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IMAGE SEGMENTATION WITH COLOR AND TEXTURE

J. F. Boulter

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IMAGE SEGMENTATION WITH COLOR AND TEXTURE

by

J. F. Boulter

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1.0 INTRODUCTION

The objective of image segmentation is to classify homogeneous regions of an image into a limited number of groups. Such segmentation operations are becoming increasingly important in automatic digital image-analysis systems which are intended to operate with little or no operator supervision. One example is an automatic target-acquisition system (Refs. 1-3) that classifies the regions of an image into 2 groups: target and background. Another is a remote sensing system used for crop or land-usage classification. In this document, we examine the image segmentation based on the combined use of color and textural information, and we illustrate the technique by extracting a military vehicle from its background in a complex scene.

The image to be analyzed is usually the 2-dimensional projection of a 3-dimensional scene, and the segmentation groups may correspond to objects that have similar surface properties. In some cases, successful segmentation may be achieved by using differences in gray level alone. An example is the segmentation of a hot target from a cooler background in a thermal-emission image (Refs. 1-3). In other situations, segmentation schemes that are based only on differences in gray level may fail to correctly segment a scene that can easily be interpreted visually. For example, contrast in images formed by the reflection of radiation depends on the orientation and the illumination of the target surfaces, as well as on the surface material. The images of such targets may contain gray levels that are both higher and lower than the background region from which they are to be segmented. While higher-order processes, such as the analysis of the overall shape of the regions, the context of the regions (Refs. 4 and 5), previous

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experience, etc., are involved in the segmentation performed by the human visual system, additional local features may also yield useful information. In particular, color (Refs. 6 and 7) and texture (Ref. 8) are local features that may be easily obtained from many imaging systems and used for automatic image segmentation.

In Sect. 2.1, we review the general concept of classifying the individual elements of a digital image by using their locations in an N-dimensional feature space. The success of this procedure depends on the choice of local features which have sufficiently different values in the regions to be segmented from one another. We want to minimize the overlap in the feature space between the "clusters" that correspond to the different regions. As we show in Sect. 2.2, one way to do this for reflection images is to use color ratios (Ref. 7) because, ideally, they contain no contrast due to differences in surface illumination or orientation. The value of the ratio depends only on the "color" of the surface. In Sect. 2.3, we describe 2 simple algorithms to measure the local amounts of isotropic and linear textures. In Sect. 3.0, we segment a target consisting of a military truck from its background of vegetation and ground terrain by selecting the appropriate volume in the 4-dimensional space spanned by isotropic and linear textures, and by red and blue color ratios. Spatial averaging of the color and texture features increases the number of image elements correctly classified, but at the expense of a loss in the resolution of edge and other high-frequency details, and we examine this tradeoff experimentally. Since the intention of the present document is to demonstrate the combined use of local color and texture features for image segmentation, we employed an interactive digital image-processing system to locate the clusters and to perform the segmentation. Section 4.0

relates these preliminary results to automatic image segmentation where the system is first trained with preclassified imagery before it is applied to the unknown imagery.

This work was performed at DREV during the period June 1979 to December 1979 under PCN 21J12, Target Enhancement Using Spectral and Textural Information.

2.0 THEORY

2.1 Classification with Local Features

Suppose that we want to classify the individual elements of a digital image into a finite number of groups. These may correspond to distinct objects or surfaces in a scene. Classification is to be achieved by using only the local properties of the image elements. Higher-order classification, which may use macroscopic properties of the objects or surfaces, such as their shape, size, context in the scene, etc., will be considered as a separate operation that may be applied later, after the individual elements have been classified.

For each image element, we measure a set of local features, i.e. features that are either a property of the individual element, or of the elements in the close neighbourhood of it. The former may include color and gray level, whereas the latter may include texture and edge content. If the average values of the features in the groups are sufficiently different, the individual image elements can be classified by setting appropriate upper and lower threshold levels on each feature.

The first problem is to determine which local features are the most useful for distinguishing the different groups. For example, in images formed by the reflection of radiation, we should use features that characterize the reflecting surface and that are independent of viewing conditions, such as surface orientation and illumination. The latter effects may be unpredictable in practice, and will increase the variance of a given feature within a group. This increases the overlapping between the groups and makes the unique classification of the image elements more difficult. The spectral and textural features described in Sect. 2.2 and 2.3 were chosen because of their low dependence on such unpredictable effects.

The second problem consists in determining the permitted range of values for each local feature if that image element is to be classified into a given group. It is convenient to view this problem in a multidimensional space spanned by the local features. Ideally, the different groups will appear in well defined clusters in this space, and can be separated by appropriate "decision surfaces". Image elements will be reliably classified if the clusters are well separated and do not overlap one another. If clusters that correspond to different groups do overlap, then elements within the overlap region may be incorrectly classified. We may partially correct such errors by using other approaches, such as reclassifying image elements if they are surrounded in the original image by elements that have been classified into a different group (Ref. 9). In the experimental results given in Sect. 3.0, we use 2-dimensional projections to visualize the target and the background clusters in the space spanned by 2 color-ratio features and 2 textural features, and we determine the appropriate decision surfaces by inspection.

2.2 Color Features

Contrast in an image formed by the reflection of radiation depends on the orientation and the illumination of the reflecting surfaces, as well as on their intrinsic reflectivities. To perform the present classification, we wish to use features that characterize the intrinsic surface properties independent of orientation and illumination.

Suppose we obtain 2 registered images of a scene in different spectral bands, and divide one, point by point, by the other. Under certain assumptions, the contrast due to the differences in the surface orientation and illumination will be the same in the 2 images, and will cancel in the ratio (Ref. 7). Any contrast remaining in the ratio image will be due to differences in the spectral reflectivities (i.e. the "colors") of the surfaces. To achieve this, we must assume, first, that the illumination of the scene can be expressed as the product of a constant, a part that depends only on the wavelength and another that depends only on the direction of incidence and, second, that the reflectivities of the surfaces in the scene can similarly be expressed as the product of a part that depends only on the wavelength and another that depends only on the angles of incidence and reflectance. Stated differently, we assume that the way in which illumination changes as a function of surface orientation is independent of wavelength, and so is the way in which reflectivity changes as a function of the angles of incidence and reflectance.

Spectral ratioing removes information, but the assumption is that the orientation and the illumination information is difficult to predict or to allow for in practice, and will impede the correct classification

of the image elements. Consider, for example, an object that has surfaces at different orientations and which receives nonuniform illumination. We assume that all the surfaces have the same reflecting properties. If we view the object through a red and a blue filter, the 2 resulting color-component images will both contain contrast due to the differences in surface orientation and illumination. The object will occupy an extended area in the feature space spanned by the red and the blue components. Another similar object, which is illuminated with light with the same spectral content, but which has a surface color slightly different from the first, will also occupy an extended area in this feature space. If the clusters corresponding to the 2 objects overlap one another, then the elements cannot be all correctly classified by using these color features.

