Double loops flows and bidirectional Hebb's law in neural networks

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ABSTRACT

This paper presents the double loop feedback model, which is used for structure and data flow modelling through reinforcement learning in an artificial neural network. We first consider physiological arguments suggesting that loops and double loops are widely spread in the exchange flows of the central nervous system. We then demonstrate that the double loop pattern, named a mental object, works as a functional memory unit and we describe the main properties of a double loop resonator built with the classical Hebb's law learning principle in a feedforward basis. In this model, we show how some mental objects aggregate themselves in building blocks, then what are the properties of such blocks. We propose the mental objects block as the representing structure of a concept in a neural network. We show how the local application of Hebb's law at the cell level leads to the concept of functional organization cost at the network level (upward effect), which explains spontaneous reorganization of mental blocks (downward effect). In this model, the simple hebbian learning paradigm appears to have emergent effects in both upward and downward directions.

Keywords: Reinforcement learning, memory, double loop coupled resonator, functional organization cost.

1. INTRODUCTION

Research in inductive learning has resulted in introducing many algorithms[3-20-25-26] and structured knowledge models[6-8-18-22-32] to address the issue of prototype extraction out of raw data. Many problems have been encountered during this work, and among them should be noted: learning algorithms turning out to be unable to provide reliable rules under all circumstances; structured knowledge models not fitting to all formal universes; the need for preprocessing data to feed the model in order to induce prototype extraction. Artificial Neural Networks (ANN) have brought simplicity in building classifiers, but using them is quite a skill because of the data set needed features and, most often, the stability of learned prototypes implies that no more learning should be done.

A feature shared by all these models is that structure and data flow modelling are usually addressed separatedly, which appears to us as not being the case of natural intelligent systems. Taking inspiration of these, we propose the double loop concept as a pattern for both structure and data flow modelling in order to make prototype extraction the result of a dynamic process. For being efficient, this process should be self-governing and we show that this feature is achieved in the double loop model through the functional organization cost concept.

Biological data leading to consider the double loop model are explained in section 2. The double loop concept and properties are exposed in section 3. Section 4 shows what are the basic interactions between mental objects. Mental objects blocks built by spontaneously aggregating mental objects, and their properties, are described in section 5. Section 6 introduces the permanent block, here proposed as the concept structural support in the neural network. Functional organizational cost and its consequences are following, before the conclusion takes place in section 7.

2. THE DOUBLE LOOP IN THE EXCHANGE FLOWS OF THE CENTRAL NERVOUS SYSTEM

Adaptive and learning systems use feedback signals to adjust the command signal that achieves the correct final result. Such an architecture is widespread both in natural and artificial systems. We analyze the sensorimotor system as a double feedback loop (§ 2.1), rather than a simple one: arguments in favour of our analysis are provided in section 2.2.

2.1 The sensorimotor double loop

An anatomical description of the interactive capabilities and organization in the Central Nervous System (CNS) of superior mammalians give the structure of the motor and sensory systems. The first one is orientated top-down from the frontal lobe, where the motor signals to outward actuators through spine originate. The latter is orientated bottom-up from spine to the parietal lobe, where the sensory signal flow ends. This structure designs a U (figure 1). Yet a functional study of the sensorimotor feedback signals suggests that there should exist a full loop between the frontal lobe and the parietal lobe. The full extended path of the loop, closing the structural U in a functional O, travels through the associative fronto-parietal areas (figure 1).

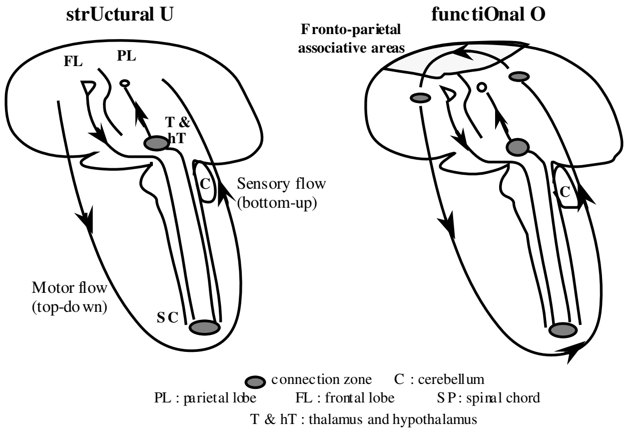

Figure 1. The structural U and the functional O in the sensorimotor systems.

Areas of discussions sustaining the hypothesis that the associative areas between the sensory parietal lobe and the motor frontal lobe achieves a complete path for signal flows, giving the opportunity to generate some internal inside loops are quite easy to validate (figure 2). An anatomical argument for this assumption would be the structure of the cortex and the multiple connections between the layers in the associative areas. But the numerous results compiled on visual system and gripping from the original work of Ungerleider and Mishkin till recently[30-31-12-13] show large scale cortical flows between areas of the CNS. This constitute in our view a much more persuasive and better physiological argument. Rosetti[28], through his work on spatial representations, shows that such an hypothesis may find echoes in other psychofunctional analysis.

Accordingly, we can assume that some bi-directional signal flows exist between the associative areas connected to both primary sensory and motor areas. As sensory signal flows spread around the parietal area, they induce secondary activation flows in the associative areas. Simultaneously and following the same scheme, motor signal flows coming from the frontal area do the same. Since the structure of the organism is stable and permanent, simultaneous flows occur very often via a self-spawning process and trigger spontaneous coupling through local loops in the associative areas. The wide functional loop is therefore completed by small local loops which, being coupled with the wide loop, form double loops rather than simple ones as a first analysis would conclude.

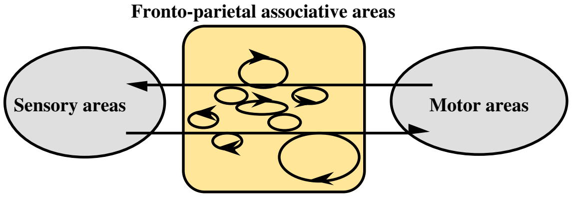

Figure 2. Induced flows inside the associative areas

1.2 The double loops around and inside the cns

Considering the exchange flows of the CNS at a larger scale, the double loop scheme can still be applied. The large loop described above in figure 1 covers only proprioceptive signals due to the activity of some cells in the motor area. This loop, which is an inside path for signals, makes the motor area loop back onto itself through the organism.

