A MODEL OF HIERARCHICAL COGNITIVE MAP AND HUMAN MEMORY DESIGNED FOR REACTIVE AND PLANNED NAVIGATION

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ABSTRACT: In the behavioural animation field of research, the simulation of populated virtual cities requires that agents are able to navigate autonomously through their environment. It is of interest to tend to the most realistic human-like planning and navigation. In order to do so, we have designed a navigation system for autonomous agents, which implements theoretical views from the field of human behaviour in urban environments.

We started from the assumptions that it would be interesting to merge a spatial cognitive map model with model of human memory, and that the representation of space in the cognitive map is hierarchical. An interest of our approach is that the agent navigation can be seen as a planned and reactive navigation loop generated in real time. We use a semantically and geometrically informed hierarchical topological graph as a representation of a large environment to be navigated in. Our model of cognitive map has a topological and hierarchical graph structure which partially maps the regions of the environment the agent has explored during the simulation. This map can be seen as a filter on the environment. It does not contain geometrical nor semantic information about the urban objects encountered, but only controls the partial access to the database while the agent recalls or perceives the urban objects. As a simplified model of human memory, we use the recall and recognition attributes, and their respective thresholds of activation to parameterize in two different ways the cognitive map.

1 Introduction.

Behavioural animation consists of a high level closed control loop, which enables autonomous agents or entities to be simulated. Such actors are able to perceive their environment, to communicate with others and to execute a number of actions, such as walking in the street or grasping an object, in accordance with the nature of the environment and with their intentions. Considering the navigation process, if more complex behaviour than obstacle avoidance is to be reproduced, it is necessary to provide additional data such as mereotopological and semantic information.
Concerning the perception of the environment, models used in behavioural animation has mainly focused on the visual field to filter what is viewed inside a global geometric database. Information used to navigate have been considered as identical for all autonomous characters and are corresponding to an exact topographic representation of the environment (Farenc & al, 1999) (Raupp-Musse, 2000) (Thomas & Donikian, 2000).
Actually, each person has a unique representation of a city map depending on his past experience, and on his knowledge of the city, this cognitive map will evolve with the time. Thus it seems relevant to endow each agents with a cognitive map structure which will hold a personal view of the agent along the simulation as well as a human-like memory model. Some interesting and founding studies can be found about cognitive maps as a structure (Kuipers, 1978) (Mallot, 1997), some related to the robotic navigation (Yeap & Jefferies, 1999) (Fernandez & Gonzalez, 1997) and some merging cognitive maps and memory systems (Jefferies & Yeap, 2001).
In this paper, we present a new model which allows to represent an individual cognitive map merged with a simple human-like memory model for navigation simulation in an environment. It allows to implement navigation as a planned and reactive navigation loop to be computed alternatively.
The section 2 and 3 present the architecture of the system and the design of the informed environment. Section 4 describes in detail the model of the cognitive map as well as the memory model merged in it, while section 5 briefly sketches our navigation algorithm.

2 Architecture of the system

As shown in the Figure 1, the system is compounded of 5 different modules, which will be described in the next sections:

- The database representing the environment and storing all the data related to it.
- The cognitive map which “filters” the information of the environment.
- The memory controller which manage the memory in the cognitive map.
- The route planning module which implements the navigation algorithms.
- And the navigation module based on the HPTS decisional system (Lamarche,2001) which manage the behaviours of the agents in the environment.

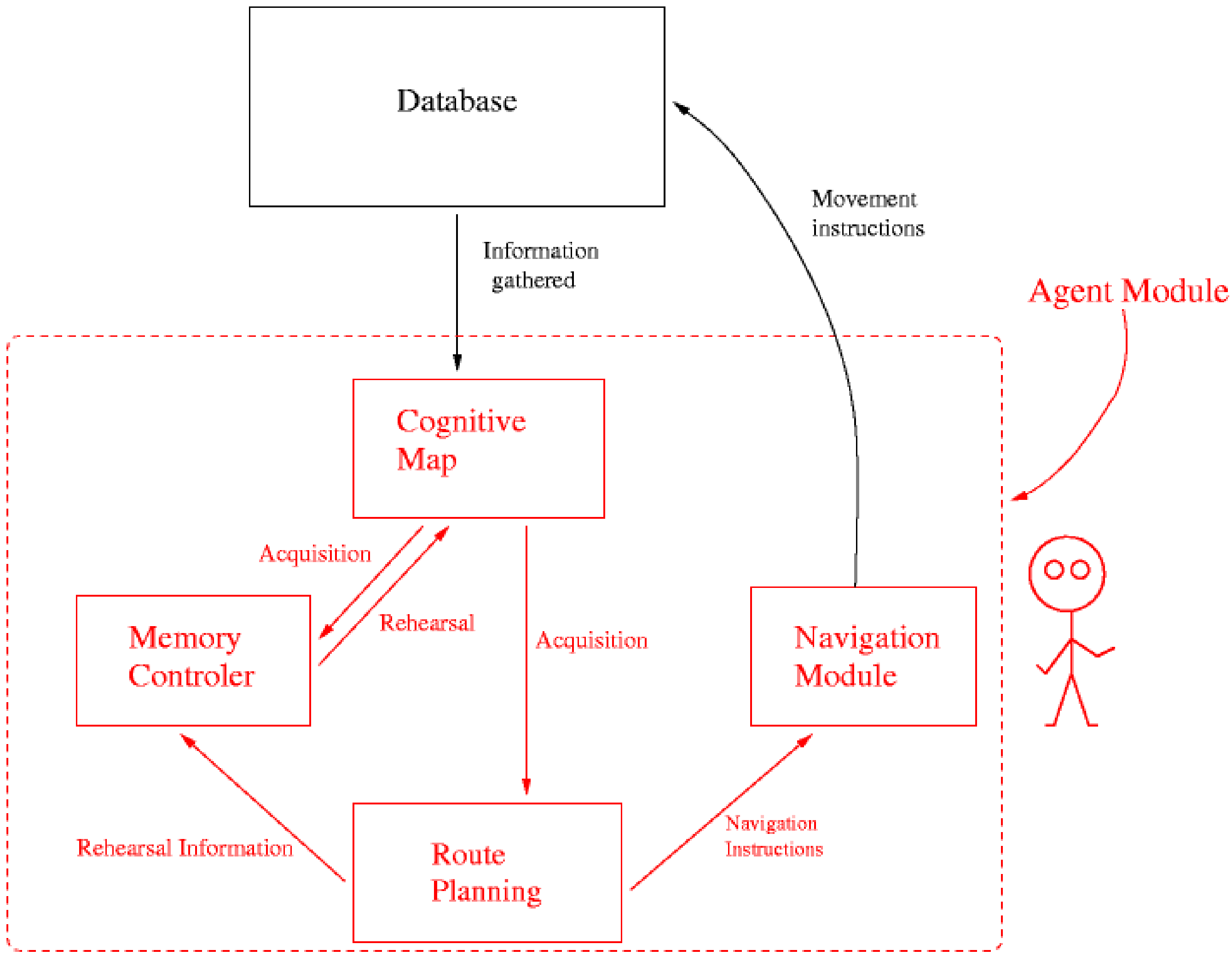

Fig 1: Architecture of the system.