Suppose we construct 2 color-ratio images by dividing the red and the blue images by the sum of the two. Both objects will appear with a uniform gray level in the 2 ratio images (Ref. 6). Ideally, contrast due to differences in surface orientation and illumination will be removed. Each object will be restricted to a single point in the feature space spanned by the red and the blue color ratios, and elements belonging to the 2 objects can be correctly classified by placing a decision surface between the 2 points.

2.3 Textural Features

Visual texture consists of repetitive patterns formed by arranging primitive elements according to certain placement rules (Ref. 10). These elements and rules may be difficult to determine, and may vary widely from one type of surface to another. As a result, a number of

other approaches such as the measurement of spatial frequency content (Ref. 11) and counting the number of maxima and minima per unit area (Ref. 12) have been used to characterize the textural properties of surfaces. We consider simple primitive elements that should appear with reasonably high probabilities in most situations. These primitives correspond to isotropic and linear textures. Holes in an acoustic tile are an example of isotropic texture, whereas wood grain is an example of linear texture.

On the basis of the 3- by 3-element region that surrounds it, we assign, to each element in the digital image, one of three properties: isotropic texture, linear texture or no texture (Ref. 8). The central element of that region is assumed to possess isotropic texture if its gray level is either higher or lower than those of the remaining 8 surrounding elements. We assign linear texture to the central element if the gray levels of all the elements along a line 3 elements long that passes through it (the line can be either horizontal, vertical or diagonal) are all either higher or lower than those of the 6 remaining elements. These algorithms are used to generate binary isotropic- and linear-texture images, each containing a "1" if that particular texture has been assigned and a "0" if it has not.

The textural features of most surfaces in complex scenes will undergo large fluctuations, even when they are measured with simple primitives. It is necessary, in general, to perform a spatial averaging of textural features before they can be used for classification purposes. We smoothed the present binary texture images with a low-pass filter that had a 2-dimensional Gaussian point-spread function. This produced 2 continuous-tone images in which gray level represents the

average amount of isotropic or linear texture present in the neighbourhood of each element.

3.0 EXAMPLES

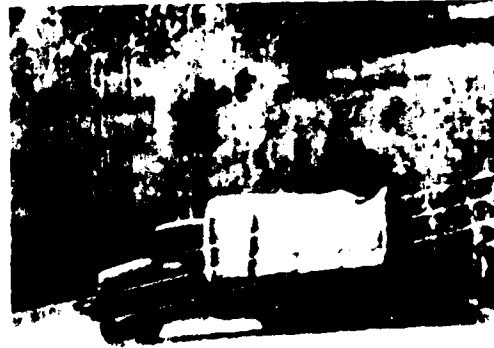
3.1 Color Segmentation

We digitized the color-transparency photograph of a canvas-back truck with 3 different color filters to produce the color-separation images shown in Figs. 1(a)-(c). We used the interactive digital image-processing system described in Ref. 13 with Kodak Wratten types 25 (red), 58 (green) and 47 (blue) color filters placed individually between the vidicon scanner and the transparency photograph. The intensity image, i.e. the sum of the red, the green and the blue color-component images, is shown in Fig. 1(d). For these, and for all subsequent photographs given here, the contrast has been normalized so that the highest gray level in the image is displayed as full white.

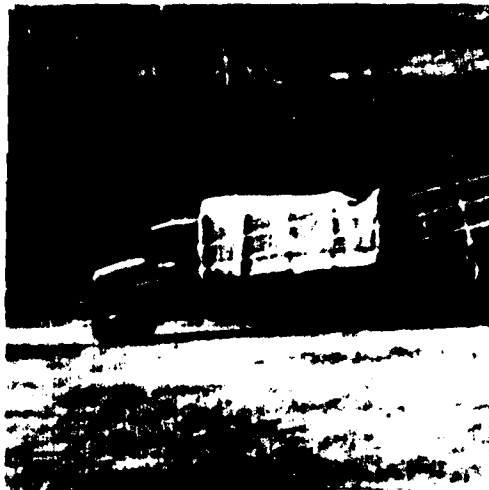
Each of the individual color images was divided by the intensity image, and the resulting normalized color-component images are shown in Fig. 2(a). A small amount of smoothing, performed by using a 2-dimensional low-pass filter with a Gaussian point-spread function, produced the images given in Fig. 2(b). Increasing the amount of smoothing yielded the 3 images shown in Fig. 2(c). Such smoothing reduces the small variations in the color of extended homogeneous regions, which may be of little or no interest for the present classification purposes, but at the expense of blurring the edges between differently colored regions.



(a) Red component



(b) Green component



(c) Blue component



(d) Intensity

FIGURE 1 - Original digitized images. A color transparency photograph was digitized 3 times with different color separation filters in the optical path to produce red (a), green (b) and blue (c) color-component images. The intensity image, obtained by summing the 3 color-component images, is given in (d).

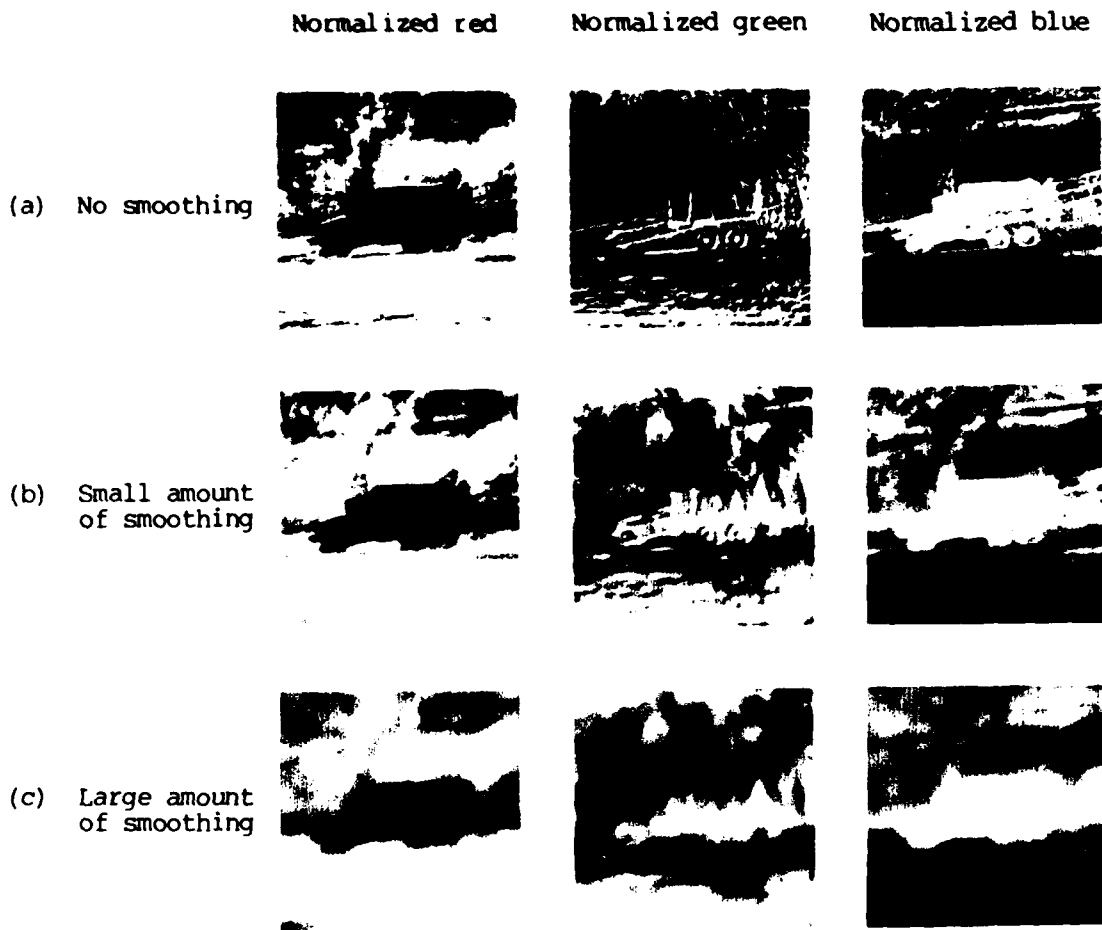
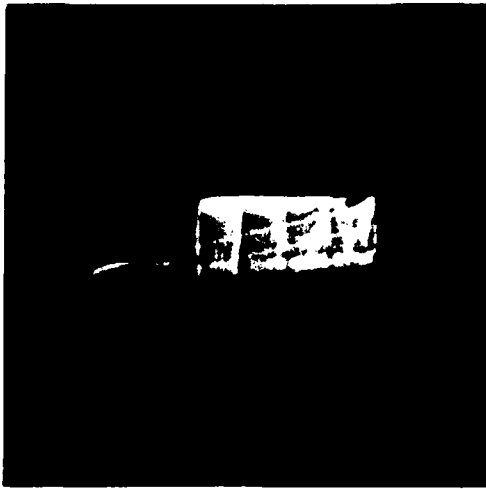


