Face Sketch Recognition using Tchebichef Moments

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Abstract- Composite sketches play an important role in crime investigation. Since composite sketches gives better accuracy compared to forensic sketches, most of the law enforcement insists for composite sketches rather than forensic sketches. This paper proposes a method for matching composite sketches to digital mug shot. Firstly facial components are detected based on the geometrical model of the face. Features are then extracted from each of the facial component using multi-scale binary patterns (MLBP) and tchebichef moments. Features extracted from these are matched using SVM classifier. Experiment is conducted on the Extended PRIP Composite database. Proposed system yields promising results.

Keywords- Composite sketch; Geometrical Model; Multi-Scale Local Binary Patterns (MLBP); Tchebichef Moment Invariant feature, SVM.

I. INTRODUCTION

Face recognition has an important application in criminal investigation. During the criminal investigations fingerprint or images in surveillance camera are used as a clue to identify the victims. Many times such clues are not available, in such situations police team search for an eyewitness and uses forensic artists to draw the sketch of a criminal based on the description of eyewitness. Sketches drawn under such situation can be of two types.

a) Forensic sketches: Forensic sketches are the facial sketches drawn by forensic artists based on the description of an eye witness. This is helpful when eye witness description is the only form of clue available in identifying the suspect.
b) Composite sketches: These are the sketches generated through computer using some software kits based on the description of eye witness.

Fig. 1 shows the example of normal images and composite sketches. Unlike forensic sketches less training is required for the generation of composite sketches and it is not time consuming. A Survey [1] show that 80% of the law enforcement agencies reported using computer generated facial sketches for suspect identification. Some of the most popular computerized facial composite software's are Identikit [2], Photo-Fit [3], FACES [4], EvoFIT [5].

Fig.1: a. Normal images b. Composite images

This paper proposes a geometrical feature based composite sketch recognition method. From each Geometrical component local features and texture information is extracted using Multiscale Local Binary Pattern (MLBP) and tchebichef moments both features are then used for matching.

II. RELATED WORK

Most of the previous work concentrates on photo to photo matching. Matching facial composites to photographs is challenging with only limited amount of published work.

Kathryn Bonnen et al [6] and Hu Han et al [7] demonstrated the potential of component based representations. Descriptors are computed from individually aligned components [6]. These descriptors give higher recognition accuracies. Multiscale local binary patterns features are extracted from each component and per-component similarity is measured [6][7]. Component based representations are relatively robust to changes in orientation.

Decheng et al [8] considered that in composite recognition, inherent structure information is more important than the local texture information accordingly SIFT and HOG are used to extract these features. Score level fusion is done and experiment were conducted using E-PRIP database this improved the recognition performance.

Qianwen wan et al [9] proposed Human Visual system algorithm based on the human visual system. This algorithm combined with Logarithm Logical Binary Pattern feature descriptor is used in automatic recognition for matching software generated facial sketches with digital image.

Tiagrajah v j et. al [10] proposed a discriminant Tchebichef Moments(DTM) to overcome the problem faced by Fisher's Linear Discriminant Analysis.

Divya Tyagi et al.[11] used a Local ternary pattern with genetic algorithm for feature extraction. SVM classifier is used for classification of faces.

Alaa Tharwat et al [12] proposed a Face Sketch recognition system using scale invariant Feature Transform (SIFT) and Local Binary Patterns (LBP) to extract features from photo and sketch. Direct LDA is used to reduce the dimensions of feature vectors. Minimum Distance and Support Vector Machines are used for classification.

In this paper to improve the efficiency of recognition, component based composite facial feature extraction using MLBP and Tchebichef Moments is proposed and classification is done using Support vector Machine.

