学術論文

Mental Task Recognition by NN with Artificial Immune System

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In this paper, we propose the development of analysis models for classification of temporal mental tasks from subjects. This study focuses on the analysis of electroencephalogram(EEG) signals to get people's task variation Artifact-free EEG brain signals were obtained by projecting selected non-artifactual independent component analysis components from EEG, EOG and EMG signals from the subject. Then artificial immune system was applied to support neural networks to analyze artifact-free EEG brain signals. In our system, it changed a learning rate of the neural network individually and adaptively, it is expected to find optimal weight or release of non-minimum value effectively. By analyzing with neural networks, we were able to discriminate several mental tasks. The average percentage of test segments correctly classified ranged from 70% to 90% for each mental task.

Keywords: Independent Component Analysis, ICA, Brain Waves, Neural Networks, Artificial Immune System, AIS.

1. Introduction

We are particularly interested in the intelligent handling of affective states commonly expressed around computer systems: frustration, confusion, disliking, liking, interest, boredom, fear, distress, and joy. Computers and other forms of technology are interacting with people in more ways than ever before. With additional sensing and processing, the expressions of mental state can be associated with other events such as what the person is doing when they get angry or stressed, what else is happening in their body concurrent with episodes of depression, or what the interface may have just done.

Tasks often involve both thinking and feeling both cognitively experienced events and physical changes in the body. Although there is no technology that can truly read manifestations of task – video recordings of facial expressions and posture or gesture changes, microphone recordings of vocal inflection changes, skin-surface sensing of muscle tension, heart-rate variability, skin conductivity, blood-glucose levels, and other bodily changes, and swallow-able or implant-able sensors or means of capturing bodily fluids for analysis. These are just a few of a growing number of possibilities.

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Our research efforts include using people's brain waves to facilitate some forms of tasks sensing, not to force this on anyone, but to allow for a larger space of possibilities for those who want to communicate and better understand task information. The tool that we used in this experiment gives us to enable not only to receive mental expression, but also to recognize meaningful patterns of mental expression.

In task recognition phase, we used neural networks with immune system. The immune system is a remarkable example of a highly scalable distributed control and coordination system. In nature, we observe that the human immune system is able to control and coordinate a massively scaled distributed object environment in a measure, decisive, dynamic, and seamless manner to deter bacterial or viral threats[1]. Equally remarkable is the immune system's dynamic nature, which allows it to respond to dynamically changing macroscopic and microscopic conditions. The immune system acts like a protective force that continually monitors the bio environment and, depending upon a perceived threat to the body, activates the necessary multi-agent control systems to defeat the threat. Thus providing the necessary protection that is essential for survival with minimal harm/impact to an individual.

2. Experiment system

2.1 Procure signals

All data used in this article was obtained with the Cyberlink™. It is a system for acquisition and processing of biological signals[2]. The Cyberlink™ accommodates three signals from electrical input. It uses a headband with three embedded electrodes, thus eliminating the cost and health risks associated with invasive electrodes. The signals can be any EMG (Eye brow clicks), EEG (brain waves), or EOG (electrical activity from the eyes) signals. The lowest frequency control signal is called the electroculargram(EOG) signal. This is the frequency region of the forehead bio potentials that is responsive primarily to eye movements and is typically used to detect left and right eye motion. The second type of control signal is called the EEG signal. It is influenced by thoughts and broadband signals created from facial movements. The third type of control signal is called the electromyogram(EMG) signal. The EMG signal primarily reflects facial muscle activity. The Cyberlink™ communicates to the outside world using either a standard RS-232 serial link with 9600bps. In this system, the Cyberlink™ is used to estimate the muscular exertion in EMG data and to filter the activity from the eyes. The obtained data of these signals are calculated and sent over a standard RS-232 serial link to a PC running the use interface software package.

2.2 Mental tasks

For this paper, the data from four subjects performing five mental tasks was analyzed. Most subjects attended four such sessions recorded on separate weeks with the Cyberlink™ system. In an experiment, the subject was seated with several environmental stimulations. Four different programs of stimulus were presented in general laboratory environment. The subject was given written instructions at the beginning of each program. The program includes: relaxing, for which the subject was asked to relax as much as possible; counting numbers, for which the subject was imagined to count from 0 to 200 step by step; listening preferred music, for which the subject chose preferred music then listen the music without any physical movements; and seeing preferred photos, for which the subject chose preferred photos then was asked to see those with physical movements as small as possible. We offered some natural scenery photos, some portraits and some fine art photos. For the audio stimuli, also the subject was offered some rhythmical music like Celine Dion's 'My heart will go on', some classical music like Bach's 'Brandenburg Concertos'. Relaxation is done with closed eyes, and all other tasks with opened eyes. These contains Data was recorded for 8 seconds during each task was repeated 20 times per session. An example signals on subband-6 from the Cyberlink™ is shown in Fig.1. It represents 'Seeing photos', 'Listening music', 'Counting numbers', and 'Relaxing' from bottom graph. These are divided into training and verifying data. The neural networks were trained with 10 different EEG segments; these were verified with more available segments. By analyzing with neural networks, we are able to discriminate these stimulated mental tasks.

