International Journal of Fuzzy Logic and Intelligent Systems, vol. 7, no. 1, March 2007, pp. 41-48

DIND Data Fusion with Covariance Intersection in Intelligent Space with Networked Sensors

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Abstract

Latest advances in network sensor technology and state of the art of mobile robot, and artificial intelligence research can be employed to develop autonomous and distributed monitoring systems. In this study, as the preliminary step for developing a multi-purpose "Intelligent Space" platform to implement advanced technologies easily to realize smart services to human.

We will give an explanation for the ISpace system architecture designed and implemented in this study and a short review of existing techniques, since there exist several recent thorough books and review paper on this paper. Instead we will focus on the main results with relevance to the DIND data fusion with CI of Intelligent Space. We will conclude by discussing some possible future extensions of ISpace. It is first dealt with the general principle of the navigation and guidance architecture, then the detailed functions tracking multiple objects, human detection and motion assessment, with the results from the simulations run.

Key words : Intelligent space, multiple vision, tracking, mobile robot, covariance intersection

1. Introduction

'Intelligent Space(iSpace)' has been proposed by Hashimoto lab. in university of Tokyo [1]. Intelligent Space is an environmental system, which is able to support human in informative and physical ways. Most of intelligent system interacts with human in a passive space, but in Intelligent Space, a space, which contains human and artificial systems, is an intelligent system itself. Human and artificial systems become clients of Intelligent Space and simultaneously the artificial systems become agents of Intelligent Space. Since the whole space is an intelligent system, Intelligent Space, a spatial system, is able to monitor and to provide services to clients easily. Specific tasks, which cannot be achieved only by Intelligent Space, are accomplished by utilizing its clients. For examples, Intelligent Space utilizes computer monitors to provide information to the human, and robots are utilized to provide physical services to the human as physical agents. Robot as well as human is supported by Intelligent Space if it is necessary. When a robot is lacking of sensors to navigate around in Intelligent Space, the robot is treated as a client of Intelligent Space and lacking information is provided to the robot by Intelligent Space.

The ultimate goal of Intelligent Space project is to accomplish an environment that comprehends human's intentions and satisfies them. It seems that such a system is hardly achieved, since a huge number of functions should be prepared and human-like intelligence is required. Even though such a complete system cannot be achieved immediately, it is convinced that a useful system can be achieved with current technology by proper system integration.

This paper is organized as follows. Section 2 introduces the basic concepts and achievements of the iSpace. Section 3 introduces the present architecture of intelligent space as a multi-purpose platform with multiple sensors, real time vision and feature tracking, which have been developed for active human support. Section 4 explains the DIND data fusion with Covariance Intersection(CI) that is ongoing research in iSpace. Section 5 introduces the measurement fusion for the application of moving object tracking.Finally, the directions for future work and conclusions are described in Section 6.

Manuscript received Mar. 5, 2007; revised Mar. 12, 2007.
This work was supported by the 2007 Research Promotion Grant funded by the Dongseo University.

2. Concepts and Achievements of iSpace

The iSpace is a space (room, corridor or street), which has ubiquitous distributed sensory intelligence (various sensors, such as cameras and microphones with intelligence) actuators (TV projectors, speakers, and mobile agent) to manipulate the space, as shown in Fig. 1. The iSpace 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 iSpace to realize intelligent services to inhabitants.

Mobile robots become more intelligent through interaction with the iSpace. Moreover, robots can understand the requests (e.g. gestures) from people, so that the robots and the space can support people effectively.

