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Automatic Image Registration through Histogram-Based Image Segmentation

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Abstract :
Image registration is the process of transforming different sets of data into one coordinate system. Automatic image registration is still an actual challenge in several fields like computer vision and remote sensing applications. In this project, a method for automatic image registration through histogram-based image segmentation is proposed. This new approach mainly consists in combining the pair of images to be registered are segmented, according to a relaxation parameter on the histogram modes delineation (which itself is a new approach), followed by a consistent characterization of the extracted objects through the objects area, ratio between the axis of the adjust ellipse, perimeter and fractal dimension and a robust statistical based procedure for objects matching. The main aim of this proposed methodology is illustrated to simulated rotation and translation. The first dataset consists in a photograph and a rotated and shifted version of the same photograph, with different levels of added noise. This allows for the registration of pairs of images with differences in rotation and translation.

Key words:

1. INTRODUCTION

The term digital image refers to processing of a two dimensional picture by a digital computer. In a broader context, it implies digital processing of any two dimensional data. A digital image is an array of real or complex numbers represented by a finite number of bits. An image given in the form of a transparency, slide, photograph or an X-ray is first digitized and stored as a matrix of binary digits in computer memory. This digitized image can then be processed and/or displayed on a high-resolution television monitor. For display, the image is stored in a rapid-access buffer memory, which refreshes the monitor at a rate of 25 frames per second to produce a visually continuous display. An image processor does the functions of image acquisition, storage, preprocessing, segmentation, representation, recognition and interpretation and finally displays or records the resulting image. The following block diagram gives the fundamental sequence involved in an image processing system. As detailed in the diagram, the first step in the process is image acquisition by an imaging sensor in conjunction with a digitizer to digitize the image. The next step is the preprocessing step where the image is improved being fed as an input to the other processes.

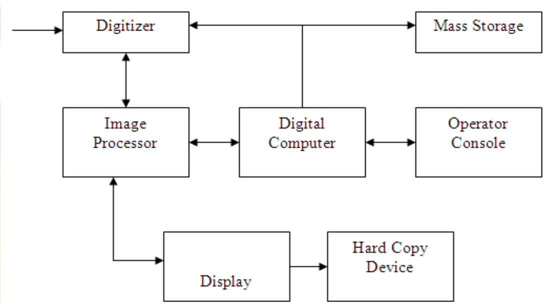

FIG 1.1 BLOCK DIAGRAM FOR IMAGE PROCESSING SYSTEM

Preprocessing typically deals with enhancing, removing noise, isolating regions, etc. Segmentation partitions an image into its constituent parts or objects. The output of segmentation is usually raw pixel data, which consists of either the boundary of the region or the pixels in the region themselves. Representation is the process of transforming the raw pixel data into a form useful for subsequent processing by the computer. Description deals with extracting features that are basic in differentiating one class of objects from another. Recognition assigns a label to an object based on the information provided by its descriptors. Interpretation involves assigning meaning to an ensemble of recognized objects. The knowledge about a problem domain is incorporated into the knowledge base. The knowledge base guides the operation of each processing module and also controls the interaction between the modules. Not all modules need be necessarily present for a specific function. The composition of the image processing system depends on its application. The frame rate of the image processor is normally around 25 frames per second.

2. PROPOSED METHODOLOGY

We propose an automatic registration through histogram based segmentation, which allows for a more detailed histogram based segmentation, rather than the traditional methods, and consequently to an accurate image registration. This project is able to estimate the rotation and/or translation between two images.The Advantages of our methodology are: This method is very advantageous to generate accurate rotation and shift of a base image with respect to unregistered image, register base image with unregistered image. HAIRIS outperformed SIFT and the contour-based approach, in particular for the remote sensing examples.

Pre-processing:

In this project before we process the images (such as base image and unregistered image) through adaptive wiener filter for removing additive random noise in both images, first we overcome significant differences between the histograms of images to be registered, an histogram equalization of unregistered image using the histogram counts of base image is performed prior to the application of the Wiener filter. In this way, the Wiener filtering on images allows both for the reduction of the image detail, as well as to the smoothing of the histogram, which becomes spiky due to the histogram equalization step.

Below procedure indicates the removal of noise in image by using adaptive wiener filter and regarding images are also shown. First take original color (RGB) image and convert the image into gray image by using matlab command rgb2gray.

