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WIDE-AREA CORRELATION AND TRACKING OF SURFACE SHIPS USING MULTIPLE SENSORS

Both local and wide-area sensors are used by the Navy to collect information on the position and identity of surface ships. For this information to be useful, a process known as correlation and tracking must be applied to the diverse sensor inputs to establish a surface picture free of positional and identity ambiguities. The basic procedures used in multisensor correlation and tracking must partition sets of sensor reports into subsets (called tracks) corresponding to single objects, and must estimate the identity and position of each object based on the information in the tracks. Because of the volume of reports, it is desirable to automate these procedures as much as is practical. This article describes a general Bayesian approach to automated correlation and tracking of surface ships that has been tested using real-world data.

INTRODUCTION

In recent years, the U. S. Navy has been faced with an increasingly extensive and demanding requirement for wide-area surveillance of surface ships. This has been necessitated by the growing tendency of foreign navies to conduct global operations and by the U. S. Navy's development of long-range antiship missiles such as Harpoon and Tomahawk. Estimates of the positions and identities of high-interest targets and the surrounding background ships over large ocean areas must be maintained for effective command and control. In addition, when a decision is made to launch long-range antiship missiles, accurate predictions of future positions of the targets must be obtained for effective missile fire control.

Data for developing wide-area surveillance pictures must be collected in many cases from sensors whose coverage extends well beyond the range of sensors on the launch platforms. Collection, processing, and dissemination of surveillance information to support the use of long-range antiship weapons is an important function of the Navy command and control system. Within this system, reports from multiple sensors and sources, consisting of the positions and (in some cases) identities of surface ships, must be partitioned into sets (tracks) associated with the same object. This process is called correlation. The sets of reports correlated with each other are then used in the tracking process to estimate positions and identities of surface ships at arbitrary times.

Sensor reports can be quite diverse in content, frequency of arrival, and quality. Some sensors provide unique identifiers of the ship under surveillance (e.g., ship name); others provide nonunique identification (e.g., the characteristics of electromagnetic emissions, which may apply equally well to all ships within a general class). Some sensors provide reports with measured positions of objects only. At various times, different sensors provide reports at varying rates, depending on such factors as specific tasking of the sensor and the number and behavior of objects under surveillance. Also, since the sensors may be remote from the facilities where correlation and tracking are performed, communication delays accrue.

Because of the diversity of communication paths, report arrival rates vary quite widely; the order of receipt of a report is not always the chronological order of observation. Typically, sensor reports are accompanied by individual assessments of error statistics, but the statistics and the degree of compliance with the implied performance may vary considerably from report to report and from sensor to sensor. A more detailed discussion of sensor or data characteristics can be found in the classified literature.

In order to maintain current tactical pictures, this stream of diverse sensor reports must be processed on an event-by-event basis, i.e., as the reports arrive at the facility performing correlation and tracking. Furthermore, the amount of data required to maintain current, accurate surveillance pictures over wide ocean areas makes automated correlation and tracking desirable. Within the present Navy command and control system, the ability to perform multisensor correlation and tracking relies heavily on manual interaction. There is a need to implement more automatic algorithms for performing these functions.

A substantial amount of research on new correlation and tracking algorithms has occurred in recent years. References 1, 2, and 3 are excellent surveys of the work and provide comparisons of the features included in many of the algorithms. However, in many specific algorithms that follow these approaches, one or more operational considerations have been ignored. Thus, for instance, of the 56 specific algorithms compared in Ref. 2, only 11 appear to satisfy the basic prerequisite of being recursive multiship algorithms capable of handling a sequence of reports where each contains measurements of a single object. Only one of the 56 algorithms is designed to recursively incorporate out-of-sequence data. Nevertheless, among the 56 candidates, an algorithm proposed by D. B. Reid[4] is promising from the standpoint of maturity and generality. Consequently, this algorithm, with required modifications, forms the basis for the correlation and tracking approach described here.

A BAYESIAN MULTIPLE-HYPOTHESIS APPROACH TO CORRELATION AND TRACKING

In an automatic correlator/tracker, an important and difficult problem is the representation and resolution of ambiguities. Frequently, ambiguities arise when shipping densities are high, when sensor errors are large, or when identifying information supplied with reports is sparse or confusing. Ambiguities cause incorrect associations of reports with current tracks. Incorrect associations, in turn, cause tracking errors and misidentifications. However, subsequent reports can often assist in resolving ambiguities. This is especially true when there is a substantial amount of data arriving out of sequence. For this reason, some information about the ambiguities must be retained as they arise. However, if all ambiguities and related information were retained as each report is processed, the storage and processing capabilities of any computer would quickly be overwhelmed.

An important feature of the correlator/tracker algorithm described here is its ability automatically to represent and resolve ambiguities dynamically and yet to adhere rigorously to limitations of computer memory and speed. This is accomplished recursively by a combination of clustering and hypothesis pruning, as will be explained later.

The input to the correlator/tracker is a sequence of sensor reports. Suppose that, at some stage in the correlation process, n reports ($M_1, M_2, \ldots, M_n$) have been received. Each report is assumed to have a measure of the position and possibly the identifying attributes of a single surface ship. (If a report contains information on multiple ship contacts [i.e., a scan], each contact is currently treated separately.) Included in each report is the time, t_i, at which the measurement was made. Also, it is assumed that a sensor error ellipse is included that indicates the estimated accuracy of the reported position.

