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SOUND SPEED ESTIMATION AS A MEANS OF IMPROVING TARGET TRACKING --ETC(U)
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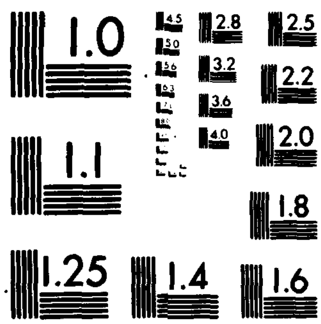

MICROCOPY RESOLUTION TEST CHART

2. "Sound Speed Estimation as a Means of Improving Target Tracking Performance," by D. L. Alspach, G. L. Mohnkern, and R. N. Lobbia, appears in the Proceedings of the 13th Asilomar Conference on Circuits, Systems, and Computers, November 1979, Pacific Grove, California.

DOCUMENT 2

SOUND SPEED ESTIMATION AS A MEANS OF IMPROVING TARGET TRACKING PERFORMANCE

D. L. Alspach
G. L. Mohnkern
R. N. Lobbia

N00014-77-C-

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SOUND SPEED ESTIMATION AS A MEANS OF IMPROVING TARGET TRACKING PERFORMANCE

D. L. Alspach
ORINCON Corporation
La Jolla, California 92037

G. Mohnkern
Naval Ocean Systems Center
San Diego, California 92152

R. N. Lobbia
ORINCON Corporation
La Jolla, California 92037

Summary

This paper addresses the issue of target tracking when confronted with a set of sound speed parameters that are partially or completely unknown. It explores the case where these parameters are augmented to the target state in an extended Kalman filter. The filter processes measurements of sound time-of-arrival difference and Doppler difference from a set of spatially displaced sensors.

For scenarios involving up to three sensors it has been found that biased target position estimates and marginal system observability occurs. This is readily verified by propagating the eigenvalues of the information matrix in time. Using this as an analysis tool, a number of geometrical sensor configurations are analyzed.

In general, it is found that with three sensors, the system is, at best, marginally observable for any geometry. However, when using four and more sensors, system observability and estimation performance are markedly improved when two of the sound speed filter parameters are specified to within a close tolerance of their actual values. When attempting to estimate all of the sound speeds (or for that matter (n-1) sound speeds, n = number of sensors), it is again noted, as in the three-sensor case, that system observability and estimation performance become degraded.

1. Introduction

In a target tracking application, one reason for poor estimation performance can be a lack of knowledge concerning the parameters of the mathematical model that relates the target state to the measurements. Since a mathematical model is a necessary ingredient to any target tracker or state estimator, use of incorrect parameters could lead to estimates that diverge from "truth" over a period of time.

It is this problem that is dealt with in this paper. More specifically, it involves a target tracking problem where measurements of time difference and Doppler difference are collected from pairs of spatially displaced sensors. The central issue is that the sound speeds from the target to each of these sensors are partially or completely unknown. These speed parameters appear in the mathematical model relating the target state to the measurements. To avoid biased target tracks, some mechanism should be found to accommodate these parameter uncertainties.

The material in this paper is basically an extension of an earlier work [1] and is more conclusive in terms of the results that were obtained for a number of different geometric scenarios involving sensor placements and target location.

We will start our discussion in Section 2 by describing the mathematical model for the given process and proceed to define an estimator that can accommodate both unknown sound speeds and the target state vector. All of the simulation results will be presented in Section 3. In addition, we will also show how we can assess system observability via the information matrix. This will play a useful role in exploring system observability for a number of different target/sensor geometric scenarios.

From the simulation results it will be seen that a minimum number of sensors are needed and, in addition, two of the sound speeds must be known correctly before accurate estimation of the target state can be achieved.

Finally, in Section 4, a summary of the results and conclusions will be presented.

