



Colour and Texture Identification Using Image Segmentation

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ABSTRACT: For addresses the image segmentation method for face matching from multiple images several general-purpose algorithms and techniques have been developed. Image segmentation is to classify or cluster an image into several parts (regions) according to the feature of image. This paper describes the Mean shift with region merging technique for image segmentation, for this a set of face images for recognition decisions need to be based on comparisons of face image database. Mean shift technique is more popular as compare to watershed segmentation technique because watershed has over segmentation and mean shift preserves 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 colour and texture. The simulated 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: Digital Image Processing, Segmentation, Face recognition Face Matching, Image segmentation, Region merging, Watershed, Mean shift.

I. INTRODUCTION

For some applications such as image recognition (or) image compression, we cannot process the whole image directly for the reason as it is inefficient and impractical. Therefore we are going for image segmentation before recognition (or) compression. Image segmentation is a basic yet still a demanding problem in computer vision and image processing. In particular, it is an essential process for many applications such as object recognition, target tracking, content-based image retrieval and medical image processing, etc. Generally speaking, the goal of image segmentation is to partition an image into a certain number of pieces which have coherent features (colour, texture, etc.) and in the meanwhile to group the pieces together for the convenience of perceiving. Meaningful Image segmentation techniques can be classified into two broad families— (1) Region-based and (2) Contour-based approaches.

Region-based approaches try to find partitions of the image pixels into sets corresponding to coherent image properties such as brightness, colour and texture.

Region-Based Techniques: The goal is the detection of regions (connected sets of pixels) that satisfy certain predefined homogeneity criteria. The heart of the above techniques is the region homogeneity test, usually formulated as a hypothesis testing problem Face recognition techniques have attracted much attention over the years and many algorithms have been developed. Especially, face segmentation is an essential step of face recognition system since most face classification techniques tend to only work with face images. Therefore face segmentation has to correctly extract only face part of given large image. Face matching is an important vision task with many practical applications such

as biometrics, video surveillance, and content based image retrieval. 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. 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 colour and texture.

II. LITERATURE REVIEW

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 analyze. 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.

Automatic Image Segmentation by Dynamic Region Merging [1], proposed by “Bo Peng, Lei Zhang, Member, IEEE, and David Zhang, Fellow”, IEEE Transactions On Image Processing, Vol. 20, No. 12, December 2011, followed by some major development and extensions in [2]. Since then, many new studies and development have been reported on mean shift theories and applications to edge-preserving nonlinear image smoothing and segmentation [3]. This paper addresses the automatic image segmentation problem in a region merging style. With an initially over segmented image, in which many regions (or super pixels) with homogeneous colour 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. They proposed a novel method for segmenting an image into distinct components. The proposed algorithm is implemented in a region-merging style. They have defined merging predicate for the evidence of merging between two neighboring regions. This predicate was defined by the SPRT and the maximum likelihood criterion. A DRM process was then presented to automatically group the initially over segmented many small regions. Although the merged regions are locally chosen in each merge stage, some global properties are kept in the final segmentations. For the computational efficiency

Mean shift for local mode seeking and clustering was initially proposed by “Nuan Song, Irene Y. H. Gu, Zhongping Cao, Mats Viberg”[3], followed by some major development and extensions in [2]. Since then, many new studies and development have been reported on mean shift theories and applications to edge-preserving nonlinear image smoothing and segmentation [3]. One attraction of mean shift is the statistical basis and its association with the density estimate. Mean shift directly estimates the local modes (maxima) without the requirement of actually estimating the pdf.

Mean shift segmentation of images is based on the fact that pixels in the same region share some similar modes. Depending on the selected features, regions with different types of similarity (e.g. intensities, colours, or texture attributes) can be estimated. By including both spatial position and range as features, mean shift takes into account both the geometrical closeness and the photometric similarity of image during image filtering and segmentation.

Enhanced Spatial-Range Mean Shift Colour Image Segmentation by Using Convergence Frequency and Position, by “Nuan Song, Irene Y. H. Gu, Zhongping Cao, Mats Viberg”, proposes an enhanced spatial-range mean shift segmentation approach[03], where over-segmented regions are reduced by exploiting the positions and frequencies at which mean shift filters converge. Based on their observation that edges are related to spatial positions with low mean shift convergence frequencies, merging [01] of over-segmented regions can be guided away from the perceptually important image edges. The proposed method has provided enhanced results with reduced over-segmentation meanwhile retaining sharp image edges.

Multi-Stage Region merging for image Segmentation proposed [5] by “Thomas Brox, Dirk Farinand Peter H.N. de” evaluates the properties of several merging criteria when applied to real-world images. These criteria proper-ties have been exploited to develop a novel algorithm, which is a multi-stage generalization of conventional region merging.

III. METHODOLOGY

The proposed method consists of mean - shift algorithm for segmentation of image. These segments were used for face matching. 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 colour.

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 colour and texture.

