NEW FACE RECOGNITION DESCRIPTOR BASED ON EDGE INFORMATION FOR SURGICALLY-ALTERED FACES IN UNCONTROLLED ENVIRONMENT

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To Family

Uche, Synara, and my yet to be born

James P. and Julie J. Olisah

Siblings

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ABSTRACT

Since plastic surgery have increasingly become common in today's society, existing face recognition systems have to deal with its effect on the features that characterizes a person's facial identity. Its consequences on face recognition task are that the face images of an individual can turn out to be distinct and may tend towards resembling a different individual. Current research efforts mostly employ the intensity or texture based descriptors. However, with changes in skin-texture as a result of plastic surgery, the intensity or texture based descriptors may prove deficient since they enhance the texture differences between the pre-surgery and post-surgery images of the same individual. In this thesis, the effect of plastic surgery on facial features is modelled using affine operators. On the basis of the near-shape preserving property of the combination of the operators, the following assumption is made: The edge information is minimally influenced by plastic surgery. In order to exploit this information in real-world scenarios, it requires that face images be evenly illuminated. However, an evenly illuminated face image is far from reality on applying existing illumination normalization techniques. Thus, a new illumination normalization technique termed the rgb-Gamma Encoding (rgbGE) is proposed in this thesis. The rgbGE uses a fusion process to combine colour normalization and gamma correction, which are independently adapted to the face image from a new perspective. Subsequently, a new descriptor, namely the Local Edge Gradient Gabor Magnitude (LEGGM), is proposed. The LEGGM descriptor exploits the edge information to obtain intrinsic structural patterns of the face, which are ordinarily hidden in the original face pattern. These patterns are further embedded in the face pattern to obtain the complete face structural information. Then, Gabor encoding process is performed in order to accentuate the discriminative information of the complete face structural pattern. The resulting information is then learned using subspace learning models for effective representation of faces. Extensive experimental analysis of the designed face recognition method in terms of robustness and efficiency is presented with the aid of publicly available plastic surgery data set and other data sets of different cases of facial variation. The recognition performances of the designed face recognition method on the data sets show competitive and superior results over contemporary methods. Using a heterogeneous data set that typifies a real-world scenario, robustness against many cases of face variation is also shown with recognition performances above 90%.

ABSTRAK

Pembedahan plastik telah menjadi suatu kebiasaan yang semakin meningkat dalam masyarakat hari ini. Oleh itu sistem pengecaman wajah juga harus mampu menangani perubahan ke atas ciri-ciri yang boleh menentukan identiti wajah seseorang. Ini menjadikan tugas pengecaman wajah lebih sukar kerana imej wajah individu boleh menjadi berbeza dan mungkin cenderung ke arah menyerupai individu yang lain. Usaha penyelidikan terkini kebanyakannya menggunakan pemerihal berasaskan keamatan atau tekstur. Walau bagaimanapun dengan perubahan tekstur kulit akibat pembedahan plastik, pemerihal berasaskan tekstur tidak lagi bersesuaian kerana ia meningkatkan perbezaan tekstur diantara imej wajah sebelum dan selepas pembedahan bagi individu yang sama. Dalam tesis ini, kesan pembedahan plastik pada ciri-ciri wajah dimodelkan menggunakan pengendali afin. Berasaskan ciri-ciri pemilikan separa-konformal daripada gabungan pengendali, andaian berikut telah dibuat: Pembedahan plastik hanya mempengaruhi secara minima maklumat pinggir sesuatu wajah. Bagi mengeksploitasikan andaian ini dalam senario dunia sebenar, imej wajah perlu diterangi dengan kecerahan yang sama rata. Walau bagaimanapun, untuk mendapat imej wajah dengan kecerahan yang sama rata adalah tidak realitistik. Oleh itu, teknik normalisasi pencahayaan baru dipanggil pengekodan *rgb-gamma* (rgbGE) dicadangkan. Teknik rgbGE ini menggunakan proses lakuran dengan menggabungkan normalisasi warna dan pembetulan gamma, yang secara bebas disesuaikan dengan imej wajah dari perspektif yang baru. Seterusnya pemerihal baru yang dinamakan magnitud kecerunan pinggir setempat Gabor (LEGGM) dicadangkan. Pemerihal LEGGM mengeksploitasi maklumat pinggir wajah dalam mendapatkan struktur corak intrinsik wajah yang lazimnya tersembunyi dalam corak wajah asal. Corak tersebut kemudiannya dibenamkan dalam corak wajah untuk mendapatkan maklumat lengkap struktur corak wajah. Selanjutnya proses pengekodan Gabor dilakukan untuk menyerlahkan maklumat diskriminatif struktur corak wajah yang lengkap. Maklumat yang terhasil dipelajari menggunakan model pembelajaran sub-ruang untuk mendapatkan perwakilan wajah yang berkesan. Analisis eksperimen yang terperinci tentang keteguhan dan kecekapan kaedah yang dicadangkan disahkan dengan bantuan set data umum pembedahan plastik dan set data yang dilabel secara bebas. Prestasi pengecaman bagi kaedah pengecaman wajah yang dicadangkan menunjukkan keputusan yang sangat baik dan kompetitif berbanding dengan kaedah kontemporari yang lain. Menggunakan set data yang melambangkan senario dunia sebenar, prestasi keteguhan berdasarkan pelbagai variasi wajah juga menunjukkan ketepatan pengecaman melebihi 90%.

