On Matching Sketches with Digital Face Images

Himanshu S. Bhatt, Samarth Bharadwaj, Richa Singh, and Mayank Vatsa

Abstract— **This paper presents an efficient algorithm for matching sketches with digital face images. The algorithm extracts discriminating information present in local facial regions at different levels of granularity. Both sketches and digital images are decomposed into multi-resolution pyramid to conserve high frequency information which forms the discriminating facial patterns. Extended uniform circular local binary pattern based descriptors use these patterns to form a unique signature of the face image. Further, for matching, a genetic optimization based approach is proposed to find the optimum weights corresponding to each facial region. The information obtained from different levels of Laplacian pyramid are combined to improve the identification accuracy. Experimental results on sketch-digital image pairs from the CUHK and IIIT-D databases show that the proposed algorithm can provide better identification performance compared to existing algorithms.**

I. Introduction

Face recognition under pose, illumination and expression is meticulously studied by researchers and many techniques have been proposed to cater to these variations [19]. However, a very important law enforcement application that has received relatively less attention is matching sketches with digital images. An automated sketch to digital image recognition system can assist law enforcement officials and make the recognition process efficient and relatively fast. Sketches and digital images can be perceived as two different modalities. Therefore, existing state-of-the-art face recognition algorithms require additional mechanism to handle non-linear variations posed due to variations in sketches and digital images.

To address this important problem, researchers have proposed algorithms to match sketches with digital images. Robert and Niels [11] proposed photometric standardization of sketches to compare it with the digital photos. They further geometrically normalized sketches and photos to match them through Eigen analysis. Wang and Tang [12] proposed Eigen transformation based approach that transforms a digital image to sketch and then performs matching. In another approach, they presented an algorithm that separates shape and texture information and then applied Bayesian classifier for recognition [13]. In their recent approach, they have used Markov random fields to automatically synthesize sketches from digital images and vice-versa [14]. This transformation reduces sketches and digital images to a single modality so that matching can be done efficiently. An approach for synthesizing sketches by preserving face geometry was proposed by Liu *et.al.* where authors used non-linear discriminative classifier for sketch recognition [7]. Li *et.al.* matched sketches and photos using a method similar to the Eigen-transform by converting sketches to photos [16]. Yuen and Man [15] used local and global feature measurements between sketches and mug-shot images. Local facial primitives include eyes, nose, lips, hair, and eyebrows and face outline whereas global features include geometric distances between fiducial points. Zhang *et.al.* [17], [18] compared the performance of humans and PCA-based algorithms with sketch-photo pairs with variations in gender, age, ethnicity and inter-artist variations. They also provide discussion about the quality of sketches in terms of artist's skills, experience, exposure time and distinctiveness of features. Complimentary information obtained from multi-sketch fusion of sketches drawn by several artists leads to better recognition rates for humans as well as PCA based algorithm. Recently, Klare and Jain [5] proposed a Scale Invariant Feature Transform (SIFT) based local feature approach where sketches and digital images are matched directly using the gradient magnitude and orientation within a local region. Klare and Jain [6] further extended their approach using Local Feature Discriminant Analysis (LFDA) to match forensic sketches.

In this paper, a computationally fast and efficient sketch to digital image matching algorithm is proposed. It has been observed by several sketch artists that "*Generating a sketch is an unknown psychological phenomenon but what a sketch artist observes while drawing a sketch are the facial texture which he/she tries to embed in the sketch through a blend of soft and prominent edges*". The proposed algorithm is designed based on this observation and hence follows two principles:

1) Information vested in local regions can have high discriminating power.
2) Facial patterns in sketches can be described by texture operators efficiently.

We thus propose an algorithm to match sketches with digital images that can handle the non-linear variations present in these modalities. Fig. 1 shows the steps involved in the proposed algorithm that starts with computing Laplacian pyramid to preserve soft edges and significant high frequency information present in the image. The algorithm extracts texture features computed using the proposed Extended Uniform Circular Local Binary Patterns (EUCLBP) at each level of the Laplacian pyramid. Matching is performed using genetic optimization based weighted Chi square distance measure. Scores for each level of Laplacian pyramid are fused using weighted sum rule fusion. Experiments performed on two

H.S. Bhatt, S. Bharadwaj, R. Singh, and M. Vatsa are with IIIT Delhi, India {himanshub, samarthb, rsingh, mayank}@iiitd.ac.in

sketch-digital image databases show the efficacy of the proposed algorithm.

