

## Chapter 6

# Spatial Navigation in Virtual World

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**Abstract** One of the most challenging and complex tasks when working with virtual worlds is the navigation process. This chapter presents the possibilities of using neural networks as a tool for studying **spatial navigation** within **virtual worlds**. How it learns to predict the next step for a given trajectory, acquiring basic spatial knowledge in terms of landmarks and configuration of spatial layout. In addition, how it builds a spatial representation of the virtual world, rather like a cognitive map. The benefits of this approach and the possibility of extending the methodology to the study of navigation in Human Computer Interaction (HCI) and other applications are described in brief. The study of computation models of navigation and the potential of using cognitive maps in the modeling of navigational processes are described. **Non-visual spatial learning** model is presented for the spatial learning through virtual world exploration. Different types of **locomotion** in virtual world with their constraints and benefits are discussed. Intended readers of the chapter would be the mobility trainer, architect, city planner, cartographer, psychologist, and game developer.

Keywords: Artificial Neural Network, Navigation Model, Spatial Cognition, Virtual World

## INTRODUCTION

One of the elementary human needs is the need to know the world around us and to be able to freely navigate within this environment. Our daily life is occupied with (indoor as well as outdoor) activities moving from one location to another. We spend much of our time moving from one place to another within or between different environments (habitats). Survival of the individual is contingent upon adaptive skills to find, learn and return to specific places and often at specific times - such as the home or the working place - quickly and safely. These skills are summarized by the word navigation. Our navigation ranges from our daily way to work and may extend even to global travel.

When we move around new environments, we subconsciously build a mental image of the space we are in. This mental image is stored in the hippocampus, and is called a "**cognitive map**". The term "cognitive map" was first used by Tolman (1948) to describe a mental representation of spatial information used for navigation. Cognitive maps are cartographic illustrations of a person's internal

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representation of the spatial environment in which they live. However, sixty years later, we still don't have any hard answers about the structure of spatial knowledge.

Swarms of social insects also construct trails and networks of regular traffic via a process of pheromone laying and following. These patterns constitute is also known as a cognitive map in brain science. The main difference lies in the fact that the insects write their spatial memories in the environment, while the mammalian cognitive map lies inside the brain. In his paper entitled 'Cognitive maps in rats and men', Tolman (1948) outlined the evidence upon which he based his theory that rats use field maps of their environment in getting from one place to another. The relevant study (Tolman, Ritchie, and Kalish 1946) used the so-called sun-burst maze.

*Definitions of the cognitive map range from the general, 'a record in the central nervous system of macroscopic geometric relations among surfaces in the environment used to plan movements through the environment.' (Gallistel, 1990) to the specific, 'The essence of such a structure is the existence of a global representation of objects within some manifold or coordinate system from which their mutual spatial relationships can be derived.'*

As people act in the environment, they perceive surrounding space and acquire knowledge about it. Downs and Stea (1973) called this fundamental process cognitive mapping.

*Cognitive mapping is formally defined in Downs and Stea (1973) as "... a process composed of a series of psychological transformations by which an individual acquires, codes, stores, recalls, and decodes information about the relative locations and attributes of phenomena in their everyday spatial environment."*

*In other words, Downs and Stea (1973) define Cognitive mapping as the process of acquiring, forming, and maintaining spatial information and spatial knowledge.*

Knowledge acquired during cognitive mapping includes the identities of places and landmarks, the patterns of path connections between places, distances, and directions between places, and so on.

## Human Spatial Cognition

The longest standing model of spatial knowledge representation is the Landmark, Route, Survey (or **LRS**) model described by Seigel and White (1975) and Goldin and Thorndyke (1982). This model not only addresses spatial knowledge but also the development process. They have identified three stages of development of an individual's cognitive representation of a large-scale navigable space (Seigel & White, 1975).

- During an initial period of familiarization, a person focuses on the important locations in the environment. Knowledge in this stage consists of a disconnected set of landmarks.
- After more exposure to an environment, people are able to link together important landmarks into routes. Knowledge of this type is said to be a route representation.
- With additional exposure, some people may develop a more flexible, map-like representation of the environment called a survey representation (also known as configurational knowledge).

An individual with a survey representation of a space understands the spatial relationship between the various landmarks in an environment independently of the routes that connect these landmarks. Survey representations facilitate spatial inferences and can allow people access to spatial information regardless of orientation (Sholl, 1987); however, they differ from real environments in well-documented ways (e.g. Tversky, 1981; McNamara, Hardy, & Hirtle 1989; Engebretson & Huttenlocher, 1996). Nevertheless, it is generally assumed that survey knowledge represents a more thorough and flexible understanding of the spatial characteristics of a large scale environment than does route knowledge.

A second model of spatial knowledge is similar to the LRS model but it is hierarchical (Stevens & Coupe, 1978; Colle & Reid, 1998). In some cases, direct exposure to an environment for extremely long durations never results in survey knowledge (Chase, 1983). In other cases, survey knowledge

develops almost immediately. The model proposed by Colle and Reid suggests a dual-mode whereby survey knowledge can be acquired quickly for local regions and slowly for remote regions. The “room effect” comes from the ability to develop survey knowledge of a room rather quickly but survey knowledge of a series of rooms develops relatively slowly and with more errors.

### **Cognitive Map and Navigation**

Navigation and mental maps are intimately tied (Weston and Handy, 2004). The literature strongly indicates that there is a relationship between cognitive maps (CMs), **wayfinding** and navigation. Cognitive maps are used to solve spatial problems and Kitchin suggests that wayfinding and navigation are the most essential spatial problems (Kitchin, 1996). Navigation and wayfinding terms have been used interchangeably to indicate "a person's abilities, both cognitive and behavioral, to reach spatial destinations" (Passini, 1984).

*Cutting defines wayfinding as a "task to find a way through cluttered environments with ease and without injury" (Cutting, 1996).*

Wayfinding is the cognitive element of navigation. It does not involve movement of any kind but only the tactical and strategic parts that guide movement (Darken, & Allard, 1999).

*Motion is the motoric element of navigation.*

A reasonable synonym for motion is travel as used by Bowman, et al. (1997). The motor component of navigation refers to the actual locomotion involved.

*Navigation in physical space (or active navigation) consisting of a cognitive component, often referred to as wayfinding, and a motor component, which is physical locomotion (Darken, & Allard, 1999).*

So navigation is the aggregate task of wayfinding and motion. It inherently must have both the cognitive element (wayfinding), and the motoric element (motion).

*Locomotion is behavior or movement from one point to another that is guided by one of the senses, most typically vision.*

### **Wayfinding and Navigation**

**Wayfinding** defined as the mental processes involved in determining a route between two points and then following that route, has long been an important site for studying spatial cognition. Kevin Lynch's (1960) book - *Image of the City* paid particular attention to making cities more navigable. In a dissertation aimed at modeling common-sense reasoning in general, Benjamin Kuipers chose learning the geography of a place as a case study. The main results were published in a journal article already mentioned, that was to have considerable influence on the field (Kuipers 1978). Shortly after the publication of that work, Riesbeck (1980) described a related problem and implemented a system to judge the clarity of driving directions, given no knowledge of the actual geographical layout.

