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Forensic Photo Sketch Matching Using Feature Texture Analysis

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Abstract — ***Face recognition is considered one of the most essential applications of biometrics for person identification. Face sketch recognition is a special case of face recognition, and it is very important for forensic applications. In this project we propose an generalise method for face photo-sketch recognition by generalising a pseudo-sketch from a single photo .The proposed method is the first generalise method that deals with face sketch recognition. In the recognition step, the artist sketch is compared with the generated pseudo-sketch. MLBP are used to extract features from the sketch images. The k-nearest neighbor classifier with standaraize euclidean distance is used in the classification step. Results for the synthesised sketches will be compared with state-of-the-art methods .Our proposed method will generates clear synthesis sketch and it defines persons more accurate than other methods.***

Keywords- Sketch/Photosynthesis; Gradient Edge Detection; Hair Detection; Contrast Stretching

I. INTRODUCTION

An important application of face recognition is to assist law enforcement. Automatic retrieval of photos of suspects from the police mug shot database can help the police narrow down potential suspects quickly. However, in most cases, the photo image of a suspect is not available. The best substitute is often a sketch drawing based on the recollection of an eyewitness. Therefore, automatically searching through a photo database using a sketch drawing becomes important. It can not only help police locate a group of potential suspects, but also help the witness and the artist modify the sketch drawing of the suspect interactively based on similar photos retrieved . However, due to the great difference between sketches and photos and the unknown psychological mechanism of sketch generation, face sketch recognition is much harder than normal face recognition based on photo images. It is difficult to match photos and sketches in two different modalities. One way to solve this problem is to first transform face photos into sketch drawings and then match a query sketch with the synthesized sketches in the same modality, or first transform a query sketch into a photo image and then match the synthesized photo with real photos in the gallery. Face sketch/photo synthesis not only helps face sketch recognition, but also has many other useful applications for digital entertainment; we will study these two interesting and related problems: face sketch/photo synthesis and face sketch recognition.

Artists have a fascinating ability to capture the most distinctive characteristics of human faces and depict them on sketches. Although sketches are very different from photos in style and appearance, we often can easily recognize a person from his sketch. How to synthesize face sketches from photos by a computer is an interesting problem. The psychological mechanism of sketch generation is difficult to be expressed precisely by rules or grammar. The difference between sketches and photos mainly exists in two aspects: texture and shape the patches drawn by pencil on paper have different texture compared to human skin captured on a photo. In order to convey the 3D shading information, some shadow texture is often added to sketches by artists.

The face recognition is very important application for criminals' identity which is involve in various types of criminals activity. But in most of the cases there is a possibility that the images of the suspect is not available then in that case a Forensic method will be apply, in forensic eyewitness. Other method that is available is software(facial composite software) which allow each user to create a facial composite (composite sketches) instead of employing forensic sketch artist but both the methods are having lack of detail information. The component based approaches (CBR) is used to measure the similarity between composite sketch and mug shot photograph. Preprocessing is apply to increase the quality. The detection of facial landmarks using active shape model (ASM) after that features are extracted with the help of multi scale local binary pattern(MSLBP).The template are also used for test sample with the help of classifier.

II. LITERATURE REVIEW

In 2005 Liu and Tang present a new sketch synthesized method to map the nonlinear relation between the photo and the sketch. They divided the input photo into local patches. For each patch, they found its local nearest neighbor patches, using the Euclidean distance, in the photo training set. Then, the corresponding sketch patches to these neighbor patches are used to synthesis a new patch in the output sketch. They used 13x13 patch size; the number of the nearest neighbors is 5 and the overlapped region equal 2/3 of the patch size. These parameters produced a performance rate 87% by using KNDA classifier [5].

In 2010, Klare and Jain proposed a Scale Invariant Feature Transform(SIFT) based local feature approach. The method consists in sampling the SIFT feature descriptors uniformly across all the sketch and photo images, then both are matched directly or using a dictionary composed by training pairs. The recognition proceeds by computing the distance of the SIFT representation between the sketch and photo. A new face recognition problem that has recently emerged is the association between sketches and photos. The consequence of this problem is the development of robust algorithms for security agencies. When a crime is observed by an eyewitness, often a verbal description of the features of the offender is employed by a police artist to draw a sketch of the suspect. Many criminals have been apprehended when identified by such sketches.*Scale*-Invariant Feature Transform (SIFT):The SIFT descriptor has been used effectively in face recognition. The SIFT descriptors are extracted from a fixed grid and the keypoint detection is not used, the histogram is also normalized[1].