The key to the correlation process is the construction of multiple "hypotheses." An hypothesis is a possible way of associating reports with ship tracks. In the case where n reports have been received, there may be m possible hypotheses, denoted $H_1^n, H_2^n, \ldots, H_m^n$. The algorithm is considered "recursive" because, on receipt of a new report, it generates new hypotheses based on that report and on the previous m hypotheses. Likewise, it is referred to as a Bayesian algorithm because the probabilities of new candidate (possible) hypotheses are calculated using the probabilities of prior hypotheses; the calculation is based on a mathematical theorem called Bayes' rule.

At each step (corresponding to a new sensor report) the candidate association hypotheses are generated and incorporated into a hypothesis matrix Ω^n, discussed below. The correlator calculates the probability of each hypothesis, H_k^n, in Ω^n and uses this information to determine which associations of the n measurements are most likely to be correct. An overview of the functions involved in this processing is shown in Fig. 1; a summary of each function is provided in the remainder of this section.

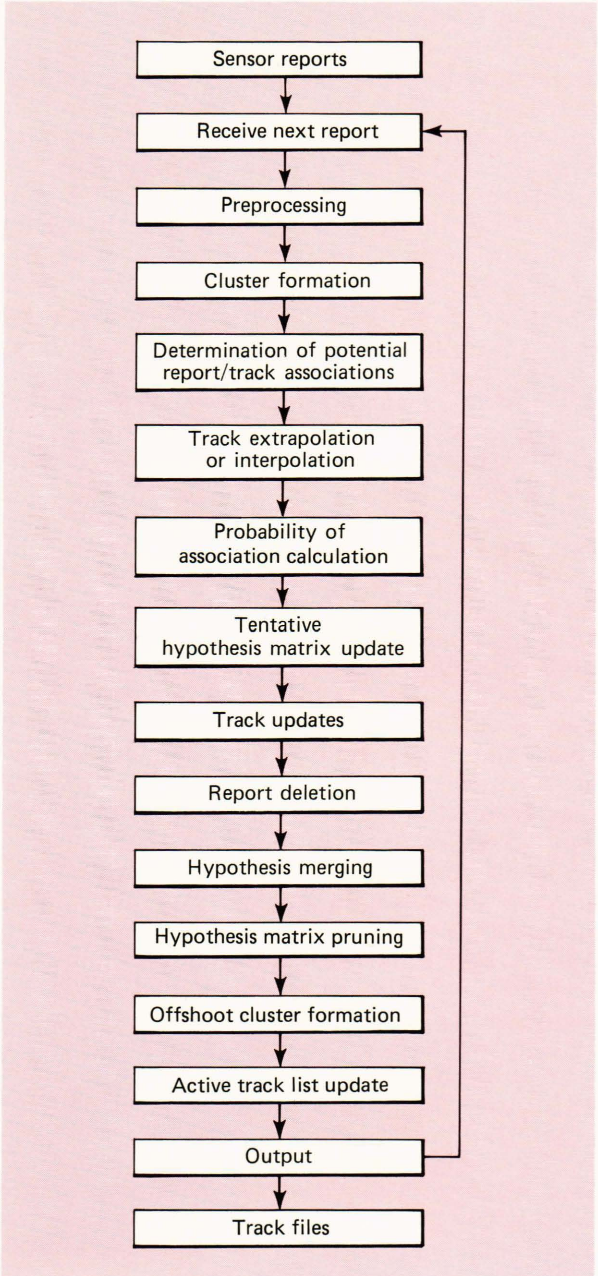


Figure 1 — Surface ship correlator/tracker structure.

The correlator/tracker processing begins with the receipt of a new report, M_{n+1}. The first function of the correlator/tracker involves report preprocessing. Preprocessing includes a number of activities. Initially, a screening procedure is carried out to determine if the report should be processed at all. This decision is based on report age, information content, and whether the position corresponds to the ocean area of interest. If the report passes this screening process, it is converted to an internal format that can be processed by the main correlator/tracker algorithm. This conversion involves translation of the error ellipse information and any attribute information into terms that are understandable by the correlation algorithm. The preprocessing function will be expanded as the correlator/tracker algorithm is made more sophisticated.

After preprocessing, the correlator determines the cluster into which the incoming report should be placed. A cluster is a set of reports associated with a single track or with tracks that cannot be separated unambiguously. In other words, if a report could be associated with two different tracks, all the reports associated with each track must be included in the cluster. Associated with each cluster of reports is a set of hypotheses, hypothesis probabilities, target state (i.e., position and velocity) estimates, and covariances. Clustering of reports minimizes the number of hypotheses needed to list all possible associations, thereby minimizing the calculation and storage requirements. The implicit assumption is that reports in different clusters are associated with one another with probability 0.

When a new report is received, the correlator compares the new reported position with the most recent estimated position for each target in each cluster. If the new position is "close enough" positionally (in the sense of a distance normalized by the sum of the covariances of the reported and estimated positions) to any target in the cluster, the new measurement is associated with that cluster. In addition to this positional test, if a new report has the same unique identification as any report in an existing cluster, the report is automatically associated with that cluster. If a report is associated with more than one cluster, all of the clusters with which it is associated are combined into a single cluster. If the report is associated with none of the existing clusters, then a new cluster is formed. The hypothesis assignments, probability calculations, and pruning operations that follow are performed only on the cluster to which the new report has been assigned.

