A Multi-Scale Circular Weber Local Descriptor Approach For Matching Sketches With The Digital Face Images

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Abstract – **One of the important cues in solving crimes and apprehending criminals is matching sketches with digital face images. This paper presents an algorithm that extracts discriminating information from local regions of both sketches and digital face images. All details information present in local facial regions are encoded using multi-scale circular Weber's local descriptor The proposed descriptor, MCWLD, is based on Weber's Law. It has several advantages, such as detecting edges elegantly, robustness to noise and illumination change, and its powerful representation ability. WLD features described previously are extracted from the 3 _ 3 neighborhood, which implies a single and fixed granularity. Motivated by this idea , we have developed the multiscale WLD for characterizing local salient patterns in different granularities. It is computed using a circular symmetric neighbor set of P pixels placed on a circle.**

Parameter P denotes the number of the neighbors, whereas R radius of neighboring pixels surrounded by central pixel.. multi-scale analysis of MCWLD can be accomplished by combining theinformation provided by multiple operators of varying Parameter P,R. MCWLD extracts features to compute a histogram by encoding both differential excitations and orientations at certain locations of an sketch and digital face image.

Further, an memetic optimization approach is proposed to assign optimal weights to every local facial region to boost the identification . Foreign sketches drawn by sketch artist is of poor quality, a pre-processing technique is used to enhance the quality of images and improve the identification performance. Comprehensive experimental evaluation on different sketch databases show that MCWLD proposed algorithm yields better identification performance compared with the existing face recognition algorithms i.e SIFT ,LBP , Gabor Algorithm face recognition.

I. INTRODUCTION

Face recognition is a well studied problem in many application domains. However, matching sketches with digital face images is a very important law enforcement application that has received relatively less attention. Forensic sketches are drawn based on the recollection of an eye-witness and the expertise of a sketch artist. As shown in Fig. 1, forensic sketches include several inadequacies because of the incomplete or approximate description provided by the eyewitness and of poor Quality hence pre processing technique is required to remove the non-linear variation present in sketches and digital face images. Generally, forensic sketches are manually matched with the database comprising digital face images of known individuals. An automatic sketch to digital face image matching system can assist law enforcement agencies and make the recognition process efficient and relatively fast.

Fig. 1. Examples showing exaggeration of facial features in forensic sketches

II. LITERATURE REVIEW

Sketch recognition algorithms can be classified into two categories: **generative** and **discriminative** approaches. Generative approaches model a digital image in terms of sketches and then match it with the query sketch or vice-versa. On the other hand, discriminative approaches perform feature extraction and matching using the given digital image and sketch pair and do not generate the corresponding digital image from sketches or the sketch from digital images.

1) Generative Approaches: Wang and Tang [1] proposed Eigen transformation based approach to transform a digital photo into sketch before matching. In another approach, they presented an algorithm to separate shape and texture information and applied Bayesian classifier for recognition [2]. Liu *et al.* [3] proposed non-linear discriminative classifier based approach for synthesizing sketches by preserving face geometry. Li et al. [4] converted sketches to photos and used a method similar to Eigen-transform for matching. Gao et al. [5] synthesized a series of pseudo sketches using embedded Hidden Markov Models (E-HMM) which are then fused to generate a pseudo sketch. Wang and Tang [6] proposed Markov Random Fields based algorithm to automatically synthesize sketches from digital face images and vice-versa. extended multiscale Markov Random Field (MRF) model to synthesize sketches under varying pose and lighting conditions.

2) Discriminative Approaches: Uhl and Lobo [8] proposed photometric standardization of sketches to compare it with digital photos. Sketches and photos were geometrically normalized and matched using Eigen analysis. Yuen and Man [9] used local and global feature measurements to match sketches and mug-shot images. Zhang et al. [10] compared the performance of humans and PCA-based algorithm for matching sketch-photo pairs with variations in gender, age, ethnicity, and inter-artist variations. They discussed about the quality of sketches in terms of artist's skills, experience, exposure time, and distinctiveness of features. Similarly, Nizami et al. [11] analyzed the effect of matching sketches drawn by different artists. Klare and Jain [12] proposed a Scale Invariant Feature Transform (SIFT) based local feature approach where sketches and digital face images were matched using the gradient magnitude and orientation within the local region. Bhatt et al. [13] extended Uniform Local Binary Patterns to incorporate exact difference of gray level intensities to encode texture features in sketches and digital face images. Klare et al. [14] extended their approach using Local Feature Discriminant Analysis (LFDA) to match forensic sketches. In their recent approach, Klare and Jain [15] proposed a framework for heterogeneous face recognition where both probe and gallery images are represented in terms of non-linear kernel similarities. Zhang et al. analyzed the psychological behavior of humans for matching sketches drawn by different sketch artists. Recently, Zhang et al. proposed an information theoretic encoding band descriptor to capture discriminative information and random forest based matching to maximize the mutual information between a sketch and a photo.

