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Medical Image Analysis

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***Abstract*— Image analysis has an important role in many applications ranging from medical imaging to astronomy. It is the process of identifying and understanding patterns that are relevant to the performance of an image based task. It is different from other image processing applications like restoration, enhancement and coding where the output is another image. The image is processed in such a way that it removes all unwanted information retaining only that part of the image which contributes significantly to the analysis task. The analysis task creates a mapping from a digital image to the description of image's content. The image description can either be a number which would represent the number of objects in the image, or it can be a degree of anomaly which would define the shape variation of an object or it can be labelling of pixels to classify different regions of the image. Until early 90s, image processing was performed with specially designed and constructed areas of memory called framestores and the performance and speed were rather slow. But, now it is possible to download image analysis software from a number of websites and perform the task of analysis with less effort.**

There are three levels in image analysis. In the low level processing, functions that may be viewed as automatic reactions are dealt where as intermediate level processing deals with the task of extracting regions in an image that results from a low level process. High level processing deals with recognition and interpretation tasks. Image analysis is performed using either bottom up approach or top down strategy. In bottom up approach, low level features are extracted from the raw image data and later, this is processed in higher levels. In top down approach, the image characteristics are hypothesized at the highest level and is proceeded towards the lower level until the raw image has been reached (Gonzalez and Woods, 2000; Mantas, 1987). Image analysis involves the study of feature extraction, segmentation and classification (Jain, 1995).

Keywords-* *(key words)

I. IAPPLICATON OF IMAGE ANALYSIS

Image analysis in the areas of medicine, biology or in movie production usually requires the processing of thousands of images. Therefore automatization is crucial in these applications. Much of the development work in image analysis has been done in the medical field since medical images contain a wide spectrum of information. Examples of medical images are those obtained using X-rays, magnetic resonance, ultrasound, cine-angiograms etc. In recent years, the design of computer-based display mechanisms (large video screens, head-mounted displays, high definition screens) which can perform better compared to the conventional display methods such as X-ray images on film or Computerised Tomography images attracted the attention of a number of researchers.

Another potential field of application where image analysis is performed is astronomical image processing. Vision models have been developed for the automated identification of the astrophysical sources and their relevant measurements depending on the image content. Several image analysis tools are available in astronomy, of which the most commonly used is the Graphical Astronomy and Image Analysis Tool (GAIA). GAIA provides the features like highly interactive environment for controlling the positions, sizes and orientations of circular and elliptical apertures, ability to automatically detect and parameterise all the objects on an image, identification of extended objects (galaxies) and profile measurements using ellipse fitting, ability to select arbitrary shaped regions on an image and replace them with a surface fit to other regions, image statistics, contouring of the displayed image, ability to display vector maps produced by the POLPACK package etc (Draper et al., 2001). Developments are still progressing in the area of astronomical image analysis since most of the software available are not sufficient in computing large variety of digital sky surveys.

II. ESEGMENTATION TECHNIQUES

Segmentation is the process of identifying regions of pixels in an image. The main goal is to divide an image into parts that have a strong correlation with objects or areas in the real world. There are three classes of segmentation procedures; global knowledge, edge based and region based. Global knowledge methods rely on knowing something about the image such as the expected pixel intensity. Edge based methods find the borders between regions. Region based methods use different properties of the image to define regions such as grey level, color, texture, shape etc.

Over the past thirty years or so, classification and segmentation has been studied using human and vision perspectives. The three decades have witnessed a slow but steady evolution of techniques ranging from co-occurrence matrices to Markov random field. The main aim is to recognise homogeneous regions within an image as distinct and belonging to different objects. The segmentation process can be based on finding the maximum homogeneity in grey levels within the regions identified. There are several issues related to image segmentation. One of the common problems encountered in image segmentation is the choosing of a suitable approach for isolating different objects from the background. The segmentation doesn't perform well if the grey levels of different objects are quite similar. Image enhancement techniques seek to improve the visual appearance of an image. They emphasize the salient features of the original image and 'simplify the task of image segmentation. The type of operator chosen has a direct impact on the quality of the resultant image. It is expected that an ideal operator will enhance the boundary differences between the objects and their background making the image segmentation task easier. Issues related to segmentation involve choosing good segmentation algorithms, measuring their performance, and understanding their impact on the scene analysis system.

