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Hierarchical Behavior Control of Mobile Robot Based on Space & Time Sensor Fusion(STSF)

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Abstract

Navigation in environments that are densely cluttered with obstacles is still a challenge for Autonomous Ground Vehicles (AGVs), especially when the configuration of obstacles is not known a priori. Reactive local navigation schemes that tightly couple the robot actions to the sensor information have proved to be effective in these environments, and because of the environmental uncertainties, STSF(Space and Time Sensor Fusion)-based fuzzy behavior systems have been proposed. Realization of autonomous behavior in mobile robots, using STSF control based on spatial data fusion, requires formulation of rules which are collectively responsible for necessary levels of intelligence. This collection of rules can be conveniently decomposed and efficiently implemented as a hierarchy of fuzzy-behaviors. This paper describes how this can be done using a behavior-based architecture. The approach is motivated by ethological models which suggest hierarchical organizations of behavior. Experimental results show that the proposed method can smoothly and effectively guide a robot through cluttered environments such as dense forests.

Key Words : Multi-sensor fusion, Mobile robot, Measurement, Image processing, Navigation.

I. Introduction

For mobile robots to operate efficiently in a human environment, they need to be able to navigate efficiently and to avoid collisions. Therefore, taking the safety factor into consideration, "collision avoidance" would essentially form the basic behavior of all behavior-based autonomous robots. The vision sensing system has traditionally been used for collision avoidance in mobile robots. It is cost effective and relatively quick in response. Processing is not time consuming either. And recently, with the reduction in size of video cameras and the increase in computing speed of computers, the use of visual sensing has become popular too. In what has become a fairly well-researched approach to multi-sensor (sonar and vision) based navigation for mobile robots, a robot is provided with an environmental map and a path to follow. The important function of vision-based processing in this case consists of "self-localization."

For literature on this approach, the reader is referred to [1], [2], and [3]. In a different approach, as reported on by [4] and [5, 6], a robot is provided with sequences of images of the interior space. By comparing these prerecorded images with the camera images taken during navigation, the robot is able to determine its location. Other previous research contributions that are relevant to mobile robot localization include [7], [8], [9], and [10].

In order to achieve autonomy, mobile robots must be capable of achieving multiple goals whose priorities may change with time. Thus, controllers should be designed to realize a number of task-achieving behaviors that can be integrated to achieve different control objectives. This requires formulation of a large and complex set of fuzzy rules. In this situation a potential limitation to the utility of the monolithic fuzzy controller becomes apparent. Since the size of complete monolithic rule-bases increases exponentially with the number of input variables [11], multi-input systems can potentially suffer degradations in real-time response. This is a critical issue for mobile robots operating in dynamic surroundings. Hierarchical rule structures can be employed to overcome this limitation by reducing the rate of increase to linear [12,13].

This paper describes a hierarchical behavior-based control architecture. It is structured as a hierarchy of fuzzy rule-bases which enables distribution of intelligence amongst special purpose fuzzy-behaviors. This structure is motivated by the hierarchical nature of behavior as hypothesized in ethological models. A fuzzy coordination scheme is also described that employs weighted decision making based on contextual

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behavior activation. Performance is demonstrated by simulation highlighting interesting aspects of the decision making process which arise from behavior interaction.

The paper is organized as follows. Section II first presents basic concepts of the behavior based system structure. Section III represents the concept of STSF is derived and hierarchical decomposition of mobile robot behavior. Section IV represents coordinating fuzzy-behavior interactions. And Mobile robot system and environment, and Obstacle description and configuration are shown in section V. Observed performances are shown in section VI. Finally section VI concludes the current research and proposes further topics.

II. Behavior Based System Structure

Reactive behaviors are control systems that make up the behavior based control system. Reactive behavior systems have proven to be very effective in accomplishing many of the complex tasks facing robotic systems today by decomposing these tasks into simpler well-defined subtasks. These behaviors can be implemented independently, which reduces behavioral interference and system complexity. This independence is due to their horizontal arrangement as illustrated in Fig. 1. These models are also referred to as parallel and serial respectively.

