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AUTOMATIC DIGITAL IMAGE REGISTRATION

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ABSTRACT

This paper introduces a general procedure for automatic registration of two images which may have translational, rotational, and scaling differences. This procedure involves 1) segmentation of the images, 2) isolation of dominant objects from the images, 3) determination of corresponding objects in the two images, and 4) estimation of transformation parameters using the center of gravities of objects as control points. An example is given which uses this technique to register two images which have translational, rotational, and scaling differences.

I. INTRODUCTION

Given two images of the same scene in coordinate spaces (x,y) and (x',y'), image registration is the determination of transformation functions f1 and f2 such that given the coordinates of a point in one of the images, we can compute the coordinates of the same point in the other image by

$$x = f1(x',y')$$
$$y = f2(x',y').$$

The parameters of transformation functions f1 and f2 are estimated using a set of corresponding control points from the two images. Selection of control points by hand is often time consuming and is susceptible to systematic errors. It is desirable to make the control point selection process automatic so that the whole registration process can be carried out automatically.

An automatic technique for selection of control points in the first image is available[4,17]. This involves selection of windows which 1) contain a large number of high gradient edges, 2) contain a large number of connected edges, 3) are unique with respect to neighboring windows, and 4) are well dispersed in the image. The upper left hand corner of the window satisfying these properties is taken as a control point. In the second image, the control points are obtained by carrying out a search for the position of best match for each window from the first image[3,16] using either the sequential similarity detection algorithm[2] or the cross-correlation technique[1].

Selection of control points automatically in this manner has shown to be satisfactory as long as the two images have only translational differences. For images with rotational, and scaling differences, the search process becomes inaccurate and unreliable. In such situations, image points which are routinely used as control points include intersections of lines (intersections of roads in aerial or satellite images) and positions where lines join (like positions where rivers join).

In this paper we introduce a technique for automatically finding corresponding control points in two images which may have translational, rotational, and scaling differences. The technique uses *center of gravities of objects as control points.* Because the coordinates of the center of gravity of a shape is the average of the coordinates of the pixels on its boundary, if any error has been made in extracting the boundary, that error is averaged over the whole boundary and so the effect on the center of gravity is small. Another beneficial property of the center of gravity as control point is that its location can be determined upto subpixel accuracy while the traditional control points (like intersection of roads) can take only discrete values. Our registration algorithm consists of following steps. 1) Segmentation of the images, 2) isolation of dominant objects from the images, 3) determination of corresponding objects in the two images, and 4) estimation of transformation parameters using the center of gravities of objects as control points.

II. IMAGE SEGMENTATION

There is no single image segmentation algorithm which can reliably segment an arbitrary image. Depending on the type of imagery, different techniques have been developed by different authors. Some of the techniques like the recursive region splitting technique[9], the semantic region growing technique[5], or the region classification technique[7] work especially good on multispectral aerial or satellite images.

For HCMM satellite images which are of interest to us, a simple segmentation technique based on gray level thresholding appears to give satisfactory results. A number of techniques have been proposed to obtain an appropriate value of the threshold. The threshold value can be selected by maximizing the global average contrast of the image[8]. In another method[10], the threshold value is determined by minimizing the sum of the squares of the differences of the original image and the thresholded image pixel by pixel. Katz[6] has determined the threshold value using the edge information present in the image. We have chosen the Katz algorithm for the segmentation of HCMM images because of its speed and performance on this type of image. The algorithm consists of the following four steps.

1. Compute the gradient of the original image, call it image G.
2. Find the high gradient pixels by thresholding image G. Replace all values above the threshold by 1 and all other values by 0. Call the new image H.
3. Multiply H by the original image, call the new image M. Note that M will contain only high gradient pixels of the original image.
4. Compute the average gray value of image M (nonzero pixels only). This will be the required threshold value.

Note that the algorithm requires a user-specified parameter in step 2.

III. FINDING CORRESPONDING REGIONS

Once the two images are segmented, we isolate regions with closed boundaries in each one of the images. A region which touches the boundary of the image is not isolated. Further, very small regions are discarded. The task is now to determine the correspondence between the two sets of regions.

Regions in the two images could be matched based on shape alone. A number of shape matching procedures are available in the literature. Fourier descriptors[12], and invariant moments[13] have been extensively used for shape matching. The distribution of chord lengths joining the center of gravities of regions to its boundary points has been proposed as a measure of shape[11].

