, as discussed in Section III-D. As can be seen, the results obtained with the nonlinear (variational) classifier are about 2% better than those from a linear method and the hypothesis that both classifiers are equal can be rejected with very high significance, which is not surprising, since we used large sample sizes. All the following results were, hence, obtained using the nonlinear method.

2) *Filtering:* The results obtained via low-pass filtering the EEG with a cutoff at 45 Hz were poorer than those obtained when using all information in the EEG up to 96 Hz. These results are summarized in Table III.

The investigations in this section, thus, suggested that we should evaluate the neuro-physiological questions about optimal cognitive tasks using the proposed nonlinear classification and extract reflection coefficients without applying additional filtering.

B. Neuro-Cognitive Examination

To assess different cognitive tasks for their viability to drive a BCI, we test for two different variables. First, we investigate the information available at different electrode sites to discriminate between cognitive tasks.

1) *Electrode Site:* The results reported in Table IV combine those obtained from discriminating among each of the first three tasks of Table I. We see that electrode site T4-P4 was significantly superior to site C3'-C3". Even more remarkable is that fusing the predictions obtained from both channels did not change the overall result. It, thus, suffices to record from electrodes T4-P4.

2) *Task Combinations:* The final objective was to assess which pair of tasks produced EEG profiles that could be most easily discriminated. In order to be able to compare the first three tasks with the combined motor imagery task (which was recorded from different electrode sites), we combined the decisions obtained from each electrode site. The results of this comparison are reported in Table V. Combining navigation and auditory tasks was significantly superior to all other task

TABLE IV
CLASSIFICATION ACCURACY FROM DIFFERENT ELECTRODE SITES

correct classifications	correct classifications	p-value
C3'-C3''	T4-P4	
63 %	71 %	$\ll 0.01$
C4'-C4'' and T4-P4	T4-P4	
71 %	71 %	1
C4'-C4'' and T4-P4	C3'-C3''	
71 %	63 %	$\ll 0.01$

TABLE V
CLASSIFICATION ACCURACY FROM DIFFERENT COGNITIVE TASK

correct classifications	correct classifications	p-value
navigation - auditory	navigation - right motor	
74 %	69 %	$\ll 0.01$
navigation - auditory	auditory - right	
74 %	71 %	< 0.01
navigation - auditory	left motor - right motor	
74 %	71 %	0.013
navigation - right motor	auditory - right motor	
69 %	71 %	0.02
navigation - right motor	left motor - right motor	
69 %	71 %	0.026
auditory - right motor	left motor - right motor	
71 %	71 %	0.40

combinations, including the traditional right versus left motor imagery hand movement tasks.

Feedback from subjects regarding their perceived ease or difficulty of performing each task indicated that the nonmotor tasks were easier to perform and required less concentration than the motor tasks. The mean scores for the 0–5 (0 being easy, 5 being difficult) rating scale used were navigation $\bar{x} = 2.1$, auditory $\bar{x} = 2.3$, and right motor $\bar{x} = 3.1$. There was no significant difference between any pairing (e.g., navigation against auditory) of task scores (Wilcoxon rank test with $n = 7$ subjects having responded to the scoring questions), but if navigation and auditory tasks were combined, they had a significantly lower score than the right motor task. ($p < 0.05$ using a Wilcoxon rank statistic. As before, $n = 7$.)

V. DISCUSSION AND CONCLUSION

The present findings have implications for both the clinical and technical aspects in the development and implementation of BCI systems. The cognitive tasks of spatial navigation around a familiar environment and auditory imagery of a familiar tune, which we selected from those previously used in brain imaging studies, have produced more reliable results than the motor imagery tasks commonly used for BCI studies. The present evaluation of signal processing methodology has also refined the data-analysis technique used in the BCI system being developed.

The spatial navigation and auditory imagery tasks were significantly better discriminated than other pairs of tasks (Table V). The poorest results were found with the navigation and right motor pair of tasks. The right and left motor tasks usually used for BCI systems were, therefore, acceptable but not as reliable as the nonmotor combination examined.

The feedback from subjects about ease/difficulty of performing the tasks generally favored the auditory and navigation tasks. Although objective feedback was limited and comments

were subjective, it was not surprising that subjects found familiar songs and surroundings easier to image than the less familiar/interesting task of imagining their hand opening and closing.

Perhaps more functional motor tasks (e.g. “imagine slicing a loaf of bread”) would provide more reliable results. Furthermore, tasks related to a person’s specific skills might enhance their ability to perform and, hence, improve the reliability of driving a BCI system, as discussed in [11] For example, mathematical tasks may suit a person with skills in this area; imagining specific motor tasks involved in a particular sport or manual skill might be appropriate for those active in a sport or for a manual worker. Other cognitive tasks need to be studied in larger populations of subjects, including those with different disabilities, to determine the most appropriate tasks to use (see the following), but there is no reason, in principle, why such tasks should not be tailored to an individual’s particular strengths and interests.

The technical findings have an impact on a number of factors in BCI technology. During the analysis, comparison was made of results obtained using the linear and nonlinear classification models. The relative advantages and disadvantages of these models were outlined in the Methods. The finding that the nonlinear results were approximately 2% more accurate, provided evidence of a refinement in the technique. This approach was, therefore, used to examine the results for determining the best task combinations and electrode sites. It was also shown that a BCI system can be designed using smaller models in pre-processing than in previous studies [10]. Examination of different filtering levels revealed that better results were obtained when all the EEG information was used up to 96 Hz rather than using a lowpass filter with a cutoff at 45 Hz.

The superior results recorded from the T4–P4 electrode site suggests that recording from only one channel would be sufficient for the nonmotor and right motor task combinations. This means that less time needs to be spent applying the electrodes, increasing efficiency and subject compliance, and also reduces the amount of equipment required (since only one amplifier is needed).

Cognitive tasks may require less skill and training time than the automatic operant conditioning tasks. Indeed, the latter has been reported to require many sessions and not all subjects produced reliable results and were, thus, not selected for further study, e.g., [24].

The present study reports results from a set of naïve subjects after only one session, and it is of note that in all subjects consistent results were obtained (i.e., it remains to be seen how much improvement could be achieved by a period of training involving repeated sessions or whether any improvement might be achieved by a biofeedback paradigm using the cognitive tasks investigated).

A recent case report of a patient with severe cerebral palsy found that, after several months of training, the patient was able to use the BCI system successfully for communication [25]. Compliance with training in this case may have been enhanced by distance supervision and support through a telemonitoring system [26].

Other studies have revealed a preference for, and effectiveness of, different tasks for driving the BCI system, which may

vary between individual subjects [27]. Such variability provides further support for designing a BCI system based on a broader range of reliable tasks, so that a choice is made available for different subjects. For example, motor tasks may be inappropriate for some paralyzed subjects; visual tasks and feedback may be inappropriate for some visually impaired people, such as those who have been totally blind since birth; following severe head injury, concentration ability can be very limited, so people may not be able to comply with the demands of certain tasks, particularly using operant conditioning methods.

Exploration of cognitive tasks other than those examined in the present study, as well as operant conditioning methods, is required. Unless such a variety of tasks is made available, and their reliability evaluated, current BCI technology may have limited value for disabled people.

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