Following assignment of the new report to a cluster, the correlator determines the set of all potential report/track associations within the cluster of interest. This entails enumerating all possible ways in which the new measurement M_{n+1} can be associated with tracks existing in the current hypothesis matrix Ω^n of the cluster (see Fig. 2). Each candidate association is defined by two numbers. The first, k, indicates the particular prior hypothesis, H_k^n, that the report is

Hypothesis number	Report 1	Report 2	Report 3	Report 4
1	1	1	3	3
2	1	2	3	2
3	1	1	3	4
4	1	2	3	3
5	1	2	0	2

Prior hypothesis number (k)	Possible associations (track numbers) of fifth report (j)
1	0, 1, 3, 5
2	0, 1, 2, 3, 5
3	0, 1, 3, 4, 5
4	0, 1, 2, 3, 5
5	0, 1, 2, 5

Figure 2 — This figure gives an example of the correlator/tracker hypothesis matrix and shows how new report associations are formed by the correlator/tracker. In (a), the rows of a sample hypothesis matrix correspond to different hypotheses and the columns to received reports. Each entry is a track number representing the track with which the report is associated under the given hypothesis. Thus, according to the first hypothesis, the first two reports came from the same target and the next two came from a second target. In (b), all possible ways in which a new report can be associated with different tracks are shown for each of the hypotheses in (a). Note that a 0 represents a false track, a 5 represents a new track (since the new report is the fifth), and a number from 1 through 4 represents a track that already exists in the prior hypothesis.

augmenting. The other number, j, indicates the specific ship track in H_k^n with which the report is being associated. If there were n_H hypotheses in Ω^n and each were to contain n_T existing tracks, $(n_T + 2)\, n_H$ associations would be formed. (This count includes association of the report with possible new tracks and false targets).

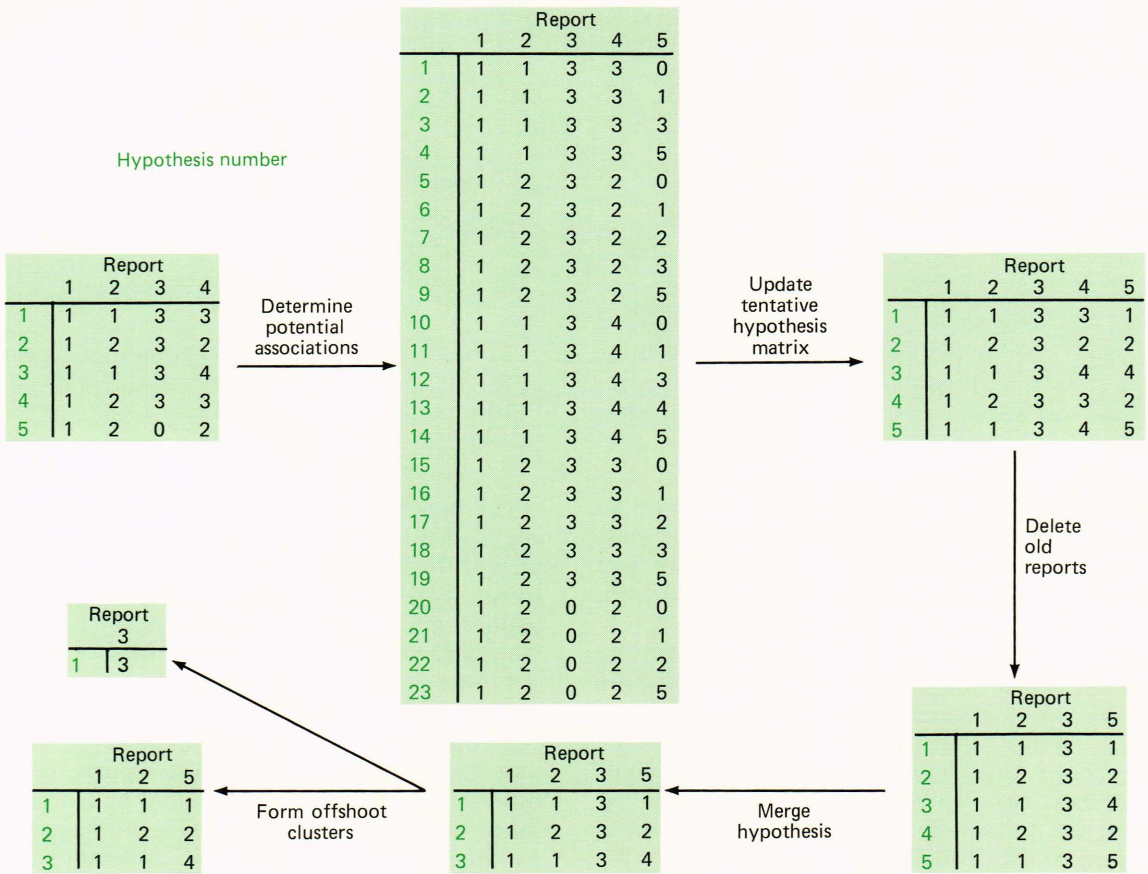
Once all possible report/track associations are determined, it is necessary to evaluate the probability that each is correct. This is done in two steps. Each candidate track existing prior to receipt of measurement M_{n+1} will have been filtered (using an algorithm based on a digital filtering technique called Kalman filtering). Starting with the filtered track positions, each track, j, of each hypothesis, H_k^n, in Ω^n is first extrapolated (or interpolated, if report $n + 1$ is out of sequence) to the time t_{n+1} corresponding to the new report. The extrapolated states and covariances are then used in the second step, which is the actual probability calculations. The results give the probability that each possible report association is the correct one. The probability calculation is a recursive computation based on Bayes' rule.