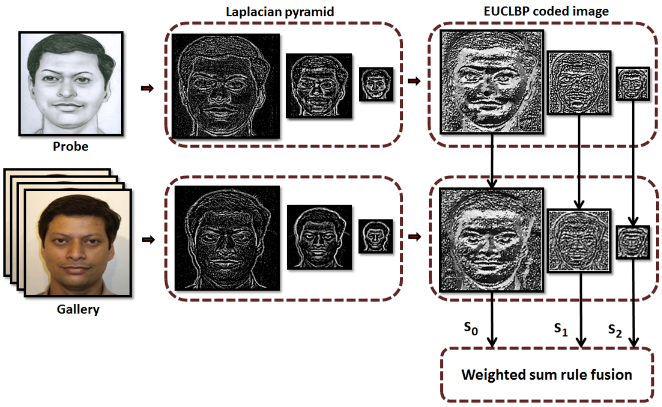

Fig. 1. Illustrating the steps involved in the proposed algorithm.

Next section presents the proposed feature extraction algorithm. Matching of sketches with digital images using EUCLBP+GA is presented in Section III and experimental results and analysis are presented in section IV.

II. Facial Feature Extraction and Genetic Optimization for Matching

The proposed feature extraction and matching algorithm is divided into two steps: (1) feature extraction, (2) weight optimization using genetic algorithm.

A. Feature Extraction using EUCLBP

Local Binary Patterns (LBP) based descriptor [9], [10] is a widely used texture operator because of its robustness to gray level changes and high computational efficiency. Basic LBP [9] is a window based feature extractor where the texture descriptor is computed based on the neighborhood. It assigns a binary value to every neighboring pixel by thresholding it with respect to the central pixel. The binary pattern thus obtained from the neighboring pixels are transformed to a gray-level value and is assigned to the central pixel. LBP representation of a given face image is generated by dividing the image into grids and computing histograms to measure the frequency of LBP values within each grid. An extension of this approach is to have the pixel neighbors well separated on a circle around a central pixel [2] [10]. The circle can have different diameters and varying number of neighbors to account for texture at different scales. Similar to basic LBP, Circular LBP (CLBP) descriptor is computed as shown in Eqs. (1) and (2):

$$C_{N,R}(p,q) = \sum_{i=0}^{N-1} f(n_i - n_c)2^i, \tag{1}$$

$$f(\cdot) = \begin{cases} 1 & if \;\; n_i - n_c \geq 0 \\ 0 & otherwise \end{cases}, \tag{2}$$

where N is the number of neighbors, n_c corresponds to the gray-level intensity of center pixel of the circle, and n_i corresponds to the gray-level intensities of N evenly spaced pixels on a circle of radius R. CLBP is extended to Uniform Circular Local Binary Patterns [10] to achieve robustness to rotation variations and dimensionality reduction. A binary pattern is called uniform binary pattern if it has at most two bitwise transitions from 0 to 1 or vice-versa. Descriptor histogram is computed where every uniform pattern has a separate bin and all non-uniform patterns are assigned to a single bin. The concatenation of all histograms pertaining to each grid constitutes the image signature. Uniform CLBP is described using Eqs. (3) and (4).

$$C_{N,R}^{riu2}(p,q) = \begin{cases} \sum_{i=0}^{N-1} f(n_i - n_c)2^i & if \;\; U(C_{N,R}) \leq 2 \\ N+1 & otherwise \end{cases} \tag{3}$$

where,

$$U(C_{N,R}) = \begin{array}{l} \sum_{i=1}^{N-1} |f(n_i - n_c) - f(n_{i-1} - n_c)| \\ +|f(n_{N-1} - n_c) - f(n_0 - n_c)| \end{array} \tag{4}$$

where n_c corresponds to the gray-level intensity of center pixel of the circle and n_i corresponds to the gray-level intensities of N evenly spaced pixels on a circle of radius R. $riu2$ represents the use of rotation invariant uniform patterns.

