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Waves, Protein Synthesis and Resonance in the Brain: a New Approach for a Long Term Memory

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Abstract

Conclusive evidence that specific long-term memory formation relies on dendritic growth and structural synaptic changes has proven elusive. Connectionist models of memory based on this hypothesis are confronted with the so-called plasticity stability dilemma or catastrophic interference. Other fundamental limitations of these models are the feature binding problem, the speed of learning, the capacity of the memory, the localisation in time of an event and the problem of spatio-temporal pattern generation. This paper suggests that the generalisation and long-term memory mechanisms are not correlated. Only the development and the improvement of the feature extractors in the cortex involves structural synaptic changes. We suggest the long-term memory has a separate mechanism which involves protein synthesis to encode the information into the structure of these proteins. A model of memory should be capable of explaining the difference between memorisation and learning. Learning has in our approach two different mechanisms. The generalisation in the brain is handled by the proper development of the links between neurons via synapses. The Hebbian learning rule could be applied only for this part of learning. Storing an internal firing pattern involves, in our approach, a new mechanism which puts the information regarding this firing pattern into the structure of special proteins in such a way that it can be retrieved later. The hypotheses introduced in this article includes a physiological assumption which has not been yet verified because it is not currently experimentally accessible.

Keywords: Waves, Protein Synthesis, Resonance, Long Term Memory

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1. Introduction

This paper is an attempt to understand how knowledge and events are stored and retrieved in the brain. Long-term memory storage entails some physical changes in neurons. How it this is accomplished in the brain is not well understood yet and continues to be a question of fundamental and practical interest. The traditional hypotheses that long-term memory requires the production of proteins and that the information is encoded somehow in the structure of these proteins are very appealing because the capacity of memory governed by such mechanisms could be huge.

Modelling neural networks is a promising approach not only to understanding the mechanism of the brain, but also to obtaining design principles for new information processors. In our modelling approach we study how to interconnect neurons to obtain a brain model or a network with the functions and abilities of a biological brain. Artificial neural networks are often used as models of biological memory because they share with the latter properties like generalisation, distributed representation, robustness and fault tolerance. However, they operate on a short-term scale and can therefore only be appropriate models of short-term memory. Among the major problems of connectionist networks and distributed memory models are “catastrophic interference” (also called “catastrophic forgetting”) and “superposition catastrophe”, and the general problem behind it called the “binding problem”. These problems are regarded as today’s key questions regarding brain function.

The problem of catastrophic interference in connectionist networks, described in (McCloskeym and Cohen, 1989) and (Ratcliff, 1990), is as follows: the memory system must be plastic to acquire new significant input while remaining stable in responses to previously learned items. When confronted with new inputs, the network totally forgets the previously trained sets. The catastrophic interference is particularly exhibited by multilayered perceptrons trained by some backpropagation-like learning algorithm. In this case, the forgetting effect is mainly due to the distributed nature of the representation (French, 1991). Each new input influences most of the weights of the network through the backpropagation of the output error and previously learned patterns become then corrupted. Some authors (French, 1991), (Ratcliff, 1990), (Kanerva, 1988), (Kruschke, 1992) have diminished the effects of catastrophic interference by reducing the receptive fields of neurons in the hidden layers in order to supply them with a more localized infor-

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mation processing. The price to pay for these improvements in long-term behaviour is longer training periods and a the necessity of higher number of hidden nodes to allow same generalisation performance. In (Angulo and Torras, 1995), the authors showed the existence of a trade-off between resistance to catastrophic interference and distributed representations. In (Wacquant and Joublin, 1992), it is presented a model of long-term memory based on radial basic function networks and inward relearning mechanisms which enable some types of neural network to improve interference behaviour. It has been demonstrated repeatedly that three-layer backpropagation networks are very sensitive to interference caused by additional training without rehearsing patterns learned earlier. Discussion about the limits, merits and the plausibility of variants of backpropagation networks as models for human long-term memory can be found in (Murre, 1995). In (Ans et al., 2004), is developed a dual-network architecture in which self-generated pseudopatterns reflect (non-temporally) all the sequences of temporally ordered items previously learned. Using these pseudopatterns, several self-refreshing mechanisms that eliminate catastrophic forgetting in sequence learning are described. A connectionist architecture that would seem to solve the problem of multiple sequence learning using pseudopatterns is presented in (Ans et al., 2002). In (Norman et al., 2005) is critically evaluated how well the Complementary Learning Systems theory of hippocampocortical interactions addresses the stabilityplasticity problem.

The superposition catastrophe and feature binding problem are closely related to each other (Fuji et al., 1996), (Triesch and von der Malsburg, 1996). Superposition catastrophe consists in the impossibility to distinguish the internal neuronal activity patterns of two stimuli when they arrive together. Different aspects of the same stimulus are not processed by the same neurons. The brain has to link together these various aspects (e.g., colour, contours, movement, sounds) in order to differentiate them from other objects (Sougne and French, 1997). Such integration processes are needed not only between neurons from the same cortical area but also between areas of different modalities. The feature binding arises in such an integration process. If two objects are presented simultaneously on the visual scene for example, the binding mechanism must link together only features of the same object without binding individual features from one object with features of the other one (French-a, 1997), (French-b, 1997). In (Barrett et al., 2008) is proposed a set of alternatives to temporal synchrony mechanisms that instead use short signatures. It can be a solution to the variable binding problem.

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In (Watanabea et al., 2001) is proposed a neural network model which gives one solution to the binding problem on the basis of functional connectivity and bi-directional connections. In (Clifford et al., 2004) is determined the limits that binding imposes on the perception of global form in static flow fields defined by oriented dot pairs. The cognitive binding problem in quantum neurodynamics is described in (Mashour, 2004). Solutions to the spatial binding problem is presented in (Holcombe, 2009). In vision research the binding problem is presented in (Dong et al., 2008) (Lorenceau and Lalanne, 2008) (Sterkin et al., 2008).

Many past experiments tried and failed to confirm the hypothesis that by transfering molecules it is possible to transfer memories (Fjerdingstad, 1971). Mixing proteins and RNA from different neurons and injecting the mixture into another neural network didn't succeed to transfer behaviour. However, this doesn't means that the memory is not encoded into that proteins/RNA. The proposed model suggests that it is, in principle, such molecular transfer of memories is possible but we must put LTM-proteins from one neuron of the first network to the coresponding neuron of the other network and not mix the LTM-proteins of different neurons.

The human brain is able to answer at what time in the past an event occurred. But this localisation in time of an event is not taken into account by many memory models, because including a temporal dimension into a memory model is not a trivial task. From our point of view, introducing a *time* dimension is essential for a plausible long-term memory model. This paper tries to find the answers to the following questions. *Are the generalisation and the memorisation properties of the brain correlated* ? How can a long-term memory mechanism be defined in which the information is encoded into the structure of the proteins ?

At the lowest level of generalisation the information input rate is limited by the spatial and temporal sampling rate of our sensory transducers. This generates a large amount of data of which only a small fraction is relevant. The relevant information must be extracted. This process of generalisation is performed by the cortex. Higher cortical areas deal with invariants of the information from lower cortical areas.

In our approach, *memorising an input pattern* means that the brain stores the internal firing patterns - the representations of the stimulus in the cortex - which were activated by the input pattern in different cortical areas. The brain stores the raw information of the input stimulus and simultaneously stores the abstracted representations of it from higher areas. Later the brain is able to retrieve both the low and the high representation of the stimulus.

There are two separated learning channels: plastic changes at the synaptic level define the “hardware” which is able to do the generalisation process; the other channel involves only the storage and retrival of activated neurons. The first hypothesis in this paper claims that *the generalisation property is not correlated with the long-term mechanism*. The brain learns how to abstract the input pattern by developing proper synaptic links between neurons and by changing the synaptic weights. The “hardware” defined by neurons and synapses in the cortex areas is responsible for the proper generalisation of the input stimulus. What the brain does when the synapses grow or the strengths of the synapses change, is to improve the cortex abstractors, to create the proper structure which extracts invariant features from raw input data.

The brain stores representations of the input pattern which are active in different cortical areas. The storing process is the same for all cortical areas and does not involve changing of the synaptic weights. The storing mechanism we propose is based on protein synthesis. The second hypothesis suggests that the information is coded into the structure of these synthesised proteins.

Recent studies performed on a wide variety of animals have revealed a molecular mechanism essential to long-term memory formation. The conversion of short-term memories into long-term ones involves the activation of certain genes. These studies (Stevens, 1994),(Ulman, 1996) have shown that a particular transcription factor, named CREB, plays a critical role in long-term learning. CREB acts more or less like a ”switch” for encoding long-term memory. Experiments performed on fruit flies have even shown that when CREB is artificially activated, a long-term memory is formed after just one training session instead of the usual ten.