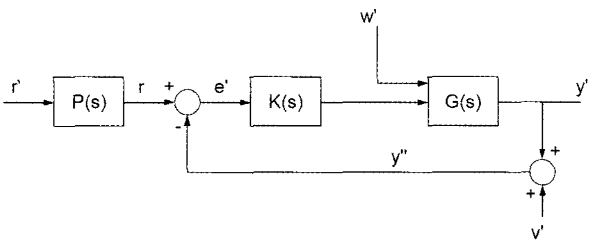


Fig. 1. Reactive (horizontal) Model

Since reactive systems are comprised of independent behaviors, a mechanism is needed to determine one control command. This mechanism is known as command arbitration, which is a distinguishing characteristic as well as the toughest problem of reactive behavior systems. Fig. 2 shows how each behavior sends information to the command fusion block which combines the information to create one output.

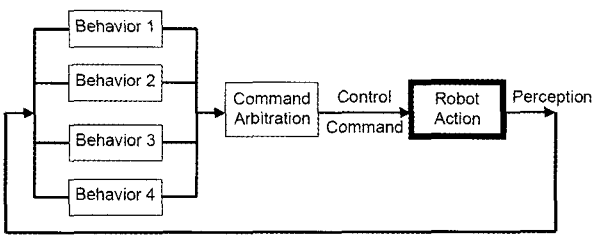


Fig. 2. Reactive Behavior Arbitration

Various arbitration methods combine this information using fusion that makes the behaviors either compete or cooperate for control of the system. These methods will be described in more detail in Section IV.

III. STSF-BASED HIERARCHICAL BEHAVIOR CONTROL

A. STSF (Space and Time Sensor Fusion)

The STSF (Space and Time Sensor Fusion) scheme combines the sensory information acquired at different instants from different sensors to determine the measurement. It may expend its applicability to the systems where the states at each instant can be predicted as shown in Fig. 3.

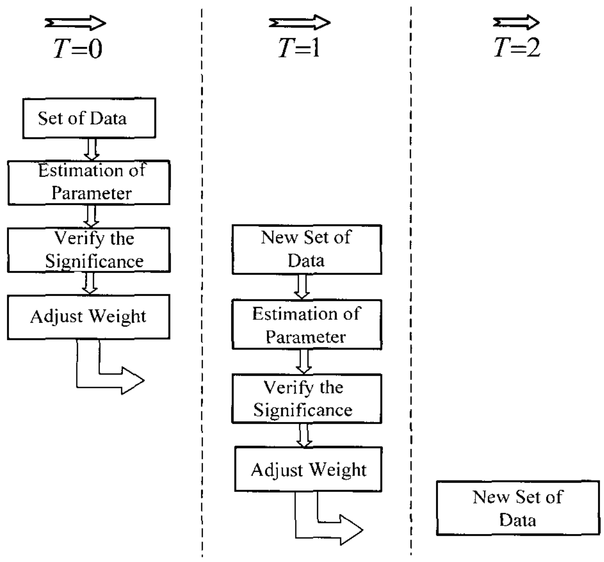


Fig. 3. Data processing for STSF.

Estimation of parameter block may provide the measurement vector at each sampling moment. The blocks of verify the significance and adjust weight are pre-processing stages for the sensor fusion. After these steps, the previous data set will be fused with the current data set, which provides a reliable and accurate data set as the result of multi-sensor temporal fusion. In the figure, the significance implies that how much the previous data set is related to the current data. An arbitrary value of significance may cause the problem to be complex. Therefore, some people may consider whether it corresponds to the same data or not, that is, 1 or 0. When the significance is 0, the weight can be adjusted simply to 0. However, when the significance equals 1, the adjustment of weight should be properly performed to provide reliable and accurate data. The STSF can be represented mathematically as follows[14]:

$$\hat{x}(k) = \sum_{i=1}^{n} W_i\{\sum_{j=1}^{k} P_j TS_i(j)\}, \quad \sum_{j=1}^{k} P_j = 1 \quad (1)$$

Note that when each of sensor information can provide the measurement vector, that is, the redundant case $TS_i(j)$ can be expanded as

$$TS_i(j) = T_{ij} + H_i z_i(j) \quad (2)$$

where T_{ij} represents the homogeneous transformation from the location of the j-th measurement to the i-th measurement.

