Oversegmentation Avoidance in Face Matching for Color Images Using Mean Shift

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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 on the basis of 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.**

Keywords: **Face Matching, Image segmentation, Region merging, Watershed, Mean shift.**

I. INTRODUCTION

Image Segmentation is a process of partitioning an image into multiple regions or sets of homogenous pixels. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyse. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. Actually, partitioning is done on the basis of same texture or colour. The result 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 ways to do this is by comparing selected facial features from the image and a facial 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 an iterative procedure to merge several regions based on the probability of the regions. Regions are merged until the user is satisfied with the segmentation. 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..

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 essential issues in a region-merging algorithm: order of merging and the stopping 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, neighboring regions are progressively merged if there is an evidence for merging according to this predicate.

[1] show that the merging order follows the principle of dynamic programming. To improve efficiency this method is combined with Automatic Image Segmentation using Wavelets. Image segmentation plays an important role 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 intensity is the prime feature. The problem of random initialization is overcome by using Histogram based estimation. The Wavelet transform solves the problem of resolution which can indicate the signal without information loss and reduces the complexity. The segmentation is faster since approximation band coefficients of DWT are considered.

Model-Based image segmentation plays a dominant role in image analysis and image retrieval. To analyze the features of the image, model based segmentation algorithm will be more efficient compared to non-parametric methods. The pixel intensity based image segmentation is obtained using Histogram-Based method, Edge-Based method, Region-Based method and Model-Based method. Model- Based segmentation algorithms are 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. Since fully automatic image segmentation is usually very hard for natural images, interactive schemes with a few simple user inputs are good solutions. This paper presents a new region merging based interactive image segmentation method. The users only need to roughly indicate the location and region of the object and background by using strokes, which are called markers. A novel maximal-similarity based region merging mechanism is proposed to guide the merging process with the help of markers.
A region R is merged with its adjacent region Q if Q has the highest similarity with Q among all Q's adjacent regions. The proposed 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 adaptive to the image content and it does not need to set the similarity threshold in advance. Extensive experiments are performed and the results show that the proposed 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 preprocessing 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 .

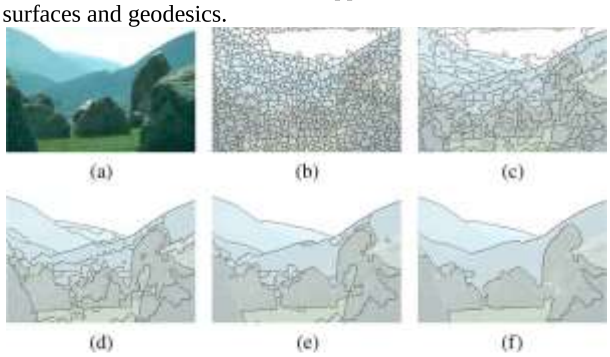
Prasad Reddy et al., [7] proposed a color image segmentation method based on Finite Generalized Gaussian Distribution (FGGD). The observed color image is considered as a mixture of multi-variant densities and the initial parameters are estimated using K-Means algorithm. The final parameters are estimated using EM algorithm and the segmentation is obtained by clustering according to the ML estimation of each pixel. However, computational time is more because of complex calculations.

Lei et al. [11] present Lazy Snapping, an interactive image cutout tool. Lazy Snapping separates coarse and fine scale processing, making object specification and detailed adjustment easy. Moreover, Lazy Snapping provides instant visual feedback, snapping the cutout contour to the true object boundary efficiently despite the presence of ambiguous or low contrast edges. Instant feedback is made possible by a novel image segmentation algorithm which combines graph cut with pre-computed over-segmentation.
A set of intuitive user interface (UI) tools is designed and implemented to provide flexible control and editing for the users. Usability studies indicate that Lazy Snapping provides a better user experience and produces better segmentation results than the state-of-the-art interactive image cutout tool,

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

Watershed Algorithm

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



Drawback of over segmentation

We can see the watershed results over segmentation.This problem is 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 oversegmentation produced by watershed algorithm. (The third column) watershed segmentation results.