In the 1980s, the development of microcomputers made it possible to consider designing navigation aid systems for private automobiles that would keep track of the location of the vehicle, relate that position to an on-board digital street map, and provide navigation assistance to the driver. An obvious way to communicate with the driver would be to display maps, and this was the design of early implemented systems, such as Etak's Navigator (Zavoli *et al.* 1985). A parallel line of work developed systems to provide verbal descriptions of routes, mainly to give to someone renting an automobile and requiring direction to some attraction. Elliott and Lesk (1982), Streeter *et al.* (1985), and Streeter and Vitello (1986) studied the nature and content of driving directions, and related these characteristics to principles of knowledge representation in artificial intelligence. This line of work was picked up by people in the GIS community (Mark 1985, Mark and McGranaghan 1986, Mark *et al.* 1987, McGranaghan *et al.* 1987), and by others working on wayfinding and navigation (Gopal *et al.* 1989, Gollode *et al.* 1993). By the late 1980s, this thread was being related to other aspects of cognitive studies of geographical space and process.

## **Virtual World Navigation**

One of the most complicated tasks when working with virtual worlds is the navigation process. All of us do form and use cognitive maps, whether in real or virtual world, to deal with and process the information contained in the surrounding environment. Cognitive map helps in visualizing the positional and location details and also the route map for reaching the destination from the current location. It helps us find our way in virtual or real environments that we have visited before, and also helps us remember the structure of the place, for example, if we are asked for directions. Quality of such visualizations directly depends on the quality of the cognitive maps. Thus a human being's spatial behavior relies upon, and is determined by the individual's cognitive map of the surrounding environment. Knowledge based systems helps to enhance capacity of machine or computer system to intelligence similar to human being at least in some aspects. Machine based training simulators are equivalent or better than human trainers in terms of efficiency and effectiveness. Our Non-visual spatial navigation (NSL) model falls in this category.

This chapter proposes a typology of navigation strategies and focuses the use of neural networks as a tool for studying navigation within virtual worlds. How it learn to predict the next step for a given trajectory, acquiring also basic spatial knowledge in terms of landmarks and configuration of spatial layout. In addition, how it build a spatial representation of the virtual world, rather like a cognitive map. The benefits of this approach and the possibility of extending the methodology to the study of navigation in Human Computer Interaction and other applications are described in brief. The study of computation models of navigation and the potential of using cognitive maps in the modeling of navigational processes are described. Non-visual spatial learning model is presented for the spatial learning through virtual world exploration. The goal of this model is to provide abstraction of non-visual spatial learning process. Using that assistive system can be developed to facilitate non-visual spatial learning and thereby enhancing mobility skills of person with limited visual. Different types of locomotion in virtual world with their constraints and benefits are discussed. Intended readers of the chapter would be the mobility trainer, architect, city planner, cartographer, psychologist, and game developer.

## **BACKGROUND - SPATIAL NAVIGATION MODELS**

Spatial navigation is an important task for autonomous agents - including humans, animals and robots. A good number of researchers have been working on building computational models of spatial navigation. Goal finding, shortcutting, detouring, exploration and cognitive mapping are just a few of the navigational tasks that are used to test models of navigation. These models take different approaches in describing how individuals perform important navigational tasks.

One approach is to build models that do not take into account the brain regions involved in spatial navigation (Kuipers 1978, Cartwright and Collett 1987, Cheng 1989, Levenick 1991, Chown et al. 1995, Trullier et al. 1997, Reid and Staddon 1998, Voicu and Schmajuk 2001, 2002). These models produce real time behavior that is comparable with individual performance in a given task.

Another biologically inspired approach is to create models that take into account the architecture of the brain regions involved in navigation without aiming to reproduce neuronal activity (Schmajuk and Thieme 1992, Bachelder and Waxman 1994, Benhamou et al. 1995, Samsonovich and McNaughton 1997). These models also produce real time behavior that is comparable with individual performance.

Still another approach is to create computational models of the brain regions involved in navigation that reproduce the experimental findings related to neuronal activity in the brain (Wilkie and Palfrey 1987, Burgess et al. 1994, Arleo and Gerstner 2000, Hasselmo et al. 2002). Owing to the high level of detail in reproducing the parts of the brain involved in navigation, the behavioral analysis includes simple navigational tasks. Freeman (1975) proposed a mathematical model that captures the dynamics

of the cell assemblies based on brain data measured in the olfactory bulb. The impulse response was used to identify the parameters of a second-order linear differential equation that describes the behavior of neuronal populations. Based on this simple model, which simulates the dynamics of cell assemblies, Freeman proposed a hierarchy of models (K0, KI, KII and KIII) that have the capacity to show a periodic behavior similar to that found in the EEG (Freeman et al. 1997) and can be used to perform robust pattern recognition of noisy and variable data (Kozma and Freeman 2001).

Here in this section we briefly discuss the following **spatial learning models**.

- Symbolic model (Kuipers, 1978)
- Connectionist model (Schmajuk and Thieme, 1992)
- Attractor networks model (Samsonovitch and McNaughton, 1997)
- Biologically inspired chaotic neural network model (Kozma et al., 2003)
- Neural network model incorporating a hierarchical cognitive map (Voicu, 2003)
- A Multiscale progressive model (Zhang, 2008)

### **Symbolic model (Kuipers, 1978)**

Kuipers presented a model of the knowledge a person has about the spatial structure of a large-scale environment: the “cognitive map.” People navigate by using their common-sense knowledge of space: they link many separate observations into a “cognitive map” and solve route-finding problems by consulting the knowledge in the cognitive map. A large-scale space is defined by the way it is perceived, not by its physical size. Its structure is deduced from a number of observations over time, rather than being perceived from one location. The places, paths and routes of a city are the most common large-scale space in most people's experience, although of course there are others: ocean, jungle, and open field.

The term “cognitive map” as used in his model, refers to a body of knowledge that a person has in his head about the spatial structure of an environment. This is to distinguish it from other related concepts, such as the expression of that knowledge as maps, models, or verbal directions. People also associate visual impressions or social facts with different parts of the environment, but those are not the structural aspects of the cognitive map that will concern us here.

The functions of the cognitive map are to assimilate new information about the environment, to represent the current position, and to answer route-finding and relative-position problems. This model (called the TOUR model) analyzes the cognitive map in terms of symbolic descriptions of the environment and operations on those descriptions.