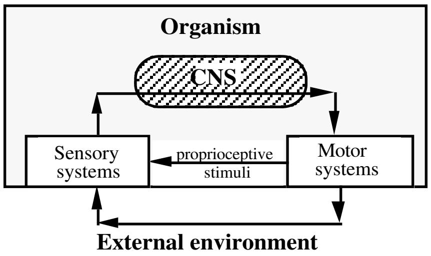

Figure 3. The two paths of feedback signal flows to the CNS: one external going through environment, and one internal going through proprioceptive perceptions.

Beside these self-induced proprioceptive signals, many motor activities produce physical modifications in the environment of the organism. Some of these modifications translate through other exteroceptive senses, most often through visual, auditory and tactile senses. All these exteroceptive flows make the CNS loop back onto itself through path convolutions external to the organism. We still have a double loop, as pictured in figure 3.

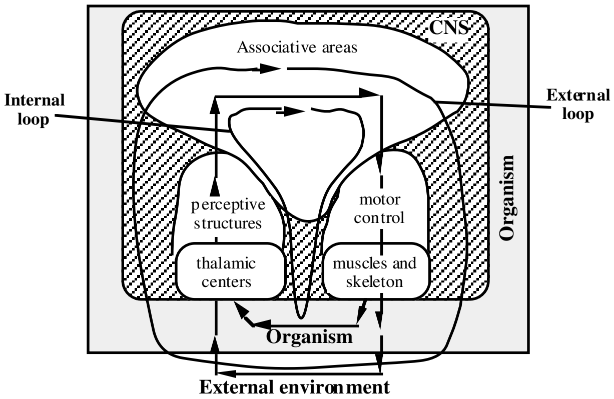

Figure 4. The nested feedback loops in the exchange flows of the CNS

Our analysis of the functional flows in the CNS suggests that the feedback loops around the sensorimotor system are nested, as pictured in figure 4 which shows three different loops that all share a common part in the associative areas. The first one passing through the external environment has been widely examined and is well-known. The second one passing through the organism is a set of interconnected systems seen as a regular configuration in physiology. The third loop going strictly through the associative areas, is the one we have assumed for the basis of our hypotheses. These three loops constitute in our point of view two nested double loops that share a common path in the CNS, especially in the associative areas.

3. THE DOUBLE LOOP MODEL: CONCEPT AND PROPERTIES

Provided the above-mentioned issues and in order to address the memory and learning phenomenons taking place in connectionist networks, we propose to explore the double loop concept from an innovative standpoint. This section describes the concept and its main properties.

3.1 Definition

We define the double loop as a dynamic flow going over a connectionist structure that is consequently a double loop. As a dynamic system, the double loop is acting as two coupled resonators. As a structure made of weights over connections, the double loop evolves according to Hebb's law principle. The double loop in our network is the fundamental concept for learning, memory and interaction between learned representations.

The double loop concept is a functional and abstract model for describing the activity of a CNS. We only assume that an established dynamic signal flow follows two different paths made of true synapses between cells, whatever these paths may be. We shall insist that every cell in the network may take an active part in many different loops that may possibly exist simultaneously. Therefore, in a CNS, there should be neither any pre-defined coupling from a cell to any particular loop, nor any matching from any cell to any special flow path. As factual evidence of any physiological loop at the cell level has not been brought up at the present time, our description of the CNS activity should be considered as a pure abstract model which is only to be tested by means of artificial networks.

The double loop model allows the superposition of a fast response dynamic process to take place over a slow changing structure. When keeping the mutual reinforcement between structure and flow, the model superimposes the slow and fast mechanisms over the two different scale levels. While learning takes place at the lowest scale synaptic level, signal flow propagation in double loops takes place at a much larger scale in the network.

3.2 The double loop concept: a structure and a flow

We have considered the double loop as the basic organization unit and we have tried to look for the consequences of such a functional architecture. A double loop made of cells would look like the drawing in figure 5, this scheme assuming that all cells have the same small size. The double loop is both a structure represented by a set of connections between cells in the network, and a dynamic functional flow over this structure. As a dynamic object, the double loop has a particular property: it expresses its existence through a stabilized output, which means it has established regular exchanges with its own environment. A stabilized double loop works as a couple of resonators which, sharing cells and connections, have their own signals sustained by external stimulation.

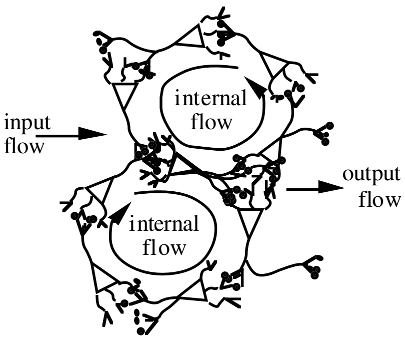

Figure 5. A double loop made of neural cells

The double loop is both a structure represented by a set of connections between cells in the network, and a dynamic functional flow over this structure (figure 6). We call this set of structural and dynamic phenomena a "mental object" with regard to its cognitive dimension as a memory unit.

Local application of Hebb's law induce mutual reinforcement between the structure and the flow over it. As the flow repeatedly goes through every synapse, the weight of each connection is increased - and this increased weights makes the structure more deeply engraved in the network. On the other hand, a strongly and deeply inscribed structure is an easier path to follow for signals as the connections are more efficient, thus achieving regular circulation of signals in the loops and regular exchanges with other structures in the network. Connectionist structure and dynamic flow mutually reinforce each other.

The mental object is a dynamic resonator: it is turned on similarly to an on-off toggle switch by a signal that is specific to its own signal flow. As long as its input flow is compatible with its own specific signal, the resonator stays on. However, it may develop negative interference with an other resonator and be turned off by an opposite signal.

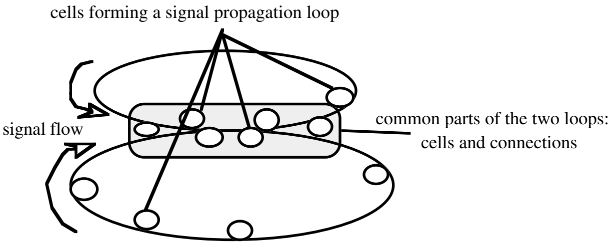

Figure 6. The signal flow in a double loop goes over cells and connections shared between the two loops.

The mental object is also a structural resonator: the structure is the permanent print of the flow that can be described as made of weights on all connections between cells. Because of the structure dispensed in the network by any learned representation, recurrence of the dynamic flow is easily turned back on every time its specific signal reaches the network.

