Localized Subspace Analysis For Digital Image Watermarking On Pyramid Directional Filter Bank

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Abstract- *Localized subspace analysis for digital image watermarking on contourlet transform is the powerful method to robust the peak signal to noise ratio (PSNR) and means square error (MSE). The hasty increase in usage of personal computers, internet, multimedia leads to simply sharing of digital data or communication, and however ease of use of numerous of image processing tools facilitates not permitted use of such data. Attackers can easily copy, remove or change digital data. It is an illegal reproduction of digital data, and it leads to innovation of some algorithms which can keep intellectual property rights of digital data. Newly, watermarking has been recognized as a main tool to accomplish copyright authentication. It can be embedded in mass data not only in spatial domain as well as but also in frequency domain. This proposed method can be implemented on laplacian pyramid and directional filter bank. it gives better results as compared to existing DWT and singular value decomposition.*

Keywords- PCA, ICA, LDA and distance measures

I. INTRODUCTION

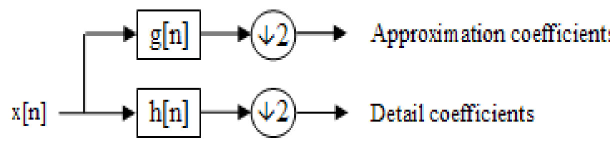
Watermarking techniques will loosely be classified supported their inherent characteristics: visible and invisible. Visible watermarks: a clear alteration of the digital image by appending a "stamp" on the image is termed a clear watermark. This system directly maps thereto of the pre-digital era wherever a watermark was imprinted on the document of option to impose genuineness. Invisible watermarks: against this, An invisible watermark, because the name suggests that this can be invisible for the foremost half and is employed with a distinct motive. whereas the conspicuousness of visible watermarking makes characteristic legitimate and illegitimate versions straightforward, its conspicuousness makes it less appropriate for all applications. Invisible watermarking revolves around such appropriate factors that embody recognizing authentic recipients, characteristic actuality supply and non-repudiation. differently of classifying watermarking technique may be a issue of its usage: strong, fragile, or Semi-fragile, and spatial or spectral watermarks. Strong watermarks: Watermarks are often accustomed hold data of possession. Such watermarks ought to stay steadfast to the original image to do what they advertise. The intactness of the watermark is a measure of its robustness. These watermarks must be able to withstand normal manipulations to the image such as reduction of image size, lossy compression of image, changing the contrast of the images, etc. Fragile watermarks: These are complementary to robust watermarks and are, as a rule, more change-sensitive than robust watermarks. They lose their mettle when they are subject even to the smallest changes. Their use lies in being able to pin-point the exact region that has been changed in the original watermarked image. The methods of fragile watermarking range from checksums and pseudo-random sequences in the LSB locale to hash functions to sniff any changes to the watermark. Semi-fragile watermarks: These watermarks are a middle ground between fragile watermarks and fragile watermarks. They engulf the best of both worlds and are more resilient than fragile ones in terms of their robustness. They also are better than robust watermarks in terms of locating the regions that have been modified by an unintended recipient. Spatial watermarks: Watermarks that are applied to the "spatial domain of the image" are said to be spatial watermarks [5]. Spectral watermarks: These are watermarks that are applied to the "transform coefficients of the image". [5] The rest of the paper is organized as follow. The ground rules for a good watermark will be laid down in the next section. After describing the various stages of the watermarking process, I will also go over three algorithms for watermarking, and finally analyze the algorithms. Report a bug the information is hidden such solely the meant recipient is aware of concerning the existence of message. In cryptography the info is reborn into a code before transmission. Embedding stage: In this stage, the image to be watermarked is preprocessed to prime it for embedding. This involves converting the image to the desired transform. This includes the discrete cosine transform (DCT), the discrete Fourier transform (DFT) and the wavelet domains. The watermark to be embedded may be a binary image, a bit stream or a pseudo-random number that adheres to, say, a Gaussian distribution. The watermark is then appended to the desired coefficients (low frequency or intermediate frequency) of the transform, as recommended by Human Visual System (HVS) research. The watermarked image is the output of this process and is obtained by performing an inverse transform on the altered transform coefficients [9]. Distribution stage: The watermarked image obtained above is then distributed through digital channels (on an Internet site). In the process, this may have undergone one of several mappings, such as compression, image manipulations that downsize the image, enhancements such as rotation, to name a few. Peter Meerwald [9] refers to the above as “coincidental attack”. Any of the above may put the watermarking scheme to test, as we will see in the ensuing section. In addition, malicious attacks also are possible in this stage to battle with the watermark. These are referred to in Meerwald’s work [9] as “hostile attacks”. Extraction stage: In this stage, an attempt is made to regain the watermark or signature from the distributed watermarked image. This stage may need a private key or a shared public key, in combination with the original image, or just the watermarked image [9]. Decision stage: In this stage, the extracted watermark is compared with the original watermark to test for any discrepancies that might have set in during distribution. A common way of doing this is by computing the Hamming distance [9].

