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Research paper

Using chaotic artificial neural networks to model memory in the brain

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ABSTRACT

In the current study, a novel model for human memory is proposed based on the chaotic dynamics of artificial neural networks. This new model explains a biological fact about memory which is not yet explained by any other model: There are theories that the brain normally works in a chaotic mode, while during attention it shows ordered behavior. This model uses the periodic windows observed in a previously proposed model for the brain to store and then recollect the information.

1. Introduction

Chaos occurs in dynamical systems that are sensitively dependent on initial conditions. Small differences in initial conditions yield widely diverging outcomes. Although such systems are deterministic, long-term predictions cannot be made [1]. There is growing evidence that future research on neural systems and higher brain functions will require a combination of classic neuroscience and the more recent nonlinear dynamics. The neuronal system composed of neurons and gliocytes is often sensitive to external forcing and internal shift in functional parameters, so that the appropriate response can be selected. This characteristic resembles the dynamical properties of chaotic systems [2–4]. It is not necessary for the brain to reach an equilibrium following a transient, but it is constantly shifting between different states. There is some evidence to support the claim that chaos occurs in many biological systems, especially in the human brain [2–25]. For example, it appears that the dynamics in electroencephalogram (EEG) signals are chaotic [8]. The EEG signals may look random to outside observers, but there are hidden patterns in their random-like appearance. The search for chaos in EEG signals started in the early 1980 s. Bressler and Freeman observed that when rabbits inhale an odorant, their EEG signals display oscillations in the high-frequency range of 20–80 Hz [26]. Odor information was then shown to exist as a pattern of neural activity that could be discriminated whenever there was a change in the odor environment. One of these attractors is shown in Fig. 1. This attractor belongs to the EEG of the olfactory bulb in a rat. This attractor seems to be showcasing a periodic attractor

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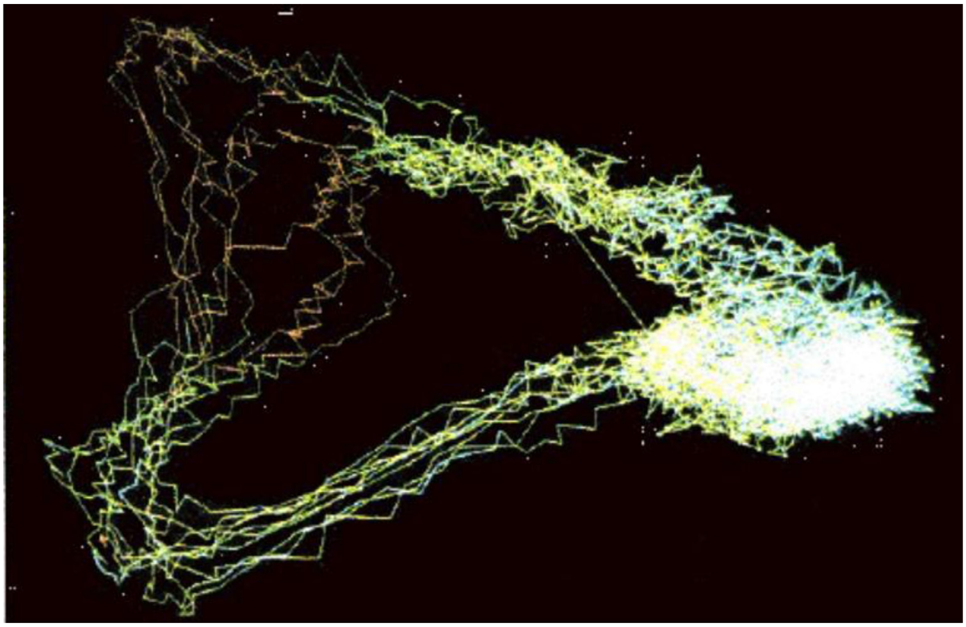

Fig. 1. Strange attractor of the EEG taken from a rat [17].

rather than chaos. Further dissection of the experimental data led to the conclusion that the activity of the olfactory bulb is chaotic and may switch to any desired perceptual state (or attractor) at any time [17]. This change could be from chaos to some kind of oscillations or periodic behavior in the case of inhaling a familiar odor. This periodic behavior seems to be due to the attention and focus regarding the process of saving or retrieving the odor information [27–29]. Some other reasons that might cause the brain to change its behavior is some sort of a malfunction or disease like epileptic seizures [30–34].

Another example of chaos in biological systems is the dynamics at the neuronal level (cellular and subcellular). The transportation and storing of information in the brain is believed to be accomplished by the impulse trains produced by neurons. These trains of impulses or action potentials are often organized as sequences of bursts. The most important information in these sequences involves their temporal patterns, which are also known as interspike intervals (ISIs). The ISIs in a single neuron can show different behaviors including chaos. These impulses are generated by the interaction between the gating of ion channels and the axon's membrane voltage. Hodgkin and Huxley were the pioneers who proposed a dynamical system model of this interaction that predicted realistic action potentials [35]. Their model has been simplified in several forms by some other researchers [6,36].

All of the behaviors that these models exhibit can be found in their bifurcation diagram. A bifurcation is a sudden change in the dynamics when a parameter of the system is incrementally changed [1]. From a dynamical systems point of view, neurons are excitable because they are near a bifurcation where a transition from resting to a sustained spiking activity occurs [37]. All the neurons undergo bifurcation by changing their state. Their new state can be periodic as in tonic spiking (called a limit cycle), or they can be chaotic (called a strange attractor). When a neuron begins to fire in a chaotic manner, its firing is called bursting.

