Proceedings of the 2002 IEEE
International Symposium on Intelligent Control
Vancouver, Canada • October 27-30, 2002

A Control Architecture for Mobile Robots Using Fusion of the Output of Distinct Controllers

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***Abstract*— This work proposes a new architecture for controlling the navigation of a mobile robot, which consists of fusing the output of distinct controllers through a decentralized information filter (DIF). The output of each controller is inputted to a local filter with a covariance associated to it. The lower this covariance is, the bigger the influence of the output of the corresponding controller on the fused output is. A fuzzy logic approach is proposed to qualitatively determine such covariances. It is also carried out an analysis of the stability of the proposed control architecture. A conjecture based on energy considerations is introduced, which assures that the overall control signal emerging from the fusion engine behaves well. In order to ensure the accomplishment of such conjecture, a supervisor is included in the proposed architecture. One out of several experiments using the proposed control architecture is also presented, in order to illustrate the system performance.**

***Index terms*—Control architecture, mobile robotics, data fusion, stability.**

I. INTRODUCTION

Control architectures are used to solve the problem of making a decision on which action the mobile robot should take in the next time instant. The two main categories of control architectures are *arbitration schemes* and *command fusion schemes*. Arbitration schemes can be classified as Priority Based, Winner-takes-all and State Based. Examples of such schemes are the Subsumption Architecture, Discrete Event Systems and Activation Networks [8]. On the other hand, command fusion schemes can be classified as Voting (e. g. DAMN [9]), Superposition (e. g. AuRA [1,2]), Multiple Objective (e. g. Multiple Objective Decision-Making Control [8]), Fuzzy Logic (e. g. Multivaluated Logic Approach [10]) and Dynamic Approach to Behavior-Based Robotics [3].

The control architecture here proposed (Figure 1) is based on the fusion of the output of a set of controllers by using a decentralized information filter (DIF). As shown in the figure, each controller receives sensorial information and produces linear/angular velocities as its output, which are inputted to some local information filters. These local filters plus a global information filter are referred to as DIF, which is an optimized fusion-method [4,7].

A covariance value of the observed data is associated to each local filter. The output of the global information filter is closer to the output of the local filter associated to the lowest covariance (the more reliable output). Fuzzy logic is used to associate a covariance to each controller according to the information coming from the sensing system.

An analysis of the stability of the whole control system thus implemented is also performed and the result is the proposition of a stability conjecture based on energy considerations, which should be accomplished in order to guarantee "good behavior" of the whole system. A supervisor (Figure 1) is introduced in the proposed control architecture, which ensures the accomplishment of the stability conjecture.

These specific topics are addressed hereinafter in the paper. Section II describes the use of fuzzy logic to determine the covariances associated to each local filter (each controller); Section III presents the stability analysis; Section IV presents some experimental results and, finally, Section V outlines the main conclusions.

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0-7803-7620-X/02/$17.00 © 2002 IEEE

II. Using Fuzzy Logic to Determine the Covariances of the DIF

When using an information filter [7], the covariance associated to the measurement error is a statistical measurement of the confidence of the data provided by each information source (sensor). When dealing with sensors (sensor fusion), the covariance matrix is obtained by testing each sensor involved in the fusion process. In the case of fusing the output of different controllers, the covariance represents a measure of the degree of suitability of a certain controller to the current environmental condition. The lower the covariance associated to a certain controller is, the more suitable it is, and the suitability degree of each controller is inferred from the information of the sensing system (here a set of ultrasonic sensors) or from information provided by the supervisory system.

One way to determine the degree of suitability of each controller is to use mathematical relationships involving the data measured by the robot sensors. The more suitable a certain controller is, the lower the result of the equation defining its covariance should be. An alternative way to calculate such covariances is the use of fuzzy logic. In this case, some linguistic variables are used to model the designer's knowledge about the robot navigation system and the robot-working environment through a rule base.

