


# Image Cover Sheet

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**TITLE**  
MULTIPLE TARGET TRACKING BASED ON CONSTELLATION MATCHING AND KALMAN FILTER

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## Multiple Target Tracking Based on Constellation Matching and Kalman Filter

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### Abstract

A new approach to multiple target tracking ( MTT ) problem is developed. The data association ( DA ) problem is solved by an attributed subgraph isomorphism approach called constellation matching ( CM ). The CM method exploits, in the most direct way, the spatial configuration of the collection of targets which are subject to temporal and spatial constraints. The CM-based tracking system combines the CM technique with the Kalman filter to track and confirm the trajectories of multiple targets. The efficiency of this new approach is demonstrated using real-life multiple target radar tracking data and the results are compared to those obtained by a multiple hypothesis tracking ( MHT ) system.

source. Once tracks are formed and confirmed, a number of quantities, such as number of targets, target kinematics and other characteristic parameters, can be estimated and predicted.

For single target tracking, a sequence of target positions can be detected from sensed data referred to as plots which can be plotted to give a trajectory of the target. The detected trajectory up to the current frame can be used to predict the position of the target using standard Kalman filter in the next frame. However, for a MTT system, the problem is more complicated. A major difficulty in tracking a large number of moving targets is the uncertainty in the origin of measurements; that is, in general it is not known what the correct association is between measurements and targets. For example, in the case of a single sensor producing noisy measurement of the ranges of  $N$  targets, there are a total of  $N!$  possible associations between the measurements and the targets. Thus even for a relatively small number of targets, the number of possible target/measurement associations can be very large. The standard approaches to MTT are based on some subset of the set of all possible associations which can result in computationally complex algorithms in the application to collections of many targets in the

### 1. Introduction

Multiple target tracking (MTT) [1] addresses the issues of using one or more sensors to simultaneously track many moving objects of interest ( targets ). It is an essential requirement for surveillance systems to interpret an environment that includes both true targets and false alarms. The objective of MTT is to partition the sensor data into sets of observations, or tracks, originated from the same

same validation gate.

In this paper, a novel method called constellation matching (CM) [2] is proposed to solve this assignment problem. The CM-based MTT system consists of two major components: association and prediction. Because Kalman filtering is sequential and optimal in the minimum mean-square sense, it is used in our MTT system to perform the prediction. As for association, this new MTT system uses the CM technique to perform observation-to-track assignment. The CM method forms a complete graph on the tracks and matches it to graphs formed by the measurements received in the next scan to minimize possible errors arising from local target positional variation or false alarms due to the presence of noise. Our MTT system then combines the CM technique with the Kalman filter to track and confirm the trajectories of multiple targets.

In Section 2, the constellation matching technique and its application to the association problem is described. In Section 3, we present the algorithm of the CM-based MTT system. Evaluation of this new MTT system using real-life radar tracking data and the comparison with a multiple hypothesis tracking (MHT) algorithm are reported in Section 4.

## **2. Data Association and Constellation Matching**

Data association (DA) is the process of assigning observations to existing tracks. It is of fundamental importance to a MTT system. For closely spaced targets, it is likely that conflicting

situations may arise in the following cases: 1) when multiple observations fall within the same gate; 2) observations fall within the gate of more than one track. In general, there are two approaches to the DA problem. One is a deterministic approach which includes nearest neighbor (NN) and global nearest neighbor (GNN) data association. The other one is the probabilistic approach based on Bayesian framework, which includes multiple hypothesis tracking (MHT), probabilistic data association (PDA) and joint probabilistic data association (JPDA).

In this paper, a novel method called constellation matching (CM) [2] is proposed for data association. Basically, the CM method is a special case of a more general methodology known as optimal attributed subgraph isomorphism [3,4], where the optimal DA is achieved by assigning observations to tracks in order to minimize a chosen objective function. In the CM method, the objective function takes into the consideration the preservation of spatial configuration of associated points between consecutive frames. The CM method is deterministic; it is, however, more general than the NN approach since it tries to preserve maximal spatial correspondence between configurations of data points in two consecutive frames. It is also similar to the MHT in the sense that it generates possible data correspondence between two consecutive frames. However, the CM method chooses the best solution for the two consecutive scans while the MHT generates a number of candidate hypotheses and uses new

data to select the best track. The general principles of CM-based DA is described in the following.

Consider a group of  $N$  targets  $\{ T_i, i = 1, \dots, N \}$  represented by an attributed graph  $G$  in which each target  $T_i$  is represented by a vertex  $v_i$  and  $d(T_i, T_j)$ , the distance between  $T_i$  and  $T_j$  is the attribute value assigned to the edge  $(v_i, v_j)$ . The attribute graph  $G$  so defined is referred to as a constellation.

Let  $G1$  and  $G2$  be the constellation in two consecutive frames respectively. Association between targets in different frames can be realized by establishing an optimal one-to-one mapping  $f$  between the vertices in  $G1$  and  $G2$  while optimizing a certain objective function  $F$ .  $F$  is defined as:

$$F(G1, G2) = \sum_{v_i, v_j \in G1, i \neq j} C(v_i, v_j) \quad (1)$$

where

$$C(v_i, v_j) = \begin{cases} 0 & \text{if any one of } v_i, v_j, f(v_i), f(v_j) \text{ is null} \\ |d(v_i, v_j) - d(f(v_i), f(v_j))| & \text{otherwise} \end{cases} \quad (2)$$

The CM technique is then the problem of choosing  $f$  that achieves optimal target matching which minimizes  $F$ , and we denote such an optimal mapping by  $f''$ .

The CM-based DA technique can be summarized as follows:

1. For each pair  $v_i$  and  $v_j$  in  $G1$ , compute  $d(v_i, v_j)$ ;
2. For each pair  $u_i$  and  $u_j$  in  $G2$ , compute  $d(u_i, u_j)$ ;
3. Find all possible mapping; that is, find a set of points  $u_1', u_2', \dots, u_N'$  in  $G2$  where  $u_i'$  can be a

null vertex ( one that assumes a null value but can still be matched to a  $v_i$  in  $G1$  ) or an actual vertex in  $G2$  so that  $u_i'$  is matched to  $v_i$  in  $G1$ ;

4. For each feasible mapping, compute the value of the objective function  $F$ ;
5. Choose the mapping  $f''$  that minimizes  $F$ .

When the number of targets is large, a combinatorial explosion may happen in the CM method, either in computation time or in storage space. Heuristics which exploit spatial/ geometric constraints of the constellation are introduced to reduce the computational complexity. The following are some of the spatial and temporal constraints we adopt:

1. One basic assumption of a MTT system is that the distance a target can reach within the time interval between consecutive frames which cannot exceed a predefined maximum value ( i.e. the maximum distance the target can travel within that interval ). Thus, a pre-specified maximum size of the predicted region is imposed while finding the possible matches between vertices in  $G1$  and  $G2$ . This spatial constraint is particularly useful in the track initiation stage because there are not enough plots to render meaningful prediction.
2. Another assumption is that the distortion of a constellation cannot exceed a certain value, i.e.  $C(v_i, v_j)$  cannot exceed a predefined maximum value. Hence, a pre-specified tolerance of the change in distance between two consecutive frames is introduced in our CM system to eliminate the infeasible matches.
3. When there are too many vertices in  $G1$

needed to match with vertices in  $G_2$ , a space partitioning method using the maximum entropy method [5] can be introduced to partition  $G_1$  into several subgraphs ( or sub-constellations ), each of which would contain say 5 to 10 vertices. Thus the solution space for CM is drastically reduced. This makes the CM method feasible and effective for scenarios with large number of plots.