FIGURE 2 - Normalized color components. The red, green and blue color-component images were normalized by dividing each by the intensity image, and the results are shown, respectively, in the left, center and right photographs in (a). The same images are shown in (b) after a small amount of smoothing, and in (c) after a large amount of smoothing.

First, we will determine which of the color-ratio features shown in Fig. 2 are most useful for differentiating the olive-drab colored truck from its background of green foliage and vegetation. The 2 binary masks shown in Fig. 3 allow us to individually measure the color contents of the target region (Fig. 3(a)) and of the background region (Fig. 3(b)). Figure 4 shows the color content of the complete scene (the left column of 4 photographs) of the target region (the center column) and of the background region (the right column). The color-content information is displayed in the form of 2-dimensional distribution functions where the gray level represents the probability. A high probability, which means that a large number of image elements have that particular combination of the 2 color features, appears as white, whereas a low probability is displayed as black. To increase the dynamic range of the distribution-function displays, the gray level is made proportional to the square root of the probability. To visualize the 3-dimensional color space, we have used 4 different 2-dimensional distribution functions. The horizontal and vertical axes for each of the 4 rows are shown to the left of the photographs. For example, for the top row, the horizontal axis represents the intensity whereas the vertical one represents the normalized red content.

The first 2 rows of images given in Fig. 4 reveal that the target and the background regions are poorly separated in intensity. The probability for both regions is distributed across most of the horizontal intensity axis, i.e. both regions have intensity values within the same range. Setting a single intensity threshold will, therefore, not distinguish the 2 regions from each other. The third row of Fig. 4 shows that the 2 regions are also poorly separated in green content. On the other hand, from rows 3 and 4, we see that the target



(a)



(b)

FIGURE 3 - The binary masks used to select the target and background regions are shown in (a) and (b) after multiplication by the intensity image.

