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Copyright Authentication By Using Karhunen-Loeve Transform

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Abstract: Authentication is a raised as one of the important subject in field of security. So many techniques for improving authentication were appeared during the last three decades.This paper presents authentication by using Karhunen-Loeve transformation for copyright authentication in digital image, where four various size of watermarking image used to embed them inside the least significant bits of the cover image. The application proved that using Karhunen-Loeve transformation is very useful to improve the authentication, where the watermarking image will appear clearly only when using all eigenvalues to retrieve the watermarking from the resulted image. The number of eigenvalues were studied to give their effect on the robustness of the authentication, the direct proportional relationship appeared between the number of used eigenvalues and the authentication.

Keywords- Karhunen-Loeve Transform, KLT, PCA watermarking, .image processing

INTRODUCTION

With the rapid development of computer network and multimedia technology, dissemination of information in the forms of audio, video and still image has become widespread. The problem of data piracy and copyright breach is a major concern when information is transmitted over networks, especially in the World Wide Web environment[1].

Digital watermarking technique has been presented and widely researched to solve some important issues in the digital world, such as copyright protection, copy protection and content authentication[2].

Digital image watermark is a signal or image of authentication, discreetly incorporated to the original digital image of interest (usually referred to as target image). Controlled distortion is introduced in the original image to produce the watermarked image. [3]. Watermarks are imperceptible data embedded in the multimedia signals. The hidden data can be extracted and identified by the intellectual property right owner, and used as an evidence of copyright[1]. The method used to insert the watermark along with a secretly kept key, form the watermarking process. The illegal subtraction of the watermark from the watermarked image is usually referred to as "attack". A good watermarking process, even if publicly available, would prevent a successful attack without distorting the original image. A large number of watermarking algorithms work with some form of unitary transformation of the image of interest, as for example the Discrete Wavelet, or Discrete Fourier, or Discrete Cosine Transform (DWT, DFT, DCT)[3].

Karhunen-Loeve transforms KLT is one of the most important methods for feature extraction, and widely used in deleting redundant feature and lossely image compression [4]. The input vectors, with high dimension and correlated, can be represented in a lower dimension space and decorrelated[5] .

The major problems in pattern recognition and image processing is the dimensionality reduction. If we can reduce the dimensionality of the feature space, then we will achieve better accuracy with lesser storage and computational complexities[6]. The KLT transform the original image into a new image with components (pixels) which ideally are statistically independent. The watermark is introduced during the transformation process[7]. KLT can be seen as a method for data compression or dimensionality reduction, and that can best be used to represent the data[8]

REVIEW OF LITERATURE

From the view of geometry, KL transform translates and rotates the axes and establishes a new coordinate according to the variance of the data. From the point of energy compressing, KL transform is the best transform. It can not only reduce the dimension while keeping the average square error the least before and after the transform, but also has excellent expression and cluster character after transform[9]. The Karhunen-Loeve Transform (KLT) (also known as Hotelling Transform and Eigenvector Transform), which is closely related to the Principal Component Analysis (PCA) and widely used in data analysis in many fields[10,11].

The KL transform has found many applications in traditional fields such as statistics and communication. In computer vision, it was used for a variety of tasks such as face recognition , object recognition , motion estimation,, visual learning, and object tracking[12]. This transform is based on the concepts of statistical properties of image pixels or pattern features. Principal component analysis (PCA) forms the baiis of the Karhunen-Loeve (KL) transform for compact representation of data . The KL transform and the theory behind the principal component analysis are of fundamental importance in signal and image processing. The principle has also found its place in data mining for reduction of large-dimensional data sets. It has been successfully applied to text analysis and retrieval for text mining as well[6].

Wang proposed a new watermarking scheme using principal component analysis(PCA). The proposed method inserts highly robust watermarks into still images without degrading their visual quality. Experimental results are presented, showing that the PCA-based watermarks can resist malicious attacks including low pass filtering, re-scaling, and compression coding[1].

