Over segmentation Minimization in Digital Image Processing Using Mean Shift Algorithm

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ABSTRACT; We proposed a novel method for face matching from face image database. In our method we have taken set of face images so recognition decisions need to be based on comparisons of face image database. This paper presents an approach to region based face matching. The low level image segmentation method mean shift is used to divide the image into many small regions. As a popular segmentation scheme for color image, watershed has over segmentation as compared to mean-shift and also mean-shift preserves well the edge information of the object. The proposed method automatically merges the regions that are initially segmented by mean shift segmentation, effectively extracts the object contour and then, matches the obtained mask with test database image sets using color and texture. Extensive experiments are performed and the results show that the proposed scheme can reliably form the mask from the face image and effectively matches the mask with face image sets.

General Terms: Digital Image Processing, Segmentation, Face recognition.

KEYWORDS: Face Matching, Image segmentation, Region merging, Watershed, Mean shift algorithm.

I.INTRODUCTION

Image Segmentation is a process of splitting an image into multiple regions or sets of similar pixels. The aim of segmentation is to easier and/or changes the depiction of an image into more meaningful and easier to analyze. Image segmentation is specially used to locate objects and boundaries (lines, curves, etc.) in images. Actually, partitioning is done on the basis of same texture or color. The outcome of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. This technique has a variety of applications and one of them is face matching.

Face matching is an important vision task with many practical applications such as biometrics, video surveillance, and content based image retrieval. A face matching system is a computer application for automatically identifying or verifying a person from a digital image or a video frame from a video source. One of the method to do this is by comparing extracted facial features from the image and a image database. Face matching has a variety of applications on commercial, security, image retrieval and law enforcement. For a given face image, face matching matches with all the given images in database. This is quite a demanding task from the perspective of pattern recognition. Although there has been a rapid growth of large scale data bases, we have focused only on the accuracy with small databases. In this work, we Consider face matching as a law enforcement application in which an unknown face is to be matched on a database.

In this work we first divide the face image into number of segments using mean-shift algorithm, then using region merging [1] iteratively merge the similar regions to find the desired mask of the face image. We used reiterative procedure to merge different regions based on the probability of the regions. Regions are merged until desired segment is obtained. We are not using watershed algorithm because watershed gives over segmented regions and is more time consuming to find the desired mask as compared to mean shift. Finally the image mask obtained after merging is compared with database face images using a histogram approximation on the basis of color and texture..

II.LITERATURE REVIEW

In region merging style image segmentation is done with combining different methods at low level such as watershed algorithm, graph-based approach, mean-shift algorithm etc. Peng et al., [1] taken initially over segmented image, in which many regions (or super pixels) with homogeneous color are detected, an image segmentation is performed by iteratively merging the regions according to a statistical test. There are two basic issues in a region-merging algorithm: sequence of merging and the ending criterion. These two issues are solved in DRM [1] by using novel predicate which

is defined by the sequential probability ratio test and the minimal cost criterion. This method uses Watershed algorithm to produce over segmented image having many regions, neighbouring regions are progressively merged if there is an evidence for merging according to this predicate.

[1] Shows that the merging order follows the principle of dynamic programming. To improve efficiency this method is combined with Automatic Image Segmentation using Wavelets transform. Image segmentation is important method in biometrics as it is the first step in image processing and pattern recognition. Model based algorithms are used for efficient segmentation of images where strength is the prime feature. The main issue of random initialization is overcome by using Histogram based evaluation. The Wavelet transform overcome the problem of resolution which can specify the image without information loss and minimize the complexity. The segmentation is faster where coefficients of DWT are considered. Model-based segmentation algorithm is more efficient compared to other methods. The pixel strength based image segmentation is obtained using RGB Histogram-Based method, Edge-Based method, Region-Based method and Model-Based method. Model- Based segmentation algorithms is more efficient compared to other methods as they are dependent on suitable probability distribution attributed to the pixel intensities in the entire image. To achieve close approximation to the realistic situations, the pixel intensities in each region follow Generalized Gaussian Distribution (GGD).

J. Ning et al., [5] presents Efficient and effective image segmentation is an important task in computer vision and object recognition. Fully automatic image segmentation is usually very hard for real images, coordinative schemes with a few simple user inputs are good solutions. The work presents a region merging based on interactive image segmentation method. The users require to roughly indicate the location and object region and background by using strokes, which are called markers. A novel highest similarity based region merging mechanism to guide the merging process with the help of markers.