Encoding difference of signs between the neighboring pixels is not sufficient for describing facial texture. Other important features could also be derived from the information that lies in the difference of the gray-level values. Huang *et.al.* proposed a method to encode the exact difference of gray-level intensities and reported a marked improvement in the performance of texture descriptors [4]. This forms the motivation to further extend Uniform CLBP to encode exact gray-level difference along with the original encoding. The proposed descriptor is called Extended Uniform Circular Local Binary Pattern. It provides information assimilated from the exact gray-level difference and adds a complimentary layer of discrimination on top of the original descriptor. Fig. 2(a) explains feature extraction using the proposed EUCLBP. Layer 1 is Uniform CLBP that encodes difference of signs while the other three layers encode the exact gray-level differences. We experimentally observed that Layer 1 and Layer 2 of EUCLBP are the most discriminating. Therefore, the final descriptor is the concatenation of Layer 1 and Layer 2 histograms.

B. Weighted Chi Square Matching using Genetic Optimization

As shown in Eq. (5), weighted chi square distance measure can be used to match EUCLBP descriptors.

$$\chi^2(x,y) = \sum_{i,j} \omega_j \frac{(x_{i,j} - y_{i,j})^2}{x_{i,j} + y_{i,j}} \tag{5}$$

where x and y are the normalized histograms (EUCLBP features), i and j correspond to the i^{th} bin of the j^{th} local region and ω_j is the weight for the j^{th} region. Ahonen [2] proposed to assign weights w_j proportional to the identification accuracy of local facial regions [2]. The weighting

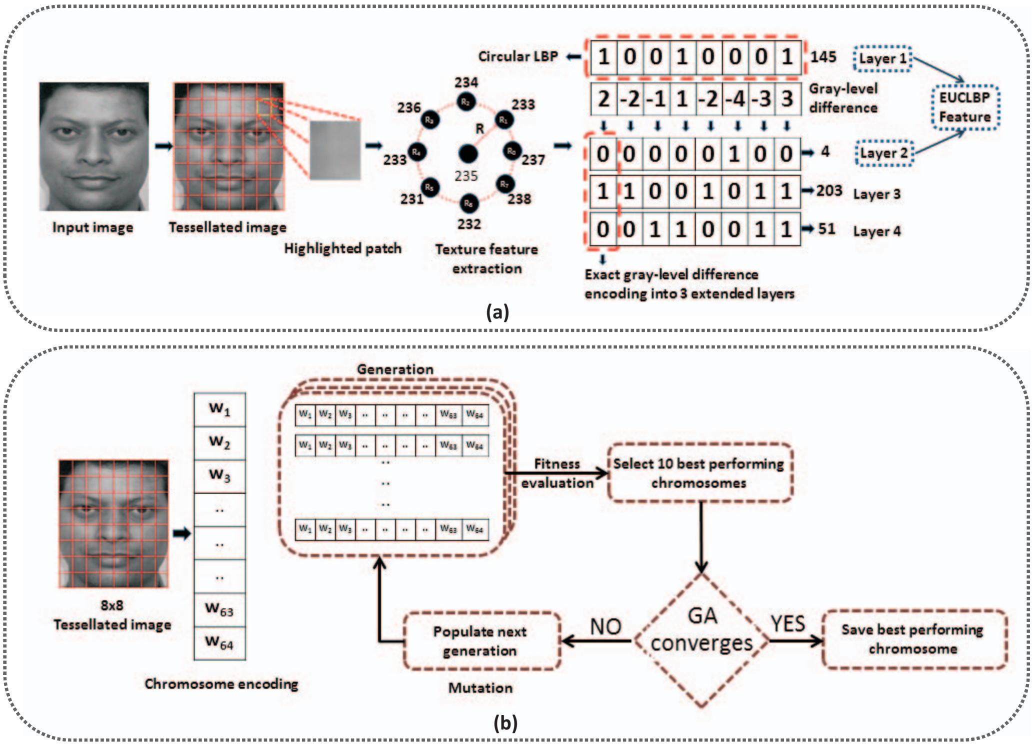

Fig. 2. Illustrating the details of feature extraction and matching, (a) feature extraction using EUCLBP and (b) weight optimization using genetic algorithm.

scheme is inspired by psychological studies which suggest that certain facial features are more discriminative compared to others. However, their results suggest that performance can be further improved if the weights are optimized.