3 The environment.

We consider here the inner city of Rennes (Brittany, France), which is compounded of approximately 2,000 buildings as a bench for our model (see Figure 2). We could model other cities, if we were provided the data to process them. The data gives information on public buildings (the city hall, the main post office, churches, etc...), private buildings and open spaces (public places, parking, etc...), the road network (roads, crossing, pavements) and the city furniture (benches, trees, traffic lights).

3.1 The database.

A specific parser has been developed, to parse and analyse the city data , in order to convert it into an inner representation, which is a semantic informed hierarchical topological graph. This graph, which we will later call the database, is the basic tool for simulation and the building brick of the system. The different modules managing the agents behaviour, extract the necessary information from this database via a system of dynamic requests. This database has been designed upgrading previous work done by G. Thomas (Thomas & Donikian, 2000) and extended in the DynamiCity Project.

We added a generic topological connector, which topologically links the road network to the set of buildings. It realizes specific gathering of urban object, to implement the concept of local area (Penn, 2001). By now, it regroups each building lying in a convex set of road sections and crossing to form a block of buildings, and link it to road sections which can be themselves gathered and regrouped in bigger road sections. Thanks to the genericity of the model, if the connector is given specific heuristic of gathering, several layers abstraction implementing a hierarchy of views is possible in an automatic way.

Fig. 2: The city of Rennes virtual mockup

The database is computed in a static way. Once the city data is parsed in an inner representation format, the topological connector is applied and the database is semantically informed, one can consider the database hardly change during the simulation. All the changes, modifications or various updates and upgrades will be performed in the cognitive map. Our implementation of the database can be seen as a collection of information the agent can gather and obtain from the environment without analysing it. The information stored in the database are “objective” data, in the sense that it does not change relatively to whom collects it. The “subjective” information will be stored in the cognitive map of each agent.
So the database can be seen as the common core of information each agent can access. We have structured it as a semantically informed hierarchical topological graph, which is detailed in the next section.

3.2 The hierarchical-topological graph.

The informed hierarchical-topological graph (IHT-graph) is compounded of three different layers

1. the Basic Topological Layer which contains real urban objects modelled as simple spaces.
2. the Composite Space Layer
3. the Local Area Layer

The base objects of IHT-graph are simple spaces.

- A simple space (E_s) can be buildings, road sections, crossings, public places, etc…
- Urban objects and furniture as benches, trees, traffic lights are named punctual objects (O_p) and are stored in the simple space (E_s) where they are located.
- Simple spaces (E_s) are linked together via a system of frontiers (F) to form the first layer (basic topological layer) of the IHT-graph.
- The geometrical abstraction from buildings to blocks, and from road sections to roads are modelled using the composite spaces (E_c). Note that two E_c can not overlap each other.
- A composite space (E_c) is a space which parameters are its frontiers and the list of its sons, knowing that the son of a composite space can be an E_s or an E_c of lesser importance, in this sense that it is geometrically included in the boundaries of its father E_c, which then allows a hierarchy of several composite spaces (E_c) levels in the composite space layer.
- The edges linking two composite spaces, contains pointers to all the frontiers linking the E_s included in one another, forming the composite space layer of the IHT-graph.
- Local areas (Eloc) are composite space that can overlap, sharing common sons in the composite space layer. The overlapping can be viewed as the implementation of "fuzzy" borders for local area.
- The edges linking two different local areas, contains pointers to all the composite spaces common to the two local areas.