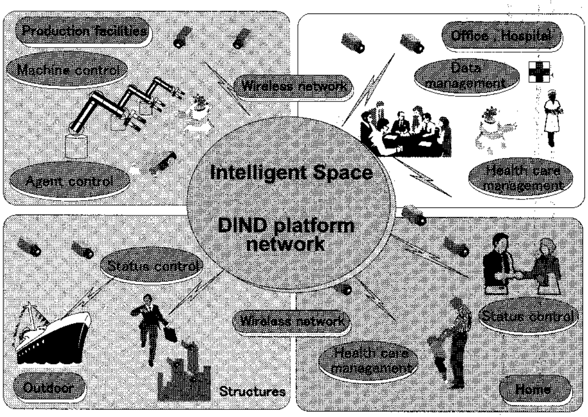

Fig. 1. Vision of Intelligent Space, as a human support system for more comfortable life

The Intelligent Space can physically and mentally support people using robot and VR technologies; thereby providing satisfaction for people. These functions will be an indispensable technology in the coming intelligence consumption society. Inhabitants in the iSpace are producing intelligent reactions against instantaneous situation. The iSpace evaluates situations (actions-reactions) from sensed information. The ranges of the services of the mobile agents are from guiding in the exhibition area to delivering parcels in a train station. For both type of services, the mobile robots have to navigate in a human shared environment, which is very dynamic, because the inhabitants changes its position quite often.

These intelligent devices have sensing, processing and networking functions, and are named distributed intelligent networked devices (DINDs) [2]. These devices observe the positions and behaviour of both humans and robots coexisting in the iSpace. The information acquired by each DIND is shared among the DINDs 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.

3. Architecture of Intelligent Space

3.1 New Intelligent Space Scheme

The Intelligent Space is constructed as shown in Fig. 2. Figure 3 shows the present configuration of the Intelligent Space in the Hashimoto Lab. Our laboratory room, which is about 5 m in both width and depth, is used for the iSpace. 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 iSpace 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.

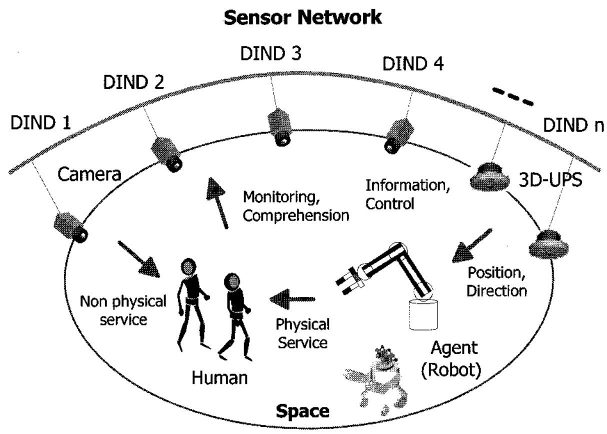

Fig. 2. Structure of Intelligent Space(iSpace)

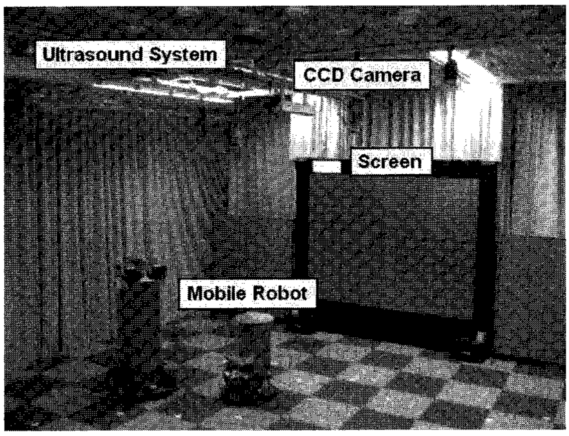

Fig. 3. Experiment environment

- **Camera system**

In the iSpace, CCD cameras are adopted as sensors for tracking the objects in the space. The cameras are placed so that the whole area of the room is covered. The placement of the cameras can also be optimized to expand the viewable area of the cameras, which was a subject of our previous research [3].

In our currently used system, the human and robot tracking is done by background subtraction and using color information [4]. Skin color is used for human tracking. The robot tracking makes use of color markers positioned on top of the robot. Using the information from all cameras the position of both the humans and robots can be reconstructed. The tracking software also provides a GUI for easy operation.