In 2011 B. Klare, Z. Li, and A. Jainproposed a sketch which is drawn by the expert artist according to the verbal description provided by an eyewitness is called as a forensic sketch. In this paper they have proposed matching a forensic sketch to mug shot data base that is to be maintained by law enforcement agencies. They have used a LFDA i.e local feature based discriminant analysis for individually representation of both sketch and photo for this they have used a SIFT feature descriptor and multi scale local binary pattern with the help of LFDA is used to perform matching between sketches and photos by keeping distance between them should be minimum with the help of SIFT i.e scale invariant feature transformation is used to detect and describe the local feature of an image and SIFT operator is also used to quantized both the spatial location and gradient orientation after that computes a histogram in which each bin is a combination of particular location and orientation. The LBP i.e local binary pattern is used to describe the face at multiple scales but LBP cannot capture dominant feature with large scale structure so, for improvement in accuracy they were using a MLBP i.e multi scale local binary pattern. Both the MLBP and SIFT feature descriptor was recognize the heterogeneous face based on sketches[6].

III. PROPOSED WORK

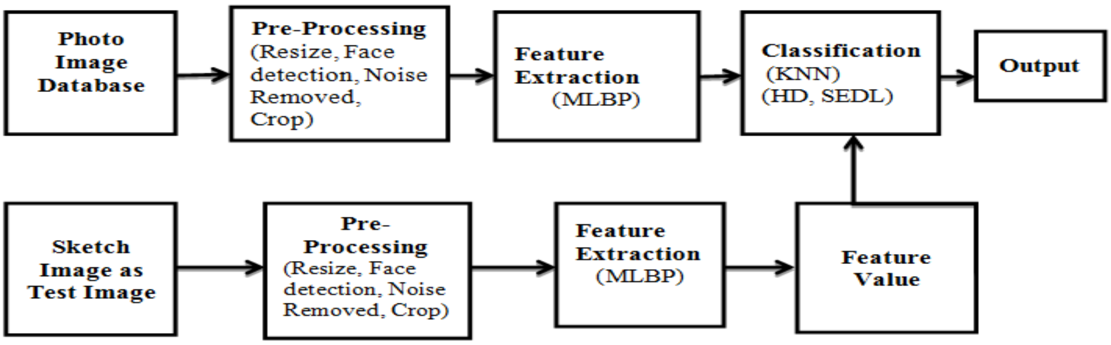

Figure 3.1: Block diagram of sketch detection

3.1 Steps for Proposed Method.

Step1: Load the Database.

Step 2:Pre-Processing

- Resize the sketch in 256 x 256.
- Noise is removed using the median filter.
- Face detection using viola-jones algorithm.
- Crop the sketch.

Step 3: Feature Extraction using MLBP.
Step 4: Sketch image as test image.
Repeat the *Step* 2 and 3.
Step 5: Feature Value.
Step 6: Classification.
Step 7: Output.

3.2 Image Database:

The experiments are conducted on the CUHK face sketch database. It contains 188 pairs of faces photos and their corresponding artist sketches. Some samples of the CUHK database are shown in Fig4.2. Images are in a frontal pose with a normal expression and size 900x1200pixels. We cropped images to remove the background and keep only the face region. The suitable image size that preserves the face details is 130x100 pixels.

Figure 3.2: Samples CUHK student images database

3.3. Pre-Processing:

- Resize the photo or sketch .Original size of photo and sketch is 1024x768 and 414x582 its convert into 256x256.
- Median filtering is an on linear operation often used in image processing to reduce “salt and pepper noise. A median filter is more effective than conventional when the goal is to simultaneously reduce noise and preserve edges.

Figure 3.3:Noise removed

- Face detection proposed by Viola and Jones based on statistic methods is most popular among the face detection approaches. This face detection is a variant of the AdaBoost algorithm which achieves rapid and robust face detection. They proposed a face detection method based on the AdaBoost learning algorithm using Haar features that detected the face successfully with high accuracy. However the accuracy of the method is still not enough when this method is used to detect facial feature. we have Viola Jones, skin color pixel detection and physical location approximation technique to have a hybrid design which can detect face, mouth and eyes more accurately while consuming less time.