Knowledge about a particular environment is represented in terms of route descriptions, a topological network of paths and places, multiple frames of reference for relative positions, dividing boundaries, and a structure of containing regions. The current position is described by the “*You Are Here*” pointer, which acts as a working memory and a focus of attention. Operations on the cognitive map are performed by inference rules which act to transfer information among different descriptions and the “You Are Here” pointer. The TOUR model shows how the particular descriptions chosen to represent spatial knowledge support assimilation of new information from local observations into the cognitive map, and how the cognitive map solves route-finding and relative-position problems.

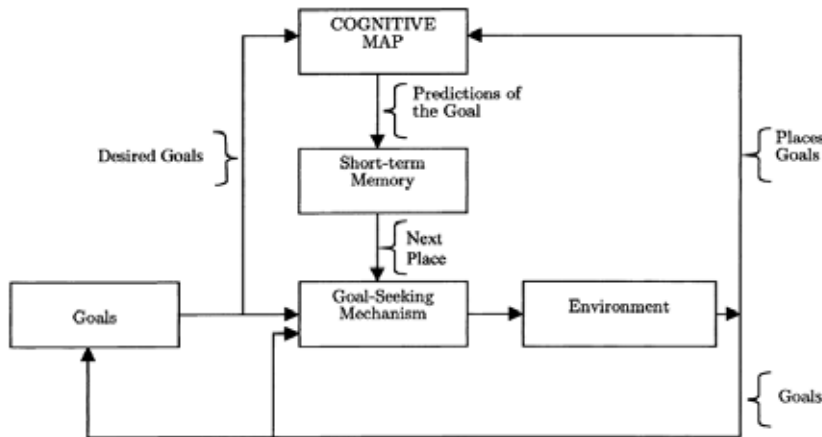
A central theme of this research is that the states of partial knowledge supported by a representation are responsible for its ability to function with limited information or computational resources. The representations in the TOUR model provide a rich collection of states of partial knowledge and, therefore, exhibit flexible, “common-sense” behavior.

### Connectionist (Schmajuk and Thieme, 1992)

Schmajuk and Thieme (1992) have offered a biologically plausible theory that includes (a) an action system consisting of a goal-seeking mechanism with goals set by a motivational system and (b) a cognitive system in which a neural network implements a cognitive map. The cognitive map represents the connectivity between places and the connectivity between places and goals. The goal-seeking mechanism changes from random exploratory behaviour to approach behaviour when either (a) the goal is found or (b) one place in the cognitive map generates a prediction of the goal that is stronger than the predictions generated by all other alternative places.

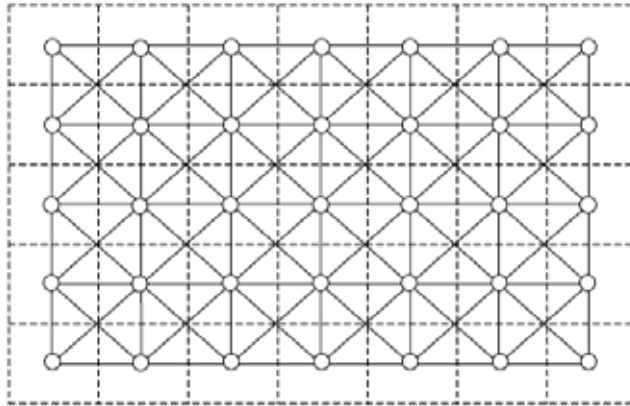
Voicu and Schmajuk (2001a, b) described a modified version of the Schmajuk and Thieme (1992) model. The new model differed from the original one in two ways. First, whereas the early model assumed no a-priori knowledge of the space to be explored, the modified model assumed a representation of the environment as a set of potentially connected and unexamined locations. Second, whereas in the original model the decision of what place to move next was based on the comparison of the predictions of the goal when each of the alternative places is briefly entered, in the new model this decision was based on the comparison of the activation of each of the alternative places when the goal is activated.

Fig. 1 shows the Schmajuk and Thieme (1992) model of spatial exploration and navigation with the modifications introduced by Voicu and Schmajuk (2001a, b). The system entails (a) an action system including a goal-seeking mechanism with goals defined by (b) a motivation system, (c) a cognitive system including a neural network which implements a cognitive map, and (d) a short-term memory where the reading of the cognitive map is temporarily stored.



**Fig. 1.** A system for spatial exploration and navigation. Block diagram of the model showing the interaction between the action system (goal-seeking mechanism), motivation system (goal), cognitive system (cognitive map), short-term memory, and environment.

Once the motivation system defines a goal for the simulated animal (e.g. food for hunger, unexamined places for exploration), the action system starts the search for those goals. If the goal is perceived, the simulated animal moves towards it. If it is not perceived, but it can be predicted by the cognitive map, the simulated animal enters the place that best leads to the location of the goal. If the goal is neither perceived nor predicted, then the simulated animal engages in exploratory behaviour using the cognitive map.



**Fig. 2.** The canvas. Squares in broken lines represent the places to be explored. Solid lines represent connections between places. The empty canvas is a lattice representing the potential continuity of the space to be explored. Adjacent places are assumed to be linked and each place is designated as unexamined (represented by an open circle.)

The map of the environment is drawn on an empty canvas that represents each location in the space to be mapped. Fig. 2 shows that the canvas is a lattice representing the potential continuity of space. In the figure, dashed-side squares represent places, the circles indicate their centres, and the solid lines linking the circles represent possible movements from one place to another. Although the places used here are square, places with arbitrary forms can also be used as long as they preserve the continuity of space. Places are of approximately the size of the footprint of the agent.

### **Attractor networks (Samsonovitch and McNaughton, 1997)**

A minimal synaptic architecture was proposed for how the brain might perform path integration by computing the next internal representation of self-location from the current representation and from the perceived velocity of motion. In the model, a place-cell assembly called a "chart" contains a two-dimensional attractor set called an "attractor map" that can be used to represent coordinates in any arbitrary environment, once associative binding has occurred between chart locations and sensory inputs. In hippocampus, there are different spatial relations among place fields in different environments and behavioral contexts. Thus, the same units may participate in many charts, and it is shown that the number of uncorrelated charts that can be encoded in the same recurrent network is potentially quite large. According to this theory, the firing of a given place cell is primarily a cooperative effect of the activity of its neighbors on the currently active chart. Therefore, it is not particularly useful to think of place cells as encoding any particular external object or event. Because of its recurrent connections, hippocampal field CA3 was proposed as a possible location for this "multichart" architecture; however, other implementations in anatomy would not invalidate the main concepts. The model is implemented numerically both as a network of integrate-and-fire units and as a "macroscopic" (with respect to the space of states) description of the system, based on a continuous approximation defined by a system of stochastic differential equations. It provides an explanation for a number of hitherto perplexing observations on hippocampal place fields, including doubling, vanishing, reshaping in distorted environments, acquiring directionality in a two-goal shuttling task, rapid formation in a novel environment, and slow rotation after disorientation. The model made several

