Title
Analysis of early hypoxia EEG based on a novel chaotic neural network

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Normal and Hypoxia EEG Recognition Based on a Chaotic Olfactory Model

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Abstract. The KIII model of the chaotic dynamics of the olfactory system was designed to simulate pattern classification required for odor perception. It was evaluated by simulating the patterns of action potentials and EEG waveforms observed in electrophysiological experiments. It differs from conventional artificial neural networks in relying on a landscape of chaotic attractors for its memory system and on a high-dimensional trajectory in state space for virtually instantaneous access to any low-dimensional attractor. Here we adapted this novel neural network as a diagnostic tool to classify normal and hypoxic EEGs.

1 Introduction

Biological neural systems are complex but rapid and reliable in pattern classification. We follow the architecture of the olfactory system to construct a high dimensional chaotic network, the KIII model, in which the interactions of globally connected nodes are shaped by reinforcement learning to support a global landscape of high-dimensional chaotic attractors. Each low-dimensional local basin of attraction corresponds to a learned class of stimulus patterns. Convergence to an attractor constitutes abstraction and generalization from an example to the class. KIII model has performed well on several complex pattern recognition taskss [1], [2], [3].

Here we present a new application of the KIII network for recognition of normal and hypoxic EEGs based on the feature vectors of 30-60 Hz sub-band wavelet packet tree coefficients constructed using wavelet packet decomposition.

2 KIII Model Description

Biologically, the central olfactory neural system is composed of olfactory bulb (OB), anterior nucleus (AON) and prepyriform cortex (PC). In accordance with the anatomic architecture, KIII network is a multi-layer neural network model, which is composed of several K0, KI, KII units [4]. Among the models, every node is described by a second order differential equation. The parameters in the KIII network are optimized to fulfill some criteria that were deduced in electrophysiological experiments [5].

In the KIII network, Gaussian noise is introduced to simulate the peripheral and central biological noise source, respectively; the peripheral noise is rectified to simulate the excitatory action of input axons. The additive noise eliminates numerical instability of the KIII model, and makes the system trajectory stable and robust under statistical measures. Because of this kind of stochastic chaos, the KIII network can approximate the real biological intelligence for pattern recognition [6], [7].

3 Application to Normal and Hypoxic EEG Recognition

3.1 Data Acquisition

A mixture of nitrogen and oxygen at normal atmosphere pressure was used to simulate different altitudes in the atmosphere by adjusting oxygen partial pressure: It was provided to subjects via a pilot mask. In the first day, when the subjects stayed at normal atmosphere, they were tested for auditory digit span and serial addition/subtraction tests while the EEGs were recorded. In the second day, after the subjects stayed at environment simulating 3500 m altitude for 25 minutes, they repeated the aforementioned test procedure. The experiments were carried out during the same time period each day. Five healthy male volunteers around 22 years old were taken as subjects. Immediately after thebehavioral evaluations 1.5 seconds EEGs were recorded for analysis under both normal oxygen partial pressure and 3500 m altitude.

EEG data were taken from 30 Channels including: FP1, FP2, F7, F3, FZ, F4, F8, FT7, FC3, FCZ, FC4, FT8, T3, C3, CZ, C4, T4, TP7, CP3, CPZ, CP4, TP8, T5, P3, PZ, P4, T6, O1, OZ and O2 (10/20 system). The reference was (A1+A2)/2 (A1 = left mastoid, A2 = right mastoid). The EEG amplifier used was NuAmps Digital Amplifier (Model 7181) purchased from Neuroscan Compumedics Limited, Texas, USA. Sampling rate was 250 S/s. All values are in μVolt.

3.2 Evaluation of the severity of the effects of hypoxia by neurobehavioral (NE) testing

NE is a sensitive and reliable tool for early detection of adverse effects of the environmental hazards on central nervous system. In the normal and simulating 3500m altitude experiments, auditory digit span and serial addition and subtraction were utilized to evaluate the degree of hypoxia. The result of the test is shown in Table 1. T-tests were performed on the NE under normal and hypoxia conditions. As a result, the NE scores of normal and hypoxia were different observably ($p<0.05$). Furthermore, the scores under the hypoxia condition were lower distinctly, which means that subjects' behavior capability became weaker under the hypoxia condition.

