Multi-Sensor Data Fusion with Covariance Intersection in Robotic Space with Network Sensor Devices

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Abstract

In this paper, as the preliminary step for developing a multi-purpose "Robotic Space" platform to implement advanced technologies easily to realize smart interface to human. We will give an explanation for the Robotic Space system architecture designed and implemented in this study and a short review of existing techniques, since there exists several recent thorough books and review paper on this paper. We will focus on the main results with relevance to the Multi-Sensor Data Fusion with CI of Robotic Space. It is dealt with the general principle of the using the covariance intersection framework to combine mean and covariance estimates without information about their degree of correlation provides a direct solution to the distributed data fusion problem.

Keywords: Multiple Sensor, Data Fusion, Human Interface, Sensor Network

1. Introduction

The Robotic Space is a space (room, corridor or street), which has ubiquitous distributed sensory intelligence (various sensors, such as cameras and microphones with intelligence), mobile actuators (mobile robots) to manipulate the space, as shown in Figure 1. The Robotic Space propagates mobile robots in the space, which act in the space in order to change the state of the space. These mobile robots are called mobile agents. Mobile Agents cooperating with each other and with the core of the Robotic Space to realize intelligent services to inhabitants. Mobile robots become more intelligent through interaction with the Robotic Space. Moreover, robots can understand the requests (*e.g.* gestures) from people, so that the robots and the space can support people effectively by using network sensor devices [1].
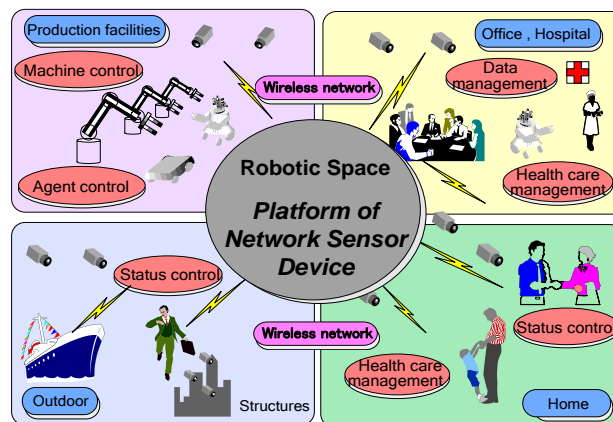

Figure 1. Vision of Robotic Space, As A Human Interface with Robots

These sensor devices have sensing, processing and networking functions, and are named distributed network sensor devices (NSDs) [2]. These devices observe the positions and behaviour of both humans and robots coexisting in the Robotic Space. The information acquired by each NSD is shared among the NSDs through the network communication system. Based on the accumulated information, the environment as a system is able to understand the intention of humans. For supporting humans, the environment/system utilizes machines including computers and robots.

2. Structure of Robotic Space

2.1. Robotic Space Interface

The Robotic Space which is about 5 m in both width and depth, is used for the Robotic Space as shown in Figure 2. The present configuration involves eight pan-tilt-zoom CCD cameras, handled by 4 sensing nodes (PCs), an ultrasound positioning system and two mobile robots. Moreover, the Robotic Space has a large size screen and speakers for presenting information to the users of the space. All the modules are connected through the local area network. Also, for achieving appropriate conditions for the operation of cameras, the lighting in the space can be easily adjusted.
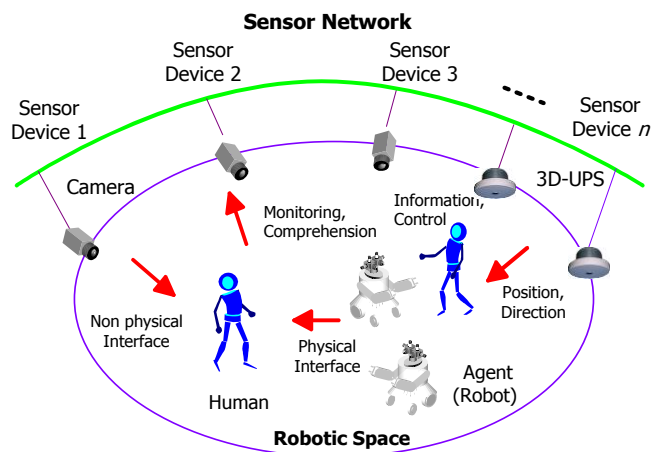

