

PERCEPTION AND NAVIGATION MODELING IN HUMANS AND INTELLIGENT SYSTEMS

MASOUD GHAFFARI

Center for Robotics Research
University of Cincinnati
Cincinnati, Ohio

ERNEST L. HALL

Center for Robotics Research
University of Cincinnati
Cincinnati, Ohio

ABSTRACT

The purpose of this study is to present a model based on similarities in human navigation and robot navigation. It uses a hierarchical structure in three levels of landmarks, route, and survey knowledge. Recent cognitive models suggest that people use these types of spatial knowledge to perform many daily tasks. A similar approach was used for the robot navigation. The robot was able to finish the course successfully. This is an attempt to use biologically inspired theories in robotics and provide a test bed for biological hypotheses.

INTRODUCTION

Human and robot navigation have similarities and differences. The basic navigation issues are the same. Therefore, general theoretical and analytical approaches dealing with navigation in both areas can be integrated and both fields can benefit from each other. The difference is in how researches in each area deal with the problem. In human navigation the main question is how human processes information and what is the mechanism that enables humans and animals to navigate. On the other hand robotics researchers are looking for techniques to implement navigational abilities in real applications and whether or not it is biologically inspired is not an issue.

Two approaches are complementary. Biological systems proof that an efficient and practical navigation system is achievable. On the other hand, robotics research can provide a valuable tool to test biological hypotheses. It can isolate a specific problem and examine psychological and biological questions.

This paper is a part of studies aiming toward the human perception processing. The purpose of these studies is to develop a model for computing on the perceptions that lie in the natural language and to implement the model for the robot control that is influenced by human behavior. The goal is to enhance the mobile robot technology by adding this perception-processing model to current state of the art, which mainly is based on converting the propositions to measurements and not computing on perceptions directly. The proposed research tries to offer a complementary approach to the traditional methods and it is not a substitute for them. It tries to explore similarities and differences of navigation in humans and robots and present a model for the perception-based navigation.

PREVIOUS WORKS

The difficulty of autonomous navigation comes from the unstructured, unpredictable, dynamic environment of robots and immature current technology of artificial intelligence. Most researches in this area are experimental and real products are rare. The real world is often quite hostile to robotic systems. Things move and change without warning, at the best only partial knowledge of the world is available, and any prior information available may be incorrect, inaccurate, or obsolete (Arkin, 1999).

The classical AI methodology has two important assumptions: the ability to represent hierarchical structure by abstraction, and the use of “strong” knowledge that utilizes explicit representational assertions about the world (Boden, 1995). The assumption was that knowledge and knowledge representation are central to intelligence, and that robotics was no exception. Perhaps these were the results of studying higher human-level intelligence and not lower life forms of creatures. Behavior-based robotics systems reacted against these traditions (Arkin, 1999).

Behavior-based control shows potentialities for a robot-navigation environment since it does not need the building of an exact world model and a complex reasoning process (Duro, Santos, & Becerra, 2003). However, much effort should be made to solve aspects like formulation of behaviors and the efficient coordination of conflicts and competition among multiple behaviors. In order to overcome these deficiencies, some fuzzy-logic-based behavior control schemes have been proposed (Barber & Skarmeta, 2002).

Behavior-based control is an effective method for designing low-level primitives that can cope with real-world uncertainties, and AI has developed effective tools for symbol manipulation and reasoning (Lauria, Bugmanna, Kyriacou, & Klein, 2002). Integration of these two could result a better understanding and modeling of human perception

Michaud et al. proposed an architectural methodology that is based on the idea of intentional configuration of behaviors. They use three levels of *behavior*, responsible for driving actions from sensory information, *recommendation*, which recommends different behaviors, and *motivation*, which is used to monitor the agent’s goals and to coordinate the proper working with other modules (Michaud, Lachiver, & Dinh, 2001).