To determine the covariances using fuzzy logic, three fuzzy variables (antecedents) are used. They are the least robot-obstacle distance measured by the frontal ultrasonic sensors (d_{min}), the product of the distances measured by the ultrasonic sensors at the right (d_r) and left (d_l) sides of the mobile robot, and the least value between d_l and d_r. The fuzzy sets and the membership functions of these antecedents are identical and are shown in Figure 2. The consequent is the covariance associated to each one of the four controllers in figure 1. They are R1 for the controller responsible for the navigation in corridors, R2 for the point-to-point controller, R3 for the controller responsible for obstacle avoidance and R4 for the controller responsible for wall following. The defuzzyfication is performed by using the fuzzy mean method [4].

Tables 1 and 2 show the fuzzy rules adopted to determine the covariance assigned to each controller. There, TS means too small, S means small, M means medium, B means big and TB means too big. These rules can be interpreted in the following way: case d_{min} is small, the collision risk is big, a small covariance should be assigned to the obstacle avoidance controller, while a bigger one should be assigned to the other controllers. When d_{min} is not small, the covariance

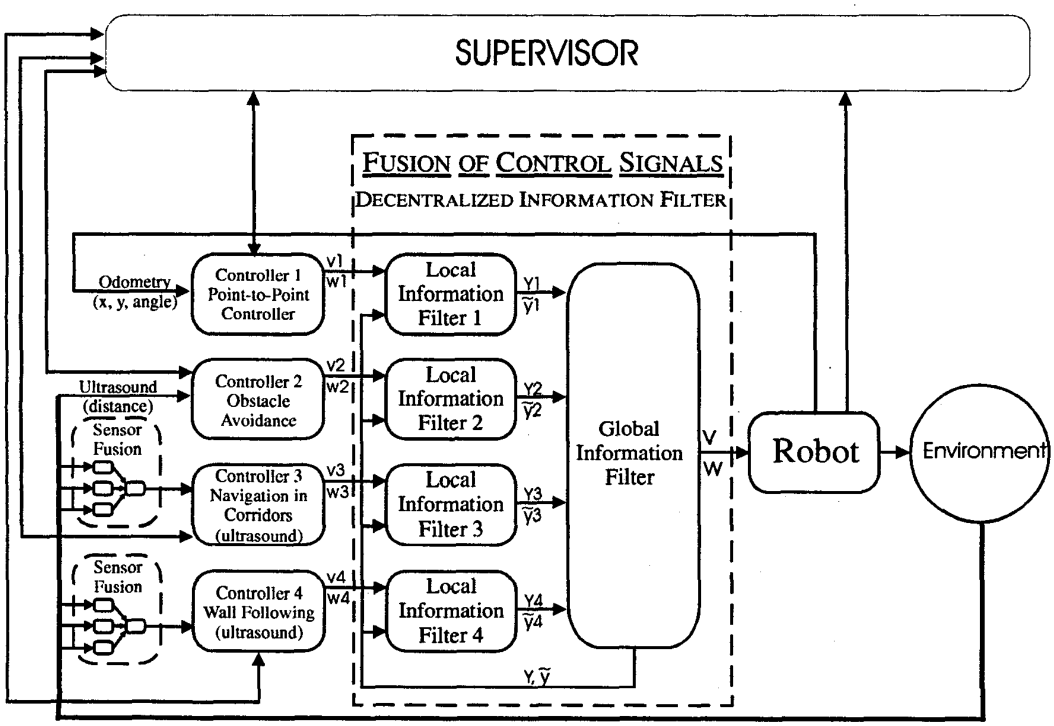

Fig. 1. The proposed architecture including the supervisor.

assigned to the obstacle avoidance controller should have a big relative value. If, besides this, the product $d_l \times d_r$ is small, it means that the robot is in a corridor. Therefore, the controller responsible the corridor navigation is the one that should have the smallest covariance. If d_{min} and the product $d_l \times d_r$ are not small but d_l or d_r is small, there is a wall in the left or right side of the robot. In this case, the wall following controller is the one to which it should be assigned the smallest covariance. Finally, in the case d_{min}, d_l, d_r and the product $d_l \times d_r$ are not small, the robot is in an open environment and free to go to its destination point, so that the point-to-point controller should have the smallest covariance.

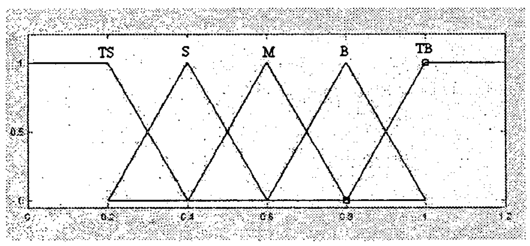

Fig. 2. Membership function of the input variables.

