



Route planning using an emergent hierarchical architecture
by Clemente Ignacio Izurieta

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in
Computer Science

Montana State University

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Abstract:

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Places are considered to be connected to one another when there is a traversable route that directly links them. Each time the route is traversed, the cognitive relationship between the two places strengthens. If a place is visited often enough, it will come to symbolize an entire region. Once a region is symbolized, all other places in the region are inhibited, allowing each region to be only symbolized by one place. This process can continue indefinitely, leading to a hierarchy with more and more levels.

We explore some of the properties of such a hierarchical model including how it develops and how it affects the quality of a planned route.

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APPROVAL

of a thesis submitted by
Clemente Ignacio Izurieta

This thesis has been read by each member of the thesis committee and has been found to be satisfactory regarding content, English usage, format, citations, bibliographic style, and consistency, and is ready for submission to the College of Graduate Studies.

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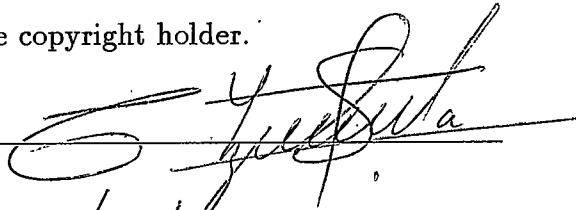
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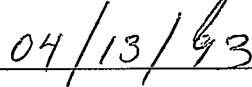
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Signature

A handwritten signature in dark ink, appearing to be "S. J. Suta", written over a horizontal line.

Date

The date "04/13/93" handwritten in dark ink over a horizontal line.

This thesis is dedicated to my parents Clemente and Georgina Izurieta:

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ABSTRACT

A cognitive map is a representation of an environment that consists of both nodes and connections. How this hierarchical structure might emerge from a computational standpoint is the focus of this research.

The system builds a cognitive map by traversing routes in an environment. A hierarchical structure emerges when a certain place has been visited often enough to justify its coming to be representative of an entire region.

Places are considered to be connected to one another when there is a traversable route that directly links them. Each time the route is traversed, the cognitive relationship between the two places strengthens. If a place is visited often enough, it will come to symbolize an entire region. Once a region is symbolized, all other places in the region are inhibited, allowing each region to be only symbolized by one place. This process can continue indefinitely, leading to a hierarchy with more and more levels.

We explore some of the properties of such a hierarchical model including how it develops and how it affects the quality of a planned route.

INTRODUCTION

A cognitive map is an individual's representation of an environment. Figure 1 shows the major steps involved in building a cognitive map. The first component is the physical world, and represents the environment that the system is trying to learn. The second component is a primitive description of the environment, where places in the physical world are represented as nodes in an undirected graph. A connection between two nodes exists if there is a corresponding path between the corresponding places. One paper [Yeap, Hardley 91] refers to this second component as a raw map with very little *a priori* cognitive information. Most commonly, other literature [Hirtle, Jonides 85] refer to this information as spatial information. Distance and relative locations of places are examples of this type of information. The third component of a cognitive map, also known as a full map [Yeap, Hardley 91], contains the non-spatial characteristics of an environment. These characteristics are learned over a period of time, and represent an individual's experience. For example, associating a cluster of places as belonging to a specific region is a process that requires extensive knowledge of an environment. It is this experience that makes cognitive maps unique.

In this system, the raw map is given by a Euclidean map. The Euclidean map is a simple graph representation of a two dimensional environment, where navigation is only possible within a planar surface. Vertical movements are not allowed. Numer-

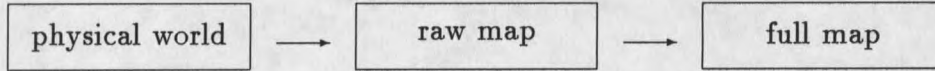


Figure 1: A cognitive map and its components

ous algorithms exist that concentrate on developing raw maps through exploration. For example, [Lumelsky, Mukhopadhyay, Sun 90] describe two algorithms for acquiring raw maps of planar terrains with obstacles. This thesis concentrates on attaining the full map. An initial raw map is given as a basis from which experiences will be built, and non-spatial characteristics will evolve as the individual familiarizes himself with the environment.

There are an infinite number of non-spatial attributes that may be recorded in a cognitive map. We are interested in developing non-spatial characteristics that will assist in route planning and environment representation. Evidence suggests that humans remember only the major landmarks when planning routes, and fill in the rest of the route as they navigate through the environment. Numerous experiments [Allen, Kirasic 85] have been designed to see how route knowledge on macrospatial environments is retained. Studies on macrospatial environments are concerned with the development of knowledge in large scale environments. In their findings they suggest that “individuals tend to organize their experience into distinct segments.” They show how this segmentation affects an individual’s proximity judgements, and distance estimates. Segmentation of routes also suggests that information might be

stored in some sort of hierarchical structure. A series of studies [Hirtle, Jonides 85] experiment with this idea and show how it affects human orientation judgement. They suggest that landmarks that are close in proximity tend to be associated with a particular region. Numerous psychological experiments have been carried out in this subject, for example, an experiment where "most subjects judge Reno, Nevada to be northeast of San Diego, California, even though it is actually northwest" [Stevens, Coupe 78] shows that individuals use some kind of "superordinate relationship" such as a hierarchy of landmarks to make their decision.

In the system introduced in this thesis (Bushman), a hierarchical structure is used to store route information. The hierarchical structure is dynamic in the sense that it *grows* as the individual navigates through the environment. As new associations of places are formed, new levels in the hierarchy emerge. The hierarchy becomes a kind of database that stores route knowledge in a global sense, and most of this information is used when planning a route to some destination. Figure 2 shows a hierarchical structure consisting of three levels.