2. System Definition

One area where the uncertain model parameter problem could arise is depicted in Figure 1. It could equally well apply to tracking of vehicles on the Earth via geophones or any place that the signal does not travel with an infinite effective or known velocity. We have a set of i spatially displaced sensors (distance to target = R_i). If the target generates or reflects sound at time instant, t, because of the sound travel time to each sensor (sound speed = c_i), it will be sensed at each sensor at times $t_1, t_2, \ldots, t_i$. In addition, if the target moves at a velocity, v, the Doppler sensed at each sensor will be different. To estimate the target state, i.e., position, speed, and course, measurements of sound time-of-arrival difference and Doppler difference for a sensor pair i-j ($i,j=1,2,3,\ldots,i\neq j$) can be processed through a Kalman filter. Using spherical geometry, these measurements can be related to the target state by the following equations [1]:

$$\tau_{ij} = t_i - t_j = \frac{R_i}{c_i} - \frac{R_j}{c_j} \tag{1}$$

$$f_{ij} = f_i - f_j = \left(-\frac{\dot{R}_i}{c_i} + \frac{\dot{R}_j}{c_j}\right) f \tag{2}$$

where

$$R_i = \cos^{-1}[\sin x_1 \sin\lambda_i + \cos x_1 \cos\lambda_i \cos(x_2-\theta_i)] \tag{3}$$

$$\dot{R}_i = \frac{x_3[\sin x_1 \cos\lambda_i \cos(x_2-\theta_i) - \cos x_1 \sin\lambda_i]}{\sin R_i} + \frac{x_4 \cos x_1 \cos\lambda_i \sin(x_2-\theta_i)}{\sin R_i} \tag{4}$$

In the above equations, $x_i, i=1,2,3,4$ represents the target latitude, longitude, latitude rate, and longitude rate, respectively. The latitude and longitude of hydrophone i is λ_i and θ_i. An implicit assumption in (4) is that the sensors are stationary.

Throughout the paper we will take the target state vector to be $\overline{x}^T = [x_1, x_2, x_3, x_4]$. The reason for doing this is that target motion can be described by a linear set of equations. In discrete-time form, the equations for the target dynamics are given by:

$$\overline{x}(k+1) = \underbrace{\begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{\Phi(\Delta t)} \overline{x}(k) + \underbrace{\begin{bmatrix} w_1(k) \\ w_2(k) \\ w_3(k) \\ w_4(k) \end{bmatrix}}_{\overline{w}(k)} \tag{5}$$

where Δt = sampling interval; i.e., the time between measurements of τ_{ij}, f_{ij}; $v(k)$ is a zero-mean, white noise vector sequence that perturbs the target from otherwise constant course/speed motion; and where

$$E\{\bar{v}(k)\, \bar{v}^T(j)\} = Q_k\, \delta_{kj} \; .$$

It is a simple matter to display speed and course at any time by using the equations below:

$$\text{SPEED} = \sqrt{x_3^2 + x_4^2 \cos^2 x_1} \qquad (6)$$

$$\text{COURSE} = \tan^{-1}\left(\frac{x_4 \cos x_1}{x_3}\right) \qquad (7)$$

Since the measurement model is nonlinear (eq. 1-4), one can implement an extended Kalman filter to track or obtain estimates of the target state vector, $\hat{x}(k)$. This is easily done by linearizing the measurement equations about the most current state estimate, $\hat{x}(k)$, to obtain a linear measurement equation, $H(\hat{x}(k))$. The equations for the filter are standard [2] and are summarized below:

$$\hat{x}(k+1/k) = \Phi(\Delta t)\, \hat{x}(k/k) \qquad (8)$$

$$P(k+1/k) = \Phi(\Delta t)\, P(k/k)\, \Phi^T(\Delta t) + Q_k \qquad (9)$$

$$\hat{x}(k+1/k+1) = \hat{x}(k+1/k) + k_{k+1}[z(k+1) - h(\hat{x}(k+1)/k))] \qquad (10)$$

$$P(k+1/k+1) = [I - k_k H(\hat{x}(k+1/k))]\, P(k+1/k) \qquad (11)$$

$$K_{k+1} = P(k+1/k)\, H(\hat{x}(k+1/k))\, [H(\hat{x}(k+1/k))\, P(k+1/k)\, H^T(\hat{x}(k+1/k)) + R_k]^{-1} \qquad (12)$$

where

$$z^T(k) = [\tau_{ij}(k),\ f_{ij}(k)]$$

$$h^T(\hat{x}(k+1/k)) = [\hat{\tau}_{ij}(k),\ \hat{f}_{ij}(k)] = \left[\left(\frac{\hat{R}_i}{c_i} - \frac{\hat{R}_j}{c_j}\right),\ f\left(\frac{\dot{\hat{R}}_i}{c_i} - \frac{\dot{\hat{R}}_j}{c_j}\right)\right] \qquad (13)$$