▪ **Ultrasound positioning system**

The ultrasound positioning system in the iSpace is used to obtain the 3D position of objects in the space. In consists of small size transmitters and 96 receivers positioned on the ceiling and connected to the control unit. The transmitters send an ultrasound signal, which is detected by the receivers from which the position of the transmitter can be calculated. In order to obtain the information form the positioning system the nodes on the network access a network server connected with the system.

▪ **Mobile robots in the iSpace**

In the iSpace we currently use two mobile robots. One is a Pioneer 2-DX robot and the other a Pioneer 2-AT mobile robot, both produced by ActivMedia Robotics (www.activrobots.com). A PC is mounted on each mobile robot in order to provide processing of date from the sensors mounted on robots and for communication with the iSpace via wireless LAN.

For the detection of the robot position data fusion of information from cameras, ultrasound system and robot wheel encoders are implemented. Based on the obtained position, tracking and position control of the robot are performed. The observations from both cameras and the ultrasound positioning system are also used to detect the humans and obstacles in the space, which is in turn used for planning the path of the robots.

4. DIND Data Fusion with Covariance Intersection(CI)

4.1 Distributed Data Fusion Network

One of the most important areas of research in the field of control and estimation is distributed data fusion. The motivation for decentralization is that it can provide a degree of scalability and robustness that cannot be achieved with traditional centralized architectures. In industrial 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 intelligent 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.

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 intelligent network devices (DIND) for the intelligent space. The goal of DIND is to equip all intelligent space entities - car, ships, and even individual mobile agents - with communication and computing capabilities to allow each to represent a node in a vast decentralized command and control network. The idea is that each entity can dynamically establish a communications link with any other entity to obtain the information it needs to perform its multi-tasking role.

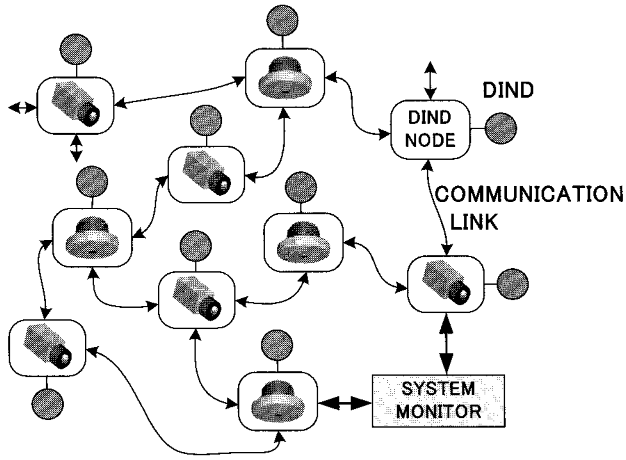

Fig. 4. A distributed data fusion network. Each box represents a fusion node. Each node possesses 0 or more sensors and is connected to its neighbouring nodes through a set of communication links

A distributed data fusion system is a collection of processing nodes, connected by communication links, as shown in Fig. 7, 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. In a centralized system, however, the failure of a common communication manager or a centralized controller can result in immediate catastrophic failure of the system.
- Distributed systems are flexible in the sense that nodes can be added or deleted by making only local changes to the network. For example, the addition of a node simply involves the establishment of links to one or more nodes in the network. In a centralized system, however, the addition of a new node can change the topology in such a way as to require massive changes to the overall control and communications structure.

4.2 Using Covariance Intersection for Distributed Data Fusion

Consider again the data fusion network that is illustrated in Figure 4. The network consists of N DIND 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).

