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COMPUTERIZED CROWD ADMINISTRATION SYSTEM BUILT ON FACE IDENTIFICATION SYSTEM

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Abstract— This paper is based on face detection and recognition algorithms. Detects the group of students in class room and marks the attendance by recognizing them. The system architecture and algorithms used in each stage is presented and Different real time scenarios are considered to evaluate the performance of various Face recognition systems. we have utilized a new, real-world source of images to test a variety of algorithms for holistic performance with respect to the potential application , this paper focuses on localizing parts in natural face images, taken under a wide range of poses, lighting conditions, and facial expressions, in the presence of occluding objects such as sunglasses or microphones

Keywords— Face recognition systems, holistic performance, Localization, attendance system, algorithms

I. INTRODUCTION

Face recognition is one of the major issues in biometric technology. It identifies and/or verifies a person by using 2D/3D physical characteristics of the face images. The baseline method of face recognition system is the Eigen face by which the goal of the method is to project linearly the image space onto the feature space which has less dimensionality. One can reconstruct a face image by using only a few eigenvectors which correspond to the largest eigenvalues, known as Eigen picture,, Karhunen- Loeve transform and principal component analysis ,Several techniques have been proposed for solving a major problem in face recognition such as fisher face , elastic bunch graph matching and support vector machine. However, there are still many challenge problems in face recognition system such as facial expressions, pose variations, occlusion and illumination change. Those variations dramatically degrade the performance of face recognition system. It is evident that illumination variation is the most impact of the changes in appearance of the face images because of its fluctuation by increasing or decreasing the intensities of face images due to shadow cast given by different light source direction. Therefore the one of key success is to increase the robustness of face representation against these variations [1].

In order to reduce the illumination variation, many literatures have been proposed. Belhumeur et. al.suggested that discarding the three most significant principal components can reduce the illumination variation in the face images. Nevertheless, the three most significant principal components not only contain illumination variations but also some useful information, therefore, the system was also degraded as well. Wang et. al. proposed a Self Quotient Image (SQI) by using only single image. The SQI was obtained by using the weighted Gaussian function as a smoothing kernel function. The Total Variation Quotient Image (TVQI) and Logarithmic Quotient Image (LTV) have been proposed by which the face image was decomposed into a small scale (texture) and large scale (cartoon) images. The normalized image was obtained by dividing the original image with the large scale one. The TVQI and LTV have a very high computational complexity due to the second order cone programming as their kernel function.

However these methods are suitable only for illumination variation but not for other variations. Whereas the face representation based method has more robustness. It is not insensitive to illumination variation but insensitive to facial expression as well, such as Local Binary Pattern (LBP) and its extension; it was originally designed for texture description. The LBP operator assigns a label to every pixel of an image by thresholding the 3x3-neighborhood of each surrounding pixel with the centre pixel value and a decimal representation is then obtained from the binary sequence (8 bits). The LBP image is subsequently divided into R non overlapping regions of same size and the local histogram over each region are then calculated. Finally the concatenated histogram can be obtained as a face descriptor. The procedure consists of using the texture descriptor to build several local descriptions of the face and combining them into a global description. Instead of striving for a holistic description. The facial image is divided into local regions and texture descriptors are extracted from each region independently. the LBP labels for the histogram contain information about the patterns on a pixel-level, the labels are summed over a small region to produce information on a regional level and the regional histograms are concatenated to build a global description of the face.

An image is a rectangular grid of pixels. It has a definite height and a definite width counted in pixels. Each pixel is square and has a fixed size on a given display. However different computer monitors may use different sized pixels. The pixels that constitute an image are ordered as a grid (columns and rows); each pixel consists of numbers representing magnitudes of brightness and colour. The image pixels table is shown in fig.1