Price and Reddy[14,15] extracted a number of features from each region including roundness (perimeter^2/4πarea), length to width ratio, color, intensity, location, relative position to match the regions in the two images. Their matching technique seems to best fit our problem and we have used it with some modifications in the example given in section V.

IV. TRANSFORMATION FUNCTIONS

Selection of the right transformation function is another important factor in the registration of digital images. The best transformation function for registering two images which have only translational differences is very simple and has only two unknown parameters. Applying a transformation function with more parameters makes the registration process costly and probably less accurate. On the other hand, images of the same scene taken at different angles require a transformation function with 8 unknown parameters (the projective transformation) and a transformation function with less parameters cannot register them accurately.

Usually it is known (or assumed) that the two images have only specific differences and can be registered using an appropriate transformation function. There are cases though, where no a-priori information is available about the images and we have to select the best transformation function to register them. Using the control points, it is possible to find some knowledge about the images and then select the appropriate transformation function. For example,

1. Using two pairs of corresponding control points, it is possible to find two corresponding line segmentss in the two images. If the ratio of corresponding

line segments is not equal to 1, it shows that the two images have scaling differences.

2. If the ratio of corresponding line segments are not the same for different line pairs, it shows that one of the images is geometrically distorted with respect to the other.
3. If the angle between corresponding line pairs in the two images are different, it shows that the images have not been obtained from the same angle.

The above information helps in the selection of the right transformation function.

To be able to estimate parameters of a transformation function with n unknowns we need at least n/2 corresponding control points (which are not colinear). Usually more control points are used and parameters are estimated by minimizing the mean-square error.

V. AN EXAMPLE

To show how the proposed technique works, we have taken a 240x240 subimage of the day-visible image obtained by the HCMM satellite on 26 September 1979 from an area over Michigan(scene id:A-A0518-18110-1). The digital image acquired by the satellite (figure 1) was used as the first image. The second image was the digitized image of the print of the same scene provided by the National Space Science Data Center. We arbitrarily digitized the print so that the second image is translated, rotated, and has scaling differences with respect to the first image, as shown in figure 2. The digitization was done using the Spatial Data System Vidicon in the Pattern Recognition & Image Processing Laboratory of the Computer Science Department, Michigan State University.

A. SEGMENTATION

The Katz technique[6] was used to segment the images. The gradient images were clipped at 98% of the gradient histogram area. Thus average intensity of the 2% of the highest-gradient pixels was used as the threshold value for segmenting the gray level images. We found that other day-visible images of HCMM can be segmented satisfactorily using the same parameter value (98%). Figures 3 and 4 contain the segmented images of figures 1 and 2, respectively.

B. CONTROL POINTS

Ten control points were used to register the two images. To obtain the control points, we have used a technique similar to the one proposed by Price and Reddy[15] to find corresponding regions in the two images.

Object size (perimeter) and shape (roundness=perimeter^2/ 4πarea) were used to find the two most similar object pairs in the two images. Let's call them P and Q. Now relative distance (distance of the center of gravity of an object to the center of gravity of P/distance between center of gravities of P and Q), and relative position (angle beteen the line connecting the center of gravity of an object to the center of gravity of P, and the line connecting the center of gravities of P and Q) are used to match the rest of the objects. Since we have two kinds of objects (bright objects in dark background and dark objects in bright background) , the match is carried out only between objects of the same kind. Once the corresponding objects in the two images are determined, their boundaries are extracted (see figures 5 and 6), and their center of gravities are computed which are the control points.

C. TRANSFORMATION FUNCTIONS

The two images which we are registering have been derived from a single image by artificially introducing translational, rotational, and scale change. Therefore, one would suspect that the transformation of Cartesian coordinate systems would be able to bring the images into registration. Using the control points, we computed the ratio of corresponding line segments and found that the ratios change slightly when changing the line pairs. This shows that one of the images has small geometric distortion with respect to the other. Such distortion might be due to the digitizer lens or shrinking of the print's paper. The transformation function that can register images with geometric distortions is the polynomial mapping function. We used a second order polynomial mapping function given by,

$$x' = a0+a1x+a2y+a3xy+a4x^2+a5y^2$$

$$y' = b0+b1x+b2y+b3xy+b4x^2+b5y^2$$

Figure 7 shows a resampled image of figure 2 using the above polynomial mapping function with the nearest neighbor technique. We also used the transformation of Cartesian coordinate systems and the affine transformation. However, these transformation functions did not give satisfactory results.

