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ADVANCED TARGET TRACKER CONCEPTS.(U)

APR 81 P M NARENDRA, B L WESTOVER DAAK70-79-C-0150

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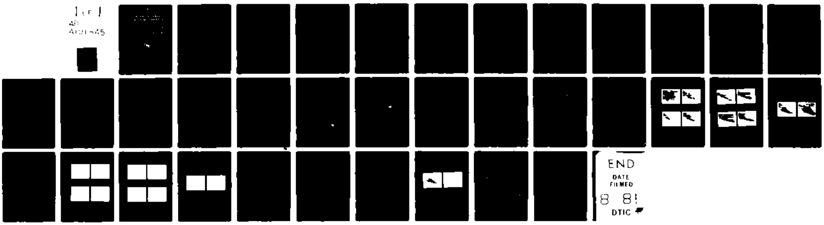

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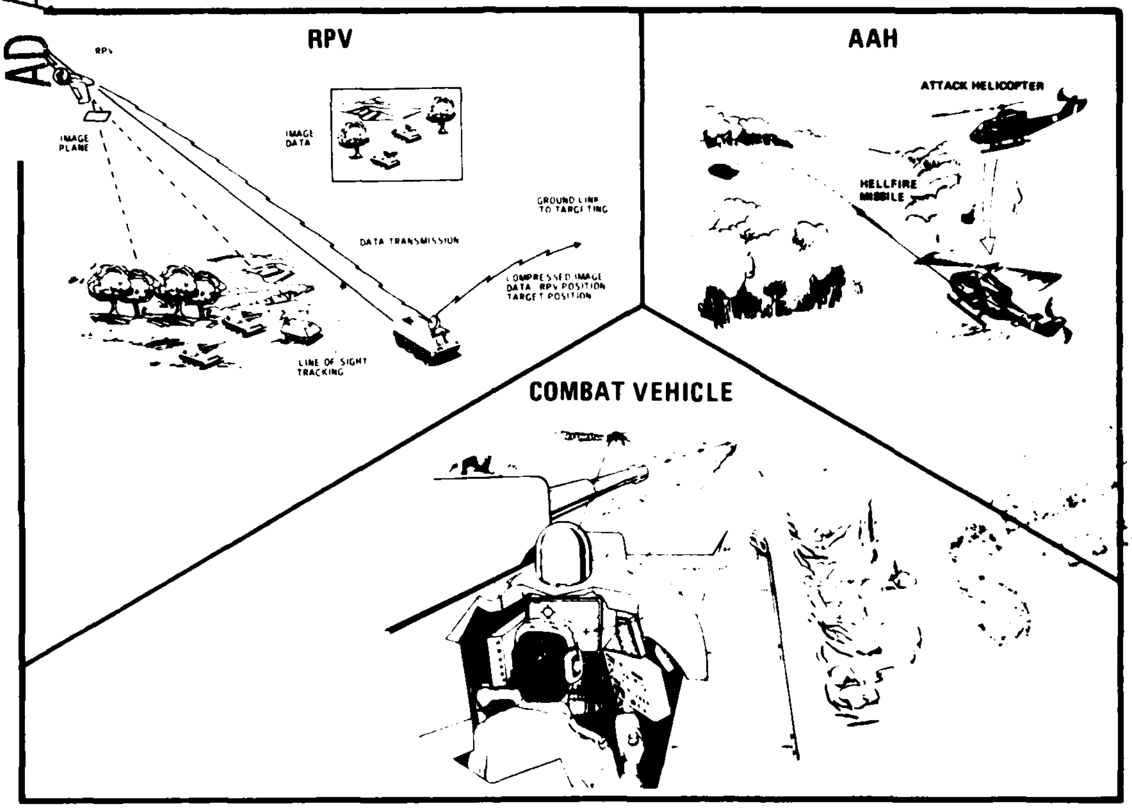

FOURTH QUARTERLY PROGRESS REPORT

1 JULY 1980 TO 1 OCTOBER 1980

Prepared for
UNITED STATES ARMY
Night Vision and Electro-Optics Laboratory
Fort Belvoir, Virginia 22060

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SECURITY CLASSIFICATION OF THIS PAGE (WHEN DATA ENTERED)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER	2. GOV'T ACCESSION NUMBER	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (AND SUBTITLE) ADVANCED TARGET TRACKER CONCEPTS		5. TYPE OF REPORT/PERIOD COVERED Quarterly Progress Report, 30 June '80 - 30 Sept. '80
		6. PERFORMING ORG. REPORT NUMBER 81SRC20
7. AUTHOR(S) P. M. Narendra ~~and~~ B. L. Westover		8. CONTRACT OR GRANT NUMBER(S) DAAK70-79-C-0150
9. PERFORMING ORGANIZATIONS NAME/ADDRESS Honeywell Inc., Systems & Research Center 2600 Ridgway Parkway, P.O. Box 312 Minneapolis, Minnesota 55440		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
11. CONTROLLING OFFICE NAME/ADDRESS Night Vision and Electro-Optics Laboratory Fort Belvoir, Virginia 22060		12. REPORT DATE April 1981
		13. NUMBER OF PAGES 36
14. MONITORING AGENCY NAME/ADDRESS (IF DIFFERENT FROM CONT. OFF.)		15. SECURITY CLASSIFICATION (OF THIS REPORT) Unclassified
		15a. DECLASSIFICATION DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (OF THIS REPORT)

DISTRIBUTION STATEMENT A
Approved for public release;
Distribution Unlimited

17. DISTRIBUTION STATEMENT (OF THE ABSTRACT ENTERED IN BLOCK 20, IF DIFFERENT FROM REPORT)

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18. SUPPLEMENTARY NOTES

The project monitor at NV&EOL is Cpt. Benjamin Reischer.

19. KEY WORDS (CONTINUE ON REVERSE SIDE IF NECESSARY AND IDENTIFY BY BLOCK NUMBER)

Pattern recognition
Multiple targets
Target tracking
Target cueing
Target screening
Image processing
Scene analysis
Artificial intelligence
Critical aimpoint
Terminal homing

20. ABSTRACT (CONTINUE ON REVERSE SIDE IF NECESSARY AND IDENTIFY BY BLOCK NUMBER)

Conventional target tracking approaches rely on numerical correlation over successive frames on a window around the target. They are therefore sensitive to partial obscuration and changes in target and background appearances. Furthermore, multiple-target tracking requires replication of the hardware.

~~In~~ this ~~fourth quarterly~~ report, ~~we~~ present the results of the continuing development of a multiple-target tracking approach based on a dynamic scene model derived (cont.)

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20. Abstract (concluded)

from the analysis of a time sequence of imagery. Simulation results demonstrate multiple-target tracking in cluttered backgrounds and in imagery from fast-moving platforms. The approach can be implemented as an integral part of the Honeywell target screener system.

Our approach to the problems of terminal homing and critical aimpoint selection is described.

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SECTION 1

INTRODUCTION

This is the Fourth Quarterly Progress Report on Advanced Target Tracker Concepts, NV&EOL Contract No. DAAK70-79-C-0150. It reports the results of the work performed between 1 July 1980 and 1 October 1980.

Tracking targets in video from TV and FLIR sensors is essential for fire control in weapon systems using electro-optical target acquisition. Typical Army applications include the remotely piloted vehicle (RPV), the advanced attack helicopter (AAH), and the combat vehicle (CV). Target tracking in these applications yields the target position for accurate pointing of a laser designator for a smart munition, such as Hellfire and Copperhead, or for fire control of conventional weapons.

Currently fielded trackers rely on numerical correlation over successive frames on a window around the target to be tracked. Several variations of the basic correlation scheme exist, and a detailed survey can be found in "Assessment of Tracking Techniques."[1] Conventional trackers are capable of tracking a manually acquired single target in relatively clutterfree backgrounds. However, target tracking requirements for the increasingly sophisticated weapon systems have grown beyond the capabilities of the current correlation trackers.

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[1]Benjamin Reischer, "Assessment of Target Tracking Techniques," Proceedings of SPIE, Vol. 178, Smart Sensors, 1979, pp. 67-71.

In this program Honeywell Systems and Rsearch Center is developing an advanced target tracker approach, based on dynamic scene analysis, which will satisfy these requirements. This approach integrates the target screening and tracking functions which can provide automatic acquisition and multiple-target tracking through low signal-to-noise and high clutter conditions. This is done with a target screener and minimal additional hardware.

Figure 1 is an overview block diagram of the basic approach which builds the advanced tracking function upon the scene analysis functions performed by the target screener. The basic premise is very simple: the target screener segments and classifies significant objects (targets and clutter) in real time on a frame-by-frame basis. Symbolic descriptions of the objects in each frame are used to find the corresponding objects in previous frames encompassing the history of the scene.

