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Estimation of the Amount of Drug to be Applied to the Patient Using Elman Recurrent Artificial Neural Network

Elman Geri Beslemeli Yapay Sinir Ağı Kullanılarak Hastaya Uygulanacak İlaç Miktarının Tahmini

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ABSTRACT

In this study, Elman recurrent neural network has been used in order to determine the depth of anesthesia in the continuation stage of anesthesia and to estimate the amount of medicine to be applied at that moment. The applied artificial network is composed of three layers, namely the input layer, the hidden layer and the output layer. Fast back-propagation learning algorithm (Traingdx) has been used in the training of the network, and nonlinear activation function sigmoid (sigmoid function) has been used in the outputs of the hidden layer and the output layer. The values of the power spectral density values of 10-second EEG(elektroensefalografi*)* segments which correspond to 1-50 Hz frequency range; the ratio of the total power of PSD(power spectral density*)* values of the EEG segment in that moment in the same range to the total of PSD values of EEG segment taken prior to the anesthesia; similarly, the ratio of the total of PSD values of EEG data to the total of PSD values of the previous EEG data; and the amount of anesthetic medicine have been entered into the inputs of artificial neural network.

MAKALE BİLGİSİ

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EEG güç spektrumu,
Elman tekrarlayan sinir ağları.

ÖZET

Bu çalışmada anestezi aşamasında, anestezi derinliğini belirlemek ve o anda uygulanacak ilaç miktarını tahmin etmek için Elman geribeslemeli sinir ağı kullanılmıştır. Uygulanan yapay sinir ağı, giriş katmanı, gizli katman ve çıktı katmanı olmak üzere üç katmandan oluşmuştur. Ağın eğitiminde hızlı geri beslemeli öğrenme algoritması (Traingdx), gizli katman ve çıktı katmanının çıktılarında doğrusal olmayan aktivasyon işlevi için sigmoid fonksiyonu) kullanılmıştır. 1-50 Hz frekans aralığına karşılık gelen 10 saniyelik EEG segmentlerinin güç spektral yoğunluk değerlerinin değerleri; aynı aralıktaki EEG segmentinin o andaki PSD değerlerinin toplam gücünün anestezi öncesi alınan EEG segmentinin toplam PSD değerlerine oranı; benzer şekilde, EEG verilerinin toplam PSD değerlerinin önceki EEG verilerinin toplam PSD değerlerine oranı; ve anestezik ilaç miktarı yapay sinir ağının girdilerini oluşturmaktadır.

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1. INTRODUCTION

Determining the depth of anesthesia during the general anesthesia in the surgical operations is an important problem and a quite complicated issue [1]. In recent years, the use of EEG for this purpose has caught more attention [2]. Due to the fact that current medical techniques cannot provide a real-time measurement of the condition of the central nervous system, they cannot keep the depth of anesthesia at a safe level with an absolute stability. The depth of anesthesia may change from one moment to another [3].

Current medical techniques cannot measure the status of central neural system (CNS) on real-time basis; therefore, they cannot determine anesthetic depth at full accuracy and safety. Anesthetic depth can change from one moment to another [4]. Aestheticians cannot set the dosage in time to protect the patient from pain without an effective conscious monitor [5]. EEG monitorization is used for determining the pharmaco-dynamic effect of the anesthetic medicine or the improvement of CNS on real-time basis [6]. EEG spectrum which shows the power intensity against frequency of EEG data can be categorized into the following bands: d (1-3 Hz), q (4-7 Hz), a (8-13 Hz), b1 (14-30 Hz), b2 (31-50 Hz). When the results of conducted studies are taken into consideration, it can be seen that BIS is the best among electroencephalographic parameters for determination of anesthetic-hypnotic depth during surgical operation [7]. Increase of EEG delta activity is evaluated as a finding of anesthetic depth [8]. A fuzzy logic-controlled system has been designed for sevoflurane, the anesthetic agent, by means of using the blood pressure and pulse data taken from patient [9].