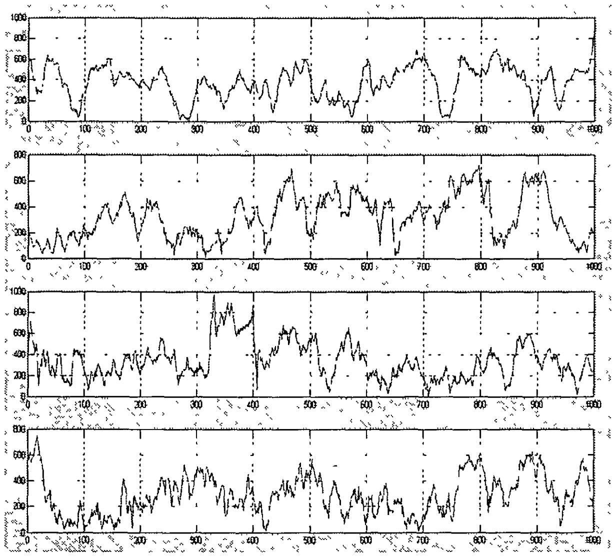

Fig. 1 Different mental state's pattern in subband-6.

2.3 Brain waves

The Cyberlink™ brainfingers controller is a device that responds to forehead voltages (bio-potentials) resulting from subtle facial muscle, brainwave and eye movement activity. The Cyberlink™'s user wears a thin, lightweight, cloth headband containing three plastic sensors that detect the voltages found at the forehead. These sensors are electrically conductive plastic, reusable, inexpensive to replace, and have been found to last for more than three months of continuous use. The headband connects to a Cyberlink™ interface box that amplifies and digitizes the forehead voltage into three signals. These three signals are an eye movement signal, a brain-body signal and a muscle signal. The brain-body signal (in the range 1 Hz to 45 Hz) contains both brainwave and body muscle bio-potentials. The lower ten continuous signals span the accepted EEG theta, alpha and beta frequencies as brainfingers. The three lowest frequency brainfingers are sensitive to left/right eye movements. When no other means of control is possible. The middle three brainfingers are sensitive to alpha brainwaves. Initially alpha region brain waves' control requires relaxing of one's thoughts and softening of one's visual focus to make the alpha brainfinger signals increase. In some other cases, learning alpha region brain waves' control is like learning a new motor skill and thus takes practice and time to learn. Four of the brainfinger signals are in the beta brainwave region. An increase in beta energy is usually associated with increased mental focus/activity. Brainfingers in the beta frequency range are also sensitive to low frequency muscle activity. Thus a good way to learn beta region brain waves' control is by performing some sort of intense mental activity coupled with the subtlest of muscle activity such as imagining/trying to contract the top of the scalp. The beta brainfingers can be adjusted to the resulting small signal changes. Learning beta brainfinger control takes time and practice. Fig.2. represent 10 sub-band brain fingers from the Cyberlink™.

2.4 Independent component analysis

Independent component analysis (ICA) (as defined by Comon) is a method for solving the blind source separation problem[3]: to recover N independent source signals, $\boldsymbol{s}=\{s_1(t), s_2(t),\ldots,s_N(t)\}$ (e.g. different voices, music, or other sound sources) from N linear mixtures, modeled as the result of multiplying the matrix of source activity waveforms, s, by an unknown square matrix $\boldsymbol{A}$. Given almost no advance knowledge of the nature of the sources or of the mixing process, the task is to recover a version, u, of the original sources, identical to s, save for scaling and source order. To do this, it is necessary to find a square matrix, $\boldsymbol{W}$, specifying filters that linearly invert the mixing process. The key assumption used to distinguish sources from mixtures is that sources, s_i, are statistically independent,