Example:

OriginalRGB = imread (image1.bmp);
Gray image=rgb2gray (originalRGB);

Fig2.1 : original RGB image and its gray image

Add Gaussian noise with variance 0.025 and mean 0 in gray image using imnoise command and remove that noise using adaptive wiener filter.

Example:

J = imnoise (Gray image, 'gaussian', 0, 0.025);
H=wiener2 (J, [3 3]);

FIG 2.2: Noisy And Noise Removed Image

Use of Histogram Equalization of image:

It enhances the contrast of images by transforming the values in an intensity image so that the histogram of the output image approximately matches a specified histogram.

Fig2.3: Original Gray Image And Its Histogram Equalization Image

Histogram-Based Segmentation And De-lineation:

In this module before going to segment an image, first we are going to analyzing the histogram of the image. The basis of histogram analysis approach is that the regions of interest tend to form modes (a dominating peak that could represent a region) in the corresponding histogram. For example, a light object in a dark background might produce two modes in the image's gray level histogram, one is at the bright intensity side, and the other is at the dark intensity side. Then, a typical image segmentation approach based on histogram analysis generally carries out three steps: First, recognize the modes of the histogram. Second, remove the unwanted peaks (too small compared to the biggest peak) in the histogram, suppose i_{max} is the value of the highest peak satisfying h_{max}=h (i_{max}) . For any peak j, if h((j)/h_{max}) <0.05 then peak is removed. Since the values have been normalized to the range [0, 1], h_{max} is equal to 1. Therefore, the points with h (j) <0.05 will be removed. Third, find the valley between different two highest modes. Fourth, apply threshold to the image by using deepest valley between two highest peaks.

The method used for mode delineation is based upon the analysis of the consecutive slopes of the histogram. Let x (m) be the image histogram counts, m=0…M. and the sequence of the consecutive slopes, where M+1 is the number of histogram levels (M=255 for an 8-b image). The idea behind this approach is to choose an adequate threshold for considering whether or not one is in the presence of a mode, which is characterized by a significant increase and/or decrease on the slopes sequence .

$$\boldsymbol{y(n) = x(n) - x(n-1)} \quad (2)$$

Therefore, one obvious and functional solution for delineating a mode is to obtain a confidence interval for the slopes sequence, where the presence of a mode is detected by the slopes which are outside the 99% confidence interval. In order to achieve a robust detection through the statistical approach of the confidence interval, a preprocessing of the slopes is required, in order to smooth the slopes sequence irregularity outside the presence of a mode, which may induce the detection of false modes. This preprocessing is performed through a second-order low-pass Butterworth filter, with a normalized cutoff frequency at 0.25.

IMAGE SEGMENTATION:

Generally image segmentation means separating background and foreground image. Below procedure indicates the general image segmentation procedureFirst of all take gray image (black and white image) and calculate threshold using graythreshfunction.Second segment the gray image using im2bw command

For Example:

A=imread ('grayimage.bmp');
Threshold=graythresh (A);
Segmented Image=im2bw (A, Threshold);

In this project, Segment the image using threshold i.e. deepest valley that is in between two highest modes (or) peaks, but not graythresh.

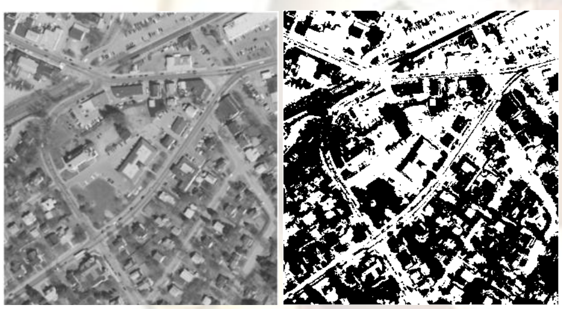

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FIG 2.3: Original Gray Image And Its Segmented Image

Matching:

The matching step begins with the evaluation of a cost function, between every possible two-by-two combination of objects obtained by the segmentation of the two images, for every possible combination of the alpha values considered for both images. This leads to a matrix with n1 rows and n2 columns, where n1and n2 correspond to the number of extracted objects from images 1 and 2, respectively. The cost function, evaluated for the values of the properties of the objects from images 1 and 2, is defined as follows

Cost function= $(A_{rea1}-A_{rea2})/Avg\ (A_{rea}) + (AR_{at1}-AR_{at2})/Avg\ (AR_{at}) + (P_{erim1}- P_{erim2})/Avg(P_{erim}) + (D_{b1}-D_{b2})/ Avg(D_b)$.

