MORPHODYNAMIC NETWORKS : THE EXAMPLE OF ADAPTIVE FIBRES

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Abstract

Connectionist models are described by graphs, involving parametrized nodes and parametrized connections. We propose to extend the connectionist formalism to models where the structure of the system is not only a graph, but involves also different topologic structures. The topological nature of these models enables to provide easily stategies of cooperation between individual component transformation and component regeneration. Adaptive fibres is a new model which follows the principles of our general framework. These fibres aim at addressing the problem to learn simultanously several functions, thanks to the recurring presentation of learning sets. They also aim at recognising one of these learned functions among a large number of others very rapidly (without testing every possible solution).

1.Introduction

This paper has two purposes. The first one is to propose a general framework in which the comparison of the main models of Artificial life and connectionism could be done. The second one is to show that this framework suggests new aeras to explore, and new models to create. An example of such a model is described.

The necessity of a common framework for different connectionist models has already been pointed out (Farmer 1990). A connectionist model is described by a graph, involving parametrized nodes and parametrized connections. To each node is associated an activation variable. Three dynamics can be defined in the network : the activation dynamics which modify the activations of the nodes, the learning dynamics which modify the parameter values, and the graph dynamics. Farmer shows that this framework is appropriate for models such as neural networks, immune networks, classifier systems, autocatalytic networks.

We propose to extend the connectionist formalism to models where the structure of the system is not only a graph, but involves also different topological structures. In particular, we emphasize the description of systems involving geometric elements which can produce by a collective behavior an adaptive geometric form. In these models the interactions between the elements of the system are not only expressed by connections in a graph, but also through different topological relations in the space where the geometric elements are defined. We call these models *morphodynamic networks* because they can be considered as geometric adaptive forms in a mathematical space. In morphodynamic networks, one can distinguish the individual component modifications concerning the values of variables describing the component, and the component regeneration (creation, destruction and linking) which modifies the set of variables describing the whole network.

The topological nature of these models enables to easily provide stategies of cooperation between individual component transformation and the component regeneration. Such a cooperation can be very important from the point of view of the learning theory (Deffuant 92). Moreover, elaborated processes of component regeneration are easier to implement when using the geometric properties of the system.

In particular, we propose to study the case of a system involving two types of components which could be interpreted as short term (STM) and long term memory (LTM) components. The STM components have regeneration processes which are faster than those of the LTM components. However, LTM and STM components influence each other for their own production.

We give an example of a new model, the adaptive fibres, which follows the principles of our general framework. The basic geometric components are linear segments, which approximate the features of 2-dimensional figures given by a distribution of points. The STM fibre is built as rapidly as possible in order to fit the current distribution of points. The LTM fibres enable to memorize the already encountered forms and to accelerate the building of the STM fibre.

Firstly, the connectionist formalism is recalled and then the framework for morphodynamic networks is introduced. The adaptive fibres are then described as an illustration of our general framework.

2. Connectionist and morphodynamic networks

In this section, we recall rapidly the main points of the connectionist formalism. Then the extension of this formalism concerning morphodynamic networks is described. Finally, the case of a system with 2 levels of components is developped.

2.1. The connectionist model

A connectionist model is defined by a graph involving parametrized nodes and connections, and nodes variables corresponding to the state of the node. Three types of dynamics can take place in such models :

- state dynamics,
- connection and node parameters dynamics ,
- graph dynamics (connection creation/destruction, node creation/destruction).

This general framework is particularily appropriate for neural networks for which it is naturally used. However, Farmer (Farmer 1990) shows that classifier systems, immune networks and autocatalytic networks can be described in it. This can be summerized by the table 1:

Generic	Neural net	Classifier system	Immune net	Autocatalytic net
node	neuron	message	antibody type	polymer species
state	activation	intensity	antibody antigen concentration	polymer concentration
connection	axon / synapse / dendrite	classifier	chemical reaction of antibodies	catalysed chemical reaction
parameters	connection weight	strength and specificity	reaction affinity lymphocyte conc.	catalytic velocity
sate dynamics	sum/sigmoid	linear threshold and maximum	bell-shaped	mass action
parameter dynamics	Hebb/backprop	bucket brigade	clonal selection	approach to attractor
graph dynamics	synaptic plasticity	genetic algorithms	genetic algorithms	artificial chemistry rules

Table 1 : a rosetta stone for connectionism (Farmer 1990)

This work is of a great importance because it enables to point out the real similarities and differences between several models.

We propose now to enlarge the framework to models for which a graph description is not sufficient. In such models therefore, the interaction rules are more elaborated than simple connection links.

2.2. Morphodynamic networks

Some models that have been developped and studied in the field of Artificial Life do not fit exactly the connectionist formalism. This is the case of models in which the relations between the components of the network depend on other topological relations than simple connections. Among others, ant colony models (Deneubourg et Goss 1989), perceptron membranes (Deffuant 1992) can be put in this category. Another example of such a network is provided further (the adaptive fibres).