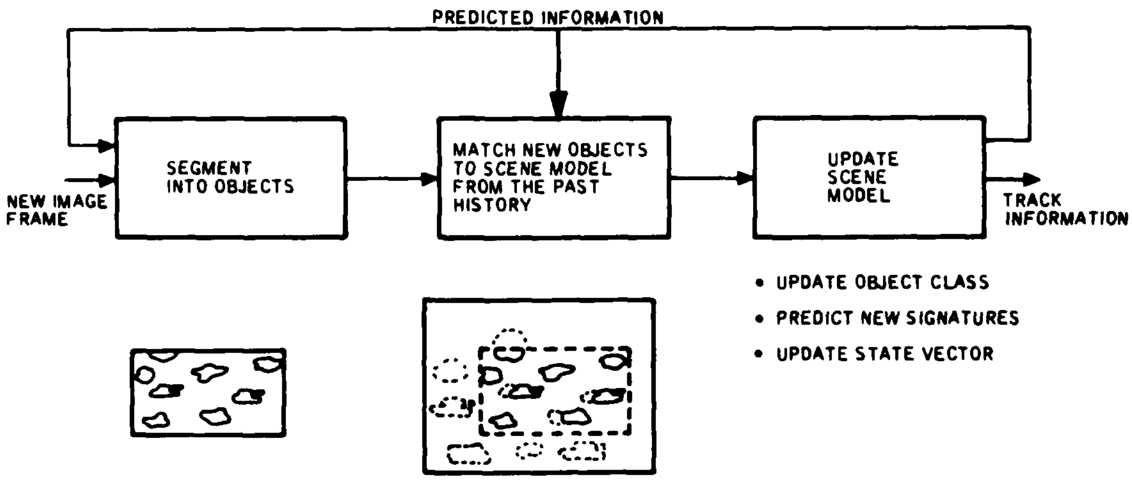


Figure 1. Overview of the Advanced Target-Tracking Approach

Once the corresponding object matches are made, the scene model, which includes the sensor and object dynamics as well as the target classes, is updated. Because we are keeping track of the positions of all the objects in the scene (targets and clutter), we can predict impending occlusion and future target/background signatures. Multiple-target tracking, of course, comes free. The scene model, based on the past history of the scene, can extend beyond the current field of view. This allows reacquisition and tracking of targets which wander in and out of the field of view because of sensor platform motion.

A complete block diagram of the major functions necessary to implement the advanced target-tracker concept is shown in Figure 2.

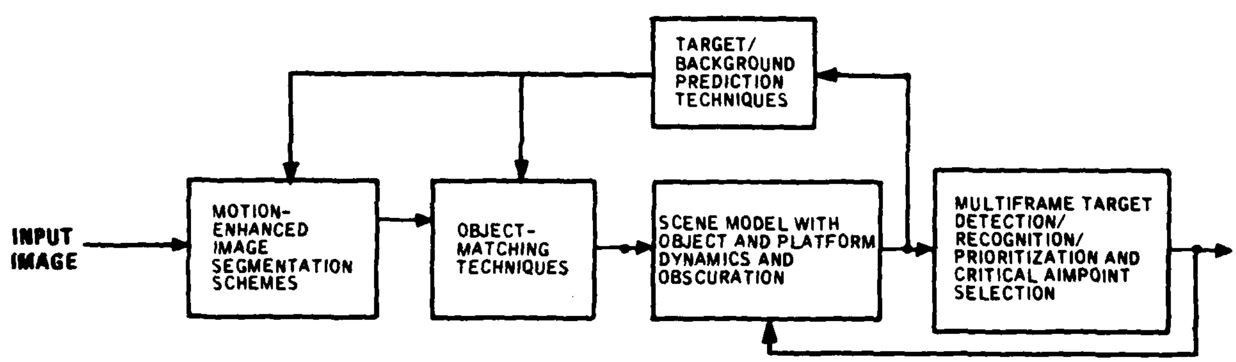


Figure 2. Advanced Target Tracker Program Overview with the Key Functions

The functions representing the major thrusts of the current program are:

- Efficient motion-enhanced scene segmentation schemes,
- Object-matching techniques capable of precise matching of objects in the new frame to the scene model derived from previous frames,
- A scene model capable of characterizing object and platform dynamics, target/background signatures, and object occlusion,
- Target/background signature prediction techniques to improve the probability of target acquisition in low signal-to-noise ratios,
- Advanced target detection/recognition/prioritization and critical aimpoint selection algorithms which can exploit the dynamic multiframe information.

SUMMARY OF PROGRESS

In this reporting period we have accomplished the following results:

- Velocity estimator improvement: We have developed an algorithm which promises to be a robust estimator of the target velocity even in the presence of extensive scene motion. The technique is capable of measuring subpixel target motion between frames and averaging the velocity estimates over several frames. We have demonstrated consistent velocity estimates for the 200-frame tracking sequence. The improved velocity estimator makes possible reliable prediction of shapes and occlusion in future frames.
- Target Homing and Critical Aimpoint Selection: We have begun work on the terminal homing and critical aimpoint selection facets of the tracking system. We are addressing two issues--avoiding the drifting of the target track point as the

sensor approaches the target and automatically selecting the critical aimpoint itself. The tracking technique based on our object models makes possible the association of the aimpoint from one frame to the next over several frames and thus prevents the drifting of the aimpoint common to all conventional target trackers. We have digitized a FLIR sequence from a terminal homing run to evaluate this tracking simulation in the terminal homing application. We have also processed these frames through the segmentation program as a first step in the simulation.

We have devised a model-based approach for autonomous selection of the critical aimpoint, extending our results from the advanced pattern matching techniques (NV&EOL Contract #DAAK70-79-C-0114) and the syntactic target recognition results from the automated imagery recognition system (DARPA Contract #F33615-76-C-1324).

PLANS FOR THE NEXT REPORTING PERIOD

In the next reporting period we intend to complete all system simulation:

- Process the 200-frame sequence with the new velocity estimator incorporated into the system simulation,
- Complete the terminal homing tracking part of the system simulation and apply it to the result of the segments on the homing sequence obtained in this reporting period,
- Perform limited simulations of the model-based critical aimpoint selection technique on representative FLIR imagery,
- Perform systems analysis with typical missile parameters to evaluate the feasibility of the proposed critical aimpoint selection technique,

o Incorporate a presegmentation motion detection technique based on change detection which utilizes the predicted background motion parameters.

ORGANIZATION OF THE REPORT

The remaining sections of the report are organized as follows:

- o Velocity Estimation
- o Terminal Homing
- o Critical Aimpoint Selection

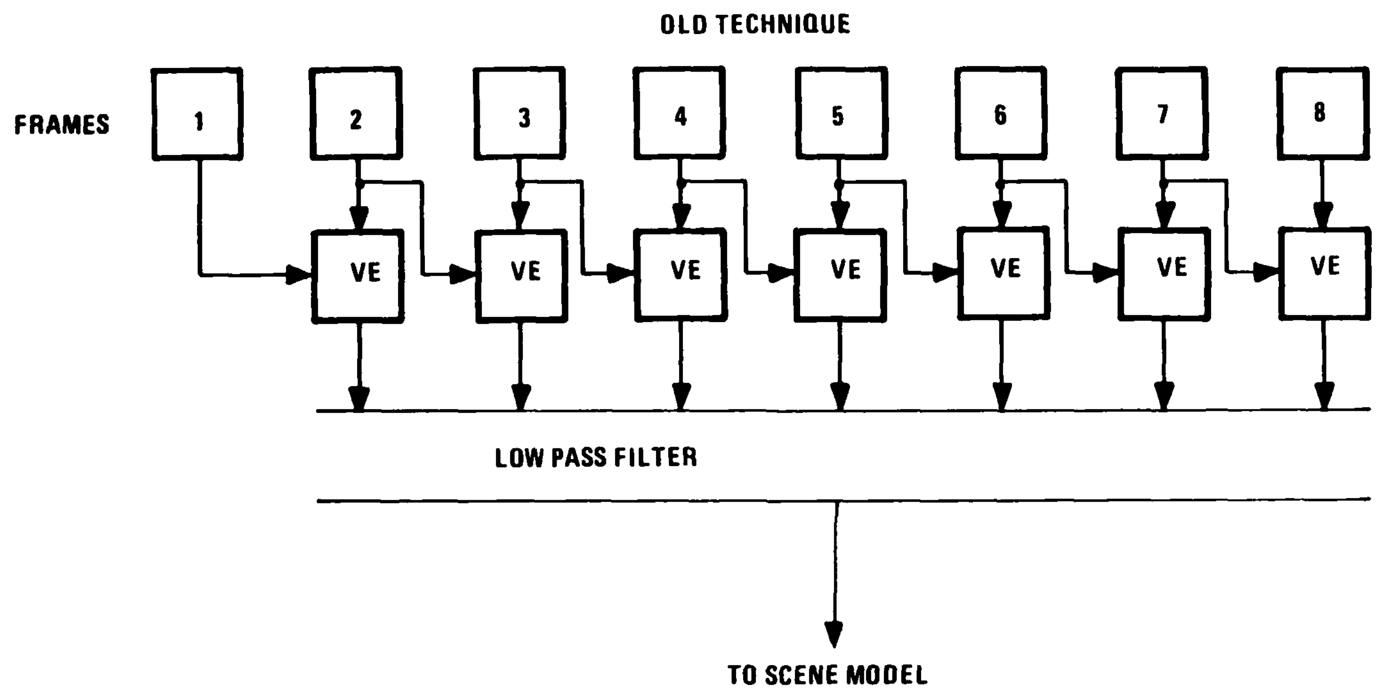
SECTION 2

VELOCITY ESTIMATION

In previous reporting periods we have developed techniques for estimating platform dynamics between frames, using the object matches in those frames. With these techniques we have successfully demonstrated that scene motion can be determined to within several pixels. We have also shown that when this scene motion is removed, a moving target is easily distinguished from stationary clutter. We have incorporated the information from several frames into a useful model of the objects in the scene. The model includes shape, position, and velocity data.

In this reporting period we have modified the velocity estimation algorithm to give a more accurate estimate. Previously, computation of the velocity of an object was based on a match between the current frame and the previous frame. The velocities computed by this technique were small for all objects in the scene, both moving and stationary, because of the small translation of the target between frames. The velocity estimation approach we currently use is based on object matches between frames which are more widely spaced. This approach gives a better estimate of the target velocity.

The target velocity approach, described in the previous report, is diagrammed in Figure 3. The silhouette matcher finds object matches betwen frames 1 and 2. It also computes the displacement of the object between frames. The effects of the scene motion are removed from the computed displacement to yield the object velocity in the image. Similarly, matches between frames 2 and 3 determine the velocity of the objects in frame 2. The output of the velocity estimation is averaged



							TOTAL	
ACTUAL MOTION BETWEEN FRAMES	0.25	0.75	0.1	0.3	0.4	0.4	2.2	PIXELS
ESTIMATED MOTION (ROUNDED OFF)	0	1	0	0	0	0	1	PIXELS

Figure 3. Target Velocity Estimation (Old technique)

over several frames and then stored in the scene model. The stored velocity is then used for shape prediction, occlusion recognition, and position estimation as described in the previous report.

This velocity estimation approach is adequate for frame-to-frame tracking of moving targets and for targets which are partially obscured. Examples of the successful application of this approach were presented in the previous quarterly report. However, for prolonged obscurations of the entire target, a more accurate estimate of the target velocity is required. Without an accurate velocity estimate, the error between our predicted position of the obscured target and the actual position will increase with every frame. Since our shape prediction algorithm relies on knowing an accurate position for the target, we will be unable to mactch the obscured target when it does appear.

There are several sources of error in our velocity estimation procedure. First, the small interframe motion of a moving target (usually less than 1 pixel) is lost in the 1 to 3 pixel error associated with the scene motion estimate. Further error is introduced in the silhouette matches. This algorithm rounds all object motion to the nearest pixel. Thus, for small interframe target motion, we can introduce up to 50 percent roundoff error. The effect of roundoff error is also shown in Figure 3. The actual target motion over six frames is 2.2 pixels; however, because of roundoff we only see a 1 pixel translation.

In order to minimize the effects of scene motion and roundoff error on the velocity estimation, we use the approach diagrammed in Figure 4. Frames which are widely spaced in time (usually 3 to 10 frames or 0.3 to 1.0 second) are matched.

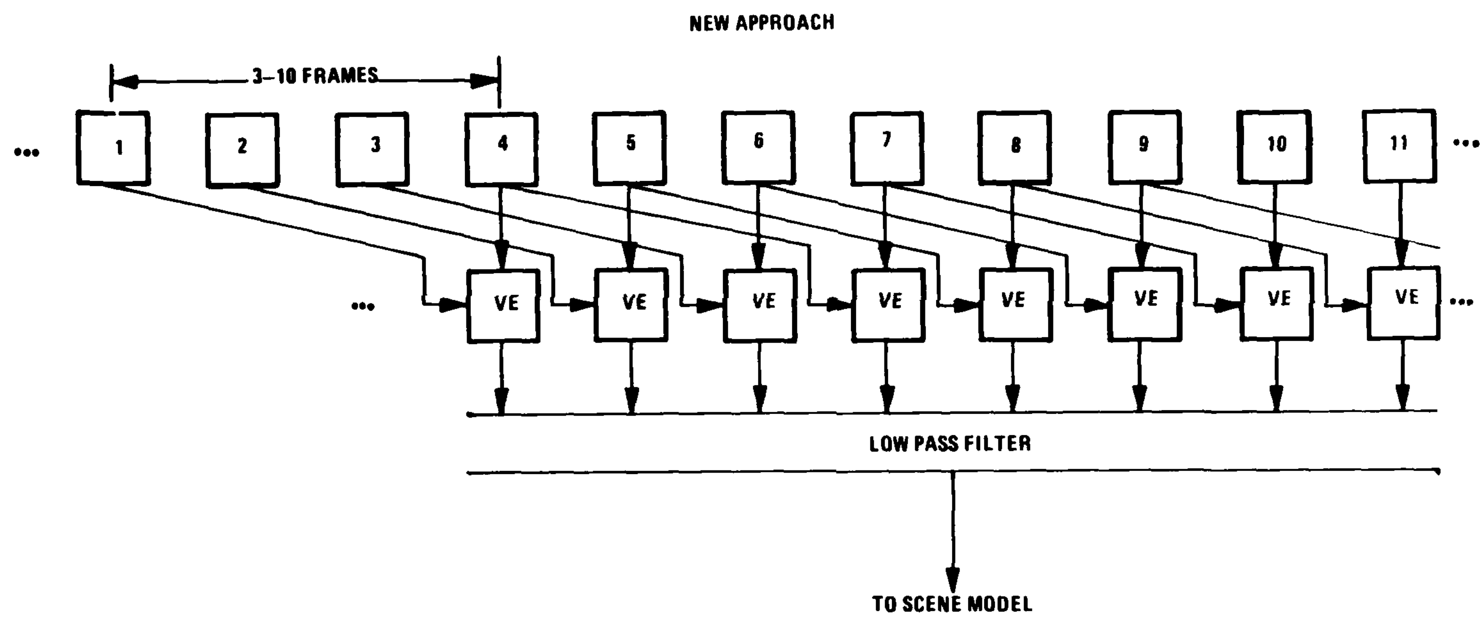


Figure 4. Target Velocity Estimation (Updated technique)

During this time the moving targets will have moved several pixels relative to the stationary background objects. In this manner the roundoff error can be reduced from 0.5 pixel in one frame (50 percent) to 0.5 pixel in three or four frames (12 to 15 percent).

Furthermore, we have found that the error in the scene motion transformation is independent of the number of frames between two frames. We have successfully aligned frames which have been separated by 30 frames and displaced by over 60 pixels. Therefore, if we match frames which are separated by several frames, then the relative motion of the target will have increased and the effects of errors in the scene motion transformation will be diminished.

Frame-to-frame matching is still performed in order to have accurate and current position and shape information. The frame-to-frame matching also provides links between the frames used for the velocity estimation. The matching objects in the two widely separated frames can be found by the successive frame matches. Using these links, we can rapidly find matching objects in the two frames used for velocity estimation, even though these frames may be as far as 1 second apart.

SIMULATION RESULTS

The velocity estimation algorithm described in the previous paragraph has been implemented as part of the Advanced Target Tracker Simulation in the Honeywell Image Research Laboratory. The velocity estimation procedure is controlled by several parameters which are set when the simulation is initialized. These parameters control the frequency at which velocity estimation is performed and the delay between frames which are used in the calculations. The results discussed in the following paragraphs were obtained by performing the velocity estimation every other frame and matching frames which were 0.8 second apart.

In order to demonstrate the improvement in our velocity estimator, we have made histograms of the distribution of object velocities using the two estimation techniques. These are shown in Figures 5 and 6. The histogram in Figure 5 contains the velocities as computed by the old method. Notice that both the stationary background objects and the moving targets have very small computed velocities. These velocities are based on the motion of the objects between successive frames (0.1 second in our simulation). As we expect, the motion of the targets between successive frames is very small.