Figure 2. Environment of the Robotic Space

3. Multi-Sensor Data Fusion with Covariance Intersection (CI)

3.1. Distributed Sensor Network

One of the most important areas of research for control and estimation in the Robotic Space is distributed data fusion. The motivation for decentralization of multi-sensor is that it can provide a degree of scalability and robustness that cannot be achieved with traditional centralized sensor fusion network. In human interface applications, decentralization offers the possibility of producing plug-and-play systems in which sensors can be slotted in and out to optimize a trade off between price and performance. This has significant implications for robotic space with network sensors as well because it can dramatically reduce the time required to incorporate new computational and sensing components into fighter aircraft, ships, and other types of platforms [3-4].
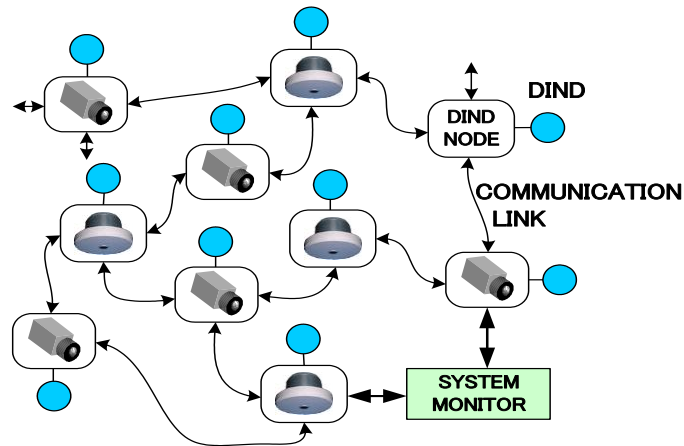
Figure 3. A Distributed Data Fusion Network. Each Box Represents A Fusion Node. Each Node Possesses 0 or More Sensors and is Connected To its Neighbouring Nodes through A Set of Communication links

The benefits of decentralization are not limited to sensor fusion onboard a single platform; decentralization also can allow a network of platforms to exchange information and coordinate activities in a flexible and scalable fashion that would be impractical or impossible to achieve with a single, monolithic platform. Interplatform information propagation and fusion form the crux of the distributed network sensor devices (NSD) for the robotic space.

A distributed data fusion system is a collection of processing nodes, connected by communication links, as shown in Figure 3, in which none of the nodes has knowledge about the overall network topology. Each node performs a specific computing task using information from nodes with which it is linked, but no "central" node exists that controls the network. There are many attractive properties of such decentralized systems [5-6], including:

•Distributed systems are reliable in the sense that the loss of a subset of nodes and/or links does not necessarily prevent the rest of the system from functioning.

•Distributed systems are flexible in the sense that nodes can be added or deleted by making only local changes to the network.

3.2. Using Covariance Intersection for Multi-Sensor Data Fusion

Consider again the data fusion network that is illustrated in Figure 4. The network consists of N NSD nodes whose connection topology is completely arbitrary (*i.e.,* it might include loops and cycles) and can change dynamically. Each node has information only about its local connection topology (*e.g*., the number of nodes with which it directly communicates and the type of data sent across each communication link).

Assuming that the process and observation noises are independent, the only source of unmodeled correlations is the distributed data fusion system itself. CI can be used to develop a distributed data fusion algorithm which directly exploits this structure. The basic idea is illustrated in Figure 4. Estimates that are propagated from other nodes are correlated to an unknown degree and must be fused with the state estimate using CI. Measurements taken locally are known to be independent and can be fused using the Kalman filter equations [5-6].