Panagiotis and Tania proposed a novel method for watermarking of single realizations of grayscale digital images using the KLT. The proposed method is encouraging as far as imperceptibility and robustness are concerned[7]. And they proposed another novel method for watermarking of single realizations of grayscale textured images using KLT. The proposed method is encouraging as far as imperceptibility and robustness are concerned[3].

The number of ways is embedded into the target block is also enormous. This implies that a PCA watermark is very difficult to be extracted and counterfeited by any unauthorized attempts. Current studies combining PCA with other transform techniques, applying the HVS, etc., for the enhancement of reliability and robustness[1].

KARHUNEN-LOEVE RANSFORM(KLT)

The KLT was originally introduced as a series expansion for continuous random processes by Karhunen and Loeve. For random sequences Hotelling first studied what was called a method of principal components, which is the discrete equivalent of the KL series expansion. Consequently, the KL transform is also called the Hotelling transform or the method of principal components[4].

The KLT is an optimal method for approximating a set of vectors or images, which was used in image processing and computer vision for several tasks such as face and object recognition. Its computational demands and its batch calculation nature have limited its application.

This transform make the internal information come out. It could be more easily for us to well understand the information distribution, information structure and information magnitude, and to get the information features about the data.

KLT indicates the all information in an orthogonal space. New variables are independent each other. Eigenvalue illustrates the information magnitude. The bigger eigenvalue is, more the information has[13].

METHODOLOGY

Consider vectors fk sized R×1, k = 1, 2, ... , K, as samples drawn from a stochastic process. The principal component transform, or Karhunen-Loeve transform [1], is defined as

$$g_k=Af_k,\quad k=1, 2,...,K \qquad (1)$$

Where A is an R×R transform matrix with columns being eigenvectors of the covariance matrix CF of the image process F. The columns in A is arranged such that the corresponding eigenvalues are in a descending order.

PCA decorrelates the elements in the vectors so that the covariance matrix CG of the transform-domain process G is diagonal, with the diagonal entries equal to the variances of the vector elements in the transform domain.

An image S, sized M×N, may be segmented into I×J = K small data groups, each of which arranged as a 2D array sized P×Q where P=M/I, and Q=N/J. These data groups can also be organized into R×1 vectors, where R=P×Q. The way in which the image data are divided and reorganized can be varied considerably.

In this study, a simple interleaving sub-sampling scheme is used:

$$f_{i,j}(p,q)=S[P(i-1)+p,Q(j-1)+q],\quad \begin{matrix} i=1,2,\ldots,I \\ j=1,2,\ldots,J \\ p=1,2,\ldots,P \\ q=1,2,\ldots,Q \end{matrix} \qquad (2)$$

or alternatively, using a single subscript and the vector representation:

$$f_k=f_{i,j},\quad k=(i-1)J+j=1,2,\ldots,K \qquad (3)$$

The image is now viewed as K samples drawn from an R-dimensioned stochastic process, F, on which PCA as described in (1) may be performed. The resulting transform-domain image G can be considered as K vectors sized R×1, arranged in the same way as (2) for F, namely,

$$(4)\quad \begin{bmatrix} G= & g_{11} & g_{12} & \cdots & g_{1K} & \\ & g_{21} & g_{22} & \cdots & g_{2K} & =[g_1\, g_2\, \ldots . g_K] \\ & . & . & & . & \\ & . & . & & . & \\ & . & . & & . & \\ & g_{R1} & g_{R2} & \cdots & g_{RK} & \end{bmatrix}$$

Reorganize the rows in G into R blocks of size I×J (=K):

$$q1,q2,\ldots,qr,\ldots,qR \qquad (5)$$

with respective eigenvalues of the covariance matrix CF equal to

$$\lambda r:\lambda 1>\lambda 2>\ldots>\lambda r>\ldots>\lambda R> \qquad (6)$$

The component qr in (5) can be written in a matrix

$$q_r = \begin{bmatrix} g_{r,11} & g_{r,12} & \cdots & g_{r,1J} \\ g_{r,21} & g_{r,22} & \cdots & g_{r,2J} \\ \vdots & \vdots & & \vdots \\ g_{r,I1} & g_{r,I2} & \cdots & g_{r,IJ} \end{bmatrix} \quad (7)$$

The eigenvalue λr is the variance (energy) of block qr. The first block q1 contains most of the energy, while the energy contents decreases rapidly as the subscript rising due to the high degree of energy concentration of PCA.