However, when the multi-sensors are utilized in the complementary mode, the transformation relationship cannot be defined uniquely; instead it will be defined depending on the data constructing algorithm from the measurements.

B. Behavior Hierarchy

The behavior control paradigm has grown out of an amalgamation of ideas from ethology, control theory and artificial intelligence [3, 4]. Motion control is decomposed into a set of special-purpose behaviors that achieve distinct tasks when subject to particular stimuli. Clever coordination of individual behaviors results in emergence of more intelligent behavior suitable for dealing with complex situations. The paradigm was initially proposed by Brooks [4] and realized as the 'subsumption architecture' wherein a behavior system is implemented as distributed finite state automata. Until recently [5, 6, 7], most behavior controllers have been based on crisp (non-fuzzy) data processing and binary logic-based reasoning. In contrast to their crisp counterparts, fuzzy-behaviors are synthesized as fuzzy rule-bases, i.e. collections of a finite set of fuzzy if-then rules. Each behavior is encoded with a distinct control policy governed by fuzzy inference. Thus, each fuzzy-behavior is similar to the conventional fuzzy controller in that it performs an inference mapping from some input space to some output space. If X and Y are input and output universes of discourse of a behavior with a rule-base of size n. the usual fuzzy if-then rule takes the following form

$$IF\ x\ is\ \widetilde{A}_i\ THEN\ \ y\ is\ \widetilde{B}_i \quad (3)$$

where x and y represent input and output fuzzy linguistic variables, respectively, and $\widetilde{A}_i$ and $\widetilde{B}_i$ (I =1...n) are fuzzy subsets representing linguistic values of x and y. Typically, x refers to sensory data and y to actuator control signals. The antecedent consisting of the proposition "x is $\widetilde{A}_i$" could be replaced by a conjunction of similar propositions; the same holds for the consequent "y is $\widetilde{B}_i$".

The proposed architecture is a conceptual model of an intelligent behavior system and its behavioral relationships. Overall robot behavior is decomposed into a bottom-up hierarchy of increased behavioral complexity in which activity at a given level is dependent upon behaviors at the level(s) below. A collection of primitive behaviors resides at the lowest level which we refer to as the primitive level. These are simple, self-contained behaviors that serve a single purpose by operating in a reactive or reflexive fashion.

They perform nonlinear mappings from different subsets of the robot's sensor suite to (typically, but not necessarily) common actuators. Each exists in a state of solipsism, and alone, would be insufficient for autonomous navigation tasks. Primitive behaviors are building blocks for more intelligent composite behaviors. They can be combined synergistically to produce behavior(s) suitable for accomplishing goal-directed operations.

A behavior hierarchy for indoor navigation might be organized as in Fig. 4. It implies that goal-directed navigation can be decomposed as a behavioral function of **goal-seek** and **route-follow**. These behaviors can be further decomposed into the primitive behaviors shown, with dependencies indicated by the adjoining lines. **Avoid-collision** and **wall-follow** are self-explanatory. The doorway behavior guides a robot through narrow passageways in walls **go-to-xy** directs motion along a straight line trajectory to a particular location. The circles represent weights and activation thresholds of associated primitive behaviors. As described below, fluctuations in these weights are at the root of the intelligent coordination of primitive behaviors. The hierarchy facilitates decomposition of complex problems as well as run-time efficiency by avoiding the need to evaluate rules from behaviors that do not apply.

Note that decomposition of behavior for a given mobile robot system is not unique. Consequently, suitable behavior repertoires and associated hierarchical arrangements are arrived at following a subjective analysis of the system and the task environment.

