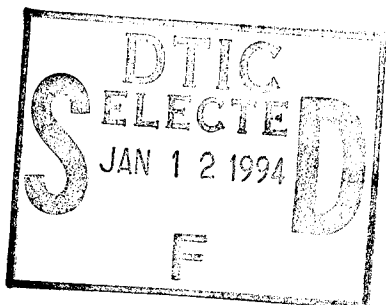


Serial No. 324,638

Filing Date 18 October 1994

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NOTICE

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2  
3 SYSTEM AND MEHTOD FOR RAPIDLY TRACKING  
4 HIGHLY DYNAMIC VEHICLES

5  
6 STATEMENT OF GOVERNMENT INTEREST

7 The invention described herein may be manufactured by or for  
8 the Government of the United States of America for Governmental  
9 purposes without the payment of any royalties thereon or  
10 therefor.

11  
12 CROSS-REFERENCE TO RELATED APPLICATIONS

13 This patent application is co-pending with related patent  
14 application entitled SYSTEM AND METHOD FOR RAPIDLY TRACKING  
15 VEHICLES OF SPECIAL UTILITY IN LOW SIGNAL-TO-NOISE ENVIRONMENTS,  
16 Navy Case No. 76256 by the same inventors as this application.

17  
18 BACKGROUND OF THE INVENTION

19 (1) Field of the Invention

20 The invention relates generally to the field of signal  
21 processing and more particularly to a system and method for  
22 rapidly detecting a moving target and determining its movement  
23 characteristics, such as range, bearing, speed and course in a  
24 noisy environment.

1 (2) Description of the Prior Art

2 Detection of a moving object, such as a target, and  
3 determination of its range, bearing, speed and course in an ocean  
4 environment, is a difficult task, particularly if the target is  
5 moving relatively noiselessly and it is desired to perform the  
6 detect as early as possible. Typically, acoustic sensors are  
7 used to detect acoustic energy (sound waves) emitted by a moving  
8 object and convert such energy to electrical signals, and complex  
9 signal processing operations are performed in connection with the  
10 electrical signals to isolate and provide the desired  
11 information. An ocean environment is generally very noisy, and  
12 so low-level acoustic signals typical of quietly-moving targets  
13 and the high level of ambient noise joint to provide a relatively  
14 low ratio of desired signal-to-noise in the electrical signal  
15 provided by the sensor, which makes early and accurate detection  
16 quite difficult. In current systems, signals that do not have a  
17 signal-to-noise ratios above a selected predetermined threshold  
18 value are ignored, in which case such signals are not available  
19 to provide information which may potentially be useful in  
20 characterising the motion of the target.

21  
22 SUMMARY OF THE INVENTION

23 It is therefore an object of the invention to provide a new  
24 and improved system and method for rapidly tracking moving  
25 objects in a noisy environment.

1           In brief summary, the invention provides a trajectory  
2 estimation system for estimating a trajectory of a target in  
3 response to a series of data items which generated in response to  
4 motion of the target. The trajectory estimation system includes  
5 a data segmentation means and a trajectory selection means. The  
6 data segmentation means processes the series of data items in  
7 accordance with a regression/multiple-hypothesis methodology to  
8 generate a plurality of segments, each having associated data  
9 items which have similar features. The trajectory selection  
10 means for processing said segments in accordance with a multiple-  
11 model/hypothesis methodology to generate a corresponding  
12 statistically-supportable candidate trajectory motion estimate of  
13 target motion thereby to provide indicia of an overall trajectory  
14 of the target.

15  
16                           BRIEF DESCRIPTION OF THE DRAWINGS

17           This invention is pointed out with particularity in the  
18 appended claims. The above and further advantages of this  
19 invention may be better understood by referring to the following  
20 description taken in conjunction with the accompanying drawings,  
21 in which:

22                   FIGS. 1A and 1B together constitute a functional block  
23 diagram of a system constructed in accordance with the invention;

24                   FIGS. 2A through 3 comprise flow diagrams illustrating the  
25 operation of the system depicted in FIGS. 1A and 1B.



1 arrangement 12 that did not exceed the predetermined detection  
2 threshold value) to detect similarities. A beam regions bound  
3 module 15 receives the beam maps and similarity information, and  
4 bounds the beam maps based on a *priori* information, such as  
5 kinematic and other information known about likely targets.  
6 The detection threshold comparator 14 and beam regions bound  
7 module 15 repeat the operations with each beam map recorded by  
8 the sensor arrangement 11 prior to the signal follower 13  
9 determining that a signal exceeded the signal-to-noise threshold  
10 value. This allows the detection threshold comparator 14 and the  
11 beam regions bound module 15 to obtain information concerning the  
12 target from the signals recorded prior to detection (that is,  
13 prior to the signal follower module 13 determining that a signal  
14 exceeded the signal-to-noise threshold value), so that the system  
15 10 will not have to rely solely on signals received after such  
16 time. In addition, the system 10 facilitates a restriction on  
17 the number of signals that it will have to analyze and allow for  
18 subsequent information to be recorded at signal-to-noise ratios  
19 lower than the detection threshold values. In particular, a  
20 measurement track formations module 16 receives the information  
21 from the beam map bounds module and applies a lower signal-to-  
22 noise ratio threshold value than that applied by the signal  
23 follower module 13 to the beam maps recorded by the sensor  
24 arrangement prior to signal detection as determined by the signal  
25 follower module 13. The measurement track formations module 16  
26 repeats these operations through a series of iterations, in each

1 iteration applying a lower signal-to-noise ratio than in the  
2 previous iteration, to extract signal information from the  
3 background noise and clutter in those beam maps. For each of the  
4 beam maps that satisfy the signal-to-noise criteria for each of  
5 the iterations, the measurement track formations module 16  
6 performs an inverse fast Fourier transform operation to transform  
7 the bounded beam maps to provide a time-based signal for later  
8 processing.