Transform step of KLT is following[5] [14].

- Input the original data X, which is a M×N matrix.
- Calculate the covariance matrix of X, which is a N×N.
- Calculate the eigenvalues and eigenvector L of C, eigenvalues are sort by size, each eigenvector as a column and correspond to a certain eigenvalue
- Calculate the eigenvalues and eigenvector L of C, eigenvalues are sort by size, each eigenvector as a column and correspond to a certain eigenvalue.
- Calculate the eigenvector which correspond to the choosing eigenvalues, X=LY.

PERFORMANCE MEASUREMENT

To know the amount of difference between the original image and the target image, three kinds of performance measurement applied. To demonstrate the performance of this scheme, We use the Peak Signal to Noise Ratio (PSNR) for evaluating the quality of the images, and Correlation Coefficient (CC) to judge the difference between original images and extracted images. [15][16]

$$MSE = \frac{1}{mn}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}\left[steg\_im(x,y) - cover\_im(x,y)\right]^2 \quad (8)$$

$$PSNR = 10\log_{10}\left(\frac{(\text{Max value of Gray level})^2}{MSE}\right) \quad (9)$$

$$CC = \frac{\sum_m\sum_n (A_{mn}-\bar{A})(B_{mn}-\bar{B})}{\sqrt{\left(\sum_m\sum_n (A_{mn}-\bar{A})^2\right)\left(\sum_m\sum_n (B_{mn}-\bar{B})^2\right)}} \quad (10)$$

$\bar{A}, \bar{B}$ Average or mean of matrix elements

Cover image watermarking image

Figure (1): Used images

THE ALGORITHM APPLICATION

The applied algorithm involves four steps as follows:

Step 1 : involved using least significant bit (LSB) technique to embed the watermarking image within the cover image (standard Lena image used as a cover) see Fig. 1. The cover images were (512x512 pixel, gray), and (256x256 pixel, gray) with watermarking images (16x16 pixel, gray), (32x32 pixel, gray), (64x64 pixel, gray) and (128x128 pixel, gray).

Step 2 : KLT applied on the resulted images.

Step 3 : selected portions of eigenvector toke and then inverse of KLT applied. Then the watermarking image extracted from the results, and then the cover image and the watermarking image displayed as shown in the Fig. 2, and Fig. 3.

Step 4 : MSE, PSNR, measured by using (8),(9) for the resulted images (for both cover and watermarking images) to evaluate the quality of them, CC measured too to judge the difference between the extracted images and the originals by using (10). The results shown in the tables (1,2,3,4,5), and drawn in Fig. 4, and Fig. 5.

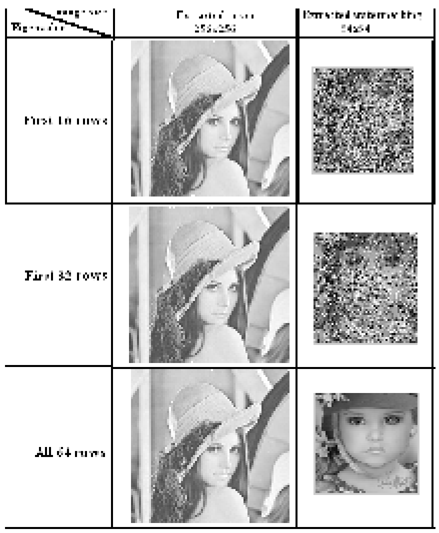
DISCUSSION OF RESULTS

Both of Fig.2 and Fig.3 show the watermarking image which extract from resulted image. The extracted cover image with size (256×256) appears clearly in Fig.2 when using first 16 rows of eigenvalue. While the extracted watermarking image with size (64×64) not appear clearly, that due to use LSB method for embedding and that the energy is concentrated at the beginning of the KL values which gives the important features of the image, i.e. the bits which had the watermarking image features had least energy. While using first 32 rows of the eigenvalue leads to clarify the extracted watermarking image more but still some noise exist. When using first 64 rows of the eigenvalue (all values) leads to extracted watermarking image appear clearly without noise, that's due to using all values with high and low energy.