A region q is merged with its adjacent region p if p has the highest similarity with p among all p's adjacent regions. This method automatically merges the regions that are initially segmented by mean shift segmentation, and then effectively extracts the object contour by labeling all the non-marker regions as either background or object. The region merging process is essential to the image content and it does not need to set the similarity parameter in advance. A substantial experiment shows that this scheme can reliably extract the object contour from the complex background.

Kostas et al , [6] A hybrid multidimensional image segmentation algorithm is proposed, which combines edge and region-based techniques through the morphological algorithm of watersheds. An edge-preserving statistical noise reduction approach is used as a pre-processing stage in order to compute an accurate estimate of the image gradient. Then, an initial partitioning of the image into primitive regions is produced by applying the watershed transform on the image gradient magnitude. This initial segmentation is the input to a computationally efficient hierarchical (bottomup) region merging process that produces the final segmentation. The latter process uses the region adjacency graph (RAG) representation of the image regions.

At each step, the most similar pair of regions is determined (minimum cost RAG edge), the regions are merged and the RAG is updated. Traditionally, the above is implemented by storing all RAG edges in a priority queue. We propose a significantly faster algorithm, which additionally maintains the so-called nearest neighbor graph, due to which the priority queue size and processing time are drastically reduced. The final segmentation provides, due to the RAG, one-pixel wide, closed, and accurately localized contours/surfaces. Experimental results obtained with two-dimensional/three-dimensional (2-D/3- D) magnetic resonance images are presented .

Prasad Reddy et al., [7] proposed a color image segmentation method based on Finite Generalized Gaussian Distribution (FGGD).

Lazy Snapping separates rough and fine scale processing, making object determination and detailed adjustment easy. Moreover, Lazy Snapping defines instant visual feedback, snapping the cutout contour to the true object boundary efficiently despite the presence of ambiguous or low contrast edges. Fast outcome is made possible by a image segmentation algorithm which combines graph cut with pre-computed over-segmentation.

A set of inherent user interface (UI) tools is designed and implemented to provide flexible control and editing for the users. Accessibility studies indicate that Lazy Snapping provides a bet liter user experience and produces better segmentation results than the state-of-the-art interactive image cutout tool,of multi-variant substances and the primary parameters are estimated using K-Means algorithm. The final parameters are define using EM algorithm and the segmentation is obtained by clustering according to the ML estimation of each pixel. However, calculation time is more because of complex calculations.

Zhixin and Govindaraju [8] proposed hand written image segmentation using a binarization algorithm for camera images of old historical documents. This algorithm applying a linear approximation to determine the flatness of the background. The document image is optimized by adjusting the pixel values relative to the line plane approximation.

Watershed Algorithm
Watershed is a easier, inherent and efficient method for segmenting an image. The Watershed Algorithm shows a few limitations such as over –segmentation and poor detection of low boundaries. This Segmentation process merges regions of the watershed over-segmentation by minimizing a specific criterion using graph-cuts optimization. Method Two methods were introduced, the first is based on regions histogram and dissimilarity measures between adjacent regions. This method deals with efficient approximation of minimal surfaces and geodesics.

(a)   (b)   (c)
(d)   (e)   (f)
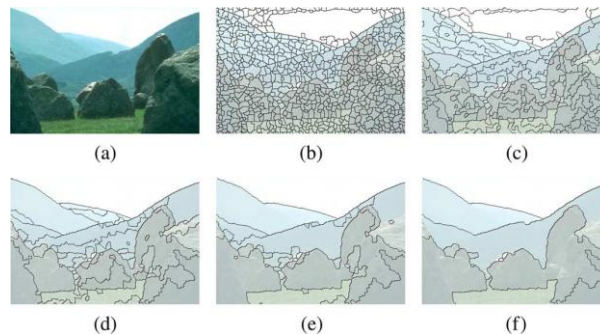
Drawback of over segmentation

We can see the watershed results over segmentation. This problem are reduced   to great extent by using mean shift. Segmentation results by the proposed algorithm. (From left to right; the first column) The original images. (Second column) The over segmentation produced by watershed algorithm. (The third column) watershed segmentation results.

