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AUTOMATIC TARGET DETECTION USING TEXTURAL INFORMATION,(U)
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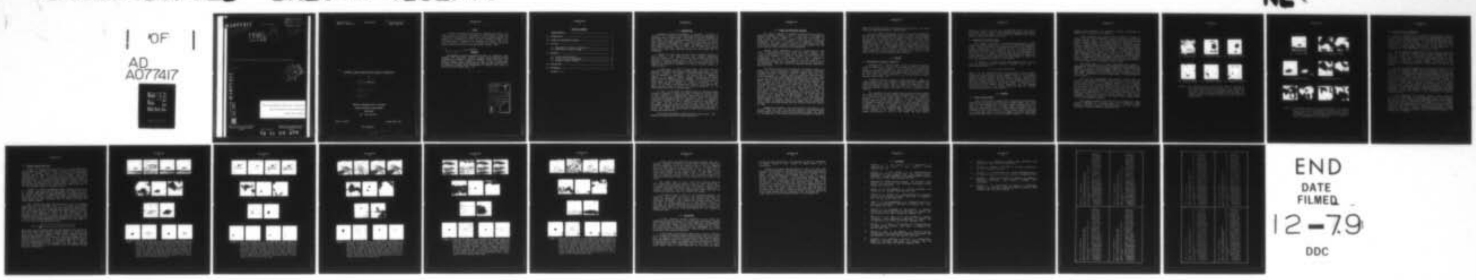

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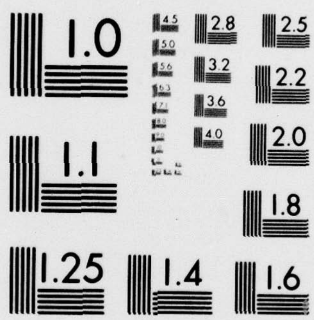
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AUTOMATIC TARGET DETECTION USING TEXTUAL INFORMATION

J.F. Boulter

Centre de Recherches pour la Défense
Defence Research Establishment
Valcartier, Québec

BUREAU - RECHERCHE ET DEVELOPPEMENT
MINISTERE DE LA DEFENSE NATIONALE
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6 AUTOMATIC TARGET DETECTION USING TEXTURAL INFORMATION

by

10 J. F. Boulter

11 Aug 79

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CENTRE DE RECHERCHES POUR LA DEFENSE

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VALCARTIER

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RESUME

On décrit une technique de traitement numérique pour mesurer des traits locaux de texture isotropique et directionelle. On utilise l'information texturale ainsi obtenue pour détecter automatiquement des cibles, en l'occurrence un TTB, un char d'assaut, un camion et un hélicoptère avec un arrière-plan de végétation et de terre. Ces cibles sont difficiles à détecter si on emploie les différences entre les niveaux de gris moyens ou la localisation des contours. (NC)

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ABSTRACT

~~We describe~~ a digital processing technique for measuring local isotropic and directional textural features, and we use the textural information so obtained to perform automatic target detection. The present targets, which consist of an APC, a tank, a truck and a helicopter located against backgrounds of vegetation and ground terrain, are difficult to detect using differences in average gray level or location of target edges alone. (U)

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1.0 INTRODUCTION

Depending on how much information is available, an object of interest, i.e. a target, can be distinguished from its background in a stationary scene in various ways. When there is detailed knowledge of the target, the scene can be searched for an object with the correct shape, size and surface properties. In military situations, we usually have incomplete knowledge of the target; the range or orientation of a tank target may not be known, for example. One approach here is to use more general features, such as gray level or color, edge content, texture etc., which have different values for the target and its background.

Texture has been used for some time for automatic analysis of aerial imagery - crop classification, land resource monitoring, pollution control etc., but it has only recently been applied to the detection of military targets (Refs. 1 and 2). In this report we describe an approach for measuring the local textural properties of an image and for using this information to detect military targets in complex scenes.

In particular, we look at cases where the target cannot be detected easily using conventional methods based on gray-level or edge features. Consider, for example, a vehicle painted a solid color to match a background of vegetation. The vehicle may be immediately apparent to an observer because its smooth surfaces have a different texture than the vegetation, but an automatic target-detection system based solely on target/background contrast, or on the detection of target edges, may fail to locate it. Textural information is only useful if the target is sufficiently well resolved in the image in both space and gray level to permit its textural properties to be distinguished from those of the background.

In Sect. 2.0 we modify the standard method of classifying image elements as belonging to either the target or background regions based on their location in N-dimensional feature space, to make it better suited to detecting the present military targets. Section 3.0 describes a technique for assigning specific textural features, in particular isotropic, horizontal, vertical or diagonal textures, to each element of the image. In Sect. 4.1 we illustrate how this algorithm can distinguish regions of different texture in complex scenes, and in Sect. 4.2 and 4.3 we demonstrate how these textural properties can be used to detect tank, truck, APC and helicopter targets against backgrounds of foliage and ground terrain.

This work was performed at DREV during the period April 1978 - December 1978 under PCN 21J07, Target Acquisition.

2.0 TARGET AND BACKGROUND FEATURES

The present approach to automatic target detection consists in measuring a number of features such as gray-level or multispectral content, edge content, texture etc. at each point of the image. If these features have different average values for the target and background, then the 2 regions can be separated by suitable thresholding. To detect a target in this way, we must know before hand, or be able to determine through an adaptive training process, how the target features differ from those of the background.

Consider image segmentation using only a single feature - gray level. If the distribution of gray levels in an image is bimodal, with 1 peak corresponding to the target and the other to the background, the target can be selected by placing a threshold at the gray level corresponding to the valley between the 2 peaks. Extended to N-dimensional feature space, this requires that the location of 2 clusters be determined, one corresponding to the target and the other to the background. Then the 2 regions are separated using an appropriate decision surface.

