Engineering Letters, 24:1, EL_24_1_08

Enhanced Face Recognition Using Discrete Cosine Transform

Zahraddeen Sufyanu, *Member, IAENG,* Fatma S. Mohamad, Abdulganiyu A. Yusuf, and Mustafa B. Mamat

Abstract— **In signal processing, important information is mainly required and processed. Discrete Cosine Transform (DCT) provides a great compaction capabilities. One of the challenges of face recognition using DCT and any other algorithm is poor illumination of the acquired images. In this paper, anisotropic diffusion illumination normalization technique (AS) and DCT were used for recognition. The AS was employed as a preprocessor before applying the DCT as a feature extractor. The new face recognition technique named 'ASDCT' was assessed on ORL, Yale, and extended Yale-B databases. Performance metrics were generated and evaluated by verification and identification rates using nearest neighbor classifier (NNC). Appearance based techniques were also exploited for comparison with the new method, and results show that 'ASDCT' outperformed many renowned algorithms in the literature. It has produced up to 93.4% verification rate at False Acceptance Rate (FAR) =0.1% on ORL database. Therefore, its performance using both controlled and uncontrolled databases is considerably good. It is believed that, the new framework enhances the DCT feature extraction for more efficient face recognition.**

Index Terms— **Decorrelation, discrete cosine transform, face recognition, illumination, nearest neighbor classifier**

I. Introduction

BIOMETRICS is essentially a pattern recognition system [1], which uses physiological and behavioral characteristics of a person. Physiological characteristics may be fingerprint, eye (iris-pattern, retina-scan), face, hand geometry or palm-print [2]. Whereas behavioral characteristics may be voice, signature, or other keystrokes dynamics. Such characteristics are called 'traits', they are unique and varied across persons. They are found to be general and natural, user-friendly and nonintrusive. However, the extensive variation of those features over one another makes them attractive to the researchers. Besides, they are personal; one cannot forget or lose them except in an accident. The history of face recognition technology started since 1960s with the development of a semi-automated system [9]. Thereafter, massive advancement has been made in this field. Face recognition system was not the first biometric technology to be introduced, but has become one of the most attending biometric attributes. It is also the most important biometric authentication technology. The advent of face recognition solves more advanced problems of authentication in highly secured systems. Thus, automatic face recognition has received much attention within the computer vision community over the past three decades [3]. And it spans numerous fields and disciplines [4].

Although there are other reliable methods of biometric identification such as fingerprint and iris scans, but face recognition is proven more effective. The advantages of facial identification lie on cost and user's convenience. Six biometric attributes were considered by Hietmeyer in [5], where facial features scored highest in terms of compatibility in a Machine Readable Travel Documents (MRTD) system. Therefore, commercial application of face technology has received large interest, especially in credit card companies to reduce fraudulent usage of the credit cards. Hence, encoding each card with facial features for identification would highly minimize bank card frauds.

In addition, human's face recognition is a matured field which resulted to a higher demand for accurate and fast user authentication. Although this field is considered matured for automatic solutions, there are always problems right from image acquisition to classification. And researchers considered these problems very challenging to solve. Meanwhile, to attain a successful recognition performance, most current recognition approaches require some control over the imaging conditions, because many real-world applications require operational flexibility [6]. The proper recognition under pose variations, illuminations, occlusions and expressions is the optimal target of any algorithm and solution against any unauthorised action. Many research focus on establishing secured identification systems. A face system is separated into three main stages namely; preprocessing, feature extraction, classification and recognition [7].

Furthermore, several improvements on recognition systems were made, yet there was no benchmark strategy for recognition systems [8]. Researches on face recognition mostly fall into two main categories, namely: holistic and feature-based [9]. Holistic based is the global approach to face recognition which relies on encoding the entire facial

Manuscript received February 28, 2015; revised October 28, 2015. This work was financially supported by Kano State Scholarship Board, batch 502, under the Kano State Government Nigeria, and academically supported by Universiti Sultan Zainal Abidin (UniSZA), Kuala Terengganu, Terengganu, Malaysia.

Z. Sufyanu was an Electrical Engineer in Dangote Cement Plant Obajana, Lokoja, Kogi State, Nigeria. He is at present with Faculty of Informatics and Computing, Universiti Sultan Zainal Abidin Malaysia (email: sufyanzzz@yahoo.com).

F. S. Mohamad is a Deputy Dean of Graduate School, Universiti Sultan Zainal Abidin Malaysia (phone: +601-9906-6074; e-mail: fatma@unisza.edu.my).

A. A. Yusuf is with the Faculty of Informatics and Computing, Universiti Sultan Zainal Abidin, Malaysia, on leave from National Biotechnology Development Agency (NABDA), Abuja, Nigeria (e-mail: abdulg720@gmail.com).

M. B. Mamat is currently a Professor at Universiti Sultan Zainal Abidin Malaysia (e-mail: must@unisza.edu.my).

image, whereas feature-based approach to face recognition relies on detection and characterization of individual facial features [10]. Ahmed and Rao in [11] initially introduced a Discrete Cosine Transform (DCT) in the early seventies. Since then, the DCT has become very popular and several versions of it have been proposed [12]. Few numbers of DCT coefficients were used to reduce redundancy and recover the original image from the selected coefficients. The coefficients with largest magnitude (i.e. low frequency) are mainly located in the upper left corner of the DCT matrix. This section is related to illumination variation and smooth regions such as forehead and cheeks of the face image. But the coefficients with lowest magnitude (i.e. high frequency) are situated in the bottom right corner of the DCT matrix. This section is related to noise and detailed information about edges in the image. And the coefficients with mid magnitude (i.e. medium frequency) are found in the middle region. This represents the general structure of the face in the image.

The three sections appear in DCT matrix as represented in Fig. 1. Therefore, amplitude distribution of the DCT coefficients for 8 x 8 blocks measured for a test image is depicted in Fig. 2. This shows the variations of DCT coefficients of an image.

