MOBILE ROBOT NAVIGATION BASED ON THE FUSION OF CONTROL SIGNALS FROM DIFFERENT CONTROLLERS

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Abstract

This paper proposes an alternative approach to deal with the problem of mobile robot navigation, which is called *fusion of control signals*. The proposed technique has presented good results when the robot has to execute relatively complex tasks, as it is shown in the illustrative example here presented. The technique is developed with basis on the decentralized information filter, whose equations are here derived from the equations of the decentralized Kalman filter and the information filter. Motion controllers available in the literature are used to produce the control signals that are fused in order to produce the overall output signal to be sent to the actuators.

1 Introduction

Three approaches are normally used to solve the problem of mobile robot navigation: the classical one, the behavior-based one and the hybrid one.

The classical mobile robot control architectures decompose the control system in a sequence of functional components [12]. In these architectures, the data are initially collected from all sensors available onboard the robot. Problems with noise and data conflicts are solved in such a way that it is possible to build a consistent model of the "real world". This model should include information about dimension, form, position and orientation of each object present in the working area of the mobile robot [12]. In most cases a great part of the model or map of the "world" is programmed in the robot memory before it starts functioning, which limits its operation to an environment it "knows". In this case, the sensors are used only to determine the position of the robot in the map [9,10,7]. Once the model of the "world" of the robot working environment is available, the robot starts using it to plan sequences of actions whose objective is to execute a certain task. Finally, the generated plan is executed by sending the suitable control signals to the actuators.

The behavior-based control architectures follow a quite different scheme. The behaviors are layers of a control system that work in parallel whenever the suitable sensors fire them [12,7,2,13]. The problem of conflicting sensorial data present in the classical architectures changes to a problem of conflicting behaviors. Thus, the necessary integration is implemented at the level of behavior output, instead of the level of sensor output (behavior integration). An arbitration scheme with priorities is used to determine which behavior is dominant in each situation. In such architectures, the idea of a behavior calling another behavior as a sub routine does not exist. Actually, all behaviors are executed in parallel, and higher level behaviors temporarily suppress the output of lower level behaviors. When the higher level behaviors are not being fired by a given sensorial condition, they stop suppressing the lower level behaviors, which resume the robot control. This way, such architectures are inherently parallel architectures and the sensors interact directly with all control layers. Each behavior, in addition, also interacts directly with the actuators. Finally, in behavior-based control architectures there is no unified data structure or "geometric world" models.

The hybrid architectures were developed with the objective of solving limitations inherent to both approaches previously mentioned by adopting a combination of a few coherent and well-defined models [7]. They integrate low- level and high-level control considerations in a coherent structure. Thus, a reactive system (behaviours without memory) executes low-level tasks, and a task planning system defines tasks of higher level. Such architectures separate the control system in two or more independent parts that are in communication. The low-level processes are in charge of the robot integrity every time, while the task planning is in charge of selecting a sequence of actions to be executed.

In this work, it is proposed a new approach to address the problem of mobile robot navigation. It is based on the fusion of different control signals generated by distinct controllers.

Before addressing the topic of fusion of control signals, however, it is convenient to make clear how sensor fusion will be understood hereinafter, once there is still not a common language for referring to this topic in the literature [1,8,11]. Although firstly associated to sensorial data, this terminology is straightforwardly extended to the control signals used here.

Sensorial integration is a term that refers to the systematic use of data coming from various sensing devices. The term sensor fusion, by its turn, refers to a particular case of sensorial integration in which the data coming from various sensing devices are combined in a single data-structure [1].

In the case here addressed, it will become clear that the data to be manipulated are translated to control signals, thus effectively characterizing a fusion process.

The paper is organized in a few sections, starting with this introductory one highlighting the main aspects of the approaches yet available to address the problem of mobile robot navigation. In the sequence, Section 2 describes the derivation of the decentralized information filter used in our approach, while Section 3 details how the fusion of control signals is used for controlling the robot navigation. Following, Section 4 brings a brief description of the controllers whose output signals are fused, and Section 5 describes a practical experiment using this technique to control a Pioneer II DX mobile robot. Finally, Section 6 presents the main conclusions of this work and suggests some topics for further study.

2 Derivation of the Decentralized Information Filter

Both the Kalman filter and the information filter can fuse the data coming from two or more sensors in an optimized way, as it is illustrated in Figure 1.