II. DWT and SVD

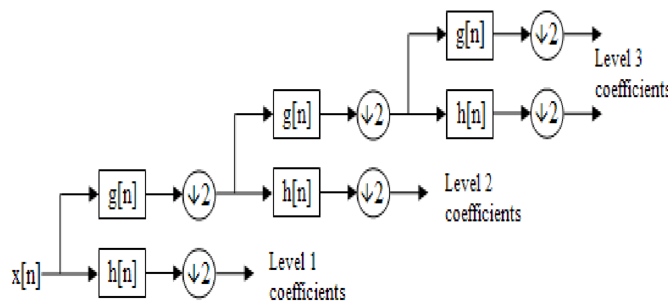
Discrete wavelet transforms (DWT)

The most commonly used set of discrete wavelet transforms was formulated by the Belgian mathematician Ingrid Daubechiesin 1988. This formulation is based on the use of recurrence relations to generate progressively finer discrete samplings of an implicit mother wavelet function; each resolution is twice that of the previous scale. In her seminal paper, Daubechies derives a family of wavelets, the first of which is the Haar wavelet. Interest in this field has exploded since then, and many variations of Daubechies' original wavelets were developed.[1]. The dual-tree complex wavelet transform (ℂWT) is a relatively recent enhancement to the discrete wavelet transform (DWT), with important additional properties: It is nearly shift invariant and directionally selective in two and higher dimensions. It achieves this with a redundancy factor of only {\displaystyle 2^{d}} substantially lower than the undecorated DWT. The multidimensional (M-D) dual-tree ℂWT is no separable but is based on a computationally efficient, separable filter bank (FB).[2]. The discrete wavelet transform has a huge number of applications in science, engineering, and mathematics and computer science. Most notably, it is used for signal coding, to represent a discrete signal in a more redundant form, often as a preconditioning for data compression. Practical applications can also be found in signal processing of accelerations for gait analysis,[6] image processing,[7] in digital communications and many others.[8] [9][10]

It is shown that discrete wavelet transform (discrete in scale and shift, and continuous in time) is successfully implemented as analog filter bank in biomedical signal processing for design of low-power pacemakers and also in ultra-wideband (UWB) wireless communications.[11]



The objective of the proposed work it to study the use of edge and texture orientation as watermarking image features in watermarking image retrieval. The basic architecture of Digital watermarking system is shown in figure.



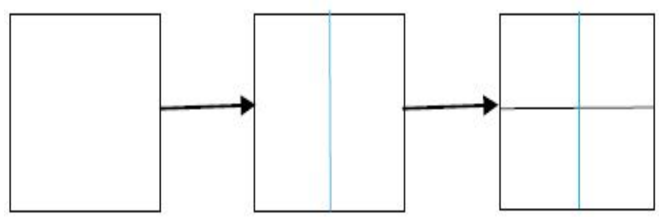


Fig.2 The process of 2-D DWT decomposition

Fig: decomposition in DWT

The facial expression recognition based on dimensionality reduction techniques system is proposed in this work. There are two issues in building a digital watermarking system. Every watermarking image in the watermarking image data base is to be represented efficiently by extracting significant feature. Relevant watermarking images are to be recognized using similarity measure between query and every watermarking image in the watermarking image data base. The performance of the proposed digital watermarking system can be tested by retrieving the desired number of watermarking images from the database. The advantage recognition rate and recognition time is the main performance measures in the proposed digital watermarking system. The average recognition rate is known as the average percentage number of images belonging to the same watermarking image as the query watermarking image in the top 'N' matches. 'N' indicates the number of recognized images.