The generic morphodynamic network is described by the following elements :

- a mathematical space in which the system is defined,
- elementary components, described mathematically by a geometric form and a position in the chosen space.
- a topological interaction domain is defined from the geometric form of the component. Thanks to this domain, components can interact without explicit link.

Two types of dynamics can be distinguished in such networks :

Component modification

The component modifications are due to interactions with other components or with the environment of the system. These interactions modify the values of the variables defining the components. The rules governing these modifications depend on topological domains.

Component regeneration

- Component production : allows to complexify and develop the geometric form.
- Component linking : putting in common part of themselves, they enhance the coherence of the network.
- Component destruction : enables the elimination of useless components and to satisfy simplicity criteria concerning the structure.

Connectionist networks can be seen as a particular case of such networks for which the basic elements are nodes in a graph, the interaction domain being defined by the connections of the network. The graph dynamics corresponds to the component regeneration.

However, the elementary components of morphodynamic networks will generally be geometric in order to build an adaptive geometric form.

2.3. Regularity extraction and 2-level morphodynamic networks

A 2-level morphodynamic network is characterized by the existence of 2 different types of components, called C1 and C2. In such networks, C1 and C2 regeneration can influence each other.

In this case, if we suppose that components C2 have slower modification dynamics, then C2 level can play the role of higher regularity extraction than the C1 level. For, it can take into account events on larger time-scales. This is for instance the case in ants models where pheromone substances play the role of C2 components, and the ants themselves are C1 components. The C2 components (pheromone), which have production rules depending on the state components C1 (the ants), can be seen as a long term memory of the system.

This differenciation in the dynamics of the components is very promising in term of cognitive performances because regularities of different levels can be extracted. In the following section, our general framework is more precisely illustrated by the model of the Adaptive Fibres.

3.The Adaptive Fibres

The Adaptive Fibres are designed in order to deal with a particular learning problem : the problem of regularity extraction in recurrent noisy situations, and the fast recognition of these regularities. In its general formulation, this problem is a major cognitive issue. It is here restricted to 2-dimensional figures.

3.1. The problem

In the framework of the formal learning theory, (Valiant 84, Baum & Haussler 89, Boucheron 92) adaptive systems (like neural networks) learn to approximate a function f from a set A to a set B thanks to a set of learning examples drawn form a probability distribution μ on A x B. In this framework, if a network has learned a function f, and if a new set of examples drawn from a probability distribution μ' on A x B, corresponding to a new function f', is learned by the network, then, in the general case, the network forgets the first function f.

Adaptive fibres aim at addressing the problem to learn several functions, thanks to the recurring presentation of several learning sets drawn form probability distributions corresponding to each function. They also aim at recognising one of these learned functions among a large number of others very rapidly (without testing every possible solution).

We restrict the problem in this paper to functions defined by probability distributions of points from R^2. This restriction is however important because it includes the problem of 2-dimensional forms recognition and regularity extraction.

We consider therefore a set K of probability distributions μ_k on R^2, corresponding to noisy figures in R^2. The figures μ_k may be letters, symbols, images from a camera etc...
Periodically with the period T, a probability distribution μ_k is chosen (with the probabilty π_k). Then a set E_k of N learning examples e_{kj} drawn from μ_k is presented to the system (figure A1).

In order to deal with this problem, 2-level morphodynamic networks provide an interesting solution. The Adaptive Fibres involve therefore two types of components called short-term memory (STM) and long term memory (LTM) fibres. The difference between them concerns only their dynamics.

3.2. Definition of a fibre and global functioning

A fibre F is a network of segments S_i (a set of interacting segments), given by their extremities in R^2.

$$F = \{S_i = (X_i, Y_i) \in R^2 X R^2\} \quad \text{for } i = 1 \dots |F|$$

Two segments are linked by one extremity when this extremity is common to both of them.

One fibre F defines a figure in R^2. To this figure can be associated a function I from R^2 to [0,1], given by a gaussian function of the distance to the fibre. This function I is used in order to define the interaction rule between the segments and a point P (cf. figure 1).

$$I(F,P) = \exp\left(\frac{d^2(F,P)}{\sigma^2}\right)$$

Where d(F, P) is the distance from P to the fibre, and σ a parameter. This distance is defined as the distance from P to the nearest segment of the fibre. The distance of from P to a segment S being the distance from P to the nearest point of the segment (with the euclidian distance). The function I will be used in order to approximate the probability distributions from which the learning examples are drawn (cf. figure 2).