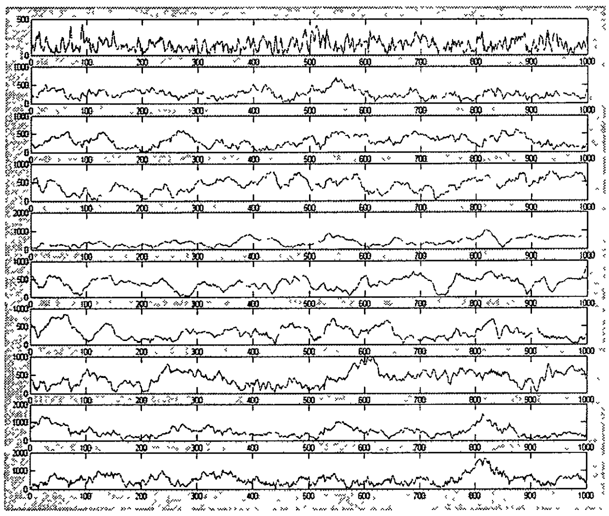

Fig. 2 Temporal signal subband 1-10.

while their mixtures, x_i, are not. In contrast with de-correlation techniques such as principal component analysis (PCA), which ensure only that output pairs are uncorrelated, ICA imposes much stronger criterion, statistical independence, which occurs when the multivariate probability density function (p.d.f.) factorizes: statistical independence requires that all second-order and higher-order correlations of the u_i are zero, while de-correlation only seeks to minimize second-order statistics (covariance or correlation). Bell and Sejnowski [11] proposed a simple neural network 'infomax' algorithm that blindly separates mixtures, x, of independent sources, s, using information maximization (infomax). They showed that maximizing the joint entropy, $H(y)$, of the output of a neural processor minimizes the mutual information among the output components, $y_i = g(u_i)$ where $g(u_i)$ is an invertible bounded nonlinearity and $u = Wx$. Recently, Lee et al. extended the ability of the infomax algorithm to perform blind source separation on linear mixtures of sources having either sub- or super-Gaussian distributions based on ideas from Girolami and Lee et al.[10].

In our application, in blind source separation, the original independent sources are assumed to be unknown, and we only have access to their weighted sum. In this model, the signals recorded in an EEG study are noted as $x_k(i)$ (i ranging from 1 to N, the number of sensors used, and k denoting discrete time). Each $x_k(i)$ is expressed as the weighted sum of M independent signals $s_k(j)$, following the vector expression:

$$\boldsymbol{x}_k = \sum_{j=1}^{M} a(j)\, s_k(j) = \boldsymbol{A}\boldsymbol{s}_k \qquad (1)$$

where $\boldsymbol{x}_k = [x_k(1),\ldots,x_k(N)]^{\mathrm{T}}$ is an N-dimensional data vector, made up of the N mixtures at discrete time k. The $s_k(1),\ldots, s_k(M)$ are the M zero mean independent source signals, and $\boldsymbol{A}=[\boldsymbol{a}(1),\ldots,\boldsymbol{a}(M)]$ is a mixing matrix independent of time whose elements a_{ij} are the unknown coefficients of the mixtures. In order to perform ICA, it is necessary to have at least as many mixtures as there are independent sources ($N \geq M$). When this relation is not fully guaranteed, and the dimensionality of the problem is high enough, we should expect the first independent components to present clearly the most strongly independent signals, while the last components still consist of mixtures of the remaining signals. In our study, we did expect that the artifacts, being clearly independent from the brain activity, should come out in the first independent components. The remaining of the brain activity may need some further processing. The mixing matrix $\boldsymbol{A}$ is a function of the geometry of the sources and the electrical conductivities of the brain, cerebrospinal fluid, skull and scalp. Although this matrix is unknown, we assume it to be constant, or slowly changing. The problem is now to estimate the independent signals $s_k(j)$ from their mixtures, or the equivalent problem of finding the separating matrix $\boldsymbol{B}$ that satisfies

$$\hat{s}_k = \boldsymbol{B} x_k \tag{2}$$

2 4 1 Applying ICA to EEG continuous signals

Use of ICA for blind source separation of EEG data is based on two plausible premises: (1) EEG data recorded at multiple scalp sensors are linear sums of temporally independent components arising from spatially fixed, distinct or overlapping brain or extra-brain networks; (2) the spatial spread of electric current from sources by volume conduction does not involve significant time delays. In EEG analysis, the rows of the input matrix, x, are EEG signals recorded from CyberLink™ electrodes and the columns are measurements recorded at different time points. ICA finds an `un-mixing' matrix, B, which decomposes or linearly un-mixes the EEG sub-bands scalp data into a sum of temporally independent and spatially fixed components, $\hat{s}_k = \boldsymbol{B} x_k$. The rows of the output data matrix, $\hat{s}_k$,are time courses of activation of the ICA components. The projection of the ith independent component onto the original data channels is given by the outer product of the ith row of the component activation with the ith column of the inverse matrix. Artifact-free EEG brain signals were obtained by projecting selected non-artifactual ICA components from EEG, EOG and EMG signals from the subject. Removing EOG activity from frontal channels revealed alpha activity near 12Hz that occurred during the eye movement but was obscured by the eye artifact in the original EEG traces. Close inspection of the EEG records of 11.45Hz sub-band (Fig. 3), F5, sub-band6 in CyberLink™, confirmed its existence in the raw data. In figure, the left shows mixed brain wave, contains sub-band6 and EOG signal, the right shows unmixed EEG and EOG signal from the original mixed brain wave. Each graph's maximum height is 1 in the system. Fig. 4 shows the spectrum of the temporal EEG by the same signal in Fig.4. It shows there is signal decreasing around 10Hz by the affection of EOG. It uncover that ICA can reveal the EEG present in the EOG artifacts. Removing artifacts from the data revealed underlying EEG activity indicated us to use EEG signals controlling outer tools.