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LIST OF ABBREVIATIONS

AHE	-	Adaptive version of histogram equalization
AS	-	Anisotropic smoothing
BHE	-	Block based local histogram equalization
CAQI	-	Classified appearance-based quotient image
CIE L*U*V*	-	Commission international de l'Eclairage L-luminance UV-chrominance
CMC	-	Cumulative match characteristics curve
CLBP	-	Circular local binary pattern
CLBPHF	-	Completed local binary pattern histogram features
CLBP-M	-	Completed local binary pattern-magnitude
CLBP-M-S	-	Completed local binary pattern-magnitude-sign (phase)
CLBP-S	-	Completed local binary pattern-sign (phase)
DCT	-	Discrete cosine transform
DoG	-	Difference of Gaussians
EER	-	Equal error rate
ER	-	Error Rate
ES	-	Evaluation scenario
ES-1	-	Evaluation scenario-1
ES-2	-	Evaluation scenario-2
FACE	-	Face analysis for commercial entities
FAR	-	False acceptance rate
FARO	-	Face recognition against occlusion and expression
FFT	-	Fast Fourier transform
FRR	-	False rejection rate
FDA	-	Fisher discriminant analysis
GC	-	Gamma correction

GE	-	Gamma encoding
GFRPS	-	Geometrical face recognition after plastic surgery
GLCM	-	Grey-level co-occurrence matrix
GPROF	-	Gabor patch classifiers via rank-order list fusion
GRAB	-	Generalized region assigned binary
GT	-	Georgia tech face data set
HE	-	Histogram equalization
HSI	-	Hue saturation intensity
HOGOM	-	Histogram of Gabor ordinal measures
Homo	-	Homomorphic filtering
Homo-1	-	Homo in direct-mode
Homo-2	-	Homo in designed mode
HSV	-	Hue saturation value
IGM	-	Image gradient magnitude
IGO	-	Image gradient orientation
ISOMAP	-	Isometric mapping
IR	-	Identification rate
$\kappa-$PCA	-	Principal component analysis model
$\kappa-$LSDA	-	Locality sensitive discriminant analysis
$\kappa-$sLPP	-	supervised locality preserving projection
k-NN	-	number of nearest neighbour
LBP	-	Local binary pattern
LBPHF	-	Local binary pattern histogram Fourier features
LDA	-	Linear discriminant analysis
LE	-	Laplacian eigenmaps
LEGGM	-	Local edge gradient Gabor magnitude (pattern)
LEGGM-PCA plus LDA	-	LEGGM-PCA plus LDA new feature vector
LEGGM-LSDA-LGE	-	LEGGM-LSDA-linear graph embedding new feature vector
LEGGM-LSDA-OLGE	-	LEGGM-LSDA-orthogonal linear graph embedding new feature vector
LEGGM-sLPP-LGE	-	LEGGM-sLPP-LGE new feature vector
LEGGM-sLPP-OLGE-	-	LEGGM-sLPP-OLGE new feature vector
LFA	-	Linear Fisher analysis

LFW	-	Labelled faces in the wild
LFW158	-	Labelled faces in the wild of 158 subjects
LFW610	-	Labelled faces in the wild of 610 subjects
LGBP/		
LGBPHS	-	Local Gabor binary pattern/LGBP histogram sequence
LGE	-	Linear graph embedding
LGXP	-	Local Gabor XOR pattern
LHE	-	Local histogram equalization
LHM	-	Local histogram matching
LN	-	Local normalization technique
LNORM	-	Local normal distribution
LOG-DCT	-	Logarithm domain based discrete cosine transform
LPP	-	Locality preserving projection
LSDA	-	Locality sensitive discriminant analysis
LSSF	-	Large and small scale features
LT	-	Local transform
MAS	-	Modified anisotropic smoothing
MAS-1	-	MAS in direct-mode
MAS-2	-	MAS in designed mode
MSR	-	Multi-scale retinex
MVU	-	Maximum variance unfolding
MAS	-	Modified anisotropic smoothing
NN	-	Nearest neighbour
OLGE	-	Orthogonal linear graph embedding
PCA	-	Principal component analysis
PCA plus LDA	-	Principal component analysis plus linear discriminant analysis
PDE	-	Partial differential equation
PIFS	-	Partitioned iterated function system
Q-Q	-	Quantile-quantile
rgb/RGB	-	red, green, and blue (colour channels)
rgbGE	-	rgb gamma encoding
rgbGE-1	-	rgbGE without post-processing in direct-mode
rgbGE-2	-	rgbGE without post-processing in designed-mode
rgbGE-3	-	rgbGE with post-processing (logarithm domain) in designed

		mode
RHS	-	Right hand side
ROC	-	Receiver operating characteristics curve
SIFT	-	Scale invariant feature transform
SLBT	-	Shape local binary feature
sLPP	-	Supervised locality preserving projection
SQI	-	Self-quotient image
SSIM	-	Structural similarity image quality map
SSR	-	Single scale retinex
SURF	-	Speeded-up robust features
SVM	-	Support vector machine
TPLBP	-	Three-patch local binary pattern
V1-like	-	Human visual cortex inspired algorithm
VR	-	Verification rate
WN	-	Wavelet normalization
YIQ	-	Y-luminance, IQ-chrominance
YUV	-	Y-luminance, UV-two chrominance

LIST OF SYMBOLS

A	-	Sample face image
A_i	-	*i*th face image of a subject
A_j	-	*j*th neighbourhood face image of the *i*th face image data point
$A^{(t)}$	-	Sample face image from a training set
$\tilde{A}_i$	-	*i*th test image of a subject
$A_K^{(n)}$	-	*K*th sample image of *n*th subject
$A_{K,q}^{(n)}$	-	*K*th sample image of *n*th subject taken under a lighting condition *q*
ξ	-	Sample space of images η_{X_i,Y_j}
det(.)	-	Determinant
η_{X_i,Y_j}	-	Metric distance between the two images X_i,and Y_j,
E[.]	-	Expectation operator
μ_{X_i}	-	Mean of X_i
μ_{Y_j}	-	Mean of Y_i
σ_{X_i}	-	Standard deviation of X_i
σ_{Y_j}	-	Standard deviation of Y_i
H_s	-	Mathematical operators that represent specific plastic surgery procedure
V	-	linear map
Q_n	-	Shape preserving operator $n = i, j$
I_k	-	Intensity image formed at varying colour response
c	-	pixel spatial coordinate (x, y)

