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AUTOMATIC INTERPRETATION OF AWAKED EEG BY USING CONSTRUCTIVE NEURAL NETWORKS WITH FORGETTING FACTOR

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Abstracts The automatic interpretation of awake background electroencephalogram (EEG), consisting of quantitative EEG interpretation and EEG report making, has been developed by the authors based on EEG data visually inspected by an electroencephalographer (EEGer). The present study was focused on the adaptability of the automatic EEG interpretation which was accomplished by the constructive neural network with forgetting factor. The artificial neural network (ANN) was constructed so as to give the integrative decision of the EEG by using the input signals of the intermediate judgment of 13 items of the EEG. The feature of the ANN was that it adapted to any EEGer who gave visual inspection for the training data . The developed method was evaluated based on the EEG data of 57 patients. The re-trained ANN adapted to another EEGer appropriately.

Keywords Automatic EEG interpretation, Awake background EEG, Artificial neural network, Dynamic node creation method, Structural learning algorithm, Adaptability

1. INTRODUCTION

The automatic integrative interpretation of awake background EEG, had been developed by the authors and presented at the KACCs in series: quantitative EEG interpretation (Nakamura et al. 1990), EEG report making (Nakamura et al. 1992a), and pre-processing for artifacts detection and reduced vigilance level detection (Nakamura et al. 1994). The proposed automatic EEG interpretation has been in good agreement with the EEGer's visual inspection. However, integrative interpretation or final decision of an EEG record whether it is normal or abnormal one is a subjective task, since the judgment for a particular record slightly varied with the EEGer. Therefore, it is important to develop an algorithm for decision making, that satisfies the criteria of each EEGer who visually inspects the EEG records. Use of artificial neural network (ANN) for automatic EEG interpretation is profitable to overcome this problem. ANNs are trained and have an ability to construct their internal configuration of the knowledge without any external control (Klöppel 1994). These features could make the construction task more simple.

The present study consists of the development of an ANN for the integrative EEG interpretation and the adaptation of the designed neural network for any other EEGer who visually inspected the EEG records. The proposed constructive neural network with forgetting factor was developed using a combination of the dynamic node creation method (DNCM, Ash 1989) and the structural learning algorithm (SLA, Ishikawa 1990). The method was evaluated based on the EEG data of 37 patients visually inspected by an EEGer (EEGer A) and the EEG data of 20 patients visually inspected by another EEGer (EEGer B).

2. METHOD

2.1 Data Acquisition and Visual Inspection of EEGs

The EEGs from 57 patients, aged between 18-64 years, with various neurological disease were recorded using 16 cup electrodes fixed to the scalp at points Fp_1, F_3, C_3, P_3, O_1, Fp_2, F_4, C_4, P_4, O_2, F_7, T_3, T_5, F_8, T_4, and T_6 (International 10-20 System) in reference to the ipsilateral ear electrode (A_1 and A_2). The recording was done with the time constant of 0.3 sec, the high cut filter of 120 Hz, a paper speed of 3 cm/sec and a sensitivity of 0.5 cm/50 μV.

The procedures for visual inspection are the following: ten consecutive strips of EEG, each 5 sec long, were subjected to visual inspection by qualified EEGers (EEGer A, H.S.; EEGer B, A.I.). The features taken into account for visual evaluation of EEG record consisted of the frequency, amplitude, shape of the waves in the spatial and temporal distributions of the scalp. The criteria applied was categorized into 16 items (see Fig. 1). These items were classified into 8 items related to the posterior dominant rhythm, 2 items related to beta rhythm (β-more than 13 Hz), and 2 item of each of theta rhythm (θ-from 4 Hz to less than 8 Hz), delta rhythm (δ-less than 4 Hz) and non-dominant alpha rhythm (α-from 8 to 13 Hz). Every item of EEG was graded into 4 scores: normal (0), mildly abnormal (1), moderately abnormal (2) and markedly abnormal (3). Based on the interpretation of these items the EEGer made a final judgment about the normality or abnormality of the record whose scores were also assigned between 0 and 3.

