Recognizing Surgically Altered Faces using Local Edge Gradient Gabor Magnitude Pattern

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***Abstract*—For humans, every face is unique and can be recognized amongst similar faces. This is yet to be so for machines. Our assumption is that beneath the uncertain primitive visual features of face images are intrinsic structural patterns that uniquely distinguish a sample face from those of other faces. In order to unlock the intrinsic structural patterns, this paper presents in a typical face recognition framework a new descriptor, namely the local edge gradient Gabor magnitude (LEGGM) descriptor. LEGGM first of all uncovers the primitive inherent structural pattern (PISP) locked in every pixel through determining the pixel gradient in relation to its neighbors. Then, the resulting output is embedded in the pixel original (grey-level) pattern using additive function. This forms a pixel's complete structural pattern, which is further encoded using Gabor wavelets to encode the frequency characteristics of the resulting pattern. From these steps emerges an efficient descriptor for describing every pixel point in a face image. The proposed descriptor-based face recognition method shows impressive results over contemporary descriptors on the Plastic surgery database despite using a base classifier and without employing subspace learning. The ability of the descriptor to be adapted to real-world face recognition scenario is demonstrated by running experiments with a heterogeneous database.**

***Index Terms*—plastic surgery; face descriptor; face recognition.**

I. Introduction

For humans, every face is unique and can be recognized amongst similar faces. In having machines execute human operations with high precision is the general direction of research for all fields. Most importantly is the area of information security where prevention of unauthorized access electronically or physically cannot be compromised. Therefore, careful consideration into scenarios such as plastic surgery and its effect to face recognition should be of optimum concern to the research community. Why? Because modified faces due to plastic surgery appear distinct or begin to resemble the face of another individual. In such a case, existing feature extraction approaches might fail. So there should be a way to identify those features that remain unchanged after a face undergoes plastic surgery and still does not intercept with features of the face of another individual. However, it might be difficult to identify such features.

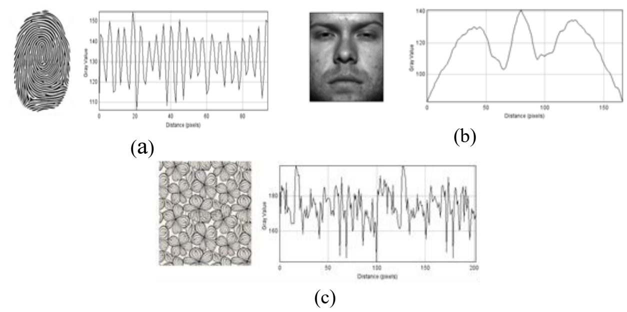

Fig. 1. Profile plot of various patterns.

The face image pattern (two dimensional: 2D) unlike other patterns such as fingerprint image, or a natural scene image, has more uncertain primitive visual features, that is, there isn't clear distinctiveness of facial features on intensity description (grey-level). To demonstrate this claim, given in Fig. 1 is the profile plot of fingerprint, a natural scene image and face image drawn in order to interpret the distinctiveness of their visual features with respect to pixel information.

As can be observed in Fig. 1 the fingerprint, natural scene images show to possess some form of distinctive features such as lines, contours, points, edge, texture or shape patterns and it translates to the distinctiveness shown at pixel level information through the profile plot. For the very reason of uncertainty of face image primitive visual features at intensity grey (level), pattern representation still remains an important problem in face recognition and related areas of image understanding.

With the common goal to tackle the problems in face recognition, a number of research disciplines have emerged with numerous face recognition methods. The holistic based representation methods such as the principal component analysis (PCA) [1] and its classification counterpart, the linear discriminant analysis (LDA) [2]. However, the holistic based representation methods are generally known to perform poorly as feature extraction methods, but are mostly applied as dimensionality reduction methods.

Other methods include: methods representing local appearance information. The local binary patterns and its variants such as the local binary pattern histogram Fourier features (LBP-HF) [3], completed local binary pattern (CLBP), which comprises of CLBP-M-S (magnitude and phase), CLBP-

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S (phase), CLBP-M (magnitude) [4]. The Gabor representation and its variants such as histograms of Gabor ordinal measures (HOGOM) [5], local Gabor binary pattern histogram sequence (LGBP) [6], local Gabor XOR patterns (LGXP) [7]. These methods retain different levels of information that are not usually apparent in grey-level (intensity description) face images. However, the type of the local details retained plays a vital role in face recognition tasks, especially in complex instances where many appearance variation factors are entangled. In such cases, the representation method that best disentangles the variation factors in order to represent only significant features will suffice.