In this figure, we see an example of a hierarchy where the physical world is made up of some dark locations, and some light locations. The dark locations represent regions in the physical world. Two such regions are depicted. A location emerges to become a landmark, when it has been visited often enough to justify its coming to be representative of a region. The two vectors depicted originate from such locations. The squares at the end of the vectors represent the emerged higher level landmarks,

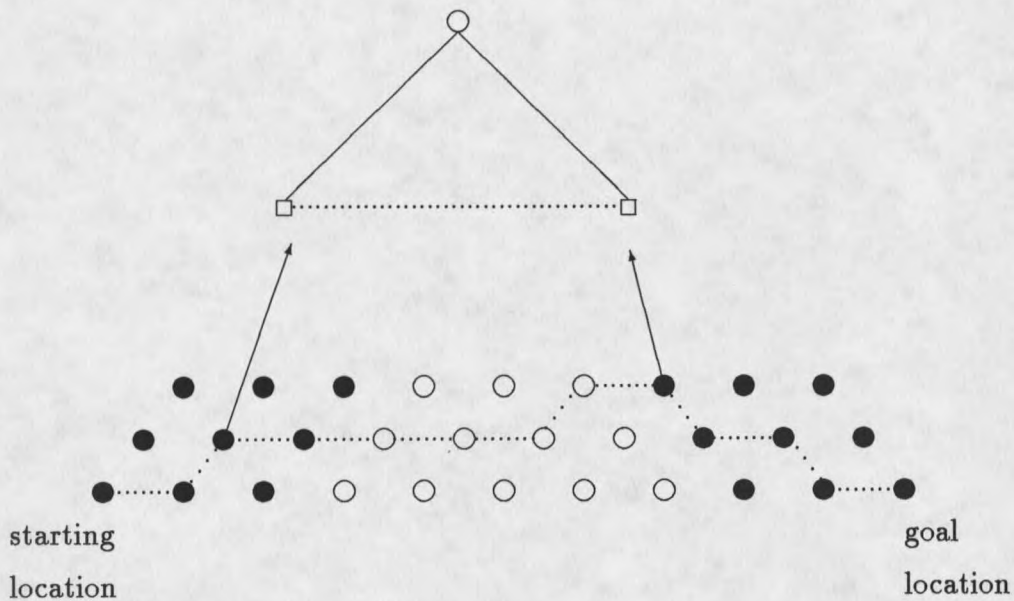


Figure 2: Hierarchical structure used for planning routes

with the dotted line representing a logical connection between them. Connections of this type are needed to maintain logical relationships between landmarks. The circle represents yet another region, this time however, it represents the region of squares. To plan a route from a starting location to some goal, the first region associates itself with a higher landmark in the hierarchy. It associates itself by finding a location in the current level that has been traversed enough times to become a representative landmark of the region. The same is done by the other region. A route is now planned at this higher level. Once this process is finished, we drop a level in the hierarchy and plan a route from the start location to the location that represents the current region at the next level, then we plan to the location that represents the region where the goal location is located, and finally we plan to the goal location.

The following chapters provide a detailed discussion of how the system operates, and several tests on the robustness of the system are performed. Future research will be discussed that shows what areas of this system need to be pursued in the future.

A REVIEW OF RELATED WORK

Before any planning can take place, a representation of the world is essential. There are numerous ways of providing a representation of the world, such as, undirected graphs, hierarchies, self organizing neural networks, and even rules in a production system. Once a representation is chosen, the selection of a method that best utilizes the representation needs to be selected. This method should have the ability to search the knowledge in the representation in such a way that goals are accomplished in an efficient manner. The following section gives a partial overview of some approaches to world representation and route planning.

Kuipers

One system [Kuipers 78] attacks the problem of modelling human routes in terms of a production system. The knowledge about routes is stored as two types of associative links:

- Link $V \rightarrow A$ means that when the current view is V , then action A is taken to follow the route.
- Link $(V, A) \rightarrow V'$ means that if the action A is taken in the context of view V , the result will be view V' .

If a route consists of links of both types, then the entire route can be reproduced in the absence of the environment, however, if links of type $V \rightarrow A$ are the only ones present, the route can only be traversed physically. This is due to the fact that the environment itself contains links of the type $(V,A) \rightarrow V'$.

The method used by Kuipers is not without its counterpart in biology. Studies about orientation techniques used by honey bees [Whener, Raber 79] show that reconstruction of paths is carried out using sunlight as a reference. Most importantly however, bees are assumed to memorize two dimensional photographs of the environment which they use together with the sunlight cues to reconstruct routes.

RUR

This system [Nehmzow, Smithers 90] was developed to explore map building abilities using self organizing neural networks integrated in RURs (Really Useful Robots). Basically, the robot is placed within some environment, and allowed to explore the environment over a period of time. During this time the robot navigates the same map a number of times. Each time that the robot encounters a corner, an input vector describing this corner is given to the neural network. After a number of trials in the environment, the robot has adjusted the weights of the neural network in such a way that it is now able to recognize different areas of the map. When this state is reached, it is said to have an internal representation of the environment, a cognitive map.

This mechanism can also be compared to the recognition abilities that bees use to navigate. As described in one system [Kuipers 78], bees use two dimensional pictures of the environment to help aid navigation and reconstruction of routes. A method similar to a self organizing neural network could be being used to actually recognize this two dimensional picture. Various studies [Gould 88] support this thread of investigation. One such study states that "bees compare stored retinal patterns to the current retinal pattern to calculate a flight direction vector."

Toto

Toto is a robot equipped with sonar sensors and a compass. The robot [Mataric 90] is based on the subsumption architecture by Rodney Brooks. There are three layers of competence that are used by Toto, however, this overview will only concentrate on the map building layer. Competence layers act independently to carry out specific tasks needed by the robot. The internal representation of the environment is achieved using a network of locations representative of some physical world. Each node in the network has the ability to send and receive signals from adjacent nodes. Building a cognitive map is achieved through exploration of the environment, and assigning a new node to newly encountered locations. Finding a route to a given goal is achieved through a process called *spreading activation* and works by having the goal node in the network send a signal to adjacent nodes, which in turn spread the signal in the same manner as the goal node. When the signal reaches the node

where the robot is located, all that the robot needs to do, is follow the signal from the direction it arrived.