All this evidence led scientists to consider the human brain as a dynamical system that is generally chaotic but can have transitions between different states (or undergo bifurcations) [2–5,8,10–25,38]. For example, when an epileptic patient has a seizure, the EEG is more similar to a periodic signal [39]. Based on properties of chaos and periodic windows and the physiological facts about the human attention system, a hypothesis was proposed that during intense focus the EEG changes from chaotic to a periodic window [27–29].

In psychology, memory is the process by which the information from the outside world is encoded, stored and then accessed by a human being. In the encoding stage, the information is received, analyzed and then translated by the brain into the language in which the data is stored. In the storing stage, the encoded data is stored in the human brain in a permanent way for future access. The third and final stage of memory is the retrieval of the memory which is also referred to as recall or recollection which is calling back the stored information in response to some cue for use in a process or activity. In this stage the stored memory should be located and then accessed by the brain in a state of full attention [40].

It seems that the brain has a chaotic structure in the encoding stage of data storage [41]. This encoding seems to be done by specifying an attractor for the related data and retrieving the attractor whenever that same data is called back [17,18]. Multiple studies have claimed that the attractors associated with remembering or recalling a piece of information (or in general during intense focus) is periodic and ordered [2,16–18,21,28]. This seems logical, since encoding any data to a chaotic attractor will lead to an unpredictable output.

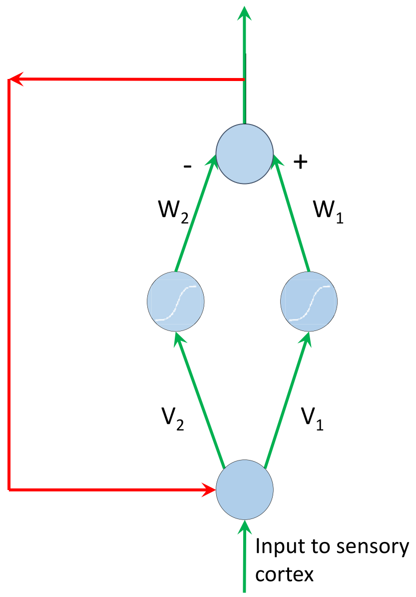

Fig. 2. Proposed model for the attentional system [27]. The nonlinear functions of the nodes are hyperbolic tangents.

In the current study, a novel model for human memory is proposed based on the theory of chaotic neural networks. This model uses the periodic windows in a chaotic model of the brain to encode, store and then recollect the information. In Section 2, chaotic models for the brain using neural networks are reviewed. In Section 3, a new model for human memory is introduced, and the following section describes the results of the information retrieval process. Finally, the conclusions are given in section 5.

2. Chaotic neural network models of the brain

An artificial neural network (ANN) is a mathematical tool inspired by the biological neural networks in the human brain [42]. An ANN can be represented by a network composed of neurons as nodes and synapses as the weights between the nodes that will define the effect that each node's firing has on creating the action potential in adjacent nodes. There are various types of network architectures. Some networks use feedback from the output to the input to make the ANN a dynamical system. These networks are also called recurrent neural networks. Some of these recurrent ANNs are capable of chaos. Substantial evidence for chaos has been found in biological studies of natural neuronal systems [2,5,8,18,43]. The basic goal of this study is to use deterministic chaos as a powerful mechanism for storage and retrieval of information in a dynamical ANN. It is suggested that the chaos in neural networks plays an essential role in memory storage and retrieval [18,44,45]. Indeed, chaos may provide advantages over alternative memory reserving methods used in ANNs: First of all, chaotic systems are easily controlled in the sense that a small change in the system parameters can affect the behavior of the controlled system. For example, a slight adjustment of an effective parameter in a dynamic chaotic system can cause it to switch from chaotic to periodic. Moreover, a particular system with a specific chaotic behavior can have infinitely many periodic windows. If each of these periodic windows could be used to represent an internal memory state of the network, then, hypothetically, a chaotic network can provide an unlimited memory space [45]. Therefore, these periodic signals (the output of the system in a periodic window) can be used as the encoding of the brain for storing specific information.

Recently, a model for the human attention system using a chaotic ANN has been suggested [27]. In this model, the authors used a nonlinear neural network illustrated in Fig. 2 to represent the problem of undesired attention alternation in individuals with attention deficit disorder (ADD).

The mathematical equation describing Fig. 2 is as follows:

$$E(x) = I(x) = \tanh(x)$$

$$out(n+1) = W_1 \times E(x_1) - W_2 \times I(x_2)$$

$$x_1 = V_1 \times out(n),\ \ x_2 = V_2 \times out(n)$$

$$\Rightarrow out(n+1) = W_1 \times \tanh(V_1 \times out(n)) - W_2 \times \tanh(V_2 \times out(n))$$

The relation between the input and output of this network are related by these equations. The last line of the equations (the red equation) shows the overall map representing this network.