9 The signal information from the measurement track formations  
10 module 16 is then used by a data segmentation module 20 (FIG. 1B)  
11 and a trajectory estimation module 22 (FIG. 1B) to determine the  
12 range, bearing, speed and course of the target which is the  
13 source of the signal. The operations of the data segmentation  
14 module 20 and the trajectory estimation module will be described  
15 below in detail in connection with FIGS. 2A and 2B (the data  
16 segmentation module 20) and FIG. 3 (the trajectory estimation  
17 module 22). Briefly, however, the data segmentation module 20  
18 receives the signal information from the measurement track  
19 formations module 16 and, using that information and a *priori*  
20 kinematic and other knowledge concerning likely targets from a  
21 *priori* knowledge input 21, generates one or more hypotheses  
22 regarding movement of the target. The trajectory estimation  
23 module 22 receives the hypotheses and selects one as the most  
24 likely hypothesis, effectively selecting the most likely  
25 trajectory (range and bearing) of the target. The trajectory  
26 that is selected is verified by a trajectory analysis and

1 validation module 23 and a trajectory characteristics module 24  
2 using conventional statistical measures testing the likelihood or  
3 probability that a trajectory is representative of the  
4 information contained in the signals received by the sensor  
5 arrangement 11.

6 As noted above, the data segmentation module 20 (FIG. 1B)  
7 generates a set of hypotheses  $H_j$ , each containing one or more  
8 segments  $S_j$ . Each segment  $S_j$  is a hypothesized line segment that  
9 the data segmentation module 20 generates in response to the  
10 signal information, represented by a series of data items, that  
11 the data segmentation module 20 receives from the measurement  
12 track formations module 16. The data segmentation module 20  
13 generates the segments  $S_j$  in a series of iterations for each  
14 successive data item it receives. In each iteration, the data  
15 segmentation module 20 effectively attempts to add the data item  
16 to each segment  $S_j$  that it had initiated during previous  
17 iterations, and generates a likelihood measure indicating the  
18 likelihood that the data item actually belongs to each of the  
19 segments  $S_j$ . In addition during each iteration, the data  
20 segmentation module 20 initiates a new segment  $S_N$  containing only  
21 the new data item, for the possibility that the data item is the  
22 first data item of a segment, and generates a likelihood measure  
23 indicating the likelihood that the data item is the first data  
24 item for a new segment; in each subsequent iteration, the new  
25 segment will be used along with other segments initiated during  
26 previous iterations as possible segments for subsequent data

1 items. In addition, during each iteration the data segmentation  
2 module generates a "false alarm" hypothesis  $H_{iFA}$  for the  
3 possibility that the data item does not belong to any segment.  
4 The trajectory estimation module 22 prunes the hypotheses and the  
5 various segments, and over a series of iterations, the data  
6 segmentation module 20 and trajectory estimation module 22  
7 cooperate to narrow the hypothesized segments  $S_j$ .

8 The operations performed by the data segmentation module 20  
9 and the trajectory estimation module 22, each during one  
10 iteration, are depicted in FIGS. 2A, 2B (data segmentation module  
11 20, and FIG. 3 (trajectory estimation module 22). With reference  
12 initially to the data segmentation module 20, the data  
13 segmentation module 20 represents each segment as a reduced set  
14 of regression coefficients, or "features" in the signal  
15 represented by the data stream. With further reference initially  
16 to FIG. 2A., upon receiving a new data item, identified herein as  
17 " $z_1(t)$ " (step 100), the data segmentation module initially  
18 performs a series of steps 101 through 103 to test the  
19 statistical consistency of the data item  $z_1(t)$  with each segment  
20  $S_j$ .

21 In determining the statistical consistency, if it is assumed  
22 that a segment  $S_j$  consists of "n" data items previously assigned  
23 to the segment  $S_j$ , the data segmentation module 20 initially  
24 forms a predicted data item value  $\hat{z}_1(t/n)$  as set forth in  
25 Equation 1:

1

$$\hat{z}_1(t) = a_0(t^*) + a_1(t^*) + \frac{1}{2}a_2(t^*) \frac{(t-t^*)^2}{2} \quad (1)$$

2

3

4

5

6

where  $a_i(t^*)$  are the  $i$ 'th time derivatives of the measurement  $z_1(t)$  evaluated at time  $t^*$  (step 101). In this case, the data segmentation module 20 uses  $t^*$  as the midpoint of the successive data intervals for the successive data items to minimize estimation errors for the regression operation.

7

8

9

After generating the predicted data item value  $\hat{z}_1(t/n)$  via equation (1), the data segmentation module 20 generates a normalized squared residual value (step 102) as

10

$$\hat{r}(t/n) = [z_1(t) - \hat{z}_1(t/n)]^T c(t/n) [z_1(t) - \hat{z}_1(t/n)] \quad (2)$$

11

12

13

14

15

16

17

and performs a chi-squared test in connection with  $\hat{r}(t/n)$  to determine whether it satisfies a threshold "gating" value (step 103), which in one embodiment is set to the value thirty-six. If the data segmentation module 20 makes a negative determination in step 103, it will ignore the data item received in step 100, and will return to step 100 to repeat the operations in steps 101 through 103 in connection with the next data item.