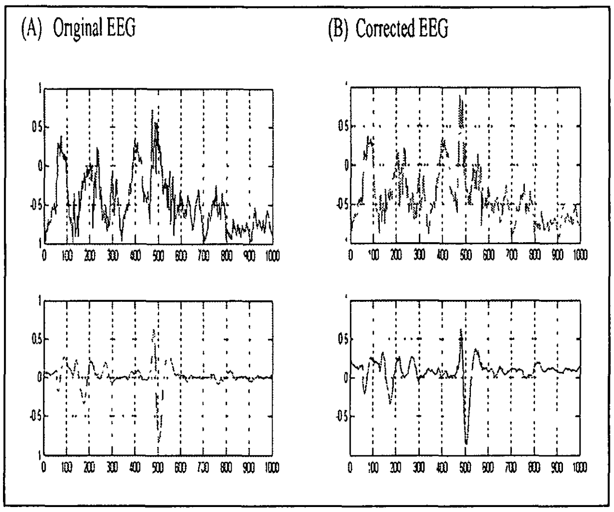

Fig. 3 Demonstration of EEG artifact removal by ICA.

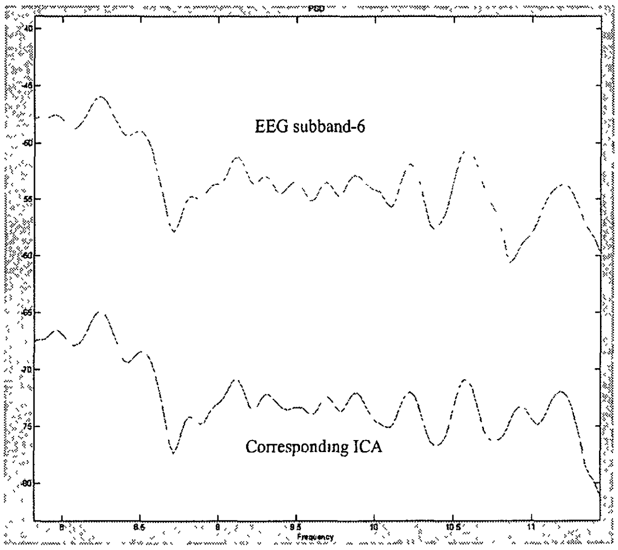

Fig. 4 The spectra of the temporal EEG.

3. Immune system

3.1 Human immune system

The human immune system has evolved into a network of specialized interconnected systems that range from general immune cells to antigen specific lymphocytes. Together these systems perform various levels of immune response and functionality in efficient manner. On the surface, the human immune system has a clear and basic role: the monitoring and preservation of the identity of the body. The operations of this diffuse system are individually simple, but combine to construct a rich and complex web of interaction and coordination that, while not optimal, display exceptional levels of robustness and flexibility, especially with regards to unknown situations and conditions.

Given the rich chemical environment present in a highly

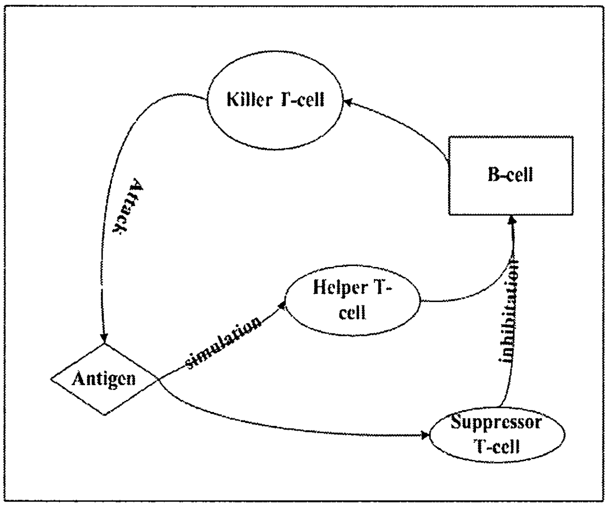

Fig. 5 Brief description of AIS.

evolved organism, it is inevitable that foreign organisms will attempt to invade in an effort to make use of these resources. To counteract this, in vertebrates the immune system has evolved to identify and dispose of foreign material.