If all possible associations were carried in the correlator/tracker as potential hypotheses, the computational burden would rapidly become unwieldy. Consequently, only the most probable of these are formally promoted as candidate hypotheses and are incorporated into the tentative updated hypothesis matrix, denoted Ω_T^{n+1}, for the cluster being processed.

For those associations that have been retained as candidate hypotheses in Ω_T^{n+1}, it is necessary to update the corresponding ship tracks. The Kalman-filter-based tracking algorithm that is used was designed with the objective of achieving good low-level maneuver response at relatively low reporting frequencies while retaining stability against positional

Example of Correlator/Tracker Hypothesis Matrix Processing

This example illustrates the processing of the correlator/tracker hypothesis matrix when a new report (the fifth) is received. The hypothesis matrix prior to the receipt of the fifth report is assumed to be given in the upper left of the figure. The correlator determines all possible ways in which the fifth report can be associated with different tracks for each of the hypotheses in this matrix. The resulting matrix containing all of these possible association hypotheses is shown in the top center. (This matrix is constructed from the same associations enumerated in Fig. 2.) Of these 23 associations, only the 5 most likely are formally promoted as candidate hypotheses. These are incorporated into the tentative updated hypothesis matrix shown at the upper right. After this matrix is formed, it is determined that the fourth report is too old, and it is deleted (lower right). In the resulting matrix, hypotheses 2 and 4 are now identical. If the state estimates for corresponding tracks in both hypotheses are close enough, the two hypotheses are merged. Likewise, hypotheses 3 and 5 are equivalent. (Both say that the first two reports arose from the same ship and that the third and fifth reports came from different ships.) Consequently, these hypotheses are also merged if their state estimates are close. If both pairs of hypotheses are merged, the matrix in the bottom center results. Finally, because there is no ambiguity concerning track 3 (i.e., the only column in which it appears consists solely of 3's), the third report is taken out of the matrix to form a new cluster of its own, as shown at the lower left of the figure.



	Report 1	2	3	4
1	1	1	3	3
2	1	2	3	2
3	1	1	3	4
4	1	2	3	3
5	1	2	0	2

	Report 1	2	3	4	5
1	1	1	3	3	0
2	1	1	3	3	1
3	1	1	3	3	3
4	1	1	3	3	5
5	1	2	3	2	0
6	1	2	3	2	1
7	1	2	3	2	2
8	1	2	3	2	3
9	1	2	3	2	5
10	1	1	3	4	0
11	1	1	3	4	1
12	1	1	3	4	3
13	1	1	3	4	4
14	1	1	3	4	5
15	1	2	3	3	0
16	1	2	3	3	1
17	1	2	3	3	2
18	1	2	3	3	3
19	1	2	3	3	5
20	1	2	0	2	0
21	1	2	0	2	1
22	1	2	0	2	2
23	1	2	0	2	5

	Report 1	2	3	4	5
1	1	1	3	3	1
2	1	2	3	2	2
3	1	1	3	4	4
4	1	2	3	3	2
5	1	1	3	4	5

	Report 1	2	3	5
1	1	1	3	1
2	1	2	3	2
3	1	1	3	4
4	1	2	3	2
5	1	1	3	5

	Report 1	2	3	5
1	1	1	3	1
2	1	2	3	2
3	1	1	3	4

	Report 1	2	5
1	1	1	1
2	1	2	2
3	1	1	4

	Report 3
1	3

error outliers. It also includes a capability for detecting major changes in platform course that require automatic reinitialization of the filter.[5]

As reports continue to enter the system, a point is reached when some older measurements contribute negligible information concerning the current state of ocean traffic, yet their retention adds to the overall storage burden. Consequently, it is expedient to delete such reports from the tentative updated hypothesis matrix Ω_T^{n+1}. The report deletion function in the

Association Probability Calculations

A new report received by the correlator/tracker can conceivably be associated with any track of any previous hypothesis. To determine which associations are most likely to be correct, it is necessary to calculate the probability of each candidate report association hypothesis.

Suppose it is desired to calculate the probability that new measurement M_{n+1} is associated with track j in the kth prior hypothesis, H_k^n. This association of the new report is denoted by A_j^k. (Track j can represent either a previously existing track in H_k^n, a new track, or a false track.) In essence, it is desired to calculate the probability that a new hypothesis H_m^{n+1} is correct, where H_m^{n+1} is the combination of prior hypothesis H_k^n and the association A_j^k. This probability is conditioned on all of the received measurements (denoted $M^{n+1} = \{M_1, M_2, ..., M_n, M_{n+1}\}$) as well as on the correct hypothesis at prior step n being one of the hypotheses in Ω^n. (The event that the correct association hypothesis is in Ω^n is denoted by H^n.) Then, by Bayes' rule, the probability that H_m^{n+1} is correct is calculated by