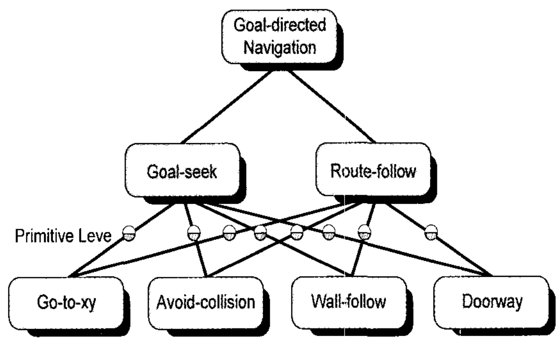


Fig. 4. Hierarchical decomposition of mobile robot behavior.

IV. COORDINATING FUZZY-BEHAVIOR INTERACTIONS

A. Degree of applicability

Complex interactions in the form of behavioral cooperation or competition occur when more than one primitive behavior is active. These forms of behavior are not perfectly distinct they are extremes along a continuum [8]. Coordination is achieved by weighted STSF and behavior modulation embodied in a concept called the *degree of applicability* (DOA) The DOA is a measure of the instantaneous level of activation of a behavior and can be thought of in ethological terms as a motivational tendency of the behavior. Fuzzy rules of composite behaviors are formulated such that the DOA, $\alpha_j \in [0,1]$, of primitive behavior j is specified in the consequent of *applicability rules* of the form

$$IF\ x\ is\ \tilde{A}_i\ THEN\ \alpha_j\ is\ \tilde{D}_i \tag{4}$$

where $\tilde{A}_i$ is defined as in (1). $\tilde{D}_i$ is a fuzzy set specifying the linguistic value (e.g. "*high*") of α_j for the situation prevailing during the current control cycle. This feature allows certain robot behaviors to influence the overall behavior to a greater or lesser degree depending on the current situation.

B. The heading control and related behaviors

The control command for the heading control activity is the heading angular change $\Delta\theta$. This has to be defuzzified into an odd number of symmetric fuzzy sets to represent possible command alternatives depending on the intended control action. Any reasonable number of fuzzy sets can be used; four fuzzy sets were found to sufficiently represent the relative importance of the command alternatives with the linguistic symbols Not Acceptable (NA), Acceptable (A), Favored (F), and Highly Favored (HF). The goal seeking structure of the fuzzy behavior control system for heading control is illustrated in Fig. 5.

The five fuzzy sets are named: Large Right Turn (LRT), Slight Right Turn (SRT), No Turn (NT), Slight Left Turn (SLT), and Large Left Turn (LLT) as shown by the dashed lines of Fig. 6. Each behavior i assigns a relative importance to each command alternative j by some parameter $\alpha_j \in [0, 1]$; the larger values correspond to higher importance. This parameter is also expressed by fuzzy sets on the interval [0, 1].

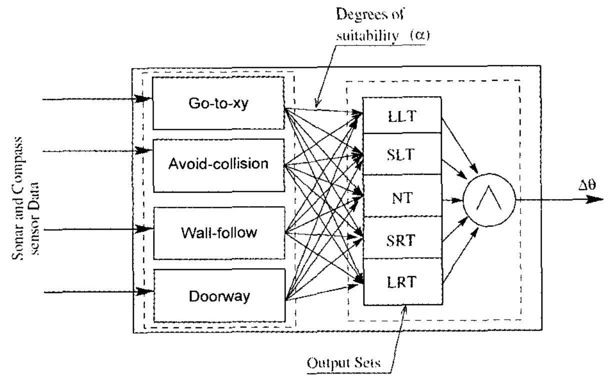


Fig. 5. The Fuzzy Behavior Control System for the Heading Control Activity.