This decision surface will be different for different classes of images, but can be determined by analysing a sufficiently large number of images with similar properties. Consider 2 images which fall into different classes: a thermal image of a small hot target against a cooler background, and a panchromatic photograph taken in visible light of an olive military vehicle against a background of green vegetation. Suppose that we construct the 2-dimensional distribution functions of the 2 images by using gray level and texture as the features. The distribution function for the thermal image will show the target well resolved from the background in gray level but poorly resolved in texture. The decision surface should be a line parallel to the texture axis located between the average gray levels of the target and background. In the visible-light photograph, the average gray level of the vehicle may be almost the same as that of the foliage while the textures of the 2 regions may be quite different. In this case, the decision surface should be a line parallel to the gray-level axis located between the average textures of the target and background. Other classes of images may require more complex lines as the decision surfaces, and the problem becomes even more difficult when more features are used.

Summarizing, we measure a set of N features at each point of the original image and then use a decision surface in this N-dimensional feature space to classify the points as belonging to either the target or the background. The decision surface can be obtained for classes of images with similar features by determining the locations of the known target and background elements in feature space.

We will modify this approach so as to use a priori knowledge of the individual target and background features, rather than knowledge derived from the N-dimension distribution function in feature space. The procedure is to generate feature images in which the gray level represents the local value of the feature. Then we use a priori knowledge to gray scale transform each image so that features that the target possesses to a higher degree than the background appear with a higher gray level. The transformed feature images are multiplied together to yield an image in which a high gray level represents a high target probability. The location of the maximum gray level in this image is taken as the most probable target position.

3.0 TEXTURE

3.1 Measurement of Textural Properties

Rosenfeld (Ref. 3) defines visual texture as "repetitive patterns in which 'elements' or 'primitives' are arranged according to 'placement rules' ". In complex images it may be difficult to determine the primitives and their placement rules, and various local properties, such as spatial frequency content, edge content, number of maxima or minima per unit area, gray level statistics etc., have been used as texture measures instead (Refs. 3-11).

We describe texture in terms of 5 simple primitives. These are single elements and line segments 1 element wide and 3 elements long oriented along the horizontal, vertical, diagonal-1 (upper left to lower right) and diagonal-2 (upper right to lower left) directions. The primitives represent isotropic, horizontal, vertical or diagonal texture features.

The algorithm we use to measure the textural features is simple and is well suited to real-time hardware implementation. It considers a 3- by 3-element region to determine which of the 5 features should be assigned to the central image element. To assign a given textural feature requires that the central element, or a line 3 elements long which passes through the central element, be a local maximum or minimum. A maximum or minimum is declared if the central element, or the 3 elements along the line, are greater than or less than all the remaining elements within the 3- by 3-element region. This procedure is applied to all elements of the original image to generate 5 binary texture images, each containing a "one" if the element has that textural feature, or a "zero" if it does not. As described in Sect. 3.2, each of the binary texture images is then smoothed by spatial integration to generate 5 gray scale images in which gray level represents the average amount of textural feature per unit area.

3.2 Smoothing the Texture Images

The textural properties of targets and backgrounds are seldom constant and usually vary from one region of the target or background to another. Noise introduced by the image detector will cause additional texture fluctuations. Our assumption is that the average textural features of the target are different from those of its background, so that some type of spatial averaging must be applied to smooth the texture images. In the present case, this smoothing is also required to convert the binary texture images into gray scale images in which the gray level represents the amount of local texture.

We smooth the 5 binary texture images obtained in Sect. 3.1 by using a circularly symmetric gaussian low-pass filter with a point-spread function:

$$F(i,j) = \exp[-(i^2+j^2)/2\pi s^2]$$

where s is the standard deviation of the gaussian in image elements. Simpler smoothing operations, such as summing within N- by N-element subregions, would probably produce similar results. Increasing the amount of smoothing improves the discrimination between regions with different average textural features, but at the expense of a loss of resolution of spatial details. The largest amount of smoothing that will preserve the required spatial resolution, e.g. of the smallest details of interest in the target, should be used for maximum target/background texture discrimination.

4.0 EXAMPLES

4.1 Texture Discrimination

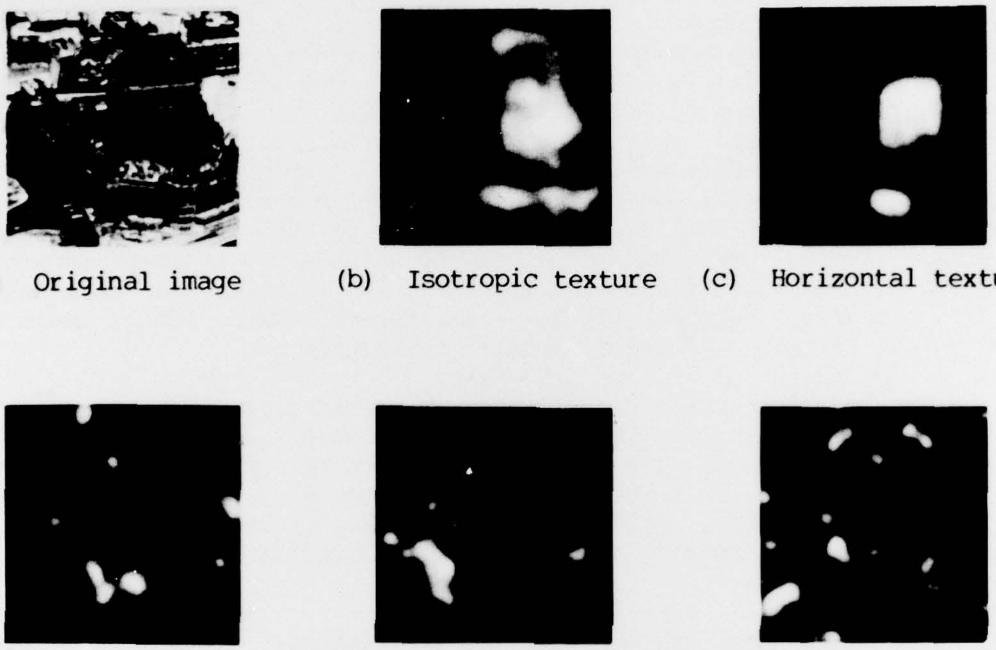
This section gives 2 examples which illustrate how the foregoing algorithm can distinguish between regions in complex images which have different textural properties. The texture images contained here and in Sect. 4.3 are obtained from original images containing 256 by 256 elements as described in Sect. 3.0. Unless otherwise stated, they are displayed so that a large amount of a local textural feature corresponds to a high gray level. In the first example, the texture images were gaussian smoothed using the value s=8 elements, whereas in the second example, which contained less pronounced textural differences, the smoothing was increased to s=15 elements.