III. METHODOLOGY

The proposed method of composite sketch based face recognition system contains training & testing of the images. During the training phase face images are trained, in each Image face region is detected, different facial components like eyes, nose and mouth are detected. Local and texture features are extracted by using Multiscale local binary pattern (MLBP) and Tchebichef moments from each of the facial components. Feature vector extracted are then stored in the knowledge base for matching test images. Matching is done by using Support vector machine. The detailed methodology is as shown in figure 2.

A. Preprocessing

The main purpose of pre-processing is to improve the image quality by suppressing distortion present in an image. This process can improve the face recognition rate. In preprocessing image resizing can also be done to decrease the number of pixel values. All the composite sketches present in the database has been standardized to 200X150 pixels. This helps to compute further steps at a faster rate. The color image i.e RGB image is converted to gray scale image this reduces the difficulty in performing the operations in each color domain independently.

B. Face Detection

Face detection is a method of identifying face in an image. AdaBoost is a technique to detect face. It mainly concentrates on combining a set of week classifiers to make a strong classifier. Initially the AdaBoost has to be trained by positive and negative images. Then features are extracted. Features are the numerical values extracted from the images. Haar features are used to detect face in an image. Initially training set S contains

$$S = \{(x_i, y_i): x_i \in R^d, y_i \in \{-1, +1\}, i=1,\ldots\ldots,m\}.$$

Distribution D over data set S is given such that

$$\sum_i D(i) = 1$$

For an input weak learner calculates a weak classifier h_t, where h_t will be in the form

$$h_t : R^d \rightarrow \{-1, +1\}$$

For each weak classifier h_t the error value ϵ_t is calculated. The best feature which is having lowest error rate ϵ_t is selected at each round all training examples are reweighted and normalized. At the end strong classifier is a weighted linear combination of all week classifier.

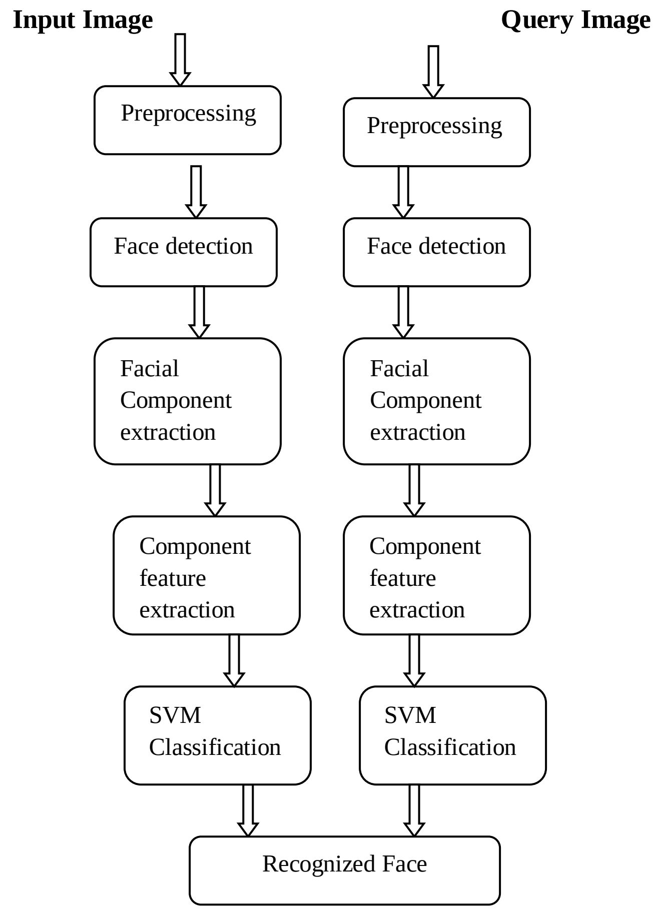

Fig.2: Architecture of the proposed System

C. Component identification and feature extraction

Geometrical components of the face is different from one person to another hence, with single algorithm it is not possible to extract all the components of the face. Important step in facial component identification is to track the position of the eyeball row [15] from this we can predict the other facial component regions and then exact regions are located using different algorithms.