3.4 Feature Extraction:

3.4.1 MLBP

The original LBP operator labels the pixels of an image with decimal numbers, which are called *LBPs* or *LBP codes* that encode the local structure around each pixel. It proceeds thus, as illustrated in Fig.3.4: Each pixel is compared with its eight neighbors in a 3 × 3 neighborhood by subtracting the center pixel value; the resulting strictly negative values are encoded with 0 and the others with 1. For each given pixel, a binary number is obtained by concatenating all these binary values in a clockwise direction, which starts from the one of its top-left neighbor. The corresponding decimal value of the generated binary number is then used for labeling the given pixel. The derived binary numbers are referred to be the LBPs or LBP codes.

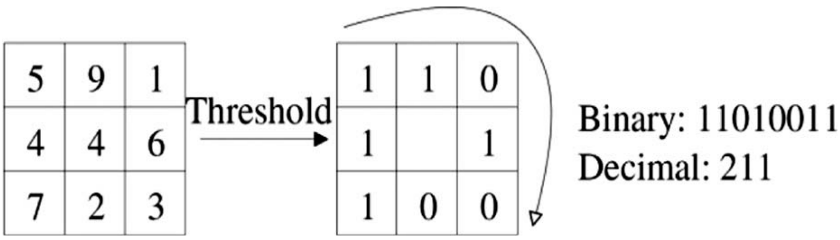

Figure 3.4: Example of the basic LBP operator

3.5 Classification

In pattern recognition, the *k* Nearest Neighbors algorithm (or *k*NN for short) is a nonparametric method used for classification and regression. In both cases, the input consists of the *k* closest training examples in the feature space. The output depends on whether *k*NN is used for classification or regression:

In *Knn classification*, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its *k* nearest neighbors (*k* is a positive integer, typically small). If $k = 1$, then the object is simply assigned to the class of that single nearest neighbor.

In *kNN regression*, the output is the property value for the object. This value is the average of the values of its *k* nearest neighbors. *K*NN is a type of instance based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The *k*NN algorithm is among the simplest of all machine learning algorithms**.**

IV. SYSTEM ARCHITECTURE

In the development and implementation of this project the aim is to be built such a system that will determine the accuracy.

4.1 Architecture of proposed system

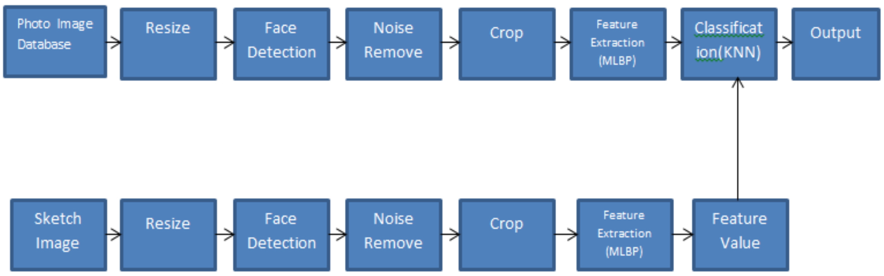

Figure 4.1: Architecture of proposed system

4.2 System Working

4.2.1 Image database

The experiments are conducted on the CUHK face sketch database. It contains 188 pairs of faces photos and their corresponding artist sketches. Some samples of the CUHK database are shown in Fig. Images are in a frontal pose with a normal expression and size 900x1200pixels. We cropped images to remove the background and keep only the face region. The suitable image size that preserves the face details is 130x100 pixels.

Figure 4.2: Samples CUHK student images database

4.2.2 Pre-Processing

4.2.2.1 Resize

Resize the photo or sketch .Original size of photo and sketch is 1024x768 and 414x582 its convert into 256x256.

4.2.2.2 Face Detection

Face detection proposed by Viola and Jones based on statistic methods is most popular among the face detection approaches. This face detection is a variant of the AdaBoost algorithm which achieves rapid and robust face detection. They proposed a face detection method based on the AdaBoost learning algorithm using Haar features that detected the face successfully with high accuracy. However the accuracy of the method is still not enough when this method is used to detect facial feature. In research we have integrated Viola Jones, skin color pixel detection and physical location approximation technique to have a hybrid design which can detect face, mouth and eyes more accurately while consuming less time.