Fig.3 shows that extracted cover image with size (512×512) appear clearly by using only first row of the eigenvalue. But the watermarking image with size (128×128) didn't appear when using only first row, first 8 rows, first 16 rows and first 25 rows from eigenvalue. While using first 32 rows of eigenvalue leads to appear the extracted watermarking image but with noise. Least noise in the extracted watermarking image when first 45 rows of eigenvalue used, and clear extracted watermarking produced when 64 rows (all rows) of eigenvalue used.

Table 1 shows that both PSNR values and correlation values for (128×128) watermarking image embedded in (512×512) cover image had directly proportional with number of rows of eigenvalue that used to extract the watermarking image, see Fig. 4a and Fig.5a.

The results in the tables 2,3,4,5 confirm the direct proportion between PSNR and correlation values with the number of the rows of eigenvalue that used to extract the image, where for each table differ size for cover and watermarking images used, see Fig. 4b, 4c, 4d, 4e and Fig. 5b, 5c, 5d, 5e.



Figure(2): Extracted images from KL space.

TABLE(1): PSNR & CORRELATION (COVER IMAGE 512×512 & EXTRACTED WATERMARKING IMAGE 128×128).				
# Of EigenValue	PSNR		Correlation	
	Cover image 512×512	Extracted watermarking image 128×128	Cover image 512×512	Extracted watermarking image 128×128
First Row	24.5278	7.6370	0.9511	-0.0134
First 8 Rows	36.5417	9.1015	0.9970	0.0490
First 16 Rows	45.8150	10.3660	0.9996	0.2340
First 25 Rows	50.4312	11.1665	0.9999	0.3185
First 32 Rows	51.5340	12.30	0.9999	0.4487
First 45 Rows	50.9346	13.3550	0.9999	0.5418
All 64 Rows	50.4602	70	0.9999	1

