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JPEG Compressed Domain Face Recognition: Different Stages and Different Features

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Abstract—**JPEG compression standard is widely used for reducing the volume of images that are stored or transmitted via networks. In biometrics datasets, face images are usually stored in JPEG compressed format, and should be fully decompressed to be used in a face recognition system. Recently, in order to reduce the time and complexity of decompression step, face recognition in compressed domain is considered as an emerging topic in face recognition systems. In this paper, we have tested different feature spaces, including PCA and ICA in various stages of JPEG compressed domain. The goal of these tests was to determine the best stage in JPEG compressed domain and the best features to be used in face recognition process, regarding the trade-off between the decompression overhead reduction and recognition accuracy. The experiments were conducted on FERET and FEI face databases, and results have been compared in various stages of JPEG compressed domain. The results show the superiority of zigzag scanned stage compared to other stages and ICA feature space compared to other feature spaces, both in terms of recognition accuracy and computational complexity.**

Keywords- Face Recognition, JPEG Compressed Domain, JPEG Decompression, Face Database, Feature Extraction.

I. INTRODUCTION

Automatic face recognition has received substantial attention from research community and the real-world requirements for more than five decades [1, 2]. Thus, it has been turned into a vast theoretical-practical domain which is widely used in legal and commercial applications with high universality, collectability, acceptability and circumvention [3]. Despite this wide range of applications, it still remained several challenges in demanded applications, including particularly face recognition in compressed domain [4].

Simultaneously with improvements of biometric systems, some important issues such as storage constraints, bandwidth limitations and concerns on multimedia data computation complexity have been increasingly incorporated into designing efficient methods for multimedia compression [5]. JPEG is considered as the most common method for still images compression and nowadays, almost all of the multimedia applications and operating systems are able to decode images which have been encoded using this standard [6].

Due to the following reasons, JPEG compressed domain recognition has been turned into an important issue in face recognition systems: (1) necessity of storage reduction in design of large face datasets and (2) obligation of working with compressed images, in case of already constructed datasets. JPEG is able to compress images with significant compression ratio, without noticeable degradation in their visual quality.

Thus, compressing facial images leads to a significant reduction in the amount of the database's storage space, e.g. 10 times. It is worth mentioning that there are other approaches for reducing the size of the a face database such as storing facial features instead of images' pixels [7], data fusion [8], Kalman Filtering [9], generating 3D model of multiple instances of a single face [10], and canonical face modeling [11]. However, unlike JPEG compression standard, these approaches are application specific and have not been widely used in face recognition systems.

Concerning the second reason, occasionally, using JPEG compressed images in a face recognition system is mandatory, since only the compressed version of images are available. To be more specific, most of the modern cameras store directly their output images in this standard format [12], and most of the images on the World Wide Web are JPEG compressed images.

Complete decompression of images causes a computational overhead in recognition systems. The block diagrams of JPEG compression/decompression operations are shown in Fig. 1. In the First step of encoding process, color transformation is performed, in order to convert RGB color space to $Y'C_BC_R$ color space. Afterward, image components including luminance and two chrominance components are separately divided to 8×8 blocks, and 2-D DCT is applied on the image's blocks. Subsequently the transformed coefficients are quantized using a quantization table. In the zigzag step, through zigzag scan, 2-D blocks of image are mapped to a 1-D sequence. Then, regarding the similarity between DC components of adjacent blocks and the continuous zeros in AC sequences, DPCM and RLC methods are respectively applied on DC and AC coefficients, and subsequently, they are labeled in a quantization step. Finally, the labeled coefficients are binary entropy encoded using a Huffman encoder. The JPEG decoder, shown in Figure 1.B, is composed of the inverse processing steps in reverse order.

As it can be seen, decompression process involves several stages causing a computational overhead on face recognition applications. Thus, in order to reduce the decompression overhead, face recognition in compressed domain has been considered by researchers. Delac et al. [13] proposed to use frequency coefficients in compressed domain, instead of pixel values, as input to a face recognition system. Some researches have been done on JPEG compressed domain face recognition [13-21]. Their results reveal that using the compressed coefficients not only reduces the computational overhead of decompression phase, but also leads to slight improvements in recognition accuracy.

In this paper, we focus on an important issue in this subject. For the first time, we have tested different feature spaces, including PCA and ICA in various stages of JPEG compressed domain. The goal of these tests is to determine the best stage in JPEG compressed domain and the best features to be used in face recognition process, regarding the trade-off between the decompression overhead reduction and recognition accuracy. The experiments have been conducted on FERET [22, 23] and FEI [24] face databases. PCA [25] and ICA [26] methods have been used for feature extraction in JPEG compressed domain. The following metrics have been used to compare the results of the experiments: recognition rate [23], Average UnMatched Similarity Value (AUMSV) [27], and time estimation including time complexity and runtime.

Block diagram of the JPEG domain face recognition system is shown in Fig. 2. First, compressed probe images are partially decompressed in various stages of JPEG compressed domain. Then, the extracted coefficients are used as input to various feature extraction methods. Finally in the matching phase, the extracted vectors of the probe images are compared with those of the gallery images in the database which are obtained using the same process.
The rest of this paper is organized as follows: Section 2 is dedicated to a review of the related works. Section 3 includes description of methodologies and principles used in this work. The experimental results, comparisons and analysis are presented in Sections 4 and Section 5 concludes the paper.