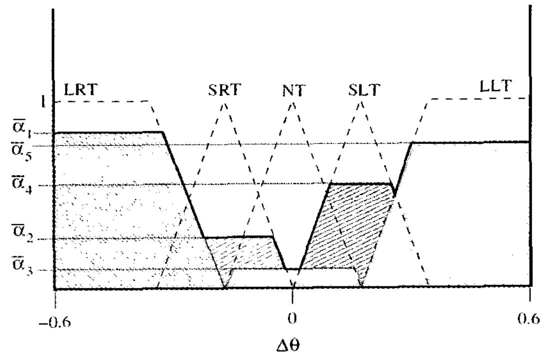


Fig. 6. A Typical Compound Fuzzy for $\Delta\theta$.

V. Experimental Configuration

A. Mobile robot system and environment

After satisfactory simulation performance [14], the proposed navigation control system has been implemented and tested in a laboratory environment on a Pioneer-DX robot equipped with a CCD camera and ultrasonic sensor ring (Fig. 7) [15]. This robot, which is manufactured by Activ Media Robotics, is a differentially driven platform configured with two drive wheels and one swivel caster for balance. Each wheel is driven independently by a motor with 19.5:1 gear ratio which enables the robot to drive at a maximum speed of 1.2 m/s and climb a 25% grade. The proposed system was prepared using fuzzy TECH software, which generated C++ code that was implemented on the Pioneer-DX.

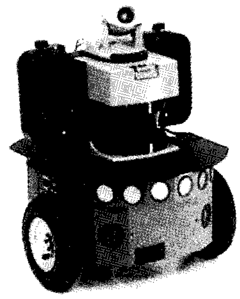


Fig. 7. Pioneer-DX mobile robot and active camera system.

Ultrasonic sensor is good in distance measurement of the obstacles, but it also suffers from specular reflection and insufficient directional resolution due to its wide beam–opening-angle. So, we use a sensor fusion method to decide the distance and width of obstacles and avoid them during the navigation. Pioneer-DX examines whether measured value is data of distance to real obstacle or distance to its shadow. If difference of measured data by vision and ultrasonic sensor is within the error tolerance, Pioneer-DX uses measured data by vision sensor as distance to obstacle. Otherwise, Pioneer-DX uses measured data by vision sensor as distance to obstacle.

Fig. 8 depicts sensing coverage of vision and ultrasonic sensor used this experiment. Ultrasonic sensor can detect obstacles within 7m and Vision system can detect obstacles within the range of between 130cm and 870cm.

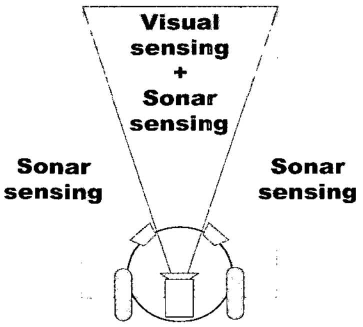


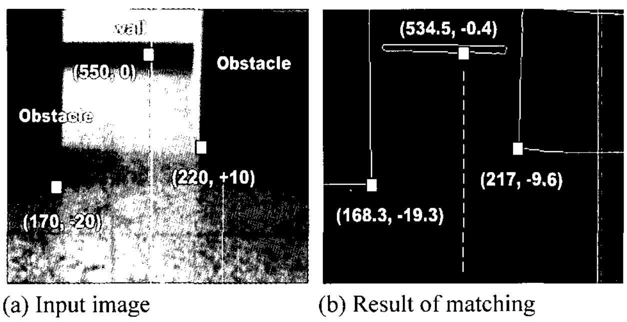
Fig. 8. Sensing coverage of vision and ultrasonic sensor.

B. Obstacle description and configuration

A dense forest in which trees become obstacles to robot motion was chosen as the experimental environment. Such obstacles are very difficult to navigate through because they are relatively small with irregular spacing. Obstacles were simulated by 1m height by 1x1m, 1x2m width box sections. These box size scale appropriately to the vehicle size and accurately depict the trunks of obstacle.