An interesting paper regarding bacteriorhodopsin protein describes the major advantages of using this protein for 3-D memories and holographic storage media applications (Birge, 1992). This protein shows a long stability in time and suggests that a protein with similar properties could be synthesised inside a neuron. Since most of the molecules present in the nervous system are replaced at regular intervals, the persistent changes in neuronal function and structure, thought to underlie the storage of long-term memory, would seem to require some mechanism that can survive this molecular turnover (C.H. and Kandel, 1993),(Crick, 1984),(Lisman, 1985).

In each cortical area the firing map of the active neurons is memorised and after that the same firing neurons can be activated by activating the same neurons. A short description of the hypothesis is given below.

Our long-term memory model is based on interference between a “reference wave” and the internal neuronal representation of an object. The storing and retrieving process is similar with the production and reconstruction of a hologram. In holography, the hologram is formed by the interference of the secondary wave arising from the presence of the object with the strong background wave and it is recorded on a photographic plate. If the plate, suitably processed, is replaced in the original position and is illuminated by the same background wave alone, the wave that is transmitted by the plate contains information about the original object. Models of biological memory based on holography were proposed in the past (Heerden, 1963),(Metcalfe-Eich, 1985). What are the corresponding equivalents of interference patterns, filters and coherent beams of light in the neural hardware of the brain has not been discussed though.

In the brain an object is represented by firing neurons in different higher brain areas. The state of these neurons together represent the internal neuronal image of the object. In our model, the internal firing pattern takes the place of the secondary wave. We introduce the reference wave as a field which covers all the neuronal space. Each neuron interacts with this field. In our approach, specific proteins are synthesised inside each firing neurons and these proteins memorise the state of the neuron at the moment when they were synthesised. The proteins which are produced in this process are very sensitive to the frequency of the reference wave. The frequency of the reference wave changes in time. For each moment of time there is a specific frequency of the reference wave. Proteins in this model are like the photographic plate in holography. The retrieving process is similar to the reconstruction of the hologram. By generating a proper retrieving wave of the same frequency as the frequency at the storing time, only the proteins inside the neurons which are sensitive to that frequency will resonate. The resonance will trigger a chemical reaction (similar with the chemical reactions in the retina triggered by specific light frequencies) and will produce the firing of the neuron. This mechanism will reconstruct the firing map in all the neuronal regions where the retrieving wave is strong enough. The firing map will then be the same as the firing map at the storage time.

There are several types of models depending on the levels of memory: brain, neuronal level, and molecular level. Our proposed model attempts to link together these three levels by defining a mechanism which is able to communicate between these levels.

We analyse the properties of a neural network composed by such neurons. We show how this approach overcomes catastrophic interference and the feature binding problem. We investigate the storage and the generation of the complex spatio-temporal neural patterns like sequences of images in the visual cortex, sequences of sounds in auditory cortex and sequences of motor patterns. The design of a new associative memory, capable of locating an event in the past and capable for multiple associations, is proposed. Also the capacity and the access speed of such memory are discussed. Possible damage of the encoding and decoding mechanisms in our model will lead to the behaviours similar to the ones observed in clinical instances of retrograde and anterograde amnesia.

2. The Model

2.1. The Encoding and Decoding Mechanisms

The human brain can be imagined as an enormous vector of up to one hundred billions elements, where each element is a neuron. It is a well accepted fact that many neurons “represent” things that are outside of the brain. The visual cortex, for example, contains neurons that are activated if a particular pattern is present in the visual field. If we think of neurons in a simplistic way and describe their activity using only the states “active” and “inactive” then each object is represented in the brain as a neuronal vector of binary elements. The neurons of the brain are heavily interconnected, by synaptic connections, through which activity from one neuron is transmitted to another. It is well accepted that synaptic connections can differ in their efficiency of transmitted activity. Because of this, the brain is not only a vector of neuronal elements. It can also be seen as a vector of synaptic elements, with values corresponding to the efficiency of the individual synapses. The values of the elements of the synaptic vector change much more slowly than the values of the neuronal vector. One of the well spread paradigms is that the long-term memory is stored in this synaptic vector and that learning means changing the values of some elements of this vector. The synaptic vector is responsible in this way for both storing/retrieving and feature generalisation. The strong interaction between the storage and feature extraction mechanisms involves also strong interaction between information stored into this type of memory. Our aproach decreases the strength of this interaction by proposing a new mechanism of storage.

To memorise a pattern represented as a state of a neuronal system means to be able to reproduce simultaneously the states of all neuron involved in that pattern representation.

The lowest representation of a pattern with minimum generalisation of its features can be found in the low cortical areas. At this level, for example, changing the position of a visual pattern in the visual field will create another internal firing pattern. By comparison, in the high cortical area, the internal firing pattern will be the same because the representation of the object here is position-invariant.

Throughout this paper we follow the *place coding paradigm*. We regard a group of firing cells as a spatial pattern representing the input pattern. We assume that the features of a stimulus are represented by binary (active - inactive) neurons, or can be reduced to this binary representation. With this assumption, at low level, each feature has a unique internal spatial representation. The position of the firing neurons encodes raw information about the pattern (colour, intensity, position). Changing a feature of this pattern will be reflected in changes in the position of the firing neurons in this area.

In the higher areas, for the same stimulus, the behaviour of the firing neurons is different compared with the behaviour of the firing neurons in lower areas. When one feature of the stimulus is modified, *the place of firing neurons in high area will be the same for some special feature changing.* For example in the higher visual areas, the firing pattern will be the same (invariant) when the visual stimulus is rotated, translated, scaled or the intensity of the light is changed. The invariance of representation in higher areas regarding some special transformation of the raw features involves the generalisation of the information. The link between lower areas and higher areas is made by the wires of axons and synapses

state of neuron.

2.2. The Interaction between One Neuron and the Reference Wave

In this section we define the properties of the neurons and describe their behaviour in the presence of a reference wave. We analyse the flow of information from the learning stage to the retrieving stage at the individual neuron level. The model of neuron which is used in this paper has the following properties:

- The neuron has two possible states: active and inactive.

- There is a reference scalar field around the neuron with a time varying frequency and there is a unique correspondence between the frequency of this reference wave and time.

- When the neuron fires, special molecules are synthesised in inside its cell once every few hundreds of milliseconds (the psychological time interval) until the neuron becomes inactive. This is the storage phase (Figure 1 left).

- The synthesised molecules are sensitive only to the unique frequency of the reference wave present at their production time.

- When, at a later stage, a retrieving wave with the same frequency and with enough intensity is present, the resonance of the corresponding molecules occurs and triggers a chemical reaction resulting in the firing of the neuron. This is the retrieving phase (Figure 1 right).

- When the neuron is active, all synthesised molecules generate a wave of small intensity and corresponding frequency. At every moment there is *a spectrum intensity-frequency associated to an active neuron defined by the synthesised molecules till that moment.* This spectrum represents the stored information. The intensities of the waves generated do not decrease appreciably with the distance.

- When the frequency of the retrieving wave is changed e.g. from $f(t_1)$ to $f(t_2)$, the sequence of the states of the neuron in the interval $[t_1, t_2]$ will be reconstructed. This property is important in memorising and retrieving complex spatio-temporal patterns like sequences of images, sounds or motor patterns by only modifying one parameter, the frequency of the retrieving wave.

Let us consider a neural network which consist of N such neurons. The state of a neuron k at the time t, in our approach is defined by the state of the membrane $S(k,t)$ *and the states of the proteins* $P(k,f)$ which were synthesised and are involved in the LTM mechanism. One protein which belongs to the cell k and has the resonance frequency f will be noted as $P(k,f)$. We will describe mathematically the interaction between the protein and the cell membrane and also the interaction between the protein and the reference wave.

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To store the state of the membrane at time t the following processes occur. The membrane of the neuron k having the state $S(k,t)$ will generate inside de cell a specific chemical reaction which will transfer the information about the state of the membrane to the place where the LTM proteins are synthesised (which can be a LTM ribosome). At the same time, a reference wave $U(f,t)$ is present and will interact with the LTM ribosome and a LTM protein will be synthesised. This protein will resonate at the frequency of this reference wave. The resonance will generate the reproduction of the state of the membrane via another chain of chemical reactions.

The state of the membrane of a cell can be described in many ways, from the most simple descriptions like the binary neuron to more realistic and complex ones using Fitz Hugh-Nagumo equations. The choice is not essential for the LTM mechanism but is important for the abstraction mechanism which will be the subject of future work.

We chose a binary neuron $S(k,t) = \{0,1\}$. The LTM proteins which were synthesised and are inside the body of the cell can be described by an active or non active binary parameter $P(k,f) = \{0,1\}$. A neuron k at time t is described by the state of the membrane and the LTM-proteins which are alredy into the neuron:

$$(S(k,t), P(k,f_1), P(k,f_2..)$$

The LTM proteins can be activated in two ways.