To illustrate the idea of using CM for DA, an example using the real-life radar tracking data is shown in figures 1 to 4. Data are extracted from five consecutive frames.  $A_s$  are used to denote plots received in scan number 1, 3 and 5, and  $B_s$  are used to represent those in scan 2 and 4. For figures 2 to 4, numbers of plots are the same for the two consecutive frames, and we observe that the CM produces correct associations for four scans. In figure 1, there is an extra plot in the first scan, however, the CM method can still perform a correct graph matching between the two frames of data.

### 3. A Constellation Matching Based MTT System

The CM-based MTT system proposed in this paper consists of five major components:

#### 1. Data pre-processing

The measured kinematic quantities of data points may not be in the suitable form for performing MTT function. Hence, the first step in our MTT system is data pre-processing which transform the original data format received by the radar to a suitable one to be used for subsequent analysis. In this study, the radar data is

transformed from polar to Cartesian coordinates.

#### 2. Gating and clustering

The purpose of this step is to classify an observation into one of the two categories: isolated observation and closely spaced observation. Clustering is used to form constellations for the future target association. Gating is used to partition the measurements in the next frame into two categories: i) candidates within the connected neighborhoods ( or gates ) of points in the previous frames, and ii) data points that can be considered for new tentative track initiation. Figure 5 illustrates the application of gating to four new observations based on the gates of two points in the previous frame. In figure 5,  $P_1$  and  $P_2$  are the tracks. Let  $O_1$ ,  $O_2$ ,  $O_3$  and  $O_4$  be four observations in the current frame.  $Gate_1$  and  $Gate_2$  are the circular gates of  $P_1$  and  $P_2$  respectively with the maximum estimated target displacement between consecutive time frames as their respective radius. Here,  $O_1$ ,  $O_2$  and  $O_3$  are within  $Gate_2$  whereas  $O_1$  is also within  $Gate_1$ . Hence,  $O_1$ ,  $O_2$  and  $O_3$  can all be considered to be associated with  $P_2$  whereas  $O_1$  can be considered as associated with either  $P_1$  or  $P_2$ . These three observations belong to the first category.  $O_4$  is outside of both gates and hence cannot be associated with either  $P_1$  and  $P_2$ . Hence,  $O_4$  belongs to the second category.

#### 3. Data association using CM

CM method is used to obtain the correspondence between the observations in the last frame and those in the new frame as described in the previous section.

#### 4. Track formation

In this step, each assigned observation is put into its corresponding track which records the trajectory of the associated target. The maximum size of the predicted region is used as the radius of the circular gate for the measurement association. There are two possible situations: isolated observations and closely spaced observations. Once a new scan of measurement is received, three cases may arise for an isolated observation:

- i) If there is no measurement in its association gate, the region is enlarged to the pre-specified size. If there is still none, then no assignment can be made to that isolated observation.
- ii) If only one observation is found in its association gate, then it is assigned to the proceeding isolated observation.
- iii) If more than one observation is found in its association gate, then use the prediction to choose the most suitable observation for the assignment.

Closely spaced targets are those whose predicted regions overlap with others. We group these observations to form a cluster, and these observations together become the vertices of  $G1$ . In the new frame, choose those observations that lie within the combined region ( or cluster ) to form another constellation  $G2$ . Then apply CM to find the target association between  $G1$  and  $G2$ .

#### 5. Trajectory prediction

In the CM-based MTT system, a Kalman filter given as

$$\begin{aligned} \mathbf{x}(k) &= (x(k), y(k))^T \\ \hat{\mathbf{x}}(k+1) &= \Phi \hat{\mathbf{x}}(k) + K(k)[m(k) - H\hat{\mathbf{x}}(k)] \\ K(k) &= \Phi P(k) H^T [H P(k) H^T + R(k)]^{-1} \\ P(k+1) &= [\Phi - K(k)H] P(k) \Phi^T + Q(k) \end{aligned} \quad (3)$$

where  $\mathbf{x}(k) = (x(k), y(k))$  is the  $k$ th time point of the specific target, is used for trajectory prediction to provide predicted gating to reduce the number of measurements for data association.

#### **4. Real Data Analysis and Comparison with the MHT**

In September 1986, under the auspices of the Technical Cooperation Program, Canada and United States established a data base of raw radar data on formations of closely spaced military aircraft to support research and development on multiple target tracking. The experiment took place at Canadian Forces Base, Cold Lake, Alberta. Six CF-18 fighter aircraft, flying prescribed routes in prescribed formations, served as "raid" targets. Formations of CF-18 fighter were flown in two missions, each consisting of two tests. For the first mission, a formation of three aircrafts and a formation of two aircrafts were used; for the second mission, two formations of three aircrafts were used. The layouts of the two formations are shown in figure 6. For each test, the spacings between aircrafts in the group and between groups were varied. In both tests, the aircraft flew the same prescribed routes. Flying time per test was about one half hour.

Only four types of data were kept for the database: primary radar detections (ASR),

secondary radar detections (SSR), correlated detections from primary and secondary radars (SSRC) and time marks (TIME). There are four data sets designated as R1T1.dat, R1T2.dat, R2T1.dat and R2T2.dat. Table 1 reports the statistics of the experimental results of the CM-based MTT system. The first row tabulates the total number of CMs conducted between consecutive frames. The second row reports the number of CMs that yield correct data association out of the total number tabulated in the first row. The third row reports the number of CMs which do not yield completely correct data association due to abrupt change of the trajectory. The fourth row reports the number of CMs which do not yield completely correct data association due to the presence of noise. The fifth row reports the number of CMs which do not yield completely correct data association due to the missing information in the plots.

In order to understand the CM-based tracking technique further, various experiments are conducted. First, we remove all the plots without target ID to make it easier to evaluate the tracking performance. Since it is impossible to show the complete result of the CM for all frames in detail ( there are totally around 180 frames ), we show part of the matching results in Figure 7. In order to get detailed information on the change of formation of this constellation we also plot a sequence of time frames in Figure 8 where the tracks start from the lower right corner of the figure.

Next we use the ASR data to analyze the performance of the CM method. There are

usually five or six targets in a data set, but only two of them are given ID. To test the correctness of CM, we could only use targets with known ID's for confirmation; i.e., during each step of target association, we match all the observations ( both ASR and SSR ) between the two consecutive frames. But for testing, we are only able to determine if the matches are correct for the SSR data. If a target in the previous frame is associated with the target in the succeeding frame with the same ID, we consider it a correct match. Part of the global results for one CM is shown in Figure 9. Also, a sequence of time frames starting from the lower right corner are plotted in Figure 10 to illustrate the matching results. Figure 11 and 12 show the global results for two typical targets in R1T1.dat ( with ID numbers of 130 and 205 respectively ).