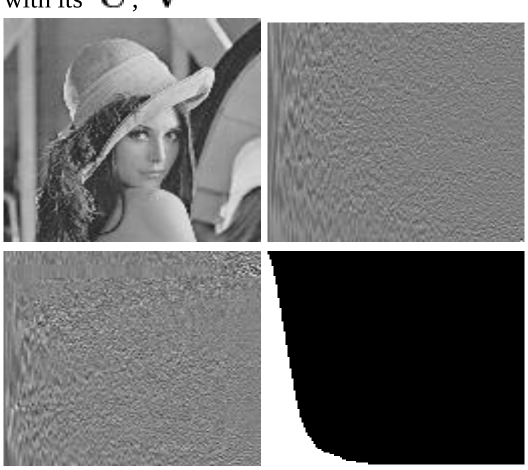
A. Singular Value Decomposition

Let the 2D image array be represented by a matrix $\mathbf{A}=[a_{ij}]_{M\times N}$ with rank equal to R. Here we assume $R \leq M \leq N$. Now we consider the following eigenvalue problems for the $M \times M$ *eigenimages* $\sqrt{\lambda_i}[\mathbf{u}_i\mathbf{v}_i^T]$, where the outer product $\mathbf{u}_i\mathbf{v}_i^T$ is an M by N matrix.

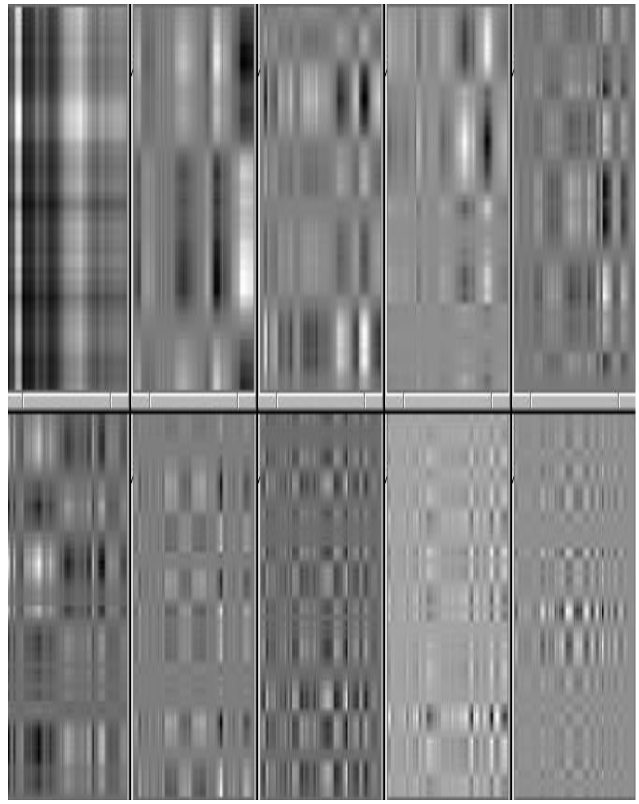
SVD transform pair:

$$\begin{cases} \mathbf{U}^T\mathbf{A}\mathbf{V}=\mathbf{\Lambda}^{1/2} \\ \mathbf{A}=\mathbf{U}\mathbf{\Lambda}^{1/2}\mathbf{V}^T \end{cases}$$

Example: The Lenna image $\mathbf{A}$ of size $N=128$ together with its $\mathbf{U}$, $\mathbf{V}$



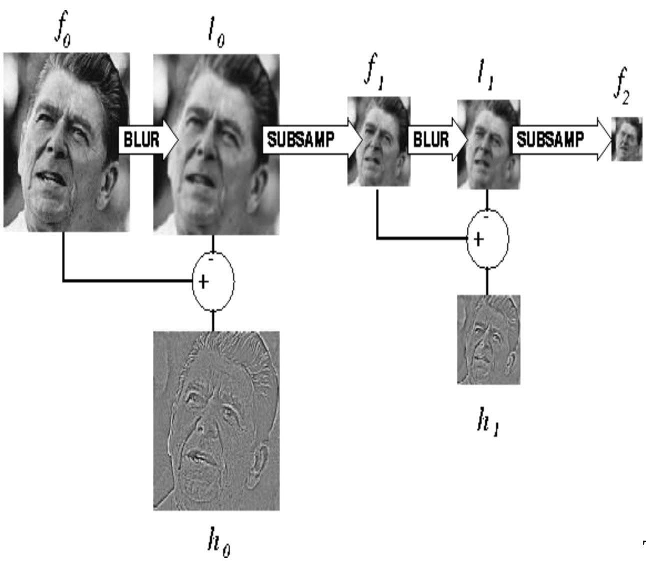
The first 10 eigen-images of the Lenna image:



Principal Components Analysis (PCA) is a statistical technique for data reduction which is taught to students mostly with a pure mathematical approach. This paper describes how teachers can introduce students to the concepts of principal components analysis by means of letter recognition. The described approach is one of an active learning environment (with hands-on exercises can be implemented in the classroom), a platform to engage students in the learning process and may increase student/student and student/instructor interaction. The activities require use of some basic matrix algebra and Eigen-value/eigenvector theory. As such they build on knowledge students have acquired in matrix algebra classes.

Former attempts to develop a more creative instruction approach for PCA can be found with Dassonville and Hahn (Dassonville, 2000). They developed a CD-ROM geared to the teaching of PCA for business school students. The test of this pedagogical tool showed that this new approach, based on dynamic graphical representations, eased the introduction to the field, yet did not foster more effective appropriation of those concepts. Besides, when the program was used in self tuition mode, the students felt disconnected from the class environment, as Dassonville and Hahn claim themselves. Provides real world data with their analysis stories about various topics, PCA included. Since only applications are presented, without any background information about the method itself, students unfamiliar to PCA, will not reach a deeper understanding about PCA and will keep stabbing at a recipe approach

Pyramid directional filter bank (PDFB)



To rigorously define ICA we can use a statistical “latent variables” model. Assume that we observe n linear mixtures x1...xn of n independent components. Let us denote by A the matrix with elements aij . Generally, bold lower case letters indicate vectors and bold upper-case letters denote matrices. All vectors are understood as column vectors; thus xT, or the transpose of x, is a row vector. Using this vector-matrix notation, the above mixing model is written as x = AS. The statistical model is called independent component analysis, or ICA model. The ICA model is a generative model, which means that it describes how the observed data are generated by a process of mixing the components si. The independent components are latent variables, meaning that they cannot be directly observed. Also the mixing matrix is assumed to be unknown. All we observe is the random vector x, and we must estimate both A and s using it. This must be done under as general assumptions as possible. However, in the basic model we do not assume these distributions known (if they are known, the problem is considerably simplified.) For simplicity, we are also assuming that the unknown mixing matrix is square, but this assumption can be sometimes relaxed. Then, after estimating the matrix A, we can compute its inverse, say W, and obtain the independent component.

III. PROPOSED ALGORITHM

Proposed method is presented below:

Choose an image W with the size (M*N), M and N are rows and columns.
2. Decompose the image in the contourlet transform domain as thirty two sub bands with contourlet coefficients.
3. Select the high frequency sub bands with directionality and anisotropy.
4. These sub bands are used to increase the robustness.
5. The watermark image to be embedded can be arranged as a set of matrices W s, d (i, j) with the size (WM *WN) and pseudo random binary values
s and d are indicate the scale and the direction of contourlet sub bands.
6. Watermarked image is generated as the combinations of watermark image are product with the same size of pseudo random data and highest frequency sub band of original image.
7. Embedded watermark into the sub bands of an image is accomplished according to

O' s, d (i, j) = O s, d (i, j) +& M s, d (i, j) W s, d (i, j)
Where O s, d (i, j) and O' s, d (i, j) are the original contourlet coefficient and the watermarked contourlet coefficients.
8. Perform inverse operation for entire watermarked image.
9. Extract the original image and secret image from the watermarked image.
10. Calculate the MSE and PSNR values from the images MSE = (O' s, d (i, j) - O s, d (i, j))2/M*N

PSNR = 10*log (28-1)2/MSE

Recognition performance in terms of average recognition rate and recognition time of the proposed digital watermarking system is tested by conducting an experiment on hybrid approach watermarking database. A watermarking database [6] test set was constructed by selecting 100 images of 10 individuals, ten images per person. These images of a person used for training and testing. the experimental results are tabulated in Table 1. Since the recognition accuracy of the sub-pattern
Image, several sizes of sub-pattern images were used in our experiments as shown below: 56×46(S=4), 28×23(S=16), 14×23(S=32), 7×23(S=64), and 4×23(S=112). Result has been presented in hybrid approach with S<64.