A central difficulty of employing a very efficient recognition procedure is that antibodies may also recognize and destroy the tissue of the organism in which they reside. To prevent this, the immune system must either block the production of antibodies that react with the molecules of the host organism; or alternatively eliminate or suppress them once they are produced. This is called the self, non-self recognition problem. Lymphocytes come in two major types: B cells and T cells. The peripheral blood contains 20–50% of circulating lymphocytes; the rest move in the lymph system. Roughly 80% of them are T cells, 15% B cells and remainder are null or undifferentiated cells. Their total mass is about the same as that of the brain or liver. B cells are produced in the stem cells of the bone marrow; they produce antibody and oversee humeral immunity. T-cells are nonantibody- producing lymphocytes which are also produced in the bone marrow but sensitized in the thymus and constitute the basis of cell-mediated immunity. Parts of the immune system are changeable and can adapt to better attack the invading antigen.

3.2 Artificial immune system

What we are doing in this paper is to construct a system, which follows the human immune system, followed as Artificial Immune System, AIS in short. The simple construction of T-cell regulation is shown in Fig.5. Effective analysis, estimation of prognosis and control of dynamics of complex signals poses difficult problems. In application field, the immune system inspired some people to develop pattern recognition method[5,6], to develop control system[4]. It showed us the possible way to decrease training time in NN systems. Both neural networks and immunity-based systems are biologically inspired techniques that have the capability of identifying patterns of interest. They use learning, memory, and associative retrieval to solve recognition and classification tasks. The immune system possesses self-organizing memory and it remembers its categorizations over long periods of time[7]. It provides an excellent model of adaptive processes operating at the local level and of useful behavior emerging at the global level. AIS allows the system to respond quickly via a directed, but general method and then focuses its response in time as it proceeds through various errors of response. That models and related concepts and in the end results in a directed, but flexible, system that mimics that nature of the immune system's control structure. The amount of foreign materials at the *k*th generation $\varepsilon(k)$ can be decided as a kind of non-self.

$$\varepsilon(k)=\alpha(k-1)-T_{kill}(k-d) \tag{3}$$

where α is multiplication factor for foreign materials. T_{kill} is the amount of the killer T-cells, and the d is the dead time. The output from the helper T-cells stimulated by the foreign materials to the B-cells $T_{help}(k)$ is defined as

$$T_{help}(k)=K_1\varepsilon(k) \tag{4}$$

where K_1 is the simulation factor, whose sign is positive. Although the suppressor T-cells inhibit all other cell activities. Considering an application to feedback control, we assume that the effect of the suppressor T-cells for the B-cells $T_{\sup}(k)$ is defined as

$$T_{\sup}(k)=K_2\{T_{kill}(k-d)-T_{kill}(k-d-1)\}^2\varepsilon(k) \tag{5}$$

where K_2 is the suppression factor, whose sign is positive. In Eq. (3), the squared term is introduced to account for the effect of the reaction between the killer T-cells and the foreign materials at the *(k-3)*th generation. Thus, the total stimulation received by the B-cells *B(k)* is

$$B(k)=T_{help}(k)-T_{\sup}(k) \tag{6}$$

The activity of the B-cells is given by integrating stimulation *B(k)*. Assuming that the amount of killer T-cells is given by the differentiation of the activity of the B-cells, the amount of killer T-cells T_{kill} is defined by

$$T_{kill}(k) = K_1\varepsilon(k) - K_2\{T_{kill}(k-d) - T_{kill}(k-d-1)\}^2\varepsilon(k)$$
$$= K_p[1-\gamma\{T_{kill}(k-d) - Tkill(k-d-1)\}^2]\varepsilon(k) \quad (7)$$

3 3 Resilient Backpropagation using Immune Feedback law

For the neural network training, it consumes huge time. What we want to do is to decrease this huge time with AIS to support neural networks. It has been suggested[8] that the immune system functions as a kind of "second brain" because it can store memories of past experiences in strengths of the interactions of its constituent cells, and it can generate responses to new and novel patterns. Furthermore, the immune response develops in time and the description of its time evolution is an interesting problem in dynamical systems[9]. With this characteristic, we suggest to use immune feedback law to decrease training time with adaptive learning in neural networks. 'Resilient backpropagation' is a local adaptive learning scheme, performing supervised batch learning in multi-layer perceptrons. The basic principle of the model is to eliminate the harmful influence of the size of the partial derivative on the weight update. The size of the weight change is exclusively determined by a weight-specific, so-called 'update-value' $\Delta_{ij}^{(t)}$:

$$\Delta w_{ij}^{(t)} = \begin{cases} -\Delta_{ij}^{(t-1)}, \ if \ \dfrac{\partial E^{(t)}}{\partial w_{ij}} \rangle 0 \\ +\Delta_{ij}^{(t-1)}, \ if \ \dfrac{\partial E^{(t)}}{\partial w_{ij}} \rangle 0 \\ 0, \ else \end{cases} \quad (8)$$

where $\dfrac{\partial E^{(t)}}{\partial w_{ij}}$ denotes the summed gradient information over all patterns of the input set.

