Published Quarterly
Mangalore, South India
ISSN 0972-5997
Volume 2; Issue 1; January-March 2003

Original Article

A power spectrum based backpropagation artificial neural network model for classification of sleep-wake stages in rats

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Citation: Sinha RK, Agrawal NK, Ray AK. A power spectrum based backpropagation artificial neural network model for classification of sleep-wake stages in rats. *Online J Health Allied Scs.* 2003;1:1
URL: http://www.ojhas.org/issue5/2003-1-1.htm
Open Access Archive: http://cogprints.ecs.soton.ac.uk/view/subjects/OJHAS.html

Abstract

Three layered feedforward backpropagation ANN (Artificial neural network) architecture is designed to classify sleep-wake stages in rats. Continuous three channel polygraphic signals such as EEG (electroencephalogram), EOG (electrooculogram) and EMG (electromyogram) were recorded from conscious rats for eight hours during day time. Signals were also stored in computer hard disk with the help of analog to digital converter and its compatible data acquisition software. The power spectra (in dB scale) of the digitized signals in three sleep-wake stages were calculated. Selected power spectrum data of all three simultaneously recorded polygraphic signals were used for training the network and to classify SWS (slow wave sleep), REM (rapid eye movement) sleep and AWA (awake) stages. The ANN architecture used in present study shows a very good agreement with manual sleep stage scoring with an average of 94.83% for all the 1200 samples tested from SWS, REM and AWA stages. The high performance observed with the system based on ANN highlights the need of this computational tool into the field of sleep research.
Key words: ANN, Power spectrum, Sleep-wake states

Introduction

Sleep can be defined as state of consciousness from which a person can be aroused by appropriate sensing or other stimuli (1). The conventional form of polygraphic sleep analysis of analog records need physician's skill and requires much labor. Computers, digital filters and other signal processing techniques are applied to quantify sleep recordings and thereby ease clinical utility. Several studies of application of computerized methods for sleep stage detection and its automatic analysis have been published in near past (2-10). Most of the methods are based on threshold criteria and the sleep stages determined by whether or not the data set is greater than these threshold values. But these methods are found unable to minimize the false detection. To overcome the problems of false detection, ANN (artificial neural network) has been used for computerized staging of sleep (11, 12). The development of backpropagation ANNs permitted the discovery of nonlinear relationship between input and output patterns (13). Input propagates in a feedforward fashion and gradient decent method to minimize the output errors by altering the strength connection between the layers of nonlinear least mean square algorithms (14).

Previous ANN based sleep-wake stage recognition methods used measures of polygraphic signals such as amplitude, frequency, series of consecutive waves, measuring thought to reflect in a general sense what expert electroencephalographers attempt during sleep stage scoring. It is felt that instead of analyzing only amplitude and frequency changes, obtaining power spectra of three polygraphic signals such as EEG (electroencephalogram), EOG (electrooculogram) and EMG (electromyogram) conveys more information and hence can be used more efficiently in ANN (15). Thus, in the present work, we have designed an architecture of backpropagation ANN to get optimized performance in recognition of sleep-wake patterns by presenting selected power spectrum data of three polygraphic signals.

Methods

Subjects: Five adult male Charles Foster rats of 100-150 gram weight, age 8-10 weeks, obtained from Central Animal House, Institute of Medical Science, Banaras Hindu University, Varanasi (India) were housed in polypropylene cages on light cycle (12 hours light and 12 hours dark) at 24± 1° C with food (obtained from Hindustan Liver Limited, India) and water *ad libitum.*

Surgery and recording environment: Surgery was conducted under Pentobarbital (35mg/kg *i.p.*) anesthesia. Electrodes for EEG, EOG and EMG were implanted aseptically and chronically as described earlier (16, 17). Electrodes were soldered (well before the implantation) to a seven pin socket connector and the whole array was fixed to the skull with the dental acrylic. Animals were allowed a minimum one week recovery period from surgery and were habituated to recording environment for a period of two to three days before commencement of polygraphic sleep recording.