$I_k(c)$	-	Intensity colour image at the spatial coordinate c
S_k	-	Specular reflection of an image surface of varying colour responses.
$S^c(\lambda)$	-	Spectral reflectance on surface (image) at spatial coordinate c
$E(\lambda)$	-	Spectral power distribution of the light incident on an image at the time of capture
$C_k(\lambda)$	-	The spectral sensitivity of the image capturing sensor at the wavelength λ
$\{r, g, b\}$	-	Colour channels signifying red, blue and green
w_d	-	Diffuse term of the light incident on an image at the time of capture
w_s	-	Specular terms of the diffuse term of the light incident on an image at the time of capture.
$D_k(c)$	-	Diffuse component of the incoming light at image spatial coordinate c
G_k	-	Specular component of the incoming light at image spatial coordinate c
$\Gamma_k(c)$	-	Gamma normalized colour channel image at c
$I(c)$	-	Original image
$\hat{I}(c)$	-	Image normalized using rgbGE illumination normalization technique
$I'(c)$	-	Greyscale version of image normalized by rgbGE in logarithm domain
$I''(c)$	-	rgbGE normalized image with enhanced visual quality
κ	-	General representation of all the subspace models
$\beta_k(c)$	-	General representation of normalized RGB colour channels at the spatial coordinates c
I_{output}	-	Power-law output image
γ	-	Exponent of the power function for gamma correction
$G'(c)$	-	Gamma encoded intensity image

$\Psi_k(c)$	- Defined chromaticity of a surface for rgbGE normalization
$\delta_{\max}$	- Desired maximum intensity value for image contrast stretching
$\delta_{\min}$	- Desired minimum intensity value for image contrast stretching
$I'_{\max}$	- Maximum intensity value of rgbGE in logarithm domain normalized image
$I'_{\min}$	- Minimum intensity value of rgbGE in logarithm domain normalized image
$f(c)$	- Gaussian smoothed rgbGE in logarithm domain normalized image
$G(c;\sigma)$	- Gaussian smoothing filter
∇	- Gradient operator
∇^2	- Laplacian operator
Ξ	- Edge gradient image
$I'_{\varpi}(c)$	- Rescaled to [0, 1] rgbGE logarithm domain normalized image $I'_{\max}(c)$
$\chi(c)$	- Face image complete face structural information
$l_{\mu,v}$	- Gabor encoding wave vector at scale μ and orientation *v*
$l_{\max}$	- Maximum Gabor encoding wave vector
s_f	- Spacing factor between Gabor kernels in the frequency domain
ϕ_μ	- Maximum frequency of Gabor encoding
$\psi_{\mu,v}(c)$	- Family of Gabor kernels
$\mathrm{O}_{\mu,v}(c)$	- Response of spatial-frequency Gabor kernels to the facial structure defined face pattern at pixel point at five scales and eight orientations
$LEGGM_{\mu,v}(c)$	- Local edge gradient Gabor magnitude pattern at five scales and eight orientations
$LE\hat{G}GM_{\mu,v}(c)$	- Down-sampled $LEGGM_{\mu,v}(c)$ feature

$\xi_{\mu,v}(c)$	-	Real part of the Gabor kernels at five scales and eight orientations
$\wp_{\mu,v}(c)$	-	Imaginary part of the Gabor kernels at five scales and eight orientations
$\sigma_{LE\hat{G}GM}$	-	Variance of the $LE\hat{G}GM_{\mu,v}(c)$
$LE\hat{G}GM'_{u,v}(c)$	-	Standardized down-sampled $LE\hat{G}GM_{\mu,v}(c)$ feature at five scales and eight orientations
$LE\hat{G}GM'^{i}_{u,v}(c)$	-	All forty $LE\hat{G}GM'_{u,v}(c)$ features for describing *i*th sample image of a data set
$Z_{\mu,v}$	-	Concatenated $LE\hat{G}GM'_{u,v}(c)$ feature vector (forty features) for a sample image
$\Im\{\cdot\}$	-	Fast Fourier transform of a signal
$^{-}\Im\{\cdot\}$	-	Inverse fast Fourier transform of a signal
$\Re^{D}$	-	A high-dimensional (*D*) coordinates space where several (*D*) real variables can be treated as a single variable
$\Re^{d}$	-	A low-dimensional (*d*) coordinates space where several (*d*) real variables can be treated as a single variable
Δ	-	Eigenvalue of the scatter matrix
W	-	Eigenvector of the scatter matrix
W^{T}	-	Transpose of the matrix *W*.
$J(.)$	-	Cost-function of the transpose of the matrix for various subspace model
S_{ω}	-	Within-class scatter matrix for LDA
S_{b}	-	Between-class scatter matrix LDA
S_{ij}	-	Adjacency matrix that describes the neighbourhood, N of sample points A_i and A_j
S_{ij}^{p}	-	The unconnected sample points

$S_{w,ij}$	-	Adjacency matrix (cconnectedness) graph for sample points A_i and A_j of within a class
$S_{b,ij}$	-	Adjacency matrix (cconnectedness) graph for sample points A_i and A_j of between classes
M_i	-	Mean value of a class
M	-	Grand mean of the classes of a data set
$P(\Omega_i)$	-	Probability of the *i*th class
y_i	-	Low-dimensional feature vectors of the *i*th projection sample

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The human mind has an intuitive ability to effortlessly analyse, process and store information about a face for the purposes of identification and authentication. Studies in the fields of cognitive science, psychology and perception, point to the visual cortex as being a major contributor to the recognition ability of the human mind. The visual cortex interprets a face to being composed of series of shapes, which are processed piece-wisely on horizontal level [1]. To recognize an individual, all the parts of the face that are individually processed, are put together to make sense of a person's identity. Studies [1]-[2] have shown that there is no limit to the visual processing capability of human's, because even in situations where certain features are not sufficiently available, that is, they might be altered, camouflaged or disguised, a high degree of recognition can still be achieved. Several years of extensive research efforts have been geared towards developing machines with visual processing capabilities that can emulate the recognition capability of the human visual system. However, there is yet to be such very effective biometric system that can be deployed effectively as the human visual system.