To compare the efficiency of the CM-based MTT technique with conventional methods, a multiple hypotheses tracking (MHT) [7] algorithm is implemented and applied to the same real data sets for comparison. The main idea of MHT is that if a difficult association decision arises when a new scan of plots is received, MHT attempts to defer the decision by assigning all reasonably likely association as hypotheses. Each hypothesis is then given a probability given as

$$P_A(k) = \frac{1}{C} P_D^{Nc} (1 - P_D)^{Nt - Nc} \beta_{rt}^{Nr} \beta_{kt}^{Nn} \left[ \prod_{j=1}^{Nc} N(y_k - Hx_j, B) \right] P_A(k-1) \quad (4)$$

where  $P_D$ ,  $\beta_{rt}$ ,  $\beta_{kt}$  are the probability of detection, the density of the false targets, and the density of



new targets, respectively.  $c$  is a normalization constant and  $P(k-1)$  is the probability of the hypothesis  $L_i(k-1)$ .  $N(x, B)$  denotes the normal distribution and  $B = HP_c H' + R$  where  $P_c$  is the covariance of a target estimate for the prior hypothesis  $L_i(k-1)$  and  $R$  is the measurement noise covariance. It is anticipated that incorrect hypotheses will lead to highly unlikely cumulative probabilities, and hence only the most likely hypothesis will be found at the end.

Although the MHT is theoretically sound, its major handicap is the high computation cost due to the exponentially growing hypothesis tree. The situation becomes worse when the number of targets or clutter are large. In order to limit the growth of the hypothesis tree, four auxiliary techniques used in the CM-based MTT method are also introduced in the MHT algorithm so that we can have a fair comparison.

1. Gating: the same gating used in the CM-based MTT method is used here. In other words, those plots that fall outside of the gate are not used for potential hypotheses of the target.
  2. Pruning: hypotheses with low probability are eliminated to keep a manageable hypothesis tree. In our implementation, we limit the number of new tracks generated to a maximum of three.
  3. Merging: those tracks or hypotheses whose effects are similar ( say with the same value within the newest frames ) are merged to form a new track or hypothesis.
  4. Clustering: those hypotheses which interact with each other are combined into one cluster.
- The flow chart of our MHT implementation is

given in Fig.13.

The same four data sets are applied to both MTT systems and the statistical results are listed in Table 2. The statistical results are made using same targets along same time frames. From Table 2, the CM method appears to have a better performance than the MHT for these four real data sets. Figure 14 shows an example of the comparison between the tracking of the same target using the CM method and the MHT, and the improvements of the CM method are highlighted.

## 5. Discussion and Conclusion

In this paper, a new multiple target tracking system based on the constellation matching technique is introduced. Preliminary experimental results using real-life radar tracking data indicate that the CM-based MTT system is efficient in the sense that it produces over 80% of correct target associations. It fails only when the aircraft performs high maneuvering turns and missed detections occur. Comparing with the MHT, the CM-based MTT shows improvement in the computational cost and tracking accuracy due to the effective use of spatial constraints.

## References

1. J. K. Uhlmann, "Algorithms for Multiple Target Tracking," *American Scientist*, Vol.80, pp.128-141, 1992
2. A. K. C. Wong and R. Salay, "An Algorithm for Constellation Matching," *Proc. of the Eighth International Conference on Pattern*

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- Recognition, pp.546-554, 1986
3. D. E. Grahraman, A. K. C. Wong and T. Au, "Graph Optimal Monomorphism Algorithms," IEEE Trans. on Systems, Man and Cybernetics, Vol.10, pp.189-196, 1980
  4. A. K. C. Wong, M. I. You and S. C. Chan, "An Algorithm for Graph Optimal Monomorphism," IEEE Trans. Systems, Man and Cybernetics, Vol.20, pp.628-636, 1990
  5. D. K. Y. Chiu, A. K. C. Wong and B. Cheung, "Information Discovery through Hierarchical Maximum Entropy Discretization Synthesis," in Knowledge Discovery in Databases, edited by G. Piatetsky and W. Frawley, pp.125-140, 1991
  6. M. Gregoire, "Raid Tracking Trials (RATT): Digital Plot Data Base," Defence Research Establishment Ottawa Report No.1026
  7. S. S. Blackman, Multiple Target Tracking with Radar Applications, Artech House, 1986