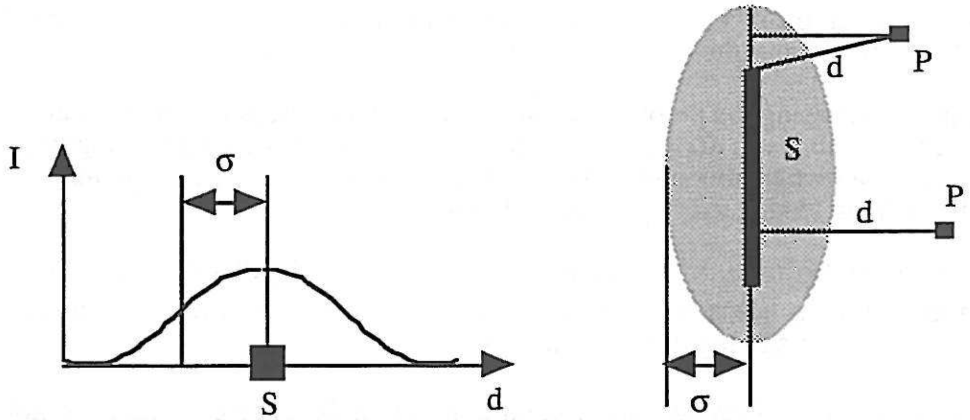

Figure 1 : interaction rule function of a segment.
The function corresponds to a gaussian of the distance to the segment..

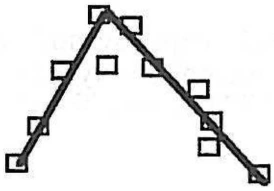

Figure 2 : Examples of set E_k drawn from probability distribution μ_k on R^2 and its approximation by a fibre.

The goal of the model is therefore to approximate as rapidly as possible the probability distributions μk when a set of examples drawn from this distribution is given.

The model is defined by :
- a unique current STM fibre which approximates the current set of points,
- a network of LTM fibres.

When a new set of points is given to the model, it is compared to a restricted number of LTM fibres, among which the most compatible are activated. The activated LTM fibres are used in order to build the current STM fibre. When no LTM fibre is compatible enough with the current set of points, the STM fibre follows its own dynamics, and the result is used in order to produce new LTM fibres. These dynamics are now described with more details.

3.3. The STM fibre

The STM fibre is thus used in order to approximate the current state of the learning set. It is helped in this task by the LTM network which is involved in the STM component production.

3.3.1. Component modification

We consider that a fibre is surrounded by examples (points), drawn from a given probability distribution. A point P attracts the nearest segments thanks to a gradient descent on the function:

$$J(F, P) = 1 - I(F, P)$$

The point P is chosen at random in the current training set. The corresponding component modification, which is given by translations of the points defining the extremities of the segment is easy to compute (cf. Figure 3).

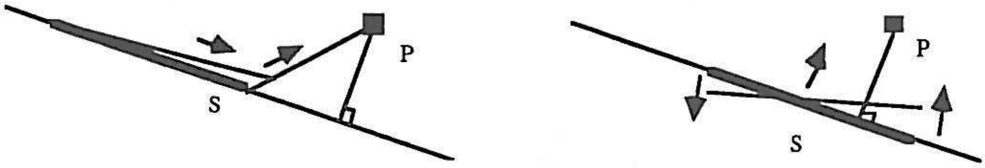

Figure 3 : component modification in STM fibres.
The segment is attracted by the point according to the differential of E(F, P)

3.3.2. Component regeneration in the STM fibre

Production

At the intialization of the system, a first segment is created at random. Then, in normal functionning, LTM fibres are responsible for the STM-segment production (cf 3.4).

Moreover, the STM fibres have their own segment production process, which is given by a probability for existing segments to be cut into two parts.

Linking

By sharing one extremity, several segments may physically link them together. This occurs when the distance between their extremities is below a given threshold (cf. figure 4). Two linked segments are in direct interaction, when one is moving the linked ones are also moving.

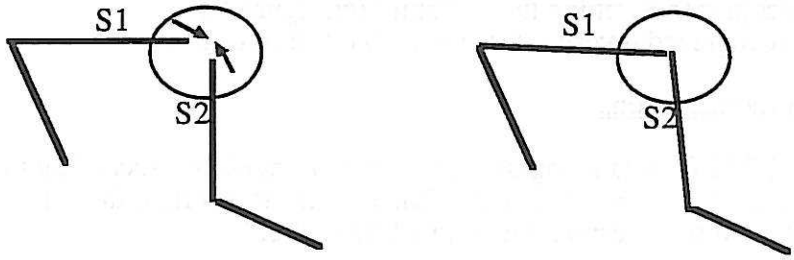

Figure 4 : linking STM components.
When the extremities of two STM components are close to each other enough they merge and provide a link between both segments.

Destruction

A segment S_i is eliminated when the number of points P_j located in its interaction domain D_i is below a given threshold. Such a segment is considered as useless. This procedure provides a simplification of the approximation given by the fibre which allows to extract the main features and ignore some of irrelevant details.