Segmentation Algorithm : Mean-shift by region merging

The details of mean shift are discussed as below .
Given m data points yi, i = 1,… , n in the d-dimensional space Rd, the multivariate
kernel density estimator with kernel K(y) is

$$f(y) = \frac{1}{mrd} \sum_{i=1}^{m} k(\frac{y - yi}{r})$$

where r is one bandwidth parameter satisfying r $>$ 0 and K is the radially symmetric kernels satisfying
K(y) = c k,d k(y2),
where d, c, k is a normalization constant which induces K(y) integrate to one. The func-tion k(y) is the profile of the kernel, only for y$\geq$ 0.
Applying the profile notation, the density estimator can be written as

$$fr, k(y) = \frac{ck,d}{mrd} \sum_{i=1}^{m} k \left(\left\| \frac{y-yi}{r} \right\| \right)$$

For inspecting a feature space with the density f(y), to find the modes of this density. The modes are located among the zeros of the gradient $\Delta f(y)=0$
The second term is the mean shift i.e.

$$mh, g(x) = \frac{\sum_{i=1}^{n} xig \left(\left\| \frac{x-xi}{h} \right\| 2 \right)}{\sum_{i=1}^{n} g \left(\left\| \frac{x-xi}{h} \right\| 2 \right)} - x$$

Mean-shift is an extremely versatile tool for feature space analysis and suitable for arbitrary feature spaces but the kernel bandwidth is the only factor can control the output and the computation time is quite long.

To find the cluster center for point P1, repeatedly find the centroid of point inside a sphere (initially at P1) and recenter the sphere of a centroid until the sphere is stationary.
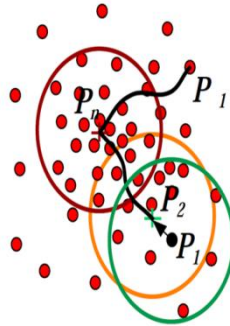

Figure 11: Illustration of Mean-shift analysis

III. PROPOSED METHODOLOGY

In this work we first uses mean- shift algorithm for segmentation of image. Image Segmentation is important in biometrics as it is the first step in pattern recognition and image processing. Now by using dynamic region merging approach we merge the similar regions on the basis of color.

We use recursive and interactive approach for the segmentation of the image. User start the process and the model starts merging the regions, after first iteration some regions that are most probable merged with each other and results with less regions and fewer pixels. Probability is calculated for each iteration.This process sustain until the desired process complete or there are no region remains in the image. Once the desire process complete it can stop the process. The final segment portion is obtained by the user intervention. The user can also find the final segmented image to extract the object of interest from the image. Then finally we match the mask with database face images on the basis of color and texture.

The flowchart of the proposed algorithm is given below:
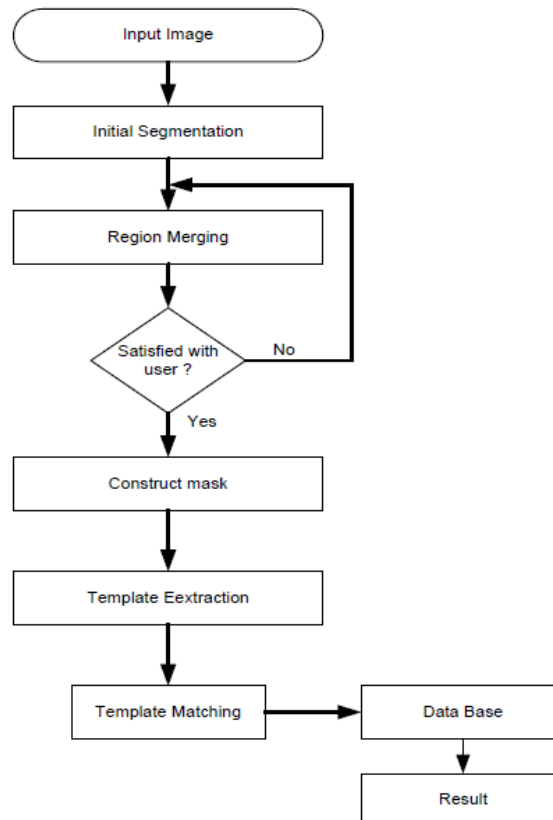
Fig. 1: Flow chart of proposed approach

A. IMAGE SEGMENTATION

Initial Segmentation

Initial Segmentation has done by using mean-shift algorithm. The mean shift algorithm is a clustering technique which is nor parametric and neither require prior knowledge of the number of clusters nor constrain the shape of the clusters. The mean shift clustering algorithm is a applicable for the mode finding procedure.