Using conventional notation [7], the estimate at the *i*-th node is $\hat{\mathbf{x}}(k \mid k)$ with covariance $\mathbf{p}_i(k \mid k)$. CI can be used to fuse the information that is propagated between the different nodes. Suppose that, at time step k + 1, node *i* locally measures the

observation vector $\mathbf{z}_i(k\,|\,k)$. A distributed fusion algorithm for propagating the estimate from time step k to timestep k + 1 for node i is:
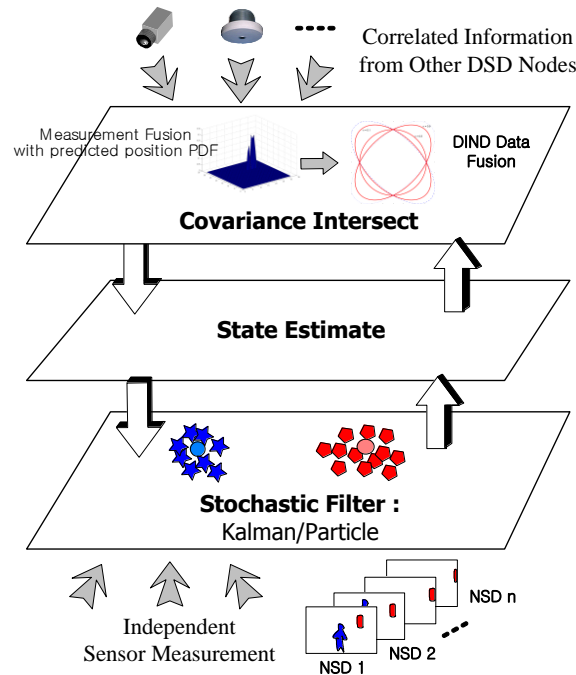
Figure 4. A Canonical Node in a General Data Fusion Network that Constructs Its Local State Estimate Using CI to Combine Information Received From Other Nodes and a Stochastic Filter to Incorporate Independent Sensor Measurements

1. Predict the state of node i at time k + 1 using the standard Kalman filter prediction equations.

2. Use the Kalman filter update equations to update the prediction with $\mathbf{z}_i(k+1)$. This update is the distributed estimate with mean $\hat{\mathbf{x}}_i^*(k+1\,|\,k+1)$ and covariance $\mathbf{p}_i^*(k+1\,|\,k+1)$. It is not the final estimate, because it does not include observations and estimates propagated from the other nodes in the network.

3. Node i propagates its distributed estimate to all of its neighbors.

4. Node i fuses its prediction $\hat{\mathbf{x}}_i(k+1\,|\,k)$ and $\mathbf{p}_i(k+1\,|\,k)$ with the distributed estimates that it has received from all of its neighbors to yield the partial update with mean $\hat{\mathbf{x}}_i^+(k+1\,|\,k+1)$ and covariance $\mathbf{p}_i^+(k+1\,|\,k+1)$. Because these estimates are propagated from other nodes whose correlations are unknown, the CI algorithm is used. As explained above, if the node receives multi-sensor estimates for the same time step, the batch form of CI is most efficient. Finally, node i uses the Kalman filter update equations to fuse $\mathbf{z}_i(k+1)$ with its partial update to yield the new estimate $\hat{\mathbf{x}}_i(k+1\,|\,k+1)$ with covariance $\mathbf{p}_i(k+1\,|\,k+1)$. The node incorporates its observation last using the Kalman filter equations because it is known to be independent of the prediction or data which has been distributed to the node from its neighbors. Therefore, CI is unnecessary. This concept is illustrated in Figure 5(a).

4. Measurement Data Fusion

In moving object tracking algorithms as well as in numerous other applications, information from different sources needs to be combined. This data fusion is most widely realized by the Kalman filter and its derivatives such as the extended Kalman filter for non-linear systems. The Kalman filter represents an optimal fusion with respect to various characteristics of the information that is being combined and its outcome.