III. Stability of the Control System

The control system should be guaranteed to comply with some "good behavior" conditions, which we will try to express as a stability condition. As part of this condition, the different controllers used should be stable in the Lyapunov sense, thus ensuring the assignment of decreasing energy functions to them (normalized Lyapunov functions). This allows defining an overall energy function as the sum of the energy functions associated to all the controllers included in the system.

For analyzing the system stability, we consider now two navigation cases related to the proposed control structure. In the first one the active controllers in certain navigation condition are such that they have a common control objective. In the second one, the more general case of different controllers having different control objectives is regarded.

A. Common Control Objective

In this subsection, the stability of the control system resulting from the fusion of different controllers with the same control objective is analyzed. For example, suppose that three controllers are available to accomplish the task of navigating along a corridor. The first controller is based on information provided by an ultrasonic system that informs to the control system the relative position of the robot related to the middle of the corridor. The second controller tries to equalize the optic flow measured on the right and on the left corridor walls. The last controller equalizes the angle formed by the junction of the walls and the floor on the image plane. Each one of these controllers generates a control signal for the angular velocity.

Table 1 Fuzzy rules determining the covariance of the controller responsible for navigating in a corridor.

$d_l \times d_r$ / d_{min}	TS	S	M	B	TB
TS	R_1=TB	R_1=TB	R_1=TB	R_1=TB	R_1=TB
S	R_1=S	R_1=M	R_1=B	R_1=TB	R_1=TB
M	R_1=TS	R_1=TS	R_1=TS	R_1=TB	R_1=TB
B	R_1=TS	R_1=TS	R_1=TS	R_1=TB	R_1=TB
TB	R_1=TS	R_1=TS	R_1=TS	R_1=TB	R_1=TB

Table 2 Fuzzy rules determining the covariance of the point-to-point, obstacle avoidance and wall following controllers.

Min(d_l,d_r) / d_{min}	TS	S	M	B	TB
TS	R_2=TB R_3=TS R_4=TB	R_2=TB R_3=TS R_4=TB	R_2=TB R_3=TS R_4=TB	R_2=TB R_3=TS R_4=TB	R_2=TB R_3=TS R_4=TB
S	R_2=TB R_3=TS R_4=S	R_2=TB R_3=TS R_4=M	R_2=TB R_3=TS R_4=B	R_2=TB R_3=TS R_4=TB	R_2=TB R_3=TS R_4=TB
M	R_2=TB R_3=TB R_4=TS	R_2=TB R_3=TB R_4=TS	R_2=TB R_3=TB R_4=TS	R_2=TB R_3=TB R_4=TB	R_2=TB R_3=TB R_4=TB
B	R_2=TB R_3=TB R_4=TS	R_2=TB R_3=TB R_4=TS	R_2=B R_3=TB R_4=TS	R_2=S R_3=TB R_4=TB	R_2=TS R_3=TB R_4=TB
TB	R_2=TB R_3=TB R_4=TS	R_2=TB R_3=TB R_4=TS	R_2=B R_3=TB R_4=TS	R_2=S R_3=TB R_4=TB	R_2=TS R_3=TB R_4=TB

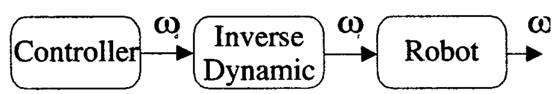

Fig. 3. System with one controller.

Firstly, consider that only one controller is used, as depicted in Figure 3. Consider also that the robot angular velocity dynamics can be modeled as

$$\frac{\omega}{\omega_r} = \frac{k}{s^2 + as + b} \tag{1}$$

so that ω_r can be written as

$$\omega_r = \frac{1}{k}\left(\ddot{\omega} + a\dot{\omega} + b\omega\right) \tag{2}$$

Now, using an inverse dynamics control law given by

$$\omega_r = \frac{1}{k}(\eta + a\dot{\omega} + b\omega) \tag{3}$$

where

$$\tilde{\omega} = \omega_d - \omega \tag{4}$$

$$\eta = \ddot{\omega}_d + k_d\dot{\tilde{\omega}} + k_p\tilde{\omega} \quad k_p, k_d > 0 \tag{5}$$

the closed loop equation for the exact knowledge of the robot dynamics is given by

$$\eta = \ddot{\omega} \tag{6}$$

Then, replacing the control law of Equation (5) one gets

$$\ddot{\tilde{\omega}} + k_d\dot{\tilde{\omega}} + k_p\tilde{\omega} = 0 \tag{7}$$

which implies that $\tilde{\omega}(t) \to 0$ when $t \to \infty$.