$$P(H_m^{n+1} \mid H^n, M^{n+1}) =$$

$$\frac{p(M_{n+1} \mid H_k^n, A_j^k, M^n)\, P(A_j^k \mid H_k^n, M^n)\, P(H_k^n \mid H^n, M^n)}{\sum_r \sum_i p(M_{n+1} \mid H_r^n, A_i^r, M^n)\, P(A_i^r \mid H_r^n, M^n)\, P(H_r^n \mid H^n, M^n)} ,$$

where the summations are taken over all new associations and prior hypotheses. The third factor in the numerator is the probability of the prior hypothesis; its presence makes the calculation recursive. The second factor is the a priori probability of making a particular association of the new report without knowing anything about the report. The first factor in the numerator is the likelihood of the new report. This likelihood function is based on a uniform probability density function if the association A_j^k of M_{n+1} is with a new track or false track. If the association is with a previous track in H_k^n, the likelihood function is based on a Gaussian density function. In the latter case, evaluation of the likelihood requires use of the jth track filter innovation vector $\tilde{Z}_j$, and error covariance matrix B_j. These are extrapolated (or interpolated) to the time, t_{n+1}, of the new report. If M_{n+1} also contains a unique ship identification, the likelihood computation may include an additional Bayesian calculation of the likelihood of the identification.

Finally, after deletion of low probability hypotheses from the resulting hypothesis matrix Ω^{n+1}, it is necessary to renormalize the remaining probabilities to obtain $P(H_m^{n+1} \mid H^{n+1}, M^{n+1})$. This is done according to

$$P(H_m^{n+1} \mid H^{n+1}, M^{n+1}) = \frac{P(H_m^{n+1} \mid H^n, M^{n+1})}{P(H^{n+1} \mid H^n, M^{n+1})} ,$$

where

$$P(H^{n+1} \mid H^n, M^{n+1}) = \sum_r P(H_r^{n+1} \mid H^n, M^{n+1})$$

The summation on r is over all hypotheses remaining in Ω^{n+1} after hypothesis matrix pruning in the correlator/tracker processing.

current algorithm eliminates the reports that have an associated measurement time that precedes the most recent report measurement time in Ω_T^{n+1} by more than a given age threshold. Old reports are deleted from all clusters at this point.

After old reports are deleted from Ω_T^{n+1}, it may be found that two or more of the hypotheses associate all of the remaining reports with ship tracks in an identical manner. Depending on the corresponding state estimates, these hypotheses may be judged to be equivalent. If so, they are merged into a single hypothesis. The probability of the resultant hypothesis is the sum of the probabilities corresponding to the merged hypotheses. The state estimates for each of the associated tracks are taken from the more likely of the two merged hypotheses.

The next step involves further pruning of the tentative hypothesis matrix to eliminate remaining low probability hypotheses. The desire is for the final updated hypothesis matrix, Ω^{n+1}, to contain no more than a preset number of candidate hypotheses. In preparation for receipt of the next report, the remaining hypothesis probabilities are renormalized.

The hypothesis matrix is then examined to see if any reports have unambiguous associations. Any column of the hypothesis matrix containing all identical entries corresponds to a report for which every hypothesis makes the same association. In other words, the association is made for that report with probability 1. One or several columns of identical entries with no references in any of the other columns indicate that there is no ambiguity in associating the corresponding reports, and only those reports, into a single track. The columns are removed from the old cluster to form a new cluster with the single hypothesis that all of the reports are associated with the same target. A column with all entries indicating false alarms corresponds to a report that has been identified as a false alarm with probability 1; such a column is deleted from the hypothesis matrix.

Finally, Ω^{n+1} for each cluster is scanned to determine which tracks are still active in the hypothesis matrices. This provides useful output from the algorithm and facilitates formation of the report/track associations when the next report is received. The most likely hypotheses, their probabilities, and the corresponding track parameters are output at the conclusion of report processing.

EXAMPLE OF CORRELATOR/TRACKER PERFORMANCE

The preceding section described the overall functioning of the correlator/tracker algorithm. In this section, a simple example is analyzed pictorially to illustrate some of the features discussed before. In the example, two ships move along straight-line paths that are perpendicular. Sensor reports on ship 1 are assumed to come in every hour on the hour, while reports on ship 2 arrive every hour, 15 minutes after the hour. There is a small amount of noise in the measurements, and each reported 90% ellipse is actually circular with a 10 nautical mile radius. None of the reports supplies any unique identification information, so the correlator must depend only on the positional data.

Figure 3a shows the 22 reports (correctly associated together) that were used for this example, along with the estimates generated by a tracker. Figure 3b shows the most likely hypothesis produced by the correlator/tracker 2 hours after initiation of operation (after five reports have arrived). There is as yet no confusion, and the pictured hypothesis is, in fact, the correct hypothesis. However, the fifth report is close enough to both tracks that they have been combined into one cluster. (Until the fifth report was processed, two clusters existed, one for each track.) The single cluster is indicated in Fig. 3b by the untinted area surrounding all the reports. One hour later, when two more reports have been processed, Fig. 3c shows that the most likely hypothesis (according to the correlator) is not the right one; the third report from ship 2 (the red one) had been incorrectly associated with the track for ship 1 (blue). Observe that there is still just one cluster.

Figure 3d demonstrates how later reports can cause the correlator to revise decisions of previous associations. Three new reports have arrived, and now the top-rated hypothesis is the correct one; the third report from the red target (the sixth report overall) is now correctly associated with the other reports from that target.