1. If the membrane of neuron k is active, an LTM protein j will generate a wave with a small amplitude I_j with the specific protein's frequency $I_j(k,f) = S(k,t)$ for all the N proteins inside cell k with $j = 1,2,...,N$.
2. If the retrieving wave $R(f,t)$ has the frequency close to or the same as the protein's resonance frequency and the intensity of this retrieving wave is strong enough (above $I_{treshold}$), a chemical mechanism is triggered and the cell becomes active. In the simple case in which only one protein is enough to activate the membrane:

$$S(k,t) = \delta(f_r - f_p) * Step(I - I_{treshold}) \tag{1}$$

where:

$\delta(fr - fp) = 1$ if $fr = fp$ and 0 otherwise
$Step(I - I_{treshold}) = 1$ if $I > I_{treshold}$ and 0 otherwise
f_r is the reference wave frequency
f_p is the resonance frequency for that protein

The interaction between proteins, the membrane and the field can be written as:

$$P_j(k, f) = S(k, t) * (1 - \delta(f_r - f_p)) + \delta(f_r - f_p) * Step(I - I_{treshold}) * (1 - S(k, t)) \tag{2}$$

In a more complex case the membrane can be activated if a proper number $N_{treshold}$ of proteins are active and we can write:

$$S(k, t) = Step\left(N_{treshold} - \sum_j P_j(k, f)\right) \tag{3}$$

In this case, the cell will be activated only if the activated proteins will be more than $N_{treshold}$. The mechanism proposed here gives the link between three modelling levels: molecular level, neuron level and brain level. The comunication between these levels is based on chemical reactions (proteins - membrane of the neuron), the resonance waves generated by proteins, and the usual synapses between neurons.

So, can one speak of long-term memory for a single, isolated neuron ? In our approach, yes. The neuron model we propose is able to “answer” the question: *when in the past the neuron was activated* ? This is because it stored this information into the proteins and we can activate this neuron sending a proper retrieving wave to it. There are two locations inside the neuron which are related with learning: (1) inside the body of the neuron are stored the moments when it fired (long-term memory) and (2) inside the synapses are stored only the plastic changes which define the features extractors.

2.3. Behavior of a Population of Neurons in the Presence of the Reference Wave

The representation of a visual pattern in the primary visual cortex at a given moment consists of a corresponding firing map in that area. The cells firing at that moment define a spatial firing pattern.

The spectrum intensity - frequency of the retrieving wave for a population of cells will be simply the scalar sum of the spectra for each cell:

$I(f, t) = \sum_k I(k, f)$ for all neurons and proteins with the resonance frequency f.

The association between the frequency of the reference wave and this firing pattern is made by the synthesis of the proteins in each firing cell.

From now on, these proteins will contain the information represented in that area: shape, colour, position.

In order to retrieve this information, we simply must create a proper intensity and frequency of the retrieving wave. The frequency must be the same as the frequency of the reference wave associated with the firing pattern. The proteins sensitive to this frequency will resonate and the corresponding cells will fire, reproducing the same spatial firing pattern. We shall discuss how this retrieving wave can be generated by firing patterns from other neuronal pools, other areas, or from the same population of cells. We shall see how a part of the input stimulus is able to create through this mechanism the proper retrieving field for the entire pattern. Based on these facts we describe the associative property of the proposed long term memory model. Our approach enables memorisation of a complex spatio-temporal pattern. In the auditory lower area this mechanism enables a sequence of sounds to be stored, retrieved and generated. In motor lower area a complex motor pattern can be generated by only changing one parameter which is the frequency of the retrieving wave.

3. Simulation and Results

The proposed model has been implemented in C on a SUN SPARC station running UNIX. To communicate with the program we designed also a user friendly interface written in Motif under Xwindows. For simulation, we used images with 256 gray levels and the dimension 250 × 250. We first stored 49 images into long-term memory and then we performed the experiments described below.

We simulated the behaviour of the LTM at the lowest level of generalisation (no translation, rotation, scaling or other invariance). *The LTM is not correlated with the level of generalisation from higher cortical areas.* A firing pattern in visual cortex can be represented as an image but the meaning of the image is only the firing pattern in that cortical area. Hence the results can be applied to other modalities without any changes. We call *pattern* or *firing pattern* an internal representation in the cortical area. If it is a lower area we consider that the pattern and the representation of the pattern are the same or can be defined as an univocal map between the pattern and its representation. A firing pattern in a given cortical area is thus equivalently defined as the population of the activated cells in that area.

3.1. Associativity

This section provides a description of the associative property of the long term memory and the results we obtained. There are many possible associations in the brain, for example between:

- high representation of a pattern - low representation of the same pattern
- high representation of a pattern - high representation of another pattern from another area or from the same area.
- low representation of the pattern - low representation of another pattern
- representation of one feature of a pattern - representation of another feature of the same pattern
- parts of one pattern - parts of the same pattern
- a spatial pattern - a spatio-temporal pattern

The representation of a stimulus is defined in this paper as the spatial pattern of firing cells generated in the areas when the stimulus is presented. In our approach the association of two neuronal representations from the same areas or different areas is based on the simultaneous firing of cells. The link between simultaneous patterns is made via the reference wave (Figure 2). The patterns will have the same associated frequency or, if the patterns were coupled for a long time interval, they will have corresponding frequencies in common. After ”conditioning” the patterns the presentation of one pattern A will begin to elicit the firing of the associated pattern B. When pattern A is also associated with another pattern C, this firing pattern will also be active. The association is strong if at the learning phase there were many pairings of the patterns. If there were few pairings, the resonance will not occur because the retrieving intensity field will be below the proper intensity.

3.1.1. Auto Associative Memory

Figure 3 Shows the spectra we obtained when different parts of the same pattern are presented. We stored these six face patterns into the memory among the other 42 patterns. At time $t = 19$ the entire face (a) was stored, at times $t = 22, 27, 33, 36, 46$ were stored respectively the occluded patterns b,c,d,e and f. After this preparation we presented to the LTM these images. As we can see in Figure3.a there are six peaks which correspond to the resonance of the memorised partial patterns. All images from the memory resonate but the amplitudes (corresponding to the number of activated neurons) are around 1000 or less which is very small compared with 30.000 or 120.000 for the peaks.

When a more or less occluded pattern is presented the spectrum changes but the main peaks are in the same place. What is important is the peak with the frequency 19 which represents the full pattern. This peak has an amplitude around 100.000 for the spectra b and c, around 50.000 for d,e and around 20.000 when the occlusion hides a big part of the face in case f. The results demonstrate the LTM auto-associativity. The firing pattern corresponding to a part of the face will activate the retrieving wave with the frequency 19 (or in case when the face has been memorised many times in the past the corresponding retrieving frequencies will be activated as well). Parts of the same face will also resonate with each other.

In order to simulate a higher cortical area we need to define the feature extractors which create the firing pattern in that area. The feature extractor must be invariant to translation, rotation, scaling and some deformations of the input stimulus. The definition of such a feature extractor is given in "A Repesentation Invariant to Translations, Rotations and Iluminations" - in work. In this case the resonance will also occur after a rotation, translation or scaling of the image.

3.1.2. Association Between Two Patterns

As described, a firing cell will create a very small intensity wave containing all the frequencies memorised by the proteins. Each firing cell has a corresponding spectrum of intensities/frequencies. Each firing pattern has a corresponding spectrum and this spectrum is the scalar sum of the individual spectrums of the firing cells. If the peaks in this firing pattern spectrum are high enough the waves generated will induce resonance in proteins from cells of another area or in the same area. Based on the learning process, there are one or more channels of resonance between two firing patterns. The main condition is that the spectra of the patterns must have in common at least one frequency component in order to initiate the resonance. This association is in bi-directional and the resonance can be initiated either by one firing pattern or by the other. The meaning of *association* in our approach is the possibility that a firing pattern is able to create a retrieving field for another firing pattern from the same area or from other areas or modalities.

To illustrate how LTM makes the association, a scene with two patterns, a knife and a scissors (Figure 4 a), were memorised seven times in the past at: $t = 4, 15, 23, 40, 46, 49$. There were 49 patterns in the memory. We presented to the LTM three patterns: the scene (a), only the scissors (b) and only the knife (c) . When only the scissors or only the knife is presented, the spectrum of the retrieving field has the same main resonance as the scene but with the amplitude less than 100.000. This spectrum is able to trigger the retrieval of one object when the other one is presented. When we show the scissors, this will activate the scene scissors + knife. The scene *scissors* + *knife* will activate the *knife*. By this mechanism two firing patterns can be associated.

