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Matching Sketches with Digital Face Images using MCWLD and Image Moment Invariant

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Abstract : *Face recognition is an important problem in many application domains. Matching sketches with digital face image is important in solving crimes and capturing criminals. It is a computer application for automatically identifying a person from a still image. Law enforcement agencies are progressively using composite sketches and forensic sketches for catching the criminals. This paper presents two algorithms that efficiently retrieve the matched results. First method uses multiscale circular Weber's local descriptor to encode more discriminative local micro patterns from local regions. Second method uses image moments, it extracts discriminative shape, orientation, and texture features from local regions of a face. The discriminating information from both sketch and digital image is compared using appropriate distance measure. The contributions of this research paper are: i) Comparison of multiscale circular Weber's local descriptor with image moment for matching sketch to digital image, ii) Analysis of these algorithms on viewed face sketch, forensic face sketch and composite face sketch databases.*

Keywords *- composite sketches, image moment, support vector machines, weber's local descriptor*

I. Introduction

There are three types of sketches: forensic sketches, viewed sketches and composite sketches. Forensic sketches are the sketches drawn by specially trained artists based on the description of criminal by an eye witness. Viewed sketches are the sketches drawn by an artist, directly looking at the subject or the photograph of the criminal. Composite sketches [7] are drawn using software tools that facilitate an eyewitness to select different facial components from a wide range of pre-defined templates. The eyewitness selects the most resembling facial template for each feature based on his/her recollection from the crime scene. These tools allow processing each feature individually and then combine all the features to generate a composite sketch. Compared to hand drawn sketches the composite sketches require lesser effort both in terms of cost as well as time. Fig 1. shows the example of viewed, forensic and composite sketches and its corresponding photograph. Matching sketches with digital face images is a very important law enforcement application. Developments in biometric technology have provided additional tools to criminal investigators that help to determine the identity of criminals [1].

(a) (b) (c)

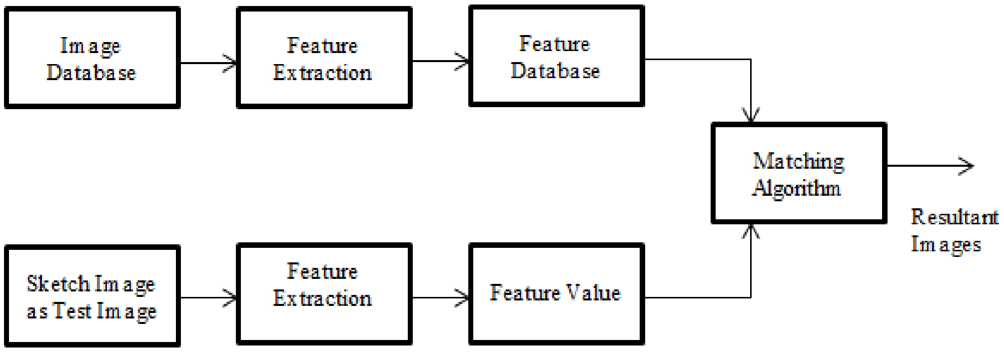
Fig 1. (a)Viewed sketch and it's corresponding photograph, (b) Forensic sketch and it's corresponding photograph, (c) Composite sketch and it's corresponding photograph.

If a fingerprint is found at the scene of crime or a surveillance camera captures an image of the face of a suspect, these are used in determining the suspect using different biometric identification techniques. In many cases such type of above information is not present. The technology to efficiently capture the biometric data like finger prints within a short period of time is impractical. So in many cases an eyewitness is available in crime who had seen the criminal. The forensic artist draw sketch that portrays the facial appearance of the criminal. Sketches drawn by using such process is called as forensic sketches. When sketch is ready, it is sent to the law enforcement officers and media outlets with the hope of catching the suspect. Generally, these sketches are manually matched with the database consisting of digital face images of known individuals. If the criminal has been imprisoned at-least once, a mug shot photo (photo taken, while the person is being sent to jail) is available.

Using an efficient sketch matching system, the police can narrow down the potential suspects which will reduce the future crimes by the same criminal. Fig 2. shows the representation of sketch matching system.

The Weber's local descriptor [2] is based on Weber's law and it is similar to Scale Invariant Feature Transform (SIFT) and Local Binary Pattern (LBP). It is similar to LBP in analyzing small neighborhood regions and to SIFT in computing histogram using gradient magnitude and orientation. WLD has some unique features that compute the salient micro patterns in a relatively small neighborhood region.