EEG has been recommended in many studies as a significant method in determining the depth of anesthesia [10]. Bispectral index (BIS) is an experiment-based parameter which is obtained statistically. Obtained by using the high frequency (30-47 Hz) components of the EEG data, this parameter holds a great importance in determining the depth of anesthesia [11]. Although BIS is an important parameter in determining the unconsciousness condition, it is not an absolute measure of the unconsciousness levels but an indication of the possible condition of the level of anesthesia.

Feedback artificial neural networks are called as dynamic neural networks. The most popular of these networks are Hopfield network and Elman network. Hopfield network structure has not been considered as appropriate to our study since it has a single layer structure. Elman recurrent neural network which we have used in our study has a multilayer network structure consisting of the input layer, the hidden layer and the output layer. In the Elman recurrent neural network, sigmoid function exists in its hidden layer and linear activation function exists in its output layer.

The back propagation (BP) algorithm is widely recognized as a powerful tool for training feed forward neural networks (FNNs). But since it applies the steepest descent method to update the weights, it suffers from a slow convergence rate and often yields suboptimal solutions [12, 13]. A variety of related algorithms have been introduced to address that problem. A number of researchers have carried out comparative studies of MLP training algorithms [12]. The BP with momentum and adaptive learning rate algorithm [14], used in this study are these type algorithms.

53 input layer neurons have been applied in the input layer of the Elman recurrent neural network which we have used in this study. EEG spectrum information of the patient has been applied on the last 50 neurons of these neurons as an input data. The first three values are respectively "Total power/normal power", "Total power/previous power" and "previous amount of anesthesia" information. Due to the fact that input values applied on the artificial neural network contain more detailed information, the network has been ensured to have been trained with less error [15].

2. ACTUALIZED NN SYSTEM

Elman recurrent neural network is composed of three layers. There are 53 neurons in the input layer, 30 neurons in the middle layer and 1 neuron in the output layer (Figure.1). Nonlinear activation function sigmoid (sigmoid function) has been used in the hidden layer nodules whereas linear activation function has been used in the output layer nodules.

As input layer information, PSD values within 1-50 Hz frequency range have been entered, which have been obtained by taking (Power Spectral Density) values of 10-second EEG records that have been received from the patient once in every 5 minutes before and during the anesthesia. During the anesthesia, the information regarding the ratio of the total of PSD values of 10-second EEG segment at that moment to the total of PSD values of 10-second EEG segment recorded before the operation has been also entered. In addition to this information, the information regarding the ratio of the total of PSD values of 10-second EEG segment at that moment during the anesthesia to the total of PSD values of 10-second EEG segment previously recorded, and anesthetic gas amount has been also entered. With the application of the previous anesthesia value on the NN input, the effect of the previous anesthetic gas amount on the depth of anesthesia has also been ensured to have been evaluated by the NN.

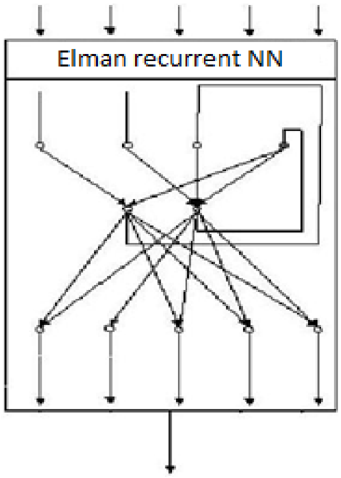

Figure 1. Structure of Elman recurrent neural network [16]

3. RESULTS AND CONCLUSIONS

In this study, Elman recurrent neural network has been used in order to determine the depth of anesthesia in the continuation stage of anesthesia and to estimate the amount of medicine to be applied at that moment. The applied artificial network is composed of three layers, namely the input layer, the hidden layer and the output layer. This network has been designed so as to have 53 neurons in the input layer, 30 neurons in the hidden layer and 1 neuron in the output layer. Fast back-propagation learning algorithm (Traingdx) has been used in the training of the network, and nonlinear activation function sigmoid (sigmoid function) has been used in the outputs of the hidden layer and the output layer.

