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Multipurpose image watermarking in the domain of DWT based on SVD

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***Abstract*— In this paper, we projected a new method is a multipurpose image watermarking in the domain of DWT based on SVD has been implemented. First an input image can be decomposed as different sub images using discrete wavelet transform. Then the sub pattern images are implemented with the help of single value decomposition. Choose any other sub band image has to be used to introduce in the any subpart of the given input image. Same procedure has been used as inversed to same sub band image to get the original image. Then mean square error has to be implemented to check the both original image and watermarked image. Finally peak signal to noise ratio (PSNR) to measure the better efficiency. This proposed paper gives better experimental results as compared to existing methods.**

***Index Terms*— MSE, PSNR, DWT and SVD.**

I. INTRODUCTION

The process of embedding information into another object/signal can be termed as watermarking. It is mostly agreed that the watermark is one, which is imperceptibly added to the cover-signal in order to convey the hidden data. The term "digital watermark" was first coined in 1992 by Andrew Tirkel and Charles Osborne. Actually, the term used by Tirkel and Osborne was originally used in Japan--from the Japanese-- "denshi sukashi" -- literally, an "electronic watermark". Digital watermarking is the process of embedding information into a digital signal which may be used to verify its authenticity or the identity of its owners, in the same manner as paper bearing a watermark for visible identification. In digital watermarking, the signal may be audio, pictures, or video. If the signal is copied, then the information also is carried in the copy. A signal may carry several different watermarks at the same time.

Digital watermarking can be classified as visible and invisible watermarking. In visible digital watermarking, the information is visible in the picture or video. It changes the signal altogether such that the watermarked signal is totally different from the actual signal. Typically, the information is text or a logo, which identifies the owner of the media. The image on the right has a visible watermark. When a television broadcaster adds its logo to the corner of transmitted video, this also is a visible watermark.

In invisible digital watermarking, information is added as digital data to audio, picture, or video, but it cannot be perceived as such, although it may be possible to detect that some amount of information is hidden in the signal. They do not change the signal to a perceptually great extent, i.e., there are only minor variations in the output signal. The watermark may be intended for widespread use and thus, is made easy to retrieve or, it may be a form of steganography, where a party communicates a secret message embedded in the digital signal. In either case, as in visible watermarking, the objective is to attach ownership or other descriptive information to the signal in a way that is difficult to remove. It also is possible to use hidden embedded information as a means of covert communication between individuals.

One application of watermarking is in copyright protection systems, which are intended to prevent or deter unauthorized copying of digital media. In this use, a copy device retrieves the watermark from the signal before making a copy; the device makes a decision whether to copy or not, depending on the contents of the watermark. Another application is in source tracing. A watermark is embedded into a digital signal at each point of distribution. If a copy of the work is found later, then the watermark may be retrieved from the copy and the source of the distribution is known. This technique reportedly has been used to detect the source of illegally copied movies. Digital watermarking is a technique which allows an individual to add hidden copyright notices or other verification messages to digital audio, video, or image signals and documents. Such a message is a group of bits describing information pertaining to the signal or to the author of the signal (name, place, etc.). The technique takes its name from watermarking of paper or money as a security measure. Digital watermarking can be a form of steganography, in which data is hidden in the message without the end user's knowledge.

Basics concepts of k-mean algorithm and k-medoids are discussed in section II. Proposed method is discussed in section III. Experimental results are presented in section IV. Concluding remarks are discussed in section V.

