A Novel Biometric Watermaking Approach Using LWT- SVD

Meenakshi Arya[1] and Rajesh Siddavatam[2]

[1] Lecturer, [2] Associate Professor
Department of CSE & IT,
Jaypee University of Information Technology, Waknaghat,
Solan, Himachal Pradesh, India
meenakshi.arya@juit.ac.in, srajesh@juit.ac.in

Abstract. The lifting wavelet transform (LWT) is a recent approach to wavelet transform, and singular value decomposition (SVD) is a valuable transform technique for robust digital watermarking. While LWT allows generating an infinite number of discrete biorthogonal wavelets starting from an initial one, singular values (SV) allow us to make changes in an image without affecting the image quality much. This paper presents an approach which tries to amalgamate the features of these two transforms to achieve a hybrid and robust digital image watermarking techniques. Certain performance metrics are used to test the robustness of the method against common image processing attacks.

Keywords: Biorthogonal wavelets, Biometric watermarking, Lifting wavelet transform, Singular value decomposition.

1 Introduction

Biometrics based authentication systems are becoming increasingly popular as they offer enhanced security and user convenience as compared to traditional token-based (I.D. card) and knowledge based (password) systems. Biometric watermarking refers to embedding a biometric trait like fingerprint [1], face [2], handwritten signature [3] etc. for the purpose of content authentication.

In [7], LSB and DWT have been synergistically combined to embed face template in fingerprint image while the same idea was applied in [4] for embedding offline handwritten signature in a host image. Vatsa et al. [6] developed a v- SVM based biometric watermarking method which was further revised by Cheng et al. [5] for biometric watermarking based on offline handwritten signature.

In the current literature, neither lifting wavelet transform nor singular value decomposition have been used for biometric watermarking. In this paper, a novel LWT-SVD based biometric watermarking technique for offline handwritten signatures has been proposed. The lifting scheme has been used firstly for separating the significant pixels of the host image from the insignificant ones and then the Singular Value Decomposition (SVD) is applied. The watermark is embedded at this level using a gain factor (k). The watermarked image is then obtained by taking inverse LWT transform. The proposed algorithm gives excellent results for various attacks on the host image. The rest of the paper is organized as follows: Section 2 explains the theoretical

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framework of SVD and LWT while Section 3 presents the proposed method. In Section 4, the significance measures PSNR and SSIM have been described to assess the quality of the watermarked image and the recovered signature image. The efficiency of the proposed method along with the results have been presented in Section 5. Section 6 concludes the work.

2 Theoretical Framework of Lifting Wavelet Transform (LWT) and Singular Value Transform (SVD)

2.1 Lifting Wavelet Transform (LWT)

The basic idea of wavelet transforms is to exploit the correlation structure present in most real life signals to build a sparse approximation. The lifting scheme is a technique for both designing fast wavelets and performing the discrete wavelet transform. The technique was introduced by Swelden [8, 9]. While the discrete wavelet transform applies several filters separately to the same signal, the signal is divided like zipper for the lifting scheme. Then a series of convolution- accumulate operations across the divided signals is applied. Generally speaking, lifting scheme includes three steps that are splitting, prediction and update. The basic idea of lifting is described here briefly:

Split: The original signal is divided into two disjoint subsets. Although any disjoint split is possible, we will split the original data set $x[n]$ into $x_e\,[n]\; x[2n]$, the even indexed points and x_o[n] $x[2n\; 1]$, the odd indexed points.

Predict: The wavelet coefficients d[n] is generated as error in predicting xo[n] from x_e [n] using prediction operator P.

$$d[n] = x_{\mathrm{o}}[n] - P(x_{\mathrm{e}}\,[n])\,. \tag{1}$$

Update: $xe\;[n]$ and $d[n]$ are combined to obtain scaling coefficients c[n] that represent a coarse approximation to the original signal $[n]$. This is accomplished by applying an update operator U to the wavelet coefficients and adding the result to $x_{\mathrm{e}}\,[n]$:

$$c[n] = x_{\mathrm{e}}\,[n] + U(d[n]). \tag{2}$$

These three steps form a lifting stage. Iteration of the lifting stage on the output c[n] creates the complete set of DWT scaling and wavelet coefficients c_j [n] and d_j [n]. At each scale we weight the c_j [n] and d_j [n] with k_e and k_o respectively as shown in Fig. 1. This normalizes the energy of the underlying scaling and wavelet functions.

