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Plastic Surgery Face Recognition Using Photometric based illumination normalization Techniques and Gabor Faces

دراسة التعرف علي الوجه للجراحات التجميلية بأستخدام تقنيات الأضاءة وتمثيل غابور للوجه

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ملخص :

ثمة تحد كبير و جديد لدراسات التعرف علي الوجه و الذي لم يؤخذ في الاعتبار من قبل و هو الجراحة التجميلية للوجه .حيث توافر التكنولوجيات المتقدمة، و خفض التكاليف من أي وقت مضى، جعل توافر الجراحة التجميلية للوجه بشكل متزايد و بأسعار معقولة، وبالتالي على نطاق واسع. والأبحاث والنتائج القليلة السابقة على الجراحة التجميلية للوجه لم تستطع حتي الآن على توفير مستويات مقبولة من أداء الاستدلال. في هذه الورقة نقترح تركيبة فعالة قادرة علي تحسين معدلات التعرف. حيث أن صورة الوجه تتأثر بشدة من جراء ظروف الإضاءة التي من شأنها أن تعيق عملية التعرف على الوجوه تلقائيا. و بالتالي أجرينا دراسة لتأثير مختلف تقنيات الإضاءة الضوئية على صور الجراحة التجميلية في هذه الورقة. حيث تم تقليل فعالية وتأثير الإضاءة، ويتم تعزيز التباين بواسطة معادلة الرسم البياني. الذي أدى ليس فقط الي تقليل تأثير الإضاءة ولكن أيضا الي ابراز الحواف والتفاصيل التي من شأنها تحسين التعرف علي الوجه. و من خلال الجمع بين تقنيات الإضاءة الضوئية و تمثيل غابور الذي أثبت أنه أداة قوية لاستخراج المعلومات الأساسيه للوجه ومجموعة من تقنيات التعرف علي الوجه يعطينا مزايا كثيرة، حيث لا حاجة لمعلومات مسبقة عن مصادر الضوء أو الشكل الثلاثي الأبعاد أو الحاجة الي العديد من العينات للتدريب اللازم و بالتالي يمكن تطبيقها مباشرة على صورة تدريبية واحدة للشخص.

Abstract:

A rising apparent great challenge to face recognition which is not much considered before is plastic surgery. The availability of advanced technologies, at ever decreasing costs, makes facial plastic surgery increasingly affordable and thus widespread. Previous research and results on plastic surgery were unable to provide acceptable levels of identification performances using current state of art face recognition techniques. This paper proposes an effective combination scheme that is able to improve plastic surgery verification/lidentification rates . As The appearance of a face image is severely affected by illumination conditions that will hinder the automatic face recognition process. A study of the effect of different photometric illumination techniques is carried on plastic surgery images in this paper. The effect of illumination is effectively reduced, and the contrast is enhanced by histogram equalization. The resulted face image is not only reduced illumination effect but also preserved edges and details that will facilitate further face recognition task. By combining photometric illumination techniques with Gabor representation of the images which have proven themselves to be a powerful tool for facial feature extraction and robust face recognition[1] and a group of holistic face recognition techniques gives us the advantages of no need of any prior information of light sources or 3D shape, nor many training samples needed thus can be directly applied to single training image per person condition . Experimental results carried on plastic surgery database, an ad-hoc database reported by singh et al [2] shows a significant improvement in recognition rates than that reported before at different cases of plastic surgery.

Keywords— **face recognition, plastic surgery, photometric illumination , Gabor.**

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I. INTRODUCTION

Over the last few years, face recognition technology has become one of the most important biometric technologies, for its non-intrusive nature and its potential applications like personal identification, security access control, surveillance systems, telecommuni - cations, digital libraries, human-computer interaction , military and so on [3].Five factors can significantly affect the performance of face recognition system: illumination, pose, expression, occlusion and ageing [4]. Another challenging factor that is not much considered before is Plastic surgery[5].

Plastic surgery is generally used for improving the facial appearance, for example, removing birth marks, moles, scars and correcting disfiguring defects. However, it can also be misused by individuals to conceal their identities with the intent to commit fraud or evade law enforcement. Face recognition after plastic surgery can lead to rejection of genuine users or acceptance of impostors. While face recognition is a well studied problem in which several approaches have been proposed to address the challenges of illumination [6], pose [7, 8], expression [9], ageing [4] and disguise [9, 10], the use of plastic surgery introduces a new challenge to designing future face recognition systems.

In general, plastic surgery can be classified into two distinct categories.

1. Disease Correcting Local Plastic Surgery (Local Surgery): This is the kind of surgery in which an individual undergoes local plastic surgery for correcting defects, anomalies, or improving skin texture. Example of disease correcting local plastic surgery would be surgery for correcting jaw and teeth structure, nose structure, chin, forehead, and eyelids. Although the global approach may look similar, this type of surgery usually leads to varying amount of changes in the geometric distance between facial features. Such changes may cause errors in automatic face recognition and degrade the system performance.

2. Plastic Surgery for Reconstructing Complete Facial Structure (Global Surgery): Apart from local surgery, plastic surgery can be done to completely change the facial structure which is known as full face lift. This medical procedure is recommended for cases such as patients with fatal burn or trauma. In this type of surgery, the appearance, texture and facial features of an individual are reconstructed and are usually not the same as the original face. The procedure is very useful for patients, but it can also be misused by criminals or individuals who want to remain elusive from law enforcement. Thus using this procedure, the face recognition system can be easily manipulated and made ineffective.

The main aim of the paper is to present this important challenge to the research community and systematically evaluate the performance of existing face recognition algorithms on a face database that contains images before and after surgery. The organization of this paper as follows: Section 2 presents the plastic surgery database used in the present work. Section 3 presents the Gabor face representation and in Section 4 the photometric illumination techniques are described. Experimental results are reported in Section 5. Finally a conclusion is drawn in Section 6.