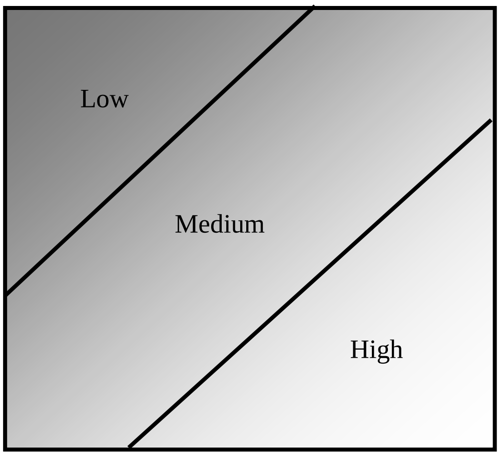

Fig. 1. Three regions of DCT coefficient matrix

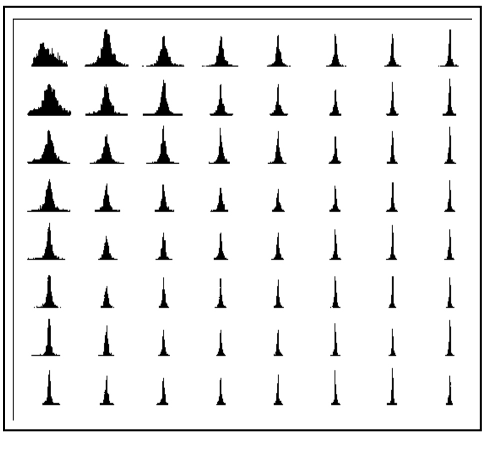

Fig. 2. Histogram of DCT coefficients of a 'bridge' image

Performance of DCT is largely affected by altering the coefficients magnitude at the top left corner of the matrix. Thus, illumination normalization is applied prior to feature extraction to compensate these coefficient variances and set the blocks to more equalized intensity.

The DCT is an efficient technique for image coding, and has been successfully used for face recognition in [17], [18], [19], and [20]. Since the most high frequency coefficients of DCT are almost zero, such coefficients can be ignored without degrading the image quality. In addition, different coefficients can be quantized based on visual sensitivity with different accuracy.

Many researchers have tried to truncate the number of DCT coefficients. The research conducted by Bilal in [13] suggested saving the first five values from every DCT block to restore the image without significant errors. In an attempt to increase the performance of a face system with variation in facial geometry and illumination [14], 2D-DCT method was proposed for feature extraction. The DCT coefficients of face images were truncated in an exponential way, and then a Principal Component Analysis (PCA) was applied for dimensionality reduction. Only a few non-zero eigenvalues related eigenvectors were considered and verified using K-nearest distance measurement. Sanderson and Paliwal in [15] suggested a feature extraction technique called DCT-mod2. The DCT was first applied to sub regions of facial images to extract a number of DCT coefficients. Then any potential illumination change was compensated through replacing the coefficients most affected by illumination with their corresponding horizontal and vertical delta coefficients. This derived a face representation insensitive to external lighting changes. And various databases with illumination-induced variability were used to assess this method. The DCT-mod2 technique resulted in promising results on all databases considered. Recently, an advanced DCT through histograms was developed in [16], which improves the compression ability of the DCT.

The feature extraction under uncontrolled illumination conditions is a major concern and a great challenge for recognition in real world applications [8]. Illumination normalization (IN) is a preprocessing technique that compensates for different lighting conditions. However, regardless of a number of IN techniques in the literature, the choice of a technique that improves a particular algorithm no matter how little is very essential. Researchers were attempted to improve face recognition under uncontrolled lighting conditions, through the choice of various techniques for illumination compensation and preprocessing enhancement.

Before carrying out the feature extraction using variety of methods, different illumination techniques were used to normalize the illuminations under such constraints. This is to restore a face image back to its normal lighting condition [21], [22], [23], [24], [25], [26]. To the best of the authors' knowledge, none has previously focussed on face recognition using DCT by finding the most suitable preprocessor. Our main motivation behind emphasizing on the DCT is because; most practical transform coding systems are based on DCT, since it provides a good compromise between information packing ability and computational complexity [27].

The present study focuses on preprocessing and feature extraction to tackle illumination challenges and improve decorrelation power of DCT for more efficient face recognition. The research also considers recognition under various expressions.

Section II of the paper describes evaluation process of the preprocessing techniques, and section III analyzes the experimental setups. In section IV, results of the proposed methodology and other techniques are assessed. Section V exposes the effects of truncation in DCT domain, whereas in section VI concluding remarks and future study are outlined.

II. Preprocessing

A. Introduction

Normalizing an illumination from images before extracting their features using DCT, compensates the coefficient variances and sets the blocks to more equalized intensity. It is very important to categorize preprocessors according to their suitability on a particular algorithm. For this reason, an empirical study was conducted to choose the best IN technique specifically for DCT performance improvement. The established 22 IN techniques were tested using extended Yale-B database. The IN technique that will be subjected to compression equivalent to that of DCT and be reconstructed with least error is the goal of this evaluation.

B. Illumination Normalization (IN) Techniques

The well-known 22 IN techniques proposed in the literature are:

(1) single scale retinex (SSR),
(2) multi scale retinex (MSR),
(3) adaptive single scale retinex (ASR),
(4) homomorphic filtering (HOMO),
(5) single scale self quotient image (SSQ),
(6) multi scale self quotient image (MSQ),
(7) discrete cosine transform (DCT),
(8) retina modeling (RET),
(9) wavelet (WA),
(10) wavelet denoising (WD),
(11) isotropic diffusion (IS),
(12) anisotropic diffusion (AS),
(13) steering filter (SF),
(14) non-local means (NLM),
(15) adaptive non-local means (ANL),
(16) modified anisotropic diffusion (MAS),
(17) gradientfaces (GRF),
(18) single scale weberfaces (WEB),
(19) multiscale weberfaces (MSW),
(20) large and small scale features (LSSF),
(21) tan and triggs (TT), and
(22) difference of gaussian filtering (DOG).

Fig. 3 describes results of the different IN techniques applied on few images from extended Yale-B database.