III. RESEARCH CONTRIBUTION

This research proposes an automatic algorithm for matching sketches with digital face images using the modified Weber's local descriptor (WLD). WLD is used for representing images at multiple scales with circular encoding. The multi-scale analysis helps in assimilating information from minute features to the most prominent features in a face. Further, memetically optimized x^2distance measure is used for matching sketches with digital face images. The proposed matching algorithm improves the performance by assigning optimal weights to local facial regions. To further improve the performance, DWT preprocessing technique is used to enhance the forensic sketch-digital image pairs.

The major contributions of this research can be summarized as follows:

1) Previous approaches for matching forensic sketches [14] generally focus on good forensic sketches only. Such a classification is often based on the similarity between the sketch and corresponding digital face image.

Since the corresponding digital face image is not available in real-time applications, matching forensic selecting good and bad forensic sketches is not pragmatic for sketches with digital face images. In this research, a pre-processing technique is presented for enhancing the quality of forensic sketch-digital image pairs. Pre-processing forensic sketches enhances the quality and improves the performance by at least $2-3\%$.

2) Multi-scale Circular WLD and Memetically optimized x^2 based algorithms are proposed for matching sketches with digital face images. The proposed algorithm outperforms existing approaches on different sketch databases.

IV. MCWLD FOR MATCHING SKETCHES WITH DIGITAL FACE IMAGES

In this section, we review Weber's Law and then propose a descriptor MCWLD.

B.1.WEBER LAW

Ernst Weber, an experimental psychologist in 19th century, observed that the ratio of the increment threshold to the background intensity is a constant. This relationship, known since as Weber's Law, can be expressed as:

$$\frac{\Delta I}{I}=K$$

where ΔI represents the increment threshold (just noticeable difference for discrimination); I represents the initial stimulus intensity and k signifies that the proportion on the left side of the equation remains constant despite of variations in the I term. The fraction ΔI/I is known as the Weber fraction.

B.2.MCWLD (Multi-scale Circular Weber Local Descriptor)

V. MATCHING SKETCHES WITH DIGITAL FACE IMAGES

Recently, Chen et al. proposed a new descriptor, Weber's local descriptor, which is based on Weber's law and draws its motivation from both SIFT and LBP. It is similar to SIFT in computing histogram using gradient and orientation, and analogous to LBP in being computationally efficient and considering small neighborhood regions. However, WLD has some unique features that make it more efficient and robust as compared to SIFT and LBP. WLD computes the salient micro patterns in a relatively small neighborhood region with finer granularity. allows it to encode more discriminative local micro patterns. In this research, WLD is optimized for matching sketches with digital face images by computing multi-scale descriptor in a circular manner (in contrast to the originally proposed square neighborhood approach). Finally, two concaneted Multi-scale circular WLD (MCWLD) histograms are matched using memetically optimized weighted x^2distance.approach.

Motivated by Weber's Law, we propose a descriptor WLD.

It consists of two components: its differential excitation (ξ) and orientation (θ). ξ is a function of the Weber fraction (i.e., the relative intensity differences of its neighbors against a current pixel and the current pixel itself). θ is a gradient orientation of the current pixel.

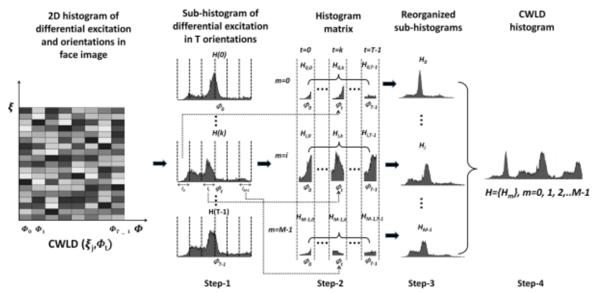

Fig. 2. Illustrating the steps involved in computing the circular WLD histogram

VI. FEATURE EXTRACTION USING MCWLD

MCWLD has two components:

1) differential excitation and

2) gradient orientation

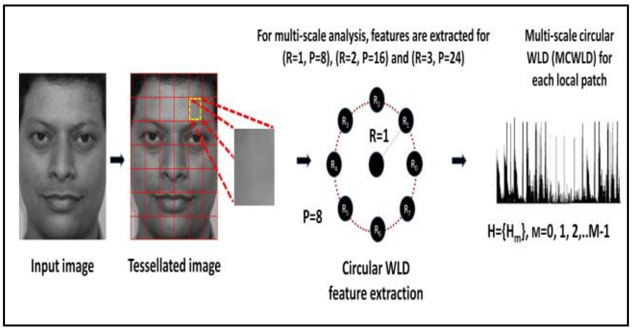

Figure .3. steps in computing MCWLD.