II. PLASTIC SURGERY DATABASE

The database used in the present work consists of 1800 full frontal face images of 900 subjects. Table I summarizes the details of the plastic surgery database, for each individual, there are two frontal face images (before and after plastic surgery). The database contains 519 image pairs corresponding to local surgeries, 381 pairs of global surgery, the local surgery images consists of 194 pairs of nose surgery (Rhinoplasty), 101 pairs of eye-lid-lift-surgery (blepharoplasty) images, 74 pairs of ear-surgery (otoplasty) images , 56 cases of brow-lift (forehead-lift) images, 32 pairs of laser-skin (resurfacing) images, 18 pairs of fat-injections images and 44 pairs of Others (Mentoplasty, Malar Augmentation, Craniofacial, Lip augmentation) images. While the global surgery images consists of 320 pairs of Rhytidectomy (face lift) images and 60 pairs of skin peeling (Skin resurfacing) images. Examples of images from the database are shown in Figure 1.

TABLE I. Plastic Surgery Database [1]

Type	Plastic Surgery Procedure	Number of subjects
Global	Face-Lift Surgery (rhytidectomy)	321
	Skin peeling (skin resurfacing)	60
Local	Nose Surgery (Rhinoplasty)	194
	Eye-Lid-Lift surgery (blepharoplasty)	101
	Ear-Surgery (otoplasty)	74
	Brow-Lift (Forehead)	56
	Laser-skin (resurfacing)	32
	Fat-injections	18
	Others(Mentoplasty, Lip augmentation)	44

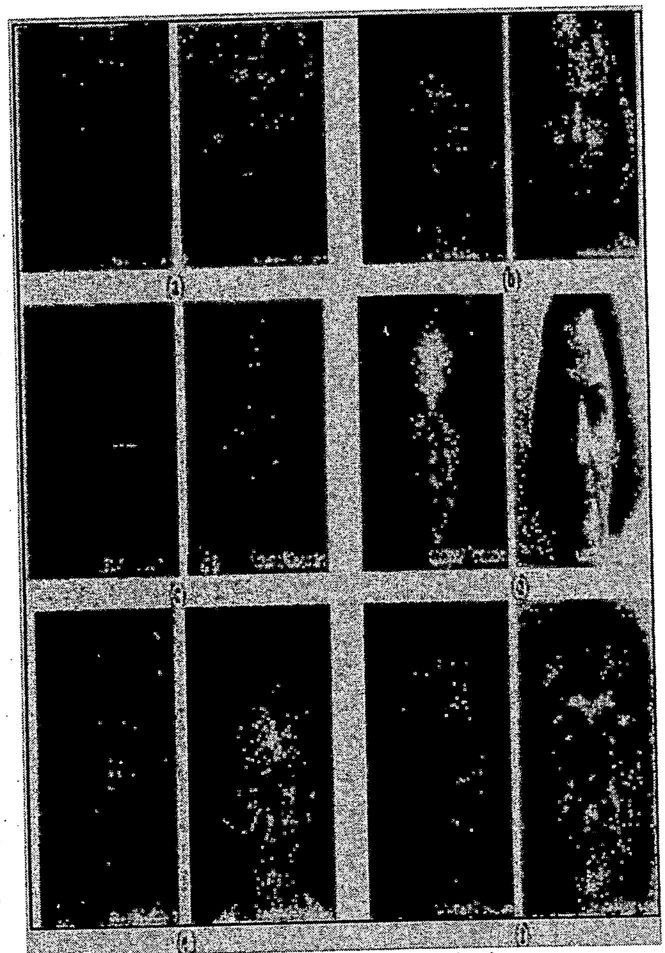


Fig. 1. Examples of images from the plastic surgery database (a) Rhytidectomy, (b) Blepharoplasty, (c)Otoplasty, (d) Forehead- Lift, (e) Resurfacing, and (f) Fat-injection surgery images.

III. GABOR FACE REPRESENTATION

The Gabor image representation is obtained by computing then convolution of the original image with several Gabor wavelets .

In general, the family of 2D Gabor filters can be defined in the spatial domain as follows [11-17]:

$$\psi_{u,v}(x,y) = \frac{f_u^2}{\pi k\eta} e^{-((f_u^2/k^2)x'^2+(f_u^2/\eta^2)y'^2)} e^{j2\pi f x'} \quad (1)$$

Where $x' = x \cos\theta v + y \sin\theta v$, $y' = -x \sin\theta v + y \cos\theta v$, $f_u = f_{max}/2^{(\frac{u}{2})}$ and $\theta_v = \frac{v\pi}{8}$. As can be seen from the filters definition, each Gabor filer represents a Gaussian kernel function modulated by a complex plane wave whose center frequency and orientation are given by fu and θv, respectively. The parameters κ and η determine the ratio between the center frequency and the size of the Gaussian envelope and, when set to a fixed value, ensure that Gabor filters of different scales behave as scaled versions of each other [1]. It should also be noted that with fixed values of the parameters κ and η, the scale of the given Gabor filter is uniquely defined by the value of its center frequency fu. While different choices of the parameters determining the shape and characteristics of the filters define different families of Gabor filters, the most common parameters used for face recognition are $\kappa = \eta = \sqrt{2}$ and $f\max = 0.25$ (based on previous published studies investigating the effect of different values of κ, η and $f\max$ on face recognition) [1,11,12]. The feature extraction procedure can then be defined as a filtering operation of the given face image $I(x, y)$ with the Gabor filter $\psi_{u,v}(x,y)$ of size u and orientation v [13-15], that is:

$$G_{u,v}(x,y) = I(x,y) * \psi_{u,v}(x,y) \quad (2)$$

where $G_{u,v}(x,y)$ denotes the complex filtering output that can be decomposed into its real ($Eu,v(x,y)$) and imaginary ($Ou,v(x,y)$) parts:

$$E_{u,v}(x,y) = Re[G_{u,v}(x,y)] \quad (3)$$

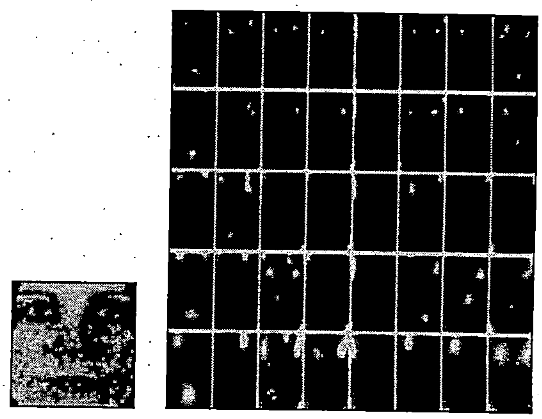
$$O_{u,v}(x,y) = Im[G_{u,v}(x,y)] \quad (4)$$

Based on these results, the magnitude ($A_{u,v}(x,y)$) and phase ($\varphi_{u,v}(x,y)$) responses of the filtering operation can be computed as follows:

$$A_{u,v}(x,y) = \sqrt{E_{u,v}^2(x,y) + O_{u,v}^2(x,y)} \quad (5)$$

$$\varphi_{u,v}(x,y) = \arctan\left(\frac{O_{u,v}(x,y)}{E_{u,v}(x,y)}\right) \quad (6)$$

Figure 2 shows an example of the Gabor face representation.



(a) (b)

Fig. 2. An example of the Gabor magnitude output: a sample image (a) and magnitude output of the filtering operation with the entire Gabor filter bank of 40 Gabor filters

IV. PHOTOMETRIC ILLUMINATION NORMALIZATION TECHNIQUES

Photometric normalization technique is any normalization technique which performs illumination normalization at the preprocessing level as opposed to techniques compensating for illumination induced appearance changes at the modeling or classification level.

The single-scale-retinex algorithm (SSR)[18], the multi-scale-retinex algorithm (MSR)[18], the single-scale self quotient image (SSQ)[18], the multi-scale self quotient image (MSQ)[18], the homomorphic-filtering based normalization technique (HOMO)[18], a wavelet-based normalization technique (WAV) [18], the isotropic-diffusion-based normalization technique (IS) [19,20], the anisotropic-diffusion-based normalization technique (AS) [19,20], the non-local-means-based normalization technique (NLM) [21], the adaptive non-local-means-based normalization technique (ANL) [21], the discrete cosine transform - based normalization technique (DCT) [18], a normalization technique based on steerable filters (SF) [18], a modified version of the anisotropic – diffusion based normalization technique (MAS) [19], the Gradient-faces approach (GRF) [22], wavelet- denoising - based normalization technique (WD) [23], adaptive single scale retinex technique (ASSR) [18] are all photometric normalization techniques. A sample image processed with different photometric illumination techniques shown in Figure 3. It can be seen from the figure that each algorithm of illumination normalization handles illumination effect differently. Effect of these algorithms will be investigated in detail in experimental results showing which is best and worst algorithm for plastic surgery face recognition.

V. EXPERIMENTAL RESULTS

This section presents the experiments conducted. It commences by describing performance measures used and basic preprocessing preceding the assessment of the proposed face recognition approaches and continues by the results of the assessment.

As the primary goal of the present work is to evaluate an effective way to handle variations

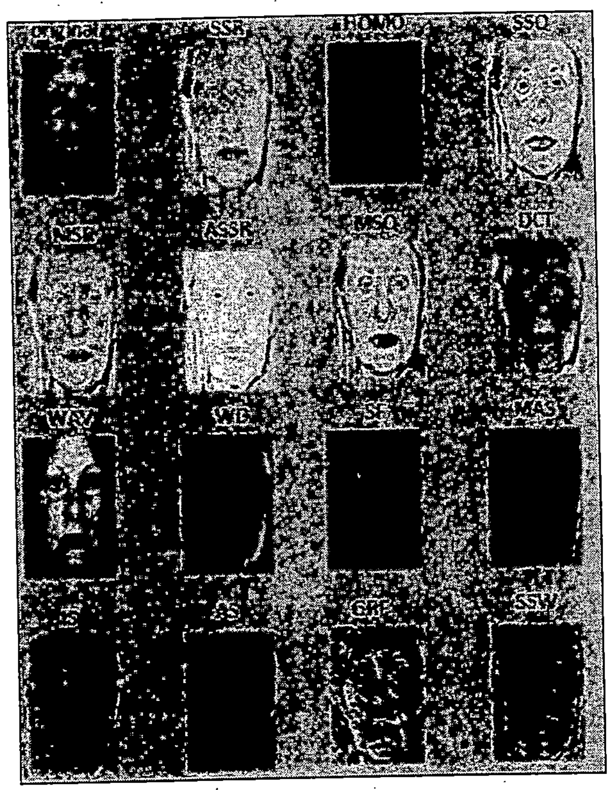


Fig. 3. A sample image processed with different photometric illumination techniques

due to plastic surgery. Such variations, however, are mostly confounded by other variations, especially illumination. A study of Gabor representation , which have proven themselves to be a powerful tool for facial feature extraction and robust face recognition. They represent complex band-limited filters with an optimal localization in both the spatial as well as the frequency domain .Thus, when employed for facial feature extraction, Gabor filters extract multi resolutional, spatially local features of a confined frequency band [1], and photometric illumination techniques, which are robust to further illumination variations, allows to better assess the net effect of plastic surgery in face recognition, were carried.