3.3 The double loop properties

This section describes the double loop properties and requisites for the learning capabilities of the network. A much more complete statement would be found in Lecerf[16].

3.3.1 A comparative function.

The mental object is inherently a discriminating signal flow building granular comparisons over time, acting thus as a comparison qualifier. When the steady state is achieved, each loop of the double resonator receives as an input a mix of its own internal flow and the external flow coming both from the remote environment (figure 7), and from the very near neighbourhood made by the other coupled loop.

The existing steady state is asserting the compatibility of this mixed flow with the structure of the double loop. As long as this compatibility is maintained, the exchanges stay regular and both internal and external flows keep going on. The mental object makes a temporal comparison achieved from time to time on both internal and external flows. But compatibility does not mean identity: changes and substitutions may take place in flow signals as long as they allow each cell to produce the same signal in phase and frequency. We call this set of changes the variation envelope of a double loop. When the external flow variable change exceeds the tolerance of variations that the existing structure of the loops may accept, the phase gap breaks the propagation of signals in the loops and the mental object goes from activated to inactivated state.

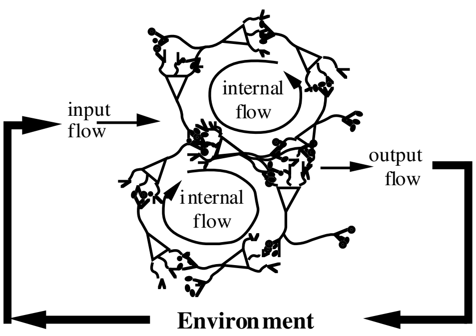

Figure 7. Other parts of the network scheme provide a feedback path for the output flow of every mental object.

Having this capability to compare signals over time, the double loop achieves an operation essential for decision making and control processes. The comparison function is a question raised by technicians interested in building auto-correcting machines like Albus[1], as well as neuro-biologists verifying the thinking mechanisms at work in the human brain like Changeux[2].

3.3.2 State.

This dynamic property is a consequence of the circulating flow: we call it the state of the mental object. A mental object is described as activated if it is the source of an output flow. Otherwise, the mental object is described as inactivated (figures 8a and 8b).

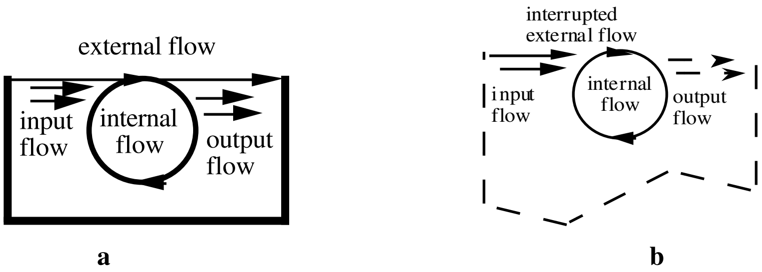

Figure 8. (a) An Output Flow Testifies the Activated State.
(b) A Non-existent Output Flow Testifies the Inactivated State of a Mental Object.

In the double loop model, one should remember that every output signal emitted by a mental object is fed back to it through its environment: there always is a path, making a loop in one way or another, that is followed by output signal flows, leading from output to input flow.

3.3.3 Flow carrier and signal propagation.

An even more abstract description of the network would lead to consider every mental object as a step in the process of signal transferring in the network from perceptive input systems to the motor output systems. In this way, double loops are the transfer medium for signals in the network, they are flow carriers (figure 9).

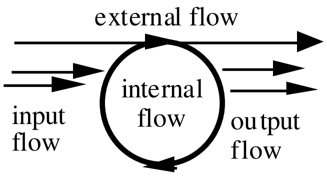

Figure 9. The loop as a transfer medium for signals in the network

The flow carrier property is a very important function of double loops: it actually leads to the control of large scale signal propagation in the network through a flow switching mechanism associated to the dynamic state of every mental object. As a flow carrier, every double loop is the feeder of other succeeding parts of the network. However one should remember the double loop is also a signal flow comparison qualifier. Therefore a modification of the input flow exceeding the variation tolerance that its structure could stand makes the mental object fall into an inactivated state. When inactivated, the mental object is no longer a feeder for the remainder of the network. The double loop structure amplifies any significant input signal modification by a changing in signal flow propagation in the network. This is another set of mechanisms resulting from the cascaded scale extrapolation of cells passing to circulating flows.

3.4. Learning

Learning in the network is an essential phase of the process that, as it is not the purpose of this paper, will be slightly described here (details would be found in Lecerf[17]). As explained earlier, the proposed learning mechanism operating in each cell is a simple form of Hebb's law principle, augmented with an epigenesis[4] equivalent mechanism. Although recent studies[19-29] claim the simplicity of this conception is questionable, many of them[7-11] seem to confirm the importance of time and synchronization mechanisms which are positive arguments for dynamic phenomenons such as resonators. Furthermore, the double loop model deals with much wider scale phenomena than cell physiology, for which the long term potentiation mechanism is a sufficient approximation. Yet a major question stays: how does a resonator - more over a double resonator - appear?

What drives a loop to exist is the internal organization of exchanges both inside and around the network, as well as the massive parallelism a CNS concurrently achieves. The exchanges are organized in such a way that outputs from the network go through a structured environment where the signals are modified and then re-injected as inputs to the network (figures 3 and 4 respectively). The pre-established internal organization of the network ensures that a path for signals through associative areas exists as the underlying perceptive and motor systems already tend to organize communication links with the environment.

Because of the structure of neural cells and the many connections they make at their axonic end every input signal is spread over a very large number of cells. This wide signal propagation and the massive parallel processing give a chance for the network to generate many responses to any input, then select an adequate response to the environment structure - and therefore, achieve as well stabilized exchanges.

It should be made clear however that the double loop concept is not a guarantee that all event may find an adequate representation in any network at any time. Likewise, most of the state-of-the-art knowledge acquired from connectionist networks over the years[5-9-10-14-15-21-23-27] is still relevant: large numbers of cells are necessary, as well as a pre-established multi-layered structure of the network. But it is the unique double loop concept advantage which fits in permanent learning with spontaneous adaptation in a feed-forward network. How is that possible ? Simply by repeating events.

Event repetition is the main learning engine in our networks. This is, in the first place, a direct consequence of Hebb's law. For any events to correspond to a representation in the network through a stamped double loop structure, exchange flows between the network and its environment must have reached an equilibrium though time, repetitions and adjustments.