The configuration of these obstacles must be chosen carefully. Firstly it is important for each obstacle configuration to have at least one traversable path. There may be more than one traversable path; however, an obstacle configuration with only one traversable path is the most difficult because the robot must be able to identify and navigate that one path. The existence of multiple paths can serve to illustrate the decision making of the algorithm by forcing the robot to choose a more straight path. The path is considered traversable if it is wide enough for the robot to negotiate and make appropriate turns.

Fig. 9. Shows that maximum matching error is within 4%. Therefore, It can be seen that above vision system is proper to apply to navigation. The mobile robot navigates along a corridor and Hall with 6mX12m widths and with some obstacles as shown in Fig. 10. It demonstrates that the mobile robot avoids the obstacles intelligently and follows the corridor to the goal.



(a) Input image (b) Result of matching

Fig. 9. Experimental result of the vision system.

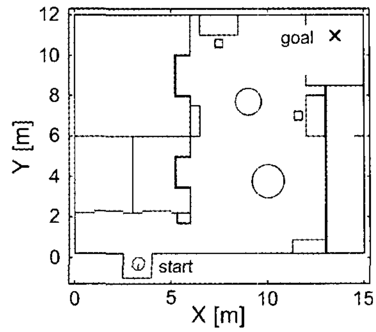


Fig. 10. Experimental environment of the *PIONEER-DX*.

VI. OBSERVED PERFORMANCE

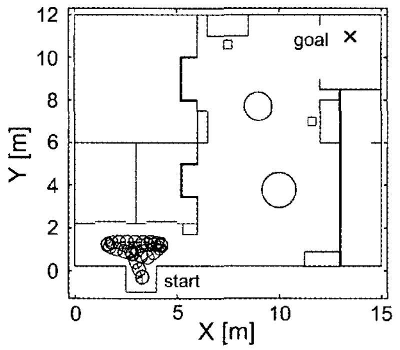
This section presents a sample of the three simulations results and applicability that show the performance of the proposed control system. It starts by describing the configuration of obstacles that the robot was to avoid.

A. NAVIGATION EXAMPLE

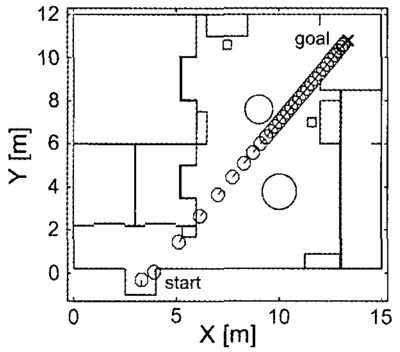
In order to demonstrate the operational aspects of the controller in the simplest manner possible we consider only the composite behavior – goal-seek. As illustrated in Fig. 4, its effect arises from synergistic interaction between primitive behaviors, go-to-xy and avoid-collision. When more behaviors are involved the approach proceeds in a straightforward manner by appending additional DOAs and any necessary antecedents to applicability rules accordingly.

The experimented mobile robot is modeled after PIONEER-DX as shown in Fig. 7, a custom-built base with a two-wheel differential drive and two stabilizing casters. It is octagonal in shape 65 cm tall and 40 cm in width. The sensor suite includes CCD camera, optical encoders on each driven wheel and 16 ultrasonic transducers arranged primarily on the front, sides, and forward-facing obliques. The simulated "world" is a hypothetical indoor layout not unlike awarehouse or office building. The initial state of the simulation is shown in Fig. 10 with mobile robot located at its docking station with pose p=$(0,0,\pi/2)^T$. Its task is to navigate to the goal located at (14m, 11m) marked by the X. The **avoid-collision** and **go-to-xy** behaviors are each shown acting alone in Fig. 11(b) and Fig. 11(b) respectively.

Recall that these behaviors are only capable of exhibiting their particular primitive roles. Thus, **avoid-collision** merely displays cyclic collision-free motion in the immediate vicinity of the robot's initial location, while **go-to-xy** displays a taxic reaction that propels the robot toward the goal irregardless of obstacles in its path. Successful completion of the task, resulting from adaptive coordination of the primitive behaviors, is shown in Fig. 12.



(a)



(b)

Fig. 11. avoid-collision and go-to-xy behaviors.