Our emphasis is that since LBP, Gabor and some of their variants are texture based descriptors (only varying in magnitude from each other) they might not be able to explore the face image information that suggest useful discriminative cues against plastic surgery effects on the face image with possible expression modality. For instance, let's take the case of a face that must have been subjected to plastic surgery and at image capture may suffer from either expression or variations in lighting conditions. So it isn't only the problem of the uncertainty in primitive visual features of a face image, but also of the ability to exploit facial features that are useful to recognition.

Therefore, this paper proposes a new facial shape and appearance descriptor namely, local edge gradient Gabor magnitude (LEGGM) pattern that exploits a sample face primitive inherent structural pattern (PISP).

The rest of the paper is organized as follows. In section II introduces the art of describing a person's face using LEGGM. In Section III, the experimental application scenario is presented in order to reflect a typical real-world experimental setting. In section IV is the experimentation and analysis, while in Section V is the conclusion.

II. LEGGM Descriptor

In a given face recognition framework, a plug-in of the local edge gradient Gabor magnitude (LEGGM) descriptor for extracting essential features for face recognition in the event of plastic surgery separated faces is proposed. The LEGGM algorithmic process for extracting essential features is illustrated in Fig. 2 and discussed subsequently. Given an illumination normalized face image, the actual processing for LEGGM descriptor comprises of five major steps: a) PISP computation, b) Complete face structural pattern computation, c) Information encoding using Gabor wavelets, d) Down-sampling, and e) Normalization. They are described briefly as: To detect the PISP of the face image, the edge gradient of each pixel based on its surrounding neighbor is first determined. Successively, an embedding process that uses an additive function to calculate at each pixel point the complete face structural pattern follows. This is explained as the integral of the structural pattern information to the global appearance information (which is of a normalized image). The resulting information from the preceding step, known as the complete face structural pattern is further process in the frequency domain using Gabor wavelets. This is to express at various

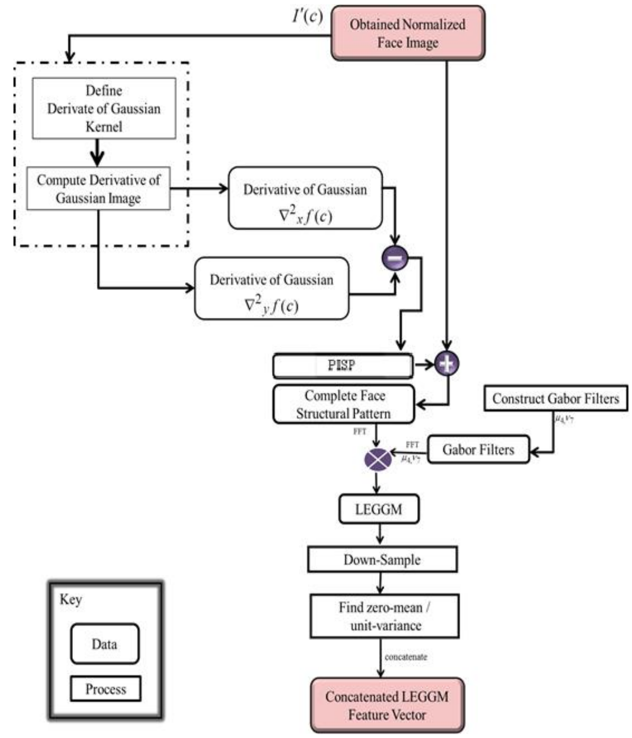

Fig. 2 The descriptor algorithmic process

frequencies of the discriminative properties of the complete face structural information. The resulting information forms LEGGM for describing a face sample. On applying Gabor wavelets at 5-scales and 8-orientations, a face image is described by forty (40) LEGGM features, which are further down-sampled using an interpolation dependent down-sampling approach. This is to mitigate the problem of redundancy resulting from Gabor wavelet. Given that there are forty (40) independent down-sampled LEGGM features for describing a sample face, their respective data will have to be standardized. Therefore, a zero-mean/unit-variance standardization method is employed on the forty (40) down-sampled LEGGM features. Finally, this standardized LEGGM features are further concatenated along the scale to obtain the augmented LEGGM feature vectors used for describing a single sample face image.