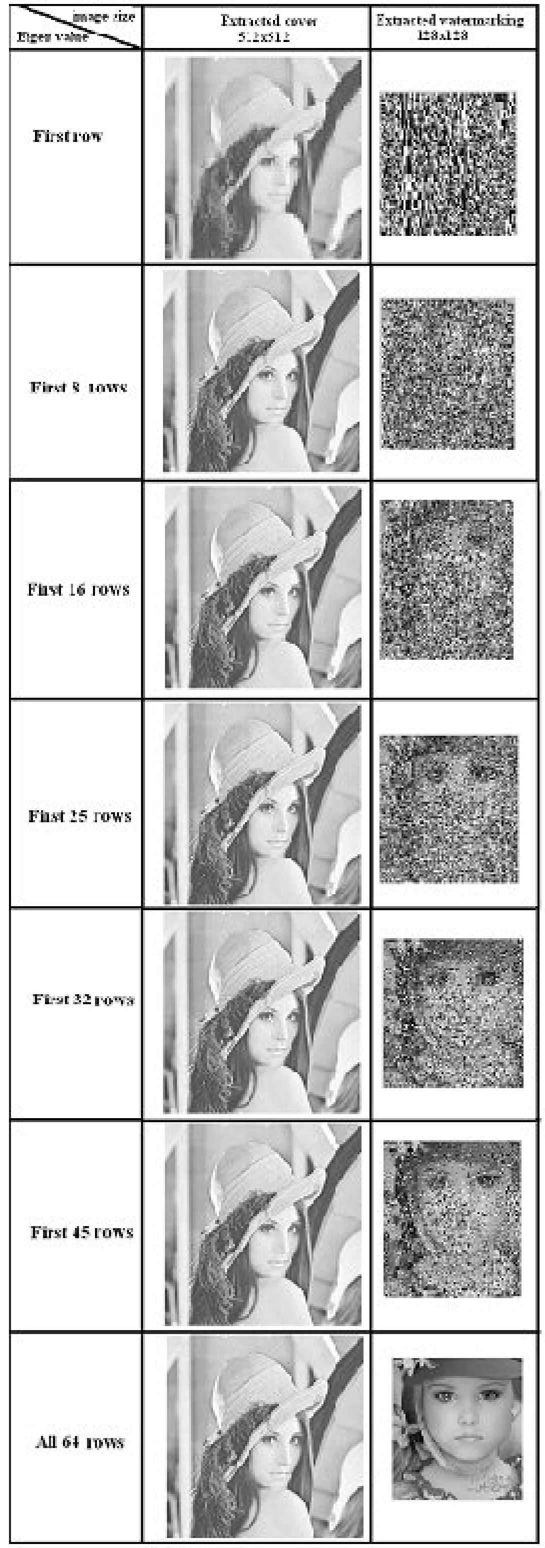


Figure (3). Extracted Images From KL Spase

TABLE(5): PSNR& CORRELATION (COVER IMAGE 256×256 & EXTRACTED WATERMARKING IMAGE 32×32).				
# Of Eigen Value	***PSNR***		***Correlation***	
	Cover image 256×256	***Extracted watermarking image 32×32***	***Cover image 256×256***	***Extracted watermarking image 32×32***
First Row	***21.8612***	***8.0108***	***0.9066***	***0.0139***
First 8 Rows	***29.8181***	***8.0776***	***0.9856***	***0.0403***
First 16 Rows	***33.7585***	***8.2432***	***0.9942***	***0.0761***
First 25 Rows	***37.0651***	***8.4637***	***0.9973***	***0.1021***
First 32 Rows	***39.2160***	***8.4591***	***0.9984***	***0.0932***
First 45 Rows	***42.2764***	***9.3226***	***0.9992***	***0.2123***
All 64 Rows	***56.5175***	***70***	***1***	***1***

TABLE(2): PSNR & CORRELATION (COVER IMAGE 512×512& EXTRACTED WATERMARKING IMAGE 64×64).				
# Of EigenValue	***PSNR***		***Correlation***	
	Cover image 512×512	***Extracted watermarking image 64×64***	***Cover image 512×512***	***Extracted watermarking image 64×64***
First Row	***24.5277***	***7.5904***	***0.9511***	***0.0223***
First 8 Rows	***36.5742***	***9.1222***	***0.9970***	***0.045***
First 16 Rows	***46.2584***	***10.6863***	***0.9997***	***0.2797***
First 25 Rows	***52.6659***	***11.817***	***0.9999***	***0.3892***
First 32 Rows	***56.3631***	***12.8798***	***1.0000***	***0.4910***
First 45 Rows	***56.3631***	***14.5266***	***1.0000***	***0.6425***
All 64 Rows	***56.5048***	***70***	***1***	***1***

TABLE(3): PSNR& CORRELATION (COVER IMAGE 512×512 & EXTRACTED WATERMARKING IMAGE 32×32).				
# Of Eigen Value	***PSNR***		***Correlation***	
	Cover image 512×512	***Extracted watermarkin g image 32×32***	***Cover image 512×512***	***Extracted watermarking image 32×32***
First Row	***24.5278***	***7.048***	***0.9511***	***0.0199***
First 8 Rows	***36.5846***	***8.8440***	***0.9970***	***0.0549***
First 16 Rows	***46.3908***	***10.4138***	***0.9997***	***0.3267***
First 25 Rows	***53.5029***	***11.3454***	***0.9999***	***0.4153***
First 32 Rows	***58.7699***	***12.4874***	***1.0000***	***0.5072***
First 45 Rows	***60.7221***	***14.2005***	***1.0000***	***0.6417***
All 64 Rows	***62.5960***	***70***	***1***	***1***