3.1.3. Multiple Association and Chain of Associations

Multiple associations and a chain of associations can both be handled by the proposed memory model. The multiple association property is based on the activation of a retrieving field which has a spectrum composed of another two or more spectra. If pattern A was associated in the past with pattern B and at other times with pattern C, the pattern A will generate the spectrum for both pattern B and C and both patterns will be activated. An example for a chain of associations is the following. If pattern A was associated with B and B with C then if the pattern A will be active it will retrieve pattern B and this will create a retrieving field for pattern C. Because the multiple associations mechanism is based on chains of associations we illustrate how LTM works for a chain of associations.

A clock was simple associated with a pair of scissors by inserting the scene *clock+scissors* (Figure 5.d) into the memory at time: $t = 15, 20, 43, 49$. At different moments of time in the past the scissors wese associated with a *knife*, *knife+scissors* (Figure 5.e) at time: $t = 7, 24, 46$. A total of 49 patterns were stored in the memory. The problem is to show how the *clock* and the *knife* will become associated with each other after this. We presented only the *clock* and we obtained the spectrum (Figure 5.a), after that the *scissors* (Figure 5.b) and the *knife* (Figure 5.c). The spectrum corresponding to the scissors includes both the spectra of the *clock* and of the *knife*. This means that if the retrieving field has the *clock* spectrum this will activate the *scissors* spectrum which in turn will activate the *knife* spectrum. This is the mechanism of a chain of associations. The *clock* can be associated with the *knife* via another pattern.

An object can be represented in different feature areas by different firing patterns. The association of these firing patterns suggests a binding to the features of the object. The next section discusses the presence of two objects together in receptive field, the superposition catastrophe and the feature binding problem.

3.2. Superposition Catastrophe. Binding Problem

Some memory models can not handle the case of two stimuli arriving at the same time. The so-called *superposition catastrophe* may happen when two patterns A and B are simultaneously in the receptive field. If there is no way to separate the group of firing cells perceiving A from the firing cells of group perceiving B, the superposition catastrophe occurs. If, however, the cell group perceiving pattern A fires in synchrony, and so does the group B but with different timing than A, the two patterns can be easily identified. This is the classical schema for the temporal resolution of the superposition catastrophe.

The gamma range oscillatory firing of neurons and their synchronisation between distant sites were observed in the visual cortex by several researchers (Gray and Singer, 1987), (Gray and Singer, 1989),(Eckhorn et al., 1988), (Engel et al., 1992). A summary of the current perspective of the oscillation coding is given in (Singer, 1994). Those stimulus-driven oscillatory activities have attracted attention as a possible example of the correlation coding proposed by von der Malsburg (Malsburg, 1994). Synchrony plays the role of binding fragmentary local information which is coded by individual oscillatory cells into an entity by synchronising the phase of oscillations. Initially there was an implicit expectation that the synchronisation would be a stationary state throughout the duration of the visual stimulation, so that it kept the binding relation. However, recent studies using time domain analysis have revealed a high degree of dynamic variability in the synchronisation process (Gray et al., 1992). The transient synchronisation has been observed also in awake monkeys (Kreiter and Singer, 1992). Such a highly transient nature of synchronisation may cast doubt on the classical claim of oscillation coding that oscillatory activities serve as an indicator of binding.

In our approach, the binding mechanism is reduced to the mechanism of association of features. To bind together two firing patterns from different areas, the LTM use the events stored in the past.

To illustrate how the LTM overcomes the catastrophic interference, two patterns were stored in the memory among other 49. A *pen* (Figure 6 a) was memorised at times: $t = 7, 21$ and 35 and a *thermometer* (Figure 6 b) was memorised at times: $t = 3, 17, 28, 41, 49$. If we showed the images separately we obtained the spectra (Figure 6 a) and (Figure 6 b), respectively. In order to observe the behaviour of LTM we presented a scene with both objects present (Figure 6 c). As can be seen in (Figure 6 c), there are two superposed spectra corresponding to the two objects. The main peaks for the scene are at 3,7,17,21,28,35,41, which are the peaks for the pen and for the thermometer. The retrieving wave for the scene will be able to activate the proteins and the neurons corresponding to the firing pattern of one object or another. The separation of the representations is made by the separation of the peaks in the retrieving wave.

The superposition of two stimuli will involve the scalar superposition of the two spectra corresponding to the stimuli. The separation of the firing patterns is made by the difference in intensity and frequency of the two spectra. The separation of the resonance channels in the proposed model elliminates the possibility of the superposition catastrophe.

The spectrum of one pattern includes all information about the past associations of the pattern with other patterns from the same or other modalities. The feature binding problem is related with the fact that, for example in the visual system, the visual object is represented in a distributed way (Kruger, 1994). An object is represented by the firing neuronal pattern in different feature areas. When two objects are at the same time present in the visual field, in each feature area there are two cell groups activated simultaneously. This situation is exactly a revival of the difficulty already defined for the superposition catastrophe. In the context of our approach, the feature binding problem is overcome in the same way as the superposition catastrophe. The binding is provided by the corresponding spectrum associated in the past for each pattern. This spectrum enables to distinguish the neuronal activity patterns from the same feature area when the stimuli come together.

3.3. Localization in Time of the Event. Memory Damages

The model proposed in this paper gives the localisation in time of a stored event. This property of the model is not taken into account by other memory models. For example, in the past at t_1 we saw the face of a person and at t_2 someone shows us a photo with the same face asking if and when we saw that face. The flow of information will be as follows. The image of the face will ”arrive” in the low visual area. The anatomical structure of the cortex will perform the generalisation of the raw image. In higher areas a group of cells will fire and these cells will be the same cells as those firing when the face was first seen at t_1. Because of this, the spectrum of the face will appear and a retrieving field will exhibit a peak in the region $\nu(t_1)$ or more than one peak if the face was seen more than once in the past. The frequency of the retrieving field will localise the face in time.

The image of a *cat* (Figure 7) was memorised at times $t = 10, 26, 31, 43$ and 47. We presented the cat and we got the spectrum from Figure 7. The retrieving field has the noise around 1000 and we obtained all five peaks having the amplitude around 120.000 and the same frequencies. The resonance occurs and the cat can be localised in the past using the frequency-to-time transformation. It is easy to imagine a special localisation area in which the firing neurons represent the moment of time corresponding to the frequency of the retrieving wave.

As a medical example, a person who has been knocked unconscious by a blow at the head can have selective memory loss for events that occurred before the blow (this is called *retrograde amnesia*) as well as for events that occur after regaining consciousness (*anterograde amnesia*). If, in the proposed model, the reference wave disappears or the protein synthesis does not work for some reason, the behaviour of the long term memory will be similar with the case of anterograde amnesia because it is impossible for the memory to store new events. Also, if the retrieving field has low intensity or the chemical reactions which trigger the firing of the cell are not properly produced, a retrograde amnesia behaviour can be seen in our model.

3.4. Catastrophic Interference, LTM Capacity

The interaction between existing memorised patterns and a new pattern is the main problem of many memory models. In our proposed model there is no destructive interference between a new pattern and previously stored patterns. The new pattern is memorised by new proteins and these proteins do not interact with other proteins of the old patterns. The catastrophic interference does not occur because there is no interference between memorised patterns. This is the reason that the proposed memory has a plausible capacity. The limits of the computer's memory imposed an artificial limit on the simulation of the LTM capacity. In principle there is no limit for the number of the patterns which can be memorised by the proposed memory model.

In Figure 8 we got the spectrum for the same *cat* but when a total of 200 patterns were stored into LTM. Each pattern has the dimensions 250 × 250 and 256 gray levels. The resonance occurs only where the cat is memorised. The other amplitudes of the retrieving field are very small (around 1000 neurons activated for each frequency). This represents the interaction between memorised patterns. The number of activated neurons which correspond to the cat pattern are more that 100.000. The noise/signal is 0.01 which in this context is very small.

3.5. Storing and Retrieving Complex Spatio-Temporal Patterns

We shall explain in this section how the proposed model is able to store and to retrieve complex spatio-temporal patterns. A spatio-temporal pattern can be a sequence of images (like the images of a moving object), a sequence of sounds (a melody) or a sequence of motor patterns. A spatio-temporal pattern is represented internally by a spatio-temporal firing pattern. Storing such a spatio-temporal firing pattern does not involve a special mechanism. It is reduced to storing a sequence of simple spatial patterns. Retrieval of the spatio-temporal pattern is simply done by creating a changing frequency of a retrieving wave in a corresponding frequency interval. The retrieving wave can be generated also by other spatio-temporal firing patterns from other areas. If the sequence of the firing patterns A_1, A_2, A_3, A_4 were memorised in this order in the interval $[f_1, f_4]$ then the same sequence will be activated if a retrieving field will change the frequency from f_1 through f_2, f_3 to f_4.