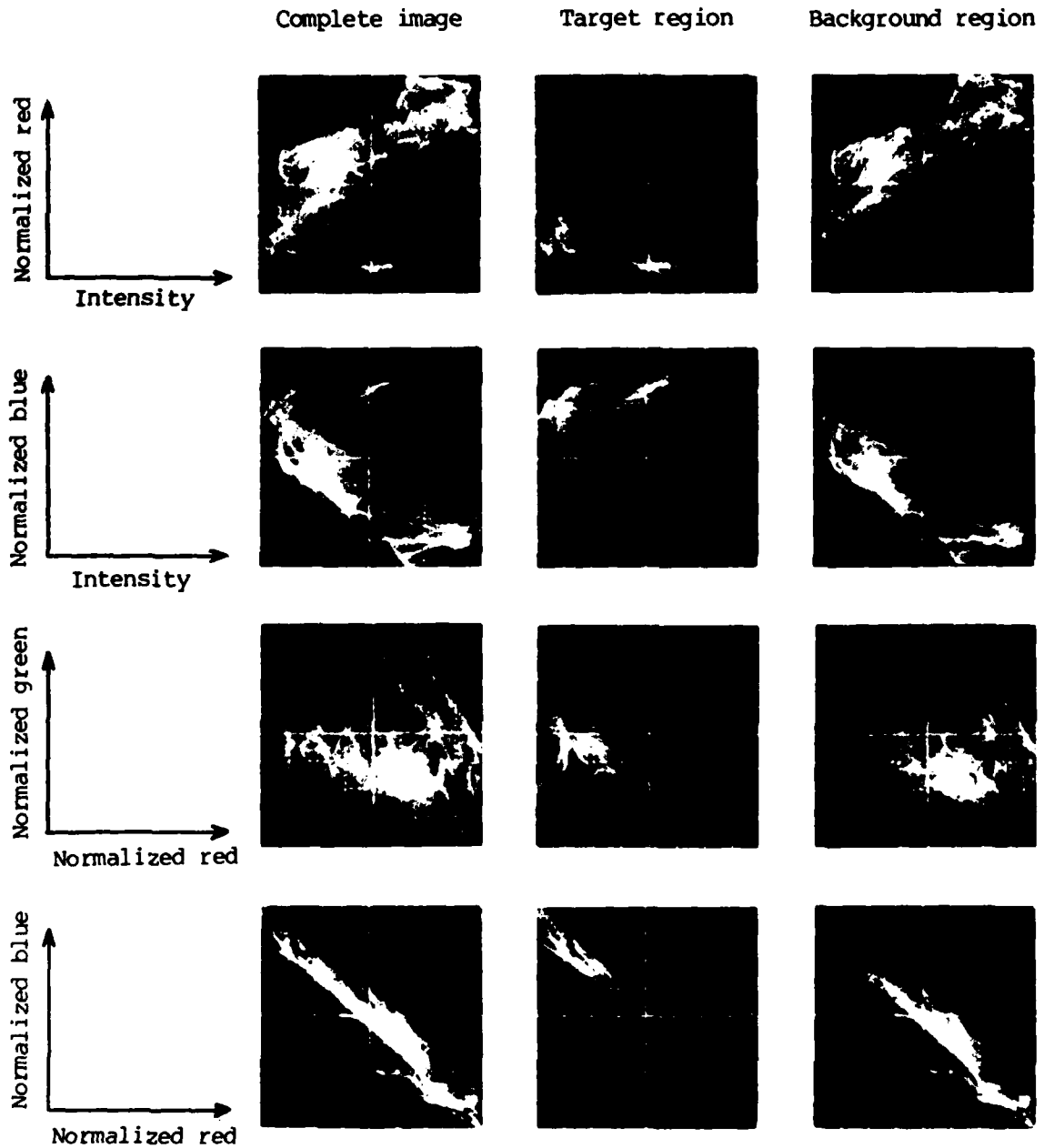


FIGURE 4 - Color content of the scene. Two-dimensional distribution functions, which show the color content of the scene, are displayed in the form of gray scale images where gray level is proportional to the square root of the probability. The color components corresponding to the horizontal and the vertical axes are shown to the left of each row. The left photograph in each row was obtained by using the complete image area, whereas the center and right ones were obtained by using masks to select the target and the background regions.

and the background regions are well separated in both normalized red and blue contents. The truck target has a higher normalized blue content and a lower normalized red content than the background.

Because of the low absorption in the red and the near infrared of chlorophyll and of other botanical colorants (Ref. 14), the reflectivity of vegetation increases rapidly from approximately 10% to 65% at 700 nm. On the other hand, the reflectivity of many man-made objects (painted surfaces etc.) is relatively constant to beyond 1500 nm (Ref. 15). These properties account for the present results which reveal that the background has a higher normalized red content than the truck. This may be useful as a general technique for enhancing the images of man-made objects against natural backgrounds, such as foliage or vegetation. For example, if we form 2 images of a scene, one in blue light and the other in red light, and divide the blue image by the red one, man-made objects will usually appear with a higher gray level than vegetation (Ref. 7). In some cases, it may be possible to segment such objects from this background by setting a single threshold level on the color-ratio feature.

By using the locations of the target and of the background clusters in the normalized color space, we now attempt to classify the individual image elements as parts of either target or background. As noted earlier, smoothing the color-component images can improve the classification accuracy at the expense of a loss in the spatial resolution of the classified regions. Figure 5 illustrates how 3 different amounts of smoothing affect the distribution of the normalized red content and the normalized blue content as measured in the complete image, the target and the background regions. Increasing the amount of

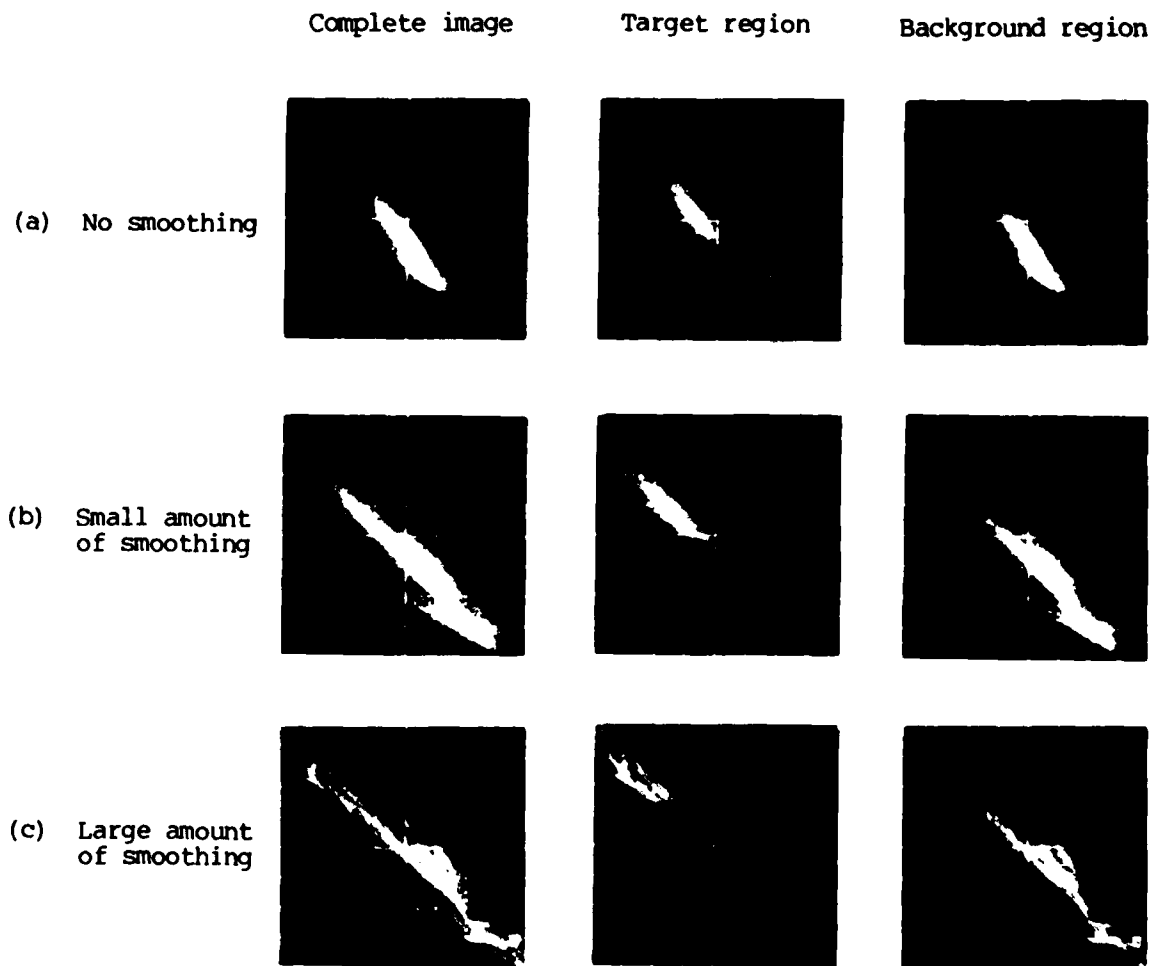


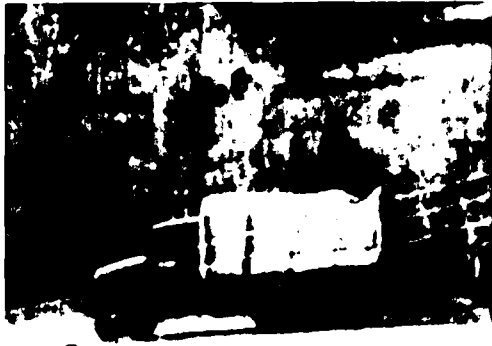
FIGURE 5 - Improvement in color classification by smoothing. Increasing the amount of spatial smoothing applied to the color-component images decreases the overlap of the target and the background clusters in the 3-dimensional color space, and improves the ability to segment the 2 regions. Photographs of the distribution of the normalized red component (horizontal axis) vs the normalized blue component (vertical axis) are shown for no smoothing (a), a small amount of it (b) and a large amount of it (c). The left photograph in each row was obtained by using the complete image area, whereas the center and right ones were obtained by using masks to select the target and the background regions.

smoothing reduces the overlap between the target and the background clusters. A certain amount of overlap remains, even with a large amount of smoothing, because of the approximate definition of the target and of the background regions by the masks shown in Fig. 3 (e.g. the background mask in Fig. 3(b) clearly retains some of the target region), and because of the blurring at the target edges caused by the smoothing. Note that a large amount of smoothing reveals structures in the 3 distribution functions that may correspond to differently colored areas in the target and the background regions.