3.4. The network of LTM Fibres

LTM fibres are organized in a network of fibres similar to the STM one. This network is used in order to build as rapidly as possible the STM fibre corresponding to the current learning set of points, and to recognize the already encountered forms. The network and its component modifications and regenerations are described.

3.4.1. Description of the network

The LTM network is made of fibres which are similar to the STM ones. Two LTM fibres can be linked when they have similar segments (cf. Figure 5). All segments of a form are also linked together.

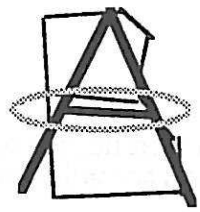

Figure 5 : LTM network
The two LTM fibres are linked by a similar segment.

An activation value is defined on the segments of the LTM fibres. This activation value is related to the probability of being chosen to be tested. A research of a form in the LTM fibre is made through the management of this activation.

When a new set of points is given to the system, the segments are chosen with a probability which is proportional to their activation. They are tested, and the distribution of activation evolves according to the fitness. This evolution enhances the activation probability of the segments linked to the tested segments which have a good fitness, and decreases the activation probability of segments linked to those of a low fitness (cf. figure A4, A6). The tested segments are added to the STM fibre if they fit the examples. This enables to eliminate or select LTM fibres by testing only a small number of segments.

At the end of the activation dynamics two possibilities occur :
• a LTM fibre is recognized as fitting the examples (cf. figure A8),
• no LTM fibre is recognized (every activation is 0) (cf. figure A4).

3.4.2. Component modifications

When a particular LTM fibre is recognized, it is slightly modified according to the component modification rules used for the STM fibre. This enables to average the LTM fibre on all the encountered sets of points corresponding to this LTM fibre.

3.4.3. Component regeneration in LTM fibres

When no LTM fibre is recognized, the STM is developped autonomously until it reaches an equilibrium. The result of this development is used in order to create a new LTM fibre (the STM fibre is duplicated) (cf. figure A5). When a LTM fibre is recognized, this fibre is reorganized according to the STM fibre obtained. These reorganizations involve production, linking and destruction of components.

Production

When the STM fibre has a segment which is different form all those of the recognized LTM fibre, this segment is added to the LTM fibre. This is the case when no LTM fibre is recognized.

Linking

Every new segment of a LTM fibre is linked to all the other components of this fibre.

Besides, the LTM network has an autonomous activity which compares couples of LTM fibres and links them together by their similar segments.

Destruction

When the STM fibre gives a better approximation with a simpler structure (less segments), the corresponding segments of the LTM fibre are eliminated and replaced by those of the STM one. The LTM fibre is therefore always ameliorated.

5. Conclusion and future work

In this paper, a general framework concerning a large family of models, the morphodynamic networks, is proposed. This framework is inspired by Farmer's Rosetta stone for connectionism. Morphodynamic networks distinguish themselves from connectionist networks by the geometric character of their components, defining topological domains of interactions. For them, the description by a simple graph with connections is not sufficicent.

The introduction of different types of components enables to implement more elaborated behaviors, in which the equivalent of a long term memory is involved. An example of such a model, the adaptive fibres, is described in the paper.

The implementation of the adaptive fibres is only at its beginning and the research for different the dynamics are still in progress. However, even at the current state of development, the following points concerning this model must be underlined :
- the model could provide fast recognition among a large number of already encountered forms,
- the model extracts automatically similar features between the encountered forms and uses these similarities in order to reduce the number of tests to make for the recognition of a given form,

Many difficulties still remain. However, the approach of 2-level morphodynamic networks gives new opportunities to deal with the form recognition problem by the direct use of topologic regularities in the model. These models could give new recognition tools that could have interesting applications in robotics for instance.

Furthermore, morphodynamic networks could be related to theories of the living, in particular the autopoiesis of F. Varela and Maturana (Varela and Maturana 1974). The component regeneration, which is in the heart of the autopoiesis property is also very important for morphodynamic networks. These approaches emphasize the modelization of a body for the artificial cognitive system. This is one of the most important characteristics of the Artificial Life stream.