The distributed network model of a cognitive map [Mataric 90] is representative of the organization of the rat's hippocampus, where each node is representative of a *place cell*. Place cells are said to fire when a rat is placed in a known location. A more biologically plausible situation is to represent a landmark with a set of nodes rather than a single node. It is very likely that places are represented by more than a single place cell in the rat's hippocampus.

Summary

The research surveyed in this section represents a small sample of a vast research area. A common thread running throughout the diverse research surveyed is a relationship with biology. In the following chapters, a detailed description of *Bushman* will be provided, and its hierarchical representation together with its planning algorithm will be studied.

THE HIERARCHY AND ALGORITHM

Bushman consists of two major components. The first component is an internal knowledge representation of a two dimensional environment. This knowledge includes the spatial and non-spatial information described in the introduction. The second component is a recursive algorithm that uses the internal knowledge representation to plan routes.

The Physical World

The physical world is represented as a graph, and consists of both nodes and connections. Each node represents a location and each edge represents a path between two locations. Each location in the graph contains the following:

- A name
- An activation threshold
- Map coordinates
- A status level
- A list of adjoining neighbours

The Emergence Of Hierarchies

The raw map forms the foundation upon which the full map will develop. The system will build a cognitive map by traversing routes in the physical world. A route is considered to be a path of successive edges between any two locations. A hierarchical structure will emerge when a certain location has been visited often enough to increase its activation value beyond some threshold. The activation value is otherwise known as the saliency of a location, and measures its importance with respect to other locations. Figure 4 shows a physical world consisting of five locations and their respective activation values. The activation value of the black location has surpassed that of the threshold, and has therefore promoted the location to become representative of an entire region. The size of a region is variable and can be preset by the user. Any locations within this region are inhibited from rising in importance, and hence rising in the hierarchy. This avoids having every location rise in the hierarchy.

In time, other locations will rise in importance and will be promoted to a new level. When a location has its importance raised, new connections will be made to other nodes at this same level of importance. The system looks for landmarks that are close in proximity to the newly promoted location (now a landmark), and creates a bidirectional connection from the new landmark to all the landmarks within a given radius at the new level. If no landmarks appear to be within the specified radius, then the newly promoted location looks for the closest possible landmark

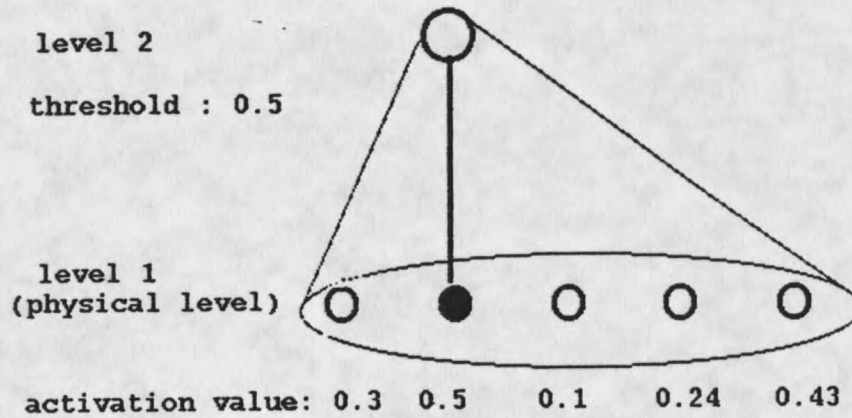


Figure 4: Emergence of a hierarchy

at the new level. Figure 5 illustrates a more complex hierarchy. This process can continue indefinitely, leading to a hierarchy with more and more levels. The raw map is eventually transformed into a hierarchy of landmarks, where the original landmarks can end up at different levels of importance, based on the experience of the computer.

The cognitive map that emerges is completely dependant upon the experiences of the route planner. This suggests that different individuals will develop distinct cognitive maps of environments based upon their experiences, and hence gives each and every one of us a sense of uniqueness. Each individual will develop their own image of the world. As [Lynch 60] puts it, "the observer himself should play an active role in perceiving the world and have a creative part in developing his image."

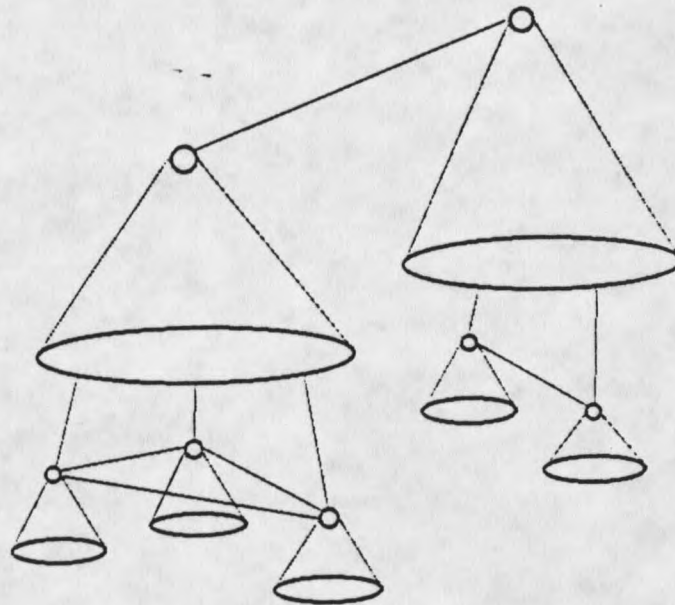


Figure 5: A complex hierarchical structure

The Algorithm

Before describing the algorithm, it is necessary to show how location coordinates, and synaptic strengths between neighbours, are used to aid route planning.