As the figure shows, averaging the instantaneous values coming from two sensors results in a variance that is neither as small as the variance of the more precise sensor nor so big as the variance of the less precise sensor. In opposition, the use of the Kalman filter results in a fusion of the data coming from both sensors whose variance is less than the variance associated to each sensor. This means that the data resulting from the sensor fusion are more precise and reliable than the data coming from each sensor individually.

For deriving the decentralized information filter it will be firstly presented the Kalman filter and the decentralized Kalman filter [3]. Afterwards, it will be presented the information filter [14], and finally the decentralized information filter will be derived from these formulations.

2.1 The Kalman Filter [3]

Suppose a system whose model is given by

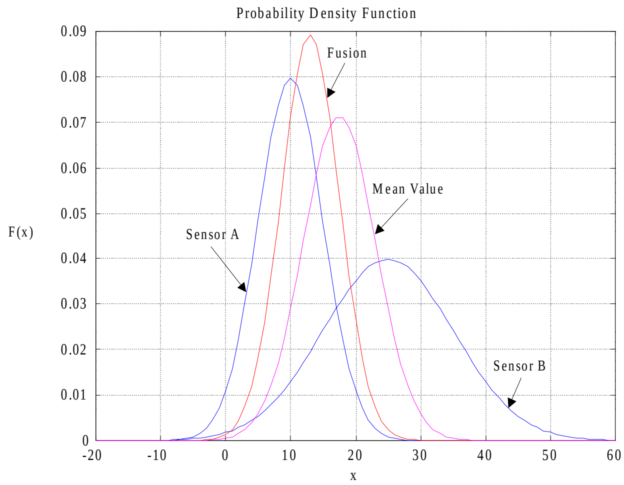

Figure 1: The fusion of the data coming from two different sensors using the Kalman filter (marked as Fusion) and their instantaneous average value (marked as Mean Value).

$$x_k = \phi_{k-1} x_{k-1} + w_k \quad (1)$$

$$z_k = H_k x_k + v_k \quad (2)$$

where ϕ is the state transition matrix, x_k is the state variable in the instant k, and z_k is the observation vector. By its turn, H is an observation matrix, $w_k \sim N(0,Q_k)$ is the noise associated to the system and $v_k \sim N(0,R_k)$ is the noise associated to the observation, both modeled as white, non-correlated, zero mean sequences containing the covariance of the process noise and the covariance of the observation noise, respectively.

The equations corresponding to the Kalman filter are

Prediction

$$\hat{x}_k = \phi_{k-1} \hat{x}_{k-1} \quad (3)$$

$$P_k = \phi_{k-1} P_{k-1} \phi_{k-1}^T + Q_{k-1} \quad (4)$$

Estimation

$$P_k^{-1} = \left(P_k^-\right)^{-1} + H_k^T R^{-1} H_k \quad (5)$$

$$\hat{x}_k = \hat{x}_k^- + K_k \left(z_k - H_k \hat{x}_k^- \right) \quad (6)$$

$$K_k = P_k H_k^T R_k^{-1} \quad (7)$$

where P is the matrix of the covariance error. This filter is illustrated in Figure 2 as a block diagram.

2.2 The Decentralized Kalman Filter with Feedback [10]

For each local filter one has

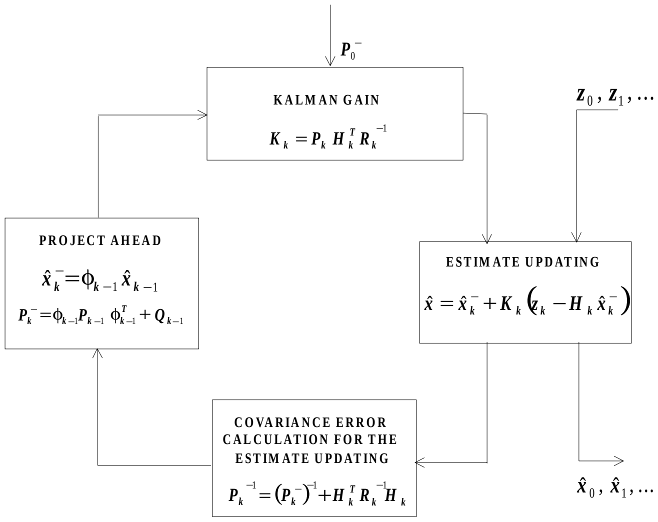

Figure 2: The Kalman filter [3].

$$\hat{x}_k = P_k \left(M^{-1} m + H_k R_k^{-1} z_k \right) \tag{8}$$

$$P_k^{-1} = M^{-1} + H_k^T R_k^{-1} H_k \tag{9}$$

where M is the initial error covariance matrix and m is the initial state vector value.