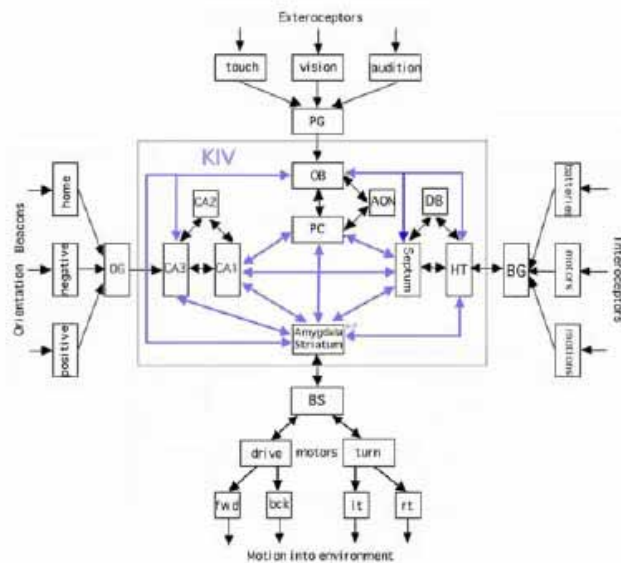
new predictions about the expected properties of hippocampal place cells and other cells of the proposed network.

### **Biologically inspired Chaotic Neural Network Model (Kozma et al., 2003)**

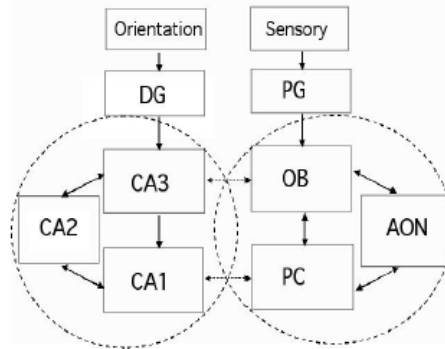
K model is a biologically plausible neural network, the development of which was based on the salamander's central nervous system. The model has the capacity to show a periodic and chaotic behavior similar to those found in the animal EEG patterns. KIII can be used to perform robust pattern recognition of noisy and variable data. The family of K sets includes K0, KI, KII, KIII and the highest level, KIV. K0 is a single node with nonlinear input-output transfer features. KI is a coupling of either excitatory or inhibitory K0 units, while KII is a double layer of excitatory and inhibitory units. KIII is a set of two or more KII units connected by feed forward and delayed feedback connection. With the proper parameters selection, the model can maintain non-convergent chaotic oscillation among all the excitatory and inhibitory nodes in the system.

The discovery that brain dynamics exhibits chaotic features has profound implications for the study of higher brain function (Skarda, C.A. & Freeman, W.J., 1987 and Schiff, S.J., 1994). The KIII model is a working example of the implementation of these chaotic principles in a computer environment. KIII exhibits a number of experimentally observed behaviours of brains, like robust pattern recognition and classification of input stimuli, and fast transitions between brain states (Chang H.J. & Freeman W.J., 1996, Freeman, W.J., 2000, Kozma, R., and Freeman, W.J., 2001, Kozma, R., et al., 2001). KIII shows very good performance in the several kinds of learning needed to categorize input data, and it can generalize efficiently in various classification problems. The operation of the KIII model can be described as follows. In the absence of stimuli the system is in a high dimensional state of spatially coherent basal activity, which is described by an aperiodic (chaotic) global attractor. In response to external stimuli, the system can be kicked-off the basal state into a local memory wing. The system resides in the localized wing for some time, then it returns to the basal state. This is a temporal burst process of the duration of up to 200 milliseconds. See Viana Di Prisco, G & Freeman, W.J., 1985 for the olfactory bulb, and Barrie J.M., Freeman W.J. & Lenhart M.D., 1996 for neocortex.

The next highest level of the K-sets is the KIV model. As in the case of all other K-sets (Freeman, 1975), the architecture and functionality of KIV is strongly biologically motivated. The data that are required for modeling neurodynamics at this level are derived by analysis of EEG recorded simultaneously from multiple electrodes in sensory and limbic structures (Kay, L.M & Freeman, W.J., 1998). KIV provides the neuroarchitecture that is needed to model the interactions of key neural populations in the primordial vertebrate forebrain. Among these parts are the sensory cortices, the motor cortices and nuclei, and the hippocampal formation, which is essential for cognitive processes such as orientation, learning and memory. Three types of sensory signals are considered in KIV: exteroceptors, interoceptors (including proprioception), and orientation signals; e.g., gravity, visual flow, magnetic fields. Each of these sensory signals provide stimuli towards the brain, namely the sensory cortices, midline forebrain (MF) unit, and the hippocampal formation (HF), respectively; see Fig. 3. The present model is motivated by the architecture and putative function at the level of the amphibian brain. It is not intended to mimic all the biological details; rather it is used to incorporate the main elements required for operation of brains at the KIV-level of functionality.



**Figure 3.** Structure of the KIV model based on Kozma, Freeman, and Erdi (2003). Abbreviations: DG, dentate gyrus; CA1-CA3, Cornu Ammonis (hippocampal sections); PG, periglomerular; OB, olfactory bulb; AON, anterior olfactory nucleus; PC, prepyriform cortex; Spt, septum; DB, diagonal band; HT, hypothalamus; BC, basal ganglia, corpus striatum including thalamus; BS, brain stem. The sparse long connections that comprise the KIV set are shown as bi-directional, but they are not reciprocal. The entorhinal cortex is omitted, because that is a neocortical structure found only in mammals.



**Figure 4.** Schematic view of the simplified KIV model with the interacting hippocampal and cortical KIII units.

The hippocampus is the main focus of cognitive mapping that supports spatial navigation and temporal orientation (short term memory). There is a rich literature of hippocampal-based navigation models (Burgess, N., Recce, M., & O'Keefe, J., 1994, and Arleo, A. & Gerstner, W., 2000). In their model, the following parts of the hippocampus are modeled: Dentate Gyrus (DG), CA3, CA1, and CA2. They need CA2 in our model to generate the hippocampal KIII dynamical system, serving as its chaotic controller. CA1, CA2 and CA3 are modeled as KII units, while DG will be a KI unit. KII units are shown to generate point attractors, limit cycle attractors, and even chaotic attractors (though lacking robustness) in the gamma band.

They model the sensory cortical (SC), midline forebrain (MF), and the hippocampal formation (HF) systems as KIII sets. Each KIII set has three KII units as components and exhibits robust aperiodic oscillations in the gamma range. Each shows spatial coherence in the form of a shared, spatially distributed, aperiodic wave form, with amplitude modulation patterns occurring in sequential frames over time, indicating the existence of landscapes of chaotic attractors corresponding to categories of sensory stimuli that have been learned. These AM patterns are manifestations of self-organizing dynamics that creates coherent activity in the form of "wave packets" (Freeman, W.J., 1975) as vectors of information in perception. The gating of bursts of KIII activity is governed by a limit cycle attractor in the KII set modeling the septum, that is fixed at frequency in the theta band, here 5 Hz (analogous to a sniff or saccade).