Segmentation Algorithm :Mean-shift through region merging

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

$$f(x) = \frac{1}{nhd}\sum_{i=1}^{n} k(\frac{x-xi}{h}),$$

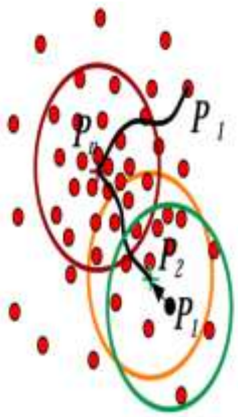
where h is one bandwidth parameter satisfying h > 0 and K is the radially symmetric kernels satisfying
K(x) = c k,d k(x2),
where c k,d is a normalization constant which induces K(x) integrate to one. The func-tion k(x) is the profile of the kernel, only for x ≥ 0.
Applying the profile notation, the density estimator can be written as

$$fh, k(x) = \frac{ck,d}{nhd}\sum_{i=1}^{n} k\left(\left\|\frac{x-xi}{h}\right\|\right)$$

For analyzing a feature space with the density f(x), we have to find the modes of this density. The modes are located among the zeros of the gradient Δf(x)=0
The second term is the mean shift i.e.

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

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.



The flowchart of the proposed algorithm is given below:

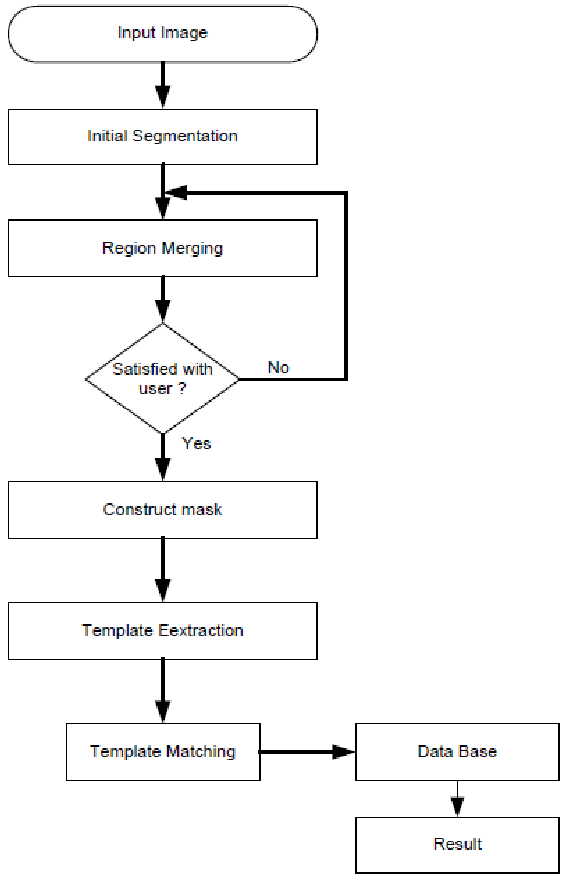


Figure 11: Illustration of Mean-shift analysis

I. PROPOSED METHODOLOGY

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

We use an iterative 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 continues until the user is satisfied or there are no region remains in the image. Once the user is satisfied it can stop the process. The final segmentation result is obtained by the user intervention. The user can also interact with 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.

Fig. 1: Flow chart of proposed approach

3. IMAGE SEGMENTATION

3.1 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 practical application of the mode finding procedure

Fig. 2 (a) Original Image (b) Initial Segmented Image by using mean-shift algorithm

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

(a) $\coprod_{i}^{n} Ri$= I where Ri ∩ Rj = ∅, i=1,n

(b) Ri is a connected region, i=1, 2….n.

(c) P(Ri) = TRUE for i=1, 2.. n.

(d) P(Ri ∪ Rj) = FALSE for i ≠ j.