In this paper, we propose a Genetic Algorithm (GA) [3] based weight optimization technique. It is a search optimization technique stimulated by the process of natural selection and evolution. GAs are efficient in searching large, non-linear search spaces. The motivation to use genetic optimization to find optimum weights for each facial patch is inspired by several properties of GA. The problem of finding the optimal weights embroils searching very large spaces and finding several suboptimal solutions. GAs are well proven in searching very large spaces to quickly reach to the near optimal solution. Fig. 2(b) represents the genetic search process to find optimal weights in weighted chi square distance measure based matching. The steps involved are elaborated as follows:

Encoding: A chromosome is a string whose length is equal to the number of tessellated facial regions. Each unit in the chromosome is a real valued number associated with the corresponding weight of the facial region.

Initial Population: Each generation is populated with 100 chromosomes. In general, the initial population is generated randomly, but for quick convergence in face recognition, weights proportionate to the identification accuracy of each region (as proposed by Ahonen [2]) are used as initial chromosomes. The remaining 99 chromosomes are generated by randomly changing one or more units in the initial chromosome. The weights are normalized such that sum of all weights in a chromosome is 1.

Fitness Function: Each individual chromosome in a generation is a possible solution. To evaluate its effectiveness, recognition is done using the weights encoded by the individual chromosome and weighted Chi square distance measure. Identification accuracy is computed on a training set and 10 best performing chromosomes are selected for mutation to populate the next generation.

Mutation: From best performing chromosomes, we again populate a new generation of chromosomes by changing one or more weights by a factor of its standard deviation in the previous best generation.

The search process is repeated till convergence, i.e. till the identification accuracy for new generation does not improve. At this point, weights pertaining to the best performing chromosome (i.e. chromosome giving best recognition accuracy on the training data) are used for testing.

Thus, genetic algorithm finds optimal weights for each facial region. It also enables to discard redundant and non-discriminating regions whose contribution towards recognition accuracy is very low (i.e. the weight for that region is 0). This leads to dimensionality reduction and better computational efficiency because then we do not need to compute texture descriptors for poor performing facial regions during testing.

III. Sketch to Digital Face Recognition

As mentioned previously, sketches and digital images can be viewed as two different modalities. Therefore, it is essential to apply some transformation that can minimize the difference between sketches and digital images. Since, a face sketch is primarily an edge representation of the actual face in which prominent edges are highlighted, edge preserving approaches can be used for this task. As shown in Fig. 1, Laplacian pyramid are constructed for the sketch-digital image pairs to preserve edges. Laplacian pyramid provides an added advantage of addressing non-linearity by providing mechanism to extract and match facial features at different levels of granularity. It is our hypothesis that information extracted from different levels of Laplacian pyramids of an image are complimentary. The algorithm locally extracts texture features and matching is performed using weighted Chi square distance measure. The sketch to digital face recognition algorithm is described as follows:

1) For a given sketch-digital face image pair, Laplacian pyramid is generated and a sequence of band pass images are obtained. This step transforms both sketches and digital images to an intermediate representation where these two different modalities can be efficiently compared. The corresponding levels of Laplacian pyramid of sketches and digital images are matched.
2) In both sketch and digital image, all the levels of Laplacian pyramid are tessellated into non-overlapping regions. On moving down the pyramid, number of regions are decreased from 8×8 for the first level, 7×7 for the second level and 6×6 for the lowest level. This accounts for minor registration errors for corresponding facial regions in sketches and digital images.
3) For each facial region, texture feature are computed using EUCLBP with radius $R = 2$ and number of neighboring pixels $N = 8$. The local texture descriptors corresponding to each facial region are concatenated to obtain feature vector at every level of Laplacian pyramid.
4) To match the EUCLBP features extracted from sketch and digital images at each pyramid level, texture histograms are first normalized. The weighted Chi square distance measure is then used to compute dissimilarity between sketches and digital images. Every facial region at each Laplacian level is assigned a weight obtained using genetic optimization.
5) Finally, weighted sum rule fusion is applied to combine distance score of each Laplacian pyramid