18

19

20

If, on the other hand, the data segmentation module 20 makes a positive determination in step 103, it assigns a probability value  $P_a(S_j)$  identifying the likelihood that the new data item

1 belongs to segment  $S_j$  (step 104), and generates an updated  
 2 segment  $S_j'$  including the new data item (step 105). The data  
 3 segmentation module 20 generates the probability value  $P_a(S_j)$  as a  
 4 function of the normalized squared residual value generated i  
 5 step 102 prior to the chi-squared test, in a conventional manner.  
 6 In one embodiment, for simplicity the probability assignment is  
 7 obtained by mapping the normalized squared residual (equation 2)  
 8 in an intuitive formula that approximates the complement of the  
 9 chi-squared distribution as follows

$$P_a(S_j) = \begin{cases} 1 - \frac{\hat{r}(t/n)}{36} & \text{for } \hat{r}(t/n) < 36 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

11 The data segmentation module 20 generates the updated segment  $S_j'$   
 12 to include the new data item (identified as the "n+1"st data  
 13 item) in the following manner. Given a value  $a(t_n^*)$  as the  
 14 current endpoint of segment  $S_j$ , the data segmentation module 20  
 15 generates a new endpoint  $a(t_{n+1}^*/n+1)$  for the data item  $z_1(t)$  as

$$a(t_{n+1}^*/n+1) = a(t_{n+1}^*/n) + K(n) [z_1(t) - \hat{z}_1(t/n)] \quad (4)$$

17 where

$$a(t_{n+1}^*/n) = A(t_{n+1}^*, t_n^*) a(t_n^*/n) \quad (5)$$

1 and

2

$$A(t_{n+1}, t_n) = \begin{bmatrix} 1 & (t_{n+1} - t_n) & \frac{1}{2}(t_{n+1} - t_n)^2 \\ 0 & 1 & (t_{n+1} - t_n) \\ 0 & 0 & 1 \end{bmatrix} \quad (6).$$

3

The new endpoint, together with the points previously assigned to

4

the segment  $S_j$ , defines an updated segment  $S_j'$ . The data

5

segmentation module 20 determines the Kalman gain  $K(n)$  for

6

equation 3 as

7

$$K(n) = R(t_{n+1}^*/n)H(t, t_{n-1}^*)c(t/n) \quad (7)$$

8

with

9

$$c(t/n) = [H(t, t_n^*)R(t_n^*)H(t, t_n^*)^T + \sigma^2]^{-1} \quad (8)$$

10

and

11

$$H(t, t_n^*) = [1 \ (t - t_n^*)] \quad (9)$$

12

and the corresponding covariance matrix of  $a(t_{n+1}^*/n+1)$  is

13

$$R(t_{n+1}^*/n+1) = [I - K(n)A(t_{n+1}^*, t_n^*)^T]R(t_{n+1}^*/n) \quad (10)$$

14

where

1 
$$R(t_{n+1}^*/n) = A(t_{n+1}^*, t_n^*)R(t_n^*/n)A(t_{n+1}^*, t_n^*)^T \quad (11)$$

2 and "I" is the three-by-three identity matrix.

3 After generating the updated segments  $S_j'$  for all segments  
4 for which the chi-squared test was satisfied in step 103, the  
5 data segmentation module 20 effectively updates the set of  
6 hypotheses  $H_i$ . In that process, the data segmentation module 20  
7 updates hypotheses  $H_{ij}$  developed during previous iterations, in  
8 connection with previous data items in the series, replacing the  
9 segments  $S_j$  in the respective hypotheses with updated segments  $S_j'$   
10 (step 106). In addition, the data segmentation module 20  
11 establishes two new hypotheses, one hypothesis  $H_{IFA}$  comprised of  
12 the original segments and the other hypothesis  $H_{IN}$  comprised of  
13 the original segments plus a new segment  $S_N$  representing the new  
14 data item. The hypothesis  $H_{IFA}$ , since it contains only the  
15 original, non-updated segments, represents the likelihood that  
16 the new data item is a "false alarm", that is, that it neither  
17 belongs to any segment  $S_j$  nor is the first data item of a new  
18 segment  $S_N$ . The hypothesis  $H_{IN}$ , on the other hand, represents the  
19 likelihood that the new data item is the first data item of a new  
20 segment  $S_N$  and that the other segments  $S_j$  are incorrect  
21 hypotheses.