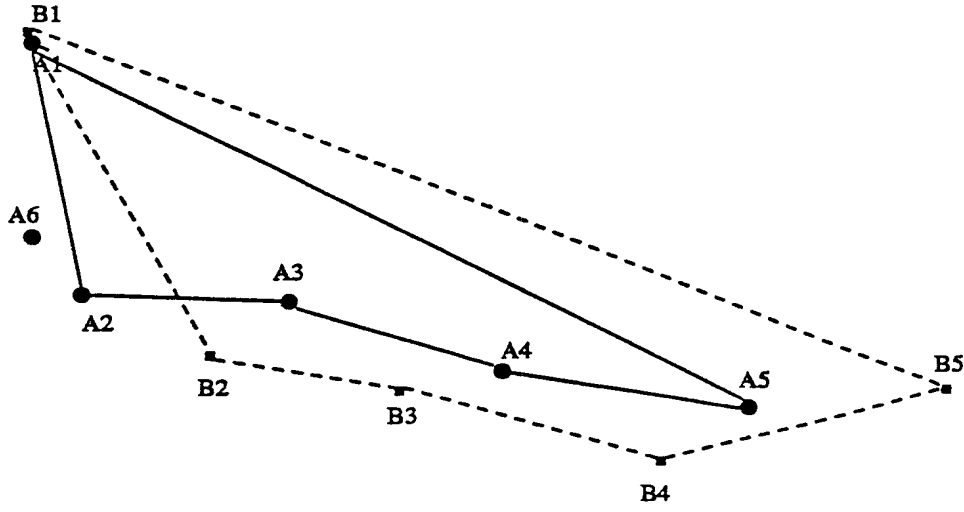


Figure 1 Pairly Constellation Matching Result 1

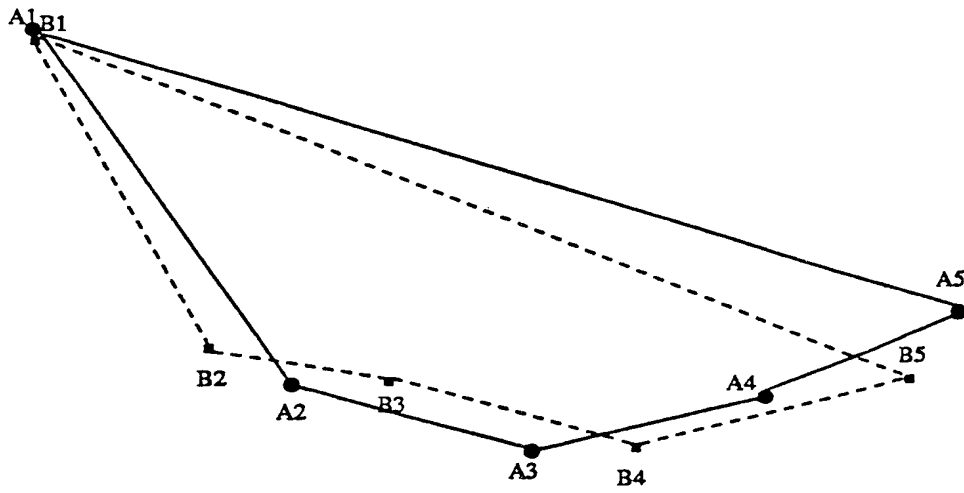


Figure 2 Pairly Constellation Matching Result 2

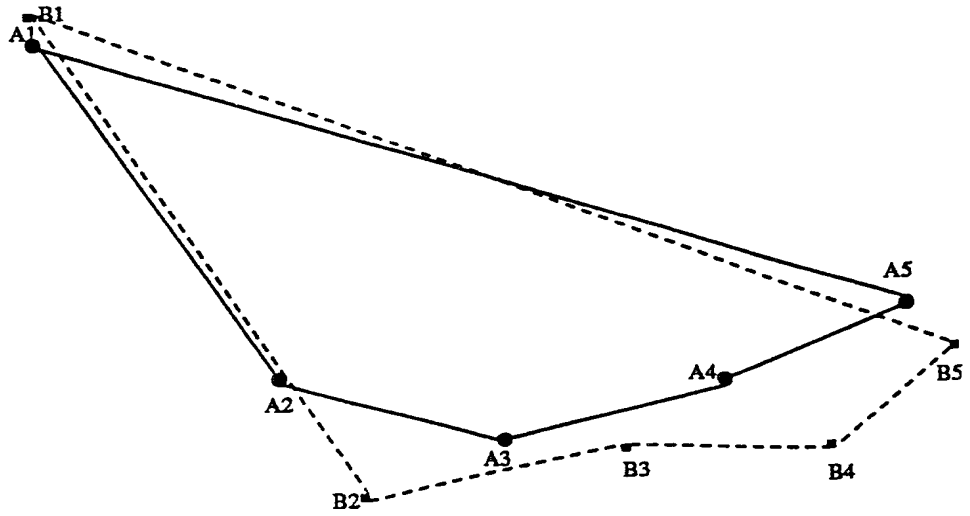


Figure 3 Pairly Constellation Matching Result 3

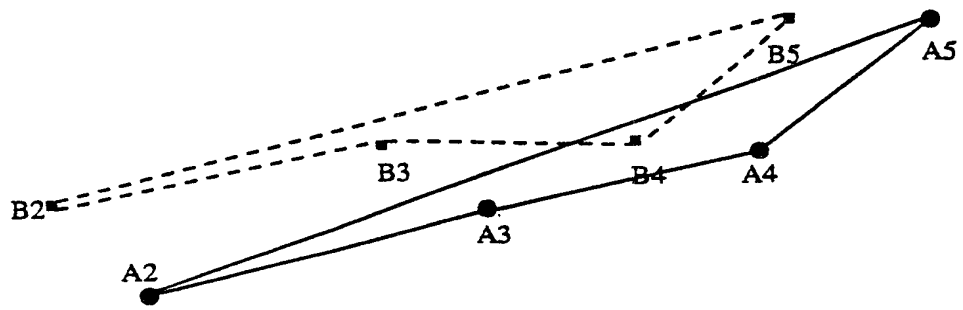
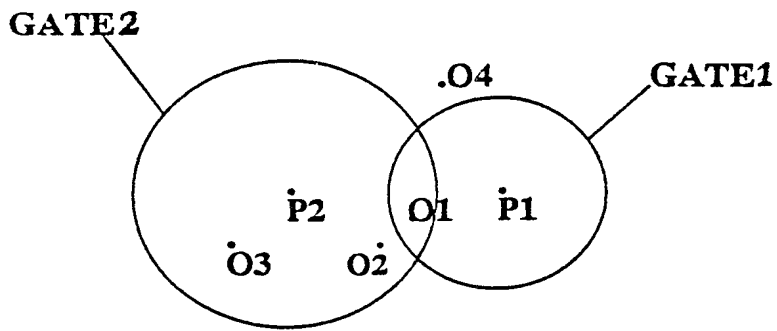


Figure 4 Pairly Constellation Matching Result 4



O1,O2,O3,O4=OBSERVATION POSITIONS  
P1,P2 =PREDICTED TARGET POSITIONS

Figure 5 Gating and Correlation for Two Closely Spaced Tracks

25-12

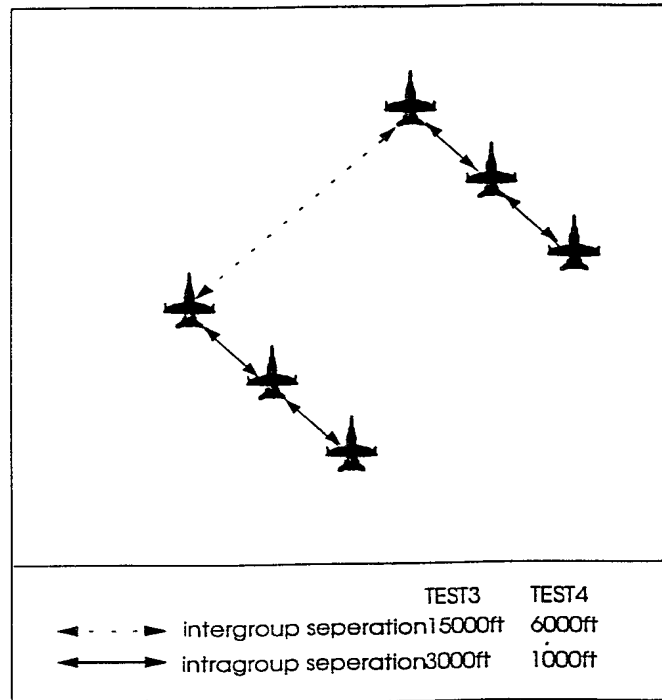
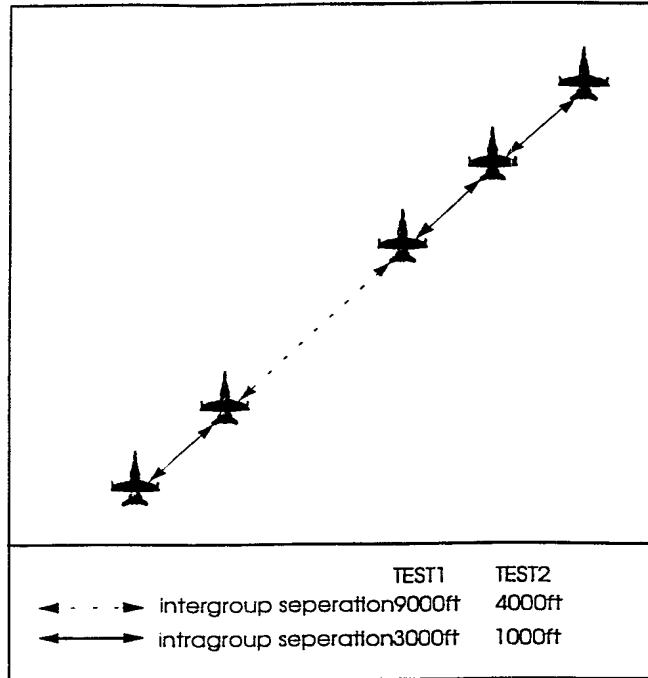