$$F_{fused} = w_0 * s_0 + w_1 * s_1 + w_2 * s_2 \qquad (6)$$

where w_0, w_1 and w_2 are the weights assigned to different levels of Laplacian pyramid, s_0, s_1 and s_2 are the corresponding distance scores and F_{fused} is the fused score. In the experiments, we observe that $w_0 = 0.2, w_1 = 0.3$ and $w_2 = 0.5$ provide the best recognition performance.
6) In identification mode (1:N), this procedure is applied for each probe and top matches are obtained based on the fused scores.

IV. Experimental Results

To evaluate the performance of the proposed algorithm, two databases were used: CUHK database [14] and IIIT-D sketch database prepared by authors. Since the application of sketch recognition is more dominant in law enforcement with identification scenario, the performance of the proposed algorithm is evaluated in the identification mode. Section IV-A provides the specifications of the database used for evaluating the proposed algorithm, Section IV-B explains the experimental protocol and Section IV-C lists the foremost annotations about the experiments.

A. Database

The CUHK sketch database [14], available in public domain, comprises 188 sketch-digital image pairs from the CUHK student database, 123 sketch-digital image pairs from the AR database [8] and 295 sketch-digital images pairs from the XM2VTS database. In total, there are 606 sketch-digital image pairs. Since the XM2VTS database is not available freely, we have used only 311 sketches from the database and not the sketches corresponding to the XM2VTS database. The CUHK sketch database has sketch and digital image pairs with constant background and controlled illumination. The pairs perfectly overlay unlike conditions that a real sketch to digital image matching algorithm might encounter. We observed that the challenge of sketch to digital face recognition lies in understanding the inherent non-linearity between these modalities, which is not entirely possible with such well formed database.

To evaluate some of the challenges of real world sketch recognition, we prepared a database of 231 sketch-digital image pairs where sketches were drawn by a professional sketch artist for images collected from different sources. In this database, 67 sketch-digital image pairs correspond to images in the FG-NET aging database [1], 92 sketch-digital image pairs are from images present in the Labeled Faces in Wild database (LFW) [4], and 72 sketch-digital image pairs belong to the students and faculty members at IIIT-Delhi. Fig. 3 shows sketch-digital image pairs from the CUHK database and the IIIT-D sketch database. As shown in Fig. 3(b), the sketch-digital images present in the IIIT-D database are more challenging compared to the CUHK database. Further, the digital images are also collected with variations in pose, expression and illumination.

B. Experimental Protocol

To evaluate the efficacy of the proposed algorithm, referred as EUCLBP + GA, both CUHK and IIIT-D databases are used and the performance is compared with existing algorithms in the identification scenario. Two algorithms that have been proposed specially for matching sketch-digital image pairs have been used for comparison. These algorithms are:

1) Eigen Transform [12] and
2) SIFT based face recognition algorithm [5]

Three sets of experiments are performed using the sketch-digital face databases. In all three experiments, digital image

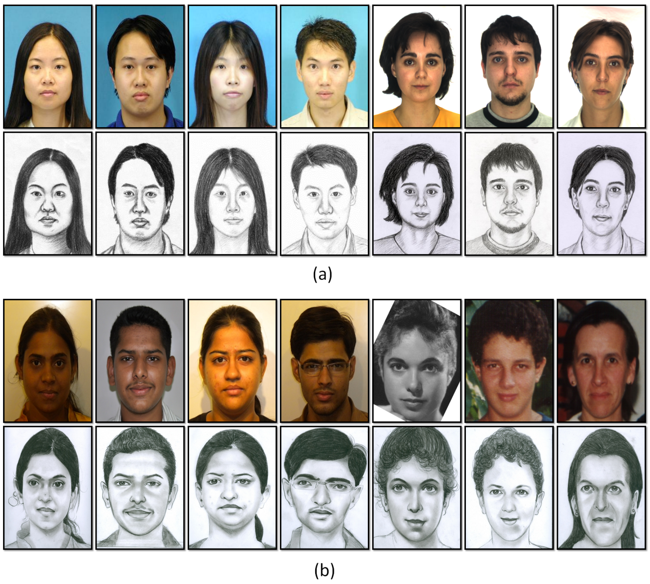

Fig. 3. Sketch-digital image pairs from the (a) CUHK database and (b) IIIT-D database.