TABLE(4): PSNR& CORRELATION (COVER IMAGE 256×256 & EXTRACTED WATERMARKING IMAGE 64×64).				
# Of EigenValue	***PSNR***		***Correlation***	
	Cover image 256×256	***Extracted watermarki ng image 64×64***	***Cover image 256×256***	***Extracted watermarking image 64×64***
First Row	***21.8609***	***8.1772***	***0.9066***	***-0.0374***
First 8 Rows	***29.8100***	***8.4533***	***0.9856***	***-0.0017***
First 16 Rows	***33.7293***	***8.6861***	***0.9942***	***0.0222***
First 25 Rows	***36.9797***	***8.7797***	***0.9973***	***0.0503***
First 32 Rows	***39.9983***	***8.7967***	***0.9983***	***0.0989***
First 45 Rows	***41.8048***	***9.7338***	***0.9991***	***0.2165***
All 64 Rows	***50.4536***	***70***	***0.9999***	***1***

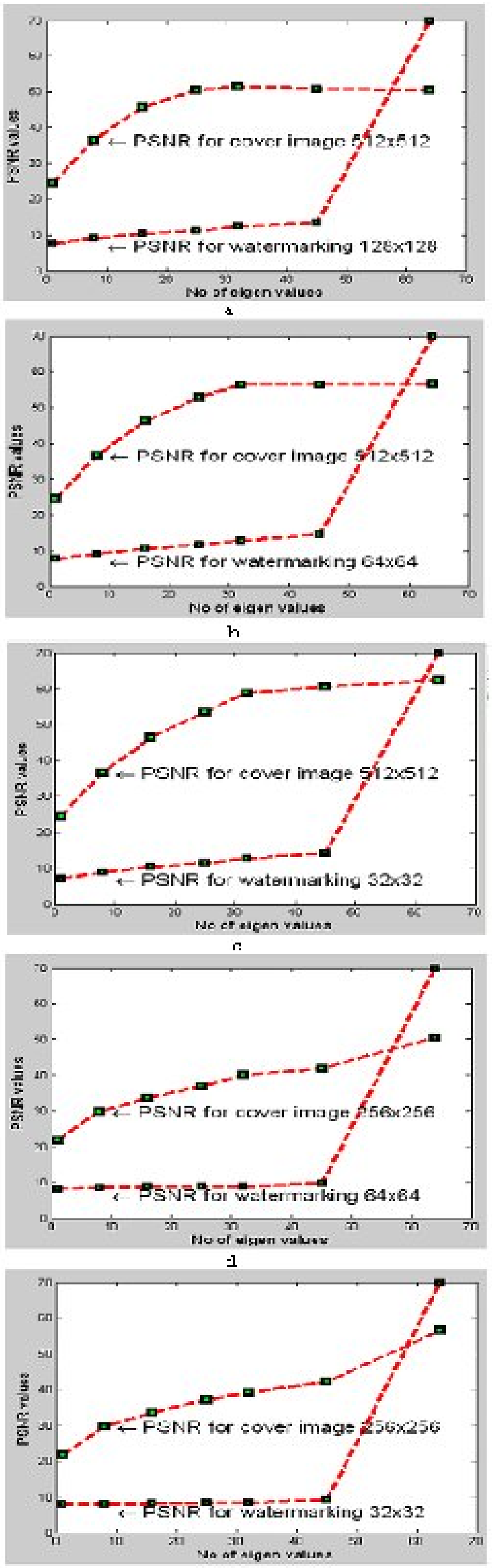


Figure (4) : PSNR values for cover image & watermarking

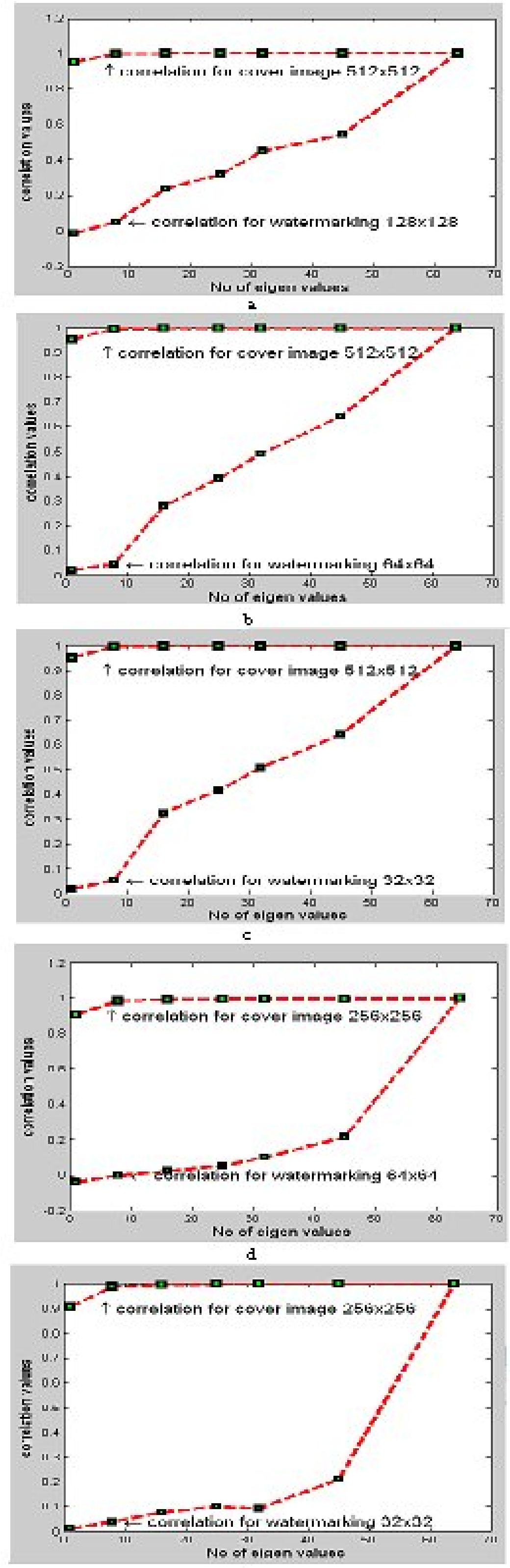


Figure (5): Correlation values for cover image & watermarking

CONCLUSIONS

As a conclusion of all results seen before, the image size of watermark does not affect the PSNR and correlation factor which was so close to one especially when whole the eigenvalues were included and indeed in the LSB, i.e. the watermarking clearly appear.

