Technical note

Conscious mental tasks and their EEG signals

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1 Introduction

THE PRIMARY goal of this technical note is to take advantage of the nonlinear property of neural networks to study the feasibility of constructing an alternative human-machine interface. The new form of communication proposed uses only the electroencephalogram (EEG) signals generated from different mental tasks without any vocalisation or overt physical action. The results reveal some phenomena which cannot be observed by using the linear classifier and show us the direction for further research.

A nonlinear classifier is better than a linear classifier, because the former can form arbitrarily complex decision regions and thus obtain a much more accurate result. This note also verifies that the EEG signals contain more complicated messages than those obtained by using the linear classifier. When compared with the chaotic features observed in some aspects of human physiology, the results of our investigation can be explained reasonably. Moreover, many topics worth future study are considered.

The objective of the research on using brainwaves as the human-machine interface is to construct a system which allows the handicapped to communicate with their surroundings. Because all brainwaves can be recorded without the subject having to speak or make overt movement, a severely physically disabled person who has no control over his motor responses but does have control of his thoughts could use the system effectively. Thus, over the past few years, there have been studies in the area of developing this kind of human-machine interface.

Many previous studies concentrated on the user's mental response to external stimuli. The results of these studies have demonstrated that, when the subject is required to classify a series of items which come from two possible categories and one of the categories appears only rarely, these rare items will elicit an event-related potential (ERP) with a positive peak which occurs about 300 ms after the occurrence of the rare item. This ERP is called the P300 (FAREWELL and DONCHIN, 1988).

The appearance of the P300 signals the subject's recognition of a rare event without vocalisation or overt movements. Often the subject is required only to mentally count or pay attention to the occurrences of the rare items. For example, a series of '1' and '2' appear at different rates: '1' occurs 45 times and '2' occurs five times; in this case the P300 can be measured approximately 300 ms after '2' occurs. Based on this idea, Farewell and Donchin developed a character input system that realised 2·3 characters per minute by using the P300 component of the ERP generated upon seeing the input character flash on a computer screen. The primary drawback of such a system from the viewpoint of the human-machine interface is that it must rely on external stimuli, which may be ineffective for some disabled persons. Also, system delay is unavoidable when using responses to external stimuli and, therefore, the input speed will slow down (HIRAIWA *et al.*, 1990).

Another study has investigated the EEG topography preceding voluntary movements. DEECKE *et al.* (1969) divided the potentials recorded preceding voluntary finger movements into three components. The first is a slowly increasing surface negative readiness potential (RP) which starts about 850 ms before the movement and is bilaterally symmetrical over the cortex. The second is a pre-motion positivity (PMP), which is also bilaterally symmetrical and starts about 86 ms before the movement. The third is a surface negative motor potential (MP) which starts about 56 ms before the movement.

One study further demonstrated that the RP generated prior to some voluntary movements contains some information about those movements (HIRAIWA *et al.*, 1990), such as a co-operative movement of the muscles of speech to pronounce syllables and the finger movements which could control a joystick. Therefore, RPs generated prior to controlling the joystick and pronouncing syllables can be the input of machines. The temporal signals of the RP recorded 0·33 s and 0·66 s preceding the movements were selected to be the input of the neural network, back-propagation model, and the corresponding movements and syllables were presented to the network as the desired output.

Other research used the EEG signals generated from different mental tasks (KEIRN and AUNON, 1990). These signals were processed by fast Fourier transform (FFT) and power spectra analysis, and were then classified into one of the mental tasks with the Bayes quadratic classifier. It is obvious that signals processed by power spectra analysis are more reliable than temporal signals.

Therefore, this technical note is mainly based on the study of Keirn and Aunon. All the experiments were

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repeated while proper neural networks were substituted for the Bayes quadratic clsssifier to perform the overall analysis. The principal difference is that the Bayes quadratic classifier can only perform linear classification and assume the feature values are normally distributed, whereas neural networks can perform nonlinear classification and the distribution of the feature values has no influence on the performance of the network. Also, because of the limitation of the linear classifier, Keirn and Aunon only proposed the classification accuracy rates between any pair of mental tasks for one subject in one session, whereas this report has analysed the accuracy rates among all mental tasks for every subject in every session.