The coordinates of a location help calculate its relative direction from another location. For example, if location A has coordinates $(1,0)$, and location B has coordinates $(1,1)$, then we say that location B is north of location A. Similarly, location A is south of location B. The synaptic strength between any two locations is representative of the experience that exists in traversing this segment of a route. When a segment between two locations is traversed, then the segment's synaptic strength is increased by a constant amount. Navigation from one location to another

$$W1 * \text{ORIENTATION} + W2 * \text{SYNAPTIC STRENGTH}$$

Figure 6: Navigation formula

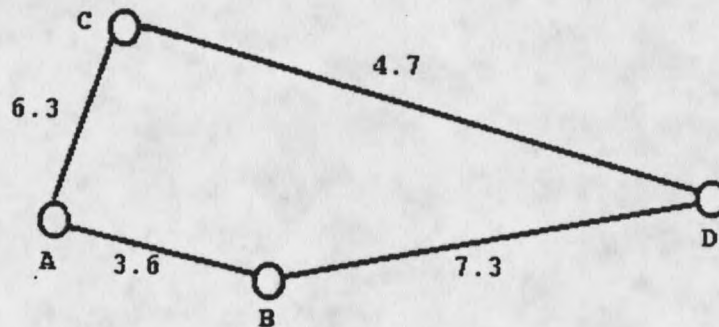


Figure 7: Navigation example

is now dependant on both orientation and synaptic strength using the formula in figure 6. Each of the parameters (orientation and synaptic strength) has a weight associated with it. If the weight associated with synaptic strength is set to zero, then navigation will be based entirely on orientation, and vice versa. Testing for optimal values of these two weights is carried out in the next section of this thesis.

As an example, figure 7 shows one level of the hierarchy with four interconnected locations. We wish to navigate from location A to location D.

Assume that the orientation weight is set to zero, and hence navigation will

be carried out using only past experience. The first segment of the route is from location A to location C. Since there is a higher synaptic strength connection flowing from A to C than from A to B, this becomes the choice with the highest weight. (If we had carried out navigation based entirely on orientation, then location B would have been chosen as the next location in our path.) Continuing the example at C, the next route segment is from C to D, and since this is our goal, the navigation process stops.

We are now ready to examine the route planning algorithm. Figure 8 shows a pseudocode description. The elegance of this algorithm is apparent. The algorithm uses a recursive method that exploits the hierarchy developed so far to navigate from a location to a destination. The system takes advantage of its hierarchies to perform local, and global navigation. If two locations fall within the same region, then there is no need to use the hierarchies, and navigation can be carried out by simply using the navigation formula within the region. This process is known as local navigation. If however, the start and destination locations fall in different regions, then the algorithm makes use of the current hierarchy to navigate. This is known as global navigation. [Mataric 91].

The best possible way to understand how the algorithm works, is by doing a walkthrough with a very simple example. The initial setup of the environment is described by figure 9. The physical world is represented with the underlying seven by seven square grid raw map. Three locations have emerged to a higher level, and

ALGORITHM

```

Plan( start, goal, level )
{
  IF start == goal THEN
    return

  ELSEIF a landmark at (level + 1) is attainable from both
        start and goal THEN

    newstart <- the (level + 1) landmark connected to start
    newgoal  <- the (level + 1) landmark connected to goal
    Plan( newstart, newgoal, level + 1 )
    Navigate( start, newstart )
    Navigate( newstart, newgoal )
    Navigate( newgoal, goal )

  ELSE
    Navigate( start, goal )
}

```

Figure 8: Route planning algorithm

are depicted as nodes with a cross on top. Each of these higher level landmarks is representative of some region at the lower level of the cognitive map, and each of these regions is enclosed by a rectangular perimeter. Given this initial setup, the algorithm will plan a route from landmark x to landmark y .

The algorithm is initially called as follows:

- Plan(X , Y , 1)

The third argument to the procedure indicates that execution starts at level one, which is the physical world. Since the start location is not the goal location ($X \neq Y$), but the start and goal locations can attain a higher level, then the *elseif* section of the algorithm evaluates true and is executed. Location X associates itself with higher level landmark A which becomes the new start, and location Y associates

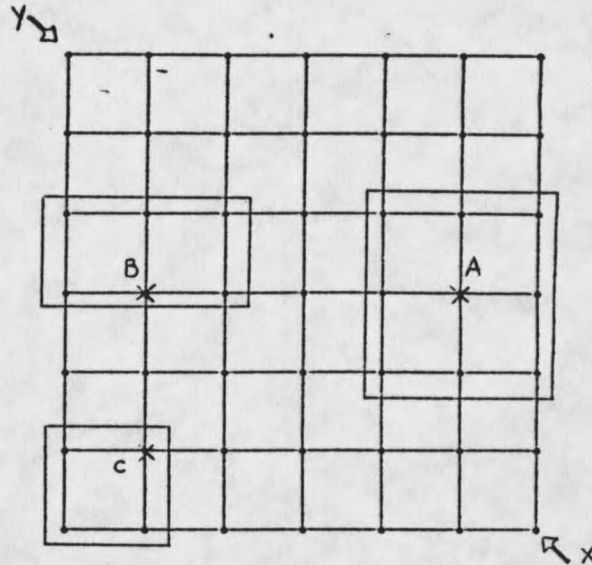


Figure 9: A sample cognitive map

itself with landmark B, which becomes the new goal. At this stage, a recursive call is made to procedure *Plan*, and it looks as follows:

- $\text{Plan}(A, B, 2)$

The third argument to the procedure indicates that planning is to occur at level two of the hierarchy from landmark A to landmark B. Since the start landmark (A) is not the goal landmark (B), and there are no more attainable levels in the hierarchy, the *else* part of the algorithm is executed, and the navigation from A to B, as shown in figure 10, is carried out. This navigation process was described in the previous section, and is carried out based on orientation, and synaptic strength factors. Route planning at higher levels produces logical routes.