The histogram in Figure 6 contains velocities as computed by the method described in the previous paragraphs. Notice that the computed velocity of most of the background objects is less than 3 pixels over the eight frames. The moving targets have shown a velocity of 4 or more pixels. The velocities in this histogram are a more accurate representation of the actual velocities of the objects in the scene than are those in Figure 5.

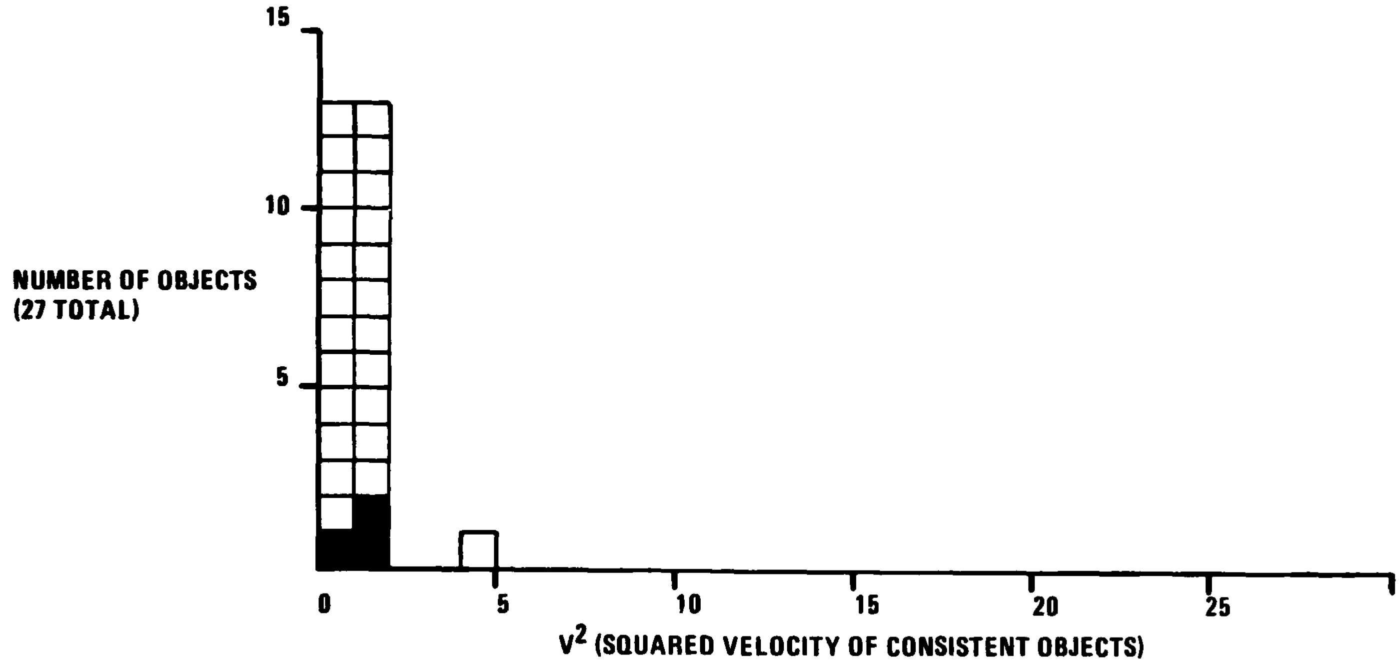


Figure 5. Distribution of Object Velocities (Previous simulation)

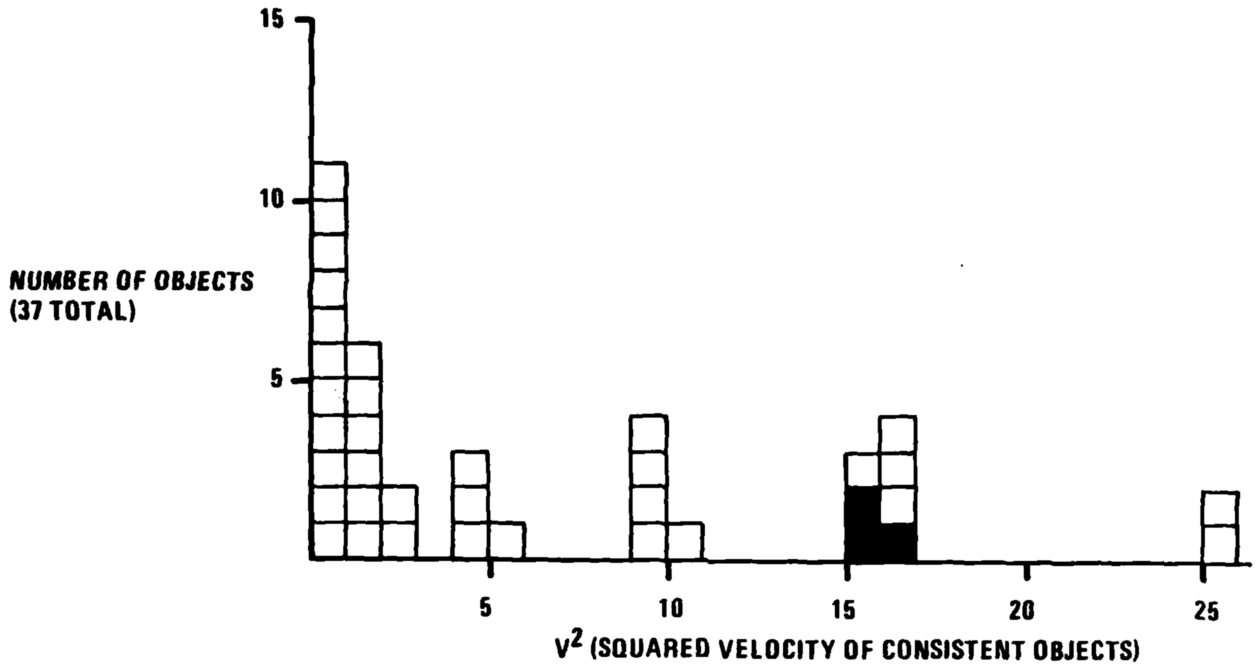


Figure 6. Distribution of Object Velocities (Current simulation)

SECTION 3

TERMINAL HOMING

This section addresses the terminal homing facets of the advanced target tracking system. As we have seen earlier, the advanced target tracking system being developed in the current program has applications not only in stand-off platforms, like combat vehicles and attack helicopters, but also in remotely piloted vehicles and terminal homing munitions (projectiles and missiles). In the latter applications, the key issues are:

- Tracking a target (or targets) as the sensor rapidly moves toward it,
- The selection of a critical aimpoint on the target either to guide a terminally homing munition or for laser illumination for a laser seeker.

Tracking while homing and critical aimpoint selection are addressed in Section 4.

TRACKING IN THE TERMINAL HOMING MODE

With conventional trackers the principal hurdle to successful tracking in the homing mode is that the target grows in size as the munition approaches it, almost filling the field of view. Conventional trackers (centroid, edge-based, and correlation trackers) are essentially designed to track small objects in a small 16 x 16 to 32 x 32 pixel tracking window. For various reasons they tend to lose track as the sensor approaches the target. Centroid-based trackers which depend on a thresholdable target contrast with respect to the background do not work at all when the target itself fills the field of view. Edge-based trackers, on the other hand, tend to drift to the edge of the target and upon impact only glance it, lowering the probability of kill. Correlation trackers, which utilize correlation against a reference window from one frame to the next, do possess the ability to update the reference, in an attempt to keep the continuity of the track point on the target. While this works reasonably well at long ranges, at closer ranges, when the target is growing rapidly, the usual form of recursive filter applied for reference prediction breaks down. Further, even correlation trackers require internal target contrast. As the target almost fills the field of view, the tracker has no way of knowing the location of the track point it has been following from the longer range.

The symbolic object model-based tracking technique developed in the current program offers a consistent framework for successful tracking in the terminal homing mode as well. The approach is based on the fact that large extended objects in the field of view can be represented by the network structure connecting the object models in each frame. This provides a framework for representing large multicomponent objects in the terminal phases of a terminal homing mode. Even more important, the object model (with its links to the past frames) provides a natural means for associating the track point in the current frame with the previous track points at longer ranges.