Equipment: Three channel polygraphic signals such as cortical EEG, EOG and EMG were recorded through 8-channel polygraph (Medicare, India). The polygraph was interfaced with a computer (IBM PC-Pentium I) through 12 bit Analog to Digital converter (ADC) (ADLiNK, 8112HG, NuDAQ, Taiwan) with its supporting software (VISUAL LAB-M, Version 2.0c, Blue Pearl laboratory, USA).

Recording Procedure: The test chamber (35 cm ´ 25 cm ´ 30 cm) was constructed entirely of perspex and was located in a constantly illuminated (500-600 lux white light), sound insulated shielded chamber (300 cm ´ 180 cm ´ 240 cm). The sleep recordings were done continuously from 8.00 A. M. to 4.00 P. M. IST on the recording day. The paper recording of electrographic signals were done on the polygraph via signal conditioning box, which amplifies and filters the signals. All paper recordings were performed at the chart speed of 5 mm/sec. The amplifier for EEG recording was set with the sensitivity of 10 m V/mm with band pass frequency cutoff of 1 Hz and 75 Hz, respectively for lower and higher cutoffs. For EOG, the sensitivity was set as 20 m V/mm with filtering frequency between 0.3 Hz and 35 Hz for lower and higher cutoff, respectively. Similarly the EMG amplifier setting was done with a sensitivity of 10 m V/mm with the lower cutoff frequency of 3 Hz and the higher cutoff frequency of 75 Hz. The notch filter for the rejection of AC line frequency was kept 'ON' for EEG and the EOG recordings and kept 'OFF' for the recording of EMG.

The electrographic signals were not only recorded on papers, but also in two minutes separate data files to the computer hard disk after digitization of the traces at 256 Hz. The power spectrum of electrophysiological signals (EEG, EOG and EMG) were performed in one second epochs (18) for selected data for SWS (slow wave sleep), REM (rapid eye movement) sleep and AWA (awake) conditions before feeding them to ANN. The paper recording helps in selection of epochs of electrographic signals from different sleep-wake states. The power spectrum by using FFT reduces the number of neurons in the input vectors and avoids requirements of ensuring time invariance of the signals. The digitized and transformed samples were first used to train the network model so as to adjust the weights of the neurons in the hidden layer. Subsequently, similar unclassified sets of samples were given randomly to the network during the test phase.

Neural Network model: In comparison with other ANNs, the backpropagation neural network has the advantages of available effective training algorithms and better understood system behavior. It has a hierarchical design consisting of fully interconnected layers of propagating nodes, with one or more hidden layers between input and output nodes. This network is designed to reveal the nonlinear relationships between complex input and output (13, 14). Figure-1 shows the schematic structure of backpropagation network used in the present study. Nodes in each layer are interconnected in a feedforward fashion.