Table 1. Performance of NES under normal and hypoxia states

Subject	Auditory Digit Span Scores		Serial Addition And Subtraction Scores	
	Normal	Hypoxia	Normal	Hypoxia
1	30	29	28	21
2	28	24	31	16
3	25	21	20	20
4	32	23	24	15
5	19	9	18	12

3.3 Feature Vector Extraction

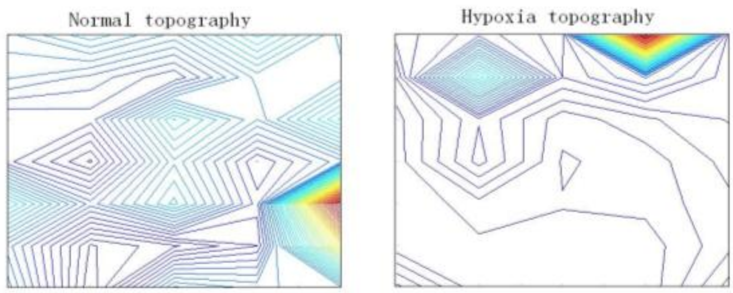

Fig. 1. A feature vector topography of the normal and hypoxia EEG

By wavelet packet decomposition, the original waveform can be reconstructed from a set of analysis coefficients that capture all of the time (or space) and frequency information in the waveform [8]. In our analysis, we use the COIF5 wavelet. The number of levels of decomposition is chosen as two and wavelet packet tree coefficients of a 30-60Hz sub-band are abstracted. The feature vector is a 30-dimensions vector due to 30 EEG channels. For each channel, the square of the wavelet packet tree coefficients are summed up as one dimension of the feature vector. According to the topology of the EEG channel, feature vectors can be transformed as a feature topography. A typical feature topography sample of comparing normal and hypoxic EEGs collected from the same subject is illustrated in Fig. 1.

3.4 Learning Rule

There are two main learning processes: Hebbian associative learning and habituation. Hebbian reinforcement learning is used for establishing the memory basins of certain patterns, while habituation is used to reduce the impact of environment noise or those non-informative signals input to the KIII network. The output of the KIII network at the mitral level (M) is taken as the activity measure of the system. The activity of the *i*th channel is represented by SD_{ai}, which is the mean standard deviation of the output of the *i*th mitral node (Mi) over the period of the presentation of input patterns, as Eq.(1). The response period with input patterns is divided into equal segments, and the standard deviation of the *i*th segment is calculated as SD_{aik}, SD_{ai} is the mean value of these *S* segments. SD_a^m is the mean activity measure over the whole OB layer with *n* nodes (Eq.(2)).

$$SD_{ai} = \frac{1}{S}\sum_{k=1}^{s} SD_{aik} \tag{1}$$

$$SD_a^m = \frac{1}{n}\sum_{k=1}^{n} SD_{ai} \tag{2}$$

The modified Hebbian rule holds that each pair of M nodes that are co-activated by the stimulus have their lateral connections $W(mml)_{ij}$ strengthened. Here $W(mml)_{ij}$ stands for the connection weights both from *Mi* to *Mj* and from *Mi* to *Mj*. Those nodes whose activities are larger than the mean activity of the OB layer are considered activated; those whose activity levels are less than the mean are considered not to be activated. Also, to avoid the saturation of the weight space, a bias coefficient K is defined in the modified Hebbian learning rule, as in Eq.(3). $W(mml)_{ij}$ is multiplied by a coefficient *r* (*r*>1) to represent the Hebbian reinforcement.

$$IF \quad SD_{ai} > (1+K)SD_a^m \text{ and } SD_{aj} > (1+K)SD_a^m$$

$$THEN \quad W(mml)_{ij} = W(mml)^{high} \text{ and } W(mml)_{ji} = W(mml)^{high} \tag{3}$$

$$OR \quad W(mml)_{ij} = r \times W(mml)_{ij} \text{ and } W(mml)_{ji} = r \times W(mml)_{ji}$$

Two algorithms to increase the connection weight are presented, algorithm 1 is used to set the value to a fixed high value $W(mml)^{high}$ as in previous references and algorithm 2 is a new algorithm that will multiply an increasing rate to the original value. For the habituation learning, a continuous habituation strategy is used, which means that habituation occurs cumulatively at each time step [1].