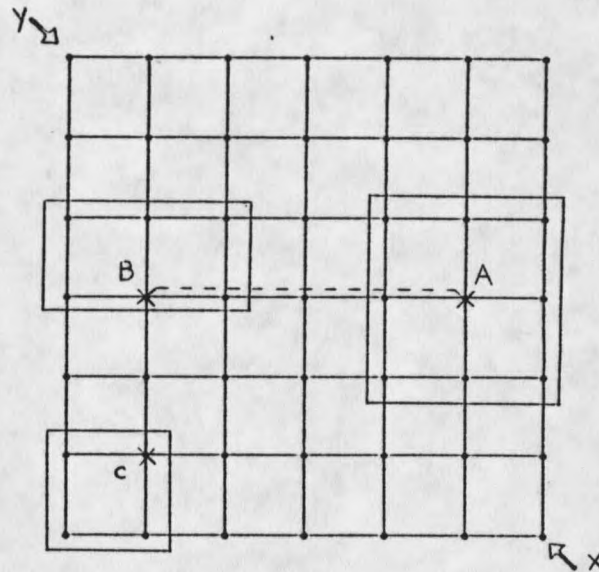


Figure 10: Planning of route at level two

The algorithm now returns from the recursive call, and resumes execution in the *elseif* section immediately after the call to $Plan(X, Y, 1)$. Three calls are made to procedure *Navigate*. Note that navigation now takes place at level one of the hierarchy. The first call plans a route from the original start location (X) to the region represented by landmark A. The second call plans a route from A to B. Note that this is not a logical route like the one at level two, it is the physical route at level one of the hierarchy. The third and final call plans a route from the region represented by landmark B to the goal location (Y). This final stage of the algorithm is depicted in figure 11.

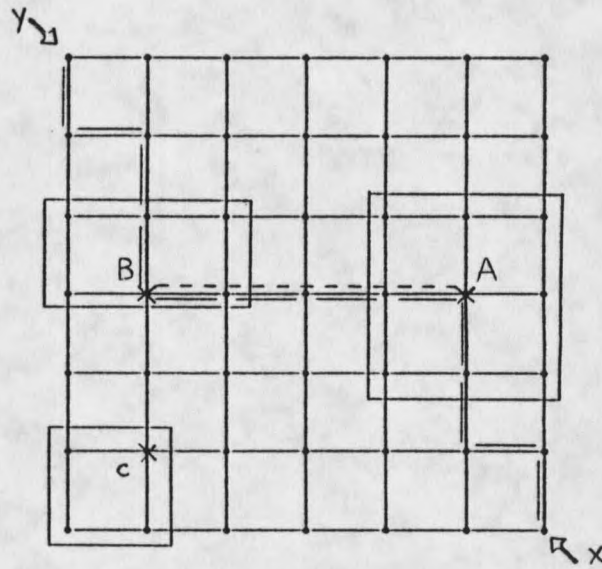


Figure 11: Planning of route at level one

EMPIRICAL ANALYSIS OF BUSHMAN

This section empirically analyzes the behaviour of the algorithm: The likeliness of locations rising to higher levels in the hierarchy, the tradeoff between navigating on past experiences and/or orientation, the restructuring of the hierarchy as new locations emerge and how it affects route planning, and the factors leading to useful and detrimental higher level landmarks, are explored.

Probability Of A Location Rising To A Higher Level

Locations provide the basis for building cognitive maps. Humans can learn to navigate in different environments and use landmarks to help guide their route selections. "After taking the same path several times it becomes unlikely that he watches for street names, but rather certain landmarks located at key positions guide him." [Palakal, Thai 90].

An important aspect of landmarks is that some of them become representative of different areas. Many factors contribute to the selection of landmarks within a region. Unorthodox architecture, color, height, geographical location, past experiences, etc, are some of these factors. Our system uses only the activation value of locations to determine their saliency. We expect that locations towards the center of a region will become salient, and hence landmarks. These landmarks are more

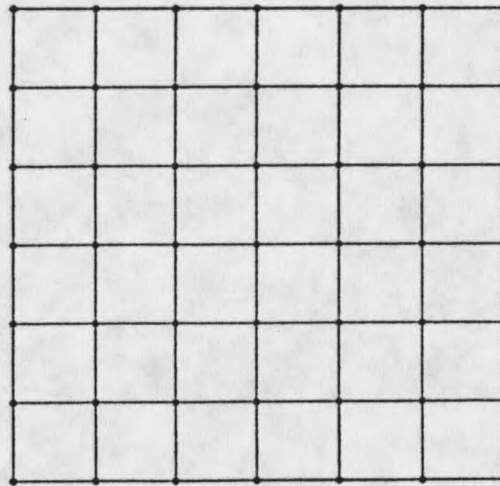


Figure 12: Square grid of locations

likely to be used as part of any given route. A square grid of locations provides an intuitive and clear test bed for this experiment. Figure 12 shows the physical world used as the starting configuration.

The experiment is performed by randomly generating one hundred different start and destination locations. A route will be planned for each such pair. The system is set up so that the route planning algorithm is only allowed to rise one level in the hierarchy, so that the development of a two level cognitive map can be observed. As locations rise to the second level and become landmarks, they can be used in the planning process. There are a number of parameters that help determine the way navigation is carried out between two different locations. Among some of these parameters are the size of the inhibition radius, and the weights of the navigation formula described in the previous chapter. The inhibition radius prevents

GRID MAP SUBDIVIDED INTO REGIONS

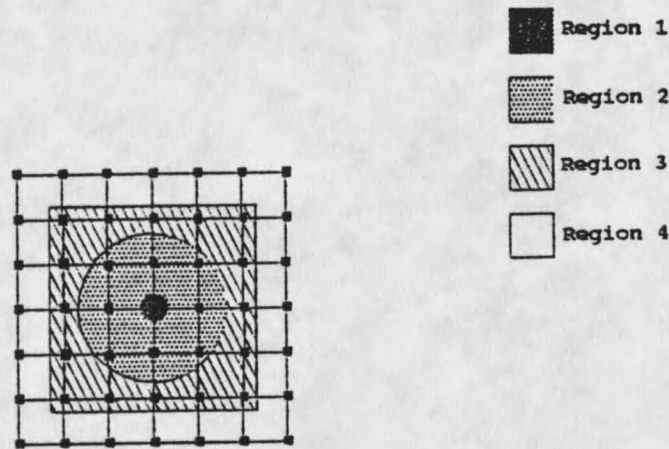


Figure 13: Subdivided square grid of locations

other locations within a certain proximity of a known landmark from becoming landmarks themselves, thus avoiding overpopulation of landmarks. Different settings are tried, and a comparison of results is carried out. Each test is carried out one hundred times, and the average results are taken to be representative of a given scenario. Figure 13 shows the subdivided square grid of locations into different regions.