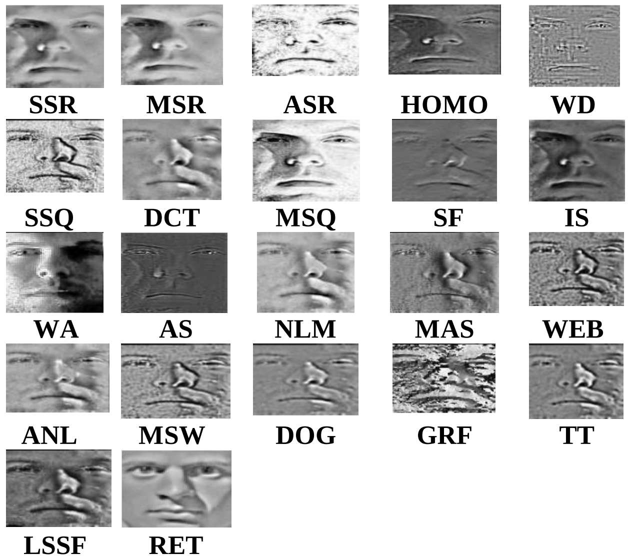

Fig. 3. Results showing effect of the 22 IN techniques applied on extended Yale-B images

C. Evaluation of the IN Techniques

Several images from the extended Yale-B were automatically normalized one after the other by implementing each of the IN technique source codes. These images were compressed using principle of JPEG compression. The compression was carried out to test which illumination technique would compensate lighting effect without significantly degrading the quality of the images. Accordingly, the following steps were computed:

1) Input image
2) Set compression quality between 1 to 100
3) Apply compression using DCT
4) Reconstruct the images
4) Plot both the original image and the DCT compressed image
5) Save the images to file
6) Perform error calculations

For compression in this study, 60% of the coefficients were extracted. The compressed features were obtained by run-length encoding, and then reconstructed using inverse DCT. The reconstructed features were retrieved to determine the quality variation between each original image of IN technique and its reconstructed image. After that, error measurements were computed using these metrics: Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). In addition, average results of the images were calculated.

The results reported AS technique as the highest PSNR and the lowest MAE as indicated in Table I. This signifies its best illumination compensation ability. For this reason, the AS is proven as the best and most suitable technique for recognition using the DCT. Hence, the filtered images of AS demonstrated high similarity with their original images despite lossy compression. The AS was introduced to the field of face recognition by Gross and Brajovic in [28]. The technique estimates the luminance function using anisotropic smoothing. Therefore, the design of DCT with the AS will compensate lighting effects, noise, and preserve object boundary effectively.

TABLE I
COMPARISONS OF THE 22 ILLUMINATION NORMALIZATION TECHNIQUES, ONLY PSNR HAS UNIT OF dB

S/N	TECHNIQUE	PSNR	MSE	RMSE	MAE
1	**WEB**	53.885	0.804	0.897	1.483
2	**WD**	53.003	0.985	0.992	1.687
3	**WA**	53.650	0.849	0.921	1.368
4	**TT**	53.912	0.799	0.894	1.498
5	**SSR**	52.629	1.073	1.036	1.752
6	**SSQ**	51.114	1.521	1.233	2.052
7	**SF**	55.830	0.514	0.717	1.232
8	**RET**	52.425	1.125	1.061	1.800
9	**NLM**	51.760	1.311	1.145	1.946
10	**MSW**	53.060	0.972	0.986	1.650
11	**MSR**	51.990	1.243	1.115	1.876
12	**MSQ**	50.171	1.890	1.375	2.297
13	**MAS**	54.348	0.722	0.850	1.432
14	**LSSF**	54.937	0.631	0.794	1.297
15	**IS**	56.574	0.433	0.658	1.089
16	**HOMO**	56.181	0.474	0.688	1.150
17	**GRF**	52.591	1.082	1.040	1.629
18	**DOG**	53.460	0.886	0.941	1.595
19	**DCT**	52.716	1.052	1.026	1.744
20	**ASR**	49.419	2.248	1.499	2.543
21	**AS**	**58.199**	**0.298**	**0.546**	**0.931**
22	**ANL**	52.418	1.127	1.061	1.802

III. EXPERIMENTAL SETUP

This section describes the experimental setup for the study. The DCT was applied on the preprocessed images implemented using the AS technique. The performance of the proposed DCT and other techniques were evaluated on Olivetti Research Laboratory (ORL), Yale and extended Yale-B face databases. ORL and Yale are well-known and most commonly used databases for face recognition using the DCT in the literature. These databases provide a successful accuracy. The ORL contains 10 different images of 40 distinct subjects. Each subject involves images of the following two orientations: slightly lighting variations and facial expressions which comprise open or closed eyes, smiling or non-smiling and with or without glasses. All the images were taken against a dark homogeneous background and the subjects are in up-right, frontal position with tolerance for some side movement. The Yale face database contains 165 face images of 15 individuals. There are 11 images per subject; each subject involves images of the following facial expression or configuration: center-light, glasses/no glasses, happy, left-light, normal, right-light, sad, sleepy, surprised, and wink. The extended Yale-B was also chosen to evaluate the recognition despite illumination variations. This database contains gray scale frontal images of 38 subjects under 9 poses and 64 illumination conditions. The entire test set images used in the experiment were manually aligned, cropped, and then resized to 168 x 192. [29]. Samples of images in these databases are shown in Fig. 4. For the ORL database all images were used for the study, whereas in Yale and extended Yale-B face databases 10 images from each subject were used, leading to a total of 150 images and 280 images respectively. In addition, the selection was done randomly for the extended Yale-B.

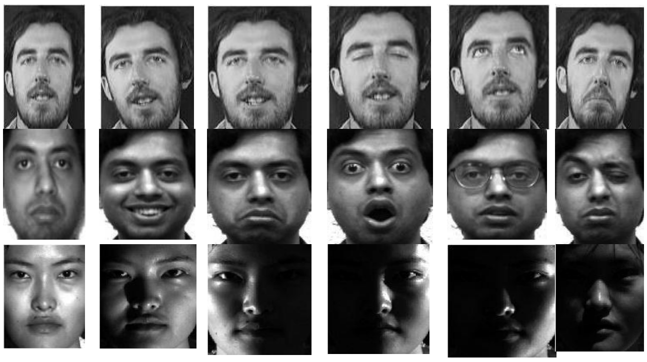

Fig. 4. Sample of images extracted from ORL (first row), Yale (second row) and extended Yale-B (third row) databases

After the necessary preprocessing to make the images suitable for efficient feature extraction, an AS was applied to remove the illumination variations. In all the experiments, training was performed using three images from each user in the databases and seven others were used for subsequent testing. Sample images of one subject used for training and testing is shown in Fig. 5.

Fig. 5. Example of training images (first row) and testing images (second row) from a subject in ORL database

Suppose k is the number of training images, and l is the total number of images belonging to a particular subject in each database. The training process begins by computing a mean image from the k training images. Therefore, the mean image $A_i(x,y)$can be described in (1).

$$A_i(x,y) = \frac{1}{k}\sum_{j=1}^{k} I_j^{(i)}(x,y) \qquad (1)$$

where $I_j^{(i)}(x,y)$ represents a sample image j of subject i from the number of subjects considered.