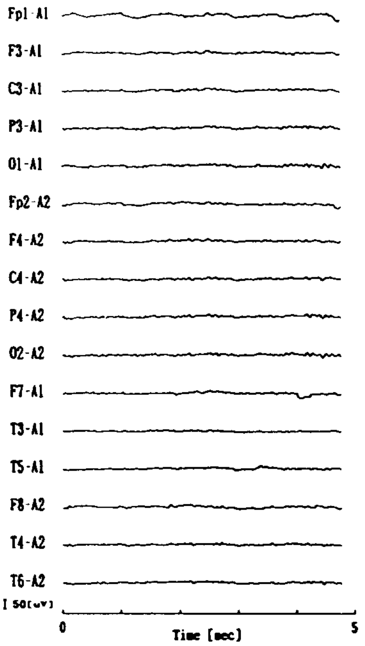
For the purpose of the present study, the EEG records were divided into two groups of data. Group A, interpreted by EEGer A, consisted of a total of 37 EEG records and divided in 22 records for training the prime ANN and 15 other records for testing. Group B, interpreted by EEGer B, consisted of a total of 20 EEG records and divided in 12 records for the training of the ANN to be adapted and 8 for testing it.

2.2 Design of the ANN

The aim of the ANN is to make the integrative interpretation or final judgment of the EEG based on the intermediate results of the quantitative interpretation. To design the ANN we employed 3 layers and fully connected units as for the initial configuration (see Fig. 2). Each unit was interconnected through weights which would be determined based on teaching signal given by the EEGer. The input units for the ANN were 13 out of 16 items of quantitative interpretation that characterize the visual inspection done by the EEGer. A bias unit was introduced in both the hidden and output layer, respectively. The input value for the bias units was fixed at one and the weights were trainable. The output signal of the units at the hidden layer was given through a bipolar sigmoidal function as:

$$S_j = \frac{1}{(1 + exp^{-u_j})} - \frac{1}{2} \tag{1}$$

where u_j was the activation or input of the hidden unit j.



Items			EEGer Value	EEGer Score
DOMINANT RHYTHM	1	Existence	yes	0
	2	Organization	mildly to moderately abnormal	2
	3	Asymmetry [%]	0	0
	4	Frequency [Hz]	9.0	0
	5	Asymmetry [Hz]	0	0
	6	Amplitude [μV]	25	0
	7	Asymmetry [%]	0	0
	8	Extension [μV]	till C, MT	0
β	9	Amplitude [μV]	5~10	0
	10	Asymmetry [%]	0	0
θ	11	Duration [%]	10	2
	12	Electrodes	mainly Fp, F, (C)	—
δ	13	Duration [%]	0	0
	14	Electrodes	—	—
α	15	Duration [%]	20	1
	16	Electrodes	Fp, F (both sides)	—

Mildly abnormal waking and drowsy record (final judgment: 2)
because of:
1. disorganized background activity, and
2. occasional θ waves bianteriorly.
Suggests mild diffuse cerebral hypo function

Fig. 1. Five sec long time series of an EEG record subjected to visual inspection by EEGer A. The EEGer evaluates the recorded electrical activity and categorized it into 16 items, scoring it between 0 and 3. At the same time EEG report is written, a term for grading the whole EEG appeared first and terms for expressing abnormalities of each item succeeded afterwards.

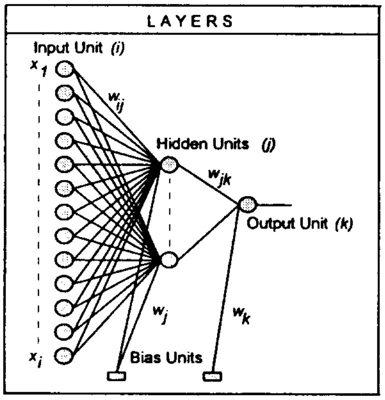


Fig. 2. Layers and units of an artificial neural network

The output unit of the ANN was considered to have a linear transfer function. The final judgment made by the EEGer was used as the teaching signal for the ANN.

The training of the ANN was performed such that the output of the network produced the values similar to those of the final judgment made by the EEGer. The testing consisted in verifying the generalization capability of the ANN or its ability to return appropriate results with data which were not used to train it. The judgment emitted by the ANN was considered correct if the absolute value of the difference between the teaching signal and the output of the ANN was less than 0.5. The initial weights for the training were selected randomly with values ranging from 0 to 1.