MCWLD representation for a given image is constructed by tessellating the digital face image and sketch image and computing a MCWLD descriptor for each region. As shown in Fig. 2. MCWLD descriptor is computed for different values of parameters P and R, where P is the number of neighboring pixels evenly separated on a circle of radius R centered at the current pixel. Multi-scale analysis is performed by varying the radius R and number of neighbors P. multi-scale analysis is performed at three different scales with parameters as

(R = 1, P = 8), (R = 2, P = 16) and (R = 3, p = 24).

Sketches and digital face images are represented using MCWLD as explained below:

1) *Differential Excitation*:

Differential excitation is computed as an arctangent function of the ratio of intensity difference between the central pixel and its neighbors to the intensity of central pixel.

The differential excitation of central pixel ξ (xc) is computed as:

$$\xi\,(xc)=arctan\{\ \sum_{i=0}^{P-1}\left(\frac{\mathrm{xi-xc}}{\mathrm{xc}}\right)\}\quad \ldots(3)$$

where xc is the intensity value of central pixel and P is the number of neighbors on a circle of radius R. If ξ *(xc)* is positive, it simulates the case that surroundings are lighter than the current pixel. In contrast, if ξ *(xc)* is negative, it simulates the case that surroundings are darker than the current pixel.

2) Orientation: The orientation component of WLD is computed as:

$$\theta(xc)=arctan\{\ \frac{x\left(\frac{P}{2}+R\right)-x(R)}{x(p-R)-X(\frac{P}{2}-R)}\}\quad ..(4)$$

The orientation is further quantized into T dominant orientation bins where T is experimentally set as eight.

3) Circular WLD Histogram: For every pixel, differential excitation (ξ) and orientation (θ) are computed using Eqs. 3 and 4 respectively. As shown in Figure 2. A 2D histogram of circular WLD feature, CWLD(ξ j ,θ t), is constructed where j = 0, 1, ...,N − 1, t = 0, 1, ..., T − 1, and N is the dimension of the image. Each column in the 2D histogram corresponds to a dominant orientation, θt, and each row corresponds to a differential excitation interval. Thus, the intensity of each cell corresponds to the frequency of a certain differential excitation interval in a dominant orientation. A four step approach is followed to compute CWLD descriptor.

Step-1: The 2D histogram CWLD(ξ j ,θ t) is further encoded into 1D histograms. Differential excitations ξ, are regrouped into T orientation sub-histograms, H(t),

where t = 0, 1, ..., T – 1 corresponds to each dominant orientation.

Step-2: Within each dominant orientation, range of differential excitation is evenly divided into M intervals and then reorganized into a histogram matrix. Each orientation sub-histogram in H(t) is thus divided into M segments, Hm,t where m = 0, 1, ...,M − 1 and M = 6. For each differential excitation interval *l*m, lower bound is computed as *m,l=(m/M-1/2)π* and upper bound *ηm,u* is computed as

ηm,u= [(*m+1*) */M-1/2*]*π*

Each sub-histogram segment Hm,t is further composed of S bins and is represented as:

Hm,t = hm,t,s where s = 0, 1, ..., S − 1, S = 3 and hm,t,s is represented as:

hm,t,s= Σ δ(sj==s),(sj=[$\frac{\xi j - \eta m,l}{\eta m,n-\eta m,l/s} + \frac{1}{2}$]) Here j = 0, 1, ...,N −1, m is the interval to which differential excitation ξ j belongs i.e. ξ j ϵ *l*m, t is the index of quantized orientation, and δ(·) is defined as follows:

$\delta(\cdot)=\{\begin{smallmatrix} 1 & if\ function\ \ is\ true \\ 0 & otherwise \end{smallmatrix}$

Step-3: Sub-histogram segments, Hm,t, across all dominant orientations are reorganized into M one dimensional histograms.

Step-4: M sub-histograms are concatenated into a single histogram thus representing the final 6×8×3 (M×T×S) circular WLD histogram. The range of differential excitation is segmented into separate intervals to account for the variations in a given face image, and assigning optimal weights to these Hm segments further improves the performance of CWLD descriptor.

4) Multi-scale Circular WLD: In Multi-scale analysis, CWLD descriptor is extracted with different values of P and R and the histograms obtained at different scales are concatenated in range (0-255).

In this research, multi-scale analysis is performed at three different scales with parameters as

(R = 1, P = 8), (R = 2, P = 16) and (R = 3, p = 24). A face image is divided into 6×7 non overlapping local facial regions and MCWLD histogram is computed for each region. MCWLD histograms for every region are then concatenated to form the facial representation.