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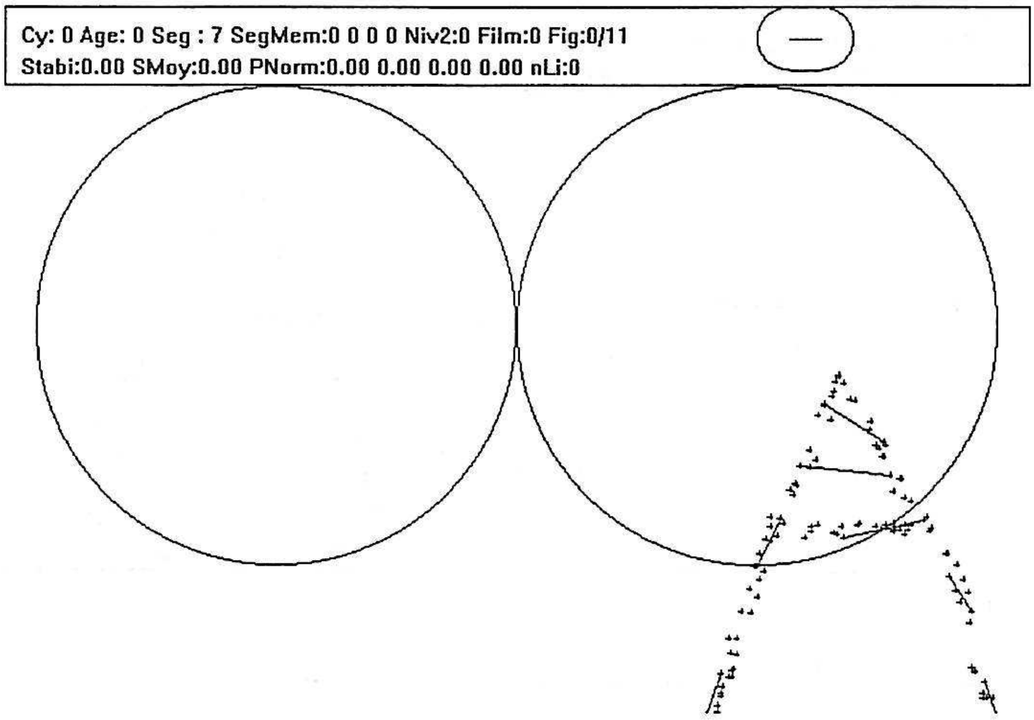

Figure A1 : A new set of examples is given to the system, the STM fibre is randomly initialized on it

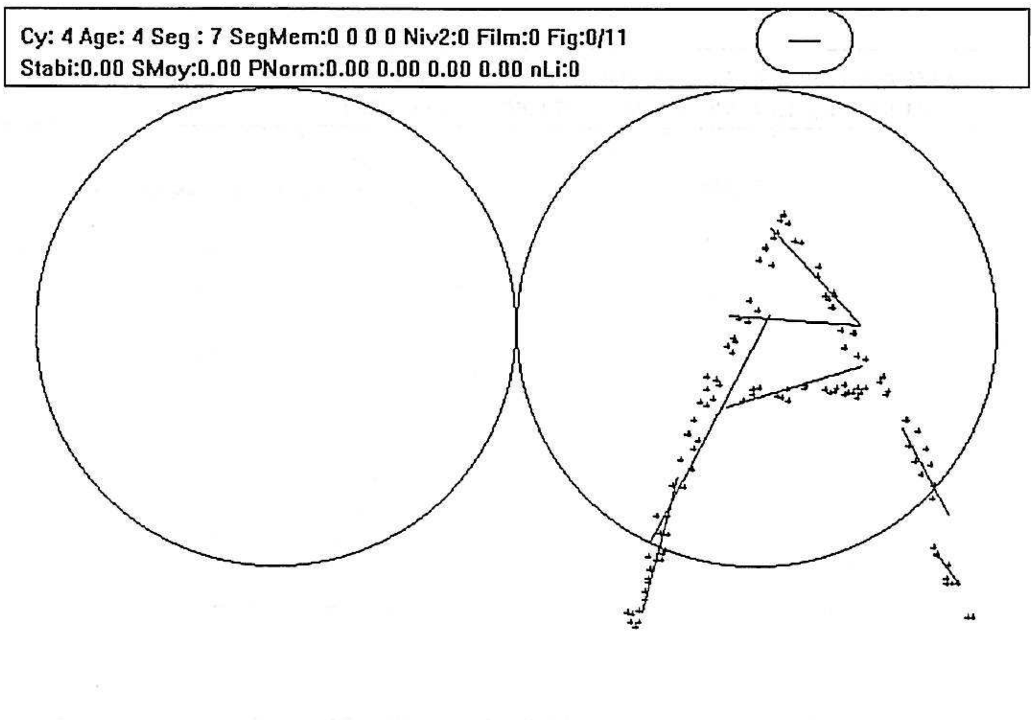

Figure A2 : the STM fibre enables the system to both approximate
the data and center the figure