The results reveal that almost all classification accuracy rates are zero except those of a few mental tasks. A study concerned about chaos and fractals in human physiology has shown that most healthy people have a chaotic heart rate, and many systems controlled by the neural system exhibit chaotic dynamics (GOLDBERGER *et al.*, 1990). If we explain the result of this study from the same point of view, it is not difficult to understand why almost all the accuracy rates are zero. Many possibilities, including inherent ability and external influences, are also proposed to explain the high accuracy rates of some mental tasks for some subjects obtained in this investigation. Moreover, directions for further research are indicated.

2 Experiments

A total of five subjects, one female and four male, took part in the experiments. Each subject completed at least two sessions and each session was recorded in separate weeks. Each mental task was repeated ten times per session; five times with eyes open and the other five times with eyes closed.

The subjects were seated comfortably and the experienced nurse placed electrodes on their heads to record the signals. The subjects were instructed to perform the mental tasks without speaking or overt movements. Meanwhile, a computer recorded the EEG signals from the electrodes for 10 s during each mental task, as shown in Fig. 1.

There were five distinct mental tasks to be performed (KEIRN and AUNON, 1990).

Task 1 Baseline measurement: The subject was instructed to simply relax and think of nothing in particular.

Task 2 Multiplication problem solving: The subject was given a nontrivial multiplication problem to solve. Each problem was different and was designed so that the answer could not be obtained within 10 s.

Task 3 Geometric figure rotation: The subject was instructed to visualise a complex three-dimensional block being rotated about an axis. An example of one of the block figures is shown in Fig. 2.

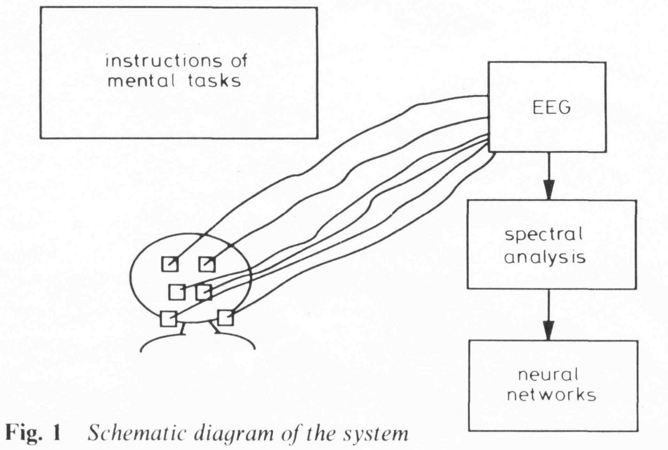

Fig. 1 *Schematic diagram of the system*

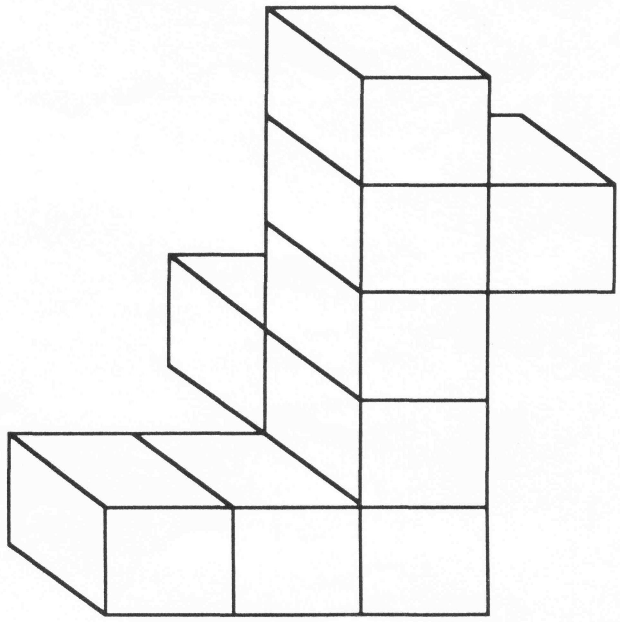

Fig. 2 *Example of one of the figures used for the geometric figure rotation*

Task 4 Mental letter composing: The subject was instructed to mentally compose a letter to a friend or a relative. As the task was repeated several times, the subject was told to try to pick up where he or she left off in the previous task.

Task 5 Visual counting: The subject was asked to imagine a blackboard and to visualise numbers being written on the board sequentially, with the previous number being erased before the next number was written. The subject was further told to pick up counting from the previous task rather than starting over each time.