R_k = covariance matrix of additive white noise that contaminates $z(k)$

$$H(\hat{x}(k+1/k)) = \left.\frac{\partial h(\bar{x}(k))}{\partial \bar{x}(k)}\right|_{\bar{x}(k) = \hat{x}(k+1/k)} \qquad (14)$$

From (1), (2), (13), and (14) it is easy to see how sound speed, c_i, enters into the measurement model. In [1], it was shown that when incorrect values of c_i were used in the filter model (assuming one did not know the true c_i), the resulting state estimates were found to be biased off from the true target state. In some cases these biases were significant, and consequently the deviation from truth was as significant.

To compensate for this problem, the sound speeds were treated as additional state variables and augmented to the target state. Since the sound speeds were constant over the estimation interval, the state dynamics were simply defined by $\dot{c}_i = 0$. The extended Kalman filter was then implemented for this augmented state vector to generate estimates of both the target state and the unknown sound speeds.

In the next section, we will summarize some of the earlier results that were obtained and then present more exhaustive results that indicate a definite trend occurring.

3. *Simulation Results*

To examine the effects of estimating unknown sound speeds, we selected a number of different cases involving different target motion scenarios and three-sensor configurations as shown in Figure 2.

The locations of the sensors are defined in Table 1 and the target motion scenarios (cases 1-24) are summarized in Table 2.

Table 1. Location of sensors.

Array	Latitude, λ	Longitude, θ
1	5 deg	0 deg
2	-2.5 deg	4.33 deg
3	-2.5 deg	-4.33 deg

Table 2. Target motion scenarios.

Case Number	Starting Position Latitude	Starting Position Longitude	Speed	Course
1	.5 deg	.5 deg	10 knots	0 deg
2				90 deg
3				180 deg
4				270 deg
5	2.5 deg	0 deg		0 deg
6				90 deg
7				180 deg
8				270 deg
9	-1.3 deg	0 deg		0 deg
10				90 deg
11				180 deg
12				270 deg
13	-1.3 deg	-2.0 deg		0 deg
14				90 deg
15				180 deg
16				270 deg
17	0 deg	2 deg		0 deg
18				90 deg
19				180 deg
20				270 deg
21	0 deg	-4 deg		0 deg
22				90 deg
23				180 deg
24				270 deg

We made the following assumptions:

(a) The covariance matrix of the discrete-time process dynamics was defined by:

$$Q(k) = \begin{bmatrix} q_{33}^2 \frac{\Delta t^3}{3} & 0 & q_{33}^2 \frac{\Delta t^2}{0} & 0 \\ 0 & q_{44}^2 \frac{\Delta t^3}{3} & 0 & q_{44}^2 \frac{\Delta t^2}{2} \\ q_{33}^2 \frac{\Delta t^2}{2} & 0 & q_{44}^2\, \Delta t & 0 \\ 0 & q_{44}^2 \frac{\Delta t^2}{2} & 0 & q_{44}^2\, \Delta t \end{bmatrix}$$

where $q_{33}^2 = q_{44}^2 = (.0091827)^2$ knots/sec is the power spectral density of the random noise perturbing the velocity state equations of the continuous system. This randomness in the target velocity for the continuous system translates both into a position and velocity uncertainty in the equivalent discrete-time model. The values of q_{33} and q_{44} roughly correspond to a standard deviation of .34 nautical miles in position and .6 knot in velocity over a time interval of one hour in the discrete-time model.

(b) The measurement matrix covariance matrix was defined by:

$$R(k) = \begin{bmatrix} r_{11}^2 & 0 \\ 0 & r_{22}^2 \end{bmatrix}$$

(c) Δt=300 sec was the nominal time interval between measurements.