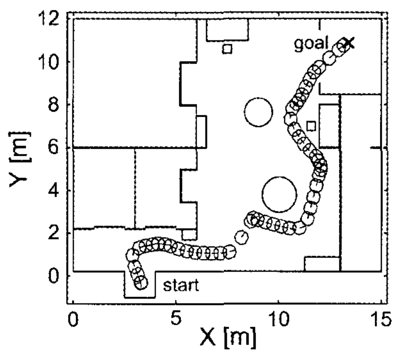


Fig. 12. Successful completion of the task.

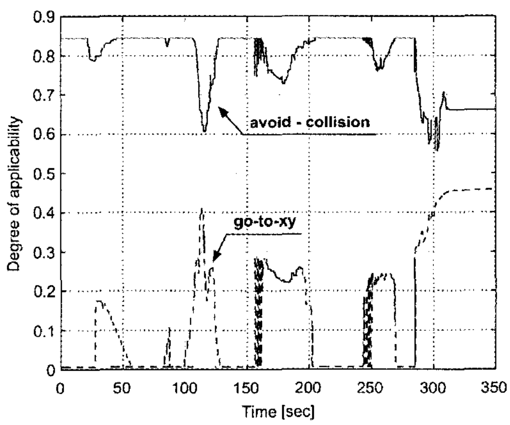


Fig. 13. Behavior interaction during goal-seeking.

The mobile robot, pioneer-DX, navigates along a space with 6mX12m widths and with some obstacles as shown in Fig. 12. It demonstrates that the mobile robot avoids the obstacles intelligently and navigates the space to the goal. In Fig. 13, the behavioral interaction during the run is shown as a time history of the DOAs of each primitive behavior. The interaction dynamics shows evidence of brief bouts of competition (overlapping oscillations) and cooperation with varying levels of dominance. Initially, **avoid-collision** has the dominant influence over the robot due to the close proximity of walls at the docking station.

It virtually maintains dominance throughout the task due to the relatively uniform clutter in the environment. The first bout of competition corresponds to the robot's approach toward the obstacle located at (10, 4); a second bout occurs as it enters the goal room. Elsewhere, applicabilities vary continuously reflecting levels of activation recommended by the behavior control system.

Fig. 14 presents additional experimental results when the robot navigates the same as in Fig. 12. It shows the data plot of the robot localization error according to the motion information of mobile robot.

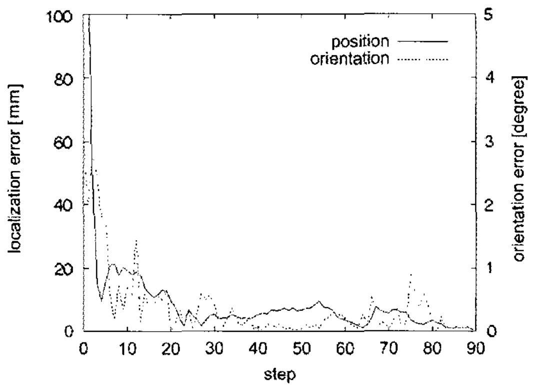


Fig. 14. Position and orientation estimation of a mobile robot.

VII. Conclusion

In this paper, STSF-based fuzzy behavior system was introduced. The effectiveness of fuzzy-behavior was demonstrated through the preliminary and navigation experiments. A fuzzy control algorithm for both obstacle avoidance and path planning is proposed so that it enables the mobile robot to reach to target point under the unknown environments safely and autonomously.

The hierarchy of fuzzy-behaviors provides an efficient approach to controlling mobile robots. Its practical utility lies in the decomposition of overall behavior into sub-behaviors that are activated only when applicable. When conditions for activation of a single behavior (or several) are satisfied, there is no need to process rules from behaviors that do not apply. This would result in unnecessary consumption of computational resources and possible introduction of "noise" into the decision-making process. The modularity and flexibility of the approach, coupled with its mechanisms for weighted decision making, makes it a suitable framework for modeling and controlling situated adaptation in autonomous robots. To date, simulations have been used to predict the performance of a real robot on which real-time experiments are currently being prepared.