Now, if more than one controller with the same control objective is used – like in Figure 4 – and supposing that all the state variables associated to them are available at each time instant, one can write the set of equations

$$\omega_{r1} = \frac{1}{k}(\eta_1 + a\dot{\omega} + b\omega)$$

$$\omega_{r2} = \frac{1}{k}(\eta_2 + a\dot{\omega} + b\omega)$$

$$\vdots$$

$$\omega_{rn} = \frac{1}{k}(\eta_n + a\dot{\omega} + b\omega)$$

Then, the fused control signal is

$$\hat{\omega}_r = \frac{1}{k}(\hat{\eta} + a\dot{\omega} + b\omega) \tag{8}$$

For an ideal control command $\omega_d = \omega_{di} + \Delta\omega_{di}$ it corresponds an ideal η such that

$$\eta = \eta_1 + \Delta\eta_1$$

$$\eta = \eta_2 + \Delta\eta_2$$

$$\vdots$$

$$\eta = \eta_n + \Delta\eta_{n1}$$

which results in

$$\eta = \hat{\eta} + \Delta\hat{\eta} \tag{9}$$

By equating Equations (8) and (2) one gets

$$\hat{\eta} = \ddot{\omega} \tag{10}$$

and, finally, taking Equation (9) into account,

$$\hat{\eta} = \eta - \Delta\hat{\eta} = \ddot{\omega} \tag{11}$$

Now, from Equations (5) and (11) it is possible to write the following dynamics for the angular velocity error

$$\ddot{\tilde{\omega}} + k_d\dot{\tilde{\omega}} + k_p\tilde{\omega} = \Delta\hat{\eta} \tag{12}$$

Defining the state vector $x = [\tilde{\omega} \quad \dot{\tilde{\omega}}]^T$, Equation (12) can be written as

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \boldsymbol{\delta}(\mathbf{x}) \tag{13}$$

where

$$\mathbf{A} = \begin{pmatrix} 0 & 1 \\ -k_p & -k_d \end{pmatrix} \quad \boldsymbol{\delta}(\mathbf{x}) = \begin{pmatrix} 0 \\ \Delta\hat{\eta} \end{pmatrix}$$

Now, it is easy to prove that the system described by Equation (13) has an ultimately bounded solution [6].

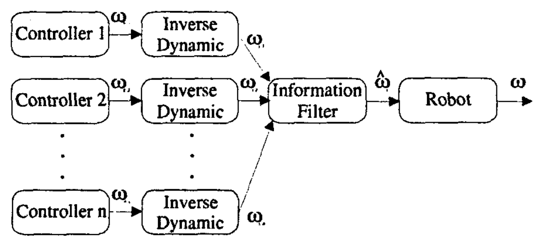

Fig. 4. Output fusion of different controllers.

This means that there are *b*, *c>0* such as for each $\alpha \in (0,c)$ there is a positive constant $T = T(\alpha)$ such that

$$\|\mathbf{x}(t_0)\| < \alpha \Rightarrow \|\mathbf{x}(t)\| \le b \; \forall t \ge t_0 + T(\alpha) \tag{14}$$

where *b* is the ultimate bound.