Typically, machines use captured still or video images in the recognition process. Hence, depending on the application scenario several factors can come to play in the formation of the images, which will incidentally affect the recognition capability of the machine. Such factors can be regarded as scene-centric conditions and appearance-centric conditions. Examples of the scene-centric conditions are illumination, pose and scale. The appearance-centric conditions include the reversible conditions such as expression, disguise and make-up, and the irreversible conditions such as aging and plastic surgery.

Now let us look at how the above mentioned conditions come to play in the recognition capabilities of machines that are deployed in various application domains. These domains include transaction authorization, social welfare and security.

1. *Transaction Authorisation.* The unreliability and unpredictability of password protection have in recent time motivated the use of physical access control systems. Most enterprise computers incorporate the face biometric for identity authentication. For the identity of the system user to be determined, there should be existing facial information of the individual in the system. As such, the identity of the user that is carrying out the transaction will be matched to his/her enrolled image in the system in order to ascertain if the person is who he/she claims to be. This is a case of one-to-one verification. There are a number of potential applications in this domain, some of which are automated teller machines in banking, single-sign-on to multiple networked services, access to encrypted documents, issuing of national and international identification passports, voters registration, and so on. In these application scenarios it is possible to control the effect of scene-centric and reversible appearance-centric conditions on the captured image and subsequently the recognition system. However, it is obvious that the irreversible appearance-centric conditions cannot be controlled easily by any common standard.

2. *Social Welfare.* Face recognition is increasingly being integrated into social media applications and personal devices. The automatic easy tag feature of most applications such as Facebook, Google and iPhones use the face recognition in order to suggest to the user persons who they might likely want

to tag to an image. Other applications are the face identification smart logon feature of most personal devices such as the personal PC/laptop, mobile phones, and modern home authentication devices. Imagine you are requesting to login into your mobile device and you are unable to gain access to your device simply because the environment under which your image is captured is not properly illuminated. Other scene-centric conditions and the appearance-centric conditions can as well affect the recognition capability of the device. This is so since the mobile user may not be able to control the conditions in the various environment within which he finds himself.

3. *Security*. Under this domain there are several potential applications of face recognition some of which are law enforcement, forensic, surveillance, and border/airport control. The recognition scenario under this domain is the task of identifying a new enrolled face sample that is compared against an entire collection of previously enrolled face images of different persons'. The identification task is a one-to-many phenomenon that can be used to link or ensure that the enrolled sample is not laying claim to more than one identity. The process of registering a user face image in this domain can range from controlled to uncontrolled. This is to say that the formation of the face images of a person can be of different scenes, therefore it can be subject to scene-centric conditions. Also, as the face images of individuals are constantly updated, the appearance-centric conditions can be a factor in the image formation.

Having put forward a clear explanation of the meaning of scene-centric conditions and appearance-centric conditions together with how they can impact on face recognition performance under different application domains, the individual conditions that are categorized as the scene-centric and the appearance-centric conditions will in some places in this thesis where their individual meaning is not significant be collectively referred to as unconstrained conditions.

Recognition systems, particularly for the face, has seen many years of research progress in addressing scenarios where variance in natural scene images, and unconstrained conditions such as pose, scale, expressions, aging, and illumination [3]-[10] are involved in image formation. Likewise, numerous algorithms, techniques and methods have for over the years been developed and implemented in existing face recognition systems in order to be able to address these challenges. However, common to the application domains discussed earlier is the irreversible-appearance changing conditions, which cannot be controlled by adopting any physical measures in face image capture. Therefore, the need for face recognition systems that is robust against the irreversible facial appearance changing condition such as the plastic surgery is crucial for real-world face recognition application domains.

1.2 Problem Background

Facial appearance changes as a result of plastic surgery can manifest itself in the form of textural variations, and geometrical variations in the size and the relative position of the facial features. The challenges plastic surgery poses to face recognition systems can be classified as being twofold, *intra-person* dissimilarity and *inter-person* similarity. The facial appearances of an individual can become different after undergoing plastic surgery procedures (intra-person dissimilarity), but can also tend towards the appearance of a different individual (inter-person similarity). Before formulating the problem that this thesis addresses, let us first go through the contributions made so far by previous researchers on the recognition of faces after plastic surgery.

Singh *et al*. [11] pioneering work on the implication of plastic surgery in face recognition, where the global-based face representation approaches were found to not be hardy against plastic surgery problem, have laid the foundation for the emerging approaches/methods developed so far for addressing the challenges posed by plastic surgery on existing face recognition systems. In very recent time the recognition of faces that have undergone plastic surgery has seen the use of intensity/texture based facial descriptors [12]-[22]. While the approaches in these literatures show considerable improvement in recognition accuracy compared to the accuracies reported in [11] there is still a considerable amount of work to be done to mitigate the influences the irreversible appearance-centric conditions caused by plastic surgery have on face recognition systems. This is for the fact that the approaches presented in the literatures show to indicate a misconception of the effect plastic surgery procedures actually have on facial features. In Figure 1.1 some pre-surgery and post-surgery sample faces are shown, which in the later part of this section will be used to demonstrate how the effects of plastic surgery procedures have been misconstrued in the previous studies.