The accuracy of the whole registration process to a large extent depends upon the accuracy of control points. In order to check the accuracy of the control points we segmented the images with different threshold values (from 90% to 99.5%) and computed the center of gravities of the objects for each threshold value. The maximum shift in the center of gravity was 0.7 pixels and the average shift was 0.4 pixels. Therefore, the center of gravities appear to be stable over a reasonable range of threshold values used in the segmentation process.

VI. CONCLUSION

An automatic technique for registration of images that may have translational, rotational, and scaling differences has been presented. This technique can also be applied to images with small shearing and geometric distortions (such that in the domain of an object the shearing and geometric distortions is negligible). Images with distortions due to earth rotation, earth curvature, and scanner nonlinearity can be registered using this technique.

More research is required to see the feasibility of this technique in registering images obtained by different satellites and/or different sensors.

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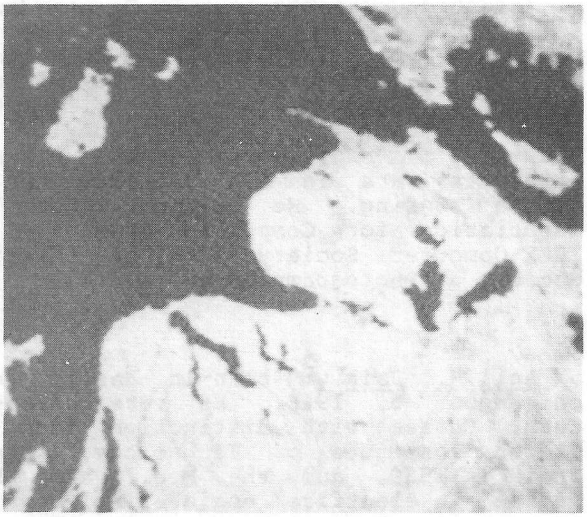

Figure 1. Digital image acquired by HCMM satellite.

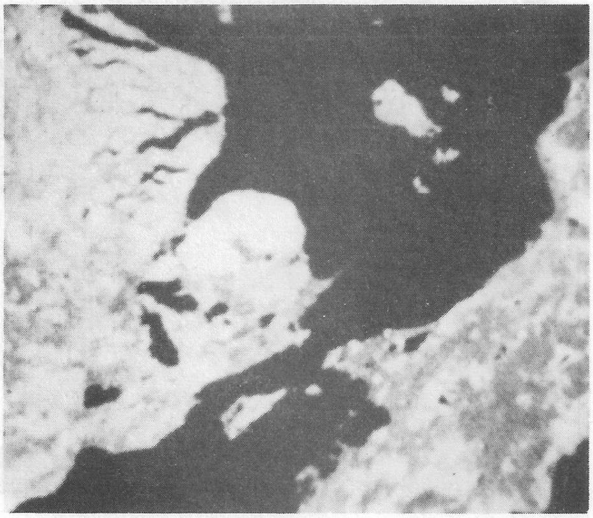

Figure 2. Digitized image of the print.

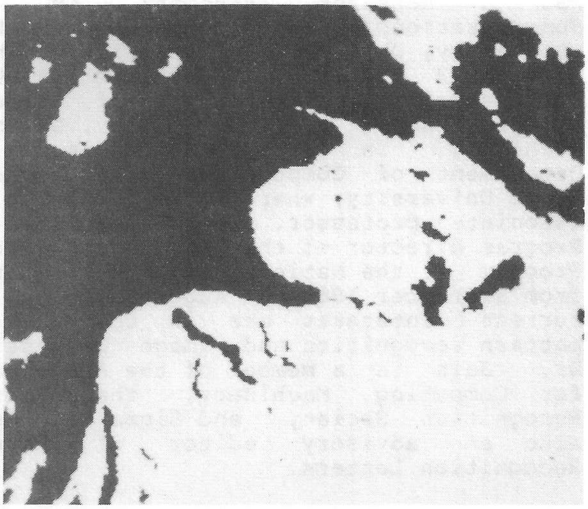

Figure 3. Segmentation of image of figure 1.