This feature of proposed LTM is a very important one and is not trivial. In the primary motor cortex a very precise spatio-temporal firing pattern is generated for a specific movement. To activate simultaneously hundred or thousands of cells and to activate a sequence of another thousands cells from the same area in the next milliseconds, is not a simple task. The proposed LTM model can handle the simultaneous activation of specific populations of cells and also the successive activation of sequences of specific cells. We reduced the high dimensionality of the problem of activating many cells simultaneously to a one-dimensional problem, the variation of the retrieving field frequency.

4. How the Memory Works

In this section we describe in an intuitive way how the proposed memory works for few cases of visual-visual associations.

Let's suposse we already have stored into the memory a set of scenes $S_1, S_2 ... S_N$ in time order $t_1, t_2 ... t_N$. Each scene contains two images: $S_k = \{A_k, B_k\}$ or a single image $S_j = C_j$ The representation of the scene S_k in high visual area means the set of activated neurons noted by $R(S_k)$ from that area when the scene is presented. One of the main properties of the representation

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is: $R(A \cup B) = R(A) \cup R(B) \cup InteractionFactor$ which means that the representation of one image does not destroy the representation of the other when the images are presented together.

How the memory will behave if we will present to it an image C ? The desired effect in this case would be for example to retrieve all the images which are related with C. If C is a part of a stored image C_s, then to get this entire image C_s. If C is one of a stored pair A_s to get the associated image B_s also. If C is a translated version of a stored C_tr to get this C_tr.

Presenting the image C will activate the neurons from the high visual area $R(C)$. Each activated neuron n_a will create a weak field $w(n_a)$ which will have a spectrum specific to the history of the neuron. The sum of all the waves generated by the activated neurons in that area will be the activated wave $W = \sum_{alln_a} w(n_a)$ coresponding to C.

Analysing the spectrum of W we can get information about the connection between the image C and other stored images. A peak in the spectrum of W coresponding to the frequency f means that a set or subset of the same neurons were activated in the past at the time $t(f)$ coresponding to that f. If we now 'put the attention' on that peak and we generate a retrieving field strong enough with that given frequency we will retrieve the scene stored at $t(f)$ in the past. The retrieved scene depends on the way we make the abstraction which links the low and high visual areas. If for example the abstraction implements a translation invariance representation $(R(translated(C)) = R(C))$ the memory will be able to handle the recognition of a translated version of a stored image.

Each peak from the spectrum of W of the image C can be interpreted knowing the generalisation rules we used to create the representation. The generalisation rules define the invariance of the representation to specific transformations of the input image (rotation, scale, translation or deformation).

The output of the memory will be peaks of the spectrum $\{f_j\}$. Each peak indicates that in the past a similar image or part of the image was presented. The similarity is defined by the representation algorithm used.

The amplification of a specific frequency from the spectrum of the image C means focussing the atention on the event corresponding to that frequency. As we saw, by creating a strong wave having the frequency f we force the resonance of the stored images (or sounds or movements). In this way it is possible to travel through memories via associated frequencies like in this chain of resonances:

$$R_1 \rightarrow f_1 \rightarrow (amplification) \rightarrow R_2 \rightarrow f_2 \rightarrow (amplification) \rightarrow R_3 \tag{4}$$

where $R_{1,2,3}$ are the representations of images or sounds or movements or somatosensory inputs.

We do not given in this paper a specific implementation of the abstraction part of the memory model. In order to ilustrate how it works we do not use any abstraction or generalisation of the input images.

We defined the general framework which gives freedom to chose a specific invariant representation of the raw image. Future work will define such a representation which can be invariant to a desired deformation.

5. Conclusions

This paper proposes a new storing and retrieving memory mechanism, similar with the creation and reconstruction of a hologram. The internal neuronal representation of a stimulus interacts with a reference field at the molecular level. The synthesised molecules inside the firing cells contain the information about the moments of time the cell fired. These molecules are sensitive to the frequency of the reference field corresponding to their production time. If a retrieving field with the same frequency and enough intensity is present, the resonance of these molecules triggers a chemical reaction which will generate the firing of the cells. The firing pattern will be the same as the firing pattern at the storing time.

The long term memory is presented as a candidate of the paradigm the brain may actually adopt. The model includes a physiological assumption that has not been yet verified or is currently experimentally inaccessible. The source and nature of the reference field is the subject of future work. We want to emphasise that, because of its generality, the proposed model can be viewed as a frame for more specific models, for example: a model of the chemical reaction that occurs at firing, a model of the interaction between the proteins and the introduced field and a model of the mechanism of generalisation.

The time variable is very important in this model. The reference wave represents the "internal clock" which defines the moment of time when stimulation occurs. The retrieving field of a population of cells contains information about the temporal location of the event because the time is embeded into the model through the frequency-time relation.

The central message of our approach is that the generalisation mechanism is performed by the hardware of the brain, by synaptic modifications. Changes in synaptic weight translate only in improvements in the way in which the brain will perform the future abstraction of the input patterns, the furure invariant feature extraction. *For storing a firing pattern, the brain uses another mechanism which is not directly correlated with the generalisation mechanism.* We suggested in this paper a mechanism for storing the firing patterns into the structure of special synthesised proteins. There are few other alternatives which can be used in order to store the patterns at the molecular level. We also can choose not the synthesis of a new protein but only the modification of the structure of an already existing one. This will be the subject of future work.

The learning consists of two superimposed mechanisms. The brain learns in time how to abstract things and memorises the firing patterns which are activated by these things in different cortical areas, at different level of abstractization simultaneously. A new synapse configuration in one area will generate a new firing pattern in a higher area. The firing pattern in the high area depends on the links between that area and lower areas. If the links (synapses) are changed, the firing pattern will change also. This represents the indirect interaction between the two mechanisms.

The model suggests that a neuron has its own history of firing stored into proteins. In this way a single neuron has a long-term memory. When the neuron is activated the molecular mechanism stores this event into the LTM-proteins and also there are changes at the synaptic level which are not related with the memory but with the plasticity of the links between cells.

From a physiological point of view the plausibility of the mechanism proposed here is an open question. New neurophysiological experiments could be designed to provide the answers of the open questions which arise from our approach.

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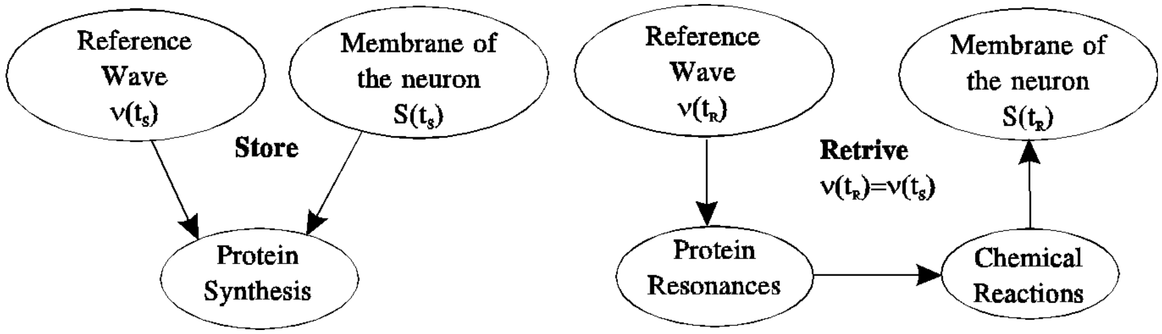


Figure 1: The mechanism of storing (left) and retrieving (right) the state of a neuron

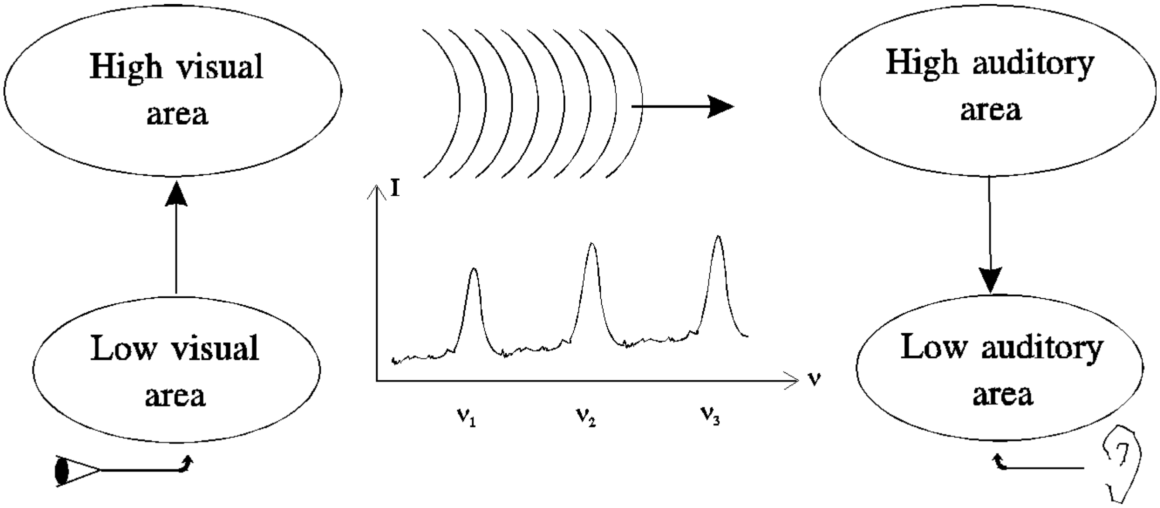


Figure 2: The resonance between a firing pattern from high visual area and a firing pattern from auditory high area. The flow of information from an image through to the name of the image