Figure 7 illustrates our concept, which is now being implemented. At very long ranges, a target is only seen as a blob (which could correspond to the engine on a tank). The autonomous acquisition capability built into the tracker detects the blob and the system keeps track of it as a distinctive object in the field of view. As the sensor approaches the target, lower contrast parts of the target (and also the background) become visible and are segmented and become part of the scene model. The proximity association rules allow the representation of multicomponent objects like a hot engine and a cold hull. When this happens, note that we can still distinguish the original track point in relation to the new

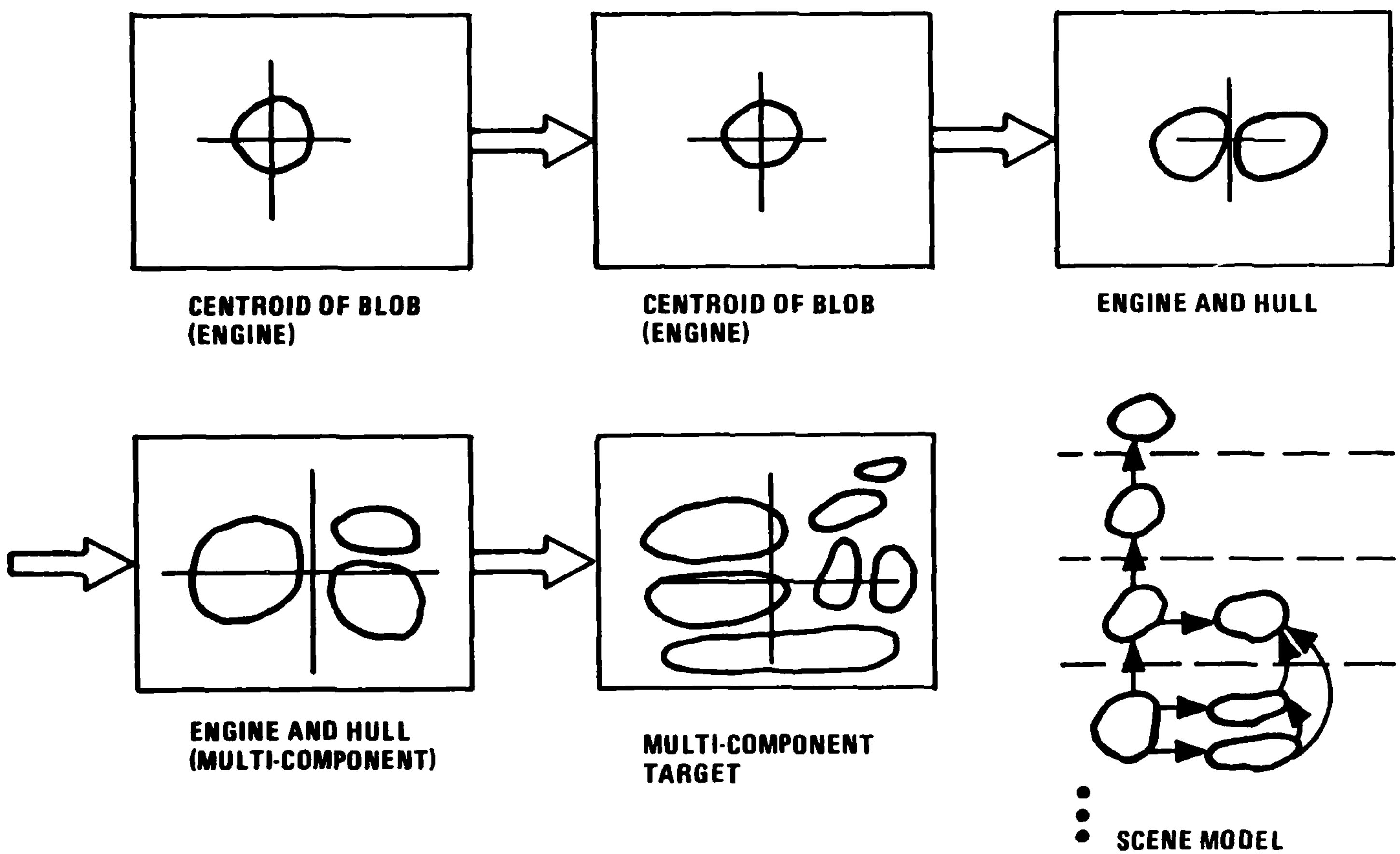


Figure 7. Critical Aimpoint Selection

object model. As the sensor draws even closer, the object components which were segmented as individual objects tend to break up because inner contrast within the blobs becomes apparent. The object model, however, matches the new components to the older extended components and establishes links as shown in Figure 7. These links help associate the original track point in relation to the new object models. Thus, even when a target entirely fills the field of view, we still know where we are relative to the original track point because the history of the track point has been associated through the object model. This is the key to the success of this approach, which prevents the drifting of the aimpoint as the sensor approaches the target (as happens in the conventional target trackers).

TERMINAL HOMING SIMULATION

We are now implementing the above approach in the system simulation. The current simulation requires minor modifications to accommodate the history of the object models over several frames as required in the terminal homing scenario. To develop and evaluate the above approach, we have digitized a 45-frame sequence containing a homing run on a tank from our FLIR video tape library. Figure 8 shows a representative set of images from this sequence from long range (with the target approximately 20 pixels wide) to near-in (200 pixels wide). This sequence illustrates the problem which a conventional target tracker in a terminal homing mode would face. For example, as the sensor approaches the target, the perspective changes. The gun barrel which was hardly visible at long ranges becomes a dominant feature at close ranges. Further, the internal contrast of the target is vividly seen in the close-up frames in the sequence.

The terminal homing tracking system will operate on the object models extracted by the scene segmenter. Therefore, we have processed 45 frames from this sequence through the PATS segmentation simulation

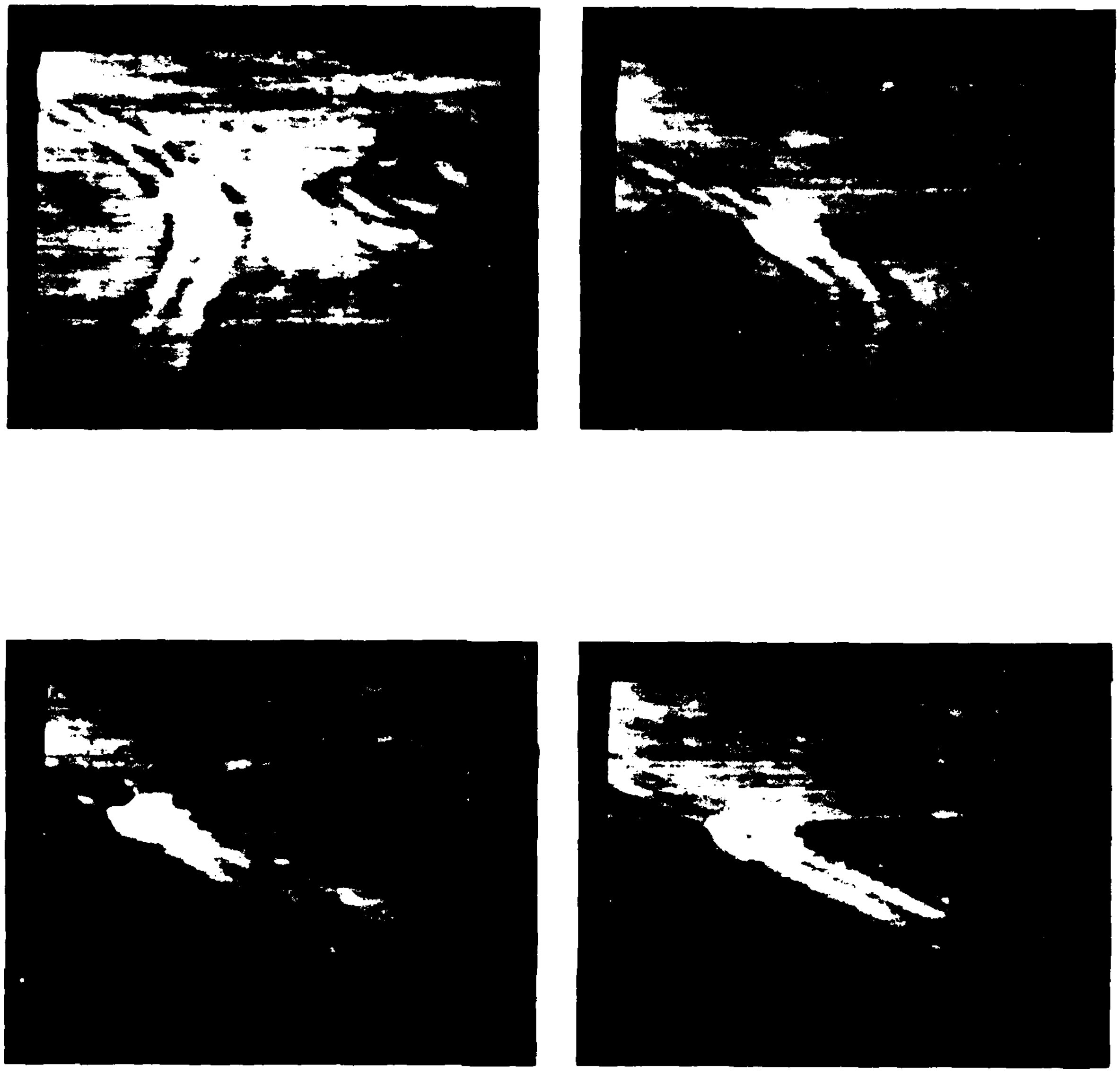


Figure 8. Representative Frames From Homing Sequence. The target grows from approximately 20 pixels wide to almost 200 pixels with a marked increase in internal contrast.