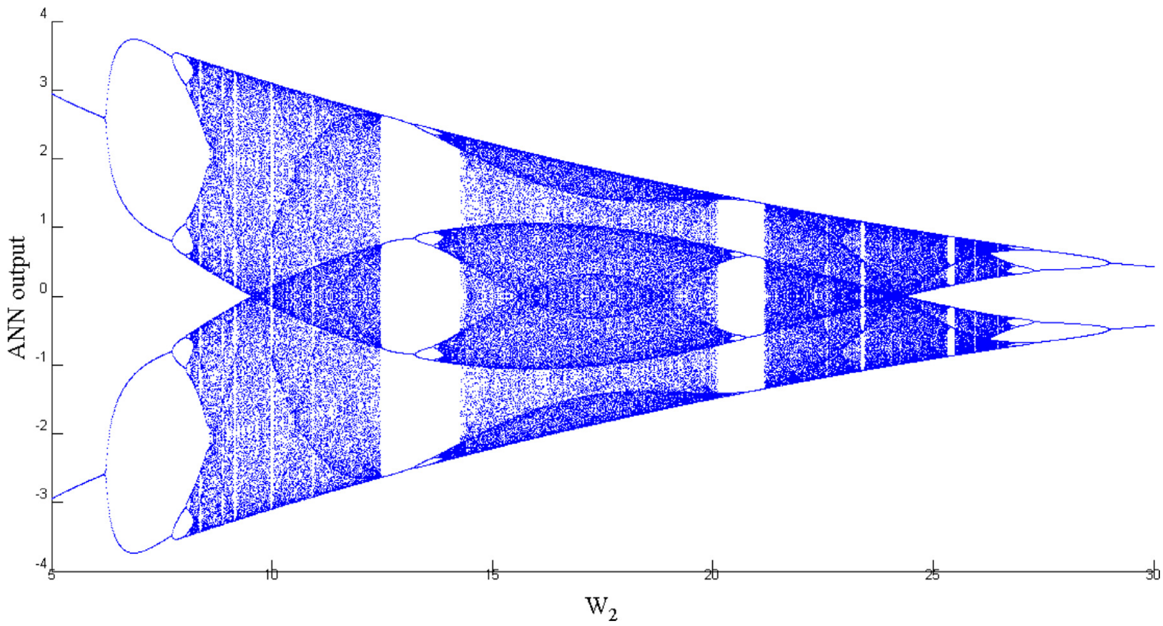

Fig. 3. Bifurcation diagram for the recurrent ANN in [27] by changing parameter W_2 with $W_1 = 5.821$, $V_1 = 1.487$, $V_2 = 0.2223$.

In this model, E(x) and I(x) are the activation functions of neurons. Hyperbolic tangent activation functions are considered for both. In Fig. 2 these neuron functions are shown as hyperbolic curves inside the circles. Their outputs are multiplied by (W_1) and (W_2) to result in the total output. However, the output of the left part enters the output neuron with a negative mark that models the inhibitory brain action, and the output of the right neuron which enters the output neuron with a positive mark, models the excitatory brain action. All coefficients ((W_1), (W_2), (V_1), and (V_2)) are associated with the brain synapses' weights that are regulated by the release of different neurotransmitters. In this study we investigate the changes in the values of W_2 which represent an inhibitory neurotransmitter (which can be correlated with the amount of dopamine) to model the variation in attention level. However, the effects of the excitatory neurotransmitters can also be investigated.

According to [27] the attention switching symptom of ADD is behaviorally similar to intermittent chaos. Intermittency is a property of dynamical systems in which the dynamics switch back and forth between two qualitatively different behaviors (e.g. periodic to chaotic) even though all the control parameters remain constant and no significant external noise is present. In this case, the periodic behavior represents intense focus, and the chaotic behavior is similar to a deficiency of attention.

The frontal lobe of the brain is a very important part of a complex cognitive processing system. It has various connections to different areas of the brain. The frontal cortex has an important role in controlling the attention level, focusing, restraint, and patience [46]. This area is also essential in the excitation/inhibition balance in information processing. It has been reported that the neurotransmitter dopamine has a considerable effect on frontal lobe's function [47]. Attention deficit disorder or ADD is also believed to be associated with decreased dopamine activity [27,48]. Dopamine plays a major role in the brain system which is responsible for reward-driven learning [49]. Every type of reward that has been studied and also some stressful situations increase the level of dopamine transmission in the brain [50].

In [27], the authors considered one of the parameters of the model as a representative of the dopamine level in the brain. With this assumption, one can control the attention level of the brain by changing this parameter. The bifurcation diagram in Fig. 3 displays the different behaviors of the output of this recurrent ANN when W_2 (which is the parameter that represents the dopamine level) is changed. As seen in Fig. 3, there are several periodic windows in the bifurcation diagram of the recurrent ANN. If any of the periodic windows in this diagram could serve as a specific attention state, then a specific memory can be stored in any of them, and if the brain needs to access those memories, it only needs to return to the same state of attention in which the memory was stored (or reach the same value of W_2).

Note that any other parameter could have been used to plot the bifurcation diagram and represent different attention levels. As we have stated before, W_2 represents the inhibitory neurotransmitter level in the brain, and using W_2 was just an arbitrary choice of parameter. In other words, we are only modeling the attention that is caused by dopamine (inhibitory neurotransmitter), and one might choose to also investigate the effect of changes in the excitatory neurotransmitters (W_1).

3. The proposed model

Memory is a process of encoding, storing, and retrieving information. Our model uses all three of these stages to resemble human memory. In this section, we describe the stages of encoding and storage, and in the next section, we demonstrate the retrieval process.