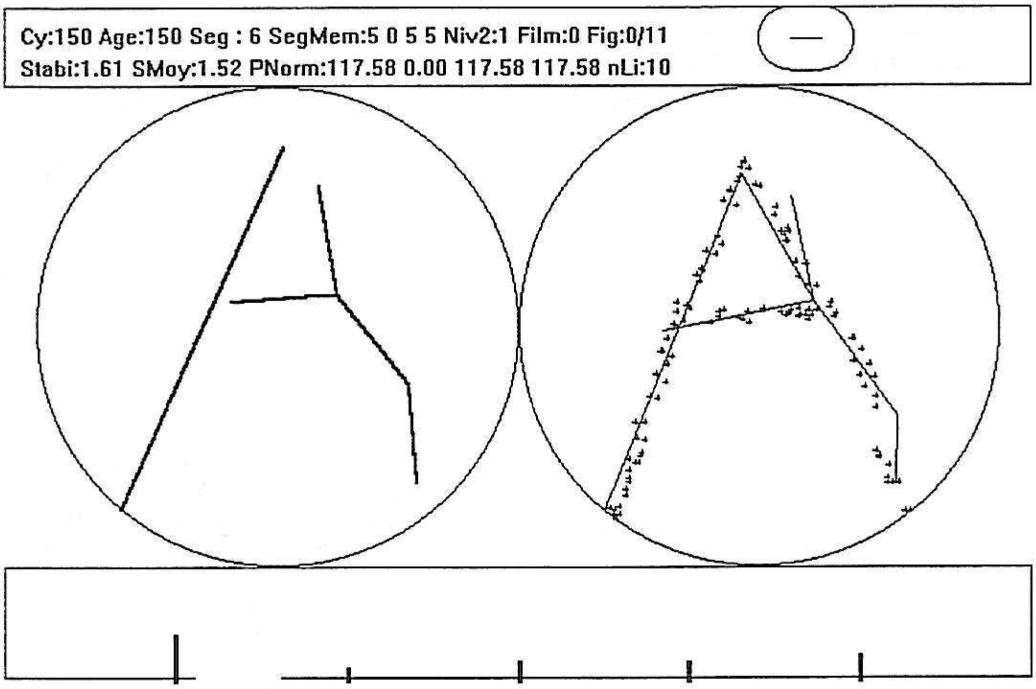

Figure A3 : When the approximation given by the STM fibre is stable (right), it is stored in the LTM fibre (left)

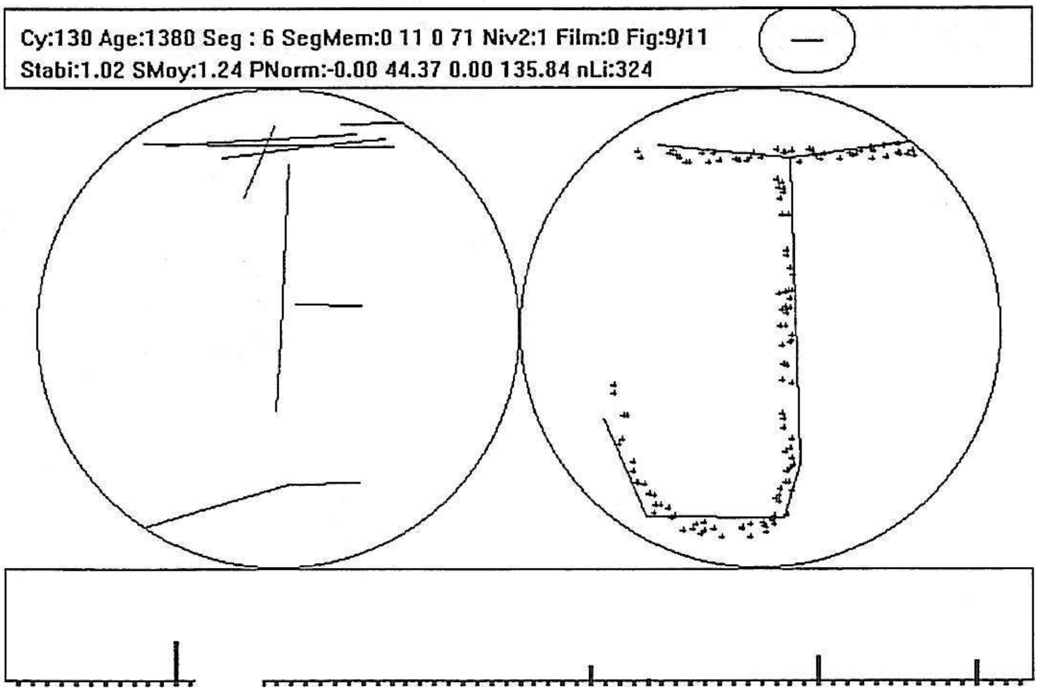

Figure A4 : When a new set of example is given to the system (right), it tries to recognize it in the stored LTM fibres (left)