The use of the illumination normalized image as opposed to the original grey-level image is due to the fact that edge gradient distribution of an image is a function of illumination and surface reflectance [8]. This means that the image surface properties can limit the distribution of the image gradient. In other words, to be able to capture the actual edge gradients, which reflect an objects surface properties such as shape, curves, regions, boundaries and/or outlines, an illumination insensitive image is preferred. However, it should be noted that the use of the illumination normalized image in the designed descriptor architecture is only on the basis that the image that is an input to the face recognition system might be illumination deficient. Otherwise, the image in its original grey-level is sufficient.

The local edge gradient Gabor magnitude (LEGGM) pattern at pixel position c for an ith image sample is formally defined as follows:

$$LEGGM_{u,v}^{i}(c) = [LEGGM_{0,0}^{(T)}(c), LEGGM_{0,1}^{(T)}(c), \cdots, LEGGM_{4,7}^{(T)}(c)]^{T} \quad (1)$$

and simplified as,

$$= Z^{i}{}_{\mu,\nu} \quad (2)$$

where $Z^{i}{}_{\mu,\nu}$ is the augmented features of the forty (40) down-sampled and normalized LEGGM features, which can be used to describe a face image. T is the transpose operator.

III. Experimental application scenario

Face recognition task for application purposes can be defined as a function of face identification and verification. While some of the application areas can be strictly categorized under identification task or verification task, some of them cut across the two tasks. The category within which each application area can be described is illustrated in Fig 3.

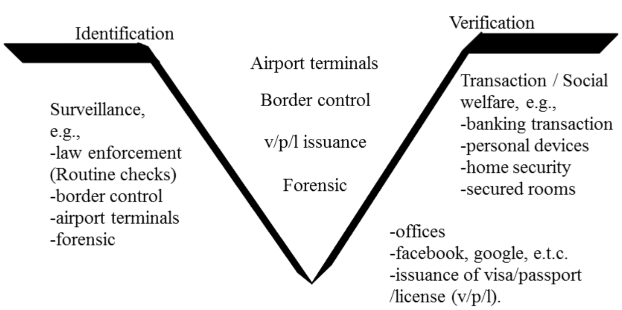

Fig. 3. Face recognition application domains and their respective task at a glance

The application scenario such as the airport scenario as mentioned in Fig. 4 cuts across everyone's living affairs and embodies the two tasks of identification and verification. Imagine after long years of hard work in the busy work-force and someday out of the blues you decided to reward yourself by taking a shot at plastic surgery. Having undergone a facial aesthetic plastic surgery procedure, you decide to go on a casual trip to a tourist destination. Or perhaps you were called in to attend to some work demands at branch miles away that requires you to fly. Now, considering the outcomes of the surgery, two incidents are possible: 1) your facial appearance becomes different after undergoing plastic surgery procedures, and 2) your facial appearance could also tend towards the appearance of a different individual. Suppose then that on your causal trip, incident 2) occurs on your stop at the airport terminal resulting in you being identified as a wanted criminal from a list of suspects, or on your official trip incident 1) causes a denial of your travel rights, that is, your identity could not be verified. What then could possibly be your fate? Let us leave the answer to you, but from a technology point-of-view, the

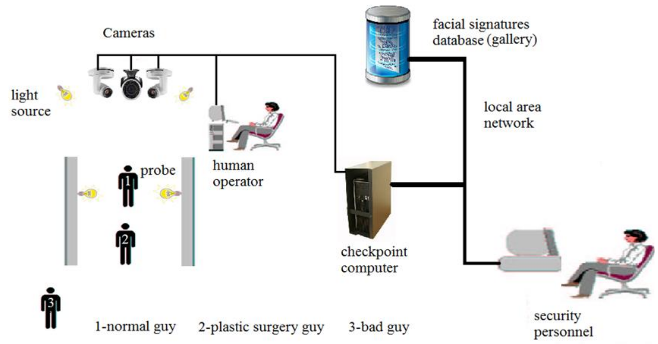

Fig. 4. Overview of typical airport application of face recognition

occurrence of such incidents should be 99.00% avoided. Therefore, recognition of a person even after undergoing plastic surgery should be moving towards such percentile.