Then the DCT of the mean image $A_i(x,y)$ is computed. The definition of the DCT for an input image $f(x,y)$ and output image $F(u,v)$ of size $M \times N$ can be written in (2). However, 19 coefficients were retained from each DCT matrix and thereby used for recognition.

$$F(u,v) = C_{(u)}C_{(v)}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} f(x,y)\ \cos\left[\frac{(2x+1)u\pi}{2M}\right] . \cos\left[\frac{(2y+1)v\pi}{2N}\right], \begin{matrix} 0 \le u \le M-1 \\ 0 \le v \le N-1 \end{matrix} \qquad (2)$$

where

$$C_{(u)} = \begin{cases} \frac{1}{\sqrt{M}}, & u = 0 \\ \sqrt{\frac{2}{M}}, & 1 \le u \le M-1 \end{cases} \quad \text{, and}$$

$$C_{(u)} = \begin{cases} \frac{1}{\sqrt{N}}, & v = 0 \\ \sqrt{\frac{2}{N}}, & 1 \le v \le N-1 \end{cases}$$

The following outlines the algorithm implementation procedures of the proposed DCT using JPEG coding of a still image:

1. Load the images of same sizes from a database
2. Implement a 2-dimensional DCT
3. Initialize the matrix to zeros
4. Perform a block DCT for a given image on 8 x 8 blocks
5. Apply JPEG default normalization matrix (QM) to normalize the DCT transformed coefficients
6. Scale the DCT transformed image by maximum coefficient value in the transformed image (i.e. a scale factor, QP)
7. Perform an integer conversion of the DCT transformed image
8. Select the number of DCT coefficients 1 through 64 for the image to be compressed, this is called Quantization
9. Perform ordering of the transformed coefficients by zig-zag scan using Matlab matrix indexing power
10. Construct Run-Level coding by pairing the Zig-Zaged single column
11. Save the required bit streams as feature vectors during enrollment, then compare the saved features with new features during testing and
12. Measure and evaluate the performance (verification and identification rates) of each algorithm by using nearest neighbor classifier.

After computing the similarity matrices the results are evaluated graphically and some numerical results are displayed. The proposed framework is demonstrated in Fig. 6.

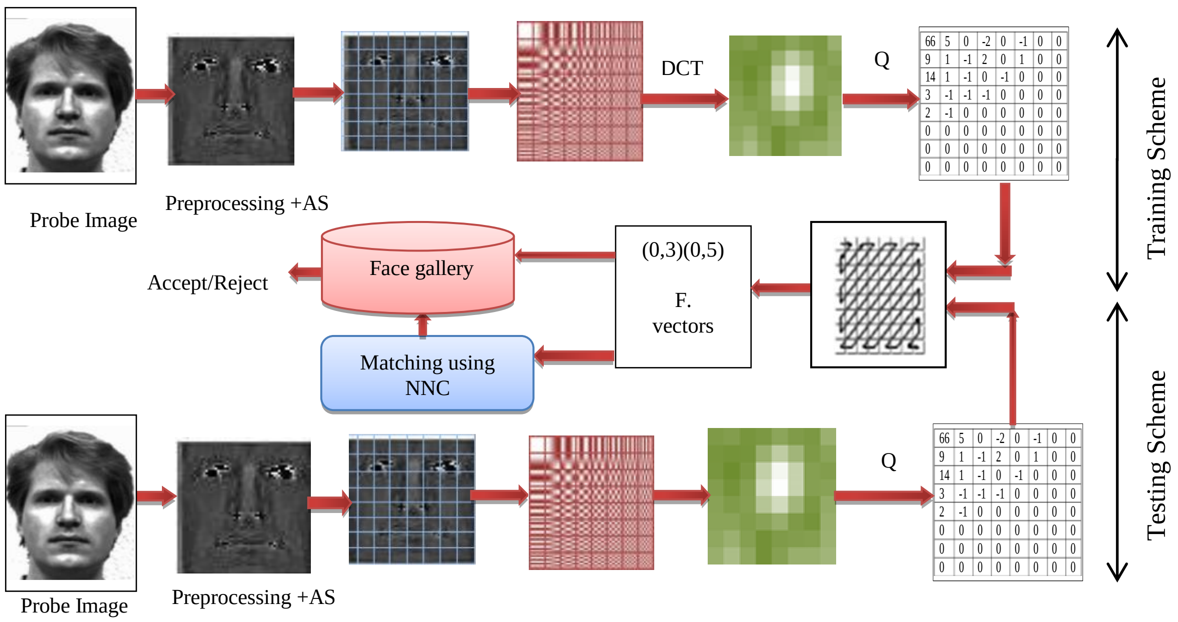

Fig. 6. Framework of the ASDCT for enrollment and verification

The following popular appearance based algorithms were exploited: PCA, Kernel Principal Component Analysis (KPCA), Linear Discriminant Analysis (LDA) and Kernel Fisher Analysis (KFA) for performance comparison with the proposed method ASDCT. The performance effectiveness of each algorithm was measured and evaluated using Mahalanobis Cosine (MAHCOS) similarity. The verification and identification rates were recorded.

IV. Results and Discussion

In order to observe the behavior of recognition process, different algorithms have to be tested on some selected databases. And extensive experiments have to be conducted and evaluated by varying False Acceptance Rate (FAR). Then the verification results should be observed normally at 0.01, 0.1 and 1.0 percentages of the FAR. Fig. 7 shows the DCT matrix obtained from the normalized images using the AS. The normalizing effect of this technique can be visually observed within certain limit. With poor illuminations it is difficult for all algorithms and classifiers to recognize the faces, since illuminations appeared in images as noise. However, recognition with DCT can be greatly improved by applying the AS for compensating illumination in uncontrolled enviroments.