Viola-Jones technique is based on exploring the input image by means of sub window capable of detecting features. This window is scaled to detect faces of different sizes in the image. Viola Jones developed a scale invariant detector which runs through the image many times, each time with different size. Being scale invariant, the detector requires same number of calculations regardless of the size of the image.

The system architecture of Viola Jones is based on a cascade of detectors. The first stages consist of simple detectors which eliminates only those windows which do not contain faces. In the following stages the complexity of detectors are increased to analysis the features in more detail. A face is detected only if it is observed through the entire cascade. These detectors are constructed from integral image and Haar like Features shown in Figure4.3.

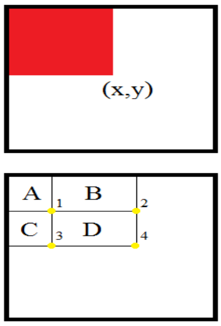

Figure 4.3: Viola Jones integral image construction.

The first step of this algorithm is to convert the input image into an integral image. This is done by making each pixel equal to the entire sum of all pixels above and to the left of the concerned pixel. By doing so, sum of all pixels inside any given rectangle can be calculated using only four values.

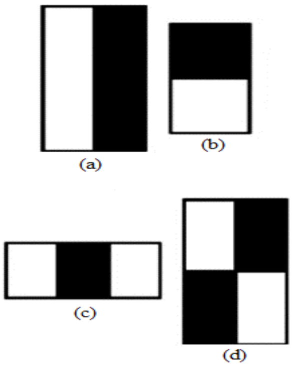

Figure 4.4: Viola Jones Haar like features

Sum of the rectangle ABCD = D - (B + C) + A

The face detector in Viola Jones method analyzes a sub-window using features. These features consist of two or more rectangles. Each feature gives a single resultant value which is calculated by subtracting the sum of the white rectangle(s) from the sum of the black rectangle(s). Different types of features are shown in Figure 2. Viola and Jones used a simple classifier built from computationally efficient features using AdaBoost for feature selection. AdaBoost is a machine learning boosting algorithm that constructs a strong classifier through a weighted combination of weak classifiers. Mathematical description of weak classifier is, where x is a sub-window, f is the applied feature, p the polarity and θ is threshold that concludes whether x should be classified as a negative (non-face) or a positive (face). Viola-Jones face detection algorithm scans the detector several times through the same image –each time with a new size. The detector detects the non face area in an image and discards that area which results in detection of face area. To discard non face area Viola Jones take advantage of cascading. When a sub window is applied to cascading stages, each stage concludes whether the sub window is a face object or not. Sub windows which contain some percentage of having faces are passed to next stage and those which are not faces are discarded. Final stage is considered to have a high percentage of face objects.

4.2.2.3 Noise Remove

Noise is any undesirable signal. Noise is everywhere and thus we have to learn to live with it. Noise gets introduced into the data via any electrical system used for storage, transmission, and/or processing. In addition, nature will always plays a "noisy" trick or two with the data under observation. When encountering an image corrupted with noise you will want to improve its appearance for a specific application. The techniques applied are application-oriented. Also, the different procedures are related to the types of noise introduced to the image. Some examples of noise are: Gaussian or White, Rayleigh, Shot or Impulse, periodic, sinusoidal or coherent, uncorrelated, and granular.

- **Median Filter**

Median filtering follows this basic prescription. The median filter is normally used to reduce noise in an image, somewhat like the mean filter. However, it often does a better job than the mean filter of preserving useful detail in the image. This class of filter belongs to the class of edge preserving smoothing filters which are non-linear filters. This means that for two images *A(x)* and *B(x)*:

$$\textbf{median}\,[A(x)+B(x)] \neq \textbf{median}\,[A(x)]+\textbf{median}[B(x)]$$

These filters smooth the data while keeping the small and sharp details. The median is just the middle value of all the values of the pixels in the neighborhood. Note that this is not the same as the average (or mean); instead, the median has half the values in the neighborhood larger and half smaller. The median is a stronger "central indicator" than the average. In particular, the median is hardly affected by a small number of discrepant values among the pixels in the neighborhood. Consequently, median filtering is very effective at removing various kinds of noise.