II. DIGITAL WATERMARKING

A simple example of a digital watermark would be a visible "seal" placed over an image to identify the copyright. However the watermark might contain additional information including the identity of the purchaser of a particular copy of the material. According to the human perception, the digital watermarks can be divided into two different types as follows: visible and invisible. Visible watermark is a secondary translucent overlaid into the primary image as shown in the figure. Visible watermarks change the signal altogether such that the watermarked signal is totally different from the actual signal, e.g., adding an image as a watermark to another image. Stock photography agencies often add a watermark in the shape of a copyright symbol ("©") to previews of their images, so that the previews do not substitute for high-quality copies of the product included with a license. Visible watermarks can be used in following cases: Visible watermarking for enhanced copyright protection. In such situations, where images are made available through Internet and the content owner is concerned that the images will be used commercially (e.g. imprinting coffee mugs) without payment of royalties. Here the content owner desires an ownership mark, that is visually apparent, but which does not prevent image being used for other purposes (e.g. scholarly research).Visible watermarking used to indicate ownership originals. In this case images are made available through the Internet and the content owner desires to indicate the ownership of the underlying materials (library manuscript), so an observer might be encouraged to patronize the institutions that own the material. Invisible watermarks do not change the signal to a perceptually great extent, i.e., there are only minor variations in the output signal. An example of an invisible watermark is when some bits are added to an image modifying only its least significant bits. Invisible watermarks that are unknown to the end user are steganographic. While the addition of the hidden message to the signal does not restrict that signal's use, it provides a mechanism to track the signal to the original owner. Another application is to protect digital media by fingerprinting each copy with the purchaser's information. If the purchaser makes illegitimate copies, these will contain his name. Fingerprints are an extension to watermarking principle and can be both visible and invisible. There are various spatial and frequency domain techniques used for adding watermarks to and removing them from signals. Purely spatial techniques are not robust to some attacks to the signal like cropping and zooming, whereas most frequency domain techniques and mixed-domain techniques are quite robust to such attacks. The communication of a digital watermark may be viewed as an exercise in digital communication. The message bits are encoded and embedded in a suitable carrier. The properties that are desired of the watermark, such as imperceptibility, robustness to noise and to image editing such as cropping and rotation are the factors that drive the choice of carrier. In robust watermarks, it is the combination of low signal amplitude (because the watermark is invisible) and large bandwidth (because images are typically quite large), as well as the relatively short length of the message, that dictates the use of spread spectrum for encoding the message bits. Spread spectrum is a robust and secure form of communication. In image watermarking, the spread spectrum signal is typically placed in the frequency domain to produce a watermark that is immune to image processing. Image compression techniques, such as JPEG, inspired the use of the frequency domain for embedding imperceptible watermarks in images. The first frequency domain technique was devised by Scott Burgett, Eckhard Koch, and Jian Zhao, who utilized the Discrete Cosine Transform. This and other transforms, such as the Wavelet transform, were used by Joseph O Ruanaidh, who later developed rotation and translation invariant watermarks based on the Fourier transform. Ingemar Cox popularized the use of Spread spectrum techniques for robust watermarking. Geoff Rhoads, Chief Technical Officer and founder of Digimarc Corporation, developed the PictureMarc technology.

III. PROPOSED METHOD

Proposed Algorithm

Proposed method is presented below:

1. Select the high frequency subbands with directionality and anisotropy.
2. These subbands are used to increase the robustness.
3. 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.
4. Watermarked image is generated as the combinations of watermark image are product with the same size of pseudo random data and highest frequency subband of original image.
5. Embedded watermark into the sub bands of an image is accomplished according to

   $$O'_{s,d}(i, j) = O_{s,d}(i, j) + \Omega M_{s,d}(i, j) W_{s,d}(i, j)$$

   Where $O_{s,d}(i, j)$ and $O'_{s,d}(i, j)$ are the original contourlet coefficient and the watermarked contourlet coefficients.
6. Perform inverse operation for entire watermarked image.
7. Extract the original image and secret image from the watermarked image.
8. Calculate the MSE and PSNR values from the images

