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Gender and Identity Recognition in a Visually Lossless Encoded Image

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Abstract— The last decades have experienced astounding growth in the use of images that has resulted in large repositories of images that have to be stored and transmitted, bringing new techniques and standards to compress such data sets efficiently. Lossless, or numerically lossless, methods commonly achieve moderate compression ratios, whereas lossy methods achieve higher compression ratios at the expense of image fidelity. Performing recognition algorithms on these compressed images require extraction of original image from the codestream. The goal of this research is to examine the feasibility of implementing gender recognition algorithm and identity recognition algorithm directly into JPEG2000 compressed domain avoiding inverse discrete wavelet transform (IDWT). Such an approach would consequently enable the use of compressed images in recognition purposes, thus reducing both computational time and storage requirements.

Keywords— JPEG2000, Visibility threshold, Bit plane coding, Eigen faces, Discrete Wavelet Transform, Dead Zone Quantization

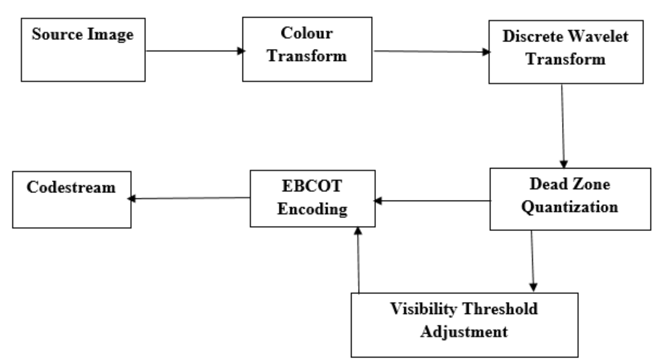
I. INTRODUCTION

Recognition Algorithms have gained much attention in recent years and have become one of the most successful applications of image analysis and understanding. They have been widely used in applications in the field of security, learning, role recognition, etc. Images are expected to be increasingly stored in compressed form. Although JPEG is currently a de facto standard for storing still images, JPEG2000 [1] seems to give promising results and will probably replace JPEG in near future. Wavelets were never used as Cohen- Daubechies-Feauveau (CDF) 9/7 wavelet, which is a part of JPEG2000standard. In this project, we explore the performance of some well-known recognition algorithms like Gender Recognition and Identity Recognition using Eigen Faces in JPEG2000 compressed domain.

Compressed domain means that instead of decompressing the compressed images and then using (distorted) pixel values as input to face recognition methods, transformed coefficients are used as inputs. The decoding process should be interrupted after the entropy decoding and the obtained DWT coefficients used as inputs to classification methods. LL subband of DWT transform consists of almost all the features as the original image. Thus, instead of applying recognition algorithm on larger sized images, we can directly apply it to smaller sized LL subband which would make it computationally efficient.

The recognition can be made more efficient by reducing quantization distortion in the compressed image. We also present a method to reduce the size of codestream and hiding the coding artifacts caused by quantization in JPEG2000 by visibility threshold masking. The obtained wavelet coefficients are then encoded using EBCOT encoder [2] or Bit-Plane Encoder which returns the codestream.The codestream obtained is then decoded using Bit-Plane Decoder. LL Subband of the decoded image is used as an input for recognition algorithms.

We explore the performance of closest matching Gender Recognition Algorithm and Identity Recognition Algorithm in JPEG2000 compressed domain. It is visual information from human face that provides one of the more important sources of information for gender classification. The situation is different for a computer and a human. Here we use Eigen values and Eigen vectors to determine the Eigen faces (general face which can represent all others faces) of an image. These Eigen faces are then used to find the closest match of the input image with the training data.
Then we apply the Eigen face approach to recognize the identity of a person which is a very important and yet an unassessed problem.



I. PROCEDURE

A. *Encoding Phase*

Experimental results in [11] indicate that face recognition performance in JPEG2000 compressed image is comparable, or even better in some cases, than face recognition performance in pixel domain. These results can be used to perform the gender recognition algorithm, proposed in [10], in our model of visually lossless encoded image.