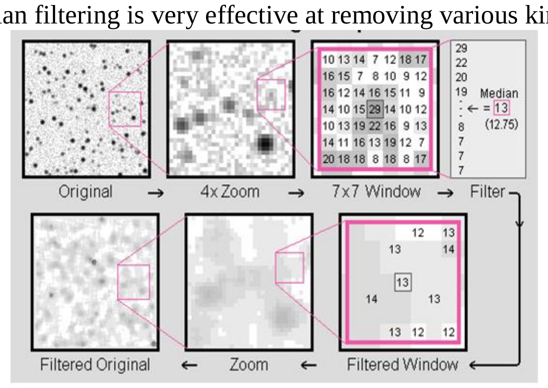

Figure 4.4: Median filtering Example

Like the mean filter, the median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the *mean* of neighboring pixel values, it replaces it with the *median* of those values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and *then* replacing the pixel being considered with the middle pixel value. (If the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is used.)

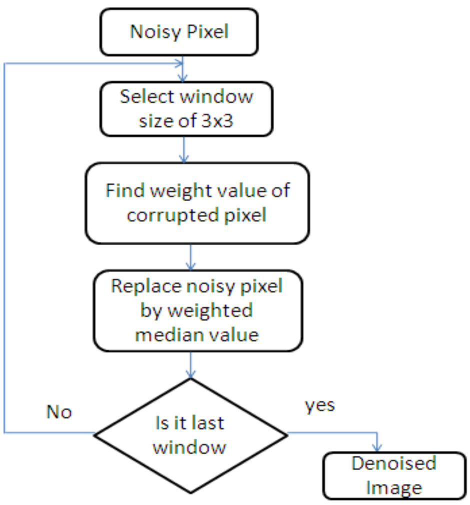

Figure 4.6: Flow Chart of Median Filter

4.2.2.4 Crop

I=imcrop creates an interactive. Crop image tool associated with the image display in the current figure called the target image. The crop image tool is a moveable, resizable rectangle that you can position interactively using the mouse. When crop image tool is active, the pointer changes to cross hairs. When you move it over the target image. Using the mouse, you specify the crop rectangle by clicking and dragging the mouse. You can move or resize the crop rectangle using the mouse. When you are finished sizing and positioning the crop rectangle, create the cropped image by double clicking the left mouse button or by choosing crop image from the context menu, imcrop return the cropped image, I. The following figure illustrates the crop image tool with the context menu displaying for more information about interactive capabilities of the tool**.**

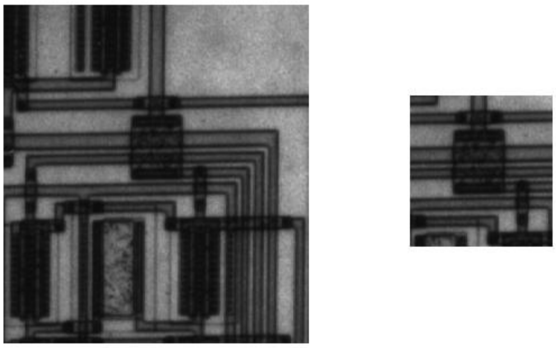

Figure 4.7: Crop Image

4.2.3 Feature Extraction

4.2.3.1 MLBP

The local binary pattern operator is an image operator which transforms an image into an array or image of integer labels describing small-scale appearance of the image. These labels or their statistics, most commonly the histogram, are then used for further image analysis. The most widely used versions of the operator are designed for monochrome still images but it has been extended also for color (multichannel) images as well as videos and volumetric data. The basic local binary pattern operator, introduced by Ojala et al., was basedon the assumption that texture has locally two complementary aspects, a pattern andits strength. In that work, the LBP was proposed as a two-level version of the texture unit to describe the local textural patterns. The original version of the local binary pattern operator works in a 3 × 3 pixel block of an image. The pixels in this block are threshold by its center pixel value, multiplied by powers of two and then summed to obtain a label for the center pixel. As the neighborhood consists of 8 pixels, a total of 28 = 256 different labels can be obtained depending on the relative gray values of the center and the pixels in the neighborhood.

