Man-Machine Communications Through Brain-Wave Processing

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THE FEASIBILITY OF MAN TO MACHINE COMMUNICATION through brain-wave processing is the topic of this paper. We are interested in determining whether or not it could be possible to monitor changes in the electroencephalogram (EEG) produced voluntarily by a subject and translate these changes into a set of commands to be issued to an external device. The EEG literature is rich with observations where changes in the character of the brain waves based on a variety of mental tasks are detectable [1–7]. These references are concerned primarily with the investigation of hemispheric specialization. For instance, it was found that the alpha band power (8–13 Hz) was less in the left hemisphere than in the right for verbal tasks, and less in the right hemisphere than in the left for spatial tasks [2]. This phenomenon is referred to in the literature as alpha band asymmetry. In one paper [6], a subject is described who can voluntarily suppress alpha waves in the left or right hemisphere. These papers all suggest that there are measurable differences in the EEG that correlate with different types of mental processes. With this in mind, one can see the possibility of training a subject to produce and control mental processes that can be distinguished from one another by an external device using the measured EEG data as input.

It was not the goal of this research to prove or disprove the theory of hemispheric specialization; however, we chose mental tasks based on research in this area in hopes of producing measurably different responses in the EEG that could be used to distinguish among the various tasks. For instance, if we can reliably detect the difference between a right hemisphere task and a left hemisphere task, and distinguish both from a resting condition, then we could construct an "alphabet." The alphabet would be used to translate the measured differences in the EEG patterns into a sequence of letters, leading to a command. For example:

Let the letter A signify the detection of a right hemisphere task.

Let the letter B signify the detection of a left hemisphere task.

Let the letter C signify the detection of a resting condition for x seconds.

One could then construct the following command sequences:

AC = STOP
CAB = GO
BAC = TURN RIGHT 90 DEGREES
etc...

Such a system could allow a severely physically handicapped person to communicate with his surroundings. Here the distinction must be made between physically and mentally handicapped. A physically disabled person who has no control over his motor responses but does have control of his thoughts could use the system effectively. If other tasks could be reliably detected, then the system could be enhanced further and a more complete set of commands could be generated.

EXPERIMENTAL TASKS AND CONDITIONS

The subjects were seated comfortably in a sound controlled booth with dim lighting. Electrodes were placed at O_1, O_2, P_3, P_4, C_3, and C_4, according to the 10-20 System [8]; an additional channel was also used to record eye blinks. Data from all of the electrodes were sampled at 250 Hz for 10 sec during each task, and each task was repeated 5 times per session. Each subject attended two of these sessions, and each session was recorded on separate weeks. Five subjects, one female and four male, between the ages of 21 and 48 completed both sessions.

There were a total of five distinct tasks, and each task was performed under both eyes open and eyes closed conditions. Therefore, a total of 10 different experimental conditions were investigated. The first task was simply a baseline measure of the EEG where the subject was told to simply relax and try to think of nothing in particular. In the second task, the subject was given a non-trivial multiplication problem to solve. For the third task, a drawing of a 3-dimensional object was given to the subject to study for 30 seconds, after which he was instructed to visualize the object being rotated about an axis. Mental composition of a letter to a friend or relative comprised the fourth task. The fifth task required the subject to visualize numbers being written on a blackboard sequentially, with the previous number being "erased" before the next was written. In all of the tasks, the subjects were instructed not to vocalize or make overt movements. Further information about the experimental procedure can be found in [9].

DATA COLLECTION, ANALYSIS, AND RESULTS

A program was written to check the data for muscle artifact contamination caused by eye blinks or head movement. Approximately two seconds of artifact-free EEG was extracted from each repetition of each task and saved for subsequent analysis. The first quarter second of each two

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second segment was also saved for later analysis.

Classification Method. Feature sets were created from an estimate of the spectral density of the EEG for each task. These sets were used to test classification accuracy among the various tasks using a Bayes quadratic classifier. The spectral density was estimated using the Wiener-Khinchine (W-K) method.

The Bayes quadratic classifier has the following form, assuming that the features are normally distributed:

$$h(X)=\frac{1}{2}(X-M_1)^T\Sigma_1^{-1}(X-M_1)$$
$$-\frac{1}{2}(X-M_2)^T\Sigma_2^{-1}(X-M_2)$$
$$+\frac{1}{2}\ln\left[\frac{|\Sigma_1|}{|\Sigma_1|}\right]\lessgtr\ln\left[\frac{P(\omega_1)}{P(\omega_2)}\right]$$
$$\rightarrow X\in\begin{cases}\omega_1\\ \omega_2\end{cases}\qquad(2)$$

In this equation, X is the unknown vector we are trying to classify, and $P(\omega_1)$ and $P(\omega_2)$ are the known probabilities of class 1 and class 2, which in this case are equal, so the threshold is zero. The mean (M_1, M_2) and covariance matrices (Σ_1 and Σ_2) are usually estimated from a sample of known vectors, and then the classifier can be tested on unknown data. The method for testing classification accuracy used in this report is the Leave-One-Out-Method (LOOM) [10]. The LOOM trains on all but one of the vectors and then tests on the one that is left out. This process is then repeated, leaving a different vector out each time until all of the data have been tested. The classification accuracy is then determined by dividing the number of correctly classified records by the total number of records. This method is known to be more conservative than the C method [10], which trains and tests on the same set of data.

