NEUROLOGICAL DIAGNOSES BASED ON EVOKED BRAIN WINDOWS AND ON HOLOGRAPHIC LEARNING

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The evoked potentials have been generated in response to auditory stimuli to a person, and light stimuli to insects, resulting in two datasets, HUMAN and INSECT. In both datasets the responses are composed of several peaks with variable latencies. The brain-window logic is used to explain the evoked responses. Brain-windows are generated through mutual coupling of biological oscillators, and modulated by the memory that stores the past history and the present behavior. Latencies of the peaks provide necessary information to discriminate between normal subject and pathological states resulting from injury, tumor or multiple sclerosis. The holographic neural network classifies the subjects, based on the peak latencies. Combining brain-window theory with the holographic learning opens new possibilities for neurological diagnoses, as well as for a new kind of fuzzy neural networks.

1 Introduction

Evoked potentials are frequently used in the brain research. Souček and Carlson [1,2] have found that insect brain generates special kind of evoked time sequence: brain-windows. The brain-window theory is used here to explain the human evoked potentials. Two datasets have been used, called INSECT and HUMAN.

INSECT. A firefly flash is a brilliant burst of light which serves as a signal in a dynamic courtship communication system between males and females. Because it is possible to observe and recored firefly flashes from a distance and to communicate with firefly using artifical flashes, these animals provide ideal material for the analysis of insect brain functions.

The fireflies Photuris versicolor were courted using artificial flashes provided by a flashlight. The flashlight was driven with a relay controlled stimulator. The duration of the flashes varied between 0.1 and 0.2 seconds. The artificial flashes and female responses were recorded using a hand-held photomultiplier, the output of which was fed into a tape recorder. For details see [1,2].

HUMAN. Brainstem Auditory Evoked Potentials (BSAEPs) are generated in response to a brief auditory stimuli with seven peaks appearing within 10 ms following the stimulus in normal subjects. Pathological states resulting from head injury, acoustic tumors and multiple scleroses give rise to delays in the transmission of electrical signals and consequently the peaks are abnormally located. The BSAEPs were obtained from the Vertex-left mastoid, Vertex-right mastoid electrode locations on the scalp employing a Nivolet Pathfinder II system. Details can be found in [3,4,5].

2 The Brain Windows

The theory that explaines the HUMAN and INSECT datasets is based on fuzzy, adjustable logic called "brain windows". The logic is supported by a network of coupled nonlinear oscillators. Upon receiving stimulus, the brain generates a sequence of time windows of different widths. Receiving and sending windows are interleaved in the sequence. Each receive window recognizes a particular subgroup of stimulus intervals. Each sending window determines the latency of the response from the brain. The windows are arrayed in priorities and controlled by the memory. Memory stores the past history. Brain windows are generated through mutual coupling of the primary oscillator, answer oscillator, and window generator, see Figure 1. Hence, the brain windows are directly related to the inherent biological oscillators and to the memory. The oscillator generates a primary waveform $P(t)$ with a period T_1. Upon receiving a stimulus, the memory M_1 is charged and slowly discharges back toward zero (Figure 1a). In this way, M_1 modulates the primary waveform (Fig. 1b). Hence, $M_1(t)$ is equivalent to the phase-response curve (PRC). The positive and negative phases of the primary waveform designate receive and send wondows. Receive windows, defined by the positive phase of $P(t)$, are periods during which a second stimulus can command an answer. Send windows, during which a response can actually be generated by the brain are defined by negative phases of $P(t)$. A second memory, M_2, recalls the past history of stimulation. Depending on the past history, M_2 can take any value in the range $-1 < M_2 < 1$. The intersection of the memory M_2 and the primary waveform $P(t)$ defines the sequence of the receive-send brain windows. Figures 1c, d, e show three receive-send windows sequences for the memory values M_2', M_2'', M_2''', respectively. The basic carrier of information is the interval I between two stimuli. The second stimulus is matched against the train of receive windows. Each receive window recognizes a particular group of intervals. In this way, the brain receives and analyzes the stimulation interval I. This interval can be considered as a question in the communication. The logic of the brain generates the answer to the received question. The answer information is coded in the latency L of the response. The latency is matched against the train of send windows. Each send window defines a particular group of latencies as a group of legal answers. Hence, the receive interval I (question) will produce the answer with the latency L only if I matches one of the receive windows and L matches one of the send windows. The brain windows operate with external, as well as with internal stimuli and responses.