22 The data segmentation module 20 then proceeds to a series of  
23 steps to generate several likelihood scores for each hypothesis.  
24 In particular, the data segmentation module generates a raw

1 likelihood score  $P(H_i/n+1)$  for the original (non-updated)  
 2 hypotheses  $H_i$  as

$$3 \quad P(H_i/n+1) = P(H_i/n) \left[ \left( 1 - \prod_{j=1}^K 1 - P_a(S_j) \right) (1 - P_N) (1 - P_{FA}) + P_N (1 - P_{FA}) + P_{FA} \right] \quad (12)$$

4 where " $P_N$ " represents the *a priori* likelihood that the data item  
 5  $z_1(t)$  starts a new segment, " $P_{FA}$ " represents the *a priori*  
 6 likelihood that data item  $z_1(t)$  is a "false alarm," that is, that  
 7 it does not belong to any segment, and " $K$ " is the number of  
 8 segments  $S_j$  in the collection of segments in hypothesis  $H_i$ . The *a*  
 9 *priori* likelihood values are provided by the *a priori* knowledge  
 10 input module 21, and are generated in any conventional manner.  
 11 The data segmentation module 20 then, for each hypothesis  $H_i$  in  
 12 the collection of hypotheses  $H$  updated in step 106, generates  
 13 likelihood scores for a series of hypotheses  $H_{ij}$ , where each  
 14 hypothesis  $H_{ij}$  corresponds to the collection of segments in  
 15 hypothesis  $H_i$ , but replacing the original of segment  $S_j$  with the  
 16 updated segment  $S_j'$ , as well as for the hypotheses  $H_{iN}$  and  $H_{iFA}$   
 17 (step 110). In those operations, the data segmentation module 20  
 18 generates the likelihood score  $P(H_{ij})$  for each hypothesis  $H_{ij}$  as

$$19 \quad P(H_{ij}) = P(H_i/n+1) \frac{\left[ 1 - \prod_{j=1}^K (1 - P_a(S_j)) \right] (1 - P_{FA}) \frac{P_a(S_j)}{1 - P_a(S_j)}}{\sum_{j=1}^K (1 - P_a(S_j))} \quad (13),$$

1 the likelihood score  $P(H_{iN})$  for the augmented hypothesis  $H_{iN}$  (that  
2 is, the hypothesis that the data item is the first data item for  
3 a new segment) as:

$$4 \quad P(H_{iN}) = P(H_i/n+1) \left[ \prod_{j=1}^k (1 - P_a(S_j)) \right] (I - P_{FA}) \quad (14),$$

5 and the likelihood score  $P(H_{iFA})$  for false-alarm hypothesis  $H_{iFA}$  as

$$6 \quad P(H_{iFA}) = P(H_i/n + 1) P_{FA} \quad (15).$$

7 After generating the likelihood scores, the data  
8 segmentation module 20 prunes the hypotheses  $H_{ij}$ ,  $H_{iN}$  and  $H_{iFA}$  by  
9 deleting the hypotheses that have likelihood scores below a  
10 predetermined threshold value (step 111). The data segmentation  
11 module prunes a segment  $S_j$ , that is, it completely eliminates the  
12 segment, when the segment is no longer contained in any  
13 hypothesis  $H_{ij}$  for any index "i".

14 After performing steps 100 through 111 for one data item,  
15 the data segmentation module 20 returns to step 100 to process  
16 the next data item. The data segmentation module 20 performs  
17 steps 100 through 111 for each data item representing a signal it  
18 receives from the measurement track formation module 16.

19 After generating the hypotheses  $H_i$  for a set of data items,  
20 the data segmentation module 20 then transfers the set of pruned  
21 segments  $S_j$  contained in the hypotheses  $H_{ij}$  and  $H_{iN}$  to the  
22 trajectory estimation module 22. The trajectory estimation

1 module 22 then performs a discrete grid search procedure depicted  
2 in FIG. 3 in connection with all of the segments  $S_j$  to select one  
3 segment  $S_j$  as being most representative of the information  
4 represented by the data items. With reference to FIG. 3, the  
5 trajectory estimation module 22 uses as the various target  
6 variables representing the target states such target variables as  
7 range "r", bearing "b", speed "s", course "c" and course rate  
8 " $\dot{c}$ ", and establishes a series of "bins" with the minimum and  
9 maximum values for each of these variables as determined from a  
10 *priori* knowledge of the possible target (step 120). The result,  
11 if the target variables  $r$ ,  $b$ ,  $s$ ,  $c$  and  $\dot{c}$  are considered to form  
12 a five-dimensional space, is a five-dimensional grid of a size  
13 determined by the minimum and maximum values for each variable.

14 In selecting a segment  $S_j$  as the potentially correct  
15 segment, the trajectory estimation module 22 makes the  
16 determination based on certain ones of the variables, as  
17 indicated by the nature of the particular data items, in this  
18 case range "r" and bearing "b". After the grid is established,  
19 for each discrete point in the grid, the trajectory estimation  
20 module 22 generates a marginal density value  $P_{ij}$  (step 121) along  
21 the coordinates "i" and "j" of these data items as

$$P_{ij} = \sum_{klm} e^{-\frac{1}{2} |z - \mathcal{Z}(r_l, b_j, s_k, c_l, \dot{c}_m)|^2} \quad (16).$$

1 The trajectory estimation module 22 then identifies the point  
2  $(i,j)$  at which the marginal density value is a minimum (step  
3 122), and adjusts the perspective of the grid so that it is  
4 centered over that point (123). The trajectory estimation module  
5 22 determines whether a selected accuracy level, as determined by  
6 the resolution of the grid generated by the trajectory estimation  
7 module 22, has been reached (step 124), and if not returns to  
8 step 120 to repeat the operations. The trajectory estimation  
9 module 22 repeats the operations until the selected accuracy  
10 level has been reached, and if so it performs a chi-squared test  
11 in connection with the segment  $S_j$ . It will be appreciated that  
12 the trajectory estimation module 22 will perform these operations  
13 in connection with all of the segments  $S_j$ , and it will use the  
14 results of the chi-squared tests for all of the segments to  
15 identify one as being most representative of the data, and that  
16 segment is selected as the correct one.