Figure 1 shows an aerial view of a part of Quebec City taken in winter, along with the corresponding isotropic, horizontal, vertical and diagonal texture images. We can easily see the correlation between specific textural regions in the original image and structures in the first 4 texture images. For example, the areas of the building where windows are apparent generally have a high value of isotropic texture, and the areas where the rows of windows are almost horizontal appear strongly in the horizontal texture image. A tower, which lacks significant horizontal texture, can be seen in the horizontal texture image intruding into the lower right corner of the prominent square area. Similarly, areas where the rows of windows are aligned along the vertical or diagonal-1 directions appear in the vertical or diagonal-1 texture images. Because of the orientation of the building, there is less useful structure in the diagonal-2 texture image.

The second example, Fig. 2, shows a canvas-back truck against a background of trees, along with the 5 corresponding texture images, each displayed in 2 ways. The left image of each pair is a direct display where a large amount of texture produces a high gray level. For the right image, the polarity of the display has been reversed with a linear gray scale transformation so that a large amount of texture produces a low gray level.

The truck has considerably less isotropic texture than its surround - the shape of the vehicle is clearly visible in the isotropic texture images, and there is a dominant maximum in the horizontal texture near the cab. A moderate amount of vertical texture is apparent on some areas of the truck, but this extends into the background region where vertical tree trunks are visible. Only 0.10% of all image elements were assigned either of the 2 diagonal texture features. This compares with probabilities of 5% for isotropic texture, 0.8% for horizontal texture and 1.5% for vertical texture. Little useful information is probably contained in the diagonal texture images because of the large statistical variance.

The preceeding examples illustrate that we can measure the local textural properties of a complex image with a relatively simple algorithm. Sections 4.2 and 4.3 consider one way to use this textural information to perform automatic target detection.

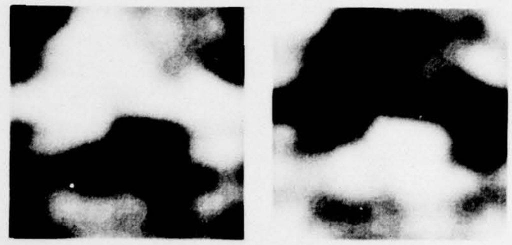


(a) Original image (b) Isotropic texture (c) Horizontal texture

(d) Vertical texture (e) Diagonal-1 texture (f) Diagonal-2 texture

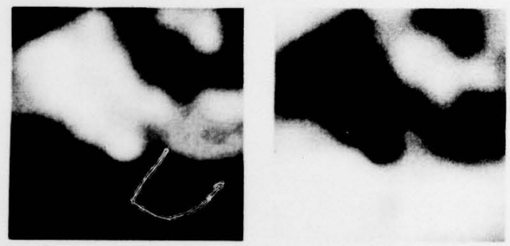
FIGURE 1 - Five textural features of the original image (a) are shown in the form of gray scale images in (b) to (f). A large amount of local textural feature in the original image produces a high gray level in the corresponding texture image. The horizontal rows of windows on the side of the building, for example, produce a well defined square area in the horizontal texture image.

(a) Original image



(b) Isotropic texture

(c) Horizontal texture



(d) Vertical texture

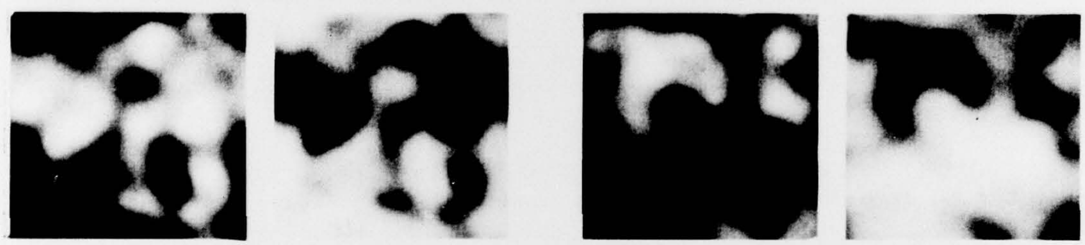


FIGURE 2 - Five textural features of the original image (a) are shown in the form of gray scale images in (b) to (f). In the left image of each pair, a large amount of local textural feature corresponds to a high gray level, whereas in the images on the right the polarity of the display has been reversed so that it corresponds to a low gray level.

4.2 Target Detection Assumptions

Since our objective is to investigate the importance of textural information for automatic target detection, we choose examples where the targets cannot be easily segmented from their backgrounds on the basis of gray level or edges alone. The targets are man-made objects consisting of a truck, a helicopter, a tank and an APC. All have backgrounds of foliage and ground terrain. In most cases there is a noticeable difference between the texture of the target and its background, but little difference in average gray level.

Only the isotropic, horizontal and vertical textural features are used. We exclude the 2 diagonal textural features because they occur with a low probability in the present images. Diagonal or other directional textures may be useful for targets which, because of their orientation in the image or their surface features, do not have significant horizontal or vertical texture. In addition to the textures, we use local edge content as a fourth feature to detect the targets.

We make 3 a priori assumptions on how the characteristics of the targets and backgrounds differ from one another. First, it is reasonable to believe that the smooth metallic surfaces of the targets will have less isotropic texture than their backgrounds of foliage and ground terrain. Second, the present targets will probably have more horizontal and vertical textures than their backgrounds. Because of their construction, the targets tend to have structures which are parallel or perpendicular to their orientation - which is mainly horizontal in the present examples. As mentionned in the preceeding paragraph, other directional textures may be preferable for targets which have different orientations or surface characteristics. The third assumption is that the targets will have more sharp edges than their backgrounds due to rapid changes in the reflectivity of adjacent metallic surfaces.