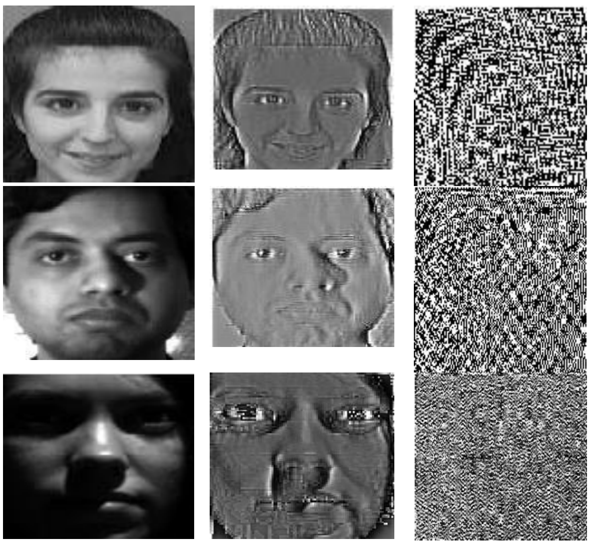

Fig. 7. Sample of results from ORL (first row), Yale (second row) and extended Yale-B (third row) showing gray scaled images, normalized images using AS and DCT matrices across the column.

Obviously, the results are expected to vary across the databases. Receiver operating characteristic (ROC) and cumulative match characteristic (CMC) curves are generated to describe the results of each method. The verification rates were presented at different FAR in the ROC curves; while CMC curves depicted the rank recognition rates.

Fig. 8 and Fig. 9 show performance curves of the ASDCT on ORL database. The performance is demonstrated based on aggregate statistics and relative ordering of match scores. The new method achieved highest recognition accuracy.

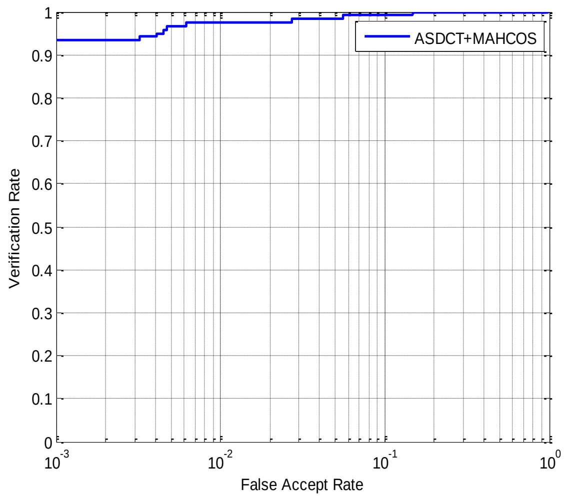

Fig. 8. ROC curve of ASDCT with MAHCOS distance on ORL face database

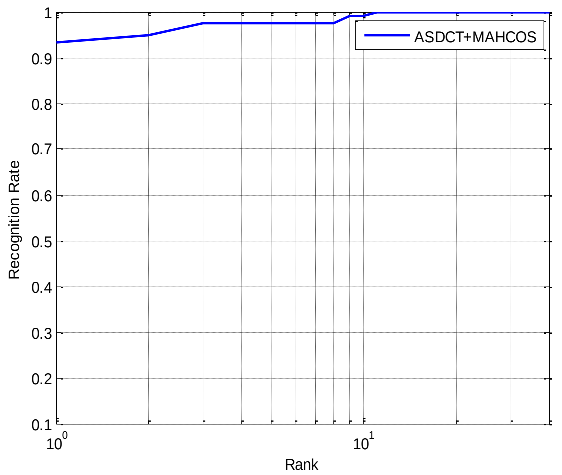

Fig. 9. CMC curve of ASDCT with MAHCOS distance on ORL face database

The ASDCT algorithm proved high performance over the other considered algorithms with verification rate of 86.00% at 0.1%FAR using Yale database. The latter performed better using this database. The Fisherface (LDA) method appears to be the best after the new method in terms of suppressing the illuminations, with 74.44% at 0.1%FAR. Fig. 10 shows the representations of the entire results generated from Yale face database.

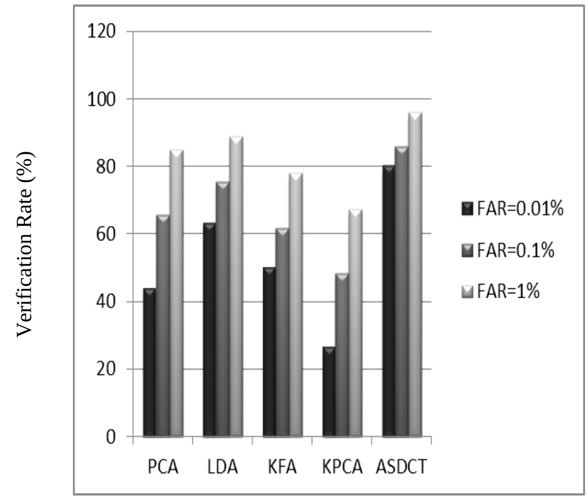

Fig. 10. Performance comparison of ASDCT and other methods on Yale face database

Similarly, using the ORL database, all the algorithms performed better. And there is a significant improvement in the Fisherface method from 74.44% to 78.34% at 0.1% FAR. In this regard, the new technique outperformed the others with up to 93.40% at 0.1% FAR, while it remains better with other databases. Fig. 11 shows the comparison of the results generated from ORL face database.

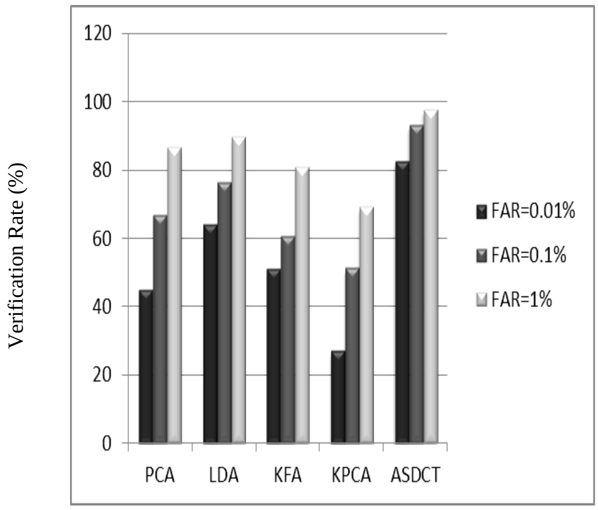

Fig. 11. Performance comparison of ASDCT and other methods on ORL face database

All the algorithms observed a significant performance reduction using the extended Yale-B, except the new method with up to 83.75% at 0.1% FAR. This is because most of the images in this database were poorly illuminated and poor illumination hinders recognition accuracy. Furthermore, removing some principal components does improve the performance of the Eigenface method in the presence of lighting variation. However, it does not achieve minimal error rates compared to other methods described here. The KPCA exhibited lowest performance with only 30.57% at FAR=0.1%. Fig. 12 illustrates the results conducted on extended Yale face database B.