Skubic et al. developed two modes of human-robot communication that utilized spatial relationships. First, using sonar sensors on a mobile robot, a model of the environment was built, and a spatial description of that environment was generated, providing linguistic communication from the robot to the user (Skubic, Chronis, Matsakis, & Keller, 2001; Skubic, Perzanowski, Schultz, & Adams, 2002). Second, a hand-drawn map was sketched on a PDA, as a means of communicating a navigation task to a robot (Skubic, Matsakis, Forrester, & Chronis, 2001). The sketch, which represented an approximate map, was analyzed using spatial reasoning, and the navigation task was extracted as a sequence of spatial navigation states.

HUMAN PERCEPTION

Perception is the name given for the process of the organization, interpretation and the explanation of the data that reaches the brain from the sense organs. The data reaching the sense organs have no importance without perception. The information from the senses has to be perceived, in other words explained. We can only decide what kind of a reaction we are going to perform as a result of the sensory information only after perception.

Perception is a vital part of human reasoning. Human do a variety of physical and mental tasks without any measurements and computations. Some examples of these activities are driving in traffic, parking a car, cooking a meal, playing an instrument and summarizing a story. In fact, the capability to perform these tasks is based on the brain's ability to manipulate perceptions, perceptions of time, distance, force, direction, speed, shape, color, likelihood, intent, truth and other attributes of physical and mental objects (Zadeh, 1999).

The relationship between perception and action are often discussed in the context of ecological psychology (Kubota, Hisajima, Kojima, & Fukuda, 2003). The new trend in fuzzy logic focuses on the perception processing and preliminary results are emerging (Dvorak & Novak, 2004; Novak & Perfilieva, 2004; Novak, Perfilieva, & Mockor, 1999).

The literature on perception is huge, including thousands of papers and books in the areas of psychology, linguistics, philosophy, brain science, and many others (Carruthers & Chamberlain, 2000). And yet, what is not in existence is a theory in which perceptions are treated as objects of computation. Such a theory is needed to make it possible to conceive, design, and construct systems which have a much higher machine intelligence than those we have today (Zadeh, 1999).

HUMAN NAVIGATION MODELING

Humans use spatial relationships to describe their environment and to navigate, for example, a pothole or to veer around a desk and pass through a doorway. Recent cognitive models suggest that people use these types of spatial knowledge to perform many daily tasks. They also emphasize in importance of spatial knowledge and how it develops (Previc, 1998; Skubic et al., 2002).

Spatial cognition includes acquisition, organization, use, and revision of knowledge about spatial environments (Werner, Krieg-Brückner, Mallot, Schweizer, & Freksa, 1997). Natural language descriptions of spatial situations can be viewed as the linguistic image of mental/internal representations of these situations. In particular, this concerns the partial correspondence between the spatial inventory of natural language and the 'cognitive ontology' of space. In this framework, the following problem areas require attention (among others): Which cognitive entities can we assume to exist in the system of natural language (dimensionality, shape, orientation, etc.)?

The spatial cognition priority program is particularly oriented towards cognitively oriented sub areas of computer science / artificial intelligence, psychology, linguistics, anthropology, and philosophy which are concerned with complex behavior in dealing with physical space.

Different forms and representations of spatial information can be identified in systems navigating in complex surroundings. One of the most common distinctions in spatial navigation research concerns the difference between landmark, route, and survey knowledge of an environment (Werner et al., 1997). In human navigation three distinctive terms should be defined, landmarks, routes and survey knowledge.

Landmark: A landmark is a unique object at fixed location. It could be a visual object, odor, sound, or a tactile percept. A landmark is a decision making point. It could be a confirmation for continuing the previous pattern and decision or it could result to a new decision.

Route: A route corresponds to a sequence of objects or events as experienced during navigation (e.g. tunnels, trails, roads, corridors). Sequences can either be continuous or discrete. Examples of objects are pictures and movements, and examples of events are decisions like left or right turns.

Survey knowledge: Survey knowledge is a navigation environment model that contains routes and landmarks. A map is an example of the survey knowledge.