3 Data analysis

3.1 *Data extraction*

Only data from the six channels, C3, C4, P3, P4, O1 and O2 (KEIRN and AUNON, 1990), as shown in Fig. 3, were used in the analysis process. Approximately 5 s (1152 sample points) of EEG was extracted from each repeated task. FFTs were performed every 128 sample points with a frame size of 256, and thus eight periods of frequency values were obtained for the 5 s samples for each channel. By averaging over the eight periods of frequency values, the power spectra was calculated to accumulate the power values in four frequency bands: δ(0–3 Hz), θ(4–7 Hz), α(8–12 Hz) and β(13–20 Hz). One spectrum is shown in Fig. 4. The 1152 EEG values were subtracted by their own mean value and thus the expectation, i.e. the mean, of the 1152 values was zero. Moreover, the FFT length was 256 and

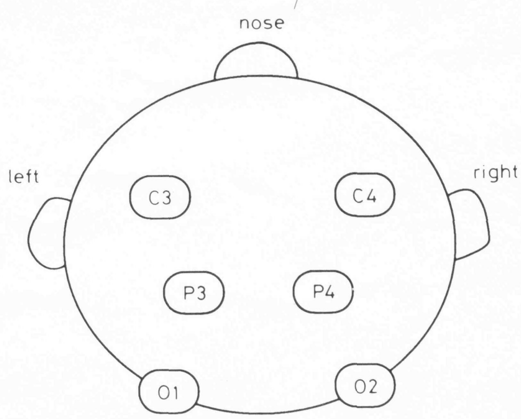

Fig. 3 *Location of six-channel electrodes*

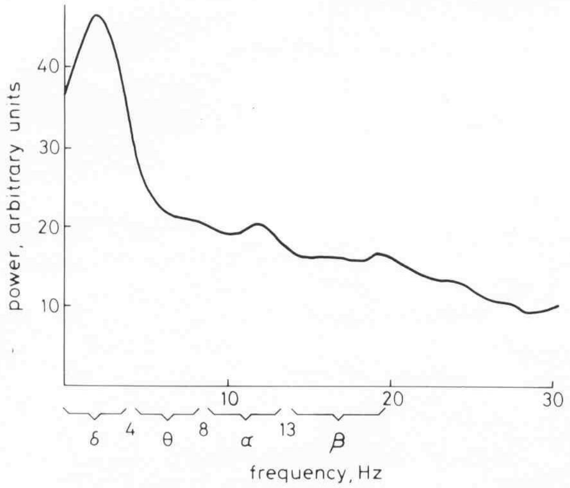

Fig. 4 *Power spectrum for subject 1 in the second session under eyes-open condition (C3 channel). This spectrum was obtained by averaging over the eight periods of the frequency values. Then, the power values in four frequency bands: δ, θ, α and β, as shown in the above, can be accumulated*

the overlapping length was one-half of the FFT length (128), so the variance of the estimation of power spectra can be proved to be proper (WELCH, 1967).

This procedure resulted in 24 power values (total of six channels) for each repetition of the task, and then the power values became the input to the neural network.

3.2 *Neural network training*

The Hopfield (HOPFIELD, 1982) and back-propagation (BP) models (RUMELHART *et al.*, 1986) are most commonly used in many applications among all neural network models, but they cannot be easily applied to solve the problem in this experiment. The main drawback of the Hopfield model is that the network may merely converge to a local minimum, not a global minimum, after training. Simulated annealing (KIRKPATRICK *et al.*, 1983) can raise the probability of the network converging to the global minimum, but it cannot make the probability 100 per cent within a finite time. Therefore, the performance of the network is beyond control (HOPFIELD, 1982; KIRKPATRICK *et al.*, 1983; HOPFIELD and TANK, 1985).

Although it is one of the most powerful and widespread neural networks, the BP model also has a property which is not compatible with our problem. There are 24 input values, but only five possibilities of output in this experiment. For a BP model with 24 nodes in the input layer, there could be many variations in its storage. For example, if a database of the photographs of the five thousand million people in the world is to be constructed, and if there are 100×100 pixels in one photograph, and if the BP model is applied, it will only require 10^4 nodes in the input layer to memorise the photographs of all the people in the world; i.e. only a few tens of thousands of nodes in the input layer can produce five thousand million variations in output. Thus, the BP model is not the most suitable one for solving our problem.

However, the self-organisation model (KOHONEN, 1984) can be successfully applied to the problem with a fixed number of classes. Also, the weights adapt slowly and adaptation stops after training, allowing the model to perform relatively well when noise is present (LIPPMANN, 1987). Therefore, the self-organisation model instead of the other two is chosen to be the classifier in this study.