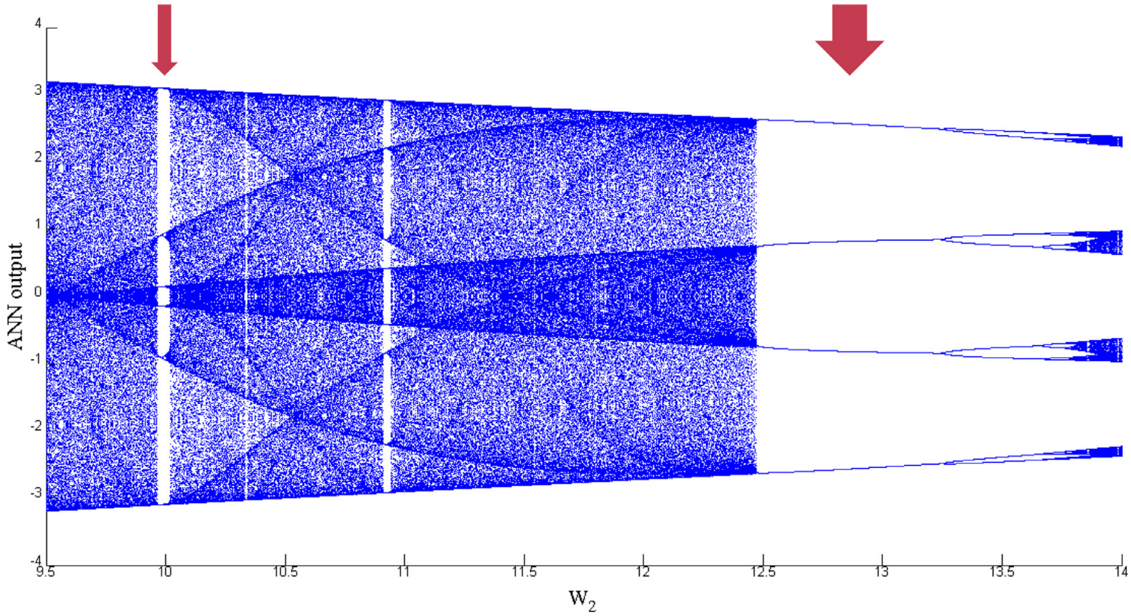

Fig. 4. The periodic windows chosen for information encoding. The brain model searches for periodic windows with enough width to encode the information.

There are theories that the brain's working behavior will become more periodic when it is intensely focusing on something like memorizing a piece of information [27–29]. This periodic behavior could be a method of encoding the data in the brain. By changing some parameters, e.g. neurotransmitters like dopamine, the chaotic behavior will shift into a periodic window, and each of these windows can be used as a memory state. Thus for the start of the encoding stage, we must change the parameters in the brain model to find the periodic windows. We use the chaotic model developed in [27]. Note that in this work our aim is not to present a new efficient computational method, but to propose a model that matches the behaviors associated with biological systems. In other words, this model is not trying to compete with some computationally efficient bio-inspired models like artificial neural networks. We are not claiming that our memory model is faster, more efficient or has more capacity than other models. We are simply trying to suggest a model that may shed a light on some parts of the mechanisms of storing and retrieving the information in the human brain. Our proposed model is very simple and is compatible with some of the biological facts, which are not considered in other existing models.

For the sake of simplicity, we only use the model to store two different memories. Thus the brain only has to find two different memory states, which are related to two different periodic windows. Wider periodic windows are better choices since the effect of noise on W_2 is alleviated. The two periodic windows depicted by arrows in Fig. 4 are suitable for this purpose.

After the brain model finds the appropriate periodic window, the output of the model in Fig. 2 will be periodic. For example, when W_2 is near 10, the output of the brain will have a period-6, meaning that the output can have only six different values.

For storing the information, a feed-forward multi-layer perceptron (MLP) neural network is used. This network is trained so that its output is as close as possible to the desired output, which is the information to be stored. The MLP ANN responsible for this part of the model is shown in Fig 5. Choosing the input for this ANN is tricky and is directly related to the encoding stage of the memory.

When one specific periodic window in the recurrent network is chosen as the memory state for that information, then the resulting periodic signal is the output of the brain model. If that output is considered in several different recurrences as a sequence, then the number of these sequences is limited. For example, if we only need three inputs for the storage ANN, then we only need to consider the output of the brain model for two previous recurrences. If the memory state is in a period-6 periodic window, then the number of different vectors that could result from the output of the model and its two previous recurrences is only six. If we train the MLP ANN to give the desired information in response to all of these vectors of inputs, then that specific information is stored and encoded to that specific periodic window of the recurrent ANN. The network that is composed of both the recurrent ANN [27] and the MLP ANN (which maps the output of the encoding part to a piece of information) is displayed in Fig. 6.

With the inputs and the outputs of the MLP neural network determined, the training process of the storage unit is done using the method of back propagation of the error.