   $$MSE = (O'_{s,d}(i, j) - O_{s,d}(i, j))^2/M*N$$

   $$PSNR = 10*\log (2^8-1)^2/MSE$$

IV. EXPERIMENTAL RESULTS

a) Feature extraction process

Method comparisons have been also performed. The recognition technique proposed here is much faster and provides better results for large face sets than non-automatic approaches. Also, our SIFT-based method produces better recognition results than unsupervised techniques using other face features, such as the Eigen faces [3,4] or the 2D Gabor filtering based characteristics [12]. Also, we have considered some other automatic classification algorithms to be applied for the face feature vectors. Thus, it is possible to use other clustering procedures, instead of the described region-growing algorithm, in combination with the validation indexes. Therefore, we have tested K-means algorithms and their variants [20], and Self-Organizing Feature Maps (SOFM), on the same facial feature vector sets and obtained weaker recognition results and also slower execution times. The performance parameters of several face recognition techniques are compared in the next table. The parameter values are registered for this SIFT-based unsupervised recognition method, the Eigenface algorithm of Turk & Pentland [3], the Eigenface-based method of Barbu [4], the 2D Gabor filtering approach [12], and an algorithm using SIFT features with K-means clustering. As it results from Table 1, the recognition technique provided here achieves the highest values for Precision, Recall and F_1, which means it outperforms the other methods.

Figure2: input image

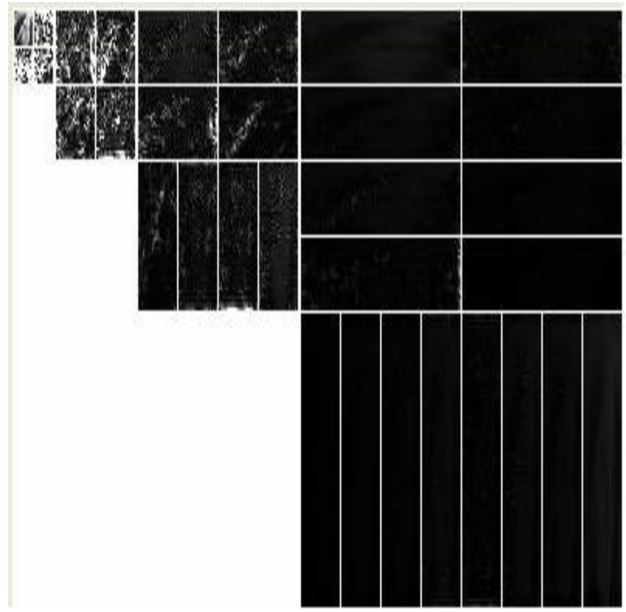

Figure3: Retrieval result

To verify the effectiveness of the proposed approach, the overall average retrieval accuracy obtained by assigning different weights to the global-based and regional-based similarity scores is shown in Fig. 9, where G and R, respectively, represent global and regional weights. It also clearly shows the effectiveness of our fusion approach (G:R = 3: 7) as it achieves the best accuracy. Additional experiments using the same test bed, the same 150 query images, and the 20 returned images are performed on several variants of our proposed method to experimentally illustrate the validity of our method. These variants include: The experimental results on 5000 images from the COREL database demonstrate that the proposed algorithm achieves good retrieval accuracy with fast speed due to the small feature vector size (i.e., 3 elements for color, 6 elements for texture, 5 elements for global EHDs, and 25 elements for semi-global EHDs). Shape or spatial information is not considered in our implementation for the efficiency consideration. It may be further integrated into the retrieval system to improve the accuracy with a compromised efficiency. Next we compare the recognition performance of IMED- embedded EFM and PEFM without normalization using the PolyU palmprint database. Fig. 7 shows the recognition rates of these two methods over different LDA dimensions. From Fig. 7, we can see that PEFM without normalization can achieve higher recognition rate than IMED-embedded EFM. This performance difference can also be explained by that, for PEFM, IMED is only embedded in the testing stage. These experimental results also indicate that, in the training stage, IMED-embedded methods even decrease the recognition performance sometimes.

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**

V. CONCLUSIONS

In this paper, we proposed method is a robust face recognition approach through different local features has been implemented. We used YALE face database in this paper. First the images are partitioned into different sub bands using discrete wavelet transform. Kernel methods are widely used for to extract the features from the different sub bands for non linear methods. sub band methods are used for extract the local features from the all sub bands. Then the all local features are formed as global features to improve the recognition efficiency. As compared to linear methods most of the researchers use non linear methods for real time applications. In this paper we proposed face recognition approach through different local features gives better results as compared to existing techniques.

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