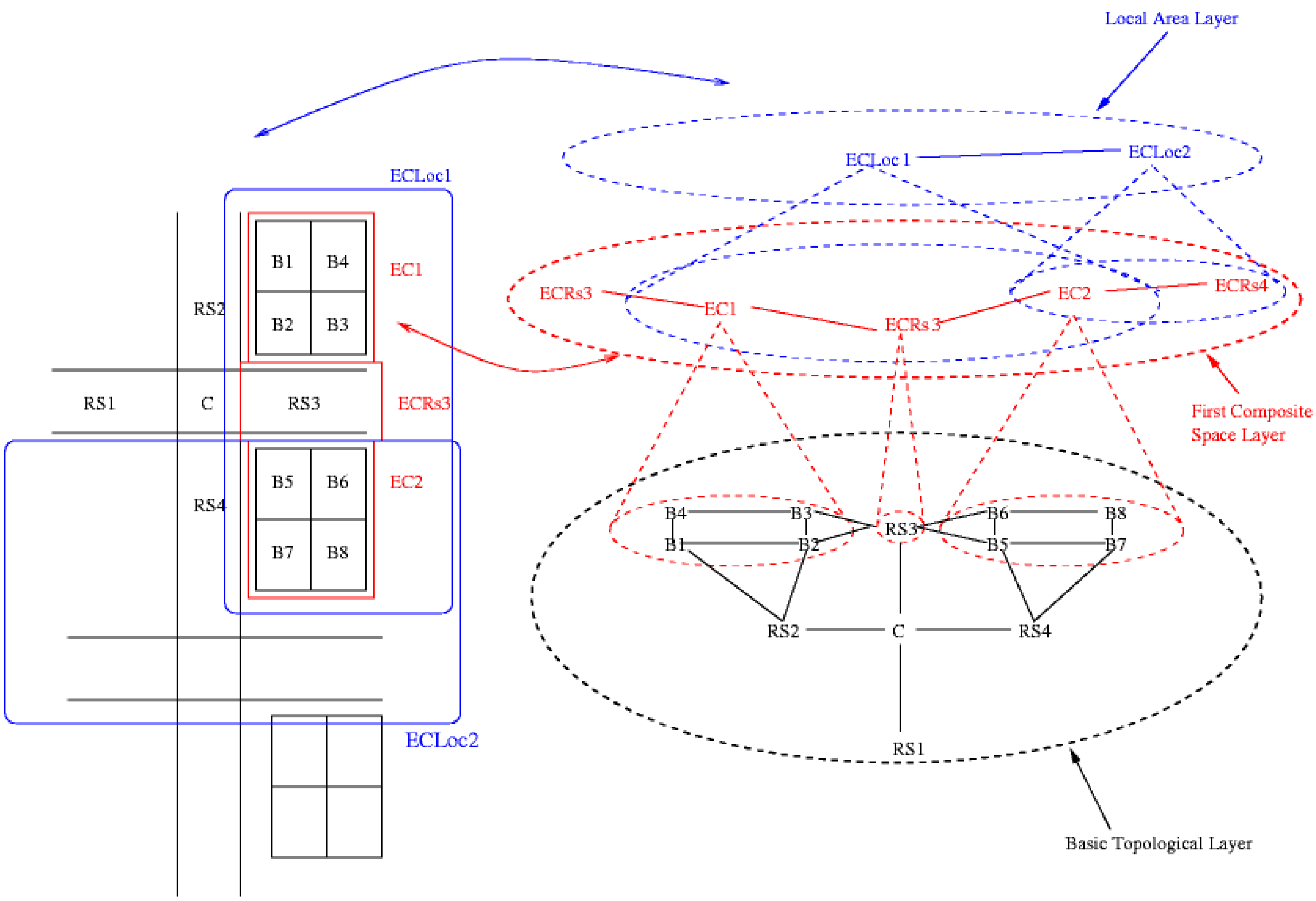

Fig 3: Simple IHT-graph.

The figure 3 gives the example of the translation in inner representation format (IHT-graph) of a very simple crossing. The basic topological layer gives the topological connections between each simple spaces (E_s) of the crossing, the Bs being buildings and Rs being road sections. The topological connector gathers all the buildings between intersections and regroups them in composite spaces (E_c). In the same way, it abstracts each road section and crossing in a composite space. They are linked together on the first

composite space layer, the frontiers between two composite spaces being the sum of the frontiers linking all the elements of the first composite space to the elements of the second one. Then the abstraction of local area is realised in the local area layer, regrouping different composite spaces. Note that the abstraction process between the two first level is automated, but the abstraction to local area is not, though it would be possible to automate it if the connector were given the necessary heuristic of gathering.
So the IHT-graph contains all the information necessary to reactive agent navigation. In order to compute a planned navigation, we need to endow the agents with a cognitive map, in which they can compute a route planning, with the elements they perceive or they recall from their past navigation.

4 The cognitive map.

4.1 Structure of the cognitive map.

From a simulation perspective, it would seem impossible to endow each agent with an exact copy of the database. Indeed the computer random access memory load would be then unbearable for any existing computing system. It is though necessary to hold a "subjective" vision of the environment for each agent of the simulation. Indeed previous work state that "mental representations of large-scale spaces differ from maps in important respect. For example, mental representations of spatial knowledge are distorted, fragmented and incomplete" (Barkowsky, 2001) (Tversky, 1993) (Montello, 1998) . Meanwhile, in our model we only consider the incompleteness and fragmentation of the information, not the fact that information can be distorted. In order to hold personal vision of the environment for each agent, we have designed a model of cognitive map based on the structure of IHT-graph, which acts as a filter on the database (see Figure 4).

4.1.1 A filter.

The cognitive map in itself does not contain any exact information on the geometrical nor semantic properties of objects contained in the database. It can be seen as a "filter" on the accesses the agent can have on the database, in this sense that it partially maps the topological and hierarchical structure of the database and gives access to the objects of the database which have already been visited, and "hides" the others.
As the pedestrian wanders around the city, the cognitive map grows with encountered objects, whose identification is stored in the cognitive map, as well as a link pointing on the real object in the database. For notation concern, we will name the cognitive map object which filters a database object, a "filter object". To each filter object is associated memory parameters, whose use will be detailed in the next sections.
The structure of the cognitive map partially maps, in topological and hierarchical ways, the one of the database. It keeps the notion of space abstraction from the basic topological layer to the one of local area. But it is added a graph of landmarks in order to implement two different representation of spaces.
The importance of landmarks in the navigation process, as a structural element in the topological representation of space is relevant. Meanwhile, from a structural and a computational perspective, it is reasonable to state that the concept of landmark and the notion of local area assume two different functions. It seems, though, of a great interest to implement this two representations of space as different structures, given that they are involved in different parts of the navigational process.

The two parts of the cognitive map can be seen related to the survey and the route spatial perspectives, the cognitive map unifying the two different visions in a single model, which could fit with the vision Taylor and Tversky (Taylor & Tversky, 1992) have of a general spatial mental model, fairly independent of the perspective employed to build it.

4.1.2 Local areas and graph of landmarks.

- The first element of the cognitive map is an IHT-graph, and is compounded, like the database, of three different layers.

  1. the Filter Basic Topological Layer
  2. the Filter Composite Space Layer
  3. the Filter Local Area Layer

  We call it the Filter IHT-graph. Its use is to spatially and semantically structure the space representation of the agent. The different levels of abstraction allows the agent to plan its route with different granularities.

- The graph of landmark is designed to implement the notion of known path in the environment (Kuipers, 1978), it is specially useful for the reactive navigation, the low-level planning and the replanning after the agents got lost in its environment. Each landmark (L) has a root object taken from any of the two first layers of the Filter IHT-graph (Filter Basic Topological Layer, Filter Composite Space Layer), and a group of sons, taken as well in the two first layers of the IHT-graph. Those sons are the objects correlated to the landmark during the navigation, which can be seen as elements of the path in which the landmark is involved. The landmarks are linked together by landmark edges, which have no geometrical basis, but only represent the association and the memory link the agent makes between two different landmarks. Note it is always possible to make a topological link between two landmarks via the spaces connected to their roots. Note also that no pre-computed path is stored in the cognitive map, the graph of landmarks gives "beacons" or major points of reference, as well as links to E_s or $E_{c,}$ as elements to compute a path, thus it can be seen as an abstract set of possible paths in the environment.

An interesting property of the fact that the graph of landmarks has root in the Filter IHT-graph is that during the navigation process it is possible to partition the graph of landmarks in zones corresponding to the local areas of the Filter IHT-graph.

Due to the different nature of the Filter IHT-graph and the graph of landmarks, their memory managing is very different from each other and will be discussed in the following sections.