Fig 2. Representation of Sketch Matching System



II. Related Works

Jiang, et al. [3] proposed Scale Invariant Feature Transform (SIFT) feature based face recognition. SIFT features are features extracted from images in reliable matching between different views of the same object. That extracted features are invariant to scale and orientation. After computing the SIFT features the common representation for sketch image and for photo is found out. To compare the similarity between photo and sketch, directly compare the distance between the two common representation vectors. The SIFT features described in this implementation are computed at the edges and they are invariant to image rotation, scaling and addition of noise.

Ambhore et al. [4] proposed face sketch to photo matching using Local Feature-Based Discriminant Analysis (LFDA). In LFDA framework [5], scale invariant feature transform (SIFT) and multiscale local binary pattern (MLBP) feature descriptors are used. Minimum distance sketch matching can be performed using this feature-based representation by computing the normed vector distance. The local binary patterns (LBP) operator takes a local neighborhood around each central pixel, thresholds the neighborhood pixels and uses resulting binary-valued image patch as a local image descriptor.

Balaji et al. [6] Extended Uniform Circular Local Binary Pattern (EUCLBP) Matching Algorithm. It extracts discriminating information present in local facial regions at different levels of granularity. Digital face images and sketches are decomposed into multi resolution pyramid which forms the discriminating facial patterns. EUCLBP use these patterns to form a unique signature of the face. For matching, a memetic optimization based approach is used to find the optimum weights corresponding to each facial region.

Chen et al. [2] proposed Weber's Local Descriptor (WLD) inspired by Weber's law. It states that the change of a stimulus that will be just noticeable is a constant ratio of the original stimulus. Weber's Local Descriptor is a dense descriptor computed for every pixel and depends on both the magnitude of the center pixel intensity and the local intensity variation. 2D WLD histogram is used for texture classification. There are two WLD components, differential excitation and orientation which is used to construct a WLD histogram.

Bhatt et al. [1] proposed Memetically Optimized Multi Scale WLD (MCWLD). Multi-scale Circular WLD is one of the most advanced types of image descriptors. WLD is optimized for matching sketches with digital face images by computing the multi-scale descriptor in a circular manner. Memetic optimization algorithm is used to assign optimal weights to every local facial region to boost the identification performance. This algorithm extracts the discriminating information from local regions of both digital face images and sketches.

Hu [8] proposed Regular Image Moment Invariant based matching sketch with digital image. Regular image moment invariants are invariant to rotation, scaling and translation. It provides information such as localized weighted average of the pixel intensities, centroid, and orientation details of an image. Image moments can efficiently encode selective information around the important features in local regions of sketches and digital face images. There are 7 image moments. Generally, each moment indicates a specific function. The first moment is the mean, the second moment is the variance and so on.

III. Proposed Work

3.1 Support Vector Machine for Preprocessing

There are various methods for image classification. SVM is one of the best known methods in pattern classification and image classification. Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm assigns new examples into one category or the other. Most of classifiers, such as neural network, decision tree, minimum distance, maximum likelihood and support vector machine require a training sample. Based on the training set the images are classified into a set of matched and unmatched images. The sketch-digital image pair that is classified based on this is considered for the further experimentation.

3.2 Matching sketches with Digital Face Images using MultiScale Circular Weber's Local Descriptor

Chen et.al [2] proposed Weber's Local Descriptor (WLD) which is based on Weber's law. Weber's law is expressed as:

$$\frac{\Delta I}{I} = k \qquad (1)$$

Where ΔI represents the increment threshold, I represents the initial stimulus intensity and k shows that the proportion on the left side of the equation remains constant despite of variations in the I term.

WLD computes the salient micro patterns in a relatively small neighborhood region with linear granularity [1]. WLD is used for matching sketches with digital face images by computing multiscale descriptor in circular manner. The multiscale circular WLD histograms of both sketch and digital face image are matched using weighted χ^2 distance measure.

The given face image is converted into gray scale image and it is resized into an adequate dimension. Multiscale Circular WLD (MCWLD) descriptor is computed for different values of P and R. P is the number of neighboring pixels on a circle of radius R centered at current pixel. For every pixel, the multiscale analysis is performed by varying the number of neighbors P and radius R (R=1, 2, 3 and P=8, 16, 24). The fig 3. represents the steps involved in matching system. MCWLD has two components differential excitation and orientation. The sketches and digital face images are represented using MCWLD as follows.