To show the efficiency of proposed method, real experiments are performed. The experimental results show that the mobile robot can navigate to the target point safely under unknown environments and also can avoid moving obstacles autonomously.

References

[1] Ren C. Ruo and Kuo L. Su, "A Review of High-level Multisensor Fusion: Approaches and applications," *Proc. Of IEEE Int'l. Conf. On Multisensor Fusion and Integration for Intelligent Systems*, pp. 25-31, Taipei, Taiwan, 1999.

[2] Jang M. Lee, B. H. Kim, M. H. Lee, M. C. Lee, J. W. Choi, and S. H. Han, "Fine Active Calibration of Camera Position/Orientation through Pattern Recognition," *Proc. of IEEE Int'l. Symp. on Industrial Electronics*, pp. 100-105, Slovenia, 1999.

[3] Hong, L., Lynch, A., "Recursive temporal-spatial information fusion with applications to target identification," *Aerospace and Electronic Systems, IEEE Transactions on*, Vo. 29 Issue. 2, p. 435-445. 1993.

[4] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum likelihood from incomplete data via the EM algorithm," J. R. Statist. Soc., vol. 39, pp. 1–38, 1977.

[5] P. Weckesser and R. Dillman, "Navigating a Mobile Service-Robot in a Natural Environment Using Sensor-Fusion Techniques," *Proc. of IROS*, pp.1423-1428, 1997.

[6] Luo, R.C., Chih-Chen Yih,and Kuo Lan Su "Multisensor fusion and integration: approaches, applications, and future research directions," *Sensors Journal, IEEE*, Vol. 2 Issue. 2, p. 107-119, April 2002.

[7] Thrun, S. "A Bayesian approach to landmark discovery and active perception for mobile robot navigation," (Tech. rep. CMU-CS-96-122). Pittsburgh, PA: Carnegie Mellon University, Department of Computer Science. 1996.

[8] W. Pieczynski, "Unsupervised Dempster–Shafer fusion of dependent sensors," in *Proc. IEEE Southwest Symp. Image Analysis and Interpretation* (SSIAI'2000), Austin, TX, Apr. 2–4, pp. 247–251, 2000.

[9] Ayala, V. Hayet, J.B. Lerasle, F. Devy, M., "Visual localization of a mobile robot in indoor environments using planar landmarks" *Intelligent Robots and Systems, (IROS 2000). Proceedings. IEEE/RSJ International Conference on*, vol. 1, p. 275-280, 2000.

[10] M. Rombaut, D. Meizel, "Dynamic data temporal multisensor fusion in the Prometheus Prolab2 demonstrator," *IEEE Int. Conference on Robotics and Automation*, San Diego, May 8-13. pp. 36-76.

[11] J. Llinas and D. L. Hall, "A challenge for the data fusion community II: Infrastructure imperatives," in *Proc. 7th Natl. Symp. On Sensor Fusion*, Albuquerque, NM, Mar. 1994.

[12] L. A. Zadeh, "Outline of a New Approach to the Analysis of Complex Systems and Decision Processes," *IEEE Transactions on Systems, Man, and Cybernetics,* 3(1): 28-44, January 1973.

[13] R. C. Smith and P. Cheeseman, "On the Representation and Estimation of Spatial Uncertainty," In *the International Journal of Robotics Research*, Vol. 5, no. 4, pages 56-68, 1986.

[14] S. Bentalba, A. ElHajjaji and A. Tachid, "Fuzzy Control of a Mobile Robot: a New Approach," *Proc. IEEE International Conference on Control Applications*, pp.69-72, October 1997.

[15] H. R. Beom and H. S. Cho, "A sensor-Based Navigation for a Mobile Robot Using Fuzzy Logic and Reinforcement Learning," *IEEE Trans. on system, man, and cybernetics*, Vol.25, No. 3, pp.464-477, March 1995.

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