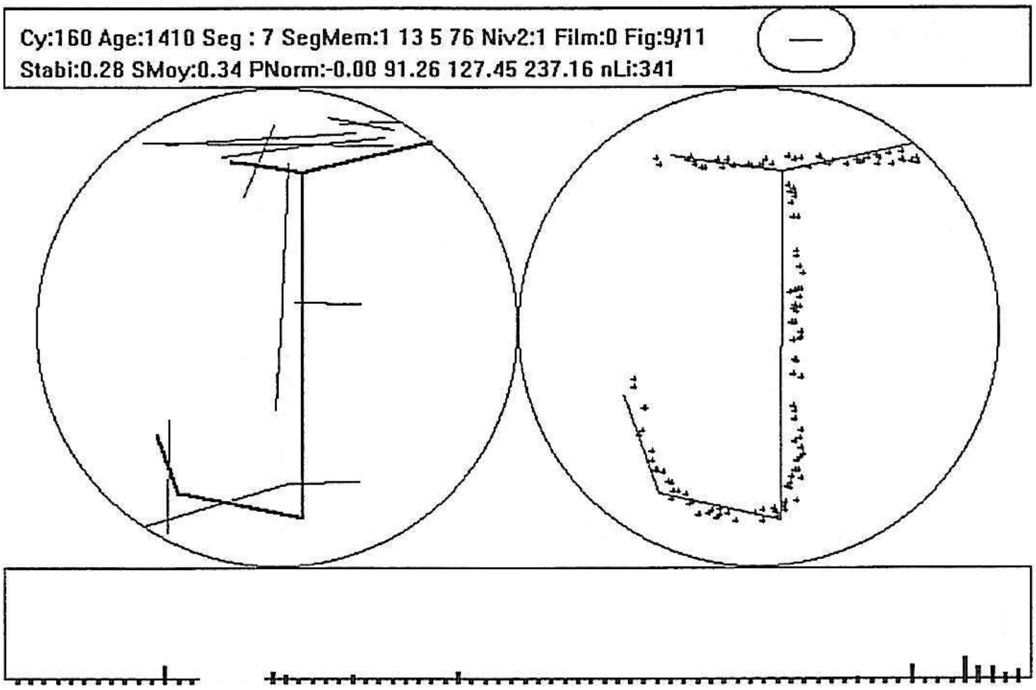

Figure A5 : When the STM fibre is stable (right), if no LTM fibre is recognized (left), the new STM fibre is merged to the current LTM fibre (left)

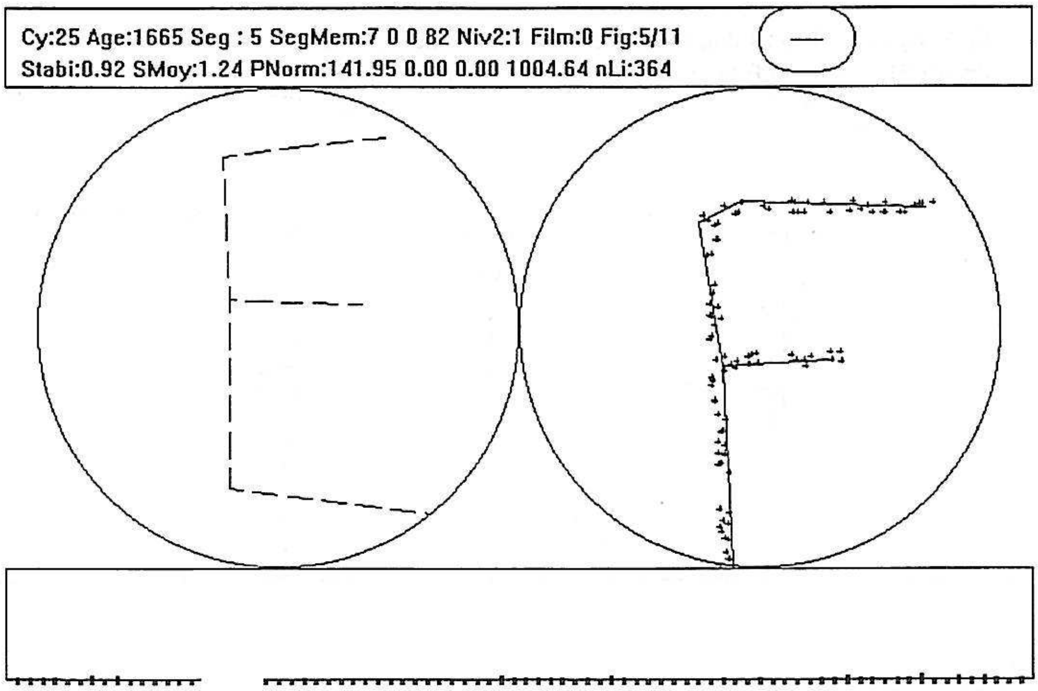

Figure A6 : At the second presentation of a given set of examples (rigth), the LTM fibres are tested (left). This changes the distribution probability on the whole LTM fibre (bottom)