As more reports are processed, it may be seen that the decision revision can also work to a disadvantage. In Fig. 4a, the next two reports have been processed, and still another hypothesis has risen to the top. In this hypothesis, the fourth report from the blue target (the seventh overall) has been incorrectly associated with the red target. Another feature of the correlator/tracker algorithm appears for the first time in Fig. 4a, namely, report deletion. For the example analyzed here, a time window of 5 hours was used. That is, any report over 5 hours old is deleted from the hypothesis matrix and, consequently, from the picture. When the twelfth report arrived (with an observation time of 6.25 hours), the first report (made at 1.00 hours) was therefore deleted and is missing from Fig. 4a. Five hours later, the situation appears as shown in Fig. 4b, wherein the reports that were causing most of the confusion have been automatically deleted (along with all the other old reports) because they are more than 5 hours old. Notice that since there are no longer any ambiguities between the tracks, the single cluster has been split into two clusters.

Figures 3, 4, and 5 demonstrate the two factors that can cause changes in the rankings of hypotheses. First, when several hypotheses have comparable probabilities, new reports that cause relatively small changes in probability can result in major switches in the relative ranking of hypotheses. This phenomenon, seen in Figs. 3c, 3d, and 4a as three different hypotheses assume the number one ranking, is also illustrated in Fig. 5. From 4 to 6 hours, the correct hypothesis moves from third to fifth to third to first to second while its probability changes only slightly.

The other factor that causes changes in hypothesis rankings is hypothesis merging, which results from report deletion. As ambiguous reports are deleted, starting at 8.25 hours, the correct hypothesis rapidly rises to the top because it is merged with other, now identical, hypotheses. By the end of this example, the hypothesis shown in Fig. 4b is the only significant one remaining.

ALGORITHM TESTING

The correlator/tracker described in this article has been subjected to testing using real-world data collected during recent Fleet exercises. Unfortunately, the value of such testing is limited by the general lack of "truth" concerning the real-world sensor reports. In particular, the true associations of the reports and the actual positions of the ships were not known for the bulk of the data. Consequently, extensive testing in the future will make heavy use of models designed to simulate ship motion and sensor reports realistically. Because ship motion is simulated, "true" ship positions are known. However, no matter what data are used in testing, quantitative assessment of correlator/tracker operation requires the evaluation of specific measures of performance. Although the development of quantitative correlator/tracker measures of performance is still in the preliminary stage, several basic measures have already been identified as meaningful. Three of these were used to evaluate the correlator/tracker's performance on the example just described. The results are shown in Table 1 (based on using the most likely hypothesis in all clusters).

Radial error is a standard measure of the locational accuracy of the correlator/tracker (particularly the tracker). It is defined as the distance between the actual position of a target and its position as estimated by the correlator/tracker.

"Freedom from impurity," P_F, indicates the purity of the tracks developed by the correlator. Whenever the correlator identifies a given track with a particular target, P_F is defined to be the number of reports in the track that were observations of the actual

