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Face Recognition Method using Mean-Shift by Means of Region Merging

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Abstract— ***We projected a original method for face matching from face image database. In this technique we have used set of face images because recognition conclusion is based on comparisons of face image database. In this paper we have presented an approach to region based face matching. Here the mean shift low level image segmentation method is used to segment the image into many small regions. As a well-liked segmentation scheme for color image, watershed has over segmentation as compared to mean-shift and also mean-shift conserves edge information of the object very well. The proposed technique mechanically merges the regions that are initially segmented by mean shift segmentation, effectively takes out the object contour and then, matches the obtained mask with test database image sets on the basis of color and texture. Extensive research are performed and the outcome shows that the projected method can reliably figure out the mask from the face image and efficiently matches the mask with face image sets.***

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

I. INTRODUCTION

Image Segmentation is a method of partitioning an image into a number of regions or sets of homogenous pixels. The objective of segmentation is to simplify and/or modify the demonstration of an image into something that is more meaningful and easier to analyze. Image segmentation is usually used to locate objects and boundaries (lines, curves, etc.) in images. Actually, partitioning is done on the basis of same texture or colour. The output of an image segmentation is a set of sections that together cover the entire image, or a set of contours taken out from the image. The phenomenon has a number of applications and one of them is face matching Face matching is a crucial vision method with many realistic applications such as biometrics, video surveillance, and content based image retrieval. A face matching system is a computer application for automatically recognize or verifying a person from a digital image or a video frame from a video source. One of the methods to perform this is by comparing selected facial features from the image and a facial database. Face matching has a number of practical application on commercial, security, image retrieval and law enforcement. For a given face image, face matching matches image with all the given images in database.

This is quite a demanding method from the point of view of pattern recognition. Even though there has been a speedy growth of large scale data bases, we have focused only on the accurateness with small databases. Here, we consider face matching as a law enforcement method in which an unidentified face is to be matched on a database. In our method we first partition the face image into number o fregions using mean-shift algorithm, then using region merging [1] iteratively merge the similar regions to uncover the desired mask of the face image. Here we have used an iterative method to merge several regions based on the likelihood of the regions. Regions are merged until the user is contented with the segmentation. Here we have not used watershed algorithm because watershed gives over segmented regions and is more time consuming to find the desired mask compare to mean shift. At the end the image mask acquired after merging is compared with database face images using a histogram estimation 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 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 oversegmented 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.

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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 analyse 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).

F. Lecumberry et al., [2] introduces a joint classification-segmentation framework with a twofold goal. First, to automatically select the SM (Shape models) that best represents the object, and second, to acuurately segment the image taking into account both the image information and the features and variations learned from the on-line selected model. A new energy functional is introduced that simultaneously accomplishes both goals. The presentation of the framework is complemented with examples for the difficult task of simultaneously classifying and segmenting closely related shapes, such as stages of human activities.

Jean Stawiaski et al., [3] introduce the use of graph cuts to merge the regions to the watershed transform optimally. 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.

J. Ning et al., [4] presents a new region merging based interactive image segmentation method in which 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 was proposed to guide the merging process with the help of markers. This method automatically merges the regions that are initially segmented, and then effectively extracts the object contour by labelling all the non-marker regions as either background or object.

F. Calderero et al., [5] presented a new statistical approach to region merging where regions are modelled as arbitrary discrete distributions, directly estimated from the pixel values. Under this framework, two region merging criteria are obtained from two different perspectives; leading to information theory statically measures: the Kullback-Leibler divergence and the Bhattacharya coefficient. The developed methods were size-dependent, which assures the size consistency of the partitions but reduces their size resolution. Thus, a size-independent extension of the previous methods, combined with the modified meging order, was also proposed.

A hybrid multidimensional image segmentation algorithm was proposed, [6] which combines edge and region-based techniques through the morphological algorithm of watersheds. An edge-preserving statistical noise reduction technique 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 (bottom-up) region merging process that produces the final segmentation.

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.

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.

Felzenswalb and Huttenlocher [9] described image segmentation based on pair wise region comparison. The algorithm makes simple greedy decisions and produces segmentations that obey the global properties of being not too coarse and not too fine according to a particular region comparison function. The method is time linear in the number of graph edges and is fast in practice.