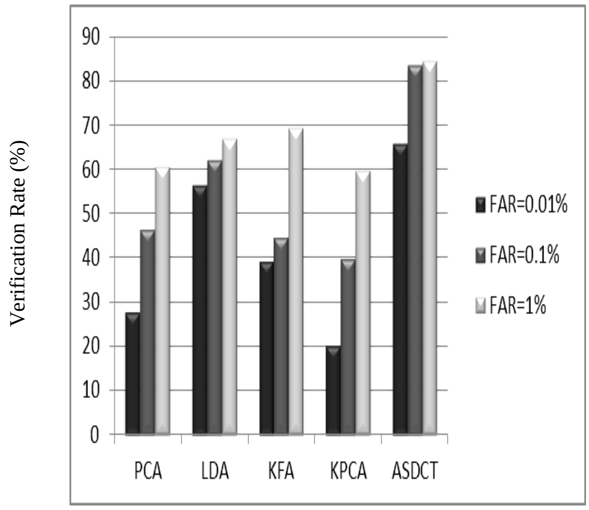

Fig. 12. Performance comparison of ASDCT and other methods on extended Yale face database B

The summary of the results are presented in Table II. It is clearly evidence that the performance of the proposed method is much higher than the other techniques reported on all the databases.

TABLE II
PERFORMANCE COMPARISON OF ASDCT AND OTHER TECHNIQUES CONSIDERED

DATABASE	METHOD	VERIFICATION RATE (%)		
		0.01% FAR	0.1% FAR	1% FAR
Yale	PCA	45.31	66.52	83.99
	LDA	64.34	74.44	90.10
	KFA	52.16	63.63	76.88
	KPCA	25.45	49.45	68.82
	ASDCT	80.00	86.00	95.95
ORL	PCA	46.01	67.89	85.97
	LDA	65.34	78.34	92.01
	KFA	52.02	61.84	82.43
	KPCA	28.00	52.03	70.10
	ASDCT	82.80	93.40	97.70
Extended Yale-B	PCA	27.90	47.01	61.50
	LDA	55.55	64.21	67.09
	KFA	38.48	44.68	68.89
	KPCA	21.30	30.57	58.87
	ASDCT	66.00	83.75	84.57

For thorough candidate's authentication analysis, other performance metrics were equally generated through the identification experiment. Equal error rate (EER), minimal half total error rate (MHTER) and rank one recognition rates representing the different techniques using ORL database are recorded in Table III. The ASDCT reported the lowest EER of 2.73%, and MHTER of 1.98%.

TABLE III
RESULTS OF ERROR RATES, IDENTIFICATION RATES AND RANK ONE RECOGNITION RATES ON THE EVALUATION DATA

METHODS (%)	MHTER (%)	EER (%)	RANK (%)
PCA	4.53	4.96	65.85
KPCA	7.90	8.99	50.3
LDA	3.96	4.32	87.77
KFA	7.01	7.35	84.78
ASDCT	**1.98**	**2.73**	**93.5**

From the basis of evaluation of the 22 IN techniques, and emperical analysis of the new method, it is deduced that applying AS in the initial stage enhances recognition accuracy of the DCT significantly. Moreover, several works using DCT and other popular feature extraction techniques were reported for further comparison with the proposed method. The emphasis was given on ORL because it is the most commonly used database especially on face recognition using the DCT that outperformed other databases.

The research investigated one of the challenges of image acquisition process, and proposed an improved approach of a single DCT. The performance comparison of the new method with few hybrid systems is presented in Table IV. In this regard, a competitive advantage can be observed. Therefore, the effect of illumination is addressed.

TABLE IV
COMPARISON OF RECOGNITION RATES OF THE PROPOSED ALGORITHM WITH OTHER TECHNIQUES USING DIFFERENT DATABASES

METHOD	DATABASE	RECOGNITION RATE (%)
PCA [30]	ORL	90
PCA [31]	Yale	81.13
MLP [27]	ORL	77.20
DCT+MLP [27]	ORL	92.90
HMM [32]	ORL	87.00
DCT [10]	CIM	84.58
KLT [10]	CIM	77.57
Hexagonal + DCT+MLP [33]	Yale	92.77
DCT [34]	BioID	92.50
DCT+ DT-WT [35]	Yale-B	88.30
DCT+ DT-WT [35]	ORL	83.30
DLDA [36]	Yale	82.14
D-DCT [37]	Yale	90.14
ODCT [38]	Yale	92.12
CCODCT [38]	Yale	91.37
DFT+DCT [39]	Color FERET	80.23
DCT [40]	ORL	88.75
Proposed method	**ORL**	**93.40**

The justifiable reason of carrying out the study is; some feature extraction algorithms are more sensitive to illumination than others, and no algorithm is however insensitive to illumination variations. Furthermore, each of the IN techniques can work better with some feature extractors than the others. Therefore, recognition using AS and few selected coefficients of the DCT reported additional performance over the traditional face recognition techniques.

The AS technique estimates luminance function using anisotropic smoothing and supports decorrelation of data in this experiment. While the proposed method preserves object boundary effectively without degrading the quality of images. Fig. 13 demonstrates the effect of AS on a poor illuminated image after the reconstruction at various compression ratios of 70%, 50%, 30%, and 10%. The advantage of the illumination compensation can be visually compared with unfiltered reconstructed images at the same compression ratio. Measurement cost and classification accuracy are two major reasons of minimizing the dimension of features [41]. This is achieved by discarding some of the extracted features that possess low discriminating ability. The selection of 19 coefficients in this research is approximately 70% of the compression ratio.

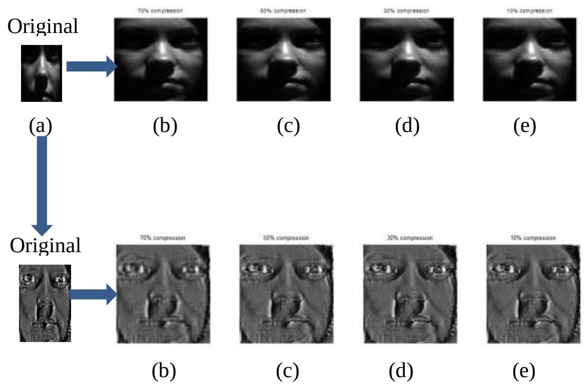

Fig. 13. Effect of AS (second row) on an image (first row): (a) original image, (b) image at 70% compression ratio, (c) image at 50% compression ratio, (d) image at 30% compression ratio, and (e) image at 10% compression ratio

Hence, anisotropic diffusion IN technique based Discrete Cosine Transform' (ASDCT) is introduced. The research mitigates the effect of illumination variations on face images using the most suitable illumination invariant, prior to features selection using the DCT.