II. RELATED WORK

In this section, we present a review of the related works done on face recognition in JPEG compressed domain. In [13], a comprehensive experiment in face recognition domain has been done on transform coefficients, using PCA [25] and ICA [26] feature extraction methods. The experiments were conducted on FERET database. The results showed that recognition rates in compressed domain were comparable and in some cases even higher than recognition rates obtained in pixel domain, i.e. from fully decompressed images. In [14], DCT coefficients were input of PCA and LDA [28] extraction methods. The experiments were simulated on FERET database and the results showed that recognition rates obtained in compressed domain were the same as in those obtained in spatial domain. In addition, it was found that using only the first 20 coefficients in DCT blocks did not reduce the accuracy. In [15], a low complexity and efficient face recognition approach in JPEG compressed domain was proposed, and in the reported experiments, quantized coefficients were compared by different distance metrics for performing recognition process. The results showed that there is no degradation in recognition rates, compared to recognition using DCT coefficients and pixel domain, where inverse quantization step was omitted in recognition process. Furthermore, Spearman and City block metrics gave the best results in FERET datasets. Authors of [16, 17] presented a face recognition system based on 2-D DCT features and psedue 2-D Hidden Markov Model [29]. The results showed high efficiency of the proposed methods in JPEG compressed domain. In [18], possibility of using a limited number of lowest frequency coefficients in JPEG compressed domain face recognition was investigated. The results showed the superiority of using a limited number of low frequency compressed coefficients and a significant improvement in computational complexity of the recognition system.

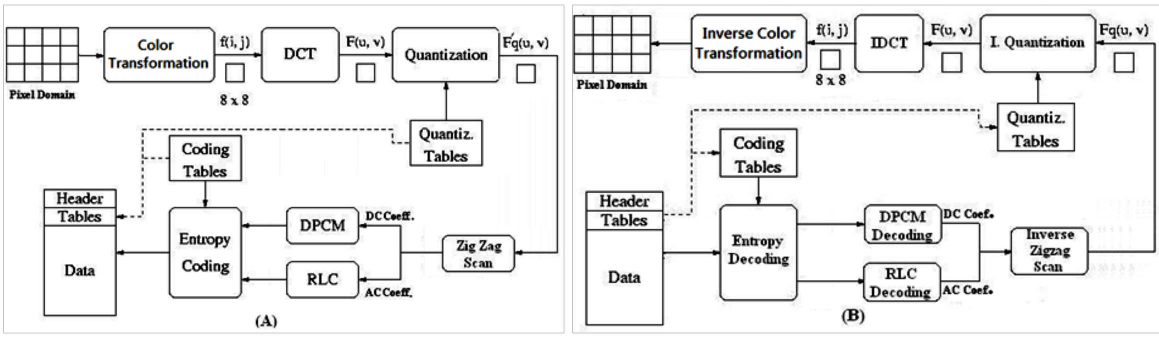

Figure 1 Block diagram of JPEG (A) coding (B) decoding procedures.

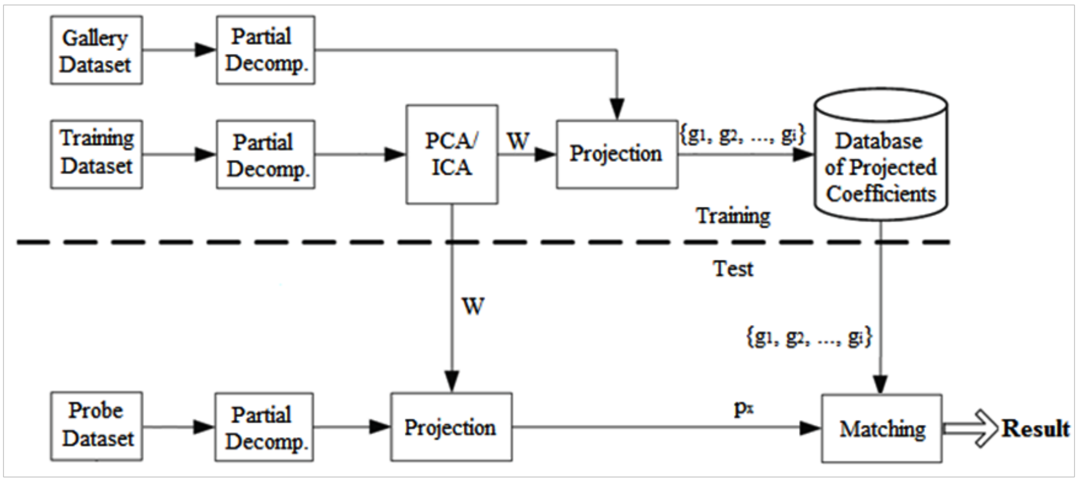

Figure 2 Block diagram of the proposed compressed domain face recognition system.

Also, face recognition systems in JPEG compressed domain have been proposed based on AdaBoost and EDBoost methods, respectively in [19] and [20]. DCT coefficients were employed as feature space and the results showed the high efficiency of the proposed approach in terms of recognition accuracy, efficiency, and illumination robustness. Finally, in [21], a novel coefficient preselection method for face recognition have been proposed for improving recognition accuracy and decreasing computational load in JPEG compressed domain. In this method, areas of the face were segmented in prominent and non-important regions, and subsequently, the DC and different number of lower frequency AC coefficients of each block were preselected, regarding the regions used for face recognition process. Experimental results showed that the method proposed in [21] outperformed other methods in JPEG compressed domain face recognition, in terms of recognition rate, as well as time and space complexity aspects.

There is a substantial challenge that has not addressed in the previous works, i.e. investigating on the proper stage for face recognition in JPEG compressed domain. Existing works applied face recognition on the final stages of JPEG compressed domain, i.e. before inverse DCT and inverse quantization steps. In this paper, a comprehensive analysis has been done for determining the best JPEG stage for recognition process, considering the tradeoff between the recognition accuracy and the complexity of the decompression process.