Mavrinac [10] proposed a color image segmentation using a competitive learning clustering scheme. Two fundamental improvements are made to increase the speed performance. i) Initialization of the system with two units rather than one ii) Reducing the number of iterations with no adverse effect and random selection among winning vectors in case of a tie. A very high number of clusters lead to over segmentation which is reduced using threshold and rival penalization.

Lei et al. [11] addresses the automatic image segmentation problem in a region merging style. With an initially oversegmented 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.

Sharon et al., [12] introduced fast multi-scale algorithm which uses a process of recursive weighted aggregation to detect the distinctive segments at different scales. It determines an approximate solution to normalized cuts in time domain i.e., linear in the size of image with few operations per pixel. The disadvantage is that the segmented image fails to give smoother boundaries.

Donnell et al., [13] introduced a phase-based user steered segmentation algorithm using Livewire paradigm that works on the image features.

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Livewire finds optimal path between users selected image locations thus reducing manual effort of defining the complete boundary. The phase image gives continuous contours for the livewire to follow. The method is useful in medical image segmentation to define tissue type or anatomical structure.

Jitendra et al., [14] proposed cue integration in image segmentation by using an operational definition of textons, the putative elementary units of texture perception and an algorithm for partitioning the image into disjoint regions of coherent brightness and texture. The method finds boundaries of regions by integrating peaks in contour orientation energy and differences in texton densities across the contour by cue integration.

Jianbo and Malik [15] proposed normalized cuts and image segmentation. Normalized cuts measure both the total dissimilarity between the different groups as well as total similarity with in the groups, which is used for segmentation. The method is optimized using generalized eigen value problem.

Hakan et al. [16] introduce a novel method for face recognition from image sets. In which each test and training example is a set of images of an individual's face, not just a single image, so recognition decisions need to be based on comparisons of image sets. Methods for this have two main aspects: the models used to represent the individual image sets; and the similarity metric used to compare the models. Here, we represent images as points in a linear or affine feature space and characterize each image set by a convex geometric region (the affine or convex hull) spanned by its feature points. Set dissimilarity is measured by ge-ometric distances (distances of closest approach) between convex models. To reduce the influence of outliers we use robust methods to discard input points that are far from the fitted model.

Costas Panagiotakis, Ilias Grinias, and Georgios Tziritas [17] proposed a framework for image segmentation which uses feature extraction and clustering in the feature space followed by flooding and region merging techniques in the spatial domain, based on the computed features of classes. They use a new block-based unsupervised clustering method which ensures spatial coherence using an efficient hierarchical tree equipartition algorithm. They divide the image into different-different blocks based on the feature description computation. The image is partitioned using minimum spanning tree relationship and mallows distance. Then they apply K-centroid clustering algorithm and Bhattacharya distance and compute the posteriori distributions and distances and perform initial labelling. Priority multiclass flooding algorithm is applied and in the end regions are merged so that segmentation results are produced.

Li Zhang and Qiang Ji [18] have proposed a Bayesian Network (BN) Model for Both Automatic (Unsupervised) and Interactive (Supervised) image segmentation. They construct a Multilayer BN from the over segmentation of an image, which find object boundaries according to the measurements of regions, edges and vertices formed in the over segmentation and model the relationships among the superpixel regions, edge segment, vertices, angles and their measurements. For Automatic Image Segmentation after the construction of BN model and belief propagation segmented image is produced. For Interactive Image Segmentation if segmentation results are not satisfactory then active input selection by user intervention selections are again carried out for segmentation.

III. PROPOSED METHODOLOGY

In this method we have initially used mean- shift algorithm for segmentation of an image. Image Segmentation plays a very crucial role in biometrics as it is the initial step in image processing and pattern recognition. After that by using dynamic region merging approach we merge the similar region on the basis of colour. The flowchart of the proposed algorithm is given below:

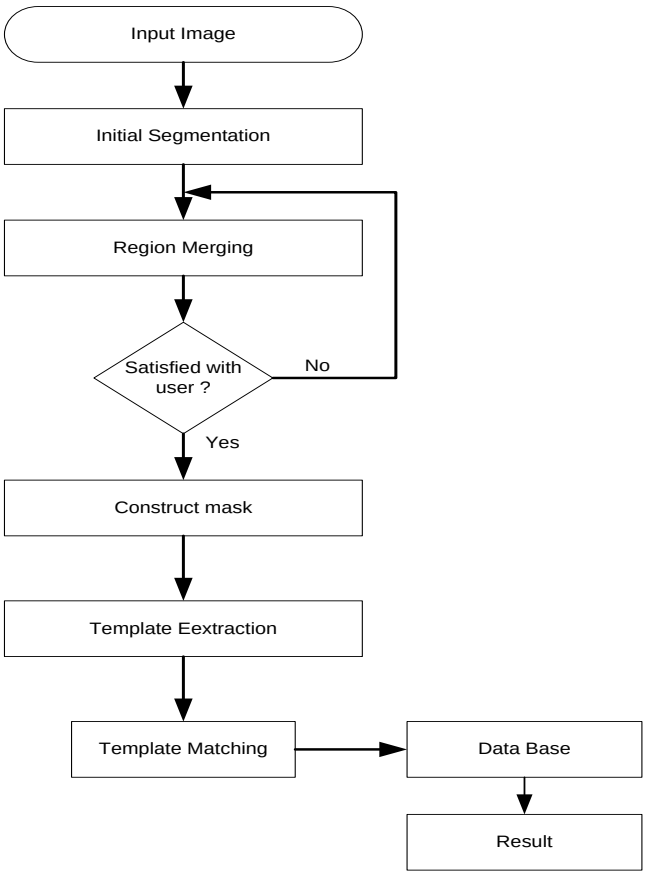

Fig. 1: Flow chart of proposed approach

Here we have used an iterative and interactive method for segmenting an image. Here the user starts the process and the model starts merging the regions, after first iteration some segments that are most probable combines with each other and results with less regions and fewer pixels. Probability is computed after each iteration. This process continues until the user is contented or no region remains in the image. Once the user is contented the process can be stopped. The resultant segmentation output is obtained by the user intervention. The customer can also interact with the final resultant image to obtain the object of interest from an image.At the end we compare the mask with database face images on the basis of colour and texture.

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IV. IMAGE SEGMENTATION FRAMEWORK

***1. Initial Segmentation*:** Initial Segmentation is done by using mean-shift algorithm. The mean shift algorithm is a clustering technique which is nor parametric and neither require previous information of the number of clusters nor restrict the shape of the clusters. The mean shift clustering algorithm is a useful 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) $\cup_{i}^{n} Ri = I$ where $Ri \cap Rj = \emptyset$, i=1,n
(b) Ri is a connected region, i=1, 2….n.
(c) P(Ri) = TRUE for i=1, 2.. n.
(d) $P(Ri \cup Rj)$ = FALSE for $i \neq j$.

Where P(Ri) is a logical defined over the points in set Ri Condition (a) shows that segmentation must be complete; each pixel in an 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 characteristics 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 regions Ri and Rj are different in the sense of predicate P.

***2. Region Merging*:** Region merging algorithm starts from a set of segmented regions. This is because a small region can provide more constant statistical information than a single pixel, and using segments for merging can improve a lot of computational efficiency. We have many small segments available in the edge map. A region can be described in several aspects, such as colour, edge [19], texture [20], shape and size of the region. Among them the colour histogram is an efficient descriptor to represent the object colour feature statistics and it is widely used in pattern recognition [21] and object tracking [22] etc. Colour histogram is extra robust compare to other feature descriptors. The reason behind this is that, the small regions of the desired object that has been segmented at the starting a lot vary in size and shape, whereas the colours of different regions from the same object will have high similarity. As a result, we use the colour histogram to represent every region. The RGB colour space is used to calculate the colour histogram. We consistently quantize each colour channel into16 levels and after that histogram of each region is computed in the feature space of 16×16×16 = 4096 bins.

In this we have chosen to use the Bhattacharyya coefficient [25, 26, 27] to measure the resemblance between sections.

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

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

***3. Constructing Mask*:** In this, after the regions are merged and the image with preferred segments is generated then we construct the mask of the image for extracting entity of interest from that. For constructing the mask of the segmented image we change it into the gray scale image. In the segmented gray scale image we assign value 255 to the pixels at the borders and 0 to the remaining pixels in the image. This constructs the mask of the image.