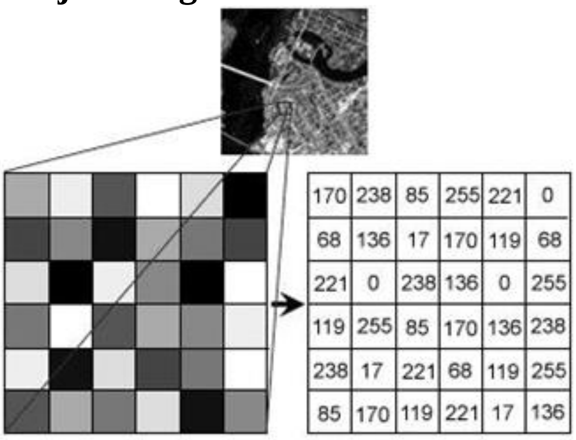

Fig:1. Image Pixels Table

II. ALGORITHMS AND TECNIQUES

A. CLUSTERING METHODS

The K-means algorithm is an iterative technique that is used to partition an image into *K* clusters. The basic algorithm is: Pick *K* cluster centres, either randomly or based on some heuristic

1. Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center
2. Re-compute the cluster centers by averaging all of the pixels in the cluster
3. Repeat steps 2 and 3 until convergence is attained (e.g. no pixels change clusters)

In this case, distance is the squared or absolute difference between a pixel and a cluster centre. The difference is typically based on pixel colour, intensity, texture, and location, or a weighted combination of these factors. K can be selected manually, randomly, or by a heuristic. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K [2].

B. COMPRESSION-BASED METHODS

Compression based methods postulate that the optimal segmentation is the one that minimizes, over all possible segmentations, the coding length of the data the connection between these two concepts is that segmentation tries to find patterns in an image and any regularity in the image can be used to compress it. The method describes each segment by its texture and boundary shape. Each of these components is modelled by a probability distribution function and its coding length is computed as follows:

1. The boundary encoding leverages the fact that regions in natural images tend to have a smooth contour. This prior is used by Huffman coding to encode the difference chain code of the contours in an image. Thus, the smoother a boundary is the shorter coding length it attains[9].
2. Texture is encoded by lossy compression in a way similar to minimum description length (MDL) principle, but here the length of the data given the model is approximated by the number of samples times the entropy of the model. The texture in each region is modeled by a multivariate normal distribution whose entropy has closed form expression. An interesting property of this model is that the estimated entropy bounds the true entropy of the data from above. This is because among all distributions with a given mean and covariance, normal distribution has the largest entropy. Thus, the true coding length cannot be more than what the algorithm tries to minimize.

C.HISTOGRAM-BASED METHODS

Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. Colour or intensity can be used as the measure. A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters. This is repeated with smaller and smaller clusters until no more clusters are formed. One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image. In this technique of image classification distance metric and integrated region matching are familiar [10].

Histogram-based approaches can also be quickly adapted to occur over multiple frames, while maintaining their single pass efficiency. The histogram can be done in multiple fashions when multiple frames are considered. The same approach that is taken with one frame can be applied to multiple, and after the results are merged, peaks and valleys that were previously difficult to identify are more likely to be distinguishable. The histogram can also be applied on a per pixel basis where the information result is used to determine the most frequent colour for the pixel location. This approach segments based on active objects and a static environment results in a different type of segmentation useful in Video tracking.

D. EDGE DETECTION

Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used as the base of another segmentation technique. The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries

E. WATERSHED TRANSFORMATION

The watershed transformation considers the gradient magnitude of an image as a topographic surface. Pixels having the highest gradient magnitude intensities (GMIs) correspond to watershed lines, which represent the region boundaries. Water placed on any pixel enclosed by a common watershed line flows downhill to a common local intensity minimum (LIM). Pixels draining to a common minimum form a catch basin, which represents a segment [3].

III. PROPOSED ALGORITHM

The use of colour information has been introduced to the face-locating problem in recent years, and it has gained increasing attention since then. Some recent publications that have reported this study include the colour information is typically used for region rather than edge segmentation. We classify the region segmentation into two general approaches, as illustrated in Fig. 2. One approach is to employ colour as a feature for partitioning an image into a set of homogeneous regions The other approach, however, makes use of colour as a feature for identifying a specific object in an image. In this case, the skin colour can be used to identify the human face. This is feasible because human faces have a special colour distribution that differs significantly (although not entirely) from those of the background objects. Hence this approach requires a colour map that models the skin-colour distribution characteristics [8].