It should be denoted, that by replacing the $\Delta_{ij}(t)$ by a constant update-value Δ.

The second step of this learning is to determine the new update-values $\Delta_{ij}(t)$. This is based on a sign-dependent adaptation process, similar to the learning-rate adaptation.

$$\Delta_{ij}^{(t)} = \begin{cases} \eta^{+} * \Delta_{ij}^{(t-1)}, if \ \dfrac{\partial E^{(t-1)}}{\partial w_{ij}} * \dfrac{\partial E^{(t)}}{\partial w_{ij}} \rangle 0 \\ \eta^{-} * \Delta_{ij}^{(t-1)}, if \ \dfrac{\partial E^{(t-1)}}{\partial w_{ij}} * \dfrac{\partial E^{(t)}}{\partial w_{ij}} \rangle 0 \\ \Delta_{ij}^{(t-1)}, else \end{cases} \quad (9)$$

where $0 < \eta^{-} < 1 < \eta^{+}$

With equations, the immune feedback low can be applied to the learning process of the multi-layer NN. To do this, we replace $T_{kill}(t)$ at the kth generation by the weight increment $\Delta w_{ij}^{(t)}$ at the tth training epoch. Also, we replace η^{-} with the AIS, can then be written as:

$$\eta- = [1-\gamma\{\Delta w_{ij}(t-d) - \Delta w_{ij}(t-d-1)\}^2] * \frac{\partial E^{(t)}}{\partial w_{ij}} + \alpha\Delta w_{ij}(t) \quad (10)$$

with the replaced foreign material factor ε by the descent $\partial E^{(t)} / \partial w_{ij}$, with $K_p = \gamma$.

In general, this works as follows: Every time the partial derivative of the corresponding weight w_{ij} changes its sign, which indicates that the late update was too big and the algorithm has jumped over a local minimum, the update-value $\Delta_{ij}^{(t)}$ is decreased by the factor η^{-}. If the derivative retains its sign, the update-value is slightly increased in order to accelerate convergence in shallow regions. Additionally, in case of a change in sign, there should be no adaptation in the succeeding learning step. The choice of the decrease factor η^{-} was led by the AIS, where as, it usually takes constant value. It varies around 0.5. The increase factor η^{+} on the other hand, has to be large enough to allow fast growth of the update-value in shallow regions of the error, whereas the learning process can be considerably disturbed, it a too large increase factor leads to persistent changes of the direction of the weight-step. In several experiments, the choice of η^{+}=1.5 gave the best result with variable η^{-}.

The weight-update and adaptation are performed after the gradient information of the whole pattern set is computed.

4. Experimental results

4 1 Neural networks with AIS

To recognize experimenters' mental tasks, a neural networks discriminator has been applied for several tasks from EEG signals. Neural networks have the capability of finding a nonlinear transformation of the pattern in order to classify more accurately. However, as we explained, the increased complexity of a neural network can result in large computation times to train the network. In this case, the immune system can help to decrease training time. The EEG data used in our analysis is obtained from the Cyberlink™ on line. It accommodates 10 sub-band EEG signals from 0.5Hz to 25Hz. The classifier implemented for this work is a standard, feedforward, neural network with one hidden layer and one output layer, trained with the error backpropagation algorithm with the immune system. In this phase, the immune system supports the training more faster then former experiments without it. Fig.6 compares backpropagation neural networks convergence with or without immune system. Neural networks with immune system led better results. The classifier implemented for this work is a standard, feed-forward, neural network with one hidden layer, contains 40 units, and one output layer, trained with the error back-propagation algorithm. In the last layer there is only one neuron producing output in the normalized range (0,1). The activation function for all units is the asymmetric sigmoid function. Let the inputs to a unit be x_i, extracted features from the output by the ICA, predefined target, of the unit be y. The weighted sum and sigmoid function are combined to produce the unit's output:

$$y = \frac{1}{1 + e^{-\sum_i x_i w_i}} \tag{11}$$

The units in the first layer are called hidden units to transform the input into another representation for the output unit. The output of the output unit is taken as the classification of the current input pattern. In our system, each neural network group classifies each mental task. To train the network, a set of training patterns and corresponding correct outputs is repetitively presented to the network. After each pass through the training data, called an epoch, the weights are adjusted to reduce the error between the correct output and the actual output of the