Methodology of Feature Creation and Selection. In order to train and test the classifier, a feature set must be created to characterize the EEG. One possible method is to characterize the EEG signal by its frequency content, which is the method used in this report. Previous researchers [5] have used the asymmetry ratio (R − L)/(R + L) to investigate alpha band asymmetry. Here, R is the area under the spectral density curve for a specific frequency band, such as alpha (8–13 Hz), for a right hemisphere lead (O_2, P_4, C_4); and L is defined similarly for the left leads (O_1, P_3, C_3). Other researchers [1] have used the power values at each lead, which are simply the R and L values alone for a specific frequency band.

We created a feature set consisting of the asymmetry ratios and the power values for each lead at four frequency bands: delta (0–3 Hz), theta (4–7 Hz), alpha (8–13 Hz), and beta (14–20 Hz). The asymmetry ratios were taken across all right to left combinations of leads, as opposed to using only the homologous pairs. This selection resulted in 36 asymmetry ratios and 24 power values for a total of 60 features. These features were formed from the two-second data segments. Each task was repeated five times per recording session, resulting in five feature sets per session that could be used to train and test the classifier. The feature sets were created for each subject for each recording session separately. A ten record feature set was also formed by combining the feature sets from both recording sessions for each subject. All of the above procedure was repeated using the first quarter-second of each of the two-second data segments. This was done to help determine how much data was necessary to accurately classify among tasks and how quickly it could be done.

The number of features to use is generally based on the amount of time it takes the program to run and the ratio of sample size to the number of features [11]. In this case, the limit was set to three features and a combination of forward sequential feature selection and an exhaustive two feature search were used to select the best set of features.

Results. Classification accuracy was tested separately on each session using five records and also on the combined ten records. All possible combinations of task pairs for eyes open cases were tested against each other, resulting in 10 test cases. The same was done for the eyes closed cases, giving an additional 10 test cases, for a total of 20. Table 1 and 2 present the results for the two-second and quarter-second data segments, respectively. The total percent classification accuracy averaged across all 20 task pairs is shown for each recording session and also for the combined sessions for each subject. Note that the combined results for subject 4 are based on 15 records, as opposed to 10, since this subject completed a third recording session.

The results presented in Table 1 will be discussed first. Counting all 5 subjects, there were 200 total test cases for the single session and 100 test cases for the combined sessions. No task pairs were classified with less than 90 percent accuracy for the single session cases. The worst case for the combined sessions was 70 percent, but only 6 out of 100 cases were below 80 percent. There were 35 cases between 80 and 90 percent, and the remaining 59 were 90 percent or better.

The results shown in Table 2 are for the quarter-second segments. For the single sessions, only 2 out of 200 were below 90 percent, with the lowest being at 80 percent. The combined sessions had 11 out of 100 below 80 percent, with a low of 70 percent. There were 55 cases that fell between 80 and 90 percent, and the remaining 34 were 90 percent or better.

Discussion. The results for the quarter-second segments compare favorably with the two-second segment results. This is important because for a working system we would like to determine the difference among tasks in as close to real time as possible. The most obvious result from these two

TABLE 1

2 Second Data, Total average accuracy across all task pairs, *based on 15 records.

	Classification accuracies in percent				
Subject #	1	2	3	4	5
1st Session	98	95.5	96	97.5	97
2nd Session	96.5	97	98	98	97.5
Combined	92	86.3	95	84.7*	91.8

TABLE 2

0.25 Second Data, Total average accuracy across all task pairs, *based on 15 records.

	Classification accuracies in percent				
Subject #	1	2	3	4	5
1st Session	98	97	98	97.5	97
2nd Session	96	97	96.9	97	96.5
Combined	89	84.5	85.4	82.3*	86.5

tables is that the combined sessions consistently had lower classification accuracies than the single sessions. One reason for this could be that the sample size for the single sessions is too small to give results that can be used to predict performance over a larger sample size. Another possible explanation is that the subject's EEG has changed substantially from one recording to the next. This is possible since the recording sessions were separated by two weeks, and it is known that the statistics of brain waves are non-stationary over extended periods of time [12]. This feature could be corrected in a real system by having the subject initialize the system prior to use. By initialize, we mean that the subject's current level of EEG responses to a number of tasks would be recorded prior to each use and then serve as reference points.

CONCLUSIONS

The results presented in this paper show that it is possible to distinguish, to a high degree of accuracy, among the various mental tasks studied, using only the EEG. The classification results presented were obtained using a suboptimal feature selection scheme and are, therefore, conservative. Later, it will be possible to use better feature selection procedures and the results should improve. The accuracies fell for the combined sessions compared to the single sessions, and this was most likely due to a combination of the sample size being small and the fact that the EEG has changed from one recording session to the next.

It may be that there is an optimum time to measure the EEG after the subject starts the task, which would make classification easier. In addition, there may be other mental tasks than the ones investigated here that would be easier to distinguish among. Each individual may have his or her own tasks that could produce more easily recognizable differences. These are areas for further investigation.

It was expected that we could distinguish between a supposed left and right hemisphere task, but it was found that we could also distinguish between two left or right hemisphere tasks. This is important because it allows us to expand the alphabet previously introduced. If enough tasks can be distinguished, then the subject could think of a single task to issue a single command instead of having to think through a sequence of tasks. A working system could provide a handicapped person with an alternative mode of communication.

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A Correspondent's Lament

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