was used as the gallery and the corresponding sketch was used as the probe. In all the experiments, 25% of the database was used for training and the remaining 75% was used for testing. The protocol for all three experiments are described below:

1) *Experiment 1:* 311 sketch-digital image pairs from the publically available CUHK database were used. 78 sketch-digital image pairs were used for training and the remaining 233 pairs were used for testing.
2) *Experiment 2:* 231 sketch-digital image pairs from the IIIT-D database were used. 58 sketch-digital image pairs were used for training and the remaining 173 pairs were used for testing.
3) *Experiment 3:* 311 sketch-digital image pairs from the CUHK database and 231 sketch-digital image pairs from the IIIT-D database were combined to prepare a database of 542 sketch-digital image pairs with variations in terms of sketch artist, background illumination in the photograph, pose and expression. 136 pairs were used for training and the remaining 406 pairs were used for testing.

The images were normalized and face region were detected to a size of 192×224 pixels. For every experiment, training is performed to compute the parameters of the feature extractor, weights using the genetic optimization for matching and finally weights of the components to be fused. This non-overlapping training-testing partitioning is repeated five times for cross validation.

C. Analysis

Along with evaluating the performance of our algorithm, comparison with SIFT feature based approach [5] and Eigen Transformation based approach [12] is performed on three different experimental settings. Eigen Transformation was one of the earliest approaches proposed for matching sketches with digital images whereas SIFT [5] based approach is the most recent one.

- The Cumulative Match Characteristic (CMC) curve in Fig. 4 shows rank 1 identification accuracy of all the algorithms. The proposed approach with EUCLBP + GA yields rank 1 accuracy of 94.12% on the CUHK database. SIFT [5] and Eigen transformation [12] based algorithms yield rank 1 accuracy of 93.44% and 71.39% respectively. As shown in Table I, the proposed approach also outperforms both SIFT [5] and Eigen Transform [12] on the IIIT-D database and the combined database.
- The performance of SIFT based algorithm [5] reduces on the IIIT-D database and the combined database because computing SIFT descriptor is very sensitive to registration errors that may arise when corresponding face patch on sketch and digital image do not perfectly overlay. As mentioned previously, sketch-digital image pairs in the CUHK Database are collected in a controlled environment so it accounts for minimum (negligible) registration errors which is not the case with the IIIT-D database or combined database. Note that in the case of forensic sketches, it is unlikely to get sketch-digital image pairs that can be perfectly registered. On the other hand, the results indicate that EUCLBP+GA gives better performance even in cases where images are not perfectly aligned.
- EUCLBP generates a holistic description of the face image by combining histograms obtained from every local region unlike the Eigen transformation [12] based approach that depends on the global information as a whole. Therefore, the improved identification accuracy of the proposed algorithm as shown in Fig. 4, validates our assertion that information vested in local regions have a high discriminating power that can be used for challenging face recognition applications.
- Genetic optimization offers two-fold benefits:
  1) Training genetic optimization is a one time process and the optimal weights obtained for each facial region helps improve the recognition accuracy inspired by the psychological findings about the significance of some facial regions in recognition process by humans as well as automated face recognition algorithms.
  2) Facilitates to discard the facial regions that do not contribute to the recognition accuracy and hence leads to dimensionality reduction and increases computational efficiency. On an average, at the end of the optimization, 16 out of 64 facial patches at each level of granularity are assigned null weights.
- Better discriminating information is assimilated for sketch recognition on moving from level-0 to level-2 in the Laplacian pyramid. This is because level-0 contains minute features which the sketch artists do not incorporate in the portrait whereas level-1 and level-2