The cortical KIII system initiates the function of pattern recognition by the agency of sensory input-induced destabilization of high-dimensional dynamics. This actualizes an attractor landscape formed by previous experience in the OB/PC, which in our model is the common sensorium for all distance receptors, as it is in the salamander (Herrick, C.J., 1948). The hippocampal KIII system, thereafter, uses the categorization embodied in the outputs of the OB and PC as its content-laden input, to which the DG contributes the temporal and spatial location of the environmental events.

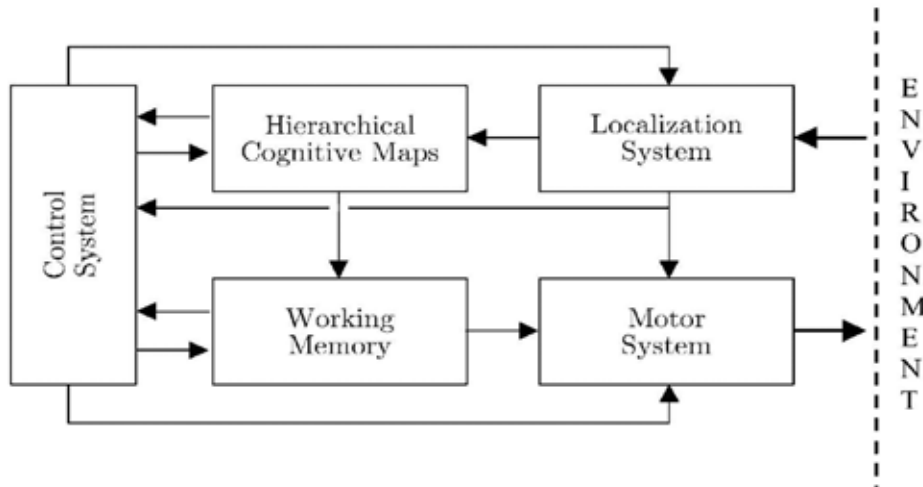
Another KIII component of the integrated KIV system, the Midline Forebrain formation, receives the interoceptor signals through the basal ganglia, and processes them in the hypothalamus and the septum. MF provides the value system of the KIV, using information on the internal goals and conditions in the animal. It provides the "Why?" stream to the amygdala, which combines this with the "What?" and "Where?" information coming from the cortex and the hippocampus to make a decision about the next step/action to be taken.

The motor part of the model limbic system is driven by the simulated amygdala. The direction of motion that it determines is based on the combined information from the three sensory systems, which collectively form the architecture of the global KIV. From EEG studies we infer that a cooperative state emerges from the collective interaction among the CA1, PC, Septum, and Amygdala, by which various behavioural patterns are formed and executed. The model given in Fig. 1 is designed to provide the platform with which to study by simulation this behaviour formation and action selection mechanism. In a very simple approach, however, we define initially only three basic behaviours: wall following, object avoidance, and backup. Backup behaviour is invoked if the robot is stuck or cannot execute a chosen action. A wide range of problems of intentional action can be solved with these three simple behaviours.

### **Neural network model incorporating a hierarchical cognitive map (Horatiu Voicu, 2003)**

They describe a computational model of spatial navigation based on experimental studies conducted with human participants. The model builds and uses a hierarchical cognitive map of a large environment. Computer simulations show that the model correctly describes experimental results including hierarchical organization of space and distance estimation. Furthermore, the model predicts that reaction time for distance estimation varies nonlinearly with distance.

The architecture of the model, except the hierarchical cognitive map, is based on a previous model (Voicu & Schmajuk, 2001). It contains five modules: a localization system that provides a unique code for each landmark in the environment, a cognitive map that builds and updates a hierarchical representation of space, a working memory used for path planning, a motor system that translates the path planning information into motor action and a control system that supervises the flow of information between the above modules (Fig. 5).



**Fig. 5.** Block diagram of the model. It shows the interaction between the control system, localization system, cognitive map, working memory, motor system and environment.

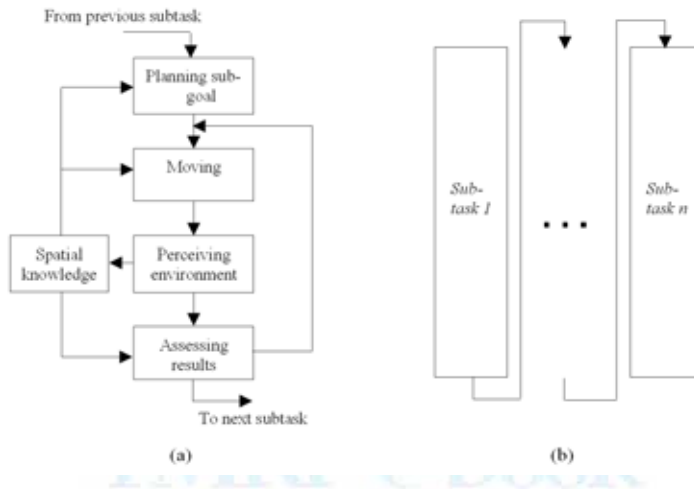
The localization system recognizes landmarks that are contained in the sector of circle that has the center in the position of the agent, an angle of  $60^\circ$  and a radius equal to one-tenth of the length of the environment. The orientation of the agent is given by the bisecting line of the sector of circle. The representation of the landmarks recognized by the localization system are stored in a short-term memory and provided to the cognitive map. The working memory stores information retrieved from the cognitive map and used by the motor system to plan and execute paths in the environment. The cognitive map contains three associative memories, implemented by hetero-associative networks (Kohonen, 1977), that build association between landmarks. All networks have recurrent connections and can exchange information. Each associative memory stores spatial information about the environment at a different resolution. The first level stores associations between all the landmarks in the environment. The second level stores associations between landmarks that have the largest number of associations at the first level. The third level stores associations between landmarks that have the largest number of associations at the second level. This hierarchy is acquired while the agent explores the environment. The cognitive map contains no a priori information related to spatial organization.

### **A Multiscale Progressive Model (Xiaolong Zhang, 2007)**

This model sees exploration-oriented navigation as an evolving process in which navigation tasks are gradually refined. Consider a scenario of going to a conference in an unfamiliar city. We usually decompose the overall goal, which is to get to the conference room, into a sequence of sub-goals: going to the neighborhood of the conference place, finding the conference place, and locating the conference room. The overall navigation task is a set of subtasks at different levels. Each subtask involves such activities as sub-goal planning, moving, perceiving the environment, and assessing the movement results (Figure 6a). The accomplishment of a subtask is the condition of the pursuit of the subtask at the next level (Figure 6b).