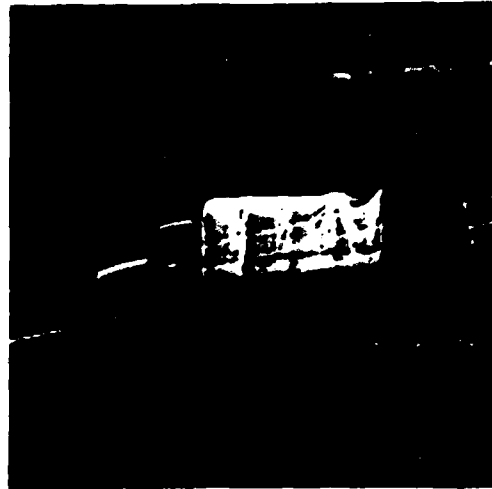
We can see from Fig. 5 that the target cluster is restricted to the upper left quadrant of the space spanned by the normalized red component and the normalized blue component. Figure 6 shows the result of retaining all image elements that have normalized color contents within these limits. Three different amounts of smoothing, corresponding to the 3 cases used in Fig. 5, produced the segmentation results given in Figs. 6(b), (c) and (d). The tradeoff is evident between a good spatial resolution, as seen in Fig. 6(b), and a good classification accuracy, as seen in Fig. 6(d).

3.2 Texture Segmentation

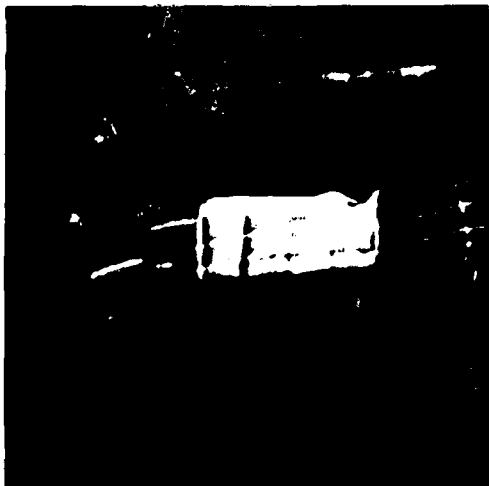
We applied the isotropic and the linear texture algorithms described in Sect. 2.3 to the green color image to produce the binary texture images shown in the left column of Fig. 7. The center and right columns in this figure show the result of applying a moderate amount and a large amount of smoothing to the 2 binary texture images. Figure 8 gives the smoothed texture content of the complete image (the left column), of the target region (the center column) and of the background region (the



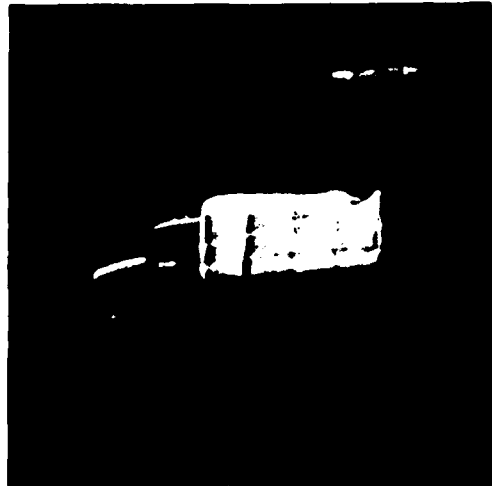
(a) Original



(b) No smoothing



(c) Small amount of smoothing



(d) Large amount of smoothing

FIGURE 6 - Segmentation based on color. The truck target is segmented from the original scene (a) by selecting a rectangular volume which contains the target cluster in the red-blue normalized-color space. When no smoothing is applied to the color-component images (b), target detail is sharp but there are many incorrectly classified points in both the target and the background regions. As shown in (c) and (d), more smoothing increases the fraction of image elements that are correctly classified, but at the expense of a loss in target spatial resolution.

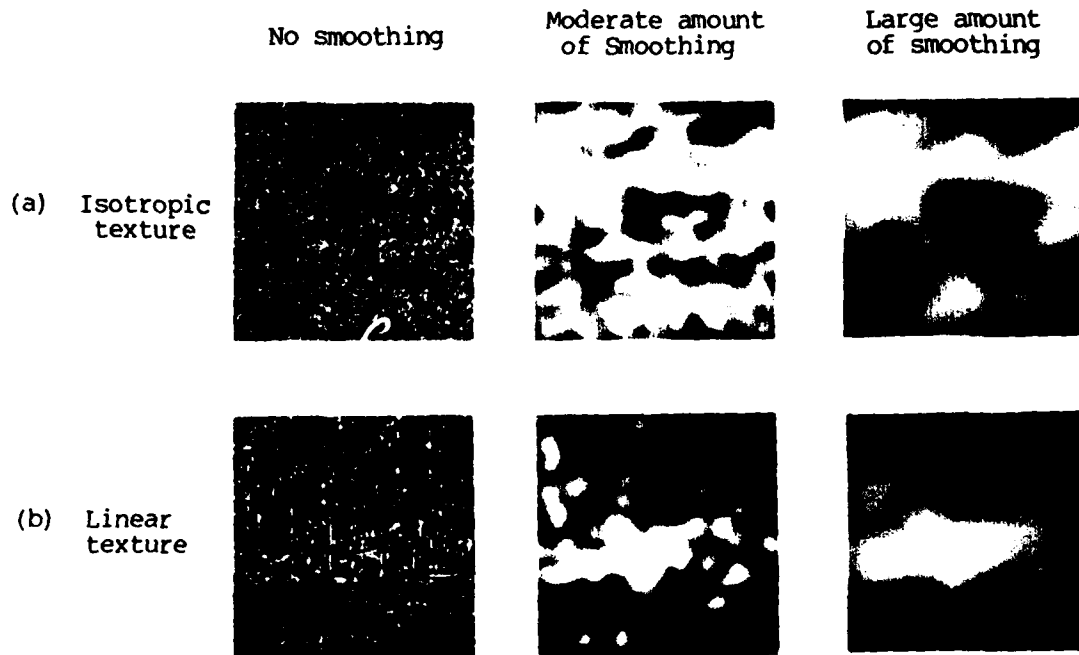


FIGURE 7 - Texture components. The isotropic texture content of the scene is shown in (a), and the linear texture content, in (b). The 2 left photographs are binary images obtained by setting an element to "1" if the 3- by 3-element region that surrounds it in the original scene possesses that texture attribute, or setting it to "0" if it does not. A moderate amount of smoothing (center image) or a large amount of it (right image) is required to make the texture images suitable for classification purposes.