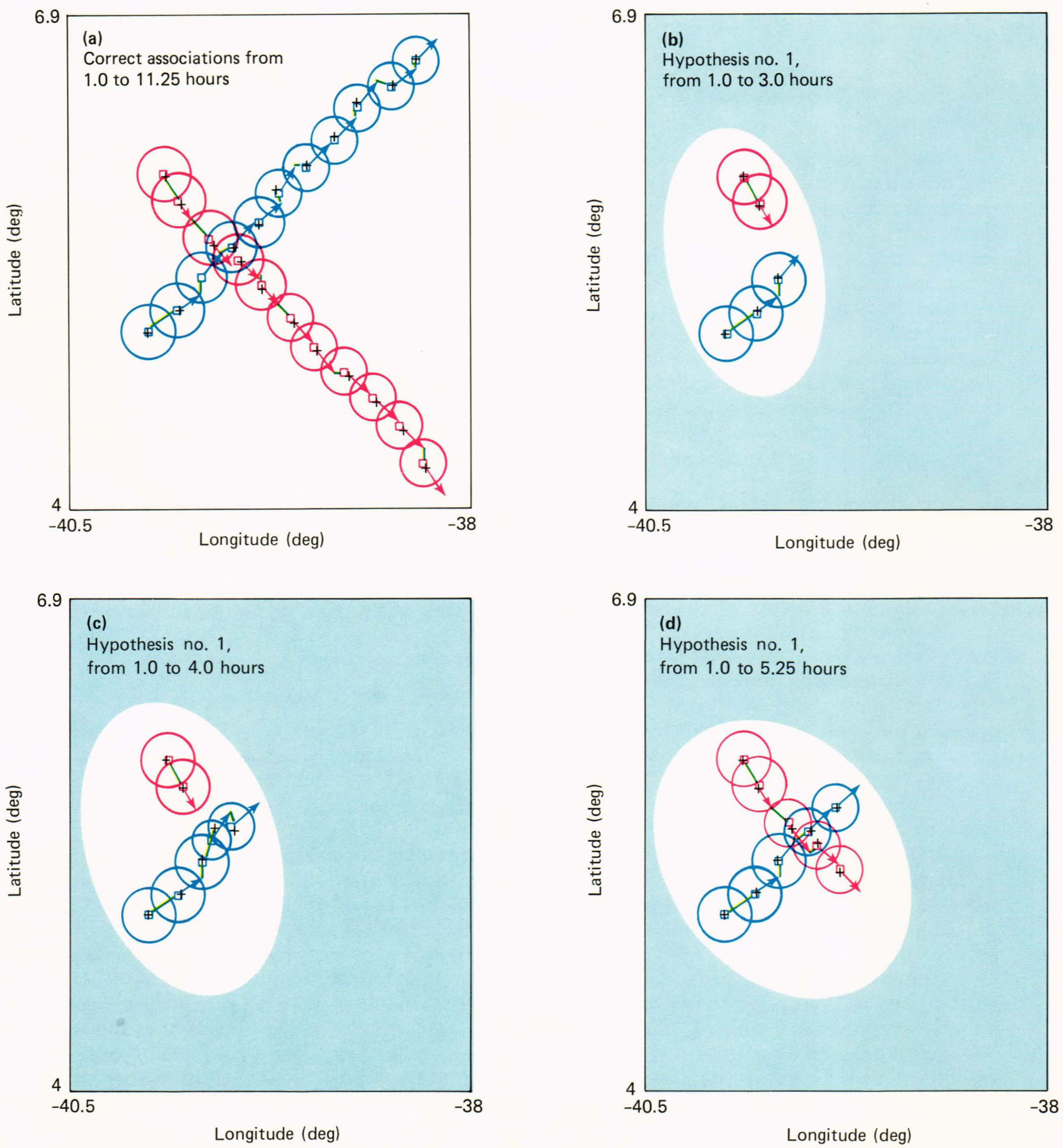


Figure 3 — The performance of the correlator/tracker algorithm is illustrated with a simple two-ship crossing-track example. Black plus signs mark the reported position of a ship; the colored squares and circles give the position and 90% confidence ellipse as estimated by the tracker at update. The colored arrows point to the estimated position of a ship projected by the tracker to the time of the next report in the track. The tip of each arrow is connected with a green line to the estimated position as updated using the next report. Figure 3a shows the true associations of all 22 reports used in the example. Figure 3b illustrates the situation as determined by the correlator/tracker soon before confusion begins. In Figs. 3c and 3d, the most probable hypothesis (according to the correlator) is shown after two more and five more reports, respectively, have arrived. Notice that the sixth report was associated incorrectly in Fig. 3c, but correctly in Fig. 3d. In Figs. 3b, 3c, and 3d, only one cluster is maintained by the correlator, as indicated by the untinted area enclosing all the reports in each figure.

target divided by the total number of reports in the track. Thus, a P_F value of 1.0 implies that all the reports in the track were truly observations of the target whose identity was associated with the track; a value of 0.5 implies that only 50% came from the target whose identity was associated with the track.

Conversely, "freedom from inconsistency," C_F, indicates how consistent the correlator was in its assignment of reports of a given target. Whenever a track is identified with a target, C_F is defined as the number of observations of the target that went into the identified track divided by the total number of

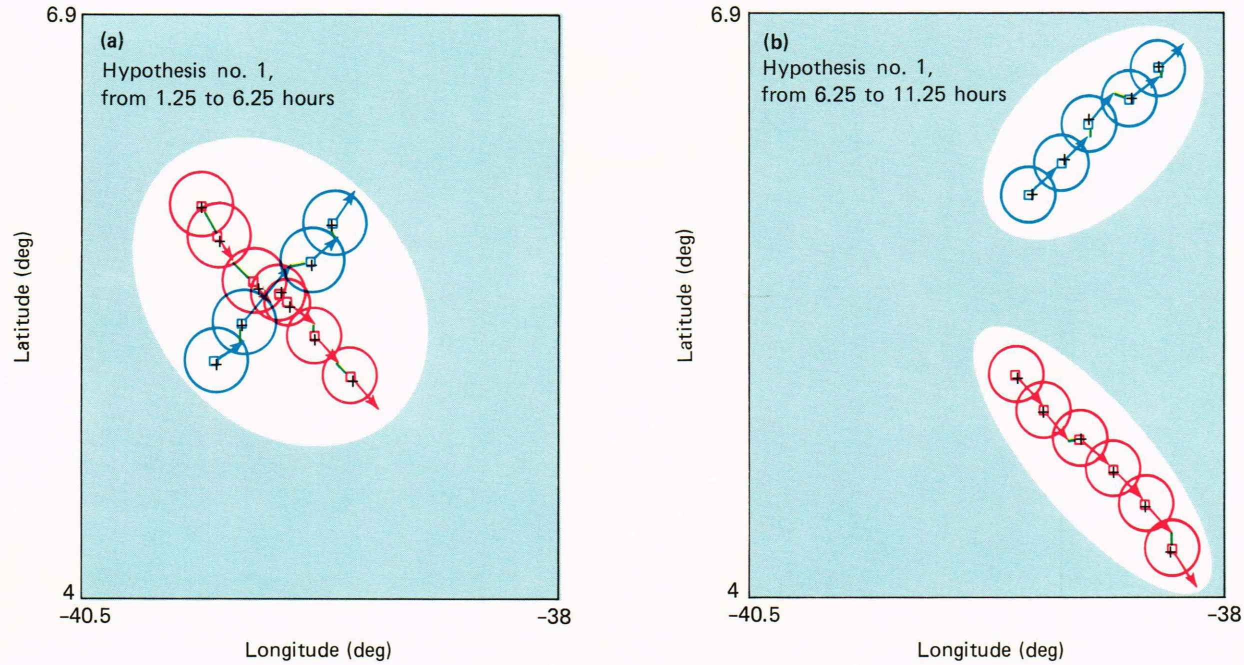


Figure 4 — The example begun in Fig. 3 is continued in Fig. 4a, as two more reports are processed, and the most likely hypothesis is shown. Since the first report was over 5 hours old, it was deleted. Note that the associations of reports six and seven have changed again. After all reports have been processed, the most likely hypothesis is as shown in Fig. 4b. Since the reports causing confusion have been deleted, this hypothesis is the only significant one remaining. Although only one cluster exists in Fig. 4a, by the time of Fig. 4b the ambiguities between the two tracks have disappeared and two distinct clusters have been formed.