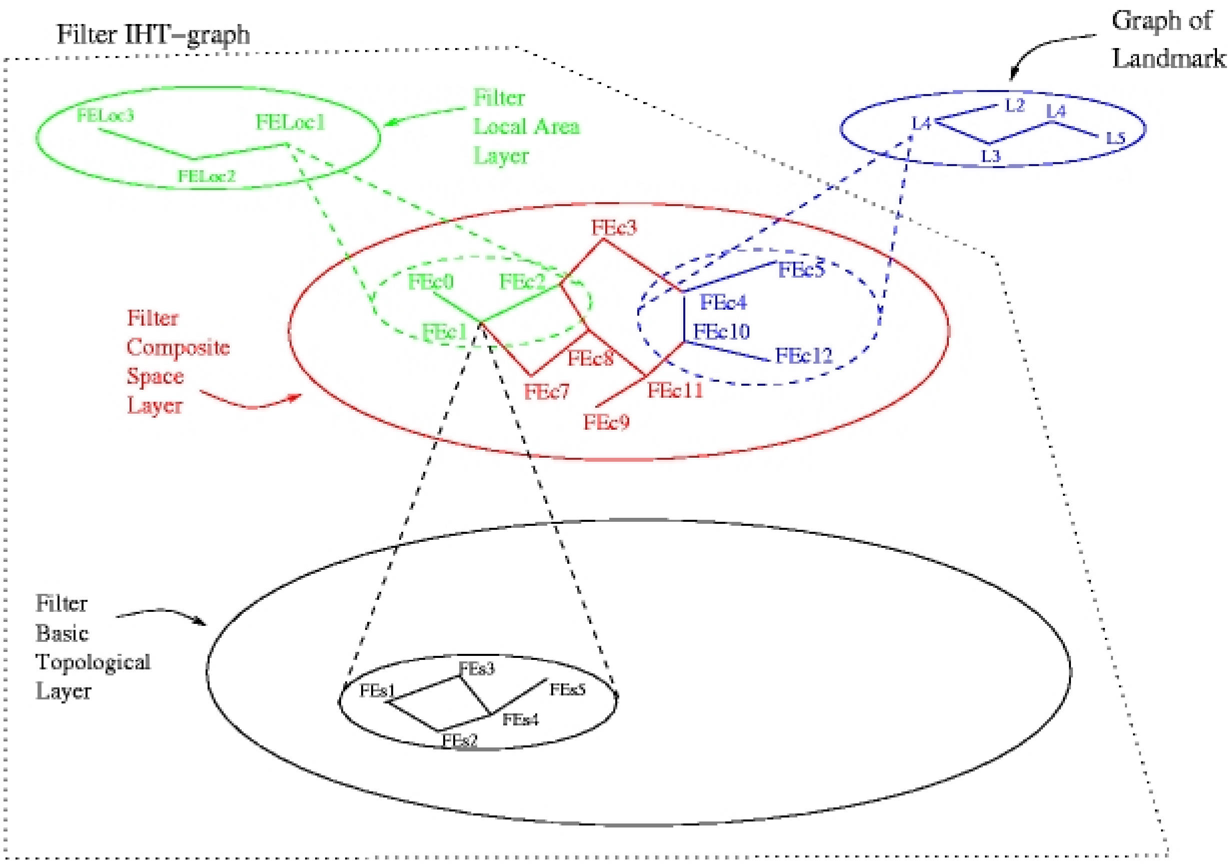

Fig 4: A simple cognitive map structure.

4.2 Merging the representation of space and a model of human-like memory.

As the cognitive map "filters" the accesses to the database, we have chosen to integrate the memory model as part of the cognitive map itself, instead of treating it as a separate module. Indeed, we are interested on the contextual aspect of long term memory. In this sense it seemed interesting to merge the memory model with the cognitive map one, so that recognition and recall can be highly correlated with the navigation and reciprocally. In order to do so, each filter object of the cognitive map is associated a recall parameter and a recognition one. As some studies shows that the recognition and the recall evolution must be considered together (Gillund & Shiffrin, 1984), we have made the choice to consider them embedded in a same structure, with interleaved processes of encoding and retrieval encoding.

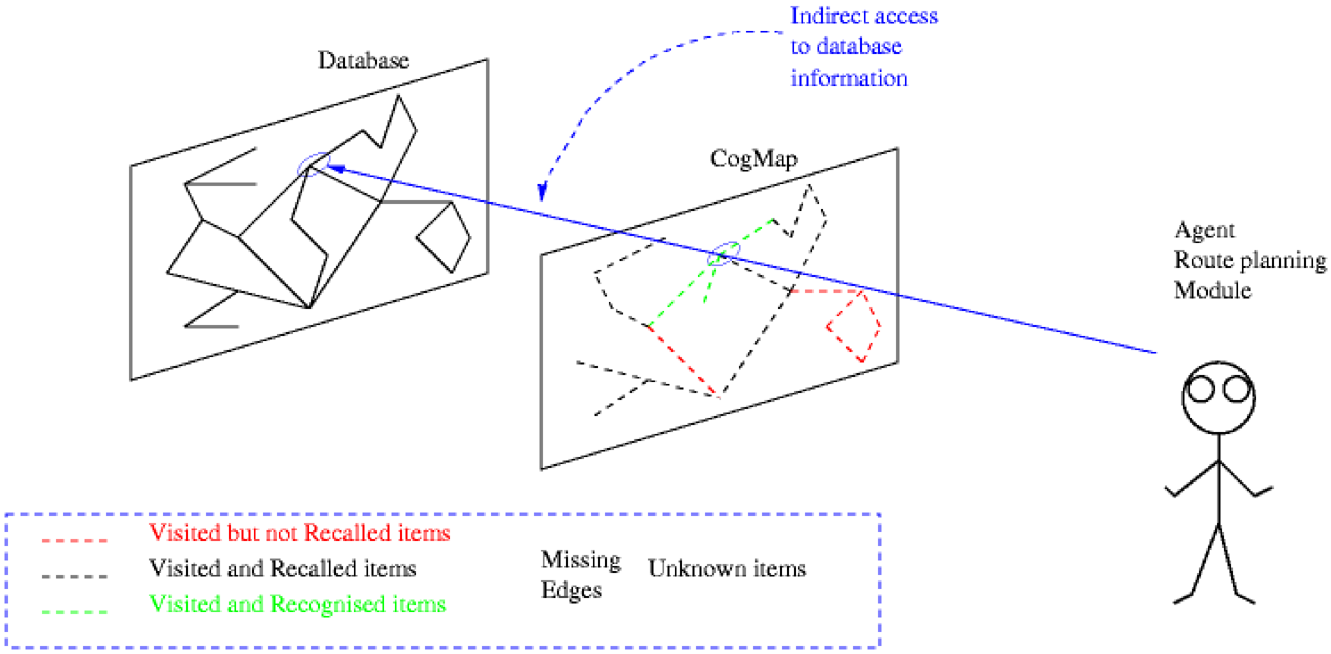

Fig 5:Database/CognitiveMap relation

4.3 Recognition and recall parameters as a model of human memory.

The memory managing of the two different parts of the cognitive map, i.e. the Filter IHT-graph and the graph of landmarks shows significant differences. The memory model of the Filter IHT-graph is a tentative to model the contextual aspect of the long-term memory. But as links and correlation between filter objects is managed in the graph of landmarks, the memory model implemented in the graph of landmarks bears more resemblance to an associative memory model. We discuss them separately in the two next sections.