2.3 Training Algorithm of the ANN

The algorithm applied to train the ANN was based on a combination of the dynamic node creation method (DNCM) and the structural learning algorithm (SLA), named constructive neural network with forgetting factor. The algorithm utilized the backpropagation learning algorithm (BPA, Rumelhart et al. 1988), in which the error was feedbacked through the ANN layer by layer and used to update the value of the weights at each layer, so that the error at the output could be minimized. The cost function of the BPA to minimize was:

$$J = \frac{1}{2}\sum_{t=1}^{n}(E_t)^2 = \frac{1}{2}\sum_{t=1}^{n}(T_t - O_t)^2 \tag{2}$$

where E_t was the error at the output of the ANN, T_t the teaching signal, O_t the output signal of the ANN, and t the training pattern.

The DNCM and the SLA were combined as follows: the criterion to be minimized was the cost function of the SLA (eq. (3)). The training began with one unit at the hidden layer. The DNCM supervised the output error of the ANN to decide when a new unit should be added to the hidden layer. Mean while, the SLA applied the weight decay calculation, in which the linking weights at each presentation of a training pattern were weakened; the weights were forced to get closer to zero. Both the grow up and the weight decay continued until the stop criterion was achieved, and finally, the weights that were closer to zero and did not affect the error criterion were eliminated.

A computer program was written in standard C and ran on a Dell Computer, model 466/ME, under the DOS operating system. To determine the most effective ANN's configuration, different initial weights of the network were adopted, because the cost function for the training had multi modal characteristics. The configuration that gave the minimum cost was selected for the problem.

2.3.1 Structural Learning Algorithm (SLA). The SLA was used to reduce the linking weights that did not affect the output response of the ANN.

The cost function used by the SLA was define as:

$$J_f = \frac{1}{2}\sum_{t=1}^{n}(E_t)^2 + \lambda\sum_{ij}\left|w_{ij}\right| \tag{3}$$

The first term in eq. (3) was the cost function due to the BPA. The second term was added to weaken the linking weights at each presentation of a training pattern; the coefficient λ was a relative weighting and w_{ij} was the linking weight from the unit i to unit j (see Fig. 2).

A change of a weight, Δw_{ij} (eq. (4)) was obtained according to the generalized delta rule (Rumelhart and McClelland 1988), which was the partial derivative of the cost function J_f with respect to a given weight, multiplied by the learning coefficient (η). This operation was defined as the change of weight due to the BPA minus a forgetting factor (ε) as:

$$\Delta w_{ij} = -\eta \frac{\partial J_f}{\partial w_{ij}} = -\eta \frac{\partial J}{\partial w_{ij}} - \varepsilon \, sgn(w_{ij}) \quad (4)$$

where J was the cost function of the BPA (eq. (2)). The forgetting factor, $\varepsilon=\eta\lambda$, was used to force each weight to be closer to zero at each iteration and $sgn(w_{ij})$ was defined as:

$$sgn(w_{ij}) = \begin{cases} 1 \text{ if } w_{ij} > 0 \\ 0 \text{ if } w_{ij} = 0 \\ -1 \text{ if } w_{ij} < 0 \end{cases} \quad (5)$$

In order to obtain the corresponding changes for those connections with the hidden units (Δw_{ij}, Δw_j) and those with the output unit (Δw_{jk}, Δw_k), it was required to take the derivative in eq. (4) with respect to the weight.

2.3.2 Dynamic Node Creation Method (DNCM). The DNCM was used to optimize the number of units at the hidden layer. The algorithm automatically increased the number of units at the hidden layer until the desired error criterion was achieved. The algorithm began with only one unit at the hidden layer and applied the SLA to minimize the output error of the ANN. A new unit was added when a flattening of the average squared error curve was detected as (see Fig. 3):

$$\frac{a_t - a_{t-w}}{a_{t_0}} < \Delta_T \quad (6)$$

where t_0 was the number of iterations after the last node was added to the hidden layer (initially is 0), t the current number of iterations, w the width of window (in trials) over which the trigger slope was determined and Δ_T was the trigger slope value. When the flatness of the error curve fell below Δ_T, a new unit was added and all the new weights were randomly initialized. The process of adding units continued until the average squared error was smaller than the desired error C_a.