These assumptions only represent general trends, and will be violated in specific cases. In the image shown in Fig. 2, for example, the vertical tree trunks in the background have more vertical texture than the truck target. Furthermore, they apply only to the present target-background combination; other situations may require different assumptions and different features. However, as the following examples will show, when the 4 features are combined according to the above assumptions, this forms a reasonable basis for detecting targets in the present class of imagery.

4.3 Automatic Target Detection

Using the approach described in Sect. 2.0, we now combine the 4 feature images to generate an image in which a high gray level represents a probable target. First, the polarity of the smoothed isotropic texture image is reversed with a linear gray scale transformation so that a high gray level represents a low value of isotropic texture. Then the resulting isotropic texture image is multiplied with the smoothed horizontal-texture, vertical-texture and edge images. We assume that only a single target is present in each case and take the location of the element with the highest gray level in the feature-product image as the target position.

Figures 3-7 show the intermediate stages leading to detection of the 5 targets. Each figure has the same format: the upper row shows the original image before and after designation of the detected target, the second one shows the smoothed isotropic (reversed polarity), horizontal and vertical texture images, the third one shows the edge image before and after smoothing, and the bottom one shows the feature-product images.

The original photograph was digitized with 256- by 256-element resolution with a vidicon scanner (Ref. 12) to produce the original image shown on the left in the first row. The second image from the left in the first row gives an enlarged and enhanced view of the target. The texture images given in the second row were smoothed with the gaussian filter, described in Sect. 3.2, with s=15 elements. For comparison, the largest of the 5 targets (the truck given in Fig. 3) has a maximum dimension of 100 elements, and the smallest one (the APC given in Fig. 6) has a minimum dimension of 20 elements. The edge image in the third row E(i,j) was calculated using:

$$E(i,j) = \sqrt{[G(i,j)-G(i+1,j)]^2+[G(i,j)-G(i,j+1)]^2}$$

where G(i,j) is the original image, and was smoothed in the same way as the texture images. Two different product images are given in the fourth row: the first shows the product of the 3 textural features, while the second shows the product of the textural features and the smoothed edge feature. Both are shown as a gray scale display and as a contour plot with 8 linear steps. In the second image from the right in the top row the target position as determined with the 3 textural features is designated by a cross, whereas in the right image in the top row, the target position as determined with the textural and edge features is designated.

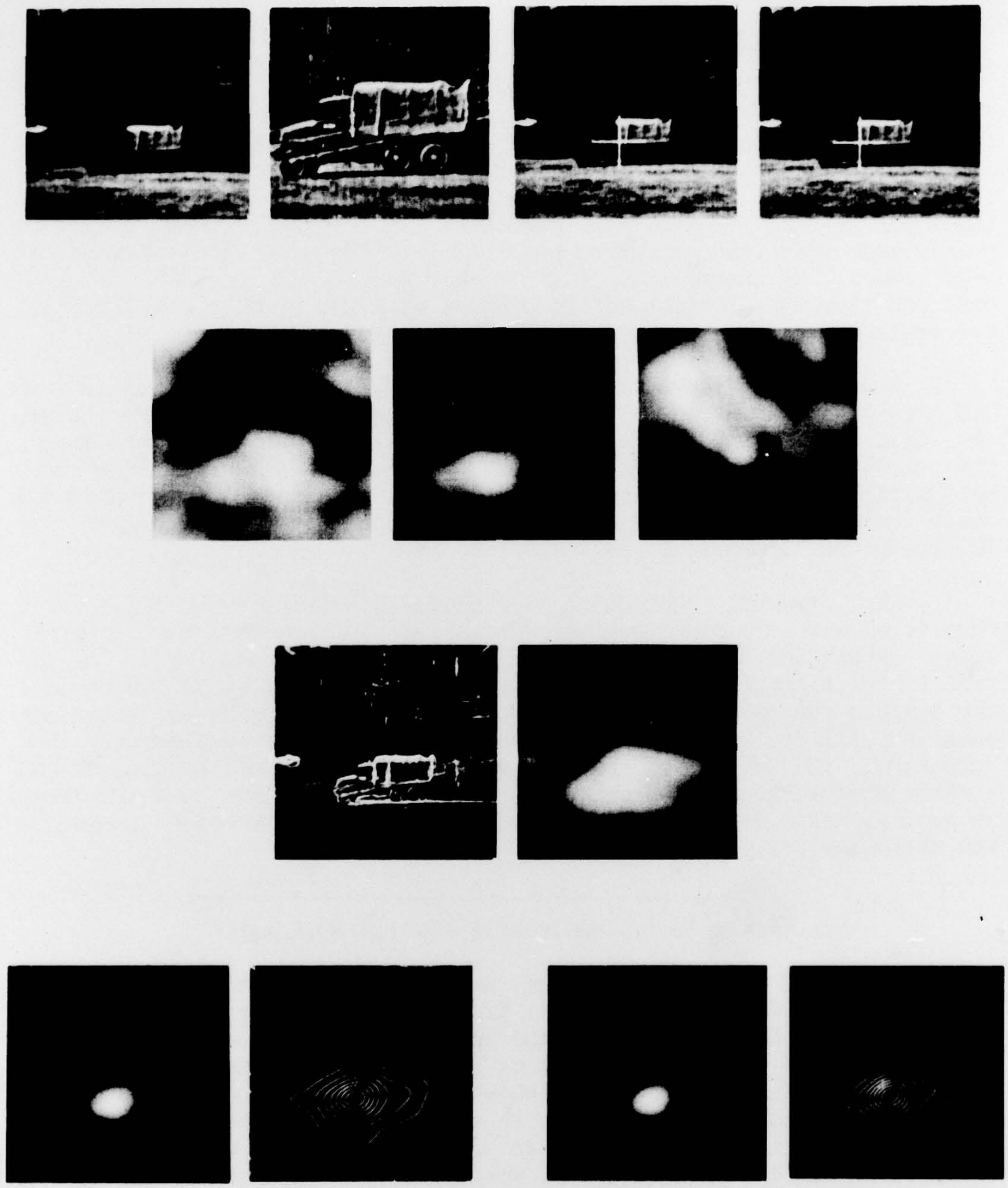


FIGURE 3 - From left to right, the top row shows the original image, the enlarged and enhanced target region, the target designated using the 3 textural features and the target designated using the textural features plus the edge feature. The second row shows the smoothed isotropic texture (reversed polarity), horizontal texture and vertical texture images, whereas the third row shows the edge image before and after smoothing. In the bottom row, the left pair shows the product of the 3 texture images and the right pair the product of the texture images with the smoothed edge image.

