Autonomous Navigation of Mobile Robot Using Behavior Based Neuro-Fuzzy System

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Abstract- The complexity of an autonomous robot's navigation task, poses several roadblocks to the use of traditional fuzzy control schemes, such as much larger input space than typical fuzzy applications, adding inputs increases the required number of set evaluations exponentially, as the size of a rule base swells, manual description becomes difficult to impossible. Therefore in this paper a new behavior based navigation system is described.A serious problem in fuzzy behavior implementation is the requirement of multiple fuzzy rules, which results in multiple output recommendations. After studying different methods used for coordination of multiple behaviors and issues of conflict resolution among competing behaviors, it has been observed that the degrees of applicability are analogous to neuronal activation levels. Therefore, a novel neuro-fuzzy system is proposed for behavior integration, which results in a more accurate and optimal path.

Keywords: autonomous system, artificial neural network, fuzzy logic system, neuro-fuzzy system, local navigation, global navigation, behavior coordination, behavior conflict resolution, perceptron, activation function

1 INTRODUCTION

For non-linear, highly complex and unpredictable systems like autonomous mobile robot navigation problem requires intelligent systems that combine knowledge, techniques, and methodologies form various sources. These intelligent systems are supposed to possess humanlike expertise within a specific domain, adapt themselves and learn to do better in changing environments, and explain how they make decisions or take actions. In confronting real world computing problems, it is frequently advantageous to use several computing techniques synergistically rather than exclusively, resulting in construction of complementary hybrid intelligent systems. At this juncture, the most visible systems of this type are neuro-fuzzy systems. Neural networks have the strong capability to recognize patterns and adapt themselves to cope with changing environments whereas fuzzy systems incorporate human knowledge and perform inferencing and decision-making. Although the fuzzy inference system has a structured knowledge representation in the form of fuzzy if-then rules it lacks the adaptability to deal with changing external conditions. Thus, incorporating neural network learning concept in fuzzy inference systems, results in better performance. The integration of these two complementary approaches, together with some optimization techniques, results in a novel discipline called neuro-fuzzy system.

One of the major problems in fuzzy behavior implementation is the fact that application of multiple fuzzy rules results in multiple output recommendation. Various methods used for coordination of multiple behaviors and issues of conflict resolution among competing behaviors are discussed. It has been observed by careful comparison of these approaches that the degrees of applicability are analogous to neuronal activation levels. Therefore, a novel neuro-fuzzy system is proposed for behavior integration which results in a more accurate and optimal path. None of the avoid-obstacle or seek-goal behaviors produce an optimal path for the mobile robot. The addition of optimal path as the desired trajectory for weight adjustment scheme of the neural netowrk takes advantage of this information and produces an optimal output recommendation. This capability of a trained artificial neural network (ANN) for approximating arbitrary input output mappings and resulting optimal path are significant and novel contributions of this paper.

III INTELLIGENT CONTROL AND EVOLUTION OF MOBILE ROBOT BEHAVIOR

In order to solve the scalability problems faced by previous fuzzy control systems, a network of independent fuzzy agents is developed. This scheme combines the principles of Minsky's "Society of Mind" agencies and Brook's layered control architecture with the flexibility of a fuzzy logic. Each agent consists of a handful of inputs, allowing the programmer to define its transfer characteristics explicitly with fuzzy rules. Multiple control recommendations are generated in parallel as independent agents. When necessary, these agents themselves can be made up smaller fuzzy agents, in a modular network. In behavior-based navigation system, goals are achieved by subdividing the overall task into small independent behaviors that focus on execution of specific subtasks. For example, a behavior can be constructed which focuses on traversing from a start to a goal location, while another behavior focuses on obstacle avoidance. The recommendation of these behaviors is then integrated with adjustable weighting factors to yield an autonomous navigation strategy for the mobile robot that requires no a-priori information about the environment.