The input image is being compressed and encoded into smaller bit streams in the Encoding Phase. The input image which has three colour components (red, green, and blue) is typically transformed to an image with one luminance component (Y) and two chrominance components (Cb and Cr) for improved compression performance. CDF 9/7 DWT Transform is then performed which is followed by Dead Zone Quantization. It employs the separable DWT to

Fig. 2. Comparison of original image and LL subband obtained after performing DWT Level 1.

decompose an image into several subbands, each having different spatial frequency and orientation [4].

Wavelet coefficients obtained after DWT transform are modelled by a generalised Gaussian Distribution [8]. These coefficients are then quantized using the dead –zone quantizer. The quantization distortion is modelled.

These quantized coefficients are further adjusted according to the Human Vision Model. Base Threshold t_b is first computed which is used to compute the adjusted threshold $\hat{t}$. This $\hat{t}$ is then used to re-quantize the wavelet coefficients. t_b depends on variance ($\sigma_b^{\ 2}$) and linear parameters (a_b and r_b) where b is the codeblock. $\hat{t}$ is computed using self-masking factor ($s_b[n]$) and texture activity (m_b).

The obtained coefficients are then encoded using EBCOT encoder [2] or Bit-Plane Encoder which returns the codestream.The codestream obtained is then decoded using Bit-Plane Decoder. LL Subband of the decoded image is used as an input for recognition algorithms.

B. Recognition Phase

After decoding the image, we get the transformed coefficients of the quantized image. The LL subband of the decoded image will have similar features as that of the original image as shown Figure 2. We can use the LL subband coefficients for gender recognition instead of using the original image which would make the recognition computationally effective.

Thus, the codestream of a compressed image is decoded and then the LL subband is fed as an input to the recognition algorithms saving time due Inverse Discrete Wavelet Transform, Inverse Colour Transform and De-quantization, thus reducing computational time and storage requirements. Also, we will improve the efficiency by using visibility thresholds for reduction of quantization distortions. These features are extracted from the LL subband of the image which are very similar to that of the original image. Gender Recognition using Eigen faces and Closest Matching is performed to recognize the gender of the image. Identity Recognition is done next by again using the Eigen faces to compute the weights of the vectors. These weights are then used to compute the minimum Euclidean Distance w.r.t training dataset.

The techniques of Eigen faces and Closest Matching classifier are combined to categorize gender from facial knowledge. We will firstly establish the Eigen faces from the training images and obtain the projection coefficients for training and testing images by the Eigen faces. The weight vectors of the input image are first computed. These weight vectors are then compared with all the images in the dataset (consisting of 200 male and 200 female images) and the closest matching image is found. The gender of the closest match of the input image is the desired output for our algorithm.

II. DESIGN AND ANALYSIS

After obtaining the wavelet coefficients they are encoded using the Bit-plane encoder. It is based on the concept of decomposing a multilevel image into a series of binary images and compressing each of these binary image. The image is decomposed into bit-planes. The number of bit-planes will depend on the highest value coefficient. A pair of bit-planes is chosen for 2 adjacent intensity positions. XOR gate is applied to the bit-planes and recorded in another bit-plane.

$$g_i = a_i \oplus a_{i+1},\ 0 \le i \le m-2$$

$$g_{m-1} = a_{m-1}$$

where $g_{m-1} \ldots g_2 g_1 g_0$ represent the intensity variations, $a_{m-1} \ldots a_2 a_1 a_0$ represent bit-plane values in each bit-plane of the original image.

EBCOT encodes each bit-plane in three coding passes. The three coding passes in the order n which they are performed on each bit-plane are s**ignificant propagation pass, magnitude refinement pass**, and **cleanup pass**.

The code block is partitioned into horizontal stripes, each having a nominal height of four samples. As shown in the diagram, the stripes are scanned from top to bottom. Within a stripe, columns are scanned from left to right. Within a column, samples are scanned from top to bottom.

Each coefficient bit in the bit plane is coded in only one of the three coding passes, and for each coefficient in a block is assigned a binary state variable called its significance state that is initialized to zero (insignificant) at the start of the encoding. The significance state changes from zero to one (significant) when the first nonzero magnitude bit is found. The context vector for a given coefficient is the binary vector consisting of the significance states of its eight immediate neighbor coefficients. For each pass, contexts are created which are provided to the arithmetic coder.