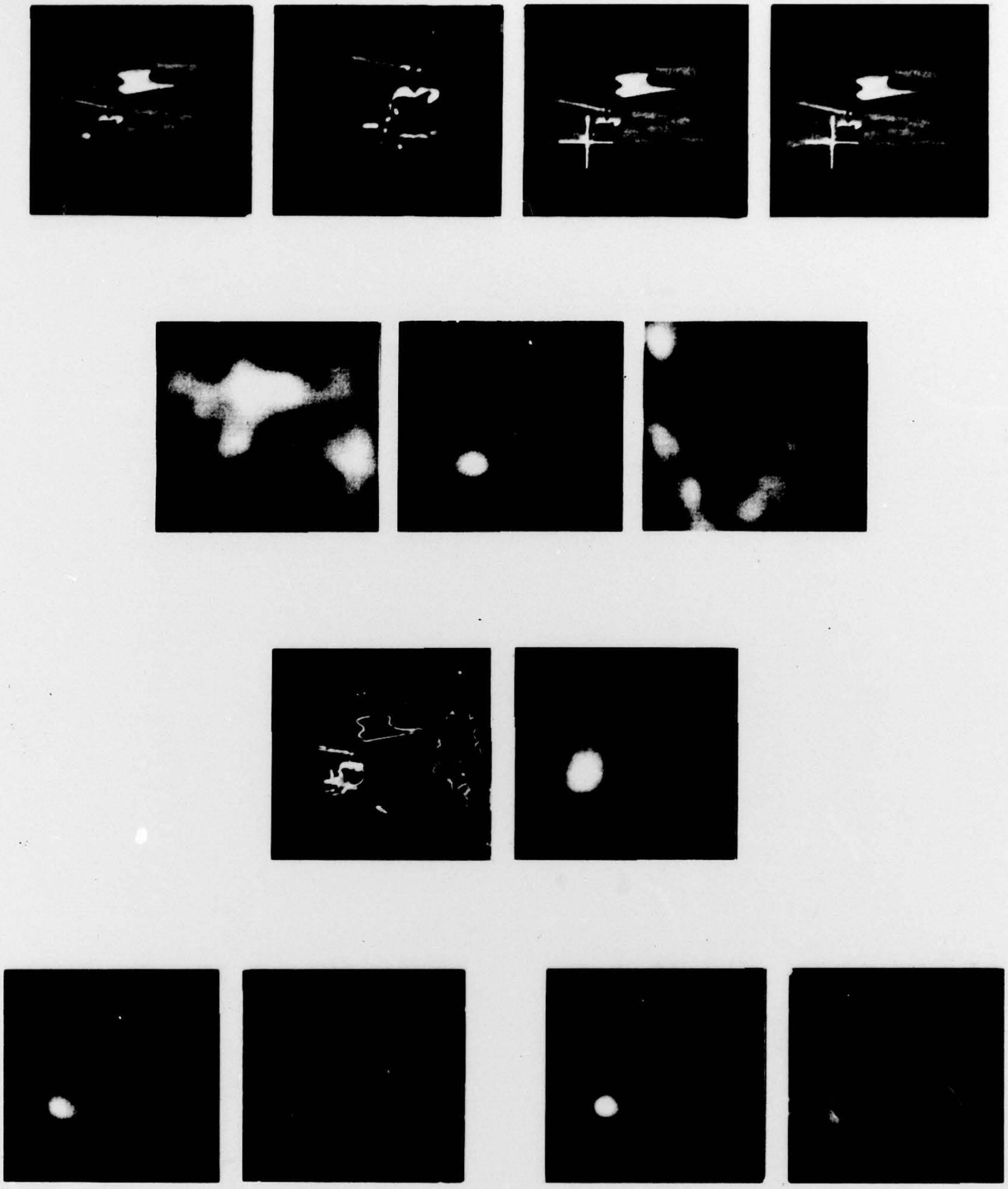


FIGURE 4 - From left to right, the top row shows the original image, the enlarged and enhanced target region, the target designated using the 3 textural features and the target designated using the textural features plus the edge feature. The second row shows the smoothed isotropic texture (reversed polarity), horizontal texture and vertical texture images, whereas the third row shows the edge image before and after smoothing. In the bottom row, the left pair shows the product of the 3 texture images and the right pair the product of the texture images with the smoothed edge image.