Fortunately, repeating events is naturally done by the double loop flow because of its own nature. Since the network has the capacity of repeating by itself its inner representations, numerous repeated learning situations with real exchanges with the environment may not be necessary. Part of the learning training may be done by the network itself through its own internal representations and inside organization built around the double loop model.

Unsupervised learning arises from the repeated crossing of signals which stabilizes the connections when steady state is achieved, and is therefore a form of reinforcement learning. Learning is an emerging property, observed at the network level, which prints its effects at the cell level. As it is working inside the double loop model, Hebb's law principle appears to have a bidirectional value both upward from cells to network and downward from network to cells.

3.5. Signal filtering

Besides, as the signal flow mixing in the double loop achieves a signal comparison, this capability gives every double loop a filter effect on the signal flow reaching it. Either this external signal flow is compatible with its own internal flow and it is then passed over in the network, either it is not compatible and it is stopped because the mental object switches to inactivated state. Indeed, when inactivated the mental object does not feed any more the network with its output flow. The dynamic signal flow comparison function makes every mental object behave as a signal filtering device.

In this section were exposed the double loop pattern connexionnist structure, its dynamic properties and how, acting as a dynamic process, it achieves a comparison qualifier function which, according to the result, gives it a flow switching and filtering capability.

4. INTERACTIONS BETWEEN MENTAL OBJECTS

The massive parallelism and the multimodal sensory permanent input flow spead over the different perceptive systems induce in the network multiple dynamic double loops that interact with each other. The main effects that appear in such conditions are chaining up, signal mixing, temporal interferences (reinforcement and inhibition) between double loops, and signal filtering.

4.1. Chaining up

The mechanism of chaining up is not more than a consequence of the neural cell structure. Every cell has a double funnel spatial structure: one for collecting the signal on its dentrites, and another one for diffusing its own signal in the network. It collects signals through an input funnel and spreads out its own computed signal through an output funnel. Subsequently, the self-maintained signal of every loop has a spatial influence zone which is much wider than the one of the loop on its own (figures 10a & 10b).

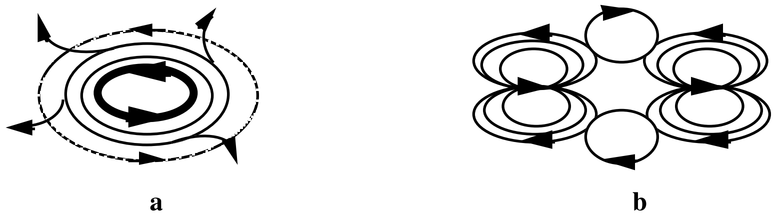

Figure 10.(a) influence zone of a loop due to the structure of neural cells
(b) influence zone of double loops and possible interaction between them

Secondary built structural lines of double loops come up as soon as some double loops appear in the network because it is the less conflicting way for dynamic flows to organize themselves (figures 11a & 11b).

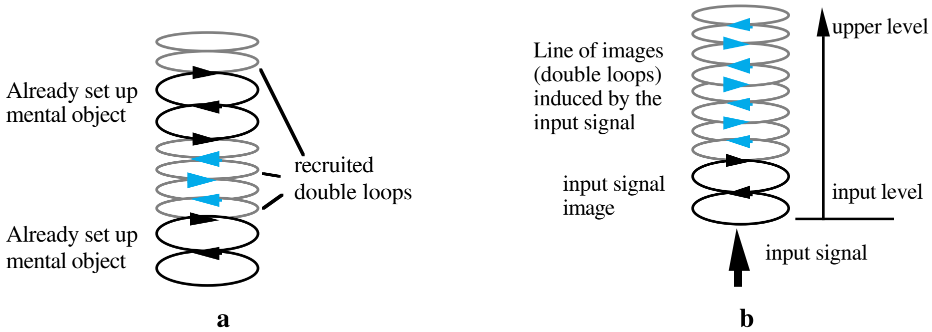

Figure 11.(a) recruitment of intermediate loops between established mental objects
(b) a line of induced loops over an established mental object

Structural lines take place in the 3D space of the network. Similarly to the vertical lines shown in the figures 10a and 10b, lateral lines may appear and develop themselves in the depth of the network as well as in its height. As lateral lines have the same meaning and the same mechanical cause as vertical lines, they are brought together as spatial interactions of mental objetcs. Combined spatial interactions in the network may be represented by the scheme in figure 12.

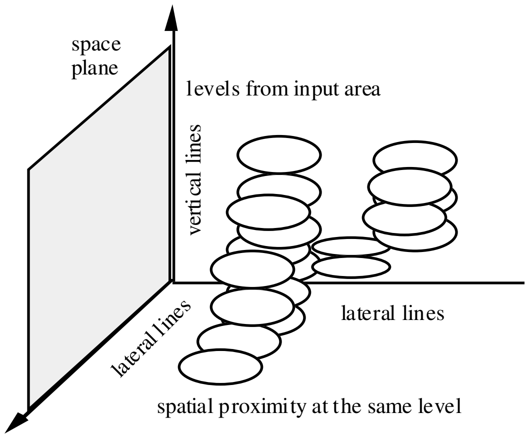

Figure 12. The Two Dimensional Spatial Interactions

4.2. Multimodal signal mixing

The multimodal signal mixing is different from the flow mixing discussed in 3.3.1 about the comparative function every mental object achieves. Indeed, the comparative function is a property of a double loop, when signal mixing is a property of the network (figure 13).

Actually, signal mixing is a consequence of the network massive parallelism and of the cell structure rather than an effect of mental objects interactions. Yet both of them depend on the same mechanism which is the cell structure with its output funnel. As every cell is spreading out its signal through its axonic tree, thus reaching many other cells, this gives absolutely no chance for a perceptive signal, for instance a sound, not to be mixed with other signals in the CNS, even after very few synaptic connections. Should the network be designed for signal processing, this characteristic would probably lead to complete inefficiency. But one should remember the network is designed for cognitive processing and, in this case, signal mixing will appear to be advantageous as it increases the connections of mental objects altogether. Multimodal signal mixing will take its full importance when considered as a facilitating factor in the mental block building process (section 5.2 below).

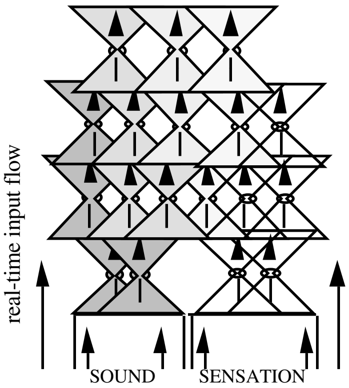

Figure 13. Signal mixing between sound and sensation in vertical lines

4.3. Temporal interferences

The second main interaction between mental objects is the temporal interference, due to phase coincidence between signal flows propagated by mental objects in the network. Indeed, one should remember that a neural cell sums up the signals through time and is thus sensitive to the timing of the signals reaching it.