Total power/normal power, total power/previous power, previous anesthesia amount, applied anesthesia amount, NN output values have been given. Total power/normal power ratio is the ratio of the total of PSD values of the EEG segment selected for the test to the total of PSD values of the EEG segment recorded before the anesthesia. Total power/previous power ratio gives information regarding the ratio of the total of PSD values of the EEG segment selected for the test to the total of PSD values of the previous EEG segment. In the previous anesthesia amount regarding the anesthesia applied on the patient in the previous condition is given. NN output is the anesthetic gas amounts suggested by the artificial neural network.

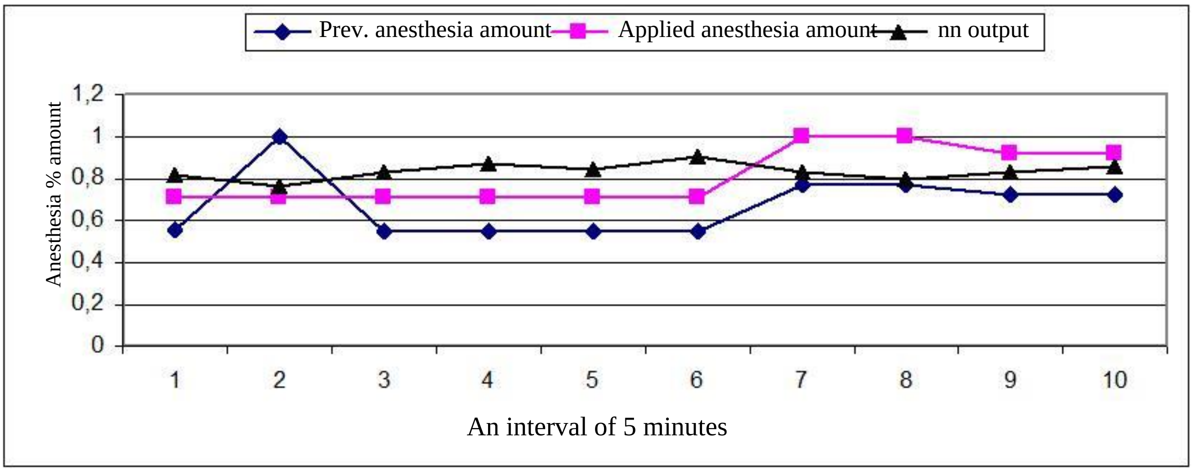

Figure 2. Applied anesthesia amount and previous anesthesia amount, artificial neural network output values

Figure 2 is examined, it is seen that Elman Recurrent neural network used for estimation is successful in estimating the amount of anesthetic gas applied.