D. Multi-scale local binary Patterns

The original Local binary pattern [13] was used as an efficient texture descriptor. A LBP operator assigns a label to every pixel of an image by thresholding 3x3 neighborhood of each pixel with centre pixel value and binary number is considered as a result. Histogram of these labels then can be used as a texture descriptor. A circular LBP is used to select pixel values p of any radius r resulting into large scale image structure. Let g_c be the gray level centre pixel and g_i (i=0,1,2,……7) be the gray level surrounding pixel. Neighbor pixel value is compared with centre pixel if it is greater binary result of the pixel is set to 1 otherwise set to 0.All the results are combined to get 8 bit binary value. The decimal value of the binary is the LBP feature. Bilinear interpolation is used when sampling point does not fall in the centre of a pixel. The basic LBP operator is as shown in the Figure 3. Let p denote the number of neighborhood points on the circle and r denote the radius. The LBP feature of a pixel's circularly neighborhoods is written from Figure 3 as in equation 1.

$$LBP_{p,r} = \sum_{i=0}^{p-1} s(g_i - g_c).\, 2^i, \quad S(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

0	1	1
1		0
0	0	1

43	57	52
56	45	11
44	20	70

Binary code

10010101

Fig.3: illustration of Basic LBP operator

The LBP operator is not robust against local changes in the texture when it is applied to face it does not describe the unique details contained in an image. Thus an improved multi-scale LBP operator (MLBP) is used to improve the discriminative power of the original LBP. MLBP support rotation in variant texture analysis in multiple scales and extract more distinctive data. MLBP operators are obtained by expanding LBP to multi-scale and concatenating their histograms separately. The multi-scale operator is as shown in figure 4. The MLBP operator is not only invariant to different illumination changes, but also scale-invariant to a certain extent.

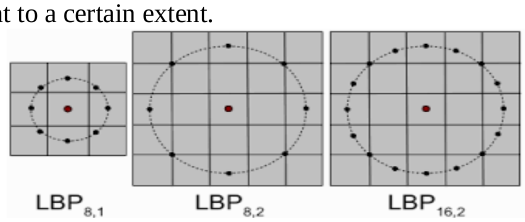

Fig.4: MLBP Operator

E. Tchebichef moments

To overcome the drawbacks of the continuous moments, Mukundan et al. proposed a set of discrete orthogonal moments based on the discrete Tchebichef polynomials [14]. In face recognition the facial features should be insensitive to large variations of light and pose. Discrete orthogonal kernels give good feature representation. These moments are less susceptible to noise compared to other types of moments.

Tchebichef polynomials of degree n are given by $t_n(x)$. $t_n(x)$ is given by[14]

$$t_n(x) = \alpha_1 x t_{n-1}(x) + \alpha_2 t_{n-1}(x) + \alpha_3 t_{n-2}(x), \quad (2)$$

Where x=0, 1, 2,……..,N-1 & n= 2,………,N-1 and

$$\alpha_1 = \frac{2}{n}\sqrt{\frac{4n^2-1}{N^2-n^2}} \quad (3)$$

$$\alpha_2 = \frac{(1-N)}{n}\sqrt{\frac{4n^2-1}{N^2-n^2}} \quad (4)$$

$$\alpha_3 = -\frac{(n-1)}{n}\sqrt{\frac{2n+1}{2n-3}}\sqrt{\frac{N^2-(n-1)^2}{N^2-n^2}} \quad (5)$$

for the above recurrence starting values can be obtained as:

$$t_0(x) = \frac{1}{\sqrt{N}} \text{ and } t_1(x) = (2x+1-N)\sqrt{\frac{3}{N(N^2-1)}} \quad (6)$$

Convolution masks M_{mn} of size 5x5 is defined as:

$$M_{mn}(x,y) = t_m(x)t_n(y), \quad m,n,x,y = 0,\ldots\ldots,4 \quad (7)$$

The above mask can give the Tchebichef moment at location (x, y)

$$T_{mn}(x,y) = \sum_{i=0}^{4}\sum_{j=0}^{4} M_{mn}(i,j) f(i+x-2, j+y-2)$$

$$m, n = 0,\ldots\ldots,4 \quad (8)$$

where f*(x,y)* denotes intensity values. We will select few Tchebichef moments for the representation of feature vector.