The lifting steps are easily inverted even if *P* and *U* are nonlinear, space-varying, or noninvertible. Rearranging equation (1) and (2) we have

$$x_e\,[n] = c[n] - U(d[n]). \tag{3}$$

$$x_o\,[n] = d[n] + P(xe\,[n]). \tag{4}$$

The original signal will be perfectly reconstructed as long as the same *P* and *U* are chosen for the forward and the inverse transforms.

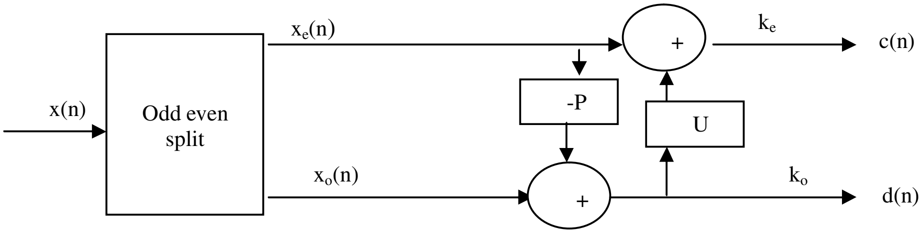


Fig. 1. Lifting Steps

2.2 Singular Value Decomposition (SVD)

The Singular Value Transform (SVD) was explored a few years ago for watermarking purposes. In recent years, SVD has been used in watermarking as a different transform as it is one of the most powerful tools of linear algebra with several applications in watermarking[10,11,12,13,14]. Singular values are the luminance values of SVD image layer, changing these values slightly do not affect the image quality much .The purpose of singular value decomposition is to reduce a dataset containing a large number of values to a dataset containing significantly fewer values, but which still contains a large fraction of the variability present in the original data. SVD analysis results in a more compact representation of these correlations, especially with multivariate datasets and can provide insight into spatial and temporal variations exhibited in the fields of data being analyzed. SVD is optimal matrix decomposition in a least square sense packing the maximum signal energy into a few coefficients as possible [11]. The SVD theorem decomposes a digital image A of size $M \times N$, as:

$$AV = U\sum. \tag{5}$$

$$A^{\mathrm{T}}U = V\sum. \tag{6}$$

Since U and V are orthogonal, this becomes the singular value decomposition

$$A = U\sum V^{\mathrm{T}}. \tag{7}$$

The full singular value decomposition of an $(M \times N)$ matrix involves an $(M \times M)$ U, an $(M \times N)$ $\sum$, and an $(N \times N)$ V. In other words, U and V are both square and $\sum$ is the same size as A. The singular value decomposition is the appropriate tool for analyzing a mapping from one vector space into another vector space, possibly with a different dimension.

3 Proposed Technique

An image comprises of certain high frequency components (edges) known as the approximation coefficients and low frequency components (smooth areas) known as the detailed coefficients. Most of the previous SVD and DWT-based watermarking techniques treat different parts of the image in the same way. Therefore, the edges and the smooth areas of the image, related to different sub-bands, accept similar effects. The HVS is less sensitive to noise on edges, hence making similar changes to perceptually significant and insignificant areas of the image consequently lead to noticeable alternation in smooth areas, thereby causing a significant degradation to the image quality.

The paper proposes a novel biometric watermarking technique with imperceptible image quality alteration. Additional advantages of the presented technique could be highlighted as high capacity and robustness of the method against different types of common attacks. Since LWT provides high redundancy in transform domain, the high capacity of the transformed host could utilize as the beneficial point to scatter the watermark data.

3.1 Biometric Feature Processing

To employ offline handwritten signature as watermark, the preprocessing algorithm as depicted in Fig 3 is applied on the signature image. Initially, the signature image is binarized and resized to an image of 300 pixels x 200 pixels. This is to isolate single stroke or a cluster of separated strokes of a handwritten signature from the background. Median filter is applied to this binary image to eliminate noise which might be present in the form of speckles, smears, scratches etc. that might thwart feature extraction. Hough transform (HT) is then applied to the signature image for projection into feature space. The step is followed by applying Principle Components Analysis (PCA) is to compress the feature space generated by HT without losing the significant attributes [15]. Lastly, PCA feature is statistically discritized into binary representation signature code as proposed in [16].

3.2 Watermark Embedding

The following steps explain the embedding phase.

(i) Let $I_{original}$ be the host image of size $N \times N$.