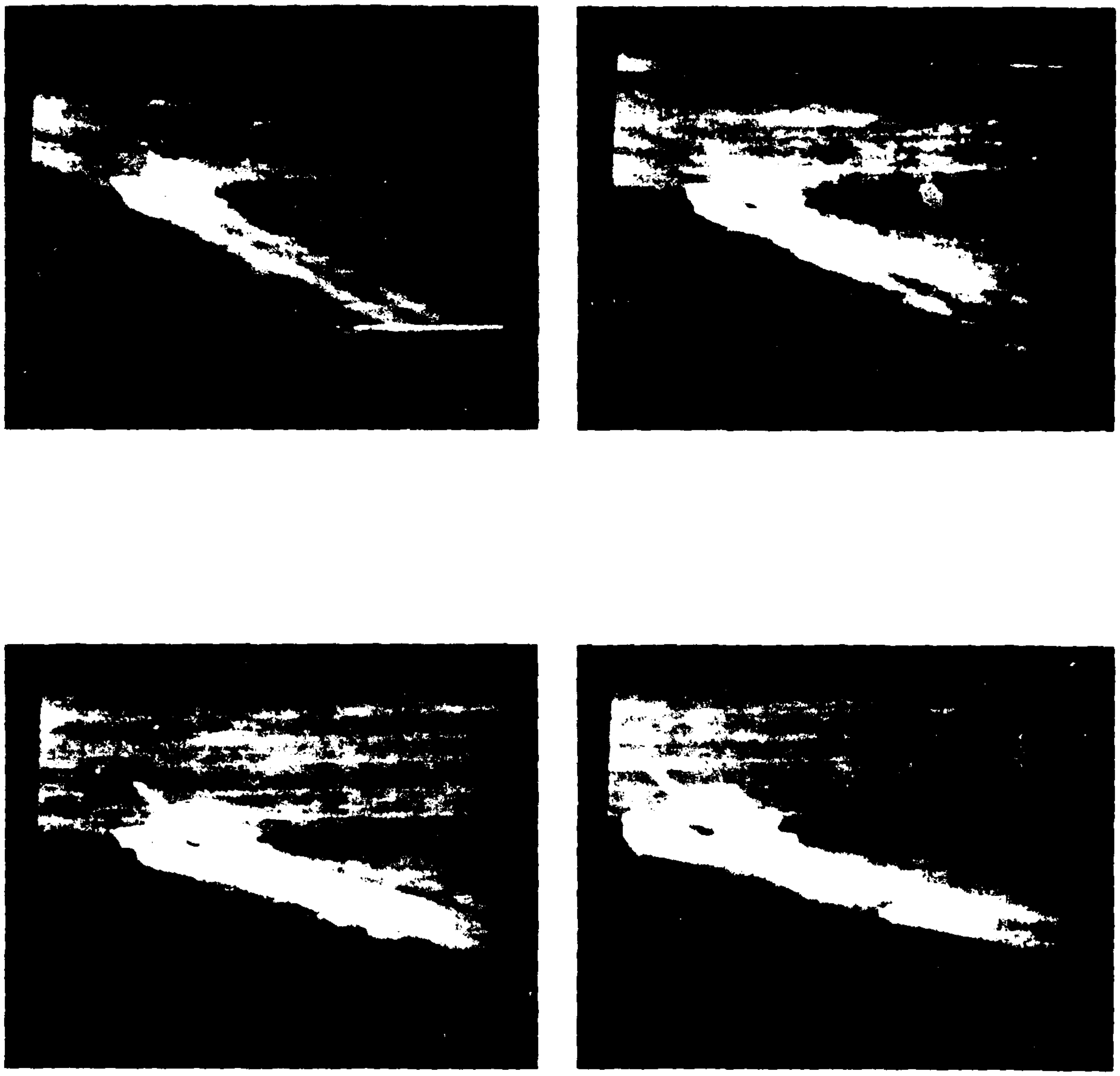


Figure 8. Representative Frames From Homing Sequence (continued)

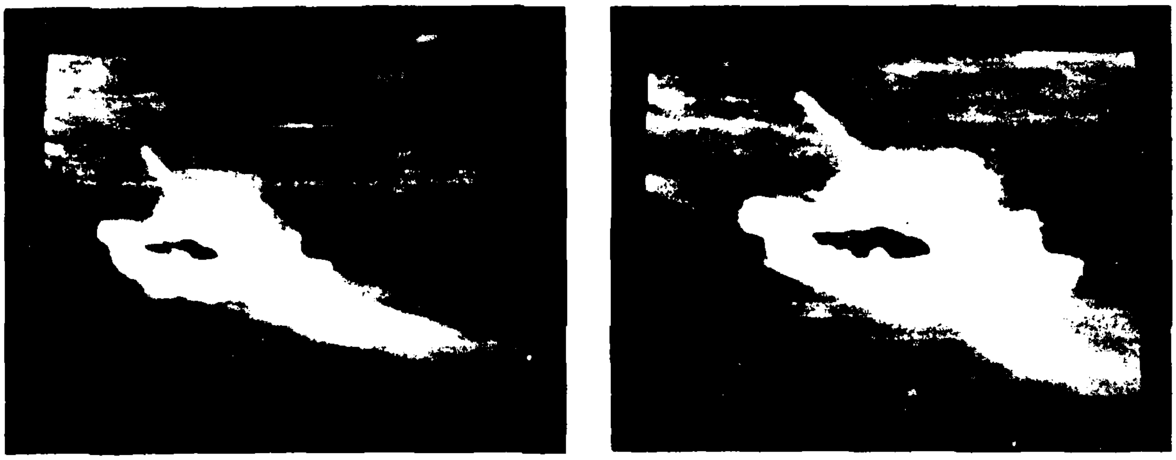


Figure 8. Representative Frames From Homing Sequence (concluded)

as a first step in the simulation. Figure 9 shows the result of the segmentation for the sequence of images shown in Figure 8. These results corroborate the basic premise upon which our concept for homing is based: at long ranges the targets appear as contiguous blobs and tend to break up into multiple components as the sensor approaches the target and its internal contrast becomes visible. The breaking up of the target as the sensor approaches is due not only to the inherent detail in the target but also to the fact that PATS has a goal-oriented segmentation scheme designed to find small blobs. The thresholds within the segmentation simulation tend to break up large targets into small pieces. However, the proximity criterion for associating object components will link the multiple components corresponding to each object with directed links within each frame.

The next step in the simulation process will be to modify the object model algorithm to extend the history of the object model over several frames and apply it to the output of the segmentation process on the above sequence. As seen above, association of the object components over the frames as the target grows larger allows the location of the track point on the target even as it fills the field of view.

MODIFICATIONS TO THE SIMULATION

In order to apply the tracker simulation to the homing sequence, we must have complete outlines of the objects in the scene. Without complete outlines it would be impossible to perform the associations we have just described. The current version of our segmentation algorithm limits the object length to 70 scan lines. This is a reasonable constraint when we are processing only long range views where a target spans only several scan lines. However, for these experiments we will process frames with targets of several hundred scan lines. The segmentation algorithm will be modified to find a complete outline of all extracted objects.