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

1.2 Region Merging

Region merging algorithm is started from a set of segmented regions. This is because a small region can provide more stable statistical information than a single pixel, and using regions for merging can improve a lot the computational efficiency. We have 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 more robust than the other feature descriptors. This is because the initially 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. Therefore, we use the color histogram to represent each region. The RGB color space 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 16×16×16 = 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 Segmeneted Image, (c) Merged Image using region merging (after 5th iterarion)

3.3 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 Matching Using Color Feature

1. First we will select image. j = Set[filename,filepath];
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 matching using texture

Calculation of Texture for Query image

1. First we take a query Image.
2. Find Image mask of query Image
3. Now we calculate texture of extracted object by calculating eight adjacency or neighbors of each pixel.
4. If pixel value is at position (i,s) then we calculate pixel value of
   (i+1,s), (i,s+1), (i-1,s), (i,s-1),
   (i+1,s+1), (i-1,s-1), (i+1,s-1), (i-1,s+1).
5. Calculate texture of all the database images with he same method.
6. Compare texture of extracted object with texture of database images.
7. Show result in percentage

4. 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:

Fig 6 (a) (b) (c)

(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:

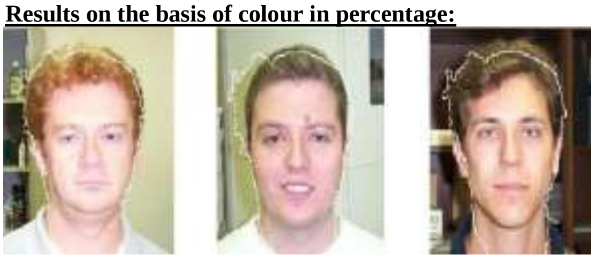
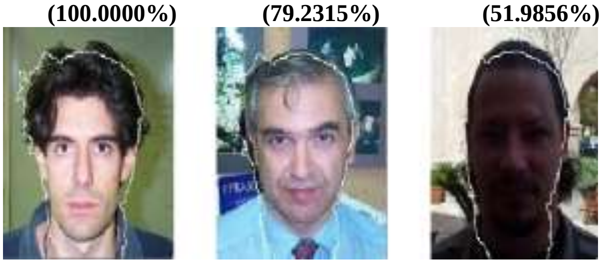


Fig.7 (a) (100.0000%) (b) (79.2315%) (c) (51.9856%)



(d) (31.0201%) (e) (26.0543%) (f) (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) (100.0000%) (b) (96.5351%) (c) (54.6784%)

(d) (69.6734%) (e) (89.0584%) (f) (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.

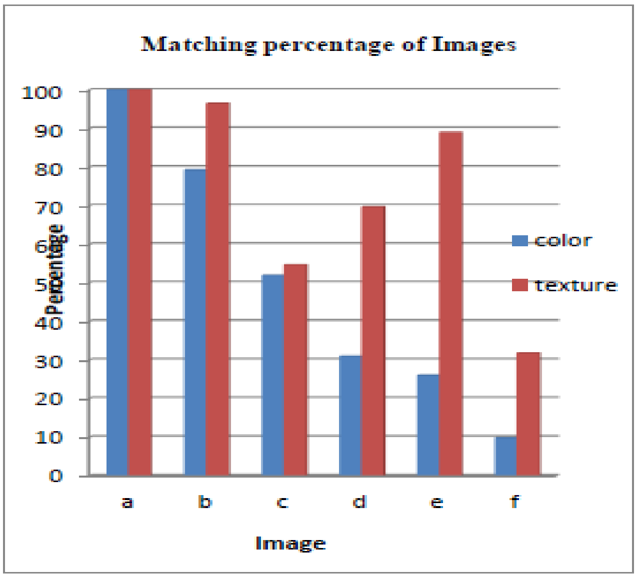


Chart 1: Shows matching percentage of images of fig.7 and fig.8 respectively with respect to desired portion of input image.

5. 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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