IV. REVIEW OF EXISTING BEHAVIOR-BASED NAVIGATION METHODS

The behavior control paradigm was initially proposed in the seminal paper by brooks [3] where it was realized in the subsumption architecture. In this architecture numbered behaviors (implemented as finite state automation) executed in parallel in response to instantaneous sensing data. The behaviors comprise of a distributed system that controls a mobile robot through arbitrated competition. Following the introduction of subsumption architecture and the emergence of the behavior control paradigm, a host of groups recognized the advantages to be gained by incorporating fuzzy logic into frame work of behavior control for mobile robots. Saffiotti et al. [4] have developed fuzzy behaviors for complex navigation tasks demonstrating the robustness of fuzzy control in blending reactive and goal-oriented behavior. Pin and Watanabe [5] developed qualitative reasoning schemes for autonomous navigation in unknown environments with emphasis placed on embedded control using VLSI fuzzy chips. A heterogeneous network of fuzzy controllers for reactive behavior-based control was implemented by Goodridge and Luo [6]. In this network, control actions are generated by outputs of independent fuzzy controllers that are linked together through a qualitative rule base. Li [7] emphasizes weighting of reactive behaviors, achieved by implicit mechanisms of fuzzy inference, as an improvement in efficiency over priority-based arbitration. Tunstel and Jamshidi [8, 9] have proposed strategies for fuzzy behavior-based mapping and fuzzy spatial map representation for navigation. Research is also being perused in the area of motion control for path execution [9]. Terrain cells are estimated from the viewable terrain image. Roll and pitch are calculated by using a least-squares method to fit a plane to the range data, and roughness is computed as the residual of the fit. These measures are normalized in the range [0,1] and a goodness value is determined, based on the minimum value of the three parameters. A certainty factor is also calculated as a function of the number and distribution of range points within a cell. A path planner then evaluates the traversability along predetermined candidate paths by taking a weighted combination of the goodness and certainty values. Votes for each path are then sent to an arbitrator that determines the best path to traverse.

V FUZZY BEHAVIOR BAED SYATEM

Given the complexity of the robot's task, there are several roadblocks to the use of traditional fuzzy control schemes, such as much larger input space than typical fuzzy applications, adding inputs increases the required number of set evaluations exponentially, as the size of a rule base swells, manual description becomes difficult to impossible. Therefore in this chapter a new behavior based navigation system is described. In behavior-based navigation system, goals are achieved by subdividing the overall task into small independent behaviors that focus on execution of specific subtasks. In the currentstudya new approach is developed for robot navigation on challenging terrain using a perception based linguistic framework. Robot navigation is accomplished by using fuzzy logic rule statements, as an alternative to conventional analytical methods. The premise of the proposed approach is to embed the human expert’s heuristic knowledge into mobile robot navigation strategy using fuzzy logic. The proposed approach is highly robust in coping with the uncertainty and imprecision those are inherent in sensing and perception of natural environments.

5.1 Evolution of Mobile Robot Behavior

To solve the scalability problems faced by traditional fuzzy control systems, a modular network of independent fuzzy behavior is developed. This scheme combines the principle of Zelinsky’s "Society of Mind" agencies [10] and Brook'slayered control architecture [83] with the flexibility of a fuzzy logic. Each behavior consists of few inputs, to enable a programmer to represent its transfer characteristics explicitly with fuzzy rules. Multiple control recommendations are generated in parallel as independent behaviors.

In a behavior-based navigation system goals are achieved by subdividing the overall task into small independent behaviors that focus on execution of specific subtasks. For example, a behavior can be constructed which focuses on traversing from a source to a destination location, while another behavior focuses on obstacle avoidance. The recommendation of these behaviors is then integrated with adjustable weighting factors to yield an autonomous navigation strategy for the mobile robot that requires no a-priori information about the environment.