Figure 6 Formation Layout for Mission 1 and 2

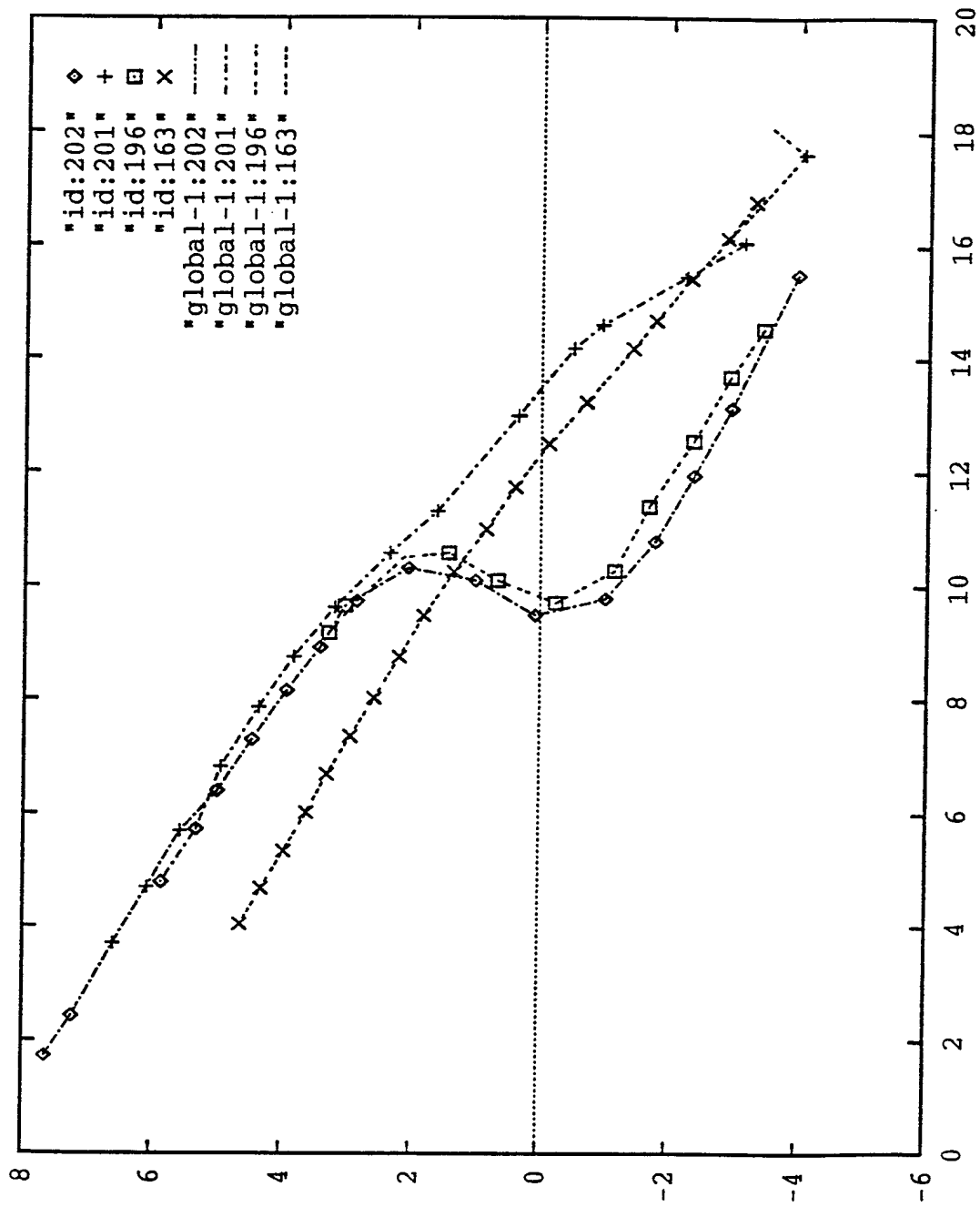


Figure 7 Part of Global Tracking Result of One Constellation ( Only for SSR )

25-14

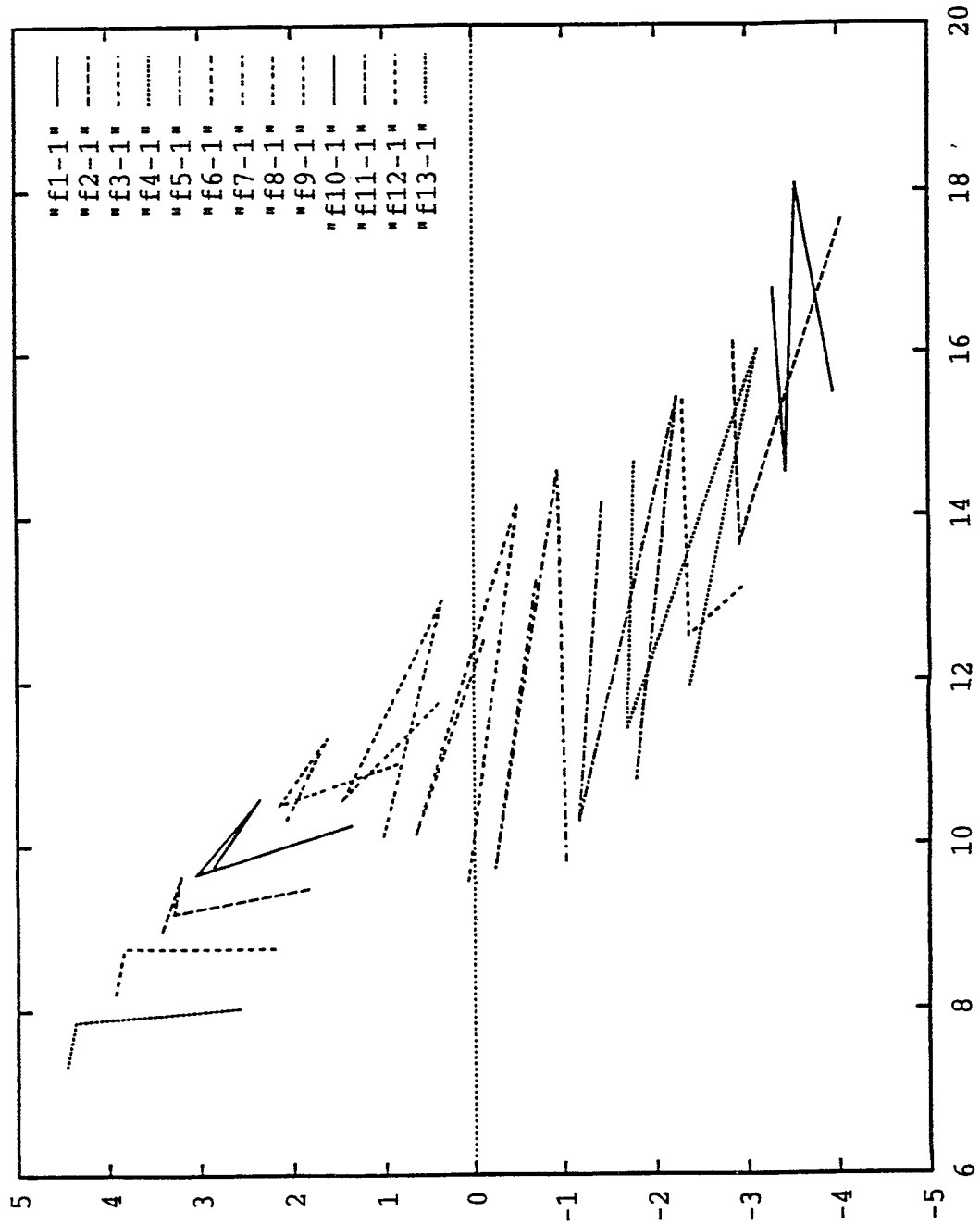


Figure 8 Part of a Sequence of Time-frames for One Constellation ( Only for SSR )