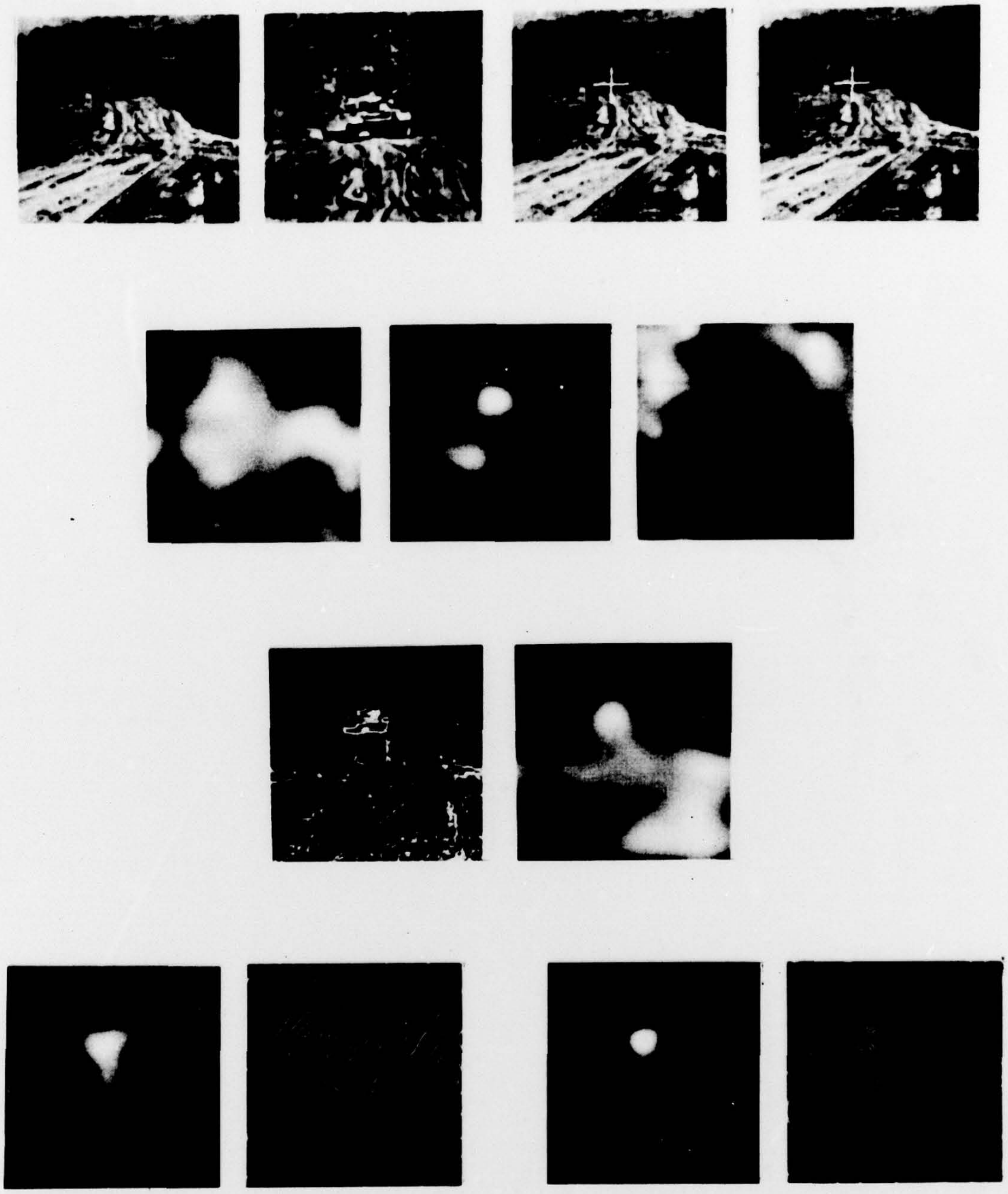


FIGURE 5 - From left to right, the top row shows the original image, the enlarged and enhanced target region, the target designated using the 3 textural features and the target designated using the textural features plus the edge feature. The second row shows the smoothed isotropic texture (reversed polarity), horizontal texture and vertical texture images, whereas the third row shows the edge image before and after smoothing. In the bottom row, the left pair shows the product of the 3 texture images and the right pair the product of the texture images with the smoothed edge image.