17 As noted above, and returning to FIG. 1B, the segment  
18 selected by the trajectory estimation module 22 is coupled to a  
19 trajectory analysis and validation module 23 and a trajectory  
20 characteristics module 24 for verification using conventional  
21 statistical measures testing the likelihood or probability that a  
22 trajectory is representative of the information contained in the  
23 signals received by the sensor arrangement 11.

24 The invention provides a number of advantages. It  
25 facilitates the detection and use of use of signals received that  
26 are below the (initial) signal-to-noise ratio, despite the fact

1 that such signals are embedded in an increased level of clutter  
2 and noise. This enables the system to determine the location and  
3 bearing of a target relatively early and quickly.

4 In addition, the invention provides an arrangement for  
5 quickly and reliably tracking a target with an environmentally  
6 perturbed minimal data set comprising only a few data items which  
7 exploits target kinematics and a *priori* knowledge, which further  
8 allows for anomalies in the data. Using multiple hypothesis  
9 techniques, such as as described in connection with the data  
10 segmentation module 20 and the trajectory estimation module 22  
11 (FIGS. 2A, 2B and 3) allows for accommodation of changes in  
12 dynamics and quick evaluation of the target dynamics. The  
13 segmentation of acoustical information, as performed by the data  
14 segmentation module 20, allows for partitioning of the data  
15 according to similar features, which, in turn, allows for rapid  
16 detection of motion changes. The discrete grid search technique  
17 performed by the trajectory estimation module 22 provides for  
18 relative stability in the non-linear estimation problem and  
19 exploitation of a *priori* knowledge of target motion.

20 It will be appreciated by those skilled in the art that the  
21 new arrangement can be implemented using special-purpose hardware  
22 or a suitably-programmed general purpose computer.

23 The preceding description has been limited to a specific  
24 embodiment of this invention. It will be apparent, however, that  
25 variations and modifications may be made to the invention, with  
26 the attainment of some or all of the advantages of the invention.

1  
2  
3

Therefore, it is the object *to cover all*  
such variations and modifications as come within the true spirit  
and scope of the invention.

2  
3 SYSTEM AND METHOD FOR RAPIDLY TRACKING  
4 HIGHLY DYNAMIC VEHICLES

5  
6 ABSTRACT OF THE DISCLOSURE

7 A trajectory estimation system for estimating a trajectory  
8 of a target in response to a series of data items which generated  
9 in response to motion of the target. The trajectory estimation  
10 system includes a data segmentation means and a trajectory  
11 selection means. The data segmentation means processes the  
12 series of data items in accordance with a regression/multiple-  
13 hypothesis methodology to generate a plurality of segments, each  
14 having associated data items which have similar features. The  
15 trajectory selection means for processing said segments in  
16 accordance with a multiple-model hypothesis methodology to  
17 generate a corresponding statistically-supportable candidate  
18 trajectory motion estimate of target motion thereby to provide  
19 indicia of an overall trajectory of the target.