The model applied in this experiment is the network with 30×30 nodes and 21 600 synapses (24×900), as

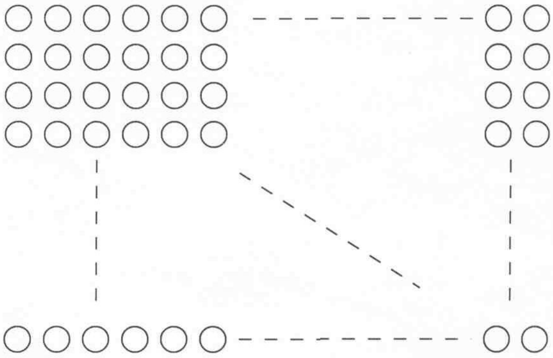

Fig. 5 *Neural network based on the self-organisation model, with size 30×30*

shown in Fig. 5. For each subject, the power values from one session, selected at random, were used as the training samples of the neural network. Data from the other sessions were used for testing. After training the network, one mapping was obtained and calibrated for each subject, as shown in Fig. 6. Based on the mapping, the testing data can be classified into mental tasks according to the calibrated neuron with the maximum response to the input.

5	5	1	2	4	4	4	4	5	5	1	1	1	1	2	2	2	2	2	5	5	5	5	4	2	2	5	5	5	5
5	1	1	1	1	1	4	4	5	5	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	5	5	5	5
5	1	1	1	1	1	1	4	5	5	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	5	5	5	5
5	1	1	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	5	5	5	5	5
5	1	1	1	1	1	2	2	2	2	2	1	1	1	2	2	2	2	2	2	3	3	3	3	2	2	2	2	5	5
5	1	4	4	4	4	4	2	2	2	2	3	3	3	3	3	3	3	3	3	3	3	3	3	2	2	2	2	5	5
4	4	4	4	4	4	4	2	2	2	2	3	3	3	3	3	3	3	3	3	3	3	3	3	2	2	2	4	4	4
4	4	4	4	4	4	4	2	2	2	2	3	3	3	3	3	3	3	3	3	3	3	2	2	2	2	2	4	4	4
4	4	4	4	4	4	4	2	2	2	2	3	3	3	3	3	3	3	3	3	3	3	2	2	2	2	2	4	4	4
4	4	4	4	4	4	4	5	5	5	5	3	3	3	3	3	3	3	2	3	3	3	2	3	3	3	4	4	4	4
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4	4	4	4	5	5	5	5	5	5	5	1	1	1	1	1	3	3	3	3	3	3	3	3	3	3	3	3	3	3
5	5	5	5	5	5	5	5	5	5	5	1	1	1	1	1	3	3	3	3	3	3	3	3	3	3	3	3	3	3
5	5	5	5	5	5	5	5	5	5	5	1	1	1	1	1	3	3	3	3	3	3	3	3	3	3	3	3	3	3
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5	5	5	5	5	5	5	5	5	5	5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	3	3
5	5	5	5	5	5	5	5	5	5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	3	3
5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	1	1	1	1	1	1	1	1	1	3	3	3
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4	4	4	4	5	5	5	5	5	5	5	5	5	5	5	5	5	2	2	2	5	5	5	5	5	5	3	3	3	3
4	4	4	1	1	1	5	5	5	5	5	5	5	5	5	5	5	2	2	2	5	5	5	5	5	5	5	5	5	3
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4	4	4	1	1	1	5	5	5	5	5	5	5	2	2	2	2	2	2	2	5	5	5	5	5	5	5	5	5	2
2	2	5	1	1	1	5	5	5	5	5	5	5	2	2	2	2	2	2	2	5	5	5	5	5	5	5	5	5	2
2	2	2	5	1	1	5	5	5	5	5	5	5	4	4	4	4	4	2	2	2	2	5	5	5	5	5	5	5	5
2	2	2	5	3	3	3	3	4	4	4	4	4	4	4	4	4	4	2	2	2	4	4	2	4	2	5	5	5	5
2	2	2	5	3	3	3	3	4	4	4	4	4	4	4	4	4	4	2	2	2	4	4	2	4	2	5	5	5	5

Fig. 6 *Mapping after training the network 100 times with data from subject 1 in the second session. The numbers represent the mental tasks to which neurons are most sensitive*

The training results show that the network after training 100 times and after training 1000 times have almost the same mapping, and therefore training 100 times is more efficient. (On an 80386 PC, training the network 100 times takes approximately 8 h).