4.4 Memory in the Filter IHT-graph part of the cognitive map.

Each filter object is associated a couple of real numbers lying in the interval from zero to one, which represents the recall and the recognition values associated to this filter object. As the agent navigates, objects enter in its visual field. Those objects which memory parameters were first initialised to zero, are added a global memory coefficient μ depending on each agent.

The μ value is altered by coefficients which depends on the type of perception of the agent. We have adapted a model of perception designed by Chopra and Badler (Chopra & Badler, 1999) which introduces three different perception modes for an agent depending on its visual attention. The perception can be either:

- Exogenous (the attention is spread on a high number of things, exceptional and peripheral events are noticed, which leads to high recall with a standard recognition)
- Passive (the perception is attracted by highly contrasted and salient zones, but the attention is quite low, which leads to a high recognition and a standard recall)

- Endogenous (the agent is supposed to be thoughtful and focused on a plan to execute. It is not prone to pay attention to its environment, which leads to standard recall and recognition)

So each time the agent perceives an object, the object memory parameters are added a small value depending on the type of perception of the agent, and of the μ-coefficient. Both of the memory parameters are as well added a value σ depending on the saliency of the observed object.

Let a space E_i , knowing that $\mu \in [0,1]$ and $\sigma E_i \in [0,1]$, the memory parameters will be:

	Recall	Recognition
a) Endogenous	$0.4*\mu+\sigma E_i$	$0.4*\mu+\sigma E_i$
b) Exogenous	$0.8*\mu+\sigma E_i$	$0.4*\mu+\sigma E_i$
c) Passive	$0.4*\mu+\sigma E_i$	$0.8*\mu+\sigma E_i$

This ensures many ways of encoding the memory parameters of an unknown space in the cognitive map, as well as the rehearsal of spaces already stored in the cognitive map.

The rehearsal and the control of the μ and σ coefficients are managed by the memory controller in a way that guarantees that the system remains numerically stable with the time. The rehearsal is simply the addition of these coefficients to the ones already affected to the object. Meanwhile, it is interesting to mention that once a parameter has reach its maximum (which is set to 1 for all the parameters), it is not added any value anymore until it has decreased below the maximum threshold.

If the perception is exogenous or passive, the semantic identification is active. That is to say, the agent is able to identify the local area in which it is navigating. As a computational consequence, the spaces compounding the hierarchy of the observed space are activated while their memory parameters are added the same value than the one of the observed space (see Figure 6). This leads quickly the memory parameters of higher composite spaces and local area to reach a maximum. This models the fact that, one exploring the town, quickly bears in mind the local areas and their organisation, even though knowing imperfectly the objects which compose them (Lynch, 1960).
If the perception is endogenous the hierarchy is not activated and only the first layer of the Filter IHT-graph is modified (the agents navigates thoughtfully without paying attention to its environment).

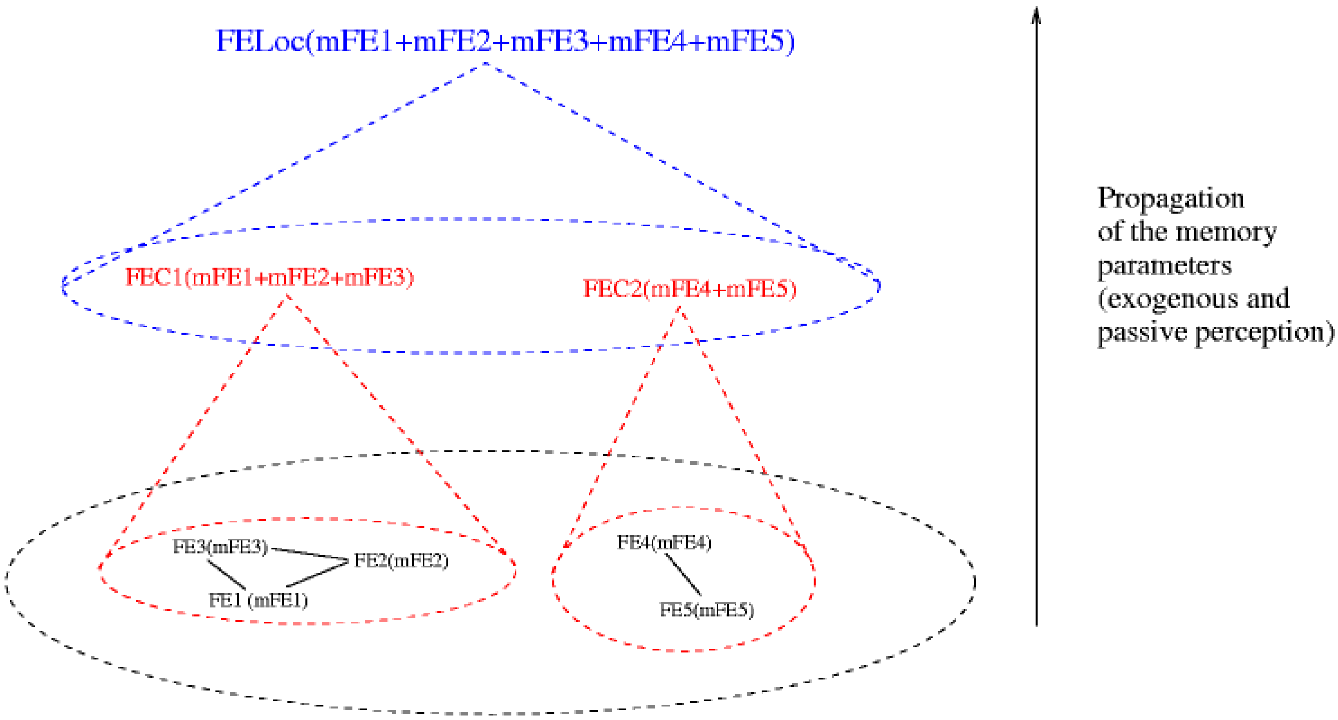

Fig 6: Propagation of parameters in Filter IHT-graph.

Note that only the nodes of the Filter IHT-graph, which represents the urban objects, are endowed memory parameters, the edges linking them together are not. Edges symbolically representing associations between objects, they are dealt with in the graph of landmarks.