The information being stored in the model is two images with different names. This information is the image of a cross and a saltire presented in Fig. 7. These two pictures include a 5 by 5 square in which the black pixels of the square are

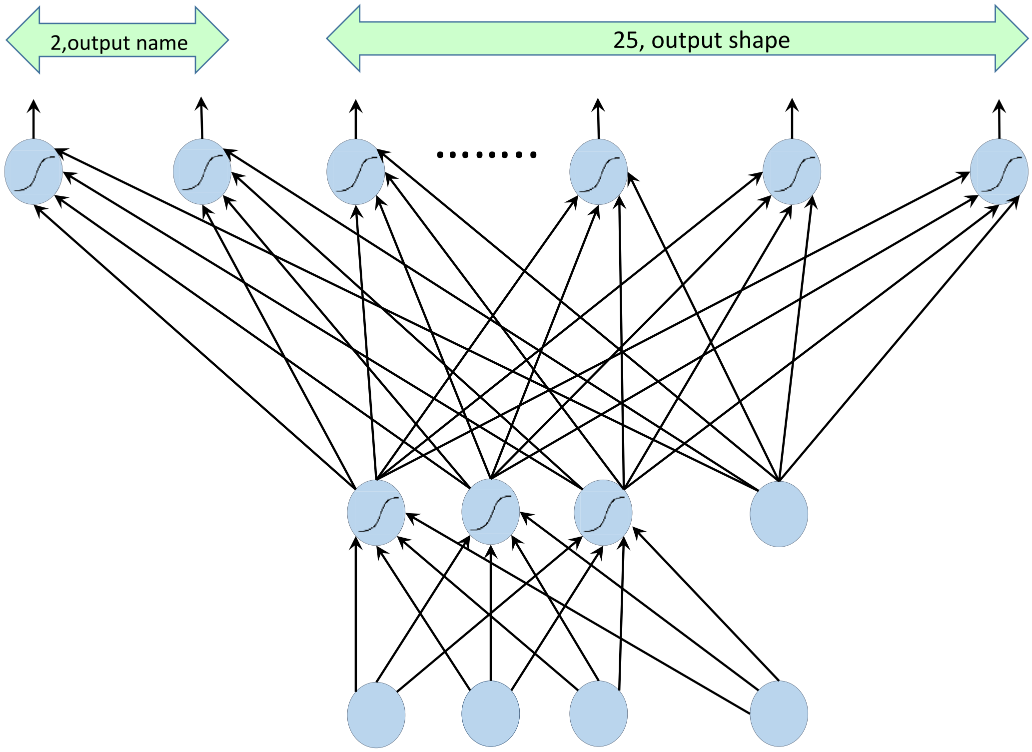

Fig. 5. Structure of the ANN responsible for data storage. The nonlinear functions of the neurons are sigmoids.

equal to one, and the white pixels are equal to zero. The pictures are then considered as binary arrays of 25 elements. The number of elements will determine the dimension of the image. If the images that we are using become noisy for some reasons, then the elements of the array that belong to that picture will not be precisely one or zero. In other words, the noisy black color will become a dark gray and the noisy white color will have a light shade of gray.

During the training process in the MLP ANN, when the difference between the current output of the network and the desired output (which in this case is either the cross or the saltire) becomes small enough, it is assumed that the information is stored properly. After the training, we use the results of the training (which are the optimum weight matrixes) in the designed neural network and find the different values of error (the difference between the output and one of the stored pictures) when the parameter W_2 is changed from 5 to 30. It is clear from Fig. 8 that the error between the output of the MLP ANN and the desired picture is the smallest at the value of the same periodic window where the picture has been stored. The reason that the error is still very small in the second periodic window is because that window is approximately equal to the previous periodic window. In such situations, the second periodic window cannot be used to encode another piece of information.

Here is a summary of this section: The method behind saving data in a multi-layer Perceptron artificial neural network (MLP ANN) is to consider a desired input and output and adjust the neuron weights (using backward propagation of errors) in a way that a given input to the network yields the desired pattern as the output of the MLP ANN with the minimum possible error. We used the recurrent ANN as a generator of inputs for the MLP network. The MLP network (Fig. 5) is acting as the saving part of the brain, and the recurrent ANN is representing the encoding mechanism of the brain. When this recurrent neural network is in the chaotic mode, no pattern can be trained to the MLP ANN, because inputs are always changing in an unpredictable way. However, every time that recurrent neural network is in a periodic window, the input will become determined and varies between only a few states. Then the desired patterns can be trained to the MLP network. Therefore, in a bifurcation diagram of a system the periodic windows could be used to encode the desired patterns. The reason that we use these periodic windows in the middle of a chaotic dynamic is not only that this resembles how some scientists claim the brain works (getting more ordered while focusing), but also, hypothetically, there could be a system, with countless periodic windows in its bifurcation diagram, which could result in a model with unlimited memory storage space. In the next section, we evaluate the model by accessing the information stored in it.

4. Results

For testing the retrieval stage of the memory, two types of evaluation can be done. First we can present the memory model with a picture that we want it to recall and ask it to retrieve the name assigned to that picture. The second method for testing the memory is to ask the model to find which is closest to a picture that it has never stored before.