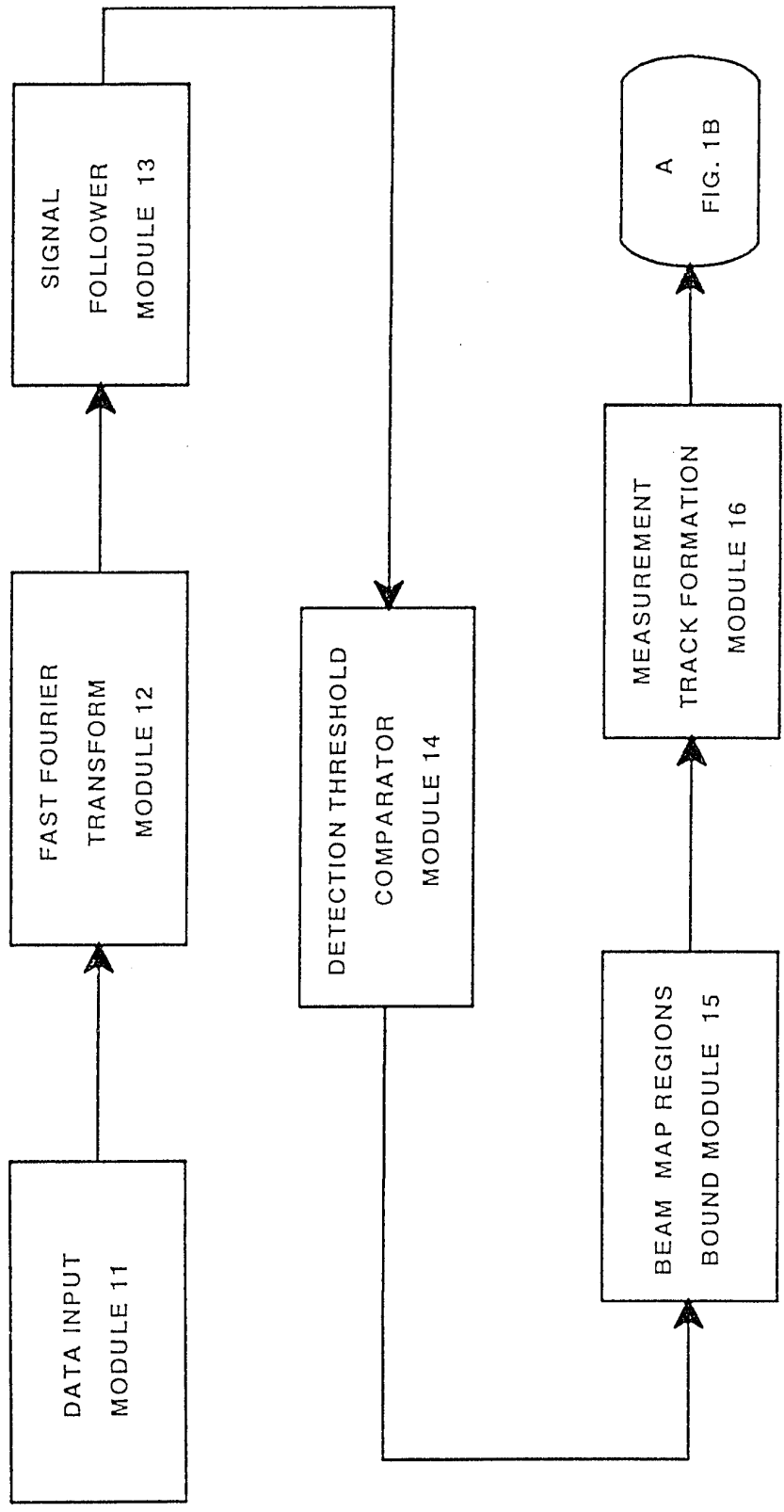


FIG. 1A

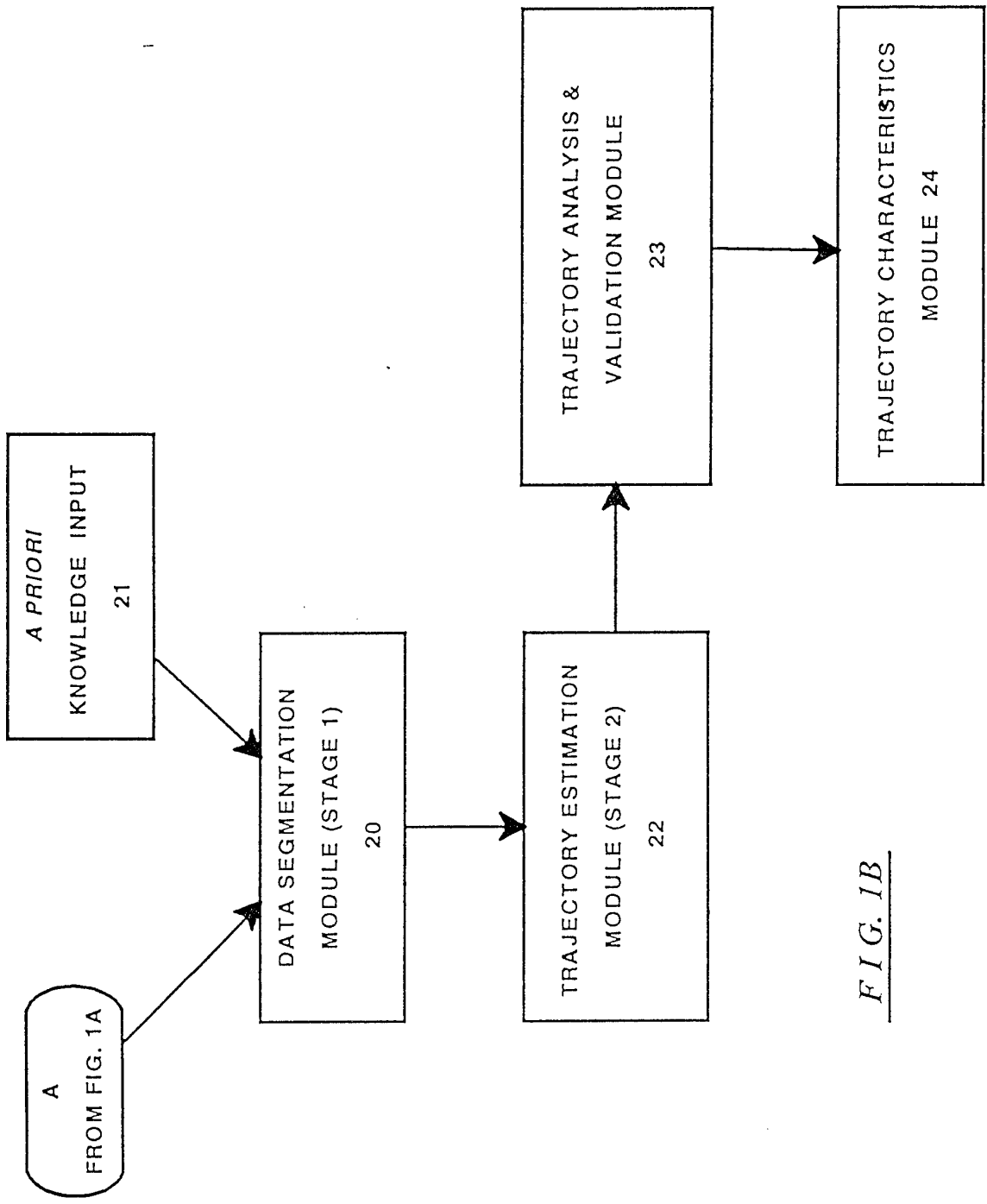