Completing a subtask requires spatial knowledge. We need spatial knowledge for goal planning, movement guidance, and navigation result assessment. During moving, we perceive the environment and update our spatial knowledge. If the sub-goal has not been achieved, further movement would be needed. Otherwise, we shift navigation to the subtask at the next level. For a particular subtask, we will need spatial knowledge appropriate to this task. When we complete one subtask and move to the

subtask at another level, required spatial knowledge also changes. For example, to find the conference place, we need a map of its neighborhood, but after we have located the conference place, we will need a floor map to help us find the conference room. What has been changed with the level of subtasks also includes action accuracy. Different subtasks may have different requirements for movement accuracy. Being in the neighborhood of the conference place needs only be accurate to tens or even hundreds of meters, but finding the door to the conference room requires position accuracy at the level of the meter. Different movement accuracies imply that people can choose different movement speeds for different subtasks to achieve efficiency, as long as movement accuracy can satisfy the error tolerance for each subtask.



**Figure 6.** A multiscale progressive model on navigation: a) is the subtask unit that shows the activities needed to complete a subtask; b) indicates the decomposition of the overall navigation task into a set of subtasks, each of which is a subtask unit.

Spatial knowledge and movement at each level need to be comparable. Spatial knowledge guides movement, and movement updates spatial knowledge. Unmatched spatial knowledge and movement may make it difficult for people to plan their actions and assess the results of the actions. For example, a map of the conference place area with a resolution of tens or hundreds of meters would be suitable for locating the conference place, but not for finding the conference room, which requires a floor map of the conference place with a resolution at the meter level. Such cross-scale transition should be smooth so that users can easily see how objects at different scales are related to each other. This will allow users to establish the connection between objects and to align spatial structures easily. For example, in order to be a specific place of a building, a user can first choose a scale level to approach the target building quickly, and then change to another scale level to adjust the final location accurately. A smooth transition of spatial knowledge between these two different scales makes the targeted building always visible. The object constancy in the smooth transition provides the user with the frame of reference in navigation. The user can clearly see how new spatial information is related to previous one and easily know where to go next for the following subtask. The granularity transformation model of wayfinding by Timpf and Kuhn (2003) saw wayfinding in the real world as a hierarchical process based on the differently-scaled maps. Their model largely focused on the cognitive aspect of navigation activities in goal planning, strategy choosing, and moving. The progressive model proposed by him, by considering both spatial knowledge and spatial actions-movement, emphasizes

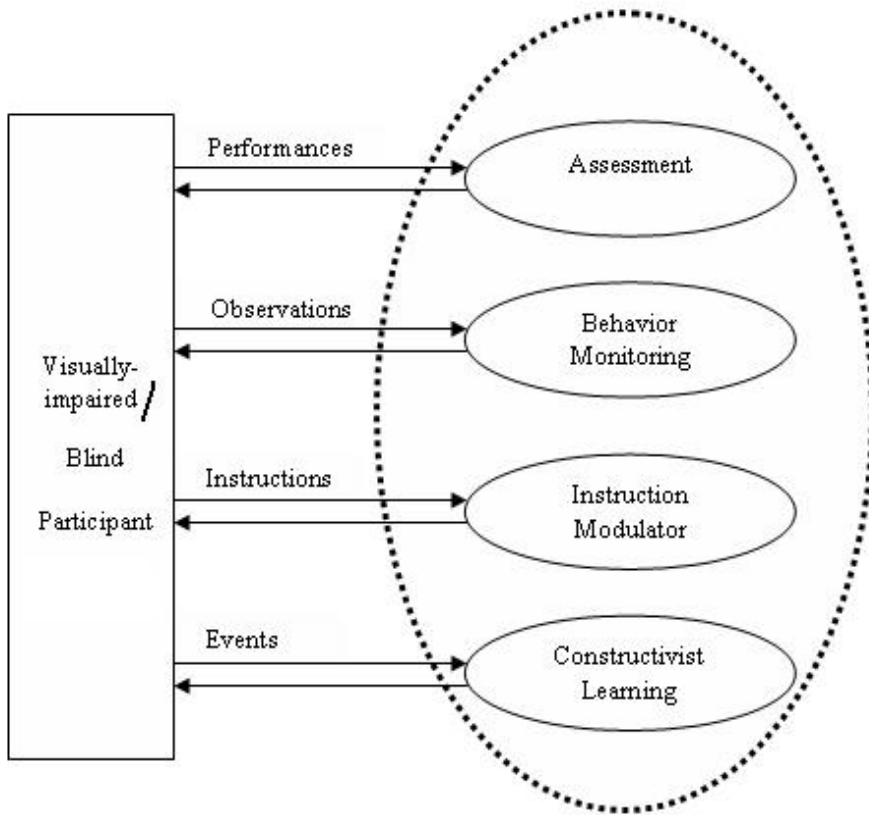
that navigation is an evolving process with gradually refined sub-goals, and argues the necessity of coupling spatial knowledge and movement as well as easily transferring them across different sub goals.

## ARTIFICIAL INTELLIGENCE IN GEOGRAPHICAL CONTEXTS

As the field of artificial intelligence matured, the knowledge representation and processing methods developed in the laboratory were applied to real world problems in the 1970s. Several applications to geographical information became visible. In 1978, Benjamin Kuipers published an elaborate model for representing human knowledge of large-scale space in an artificial intelligence framework (Kuipers, 1978). Kuipers' model built largely on the intuitive and descriptive work of Kevin Lynch (1960). In a follow-up paper, Kuipers discusses the 'map in the head' metaphor frequently employed to account for people's ability to find their way in space (Kuipers, 1982). The author uses computational models to refine the too simplistic metaphor and to discuss its implications in detail. In a subsequent paper, Kuipers discusses cognitive maps, their structure, and potential alternatives by employing a thought experiment in robotics (Kuipers, 1983). Shortly after the publication of that work, Riesbeck (1980) described a related problem and implemented a system to judge the clarity of driving directions, given no knowledge of the actual geographical layout. Davis (1983, 1986) looked at a cognitive map as a knowledge base; he developed a theory of representation, retrieval, and assimilation of geographical knowledge and implemented his theory in the MERCATOR system. MERCATOR is conceived for the use by a robot whose task is to build up a coherent representation of his visually perceived environment. Yeap (1988) also developed a computational theory of cognitive maps. Yeap's work emphasizes the cooperation of different loosely coupled modules representing different levels of information. The approach is motivated by Marr's (1982) investigations into the human representation and processing of visual information. Finally, Munro and Hirtle (1989) and Wender (1989) have developed connectionist models of cognitive maps, in contrast to the symbolic approaches listed above. Critical evidence from linguistics entered the picture in 1983 with Leonard Talmy's seminal work on how space is structured in language (Talmy 1983). This paper started the important cognitive linguistic research thread in cognitive geographical research. The artificial intelligence system CITYTOUR (Andre *et al.* 1987) was designed to answer natural language questions about the spatial relationships between objects in a city. Approaches from artificial intelligence were also applied to classic problems in cartography, especially automated name placement and other aspects of map design (Freeman and Ahn 1984, Buttenfield and Mark 1990). Couclelis (1986) reviewed artificial intelligence in geography during its early stage of widespread impact in the discipline.