Feature selection

Figure2: Sample image

A sample image from watermarking database and by using sub-pattern technique it can be divided by equal parts. Feature of the query image size is (64×1) by using sub-pattern method. Some of the recognized results when all the 10 images (N=10) in one subject of the image database are recognized are shown in figure 3. From the query image feature is taken based on sub-pattern method .After that in this paper we take only 64 feature of this query image. That may be depends up on the sub-parts of this image(S=16). For each sub-pattern we consider four positive eigenvectors that is largest eigenvector of the subpart. It is represented as only local feature of the query image. After that combination of all sub-parts local feature it can be represented as global feature of the query image. Comparative performance of all training global feature with this query image finally recognized results images with top left image as query image. Subpattern method and principal component analysis [8] can significantly improve the recognition accuracy of sub pattern vertically centered method. Since the vertical centering process centers the data by removing the mean of each image, it can be used to eliminate the effect of the values. In other words, the property of vertical centering process [9] can be helpful in eliminating the shifted values of original-pixels. Further, the sub-pattern technique can be utilized to encourage the efficiency of the vertical centering process. Therefore, sub-pattern technique is actually useful to vertical centering process of sub-pattern technique. The vertical centering may benefits for the recognition in varying illumination. Now, we have confirmed this possible forecast and strongly increased the efficiency of the vertical centering process by sub-pattern technique in this paper. From the total experimental results, it can also be seen that for expression variant test, sub-pattern technique and Eigen vector can slightly improve weighted angle based approach classifier, the similarity between a test image and training image is defined as In the weighted angle based approach method cosine measurement.

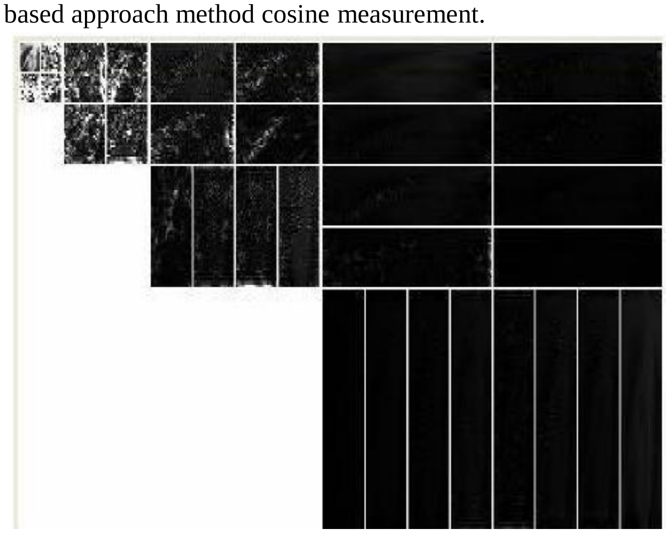


Figure 3. Decomposed image

B. Average recognized rate

The average recognized rate for the query is measured by

Table1: Comparison of Three Images With Their PSNR Value Image	DWT Watermarking PSNR (dB)	Proposed (CT) watermarking PSNR (dB)
Lena	38.1	39.54
Barbara	37.06	39.12
Peppers	36.61	38.09

C. Recognized Time

Digital watermarking system with weighted angle based approach technique for largest four eigenvector recognized time is 50.42 seconds (training time is 50 seconds and recognitized time is 0.42 seconds), hybrid approach technique for all positive eigenvector recognized time is 51.20 seconds, Existing method in PCA recognized time is 1.65 seconds, LDA time is 2.90 seconds and LPP method recognized time is 2.72 seconds.

IV. CONCLUSIONS

Facial expressions recognition based on dimensionality reduction technique. Global feature vector is generated and used for digital watermarking. Horizontal and vertical variations are considered in feature vector. Facial expression recognition based on dimensionality reduction techniques gives better performance in terms of average recognized rate and retrieval time compared to existing methods.

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