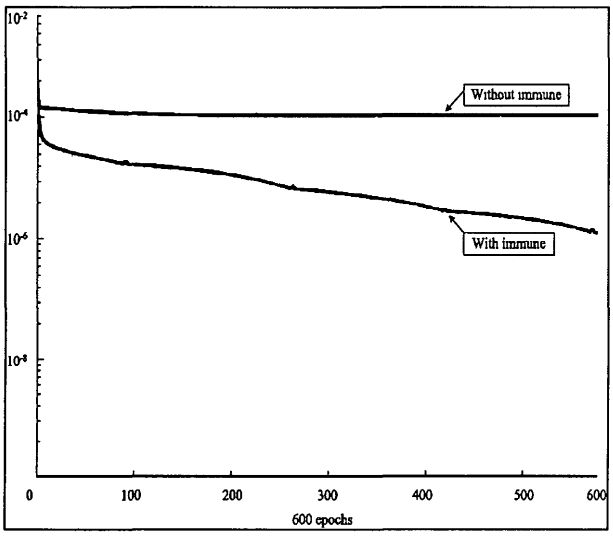

Fig.6 Compare NN results with or without Immune system.

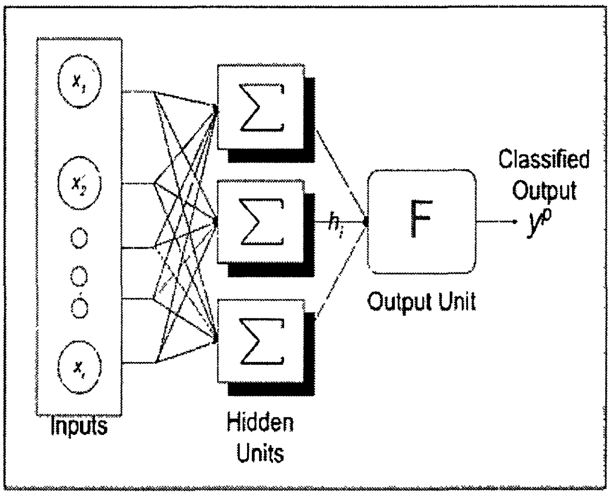

Fig. 7 NN member in NN group

network. Fig. 7 shows the relations between input and output in NN. To determine how to adjust each weight, we applied the error back-propagation algorithm. While the processing, the AIS support to converge fast to find the optimal point. For neural networks training, we constructed two layers of NN layers. The units in the first layer are called hidden units, because the outputs of these units are used internal to the network to transform the input into another representation for the output unit. We have four NN groups for four mental tasks. Fig. 8 shows the members inside of each group. The output of the output unit is taken as the classification of the current input pattern. In the experiment, 0.3 and 10 are chosen as the small momentum α, and γ in the immune feedback system respectively. Over all training patterns and, at the end of the epoch, add the result to the weights in the output unit. Initializing all weights to small, random values and then performing a gradient-descent search in the networks' weight space for a minimum of a squared error function of the network's output accomplish training the network. Different learning rates are used for the hidden layer and the output layer by following resilient backpropagation using immune feedback law. To train the network, a set of training patterns and corresponding correct outputs is repetitively presented to the network. After each pass through the training data, called an epoch, the weights are adjusted to reduce the error between the correct output and the actual output of the network.

4.2 Tasks classification

We show recognize system construction and flow in Fig.9. Mainly it consists of supported neural networks with immune system, it led us variety task classification results. To obtain the