4 Results and discussion

Having obtained mappings for each subject, the classification accuracy rates among different sessions for one subject and for different subjects were analysed. The results are shown in Tables 1 and 2; S1O(C)1 means that data are

Table 1 *Classification accuracy rates (with eyes open)*

Testing data \ Accuracy \ Training data		S1O2	S2O2	S3O2	S4O2	S5O2
S1O1	T1	0/5	0/5	5/5	0/5	1/5
	T2	4/5	4/5	1/5	0/5	1/5
	T3	0/5	1/5	0/5	4/5	0/5
	T3	0/5	0/5	0/5	2/5	2/5
	T5	2/5	0/5	0/5	3/5	3/5
S1O3	T1	0/5	0/5	0/5	0/5	4/5
	T2	3/5	3/5	3/5	0/5	0/5
	T3	0/5	0/5	1/5	1/5	0/5
	T4	0/5	0/5	0/5	1/5	3/5
	T5	2/5	0/5	3/5	3/5	0/5
S2O1	T1	1/5	1/5	4/5	1/5	0/5
	T2	0/5	5/5	5/5	0/5	2/5
	T3	1/5	0/5	0/5	1/5	1/5
	T4	0/5	0/5	0/5	0/5	1/5
	T5	2/5	1/5	0/5	0/5	3/5
S3O1	T1	0/5	0/5	5/5	0/5	3/5
	T2	1/5	5/5	3/5	0/5	2/5
	T3	1/5	1/5	1/5	1/5	0/5
	T4	0/5	0/5	0/5	2/5	0/5
	T5	0/5	1/5	2/5	2/5	0/5
S4O1	T1	1/5	0/5	0/5	0/5	3/5
	T2	0/5	5/5	2/5	1/5	0/5
	T3	0/5	0/5	1/5	2/5	0/5
	T4	3/5	0/5	1/5	0/5	2/5
	T5	1/5	0/5	0/5	1/5	0/5
S5O1	T1	0/5	0/5	1/5	0/5	1/5
	T2	0/5	5/5	3/5	1/5	1/5
	T3	1/5	0/5	2/5	5/5	0/5
	T4	2/5	0/5	0/5	0/5	2/5
	T5	3/5	0/5	3/5	2/5	0/5

Table 2 *Classification accuracy rates (with eyes closed)*

Testing data \ Accuracy \ Training data		S1C2	S2C2	S3C2	S4C2	S5C2
S1C1	T1	0/5	5/5	2/5	2/5	0/5
	T2	1/5	0/5	4/5	4/5	1/5
	T3	1/5	0/5	0/5	1/5	2/5
	T4	1/5	3/5	0/5	0/5	4/5
	T5	3/5	0/5	0/5	0/5	0/5
S1C3	T1	0/5	3/5	3/5	3/5	0/5
	T2	1/5	1/5	1/5	3/5	0/5
	T3	0/5	0/5	0/5	2/5	2/5
	T4	0/5	0/5	4/5	0/5	5/5
	T5	1/5	0/5	0/5	2/5	0/5
S2C1	T1	0/5	0/5	0/5	3/5	1/5
	T2	5/5	3/5	2/5	0/5	4/5
	T3	1/5	0/5	0/5	0/5	0/5
	T4	0/5	2/5	1/5	0/5	3/5
	T5	1/5	0/5	1/5	0/5	1/5
S3C1	T1	0/5	0/5	1/5	4/5	0/5
	T2	0/5	0/5	2/5	5/5	0/5
	T3	1/5	1/5	1/5	1/5	0/5
	T4	0/5	1/5	1/5	0/5	1/5
	T5	1/5	0/5	2/5	0/5	0/5
S4C1	T1	0/5	1/5	0/5	0/5	1/5
	T2	4/5	0/5	1/5	2/5	0/5
	T3	1/5	3/5	0/5	2/5	2/5
	T4	0/5	2/5	0/5	1/5	0/5
	T5	2/5	0/5	2/5	2/5	1/5
S5C1	T1	**	**	**	**	**
	T2	3/4	4/4	0/4	1/4	4/4
	T3	1/5	0/5	1/5	1/5	1/5
	T4	0/5	4/5	1/5	1/5	2/5
	T5	1/5	0/5	1/5	0/5	3/5

** data not available

from the first session of subject 1 under the eyes open (closed) condition; T1 means mental task 1; and so on. In Tables 1 and 2, almost all the accuracy rates, whether relating to different sessions for one subject or for different subjects, are zero except for a few special mental tasks. This result cannot be obtained by using the linear classifier. Although the linear classifier may successfully classify patterns from two different mental tasks, it will not work once the number of tasks increases and the decision region becomes more complex. This is the reason that Keirn and Aunon only proposed accuracy rates between every pair of the mental tasks. The results of their study also revealed that the accuracies fell for the combined sessions even though a high degree of accuracy between any pair of the five mental tasks for a single session was obtained.