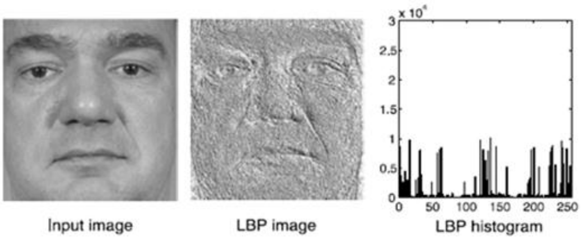

Figure 4.8: Example of an input image, the corresponding LBP image and histogram

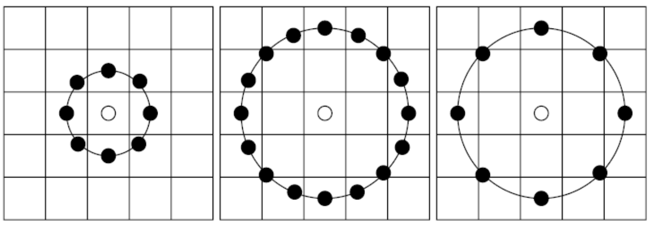

Figure 4.9: The circular *(*8, 1*)*, *(*16, 2*)* and *(*8, 2*)* neighborhoods. The pixel values are bilinearly interpolated whenever the sampling point is not in the center of a pixel.

- **Uniform Patterns**

In many texture analysis applications it is desirable to have features that are invariant or robust to rotations of the input image. As the LBP*P*, *R* patterns are obtained by circularly sampling around the center pixel, rotation of the input image has two effects: each local neighborhood is rotated into other pixel location, and within each neighborhood, the sampling points on the circle surrounding the center point are rotated into a different orientation. Another extension to the original operator uses so called *uniform patterns*. For this, a uniformity measure of a pattern is used: *U* ("pattern") is the number of bitwise transitions from 0 to 1 or vice versa when the bit pattern is considered circular. A local binary pattern is called uniform if its uniformity measure is at most 2. For example, the patterns 00000000 (0 transitions), 01110000 (2 transitions) and 11001111 (2 transitions) are uniform whereas the patterns 11001001 (4 transitions) and 01010011 (6 transitions) are not. In uniform LBP mapping there is a separate output label for each uniform pattern and all the non-uniform patterns are assigned to a single label. Thus, the number of different output labels for mapping for patterns of P bits is $P(P-1)+3$. For instance, the uniform mapping produces 59 output labels for neighborhoods of 8 sampling points, and 243 labels for neighborhoods of 16 sampling points. The reasons for omitting the non-uniform patterns are twofold. First, most of the local binary patterns in natural images are uniform. Ojala et al. noticed that in their experiments with texture images, uniform patterns account for a bit less than 90% of all patterns when using the $(8, 1)$ neighborhood and for around 70% in the $(16, 2)$ neighborhood. In experiments with facial image it was found that90.6% of the patterns in the $(8, 1)$ neighborhood and 85.2% of the patterns in the $(8, 2)$ neighborhood are uniform. The second reason for considering uniform patterns is the statistical robustness. Using uniform patterns instead of all the possible patterns has produced better recognition results in many applications. On one hand, there are indications that uniform patterns themselves are more stable, i.e. less prone to noise and on the other hand, considering only uniform patterns makes the number of possible LBP labels significantly lower and reliable estimation of their distribution requires fewer samples. The uniform patterns allows to see the LBP method as a unifying approach to the traditionally divergent statistical and structural models of texture analysis .Each pixel is labeled with the code of the texture primitive that best matches the local neighborhood. Thus each LBP code can be regarded as a micro-texton. Local primitives detected by the LBP include spots, flat areas, edges, edge ends, curves and so on. Some examples are shown in Fig.7 with the LBP8,Roperator. In the figure, ones are represented as black circles, and zeros are white. The combination of the structural and statistical approaches stems from the fact that the distribution of micro-textons can be seen as statistical placement rules. The LBP distribution therefore has both of the properties of a structural analysis method: texture primitives and placement rules. On the other hand, the distribution is just a statistic of a non-linearly filtered image, clearly making the method a statistical one. For these reasons, the LBP distribution can be successfully used in recognizing a wide variety of different textures, to which statistical and structural methods have normally been applied desperately.