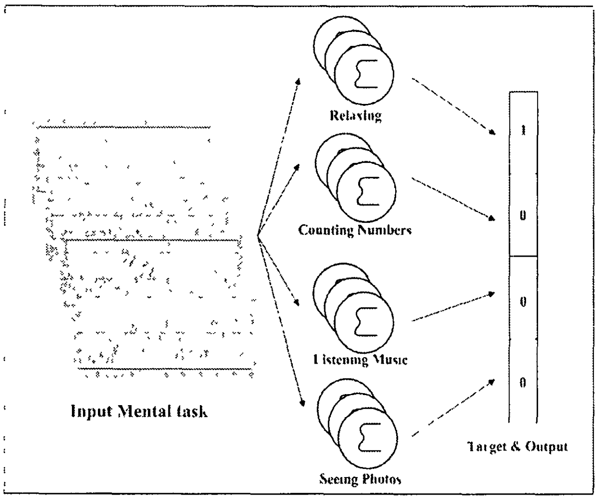

Fig. 8 NN member group

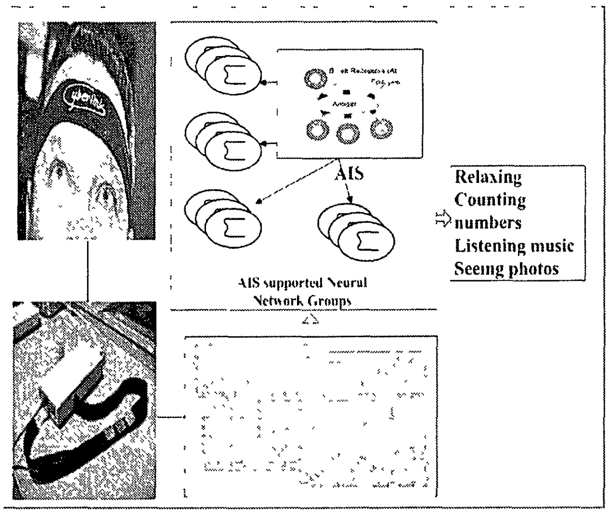

Fig. 9 System overview

results reported here, each network was trained a number of times to approximately optimize the training algorithm's parameters, the learning rates for the output and hidden layer. The immune system is the main support of neural networks. To estimate the actual benefit of using neural networks with adaptive learning rate, we observed the execution time of training various sized networks for 600 epochs using the 10 EEG sub-bands representation. The training data consist of many pairs of input/output training patterns. A mental task is introduced to neural network group with each target. Every one group has target, 0 or 1, and the input pattern for each situation in training. Fig.8 represents the construction of neural network groups' architecture. One group discriminates one mental task. The networks use the inputs to come up with an output that can be compared to the given output, target in training. The weights of the neurons are then adjusted (using back propagation with AIS) to compensate for the derived output's error. This same process is repeated several times so that on each new attempt, the output gets closer to the desired output that the programmer provided. By following the theory, as a period of brain waves is applied to every group at the same time, one mental task's NN group can be a winner. For example, in a case of 'Relaxing', with the mental task, the relaxing NN group produces 1 as a winner, and other groups must outputs 0 as a loser. The procedure makes a total output as '1000' in Fig.8. It produces '0100' as 'Counting numbers', '0010' as 'Listening Music', and '0001' as 'Seeing photos'. However, with uncertainty in brain waves, the result from each group does not make exact 0 or 1. To overcome the problem, the final decision is decided by the fuzzy with the output from each NN group's output. The fuzzy decides the output as 1 when the output 0.5 to 1, as 0 except the previous case from the networks group. It leads uncertain value to the accurate position.

The training and testing process was repeated 50 more times for each network topology. To compare various networks, the number of test segments for which the correct output unit produces the highest output are counted and expressed as a percentage of the total number of test segments. Inspection of the network's classification changes from one segment to the next suggests that better performance might be achieved by inspecting the network's input. When applying a trained to test data, we find that the neural networks perform over 70% success resulting with small number of electrodes. Table. 1 shows the results of all classification experiments as the average percent of test patterns classified correctly.

Table 1 Mental task discrimination success rate

We show recognize system	Success rate
Relaxing	80-90%
Counting numbers	70-75%
Listening music	75-80%
Seeing photos	85-90%

5. Conclusions

We have applied the immune system architecture for coordination with neural networks. The development of this architecture is based on modeling the interaction and character of both the innate and acquired aspects of the human immune system. These results in an architecture that can respond quickly, and can coordinate with neural networks effectively. Together these will lead to the development of robust, highly effective, flexible model that can respond effectively to unknown situations, are highly efficient, can adapt/lean as new challenges arise, and will be efficient enough so that they can be implemented on more complex models. For the neural networks, artificial immune system efficaciously converges them quickly more than typical adaptive learning method.

Finally, we applied these results for task classification. We obtained a technique, which is designated to get more accurate EEG classification with small number of electrodes, and to develop practical discrimination method with immune system supported neural networks. Importantly, this is achievable with a commercially available inexpensive brain-wave device and requires no significant subject training. Various features based on several mental tasks were classified with the neural networks using the adaptive learning rate back-propagation training algorithm with immune system. It led us to get more efficient and fast system compare to the former experiment in the task experiments. These results indicate that the EEG discrimination also can be used to train a subject to control desired EEG. This can be applied to a biofeedback-training device for use in an EEG-based control device. Also further investigations of subjects would be conducted to see if the technique could be used to find more mental tasks. Based on the growing number of studies showing that tasks such as anger, anxiety, depression and stress are significant medical factors, helping people better manage these tasks becomes a key role of preservative medicine. As computers assist in gathering information from patients, in helping medical patients communicate with one another and with care-providers, the need grows for task detection in the computer interface.

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