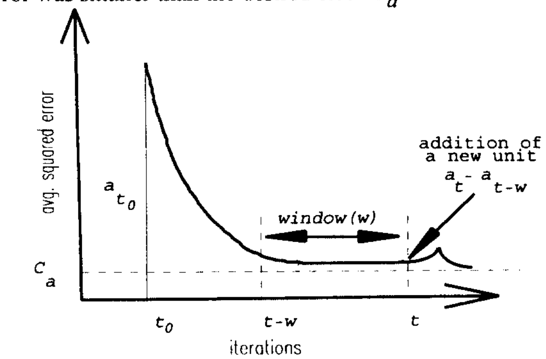


Fig. 3. A new unit was added to the hidden layer when a flattening of the average squared error was detected.

2.4 Generalization and Adaptation of the ANN

The generalization or the ability of the prime ANN to recognize patterns which were not used during the training, was verified through the testing, by using data interpreted by the same EEGer (EEGer A) and with data interpreted by another EEGer (EEGer B). During the testing, the ANN passed the testing patterns forwardly and the error between the target and the output value of the ANN was calculated without changing the weights.

To adapt the constructed ANN for another criteria of EEG interpretation, it was trained again by using both data interpreted by EEGer A and B. The procedures used to train and test the ANN were the same as the procedures stated in previous sections, with the exception that the initial configuration used to adapt the ANN was the final configuration of the trained ANN-1 (see Fig. 4b and 5a). The values of the parameters in the algorithms were the same as the previous stage.

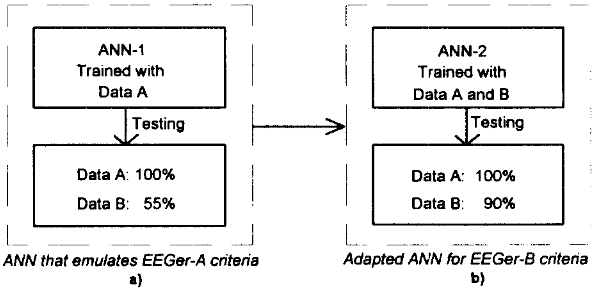


Fig. 4. Block diagram indicating the adaptation procedure. Training and testing of a) ANN-1, b) ANN-2.

3. RESULTS

3.1 Prime Artificial Neural Network (ANN-1)

The final configuration for ANN-1 was 2 units at the hidden layer eliminating 17 linking weights (see Fig. 5a). The testing of this ANN gave 100% of accuracy for the data interpreted by EEGer A. But the generalization performance of the ANN, using data interpreted by EEGer B only produces 55% of accuracy. Indicating that ANN-1 was not proper to interpret records for EGGer B. Moreover, ANN-1 was tested by using the scores for the intermediate judgment from a computerized method, for quantitative representation and automatic scoring of the EEG items (Nakamura et al. 1990), instead of the scores from the visual interpretation. The automatic intermediate judgment coupled to the ANN for the integrative evaluation of 18 EEG records gave 77.7% of accuracy.

3.2 Adapted Artificial Neural Network (ANN-2)

Since ANN-1 could not generalize well for the data by another EEGer, the adaptation process was performed. The adapted network (ANN-2) was able to interpret data either from EEGer A or B. This ANN consisted of 2 units at the hidden layer eliminating 12 linking weights (see Fig. 5b). When the generalization performance was verified, an improvement was obtained, 96.5% of accuracy over the training and testing data (2 records of 57 were interpreted incorrectly for the data interpreted by EEGer B). As can be observed in Fig. 5, the topology of both ANN were similar in reference to the units at the hidden layer. The adapted parts were the amount of linking connections and the magnitude of the weights.

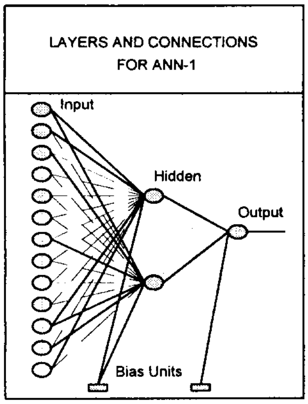
3.3 Value of the Parameters for the Algorithms

The value for the width of window (w) was selected as 225 iterations, the trigger slope value (Δ_T) 0.07, the learning coefficient (η) 0.13 and the relative weighting (λ) 1×10^{-3} to 1×10^{-6} (considered as a function of iteration number), respectively.