Based on Tables 1 and 2, it seems that constructing a human-machine interface by using different mental tasks is not as easy as expected. But, from another viewpoint, this result provides topics for further research. More and more studies have shown that many chaotic states and fractals exist in human physiology, and a paper has also been presented showing that healthier people have more chaotic heart rates (GOLDBERGER *et al.*, 1990). Each subject in this experiment had a normal EEG measurement and was certified to be healthy by the neurologist. Because brainwaves are another human physiological function, as heart rate is, it might also exhibit chaos.

The result also shows another unusual phenomenon: the high accuracy rates on the second mental task (multiplication problem-solving) in most of the cases. The errors of recording and analysing data might affect the result, but they could only have the negative influences on the experimental result and reduce the accuracy rates. For example, if the desired pattern is 'A' and the image size is 100×100, the probability of an erroneous pattern which just matches 'A' and thus will be classified as an 'A' is merely about $1/2^{10\,000}$. On the other hand, the probability of one noisy pattern 'A' which will be misclassified is much higher than $1/2^{10\,000}$. That is to say, if the EEG signals recorded were noisy, the accuracy rates could only be reduced. Thus, the high accuracy rates obtained in this experiment are reliable. Many possible reasons are proposed in the following to explain this result.

The first possibility is that it is the result of education. In this research, the five subjects, aged from 23 to 40, all finished college education and majored in engineering. They were well trained in arithmetic. GOLDBERGER *et al.* (1990) have proposed that the plasticity of chaos allows systems to cope with the exigencies of an unpredictable and changing environment, but when ageing, disease and external stimuli such as drug toxicity are present, the regularity will increase. But sometimes people need fast and precise processing routines rather than good adaptability to deal with certain things. Such processing routines can be obtained from education, social convention and other experiences, especially during the growth stage of human beings, and must be kept in the brain cells through learning. Consequently, brain cells always accept external stimuli and are learning and ageing such that chaos will no longer appear when encountering these certain things. In other words, after being trained in arithmetic, these five subjects' mental responses to certain external stimuli are already fixed instead of chaotic.

Another possibility is that these subjects' mental responses to such external stimuli are inherently fixed so that they can be selected from the general population to accept professional training in arithmetic and engineering. Regardless of whether these fixed responses are inborn or due to postnatal influences, their effects on biological evolution cannot at present be determined. Maybe these subjects will find it easy to survive and become winners in this technological age, but whether they will remain able to adapt if the environment changes is so far unknown.

There is still the possibility that the subjects' mental responses are not yet fixed. They were skilled in doing this particular mental task, and so the brain waves from the stage of concentrating on the task could be recorded, even though the recording time only lasted for 10 s. However, it may take the subjects longer before they are fully concentrating on the other tasks. Therefore, they may just be

Table 3 Classification accuracy rates using mental task 1 as baseline (with eyes open)

Testing data \ Accuracy \ Training data		S1O2	S2O2	S3O2	S4O2	S5O2
S1O1	T2	2/5	1/5	2/5	0/5	2/5
	T3	4/5	4/5	0/5	5/5	1/5
	T4	0/5	2/5	3/5	0/5	1/5
	T5	3/5	2/5	1/5	0/5	1/5
S1O3	T2	2/5	2/5	2/5	1/5	3/5
	T3	3/5	3/5	1/5	1/5	2/5
	T4	0/5	0/5	0/5	1/5	1/5
	T5	0/5	2/5	1/5	2/5	0/5
S2O1	T2	2/5	0/5	0/5	2/5	0/5
	T3	0/5	0/5	1/5	0/5	3/5
	T4	1/5	5/5	1/5	1/5	0/5
	T5	1/5	0/5	0/5	0/5	1/5
S3O1	T2	1/5	2/5	4/5	1/5	3/5
	T3	3/5	5/5	3/5	5/5	0/5
	T4	0/5	2/5	1/5	0/5	3/5
	T5	0/5	0/5	1/5	1/5	0/5
S4O1	T2	2/5	0/5	1/5	1/5	1/5
	T3	0/5	2/5	2/5	2/5	2/5
	T4	1/5	1/5	1/5	1/5	4/5
	T5	1/5	1/5	0/5	5/5	0/5
S5O1	T2	0/5	0/5	3/5	1/5	3/5
	T3	4/5	3/5	1/5	4/5	1/5
	T4	0/5	2/5	1/5	1/5	2/5
	T5	0/5	0/5	0/5	2/5	0/5