Differential Excitation: For every pixel, differential excitation [1] is computed as the arctangent function of ratio of the intensity difference between the central pixel and its neighbors to the intensity of the central pixel. The differential excitation of central pixel ξ(x_c) is computed as:

$$\xi(x_c) = \arctan\left\{\sum_{i=0}^{P-1}\left(\frac{x_i - x_c}{x_c}\right)\right\} \qquad (2)$$

where x_c is the intensity value of the central pixel and P is the number of neighbors on a circle of radius R.

Orientation: Orientation component computed as:

$$\theta(x_c) = arctan\left\{\frac{x\left(\frac{P}{2}+R\right) - x(R)}{x(P-R) - x\left(\frac{P}{2}-R\right)}\right\} \qquad (3)$$

The orientation value is quantized into T dominant orientations. T is experimentally set as eight. Before the quantization, the orientation value θ is mapped into the interval [0,2Π] to make the θ value in that range. Therefore, the quantization function is as follows:

$$\phi_t = \frac{2t}{T}\pi \qquad (4)$$

Here T=8, therefore $\phi_t = \frac{t\pi}{4}$ (t=0, 1…..T-1).

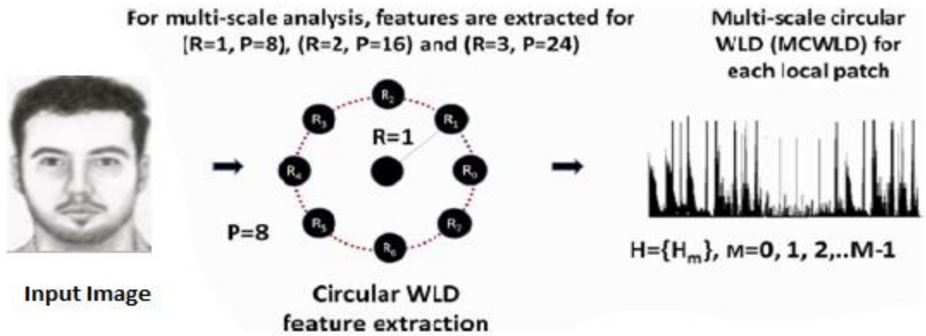


Fig 3. Steps involved in matching sketches.

MCWLD Histogram: We first compute the CWLD features for each pixel (i.e., CWLD(ξ_j, θ_t), where j=0,1..N-1, t=0,1….T-1 and N=is the dimension of the image). The differential excitation ξ_j are regrouped into T orientation sub-histograms H (t) (t=0,1…T-1). Each sub-histogram H (t) corresponds to a dominant orientation. Within each dominant orientation, the range of differential excitation (i.e., sub-histogram H (t)) is divided into M intervals $H_{m,t}$ (m=0,1….M-1 and M=6). The differential excitation value for each pixel is then differentiated on the basis of the eight different quantum levels. These differential excitation values corresponding to first quantum level are assigned to h1, differential excitation values corresponding to the second quantum level are assigned to h2 and so on. Fig 4. shows the steps involved in computing the circular WLD histogram.

For each differential excitation intervals h_n (n=0,1….N-1), the lower bound and upper bound is computed and this range is divided into M=6 segments. These sub-histogram segments $H_{m,t}$ across all dominant orientations are reorganized as M one dimensional histograms. Then the M sub-histograms are concatenated into a single histogram representing the circular WLD histogram. The multiscale circular WLD is computed with different values of P and R. Multiscale analysis is performed in three different scales i.e., (R=1, P=8), (R=2, P=16) and (R=3, P=24). These histograms at different scales are concatenated to form the facial representation.