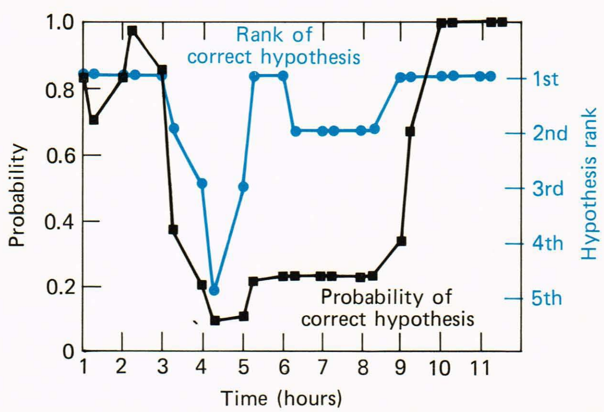


Figure 5 — The correlator/tracker may make incorrect decisions, but they are not final or permanent decisions. Although the algorithm ranks the correct hypothesis as low as fifth most probable (at 4.25 hours), later reports cause the relative standings to change, and it settles at number two from 6.25 to 8.25 hours. At that point, confusing reports begin to be deleted, so that hypotheses are merged. The probability of the correct hypothesis increases rapidly, and that hypothesis finishes at the top. (The probabilities given in this figure are calculated by the correlator and are normalized after each report, so that the probabilities of the hypotheses remaining after pruning at each step add to one.)

observations of the target. Thus, a C_F value of 1.0 implies that all reports of a target were assigned to a single track; a value of 0.5 implies that only 50% of the reports were assigned to the track identified as belonging to the target in question. Note that for a correlator that tends to create too many tracks, P_F would generally be high and C_F low; the opposite is true for a correlator that tends to create too few tracks.

To produce the numbers in Table 1, calculations were made at fixed time intervals (every hour on the half hour). (Each of the three measures of performance was computed for both ships, and means were calculated from the 10 samples corresponding to the 10 calculation times.) Therefore, the radial error for ship 1 is always based on an estimate projected a half hour ahead (from update), while that for ship 2 is based on an estimate projected a quarter hour ahead. For comparison with Table 1, the average sensor report radial error was 1.8 nautical miles for ship 1 and 2.2 nautical miles for ship 2.

Table 1 — Correlator/tracker measures of performance.

	Mean Radial Error (nmi)	*Mean Freedom from Impurity*	*Mean Freedom from Inconsistency*
Ship 1	4.0	0.975	0.915
Ship 2	4.5	0.937	0.967

SUMMARY AND FUTURE EFFORT

This article has described a correlator/tracker algorithm that accepts and processes data from multiple sensor systems, making use of not only reported geolocational data but also any other information that would uniquely identify the ship. Consistent with the operational situation, the algorithm handles reports emanating from sensors with nonunity detection probabilities and nonzero false alarm rates; it has also been structured to allow processing of reports arriving out of sequence. The correlator/tracker automatically creates multiple hypotheses, which it evaluates and prunes based on a recursive, Bayesian processing scheme. The capability for track initiation and termination is also included.

The correlator/tracker algorithm described here is newly developed and thus has much room for improvement. The algorithm should be revised to allow processing of additional types of sensor data. This includes processing of scan data, preassociated track data, and reports containing platform line-of-bearing, velocity, or nonunique identification information. Other potential design improvements are oriented toward increasing algorithm performance and reducing storage requirements and computation time. These may involve more sophisticated report prescreening and report deletion functions, track smoothing (rather than interpolation) when handling out-of-sequence data, and a feasibility check to discard unlikely associations prior to the probability calculation.

Substantial future effort is required with respect to the interface between the correlator/tracker and its user. This includes the design of operator decision aids and meaningful graphical displays. The algorithm must also be made amenable to operator intervention for the purposes of resolving highly ambiguous associations, overruling correlator decisions, and adjusting algorithm control parameters.

Finally, the correlator/tracker algorithm will require extensive testing. This testing is necessary for choosing optimal control parameters, for assessing sensitivity to different operational factors, and for determining the utility of the added features mentioned above. Quantitative evaluation of the test results will make use of the measures of performance discussed previously as well as several others. Taken as a group, these correlator/tracker measures of performance will reflect both the quality of the report associations and the quality of the tracker state estimates.

Work is continuing in order to implement these correlator/tracker design improvements and to define the additional measures of performance to use when testing the algorithm. As testing of the algorithm continues using real-world data, it will likely yield additional insight, leading eventually to an automated algorithm that provides the multisensor correlation and tracking capability necessary to maintain accurate ocean surveillance pictures in an operational environment.

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