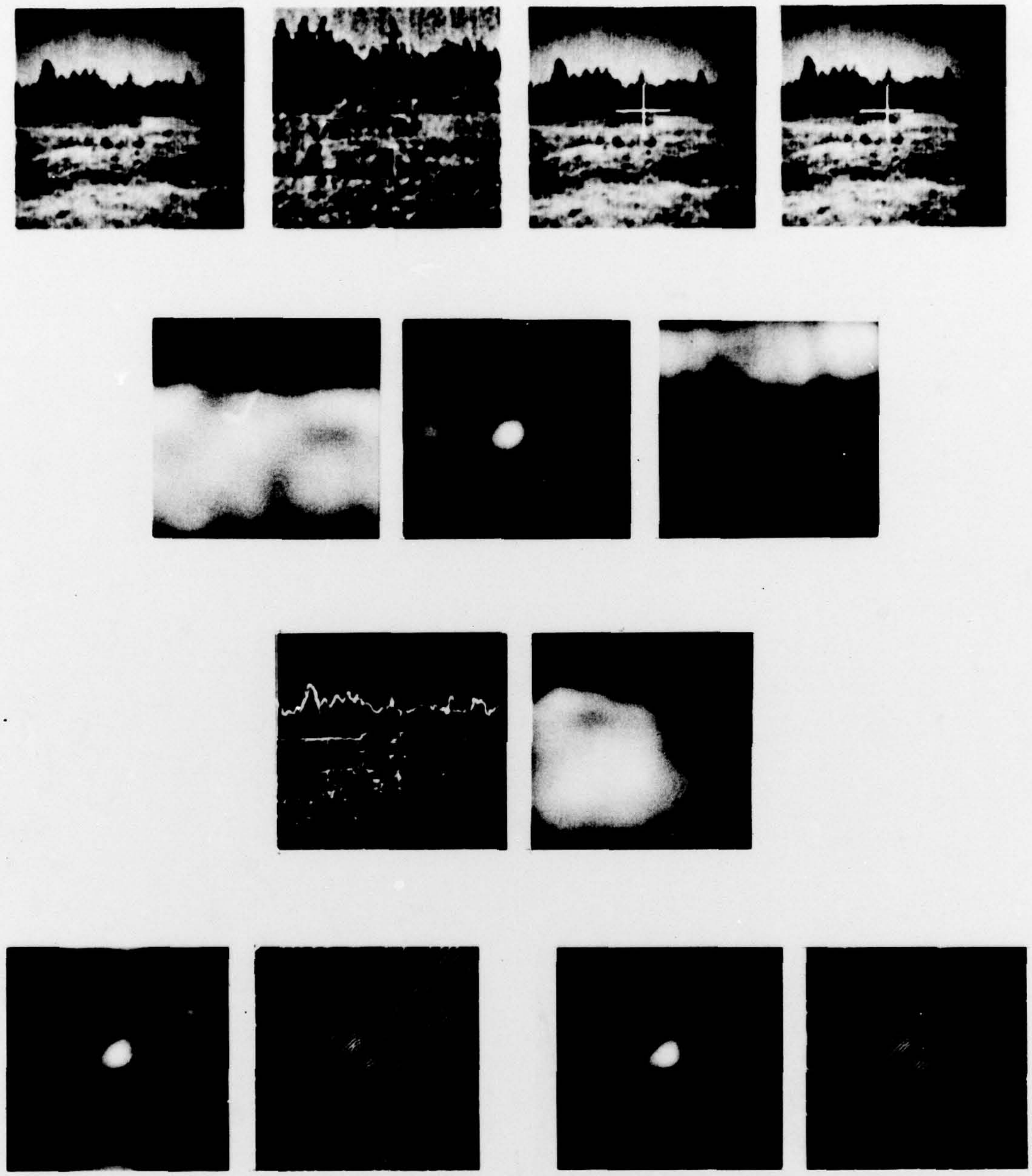


FIGURE 6 - From left to right, the top row shows the original image, the enlarged and enhanced target region, the target designated using the 3 textural features and the target designated using the textural features plus the edge feature. The second row shows the smoothed isotropic texture (reversed polarity), horizontal texture and vertical texture images, whereas the third row shows the edge image before and after smoothing. In the bottom row, the left pair shows the product of the 3 texture images and the right pair the product of the texture images with the smoothed edge image.

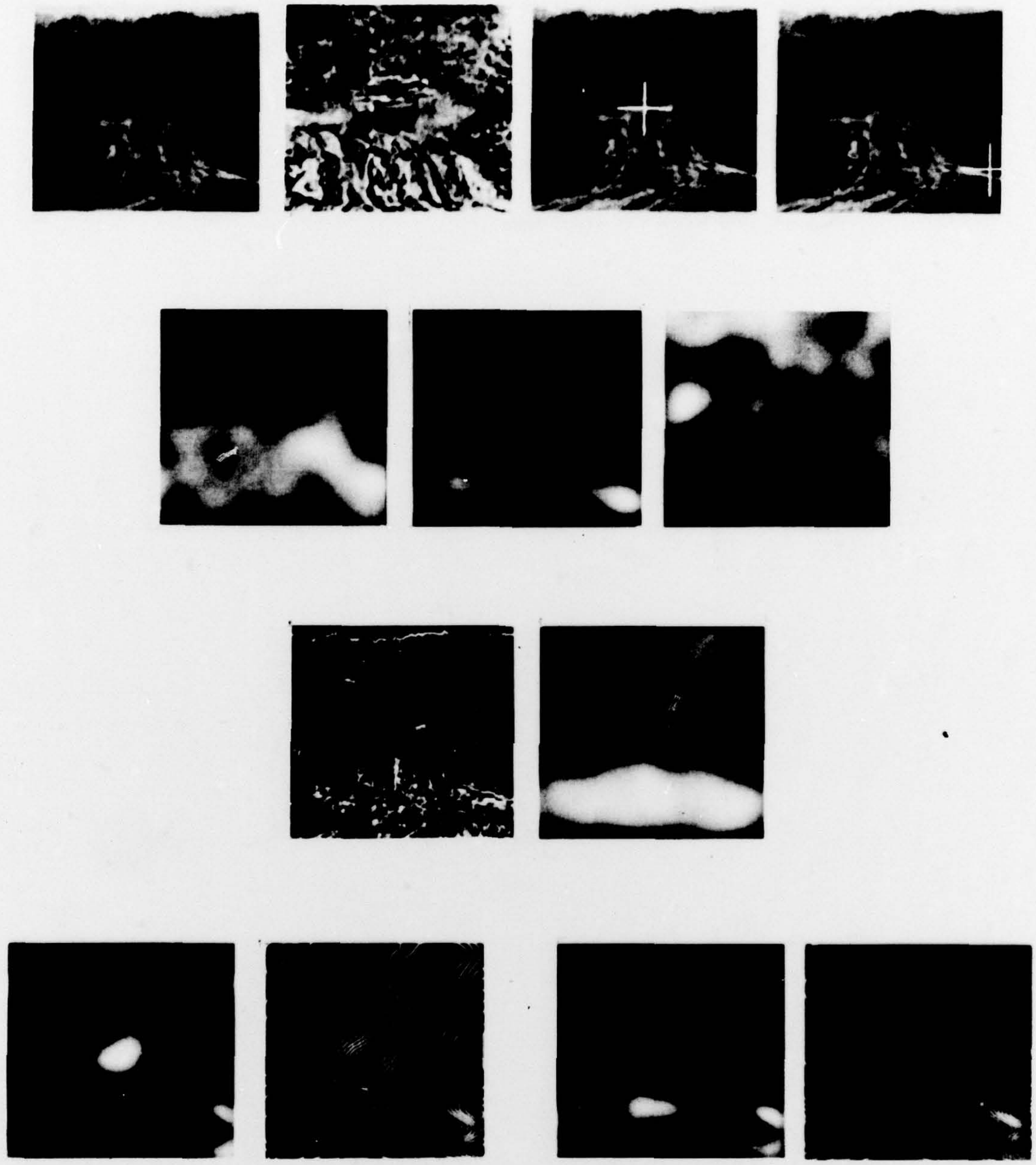


FIGURE 7 - From left to right, the top row shows the original image, the enlarged and enhanced target region, the target designated using the 3 textural features and the target designated using the textural features plus the edge feature. The second row shows the smoothed isotropic texture (reversed polarity), horizontal texture and vertical texture images, whereas the third row shows the edge image before and after smoothing. In the bottom row, the left pair shows the product of the 3 texture images and the right pair the product of the texture images with the smoothed edge image.