5.2 Behavior in Navigation Strategy

Behavior is the most important and fundamental entity of the proposed navigation strategy. Here, each behavior is considered to be composed of a set of fuzzy logic rule statements necessary to represent the navigation process for achieving the desired objective. Two types of rules namely; navigation rules and weight rules are identified for each behavior [31]. The navigation rules consist of a set of fuzzy logic rules for robot translation and rotation of the form:

If Z, then X (1)

where, the condition Zis formed with a suitable combination of fuzzy input variables and the associated fuzzy connectives. The normally fuzzy connectives used are the fundamental type operators such as AND, OR, NOT. The notation X is representing the action which is termed as fuzzy output variable.

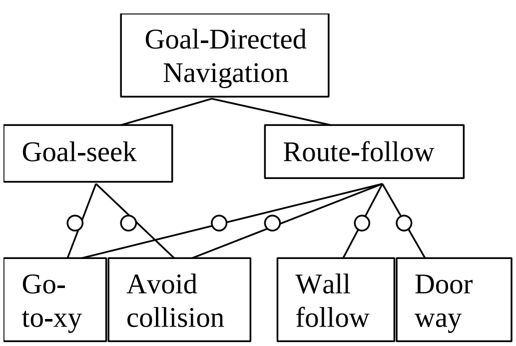
Considering rule 1 that represents the general form of a typical rule in a set of natural linguistic rules. This can be taken as analogous to the action taken by expert human pilot based on the prevailing environmental conditions. From the safety point of view, IF *sky is foggy*, THEN *altitude is low*. The output of each behavior is a recommendation of overall possible motion commands from the perspective of achieving that behavior's objective. Simultaneously, in the navigation strategy, the multiple behaviors can be active, each aimed to achieve one specific sub goal. The overall navigation strategy is implemented by integrating multiple behaviors which can be obtained by combining the outputs (recombination) of all active behavior using their weight rules. For each behavior, the weight rules consist of a set of fuzzy logic rules for weight assignment of the general form

IF *Q*, THEN *S* (2)

where Q is a logical statement describing a physical situation, and S represents a fuzzy expression of the weighting factor with which that behavior's recommendation is considered in the prevailing situation . For example, for the safety behavior of the human pilot, IF *wind speed is high*, THEN *safety weight is high.* For each behavior, the recommendation of navigation rules is scaled by the gain obtained from the weight rules. The weighted combination of all behaviors' recommendations is then defuzzified and issued as a command to the mobile robot wheel actuators for execution. Equation (1) and (2) represent a framework for embedding the human expert's knowledge into the robot navigation strategy.

5.3 Autonomous Behavior based System

A behavior-based system is a collection of several independent task-achieving modules, with a simple distributed control mechanism. Each behavior mediates directly with the external world and the behaviors are in a parallel control structure, as opposed to the traditional serial structure where interaction with the world is processed serially through sensors, reasoners, planners, actuators, etc. The behavior based systems work in decoupled fashion eliminating the centralized-shared memory. Instead of central control, they coordinate through parameter passing and communication between individual behaviors. These systems are largely reactive and communicate to the external world by making changes to itself that other behaviors of the system can perceive. The emergence of intelligence by interacting amongst each other is called *Swarm Intelligence.* Such evidence has been found in social insects like ants, wasps and bees. The same type of intelligence can be evolved from the interaction of the robots with the world using behavior-based system. The main advantages of such robots are that they avoid explicit planning and do not need explicit representation of the goals. Since some such reactive robots exhibit problems like deadlock and myopic functionality, hybrid type architectures with a deliberative component to such problems have emerged on robot navigation scenario.



Primitive Level

5.5 Hierarchy of Distributed Fuzzy Behaviors

In a network of distributed fuzzy behaviors, the overall navigation task is decomposed into a number of simple and independent fuzzy behaviors. In this architecture, the numbered behaviors are executed in parallel in response to instantaneous sensing data. The behaviors form a distributed system that controls a mobile robot through arbitrated competition. The network of distributed behavior is hierarchical in nature. The robot behaviors are decomposed into a bottom-up hierarchy of increased behavioral complexity. In this hierarchy, the behavioral activity at a given level is dependent upon behaviors at the lower level. A collection of primitive behaviors resides at the lowest levelA primitive behavior is a simple, self-contained behavior that serves a single purpose while operating in a reactive manner. Such, primitive behaviors are building blocks of more intelligent composite behaviors. In other words, they can be combined synergetically to produce more intelligent behaviors suitable for accomplishing robot navigation scheme.