Therefore when using KL transform the results show that the PSNR value was maximum value, and the correlation value was nearest to one for all size of the watermarking image, only when all eigenvector displayed. That means the watermarking image appears only when using all eigenvector, this due to that the watermarking image embed by using the least significant bit method. Therefore when using KL transform, the values at the beginning of the eigenvector array has highest energy, while the least energy values are at the end of the array values, and because of that the watermarking stored in the LSB of the image, therefore taking the first part of eigenvector will leads to appear the important features of the cover image only without watermarking.

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توثيق حقوق الطبع باستعمال تحويل كارونن-لوف

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الخلاصة

برزت الوثوقية كواحدة من المواضيع المهمة في حقل الأمنية. لذا ظهرت تقنيات عديدة لتطوير الوثوقية في العقود الثلاثة الأخيرة. تم في هذا البحث استخدام تحويل KL للتحقق من وثوقية حقوق الطبع في الصور الرقمية. حيث تم استخدام أربعة أحجام من صورة العلامة المائية لإخفائها داخل البت الأقل أهمية للصورة الغطاء. وأثبتت النتائج أن استخدام تحويل KL مفيد جداً لإثبات وثوقية حقوق الطبع, حيث أن العلامة المائية لن تظهر واضحة إلا باستخدام كل القيم المميزة. تم دراسة عدد القيم المميزة لإعطاء تأثيرها على مدى الوثوقية, وظهرت العلاقة طردية بين عدد القيم المميزة المستخدمة والوثوقية.