4.5 Modelling of the graph of landmarks.

In the graph of landmarks, only the edges are endowed memory parameters, because the graph is designed to model the memory associations between objects and landmarks or between two landmarks, the agent makes exploring its environment. Anyway, every objects pointed from the graph of landmarks, is taken in the Filter IHT-graph, it has, then, memory parameters.

4.5.1 Landmarks as a spatial and memory structural item.

We give a brief sketch of the algorithm which dynamically builds the graph of landmarks:

- The agent navigating, meets a landmark $L_{1.}$ The landmark differs from the urban objects which surrounds it by its visual or thematic saliency. The saliency σ being a parameter proper to each space, the object having a saliency parameter greater than the general threshold σ_t of saliency are considered as visually salient landmarks.
- Once the landmark is perceived the object L_1 is created in the graph of landmarks and is associated its root space (E_s or E_c).
- L_1 is associated with $\partial t1$ a time counter which is initialised to an initial value $\partial t1_0$ depending on the saliency σ_1 of $L_{1.}$ As long as the agent will get further from L1, $\partial t1$ will decrease.
- Each space E_i encountered, is linked to L_1 by a hierarchical edge which will be given a value $\partial t1_{i.}$
- The decreasing of $\partial t1$ is discretised by $\tau_i \in$N the length of the topological path linking

L and E_i. (for instance if there are four spaces lying on the path between L and E_i, τ_i will be equal to 5).

- The edge linking L_1 to E_i is thus affected the value $\partial t1_i = \frac{\partial t1_0}{\tau_i}$.
- The recall and recognition parameters $(a1_i, b1_i)$ of the edge linking L_1 to E_i are set the following values:

  - $a1_i = \partial 1t_i + aE_i$ (final recall)
  - $b1_i = 2 \times \partial 1t_i + bE_i$ (final recognition)

  aE_i being the recall parameter associated to the space E_i, upper bounded to 1.
  bE_i being the recognition parameter associated to the space E_i upper bounded to 1.
  (Note that if $aE_i = 1$ and $bE_i = 1$, they are not added values until they become lesser to 1)
- Along the navigation, any space E_i encountered will be associated with the landmark, as long as $\partial t1 > \sigma_t$.
- Two cases can appear:
  - The agent likely meets another salient landmark L_2 while $\partial t1 > \sigma_t$. Then the association process is doubled for each new space E_j encountered, with a new $\partial t2 > \sigma_t$. Each new E_j will be then linked to L1 and L2 until $\partial t1 < \sigma_t$ or $\partial t2 < \sigma_t$.
  - $\partial t1 < \sigma_t$ and the agent has not encountered any relevant landmark before while $\partial t1$ was still positive. We then make the assumption, it is forced to find arbitrarily a new landmark L_2, if the agent is still in an exogenous or passive perception mode, decreasing the saliency threshold σ_t. If not the following spaces encountered will not be linked to landmarks.

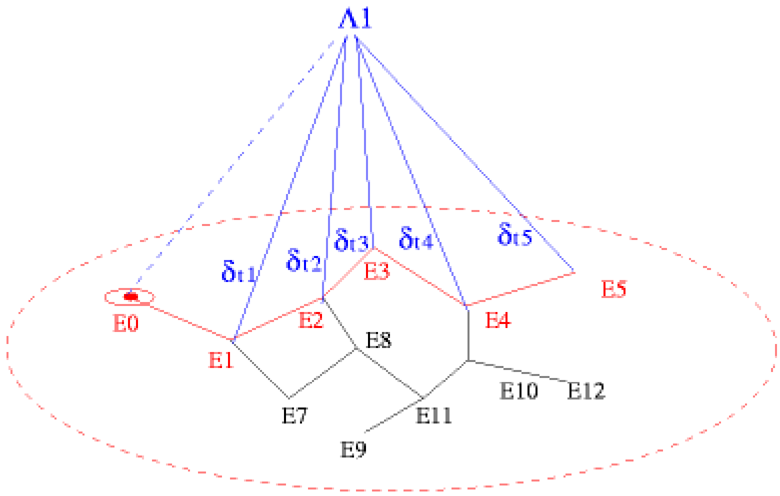

Fig 7 : Linking landmark to objects.

The first step of the construction of the graph of landmarks is realised this way, linking spaces taken from the two first layer of the graph to a particular salient space, put in relief as a landmark. The saliency detection is realised, endowing each urban object with a saliency parameter, but could be extended to the concept of saliency map stored as a property of an urban object in the informed environment (Courty, 2002).
Now it remains to explicit, to complete the graph of landmarks construction, how the inter-landmark relations are modelled.

4.5.2 Modelling the inter-landmark relation.

We define the low-level planning, stating that the more the agent knows its environment, the more it is prone to guide itself using landmarks and small features of its environment (Lynch, 1960). Michon and Denis (Michon & Denis, 2001) state a "function of a landmark is to help locate other landmarks, which are supposed to trigger a specific action". Knowing this and in order that the low-level planning can be done, we have to model an inter-landmarks relation, which will link them in the cognitive map.

4.5.2.1 Single space case

We mentioned that an edge linking two landmarks did not rely on geometrical properties. The edge linking two landmarks represents the association in memory made with these two landmarks. Two landmarks can only be correlated in memory if they share a group of spaces they are associated with. In order to quantify the recall and recognition parameters associated with an edge linking two landmarks, we must use the recall and recognition parameters of the edges linking the shared spaces to the two landmarks.

Various models have been proposed in order to model human memory (Raaijmakers&Shiffrin,1981) (Gillund & Shiffrin, 1984) (Eich, 1982), some more specific to contextual and spatial long term memory (Barkowsky, 2001) (Jefferies & Yeap, 2001). We have been inspired by the TODAM model of associative memory designed by Murdock (Murdock, 1982), based on a convolution product to encode an association between two items vectors. Indeed as shown in figure 8 , we use the recognition and recall parameters of the edges L1↔E and L2↔E as vector to make a convolution product with, which is truncated to the two first coordinates.