Information in route knowledge is accessed sequentially as an ordered list of locations. Survey knowledge in the other hand is considered as an integrated model of navigation environment. It enables the inference of spatial relationship between the arbitrary pairs of locations. In a set theory approach landmark, route, and survey knowledge can be related with a subset relationship as shown in (1).

$$\textit{landmark} \subset \textit{route} \subset \textit{surveyknowledge} \quad (1)$$

Route knowledge can be acquired in different ways. Exposure to a route can lead to a series of connections. This route knowledge can be used in similar situations. For example driving in a US city downtown may familiarize a driver with a pattern that can be used in similar situations

The study of route and survey knowledge has received a great deal of attention in spatial cognition research (Werner et al., 1997).

ROBOT NAVIGATION MODELING

The University of Cincinnati robot team has designed and constructed a robot, the Bearcat Cub as shown in Fig. 1, for the Intelligent Ground Vehicle Competition, the DARPA Grand Challenge, and many other potential applications. The Bearcat Cub is an intelligent, autonomous ground vehicle that provides a test bed system for conducting research on mobile vehicles, sensor systems and intelligent control.

The Bearcat Cub was used as a test bed to implement the human-like spatial knowledge model in a robot. The robot has two cameras for line following, a laser scanner and a stereo vision system for obstacle detection and spatial modeling, a Global Positioning System (GPS) for navigation. It has different modes of run including manual control, autonomous challenge that includes line following and obstacle avoidance, voice control, and GPS navigation. It also utilizes a hybrid power system.

A model similar to what was explained in the human navigation modeling was implemented in the bearcat cub robot. A 200 meter long, 8 meter wide *route* was marked by flags. The route had some sharp turns and some obstacles were placed randomly. Five points were marked by GPS as *landmarks*. The robot was supposed to stay in the route and reach the landmarks.

Several tests were conducted and the robot finished the course successfully. Since the GPS accuracy was limited to 10 feet, in some runs the robot reached to a certain distance of the *landmarks*. To offset the error, the results of each run were used to update the GPS coordinates of the landmarks. This corresponds to the idea of *survey knowledge* in the human navigation model.

A laser scanner was used to detect the obstacles. A remotely controlled toy car was driven in the robot route to create a moving obstacle. The robot was able to avoid the stationary and moving obstacles successfully.

Humans drive and navigate differently and there is no unique path. However, the idea of smooth driving and avoiding sudden movements is common in human navigation. A similar approach was used in the robot navigation. One example of such approach is shown in Fig. 2.

The robot detects a path that could be a line, a wall or any other indicator of a need for changing the direction. The bearcat cub has two powered wheels and a caster wheel as shown in Fig. 2. To change the direction, the wheels should move with different velocities. Eq. 2 represents the speed of each wheel for a robot with the width of w and the turn angle of θ . The t is the interesting part of the equation. It is the expected time for a turn. By its nature t is a fuzzy variable. It was used to add a human-like feature to this experiment. A table of expected values of t based on human perception for different values of θ and velocities was used. This way the robot was able to avoid obstacles, reach *landmarks*, and follow the *route* smoothly.



Figure 1. The Bearcat Cub robot

From two points, p_1 and p_2 , along the line, the robot detects the orientation of the line with respect to the robot. The appropriate steering angle, θ , is calculated to make the robot parallel to the line. In addition, a certain hugging distance, h , must also be maintained with the midpoint of the two points on the line.

This architecture is influenced by psychological models of human navigation as explained. It consist three levels of *landmark*, *route*, and *survey knowledge*. Humans use this kind of spatial knowledge to navigate

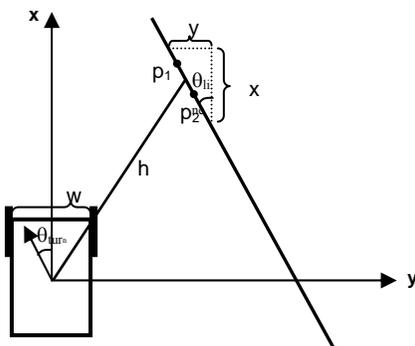


Figure 2. Top view of the robot and its steering angle θ

$$\begin{aligned} V_{\text{left}} &= V_{\text{center}} - (\theta w t / 2) \\ V_{\text{right}} &= V_{\text{center}} + (\theta w t / 2) \end{aligned} \quad (2)$$

CONCLUSIONS

A model for human navigation based on spatial knowledge was introduced. Similar approach was taken to navigate a robot through a route using landmarks and survey knowledge. Several other human like navigation methods such as voice control navigation and optical flow navigation are currently under investigation.