The magnitude refinement pass includes the bits from coefficients that are already significant. The clean-up pass is the final pass in which all bits not encoded during the previous passes are encoded (i.e., coefficients that are insignificant and had the context value of zero during the significance propagation pass).The very first pass in a new code block is always a clean-up pass.

It is worth emphasizing that the base Visibility Thresholds computed are adaptive codeblock-by-codeblock and image-by-image. This is in contrast to a fixed set of base VTs (one per sub band) is employed, independent of the image to be encoded. The adaptively of the base VTs proposed here stems from the dependence of the quantization distortion model on coefficient variance.

A. Recognition Algorithms

We Obtain a set S with M images. Each image is coverted into a vector of size N and placed into the set. The average matrix Ψ has to be calculated, then subtracted from the original faces (Γ_i) and the result stored in the variable Φ_i

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \quad (1)$$

$$\Phi_i = \Gamma_i - \Psi \quad (2)$$

Next, the covariance matrix is calculated

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n \Phi^T{}_n = AA^T \quad (3)$$

$$A = \{\Phi_1, \Phi_2, \Phi_3, \ldots\ldots, \Phi_n\} \quad (4)$$

$$L_{mn} = \Phi^T{}_m \Phi_n \quad (5)$$

Here L is a MxM matrix. Once we have found the eigenvectors, v_l, we find out u_l - the Eigen faces

$$u_l = \sum_{k=1}^{M} v_{lk}\Phi_k \quad (6)$$

We establish the Eigen faces from the training images and obtain the projection coefficients for training and testing images by the Eigen faces. The weight vectors of the input image are first computed. These weight vectors are then compared with all the images in the dataset (consisting of 200 male and 200 female images) and the closest matching image is found. The gender of the closest match of the input image is the desired output for our algorithm.

Closest Matching Algorithm

Input: Training data
Output: Gender

Closest_Matching(training_data, test_data)
Compute_EigenFaces(training_data)
Weights_train←eigen_faces ^{T} . training _data
Weights_test←eigen_faces ^{T} . test _data
For each test case vector t in test_data
For each training tuple d in training_data
X ←eucledian_dist(t,d)
End
Test_class(t) ←test_class(min(x))
End

Gender Recognition Using Closest Matching

Algorithm: Gender Recognition
Input: Encoded image
Output: Gender

EntropyDecoding(I);
Gender ←ClosestMatching(LL subband of I)

Identity Recognition Using Eigen Values and Eigen Vectors

Algorithm: Face Detection using Eigen Faces

Input: Eigen face components of images

Output: Euclidean Distance Graph

First we compare our input image with our mean image and multiply their difference with each eigenvector of the L matrix. Each value would represent a weight and would be saved on a vector Ω.

$$\omega_k = \mu_k{}^T(\Gamma - \Psi) \quad (7)$$

$$\Omega^T = \{\omega_1, \omega_2, \ldots\ldots, \omega_M\} \quad (8)$$

We now determine which face class provides the best description for the input image. This is done by minimizing the Euclidean distance.

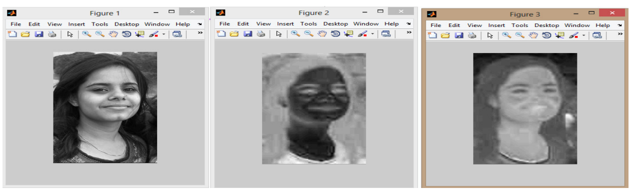
$$\varepsilon_k = \| \Omega - \Omega_k \|^2 \quad (9)$$

The input face is considered to belong to a class if ε_k is below an established threshold θ_ϵ. Then the face image is considered to be a known face. If the difference is above the given threshold, but bellow a second threshold, the image can be determined as a unknown face. If the input image is above these two thresholds, the image is determined NOT to be a face.

IV. RESULTS

A. *Colour Transform*

The input image is multiplied with a transform matrix as shown below to get the Y, Cb and Cr coefficients of the RGB image as shown in Figure 3.