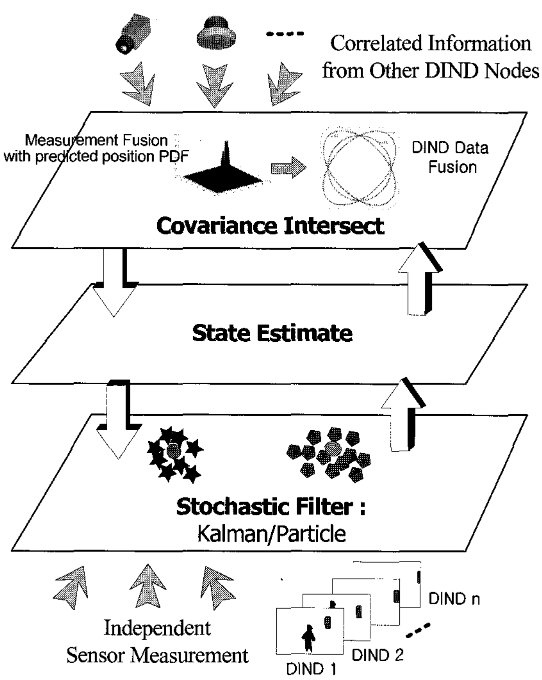

Fig. 5. A canonical node in a general data fusion network that constructs its local state estimate using CI to combine information received from other nodes and a stochastic filter to incorporate independent sensor measurements

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 Fig. 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.

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 $\mathbf{z}_i(k \mid k)$. A distributed fusion algorithm for propagating the estimate from timestep k to timestep $k+1$ for node i is:

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 $\hat{\mathbf{x}}_i^*(k+1 \mid k+1)$ and covariance $\mathbf{p}_i^*(k+1 \mid k+1)$. 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 $\hat{\mathbf{x}}_i(k+1 \mid k)$ and $\mathbf{p}_i(k+1 \mid k)$ with the distributed estimates that it has received from all of its neighbors to yield the partial update with mean $\hat{\mathbf{x}}_i^+(k+1 \mid k+1)$ and covariance $\mathbf{p}_i^+(k+1 \mid k+1)$. Because these estimates are propagated from other nodes whose correlations are unknown, the CI algorithm is used. As explained above, if the node receives multiple 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 $\hat{\mathbf{x}}_i(k+1 \mid k+1)$ with covariance $\mathbf{p}_i(k+1 \mid k+1)$. 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.

An implementation of this algorithm is given in the next section. This algorithm has a number of important advantages. First, all nodes propagate their most accurate partial estimates to all other nodes without imposing any unrealistic requirements for perfectly robust communication. Communication paths may be uni- or bidirectional, there may be cycles in the network of ISpace, and some estimates may be lost while others are propagated redundantly. Second, the update rates of the different filters do not need to be synchronized. Third, communications do not have to be guaranteed — a node can broadcast an estimate without relying on other nodes' receiving it. Finally, each node can use a different observation model: one node may have a high accuracy model for one subset of variables of relevance to it, and another node may have a high accuracy model for a different subset of variables, but the propagation of their respective estimates allows nodes to construct fused estimates representing the union of the high accuracy information from both nodes.

The most important feature of the above approach to decentralized data fusion is that it is provably guaranteed to produce and maintain consistent estimates at the various nodes.* Section 5 demonstrates this consistency in a simple example.

5. Measurement 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.

Knowing the limitations of the Kalman filter, Uhlmann [8] developed the Covariance Intersection algorithm. In the following text, the Kalman filter assumptions are outlined while developing its algorithm in a general approach, and introducing the Covariance Intersection. These methods are based on moments describing the probabilistic distribution, for example the mean and the variance, which is sufficient for a Gaussian distribution. The measurement fusion of arbitrary shaped probability density distributions (pdf's) is being addressed by discretizing the pdf's and applying Baye's rule of conditional probability [9],[10].

5.1 Kalman Filter

Kalman suggested a linear weighted combination of the two samples α and β as follows:

$$\chi = K'\alpha + K\beta , \tag{1}$$

where χ represents the fused information. The weights are chosen such that the error of χ with respect to the true event exhibits zero mean and minimum variance. For the preceding derivations, define the error as a random variable:

$$e_c = C - z = \overline{C} \tag{2-a}$$

$$e_a = A - z = \overline{A} \tag{2-b}$$

$$e_b = B - z = \overline{B} \tag{2-c}$$

Substituting these errors into the linear weighted combination of Eq. (1) and reordering yields the error equation for the estimate:

$$e_c = (K' + K - I)z + K'e_a + Ke_b \tag{3}$$

In order to obtain an unbiased estimate, we require the expected value of ec to vanish, leading to:

$$E\{e_c\} = 0 = (K' + K - I)z + K'E\{e_a\} + KE\{e_a\} . \tag{4}$$

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 $E\{e_c\} = 0$. With these simplifications Eq. (4) is reduced to:

$$K' = I - K \ . \tag{5}$$

The remaining gain K is selected such that the error variance is minimized, which can be written as:

$$\begin{aligned} P_c &= E\{e_c e_c^T\} \\ &= (I-K)E\{e_a e_a^T\}(I-K)^T + KE\{e_b e_b^T\}K^T \\ &= (I-K)E\{e_a e_b^T\}K^T + KE\{e_b e_a^T\}(I-K)^T \ . \end{aligned} \tag{6}$$

Minimizing the variance of e_c is coincident with minimizing the trace of P_c, and we define a cost function:

$$\min \ J = \operatorname{trace}[P_c] \tag{7}$$

The extremum of J can be obtained by the derivative with respect to K as follows:

$$\frac{\partial J}{\partial K} = -2(I-K)P_a + 2KP + (I-2K)P_{ab} + (I-2K)P_{ba} = 0 \ , \tag{8}$$

which yields:

$$K = (P_a + P_{ab})(P_a + P_b - 2P_{ab})^{-1} \ , \text{ where } P_{ab} = P_{ba} \tag{9}$$

Now the error covariance matrix can be rewritten as follows:

$$P_c = (I-K)P_a + 2P_{ab}K^T + KP_{ab} \ . \tag{10}$$

The Kalman filter assumes independence of the information A and B $(P_{ab} = 0)$, and the above equations can be simplified as:

$$K = P_a(P_a + P_b)^{-1} \ , \tag{11-a}$$

$$P_c = (I-K)P_a \tag{11-b}$$

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

$$P_c^{-1} = P_a^{-1} + P_b^{-1} \ , \tag{12}$$

which is the direct result of substituting the optimal gain K into the covariance equation. In addition, the weighted linear combination Eq. (1) can be rewritten using Eq. (11) as:

$$P_c^{-1}\chi = P_a^{-1}\alpha + P_b^{-1}\beta \tag{13}$$

At this point we shall recall the assumptions introduced by the Kalman Filter to arrive at the optimal weights of the linear combination of the samples a and b.

Assumption 1: unbiased information A, B and C

Assumption 2: independent information A and B

Assumption 3: minimum variance solution for C

An illustration of the Kalman filter algorithm is shown in Figure 6, 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 by applying Eq. (11). 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 6 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. (9) and (10). These estimated covariances are shown in Figure 6 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.

5.2 Covariance Intersection

Uhlmann [8] 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:

$$P_c^{-1} = wP_a^{-1} + (1-w)P_b^{-1}, \tag{14}$$

where w takes values in the range of [0,1]. Note, that the CI is a weighted expression of Eq. (12). The estimated covariance of the CI is shown in Figure 6 for $w = 0.4$. Similarly, the mean is estimated as a weighted expression of equation (13), which is:

$$P_c^{-1}\chi = wP_a^{-1}\alpha + (1-w)P_b^{-1}\beta \tag{15}$$

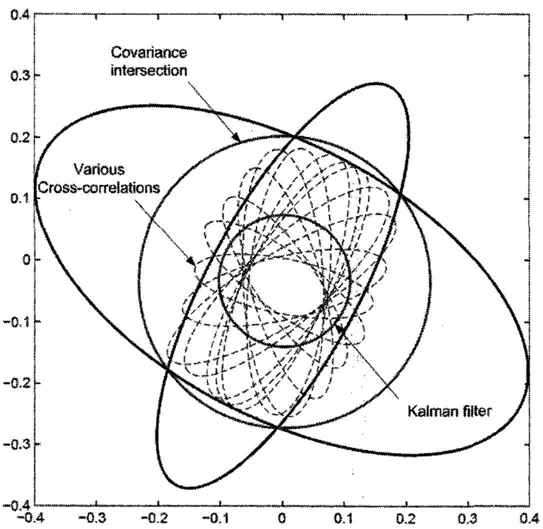

Fig. 6. The shape of the updated covariance ellipse. The variances of P_a and P_b are the outer solid ellipses. Different values of P_c that arise from different choices of P_{ab} are shown as dashed ellipses. The update with truly independent estimates is the inner solid ellipse