(a1) (a2)

(b1) (b2)

Figure 1.1 Pre-surgery (a1-b1) and post-surgery (a2-b2) images of different person faces after the surgery procedure that changes overall facial appearance

The progress so far in the literatures [12]-[22] is made with the use of intensity based or texture based descriptors such as Gabor and/or local binary pattern (LBP) for the recognition of surgically altered faces. Despite the use of texture/intensity based facial descriptors, the variations in face appearance caused by plastic surgery are addressed in these literatures from a perspective that includes the selection of facial component features that will eventually be described with any of the intensity or texture based facial descriptor algorithms. The feature selection processes are basically adopted differently by various researchers in order to minimize facial variations due to plastic surgery. The approaches adopted can be summarized here as facial region selection approaches [12]-[13], [14], [19], [21], [22], facial region/full face frontal selection approaches [15]-[16], [20] and granular selection approaches [17]-[18].

The region selection, facial region/full face frontal selection and granular-selection approaches are on the concept of locating several local facial parts, which are then described using a facial descriptor. Each processed region contributes to a classifier decision, which is further fused with that of other features for establishing an identity. For the region selection approach, the facial regions located can be adapted to the sizes of the facial regions [12]-[13], [14], [22] or located at fixed intervals across the image [19], [21]. These region selection approaches are demonstrated in Figure 1.2 and Figure 1.3, respectively.

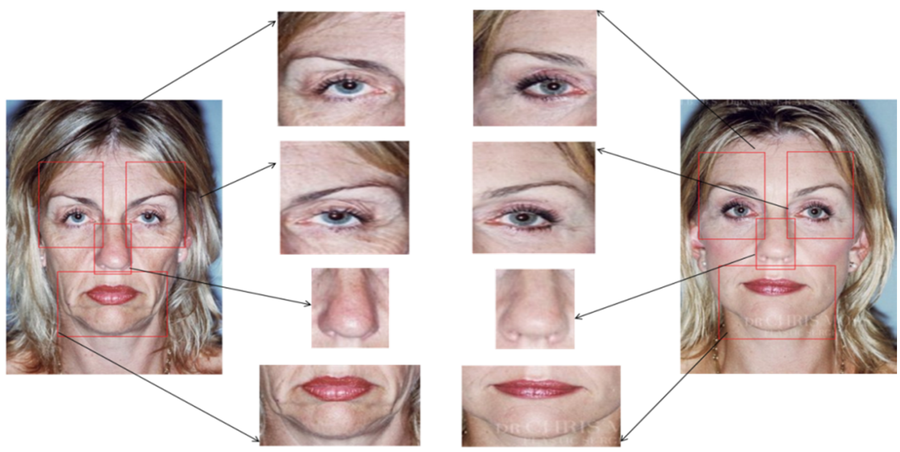
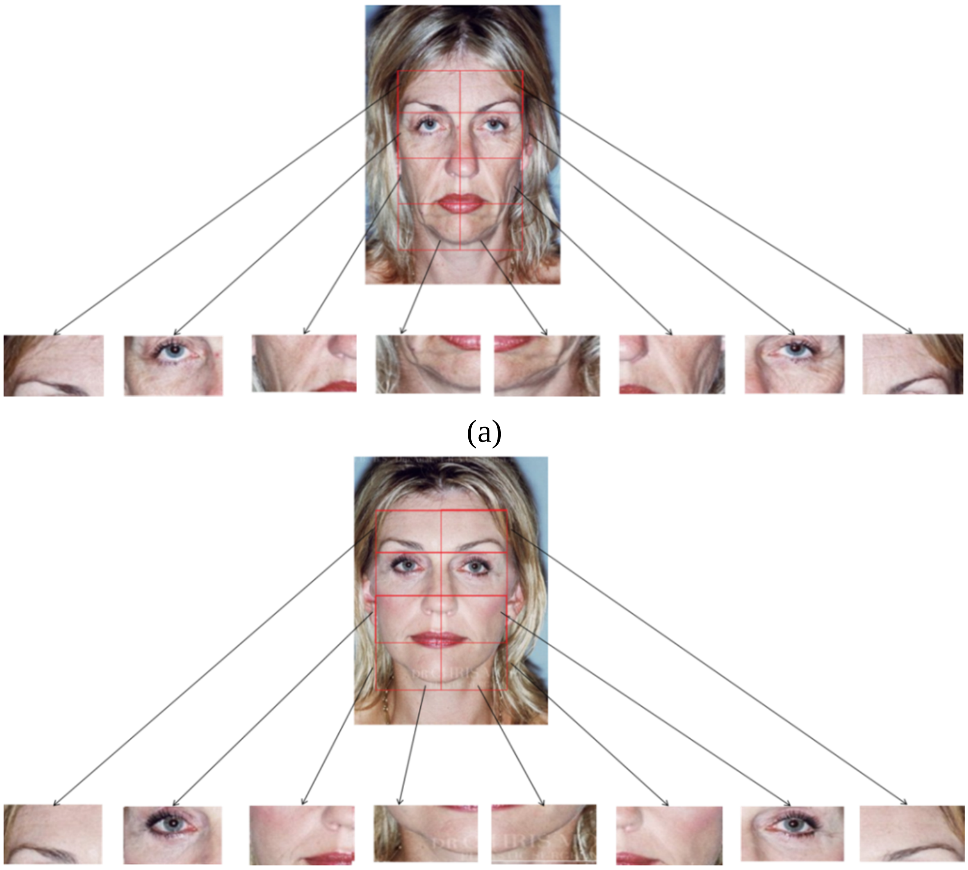


Figure 1.2 Example of region selection of facial component based approach for pre-surgery and post-surgery face images

Using facial regions that are adapted to the sizes of the facial features such as left-eye, right-eye, nose and mouth, Marsico *et al*. [12], [13] described each individual region from their intensity level. By employing the partitioned iterated function system (PIFS) each facial part region is processed using their intensity information, which are coded and reconstructed to form feature vectors for recognition. They also showed that other variation factors asides plastic surgery can also be recognition challenges. Aggarwal *et al*. [14] selected facial regions that include the eyes, nose, eyebrow and mouth, which are cropped and characterized using the principal component analysis (PCA). Feng *et al*. [22] likewise selected facial regions that are adapted to the sizes of the facial features. Their facial features included eye, nose, lip and skin, where each region containing these features is described using Gabor and grey- level co-occurrence matrix (GLCM). These facial descriptors are likely to enhance on the texture details of the face image.