Fig.2: Foreman Image with a White Contour Highlighting the Facial Region

In another approach, the skin-colour map can be designed by adopting histograming technique on a given set of training Therefore, this individual colour feature can simply be defined by the presence of Cr values within, say, 136 and 156, and Cb values within 110 and 123. Using these ranges of values, we managed to locate the subject's face in another frame of Foreman and also in a different scene (a standard test image called Carphone), as can be seen in Fig. 3. This approach was suggested in the past by Li and Forchheimer in however, a detailed procedure on the modelling of individual colour features and their choice of colour space was not disclosed [4].

Fig.**3:** Foreman and Carphone images, and their colour segmentation results, obtained by using the same predefined skin-colour map.

A. FACE SEGMENTATION ALGORITHM

In this section, we present our methodology to perform face segmentation. Our proposed approach is automatic in the sense that it uses an unsupervised segmentation algorithm, and hence no manual adjustment of any design parameter is needed in order to suit any particular input image. Moreover, the algorithm can be implemented in real time, and its un-delaying assumptions are minimal. In fact, the only principal assumption is that the person's face must be present in the given image, since we are locating and not detecting whether there is a face[7]. Thus, the input information required by the algorithm is a single colour image that consists of a head-and-shoulders view of the person and a background scene, and the facial region can be as small as only a 32×32 pixels window (or 1%) of a CIF-size (352×288) input image. The format of the input image is to follow the YCrCb colour space, based on the reason given in the previous section. The spatial sampling frequency ratio of Y, Cr, and Cb is 4 : 1 : 1. So, for a CIF-size image, Y has 288 lines and 352 pixels per line, while both Cr and Cb have 144 lines and 176 pixels per line. The algorithm consists of five operating stages, as outlined in Fig. 4. It begins by employing a low-level process like colour segmentation in the first stage, then uses higher level operations that involve some heuristic knowledge about the local connectivity of the skin-colour pixels in the later stages. Thus, each stage makes full use of the result yielded by its preceding stage in order to refine the output result. Consequently, all the stages must be carried out progressively according to the given sequence [5].

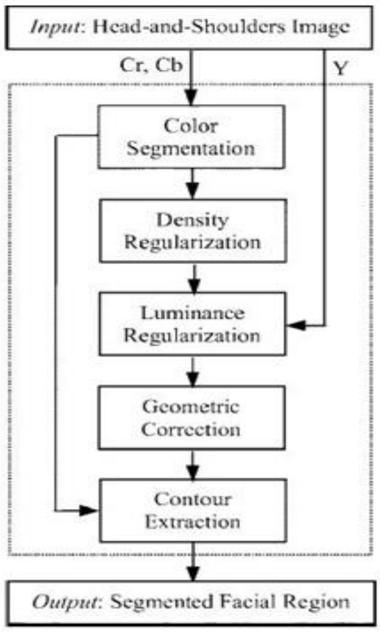

Fig.4. Outline of Face-Segmentation Algorithm

B. FACE DETECTION

A proper and efficient face detection algorithm always enhances the performance of face recognition systems. Various algorithms are proposed for face detection such as Face geometry based methods, Feature Invariant methods, Machine learning based methods. Out of all these methods segmentation proposed a framework which gives a high detection rate and is also fast algorithm is efficient for real time application as it is fast and robust. Hence we chose face detection algorithm which makes use of Integral Image learning algorithm as classifier [6].We observed that this algorithm gives better results in different lighting conditions and we combined multiple haar classifiers to achieve a better detection rates up to an angle of 30 degrees. Outline is described in fig.5