For the global filter, in the instant k one has

$$\hat{x} = P \left[\sum_{i=1}^{n} P_i^{-1} \hat{x}_i - (n-1) M^{-1} m \right] \tag{10}$$

$$P^{-1} = \sum_{i=1}^{n} P_i^{-1} - (n-1) M^{-1} \tag{11}$$

where n is the number of local filters. Figure 3 illustrates the scheme of the decentralized Kalman filter.

2.3 Information filter [14]

Information matrix

$$Y_k = P_k^{-1} \tag{12}$$

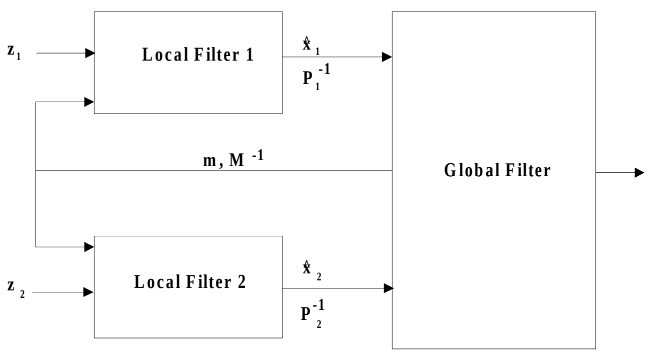

Figure 3: Decentralized Kalman filter [3].

State information vector

$$\hat{y}_k = P_k^{-1} \hat{x}_k = Y_k \hat{x}_k \tag{13}$$

Prediction

$$\hat{y}_k = L_k \hat{y}_{k-1} \tag{14}$$

$$Y_k = \left[\phi_k Y_{k-1}^{-1} \phi_k^T + Q_k \right]^{-1} \tag{15}$$

Estimation

$$\hat{y}_k = \hat{y}_k^- + i_k \tag{16}$$

$$Y_k = Y_k^- + I_k \tag{17}$$

where

$$L_k = Y_k \phi_k Y_{k-1}^{-1} \tag{18}$$

$$i_k = H_k^T R_k^{-1} z_k \tag{19}$$

$$I_k = H_k^T R_k^{-1} H_k \tag{20}$$

are respectively the coefficient of information propagation, the contribution of the state information and the matrix of information associated to each state.

2.4 Decentralized Information Filter

To the extent of the authors' knowledge, the formulation of the decentralized information filter is being proposed here by the first time, thus characterizing the first meaningful contribution of this paper. To derive the equations of the decentralized information filter, one can start from the equations presented in Subsections 2.1, 2.2 and 2.3 and proceed according to the procedure outlined below.

For the local filter, one should multiply both sides of equation (8) by P_k^{-1} and after to substitute it for $\hat{y}_k$ in Equations (12), (13) and (19), thus obtaining

$$\hat{y}_k = \hat{y}_k^- + i_k \tag{21}$$

In the sequence, starting from Equation (9) and using Equations (12) and (20) one can obtain

$$Y_k = Y_k^- + I_k \tag{22}$$

For the global filter, one can proceed in a similar way, thus obtaining the following equations for each instant k

$$\hat{y} = \sum_{i}^{n} \hat{y}_i - (n-1) \hat{y}_k^- \tag{23}$$

$$Y = \sum_{i=1}^{n} Y_i - (n-1) Y^- \tag{24}$$

where n is the number of local filters. The block diagram corresponding to the decentralized information filter thus characterized is the same of Figure 3.

2.5 Information Filter versus Kalman Filter

In algebraic terms, the information filter is equivalent to the Kalman filter [14]. However, the information filters are easier to initialize. When using Kalman filters it is necessary a previous knowledge of the system in order to obtain the initial estimate and to initialize the covariance error matrix P. By its turn, the information filter can be initialized simply making the state information vector y equal to zero and the information matrix equal to a small non-zero value (to allow inverting it). This occurs because when starting the execution of the information filter there is no information available. Actually, it starts increasing along the time. This advantage is much important for nonlinear systems, like mobile robot control, because the convergence of the Kalman filter is not guaranteed for a bad initial condition. In other words, the information filter is more robust than the Kalman filter when regarding the initialization.