(d) The filter processed measurements from the sensor pairs in a sequential manner starting with sensor pair 1-2, 1-3, 2-3, 1-2, 1-3, ..., etc.

(e) The sound speeds from the target to each of the sensors were chosen as [3]:

$$c_1 = 4857 \text{ ft/sec}$$
$$c_2 = 4850 \text{ ft/sec}$$
$$c_3 = 4870 \text{ ft/sec}$$

We started out by assuming that: first, only one of the three sound speeds was unknown and consequently was estimated along with the target state; second, two sound speeds were unknown and were estimated along with the target state; and third, all three sound speeds were unknown and estimated along with the target state. In all of these cases, it was found that biased estimates were generated by the tracker. A typical example of this is shown in Figures 3, 4, and 5 where an attempt was made to estimate the unknown sound speeds and the target state. The solid curves represent the truth model whereas the dashed curves represent the state estimates. Note the significant biases in latitude and longitude in two of the sound speeds.

Because of these biases, it was decided to examine the observability of the system for all of the cases defined in Table 2. This is easily done with the aid of the information matrix [2]. For the case involving no process noise and state vector a priori information, the information matrix is identical to the inverse of the Kalman filter covariance matrix, $P^{-1}(k/k)$. This matrix must be positive definite for stochastic observability and, provided the above conditions apply, is given in recursive form by:

$$\begin{aligned} P^{-1}(k/k) &= \Phi^T(-\Delta t)\, P^{-1}(k-1/k-1) \quad (-\Delta t) \\ &\quad + H^T(\bar{x}(k-1))\, R_k^{-1} H(\bar{x}(k-1)); \\ P^{-1}(0/0) &= 0 \end{aligned} \tag{15}$$

where $\Phi(\Delta t)$ is the state transition matrix defined in (5), $H(\bar{x}(k-1))$ is the measurement matrix linearized about the state vector $\bar{x}(k-1)$.

To assess the property of stochastic observability, the normalized eigenvalues of this matrix were computed (normalized to one) and plotted as a function of time. Figure 6 shows the results that were obtained for case 11 in Table 2. One of the position eigenvalues becomes ill-conditioned and exhibits a smaller maximum magnitude than the other position eigenvalue by a couple orders of magnitude. This analysis was repeated for all of the other 23 cases and the same general result was obtained, i.e., ill-conditioned behavior of one of the eigenvalues. Because of this and the fact that the state estimates were biased, we concluded that the system was marginally observable for a three-sensor configuration and unknown sound speeds.

As a means of enhancing system observability, it was decided to introduce more than three sensors for target tracking.

We first started with four sensors using different sensor/target motion geometries. Four cases were considered and the geometries are summarized in Figures 7 to 10.

Using the same philosophy as in the threesensor case earlier, we started out by estimating one, two, three, and then four sound speeds. For all of these cases, it was found that we could estimate the target state and up to two sound speeds without obtaining biased estimates, but as soon as we attempted to estimate three or four sound speeds, biases in the estimates again were noted. Marginal system observability again was suspect. To substantiate this we looked at the eigenvalues of the information matrix as a function of time. The functional variations of the eigenvalues were found to be relatively smooth and monotonically increasing for estimation of one or two sound speeds. An example of this is presented in Figure 11. It involved the target/hydrophone geometry defined by Figure 10 where we estimated the target state and two of the sound speeds. However, as we began to estimate three and more sound speeds, the function variation of several of the information matrix eigenvalues becomes progressively more ill-conditioned and lower in absolute magnitude--an indication that the property of system observability has been weakened.

To complete our analysis, we then explored the use of five sensors. Two geometries were selected and are shown in Figures 12 and 13.

Using the same approach as before, we began by estimating, first, one sound speed, then two sound speeds, and so on. Interestingly enough, it was found that one could now estimate up to three sound speeds before biased estimates again occurred.

For all of the above cases involving four and five receiving sensors, the general observation was that one could estimate the target state and up to two sound speeds for the four-sensor configuration, and the target state and up to three sound speeds for the five-sensor configurations.

Of course, these conclusions are based upon a finite set of examples, and to substantiate the above claim more rigorously, one would have to implement a more exhaustive set of examples.