Taking the following Lyapunov candidate

$$V = \mathbf{x}^T\mathbf{P}\mathbf{x}, \ \mathbf{P} = \mathbf{P}^T > 0 \tag{15}$$

its time derivative is

$$\dot{V} = -\mathbf{x}^T\mathbf{Q}\mathbf{x} + 2\mathbf{x}^T\mathbf{P}\boldsymbol{\delta}(\mathbf{x}) \tag{16}$$

where

$$\mathbf{A}^T\mathbf{P} + \mathbf{P}\mathbf{A} = -\mathbf{Q} \tag{17}$$

Taking bounds on both terms of Equation (16)

$$-\mathbf{x}^T\mathbf{Q}\mathbf{x} \le -\lambda_{\min}(\mathbf{Q})\|\mathbf{x}\|^2 \tag{18}$$

$$\|2\mathbf{x}^T\mathbf{P}\| \le 2\lambda_{\max}(\mathbf{P})\|\mathbf{x}\| \tag{19}$$

one can write

$$\dot{V} \le -\lambda_{\min}(\mathbf{Q})\|\mathbf{x}\|^2 + 2\lambda_{\max}(\mathbf{P})\|\mathbf{x}\|\|\boldsymbol{\delta}(\mathbf{x})\| \tag{20}$$

From Equation (13)

$$\|\boldsymbol{\delta}(\mathbf{x})\| \le |\Delta\hat{\eta}| \tag{21}$$

Regarding Equation (20) one can write

$$\dot{V} \le -(1-\theta)\lambda_{\min}(\mathbf{Q})\|\mathbf{x}\|^2 - \theta\lambda_{\min}(\mathbf{Q})\|\mathbf{x}\|^2 + 2\lambda_{\max}(\mathbf{P})\|\mathbf{x}\||\Delta\hat{\eta}| \tag{22}$$

with $0<\theta<1$. Finally, it results in

$$\dot{V} \leq -(1-\theta)\lambda_{\min}(\mathbf{Q})\|\mathbf{x}\|^2$$
$$\forall\|\mathbf{x}\| \geq \frac{2\lambda_{\max}(\mathbf{P})|\Delta\hat{\eta}|}{\lambda_{\min}(\mathbf{Q})\theta} \tag{23}$$

so that the ultimate bound [6] for the system of Equation (13) is

$$b = \frac{2\lambda_{\max}(\mathbf{P})}{\lambda_{\min}(\mathbf{Q})}\sqrt{\frac{\lambda_{\max}(\mathbf{P})}{\lambda_{\min}(\mathbf{P})}}\frac{|\Delta\hat{\eta}|}{\theta} \tag{24}$$

As a Kalman-type filter is being used to fuse the control signals, the ultimate bound on the standard deviation of ultimate error is smaller than that corresponding to the errors produced by each controller, thus assuring the "good behavior" of the system of Figure 4.

B. *Different Control Objectives*

When the controllers involved in the fusion process do not have the same control objectives, the stability analysis made in the previous subsection is not valid anymore. An example is the system presented in Figure 1, for which the four controllers have different control objectives (goal seeking, obstacle avoidance, wall following and corridor navigation). In this case, a conjecture based on navigation phases and energy associated to each controller is now discussed.

When navigating from an initial point to a destination point (goal seeking) the robot goes through several navigation phases. A navigation phase is a part of the path followed by the robot where just one control objective dominates. If the main control objective changes, a navigation phase is over and another one starts. The control system detects a change in the navigation phase when the energy function assigned to at least one of the controllers grows faster then it would grow normally. This kind of growth will be called an abrupt one, while a normal growth will be called a gradual one. Examples of navigation phases are wall following, obstacle avoidance, corridor following, goal seeking, etc. Thus, an important detail when designing a control system using the architecture in Figure 1 is that at least one controller corresponding to each distinct phase the robot will face should be provided.

Now, regarding the stability of the controllers used, the overall system energy is supposed to decrease while the robot remains in the same navigation phase. In order to ensure this, a *supervisor* is included in the control architecture to monitor the energy function of each controller and the energy function of the entire system. Then, if the energy function of the system starts gradually growing, the controllers whose energy functions are gradually growing are eliminated of the fusion process (this is equivalent to make the covariances associated to them infinite).

As the environment is unknown, the kind and the number of navigation phases the robot should pass through to accomplish its task are also unknown. It is also impossible to know the exact time at which a navigation phase change will occur. Because of this, one can consider the transition between two navigation phases as a perturbation. For this reason, the system energy function is allowed to grow during the transition between two subsequent phases.