The following figures and subsections describe such a temporal interaction, assuming that time may be represented with space between mental objects. First case is phase coincidence, in which every signal emitted by each mental object contributes to maintain the activation of both mental objects. The other case is the opposite: mental objects are out of phase and every signal emitted leads to the inactivation of the other mental object.

4.3.1. Phase coincidence

A phase coincidence phenomenon is the case when two or more signals interfere in a positive way and reinforce their each other effects. Two coinciding signals will produce a cell firing when all alone none of them had such an effect. The two signals reaching the cell with the right timing have more power than when reaching the cell independantly: they reinforce each other (figure 14).

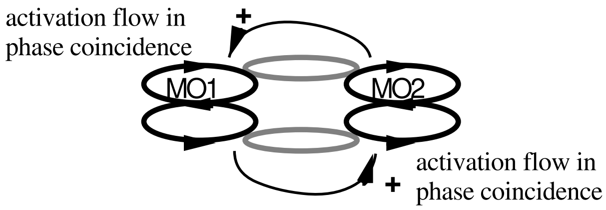

Figure 14. Phase coincidence lock between two mental objects

4.3.2. Phase opposition

On the contrary, two signals may interfere in a negative way and destroy each other by phase opposition. In this case, the second signal reaching the cell with a wrong timing will have no more effect when it normally has one. The signals are said in opposite phase and they inhibit each other effects (figure 15).

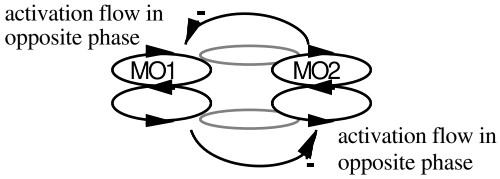

Figure 15. Opposite phase lock between two mental objects

The same phase opposition mechanism exists for the dynamic double loop flow because it is also a dynamic phenomenon. At this level, through the phase opposition mechanism, a mental object may inhibit an other one and switch it to its inactivated state.

5. MENTAL OBJECTS BLOCK : THE CONCEPT SUPPORT

Mental objects blocks support what symbolic models of artificial intelligence call an elementary concept, like a simple frame in the semantic network model[22-24].

As a mental object is the internal image built from the signals of external events in the genuine environment, a mental block is built from mental objects and, therefore, should be interpreted as a simple conceptual object.

5.1. The mental block structure

In the network, a mental block is a large aggregate of mental objects linked together by spatial and temporal interactions, which multimodal signal mixing and sequences facilitate. A block appears as the spontaneous result of mental objects interactions according to the activations and timing due to input signal flow coming up from the environment.

As explained before, permanent relations between real permanent objects in the environment are more frequently presented to the CNS. The different mental objects which are the internal representations of these real objects are therefore activated together or with the same sequence. Interactions between these representations, both spatial and temporal, are more likely to develop themselves and lead to produce a block of mental objects which will have a functional value if considered from the adaptatibility to environment point of view. This block is the representation of a set of events that are often perceived together; and the more often these events are perceived, stronger are the links between simple mental objects in the block.

As the universe around us has a coherent structure on its own, the mental objects blocks which are progressively built through repeated interactions with the environment reflects this perceived structure. This is an automatic process due to the learning mechanism in the network, and therefore it gives absolutely no garantee that the relation built in a functional block between internal representations would match with the physical rule that does exist in the genuine environment. A perceptive evidence is not a physical law: though wide plains appear to be flat, the earth is not a flat planet; as well as seeing the sun travelling in the sky over our head is not a proof that the sun is turning around the earth.

Though, as long as a mental block matches with the perceived signals coming from the real environment, this block stays up-to-date and keeps its functional role in the CNS and its own internal structure. It is a coherent representation of a set of events highly correlated in the real environment.

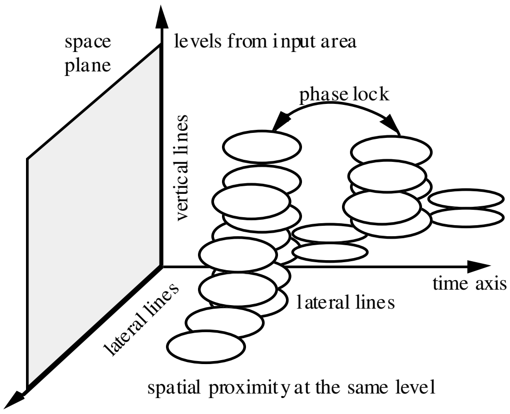

Figure 16. The mental block structure

The scheme drawn in figure 16 shows the two types of relations which take place in a mental block and illustrates the 3D structure of a mental block. First two dimensions are spatial and structural, they involve mental objects chainig up in both depth and width of the network. The third dimension is time, as phase mechanism will take place between the dynamic double loop flows in the network.

5.2. The mental block internal operating

Internal operating mechanisms in a block are mental objects interaction phenomena along the different axis dimensions of a block as soon as many flows run across the block (figure 17). In the spatial dimensions, interferences between ascending and descending flows would be observed, resulting in reinforcing the connections supporting positive interferences as well as decreasing weights when supporting negative interferences. Phase lock phenomena may also take place between the connected mental objects a block is made up. Repeated phase interactions may also contribute to changing the block internal organization by switching on some preferred paths.

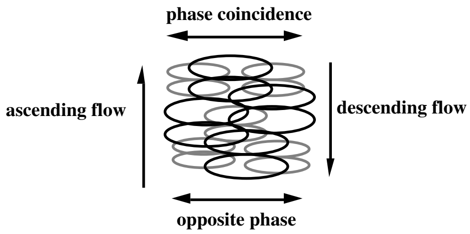

Figure 17. Internal operating mechanisms in a mental object block

According to the learning paradigm of the model, repeated events or sequences are more likely to be printed in a block. Since every block loops back to itself through the network and its environment, interactive sequences consitute the main basis on which blocks are progressively built in the network. A block may take advantage of the multidimensional signal mixing and temporal phase interferences to expand itself in associating signals coming from different input channels.