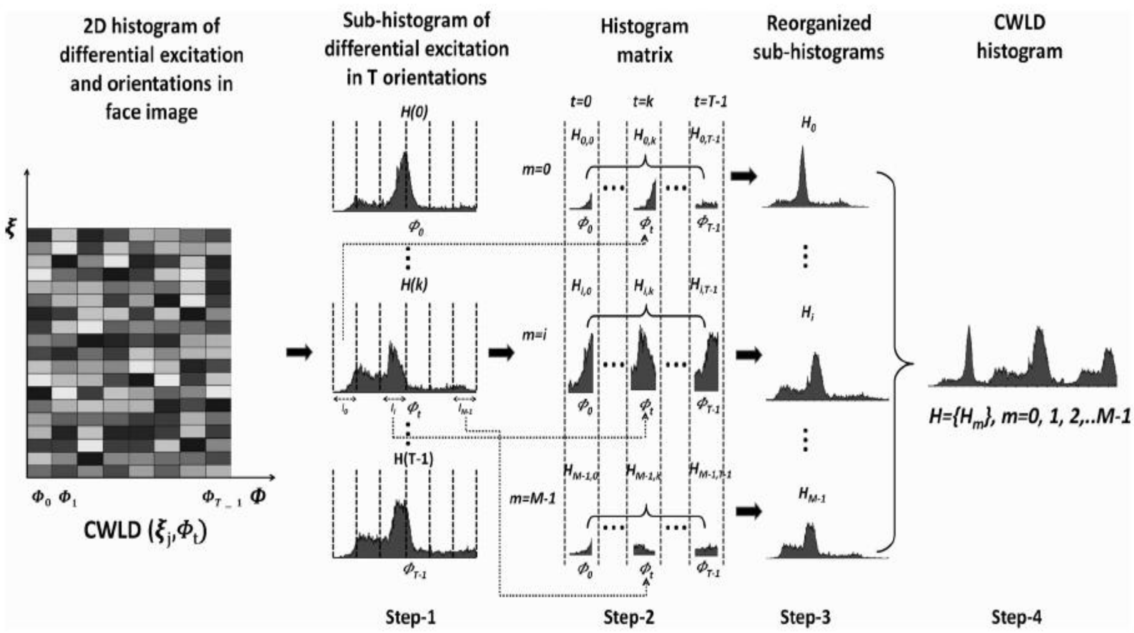


Figure 4. Illustrating the steps involved in computing the circular WLD histogram [2].

Weight for MCWLD Histogram: The MCWLD histogram represents the frequency information. Some facial regions are more discriminating than others and it will contribute more for recognition. The regions with high variance are more discriminating than flat regions. Thus, this M segments H_m play different roles for recognition. For better performance, different weights need to be assigned to diff histogram or frequency segments. Here we are taking weight as one for accurate result. Weighted χ^2 measure is used for matching two MCWLD histograms. It is represented as [1]:

$$\chi^2 = \sum_{i,j} \left[\frac{\left(p_{i,j} - q_{i,j}\right)^2}{\left(p_{i,j} + q_{i,j}\right)} \right] \tag{5}$$

where p and q are the two MCWLD histograms to be matched, i and j correspond to the i^{th} bin of the j^{th} histogram segment and $w_{i,j}$ is the weight of the j^{th} histogram segment. Here $w_{i,j}$ is taken as one based on the experimentation.

3.3 Matching Sketches with Digital Face Images using Image Moment Invariant

Hu [8] derived a set of 7 moment invariants, which are the properties of connected regions in binary images that are invariant to translation, rotation and scale. Image moment is a particular weighted average of the image pixel intensities. Function of such moments, usually chosen to have some attractive property or interpretation. It can efficiently encode the selective information around the prominent features in local regions of sketches and digital face images. Out of the 7 image moments proposed by Hu [8] second image moment M_2 is determined to be the most selective feature for representing the shape and orientation of local facial regions in sketches. Second image moment is computed as:

$$M_2 = (\eta_{20} - \eta_{02})^2 + 4{\eta_{11}}^2 \tag{6}$$

where η_{pq} represents normalized central moment. It is represented as:

$$\eta_{pq} = \frac{\mu_{pq}}{{\mu_{00}}^{\gamma}}$$

$$\gamma = \left[\frac{(p+q)}{2}\right] + 1 \tag{7}$$

where μ_{pq} is the central moment. The central image moments are regular two dimensional image moments which are shifted from the origin to image centroid $(\overline{x}, \overline{y})$. Therefore, μ_{pq}, central moment is calculated as:

$$\mu_{pq} = \sum_{x}\sum_{y} (x - \overline{x})^p \, (y - \overline{y})^q \, f(x, y) \tag{8}$$

where $\overline{x} = \frac{m_{10}}{m_{00}}$, $\overline{y} = \frac{m_{01}}{m_{00}}$. The two-dimensional regular moments of order $(p + q)$ is computed as:

$$m_{pq} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} (x)^p \, (y)^p \; f(x, y) \tag{9}$$

where $f(x, y)$ is the intensity value at (x, y) and p, q = 0,1,2….n.