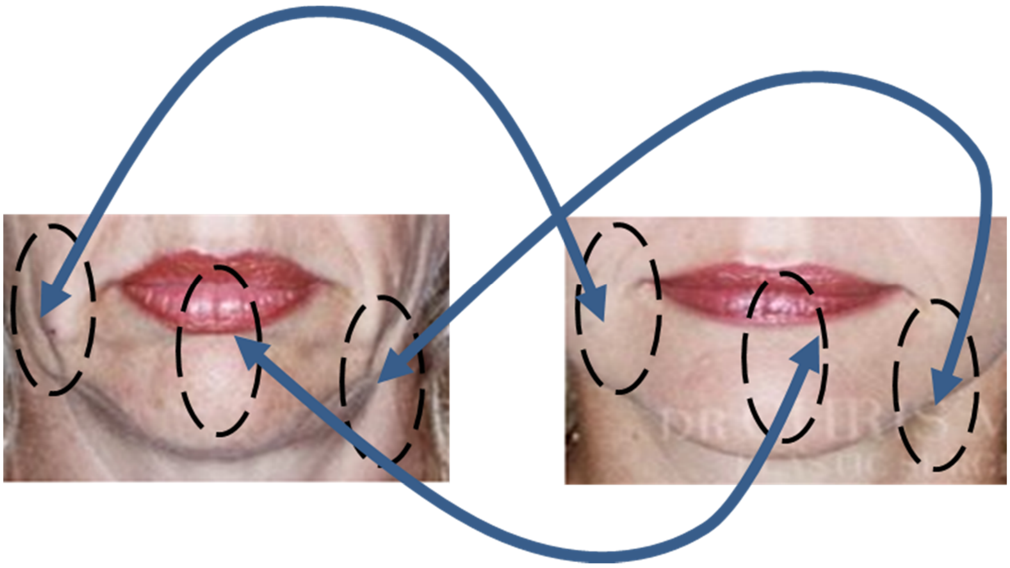


(a)

(b)

Figure 1.3 Example of region selection based on fixed sizes of facial component for pre-surgery and post-surgery face images

On locating at fixed intervals across the image, Liu *et al*. [19] divided the face into 2-by-8 patches, each containing certain features of interest. These regions (in the form of patches) were then individually described using Gabor. On the other hand, Sun *et al* [21] divided the face into 8-by-8 patches. Then each patch is independently described using the LBP and Gabor. To demonstrate the consequences of both types of region selection approach in handling facial variations between the face images of an individual, a point-match from a region in the pre-surgery face image is drawn to a corresponding point on the post-surgery image. This is shown in Figure 1.4.



(a) (b)

Figure 1.4 A close observation of the correspondence between points on a pre-surgery image (a) and post-surgery image (b)

The correspondence between points on the pre-surgery image and post-surgery image show that any matching algorithm collected at those points is likely to output mismatch. The post-surgery image (right) show great transformation in comparison to the pre-surgery image (left). A transformation which included geometrical (size and the relative position of the facial features) and textural transformations can be observed. Take a closer look at the jaw, mouth, and skin, a striking impression is that the pre-surgery image belongs to an older person while the post-surgery image is for a younger female individual. The observation made with this example illustration in Figure 1.4 is likewise suffered by approaches that also select facial region/full-frontal features [15]-[16], [20] and granular region selection [17]-[18].

Lakshmiprabha *et al.* [15] combined the periocular region, which comprises of the left-eye and right-eye, with the full-frontal face. Then, the periocular region and the full frontal face are described using Gabor and LBP. In an extended work [16] they used a shape local binary texture (SLBT) descriptor to independently describe the selected periocular region and the full frontal face image. Jillela *et al.* [20] likewise selected the full frontal face image and the periocular region. But the periocular region is obtained from the three colour channels of the face image. These regions are described using the scale-invariant feature transform (SIFT) and LBP descriptors.

The granular selection approach utilized by Bhatt *et al.* [17]-[18] divides the face into non-overlapping parts at different levels of information extraction. An example of the face image divided using a granular-based facial region selection approach is shown in Figure 1.5. Each facial region granularly selected is described independently using the extended uniform circular local binary patterns (EUCLBP) and scale invariant feature transform (SIFT).

In the respective facial image components granular based selection [17]-[18] that is demonstrated in Figure 1.5, it is obvious that variation problem still exist. The facial region/full-frontal feature [15]-[16], [20] is not demonstrated because it is a combination of full frontal image and the divided parts. Having ascertained what is implied by misconception of the effect of plastic surgery on facial features in existing works, it can be categorically stated that the challenges plastic surgery procedures poses do not lie within the cut section of the images. This is for the fact that textural and geometrical differences still exist within the region selected as demonstrated on a closer look in Figure 1.4. Thus, the effects of plastic surgery on facial features have to be well defined in order to design descriptor algorithms that can effectively address facial appearance variation problem caused by plastic surgery.

(a1) (a2)

(b1) (b2)

Figure 1.5 Example pre-surgery and post-surgery face images. The granular images (a1, a2) are horizontal granules, and (b1, b2) vertical granules

1.3 Problem Statement

A close look at the methods used by previous contributors [12]-[22] point towards a common approach where the intensity/texture based descriptors is employed in the recognition process. However, an important factor in the design of descriptors for surgically altered face images is the fundamentals of plastic surgery procedures. Medically, a number of the plastic surgery procedures, namely; Blepharoplasty, Dermabrasion, skin peeling, brow lift, cheek implant, fore-head lift, Liposhaving, and Rhytidectomy directly impact on the facial soft tissue (skin-texture). With changes in skin-texture as the major variations on face images of a person that have undergone plastic surgery, the intensity/texture-based descriptors fall short since they enhance the texture differences of the face images of an individual who have undergone plastic surgery. Hence, face recognition systems that utilize intensity/texture information might not be hardy against faces altered by plastic surgery procedures.