The major contributions of the proposed algorithm are: 1) it promotes decorrelation of DCT sufficiently and supersedes the appearance based techniques considered. 2) It compensates the effects of illumination and creates almost unvarying input images. The limitation of this study is we can only assure the use of AS for efficient recognition using DCT algorithm. Since the discovery of the most suitable illumination compensator was carried out through JPEG standard method, which is one of the typical image compression techniques that use the DCT. Therefore, to determine a preprocessor that works best with any feature extractor, the property of the extractor needs to reflect the testing criterion.

V. DISADVANTAGE OF TRUNCATING DCT COEFFICIENTS

In all spectral computations, signal is truncated before the discretization by multiplying the original signal say $x(t)$ by a rectangular window say $w(t)$, the resulted spectrum of the truncated signal equals the convolution of $w(c)$ and the spectrum of the untruncated signal. Generally, truncation introduces ripples, leakage or smearing into a spectrum [42].

The spectrum of a DCT signal is bounded at discrete frequencies, and the cosinusoidal frequencies are disturbed in an attempt to put a rectangular window. Although, the coefficients of the DCT are truncated to reduce the complexity and redundancy, but at the expense of errors and noise induction into the system. The quantization is carried out by varying step sizes of DCT coefficients through fixing a default quantization step size for each coefficient based on visual sensitivity to different frequencies.

Therefore, the quantized signal is x number of retained coefficients out of the 64 coefficients of the matrix. The larger the size of x, the better the quality of reconstructed image. The limitation of DCT is always known since truncating higher spectral coefficients blurs the images especially wherever the details are high. And coarse quantization on some low spectral coefficients introduces graininess in the smooth portions of the images. Additionally, serious blocking artifacts are introduced at the block boundaries since each block is independently encoded, often with a different encoding strategy and the extent of quantization [43]. And the size of the subset of DCT coefficients retained as a feature vector may not be large enough for achieving an accurate reconstruction of the input image [10]. One of the phenomena that may decrease this effect is by applying an overlapped transform.

Therefore, for an efficient decorrelation of images using the approach mentioned in this paper, 19 coefficients including the DC components were extracted. But the texture based illumination compensator was resulted to a smoothed matrix and uniform coefficients magnitude. Besides, the truncation affects the system and these effects were studied in [27], using error metrics; PSNR and MSE. Similarly, reduction of a number of features may reduce the discriminating power as a result lower the accuracy of the recognition system [41]. Notwithstanding, reconstruction without error cannot be achieved with truncation of any of the frequency components either high or low. For this reason, an advanced feature extraction method as a way forward for improving data compaction of the DCT is needed without truncating any of its coefficient.

VI. Conclusions

Out of The 22 IN techniques in the literature, the AS is proven as the most suitable preprocessor for face recognition using the DCT. The research used few of the DCT coefficients to increase classification accuracy for optimal feature extraction. Hence, enhanced DCT technique is developed for an efficient face recognition. The proposed method improved the performance of face recognition system under both controlled and uncontrolled illumination conditions. It also outperformed many conventional techniques, and can be tested on other biometric modalities such as palmprint.

Further research may be conducted on the block-based ASDCT with more databases. Finally, considering a significant loss of recognition rates generally using the DCT which is caused by necessitating truncation, we will also explore a new feature extraction that optimizes the matrix coefficients and increases enrollment of large users within a small memory disk, and without truncation of any DCT coefficient.

References

[1] A. Ghandehari & R. Safabakhsh, "A comparison of Principal Component Analysis and Adaptive Principal Component Extraction for palmprint recognition", *IEEE*, 2011.

[2] D. Bhattacharyya, R. Ranjan, F. A. Alisherov and M. Choi, "Biometric authentication: A review", *International Journal of u- and e- Service, Science and Technology*, vol. 2, no. 3, pp. 13-27. 2009.

[3] H. Drira, B. B. Amor, M. Daoudi, and R. Slama, "3D Face recognition under expressions, occlusions and pose variation, *IEEE Transactions on pattern analysis and machine intelligence*, vol. 35, no. 9, 2013.

[4] S. T. Gandhe, K. T. Talele, and A. G. Keskar, "Face recognition using contour matching," IAENG International Journal of Computer Science, vol. 35, no. 2, pp226-233, 2008.

[5] R. Hietmeyer, 2000. Biometric identification promises fast and secure processing of airline passengers, The International Civil Aviation Organization Journal, vol.55, no.9, pp. 10-11.

[6] G.Hemalatha, C.P. Sumathi, "A study of techniques for facial detection and expression classification" International Journal of Computer Science & Engineering Survey (IJCSES), vol.5, no.2, 2014. DOI : 10.5121/ijcses.2014.5203

[7] V. Radha, and N. Nallammal, "Neural network based face recognition using RBFN classifier," Proceedings of the World Congress on Engineering and Computer Science, vol. I, pp1-6, 2011.

[8] Z. Sufyanu, F. S. Mohamad and A. S. Ben-Musa, "Choice of illumination normalization algorithm for preprocessing efficiency of Discrete Cosine Transform", *International Journal of Applied Engineering*, vol. 10, no. 3 pp. 6341-6351, 2015.

[9] Face Recognition, Technical Report. National Science and Technology Council. Web source: www.biometrics.gov/Documents/facerec.pdf.

[10] Z. M. Hafed, M. D. Levine, "Face recognition using the Discrete Cosine Transform", *International Journal of Computer Vision*, vol.43, no.3, pp. 167–188, 2001.

[11] N. Ahmed, T. Natarajan, K. Rao, Discrete Cosine Transform, *IEEE Trans. on Computers* vol. 23, no. 1, pp. 90–93, 1974.

[12] K. Rao, P. Yip, *Discrete Cosine Transform, Algorithms, Advantages, Applications*. Academic: New York, 1990.

[13] B. K. Ahmed. "DCT image compression by Run-Length and Shift Coding techniques." *J. of university of Anbar for pure science,* vol.5, no.3, 2011. Web source: http://www.e-bookspdf.org/download/text-compression-coding-techniques.html

[14] S. K. Dandpat, and S. Meher, *New Technique for DCT-PCA Based Face Recognition*, 2011.