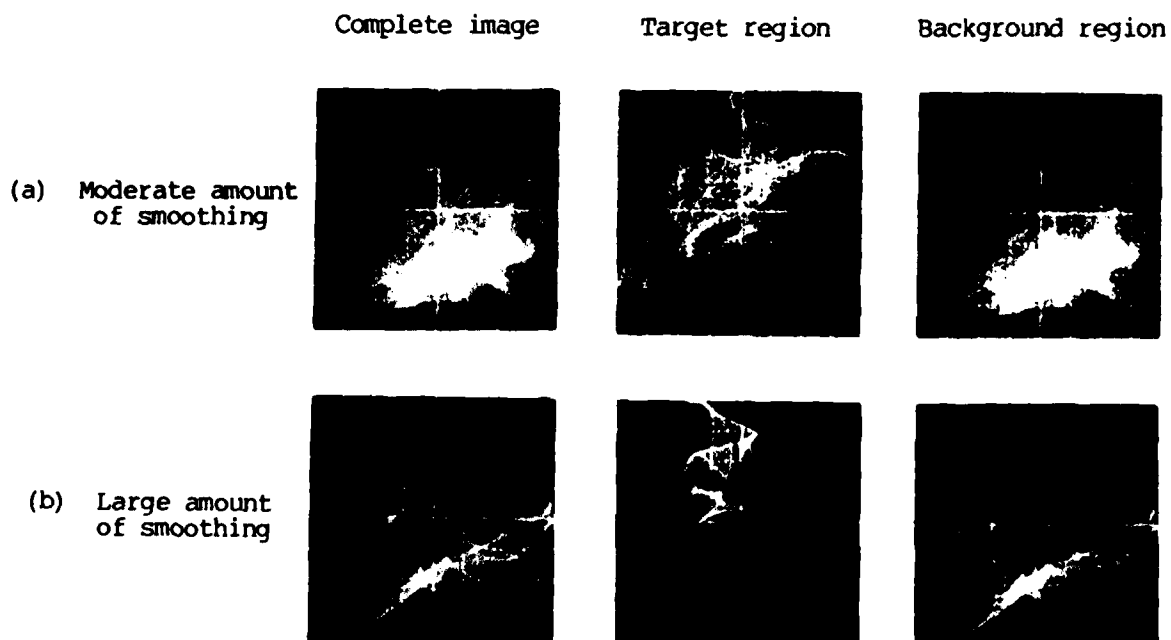
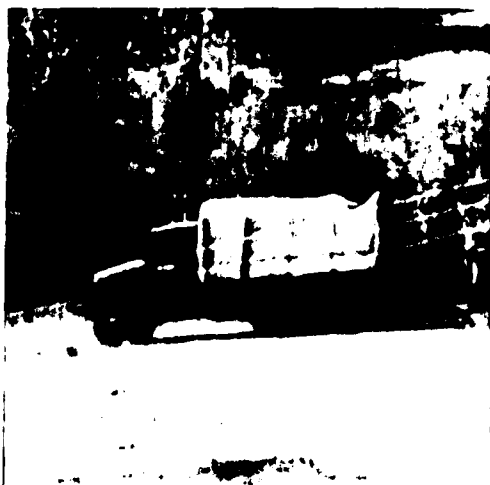


FIGURE 8 - Texture content of the scene. Two-dimensional distribution functions, which show the texture content of the scene, are displayed in the form of gray scale images where the gray level is proportional to the square root of the probability. The horizontal axis corresponds to the isotropic texture and the vertical one to the linear texture. A small amount of smoothing was used to produce the images shown in (a), whereas a large amount of it was used to produce those shown in (b). The left photograph in each row was obtained by using the complete image area, whereas the center and right ones were obtained by using masks to select the target and the background regions.

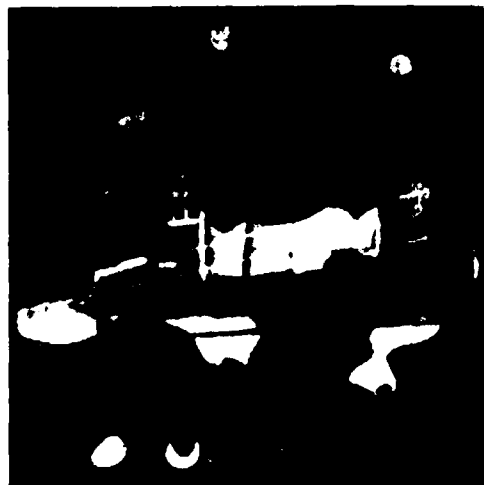
right column). The 2-dimensional distribution functions shown in this figure were produced in the same way as the color distribution functions described in Sect. 3.1. The horizontal axis of each distribution function corresponds to the isotropic texture and the vertical one to the linear texture.

In comparing the center and right columns of Fig. 8, one sees that the target region has less isotropic texture, but more linear texture, than the background region. One would expect that the truck, which is composed of relatively smooth surfaces, will have less isotropic texture than the more complex background of foliage and vegetation. On the other hand, the truck image contains more straight edges than the background, and this leads to a higher linear-texture content.

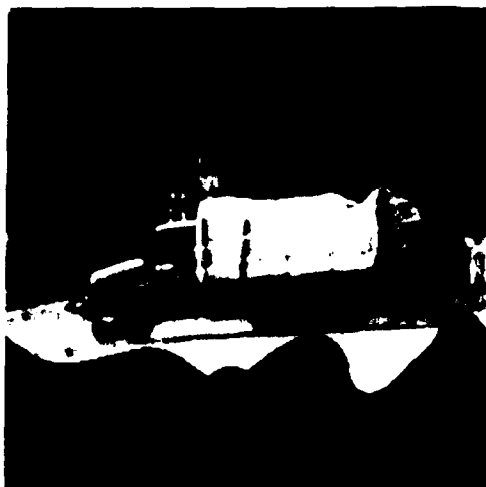
The target cluster, therefore, is located mainly in the upper left quadrant of the isotropic texture - linear texture distribution function. Figures 9(b) and (c) illustrate the target segmentations that result when we retain all image elements having textural values within these limits. The 2 results were obtained, respectively, by applying a moderate and a large amount of smoothing to the texture images before classification. Figure 9(d) shows the result if one uses a large amount of smoothing, but raises the horizontal-texture threshold and lowers the isotropic-texture threshold. This reduces the number of background elements that are incorrectly classified as part of the target, but at the expense of increasing the number of target elements that are missed. It is evident that a large amount of smoothing is required to obtain an acceptable target segmentation, and that relatively wide classification limits must be used to ensure a sufficiently low miss rate. The present textural features are useful for locating the general target area, but