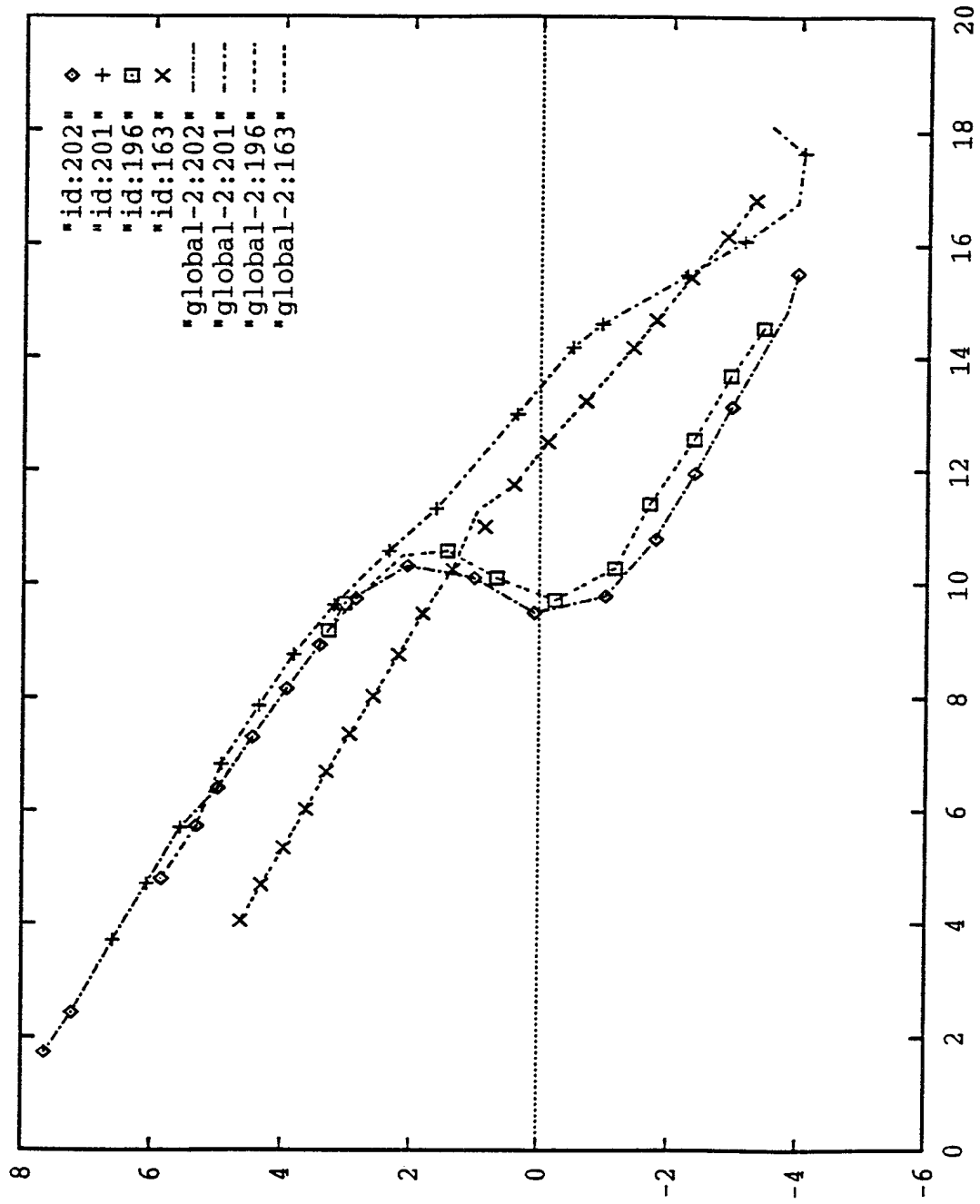


Figure 9 Part of Global Tracking Result of One Constellation ( Both ASR and SSR )

25-16

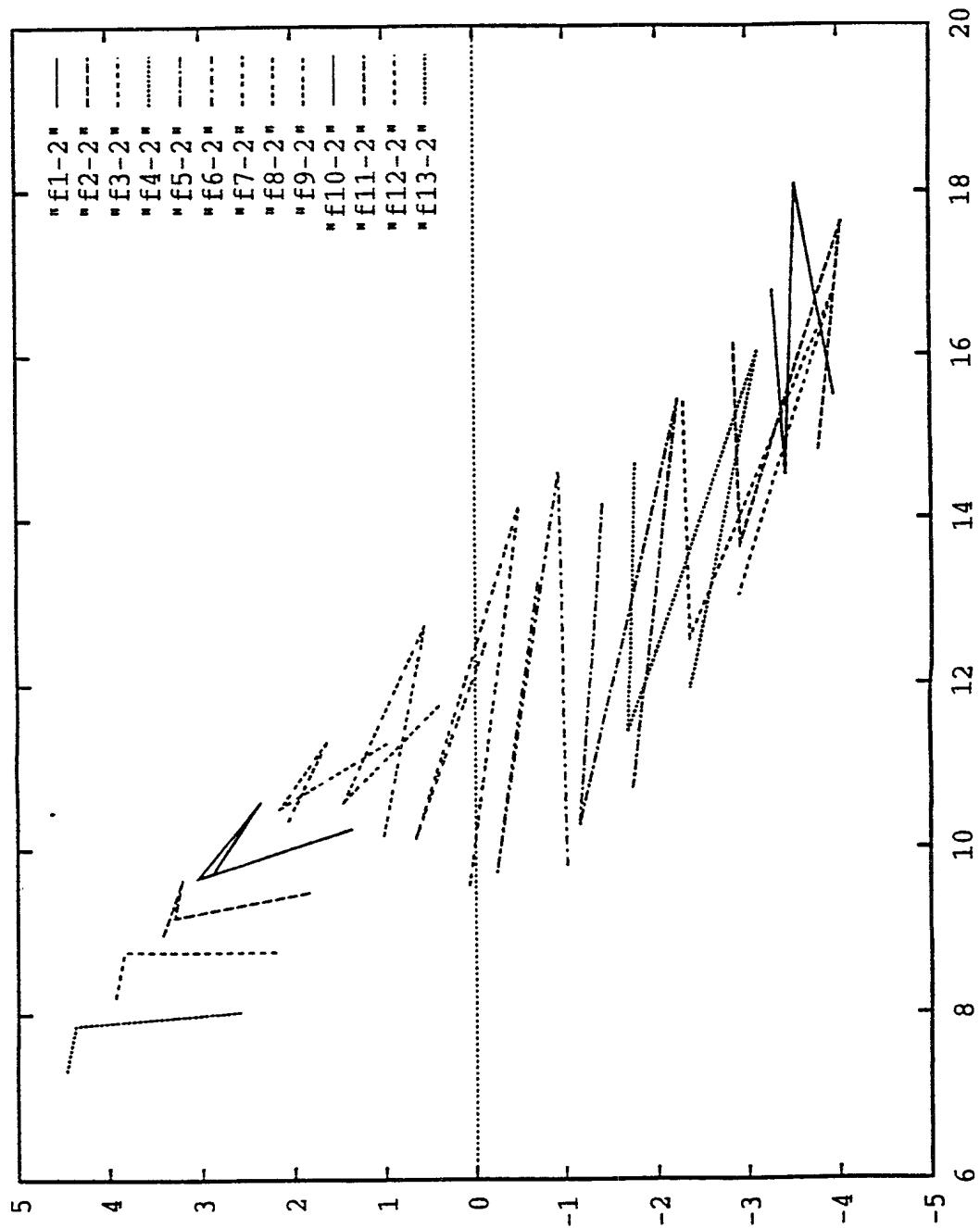


Figure 10 Part of a Sequence of Time-frames for One Constellation ( Both ASR and SSR )