To study the effect of Gabor representation and photometric illumination on facial plastic surgery face recognition, Three holistic techniques, Principal component analysis (PCA) [24] (A powerful linear method for dimensionality reduction and feature extraction), kernel principal component analysis (KPCA) [25]. (non-linear method for dimensionality reduction and feature extraction for extracting non-linear features of face patterns due to facial expressions and viewing points) and Kernel fisher analysis (KFA) [25] (non-linear method for feature extraction based on maximizing between-class scatter matrix and minimizing within-class scatter matrix for extracting the most discriminate features).. Are used as our baseline techniques for feature extraction, they were chosen for their popularity and for the fact that they are still widely used for benchmark comparison studies.

performance measures: The performance of the techniques assessed in the next section is measured as following:

For the verification experiments the false acceptance error and false rejection error rates (FAR and FRR, resp.) as well as the half total error rate (HTER) are used. The FAR and FRR are defined as follows [26]:

$$\text{FAR} = \frac{n_{ai}}{n_i} 100\% \qquad (7)$$

$$\text{FRR} = \frac{n_{rc}}{n_c} 100\% \qquad (8)$$

While HTER is given by:

$$\text{HTER}= 0.5(\text{FAR}+\text{FRR}) \qquad (9)$$

where n_{ai} denotes the number of accepted impostor (illegitimate) identity claims, and n_i represents the number of all impostor identity claims made, n_{rc} denotes the number of rejected geniune (legitimate) identity claims, and $n_c$stands for the number of all geniune identity claims made. Note that both the FAR and the FRR depend on the value of the decision threshold T. Selecting a threshold that ensures a small value of the FAR inevitably results in a large value of the FRR and vice versa, a threshold that ensures a small FRR results in a large value of the FAR. Thus, to fairly compare the different recognition techniques the decision threshold has to be set in such a way that it ensures some predefined ratio of the FAR and FRR on some evaluation dataset or, alternatively, the two error rates have to be plotted against all possible values of the decision threshold, resulting in the so-called performance curves. For our assessment we chose the latter approach and represent the results in the form of Detection Error Trade-off (DET) curves, which plot the FAR against the FRR at different values of T.

For the identification experiments results are provided not in the form of error rates, but rather in form of recognition rates. To this end, we compute the so-called rank one recognition rate (ROR) for each of the probe (test) sets of the given database. The ROR is defined as follows:

$$\text{ROR} = \frac{n_{si}}{n_s} 100\% \qquad (10)$$

where n_{si} denotes the number of images successfully assigned to the right identity and n_s stands for the overall number of images trying to assign an identity to.

Basic preprocessing: Before starting the experiments, Two pre-processing steps are applied, Firstly is background removal where the face region in the image is detected and cropped to extract the face from the surrounding background. Secondly is image size normalization where the size of the detected and cropped face image is set to

200 x200 as shown in Figure 4.

Performance evaluation of face recognition algorithm using each of the three holistic features with each of the processing techniques: Gabor Filters and illumination normalization are

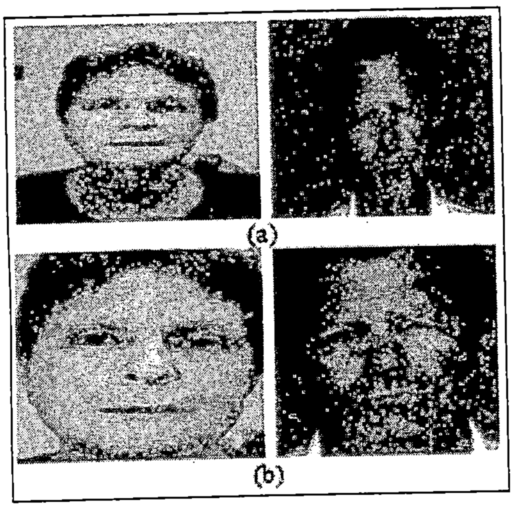


Fig. 4. a)Example of face images before processing , b)Face images after cropping and resizing

applied in three experiments and the results are reported in the next subsections. Where 50% of the images are used as training set, and 50% of the patterns are for the testing set. And the k-Nearest Neighbor classifier (k =1) for classification [27] using Mahalanobis Cosine (MAHCOS) [28] distance similarity measures.

Experiment1: Without Any Processing.

experiment1, evaluates the performance of the three holistic feature extraction techniques. As the three holistic feature extraction techniques are performed directly on the preprocessed image sets without any illumination normalization techniques or Gabor representation, ROR and HTER rates are depicted in TableII and TableIII respectively. While Figure5. shows the DET curves obtained. The results obtained for both verification (TableII) / identification (TableIII) systems and curves showed that PCA gives the best rates in case of Blepharoplasty, Otoplasty, fat-injections and Rhtidectomy plastic surgeries, while KFA gives the best rates in case of resurfacing and forehead-lift plastic surgeries. An overall best rates are obtained using PCA.

TABLEII. Experiment1 ROR rates.

Rate	Plastic surgery type / HFT	Resurf-acing-Surgery	Forehead Lift	Blepha-roplasty	Otoplasty	Fat-Injecti-ons Surgery	Rhytid-ectomy
ROR	PCA	68.9%	60.4%	59.6%	49.3%	43.8%	31.7%
	KPC-A	48.3%	52.8%	54.3%	47.9%	37.5%	33.7%
	KFA	55.2%	43.4%	44.7%	38.4%	31.3%	31.0%

TABLEIII. Experiment1 HTER rates.

Rate	Plastic surgery type / HFT	Resurfa-cing Surgery	Forehe a-d Lift	Blepha r-oplasty	Otopla s-ty	Fat-Injecti o-ns Surgery	Rhytid e-ctomy
HTER	PCA	0.0804	0.0721	0.0905	0.1723	0.2583	0.1618
	KPC-A	0.1849	0.1527	0.1011	0.2230	0.4000	0.1495
	KFA	0.0778	0.0688	0.0937	0.1821	0.2708	0.1874

Figure 5 shows that PCA and KFA gives better FAR and FFR that GKPCA on all types of plastic surgery.