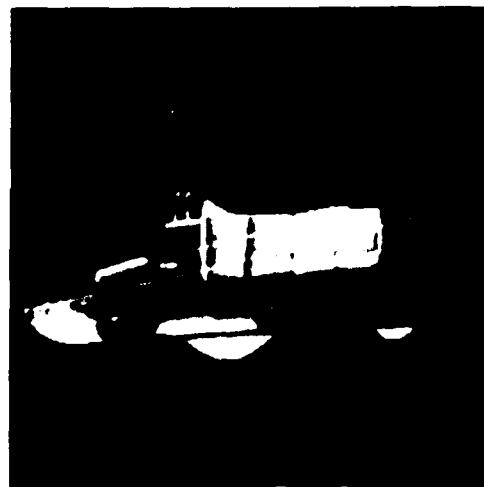
(a) Original



(b) Moderate amount of smoothing



(c) Large amount of smoothing



(d) Reduced texture limits

FIGURE 9 - Segmentation based on texture. The truck target is segmented from the original scene (a) by selecting in the 2-dimensional texture space a rectangular area that contains the target cluster. Poor segmentation results (b) when insufficient smoothing is applied to the isotropic and linear texture features before classification. Increasing the amount of smoothing (c) improves the segmentation result. Reducing the area of the region that is selected in the texture space decreases the area of the segmented target region.

they cannot give significant information on the target shape.

3.3 Color-Texture Segmentation

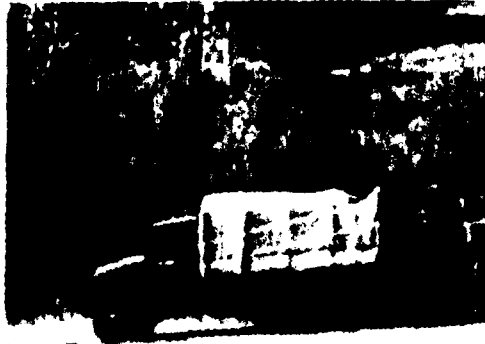
Section 3.1 illustrated that color ratios can be effective local features to use for image classification. If random fluctuations in the color-ratio features (due either to system noise or to variations in the intrinsic spectral reflectivities of the surfaces) are sufficiently low, then little or no spatial averaging may be required. The spatial resolution of the regions after classification may be close to that of the imaging system. However, regions which have the same spectral contents but which belong to different classes cannot be distinguished, and other information, such as texture, must be used.

Unless a surface is composed of closely spaced simple repetitive patterns, its local textural properties will fluctuate. In Sect. 3.2, we saw that it may be necessary to use a considerable amount of spatial smoothing before the present isotropic and linear-texture features are useful for region classification. The spatial resolution of a texture classification will, in general, be low and relatively wide classification limits must be used to ensure that the fluctuations do not result in too high a miss rate (i.e. a high false-alarm rate must be tolerated). In the present class of imagery, texture clearly provides less useful classification information than do color ratios. However, when it is suitably combined with color content, texture can supply additional information that can improve classification accuracy.

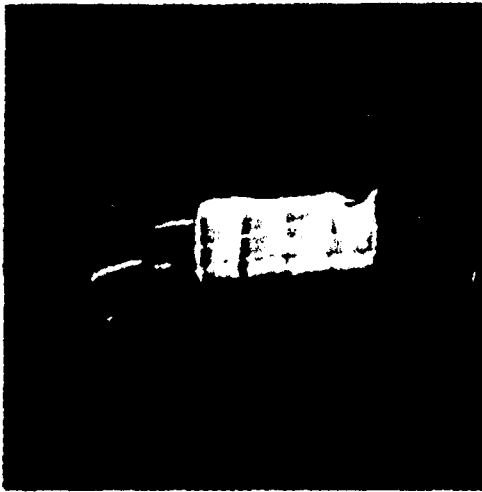
Figure 10 shows the result of segmenting the truck target from its background; this operation is based on the truck normalized red content, normalized blue content, isotropic and linear textures. The segmentation result given in Fig. 10(b) was obtained by applying a large amount of smoothing to the 2 textural features and a small amount of it to the 2 color-ratio features. For Fig. 10(c), the amount of textural smoothing was not changed, but the amount of color-ratio smoothing was increased. The combined use of the color ratio and the textural features has preserved the high spatial resolution of the color classifications shown in Fig. 6, but has removed regions of the background which were incorrectly classified as part of the target because they had the same color content as the target. In Fig. 10(b), note the sharply defined target edges which follow the true truck silhouette, and the correct classification, as belonging to the background, of foliage viewed through the truck windows.

4.0 DISCUSSION

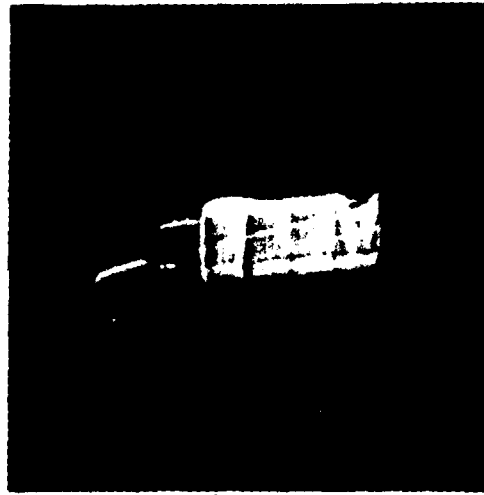
This document was intended to show that, in some situations, the combined use of appropriate color and textural features is suitable for image segmentation. The color information contributes a high spatial resolution to the segmentation, whereas the textural information aids in correctly classifying different regions that may have similar color properties. We do not claim that the textural measures, the color measures nor the classification approach employed here are, in any sense, optimum. For example, nonlinear spatial smoothing, performed either before or after the classification, may yield better results than the present linear smoothing. Furthermore, for computational



(a) Original



(b) Segmented - small amount of smoothing



(c) Segmented - moderate smoothing

FIGURE 10 Segmentation based on color and texture. The truck target is segmented from the original scene (a) by selecting an appropriate volume in the 4-dimensional space spanned by 3 local color features and 2 local texture features. In (b), a small amount of smoothing was used before each individual picture element was classified as belonging to the target or the background. This produces a sharply defined target region (note the accuracy with which the upper and lower edges of the segmented region follows the true target contours, and the correct classification, as belonging to the background region, of foliage that is viewed through the truck windows); however, several small regions of the image are incorrectly classified. Increasing the amount of smoothing (c) reduces the miss-classification rate, but at the expense of a blurring of target detail.

simplicity, we selected rectangular regions in the color-texture space. As is evident in the experimental distribution functions given in Sect. 3.0, more image elements would have been correctly classified had we used arbitrarily shaped (curved) segmentation limits.