5.3. Block inertia

Inertia is a special property of mental blocks due to their large structure since, unlike simple double loops working upon a few cells, mental blocks may be constituted by large numbers of mental objects. However, like simple double loops, mental blocks receive an input flow which they turn into an output flow feeding the remainder of the network (figure 18).

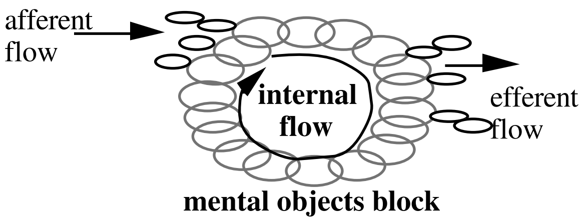

Figure 18. input and output flow over a mental object block

Thus, an activated block will widely spread its output flow over the network since it stays in a steady state with its environment (figure 19a). Unlike simple double loops which are immediately turned off by a change in the input flow, the block output flow will persist for a short period of time because of the large number of activated mental objects making up this flow (figure 19b). Some of these mental objects are turned off by the change in the input flow, but some other may not be disturbed by the change and may stay in an activated state. This extra duration of the output flow of a block is called inertia.

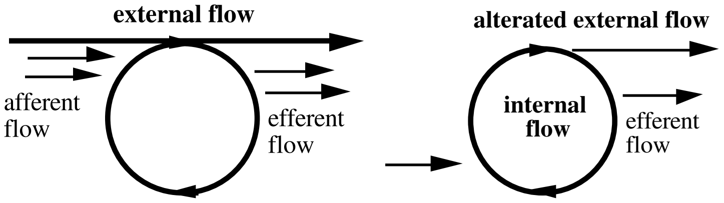

Figure 19. (a) An activated block (b) The effect of inertia on the output flow

5.4. The block activation mechanism

The criterion signing the state of activation for the block fully matches with the one defined for mental objects:

- an active block is ran across by a regular and intense internal flow, which originates a regular efferent external flow
- an inactive block on the contrary is ran across by partial and unstable internal flows, circulating by puffs, and not running completely across the block. These flows do not involve any regular efferent external flow and are thus unable to durably switch flows in the network. These partial flows take part in the basic activity of the network, while maintaining a variable set of mental objects in an activated state.

The block activation phenomenon matches also with the one exposed for mental objects: an activation impulse is necessary and there is a threshold effect. Unlike mental objects for which the state has only two values, one can distinguish for the blocks many activation levels according to the intensity of internal flows. Thus, in an inactivated block, the more the internal local flows will be numerous, closer this block will be to activation. These various levels of intensity in internal flows define the levels of activation of the block.

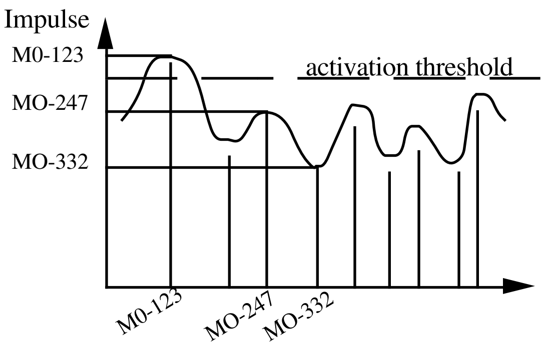

Figure 20. Mental Objects Blocks, activation level and activation impulse

Figure 20 schematizes several blocks of mental, arbitrarily called objects OM123, OM247 and OM332, and an activation threshold standardized for all the blocks. Given these conventions, only the block OM123 is activated. The impulses for activating the other mental objects are measured by the distance to the activation threshold. Thus, the impulse necessary to the activation of the block OM247 is definitely lower than the impulse necessary for the activation of the block OM332.

The level of activation has a major functional consequence: the reactivity of the block is increased when met by a stimulus. In other words, because each block of mental objects is in an unstable state of activation, the swing towards the activated state is fast under the effect of a stimulus. Closer is the block to the threshold of activation before the arrival of the signal likely to cause activation, smaller is the necessary impulse to swing the block to its threshold (figure 20).

The inactivated blocks, which do not efficiently switch flows in the network, present a localised and sporadic activity, which is irregular and related to the activated subset of mental objects which compose them. Summation of these dispersed activities form a basic activity in the network, above which one observes the less disordered activity of the activated blocks. The mental object model considers this basic activity as a facilitating factor for network reorganization.

6. THE PERMANENT BLOCK

Due to the mental objects inertia, blocks that are large enough and have quite long spatial and temporal lines become permanent, which means they always have a slight level of activation. Precisely, a special constraint has to be satisfied for permanent blocks to be brought up: the largest number of the mental objects belonging to the block should be recruited far from the primary areas in which the signal flows coming from the environment reach the CNS. These mental objects which are activated through long mental objects lines therefore only weakly depend on the real-time signal flow driven by the environment constraints and structures. They receive most of their input flow from other mental objects and contribute to activate mental objects of the same kind, taking their place in the basic activity of the network.

Permanent mental blocks, which have such an organization, are completely reactivated by external events as usual, but as they have a great inertia they stay in this activated state for a much longer period of time than the duration of the external event itself. Later on, their activation level is decreasing with passing time. Permanent mental blocks provide a support for concepts and give a mechanism for understanding interactions between cognitive representations and spontaneous cognitive reorganization.

6.1. The stability and functional organization cost

This section describes the natural tendency to stability emerging from the hebbian paradigm, and some of its consequences such like defining a zero cost operating network. Hebb's law, which controls learning at the cellular level, is a local mechanism for each cell. In spite of this local dimension, Hebb's law however has consequences at a much larger scale. This section develops the global tendency to stability resulting from this learning paradigm, and the potential conflicts which such a tendency induces in the network. For example, blocks stabilization results from solving such conflicts between mental objects.

6.1.1. The natural tendency to stability

The idea that there would exist in the network a natural tendency to stability may appear shocking, for example because it seems to oppose creativity and imagination that human beings exhibit every day. Any opposition disappears if one takes into account the influence of the scale factor. The tendency to stability do appear at the circulating flows scale level in the network, but it does not imply any symbolic significance nor any specific behavioral expression, not more than it does modify the physiology of the neurons conveying these flows. The range of this tendency is limited to some levels of scale.

At the circulating flows scale level, the tendency to stability has a significant role. It is a regulation factor for conflicts between flows and an organization mechanism generator to be added to the ones already exposed in this paper such as spatial and temporal interferences.