In view of the presented arguments above, two scenarios are evaluated. The case of recognizing plastic surgery separated faces and a heterogeneous scenario where different sets of real faces that have undergone plastic surgery and usually experimented-on faces are combined. The heterogeneous case tries to model a practical airport scenario as demonstrated in Fig. 4. To effectively represent such a scenario, four data sets are used, which are the plastic surgery data set [9], the Georgia Tech face (GT) data set [10], the labelled faces in the wild (LFW) data set [11], and a heterogeneous data set. The heterogeneous data set is created by combining subsets of the plastic surgery data set, GT data set, LFW data set with a subset of the Essex data set [12].

A. Plastic Surgery Data Set

The plastic surgery data set [9] contains near frontal faces of real people who have undergone plastic surgery. In all, there are a total of 1800 face images of 900 subjects (excluding cheek and chin surgery procedures with 21 subjects, i.e., 42 samples). A mirror samples of the 921 subjects face images is created making it a total of 3684 face samples. The experimental scenario (ES): Four images per subject, three images are used to make up the train set and also make-up the gallery set. The remaining image is used to make up the test set. It should be noted that there is no subspace learning employed for this experiment.

B. Heterogeneous Data Set

In this data set, images of different subjects from the plastic surgery data set are selected arbitrarily, a total of 321 subjects with plastic surgery. Then full frontal faces are selected from various data sets. From the Essex data set [12] are 231 subjects with illumination problem. An additional 50 subjects are added from the GT data set [10], and 38 subjects from the LFW data set [11]. This brings the total number of subjects to 640, with every subject having 3 images. Experimental Scenario (ES) with subspace learning is given as: 2 images are used to make up the train/gallery set, while the remaining image makes up the test set (probe). For all the subjects the image selected for the test set is unseen during the training phase. Some sample faces from the heterogeneous data set that make-up the heterogeneous database are given in Fig. 5.

Fig. 5. Sample faces from the heterogeneous database

IV. Experimental Results

This section reports the experimental results of applying the LEGGM to face recognition. In all the experiments the identification results and verification results are reported using the cumulative match characteristics (CMC) curve, receiver operating characteristics (ROC) curve or points from the ROC curve, and the equal error rate (EER) evaluation metrics.

A. Evaluation and Benchmarking of LEGGM with Contemporary Face Descriptors

Using ES of the plastic surgery database, the identification results of different descriptor-based face recognition methods are presented without employing any subspace learning/training. The descriptors are used in their original feature-dimension. The facial descriptors under comparison are the LBP variants, which are the CLBP-M-S, CLBP-M and CLBP-S, while the Gabor variants used are LGBP and LEGGM. The identification rates are reported on Rank basis, where the Ranks 1-10 are considered. The results of employing different facial descriptors in the recognition of faces that have undergone plastic surgery are reported for various plastic surgery procedures and their results shown in Fig. 6. From the figure the following observations are made.

The Gabor based descriptors are observed to be more robust against non-reversible facial appearance changes due to plastic surgery procedures. Their robustness is shown by their above 65% Rank-1 recognition rate that they achieved in a number of the experiments, which is more than what the LBP based descriptors achieved. The identification accuracy of LBP based descriptors is rather disappointing. They failed to reach a satisfactory recognition rate despite existing in a much lower-dimensional space. Overall, LEGGM, a facial shape and appearance descriptor, shows to have achieved the best Rank-1 identification rates. Its highest Rank-1 identification rate is above 87%, which is achieved for the case of recognizing faces that have undergone Dermabrasion surgery.

While surgery procedures to some facial features such as the eye, nose, forehead and the entire-face (which have been found in psychophysics and computer vision, to contribute largely to face recognition accuracy [13]) minimally affects outlines of the facial features. More of the effects are to the skin regions surrounding the features where the stretching of skin is done to achieve aesthetics. For surgeries that involved such procedures only a minimum-maximum of 8% and 76% correct identification rates were observed for all the descriptors compared. Though, the best performing descriptor is LEGGM facial shape and appearance descriptor, its Rank-1 identification capability did not go beyond 76% for the cases of Blepharoplasty (eye), Rhytidectomy (entire-face), brow-lift (forehead and eye) and Rhinoplasty.