## NON-VISUAL SPATIAL LEARNING (NSL) MODEL

Although a good number of researchers worked on **non-visual spatial learning**, to the best of our knowledge, yet no researcher has given a computation model to cover all the aspects of the non-visual spatial learning. Understanding how spatial learning tasks are constructed is useful in determining how best to improve navigation performance. We should decompose the various tasks of spatial learning in a generic way. So that we might be able to determine where assistance is needed, or where more learning can occur.



**Fig.7.** Components of Non-visual Spatial Learning (NSL) Model

To describe the computational model of the spatial learning, we divided whole process into following four steps (see Fig. 7).

1. Constructivist Learning
2. Instructor modulator
3. Behavior monitoring
4. Assessment

The model works like this. In first phase, a **constructivist learning** experience is to be provided that emphasizes the active participation of users in virtual environment exploration. Virtual environment exploration should be as familiar and natural as actually walking through the regions portrayed on a traditional paper map. In case of confusion or any difficulty, user can take assistance from it.

In second phase, simulated agent explores the area and creates the knowledgebase to generate the various kinds of instructions for providing assistance. Instructor modulator conforms the instructions and conveys to participants in various ways (speech, force feedback, and/or non-speech sound). It also provides guidance and directs the participant. Besides this assistance, participant can get contextual cues that help them to structure cognitive maps. Participant can interact with the various objects of virtual environment and structure cognitive map of an environment.

In third phase, partial cognitive map build till now, it is evaluated in terms of participant's behavior, navigating style (i.e. normal walk or drunkard/random walk) and participant's course with obstacles (where and when). Need based further instructions may be provided for any adjustment.

In the final phase, once the participant gets confident and memorizes the path and landmarks between source and destination, he is allowed to go for assessment or is confined to training. Participant's navigation performance, such as path traversed, time taken and number of steps taken to complete the task are recorded and evaluated. The participant's performance is evaluated in terms of statistical measures like bi-dimensional correlation coefficients (BCC), navigation time, distance traveled and number of steps taken to reach the destination place from source place. The sequence of objects falling on the traversed path and the positions where he seemed to have confusion (and hence took relatively longer time) are also recorded and conveyed to them. Performance feedback is to be given to participant.

### Constructivist Learning

A constructivist learning experience is to be provided that emphasizes the active participation of users in spatial learning through virtual environment exploration. This is kind of learning-by-exploring approach of learning. The participant interacts with the various objects of an environment. Also virtual environment exploration should be as familiar and natural as actually walking through the regions portrayed on a traditional paper map.

Participant can load layout of premises or areas through interface easily. Participant can get the brief description of the layout in the beginning. Participant can choose starting location and destination through text-to-speech guided selection. Participant can start Session by pressing key (for say F5). Session start date-time (that is also start break date-time for first break) is to be stored in the database. Now participant can start navigation. The participant navigates or explores the virtual environment using a force feedback joystick, mouse or locomotion interface. Before starting training session, participant can configure a) foot step size, b) height and c) length of their foot. Participant can start the session by pressing a particular key. System maintains session starting and ending time. Participant can end the session by pressing a particular key. In case of confusion or any difficulty, participant can take assistance from it. Participant can get information regarding orientation, whenever needed, through help key (for say F3). Participant can also get information (help) regarding Near-by (, near to near-by, or far) objects from his current location (i.e. knowing orientation) by pressing key (for say F4). Participant also gets options/direction available to move (from shortest path) by pressing key (for say F8), number of steps taken and distance covered from origin or from particular location. Participant also gets information like distance remains to travel to reach the destinations. When participants takes these type helps, system stores information regarding helps taken (i.e. When and Where – Current location). This information is used to find the confidence level of the participants. The System also generates vibration and audible alert when the participant is approaching any obstacle.

Following are the some of the common operations need to be implemented:

Load layout (as prepared by sighted)	by participant
void loadLayout(layout_name);	
Select source and destination locations	by participant
void selectSourceLocation(location_name);	
void selectDestinationLocation(location_name);	
Starting and ending session	by participant
int startSession();	
void endSession(sessionNumber);	
Take break	by participant

int takeBreak();	return next break number.	
Transition / Acceleration		by system
void transition (stepNumber);		
void accelerate();		
Get orientation help		by participant
String[] getOrientationHelp();		
Get present route help		by participant
String getPresentRouteHelp();		
Taking assistance		by participant
void askOptionToMove(presentPosition);		

### Instruction Modulator

This is kind of directed mode of navigation. The basic concept of directed mode of navigation is to augment the standard user interface in a virtual environment with a system that has knowledge about the content of the virtual world and lets users find objects and locations through assistance.

Following are the type of instructions provided by the system:

1. Directional Instructions
2. Obstacles avoidance Instructions
3. Orientation Instructions
4. Contextual Instructions
5. Temporal Instructions

In this mode of navigation, the **Instruction modulator** guides the participant through speech by describing surroundings, guiding directions, and giving early information of a turning, crossings, etc. Additionally, occurrences of various events (e.g. arrival of a junction, arrival of object(s) of interest, etc.) are signaled through vibration using consumer-grade devices. Current position in virtual environment is changed as user walks on the locomotion interface. They may use the force feedback joystick, mouse to control and move the current position indicator (referred to as cursor in this chapter). System generates (non-speech) sound for each step taken by User. Whenever the cursor is moved onto or near an object, its sound and force feedback features are activated. Thus a particular sound, which may also be a pre-recorded message, will be heard by the participant. As long as the cursor is on the object, the participant will feel the force feedback effect associated with this object. Participant can get contextual information continuously during navigation according to session's time like Morning, Afternoon, Evening, or Night. Contextual information is also according to different events of the place. For example for Railway station, contextual information is different for different events like at train arrival time, departure time and normal waiting time period. When participant is approaching or passing through class room (for school or college premises) he gets sound of teacher and students with Doppler Effect. When participant is passing through fountain or river, they heard the sound of flowing of water. Also participant gets information about path surface (i.e. Sandy, Muddy, Concrete, Slippery, or Grass-root/loan, etc.) through tactile effects.

### Behavior monitoring

The system continuously monitors and records following type of participant's behaviors:

1. Navigating style (normal /random walk)
2. Mental state (confusion/fear/lost/excited/confident)

During learning, the system continuously monitors and records participant's navigating style (i.e. normal walk or drunkard/random walk) and participant's course with obstacles (where and when). Participant can take break at any time during the session by pressing the Escape key. System stores break number, break start time and end time, and user's trajectories in the database.

Once the system finds the participant confident and memorizes the path and landmarks between source and destination, it allows him to go for assessment. The system monitors the number of step taken and distance traveled by the participant for the each break and session. If these two values are reducing or coming near the expected values and if participant's navigation style is proper then system finds that the participant is confident and ready for performance test.