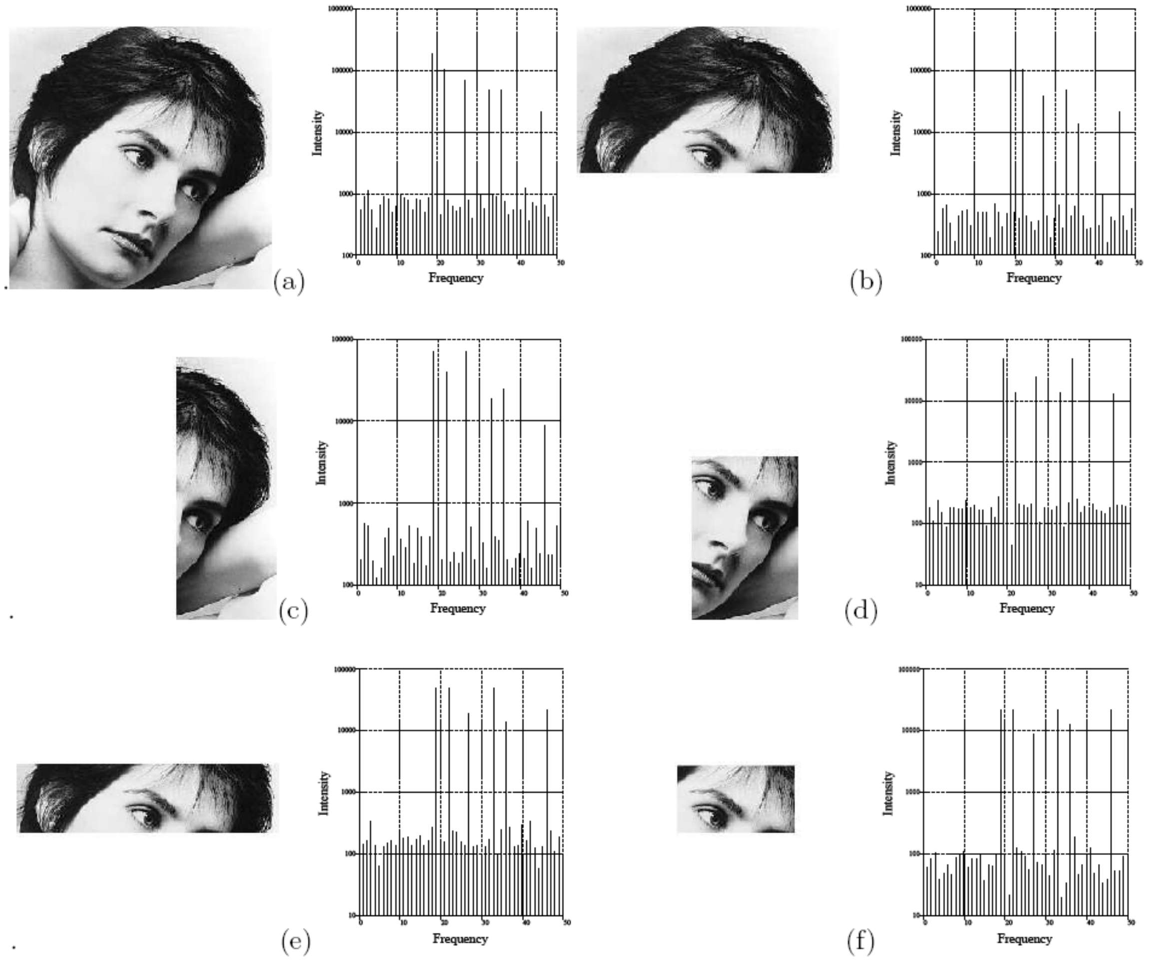


Figure 3: The auto-associative memory. The spectra we got when different parts of the same pattern is presented. We put into the memory among other 49 patterns these six patterns of an ocluded face. At time 19 the entire face (a), at times 22,27,33,36,46 we put respectively the patterns b,c,d,e and f. After this we present to the LTM these images. As we can see there are six peaks which correspond to the resonance of the memorised partial patterns. Also all images from the memory resonates but the amplitude (the number of activated proteins with that frequency) is around 1000 or less which is very small compared with 30.000 or 120.000 for the peaks

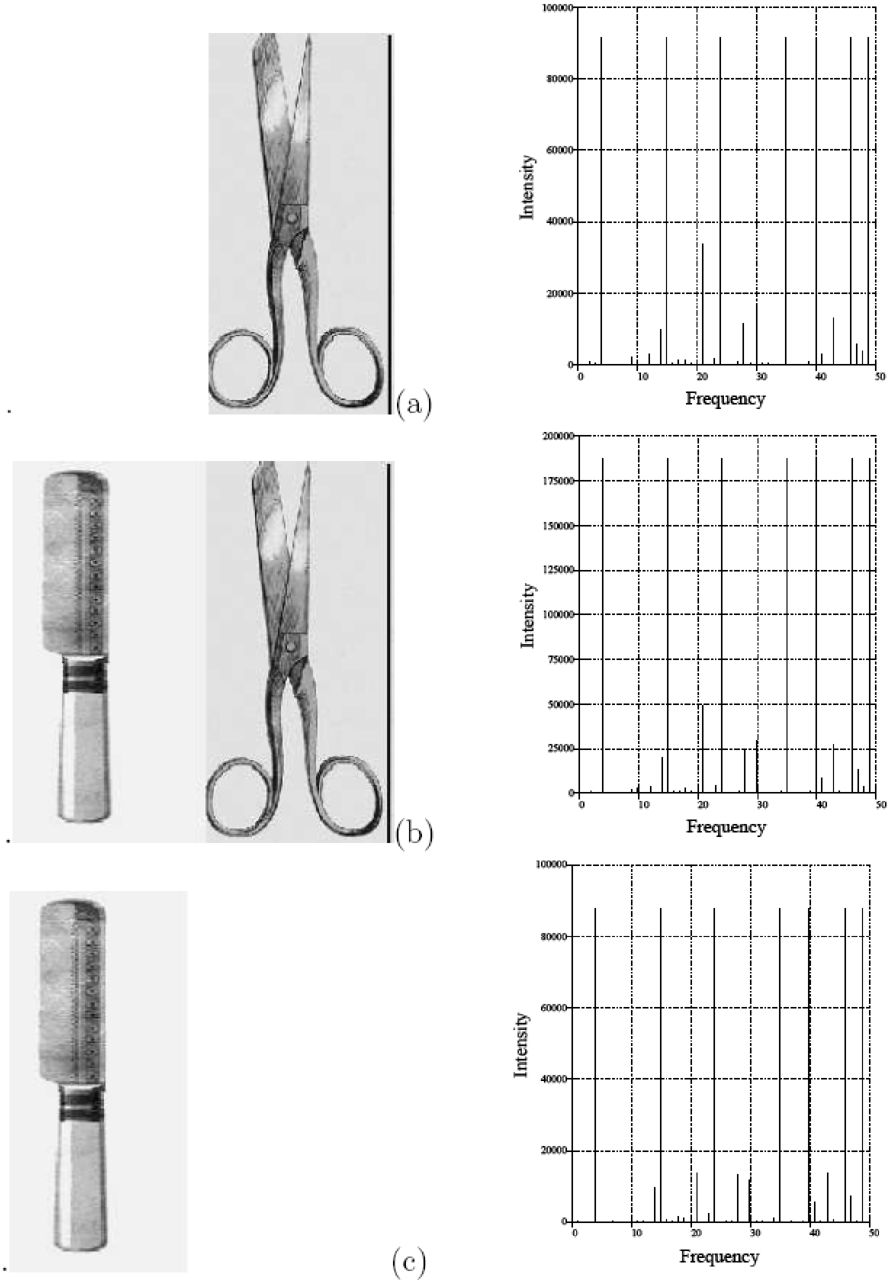


Figure 4: The associative memory. If in the past two images (a and c) were together, then (b) the presentation of one image will activate the spectrum of the other image via the common scene were both images are together