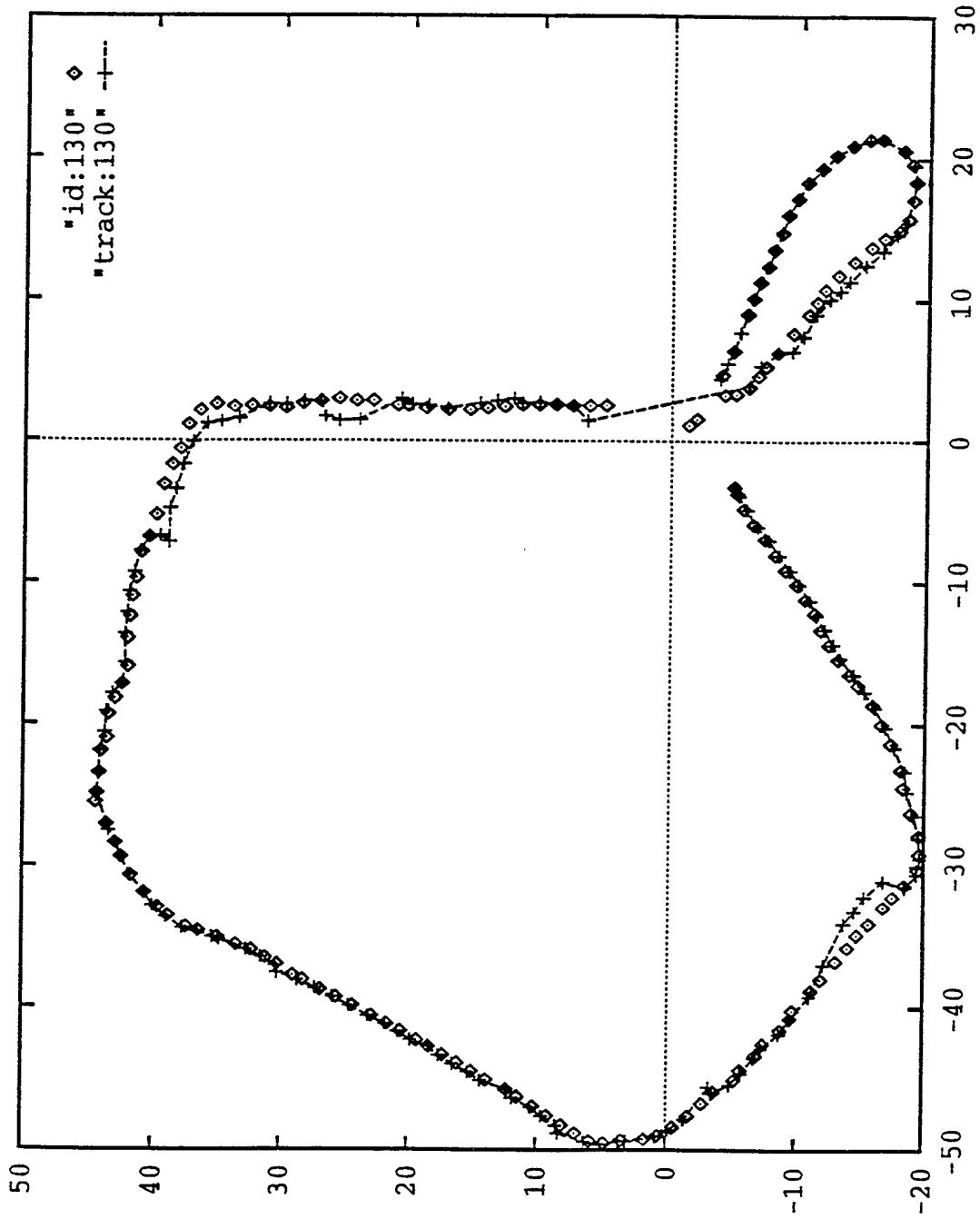


Figure 11 Global Tracking Results of One Target in R1T1.DAT ( ID 130 )

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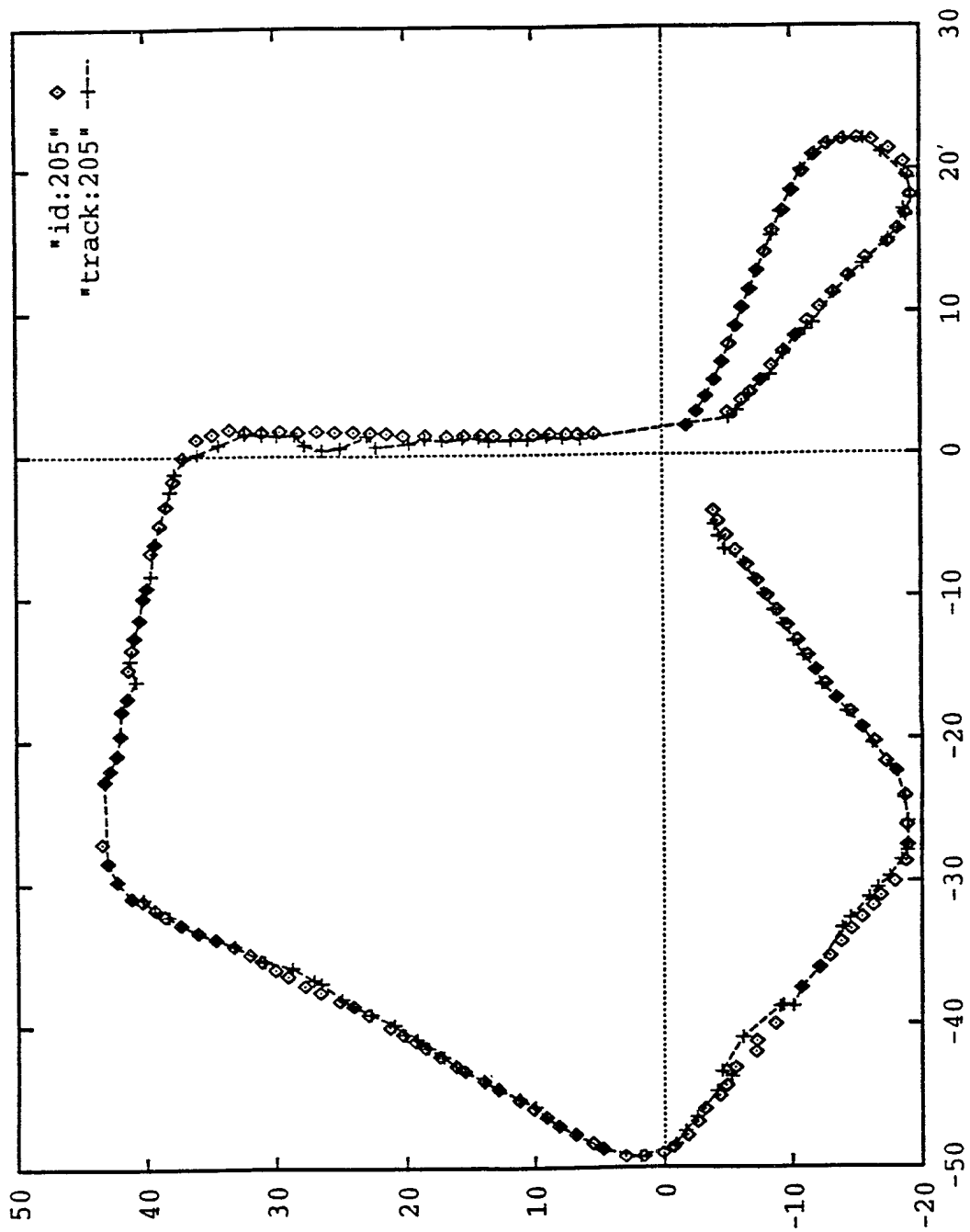