III. Description of Methods

The block diagram of the proposed JPEG compressed domain face recognition system is shown in Fig. 2. Input of the system is a normalized and registered face image. In our experiments, we have used facial images from FERET and FEI databases (Section III-A). However, since FERET facial images are not in JPEG format, they should initially be JPEG compressed (Section III-B). This is not the case for images in FEI dataset, since they are JPEG compressed.

During the training phase, Gallery and Training images are partially decompressed (Section III-B) in different stages of the compressed domain for extracting coefficients in compressed domain including AC entropy coded, DC entropy coded, RLC coded, DPCM coded, quantized and transformed coefficients. Then, PCA (Section III-C-1) and ICA (Section III-C-2) feature extraction methods are applied on partially decompressed training images for extracting appropriate feature vectors and subsequently, the extracted features are projected onto those of Gallery images, so that the extracted vectors of the Gallery images are stored in a database.

During the test phase, a probe image is also partially decompressed and is projected onto the extracted vectors of the training images to be compared with the features of the Gallery set in the database using different distance metrics (Section III-D). It is worth mentioning that the entire probe sets' images (Fb: 1195 images, Fc: 194 images, Dup1: 722 images, Dup2: 234 images and FEI: 200 images) are used in the experiments. In these tests, the experiments are performed independently in different stages of the compressed domain. Furthermore, the proposed system is evaluated using recognition accuracy as well as time estimation metrics.

The proposed system is evaluated using recognition accuracy metrics including recognition ranks and Average Unmatched Similarity Value (AUMSV), as well as time estimation metrics including time complexity and runtime, explained in Section III-E. First recognition ranks and cumulative recognition ranks are calculated for all datasets. Another recognition accuracy metric, i.e. AUMSV, is calculated in different stages of the compressed domain using coefficients of the Gallery sets (FERET: 1195 images and FEI: 200 images). Finally, runtime percentages of the decompression steps are calculated to obtain an accurate estimation of time reduction resulted from applying face recognition in JPEG compressed domain.

A. *Face Image Databases*

FERET and FEI facial image databases are used in this research. The experiments are simulated using two databases for generalization purposes. In FERET database experiments are performed using gray scale images. The standard test space [23] has done on four probe datasets, which are Fb (different expression test), Fc (different illumination), Dup1 (images taken anywhere between one minute and 1,031 days after the gallery image) and Dup2 (images taken at least 18 months after the gallery image was taken). These datasets contain respectively 1195, 194, 722 and 234 images that are compared with 1196 reference images in Fa dataset. Five images of a particular subject in the five datasets are shown in Fig. 3.

In addition, a subset of the FEI face database, composed of only frontal face images, are used in our experiments [24]. Since the number of subjects is equal to 200 and each subject has two frontal images, there are totally 400 images in this dataset. In our simulations, the first 200 images are selected as gallery and training sets and the second 200 images as probe set.

Figure 3 Five images of a particular subject in FERET's Fa, Fb, Fc, Dup1 and Dup2 datasets

It is worth to mention that for geometrically registering and normalizing facial image of the databases, we used the approach used in most of the related works [13-21]. These processes are used for eliminating the unwanted parameters in face recognition process, such as image background.

B. *JPEG Compression Step*

In case of JPEG compressed face images, a partial decompression phase should be applied to compressed images for extracting coefficients in compressed domain. However, since the gray scale uncompressed version of FERET database has been used in this research, in order to work in compressed domain, facial images are first JPEG compressed.

Two different methods have been used in previous works for JPEG image compression. In the first approach, images are compressed using software packages with different compression rates achieved by adjusting quantization tables, not necessarily JPEG standard ones [13], [15], [16], [17],[30], [31]. In the second approach, standard quantization tables are used [18], [19], [20], [21]. Comparing two approaches, the second approach is more practical, since most of JPEG compressed images (captured by digital cameras and/or on the World Wide Web) are compressed using these tables. As a consequence, in this work, we used a standard quantization table (Fig. 4) for JPEG facial image compression.

$$Q = \begin{bmatrix} 16 & 11 & 10 & 16 & 24 & 40 & 51 & 61 \\ 12 & 12 & 14 & 19 & 26 & 58 & 60 & 55 \\ 14 & 13 & 16 & 24 & 40 & 57 & 69 & 56 \\ 14 & 17 & 22 & 29 & 51 & 87 & 80 & 62 \\ 18 & 22 & 37 & 56 & 68 & 109 & 103 & 77 \\ 24 & 35 & 55 & 64 & 81 & 104 & 113 & 92 \\ 49 & 64 & 78 & 87 & 103 & 121 & 120 & 101 \\ 72 & 92 & 95 & 98 & 112 & 100 & 103 & 99 \end{bmatrix}$$

Figure 4 A JPEG standard quantization table used for gray scale image compression.

In case of color JPEG images, RGB color space is first converted to $Y'C_BC_R$ space, and only the luminance component is partially decompressed to be used in recognition process.

C. *Feature Extraction Methods*

1) *Principle Component Analysis (PCA)*

Principle component analysis (PCA), is a subspace projection technique that is widely used for feature extraction in face recognition systems [25]. Given a s-dimensional vector representation of each face, PCA tends to find a t-dimensional subspace ($t \leq s$) whose basis vectors correspond to highest variance directions in the original image space. This new subspace have smaller dimension compared to primary space, due to omitting components with smaller eigenvalues. The vectors in the new subspace have more information compared to their corresponding vectors in primary space. In our experiments, the last 40% of the eigenvectors are discarded. Also, the first eigenvector is eliminated from recognition process, in order to reduce the effects of the illumination changes, based on the results reported in [32] and [33].