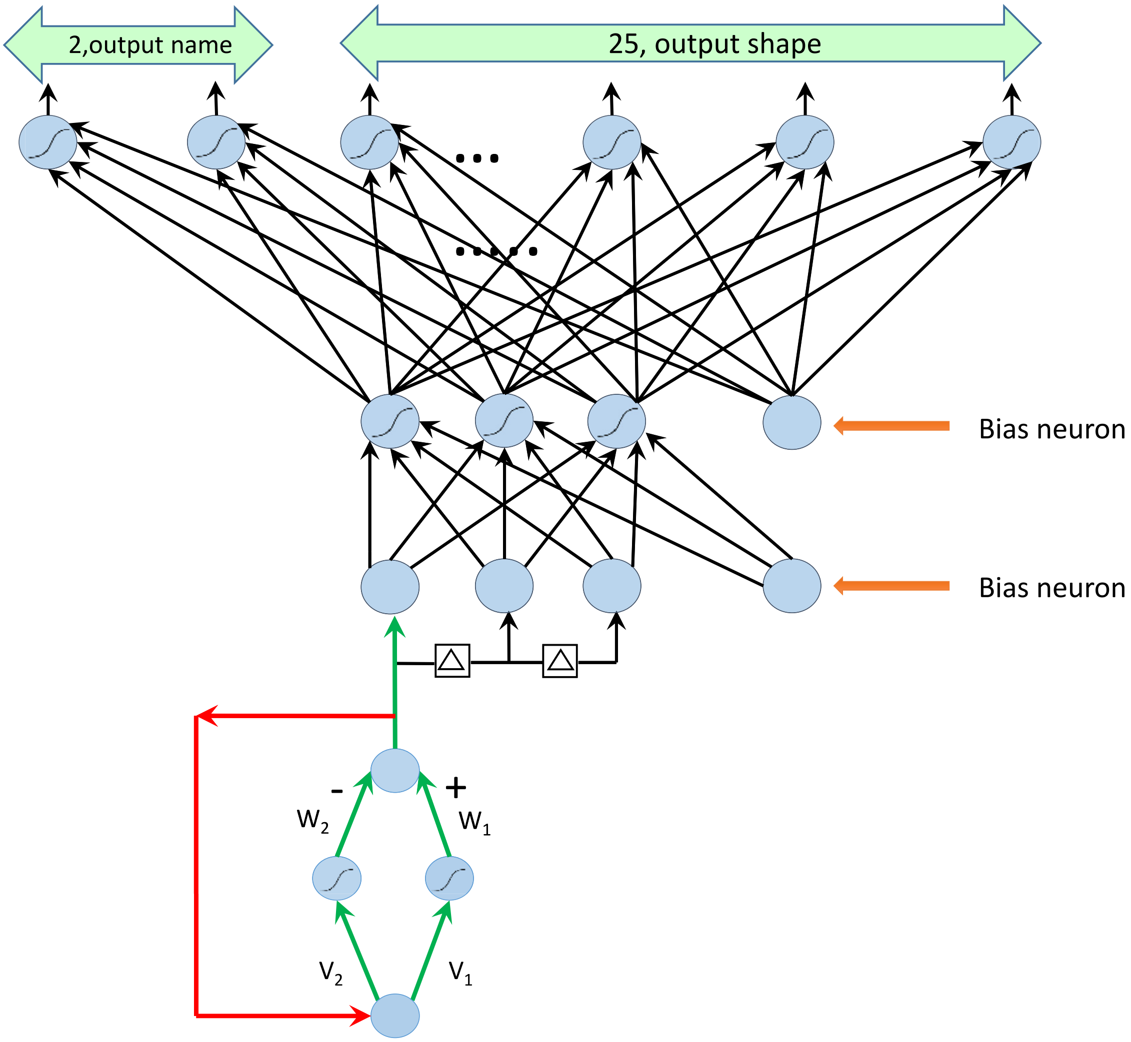

Fig. 6. Structure of the final ANN-based model for encoding and storing information.

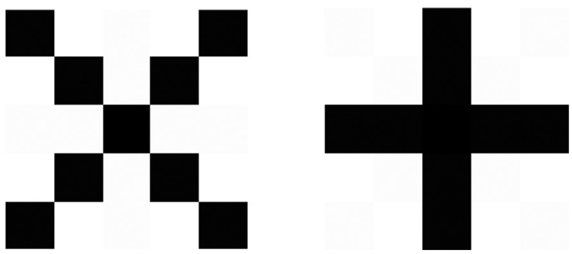

Fig. 7. The pictures being stored by the memory system.

For the first type of evaluation, when the memory is presented with a picture, the parameter assigned to the dopamine in the brain model (W_2) will start to change, as if the brain is trying to focus its attention on remembering the picture's name. With increasing attention in the brain, the behavior of the brain will become more and "more periodic". When the brain is working, more periodic means that the output of the brain model (recurrent ANN) will be the values of one of the periodic windows in the bifurcation diagram of the model (Fig. 3). Then these values will be the input of the storage network (MLP ANN). The output of the MLP ANN is then compared to the picture that the brain is asked to remember. If the error is negligible, then the brain knows that this periodic window is the one encoding the information, so the name that is also stored in the storage ANN using the same periodic window is retrieved (Fig. 9). If the error between the desired