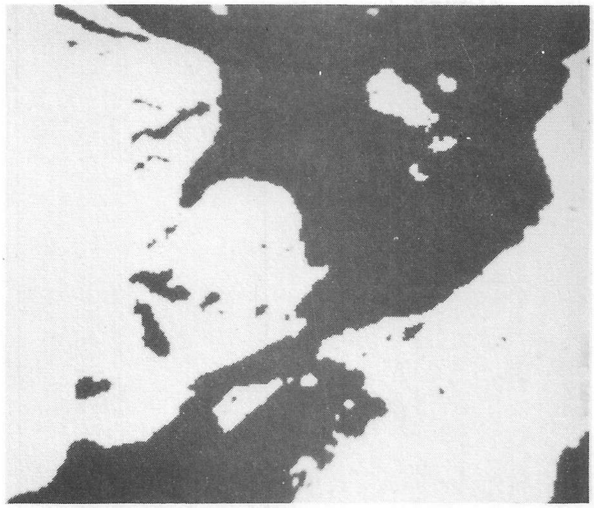

Figure 4. Segmentation of image of figure 2.

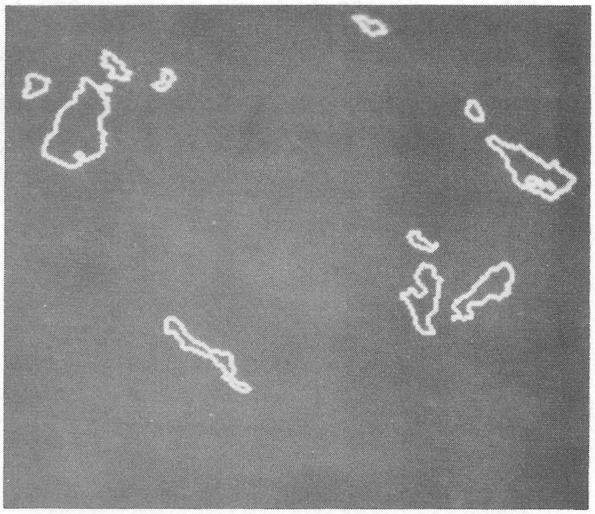

Figure 5. Dominant objects of image of figure 3.

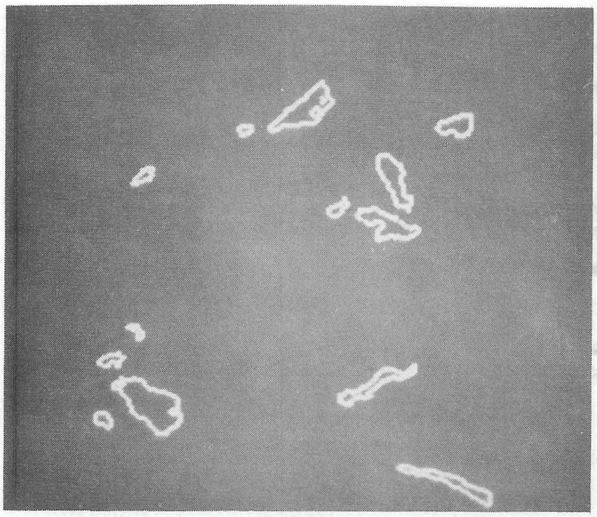

Figure 6. Dominant objects of image of figure 4.

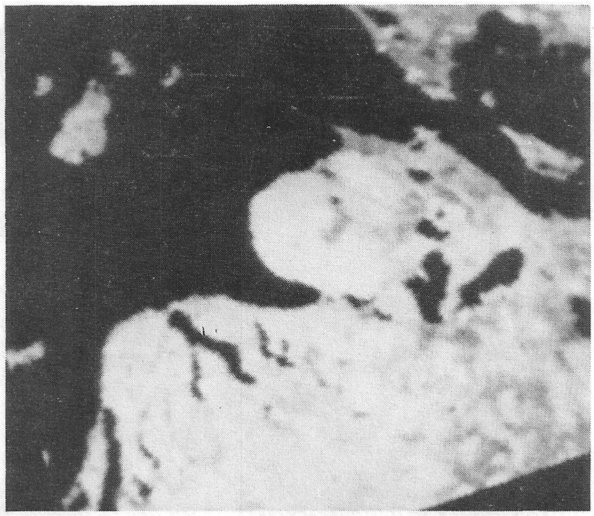

Figure 7. Resampling of image of figure 2 to register with image of figure 1.

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