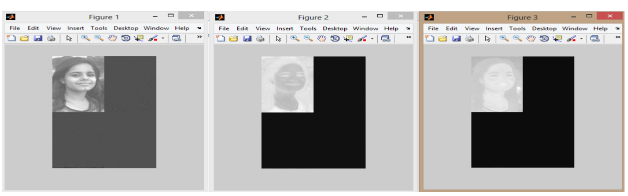


(a) (b) (c)

Fig 3. Y, Cb and Cr Components after performing colour transform on a colored image

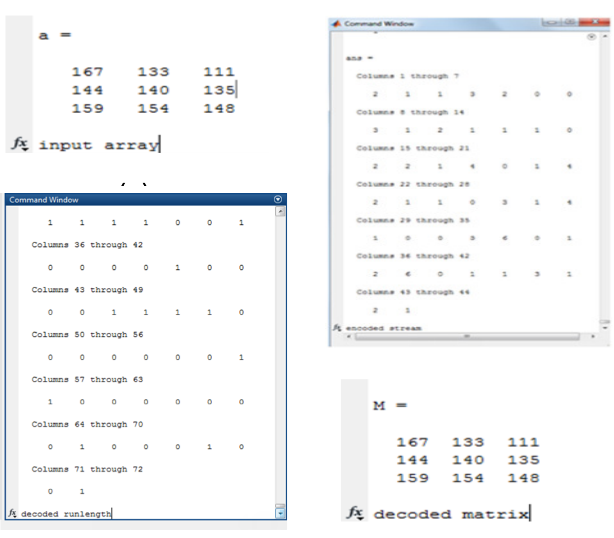
B. *DWT Transform*

Owing to more information, the Y component is chosen for further DWT transformation which yields the output as shown in Figure 4. It shows DWT level 1 where only the LL band concerned is shown.



(a) (b) (c)

Fig. 4 Output of Level 1 DWT transform on Y, Cb and Cr Components



(c)

Fig. 5 a) Input Matrix of Bit-Plane Encoder, b) Output encoded stream of Bit-Plane Encoder, c) Decoded Run Length, d) Output of Bit-Plane Decoder

C. *EBCOT and Bit Plane Encoder*

This is now fed into the Bit-plane encoder after performing the three passes of EBCOT. The input is a matrix which is encoded and then decoded to form the same matrix.

The Y component of image after DWT transform and visibility threshold adjustments is gone through 3 passes of EBCOT and then it is encoded with every Bit plane from 0 to 7. Image is further decoded by a Bit plane decoder which is then fed into the recognition algorithm.

D. *Recognition*

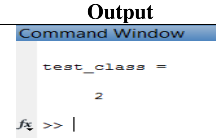
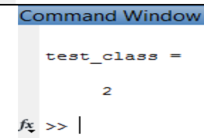
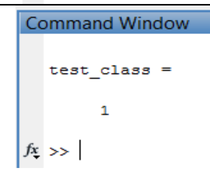
Input Image	Output
	
	
	

Table 1. Results of Gender Recognition on Compressed Images

Gender Recognition algorithms used a set of 200 images of both males and females. These are obtained from Feret's database. The images for identity recognition are from MUCT database. The algorithm is also checked for the images of friends and relatives. MATLAB R2010, R2011 and R2011 are used for the coding purposes.These gender recognition results correspond to two test classes. Test class=1 is male while Test class=2 is female.

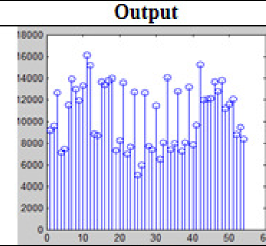
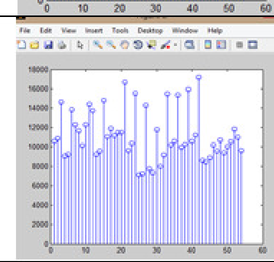
Input Image	Output
	
	

Table. 2. Results of Identity Recognition on compressed images.