The second order image moment is for each pixel in the image is calculated using Equations (6-9). Then the feature image is tessellated into 3x3 non-overlapping patches. Histogram is constructed for each local patch. The histogram that represents facial representation is computed where every uniform pattern has a separate bin and each non-uniform pattern is assigned to a single bin. The complete image signature is obtained by concatenating all the histograms of ach local patches. To compare a gallery-probe pair, the χ^2 distance measure is used.

$$\chi^2(x, y) = \sum_{i}\sum_{j} \frac{\left(x_{i,j} - y_{i,j}\right)^2}{x_{i,j} + y_{i,j}} \tag{10}$$

where x and y are the two feature histograms to be matched, i is the local region and j is the histogram bin.

IV. Experimental Analysis

The performance of MCWLD compared with image moment invariant algorithm for matching sketches with digital face images. For analysis, forensic sketches, composite sketches and viewed sketches are used.

4.1 Accuracy

The performance of proposed and existing algorithm designed for matching sketches with digital face images is compared. The preprocessing classification reduces the possibility of false positives and the number of comparisons. By preprocessing only top matched digital face images are selected for the next step. i.e., in the case of most sketches the exact match will be in the first 50%.

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The databases used in the work are IIIT-Delhi database [9], AR database[10] and PRIP composite sketch database[11]. Composite sketches for each subject are synthesized using two commercial facial composite systems: (i) FACES [12], and (ii) IdentiKit [13]. The AR database and IIIT-D viewed sketch database have variations introduced by disparate drawing styles of artists. As discussed by Zhang et.al [14] drawing styles of different artists play an substantial role in how closely a sketch resembles the actual digital photo thus influencing the performance of automatic algorithms. In viewed sketches, the sketch is closely similar to digital face images, then the identification accuracy of matched results will be high.

Previous research [15] in matching forensic sketches suggests that existing sketch recognition algorithms trained on viewed sketches are not sufficient for matching forensic sketches. Further it degrade the performance of sketch to digital image matching algorithms. Since the forensic sketches are based on the recollection of the eyewitness, they are often incomplete, inaccurate, do not closely resemble the actual digital face images. So the identification accuracy of matched results will be low. But the proposed work will increase the identification accuracy.

Again the performance of the proposed is evaluated on the PRIP database. Composite sketches may not include minute feature details as compared to what an artist can represent in hand drawn sketches, therefore composite sketches often look synthetic. Matching composite sketches with digital face images shows an even more challenging problem for automatic face recognition algorithms than matching hand-drawn sketches with digital face images. But the proposed work increases the identification accuracy of matched results.

Table 1 shows the identification accuracy of both MCWLD and Image moment invariants. Compared to MCWLD the proposed scheme improves the identification accuracy in the case of forensic and composite sketches.

Table 1. Identification Accuracy (%) Of Sketch To Digital Face Image Matching Algorithms MCWLD And Image Moment Invariant For Matching Viewed Sketches, Forensic Sketches And Composite Sketches

Algorithm	Viewed Sketches (Accuracy %)	Forensic Sketches (Accuracy %)	Composite Sketches (Accuracy %)
MCWLD	97.2	64.37	84.61
Image Moment Invariant	97.2	81.9	92.3

4.2 Time Estimation

Matlab Version: MATLAB 7.12.0
Processor: Intel Core i3
RAM: 6.00GB
System Type: 64-bit Operating System

The execution time of both the works is analyzed. The Table 2 shows the execution time of both MCWLD and Image moment invariant in the above system. From the analysis it is clear that MCWLD take double execution time in retrieving results as compared to the Image Moments.

Table 2. Total Execution Time Of Sketch To Digital Face Image Matching Algorithms MCWLD And Image Moment Invariant

Number of Images	MCWLD	Image Moment Invariant
10	0.678	0.319s
20	1.338	0.624s
100	10.704	5.328m

V. Conclusion

This research focuses on matching sketches with digital face images. The classification is used in this work because of two reasons: (1) to avoid the number of false positives and (2) to increase the computational efficiency i.e., it will reduce the number of comparisons. In the proposed algorithm, discriminative information is extracted from local facial regions using second order image moments. It provides information such as localized weighted average of the pixel intensities, centroid and orientation details of an image. Second moment is the most selective feature for representing shape and orientation of local facial regions. In the analysis including the comparison between MCWLD and IMI, is performed on using the viewed, forensic and composite sketch databases. The results show that the proposed IMI algorithm is significantly better than existing MCWLD. As a future work, we plan to include weight optimization with IMI to assign optimal weight to every local facial region. The memetic optimization can be used in weight optimization and dimensionality reduction.

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