Although the prediction equations of the information filter (Equations (14) and (15)) are more complex than the equivalent equations of the Kalman filter (Equations (3) and (4)), its estimation equations (Equations (16) and (17)) are much simpler than the equivalent equations of the Kalman filter (Equations (5) and (6)) [14]. Regarding the decentralized information filter and the decentralized Kalman filter, the formulation of the first one is simpler, which can be checked by comparing Equations (21)-(24) to Equations (8)-(11).

Furthermore, in the case of the information filter, the biggest matrix to be inverted has the same dimension of the state vector. In multi-sensorial systems the dimension of the matrices to be inverted are usually less than the dimension of the observation vector, which is the dimension of the matrices to be inverted when using the Kalman filter [14].

For these reasons, the information filter was chosen to be the fusion structure used hereinafter.

3 Fusion of Control Signals

In many applications where the sensorial data contain information about different aspects of the robot-working environment, it is not profitable to use sensor fusion.

On the other hand, the classical control algorithms, although having advantages like proof of stability and possibility of execution of well-defined tasks, can result in control equations that are too much complex, depending on the complexity of the task to be executed, thus demanding powerful hardware resources or becoming prohibitive.

When regarding behavior-based algorithms, by its turn, it is possible to have various behaviors, each one corresponding to a distinct controller, which deal with different aspects of the environment. As an example, consider the following tasks assigned to a mobile robot: if the robot is in a corridor, it should navigate along the corridor; if there is an obstacle, the robot should avoid it; otherwise, the robot should go to its destination point previously defined. Thus, complex tasks can be executed using different simpler controllers. The most common approach when using behavior-based control systems is to switch from one to another controller, thus generating non-smooth transitions in the robot path.

The fusion of the output signal of different controllers here proposed allows to take advantage of some aspects of the behaviour-based control systems while preserving the smoothness when changing the robot current path. This will be better illustrated by the experiment reported below.

The scheme proposed for fusing the control signals is shown in Figure 4. There four controllers are used, all of them producing control signals based on the sensorial information coming from the robot sensing subsystems, there including information coming from the shaft encoders. The figure also illustrates a strategy commonly adopted to obtain information that is more precise: to fuse the information coming from a group of similar sensors. This fusion is implemented before this information is inputted to the respective controller. In the sequence, a decentralized information filter is used to implement the fusion of the control signals generated by the controllers. The overall control signal thus resulting is then applied to the actuators in the robot.

Each controller has associated to it a covariance that varies with the data coming from the sensorial system according to a certain criterion. For example, consider a mobile robot that has an ultrasonic sensing subsystem, which is responsible for avoiding obstacles in the robot path. If an obstacle is close to the robot, the minimum distance measured by the ultrasonic sensors is small, which results in a covariance that is also small, so that the output signal of the corresponding controller has an increased importance in the composition of the overall control signal. This way, the navigation system is able to select, in each instant, which controller delivers the most important control signal, thus allowing smoother transitions in the robot path and then a smoother and safer navigation.

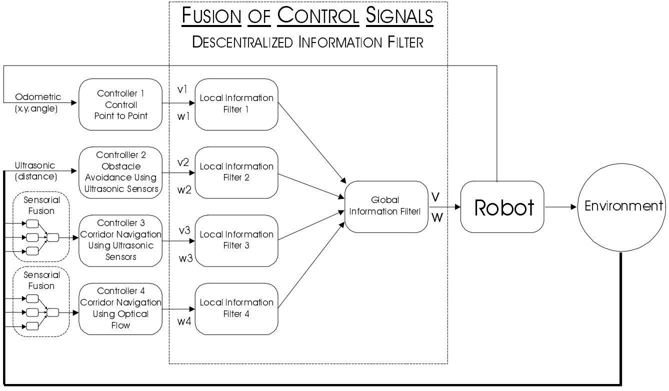

Figure 4: Structure adopted to fuse the control signals.

4 The Controllers Used

In this section the four controllers used in the structure of Figure 4 are briefly described.

4.1 Point to Point Controller

This is the first controller used in Figure 4, and is responsible for guiding the robot from an origin to a destination point previously established. Actually, it is controlled the position of the robot regarding the objective. For details on this algorithm, one can check [4], where its formulation and stability analysis is addressed.