A possible hierarchy for indoor navigation can be arranged as shown in Fig. 1.This Fig. implies that the overall task is *goal-directed navigation*. This is decomposed into simple behavioral functions namely;

(i) *Goal-seekbehavior*: collision-free navigation to some location.

(ii) *Route-follow behavior*: assuming some direction is given perhaps in the form of a path plan. These behaviors can be further decomposed into primitive behaviors namely,

(i) Wall-follow behavior:

(ii) *Avoid-collisionbehavior:*

(iii) *Doorwaybehavior*: implies one that can guide a robot through narrow openings in walls.

(iv) *Go-to-xybehavior:* will direct a robot to navigate along a straight-line trajectory to a particular location.

The interrelationships of these behaviors are described through interconnecting lines in Fig. 2. The interconnecting circles between composite behaviors and the primitive level represent activation thresholds of associated primitive behavior. The issues of behavior conflict resolution and behavior coordination is described in the ensuing section.

5.7 Coordination of Multiple Behaviors

Behavior coordination is achieved by introducing a scheme for weighted decision-making and behavior selection. The mechanism for weighted decision-making is embodied in a concept called the *degree of applicability*, which is a measure of the instantaneous level of activation of a behavior. Fuzzy rules of composite behaviors are formulated to include weighting consequents, which govern the degree of applicability of primitive behaviors at a lower level. These are called applicability rules. Let 'B_c' be a composite behavior comprised of 'n_p' primitive behaviors. Then the degree of applicability, 'α_p'of primitive behavior p (p=1, 2,n_p) is specified in the consequent of applicabilty rules of the form:

$$\text{IF } x \text{ is } \tilde{A}_i \text{THEN} \alpha_p \text{ is } \tilde{D}_i$$

Where $\tilde{A}_i \in x$,is fuzzy set representing linguistic values of input x .$\tilde{D}_i$is a fuzzy set representing the linguistic value of the degree of applicability of primitive behavior p to the situation prevailing during the current control cycle. It is defined over the unit interval [0,1].

This feature allows certain robot behaviors to influence the overall behavior to a greater or lesser degree as required by the current goal. It causes the control policy to dynamically change in response to goals and sensory input. Thus, coordination is accomplished by modulating behavioral activities using meta-rules that provide a concept of inhibition and dominance observed in animal behavior. Behaviors with partial applicability (α< 1) can be said to be inhibited, while behaviors with maximal applicability (α = max α_i) can be said to be dominant.

VI PROPOSED NAVIGATION TECHNIQUE BASED ON NEURO-FUZZY CONTROL CONCEPT

One of the major problems in fuzzy behavior implementation is the fact that application of multiple fuzzy rules results in multiple output recommendation. The output of each behavior is a recommendation of overall possible motion commands from the perspective of achieving that behavior's objective. Multiple behaviors can be active simultaneously in the navigation strategy, each aimed at achieving one specific sub goal. Integration of multiple behaviors is implemented by combining the outputs (recombination) of all active behavior using their weighting factors. For each behavior, the recommendation of navigation rules is scaled by the gain obtained from the weighting factor. Behavior coordination is achieved by introducing a scheme for weighted decision-making and behavior selection.

6.1 The Neuro-Fuzzy Concept

Neural networks have the strong capability to recognize patterns and adapt themselves to cope with changing environments whereas fuzzy systems incorporate human knowledge and perform inferencing and decision-making. Although the fuzzy inference system has a structured knowledge representation in the form of fuzzy if-then rules it lacks the adaptability to deal with changing external conditions. Thus, incorporating neural network learning concept in fuzzy inference systems, results in better performance. The integration of these two complementary approaches, together with some optimization techniques, results in a novel discipline called neuro-fuzzy system.