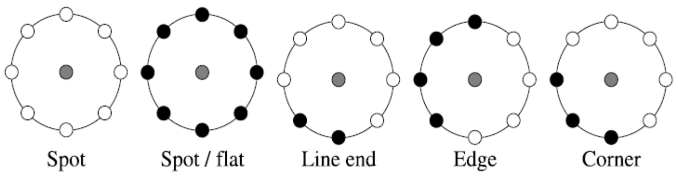

Figure 4.10:Different texture primitives detected by the LBP

- **Rotational Invariance**

Let $UP\ (n, r)$ denote a specific uniform LBP pattern. The pair (n, r) specifies a uniform pattern so that n is the number of 1-bits in the pattern (corresponds to row number in Fig.8) and r is the rotation of the pattern (column number in Fig.8).Now if the neighborhood has P sampling points, n gets values from 0 to $P+1$, where $n = P+1$ is the special label marking all the non-uniform patterns. Furthermore, when $1 \leq n \leq P-1$, the rotation of the pattern is in the range $0 \leq r \leq P-1$. Let $I\ \alpha\circ(x, y)$ denote the rotation of image $I\ (x, y)$ by α degrees. Under this rotation, point (x, y) is rotated to location (x, y). A circular sampling neighborhood on points $I\ (x, y)$ and $I\ \alpha\circ(x, y)$ also rotates by $\alpha\circ$. See Fig.9. If the rotations are limited to integer multiples of the angle between two sampling points, i.e. $\alpha = a\ 360\circ/P$, $a = 0, 1, \ldots, P-1$, this rotates the sampling neighborhood by exactly a discrete steps. Therefore the uniform pattern $UP\ (n, r)$ at point (x, y) is replaced by uniform pattern $UP\ (n, r + a \bmod P)$ at point (x,y) of the rotated image. From this observation, the original rotation invariant LBPs introduced in and newer, histogram transformation based rotation invariant features described in can be derived.

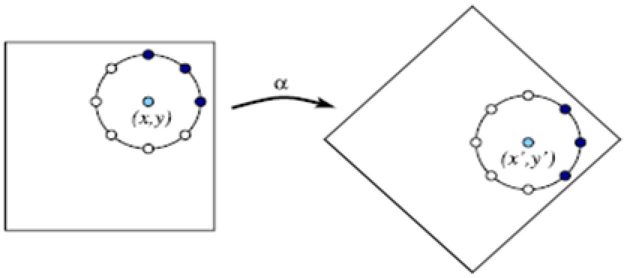

Figure 4.11: Effect of image rotation on points in circular neighborhoods

4.2.4 Classification

4.2.4.1 KNN

In pattern recognition, the *k*Nearest Neighbors algorithm (or *K*nn for short) is a nonparametric. Method used for classification and regression.[1] In both cases, the input consists of the *k* closest training examples in the feature space. The output depends on whether *k*NN is used for classification or regression:

In *kNN classification*, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its *k* nearest neighbors (*k* is a positive integer, typically small). If *k* = 1, then the object is simply assigned to the class of that single nearest neighbor.

In *kNN regression*, the output is the property value for the object. This value is the average of the values of its *k* nearest neighbors. *K*NN is a type of instance based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The *k*NN algorithm is among the simplest of all machine learning algorithms. Both for classification and regression, it can be useful to assign weight to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight of 1/*d*, where *d* is the distance to the neighbor.[2] The neighbors are taken from a set of objects for which the class (for *k*NN classification) or the object property value (for *k*NN regression) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required. A shortcoming of the *k*NN algorithm is that it is sensitive to the local structure of the data.

- **Standardize Euclidean Distance**

The euclidean distance is often used as a measure of similarity between elements (see distance. A drawback of this measure is that it depends on the range of the rating scale and the number of constructs used, i. e. on the size of a grid. An approach to standardize the euclidean distance to make it independent from size and range of ratings and was proposed by Slater (1977, pp. 94). The 'Slater distance' is the Euclidean distance divided by the expected distance. Slater distances bigger than 1 are greater than expected, lesser than 1 are smaller than expected. The minimum value is 0 and values bigger than 2 are rarely found. Slater distances have been be used to compare inter-element distances between different grids, where the grids do not need to have the same constructs or elements. Hartmann (1992) showed that Slater distance is not independent of grid size. Also the distribution of the Slater distances is asymmetric. Hence, the upper and lower limit to infer 'significance' of distance is not symmetric. The practical relevance of Hartmann's findings have been demonstrated by Schoeneich and Klapp (1998). To calculate Hartmann's version of the standardized distances see distance Hartmann.