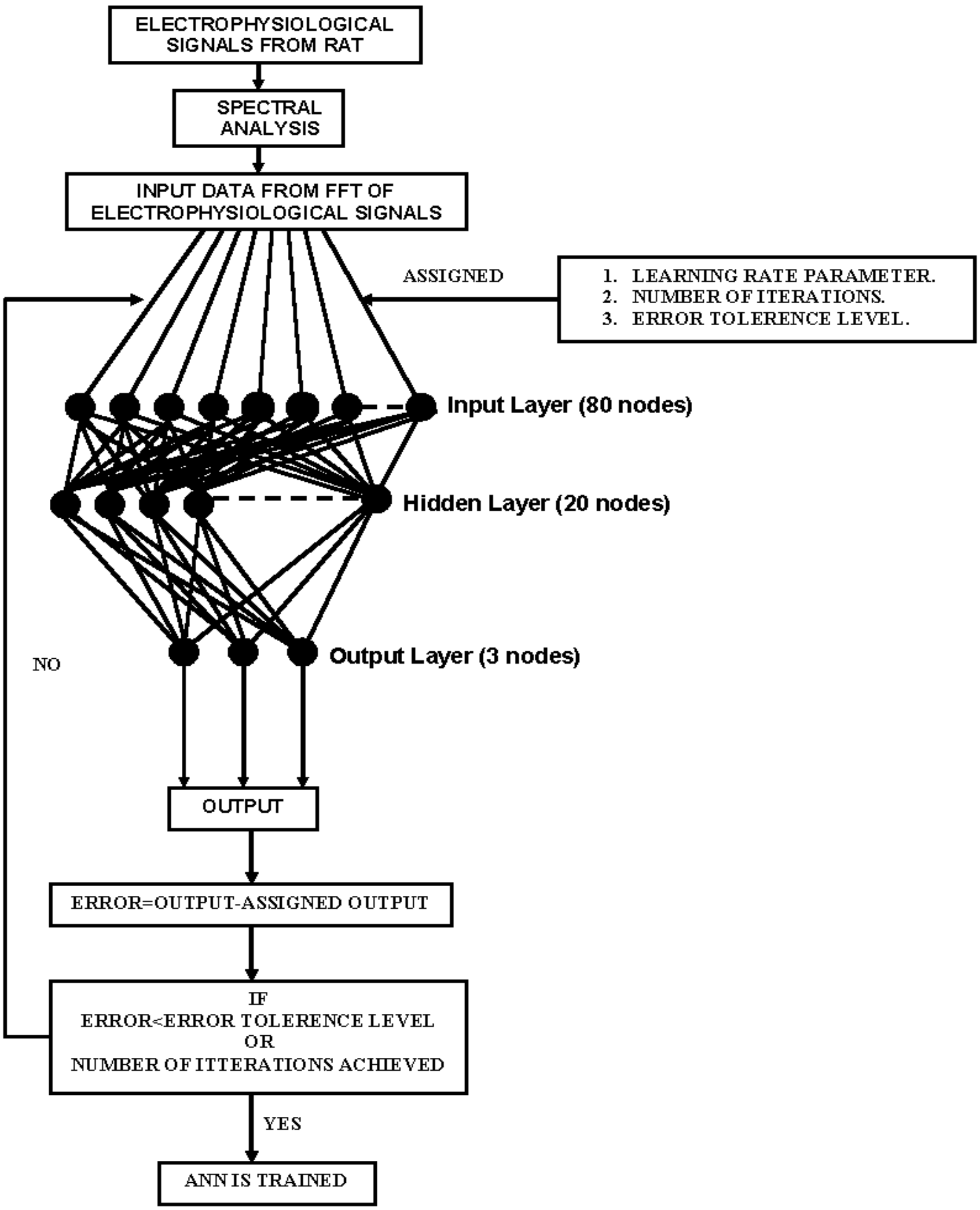

Fig. 1: Diagram shows a schematic ANN architecture in test mode for detection of sleep-wake stages. The network has 80 nodes in input, 20 nodes in hidden and 3 nodes in output layers. Selected power spectrum data from three polygraphic signals (EEG, EOG and EMG) were weighted to the input layer that finally give an output either for, SWS, REM or AWA.

The connections between different layers of nodes have associated weights which act upon the outputs of the first layer of nodes before they are processed to next. The hidden nodes have no specific functions associated with them. The hidden nodes and output nodes, however, have a sigmoid transfer function.

A three layered feedforward backpropagation program written in C++ programming language (19) was used for sleep stage analysis. It has been described earlier that single hidden layer ANNs are universal approximator and universal classifier (20); hence the present network contains only one hidden layer. The ANN has 80 nodes in input, 20 nodes in the hidden and three nodes in the output layer. The number of neurons in input layer is fixed by the input data from selected digital values of power spectrum of three polygraphic signals. One-second epochs of the simultaneous digital record from all three electrophysiological parameters were digitally preprocessed before the calculation of power spectra of each epoch. The selected numerical data from the power spectra of EEG (40 data from 10 Hz to 30 Hz), EOG (10 data from 0 to 5 Hz) and EMG (30 data from 20 to 35 Hz) were sequentially arranged to feed as input of network and assigned an output value either for SWS, REM or AWA. The sleep classification according to the output of the neural network has been used as discussed by Mamelak et al. (11) with slight modification. The criteria of classification of sleep-wake states according to the output of the network have been presented in Table-I.