2) Independent Component Analysis (ICA)

Typically PCA find a set of basis images and represent faces as a linear combination of those images. PCA extraction method depends only on pairwise relationships between pixels in the image database. In a task such as face recognition, in which important information may be contained in high-order relationships among pixels, it seems reasonable to expect that better basis images may be found by methods sensitive to these high-order statistics. Independent component analysis (ICA), a generalization of PCA, is one such method that minimizes both second-order and higher-order dependencies in the input. In this work, based on the method presented in [26], before applying ICA (using its second architecture proposed in [26]), PCA is first applied on the input image to reduce image dimension and time needed for ICA step.

D. Feature Matching

In this stage, the distance between feature vectors is calculated for face recognition. In this research, based on the results reported in [15], [18], [21] and [30], amongst all distance metrics, Cosine distance (Eq. (1)) and Spearman Correlation (Eq. (2)) are used for measuring the distance between ICA and PCA features, respectively.

It is worth to mention that before calculating Spearman Correlation between two vectors *X* and *Y*, first, the elements of these vectors are sorted in ascending or descending order and then, elements in primary vectors are replaced by their corresponding indexes in sorted vectors.

$$D_{Cosine}(x,y) = 1 - \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i^2}} \quad (1)$$

$$D_{Spearman}(x,y) = \quad (2)$$

$$1 - \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{\left[n\sum_{i=1}^{n} x_i^2 - \left[\sum_{i=1}^{n} x_i\right]^2\right]\left[n\sum_{i=1}^{n} y_i^2 - \left[\sum_{i=1}^{n} y_i\right]^2\right]}}$$

E. Performance Evaluation Metrics

Four different metrics have been used to evaluate the performance of the face recognition in different stages of JPEG compressed domain: "recognition rank", "normalized recognition rank", "similarity matrix and average unmatched similarity value" and "time metric. These metrics, are explained in the following subsections.

1) Recognition Ranks

First recognition rank and cumulative recognition rank are the most accurate metrics for determining how well a system matches images from the same people. After calculating the distance between input face image (probe image) and reference ones, a sorted list L = { L_1, L_2,…, L_n} is obtained, where L_1 is an image in the reference images set with maximum similarity with probe image and L_n is the image with minimum similarity. If the identity of L_1 is equal to that of probe image, the algorithm has done the recognition in first rank correctly. In a similar manner, if the identity of L_n is equal to that of probe image, the algorithm has done the recognition in rank-n correctly. In general, rank-n of recognition is calculated per input images according to Eq. (3):

$$RR_n = \frac{R_n}{|P|} \quad (3)$$

where R_n is the number of correct recognition in rank-n on probe dataset and |*P*| is the total number of probe images.

Cumulative Recognition Rank *n* is defined using Eq. (4):

$$CRR_n = \sum_{i=1}^{n} RR_i \quad (4)$$

2) Normalized Recognition Rate

For comparing the recognition rates obtained in two feature spaces, i.e. different stage of the JPEG compressed domain, Delac et al. (in [31]), defined two performance measures, Normalized Recognition Rank (NRR_n) and Normalized Cumulative Recognition Rank ($NCRR_n$), which are formulated respectively in Eq. (5) and Eq. (6). *RRn.Second Space* is also called Normalization Factor.

$$NRR_n = \frac{RR_n.\ First\ Space}{RR_n.\ Second\ Space} \quad (5)$$

$$NCRR_n = \frac{CRR_i.\ First\ Space}{RR_n.\ Second\ Space} \quad (6)$$

3) Similarity Matrix and Average Unmatched Similarity Value

Similarity Matrix (*SM*) is a powerful representation for distinguishing different images [27]. Each entry of this matrix, *SM*(*i,j*), indicates the degree of similarity between features of image *i* and image *j*. *SM*(*i,j*) has a value between 0 and 1. The diagonal elements of the matrix are 1, i.e. for *i* = *j*, ideallyin a biometric application, where the database entries belong to different subjects, the other elements of the matrix should be zero or close to zero.

This matrix fairly represents the ability of a feature space for class separation. However, in order to obtain a global measure, similarity matrix could be used for calculating Average Unmatched Similarity Value (AUMSV) metric, which is defined in Eq. (7) [27]. In this equation, *N* is the number of images and *SM* is the similarity matrix. The higher the discriminatory power, the smaller the AUMSV value will be.

$$AUMSV = \frac{1}{(N^2-N)} \sum_{i=1}^{N} \sum_{j=1}^{N} SM(i,j), where\ i \neq j \quad (7)$$

4) Time Estimation Metrics

Time complexity of an algorithm quantifies the amount of time taken by an algorithm to run as a function of the size of the input to the problem which is commonly expressed using *O* notation. Another metric in this domain is speedup ratio which indicates how much an algorithm is faster than another one.

IV. Experimental Results, Comparisons and Analysis

In this section, we present the experimental results, comparisons and analysis. The experiments have been done by performing a comparative studies using different feature extraction methods applied in different stages of JPEG compressed domain.

A. Experimental Results

1) Recognition Accuracy

The experimental results are obtained by applying PCA and ICA in different stages of JPEG compressed domain. Tests have been done on four datasets of FERET database (Fb, Fc, Dup1 and Dup2) as well as FEI database. First recognition rank and cumulative recognition rank up to 50^{th} rank obtained with PCA and ICA feature extraction methods are shown respectively in Fig. 5 and Fig. 6.

We have also calculated AUMSV in different stages of the compressed domain using PCA and ICA as feature extraction methods and Gallery sets of FERET and FEI databases as datasets. Table 1 shows these values.

2) Decompression Complexity

In order to compare the amount of reduction in time complexity of our proposed algorithm, decompression time complexity orders in different JPEG compressed domain stages for gray scale images are tabulated in the first row of Table 2, where *N* is the number of pixels or transform coefficients and A and D are the number of AC and DC coefficients, respectively. We have also calculated the runtime percentage and cumulative runtime percentage for each stage of decompression process, to show their relative complexity. The results obtained on Gallery images of FERET and FEI databases are shown in the second and third rows of Table 2, respectively.