Observed also in Fig. 6 is that LEGGM is mostly unaffected by skin texture changing plastic surgery procedures. The identification rates for texture changing procedures reached 87.50%. The closeness in performance of LGBP to LEGGM shows that they share something in common in comparison with the CLBP-M-S [4], CLBP-M or CLBP-S [4]. The CLBP-S performed surprisingly well from Rank 5 to 10 in the recognition of faces that have undergone Blepharoplasty surgery, while LGBP [6] performed the best from Rank-2 to Rank-10 in the recognition of faces that underwent cheek and chin surgery. Both identification performances of LEGGM and LGBP for the cheek and chin surgery altered faces may not be unconnected with their performances achieved for the texture changing procedures because the region that is modified after chin surgery is not included in the cropped face image.

From Table I, LGBP, CLBP-M-S, CLBP-M and CLBP-S show that they are most appropriate for face verification task than recognition task. Their performances in verification task differ greatly from their performances in the identification task. For instance, take the case of Rhytidectomy where the CLBP-M achieved as low as 8.44% identification rate. In the verification task it achieved as high as 84.09%, 52.60%, 69.81% and 76.62%, verification rates at points on the ROC curve where FAR is 0.1591 (EER), 0.01, 0.05 and 0.1, respectively. Similar performances are observed for the other descriptors such as LGBP, CLBP-S, and CLBP-M-S.

B. Experiments on Heterogeneous Database

Here, it is of expectation that the designed descriptor-based face recognition method will be robust against a number of image formation factors that are present in the system because of its invariant property. The results of the designed descriptor-based face recognition methods in this subsection are on the basis of the subspace learning using principal component analysis plus linear discriminant analysis (PCA plus LDA) [14], locality sensitive discriminant Analysis (LSDA) [15] and supervised locality preserving projection (sLPP) [16]. The results are reported in terms of identification rate, verification rate and EER. The plots of the results are shown in Fig. 7 and Table II.

From Fig. 7 and Table II, it can be seen that the use of PCA plus LDA performed best in all the experiments by a large margin, which can be observed from the Rank-1 up to Rank-10. The use of sLPP performed second best followed by LSDA. In