Table-I: The output patterns of the ANN defined for the training as well as for the classification of three sleep-wake states.
(AWA- Awake; REM- Rapid eye movement; SWS- Slow wave sleep; UC- Unclassified sleep patterns)

EEG	**EOG**	**EMG**	**Sleep State**
0	0	0	UC
0	0	1	AWA
0	1	0	REM
0	1	1	UC
1	0	0	SWS
1	0	1	UC
1	1	0	UC
1	1	1	UC

The first output is representing EEG synchrony, second output represents the EOG activity and the third one shows the EMG activation. Thus the SWS (100) are scored when there is synchronized EEG activity with low EMG activities and no eye movement in EOG; REM sleep (010) is scored when there is desynchronized EEG activity with frequent monophasic eye movements in EOG accompanied with very low EMG and, AWA (001) is scored when input patterns with high EMG activity with desynchronized EEG and very little movement in EOG. Other sets of outputs were treated as unclassified (UC) sleep patterns. The training set of the ANN contains 100 patterns from all three sleep-wake states calculated from different rats and randomly arranged in a file named 'TRAINING.DAT'. For training, the error tolerance and learning rate parameters were assigned as 0.01 and 0.1 to activate the network. Once the simulator reaches the error tolerance specified or achieved the maximum numbers of iterations, assigned for training, the simulator save the state of the network by saving all its weights in a file 'WEIGHT.DAT'. This file was subsequently used for the testing purpose. The training pattern of the ANN at different stage of feedback training is shown in Figure-2.

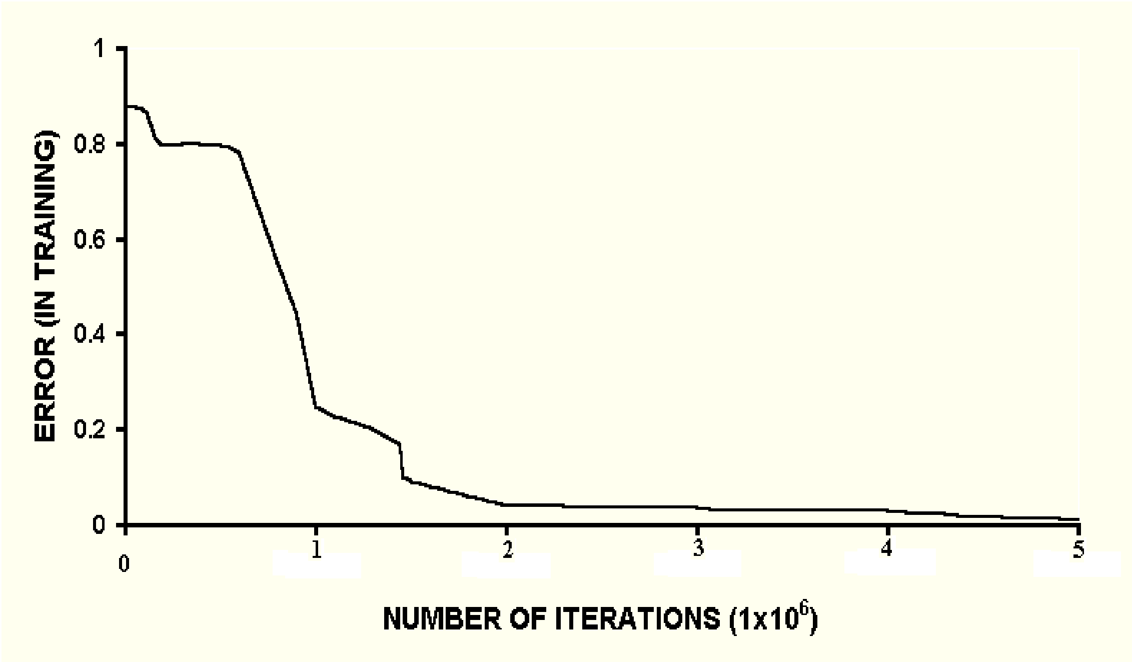

Fig. 2: Figure shows the training pattern of ANN (80-20-3) in terms of errors at different stages of feedback training.

In testing mode, the ANN was provided a set of test data, prepared similar to the training data but without assigning output values and stored in 'TEST.DAT' file. 400 data sets each from all three stages (SWS, REM or AWA), were arranged randomly in 40 separate test files, and were tested. Each file contains 30 test patterns (10 each from SWS, REM and AWA). Hence total 1200 data patterns were tested through this ANN. When test file was applied to the trained network, the network goes through a cycle of operation, covering all test data sets and generated 'OUTPUT.DAT' file containing outputs from the network for all the input data sets. The output of the network classifies the test pattern to different sleep stages.