The methodology can be understood by the following flowchart:

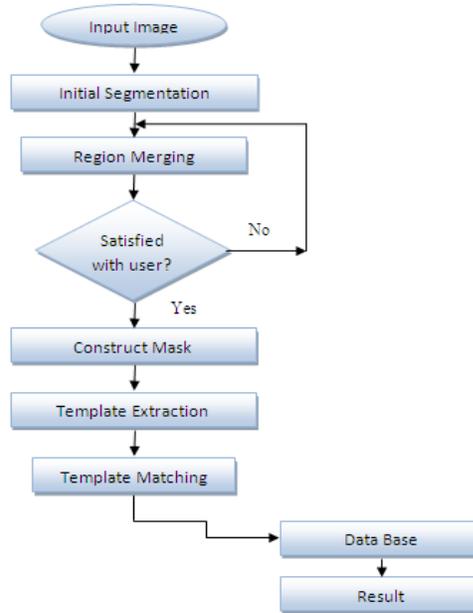


Fig. 1: Flow chart of proposed approach.

Framework of Image Segmentation

A. Initial Segmentation

Data clustering is one of methods widely applied in image segmentation and statistic. The main concept of data clustering is to use the centroid to represent each cluster and base on the similarity with the centroid of cluster to classify. mean shift algorithm is part of data clustering, too, and its concept is based on density estimation. The concept of the density

estimation-based nonparametric clustering method is that the feature space can be considered as the experiential probability density function (p.d.f.) of the represented parameter. The mean shift algorithm [3], [5] can be classified as density estimation. It adequately analyzes feature space to cluster them and can provide reliable solutions for many vision tasks.

Mean Shift Segmentation Algorithm

- 1.Convert the image into features(via colour, gradients, texture measures etc).
- 2.Choose initial search window locations uniformly in the data.
- 3.Compute the mean shift window location for each initial position.
- 4.Merge windows that end up on the same“peak” or mode.
- 5.The data these merged windows traversed are clustered together.



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 $\{ R_1, R_2, R_3, \dots, R_n \}$ which when combined formed 'I'.

B. Region Merging

A region can be described in many aspects, such as the colour, edge [13], texture [4], shape and size of the region. Among them the colour histogram is an effective descriptor to represent the object colour feature statistics and it is widely used in pattern recognition [08] and object tracking [18] etc. Colour 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 colours of different regions from the same object will have high similarity. Therefore, we use the colour histogram to represent each region. The RGB colour space is used to compute the colour histogram. We uniformly quantize each colour channel into 16 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 [17, 18] to measure the similarity between regions.

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. Colour 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 colours of different regions from the same object will have high similarity. Therefore, we use the colour histogram to represent each region. The RGB colour space is used to compute the colour histogram. We uniformly quantize each colour channel into 16 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 [17, 18] to measure the similarity between regions.



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

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C. Constructing Mask

Once the regions are merged and the image with desired segments are generated we construct the mask of the image for extracting object of interest from it. For constructing the mask

of the segmented image we convert it into the gray scale image. In the segmented gray scale image we assign value 255 to the pixels at the boundaries and 0 to the rest of the pixels in the image. This constructs the mask of the image.

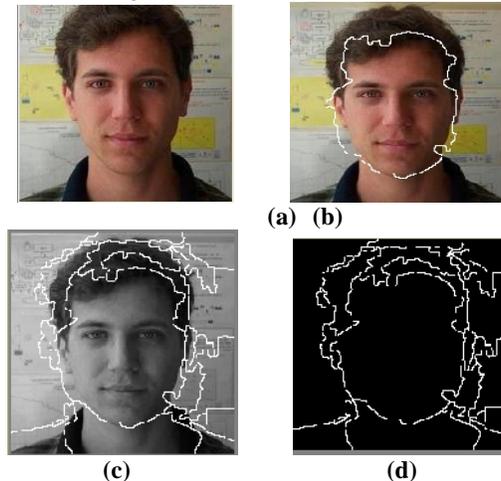


Fig. 4. (a) Input Image, (b) Segmented Image, (c) Greyscale Image, (d) Image Mask.

D. Object Extraction

For extraction of object of interest from the segmented image we use the mask and Boundary Fill algorithm. The object extraction from the image is also interactive. The user clicks on the desired region in the image. On the basis of the user click and the mask of the image the region's pixel's value set to the colour value in the image and the rest of the part of the image pixel's values are set to 0.

Boundary Fill Algorithm: It is basically a filling algorithm but we use this for object extraction with the help of image mask. The algorithm checks to see if this pixel is a boundary

pixel or has already filled. The boundary fill procedure accepts as input the coordinates of an interior point (x,y) , a fill colour and a boundary colour. Starting from (x,y) the procedure tests neighbouring positions to determine whether they are of the boundary colour. If not they are painted with the fill colour and their neighbours are tested. This process continuous until all pixels up to the boundary colour for the area has been tested. Two methods for proceeding to n pixels from seed pixel are 4-connected and 8-connected. We take the user click as a seed point (x,y) .