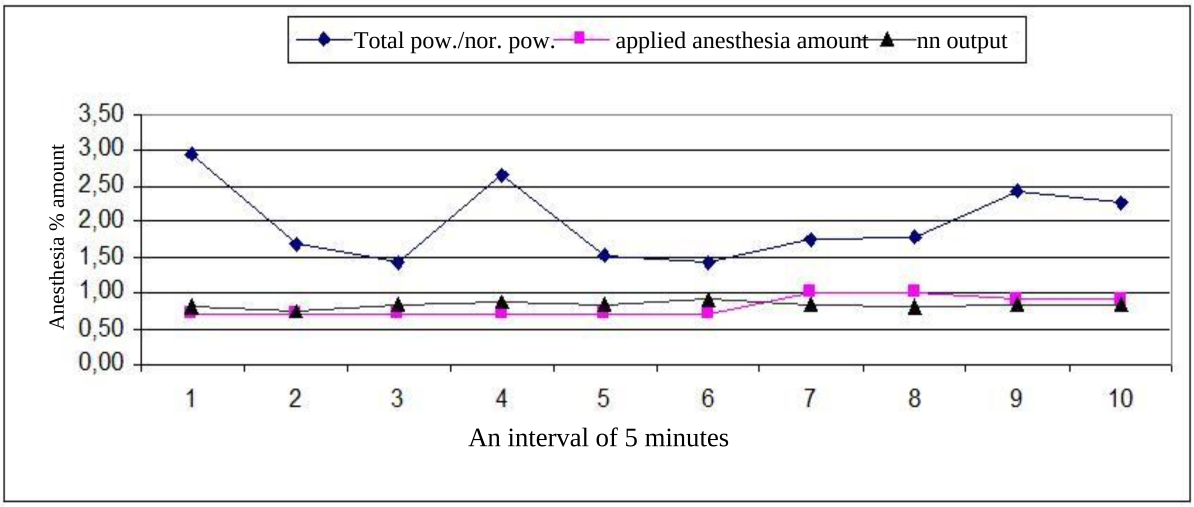

Figure 3. Applied anesthesia amount, artificial neural network output, "total power/normal power" values

In Figure 3, it is observed that anesthetic gas amount found by the artificial neural network is more appropriate compared to the change in the total power of EEG segment.

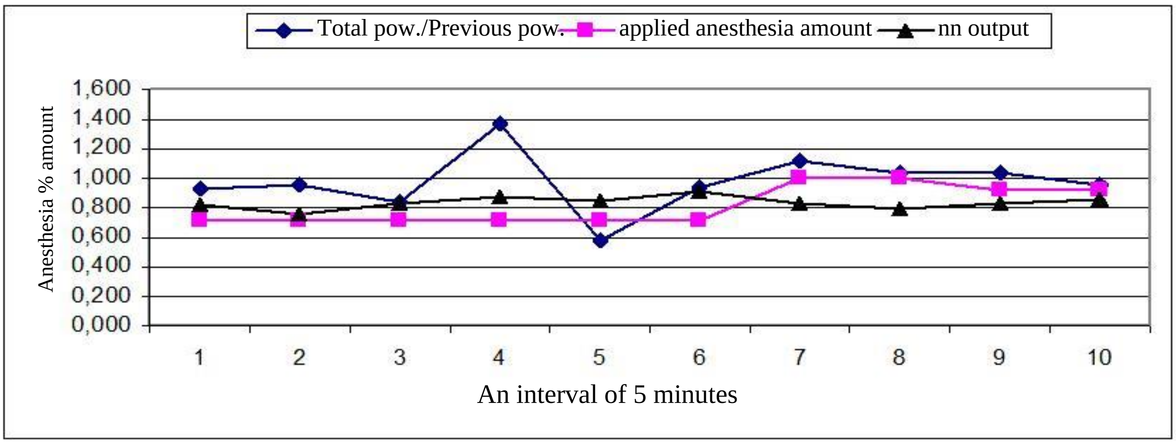

Figure 4. Applied anesthesia amount, artificial neural network output, total power/previous power values

In Figure 4, the ratio of the total power of EEG segment of that moment to the total power of previous EEG data, and whether or not EEG data tends to increase can be seen.