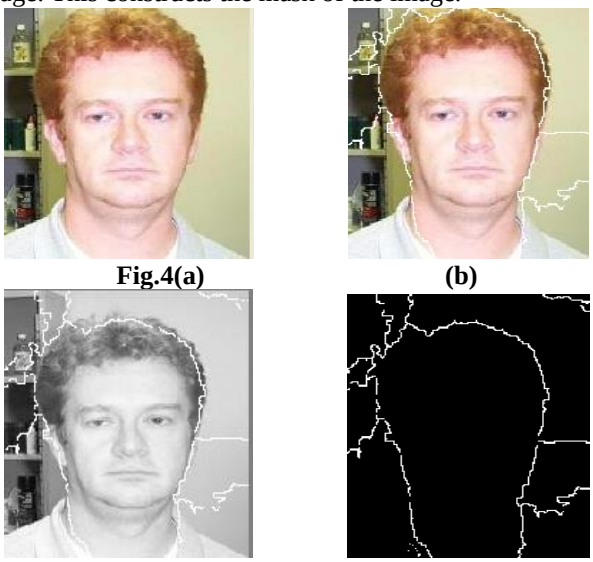

Fig.4(a) (b) (c) (d)

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

***4. Object Extraction*:** For extorting the entity of interest from the segmented image we apply the mask and Boundary Fill algorithm. The object extortion from an image is interactive too. The customer clicks on the preferred region in an image. On the basis of the customer click and the mask of an image the region's pixel's value set to the colour value in an image and remaining part of the image pixel's values are set to 0.

***Boundary Fill Algorithm*:** It is basically a filling algorithm but we apply this for object extortion with the help of image mask. It is a recursive algorithm that initiates with a starting pixel called a seed pixel, within a region and continuous painting towards the border. The algorithm verifies to see if this pixel is a boundary pixel or has already filled.

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If response is no it fills the pixel and makes a recursive call to itself using each and every neighboring pixel as a new seed. And if the response is yes, the algorithm simply returns to its caller. The boundary fill procedure admits as input the coordinates of an interior point(x,y), a fill color and a boundary color.I from (x,y) the procedure tests neighboring positions to determine whether they are of the boundary colour. If no,than 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 techniques for proceeding to n pixels from seed pixel are 4-connected and 8-connected. We take into account the user click as a seed point (x,y).

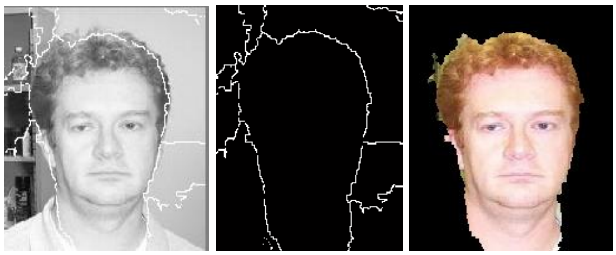


Fig.5 (a) (b) (c)

Fig. 5.(a) Greyscale Image, (b) Image Mask (c) Desired portion of Image

5. Face Matching: Later on, when get desired portion of face now we match this with the database face images on the basis of color and texture. Here we have projected two algorithms for matching one for color and other for texture.

Algortithm 1: Object Matching Using Color Feature

1. First we will select image. j = Set[filename, filepath];
2. WORK= Set(org Edge Image);
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 reqired 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 neighbours of each pixel.
4. If pixel value is at position (i,s) then we calculate pixel value of

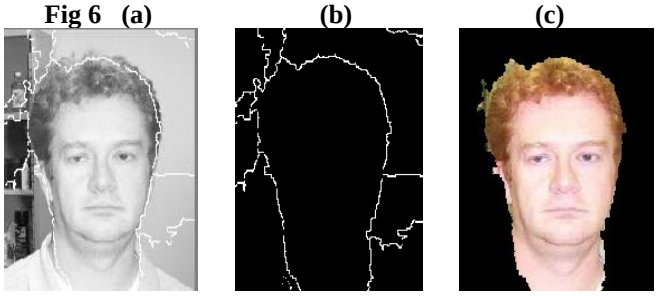
(i+1,s), (i,s+1), (i-1,s), (i,s-1), (i+1,s+1), (i-1,s-1), (i+1,s-1), (i-1,s+1).