In a similar manner, time complexity order and runtime percentages of JPEG decompression stages for color images are shown in Table 3. It is worth noting that in color JPEG decompression process, compared to gray-scale one, there is an additional stage which is inverse color transformation ($Y'C_BC_R$ to RGB). Moreover, decompression is done separately on luminance and chrominance components. Thus, the complexity order and the runtime percentages in these stages are reported for three components.

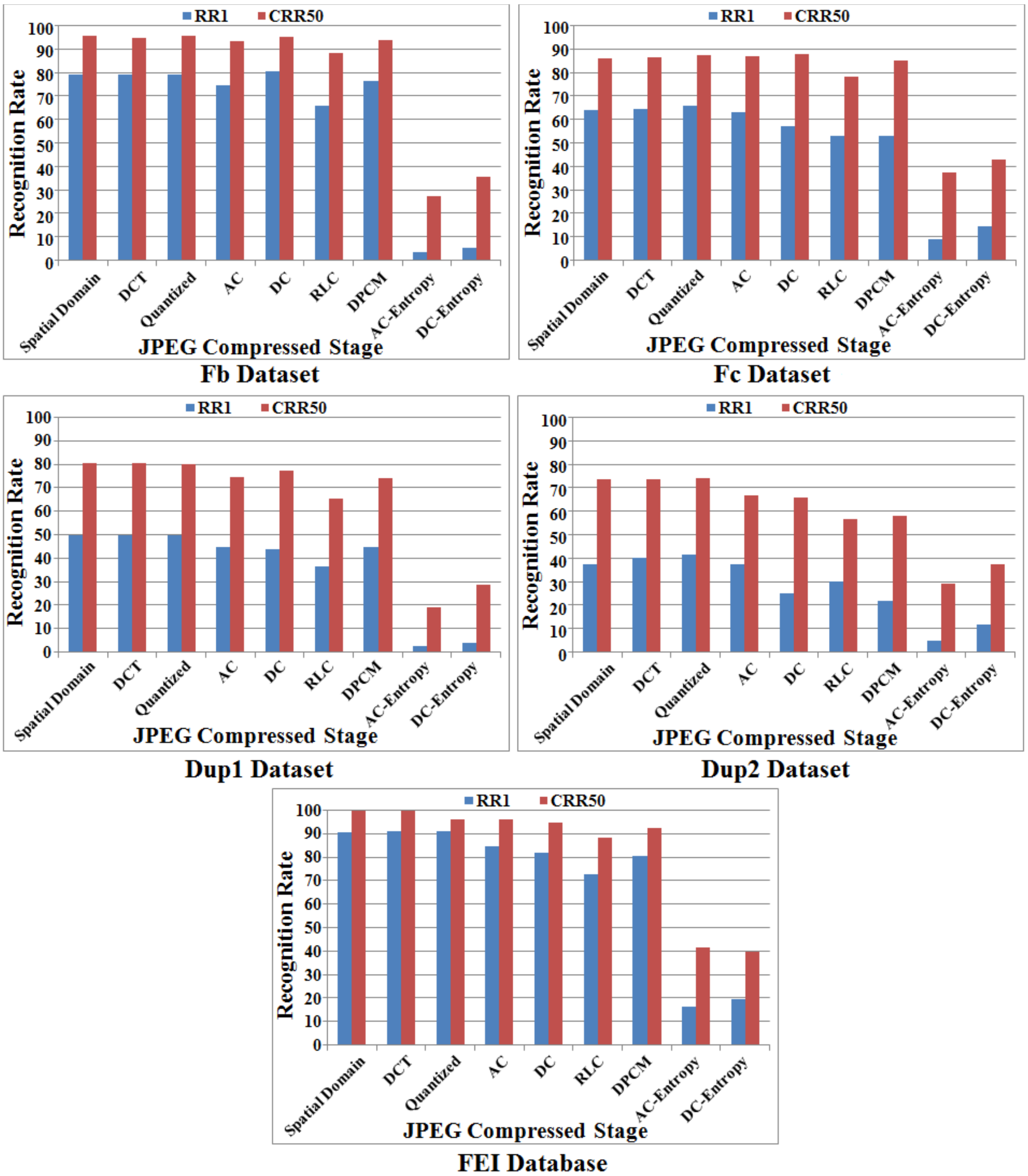

Figure 5 First recognition (RR1) and cumulative recognition ranks to 50^{th} rank (CRR50) obtained using PCA in different stages of the JPEG compressed domain with four datasets of FERET and FEI databases.