An illustration of the Kalman filter algorithm is shown in Figure 5(a), where the two events A (dotted ellipse) and B (dashed ellipse) are representations of a true event. Following the Kalman filter assumptions, we obtain a non-conservative error covariance matrix. It is non-conservative since the algorithm assumes the independence of the two events, and any relationship is neglected.

The accompanying covariance ellipse, shown in Figure 5(a) is generally smaller than the covariance ellipses of A or B and lies in the intersection of these two ellipses. Suppose the events A and B are not independent with a non-vanishing cross-covariance P_{ab}, the estimated covariance can be calculated from Eq. (2). These estimated covariances are shown in Figure 5(a) for a set of cross-covariances P_{ab}. It is notable that this set of covariance ellipses lies inside an enveloping ellipse. Clearly, an algorithm generating the enveloping ellipse exhibits a conservative estimation since it accounts for any correlation between the events A and B.

For later development of the Covariance Intersection algorithm it is noteworthy that the error covariance matrix of the Kalman filter can be expressed as:

$$P_c = E\{e_c e_c^T\} \tag{1}$$

which is the direct result of substituting the optimal gain K into the covariance equation, and e_c, e_a, e_b are an error as a random variable. In addition, the weighted linear combination Eq. (1) can be rewritten as:

$$P_c^{-1}\chi = P_a^{-1}\alpha + P_b^{-1}\beta \tag{2}$$

The means of the errors e_a and e_b are assumed to be zero, which was justified in the aforementioned case of the event A being a measurement. In addition, the event B most-likely is the prediction of the previous estimate, which also is assumed to exhibit zero error mean. In the case of a linear prediction the zero error mean is preserved and $E\{e_c\} = 0$.

Uhlmann [6] described an algorithm capable of estimating the error covariance in the spirit of the aforementioned enveloping ellipse. The so-called Covariance Intersection (CI) is characterized by the convex combination of the covariances P_a and P_b, which can be written as follows:

$$P_c^{-1} = wP_a^{-1} + (1-w)P_b^{-1}, \tag{3}$$

where w takes values in the range of [0,1]. Note, that the CI is a weighted expression of Eq. (2). The estimated covariance of the CI is shown in Figure 5(a) for $w = 0.4$. Similarly, the mean is estimated as a weighted expression of equation (2), which is:

$$P_c^{-1}\chi = wP_a^{-1}\alpha + (1-w)P_b^{-1}\beta \tag{4}$$

It has been shown that the Covariance Intersection yields a non-conservative estimate in terms of dependency of the information to be fused, resulting in an estimate with lower confidence. The weight w can be interpreted as a tuning parameter of the CI. Its selection shapes the estimated covariance either closer to the information A ($w \rightarrow 1$) or to the information B ($w \rightarrow 0$).

(a)   (b)
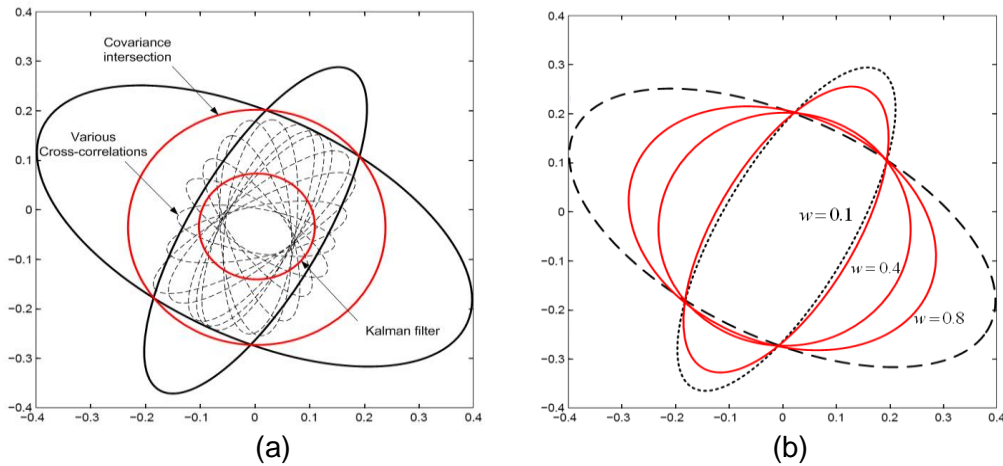
Figure 5. (A)The Shape of the Updated Covariance Ellipse. the Variances of P_a And P_b are the Outer Solid Ellipses. Different Values of P_c that Arise From Different Choices of P_{ab} Are Shown As Dashed Ellipses. The Update with Truly Independent Estimates is the Inner Solid Ellipse (B) σ Ellipses of the Covariance Intersection with Different Values of the Weight w