beginning to concentrate on those tasks after the 10 s of recording, or it may be difficult for them to keep concentrating on doing those tasks. Under such assumptions, the effects on biological evolution need not be considered, because the mental responses would not really be fixed.

But, because a person finds it easy to concentrate on a particular mental task does not mean that they find it easy to get out of that mental state. For example, some may need a long time to recover after focusing on a job, and yet some may only need a break or a nap. A person who gets out of a state slowly may not be well adapted to today's changing world. The relationship between two mental tasks and the time one needs to get out of one task and then concentrate on the next task are not discussed in this note. It is very possible that the experimental subjects still stayed in the previous task when instructed to perform another mental task.

Moreover, Table 1 shows high accuracies on the first mental task in some cases, especially for the network trained with the data of S3O2. Because there was actually no mental task performed in task 1, the subjects might be thinking of several different things or pondering on one particular thing. It is very probable that subject 1 in the first session, subject 2 in the second session and subject 3 in the first and second sessions were in similar states. Such states may vary with the subjects' moods and characteristics; for example some tend to daydream and some tend to ponder one particular subject. Also, the subjects' mood might be affected by the environment, such as the noise and temperature. (The same condition also results from the network trained with the data of S5O2.)

When Table 1 is compared with Table 2, it can be clearly seen that there are no obvious differences between the cases with the eyes open and those with the eyes closed. Because closing the eyes makes the α-waves (8–12 Hz) appear prominently, it is very possible that α-waves have no direct relationship with mental tasks. Another possibility is that closing the eyes affects the α-waves of both hemispheres and it is the asymmetry ratio of the two hemispheres that is really related to mental tasks. Therefore, the results of both conditions (with eyes open and closed) are similar.

Table 3 shows the results from using the analysis of data from mental task 1 as baseline, i.e. the power values of all the mental tasks except task 1 were subtracted from the power values of the corresponding task 1 (data of task 1 obtained in the same session) before training and testing neural networks. The remaining analysis steps are the same as those used to obtain Tables 1 and 2. The results of Table 3 are similar to Tables 1 and 2: most of the accuracy rates are near zero except some special mental tasks. But, in this case, mental task 3 (geometric figure rotation) rather than task 2 exhibits obviously high accuracy rates. As to this result, further experiments and analyses are necessary for us to find a satisfactory explanation.

In conclusion, what we do not know amounts to more than what we do know in studying the EEG signals from different mental tasks. But, after the analysis by neural networks, many clues for further study are provided. Some of the inferences need biological experiments to verify them. For example, training mice to climb ropes can be used to observe the effects on survival of the training and the innate abilities of those mice which climb well. Also, the brainwaves from epileptics and subjects with brain tumours could be further recorded to analyse whether the frequencies are chaotic. If these frequencies exhibit periodic or other special regular behaviour, an automation system for recognition of brain disease can be constructed. Such a system would save the large amounts of time which are spent by neurologists in inspecting EEG signals. From the viewpoint of the human-machine interface, if the EEG signals from different mental tasks are used as the input of a system, and if such signals vary with one's characteristics and background, experiments and analyses on subjects with different backgrounds and characteristics are necessary to find out more about the proper mental tasks to be used for expanding the instruction set of the system.

There are still many improvements that can be made to the experiment environment. Because the experiments were carried out in the National Taiwan University Hospital, the quality of the environment was beyond our control. Interferences from voices could not be avoided, and the experiment was not arranged perfectly. Once the environment has been improved, an increase of accuracy rates can be expected. All these areas for further research are beyond our present abilities owing to the limits of knowledge, resources and time. The initial results of this research are proposed here to offer data and ideas to researchers who are interested in these topics, and we hope this contributes towards progress in these studies.

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