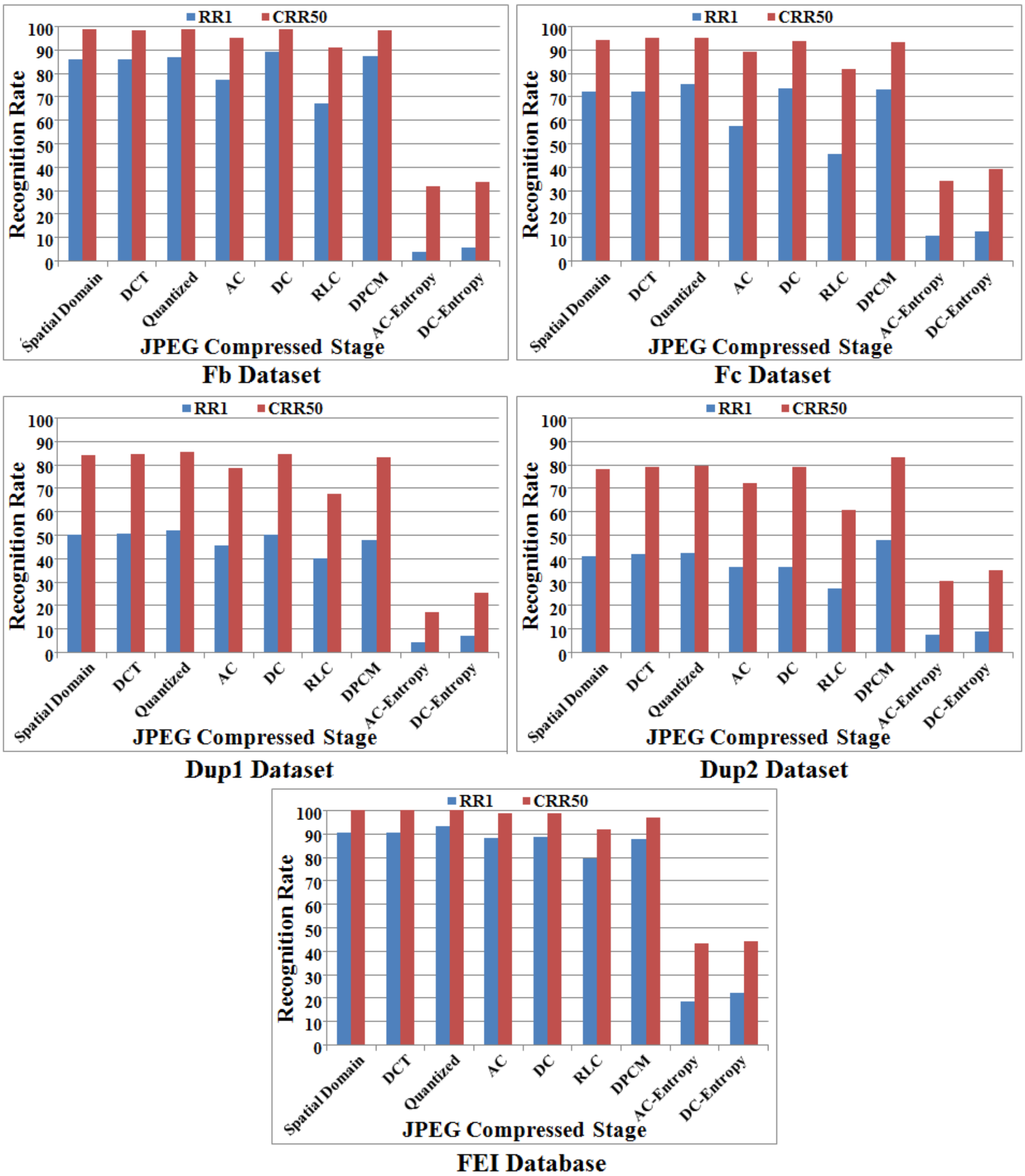

Figure 6 First recognition and cumulative recognition ranks to 50th rank obtained using ICA in different stages of the JPEG compressed domain with four datasets of FERET and FEI databases.

Table 1 AUMSV using PCA and ICA extraction method in different stages of the JPEG compressed domain.

Feature Extraction Method	JPEG Compressed Stages								
	Spatial Domain	*DCT*	*Quantized*	*AC*	*DC*	*RLC*	*DPCM*	*AC Entropy*	*DC Entropy*
PCA	5.85	5.82	5.82	7.88	7.14	10.61	9.02	29.76	27.03
ICA	4.08	4.05	4.03	6.97	6.53	9.79	8.18	27.38	26.11

Table 2 Time complexity order and runtime percentages of JPEG decompression stages for gray scale images.

Time estimation metrics	JPEG Decompression Stages						
	DC Entropy Decod.	*AC Entropy Decod.*	*DPCM Decod.*	*RLC Decod.*	*Inverse Zigzag Scan*	*Inverse Quant.*	*Inverse DCT*
Complexity order	O(D log D)	O(A log A)	O(D)	O(A)	O(N)	O(N)	$O(N^2)$
Runtime percentage	33.16	06.98	03.91	06.33	04.89	05.27	39.46
Cumulative Runtime percentage	33.16	40.14	44.05	50.38	55.27	60.54	100

Table 3 Time complexity order and runtime percentages of JPEG decompression stages for color images.

Time estimation metrics	JPEG Decompression Stages							
	DC Entropy Decod.	*AC Entropy Decod.*	*DPCM Decod.*	*RLC Decod.*	*Inverse Zigzag Scan*	*Inverse Quant.*	*Inverse DCT*	*Inverse Color Transfor.*
Complexity order	**O(D log D)**	**O(A log A)**	**O(D)**	**O(A)**	**O(N)**	**O(N)**	**$O(N^2)$**	**O(N)**
Runtime percentage	**31.98**	**06.80**	**03.81**	**06.17**	**04.77**	**05.14**	**38.28**	**3.05**
Cumulative Runtime percentage	**31.98**	**38.78**	**42.59**	**48.76**	**53.53**	**58.67**	**96.95**	**100**

B. comparative studies

1) Recognition Accuracy

Obviously, from the computational complexity point of view, the best stage for face recognition in compressed domain is the closest stage to full compressed one; in which the results are comparable with those obtained in fully decompressed stage.

We observed in our experimentations that quantized coefficient stage is the best stage in compressed domain for face recognition. Fig. 7 shows the normalized recognition (NRR_1) and normalized cumulative recognition rank ($NCRR_{50}$) curves in DCT coefficients stage using PCA and ICA extraction methods. Normalization Factors are First recognition rank and the cumulative recognition rank in spatial domain. Fig. 8 shows similar curves for quantized coefficients stage. These results clearly show that, not only the recognition accuracy in compressed domain is not degraded compared to spatial domain, but also it is slightly improved using DCT coefficients and even more in case of quantized coefficients. Concerning next stages of decompression process, Fig. 5 and Fig. 6 show that recognition accuracy will be degraded, compared to the case of spatial domain. We have also showed in Table 1 that quantized coefficients have the highest discriminatory power amongst other stages of the compressed domain.