### **Assessment**

In the assessment phase, participant navigates without system's help and trying to reach the destination. Participant gets only contextual information. The system records participant's navigation performance, such as path traversed, time taken, distance traveled and number of steps taken to complete this task. It also records the sequence of objects falling on the traversed path and the positions where he seemed to have confusion (and hence took relatively longer time). The system evaluates the participant's performance in terms of statistical measures like bi-dimensional correlation coefficients (BCC), navigation time and number of steps taken by participant to reach the destination place from source place and gives performance feedback to participant.

As mentioned earlier the simulated agent finds out the possible best path(s) between source place and destination using optimal path algorithm. The system compares optimal paths with participant's earlier recorded navigation path (during un-guided virtual navigation). Navigation paths of the participant are evaluated quantitatively using bi-dimensional regression analysis developed by Tobler. Bi-dimensional regression is applied to calculate the bi-dimensional correlation coefficients. The value of BCC near to one indicates that participant's performance is satisfactory and cognitive maps are satisfactorily formed. If its value is one then the cognitive map is almost precise. The trainer may ask the participant to give a verbal description of the area and then performs orientation and mobility tasks in the real target space.

### **Quality factors for spatial learning techniques**

There are few categories of virtual environment applications that are currently in use for productive, consistent work, but the requirements of these applications for spatial learning techniques cover a wide range. Further, there are many new applications of VEs being researched, which also may require spatial learning techniques with different characteristics. It is therefore impractical to evaluate spatial learning techniques directly within each new application. Instead, we propose a more general methodology, involving a mapping from spatial learning techniques to a set of quality factors. Quality factors are measurable characteristics of the performance of a technique. With this indirect mapping, application designers can specify desired levels of various quality factors, and then choose a technique which best fits those requirements. Our current list of quality factors for VR-based spatial learning techniques includes:

- Speed of learning (time taken to develop cognitive map)
- Navigation Efficiency (Number of steps taken and distance traveled to complete the task)
- Accuracy (proximity to the desired target)
- Spatial Awareness (the user's knowledge of his position and orientation within the environment during and after exploration)
- Ease of Learning (the ability of a novice user to use the technique)

- Ease of Use (the complexity or cognitive load of the technique from the user's point of view)
- Information Gathering (the user's ability to actively obtain information from the environment during exploration)
- Presence (the user's sense of immersion or 'being within' the environment due to navigation)
- User Comfort (lack of simulator sickness, dizziness, or nausea)

This list may not be complete, but it is a good starting point for quantifying the effectiveness and performance of virtual spatial learning techniques. Some of the quality factors, such as speed, navigation Efficiency and accuracy, are simple to measure quantitatively. Others, however, are difficult to measure due to their inherent subjective nature. To quantify these factors, standard questionnaires for factors such as ease of use (e.g. Chin, Diehl, & Norman, 1988), presence (e.g. Slater, 1995), and simulator sickness (e.g. Kennedy et al., 1993) should be part of the experimental method.

## **LOCOMOTION IN VIRTUAL WORLD**

Virtual reality provides for creation of simulated objects and events with which people can interact. The definitions of virtual reality (VR), although wide and varied, include a common statement that VR creates the illusion of participation in a synthetic environment rather than going through external observation of such an environment (Earnshaw, R. A., Gigante, M. A., & Jones, H. (1993)). Essentially, virtual reality allows users to interact with a computer-simulated environment. Users can interact with a virtual environment either through the use of standard input devices such as a keyboard and mouse, or through multimodal devices such as a wired glove, the Polhemus boom arm, or else omni-directional treadmill. The **locomotion interface** is used to simulate walking from one location to another location. The device is needed to be of a limited size, allow a user to walk on it and provide a sensation as if he is walking on an unconstrained plane.

Generally, a locomotion interface should cancel the user's self motion in a place to allow the user to go to anywhere in a large virtual space on foot. For example, a treadmill can cancel the user's motion by moving its belt in the opposite direction. Its main advantage is that it does not require a user to wear any kind of devices as required in some other locomotion devices. However, it is difficult to control the belt speed in order to keep the user from falling off. Some treadmills can adjust the belt speed based on the user's motion. There are mainly two challenges in using the treadmills. The first one is the user's stability problem while the second is to sense and change the direction of walking. The belt in a passive treadmill is driven by the backward push generated while walking. This process effectively balances the user and keeps him from falling off.

The problem of changing the walking direction is addressed by Brooks, F. P. Jr., (1986) and Hirose, M. & Yokoyama, K., (1997), who employed a handle to change the walking direction. Iwata, H. & Yoshida, Y., (1997) developed a 2D infinite plate that can be driven in any direction and Darken, R. P., Cockayne, W.R., & Carnein, D., (1997) proposed an Omni directional treadmill using mechanical belt. Noma, H. & Miyasato, T., (1998) used the treadmill which could turn on a platform to change the walking direction. Iwata, H. & Fujii, T., (1996) used a different approach by developing a series of sliding interfaces. The user was required to wear special shoes and a low friction film was put in the middle of shoes. Since the user was supported by a harness or rounded handrail, the foot motion was canceled passively when the user walked. The method using active footpad could simulate various terrains without requiring the user to wear any kind of devices.

### **Type of locomotion in virtual world**

It has often been suggested that the best locomotion mechanism for virtual worlds would be walking, and it is well known that the sense of distance or orientation while walking is much better than while

riding in a vehicle. However, the proprioceptive feedback of walking is not provided in most virtual environments. Good number of devices has been developed over the last two decades to integrate locomotion interfaces with VR environments. We have categorized the most common VR locomotion approaches as follow:

- walking-in-place devices (Sibert, Templeman, Page, Barron, McCune & Denbrook, 2004; Whitten et al, 2008),
- treadmills-style interface (Darken, Cockayne & Carmein, 1997; Hollerbach, Xu, Christensen, & Jacobsen, 2000; Iwata, & Yoshida, 1999; De Luca, Mattone, & Giordano, 2007),
- the motion foot pad (Iwata, Yano, Fukushima, & Noma, 2005),
- robot tiles, actuated shoes (Iwata, Yano, & Tomioka, 2006),
- the string walker (Iwata, Yano, & Tomiyoshi, 2007), and
- Finger walking-in-place approach.

## CONCLUSION

This model is effective to promote the development and online evaluation of cognitive maps of users. **Knowledge based systems** help to enhance capacity of machine or computer system to behave intelligently, similar to human being in some aspects at least. Machine based training simulators are equivalent or better than human trainers in terms of efficiency and effectiveness. Our Non-visual spatial navigation (NSL) model provides computational framework for spatial knowledge representation, acquisition and assessment of the acquired spatial knowledge. We are encouraged by preliminary results from our prototype implementation, which suggest that such spatial learning techniques would help visually challenged and blind people to get effectively learned for independent navigation. This is an ongoing study and we feel that our system based on our NSL model will be progressively enriched to become increasingly effective for spatial learning by them.

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