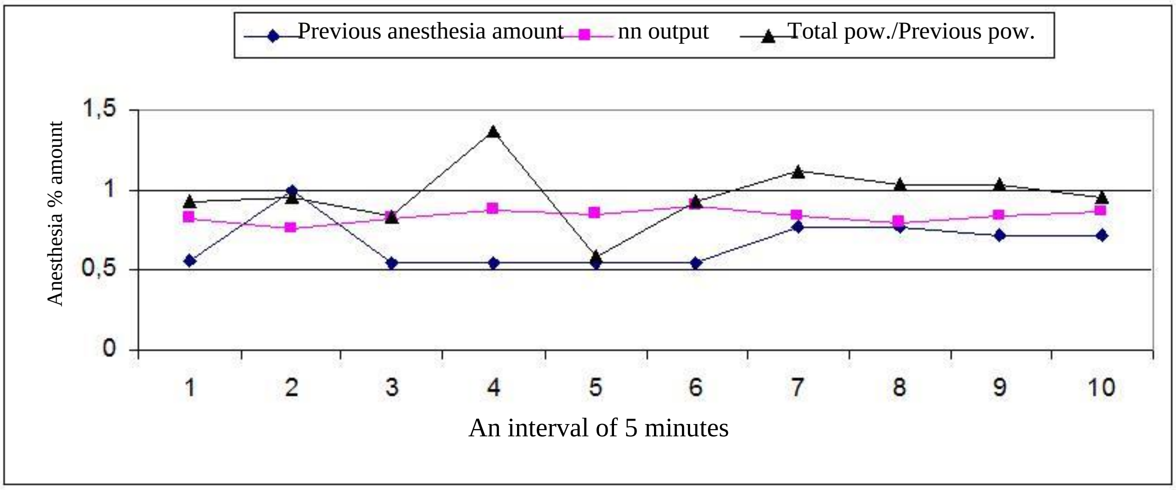

Figure 5. Previous anesthesia amount, artificial neural network output, total power/previous power values

In Figure 5, output values generated by the artificial neural network have been compared with the previous anesthesia amount data according to the change in the ratio of the total power of EEG data in that moment to the total power of the previous EEG segment.

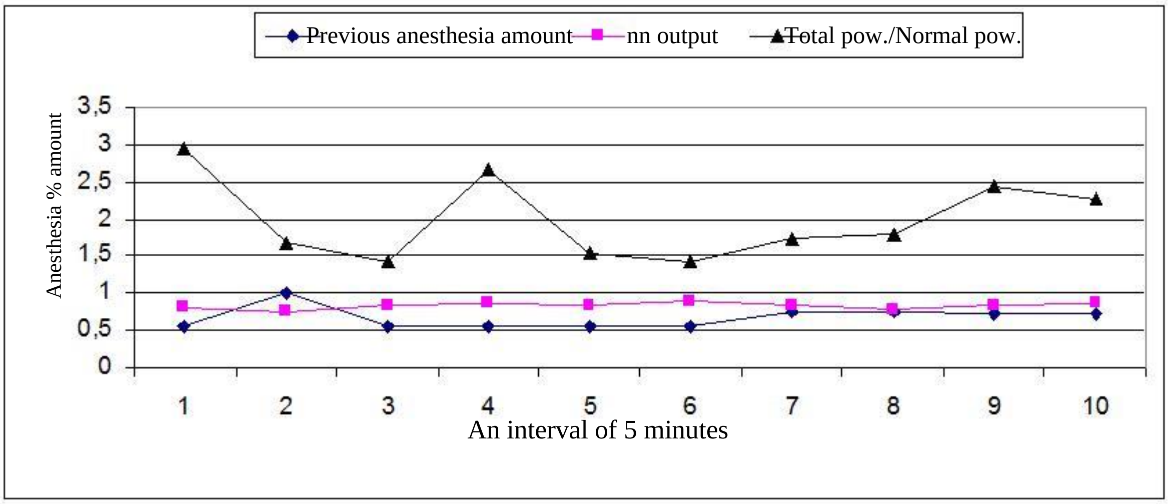

Figure 6. Previous anesthesia amount, artificial neural network output, "total power/normal power" values

In figure 6, a decrease or increase is seen according to the previously given anesthetic gas amount. In this chart, it is observed that anesthetic gas amount found by the artificial neural network is more appropriate than the applied gas amount.

In view of this study, it has been observed that the anesthetic depth check which is conducted using EEG power changes and which provides the real-time changes in the central nervous system is more precise than other measurement data. When the test data which have been applied on the designed system and the results generated by the system are observed, it has been seen that the applied method has been successful in estimating anesthetic gas according to anesthesia level.

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