3 Holographic Network for Neurological Diagnoses

Holographic networks are a new brand of neural networks, which have been developed by Sutherland [6,7]. This type of networks significantly differs from the conventional back-propagation layered type. The main difference is that a holographic neuron is much more powerful than a conventional one, so that it is functionally equivalent to a whole conventional network. Therefore there is no need to build massive networks of holographic neurons; for most applications one or few neurons are sufficient. In a holographic neurons there exist only one input channel and one output channel, but they carry whole vectors of complex numbers. An input vector S is called a stimulus and it has the form:

$$S = [\lambda_1 e^{i\theta_1}, \lambda_2 e^{i\theta_2}, \cdots, \lambda_n e^{i\theta_n}].$$

An output vector R is called a response and its form is:

$$R = [\gamma_1 e^{i\varphi_1}, \gamma_2 e^{i\varphi_2}, \cdots, \gamma_n e^{i\varphi_m}].$$

All complex numbers above are written in polar notation, so that modules are interpreted as confidence levels of data, and phase angles serve as actual values of data. The neuron internally holds a complex $n \times m$ matrix X, which enables memorizing stimulus-response associations. Learning one association between a stimulus S and a desired response R reduces to the (noniterative) matrix operation

$$X += S^{\tau} R.$$

Note that all associations are enfolded onto the same matrix X. The response R^* to a stimulus

$$S^* = [\lambda_1^* e^{i\theta_1^*}, \lambda_2^* e^{i\theta_2^*}, \cdots \lambda_n^* e^{i\theta_n^*}]$$

is computed through the following matrix operation:

$$R^* = \frac{1}{c^*} S^* X.$$

Here c^* denotes a normalization coefficient which is given by $c^* = \sum_{k=1}^{n} \lambda_k^*$.

The response R^* to a stimulus S^* can be interpreted as a vector (i.e. a complex number)

TABLE 1

	Normal	Abnormal (Multiple Sclerosis)	Total
Training Set	30	23	53
Testing Set	46	34	80

composed of many components. Each component corresponds to one of the learned responses. If S^* is equal to one of the learned stimuli S, then the corresponding response R occurs in R^* as a component with a great confidence level (≈ 1). The remaining components have small confidence levels ($\ll 1$) and they produce a "noise" (error).

It is believed that the BSAEP latencies provide necessary and sufficient information to discriminate between normal and pathological states. The experiments have shown that the 2nd, 3rd and the 4th peak latencies are the optimal features for classification. Ho et al [5] have collected a total of 133 BSAEP patterns from patients of which 53 are used for training and the rest were used for testing. Table 1 shows the number of normal and abnormal BSAEP patterns in the training and testing sets.

Holographic Neural Technology [6,7,8] is a relatively new artificial neural system paradigm that resembles to a class of mathematics found within optical holograms. An element of information within the holographic neural paradigm is represented by a complex number operating within the phase and magnitude. The input BSAEP patterns $S = \{s(0), s(1), s(2)\}$ (the 2nd, 3rd and 4th peak latencies) and output class $R = \{r\}$ ($r = -ve$ (Normal) and $r = +ve$ (Abnormal)) were converted from real values to the complex representations in the neural system by sigmoidal preprocessing operation

$$s(k) \rightarrow \lambda_k e^{i\theta_k}$$

$$\theta_k \rightarrow 2\pi(1 + e^{\frac{\mu - s(k)}{\sigma}})^{-1}$$

where μ is the mean of distribution over $S, k = 0, 1, 2, \sigma$ is the variance of distribution, and λ_k is the assigned confidence level. The above transformation maps the above input BSAEP patterns to corresponding sets of complex values.