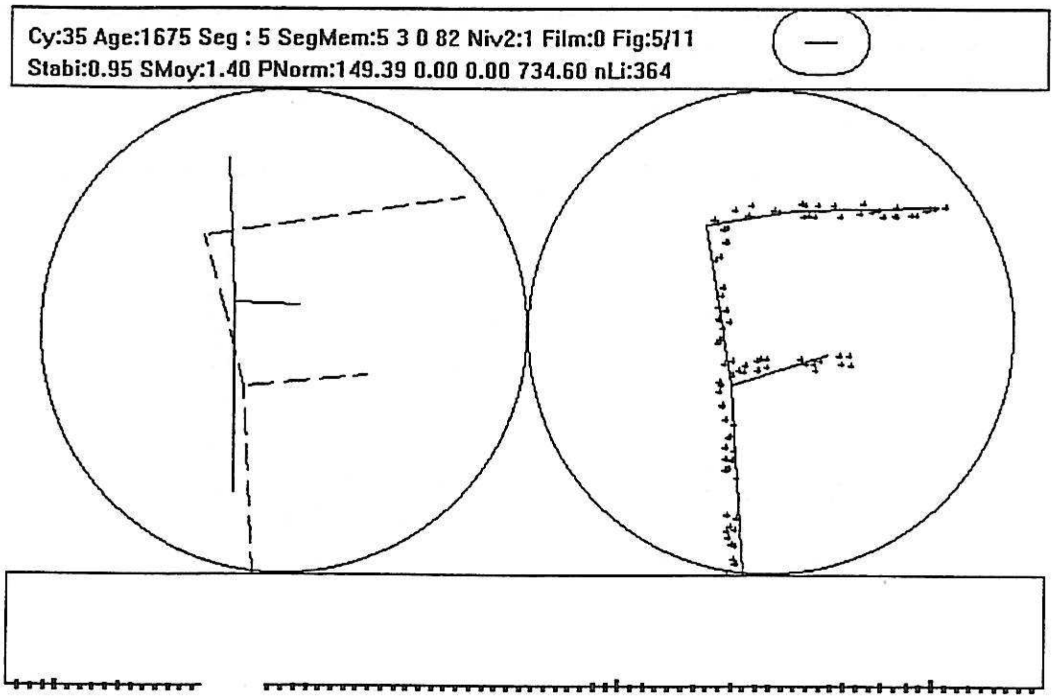

Figure A7 : Due to the evolution of probabilities on the LTM fibre (bottom),
the correct LTM fibre is find and tested (left)

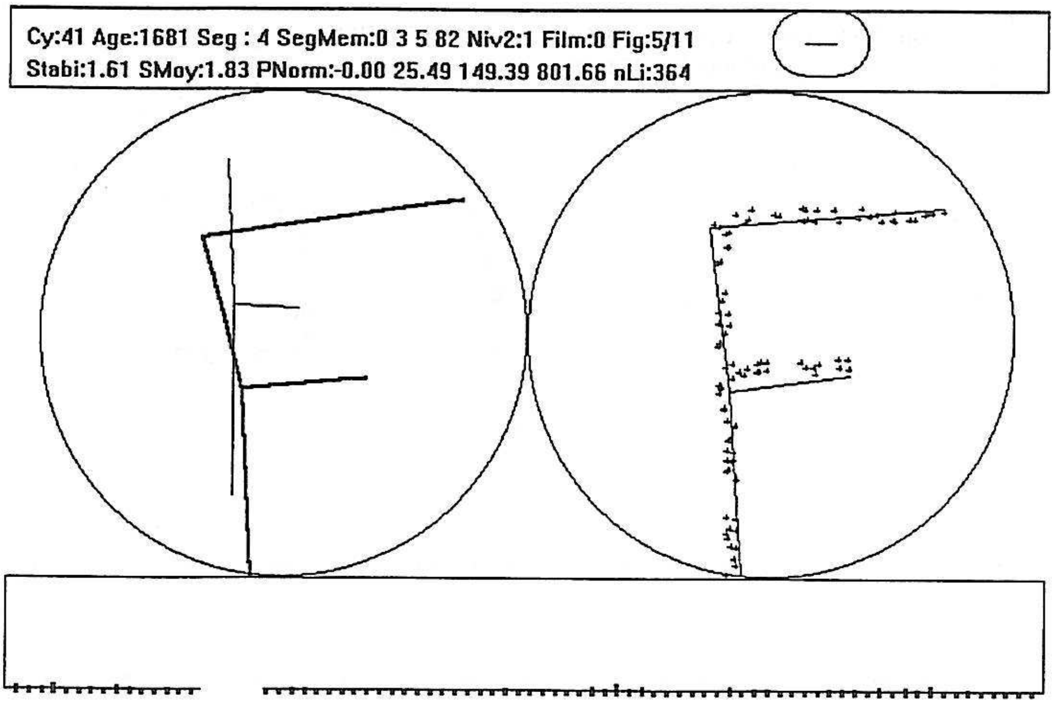

Figure A8 : The tested LTM fibre is recognized (left)