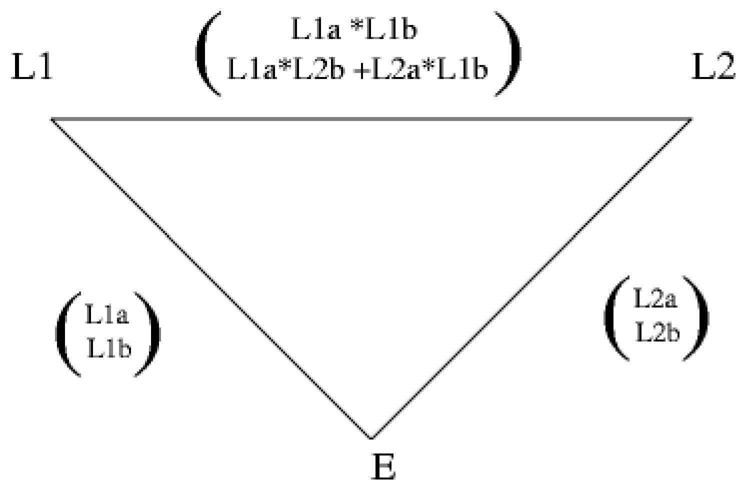

Fig8 : inter-landmarks relation, Simple Case.

As the numerical addition and multiplication do not guarantee the numerical stability of the system, we use fuzzy logic operators, which gives the following correspondence:

Numerical	Logic	Fuzzy logic
+	$\vee$	max
*	$\wedge$	min
L1a*L1b	L1a$\wedge$L1b	min(L1a,L1b)
L1a*L2b+L2a*L1b	(L1a$\wedge$L2b) $\vee$ (L2a$\wedge$L1)	max(min(L1a,L2b),min(L2a,L1b))

Hence a logical interpretation of the recall can be : to recall the relation between L1 and L2 using E, the agents must necessarily recall the relation between L1 and E, and the relation between L2 and E. Thus it seems natural than the recall relation between L1 and

L2 depends on the weakest recall relation among L1↔E and L2↔E.

A logical interpretation of the recognition is a bit more subtle. If the agents navigates from L1 to E, and once in E, it recognises there was a relation between L1 and E (depending on the recognition parameter L1b), the fact that the agent recognises an existing relation between L1 and L2, can only be possible if it recalls there is a relation between E and L2 (depending on the recall parameter L2a), but the two condition are necessary, giving L2a∧L1b.
Conversely, and starting from L2 to L1, it gives the symmetric (L1a∧L2b). Thus the recognition of the association between L1 and L2 depends on L1a∧L2b or on L2a∧L1b, giving the all expression (L1a∧L2b) ∨ (L2a∧L1b).

4.5.2.2 Multiple spaces case

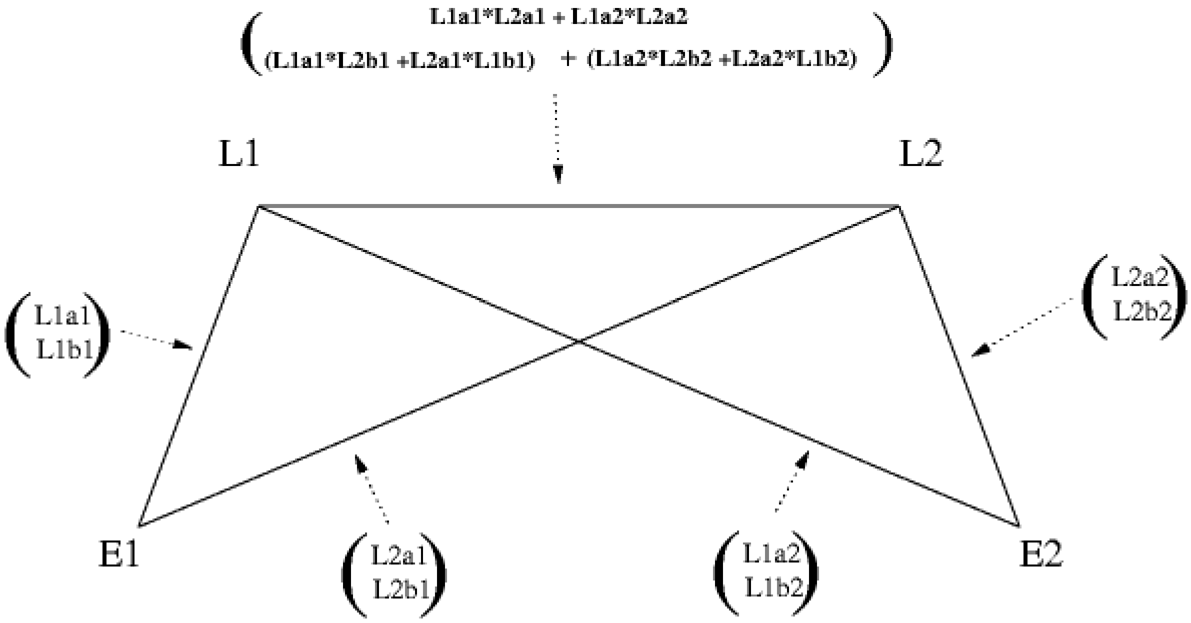

Fig 9 : Inter-landmarks relation, Multiple Case.

In the multiple spaces case, we have the sum the convolution product of each simple space case, which after interpreting it in fuzzy logic, leads the sum to become a maximum. The best single space case recall parameter and the best single space case recognition parameter are kept, knowing that most of the time they come from different single space cases. It can be interpreted as it is natural than, during the planning stage, the space which gives the best recall will show up first in memory, then it is natural that the recall value of the landmark association is the one of this single space case. For the recognition parameter it seems natural to use as well the best single space case.

4.6 The memory controller.

4.6.1 Degrading and Rehearsal.

The way the encoding and the rehearsal in the cognitive map is done, has been exposed in details in the previous sections. Meanwhile some details remains to precise.
The μ-coefficient is personal to each agent of the simulation, and represents in a way its

speed of learning. It is set at the beginning of the simulation, at the configuration stage of the agent.
Note that each time an object is recalled in the cognitive map at the navigation planning stage, the recall parameter of the object is added a value $\mu_r << \mu$, corresponding to the rehearsal it makes recalling the object.

The values of the memory parameters of all the cognitive map are uniformly degraded with the time, of a value depending on the duration of the simulation and of simulation time/real-life time ratio λ. This ratio is not the same for recognition and recall. Taking into account that recall lifetime decrease far more quickly than the recognition one, we set :

$$\lambda recall > \alpha^* \lambda recog \quad (\text{with } \alpha>1)$$

The memory controller subtract λrecall to the recall parameter and λrecog to the recognition one of all the cognitive map objects at each time step of the simulation, to ensure an uniform degradation of the memory with the time (note that if the recall and the recognition are null, they are not subtracted anything). The λ-coefficient is proper to each memory controller and thus to each agent. It represents in a way its speed of forgetting.

4.6.2 Threshold of recognition and recall.

As for the λ and μ coefficients, and as our model of memory remains a very simple one, we have set both the thresholds of recall and recognition of all the objects of the cognitive map, to 0.5, which is the half of the interval on which lies each parameter.

