Image Security and Authentication Using Probabilistic Principal Component Analysis

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***Abstract*—**Digital watermarking play an important role in information security. It majorly focusses on the authentication of the information. The authentication provides the genuinity of the owner of the information. The present paper focuses on the development of a novel Probabilistic Principal Component Analysis based Transform domain wtaremerking method (PPCATDW). The proposed PPCATDW method uses wavelet transformation domain for watermarking process. It interanlly uses pricnipal component analysis based ifnormation for the identification of the influential representation points of the input image. The proposed method is experimented with the fourteen images and the results show the efficacy of the proposed method.

***Index Terms*—** *Wavelet, Watermark, Gray scale and PCA.*

I. Introduction

In the recent years, the information is available in the form of multimedia. The security can be provided to the text. The text based security is considered as cryptography. The multimedia is in various forms like audio, video and image etc. with this form, the information can be transmitted in easily from one to another with the support of internet. With this increase of volume of information, the intruders can claim it as their own information. To overcome this problem, the digital watermarking methods are used. The watermarking method can be applicable to any form of the information. The image watermarking method [1] applied watermark to the image input and the owner of the watermarked images can be recognized efficiently. The watermarking method can be visible or invisible. The visible watermarking method can make the watermark visible to the public. The invisible watermarking method can make the watermark invisible to the public. The cryptography converts the input plain text to the cipher text where as the watermarking method converts the image to the watermarked images. With the cryptography, the existence of the message is known where as with the invisible watermarking method, the existence of the message is unknown to the intruder.

II. Related Work

The characters that are defined by the user can be considered as a feature [2]. This feature is found to be efficient for designing the invisible watermarking process. This uses the most significant bits of the selected region of the image. The identify problem is resolved with the multiple watermarking process. This process includes various transformation domain watermarking methods. Discrete Cosine Transformation (DCT) [3] can be used to design the invisible watermarking method. It divides the host image to m×n blocks. This will overcome various attacks of zooming and height-width etc. The Singular Value Decomposition (SVD) can be combined with Redundant Discrete Wavelet Transformation (RDWT) for designing the blind watermarking method [4]. It provides additional security by scrambling the input binary watermark. The spread spectrum [5] based method is found to be efficient for audio watermarking with PN sequence method. The watermark region of the input medical image can be used for the detection of the diseases [15]. It uses zero reversible watermarking method. The binary watermark image can be further processes by the mathematical morphology [4]. It uses the histogram normalization and region filling operations. The discrete wavelet and cosine transformations are used to design the hybrid watermarking process [8]. It yields improved PSNR value. The host image is decomposed in to various rectangular shaped blocks [7] and SURF features are estimated to select the region of interest for watermarking process. For the color image, the S and L blocks [9] are used to perform the digital watermarking methods. The watermarking with Fourier transformation, Wavelet transformation, Fast Wavelet transformation and Singular Value Decomposition [11, 12] is found to be robust.

III. METHODOLOGY

The Principal Component Analysis (PCA) is used forpreprocessing the input information and further to perform the analysis. Thus, it is used for reduction of dimensionality. The Probablistic PCA (PPCA) consists of isotropic Gaussian Noise model. The The present paper uses PPCA method for the selection of the region of interset. Thus, the present paper proposes a a novel Probabilistic Principal Component Analysis based Transform domain wtaremerking method (PPCATDW). The PPCATDW method uses PPCA for estimating the principal axes with the isotropic error model. The PPCA is given in (1)

$$y^T = W \times x^T + \mu + \varepsilon \qquad (1)$$

The present PPCATDW uses the wavelet transformation. The methodology of the proposed method is discussed in the following steps.

Step 1: Read the cover and watermark image

Step 2: Apply the Haar Wavelet transformation to the cover image.

Step 3: Select the LL sub band.

Step 4: Apply the PPCA to select the region of interest

Step 5: Insert the wateramark image in to the selected regions.

Step 6: Apply the inverse wavelet rtansfrmation to generate the watermarked images.

IV. Experimental Results and Analysis

In this section, we conduct several experiments on some public databases to assess the proposed mixB2DPPCA model. These experiments are designed to evaluate the performance of the proposed mix2DPPCA in reconstruction and recognition by comparing with existing models and algorithms. The relevant PCA algorithms that can be fairly compared against our proposed mixB2DPPCA are GLRAM (Generalized Low Rank Approximations of Matrices) [25], PSOPCA (Probabilistic Second-Order PCA) [27], mixture of PPCA [20] with the code from http://www.science.uva. nl/˜jverbeek. Because the zero-noise PSOPCA model and GLRAM have the same stationary point [27], we only compare with GLRAM. 4.1. Data Preparation and Experiment Setting All of the experiments are conducted on the following four public available datasets:

• A subset of handwritten digits images from the MNIST database (http://yann.lecun.com/exdb/ mnist). • The Yale face database (http://vision.ucsd. edu/content/yale-face-database).

• The AR face database (http://rvl1.ecn.purdue. edu/aleix/aleix_face_DB.html).

• The FERET face database (http://www.itl.nist. gov/iad/humanid/feret/feret_master.html).

The subset of handwritten digits images is selected from MNIST database, which contains 1000 digital images with 100 images of each digit. All images are in grayscale and have a uniform size of 28 × 28 pixels. The Yale face database contains 15 individuals, with 11 images for each individual. The images were captured under different illumination and expression conditions. The images are all 100 × 100 pixels with 256 grey levels. In the experiments, we randomly select 6 images of each person as the training samples, and use the remaining images to form the testing sample set. All images are scaled to a resolution of 64 × 64 pixels. The AR face database contains over 4,000 color images corresponding to 126 subjects. There are variations of facial expressions, illumination conditions, and occlusions (sun glasses and scarf) with each person. Each individual consists of 26 frontal view images taken in two sessions (separated by 2 weeks), where each session has 13 images. Figure 1 shows the 26 images of one subject. In the experiments, we select 30 subjects (15 man and 15 women), and only use the non-occluded 14 images (i.e., the first seven face images of each row in Figure 1).

The first seven of each subject are used for training and the last seven for testing. All images are cropped and resized to 50 × 40 pixels. FERET database includes 1400 images of 200 different subjects, with 7 images per subject. In the experiments, we select 50 subjects randomly. Five images of each subject are used for training and the remained images are used for testing. All images are cropped and resized to 32 × 32 pixels. In experiments, the initial mixing proportions are set to πk = 1/K and the initial loading matrices Lk and Rk are given randomly. Besides, we choose randomly K samples as mean matrices Mk of the mixture gaussian model and set all σ 2 k = 1.

To estimate the performance of the proposed PPCATDW method, various performance measures viz., Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR), Signal to Noise Ratio (SNR) and Root Signal to Noise Ratio (RSNR) are estimated. The estimated performance measures for the proposed PPCATDW with WM Image1 are listed in Table 1. The estimated performance measures for the proposed PPCATDW with WM Image 2 are listed in Table 2 and the estimated performance measures for the proposed PPCATDW with WM Image 3 are listed in Table 3. The results indicates the strength of the proposed watermarking method.

V. Conclusions

The Present paper proposes a novel Probabilistic Principal Component Analysis based Transform domain wtaremerking method (PPCATDW). This method focuses on the selection of the efficient region for the watermarking process, The proposed method is evaluated with various images and the result indicates that the proposed method is roust to various watermark images.

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