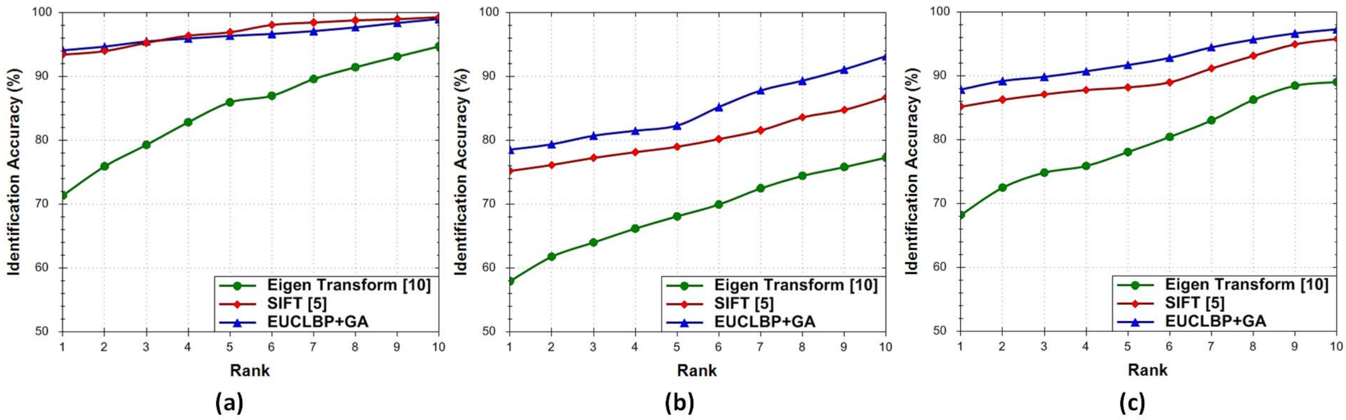

Fig. 4. CMC curves for the proposed and existing algorithms on (a) CUHK database, (b) IIIT-D database, and (c) combined database.

TABLE I
RANK-1 IDENTIFICATION ACCURACY OF THE PROPOSED EUCLBP + GA WITH EIGEN TRANSFORM AND SIFT BASED MATCHING ALGORITHMS. IDENTIFICATION ACCURACIES ARE COMPUTED WITH FIVE TIMES CROSS VALIDATION AND STANDARD DEVIATIONS ARE ALSO REPORTED.

Database	Training/Testing Images	Algorithm	Rank-1 Identification Accuracy	Standard Deviation
CUHK Database	78/233	Eigen Transform [12]	71.39%	2.03
		SIFT [5]	93.44%	0.78
		EUCLBP + GA	94.12%	0.72
IIIT-D Database	58/173	Eigen Transform [12]	57.97%	2.87
		SIFT [5]	75.24%	1.11
		EUCLBP + GA	78.58%	0.45
Combined Database	136/406	Eigen Transform [12]	68.24%	3.01
		SIFT [5]	85.20%	0.96
		EUCLBP + GA	87.89%	0.86

do not focus on the minute features and provide only high level prominent features of the face. Since these features are also emphasized by the sketch artist, these levels of the Laplacian pyramid provide better accuracy.

- To verify our hypothesis, we perform correlation analysis between different Laplacian levels. Correlation between match score obtained using Laplacian level-0 and level-1 for genuine scores is 0.73 and impostor score is 0.52, correlation between level-1 and level-2 for genuine scores is 0.55 and impostors is 0.42 and correlation between level-0 and level-2 for genuine scores is 0.69 and impostor scores is 0.49. Correlation analysis, therefore, ascertains that fusing information at different Laplacian levels improves the overall recognition accuracy.
- Average rank-1 identification accuracy along with the standard deviations across five random cross validation trials are listed in Table I. The results clearly indicate that EUCLBP + GA algorithm is more stable compared to existing algorithms.
- Finally, on a 2 GHz Intel Duo Core processor with 2 GB RAM under C# programming environment, for a given probe image, the proposed algorithm requires 0.0694 seconds to compute the EUCLPB descriptor and match it to a gallery image.