4. Conclusions

In summary, it was first noted that target tracking via extended Kalman filtering tends to produce biased estimates when the sound speeds were uncertain and incorrectly specified in the filter. Attempts to additionally estimate the sound speeds were shown to be of no avail in eliminating these biases--even when applying traditional filter parameter variations that in past applications tended to make the filter more robust to parameter uncertainties.

For this reason the observability of the system was explored in greater detail. With the aid of the information matrix, it was found that the system was marginally observable over the geographical region defined by the three receiving sensors.

Because of this, we therefore took a look at using time-difference and Doppler difference measurements from more than three sensors. In particular we looked at configurations involving four and five receiving sensors.

The results from a finite set of examples have shown that target tracking performance is improved, i.e., very small or nonexistent biases, but estimation of all sound speeds is not possible. Generally speaking, it seems that if we were given n>3 receiving arrays, it would be possible to estimate the target state and, at most, n-2 of the sound speeds to each of these sensors. The remaining two sound speeds have to be specified a priori for the filter.

Acknowledgments

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References

1. R. N. Lobbia and D. L. Alspach, "A Case Study in Adaptive Sound Speed Estimation," Twelfth Asilomar Conference on Circuits, Systems, and Components, Pacific Grove, California, November 1978.

2. A. H. Jazwinski, Stochastic Processes and Filtering Theory. New York: Academic Press, 1970.

3. R. Urick, Principles of Underwater Sound. New York: McGraw-Hill, 1967.

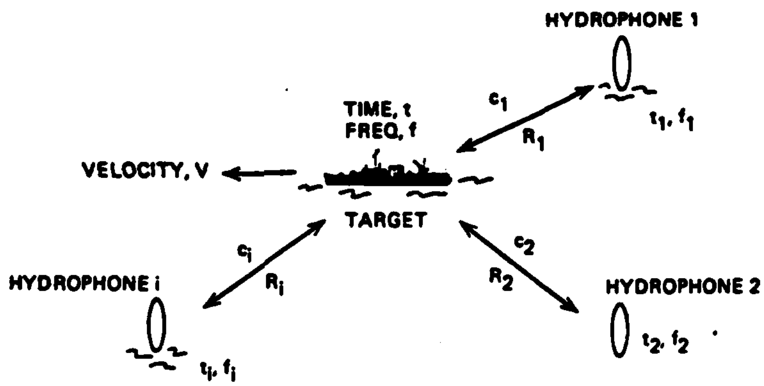

Figure 1.

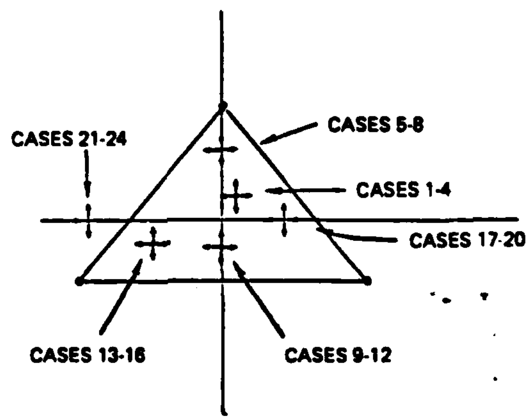

Figure 2. Target motion scenarios for sound speed estimation.

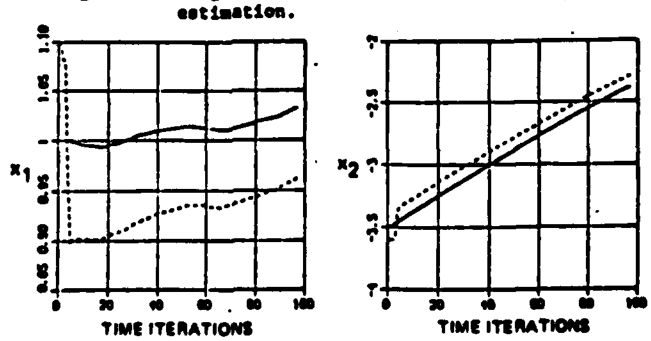

Figure 3. Target state and sound speed estimation (latitude and longitude).