F. Support Vector Machine

Support vector machine is a learning algorithm for pattern classification that finds the optimal linear decision surface according to the concept of structural risk minimization principle [18].the decision surface is a weighted combination of elements of a training data set. These are support vectors. The input to a SVM is a training data from the feature vectors of the face $\{(x_i, y_i)\}$ where x_i is the data and y_i = -1 or 1 is the label. The output of the SVM is a set of N_s support vectors s_i, coefficient weight α_i, class labels y_i of support vectors and a constant term b. the linear decision surface is w. z + b= 0, where $w = \sum_{i=1}^{N_s} \alpha_i y_i s_i$, SVM can also be extended to nonlinear decision surfaces by using a kernel K (· , ·) that satisfies Mercer's condition [18]. The nonlinear decision surface is given by

$$\sum_{i=0}^{N_s} \alpha_i y_i K(s_i, z) + b = 0 \qquad (9)$$

A facial image represented as a vector P ϵ $\mathcal{R}^N$, where $\mathcal{R}^N$ is referred to as face space. We write P1 ~ P2 if P1 matches P2 of the same face, and P1 $\nsim$ P2 if P1 face image is not matching to P2 composite sketch.

Consider an image P of person X, SVM classifier is trained with a data set consisting of facial images as one class and with other consisting of composite sketches. SVM will generate a linear decision surface, and image P is accepted if w. P + b ≤ 0, otherwise it is rejected.

This classifier is designed to minimize the structural risk. Performance of the classifier is measured based on the probability of true acceptance P_T and probability of false acceptance P_F. for best case all the images are matched i.e P_T=P_F=1. At the worst case P_T=P_F=0. Practically decision surface generated by SVM produces a single performance point for P_T and P_F. For the adjustment of P_T and P_F we parameterize a SVM decision surface by Δ. The parameterize decision surface is

$$w.\ z + b = \Delta \qquad (10)$$

Face image is matched to the sketch image if

$$w.\ P + b \leq \Delta \qquad (11)$$

If Δ = -∞ then P_T=P_F=0. If Δ = +∞ then P_T=P_F=1. All matching of face images to composite images and not matching cases will be between -∞ to +∞.

Nonlinear parameterized decision surface are given as

$$\sum_{i=0}^{N_s} \alpha_i y_i K(s_i, z) + b = \Delta. \qquad (12)$$

IV. EXPERIMENTAL RESULTS

The performance of the proposed method is evaluated on PRIP composite sketch database [4]. PRIP contains 123 faces from the AR face database [10]. The composites were created using FACES and IdentiKit softwares. Performance measures are used to obtain the results. Confusion or error Matrix describes the performance of classification. It contains a list of performance indicators like Accuracy, Misclassification Rate, True Positive Rate, False Positive Rate, True Negative Rate, Precision, Prevalence, ROC Curve. Accuracy gives the accuracy of the classifier in classification. True Positive(Tp) is the case when classifier classified correctly. True Negative or Specificity is the case when classifier predicted no. Accuracy of the classifier is given as:

Accuracy = (Tp+Tn)/Total. (13)

Precision gives number of samples correctly classified divided by the all the samples classified.

Precision = Tp/(Tp+Fp) (14)

Figure 5 shows matching digital face image with the composite sketch with all the intermediate results of the proposed method.