The origin of this tendency is extremely simple. According to Hebb's law, each neuron tends to regulate its operating by stabilizing its effective connections. Considering just the first higher scale level, i.e. the level of a looped circuit, reinforcing active connections results in a tendency to maintain a regular flow circulation in the loop. This pattern can be repeated upward from every scale level to its upper scale level. Starting from the cell level, we go through the loop and the double loop level, then through the mental objects chains and block level to the top level which is globally considering flows in the network. The global tendency to regularity is then an emergent property of the network, as a direct consequence of using the hebbian paradigm into neural cells.

Any event that breaks the regularity of flows, and thus opposing this spontaneous tendency, is a local violation of this general law. However the interactions between two mental objects often come from conflicts of influence on the cells and structures that may be in the range of both mental objects. These conflicts of influence can thus cause local or temporary violations of the global tendency, these violations finding a resolution in agreement with the general law through flow reorganization in the network.

6.1.2. The ideally operating network and cost zero

A network ideally operating would simply respect this spontaneous tendency to harmonious and regular flow circulation. Ideally operating is the respect of Hebb's law at every scale level from neurons to all the higher scale levels in which we described some more complex organization patterns: loops and mental objects, sets of mental objects.

A mental objects network in which one observes a harmonious and regular circulation flows defines the ideally operating network. By convention, the operating cost of this network respecting the generalized form of Hebb's law is "cost zero". This qualitative definition of cost zero gives an absolute reference, which will allow to measure the quality of the network operating. Indeed, with the reference of an ideally operating network, the flow irregularity defines the principle of an interaction cost measurement. Any possible additional cost is measured compared to the ideally operating network whose cost is zero.

Let us explain this quite abstract definition in a coherent and concrete expression. In the double loop model, any instability in the mental object state produces a local flow instability in the network since the efferent flow of the mental object changes. This unstable state prevents the repetition of flow which is necessary for the neurons to stabilize their connections. For this reason the mental object state instability, that is to say the instability of the double loop flows supporting the mental object, is a violation of Hebb's law. Thus, it is coherent to consider the unstable state of a mental object as the cost-unit for measuring interactions costs in the network. In addition to its memory storage function, the mental object has a functional cost unit for network operating measurement.

6.1.3. The non ideal organization cost unit

Since the general rule is the harmony and the regularity of flows, any interaction between structures of the network which locally breaks this regularity generates an additional cost of operation compared to the ideally operating network. Spatial interactions between mental objects and conflicts of influence exemplify such additional costs.

It should be noted that the network physical operating is rigorously not altered by these additional costs. The existence of the neurons constituting the network is not threatened, but as the flow circulation is subjected to the effects of the conflicts, the weights of connections made inactive will decrease. The additional cost generated by an unstable mental object is thus a cost of the organisational type: the functional organization of the network is modified. The spontaneous evolution of the blocks organization, explained in the following sections, illustrates these effects.

The comparing function of the mental object plays a fundamental role in establishing an equivalence between the mental object activated state and the regularity of flows in time. The permanence of the activated state testifies the flow regularity and, conversely, this regularity results in a permanent activated state.

Thus the mental object, comparing and switching flows over time, is the means by which are down coded at the scale level of the network structure the organizational modifications happening at higher scale levels. The mental object is the feedback support of the functional organization downto the most elementary components of the network. The hebbian paradigm thus appear to have emergent effects that apply to the neural cells from the global double loop organization.

6.1.4. The intrinsic compatibility between mental objects

Defining an organizational cost makes it possible for an observer to conceive a primitive form of intrinsic compatibility between mental objects in the network. Are regarded as compatible mental objects respecting the general form of Hebb's law, i.e. whose external flows reinforce each other. Indeed, when interacting, such mental objects do not generate any additional functional cost, because there is no violation of Hebb's law.

6.2. The internal reorganization of permanent blocks

Every permanent block is a set of many mental objects and undergoes the effects of interactions between them, i.e. spatial chaining and temporal phase effects, as well as the effects of permanent signal flows (figure 21a). Because of these interactions, the structure of mental blocks is a dynamic one and reorganize itself under the pressure of interactive exchanges with environment selecting the most compatible mental objects in the block (figure 21b). Indeed, at the very lowest scale in neural networks with mental objects, every learning process depends on signal exchanges: only repeated events may lead to stabilizing a double loop structure while reaching a steady state.

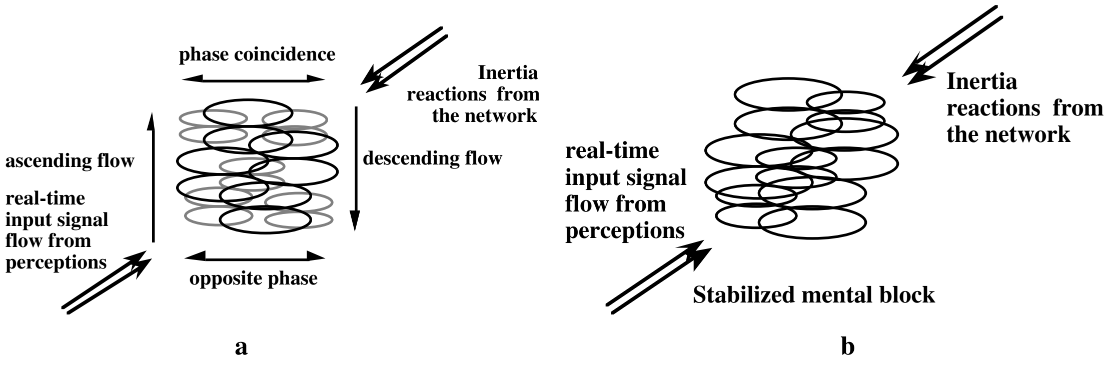

Figure 21. Spontaneous block reorganization when being continously feeded by signal flows

Mental objects belonging to the same permanent block are said compatible with each other compared to the elementary principle, i.e. Hebb's law, that rules the network at the cell level. Such compatible mental objects have positive interactions, either through spatial or temporal interferences.

7 CONCLUSION

This paper presented the double loop reinforcement learning model in which double loop mental objects are the basic unit for memory storage and operations. Furthermore, the double loop concept stands out for the mutual reinforcement between a connectionist structure and the dynamic signal flow underlying interdependence.

Due to the double loop feedback, the classical Hebb's law algorithm leads to permanent learning in spite of a feed-forward network architecture. As a dynamic object, the double loop is a signal flow comparison qualifier over time and a flow carrier in the network. Thus a signal flow modification is amplified to a change in flow propagation in the network. Changing in the scale of effects arises from this property of flow switching. Signal filtering is another consequence of using the double loop pattern as a signal flow carrier in the network.