4.2 Obstacle Avoidance

In order to avoid obstacles the information obtained from the ultrasonic sensors numbered from 1 to 6 in the robot is used. These sensors have the orientation of -50^o, -30^o, -10^o, 10^o, 30^o and 50^o, respectively. In order to do that, it is initially assigned to each sensor a linear and an angular speed, according to

$$\omega(i) = \frac{70}{i - 3.5} \tag{25}$$

$$v(i) = 80|i - 3.5| \tag{26}$$

This way, a greater linear speed and a lower angular speed (in magnitude) is assigned to the side sensors in comparison to the sensors in the front of the robot.

Finally, the linear and angular speeds of each sensor are fused through a decentralized information filter (the covariance associated to each ultrasonic sensor is the distance it measures. Thus, the closer an obstacle is to a certain sensor the lower its covariance will be and it will be more influent when composing the linear and angular speeds generated by this local controller). The sensor fusion is here used for allowing a smoother speed variation, in opposition to the use of the information on distance coming from the ultrasonic sensors. As an example, it was previously used the minimum distance measured by the sensors, which resulted in non-smooth speed variation.

4.3 Ultrasonic-based Controller for Corridor Navigation

This is a asymptotically stable controller proposed in [5] for keeping the robot in the middle of a corridor with an orientation of zero degrees related to the middle of the corridor. It uses information coming from two ultrasonic sensors installed in each side of the robot. The control objective is to keep constant the distance from each one of these sensors to the wall in each side of the corridor, which means to control the robot heading.

4.4 Controller for Navigation in Corridors Using Optical Flow

This is an asymptotically stable controller proposed in [6] for controlling the navigation of a mobile robot in a corridor, using visual feedback. It receives information on the change of environment variation (optical flow) when the robot moves itself along the corridor through the images taken by a CCD camera mounted onboard the robot.

For now, this controller has been not used in the experiment described in the sequence. This is because the manipulation of the visual data there included is too slow, thus generating processing times too long when compared to the sample time used in connection to the other controllers.

5 Practical Experiment

To demonstrate the performance of the fusion of control signals technique for controlling the robot navigation, an experiment consisting on guiding the robot from an origin to a destination point was run. During its navigation, the robot should avoid obstacles in its path and navigate along corridors. Then, the first three controllers described in the previous section are used concerning the structure of Figure 4. In all fusion stages, the decentralized information filter proposed in Section 2 is used.

The experiment was run using a Pioneer II DX mobile robot, which has 16 ultrasonic sensors and a CCD camera (see Figure 5). Its movement is controlled through a radio link by the proposed control system running in an external computer.

Figure 6 illustrates the path followed by the robot, when the starting point is (0m, 0m) and the destination point is (15m, 5m), where x refers to the horizontal axis. As shown in Figure 6, the robot is able to leave the initial point and to reach the destination point, while avoiding obstacles in its path.

Figure 5: The Pioneer II DX mobile robot.

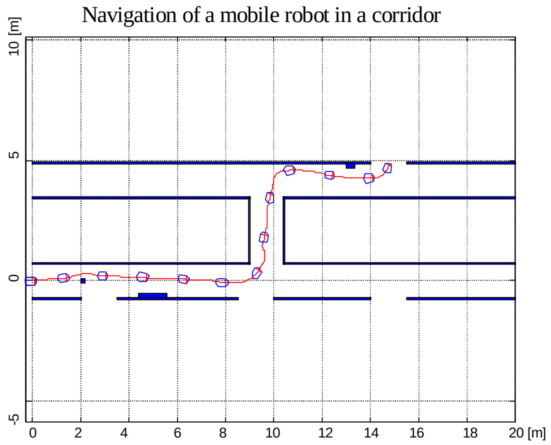

Figure 6: Navigation of the Pioneer II DX mobile robot using the fusion of control signals technique here proposed.

6 Concluding Remarks and Future Work

This paper presented a new approach to address the problem of the navigation of a mobile robot, which has been called fusion of control signals.

In order to implement the technique it is used the decentralized information filter, also proposed here, in order to fuse different control signals coming from different controllers. Information filters, including the decentralized one, are compared to Kalman filters in the paper, thus becoming clearer some advantages of using the information filters instead of the Kalman filters for performing the desired fusion.

A practical experiment using a mobile robot Pioneer II DX is also presented, which illustrates the results of the robot navigation when using the technique here proposed.

As future work, it is being considered the use of fuzzy logic to calculate the covariance associated to each controller whose output signal should be fused (see Figure 4). Nowadays this step is being concluded and the results are very interesting.

Finally, another important step just started is to demonstrate that the overall controller generated by fusing the output of a group of stable controllers is also stable.

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