We compared the efficiency of the feature extraction methods, i.e. PCA and ICA, as shown in Fig. 9.. In this figure, first recognition rank (Fig. 9.A) and cumulative recognition rank up to 50_{th} rank (Fig. 9.B) in quantized stage (the best stage in the compressed domain) are illustrated. The results presented in Fig. 9 along with those tabulated in Table 1 clearly show the superiority of ICA compared to PCA.

Based on all of the experimental results, we can conclude that quantized coefficients stage is the best stage in JPEG compressed domain, even compared to spatial domain. Also, ICA method is the best approach to be considered for feature extraction in the recognition system.

2) Time Complexity

Regarding time analysis results of the JPEG decompression stages in gray scale space (Table 1 and Table 2), it is obvious that by using quantized coefficients, inverse DCT and quantization stages are omitted in recognition process. In addition, thanks to the fact that in zigzag scan stage, quantized coefficients are not modified, zigzag scanned coefficients can be directly used in recognition process. Thus, inverse zigzag scan stage can also be omitted. As a result, by omitting the inverse DCT, quantization and zigzag scan stages, about 50% of the decompression overhead is reduced. This overhead, in term of complexity order is $O(N^2 + N + N)$ lower than that of the recognition in fully decompressed domain.

As it is mentioned in Section III-B, in case of JPEG compressed color images, only luminance components are used in face recognition system, and there is no need to decompress two chrominance components. As a result, in addition to inverse DCT, quantization and zigzag scan stages, chrominance components decompression stages are also completely omitted. This means that in a face recognition system with JPEG compressed color images as input, by using our proposed approach, about 84% of the whole decompression process can be eliminated without any degradation in recognition rate and even with an improvement in this result.

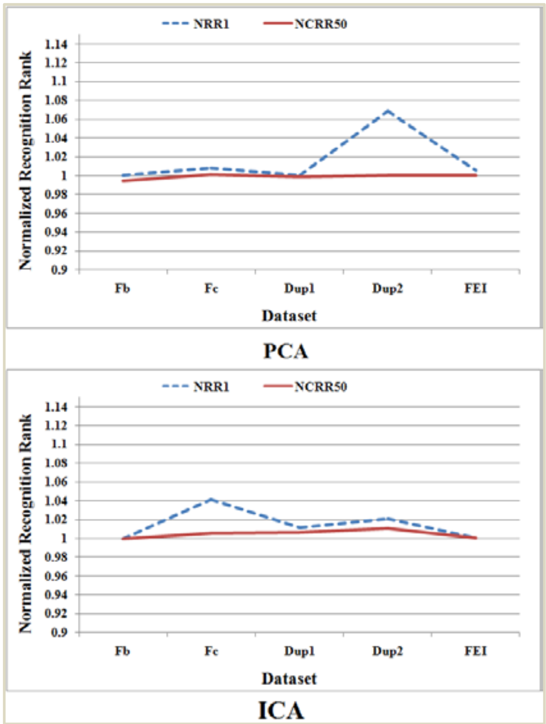

Figure 7 NRR_1 and $NCRR_{50}$ curves obtained using PCA and ICA of DCT coefficients.

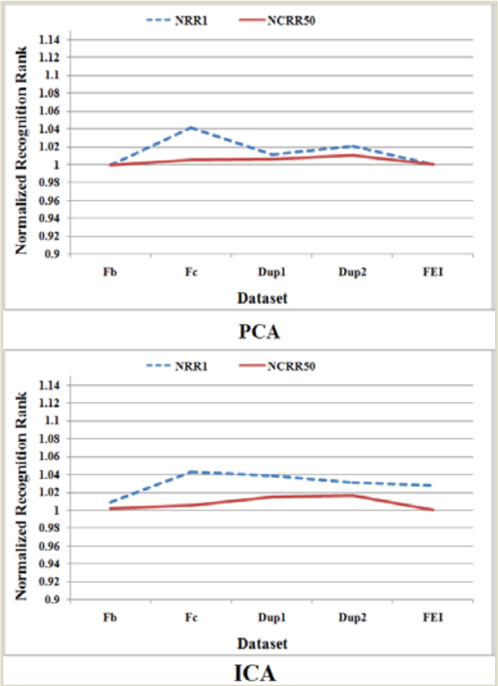

Figure 8 NRR_1 and $NCRR_{50}$ curves obtained using PCA and ICA of quantized coefficients.

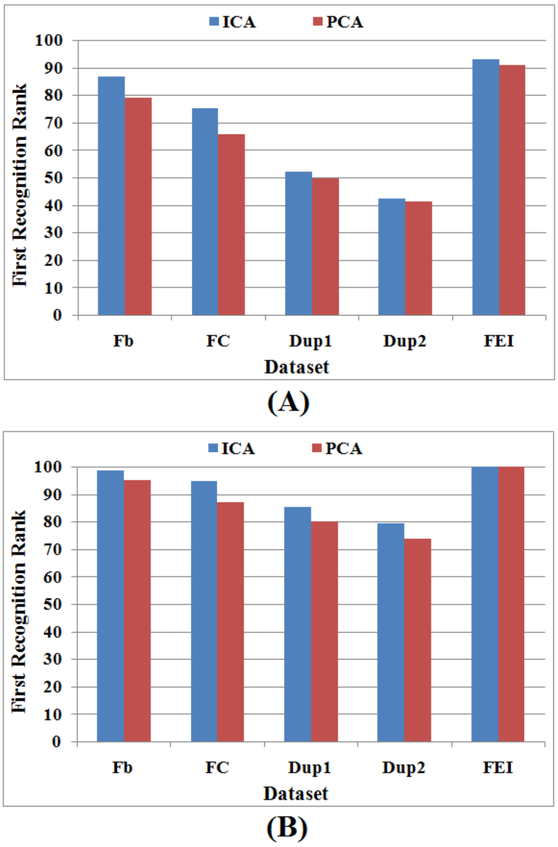

Figure 9 (A) RR_1 and (B) CRR_{50} obtained using PCA and ICA feature extraction methods in quantized stage.