A segmented image consists of two regions namely homogeneous region and transition region. The most difficult task in a vision system is to identify the sub images that represent objects. Region detection though appears simple for human is not an easy task for computers. The partitioning of images into sub images is what is done in segmentation. In other words, segmentation is grouping of pixels into regions (Ri) such that

(i) $\bigcup_{i=1}^{k} R_i = \text{Entire image}$

(ii) $R_i \cap R_j = \Phi, \quad i \neq j$

(iii) The pixels belonging to region R_i possess some common characteristics.

(iv) Pixels belonging to adjacent regions possess different characteristics.

There are different techniques for finding object regions in grey-level images. They are histogram thresholding, edge detection, tree/graph based approach, region growing, clustering.

A. Histogram Thresholding

In histogram thresholding, the picture is thresholded at its most clearly separated peak. The process iterates for each segmented part of the image until no separate peaks are found in any of the histograms. The criteria to separate peaks was based on the ratio of peak maximum to peak minimum to be greater than or equal to two.

B. Edge Detection

Edge detection provides an automatic way of finding boundaries of one or more objects in an image. From an image containing many objects edge detection allows us to single out a particular object of interest. Edge detection is used in many applications. In edge based segmentation, pixel neighbourhood elements are used for image segmentation. For each pixel, its neighbours are first identified in a window of fixed size. A vector of these neighbours as individual grey values or vector of average grey levels in windows of size 1 x 1, 3 x 5.and 5 x 5 is determined. Then a weight matrix is defined which when multiplied with these vectors will yield a discriminant value that allows the classification of pixel in one of the several classes (Cheriet et al., 1998).

C. Tree/Graph based approach

In Tree/graph based approaches segmentation is derived from the consensus of a set of different segmentation outputs on one input image. Instead of statistics characterising the spatial structure of the local neighbourhood of a pixel, for every pair of adjacent pixels their collected statistics are used for determining local homogeneity. Several initial segmentations are derived from the same input image by changing the probabilistic component of the hierarchical Region Adjacency Graph (RAG) pyramid based technique. From the ensemble of these initial segmentations, for every adjacent pixel pair, a co-occurrence probability is derived, which captures global information (about the image) at the local level (pixel level). The final segmentation of the input image is obtained by processing the co-occurrence probability field with the same RAG pyramid technique. The pixel pairs with high co-occurrence probability are then grouped together, based on the consensus about local homogeneity.

D. Region Growing

Another segmentation approach is based on region growing. Region growing algorithms take one or more pixels, called seeds, and grow the regions around them based upon a certain homogeneity criteria. If the adjoining pixels are similar to the seed, they are merged with them within a single region. The process continues until all the pixels in the image are assigned to one or more regions.

E. Clustering

Image segmentation can be performed effectively by clustering image pixels. Cluster analysis allows the partitioning of data into meaningful subgroups and it can be applied for image segmentation or classification purposes. Clustering analysis either requires the user to provide the seeds for the regions to be segmented or uses non-parametric methods for finding the salient regions without the need for seed points. Clustering is commonly used in a range of applications such as image segmentation and unsupervised learning (Jain and Dubes, 1988). A number of issues related to clustering are worth studying including how many clusters are the best and how to determine the validity of clusters. In a number of segmentation techniques, such as fuzzy c-means clustering, the number of clusters present in the image have to be specified in advance.

F. Neural Networks Segmentation

Campbell et al. (1997) proposed an automatic segmentation and classification method for outdoor images using neural networks. In their work, the images are segmented using Self-Organising Feature Maps (SOFM) based on texture and colour information of the objects. SOFMs used consisted of 64 x 64 nodes for best segmentation. A set of 28 features is then extracted from each region. The features include: average colour, position, size, rotation, texture (Gabor filters) and shape (using principal components). Classification is then performed using a Multi Layer Perceptron with 28 input nodes and 11 output nodes. The training is performed on 7000 regions and testing is done on an independent set of 3000 samples. Over 80% regions were classified correctly using Learning Vector Quantisation and 91.9% regions were classified correctly using the Multi Layer Perceptron. (Sharma, 2001)

III. ALGORITHMS USED FOR SEGMENTATION

The different segmentation algorithms implemented (Jain et al., 1995) in the present study are iterative thresholding, region growing and histogram based thresholding.