Figure 5(b) illustrates three selections of the weight w =0.1, 0.2. 0.3. The selection of the weight w can be subject to various performance criteria. First, we should ensure that the error mean of the estimate is zero. Substituting Eq. (1) into Eq. (4) and using the relation in Eq. (3) yields the true error [5]:

$$e_c = Pc[wP_a^{-1}e_a + (1-w)P_b^{-1}e_b] \ . \tag{5}$$

Clearly, the mean of the estimate is zero since e_a and e_b are unbiased. Following the development of Kalman, the weight w can be optimally selected by minimizing the error variance:

$$P_c^{-1} = w^2 P_a^{-1} + (1-w)^2 P_b^{-1} + w(1-w)[P_a^{-1}P_{ab}P_b^{-1T} + P_b^{-1}P_{ba}P_b^{-1T}]^T \tag{6}$$

Figure 6 plots a typical eigenvector of moving object in a convoy, where the global color models of position are shown [7-8]. It shows the position pdf's obtained from a sensor observation and from the prediction algorithm as well as the fused pdf derived by equation (6).
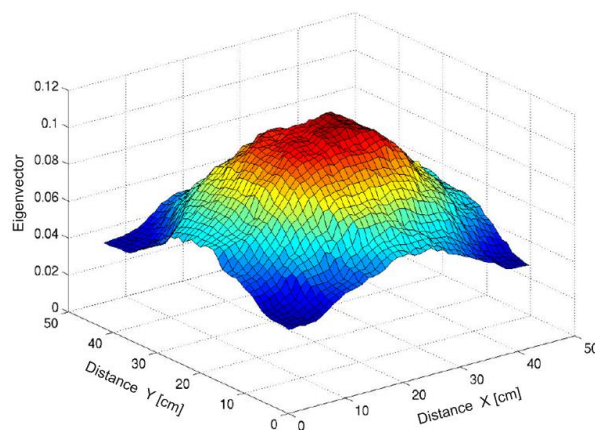
Figure 6. Eigenvector of Moving Object by Ellipse Variation of Covariance Intersection in Value of w Determination

5. Conclusion

This paper introduced the current research result on Robotic Space Project. The Robotic Space involves a ubiquitous distributed sensory network, which can track human and other object is the space; mobile robots, what gives guiding support to the humans, and utilizes the observed information of the sensory network. And we discussed the extremely important problem of data fusion in Robotic Space. It described a data fusion/update technique that makes no assumptions about the independence of the estimates to be combined.

The use of the covariance intersection framework to combine mean and covariance estimates without information about their degree of correlation provides a direct solution to the distributed data fusion problem. However, the problem of unmodeled correlations reaches far beyond distributed data fusion and touches the heart of most types of tracking and estimation. Other application domains for which CI is highly relevant include:

• Track-to-track data fusion in multiple moving object tracking systems — When sensor observations are made in a dense target environment, there is ambiguity concerning which tracked target produced each observation [9].

• Multiple model filtering — Many systems switch behaviors in a complicated manner, so that a comprehensive model is difficult to derive [10].

Acknowledgements

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