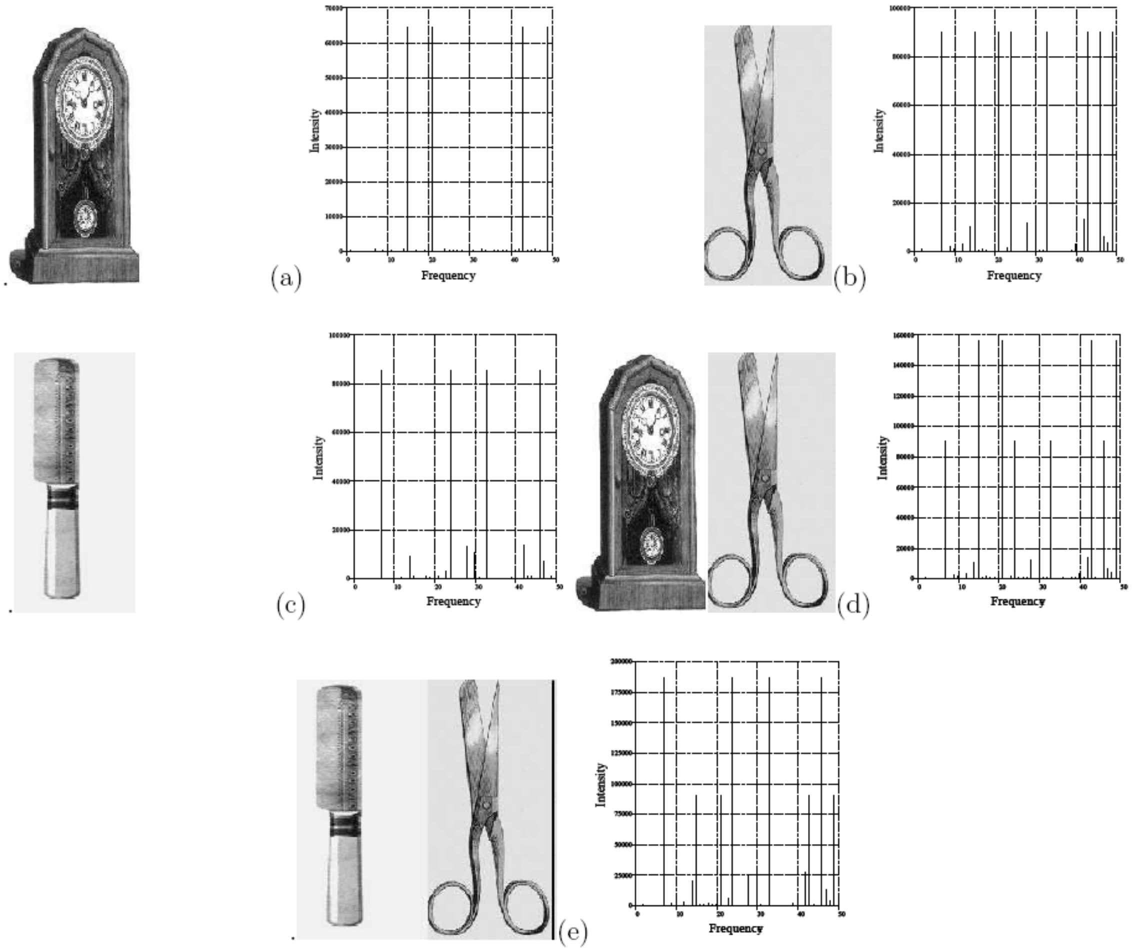


Figure 5: Chain of associations

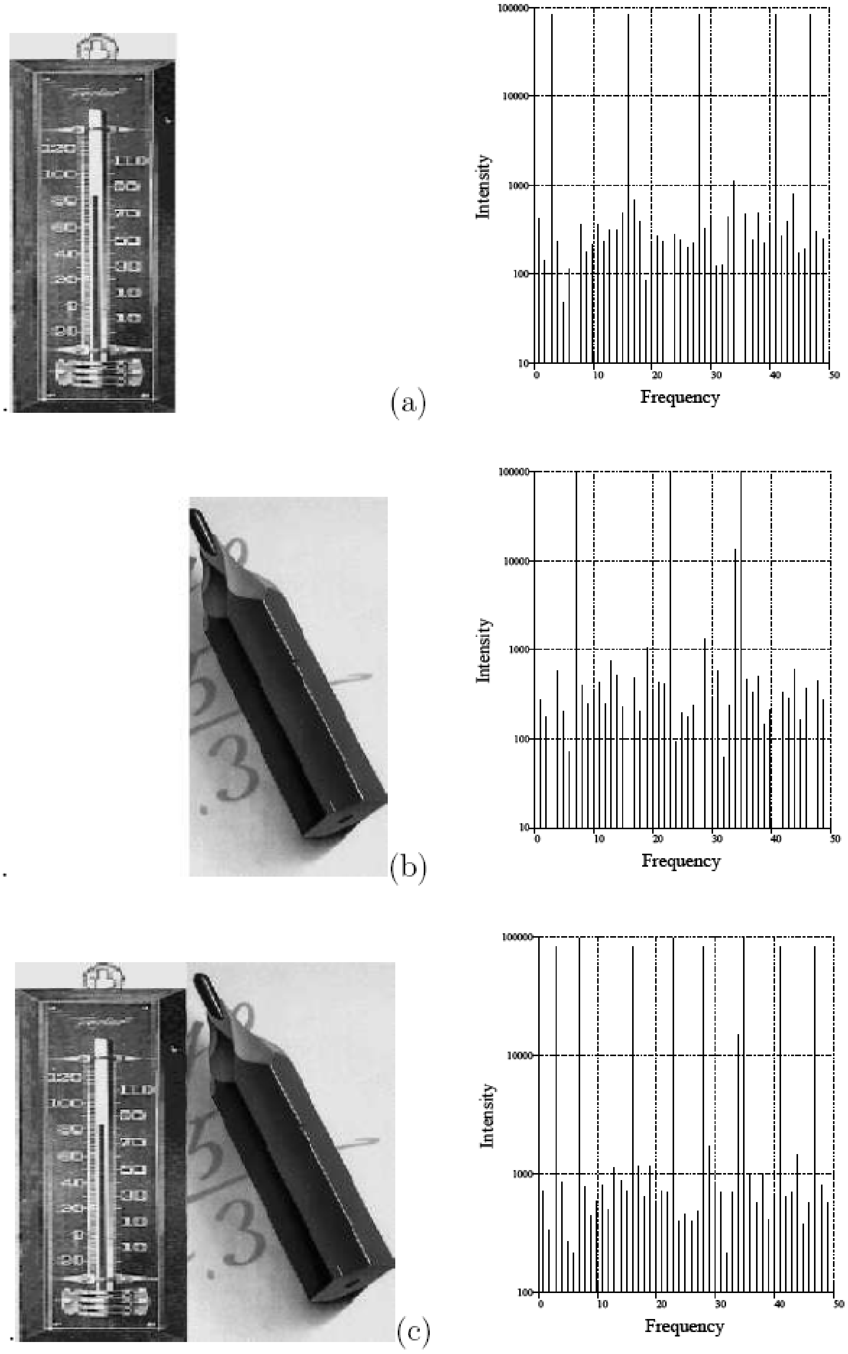


Figure 6: The catastrophic interference resolution.

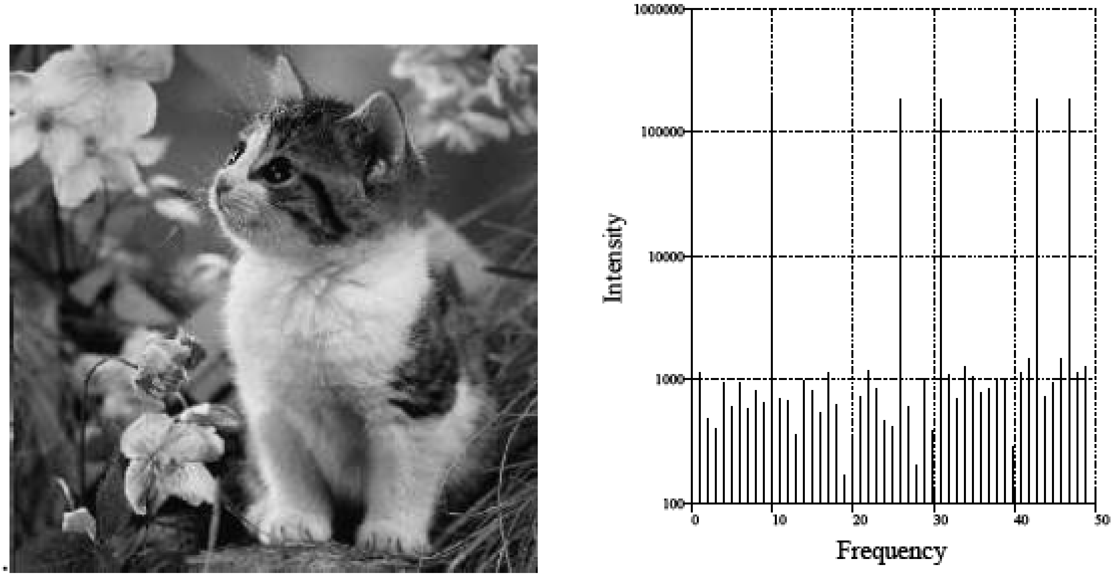


Figure 7: Location in time of an event. The image of a *cat* was memorised at times $t = 10, 26, 31, 43$ and 47. We presented the *cat* and we got this spectrum. The retrieving field has the noise around 1000 and we got all five peaks having the amplitude around 120.000 and the same frequencies. The resonance occurs and the *cat* can be localised in the past using a frequency-time transformation