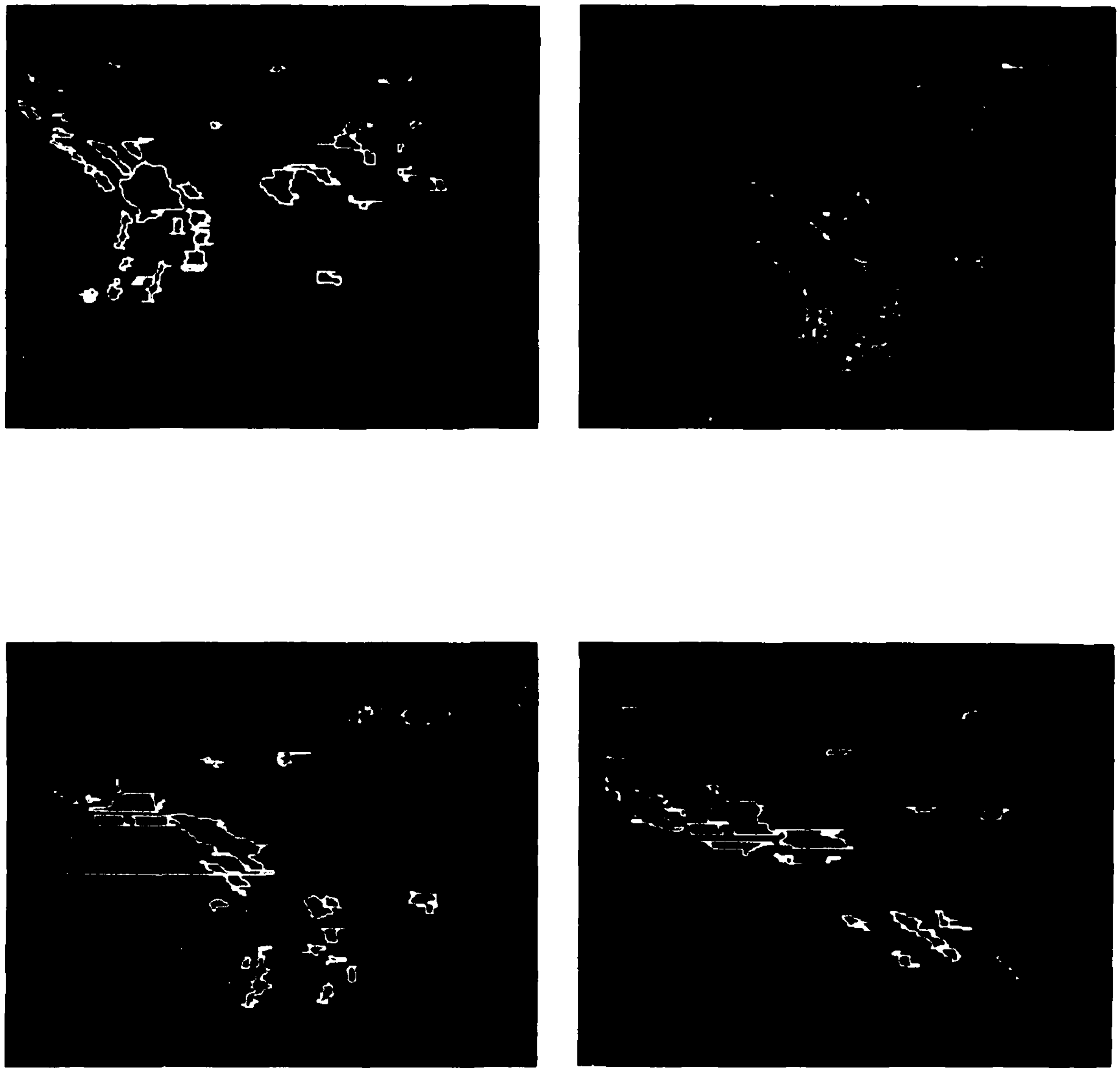


Figure 9. Segmentation Results for Images in Figure 8. Note that at long ranges the target appears as a contiguous blob and tends to break up as its internal contrast becomes visible.

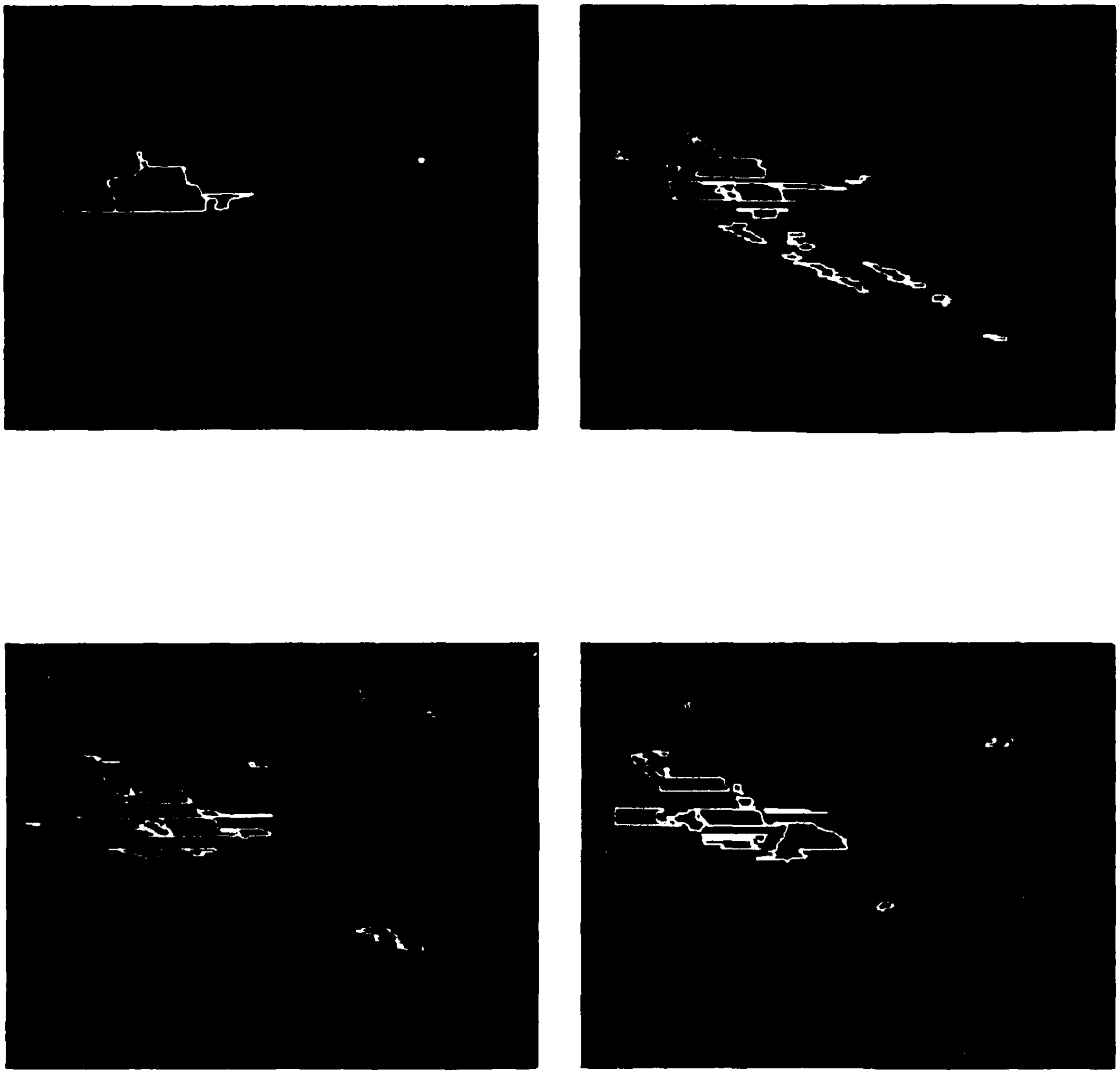


Figure 9. Segmentation Results for Images in Figure 8 (continued)

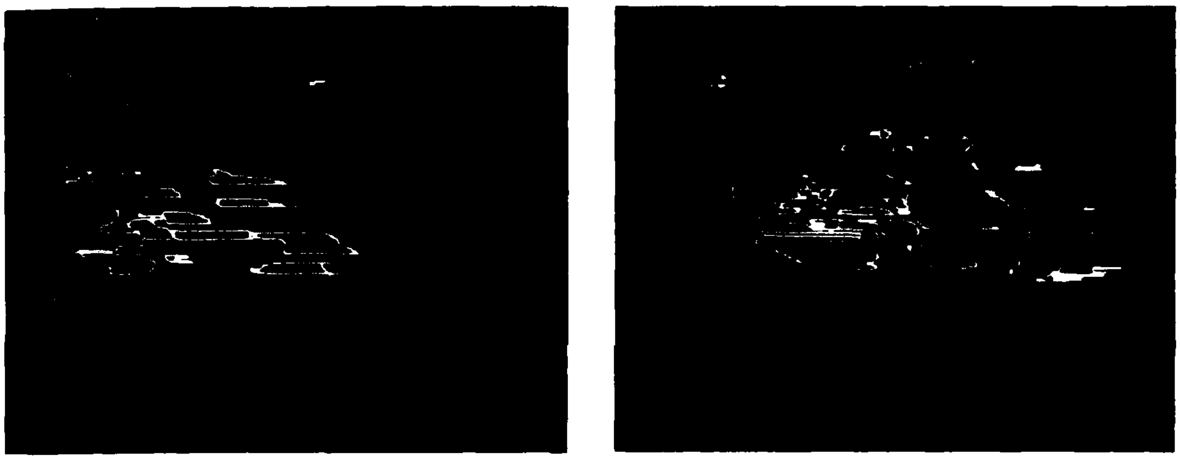


Figure 9. Segmentation Results for Images in Figure 8. (concluded)

The tracker simulation will be modified to include association rules described in previous paragraphs. We expect the targets to be broken up into separate components as the range decreases. Each of these components will match some part of the model. In response to these one-to-many matches, the program will link all the segments from the current frame. This linked list of object segments will become the model for matching in subsequent frames. The list of segments could also be input to a syntactic model matcher to identify target components and perform critical aimpoint selection as described in the next section.