Comment 1: *A plausible solution to the aforementioned problem is to exploit "the face information that is not likely to be affected by plastic surgery". This frame of reference serves as a platform for constructing robust and efficient feature descriptors that are intensity/texture insensitive for the recognition of surgically altered face images.*

This thesis addresses the concern of finding and presenting face information that is insensitive to the effect plastic surgery procedures poses on facial features, and employs such information in designing a new facial descriptor.

Also, since face images are formed by multiple interacting factors related to the conditions within which the images where captured, solving the irreversible appearance-centric problem such as plastic surgery without considering for instance, the illumination problem that constitutes a major challenge to facial descriptors, might hinder effective representation of facial features. Numerous illumination pre-processing techniques have been presented over the years to mitigate the influence of lighting variation in face images. However, a number of the pre-processing techniques diminish the intrinsic shape characteristics in the face image when further processed, while a number of the methods cause the increase in the difference margin in the face images of an individual due to over exaggeration of facial information.

Comment 2: *To address this problem the ability to take into cognizance the resultant output of illumination pre-processing is required in the design of robust face recognition systems so as not to alter the distinctive and yet discriminative facial features.*

This thesis also addresses the issue of illumination challenge posed to feature extraction process in the recognition system.

In order to proffer solutions to the challenges that this thesis addresses, the following research questions are presented in such a manner that brings to light the objectives of this thesis;

i. What constitutes information minimally influenced by plastic surgery procedures?
ii. How can such facial information be determined and exploited for recognizing surgically altered face images?
iii. What is the technique for addressing non-uniform illumination problem that do not diminish the facial information determined from (ii) and does not introduce separability between face images of a subject?
iv. What is the approach for developing a descriptor that encodes the intensity/texture insensitive facial information without compromising the ability to discriminate between different face classes?
v. Does the transformation of feature vectors, which belong to the class of heavy-tailed distribution, from high-dimensional space to low-dimensional space influence on their discriminative capabilities and how does it vary across different subspace transformation models?

1.4 Research Goal

To develop new facial shape and appearance descriptor that exploits edge information as the facial information minimally influenced by plastic surgery procedures. This is to be able to recognize faces in uncontrolled face recognition environment, where facial variation factors such as plastic surgery and illumination amongst other facial variation factors exist. To this end, face representation and illumination normalization modules are unified in a framework for face recognition.

1.5 Research Objectives

i. To define the facial information minimally influenced by plastic surgery procedures, and design a framework that integrates coherently new modules for recognizing plastic surgery altered faces in real-world face recognition system.
ii. To develop and propose new illumination normalization technique that addresses non-uniform illumination problem.
iii. To develop and propose new facial shape and appearance descriptor namely, local edge gradient Gabor magnitude (LEGGM) that is intensity/texture insensitive for intrinsic facial structural pattern characterization. And design a method of subspace learning from LEGGM for face representation.
iv. To investigate and compare the capabilities of various linear subspace methods such as principal component analysis plus linear discriminant analysis (PCA plus LDA), supervised locality preserving projection (sLPP) and locality sensitive discriminant analysis (LSDA) in capturing the discriminative information of the LEGGM pattern in the reduced space.

1.6 Scope of the Thesis

While considerable interest in face recognition has been geared towards addressing facial expression, pose, and illumination variation problems in face recognition systems, the non-reversible appearance variation problem caused by plastic surgery have barely been accounted for in such systems. Therefore, the thesis aim is to effectively characterize the distinctive facial information of a person by exploiting facial information that is minimally affected by plastic surgery. Based on the theoretical and practical findings etched into mathematical arguments, the edge information is defined to present such information. However, the edge information might be restricted to a great extent by the presence of the shear property when it is predominant as part of the affine transformations mimicking plastic surgery effect.

The proposed and developed illumination normalization technique in this thesis addresses the influence of uneven illumination and specular highlight due to illumination direction, but no consideration for the ambient component of the light source is made in this thesis.

In order to emphasize on the effectiveness of the proposed face descriptor algorithm to uniquely characterize the intrinsic and yet discriminative features of different person's face images, the non-parametric nearest neighbour classifier is adopted for classification task. For the most part, it can be argued that the nearest neighbour (NN) is best suited as a baseline algorithm because it does not depend on the information about the data distribution and so its efficiency is solely dependent on how well the face representation step is able to discriminate a person from another [23]. A certain parameter k can as well be specified for the NN, such that comparison can only be within small clusters (k-NN) of sample data. By specifying k, the comparison within small clusters of sample data can improve the decision of the NN classifier. Furthermore, on the usage of parametric classifiers, which uses the underlying distribution of the data, better classifier performance is envisaged. However, classifier performance is not within the scope of this thesis.

The validity of the developed methods, algorithms and the general framework presented in this thesis are tested on computer simulation in which face image examples that match real life face recognition scenarios are used. The experiment is firstly confined primarily to the recognition of faces across different challenging plastic surgery procedures. The term plastic surgery is used in this thesis to refer to the aesthetic (beauty) related plastic surgery. The thesis does not consider cases where there are overall or complete transformations, which are medically referred to as the reconstructive plastic surgery. However, there is no such face recognition system that exists only of persons who have undergone plastic surgery. In the real-world face recognition systems, it is common for faces to be captured from different pose (viewing angle), or of having different expressions. This means that in capturing of faces in face recognition scenarios, the system is very much unaware of the presence of persons who have undergone facial plastic surgery. Since this work is on face recognition and not on matching persons who have undergone plastic surgery with their pre-surgery images, it is therefore imperative to depict the scenario where all the facial variation factors can individually exists or come into play during the image formation process. The faces into consideration are real faces of persons typified in existing data sets used in the literature. These face images were captured as still images, hence, there is no effect of motion in the images.