VII. MEMETIC OPTIMIZATION APPROACH

In face recognition important consideration is given towards ,the recognition accuracy. Similarly, MCWLD histograms corresponding to different local facial regions may have varying contribution towards the recognition accuracy. Moreover, MCWLD histogram corresponding to each local facial region comprises of M sub-histogram segments (as shown in Step-3 of Fig.2) representing different frequency information. Generally, the regions with high variance are more discriminating as compared to flat regions, therefore, M sub-histogram segments may also have varying contribution towards the recognition accuracy. It is our assertion that while matching MCWLD histograms, different weights need to be assigned to local regions and histogram segments for better performance. Here, the weights associated with 42 local facial regions and 6 sub-histogram segments at three different scales have to be optimized. Optimizing such large number of weights for best performance is a very challenging problem and requires a learning based technique. Memetic algorithm (MA) can be effectively used to optimize such large search spaces.

It is a form of hybrid global-local heuristic search methodology. The global search is similar to traditional evolutionary approaches such as population-based method in a Genetic Algorithm (GA), while the local search involves refining the solutions within the population. From an optimization perspective, MAs have been found to be more efficient (i.e. require fewer evaluations to find optima) and effective (i.e. identify higher quality solutions) than traditional evolutionary approaches such as GA . In this research, memetic algorithm is thus used for weight optimization.

VIII. WEIGHTED x^2 MATCHING USING MEMETIC OPTIMIZATION :

For matching two MCWLD histograms, weighted x^2distance measure is used.

$$x^2(x,y) = \sum_{i,j}^{\infty} \omega j[\frac{(xi,j - yi,j)^2}{(xi,j + yi,j)}]$$

here x and y are the two MCWLD histograms to be matched, w i and j correspond to the ith bin of the jth histogram segment (j = 1, · · · , 756), and ωj is the weight for the jth histogram segment. As shown in Fig. 4, a memetic search is applied to find the optimal values of ωj . The steps involved in the memetic optimization process are described below:

The Memetic algorithm for weight optimization is summarized in Algorithm 1.

Algorithm 1 Memetic algorithm for weight optimization.

Step 1: Memetic Encoding: A chromosome of length 42×3×6 = 756 is encoded where each unit in the chromosome is a real valued number representing the corresponding weight.

Step 2: Initial Population: A population of 100 chromosomes is generated starting with a seed chromosome.

Step 3: Fitness Function: Fitness is evaluated by performing recognition using the weights encoded by each chromosome.

10 best performing chromosomes from a population are selected as *survivors* to perform crossover and mutation.

Step 4: Hill Climbing Local Search: The *survivors* obtained in Step 3 are used to find better chromosomes in their local neighborhood and *parents* are selected.

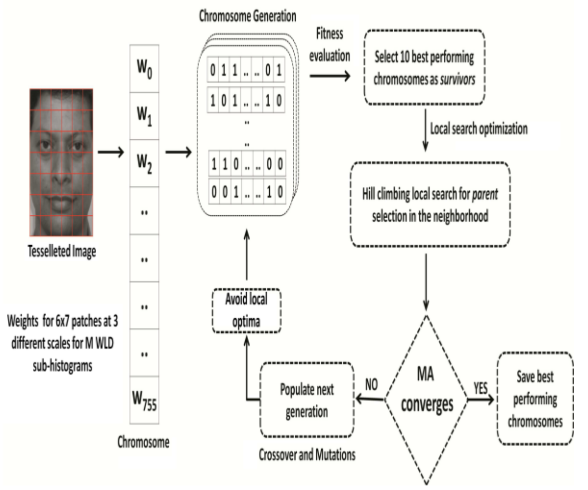

Fig. 4. Illustrating the steps involved in memetic optimization for assigning optimal weights to each tessellated face region.

Step 5: Crossover and Mutation: New population is generated from *parents* obtained after local search in Step 4. A set of uniform crossover operations is performed followed by mutation. To avoid local optima, Adaptive mutation and random offspring generation techniques are used.

Step 6: Repeat Steps 3-5 till convergence criteria is satisfied.

C. Proposed Algorithm for Matching Sketches with Digital Face Images

The process of matching sketches with digital face images is as follows:

1) For a given sketch-digital image pair, the pre-processing technique is used to enhance the quality of face images.

2) Both sketches image and digital face images are tessellated using LBP sector the image into Blocks of non-overlapping local facial regions.

3) For each block of facial region, MCWLD histograms are computed at three different scales parameter.

i.e(R=1,P=8;R=2,P=16;R=3,P=32).The facial representation is obtained by concatenating MCWLD histograms for every facial region.

4) To match two MCWLD histograms, weighted x^2 distance measure is used where the weights are optimized using Memetic algorithm.

5) In identification mode, this procedure is applied for each gallery-probe pair and top matches are obtained.

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