[15] C. Sanderson, and K. K. Paliwal, "Polynomial features for robust face authentication", *Proceedings of international conference on image processing*, *IEEE,* vol. 3, pp. 997-1000, June 2002.

[16] Z. Sufyanu, F. S. Mohamad and A. A. Yusuf, "A new discrete cosine transform on face recognition through histograms for an optimized compression" *Research Journal of Information Technology,* DOI:10.3923/rjit.2015

[17] A. A. Fathima, S. Vasuhi, N. T. N. Babu, V.Vaidehi, and T. M. Treesa, "Fusion framework for multimodal biometric person authentication system," IAENG International Journal of Computer Science, vol. 41, no. 1, pp18-31, 2014.

[18] C. Atupelage, and K. Harada, "Quantifying the visual content perceived in DCT coefficients and PKI based semi-fragile watermarking for visual content authentication of images," Advances in Electrical and Electronics Engineering-IAENG Special Edition of the World Congress on Engineering and Computer Science, pp275-286, 2008.

[19] S. Vikas, and J. P. Gupta, "Collusion attack resistant watermarking scheme for colored images using DCT," IAENG International Journal of Computer Science, vol. 34, no. 2, pp171-177, 2007.

[20] A. Reza, B. Azad, and S. Jamali. "Human face recognition with high accuracy using Diverse Feature Set and mixture of SVMs." *International Journal of Modern Education and Computer Science (IJMECS)*. DOI: 10.5815/ijmecs.2014.08.08, vol. 6, no. 8, pp. 66-74, 2014.

[21] F. Juefei-Xu, and M. Savvides. "Subspace based discrete transform encoded local binary patterns representations for robust periocular matching on NIST's face recognition grand challenge." *In IEEE transactions on image processing*, vol. 1, no. 1, pp. 1-16, 2014.

[22] M. Lee, and C. H. Park. "An efficient image normalization method for face recognition under varying illuminations." *In proceedings of the*

1st ACM international conference on multimedia information retrieval, pp. 128-133, 2008.

[23] S. Liao, D. Yi, Z. Lei, R. Qin, and S. Z. Li, "Heterogeneous face recognition from local structures of normalized appearance", *Advances in biometrics. springer berlin heidelberg*, pp. 209-218, 2009.

[24] X. Tan and B. Triggs. "Enhanced local texture feature sets for face recognition under difficult lighting conditions." *In IEEE transactions on image processing*, vol. 19, no. 6, pp. 1635-1650, 2010.

[25] S. Du and R. K. Ward. "Adaptive region-based image enhancement method for robust face recognition under variable illumination conditions", *In IEEE transactions on circuits and systems for video technology*, vol. 20, no. 9, pp. 1165-1175, 2010.

[26] Z. Lai, D. Dai, C. Ren and K. Huang "Multi-layer surface albedo for face recognition with reference images in bad lighting conditions." *In IEEE transactions on image processing*, vol. 23, no. 11, pp. 4709-4723, 2014.

[27] Z. Pan, H. Bolouri, High Speed Face Recognition based on Discrete Cosine Transforms and Neural Networks, 1999.

[28] R. Gross, V. Brajovic. "An image preprocessing algorithm for illumination in-variant face recognition", *Proc. of theyu 4th International conference on audio and video-based biometric personal authentication*, July.

[29] K.C. Lee and J. Ho and D. Kriegman, "Acquiring linear subspaces for face recognition under variable lighting ", *IEEE Trans. Pattern anal. mach. intelligence*, vol. 27, no. 5, pp. 684-698, 2005.

[30] F. Samaria, Face recognition using Hidden Markov Models. PhD thesis, Trinity College, University of Cambridge, Cambridge, 1994.

[31] R, Huang, V. Pavlovic, and D.N. Metaxas, "A hybrid face recognition method using Markov Random Fields", *ICPR04*, pp. 157-160, 2004.

[32] F. Samaria and A. Harter, "Parameterisation of a stochastic model for human face identification," *in proceedings of 2nd IEEE Workshop on applications of computer vision*, (Sarasota Florida, USA), Dec. 1994.

[33] M. Azam, M. A. Anjum and M. Y. Javed, "Discrete Cosine Transform based face recognition in hexagonal images," *IEEE*, vol. 2, 2010.

[34] A. R. Chadha, P. P. Vaidya, and M. M. Roja, "Face recognition using Discrete Cosine Transform for global and local features," *Proceedings of the 2011 international conference on recent advancements in electrical, electronics and control engineering (IConRAEeCE) IEEE Xplore: CFP1153R-ART*.

[35] K. Ramesha, and K. B. Raja, "Dual transform based feature extraction for face recognition", *International Journal of Computer Science Issues*, vol. 8, Issue 5, no. 2, Sept. 2011.

[36] H. Yu and J. Yang, "A direct LDA algorithm for high-dimensional data with application to face recognition", *Pattern Recognition*, vol. 34, no. 10, pp. 2067-2070, 2001.

[37] X. Y. Jing and D. Zhang, "A face and palmprint recognition approach based on discriminant DCT feature extraction", *IEEE Trans. on Syst. Man Cybern B*, vol. 34, no. 6, pp. 2405-2415, 2004.

[38] P. Cui, and R. B. Zhang, "A semi-supervised coefficient select method for face recognition", *Journal of Harbin Engineering University*, vol. 33, no. 7, pp. 855-861, 2012.

[39] G.M. Deepa, R. Keerthi, N. Meghana, and K. Manikantan, "Face recognition using spectrum-based feature extraction", *Applied Soft Computing Journal*, vol. 12, no. 9, pp. 2913-2923, 2012.

[40] P. Gupta and N. V. George, "An improved face recognition scheme using transform domain features," *International Conference on Signal Processing and Integrated Networks*, 2014.

[41] J. k. Anil, R. P. W. Duin, and J. Mao. "Statistical pattern recognition: A review." *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 22.1 (2000): pp. 4-37.

[42] C. Chi-Tsong, *Digital signal processing: spectral computation and filter design.* Oxford University Press, 2001, pp. 101-103.

[43] Su, Po-Chyi, Houng-Jyh M. Wang, and C-C. Jay Kuo. "Digital watermarking on EBCOT compressed images." *SPIE's International Symposium on Optical Science, Engineering, and Instrumentation*. International Society for Optics and Photonics, 1999.