4. DISCUSSION

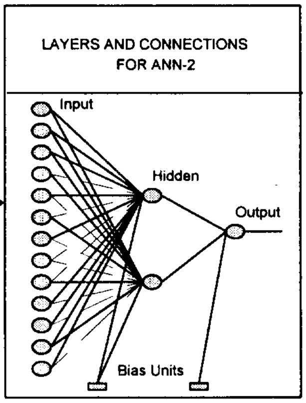
4.1 Advantage of the Algorithms

The algorithms for constructing the ANN are based on the backpropagation algorithm with co-operative use of the DNCM and the SLA to optimize the number of units in the hidden layer



FINAL WEIGHTS FOR ANN-1		
HIDDEN LAYER		OUTPUT LAYER
Unit 1	Unit 2	Output Unit
1.39	0.56	1.67
1.09	------	2.30
------	1.17	
------	------	
------	------	
------	------	
------	0.91	
------	------	
------	------	
------	------	
0.30	0.60	
------	0.73	
0.89	------	
1.22	1.96	-1.12

a)



FINAL WEIGHTS FOR ANN-2		
HIDDEN LAYER		OUTPUT LAYER
Unit 1	Unit 2	Output Unit
8.20	0.94	1.16
9.84	-0.13	2.01
-4.25	3.07	
------	------	
-2.56	------	
------	------	
4.27	------	
------	------	
------	-0.89	
-6.18	------	
3.82	------	
-1.70	1.59	
3.33	------	
12.17	3.14	-1.50

b)

Fig. 5. Final structure of a) ANN-1 and b) ANN-2. The dashed lines indicates the connections that were eliminated.

and the linking connections.

By using the bipolar transfer function instead of the unipolar one, we were able to improve the convergence ratios, learning speeds, and the generalization.

4.2 Advantage and Drawbacks Using ANNs

One of the main advantages of ANN is capability of learning and adaptability. The ANNs are able to recognize similar input patterns compared with the pattern that has been used during the learning process, and can provide useful results for different input patterns. Since the ANNs build their own knowledge representations, it is not necessary for questioning EEGers in order to develop an algorithm which emulates their way of interpretation. The only necessary information needed is a set of input patterns together with their corresponding correct answer. Furthermore, the ANN can be simply adapted for other EEGers, by only training it again with data which matches the desired criteria to emulate.

One of the drawbacks that can be detected while using ANNs is that the training itself often needs a large amount of computing time, although that the decision making performed by the ANN is fast. Another drawback is local minima of the cost function, that could be defined as a point of regionally low error during gradient descent. Since the optimization aim of the learning or training is to minimize the quantitative error, some times this minimization gets trapped in a local minima. Although these minima could not be the best possible solution to the problem, the resulting ANN will be close to optimal. To overcome this problem, it is recommended a proper selection of the initial weights for the training process. For the investigation, this problem was solved by performing several trials using different initial values for the weight of the ANN. The best ANN which gave the minimum error out of these trials was adopted.

4.3 Parameters of the Constructed ANN

The parameters of the DNCM that must be selected by the designer, the windows width (*w*) at which the flatness of the error curve will be verified and the trigger slope (Δ_T) below which a new unit must be added (see Fig 3). The selection of these two parameters is very important and will vary according to the problem. If the windows width is selected too large, the convergence process takes a long time. On the other hand, if it is too small, the algorithm adds units to the ANN in excess. For smaller values of the trigger slope, the method takes much time to add a new unit and for higher values, the number of added units are too large.

Appropriate selection of the learning coefficient (η) and the setting of the relative weighting (λ) in the SLA is also important since it may affect the convergence speed. If the relative weighting is set too large, the algorithm has problem to converge and if it is set too small, the algorithm has the tendency not to eliminate the weights. Those parameters were selected appropriately by cut and try manner in this study. However, those selections should be done theoretically in future study.

4.4 Clinical Application

There have been several attempts, computerized based model for automatic EEG interpretation (Nakamura et al. 1992b); but the designing of these methods for a proper final judgment must be done with the guidance of an EEGer or physician. While using the developed ANN's technology, this step could be simplified. Automatic EEG interpretation systems can be used as a support tool for physicians in the interpretation of EEG records and could accelerate the interpretation procedure in comparison to the conventional visual interpretation only.

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