6.2 Architecture of Proposed Neuro-Fuzzy Model

As described in Fig. 6.2, a simple perceptron having one layer of input neurons and one layer of output neurons is trained for the avoid-obstacle and seek-goal behavior and its weights have been calculated for the recommendation of the outputs from conflicting behaviors. The outputs are taken from the fuzzy behaviors and are fed into a simple neural network, which is used to calculate the output recommendation for the mobile robot steering angle and its speed. A single perceptron is simulated and is trained using back propagation of error algorithm. The mode of training is supervisory, because the steps in the algorithm involve the comparison of actual outputs with desired outputs associated with the set of training patterns. None of the avoid-obstacle or seek-goal behaviors produce an optimal path for the mobile robot. The addition of optimal path as the desired trajectory for the ANN takes advantage of this information and produces an optimal output recommendation. This capability of a trained artificial neural network (ANN) for approximating arbitrary input output mappings and resulting optimal path are significant and novel contributions of this work.

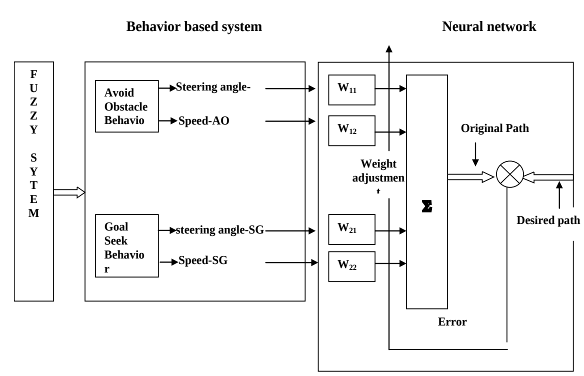


Fig. 2 Proposed neuro-fuzzy controller

6.3 Working of the Proposed Neuro-Fuzzy Model

These capabilities allow the navigation system to take preventive measures by looking ahead, preventing the robot from entry and entrapment in rock clusters and other impassable regions, and instead guide the robot to circum navigate these regions. The simulation results reported in this thesis demonstrate that the mobile robot possesses intelligent decision-making capabilities that are brought to bear in negotiating hazardous terrain conditions during the robot motion. A simple perceptron having one layer of input neurons and one layer of output neurons is trained for the avoid-obstacle and seek-goal behavior and its weights have been calculated for the recommendation of the outputs from conflicting behaviors. The outputs are taken from the fuzzy behaviors and are fed into a simple neural network, which is used to calculate the output recommendation for the mobile robot steering angle and its speed. The perceptron is simulated and is trained using back propagation of error algorithm. The mode of training is supervisory, because the steps in the algorithm involve the comparison of actual outputs with desired outputs associated with the set of training patterns. None of the avoid-obstacle or seek-goal behaviors produce an optimal path for the mobile robot. The addition of optimal path as the desired trajectory for the ANN takes advantage of this information and produces an optimal output recommendation. This capability of a trained artificial neural network (ANN) for approximating arbitrary input output mappings and resulting optimal path are significant and novel contributions of this work. These capabilities allow the navigation system to take preventive measures by looking ahead, preventing the robot from entry and entrapment in rock clusters and other impassable regions, and instead guide the robot to circum navigate these regions.

VIII SUMMARY

In thispapera new approach for robot navigation on challenging terrain using a perception based linguistic framework have been developed. Robot navigation is accomplished by using fuzzy logic rule statements, as an alternative to conventional analytical methods. The premise of the proposed approach is to embed the human expert's heuristic knowledge into mobile robot navigation strategy using fuzzy logic. The proposed approach is highly robust in coping with the uncertainty and imprecision those are inherent in sensing and perception of natural environments.