Figure 12 Global Tracking Results of One Target in R1T1.DAT ( ID 205 )

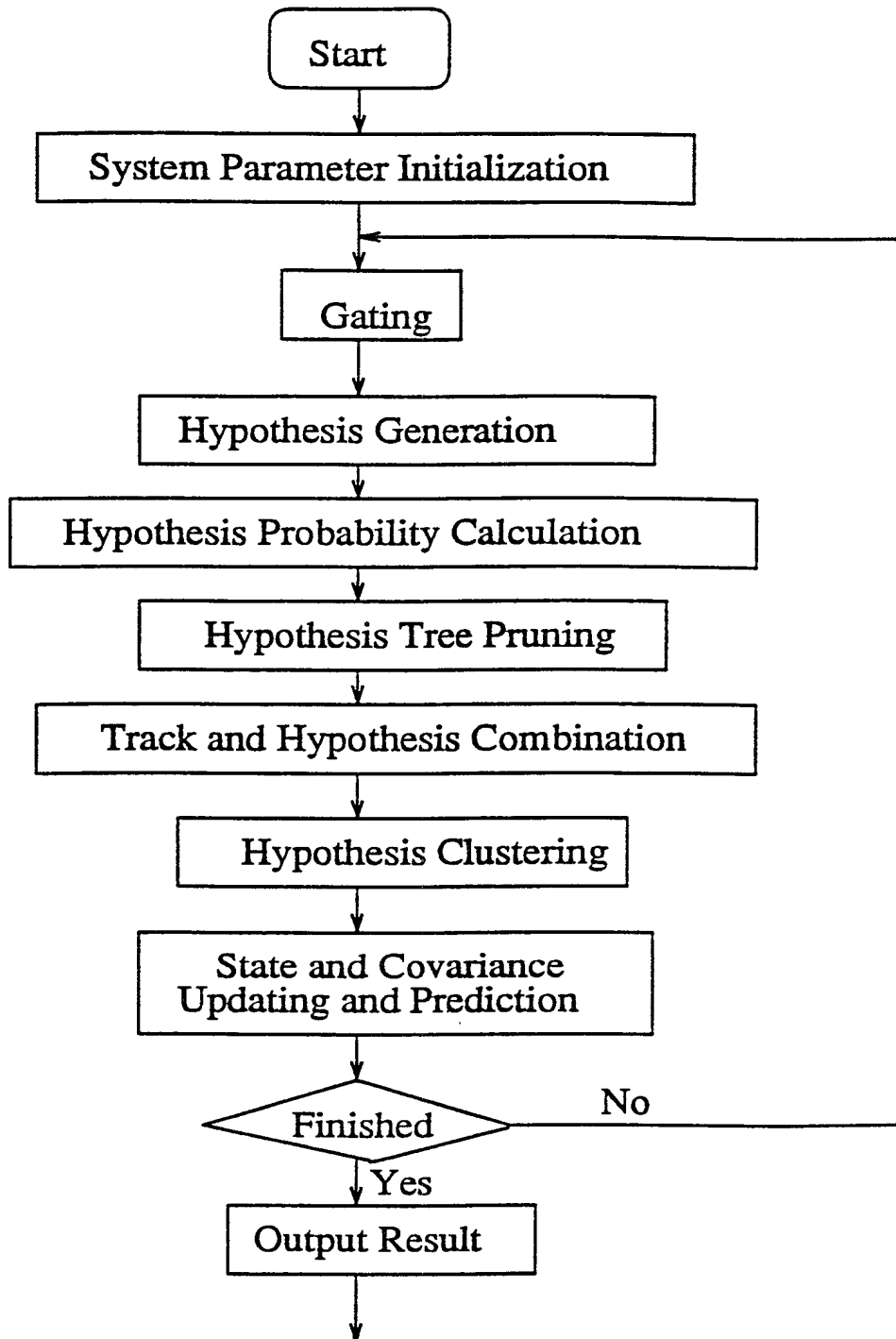


Figure 13 Multiple Hypothesis Tracking Flow Chart

25-20

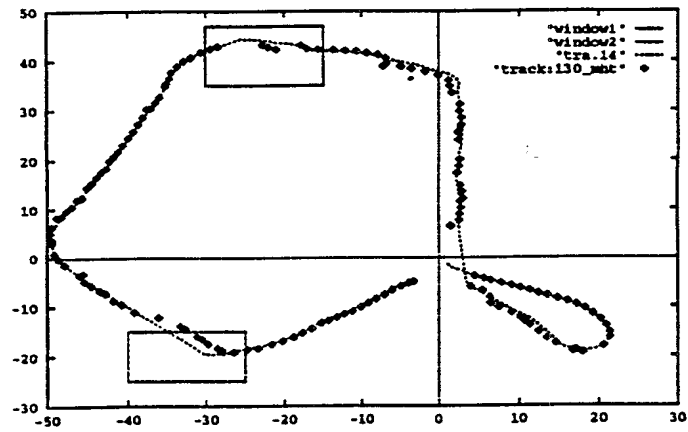
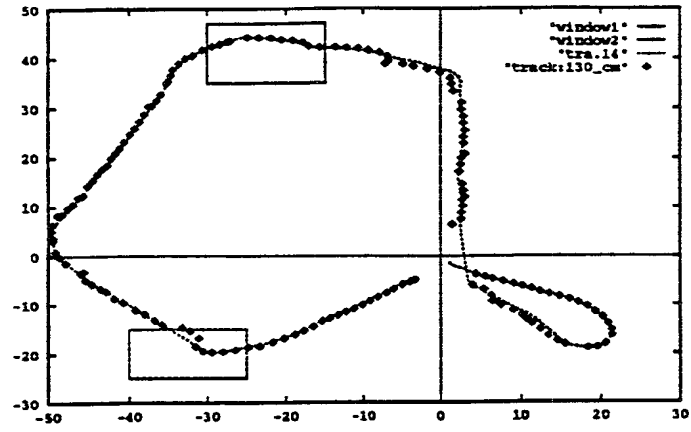


Figure 14 Comparison between the CM Method and the MHT

	R1T1	R1T2	R2T1	R2T2
No. of Occurance of Constellation Matching	172	177	187	168
No. of Correct Constellation Matching	145	143	147	137
No of Wrong Constellation Matching due to Sudden change	16	21	29	19
No of Wrong Constellation Matching due to Noise	8	5	3	8
No of Wrong Constellation Matching due to Info. Lose	3	8	6	4

Table 1 Result of the CM-based MTT System

R1T1.DAT

	Total	Correct	Wrong
CM	172	145	27
MHT	172	130	42

R1T2.DAT

	Total	Correct	Wrong
CM	177	143	34
MHT	177	127	50

R2T1.DAT

	Total	Correct	Wrong
CM	187	147	40
MHT	187	116	71

R2T2.DAT

	Total	Correct	Wrong
CM	168	137	31
MHT	168	131	37

Table 2 Statistical Results of the CM-based MTT and the MHT Tracking