FIG. 1B

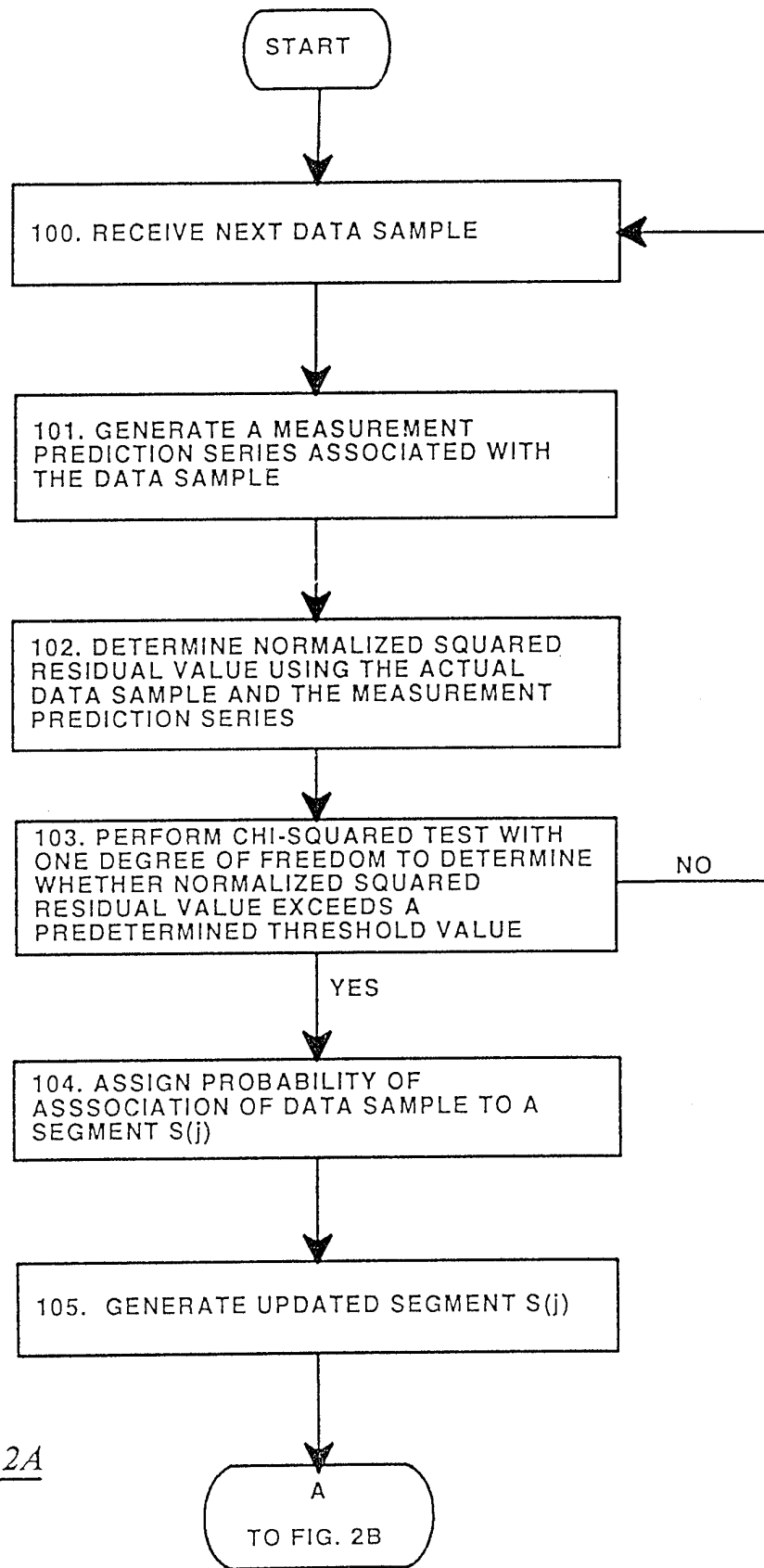


FIG. 2A