Then, the cost function values are represented in the form of boxplots, with the image which led to the lower number of segmented objects corresponding to the horizontal ("categorical") axis. A valid matching between two objects should lead to the lower values of cost function, sufficiently far from the majority. This can be statistically evaluated through the outlier detection criterion used in the boxplots representation, where a point is considered an outlier (regarding the smaller values) if it is smaller than, Q1-K*(Q3-Q1) where Q1andQ3 are the first and third quartiles, respectively. Similarly where a point is considered an outlier (regarding the higher values) if it is greater than, Q1+K*(Q3-Q1). Although K is typically considered as 1.5, in this step the more flexible value of 1 is required (also commonly used in practice), in order to reduce the loss of eventual matching candidates.

Rotation Estimation and Translation Estimation

This rotation estimation is entirely statistical base procedure; First we obtain orientation of extracted objects from base and unregistered image and perform the difference of orientation between every possible two-by-two combination of objects obtained by the segmentation of the two images and estimate robust angle by using same boxplot procedure indicated in above module.This translation estimation is entirely statistical base procedure; First we obtain orientation of extracted objects from base and unregistered image and perform the difference of orientation between every possible two-by-two combination of objects obtained by the segmentation of the two images and estimate robust angle by using same boxplot procedure indicated in above module.

General example for how to rotate and shift image

A=imread('peppers.png');B=rgb2gray(A);C=Imrotate(B,angle);

figure(1),imshow(C);

FIG2.4: Illustrates Original And Its RotatedImage

FIG2.5: Illustrates transformed and Transformed image with showing shifting location

$$\text{xform}= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 60 & 40 & 1 \end{bmatrix};$$

shift_xdirection=xform(3,1);
shift_ydirection=xform(3,2);
tform_translate=maketform('affine',xform);
[trans_imagexdataydata]= imtransform(aa, tform_translate);
cb_trans2 = imtransform(aa, tform_translate,'XData', [1 (size(aa,2)+xform(3,1))],'YData',[1 (size(aa,1)+ xform(3,2))]);

3. EXPERIMENTAL RESULTS

InthissectionwepresentagreedyhistogramclusteringalgorithmwhichtakesasinputapartitionedimageandobtainsahistogramclusteringbasedontheminimizationofthelossofMI.Thatis,wegroup thebinsofthehistogramsothattheMIismaximallypreserved.From theperspectiveoftheinformation bottleneckmethod,the binningprocessiscontrolledbyagivenpartitionoftheimage clusteringalgorithmhasbeenpreviouslypresented.

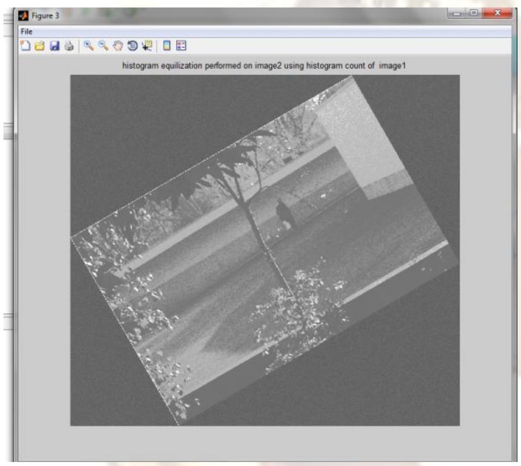

Fig.3.1Delineated Analyzed Image

5.Conclusion:

In this work, HAIRIS was applied to single-band images at a time. However, in the future, adequate transformations (such as principal component analysis, independent component analysis, among others) of multi- (or hyper-) spectral images to single band images will certainly lead to even better results, rather than using the information of a single spectral band. The proposed methodology of image registration allowed for the obtention of accurate results, even in the presence of a considerable amount of noise. Furthermore, under the scope of applications with images having less evident objects, as is the case of remote sensing images, HAIRIS has shown to correctly register a pair of images at the subpixel level covering a wide range of situations (including multitemporal and multisensor).

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