Experiment 2: Using Gabor Filters.

In Experiment2, Gabor representation of the face image is extracted followed by one of the holistic feature extraction techniques on the processed Gabor image sets without any illumination normalization, ROR and HTER rates are shown in TableIV and TableV. While Figure 6. shows the DET curves obtained. The results obtained for both verification and identification systems and curves showed that the best rates are obtained using GPCA in case of resurfacing, Blepharoplasty, Otoplasty and Rhytidectomy, while KFA gives best rates in case of forehead-lift and fat-injections. The overall highest rates have been obtained using GPCA feature extraction technique. Extracting the Gabor features prior to performing holistic approaches gives a noticeable improvement on all facial plastic surgery sets. DET curves haves shown improvements in FAR and FRR than those of experiment 1 on all types of plastic surgery.

TABLEIV. Experiment2 ROR rates.

Plastic surgery type		Resurf a-cing Surger y	Forehe a-d Lift	Blepha r-oplasty	Otopla s-ty	Fat-Injecti o-ns Surger y	Rhytid e-ctomy
Rate	HFT						
ROR	PCA	89.7%	77.4%	74.5%	65.8%	68.8%	66.3%
	KPCA	89.7%	67.9%	70.2%	61.6%	68.8%	60.5%
	KFA	86.2%	75.5%	72.3%	64.4%	68.8%	22.6%

TABLEV. Experiment2 HTER rates.

Plastic surgery type		Resurf a-cing Surger y	Forehe a-d Lift	Blepha r-oplasty	Otopla s-ty	Fat-Injecti o-ns Surger y	Rhytid e-ctomy
Rate	HFT						
HTER	PCA	0.0179	0.0740	0.0367	0.0459	0.1125	0.0705
	KPCA	0.0230	0.0810	0.0578	0.0924	0.1708	0.0931
	KFA	0.0204	0.0743	0.0466	0.0494	0.1125	0.0813

Experiment3: Using Photometric Illumination Techniques and Gabor Representation.

In experiment3, Photometric illumination normalization is first applied to each set of the six plastic surgery datasets. Then Gabor representation of the face image is extracted followed by holistic feature extraction technique. TableVI and TableVII shows the ROR and HTER results of performing 11 photometric illumination techniques: Gradient, WAV, MSQ, SSQ, DCT, SF, HOMO, MSR, WD, SSR, ASC each time with one of the three holistic feature extraction techniques. Figure 7 to Figure 10 shows the DET curves of the four highest recognition rates obtained of the 11 photometric illumination results. The results obtained for verification system shows that the best illumination normalization and feature extraction techniques are GRF and GPCA respectively, in case of resurfacing and rhytidectomy while GRF and GKFA are best illumination normalization and feature extraction respectively, in case of forhead-lift, blepharoplasty, otoplasty and fat-injections. For verification system, the best illumination normalization and feature extraction techniques are GRF and GPCA respectively, in case of resurfacing, blepharoplasty, fat-injections and rhytidectomy, while GRF and GKFA are best illumination normalization and feature extraction respectively, in case of forhead-lift and Otoplasty. Identification results obtained in TableVI shows that GRF is the best illumination algorithm dealing with plastic surgery while for verification systems WAV is the best choice.

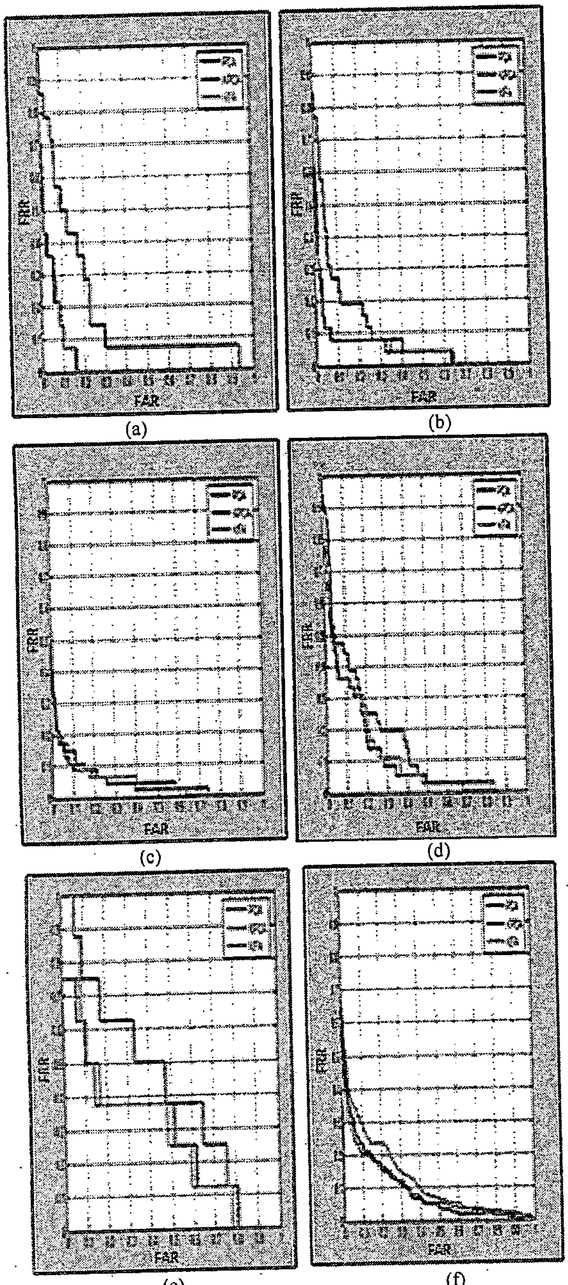


Fig. 5. DET plots demonstrating the performance of the 3 holistic algorithms on : a) Resurfacing, b) Forehead- Lift, c) Blepharoplasty, d) Otoplasty, e) Fat-injection and f) Rhytidectomy surgery images.