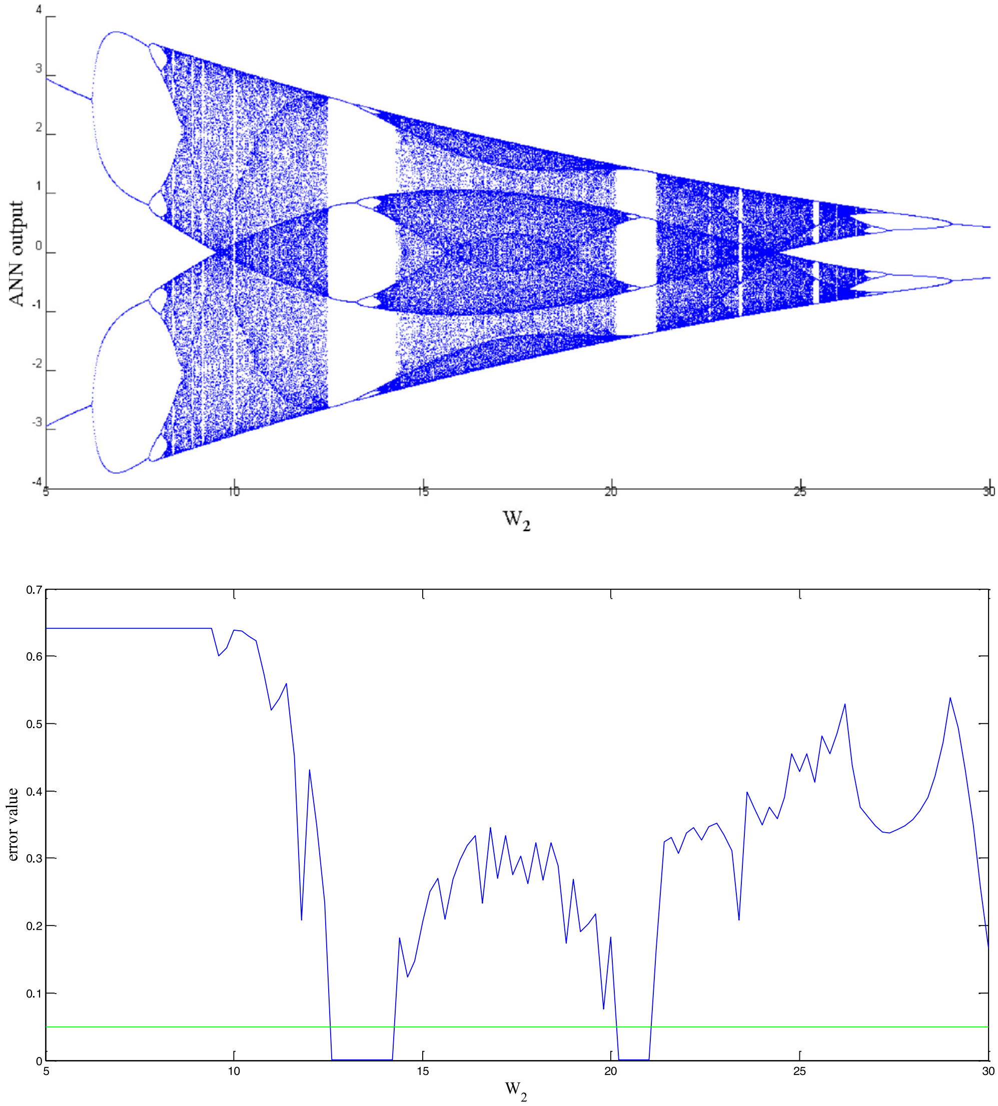

Fig. 8. Comparing error values for differen value of W_2.

picture and the MLP ANN output is more than a specific threshold, the brain keeps on changing the parameters until it switches to another periodic window. After that, the procedure is repeated as above until the desired image is found.

One of the key points for this kind of retrieval is not just finding the required data as the output of the system, but also retaining that data for a long time. To explain this matter, we must consider the difference between a chaotic mode and a periodic window. In the chaotic mode, the brain is producing different random-like signals, one of which could result in the MLP ANN's output to be the same as the desired data, but since it is always changing in time, that data cannot be maintained for a long time. In [27], attention deficit disorder is modeled by this behavior for a system in a chaotic mode. But unlike chaotic behavior, periodic windows have the same output no matter how many iterations the system runs. This results in the same retrieved data at the output of the ANN. In Fig. 10, the different outputs of the storage ANN in a time interval show that the image is never locked; it is always in transition.

Another method for testing the memory is to present it with a noisy version of the images that it had stored before. For this paper, we added a Gaussian noise to the original image. The ability of the brain model to recognize the original image for two noisy versions of the cross image is demonstrated in Fig. 11. It shows that the error is the smallest in the periodic windows where the original image (the cross) was stored. Note that by this test we have just tried to see the efficiency of the proposed model in retrieving noisy patterns. Our motivation for this test was to check if the strong ability of human brain for retrieving noisy patterns also exists in the proposed model. Our goal is not to have a competition between our proposed model and pattern recognition methods.

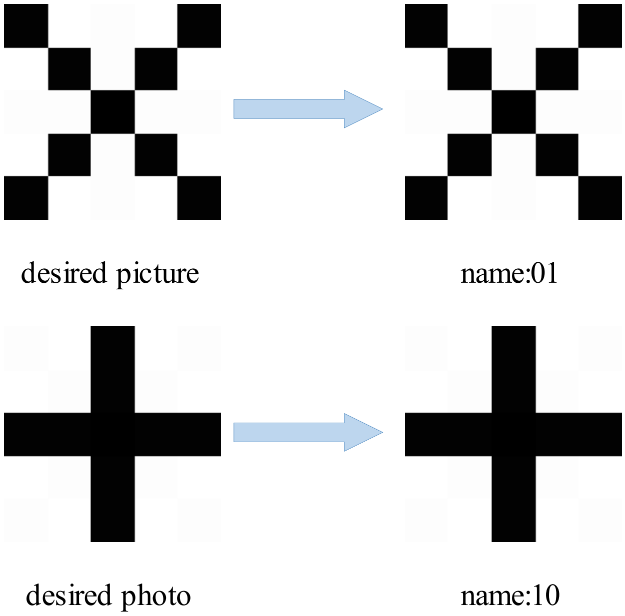

Fig. 9. The memory, when presented with some information, finds if it has that information saved, and if it had saved it before, it will find the name assigned to it.