1.7 Significance of the Research

In this section, the theoretical as well as the practical significance of this study are discussed.

The previous contributors in this field of study focus mainly on selecting facial component features [12]-[22] as a means of mitigating the effects of plastic surgery. Added to the selection of the facial component features is the use of intensity/texture based descriptors to describe each individual facial component part. These descriptors might be hardy against texture variations in the recognition of faces that have undergone plastic surgery. Therefore, to fill this gap, a theoretical basis from mathematical standpoint that points towards plastic surgery-insensitive features is derived. However, this discovery is medically inspired. The theoretical discovery can bring about a new perspective in the design of algorithms for describing faces altered by surgery. Also, this discovery can benefit a number of research disciplines as discussed as follows:

- Image understanding: it can be applied in defining the medical effects of plastic surgery and relate it to picture elements of digital images.
- Computational modelling: it can be beneficial in adding plastic surgery-related transformations to a captured image to generate series of images showing several cases of plastic surgery.

- Recognition: it can serve as a means of defining insensitive to facial distortion features for other cases of appearance distortions such as aging.

Drawing on the derived theory, this thesis develops a descriptor for characterizing the insensitive to plastic surgery effect features in faces that have been subjected to plastic surgery transformation.

Due to the constantly unfolding global crisis that can threaten the life of large amount of persons at a split of seconds, the security of citizens of every country has never been more heightened. The ability of terrorist to conceal identity using plastic surgery in order to bypass security and cause havoc to life and property cannot be ruled out. Therefore, to be able to explore a more practical scenario, unlike the previous studies where emphasis are only on the recognition of surgery images, this thesis includes other variation factors in order to mimic typical application domains. In this regards, this thesis designs a framework that integrates feature representation and illumination compensation for face recognition. Consequently, an illumination normalization technique that fits to the designed framework that circumvents the influences that poorly illuminated images will have in effectively describing a face image by its intrinsic structural patterns is develop.

More also, since plastic surgery is becoming a house hold name, it is not only a security related problem. A person of genuine identity can be denied access to a property or falsely accused of being a suspect to a crime. In essence, this study is relevant in a broader sense to real-world face recognition systems in airports, automated banking, surveillance, law enforcement, and office access systems. This is to effectively recognize faces despite being altered by surgery procedures.

1.8 Thesis Structure

The organization of this thesis is given in this section. The rest of the chapters in this thesis begin with brief section that highlights the aims of each chapter, and ends with a section that summarizes the ideas presented in the chapters. Each chapter is developed to be self-contained, but there exists cohesion among the chapters in order to ensure the free flow of presentation and understanding of the thesis content. It should also be borne in mind that in the course of this thesis, mathematical notations and definitions are introduced at various points where it is deem such action will give better cohesion and understanding to this work.

In Chapter 2, an in-depth review of literatures that gradually goes from face recognition in general to previous work on face recognition for plastic surgery images is presented. Since face recognition on the topic of plastic surgery is still an emerging research area with very little literatures, the review covers existing illumination compensation methods and face representation methods from the general face recognition point-of-view. Subsequently, a detailed review that brings to light the various approaches that has so far been used in the recognition of surgically altered face images is presented. For each of the review sections, a discussion is presented in such a way that points the reader to the limitations of existing methods and the need for the proposed methods. Furthermore, from a medical stand point, the various plastic surgery procedures and a brief discussions on each of them is presented in such a way that brings to understanding *what is modified* on account of the surgery procedure

In Chapter 3, the thesis methodology is presented where a unified framework that incorporates two modules of newly proposed and developed methods: illumination pre-processing and face representation for the recognition of surgically altered face images is proposed and designed. In the bid to achieve efficiency for the framework, an operator based model that brings to light the technical difficulty in recognising face images that have undergone plastic surgery is used to model and analyse the various types of plastic surgery procedural effects. The outcome of the analysis forms the motivation and foundation for the development of the new approaches presented in Chapter 4 and 5.

In Chapter 4, the illumination normalization technique which is a new approach for addressing the influence of illumination for effective detection of features is proposed and presented. The problem of uneven illumination and specularities are addressed in this chapter without any estimation of distribution of the illumination on each illuminated object.

In Chapter 5, a new facial shape and appearance descriptor namely, local edge gradient Gabor magnitude (LEGGM) pattern is presented. The proposed descriptor is a variant of Gabor descriptor, but encodes facial shape and appearance. However, unlike the conventional Gabor descriptor, which is limited by its encoding in the grey-level domain, the proposed LEGGM is able to overcome this limitation and provide effective facial pattern characterization. As a variant of Gabor descriptor, the LEGGM exist in high-dimensional space, which effects on classifier performance. To overcome this problem and for increased classifier performance, various linear subspace learning models such as principal component analysis plus linear discriminant analysis (PCA plus LDA), supervised locality preserving projection (sLPP) and locality sensitive discriminant analysis (LSDA) are employed for learning LEGGM data.

In Chapter 6, the implementation and evaluation of the performance of the face recognition framework from chapter 3, which integrates the newly proposed and designed modules from the preceding chapters 4 and 5, is presented with supporting discussions of the results obtained. The comparative experiments conducted in this chapter are confined primarily to face recognition across different challenging plastic surgery procedures using publicly available plastic surgery data set [11]. However, extended experiments on other publicly available data sets such as Georgia tech face (GT) data set [24] and labelled faces in the wild (LFW) data set [25] are also presented.

Finally, in Chapter 7, the thesis contributions and key findings are summarized and the directions for which the current work can be extended are presented.

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