A. Iterative thresholding

Select an initial estimate of the threshold, T.

1. Partition the image into two groups, R_1 and R_2, using the threshold T.
2. Calculate the mean gray level μ_1 and μ_2 of the partitions R_1 and R_2.
3. Select a new threshold

   $T = \frac{1}{2} (\mu_1 + \mu_2)$

5. Repeat steps 2-4 until the mean values μ_1 and μ_2 in successive iterationsdo not change.

Here the average of the pixelwise fractal dimensions is taken as the initial estimate for T.

B. Region Growing

1. Select two thresholds T1 and T2.
2. Partition the image into three regions R1, R2 and R3 .R1 contains all pixels with grey values below T1. R2 contains pixels with grey values between T1 and T2. R3 contains pixels with gray values above T2.
3. Each pixel in R2 is examined. If it has a neighbor in region in R1, then reassign the pixel to region R1.
4. Repeat step 3 until no pixels are reassigned.
5. Reassign any pixels left in region R2 to region R3.

C. Histogram based segmentation

1. Partition the image into different blocks.
2. Find fd for each block
3. Plot histogram for the fractal dimension obtained above
4. Assign the peak value as the threshold to segment the image.

Altogether, nine different algorithms are implemented on a set of images that comprise of solar images and test images. The solar images were those maintained by Bear Solar Observatory and SOHO and the test images were prepared by Jahne and Haubecker (2000).

IV. DATA SET

The above methods were applied to a set of test images and a sequence of solar images. The automatic identification of solar features, such as faculae and plages, is becoming increasingly important as the resolution and the size of solar data sets increases. The introduction of space borne solar telescopes, in addition to the ground based observations have increased the solar image data set many fold. The identification of solar features are required for the quantitative study of the solar activity, which includes locations, lifetimes, contrasts, and other characteristics of sunspots and faculae etc and the modeling of the total solar irradiance and variations of sunspot and facular properties with latitude and/or solar cycle phase.

A portion of the chromospheric image from Bear Solar Observatory (http://www.bbso.njit.edu) obtained on April 1, 2009 is chosen for study (figure 4.2 (a)). The images are recorded on photographic film and later digitized. The detection of plage regions from chromospheric image is done and is suggested as a means of understanding the shape of plages and their evolution.

The solar images selected are gray scale images of size 226 x 251 with intensity variation from 0 to 255. Solar and heliospheric observatory (SOHO) continuously monitors solar atmosphere using Extreme ultra violet Imaging Telescope (EIT) at four wavelengths 171 A0, 195 A0, 284 A0 and 304 A°, shown as blue, green, yellow and red respectively. The solar images taken at different wavelengths provide information about the features at different altitude regions of the solar atmosphere and their time evolution (http://sohowww.nascom.nasa.gov). In this work, we have tried to identify the bright -regions in the solar atmosphere from the solar images taken at different wavelengths. By analyzing the bright regions, we can get an idea about the geometry of the surface magnetic field at different altitude region of the Sun and also its time evolution.

At present, to determine the plage areas, one has to either apply a threshold or manually surround the plages with polygons. The thresholding method ignores the spatial information contained in the image. The second method uses a large amount of information and is highly subjective (Turmon and Mukhtar, 1997).

Conclusion

The purpose of image analysis is to extract symbolic information from an image. Many of the image processing techniques which are valuable as visualization tools are useful at preprocessing stages in the image analysis task. In the simplest terms, image analysis involves mapping of a concrete image into an abstract symbolic representation. The ultimate goal of image analysis is the identification of a scene and all objects in the image. Image analysis can be described as a set of techniques required to extract symbolic information from the image data.

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