SECTION 4

CRITICAL AIMPOINT SELECTION

Terminal homing is closely associated with the problem of critical aimpoint selection, that is, the selection of the desired point of impact on the target by an autonomous munition or the desired point of laser illumination by an RPV or AAH-based laser designator. The requirements for critical aimpoint selection depend upon the application. In terminal homing munitions, depending upon the maneuverability and velocity of the target, we can defer the selection of the critical aimpoint until the distinctive components of the target become visible. This leads to a model-based recognition and selection of the critical aimpoint using syntactic techniques.

In stand-off applications such as the RPV and AAH, where the critical aimpoint has to be chosen for laser illumination, the applicability of the model-based techniques depends upon the resolution of the system and the range. For extremely long ranges, when only the hot spot of the target is visible, the choice is either the centroid of the hot spot or a model-based approach which selects a point in the field of view relative to the hot spot, depending on the target orientation relative to the sensor and the class of the target being tracked.

MODEL-BASED CRITICAL AIMPOINT SELECTION

This approach requires a knowledge of the specific targets (like the T62 or T72), their radiance distributions, and the desirable critical aimpoints within the target. This is especially important in suppressed thermal signature targets where the hot engine is not obviously distinctive as it is in the targets that we have processed in our simulations. Briefly, the technique works as follows: each target class is represented by a model composed of isothermal components and their three dimensional spatial relations. The syntactic model-matching procedure attempts to match the components extracted by the segmenter with the models of the candidate targets and finds the critical aimpoint for the specific class of the target. The difficulty of this technique depends upon the amount of a priori information available. If the orientation of the target relative to the sensor is available, then the model-matching process only has to allow for rotation, translation, and scale change. For example, the orientation can be deduced either through field intelligence or from the direction of the motion of the target relative to the background. On the other hand, if the target orientation is an unknown, then the model-matching process has to account for viewing perspective differences as well.

In the next reporting period, we will attempt to develop a critical aimpoint selection algorithm based on model matching. The principal difficulty, however, is that radiance maps are not available for the targets in our FLIR data base. However, critical aimpoint selection may still be possible through recognition of distinctive components of the target--especially the gun barrel as we see in Figure 10. The knowledge of the elevation angle of the sensor and the position of the gun barrel relative to the edge of the target can be used to deduce the orientation of the target and hence the critical aimpoint of the target. Figure 11 shows the syntactic technique used for recognition of targets which will be extended in this program to perform critical aimpoint selection. Each target is represented as a hierarchical description consisting of its components. This representation technique will be modified in the next reporting period into a three dimensional model rather than merely a two dimensional one as demonstrated in the AIRS contract (Contract No. F33615-76-C-1324).

Figure 10. Critical Aimpoint Selection through Component Recognition. In many FLIR images of tanks the gun barrel would provide a good cue for critical aimpoint selection. In the example above, the barrel is clearly visible in the FLIR image and has been clearly segmenteld by the segmentation algorithm.

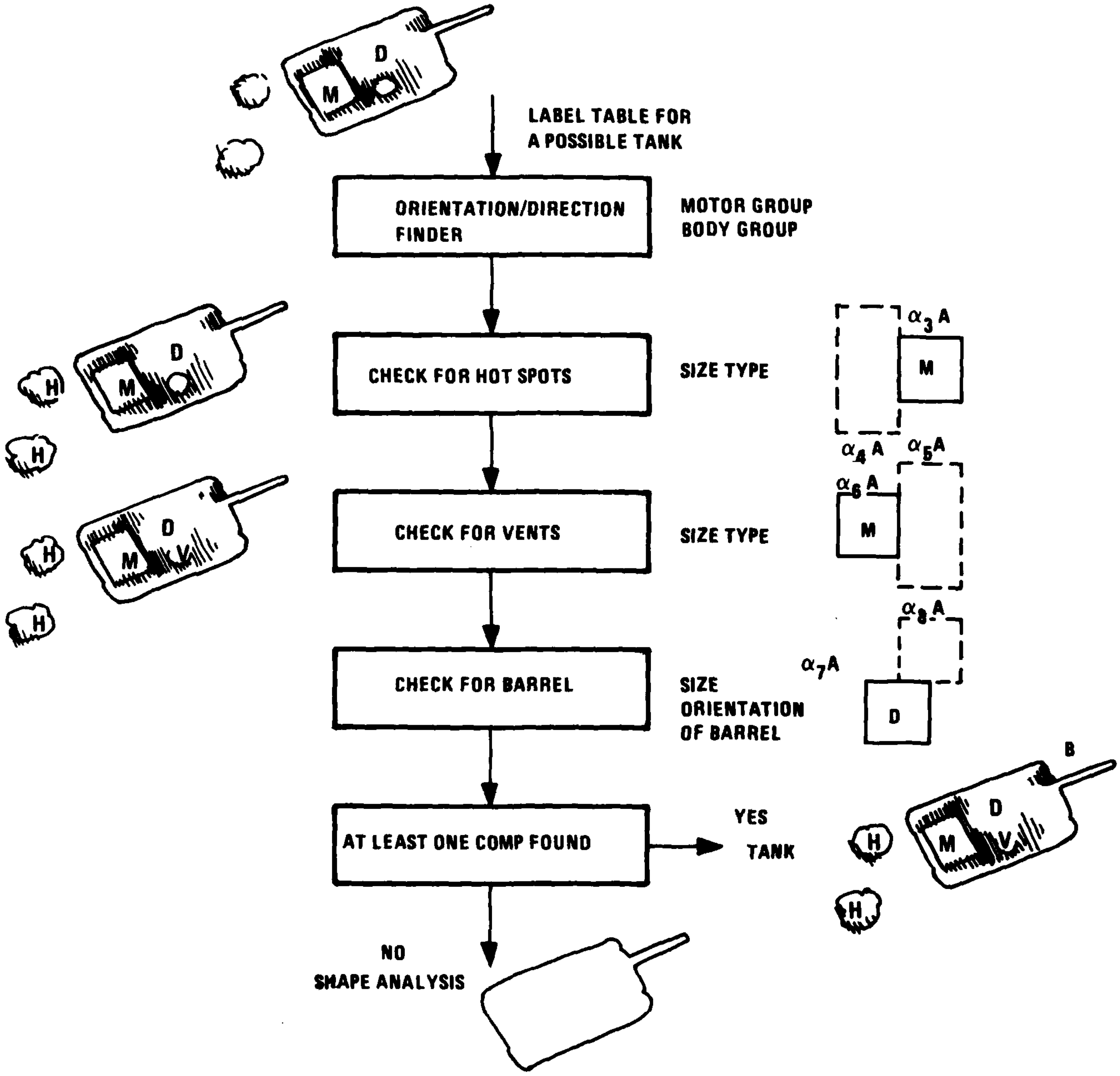


Figure 11. Syntactic Recognition Technique Which Can Be Adapted to Perform Critical Aimpoint Selection

SYSTEMS ANALYSIS FOR CRITICAL AIMPOINT SELECTION

As mentioned before, the precise technique to be used for critical aimpoint selection in a given application depends upon the available resolution of the target at the minimum range at which the aimpoint has to be selected. For example, in the autonomous muntion application, limited maneuverability may preclude changes in course close to impact. This, in turn, implies that the critical aimpoint has to be selected at longer ranges. Therefore, the parameters which will impact the effectiveness of a given critical aimpoint selection technique are:

- o Velocity of the munition
- o Maneuverability of the munition (new rate)
- o Resolution of the sensor
- o Field of view of the sensor

In the next reporting period we will assume typical parameters for these system variables to determine the feasibility of a model-based critical aimpoint selection technique for the missile application.