The proposed behavior-based robot navigation strategy using fuzzy rules has major advantages over existing analytical methods. First, the fuzzy logic rules that govern the robot motion are simple and easily understandable, and can emulate the human driver's perception, knowledge, and experience. Second, the tolerance of fuzzy logic of imprecision and uncertainty in sensory data is particularly appealing for outdoor navigation, because of the inherent inaccuracy in measuring and interpreting the terrain quality data, such as slope, roughness, and discontinuity. And third, the behavior-based strategy has a modular structure that can be extended very easily to incorporate new behaviors, whereas this requires complete reformulation for analytical methods. Multiple fuzzy navigation behaviors are combined into a unified strategy, together with smooth interpolation between the behaviors to avoid abrupt and discontinuous transitions. After observing that the coordination of multiple behaviors is analogous to neural activation levels, a neuro-fuzzy system is proposed for behavior integration. The capability of a trained artificial neural network (ANN) for approximating arbitrary input output mappings and resulting optimal path are significant and novel contributions of this work. These capabilities allow the navigation system to take preventive measures by looking ahead, preventing the robot from entry and entrapment in rock clusters and other impassable regions, and instead guide the robot to circum navigate these regions. The simulation results demonstrate that the mobile robot possesses intelligent decision-making capabilities that are brought to bear in negotiating hazardous terrain conditions during the robot motion.

REFERENCES

[1] A. Zelinsky. " A mobile robot exploration algorithm". IEEE Transactions on Robotics and Automation, 8(6): m707-717, December 1992.

[2] R. A. Brooks, " Achieving artificial intelligence through building robots," MIT, AI Memo., pp. 899, 1986.

[3] R. A. Brooks, "Intelligence without representation", Artificial Intelligence, Vol. 47, pp. 139-159, 1991.

[4] R. A. Brooks, " A robust layered control system for a mobile robot", IEEE Journal of Robotics And Automation , Vol. RA-2, pp. 14-23, Feb. 1986.

[5] J. Connell, "Creature design with subsumption architecture" in Proceedings ICJAI, 1987, pp. 1124-1126.

[6] R. C Arkin, "Behavior based robotics", Cambridge, MA: MIT Press, 1998.

[7] N. Nilsson, " Shakey the robot", SRI Interantational, Artificial Intelligence Center, Palo Alto, CA, 323, 1984.

[8] S. Tachi and K. Komoriya: " Guide Dog Robot": International Symposium on Robotic Research, Vol. 2, pp. 333-340.

[9] H. Mori, S. Kotani and K. Ishil " A Guide Dog Robot Project" HARUMOBU"": International conference on Advanced Robotics, 1993, Vol.11.

[10] H. P. Moravec, " The stanford cart and CMU rover," Robotics Inst. Carnegie Mellon University, Pittsburgh, PA, 1983.

[11] H. P.Moravec, " Towards automatic visual obstacle avoidance," in Proc. 5th IJCIA, Cambridge, MA, Aug, 1977, pp. 584.

[12 R. A Brooks, J.H. Connell, and P. Ning, "HERBERT: A second-generation mobile robot", Massachusetts Institute of Technology, Cambridge MA, AI Memo, 1016, 1988

[13] P. Maes, "Situated agents can have goals". Journal of Robotics and Autonomous Systems, Vol. 6, pp. 49-70, 1990.

[14] R. P. Bonasso and Kortenkamp, " Characterizing an architecture for intelligent, reactive agents," in Proceedings of working notes AAAI spring Symposium Lessons Learned from Implemented Software Architectures for Physical Agents, 1995, pp. 29-34.

[15] A. Saffiotti, K. Konolige, and E. Ruspini,, " A multivalued logic approach to integrating planning control," Artificial Intelligence, 1995, Vol. 73, pp. 117-143.

[16] S. Rosenschein and L. kaelbling , " A situated view of representation and control," Artificial Intelligence., 1995, Vol. 73, pp. 149-173.

[17] R. Simmons, " Structured control for autonomous robots," IEEE Transactions on Robotivs & Autmation, 1994, Vol.10, pp. 34-43.

[18] L. Matthies, E. Gatts, R. Harrisson, B. Wilcox, R. Volpe and T. Litwin "Mars microrover navigation: Performance evaluation and enhancement", Journal of Autonomous Robots, Vol. 20, no.4, pp. 291-311, 1995.