Further description and design details for one of the test robots is explained in (Ghaffari et al., 2004).

REFERENCES

- Arkin, R. C. (1999). *Behavior-based robotics*. Cambridge, MA: MIT Press.
- Barber, H. M., & Skarmeta, A. G. (2002). A framework for defining and learning fuzzy behaviors for autonomous mobile robots. *International Journal of Intelligent Systems*, 17, 1-20.
- Boden, M. (1995). AI's half-century. *AI Magazine*, 16(2), 69-99.
- Carruthers, P., & Chamberlain, A. (2000). *Evolution and the human mind, modularity, language and meta-cognition*. Cambridge: Cambridge University.
- Duro, R. J., Santos, J., & Becerra, J. A. (2003). Some approaches for reusing behavior based robot cognitive architectures obtained through evolution. In R. J. Duro, J. Santos & M. Grana (Eds.), *Biologically inspired robot behavior engineering* (Vol. 109, pp. 239-260). New York: Physica-Verlag.
- Dvorak, A., & Novak, V. (2004). Formal theories and linguistic descriptions. *Fuzzy Sets and Systems*, 143, 169-188.
- Ghaffari, M., Alhaj Ali, S. M., Murthy, V., Liao, X., Gaylor, J., & Hall, E. L. (2004). Design of an unmanned ground vehicle, bearcat iii, theory and practice. *Journal of Robotic Systems*, 21(9).
- Kubota, N., Hisajima, D., Kojima, F., & Fukuda, T. (2003). Fuzzy and neural computing for communication of a partner robot. *Journal of Multi-Valued Logic & Soft Computing*, 9, 221-239.

- Lauria, S., Bugmann, G., Kyriacou, T., & Klein, E. (2002). Mobile robot programming using natural language. *Robotics and Autonomous Systems*, 38, 171-181.
- Michaud, F., Lachiver, G., & Dinh, C. T. L. (2001). Architectural methodology based on intentional configuration of behaviors. *Computational Intelligence*, 17(1), 132-156.
- Novak, V., & Perfilieva, I. (2004). On the semantics of perception-based fuzzy logic deduction. *International Journal of Intelligent Systems*, 19, 1007-1031.
- Novak, V., Perfilieva, I., & Mockor, J. (1999). *Mathematical principles of fuzzy logic*. Boston: Kluwer Academic Publishers.
- Previc, F. H. (1998). The neuropsychology of 3-d space. *Psychological Bulletin*, 124 (2), 123-164.
- Skubic, M., Chronis, G., Matsakis, P., & Keller, J. (2001). *Generating linguistic spatial descriptions from sonar readings using the histogram of forces*. Paper presented at the IEEE International Conference on Robotics & Automation, Seoul, Korea.
- Skubic, M., Matsakis, P., Forrester, B., & Chronis, G. (2001). *Extracting navigation states from a hand-drawn map*. Paper presented at the IEEE International Conference on Robotics & Automation, Seoul, Korea.
- Skubic, M., Perzanowski, D., Schultz, A., & Adams, W. (2002). *Using spatial language in a human-robot dialog*. Paper presented at the IEEE International Conference on Robotics & Automation, Washington, DC.
- Werner, S., Krieg-Brückner, B., Mallot, H. A., Schweizer, K., & Freksa, C. (1997). *Spatial cognition: The role of landmark, route, and survey knowledge in human and robot navigation*. Paper presented at the Informatik 97.
- Zadeh, L. A. (1999, 22-25 Aug). *A new direction in fuzzy logic-toward automation of reasoning with perceptions*. Paper presented at the Fuzzy Systems, IEEE International.