Fig. 10. Output of the ANN for $W_2 = 17$ changing with time. It can be seen that the resulting images change in a random manner.

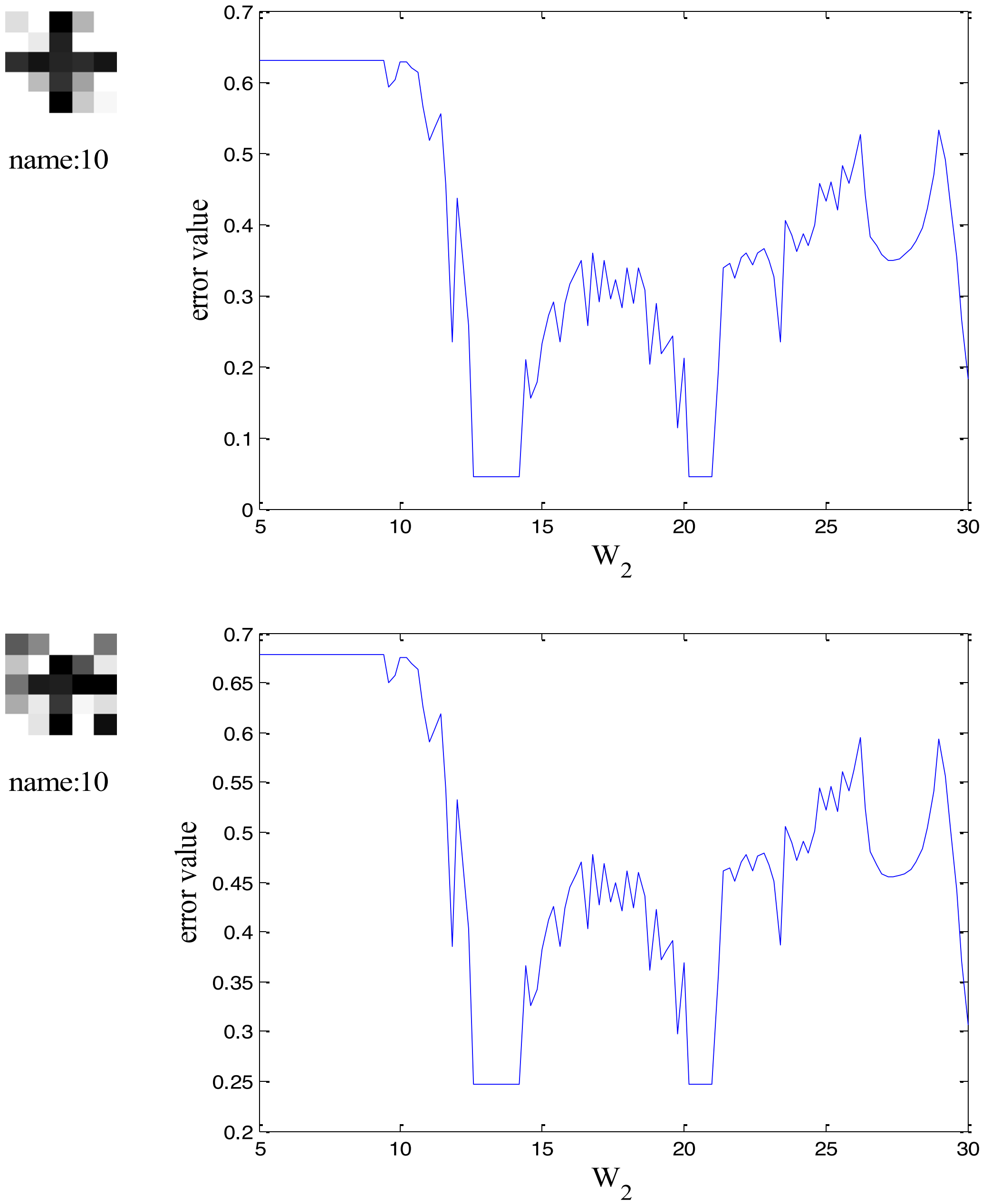

Fig. 11. Error of the ANN output and the desired output (noisy image) for two noisy samples of the cross image, showing that the minimum error value is still in the periodic window.

5. Conclusions

In this paper, we introduced a new structure to model memory in the brain. This structure is a chaotic artificial neural network that matches some biological features. It has been claimed that during attention and focusing, the brain changes its status from chaotic to more ordered (periodic) behavior. Inspired by these facts and to memorize a pattern/memory, the proposed structure uses the periodic windows in the bifurcation diagram of a chaotic model of the brain (which is a recurrent ANN). Then a storage part (MLP ANN) which is connected to the first part, tries to learn a specific memory. Although we do not want to propose a computational method, and our focus is on incorporating biological features into the model, the proposed structure has some computational merits including dealing with noisy data.

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