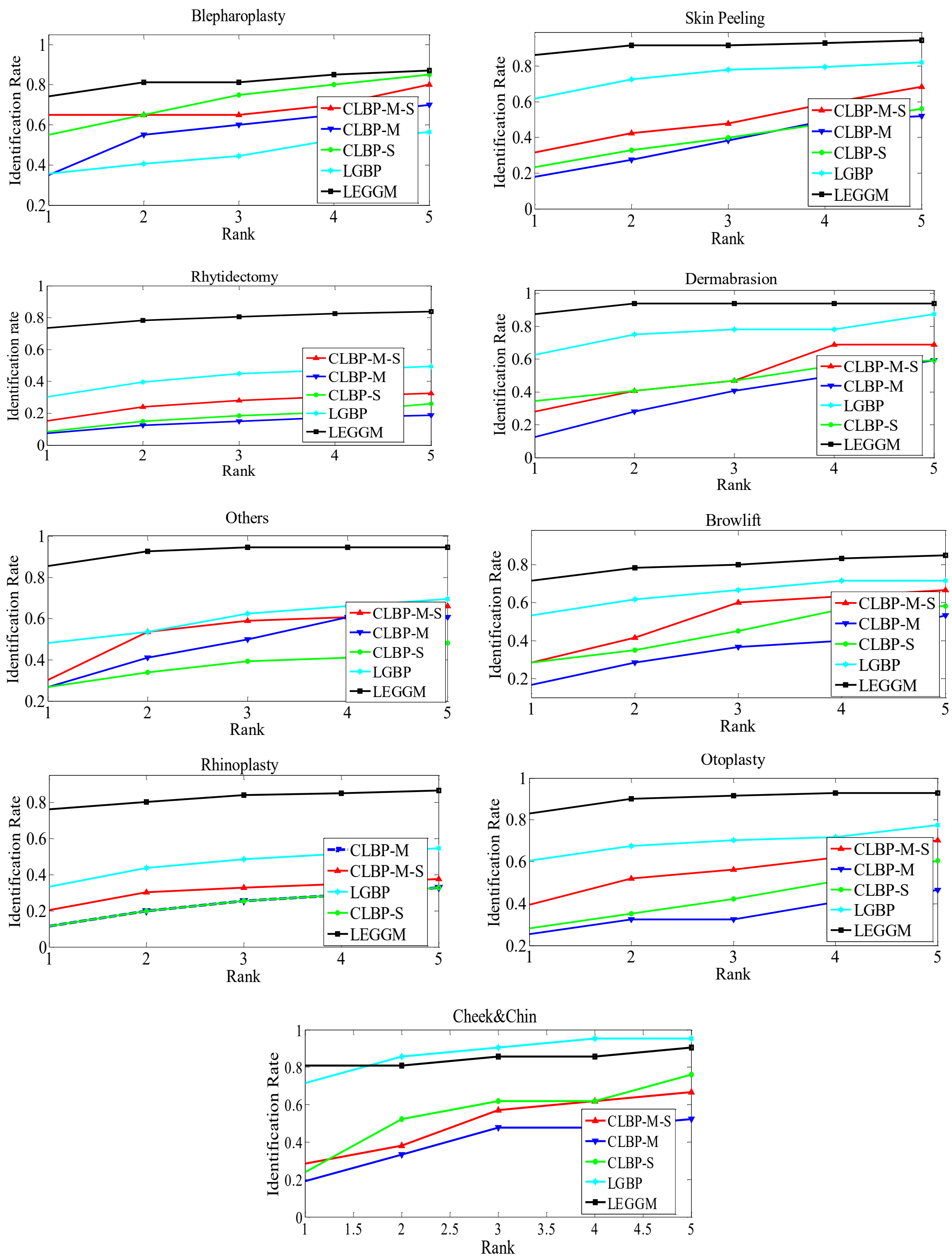

Fig. 6. Identification performances of LEGGM descriptor and existing descriptors without employing subspace learning for different plastic surgery procedures

Table I

Recognition performances of LEGGM descriptor and existing descriptors for different types of plastic surgery procedures

PSP	Method	@ FAR 0.01	@FAR 0.05	@FAR 0.1	EER	Rank-1
		Verification Rate				Recognition Rate
BL	CLPB-M-S	75.00	80.00	**100**	0.0921	65.00
	CLBP-M	60.00	70.00	80.00	0.1500	35.00
	CLBP-S	**85.00**	85.00	90.00	0.1000	55.00
	LGBP	73.29	**90.10**	95.05	**0.0693**	35.64
	LEGGM	71.29	86.14	89.11	0.1089	**74.26**
SP	CLPB-M-S	80.82	87.67	95.89	0.0818	31.51
	CLBP-M	60.27	80.82	82.19	0.1384	17.81
	CLBP-S	71.23	87.67	91.78	0.0947	23.23
	LGBP	**94.52**	**97.26**	**100**	**0.0274**	61.64
	LEGGM	83.33	88.89	93.06	0.0695	**86.11**
RY	CLPB-M-S	74.03	86.04	90.26	0.0973	15.26
	CLBP-M	52.60	69.81	76.62	0.1591	8.44
	CLBP-S	69.16	81.49	87.34	0.1135	18.48
	LGBP	**84.42**	**93.83**	**95.78**	**0.0559**	30.19
	LEGGM	76.62	87.99	92.53	0.0844	**73.38**
DE	CLPB-M-S	68.75	87.50	**96.88**	**0.0670**	28.13
	CLBP-M	53.13	75.00	84.38	0.1563	12.50
	CLBP-S	59.38	81.25	84.38	0.1250	34.38
	LGBP	**87.50**	**90.63**	90.63	0.0938	62.50
	LEGGM	75.00	84.38	87.50	0.1250	**87.50**
OT	CLPB-M-S	**78.57**	**89.29**	**92.86**	**0.0893**	30.36
	CLBP-M	67.86	80.36	82.14	0.1250	26.76
	CLBP-S	71.43	**89.29**	91.07	0.0899	26.76
	LGBP	**78.57**	87.50	89.29	0.1071	48.21
	LEGGM	76.36	89.09	90.91	0.0928	**85.45**
BR	CLPB-M-S	73.33	83.33	90.00	0.1000	28.33
	CLBP-M	60.00	75.00	75.00	0.1700	16.67
	CLBP-S	66.67	81.67	86.67	0.1169	28.33
	LGBP	**85.00**	**91.67**	**93.33**	**0.0814**	53.33
	LEGGM	58.33	78.33	83.33	0.1333	**71.64**
RH	CLPB-M-S	73.44	87.50	91.15	0.0889	20.31
	CLBP-M	68.23	82.29	88.02	0.1095	11.46
	CLBP-S	68.23	82.29	88.02	0.1095	11.46
	LGBP	**83.33**	**94.27**	**95.31**	**0.0573**	33.33
	LEGGM	78.65	88.54	92.71	0.0876	**76.04**
OTO	CLPB-M-S	81.69	91.55	**95.77**	**0.0704**	39.44
	CLBP-M	56.34	78.87	85.92	0.0985	25.35
	CLBP-S	69.01	85.92	90.14	0.1126	28.17
	LGBP	**84.51**	**92.96**	92.96	**0.0704**	60.56
	LEGGM	76.06	88.73	92.96	0.0739	**83.10**
CC	CLPB-M-S	76.19	95.21	**100**	0.0470	28.57
	CLBP-M	52.38	57.14	66.67	0.1905	19.05
	CLBP-S	71.43	85.71	90.48	0.0952	23.81
	LGBP	**95.24**	**95.24**	**100**	**0.0476**	71.43
	LEGGM	80.95	**95.24**	95.24	**0.0476**	**80.95**
TOTAL	**CLPB-M-S**	**75.76**	**87.57**	**94.76**	**0.0815**	**31.88**
	CLBP-M	**58.98**	**73.37**	**80.10**	**0.1441**	**19.23**
	CLBP-S	**70.17**	**84.48**	**88.88**	**0.1064**	**26.62**
	LGBP	**85.15**	**92.61**	**94.90**	**0.0678**	**50.76**
	LEGGM	**75.18**	**87.48**	**90.82**	**0.1653**	**79.83**