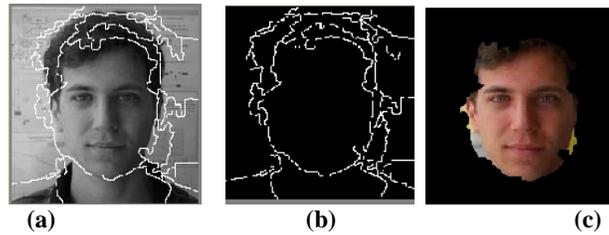


Fig. 5. (a) Grayscale Image (b) Image Mask (c) Desired Portion of image.

E. Face Matching

This module contains the interface to take the image from above module and it compares or searches with the images

already there in the database. 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 Colour Feature

1. First we will select image. $j = \text{Set}[\text{filename}, \text{filepath}]$;
2. $\text{WORK} = \text{Set}(\text{orgEdgeImage})$;
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.

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 the same method.
6. Compare texture of extracted object with texture of database images.
7. Show result in percentage

IV. RESULT AND ANALYSIS

The proposed algorithm has been implemented using Matlab 7.0.1 and tested on several face images in the database. The database contains around 500 face images Initially the images are over segmented using the mean shift method [7].

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:

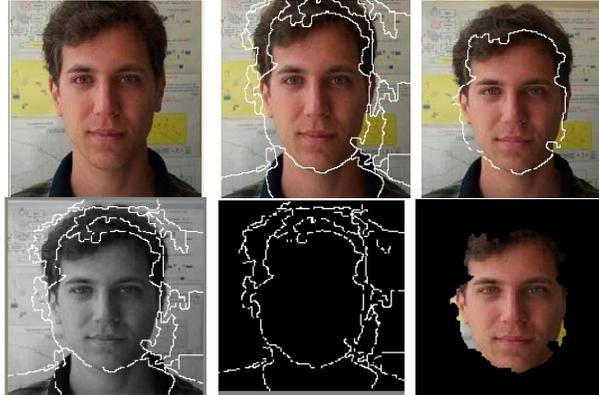


Fig. 6. (a) Input Image, (b) Initial Segmented Image, (c) Merged Image using region merging (after 5th iteration) (d) Grey-scale Image (e) Image mask (f) Desired portion of Image.

Result on the basis of colour in percentage:

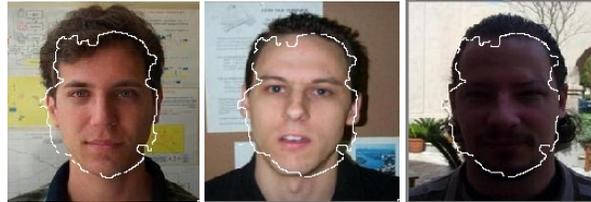


Fig. 7. (a)100% (b) 75.17% (c) 21.98%

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.

Result on the basis of texture in percentage:

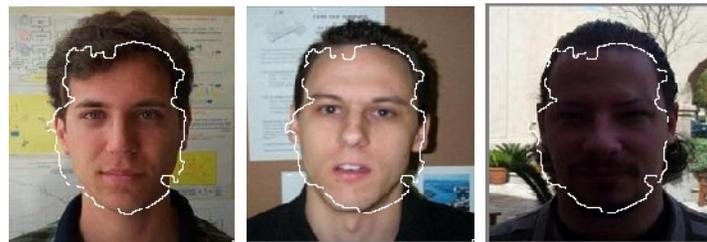
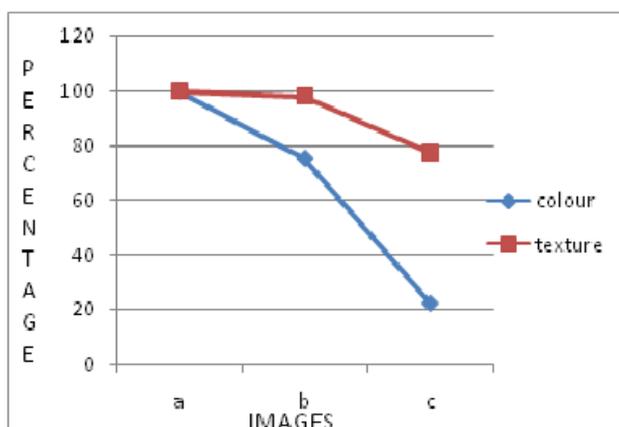


Fig. 8. (a) 100% (b) 98.02% (c)77.17%

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.



Graph 1. Matching percentage of images of Fig 7 and Fig 8 respectively with respect to the desired portion of images.

V. CONCLUSION

A new face matching technique based on interactive image segmentation has been proposed. The model performs region-merging based on the colour histogram of the image using Bhattacharya coefficient. After region merging, the object i.e. desired portion of image is extracted from the 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 the number of iterations depends on the user's satisfaction. Our results demonstrate the promising capability of the proposed face matching technique. We will try our method to get good results for the process of mean shift segmentation with region merging.

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