5 The navigation.

5.1 The real-time planning.

As Arkin highlights it (Arkin, 1989), an efficient algorithm for urban navigation should manage reactive and planned navigation together. Our algorithm is designed around two main steps (we do not give details of it, only the concepts which underlie it, as it is fairly complex in terms of cases to treat):

- The planning : the agent is given a starting point and a destination, then it plans its route between this two points computing the plan with elements taken from the Filter IHT-graph (high-level planning) and the graph of landmarks (low-level planning) through what we name the Up-Down planning.
- The reactive navigation.

5.2 Up-Down planning.

1. In the case where all the elements lying between the start point and the end point are know and recalled, the algorithm acts this way:
   - The father local areas of the starting point S and end point E are identified, say Eloc1 and Eloc2.
   - The shortest path E={Eloc1,Ei,…,Ej,Eloc2} between Eloc1 and Eloc2 is found in

the Filter Local area layer. It is the high-level planning.

- A subgraph L_s of landmarks is given by the partition of E in the graph of landmarks of the cognitive map.
- The sequence of landmarks leading from S to E, which have the higher recall is chosen in L_s, representing the best known set of paths.
- The agents is guided by its sequence of landmarks, and follows and recomputes its path refining it according to the potential recognised spaces along the previous path.

2. In the case when it lacks some local areas or landmarks on the way from S to E:

- The path is computed like above, using the know elements around S/Eloc1 and E/Eloc2.
- In the region where local areas lack, or landmarks lack, the algorithm switch in reactive navigation.

5.3 The reactive navigation.

In case the agent is really lost, i.e. walks in a zone where nothing triggers recognition or recall in its cognitive map, it follows the same direction, preferably along bigger axis or road section until it likely meets a known landmark. Then it recomputes a new path, with the Up-Down planning algorithm, if possible, from this new landmark to end point E. If it is not possible it switches again to reactive navigation mode until he likely meets a significant landmark for the planning until the end point E.

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Fig 10 : Agent wandering around the city (subjective view of the simulation)

6 Conclusion and future work.

We have presented a model of cognitive map merged with a model of human-like memory, designed to implement reactive and planned navigation. The model of human memory remains simple, but is generically designed to allow the various parameters controlling the system, to be changed relatively to the type of simulation required. In all the configuration of the navigation process, the start point and the end point of the route are supposed to be known. Which leads to a restriction of the emerging cases of planning and navigation in the simulation. We plan to extend our work, endowing one agent with the ability to ask its way to another. In a first step exchanging information from their respective cognitive map, via a system of short term memory(SMS), and then, linking the information gathered in the cognitive map and the database to a natural speech processing unit, which would offer a readable way to follow the agent's different planning stages. It would put in relief the interesting problem of the representation of non-explored items in SMS, issued from the route communication, and their integration in long-term memory.

7 Acknowledgements.

The author would like to thank specially Fabrice Lamarche and Olivier Filangi. Without them this work would not have been realised.

8 References

Arkin, R.C., 1989, "Towards the unification of navigational planning and reactive control", In Working notes of the AAAI Spring symposium on robot navigation, Stanford University.

Barkowsky, T., 2001, "Mental processing of geographic knowledge". In proceedings of COSIT'01, LNCS 2205, pp. 371-386.

Chopra-Khullar, S., Badler, N., 1999 "*Where to look ? automating attending behaviors of virtual human characters* ". In Proceedings of Autonomous Agents '99, Seattle, WA, ACM.

Courty, N., 2002, "Animation refenrencee vision: de la tache au comportement." Phd Thesis, INSA-IRISA, Rennes.

Eich Metcalfe, J. ,1982 " A composite holographic associative recall model". Psychological Review, 89(6):627--661.

Farenc, N., Boulic, R., Thalmann, D., 1999, "*An informed environment dedicated to the simulation of virtual humans in urban context".* In proceedings of EUROGRAPHICS'99, P. Brunet and R. Scopigno, editors. Blackwell.

Fernández, J.A., González, J., 1997, "A General World Representation for Mobile Robot Operations", Seventh Conference of the Spanish Association for the Artificial Intelligence (CAEPIA'97), Malaga, Spain.

Gillund, G., Shiffrin, R. M., 1984, "A retrieval model for both recognition and recall"., In Psychological review, volume 91, number 1.

Jefferies, M.E., Yeap, W.K., 2001,"The utility of global representations in a cognitive map" , ". In proceedings of COSIT'01, LNCS 2205, pp. 233-246.

Lamarche, F., Donikian, D., 2002, "Automatic orchestration of behaviours through the management of resources and priority level.". In proceedings of AAMAS'02, Volume 3, pp. 1309-1317, Bologna, Italy.

Lynch, K., 1960, "The image of the city". Cambridge, Massachusetts : MIT Press.

Mallot, H., 1997, "*Behavior-Oriented Approaches to Cognition: theoretical perspectives"*. Theory in biosciences, vol. 116, pp. 196-220.

Michon, P.-E., Denis, M., 2001,"When and Why are visual landmarks used in giving directions?". In proceedings of COSIT'01, LNCS 2205, pp. 292-305.

Montello, D. R., 1998, "A new framework for understanding the acquisition of spatial knowledge in large-scale environments", In Spatial and temporal reasoning in geographic information systems, pp. 143-154, New-York: Oxford University Press.

Murdock, B. B., 1982, "A theory for the storage and retrieval of item and associative information." Psychological Review, 89(6), 609-626.

Penn, A., 2001, "Space syntax and spatial cognition. Or, why the axial line?". In proceedings of 3rd Space Syntax Symposium. Atlanta.

Raaijmakers, J. G. W., Shiffrin, R. M., 1981, " Search of associative memory.", Psychological Review, 88, 93-134.

Raupp Musse, S., 2000, "*Human Crowd Modeling with Various Levels of Behaviour Control"*. Phd Thesis, EPFL, Lausanne, Switzerland.

Taylor, H.A., Tversky B., 1992 ,« Spatial mental models derived from survey and route descriptions. », Journal of Memory and Language, Volume 31, pp. 261-292.

Thomas, G., Donikian, S*., 2000, "Modeling virtual cities dedicated to behavioural animation"*. In Proceedings of EUROGRAPHICS'2000, M. Gross and F.R.A. Hopgood, editors, volume 19. Blackwell Publishers.

Tversky, B., 1993, "cognitive maps, cognitive collages, and spatial mental models" In Spatial Information Theory, pp. 14-24, Berlin: Springer.

Yeap, W.K., Jefferies, 1999, M.E., "Computing a representation of the local environment.", Artificial Intelligence Volume 107, pp. 265-301.