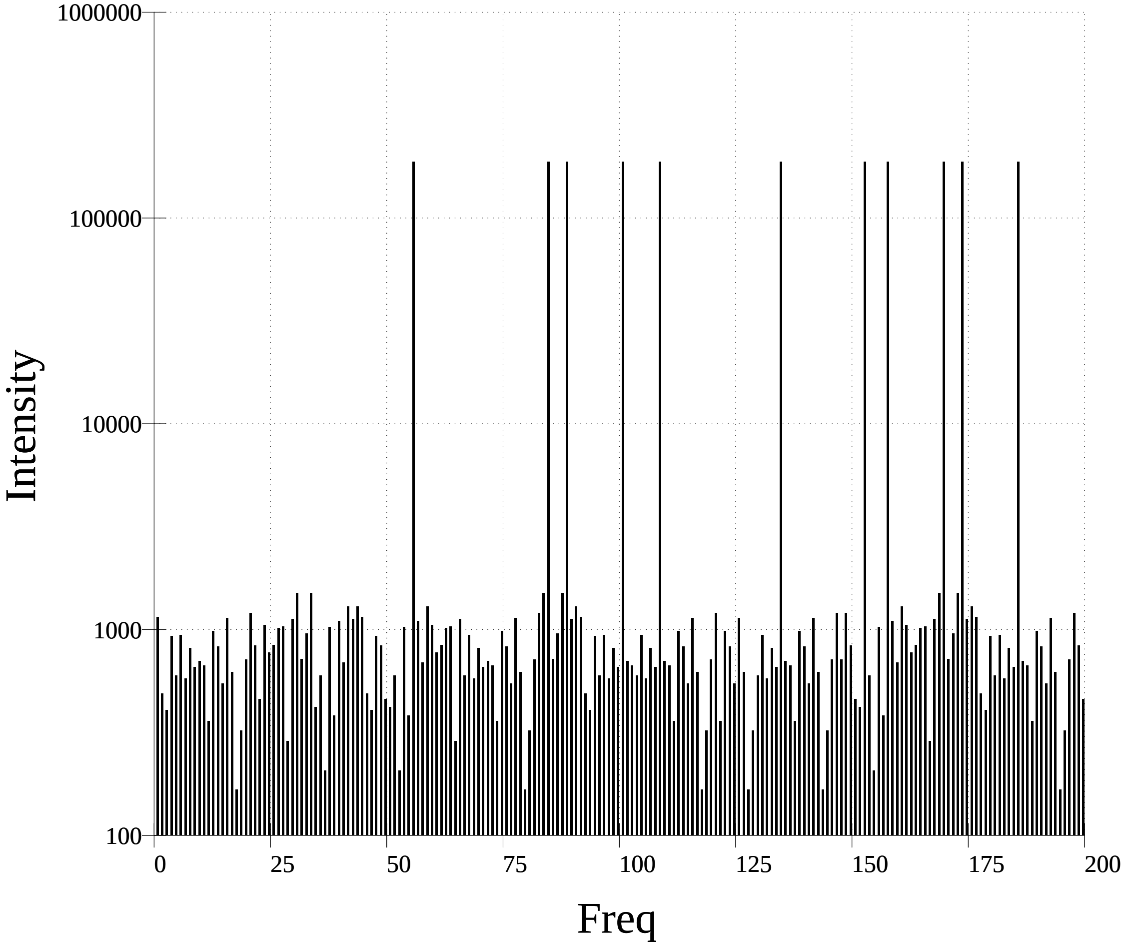
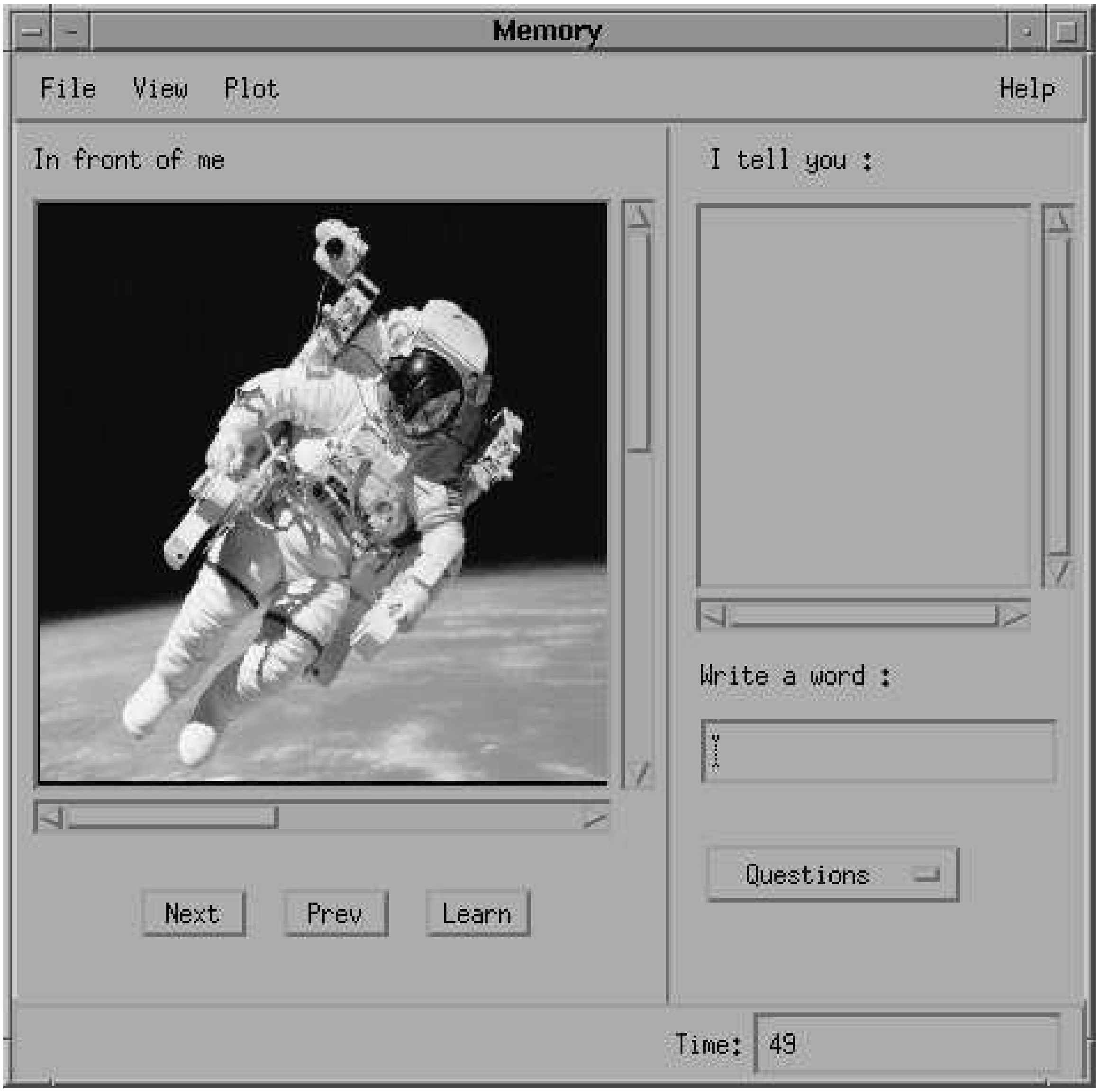


Figure 8: The LTM capacity. The spectrum for an image but when 200 patterns were stored into LTM. Each pattern has the dimension 250 × 250 and 256 gray levels. The resonance occurs only where the image was memorised. The other amplitudes for the retrieving field are very small: around 1000 neurons become activated for each frequency. This represents the interaction between memorised patterns. The number of activated neurons which correspond to the image pattern is more that 100.000. The noise/signal ratio is 0.01 which in this context is very small



Time: 49

Figure 9: The main window. The proposed model has been implemented in C language on a SUN SPARC station running UNIX. The user interface was written in Motif under Xwindows.