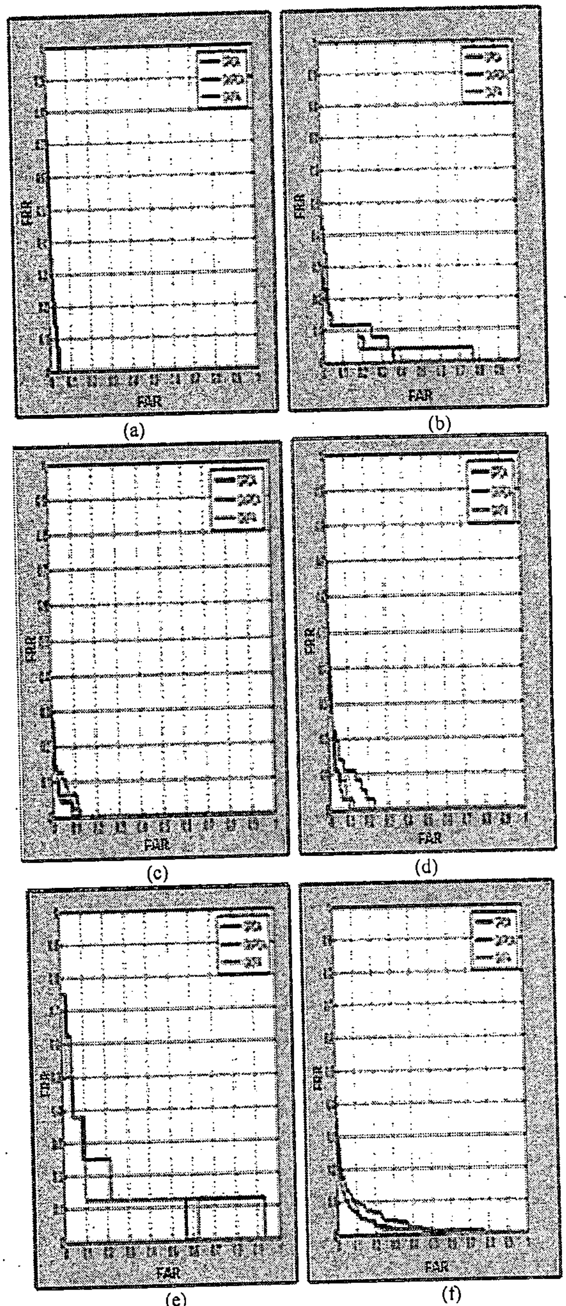


Fig. 6. DET plots demonstrating the performance of GPCA, GKPCA and GKFA on : a) Resurfacing, b) Forehead- Lift, c) Blepharoplasty, d) Otoplasty, e) Fat-injection and f) Rhytidectomy surgery images.

TABLEVI. Experiment3 ROR rates.

Plastic surgery type: Ra	HFT	Resurfa-cing Surgery	Forehea-d Lift	Blephar-oplasty	Otoplas-ty	Fat-Injectio-ns Surgery	Rhytide-ctomy
GRF	PCA	96.55%	83.02%	84.04%	78.08%	81.25%	70%
	KPCA	96.55%	77.36%	76.60%	61.64%	75.00%	63.40%
	KFA	96.55%	83.02%	85.11%	79.45%	81.25%	70.26%
WAV	PCA	96.55%	84.91%	84.04%	71.23%	68.75%	75.82%
	KPCA	93.10%	79.25%	76.60%	63.01%	62.50%	69.61%
	KFA	96.55%	84.91%	84.04%	71.23%	68.75%	75.16%
MSQ	PCA	93.10%	77.36%	78.72%	69.86%	68.75%	76.14%
	KPCA	79.31%	67.92%	70.21%	63.01%	62.50%	66.34%
	KFA	93.10%	77.36%	78.72%	69.86%	68.75%	75.49%
SSQ	PCA	89.66%	79.25%	78.72%	71.23%	75.00%	72.88%
	KPCA	79.31%	67.92%	69.15%	58.90%	56.25%	59.15%
	KFA	89.66%	79.25%	78.72%	71.23%	75.00%	72.88%
DCT	PCA	89.66%	75.47%	82.98%	67.12%	68.75%	73.53%
	KPCA	62.07%	67.92%	73.40%	58.90%	62.50%	62.09%
	KFA	86.21%	75.47%	81.91%	67.12%	68.75%	73.20%
SF	PCA	89.66%	77.36%	77.66%	67.12%	81.25%	74.84%
	KPCA	68.97%	71.70%	68.09%	54.79%	56.25%	60.78%
	KFA	89.66%	77.36%	77.66%	67.12%	81.25%	74.18%
HOMO	PCA	89.66%	75.47%	81.91%	71.23%	75.00%	71.90%
	KPCA	79.31%	67.92%	67.02%	63.01%	62.50%	62.09%
	KFA	86.21%	75.47%	81.91%	71.23%	75.00%	72.22%
MSR	PCA	89.66%	73.58%	84.04%	67.12%	56.25%	65.69%
	KPCA	75.86%	62.26%	69.15%	60.27%	50%	51.63%
	KFA	86.21%	73.58%	84.04%	67.12%	56.25%	66.34%
WD	PCA	86.21%	73.58%	79.79%	67.12%	75%	71.24%
	KPCA	75.86%	67.92%	69.15%	50.68%	62.50%	60.46%
	KFA	86.21%	73.58%	79.79%	67.12%	75%	70.92%
SSR	PCA	86.21%	73.58%	82.98%	65.75%	56.25%	64.71%
	KPCA	75.86%	64.15%	68.09%	63.01%	50%	51.31%
	KFA	86.21%	73.58%	65.75%	81.91%	56.25%	65.36%
ASSR	PCA	82.76%	69.81%	76.00%	64.38%	56.25%	58.82%
	KPCA	72.41%	58.49%	67.02%	49.32%	50%	46.41%
	KFA	82.76%	69.81%	74.47%	64.38%	63%	59.15%

TABLEVII. Experiment3 HTER rates.