Learning in the double loop model results from the functional cooperation between a local structural mechanism (i.e. Hebb's law) and a global dynamic phenomenon (i.e. the circulating flow). As well as with classical implementation of Hebb's law, emergent effects from the cell level to the network level are expected. Distributed storage of representations is one of these and it is observed.

The mental object block, an organized set of mental objects, is proposed as the support for elementary as well as complex concepts. Mental blocks share interaction mechanisms with mental objects but, due to their multidimensional structure, they have special properties such as the functional organization cost, here defined as a local Hebb's law violation.

In addition, the double loop model allows Hebb's law to support positive interactions between the functional flow and the connectionist structure, that is from the upper organization level (the loop) to the lower (the cell). As learning is achieved, we observe emergent effects from the network level down to the cell level, which turn out to give unsupervised learning a general bi-directional frame.

REFERENCES

1. J.S. Albus, *Brains behaviour and robotics*, Byte books, McGraw Hill, 1980.

2. J.P. Changeux, *L'homme neuronal*, Paris: Fayard, 1983.

3. P.Clark, T. Niblett, "The CN2 induction Algorithm." *Machine Learning Journal*, vol. 3, no. 4, pp 261-283, 1989

4. A. Danchin, P. Courrege, J.P. Changeux, "A theory of epigenesis of neural networks by selective stabilization os sysnapses", *Proceedings of National Academy of Sciences of USA*, No 70, 1973, pp. 2974-2978.

5. J.A. Feldman, D.H. Ballard, "Connectionist models and their properties", *Cognitive Science*, Vol. 6, 1982, pp.205-254.

6. D.H. Fischer, M.J. Pazzani, "Computational models of concept learning", in *Concept formation: Knowledge and Experience in Unsupervised Learning*, edited by D.H. Fischer, M.J. Pazzani, P.Langley, Morgan Kaufmann Publishers, San Mateo, CA, 1991

7. C.M. Gray , W. Singer, "Stimulus specific neuronal oscillations in orientation columns of visual cortex", Proc. Nat. Acad. Sci., vol. 86, pp 1698-1702, 1989

8. F. Hayes-Roth, J. McDermott, "Knowledge acquisition from structural decriptions", Proceedings of the International Joint Conference on Artificial Intelligence (IJCAI'77), pp. 356-362, Cambridge, MA, 1977

9. G.E. Hinton, T.J. Sejnowski, D.H. Ackley, "Boltzmann machine: constraint satisfaction network that learn", Pittsburg, *Carnegie Mellon University, technical report* CMSU-CS-84-119, 1984.

10. J.J. Hopfield, "Neural networks and physical systems with emergent collective computational abilities", *Proceedings of the National Academy of Sciences of USA*, No 79, pp. 2554-2558, 1982.

11. J.J. Hopfield, "Pattern recognition computation using action potential timing for stimulus representation", *Nature*, vol. 376, pp. 33-36, 1995

12. J.E. Hummel, I. Biederman, "Dynamic binding in a neural network for shape recogntion", *Psychological review,* No 99, 480-517, 1992.

13. M. Jeannerod *The cognitive neuroscience of Action*, Blackwell, 1977.

14. H. Klopf, *Hedonistic neuron: a theory of memory, learning and intelligence*, New York: Hemisphere Publishing Corporation, 1982.

15. Y. Le Cun & al., "Comparison of learning algorithms for handwritten digit recognition", in Proceedings of ICANN'95, Paris, 9-13 Oct 1995.

16. C. Lecerf, *Une leçon de piano, ou la double boucle de l'apprentissage cognitif*, Paris: Travaux et Documents, Université Paris 8, 1997.

17. C. Lecerf, "The double loop as a model of a learning neural system", to appear in SCI'98 Proceedings, Orlando, 1998.

18. D.B. Lenat, "The role of heuristics in learning by discovery: three case studies", in *Machine learning: an artificial intelligence approach,* edited by R.S. Michalsky, J.G. Carbonell, T.M. Mitchell, Springer-Verlag: Berlin, 1984.

19. H.Markram, M. Tsodyks, "Redistribution of synaptic efficacy between neocortical pyramidal neurons", *Nature*, vol. 382, pp. 807-810, 1996

20. R.S. Michalski, I. Mozetic, J. Hong, "The AQ15 inductive learning system: An overview and experiment." Technical report ISG 86-20, UIUCDCS-R-86-1260, Dept of Computer Science, University of Illinois, Urbana, 1986.

21. M. Minsky, S. Papert, *Perceptrons*, London: MIT Press, 1969.

22. M. Minsky, "A Framework for representing knowledge", in *The psychology of computer vision*, edited by P.H. Winston, McGraw-Hill: New York City, 1975.

23. M. Minsky, "K-lines: a theory of memory", *Cognitive Science*, Vol. 4, No 2, pp. 117-133, 1980.

24. M. Quillian, "Semantic memory", in *Semantic Information Processing*, edited by M. Minsky, MIT Press: Cambridge, MA, 1968

25. J.R. Quinlan, "Induction of decision trees", *Machine learning*, vol. 1, pp. 81-106, Kluwer Academic Publishers: Boston, MA, 1986.

26. J.R. Quinlan, *C4.5: Programs for Machine Learning*, Morgan Kaufmann Publishers, San Mateo, CA, 1993

27. D.E. Rhumelhart, D. Zipser, "Feature discovery by competitive learning", *Cognitive Science*, Vol. 9, pp. 75-112, 1985.

28. Y. Rosetti, "Des modalités sensorielles aux représentations spatiales en action: représentations multiples d'un espace unique", in J. Proust (ed.), *Perception et intermodalité: approches actuelles de la question de Molyneux*, pp 179-221, Paris: PUF, 1997.

29. T.J. Sejnowski, "Synapses get smarter", *Nature*, vol. 382, pp. 759-760, 1996

30. L.G. Ungerleider and M. Mishkin, in *Advances in the analysis of visual behaviour*, D. Ingle, M.A. Goodale, R. Mansfield (eds), Boston: MIT Press, 1982.

31. L.G. Ungerleider and M. Mishkin, "Two cortical visual systems", *Analysis of visual behaviour,* Boston: MIT Press, 1992.

32. P.H. Winston, "Learning structural descriptions from examples", in *The psychology of computer vision*, edited by P.H. Winston, McGraw-Hill: New York City, 1975.