The experiments with the holographic network show that the number of higher order terms determines not only the learning time, but also the classification accuracy [5]. The optimal number of the higher order product terms are 50. The results of using holographic network in classification of BSAEPs after the first learning trial are presented in Table 2.

TABLE 2

	Ref. diagn. Abnormal	Ref. diagn. Normal
Classif. res.: Class A	31	0
Classif. res.: Class N	3	46
Overall Performance: 96,25 %	Number of Ephocs: 1	Training Time: 1 sec

4 Results

The brain window concept has been used to explain the evoked patterns in HUMAN and INSECT datasets. The experimentaly observed evoked potential and behavior waveforms follow the theoreticaly predicted primary oscillator waveform, as presented in Figure 1. In other words, the waveforms are generated through mutual coupling of biological oscillators and modulated by the memory that stores the past history and the present behavior. Holographic network classifies BSAEP peak latencies and discriminate between normal and pathological states, with 96% accuracy. Experiments show that holographic learning of HUMAN dataset takes 1 second, while backpropagation learning takes 20 seconds.

5 Conclusion

The brain window concept has been used to explain the evoked patterns in HUMAN and INSECT datasets. The experimentaly observed evoked potential and behavior waveforms follow the theoreticaly predicted primary oscillator waveform, as presented in Figure 1. In other words, the waveforms are generated through mutual coupling of biological oscillators and modulated by the memory that stores the past history and the present behavior.

The memory stores the internal context. Memory adjusts the sequence of receive-send windows.

The stimulus interval I presenting the sensory pattern is matched against the train of receive windows. The response latency L, presenting the answer or decision, is matched against the train of send windows. The language is directly related to the physiological findings: biological oscillators and pulses (flashes).

Brain-window language is in excellent agreement with experimental data measured on Photuris versicolor female fireflies stimulated by artificial flashes. Computer analysis of a large volume of experimental data reveals the fact that data points are clustered into islands of dialogues.

INSECT dataset is explained with one level of oscillator-pulse interaction. This concept can be extended to the hierarchy of oscillator-pulse levels. Each level has its sequence of receive-send windows, and its memory (context). The sensory patterns and the decisions or commands pass through the hiearchy in opposite directions.

The HUMAN data set keeps the BSAEPs generated in response to a brief auditory stimuli with seven peaks appearing within 10 ms following the stimulus in normal subjects. The latencies of the initial five peaks of BSAEPs are highly stable in healthy normal subjects under a wide variety of physioloigical conditions such as sleep, wakefulness and anesthesia. However, in pathological states resulting from head injury, acoustic tumors,autistic disorders and multiple sclerosis the peaks are abnormally located. One explanation is the change of delays in transmission of electrical signals.

According to Chiappa [10], there is no strong primary evidence in humans to define the presumed generator sources of BSAEP waveforms. The suggested generator sources are as follows: wave I-distal eighth nerve; wave II-proximal eighth nerve or cochlear nucleus; wave III-lower pons (possibly the superior olivary complex); wave IV-mid or upper pons (possibly the lateral lemniscus tracts and nuclei); wave V-upper pons or inferior colliculus.

It is not known whether BSAEPs are being generated at synapses in gray matter nuclei or by volleys in white matter tracts, or by the result of summation of electrical activity from more than one nucleus.

Because exact generator sources of BSAEP waveforms are not known (synaptic versus tract potentials or both), the pathophysiology of abnormalities is also speculative. In experimental animals, unilateral and bilateral focal brain stem cooling produced BSAEP amplitude and latency abnormalities, respectively. However, the variety of diseases in which BSAEP abnormalities are found suggests that multiple factors can be involved, presumably including segmental demyelination and axonal and neuronal loss, and modification of the brain-window hierarchy.

The brain-window hierarchy is modulated by the memory that stores the past history and the present behavior. Hence in pathological states, the memory disturbance dictates the abnormal location of the response peaks. If this is so, than the subject treatment could be also oriented in the direction of the memory and its contents. The diagnoses might include the stimulation of the subject with the pairs or trains of auditory, light or electrical stimuli. The pattern of the train should coincide with the brain-window sequence. Further experiments, both with simple animals and with human, are needed to clear out remaining questions. The experiments include the use of anesthetic on human, and of ethanol on firefly luciferase.