Plastic surgery type: Ra	HFT	Resurfa-cing Surgery	Forehea-d Lift	Blephar-oplasty	Otoplas-ty	Fat-Injectio-ns Surgery	Rhytide-ctomy
GRF	PCA	0.0166	0.0451	0.0213	0.0463	0.2500	0.0550
	KPCA	0.0561	0.0791	0.0394	0.0758	0.1667	0.0985
	KFA	0.0166	0.0451	0.0212	0.0463	0.0542	0.0551
WAV	PCA	0.0064	0.0473	0.0164	0.0442	0.1042	0.0475
	KPCA	0.0536	0.0699	0.0352	0.1078	0.1583	0.0812
	KFA	0.0064	0.0473	0.0164	0.0448	0.1042	0.0479
MSQ	PCA	0.0089	0.0651	0.0368	0.0764	0.1292	0.0541
	KPCA	0.0612	0.0925	0.0658	0.1383	0.2333	0.0905
	KFA	0.0089	0.0651	0.0369	0.0764	0.1292	0.0546
SSQ	PCA	0.0077	0.0651	0.0313	0.0762	0.1292	0.0519
	KPCA	0.0663	0.0902	0.0631	0.1283	0.2000	0.0912
	KFA	0.0077	0.0651	0.0315	0.0768	0.1292	0.0523
DCT	PCA	0.0179	0.0717	0.0300	0.0648	0.1375	0.0512
	KPCA	0.0791	0.0917	0.0519	0.1298	0.2125	0.1003
	KFA	0.0179	0.0714	0.0300	0.0648	0.1375	0.0506
SF	PCA	0.0013	0.0677	0.0271	0.0370	0.01417	0.0512
	KPCA	0.0319	0.0973	0.0557	0.1221	0.1958	0.1032
	KFA	0.0013	0.0677	0.0271	0.0370	0.1417	0.0509
HOMO	PCA	0.0191	0.0729	0.0261	0.0471	0.1250	0.0517
	KPCA	0.0778	0.1117	0.0317	0.1204	0.1625	0.1087
	KFA	0.0191	0.0729	0.0260	0.0475	0.1250	0.0511
MSR	PCA	0.0191	0.0714	0.0312	0.0791	0.1750	0.0559
	KPCA	0.0855	0.1261	0.0550	0.1424	0.2292	0.1363
	KFA	0.0191	0.0714	0.0308	0.0791	0.1750	0.0567
WD	PCA	0.0191	0.0717	0.0365	0.0739	0.1542	0.0602
	KPCA	0.0880	0.0936	0.0645	0.1192	0.2542	0.1116
	KFA	0.0191	0.0714	0.0365	0.0723	0.1542	0.0603
SSR	PCA	0.0191	0.0710	0.0285	0.0858	0.1833	0.0596
	KPCA	0.0842	0.1224	0.0500	0.1456	0.2167	0.1405
	KFA	0.0191	0.0706	0.0289	0.0856	0.1250	0.0603
ASSR	PCA	0.0332	0.0618	0.0496	0.0934	0.2042	0.0620
	KPCA	0.0918	0.1220	0.0835	0.1703	0.2583	0.1176
	KFA	0.0332	0.0610	0.0496	0.0939	0.2042	0.0619

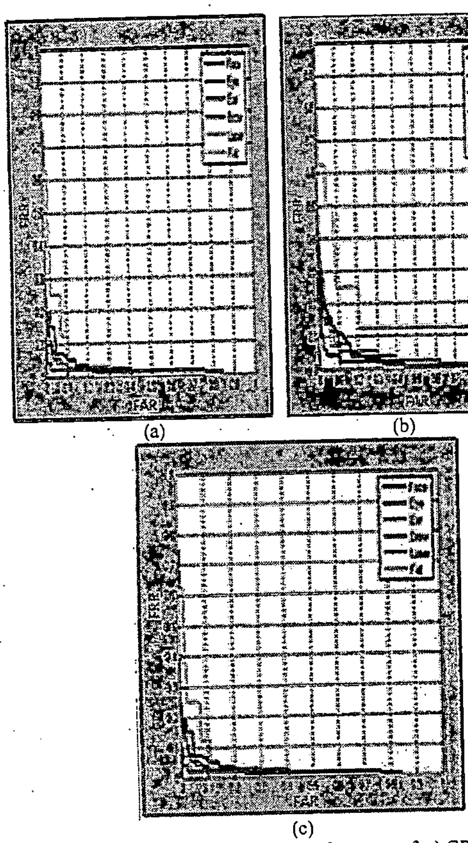


Fig. 7. DET plots demonstrating the performance of a) GPCA, b)GKPCA and c) GKFA on the 6 surgery sets using Gradient illumination normalization and normal histogram.