V. CONCLUSION

In this research, we proposed a face recognition algorithm to match sketches with digital images. The algorithm utilizes the observation that sketch artists focus on structural details along with discriminating and prominent features of the face. On the other hand a digital face image comprises of these features along with a lot of other minute information which may not be important for matching sketches. The algorithm utilizes different levels of granularity and texture features to encode facial signatures both in sketches and digital images. The proposed algorithm is compared with Eigen transform and SIFT based sketch to digital matching algorithms. The performance of the algorithm is computed on the CUHK and IIIT-D databases. The experiments show that the proposed algorithm effectively encodes the facial features that are important for sketch to digital image matching.

VI. ACKNOWLEDGMENT

Authors are thankful to Dr. A. Lanitis for providing the FG-Net face database, Dr. A. Martinez for the AR face database and Dr. X. Wang for the CUHK face sketch database. We also extend thanks to B. Klare from Michigan State University for helping with the implementation of their algorithm [5]. The authors also thank the reviewers for their useful and constructive feedback.

REFERENCES

[1] Fg-net aging database - http://www.fgnet.rsunit.com/.
[2] T. Ahonen, A. Hadid, and M. Pietikainen. Face description with local binary patterns: Application to face recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 28(12):2037–2041, 2006.

[3] E. D. Goldberg. *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison-Wesley Longman Publishing Co., Inc., Boston, MA, USA, 1989.

[4] G. Huang, M. Ramesh, and L.-M. T. Berg. Labeled faces in the wild : A database for studying face recognition in unconstrained environment, 2007.

[5] B. Klare and A. Jain. Sketch-to-photo matching: a feature-based approach. In *Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series*, volume 7667, 2010.

[6] B. Klare, L. Zhifeng, and A. Jain. On matching forensic sketches to mugshot photos. In *MSU Technical report*, 2010.

[7] Q. Liu, X. Tang, H. Jin, H. Lu, and S. Ma. A nonlinear approach for face sketch synthesis and recognition. *Proceedings of International Conference on Computer Vision and Pattern Recognition*, pages 1005–1010, 2005.

[8] A. Martinez and R. Benevento. The ar face database. *CVC Technical Report #24*, 1998.

[9] T. Ojala and M. P. D. Harwood. A comparative study of texture measures with classification based on feature distributions. *Pattern Recognition*, 29(1):51–59, January 1996.

[10] T. Ojala, M. Pietikainen, and T. Maenpaa. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(7):971–987, 2002.

[11] J. Robert G. Uhl and N. da Vitoria Lobo. A framework for recognizing a facial image from a police sketch. *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, page 586, 1996.

[12] X. Tang and X. Wang. Face photo recognition using sketch. In *Proceedings of IEEE International Conference on Image Processing*, volume 1, pages 257–260, 2002.

[13] X. Tang and X. Wang. Face sketch synthesis and recognition. *Proceedings of International Conference on Computer Vision*, pages 687–694, 2003.

[14] X. Wang and X. Tang. Face photo-sketch synthesis and recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31(11):1955–1967, 2009.

[15] P. Yuen and C. Man. Human face image searching system using sketches. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, 37(4):493–504, 2007.

[16] L. Yung-hui, M. Savvides, and V. Bhagavatula. Illumination tolerant face recognition using a novel face from sketch synthesis approach and advanced correlation filters. In *IEEE International Conference on Acoustics, Speech and Signal Processing*, volume 2, pages II –II, 14-19 2006.

[17] Y. Zhang, C. McCullough, J. Sullins., and C. Ross. Human and computer evaluations of face sketches with implications for forensic investigations. In *2nd IEEE International Conference on Biometrics: Theory, Applications and Systems*, pages 1 –7, sept 2008.

[18] Y. Zhang, C. McCullough, J. Sullins, and C. Ross. Hand-drawn face sketch recognition by humans and a pca-based algorithm for forensic applications. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, 40(3):475–545, 2010.

[19] W. Zhao, R. Chellappa, P. Phillips, and A. Rosenfeld. Face recognition: A literature survey. *ACM Computing Surveys*, 35(4):399–458, 2003.