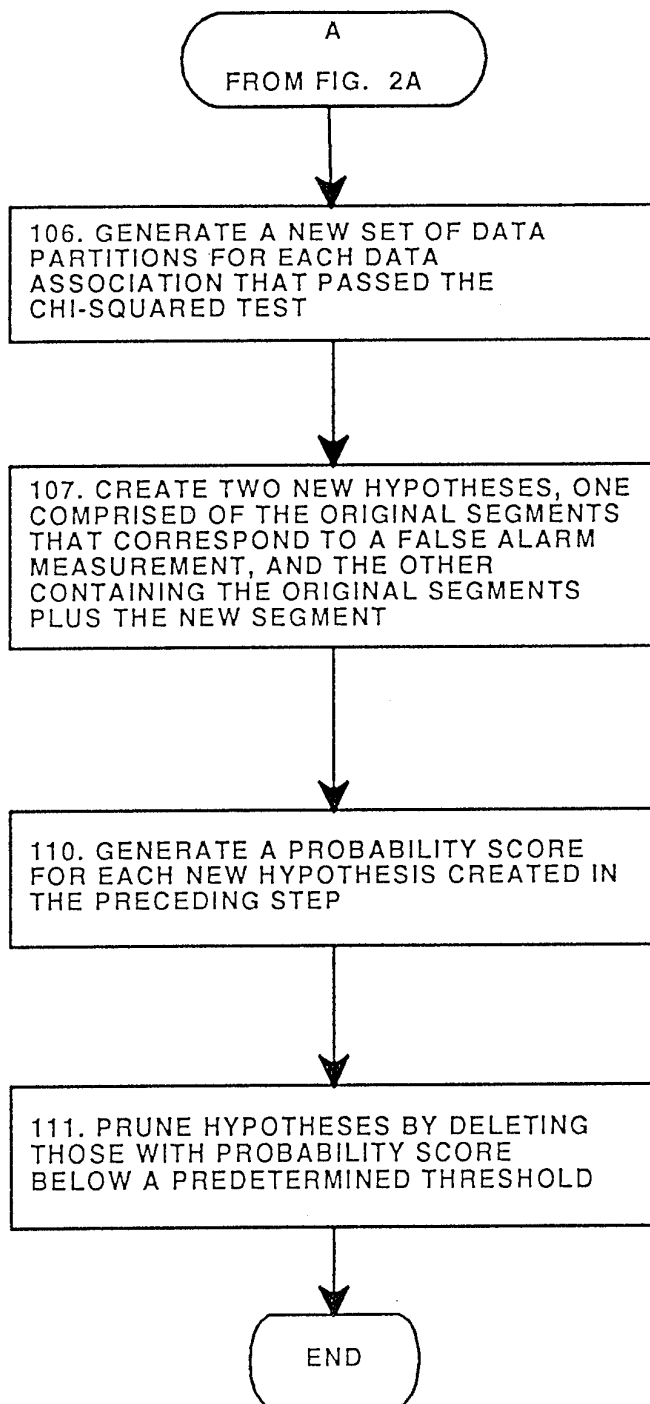


FIG. 2B

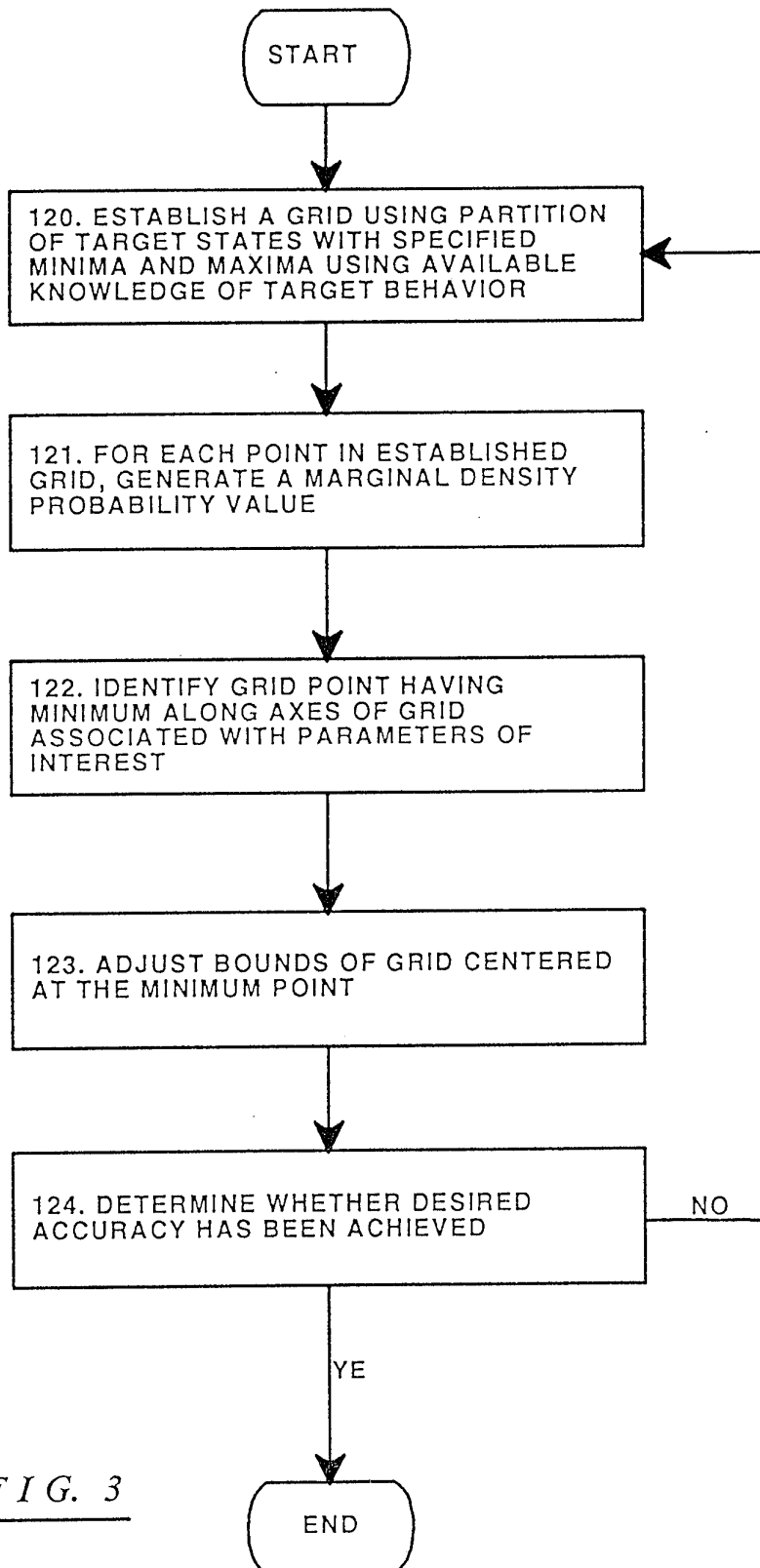


FIG. 3