At the end of a training session for two types of learning, the connection weights are fixed to perform pattern classification tests. During training, several samples for each class are given. The activity measure vector for every trail is calculated, and the mean activity of those trails, which belong to one class, is defined as the cluster center of that class. Inputs of different classes that the system is trained to discriminate form multiple clusters, each with its center of gravity. When a test pattern is given, the Euclidean distances from the corresponding point to those training pattern cluster centers are calculated, and the minimum distance to a center determines the classification. On the other hand, the concept of classification threshold was introduced into the classification rule. If the difference between the minimum Euclidean distance and the secondary minimum distance is less than the threshold value, it is regarded as a recognition failure.

3.5 Classification of Normal and Hypoxia EEG

We use the KIII model to distinguish hypoxic from normal EEGs. The KIII model learns the desired patterns --- the normal and hypoxic EEG patterns for three times in turn. The test data set contains 80 samples of normal and hypoxic EEG for individuals by 5 different subjects. We chose 40 samples in the odd position for training and used all the 80 samples for classification, and then we chose 40 samples in the even position for training and used all the 80 samples for classification. The final correction rate is from the mean of twice correction rate. In this application, a 30-channel KIII network is used with system parameters as the reference [5].

The experimental results are shown in Fig. 2. Effectively, the mean of classification rate for test data set is equal to 92%. Hypoxic EEGs can be distinguished from normal EEG by the KIII network. In other words, a new pattern in EEG, which is different from normal one, comes into being, induced by hypoxia. The conclusion of EEG classification is consonant with NE results.

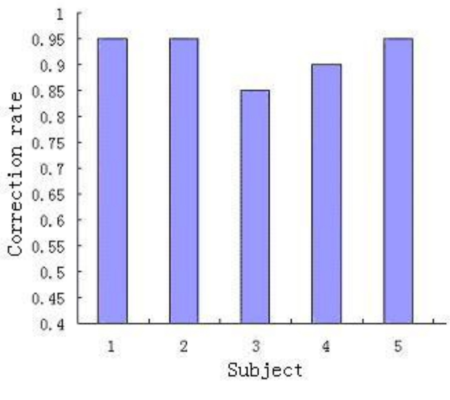

Fig. 2. Rate of correct classification of normal and hypoxic EEGs by the KIII network

4 Discussion

The lowest correction rate (85%) was observed from the subject No.3. When we compared this with the NE test results, we found that the auditory digit span scores of the subject No.3 changed less than other subjects under normal and hypoxic conditions while the scores of serial addition and subtraction remain unchanged. The results of EEG analysis and NE conformed to indicate that the effect of hypoxia on subject No.3 was less than on other subjects. To some extend, rate of correct EEG pattern classification using KIII network represents the degree of hypoxia. It provides the possibility to measure the effect of hypoxia quantitatively.

Derived directly from the biological neural system, the KIII network is more complicated yet more effective in simulating the biological neural system in comparison with conventional ANN. The KIII model has good capability for pattern recognition as a form of the biological intelligence. It needs much fewer learning trials when solving problems of pattern recognition. In our study, it is extremely time consuming to use a digital computer to solve the numerous differential equations within KIII model. This problem restricts the application of the KIII network in real time. The implementation of the KIII in analog VLSI [9] is surely a promising research for building more intelligent and powerful artificial neural network.

By providing feature vectors for classification, the EEG might be made to serve as a quantitative indicator of hypoxia in real time, which might significantly improve the safety of those who work in high altitude.

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