Navigation was carried out with various blends of orientation and past experience by changing their respective weights in the navigation formula. The results from all experiments suggest the same conclusion. The landmarks towards the center are more likely to emerge to the second level first. After a central location rises to become a landmark, it inhibits all other locations within a specified radius from

rising, hence it takes longer for subsequent locations to rise because they are located on the outer edges of the graph with lower rising probabilities. If, however, one of the edge locations emerges to the second level first, then it takes less time for other locations to emerge to the second level because the new locations are positioned towards the center of the grid. Figure 14 shows the probabilities of locations rising to the next level. The total probability of a region is the product of the number of locations in the region and the probability of any given location in the region. See figure 13 for a picture of the regions. It is interesting to see the shape that the second level of the cognitive map has, and how it evolves into a more complex structure as more routes are planned. The evolution of this level is depicted by figure 15. Each of these pictures is a separate experiment, and strongly supports the fact that landmarks evolve from the center of the map.

Experience Versus Orientation

In the previous chapter the operation of the navigation formula was described. As recalled, navigation is carried out using a combination of past experience and orientation. Each of these factors has a weight associated with it, hence we can control the method of navigation by varying the weights. The navigation formula is used to navigate at all levels in the hierarchy. Thus, it suffices to study its behaviour at the raw map level.

The domain of the graph is the difference between the orientation weight and

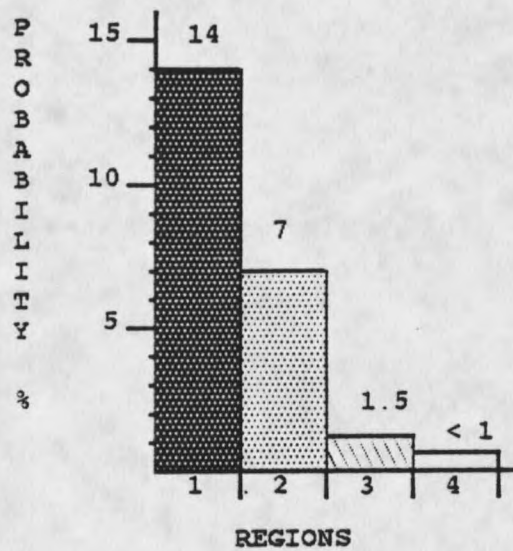
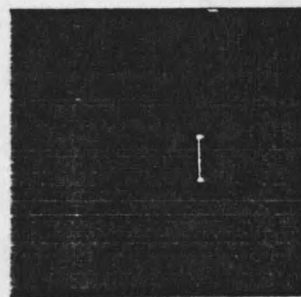


Figure 14: Probability of a landmark rising in a given region

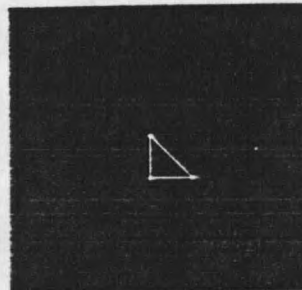
the experience weight. Figure 16 shows the performance of the navigation formula measured in terms of the number of successful routes planned. The system is allowed to plan a maximum of one hundred routes. This value is empirically large enough to make conclusions about the behaviour of the weights.

Close examination of this graph shows that when the difference between the orientation weight and the experience weight is $+1$, then all routes are successfully planned. This weight setting is representative of the scenario where navigation is entirely dependent on orientation, and the experience factor does not play a part. As the difference between the weights decreases, so does the number of successful routes planned. Eventually, when the difference between the two weights reaches a value of -0.5 , meaning that navigation is based more on past experience than orientation,

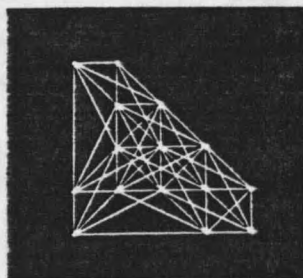
EMERGENCE OF HIGHER LEVEL MAP AFTER PLANNING :