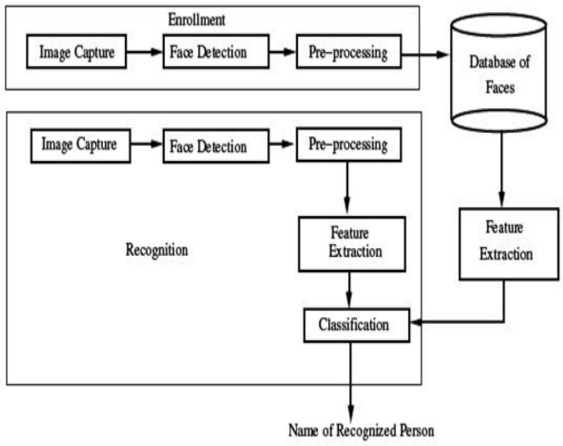

Fig.5: Outline of face detection

IV. RESULTS AND DISCUSSION

Fig.5: Input image

Fig. 6: Extracted Skin Region

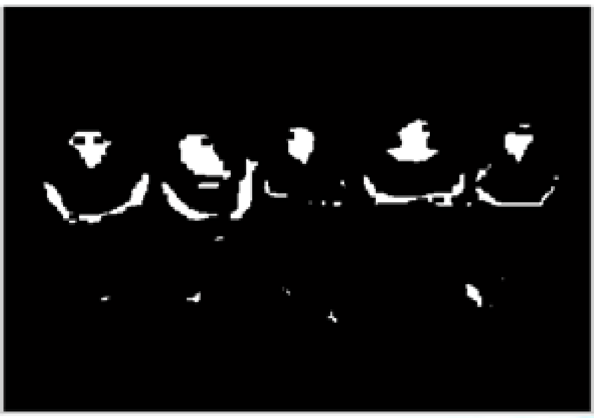

Fig. 7: Erode Image

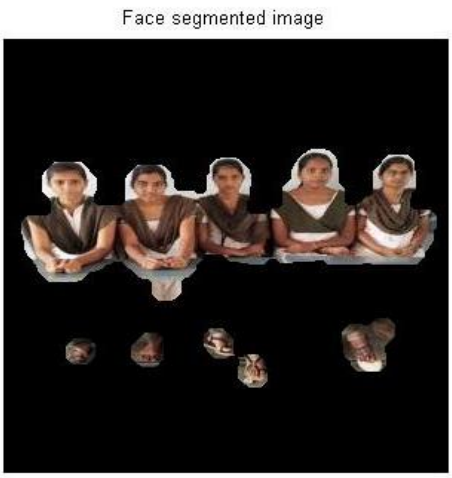

Fig.8: Face Segmented Image

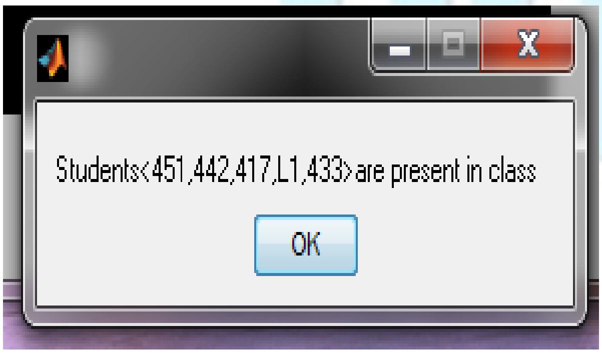

Fig9: Output

The above fig.5 represents input image to the proposed system and fig.6&7 represents intermediate outputs of the proposed system.fig.8 and 9 shows the output

V. CONCLUSION

The proposed method to perform face recognition under the combined effects of non-uniform blurs, illumination, and pose. We showed that the set of all images obtained by non-uniformly blurring a given image using the TSF model is a convex set given by the convex hull of warped versions of the image. Capitalizing on this result, we initially proposed a non-uniform motion blur-robust face recognition algorithm NU-MOB. We then showed that the set of all images obtained from a given image by non-uniform blurring and changes in illumination forms a bi-convex set, and used this result to develop our non-uniform motion blur and illumination-robust algorithm MOBIL. We then extended the capability of MOBIL to handle even non-frontal faces by transforming the gallery to a new pose.

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