The supervisor should also eliminate of the fusion process the controllers that are out of context. A specific controller is out of context when its state variables are not available. An example of this situation is a robot in the middle of a very big room. As its sensing system does not detect any wall, the wall following controller and the corridor following controller can not operate once the robot does not detect a wall or a corridor to follow.

Thus, it is ensured that the energy function of the system decreases during a navigation phase. On the other hand, it is allowed to grow in the transition between two navigation phases, once this can be viewed as a perturbation. The stability conjecture is that this is enough to guarantee the "good behavior" of the whole control system. The supervisor included in the system (Figure 1) accomplishes this.

IV. Experimental Results

In order to evaluate how the proposed control architecture performs and to check the accomplishment of the stability conjecture proposed, a practical experiment consisting of guiding a robot navigating inside an office building is shown (Figure 5).

The experiment was run using a PIONEER 2DX mobile robot having sixteen ultrasonic sensors. The robot is guided from the initial point [0m, 0m] to the destination point [12m, 5m], both inside an office building. While seeking its final goal, the robot should navigate along corridors while avoiding obstacles in its path.

Figure 5 shows the path followed by the robot, while Figure 6 shows how the system energy function behaves. To evaluate the performance of the control system during the experiment, three indexes have been considered [8]. Table 3 shows the resulting values of the performance indexes for the experiment, including the ideal values of such indexes. The safety index indicates the minimal distance measured by the ultrasonic sensors along the robot path, thus indicating the risk of collision. As shown, the robot navigation during the experiment was quite safe. The average velocity (linear velocity) index indicates the average linear velocity along the robot path. As one can see, the fusion of distinct control signals makes the robot to navigate a little slower. Finally, the smoothness index is measured calculating the average value of the magnitude of the difference between the current and the previous robot orientation, thus showing how smoothly the maneuvers are performed. As one can see, the proposed architecture effectively allows very smooth maneuvers.

V. CONCLUSION

A control architecture based on the fusion of the output of a group of different stable controllers is presented. Fuzzy logic is used to determine the covariance associated to each local filter included in the decentralized information filter used as the fusion engine. It is formally demonstrated that the fusion of the output of different controllers having the same control objective has an ultimately bounded solution. In addition, the control signal resulting of the fusion is better than the output of each single controller in the sense that the variance of the ultimate error is smaller. The stability of the output fusion of different controllers with different control objectives is also addressed. In this case, a stability conjecture is presented, which is validated through several experiments.

ACKNOWLEDGMENT

The authors thank CAPES and SETCIP for supporting a partnership between Universidade Federal do Espírito Santo/BRAZIL and Universidad Nacional de San Juan/ARGENTINA, in which this research is included.

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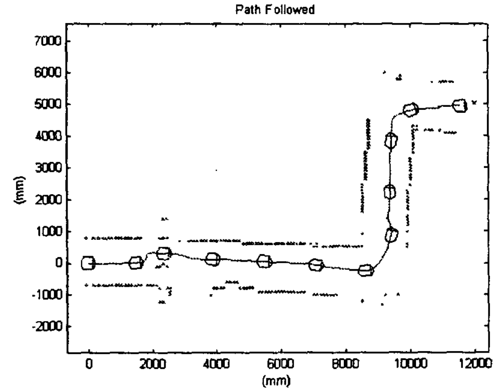

Fig. 5. Path followed in the experiment.

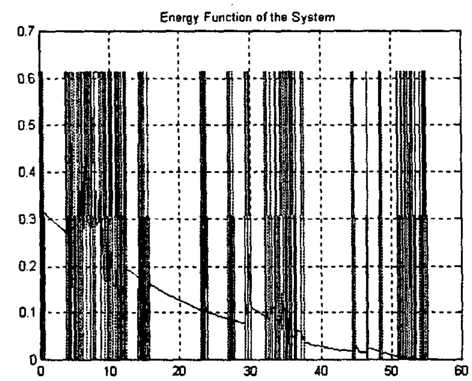

Fig. 6. Variation of the energy function with time.

Table 3: Performance evaluation indexes.

Index	*Obtained Value*	*Ideal Value*
Safety	172 mm	500 mm
Average Velocity	293 mm/s	300 mm/s
Smoothness	0.89°	0.32°
Travelled Distance	16.14 m	17.00 m
Elapsed Time	55.10 s	56.67 s