If P is set of all image pixels, then by applying segmentation we get different unique regions like { R1, R2, R3,…, Rn } which when combined formed 'P' . Basic formulation is as follows:

1. $\bigsqcup_p^n Rp = P$ where Rp $\cap$ Rj = $\emptyset$, p=1,n

2. Rp is a connected region, p=1, 2….n.

3. P(Rp) = TRUE for p=1, 2.. n.

4. P(Rp $\cup$ Rj) = FALSE for p $\neq$ j.

Where P(Rp) is a logical defined over the points in set Rp.
Stage (1) define that segmentation must be complete; every pixel in the image must be covered by segmented regions. Segmented regions must be disjoint. Stage (2) requires that points in a region be connected in some predefined sense like 4-neighbourhood or 8-neighbourhood connectivity. Stage (3) deals, the properties must be satisfied by the pixels in a segmented region e.g. P (Rp) = TRUE if all pixels in Ri have the same gray level. Last stage (4) indicates that adjacent

B. Region Merging

Region merging algorithm is started from a set of segmented regions, because a small region can provide more accurate statistical information than a single pixel, and using regions merging we can improve a lot the computational efficiency. We have so many small regions available in the edge map. A region can be described in many aspects, such as the color, edge [19], texture [20], shape and size of the region. Among them the color histogram is an effective descriptor to represent the object color feature statistics and it is widely used in pattern recognition [21] and object tracking [22] etc. Color histogram is robust feature descriptors. This is because the Primary segmented small regions of the desired object often vary a lot in size and shape, while the colors of different regions from the same object will have high similarity. So that we use the color histogram to represent each region. The RGB color detail is used to compute the color histogram. We uniformly quantize each color channel into16 levels and then the histogram of each region is calculated in the feature space of $16 \times 16 \times 16 = 4096$ bins. Here we choose to use the Bhattacharyya coefficient [25, 26, 27] to measure the similarity between regions.

Fig.3   (a)   (b)   (c)

Fig.3 (a) Original Image, (b) Initial Segmented Image, (c) Merged Image using region merging (after 5th iterarion)

C. Face Matching

After we get desired portion of face now we match this with the database face images on the basis of colour and texture. We proposed two algorithms for matching one for colour and other for texture.

Algorithm 1: Object Comparing Using Color

1. First we will select image. j = Set[imagename,imagepath];
2. WORK= Set(orgEdgeImage);
3. Start process of Region merging of Initial segmented regions i.e. WORK;

4. At every step check that whether that required object contour is obtained or not;
5. if (0) then go to step 3;
6. if (1) then select a seed pixels [p, q] from required object;
7. apply region growing method to obtain required contour;

Matching of Object with Database

8. Then we calculate histogram of input object and database images.
9. Now we compare object histogram with histograms of database images and show the results in percentage

Algorithm 2: Object Comparing using texture

Determine Texture for input image

1. Put query Image.
2. Generate Image mask of input Image
3. Now we determine texture of extracted object each pixel.
4. If pixel value is at position (s,i) then we calculate pixel value of
   (s+1,i), (s,i+1), (s-1,i), (s,i-1), (s+1,i+1), (s-1,i-1), (s+1,i-1), (s-1,i+1).

5. Calculate texture of all the database images with the above method.
6. Compare texture of extracted object with database images.
7. Display result in percentage

IV. RESULT AND ANALYSIS

In order to examine this algorithm, the experimental results were under the software environment of Matlab .We tested the proposed model on several face images in the database. The database contains around 500 face images. All of the images are first over segmented using the mean shift method [24]. After that we perform similarity region merging to merge the regions on the basis of colour. Then finally we match the desired portion of face image obtained from image mask with our database. Results have shown in figures below:

(d) (e) (f) Fig.6 (a) Input Image, (b) Initial Segmented Image, (c)Merged Image using region merging (after 5th iterarion)(d) Grey-scale Image (e) Image mask (f) Desired portion of Image

Results on the basis of colour in percentage:

Fig.7 (a) (b) (c)
(100.0000%) (79.2315%) (51.9856%)

(d) (e) (f)
(31.0201%) (26.0543%) (9.8952%)
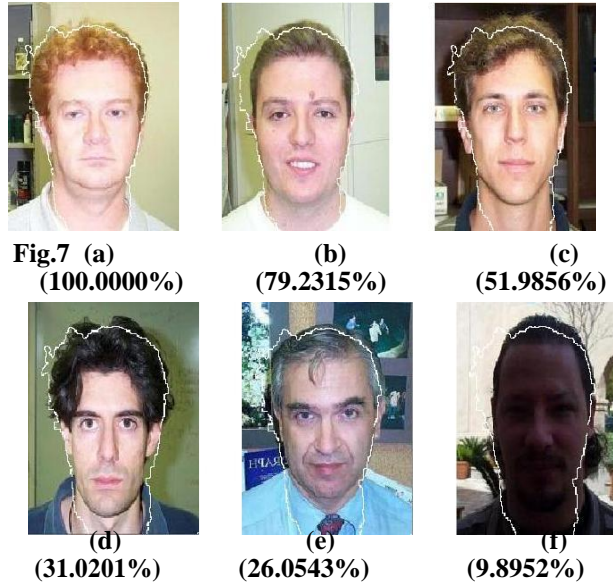
We first take an input image (fig.6), done its initial segmentation with the help of mean-shift. Perform merging iteratively to find desired portion of image, then find its image mask and extract desired portion. We compare or match the obtained desired portion with 500 database face images on the basis of colour and texture and find the results in percentage. Some of the results are shown in the fig.7 and fig.8 on the basis on colour and texture respectively. It is better than the previous methods in which watershed is used for initial segmentation because watershed gives over segmented image which takes more time in merging as compared to mean-shift. This proposed method is very efficient and simple and gives very good result.