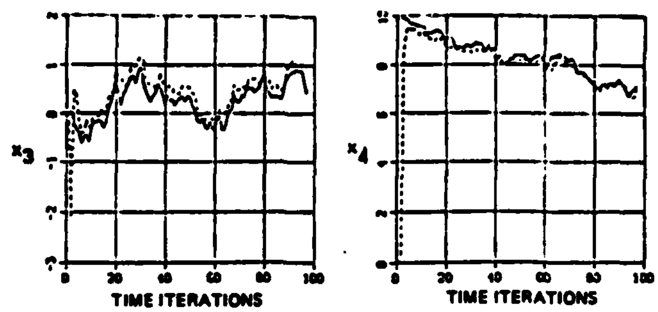

Figure 4. Target state and sound speed estimation (latitude rate and longitude rate).

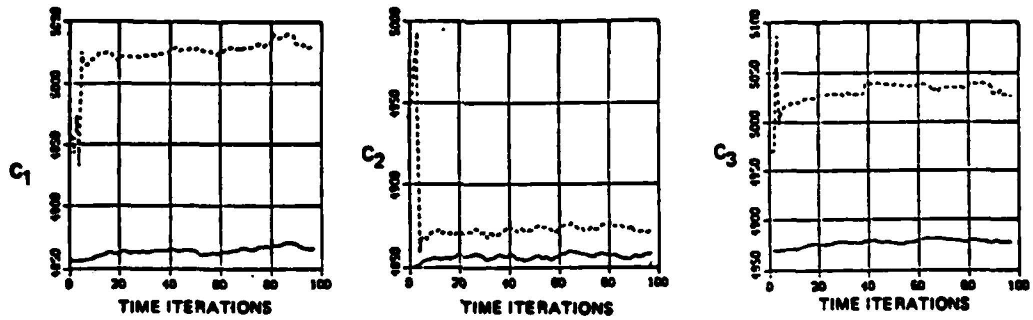

Figure 5. Target state and sound speed estimation (sound speeds).

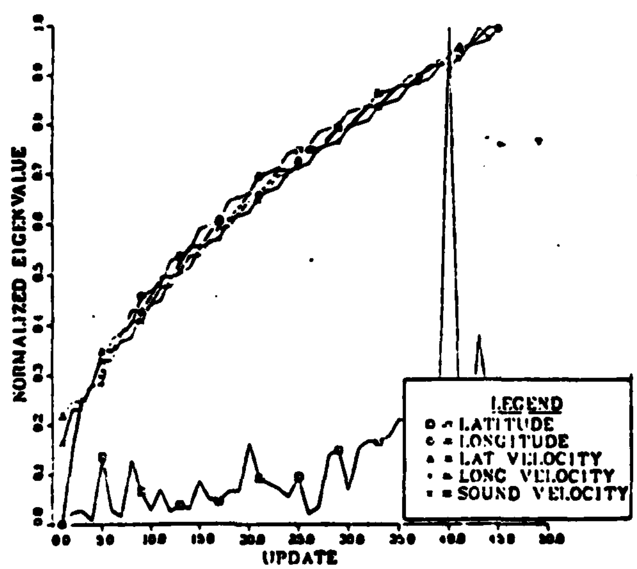

Figure 6. Information matrix eigenvalues--Case 11.

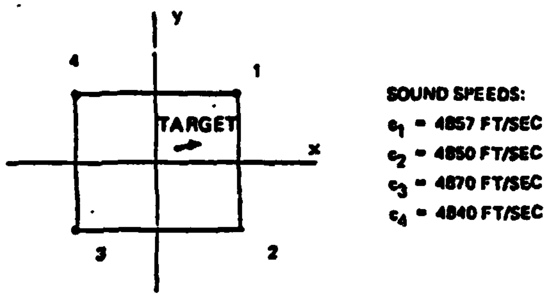

Figure 7. Geometry of four sensors--Case 1.