Combining Brain-windows with holographic learning opens new possibilities: a) explanation of other brain codes, languages and signals; b) design of a new class of fuzzy neural networks; c) new kind of neurological diagnoses; d) adaptation of holographic learning for large training and testing sets found in pattern recognition, speech and vision; e) Brain-window concept for natural language processing, reasoning and language-knowledge archives; f) interaction among the fuzzy Brain-windows representing the symbol, word, schema, frame, association map or cognitive map; g) diagnoses: Parkinson, Huntington, Wilson, Infarcations, Ischemia, Hemorrhages, Coma, Epilepsy, Hysteria, Meningitis, Surgery, etc.

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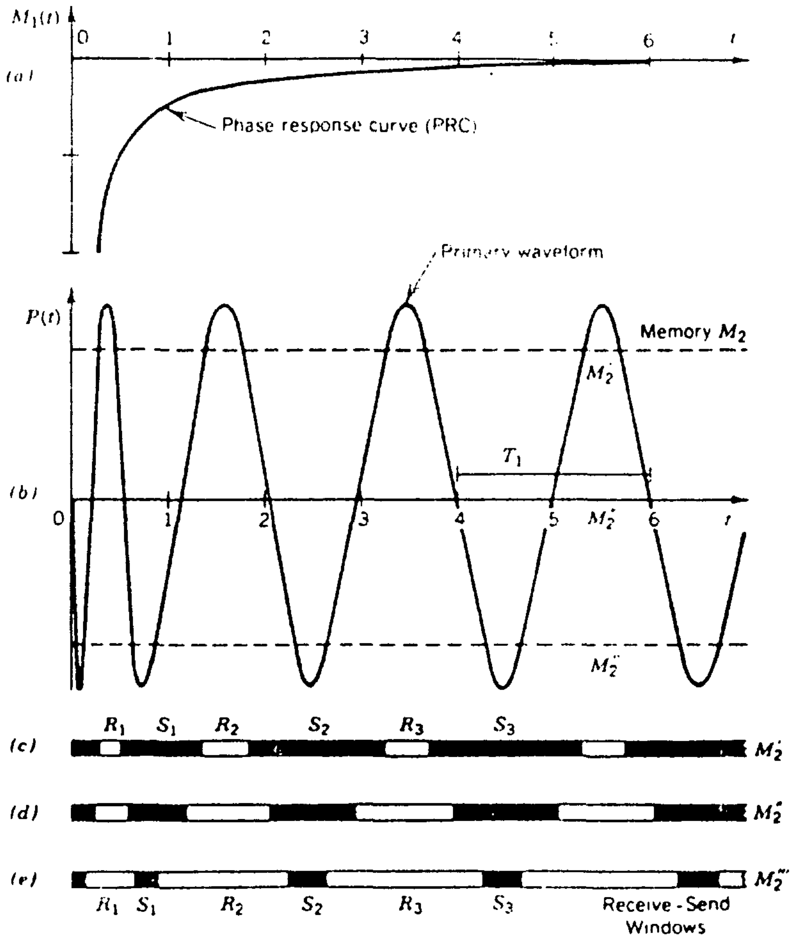

Figure 1: Brain-windows in evoked potentials and time sequences. (a) Phase-response curve (PRC). The simulus flash charges the memory (M_1) which decays with time, producing the PRC. (b) Primary waveform defined by the PRC. As the PRC declines toward zero, the period of the primary waveform increases towards the resting value. Memory levels caused by previous flashes (M_2) are shown as horizontal lines intersecting the primary waveform. These memory levels define the receive-send windows. (c,d,e) Receive-send window periods defined by memory levels (M_2): (c) highly positive memory level (M_2); receive windows narrow, send windows wide; (d) memory at zero level (M_2); (e) highly negative memory level (M_2); receive windows wide, send windows narrow.