Results on the basis of texture in percentage:

Fig. 8 (a) (b) (c)

(100.0000%) (96.5351%) (54.6784%)
(d) (e) (f)
(69.6734%) (89.0584%) (31.8459%)
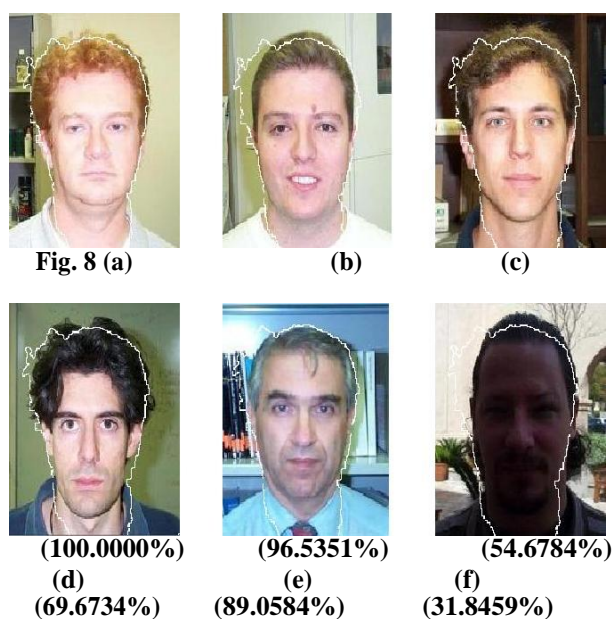
Fig.7 and 8. Shows the matching result with some of the images of database with desired portion of image on the basis of colour and texture in percentage.
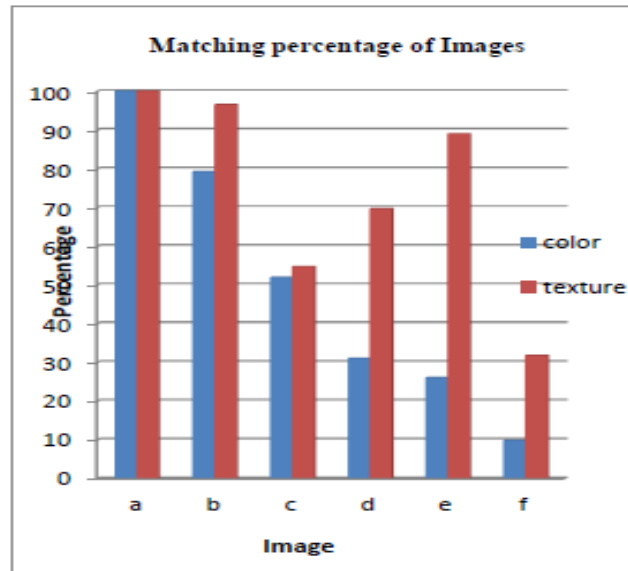
Chart 1: Shows matching percentage of images of fig.7 and fig.8 respectively with respect to desired portion of input image.

V. CONCLUSION

To summarize, we present a new face matching technique based on interactive image segmentation framework. The proposed method can systematically capture the relationships among different image regions to perform effective image segmentation. An image is first over segmented with the help of mean-shift to produce an edge map. The model performs region-merging based on the colour histogram of the image using Bhattacharya coefficient. After region merging object i.e. desired portion of image is extracted from input image. Then we match the desired portion with the database face images on the basis of colour and texture. It is an iterative procedure and number of iterations depends on the user satisfaction. Finally, we want to point out that this application is not limited to image segmentation. It can find applications in many different computer vision problems including object tracking, object recognition, content based image retrieval etc. Our experimental results demonstrate the promising capability of the proposed face matching technique.

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