Figure 5(a) shows the original face image, (b) composite face image (c) Detected face (d) Components of the face (e) Right eye (f) Left eye (g) Nose (h) Mouth

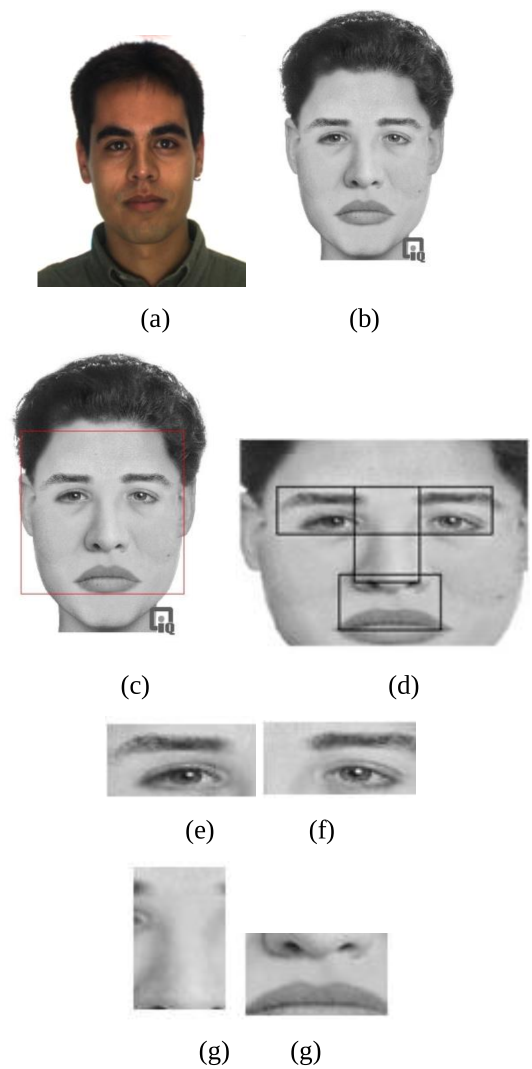

Fig.5: Example of matching digital face image with the composite sketch with all the intermediate results.

Table 2 shows the comparison of existing methods with the proposed.

Table 2: Comparison of existing methods with the proposed Model

Method	Accuracy
SIFT+LBP	**97%**
Daisy descriptor	**46%**
Human Visual System+ Log LBP	**89%**
Proposed	**98%**

Accuracy comparison Graph for the proposed and existing system is given in Figure 6.

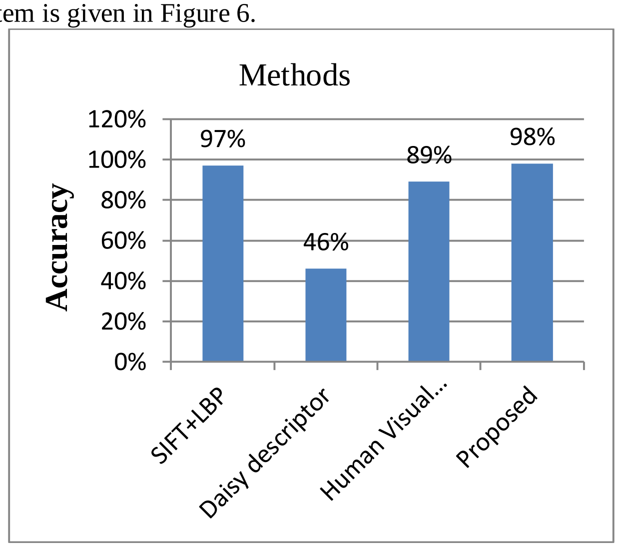

Fig.6: Accuracy comparison Graph for the proposed and existing system

V. CONCLUSION

Forensic face recognition systems gives poor recognition, for this reason this paper presents a method that uses Multiscale Local binary Pattern and Tchebichef moments as a feature vector for the representation of features from facial components for matching composite sketches to digital photos. Component based method gives good recognition accuracy compared to holistic methods. The experimental results shows improvement in performance compared to the state of the art methods.

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