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

V. RESULT AND ANALYSIS

So as to examine this algorithm, the experimental outcomes were under the software environment of Matlab .Here the proposed model has been tested on a number of face images in the database. The database holds 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 combine the regions on the basis of colour. At the end we match the desired portion of face image obtained from an image mask with our database. Results are shown below fig:

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

Matching of desrired portion of image with Data base faces Images on the basis of color in percent:

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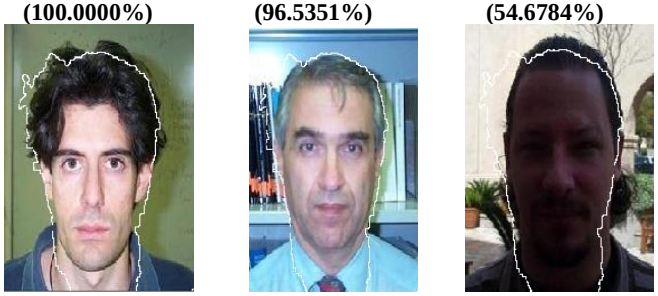
Fig.7 (a) (100.0000%) (b) (79.2315%) (c) (51.9856%)

(d) (31.0201%) (e) (26.0543%) (f) (9.8952%)

Matching of desrired portion of image with Database face Images on the basis of texture:

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 color and texture in percentage.

We initially take into account the input image (fig.6), done its initial segmentation with the aid of mean-shift. Merging has been performed iteratively to get the desired portion of an image, then find its image mask and extract desired portion. We match the obtained desired portion with 500 database face images depending on the color and texture and find the results in percentage. Few results are shown in the fig.7 and fig.8 on the basis of color and texture respectively. It is far better compare to previous methods in which watershed is used for initial segmentation. The reason behind this is that the watershed gives over segmented image which takes extra time in merging as compared to mean-shift. This proposed technique is highly efficient and simple and gives very good result.

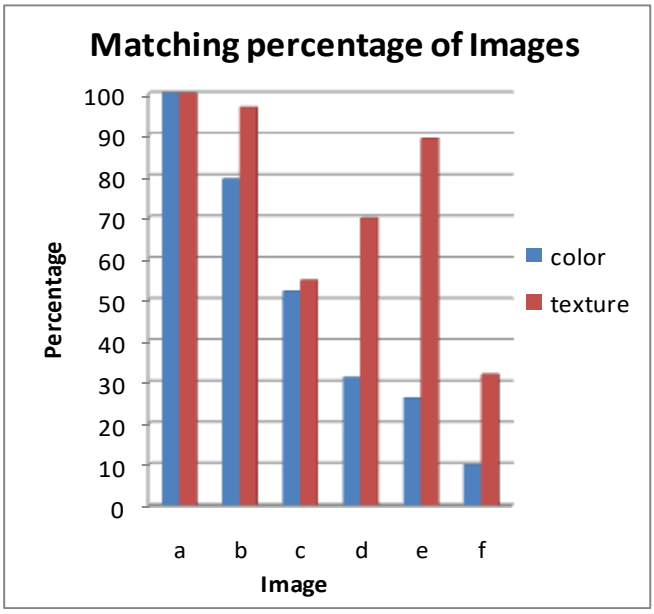


Chart 1: Shows matching percentage of images of fig.7 and fig.8 respectively with respect to desired portion of input image.

VI. CONCLUSION

To sum up, we present a new face matching technique based on interactive image segmentation framework. The proposed technique can systematically capture the relationships among different image segments to carry out effective image segmentation. An image is first over segmented with the help of mean-shift to create an edge map. The model performs region-merging depending on the colour histogram of an image using Bhattacharya coefficient. Later on after than region merging object i.e. preferred portion of an image is extracted from an input image. Then we compare the preferred portion with the database face images on the basis of color and texture. It is an iterative procedure and and carry out several iterations depending on the user satisfaction. At the end, we want to point out that this application is not restricted to image segmentation .It is applicable 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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