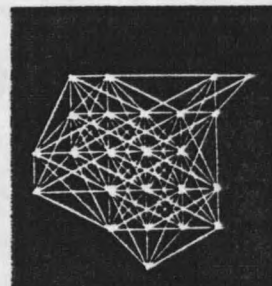
a) 10 ROUTES



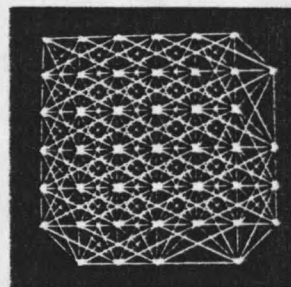
b) 30 ROUTES



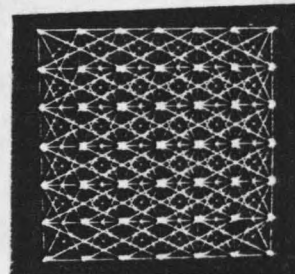
c) 50 ROUTES



d) 120 ROUTES



e) 200 ROUTES



f) 250 ROUTES

Figure 15: Evolution of landmarks in a cognitive map

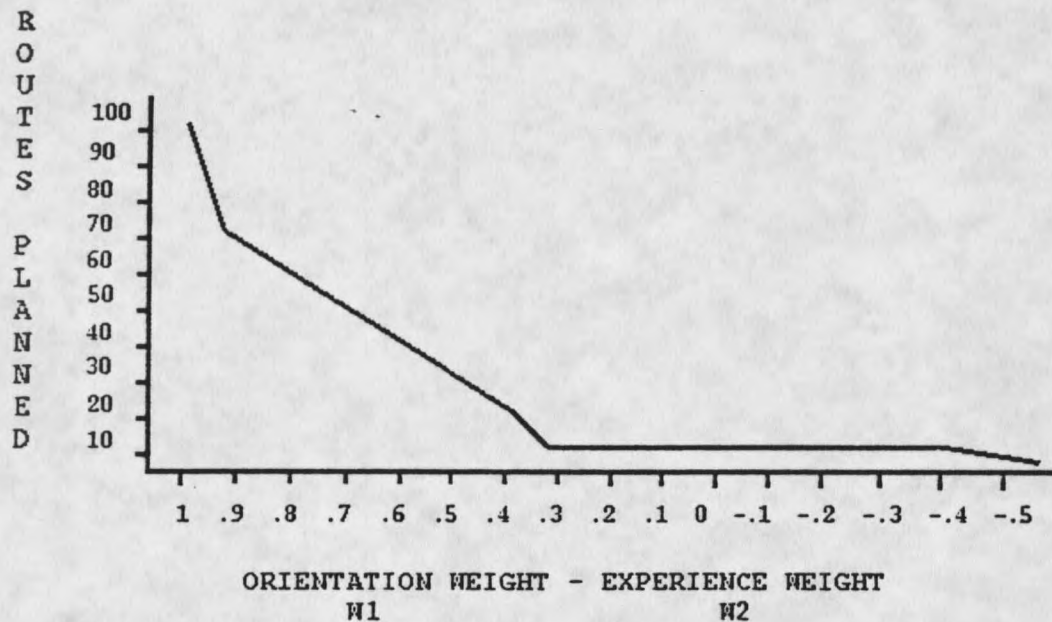


Figure 16: Experience versus orientation

the number of successful routes drops to 1. This phenomenon is easily explained. When we base our navigation entirely on past experience, we are only using the synaptic connections between the landmarks, and only the stronger connections are selected on our path. The navigation algorithm gets stuck in closed loops and is never able to reach its destination. To avoid closed loops we introduced a damping factor that reduces the synaptic connections of already traversed paths. In essence, the algorithm remembers what it has seen before, and does not choose the same path again. This occurs because every time that a landmark is encountered, the system adds a constant value to the local damping factor of the currently visited landmark, and subtracts this value from the synaptic connection, thus making another route segment potentially more attractive. The damping factor helps to prevent choosing

the same route again, but it does not help find the correct path. Eventually the destination landmark may be found by luck. The results obtained suggest that some measure of orientation is invaluable needed to serve as a heuristic that guides navigation.

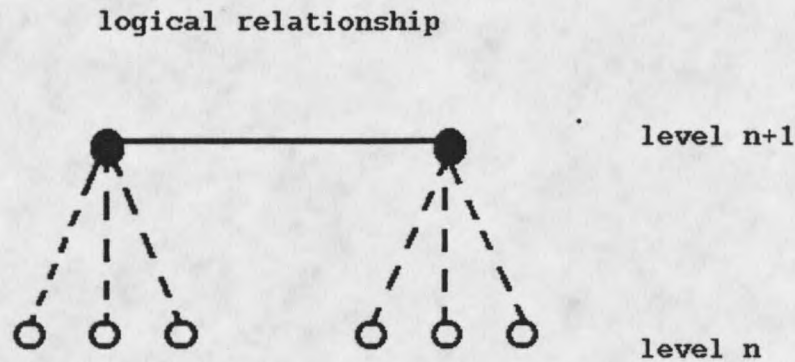


Figure 17: A hierarchical map

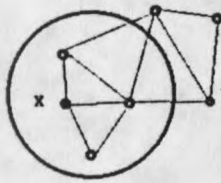
Restructuring The Hierarchy

As familiarization with an environment increases, so do past experiences. Past experiences increase when the connection between any two locations is strengthened. This implies that the hierarchy representing the cognitive map is in an everchanging state. Figure 17 shows a higher level map where the dark line represents a connection between the two dark landmarks in the current level. The dotted lines represent the landmark connections of the light locations at level n to the dark landmarks at level $n + 1$. The dark landmarks are representative of a region in the immediate level below.

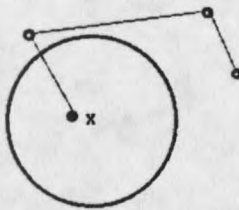
The dark connection between the two landmarks is intended to represent

a logical relationship between the two landmarks. These are the two locations that have emerged to become representative of the regions at the lower level n . The criterion for their logical relationship is that humans tend to associate similar objects in the same class, and the levels of the hierarchy are representative of these classes. Landmarks in a given level of the hierarchy represent similarly sized regions at lower levels of the hierarchy. When a new location (object) evolves into the next cognitive level (class), the logical relationship among these landmarks changes to include the new location in the cognitive level. Figure 18 shows how the connections of the cognitive map adjust to fit the emerging landmark. An emerging landmark connects itself to all landmarks within a specified radius, thus creating relationships based on proximity. If this radius is too small, and the emerging landmark cannot connect itself to any landmarks in the new level, then the closest landmark in the new level is chosen. The first landmark to emerge to a new level is the only landmark that can stand alone until new landmarks emerge. This procedure maintains the unity of the maps at each hierarchical level.

Thus, the restructuring of the cognitive levels force changes in the synapses between landmarks, hence changes in route plans. Only the landmarks within a given radius of the new emerging landmark experience these changes. When new locations emerge, the route planning algorithm makes immediate use of them in further planning. As individual levels of the hierarchy develop, the quality of routes improves. Quality of routes does not necessarily improve by finding shorter paths,



Situation 1 : Landmark X connects to all neighbours within radius.



Situation 2 : Landmark X connects to closest available landmark.

Figure 18: Adjusting level connections to fit emerging landmark

but by finding paths based on more experience with the environment. This is explained by the fact that there are more available landmarks within a map, and the navigation algorithm is provided with more options.