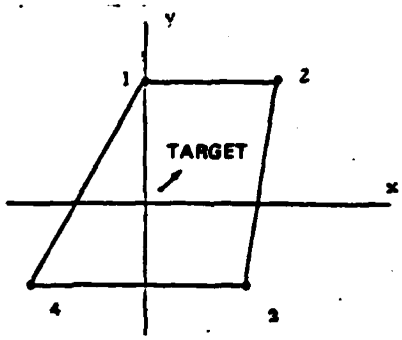

Figure 8. Geometry of four sensors--Case 2.

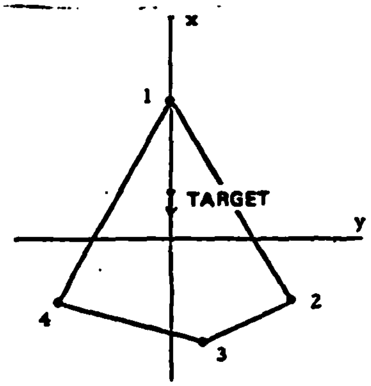

Figure 9. Geometry of four sensors--Case 3.

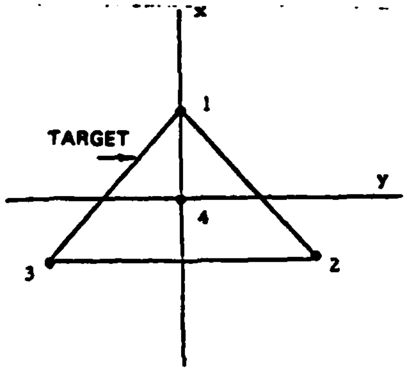

Figure 10. Geometry of four sensors--Case 4.

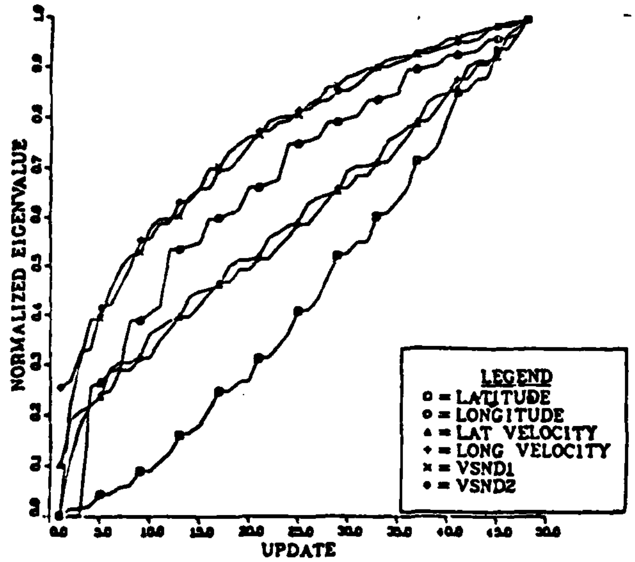

Figure 11. Information matrix eigenvalues--target state and two sound speeds.

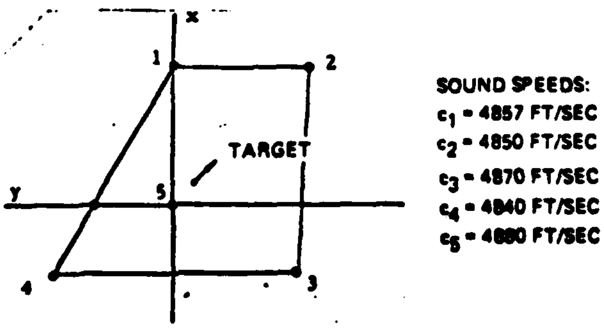

Figure 12. Geometry of five sensors--Case 1.

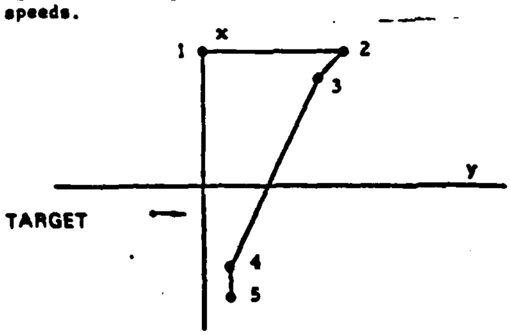

Figure 13. Geometry of five sensors--Case 2.