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 $(w \to 1)$ or to the information B $(w \to 0)$. Figure 7 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. (2) into Eq. (15) and using the relation in Eq. (14) yields the true error:

$$e_c = Pc[wP_a^{-1}e_a + (1-w)P_b^{-1}e_b]\,. \tag{16}$$

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:

$$\begin{aligned} P_c^{-1} &= w^2 P_a^{-1} + (1-w)^2 P_b^{-1} \\ &+ w(1-w)[P_a^{-1}P_{ab}P_b^{-1T} + P_b^{-1}P_{ba}P_b^{-1T}]^T \end{aligned} \tag{17}$$

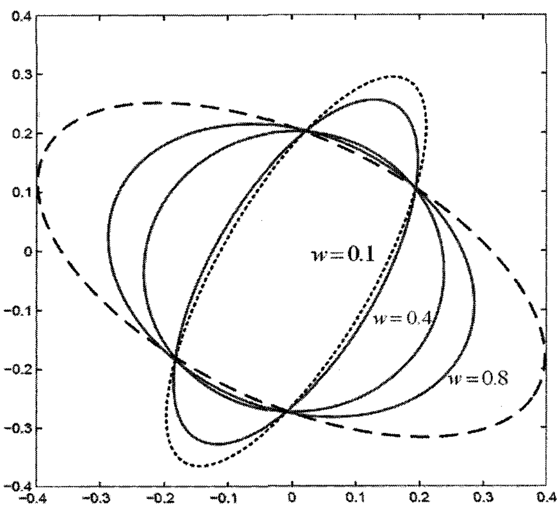

Fig. 7.1 σ ellipses of the Covariance Intersection algorithm with different values of the weight w

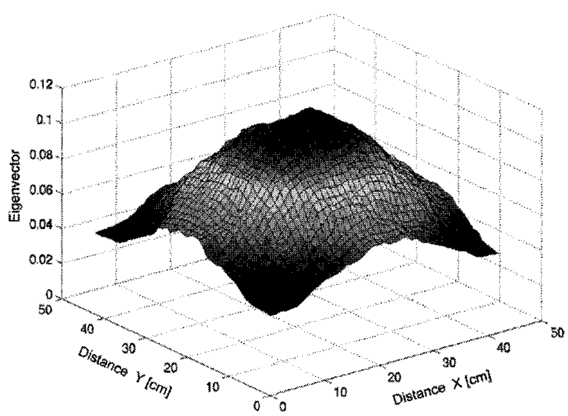

Fig. 8. eigenvector of moving object by ellipse variation of Covariance Intersection in value of w determination

Figure 8 plots a typical eigenvector of moving object in a convoy, where the global color models of position are shown [11],[12]. 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 (17).

6. Conclusion

This paper introduced the current research result on Intelligent Space Project. The Intelligent 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 iSpace. 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. If two tracks are determined to correspond to the same object, assuming independence may not be possible when combining them, if they are derived from common observation information.[13],[14]
- Multiple model filtering — Many systems switch behaviors in a complicated manner, so that a comprehensive model is difficult to derive. If multiple approximate models are available that capture different behavioral aspects with different degrees of fidelity, their estimates can be combined to achieve a better estimate. Because they are all modeling the same system, however, the different estimates are likely to be highly correlated.[14],[15]

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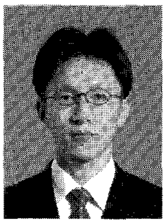

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