Further, when we perform identity recognition on the LL subband of the image we find out the distance of source image with every other image in the database. If the distance value is below the threshold value we assign the identity of the image to that image in database.

V. CONCLUSION

The efficiency observed for two algorithms, namely Gender Recognition and Identity Recognition showed that the results were similar or better when LL subband was provided as an input to the recognition system. Total number of images taken was 116(54 female and 62 male) out of which the images identified correctly are shown in Fig 8. Hence we see even by using the LL subband we get more efficiency in case of DWT level 1than when normal image is identified. Thus since we get the same efficiency we have successfully saved time for inverse colour transform, dequantization and inverse DWT by using the LL subband.
Since the LL subband occupies one fourth of the space that a normal image take we can summarize the time and space complexity in table.

	Normal Image	Compressed Domain (Level 1 DWT)	Compressed Domain (Level 1 DWT)
Time Complexity	$O(n^2)$*Size	$(O(n^2) – O(n^2/4) – O(n))$*Size	$(O(n^2) – O(n^2/16) – O(n))$*Size
Space Complexity	$O(n^2)$	$O(n^2/4)$	$O(n^2/16)$

Table 3. Time and Space Complexity of the Gender Recognition Algorithm of an Image of size n*n and Training Database with 'Size' no. of images in it

	Normal images	DWT level1:	DWT level2:
No. of male images correctly identified	54	54	53
No. of female images correctly identified	44	45	44
Efficiency	84.48%	85.34%	83.62%

Table 4. Efficiency of Gender Recognition on normal images and LL subband images

REFERENCES

[1]. Han Oh, A.Biligin, M.W. Visually Lossless Encoding for JPEG2000. IEEE Transactions on Image Processing.vol.22,no.1,pp.189-201,2013.

[2]. Tsung-Han Tsai and Lian-Tsung Tsai. JPEG2000 encoder architecture design with fast EBCOT algorithm. International Symposium on VLSI Design, Automation and Test.pp.279-282,2005.

[3]. A. B. Watson, G. Y .Yang, J. A.Solmon, J.Villasenor , "Visibility of Wavelet quantisation noise",vol.6,no.8,pp.1164-1175,1990.

[4]. D. S. Taubman and M. W. Marcellin, JPEG2000: Image Compression Fundamentals, Standards, and Practice. Boston, MA: Kluwer, 2002.

[5]. M. Bolin and G. Meyer, "A perceptually based adaptive sampling algorithm," in Proc. SIGGRAPH Conf., 1998, pp. 299–309.

[6]. A. P. Bradley, "A wavelet visible difference predictor," IEEE Trans. Image Process., vol. 8, no. 5, pp. 717–730, May 1999.

[7]. Z. Liu, L. J. Karam, and A. B. Watson, "JPEG2000 encoding with perceptual distortion control," IEEE Trans. Image Process., vol. 15, no. 7, pp. 1763–1778, Jul. 2006.

[8]. S. G. Mallat, "A theory for multiresolution signal decomposition: The wavelet representation," IEEE Trans. Pattern Anal. Mach. Intell., vol. 11, no. 7, pp. 674–693, Jul. 1989.

[9]. Vignesh Ramanathan , Bangpeng Yaoy , Li Fei-Feiy . "Social Role Discovery in Human Events ", International Conference on Computer Vision and Pattern Recognition(CVPR) ,IEEE,2013 , pp.2475-2482.

[10]. H. Sahoolizadeh, Y. A Ghassabeh. "Face recognition using eigen-faces, fisher-faces and neural networks", Seventh International Conference on Cyberneic Intelligent Systems (CIS), IEEE, 2008,pp.1-6.

[11]. K.Delac,H.Grgic,S.Grgic. "Towards Face Recognition in JPEG2000 Compressed Domain", 6th EURASIP Conference on Speech and Image Processing, Multimedia Communications and Services, IEEE, 2007, pp.148-152. [12]. Sahoolizadeh, J; Electr.Arak; Ghassabeh Y.A., ‘’ Face recognition using eigen-faces,fisher-faces and neural networks’’, 7th IEEE Conference on Cybernetic Intelligence System, 9-10 Sept 2008, pp. 1-6