PSP-plastic surgery procedure, BL-Blepharoplasty, SP-skin peeling, RY-Rhytidectomy, DE-Dermabrasion, OT-Otoplasty, BR-brow lift, RH-Rhinoplasty, OTO-others, CC-cheek&chin, EER-equal error rate, FAR-false acceptance rate

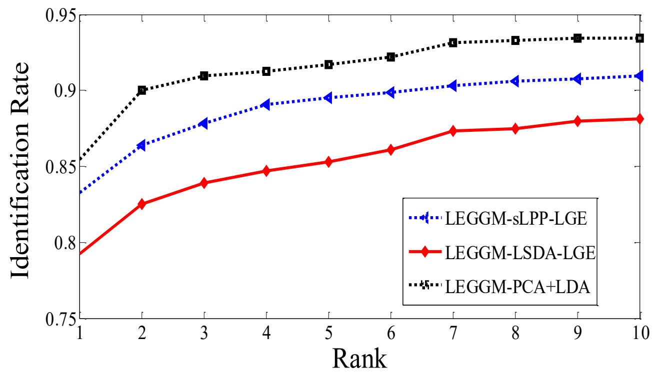

Fig. 7. Identification performance of the descriptor-based face recognition method for the heterogeneous database

Table II
Performance of the descriptor-based face recognition method in a heterogeneous case

Method	@FAR 0.01 (%)	@FAR 0.05 (%)	@FAR 0.1 (%)	EER (%)	VR (%)	Rank-1 (%)
LEGGM-sLPP-LGE	88.12	92.34	94.69	6.86	93.14	83.28
LEGGM-LSDA-LGE	83.13	89.06	91.56	8.89	91.11	79.22
LEGGM-PCA+LDA	**93.44**	**95.78**	**96.88**	**4.21**	**96.79**	**85.47**

FAR-false acceptance rate, EER-equal error rate, VR-verification rate

comparison with the previously reported experiments, LSDA can be seen to have significant increase in recognition accuracy. The obvious reason one could point at is the fact that there are more percentages of frontal-view images in the heterogeneous database than is included in the other databases (GT or LFW). That notwithstanding, far better recognition accuracies are envisaged to be achieved for the entire system if the image sets in the database are restricted to only the frontal-view images as it is commonly practiced in literatures, but that will make the system less practical.

Overall, the experiment on the heterogeneous data sets validates that the intrinsic facial characteristics of the descriptor-based face recognition method captured and retains for recognition can, to a good extent, be robust against a wide range of facial variation that is possible in a real-world face recognition scenario.

V. Conclusion

Through experimental analysis it was shown that the essential cues at local points of the face image LEGGM encodes are more effective for describing faces that have undergone plastic surgery than existing descriptors. It was further shown that the contemporary descriptors, which are either dependent on pixel intensity (greyscale) or texture dependent, do not sufficiently address face recognition problem in the event of plastic surgery. It is also observed that the proposed descriptor-based face recognition method showed that it can be adapted to real-world face recognition scenarios.

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