C. *Analysis of results*

In this Section, we present analysis and discussion on the results obtained from applying face recognition in different stages of the JPEG compressed domain. In order to analyze the efficiency of DCT coefficients in a face recognition system, first, it should be noted that appearance based face recognition methods could be directly implemented in orthonormal transformed data, e.g. DCT domain [14]. The reason for such efficiency is stability of energy in the transformed image. In addition, another property of DCT contributes in such performance. In spatial domain, the illumination changes affect entire pixels in the image space. However, these changes are only involved in DC and a few low frequency AC coefficients in DCT domain. Thus, extracted vectors using feature extraction methods are less influenced in terms of illumination changes. As a result, using DCT coefficients leads to a slight improvement in recognition accuracy, compared to the spatial domain.

Two important reasons could be mentioned for efficiency of the face recognition using quantized coefficients. First, by assigning more quantization level to more important coefficients in the quantization tables, regarding the rate-distortion issue, no significant changes will be observed in low frequency coefficients. Furthermore, the negative effects of the high frequency coefficients are significantly reduced. To be more precise, the facial expressions are presented in high frequency coefficients. Above all, the details of a face which are presented in the high frequency coefficients are noticeably changed during the time and are not useful in recognition process. Thus, by reducing the contribution of the high frequency coefficients in recognition process, recognition accuracy is improved.

By separating AC and DC coefficients, energy of an image is splitted on two parts. In our experiments, we found that approximately 41% and 59% of the facial images' energy are in DC and AC coefficients, respectively. Thus, recognition accuracy is degraded by performing recognition process on DC or AC coefficients, exclusively.

Suppose that face recognition accuracies using DPCM and RLC coded coefficients are not degraded, respectively compared to those obtained using DC and AC coefficients. Thus, DPCM and RLC coefficients could be combined in recognition system which leads to the elimination of the inverse DPCM and RLC stages in decompression process. However, the experimental results clearly showed that recognition accuracy using DPCM and RLC coded coefficients are significantly degraded. For analyzing such degradation, histograms of DPCM and DC coefficients for all used images are illustrated in Fig. 10. We performed Kolmogorov-Smirnov Test to examine behavior of the histograms and it was found that distribution of DC and DPCM coefficients are Uniform and Laplace (so-called Double Exponential [34]), respectively. This transformation is the result of calculating difference between neighbor DC coefficients during DPCM coding. As it can be seen, most of the coefficients which are corresponded to different subjects are close to zero. Thus, intra-class differences and discriminatory power (as it showed in Table. 1) are declined, so that recognition accuracy is also degraded.

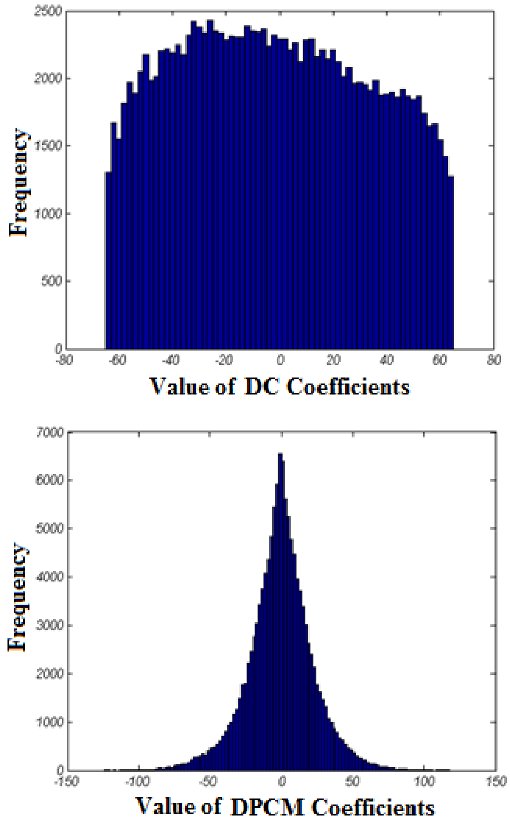

Figure 10 Histograms of DPCM and DC coefficients

In addition, it is obvious that the results obtained by performing face recognition in RLC coded coefficients are degraded, compared to those on AC coefficients. Variable length coding is the most important reason for this issue which leads to locating corresponding coefficients of RLC vectors obtained from different facial images in different positions, even for different vectors obtained from the same subject. As a consequence, the features are not appropriately represented for comparison and degradation in the recognition accuracy.

Finally, due to the degraded results in RLC and DPCM stages, recognition process in the final stage (entropy decoding) of JPEG compressed domain is not efficient.

V. Conclusions

In this paper, different feature spaces have been applied in different stages of JPEG compressed domain in order to determine the best feature space and the best stage for face recognition purpose. Experiments have been done on FERET and FEI databases using PCA and ICA feature extraction methods, and the recognition accuracy and time complexity metrics of the proposed methods have been calculated and compared in various stages of JPEG compressed domain.

Experimental results and analysis showed that quantized coefficients, in form of zigzag scanned, is the best stage of the JPEG compressed domain for face recognition. As a result, approximately 50% and 84% reduction have been reached in term of decompression process, respectively for gray scale and color JPEG images, and the recognition accuracy is improved compared to that of face recognition in spatial domain.

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