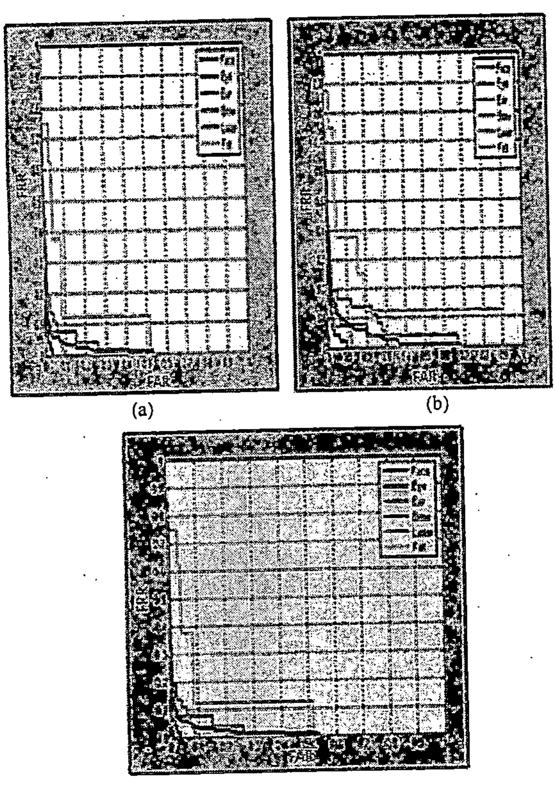


Fig. 8. DET plots demonstrating the performance of a) GPCA, b)GKPCA and c) GKFA on the 6 surgery sets using WAV illumination normalization and normal histogram.

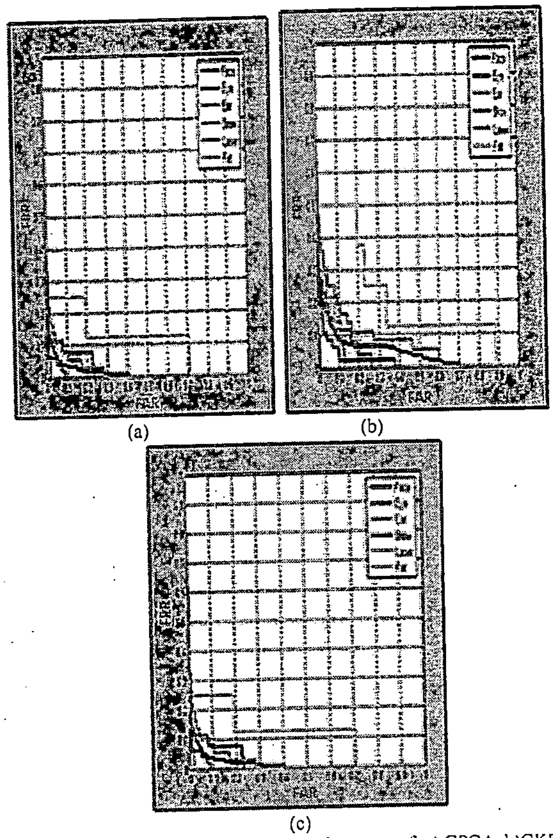


Fig. 9. DET plots demonstrating the performance of a) GPCA, b)GKPCA and c) GKFA on the 6 surgery sets using MSQ illumination normalization and normal histogram.

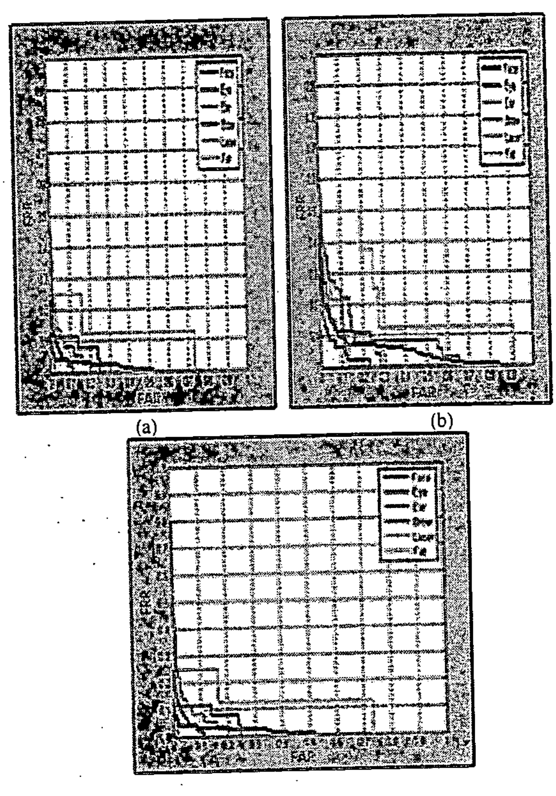


Fig. 10. DET plots demonstrating the performance of a) GPCA, b)GKPCA and c) GKFA on the 6 surgery sets using SSQ illumination normalization and normal histogram.

I. CONCLUSION

The increasing affordability and widespread of facial plastic surgery due to advancement of technology at a considerable costs imposed a new challenge to face recognition algorithms and leading to a new dimension of face recognition. The few studies that were carried on facial plastic surgery have shown that the current state-of-art recognition algorithms were unable to provide acceptable levels of identification performance.

In this paper we have shown that by using only holistic approaches we didn't get a real improvements in the recognition rates, while extracting the Gabor features prior to performing holistic approaches gives a considerable improvement in the verification/identification rates. An effective combination scheme, of combining photometric illumination techniques with Gabor representation of the images and a three of best known holistic face recognition techniques was able to improve plastic surgery recognition rates. Where for verification system a combination of Gradient-faces photo illumination approach with KFA gives the highest rank one recognition rates of 96.55%, 85.11%, 83.02%, 81.25%, 79.45% and 70.26% in case of resurfacing, Blepharoplasty, Forehead-lift, Fat-injections, Otoplasty and Rhytidectomy plastic surgery, respectively. For face identification system a combination of WAV photo illumination approach with PCA gives the best minimum error rates of 0.0064, 0.0164, 0.0473, 0.0442, 0.0475 and 0.1042 in case of resurfacing, Bleharoplasty, forhead-lift, Otoplasty, Rhytidectomy and fat-injections, respectively.opening the field of face recognition to start dealing with this upcoming new horizon of facial plastic surgery.

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