$$d_{8t}^{2} = (x_{8-Y_t})V^{-1}(x-y_t)' \text{-------------------------}(1)$$

IV. RESULT

4.1 Database Collection

The experiments are conducted on the CUHK face sketch database. It contains 188 pairs of faces photos and their corresponding artist sketches. Images are in a frontal pose with a normal expression and size 900x1200pixels. We cropped images to remove the background and keep only the face region. The suitable image size that preserves the face details is 130x100 pixels.

4.2 Performance Measure

a is the number of correct predictions that an instance is negative,
b is the number of incorrect predictions that an instance is positive,
c is the number of incorrect of predictions that an instance negative, and
d is the number of correct predictions that an instance is positive.
Several standard terms have been defined for the 2 class matrix:

- The accuracy (AC) is the proportion of the total number of predictions that were correct. It is determined using the equation:

$$AC = \frac{a+d}{a+b+c+d}$$

- The recall or true positive rate (TP) is the proportion of positive cases that were correctly identified, as calculated using the equation:

$$TP = \frac{d}{c+d}$$

- The false positive rate (FP) is the proportion of negatives cases that were incorrectly classified as positive, as calculated using the equation:

$$FP = \frac{b}{a+b}$$

- The true negative rate (TN) is defined as the proportion of negatives cases that were classified correctly, as calculated using the equation:

$$TN=\frac{a}{a+b}$$

- The false negative rate (FN) is the proportion of positives cases that were incorrectly classified as negative, as calculated using the equation:

$$FN=\frac{c}{c+d}$$

- Finally, precision (P) is the proportion of the predicted positive cases that were correct, as calculated using the equation:

$$P=\frac{d}{b+d}$$

Table 1: System Performance Table

Parameters	Values
Accuracy(AC)	96.66%
True positive rate (TP)	100%
False positive rate (FP)	100%
True negative rate (TN)	0%
False negative rate (FN)	0%
Precision (P)	96.66%

Table 2: Comparison Table

Methods	Recognition Rate
Proposed Method	96.7%
HebaGhreeb M. Abdel-Aziz, Hala M. Ebeid and Mostafa G. M. Mostafa	94%
Tang and Wang [22]	81.3%
Tang and Wang [22]	75%
Liu and Tang [21]	87%
Liu and Tang [21]	84%
Pramanik and Bhattacharjee [12]	80%

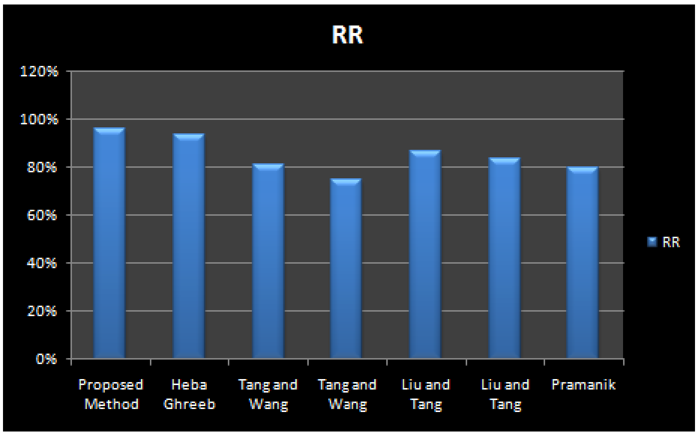

Figure 4.2: Comparison Graph

V. CONCLUSION

The method synthesizes a sketch image from a single photo image to use it for photo-sketch recognition by comparing the synthesized sketch with the artist sketch. The method synthesizes a sketch through image gradient to emphasize the dominant feature and image threshold to preserve hair features. Therefore, the method is completely unsupervised and free from any user intervention. Moreover, it is very simple and fast. In the recognition phase, MLBP are used to extract the feature of the synthesized sketches and the test sketch. The test sketch is projected on the feature space of the MLBP features. The k-nearest neighbor classifier (k-NN) with Euclidean distance is used to match images and find the nearest k-class to the tested sketch. Experimentation of the proposed method is done using the CUHK student database.

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