In all 5 cases, the targets are correctly detected with the 3 textural features. Inclusion of the edge feature slightly improves the detection capability in 4 of the 5 cases, as can be seen by comparing the 2 contour plots, but in the fifth case (Fig. 7) it prevents correct detection. Dust obscures the moving tank, in Fig. 7, and there is little edge content in the target region. The edge images in this figure show the deeply tracked roadway to have a higher edge content than the partially obscured target, and this moves the peak of the texture and edge-product image to a point below and to the right of the target.

The targets given in Figs. 6 and 7 have indistinct edges and their average gray levels are similar to those of their backgrounds - the targets are even somewhat difficult to distinguish visually. These 2 examples illustrate particularly well the potential importance of textural information, even that obtained with a simple algorithm, for automatically detecting targets in visible-light images.

A key point is that in most of the foregoing examples, the individual texture images do not show a well defined differentiation of target and background. The targets were detected only when the information contained in the 3 features was suitably combined. Notice also that the present approach is, to some extent, tolerant of violations of the assumptions made about the differences in the target and background features. An incorrect assumption about one feature, for example, can be "over ruled" if the other features fit the assumptions sufficiently well.

5.0 CONCLUSIONS

In some situations textural information can be useful for automatically detecting targets, particularly when conventional methods such as those based on gray level or target edges fail. We demonstrated that visible-light images of tank, truck, APC and helicopter targets, which were difficult to distinguish from their backgrounds of foliage and ground terrain by using gray-level or edge information alone, could be detected using textural information.

In the present target-detection application it may be preferable to use a number of different textural features rather than only a single one. We combined isotropic and directional textural features using a priori knowledge to detect the foregoing targets. More work is required to determine how to measure the appropriate textural properties, and how to combine them with other information, such as gray level or color, target edges, frame to frame comparisons etc., to better distinguish targets from their backgrounds. The usefulness of textural information to detect targets in other classes of imagery should also be investigated.

Advances in hardware expected within the next 5-10 years will increase the sophistication and performance of real-time target analysis systems. The program to develop very high speed integrated circuits (VHSI), recently announced by the Pentagon (Refs. 13 and 14), is an example of such new technology. A future tracking system, for example, may work in either of 2 modes: in the primary mode macroscopic target features such as shape, aspect ratio etc. are used (e.g. Refs. 15 and 16), whereas in the secondary mode individual image elements are classified as belonging to either the target or the background regions, based on local features such as texture, color etc. When the target is in full view, the system tracks in the primary mode and trains the secondary mode on how best to classify elements as target or background. If the target becomes partially obscured so that the primary mode is no longer effective, then the system switches to the secondary one.

6.0 REFERENCES

1. Mitchell, O. R. and Lutton, S. M., "Segmentation and Classification of Targets in FLIR Imagery", Private Communication, 1978.

2. Carlton, S. G. and Mitchell, O. R., "Object/Background Segmentation in FLIR Imagery", Proc. IEEE Computer Society Conference on Pattern Recognition and Image Processing (Chicago, May 31-June 2, 1978), IEEE, New York, NY, 1978.

3. Rosenfeld, A., "Visual Texture Analysis: An Overview", Image Analysis and Evaluation, SPSE Conference Proceedings, Toronto Canada, July 19-23, 1976.

4. Lipkin, B. S. and Rosenfeld, A., "Picture Processing and Psychopictorics", Academic Press, New York, 1970.

5. Sutton, R. N. and Hall, E. L., "Texture Measures for Automatic Classification of Pulmonary Disease", IEEE Trahs. on Computers, Vol. C-21, pp. 667-676, July 1972.

6. Read, J. S. and Jayaramamurthy, S. N., "Automatic Generation of Texture Feature Detectors", IEEE Trans. on Computers, Vol. C-21, pp. 803-812, July 1972.

7. Haralick, R. M., Shanmugam, K. and Dinstein, I., "Textural Features for Image Classification", IEEE Trans. on Systems, Man and Cybernetics, Vol. SMC-3, pp.610-621, November 1973.

8. Hayes, K. C. Jr., Shah, A. N. and Rosenfeld, A., "Texture Coarseness: Further Experiments", IEEE Trans. on Systems, Man and Cybernetics, Vol. SMC-4, pp. 467-472, September 1974.

9. Mitchell, O. R., Myers, C. R. and Boyne, W., "A Max-Min Measure for Image Texture Analysis", IEEE Trans. on Computers, pp. 408-414, April 1977.

10. Tamura, H., Mori, S. and Yamawaki, T., "Textural Features Corresponding to Visual Perception", IEEE Trans. on Systems, Man and Cybernetics, Vol. SMC-8, pp. 460-473, June 1978.

11. Schachter, B. J., Rosenfeld, A. and Davis, L. S., "Random Mosaic Models for Textures", IEEE Trans. on Systems, Man and Cybernetics, Vol. SMC-8, pp. 694-702, September 1978.

12. Boulter, J. F., "Interactive Digital Image Restoration and Enhancement", DREV R-4143/79, Unclassified

13. Connolly, R., "Pentagon to Fund Major IC Program", Electronics, pp. 81-82, September 14, 1978.

14. Robinson, A. L., "Microelectronics: Defense Department Looks to the 1980's", Science, Vol. 201, pp. 1112-1113, 22 September 1978.

15. Munteanu, C., "Digital Area Correlation Tracking by Sequential Similarity Detection", DREV R-4097/77, November 1977, Unclassified

16. Sévigny, L., "La reconnaissance de forme et l'acquisition d'objectif en infrarouge: nouvel algorithme de détection", DREV R-4099/78, Mars 1978, Non Classifié

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Research and Development Branch, DND, Canada.
DREV, P. O. Box 880, Courcelette, Que. G0A 1R0

"Automatic target detection using textural information"
by J. F. Boulter

We describe a digital processing technique for measuring local isotropic and directional textural features, and we use the textural information so obtained to perform automatic target detection. The present targets, which consist of an APC, a tank, a truck and a helicopter located against backgrounds of vegetation and ground terrain, are difficult to detect using differences in average gray level or location of target edges alone. (U)

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DREV R-4152/79 (UNCLASSIFIED)

Research and Development Branch, DND, Canada.
DREV, P. O. Box 880, Courcelette, Que. G0A 1R0

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