The performance of the ANN was measured in terms of errors, which were the number of unpredicted sleep stages compared to manual scoring. The recognition is presented in terms of percentage of correct recognition. The formula for percentage recognition of seizure episodes used by Webber et al. (21) is modified for the classification of sleep-wake states and given as:

$$\text{Performance of ANN (\%)} = \frac{\text{Number of correctly classified patterns}}{\text{Total number of patterns tested}} \times 100$$

Results

The parameters of the ANN were set to get optimized performance of the network programs over the entire set of sleep data. Different learning rates were assigned between the range of 0.01 to 0.5 to investigate the best performance of the ANN with structures of 80-20-3 (nodes of input, hidden and output) (Table-II).

Table-II: Effect of learning rate parameters on the performance of (80-20-3) ANN. The network was trained for 100 patterns for 5 millions iterations and tested for 1200 test patterns.

Learning rate	Error	Accuracy (%) (Training patterns)	Accuracy (%) (Test patterns)
0.01	0.092	98	81.75
0.05	0.053	100	92.67
0.1	0.010	100	94.83
0.2	0.179	96	88.33
0.5	0.252	92	56.50

The optimum performance was observed when the rate was chosen as 0.1 with which an overall accuracy of 100% was obtained for training sets and 94.83% for test sets. The effects of number of hidden nodes are presented in Table-III.

Table-III: Effect of number of hidden nodes on the performance of ANN (80-20-3). The learning rate parameter was assigned as 0.1 and the network was trained for 5 millions of iterations.

Hidden nodes	Accuracy(%) Normal	Accuracy(%) Stressed
10	92	65.50
18	98	90.75
20	100	94.83
25	89	74.91
40	65	33.08

In a fixed 5 millions of iterations, 20 hidden nodes were resulted in the best performance than other combinations of hidden nodes.

At initial stage of training, the performance in classification of test sets was found poor (nearly 20%) which improved quickly to about 60% after 1 million cycles, but after 2 millions cycles, the ANN performance has became moderately high (92%) and very slow increase in the percentage recognition rate was observed with further training and became almost constant with an average of 94.83% after 4 millions of iterations. The percentage recognition of sleep stages by ANN at different stage of feedback training is shown in Figure-3.