Usefulness Of Landmarks

The quality of landmarks is extremely important. In our square grid environment, this property is not readily apparent, however, if the environment is highly structured, the importance of their quality becomes obvious. Remember that landmarks help segment a route, and the presence of a poor landmark can cause the navigation to be thrown off course. Figure 19 demonstrates an effective and an

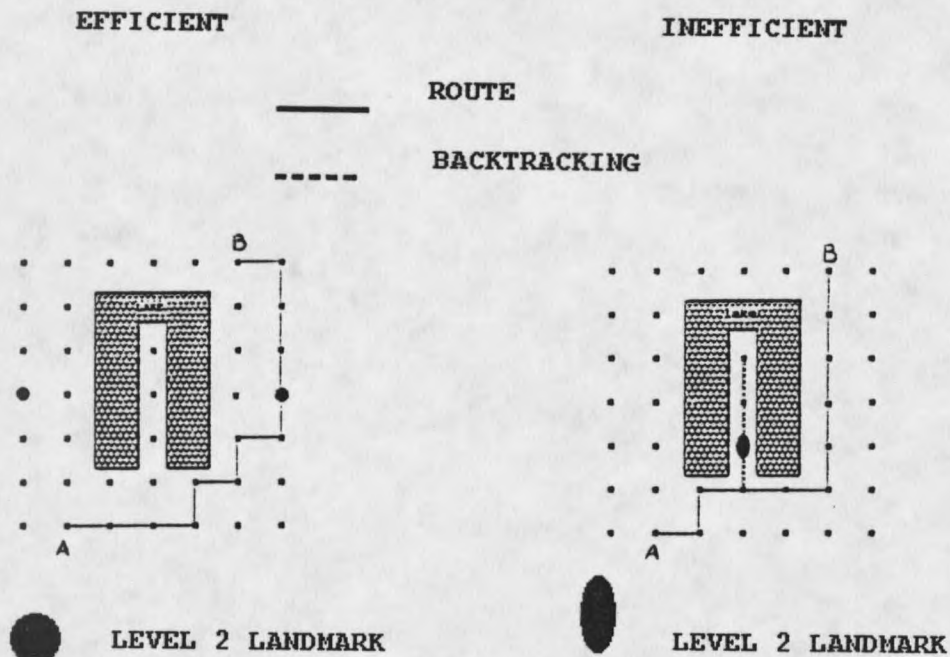


Figure 19: Efficient versus inefficient high level landmarks

ineffective use of navigating with a landmark.

One environment shows how the right location of a higher level landmark produces a quality route from A to B. The other environment shows the higher level landmark located in between the two arms of a lake. Planning a route from A to B causes the route planning algorithm to choose this landmark as an intermediate destination. The first stage of the planning produces a quality route to the higher level landmark. In the next stage of the planning however, the algorithm tries to reach the goal B and finds itself at the edge of the lake. At this time, the algorithm is forced to backtrack around the lake to reach the desired goal.

Bushman does not yet have the capabilities to predict whether a landmark

will produce quality routes at higher levels. Global knowledge of regions is required to make such predictions. It is expected that performance of the route planning algorithm would improve dramatically in highly structured environments as the one shown in figure 18, if such knowledge is incorporated.

CONCLUSION

This thesis was completed successfully with the helpful guidance of the faculty members from the Department of Computer Science. Although the system works satisfactorily, certain improvements and directions for future research are desirable.

Existing Features

Before pointing out the improvements needed by the system, it is necessary to summarize the existing features. Currently the system has the following major attributes:

- A hierarchical representation of the environment. Each level in the hierarchy represents a class of landmarks that are representative of regions at lower levels of the hierarchy. Higher levels represent bigger regions of the physical world.
- A dynamic hierarchy. When a location emerges to a new level, a restructuring process of the new level occurs to accommodate the newly emerged landmark. This process is analogous to the creation of new synaptic connections between neurons when new logical relationships are formed.
- A navigation procedure to plan routes within a level. Navigation depends on two factors, namely orientation and long term experience. It is possible to

control the way that navigation is carried out by changing the value of the weights associated with these factors.

- A recursive route planning algorithm. The algorithm uses the current information in the hierarchy to plan routes from some starting place to a given destination. The same navigation procedure is used to plan at each level of the hierarchy.

Improvements And Future Research

There are a number of future research areas that would prove to be valuable additions to the system. In the following subsections we describe each of these areas, and their respective applicability.

1. Short Term Memory. The current navigation formula uses an orientation factor, and a long term experience factor to make its decisions about which routes to follow. The long term memory factor is encoded via the strengths of the connections between landmarks. The existence of a third factor affecting the navigation equation is strongly supported by psychological literature, and is known as *short term memory*. The short term memory factor does not change the long term memory, it only affects it. For example, suppose that a mother asks her son to buy some groceries from the corner store. To achieve this task, the child needs to get to the store, but he does not need to think

of the route to get there because he has performed this task so many times that the route is now permanently stored in his long term memory. Suppose however that a recent murder occurred on the route that he usually takes. The next time the child's mother asks him to go and buy groceries, the child will take into consideration this recent murder, and may make adjustments to his normal route to the grocery store. This example shows how short term information can override long term memory.

It is an interesting problem to understand how this short term memory factor might operate, and how it might affect the navigation formula. Short term memory must also be represented from a computational standpoint.

2. Predicting The Usefulness Of Emerging Landmarks. In the previous chapter, it was shown how efficient landmarks at higher levels can have a dramatic effect on the quality of the route planned. At this stage in the development of the system, there is no way to predict the quality of emerging landmarks. A solution might be to statistically keep track of routes and the landmarks chosen within the route. A measure of efficiency could then be devised, and if a landmark proves to be inefficient, then a restructuring process would take over to delete this landmark, and find a replacement.

3. Initial Raw Map. At this stage, the raw map representing the physical world is fed into the system as an initial base from which a cognitive map can

be developed. Numerous algorithms exist to come up with this initial map, but a more biologically plausible solution is desired.

4. Inhibition. The system currently remembers places by using a damping variable described in the previous chapter. This damping variable allows the system to avoid getting stuck in closed loops when searching for a goal. A more biologically plausible solution to this problem is desire and would involve inhibition during route planning.
5. A True Distributed System. It has been suggested that the true distributed properties of a cognitive map come from using multiple nodes to represent a single landmark. These nodes are known as *place cells*. To add to the complexity of the problem, some of these place cells may be used as parts of multiple landmarks, hence depending on the current situation, a variable number of cells may represent a given landmark, and a different set may represent the same landmark at some other time in a different context.
6. A Forgetting Factor. A forgetting factor would operate by deleting or weakening certain connections between landmarks that have not been visited over some period of time.

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