We obtained the present results by observing the locations of the target and the background clusters in the color-texture space and then choosing appropriate limits to segment the target. These limits apply only to the present case, and may not be appropriate for other images. In a practical image classification system, it is usually necessary to adaptively adjust the classification limits to suit the particular input imagery. Systems intended, for example, to classify areas in satellite imagery or to interpret printed characters have successfully accomplished this by adaptive training (Ref. 16), i.e. the limits are established by providing the system with preclassified images. It has not been established to which extent such an adaptive training approach would succeed in correctly classifying the images of 3-dimensional objects which may appear with different orientations, under different illumination conditions, or which may be partially obscured. However, it is clear that features, such as color ratios and texture, which are relatively independent of such viewing conditions, will be more suitable than those which are dependent.

In some situations, it may be possible to choose features which, when combined with a priori knowledge, may allow us to achieve correct classification with little or no adaptive training. For example, the use of a fixed threshold on the blue-to-red color ratio described in Sect. 3.1, may permit the segmentation of a wide variety of man-made targets from a background of vegetation.

We performed the present study by simulation on an interactive digital image-processing system, but all processing described here is currently feasible at standard TV-video rates. For example, real-time video digitizers are available, as is the digital video circuitry to perform division and 3- by 3-element spatial convolution. Hardware to carry out multifeature classification at 30 TV frames/s is under development by at least one private industry. New approaches, such as the use of adaptive tree-based logical processing (Refs. 16 and 17), may permit high-efficiency implementations of complex image-segmentation algorithms.

5.0 CONCLUSION

We considered the problem of classifying the elements of a digital image formed by the reflection of radiation from a scene into different categories, such as target or background. Only local features, which depend either on the properties of the image element or on those of elements within a small neighbourhood of it, were employed; macroscopic properties of the regions, such as shape, aspect ratio, context etc., were not used. We should choose local features which measure properties of the objects in the scene, and that are independent of viewing conditions, such as surface orientation and illumination. Color-ratio and textural features can satisfy these requirements, and we examined their combined use for image classification.

If the objects in the scene have constant spectral reflectivities, and if the noise level introduced during the image formation and recording processes is sufficiently low, the spatial resolution of a color-ratio classification can be equal to that of the imaging system

itself. In such cases, point targets, as well as extended targets, can be classified with color-ratio features.

Visual texture is only useful for classifying extended regions that are well resolved by the imaging system (e.g., that occupy 10 elements or more across their minimum dimension). In practice, the textural properties of most homogeneous surfaces undergo relatively large fluctuations, and a significant amount of spatial smoothing is required, either before or after the texture classification is performed. The spatial resolution of a texture classification may, therefore, be low. Nevertheless, texture may be a useful feature for distinguishing between extended regions, in a scene, that cannot be separated easily by other means. For example, it may be relatively easy to camouflage a target so that it resembles the average color of its background (a land target may be painted green to imitate vegetation, a ship may be painted blue-gray to match water, etc.), but it is more difficult to match their textural properties. Note that the matching of visual color or texture for camouflaging purposes does not guarantee that appropriate processing algorithms could not distinguish the target from its background.

The combined use of color and texture information may be useful for automatically detecting or tracking visible-light images of military targets against complex backgrounds. In practice, the color and the textural properties of a surface are usually unrelated to one another, and each forms an independent, but complementary, basis for region classification. Such automatic processing should be optimized for a particular imaging situation by using all the a priori information available. Most color and texture algorithms are computationally simple, and relatively easy to implement in real-time hardware. Further

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experiments with other types of military imagery are required to determine the range of possible applications of color-texture segmentation.

6.0 REFERENCES

1. Sévigny, L., "Simulation d'un système d'acquisition automatique d'objectif infrarouge dans un contexte sol-sol", DREV R-4081/77, June 1977, UNCLASSIFIED.
2. Sévigny, L., "La reconnaissance de forme et l'acquisition d'objectif en infrarouge: Nouvel algorithme de détection", DREV R-4099/78, March 1978, UNCLASSIFIED.
3. Sévigny, L., "Extracteurs séquentiels pour l'acquisition de cibles sur images", DREV R-4153/79, August 1979, UNCLASSIFIED.
4. Gilchrist, A.L., "Perceived Lightness Depends on Perceived Spatial Arrangement", Science, Vol. 195, pp. 185-187, 14 January 1977.
5. Gilchrist, A.L., "The Perception of Surface Blacks and Whites", Sci. Am., Vol. 240, p. 112, March 1979.
6. Boulter, J.F., "Recognition of Reflection and Illumination Edges by the Human Visual System", Applied Optics, Vol. 19, pp. 2077-2079, 15 June 1980. Also published as DREV M-2488/79, November 1979, UNCLASSIFIED.
7. Boulter, J.F., "Image Enhancement by Spectral Ratioing", DREV R-4170/80, June 1980, UNCLASSIFIED.

UNCLASSIFIED

30

8. Boulter, J.F., "Automatic Target Detection Using Textural Information", DREV R-4152/79. August 1979, UNCLASSIFIED.
9. Dendronic Decisions Limited, "First Bimonthly Report - Covering the Period October 1, 1979 to November 30, 1979". UNCLASSIFIED.
10. Rosenfeld, A., "Visual Texture Analysis: An Overview", Image Analysis and Evaluation, SPSE Conference Proceedings, Toronto Canada, July 19-23, 1976.
11. Lipkin, B.N., and Rosenfeld, A., "Picture Processing and Psychopictorics", Academic Press, New York, 1970.
12. Mitchell, D.R., Myers, C.R., and Boyne, W., "A Max-Min Measure for Image Texture Analysis", IEEE Trans. on Computers, pp. 408-414, April 1977.
13. Boulter, J.F., "Interactive Digital Image Restoration and Enhancement", Comp. Graphics and Image Proc., Vol. 9, pp. 301-312, December 1979. Also published as DREV R-4143/79, July 1979, UNCLASSIFIED.
14. MacAdam, D.L., "Color Science and Color Photography", Physics Today, pp. 27-39, January 1967.
15. Richards, E.A., "Contrast-enhancement in Imaging Devices by Selection of Input Photosurface Spectral Response", Advances in Electronics and Electron Physics, Vol. 28B, Academic Press, New York, 1969.

UNCLASSIFIED

31

16. Armstrong, W.W. and Gecsei, J., "Adaption Algorithms for Binary Tree Networks", IEEE Trans. on Systems, Man and Cybernetics, Vol. SMC-9, pp. 276-285, May 1979.

17. Armstrong, W.W. and Gecsei, J., "Architecture of a Tree-Based Image Processor", in Proc. 12th Ann. Asilomar Conf. Circuits, Systems and Computers, Pacific Grove, CA, November 6-8, 1978.

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"Image Segmentation with color and texture"
by J. -f. Boulter

We examined how objects or regions in an image formed by the reflection of radiation from a scene can be segmented using differences in their color and texture. The color features (normalized red content and normalized blue content) permit good spatial resolution of the segmented regions, whereas the textural features (isotropic and linear textures) help to distinguish similarly colored objects. The color and texture features were chosen because of their low dependence on viewing conditions, such as surface orientation and illumination. As an example, we segment an olive-drab colored military truck from its background of vegetation. (U)

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