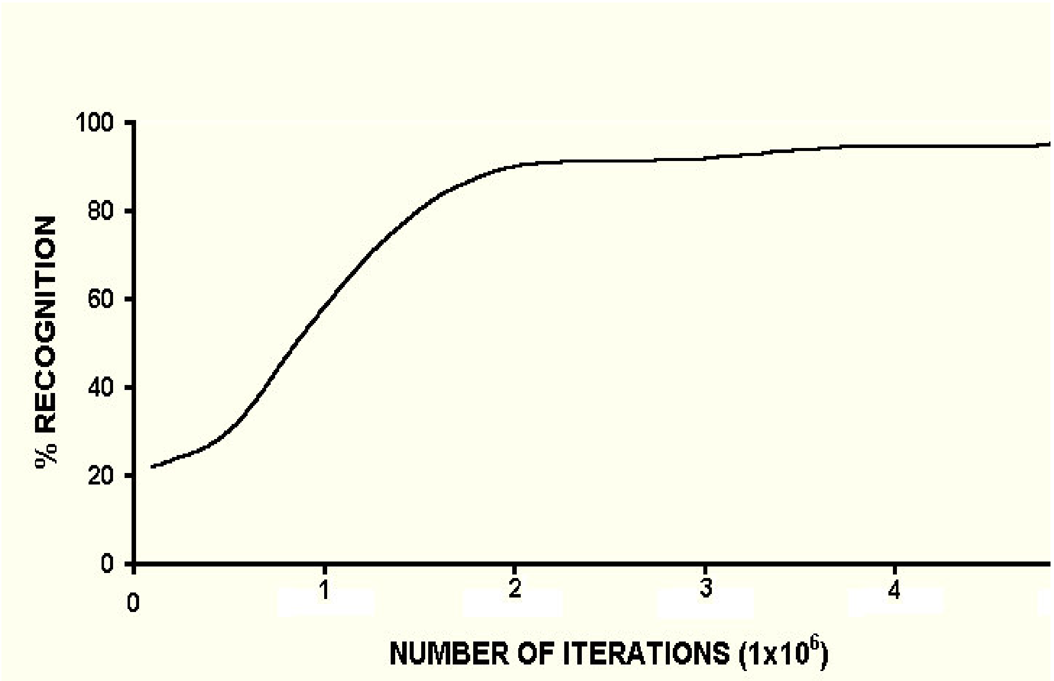

Fig. 3: Figure shows the recognition rate of ANN (in %) at different stage of feedback training.

1138 data sets out of 1200 of total sleep stage data sets were detected correctly. However, different states of SWS and the wakefulness were not sub-classified. The results of classification by the ANN model are presented in Table-IV.

Table-IV: Results of the recognition of sleep patterns for sleep-wake states

Manual Classification	Number of Samples	Classification by ANN				% Agreement
		SWS	REM	AWA	UC	
SWS	400	373	14	8	5	93.25
REM	400	3	387	6	4	96.75
AWA	400	4	8	378	10	94.50
Total (%) agreement in classification of different sleep-wake stages						94.83

The accuracy of classification of REM sleep state (96.75%) was found greater than other two sleep-wake states such as SWS (93.25%) and AWA (94.5%), respectively. The results also revealed that overall false detection by this neural architecture was observed fairly low (below 6%) in classifying all sleep-wake patterns.

Discussion

An error feedforward ANN based sleep stage recognition and discrimination with the help of selected wave bands of power spectrum of polygraphic signals is presented in this paper. The detector has been shown to perform very well with the performance of 94.83% correct detection. It has also been demonstrated that the present applied network has an effective recognition rate in classification of all three sleep-wake states. However, performance of the network was found optimum in recognizing REM sleep patterns. Results also suggest that 94.83% agreement is very high performance for an ANN in a view of fact that there are high differences in inter-observer agreement in manual sleep scoring (10). The prediction of sleep stages with the help of ANN had been earlier carried out in cats (11). The ANN was observed agreed with manual scoring of 93.3% for all epochs scored. Multilayered feedforward backpropagation artificial neural networks have also been tried to classify different sleep and wake states (22-25) in human. These neural networks were found with agreement from 65% to 90% with respect to sleep profile scored manually. Therefore, 94.83% agreement between ANN and manual staging seems to be on the high side of the expected range for the classification of sleep-wake stages.

Power spectrum analysis with the help of FFT is the most popular approaches that permits the presentation of large data in comprehensive manner and by selection of components for further processing results in significant data reduction (26, 27). The power spectrum analysis is considered as a superior method in its computational ability (28) and well accepted for data reduction for long term electrophysiological recording (17, 26). Also due to effective use in frequency analysis, this technique has been used successfully in the ANN based pattern recognition tasks related with EEG (11, 12, 29-32).

The success of the ANN in sleep-wake classification involves the optimization of the network structure and the parameters. One hidden layer was used, based on several previous studies (33, 34) which showed that one hidden layer resulted in the same performance as two or more hidden layers. However, conflicting results were reported in the literature on the number of hidden nodes (35). In the present study, various combinations of the three layered backpropagation network were tested with assigning different learning rate parameters and the most reliable performance rate for the classification of sleep-wake stages was derived with the ANN configuration of 80-20-3 (Input-Hidden-Output nodes). Simultaneously, ANN learn to associate a given input pattern with a given output pattern based on feature common to all input pattern and produce the output value. Hence, training and testing with more samples as well as by using different ANN architecture may improve the accuracy of identification. The ANN can also allow us to detect micro-sleeps (sleep-wake phases appear for very short time intervals in sleep cycles) and frequent state transition with greater sensitivity. Summarily, it can be said that ANN can provide an effective tool for recognition and determination of various sleep-wake states.

Acknowledgements

The authors are grateful to the Coordinator, School of Biomedical Engineering, Institute of Technology, Banaras Hindu University, Varanasi (India) for providing laboratory facilities for carrying out this study.

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