(ii) The Lifting Wavelet Transform $I_{lwt(i,j)}$ of the host image is calculated according to the selected decomposition level (L), sub-bands of size $\frac{N}{2^L} \times \frac{N}{2^L}$ can be achieved.

(iii) Let $S_{original}$ be the original offline handwritten signature of m x n where m<=n. Resize the signature image such that size ($I_{original}$) = size ($S_{original}$)

(iv) Calculate $S_{lwt(i,j)}$,the corresponding wavelet transform of the signature image.

(v) At L= 2, apply SVD to the horizontal detailed sub-band of the cover image as well as to the signature image.

(vi) The singular values of the cover image sub-band are modified with the singular values of the signature sub-band obtaining modified LWT coefficient at the 2nd level.

$$[I_{wm}\,(2,h)]_{singular} = \left[I_{original}\,(2,h)\right]_{singular} + k * \left[S_{original}\,(2,h)\right]_{singular}. \tag{8}$$

Embedding at this level is described as

$$I_{lwt}(2,j) = \begin{cases} S_{lwt}(2,h) \\ I_{lwt}(2,j)\,. \end{cases} \tag{9}$$

(vii) Using the inverse wavelet transformation the final watermarked image I_{wm} will be constructed.

3.3 Watermark Extraction

Since the *SVs* of the original images are needed in the extraction phase, the proposed technique is non-blind as it uses the singular vector matrices of the original signature image as the keys. The extraction phase is explained by the following steps

(i) Compute the Lifting Wavelet Transform of the watermarked image according to the selected decomposition level (L)

(ii) Locate the embedded coefficients and extract the singular values of the corresponding sub-band of the signature image through Equation 10.

$$\sum S_{wm} = (I_{wm} - I_{original})/k \tag{10}$$

(iii) Combine the SVs thus obtained to recover the 2^{nd} level approximation coefficient.

(iv) Perform 2 –level Inverse LWT to obtain the watermark.

3.4 Template Matching Based Authentication

This extracted watermark is fed as an input to the biometric feature processing algorithm for template matching. The database contains 250 offline handwritten signatures collected from 50 users at different times to capture the intrapersonal differences in signing by a single user. Initially all the steps mentioned in biometric feature processing are applied to the entire signature database to generate a feature vector comprising the feature vectors corresponding to each signature image. These steps are applied to the recovered signature image to extract its features. The Euclidean distance between the feature vector of the recovered signature and the feature vectors of all the signatures in the database is calculated according to the formula as given by Equation 11.

$$dist(x,y)(a,b) = \sqrt{(x-a)^2 + (y-b)^2}. \tag{11}$$

The database image with the least Euclidean distance with the extracted image is the corresponding template and hence the verification of the signature of the user.

4 Significance Measures

4.1 Peak Signal to Noise Ratio PSNR)

The proposed algorithm has been tested for various signal processing attacks like median filtering, salt and pepper noise addition, histogram equalization, Gaussian noise and JPEG compression. The experimental results have been gauged using Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) which have been given below.

$$MSE = \frac{1}{mn}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}(I(x,y) - W(x,y))^2 . \tag{12}$$

where I and W are the original and the watermarked images having a resolution of m*n.

$$PSNR = 10\log_{10}\frac{max^2}{MSE}. \tag{13}$$

4.2 Structural Similarity Index Measure (SSIM)

SSIM [14] is a new paradigm metric designed to improve on traditional methods like peak signal-to-noise ratio (PSNR) and mean squared error (MSE) for quality assessment. It is based on the hypothesis that the HVS is highly adapted for extracting structural information. The measure of structural similarity compares local patterns of pixel intensities that have been normalized for luminance and contrast. In practice, a single overall index is sufficient enough to evaluate the overall image quality; hence a mean SSIM (MSSIM) index is used as the quality measurement metric.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_1)}{(\mu_x{}^2 + \mu_y{}^2 + C_1)(\sigma_x{}^2 + \sigma_y{}^2 + C_1)}. \tag{14}$$

$$MSSIM(x,y) = \frac{1}{M}\sum_{m=1}^{M} SSIM(x_m, y_m). \tag{15}$$

5 Results and Discussions

The proposed algorithm based on Lifting wavelet transform and singular value decomposition generates results that are superior to the existing methods for offline handwritten signature watermarking [4,5]. The algorithm embeds the signature as a whole thus providing better authentication than the previous methods. Table 1 shows the PSNR between the original and the recovered watermark varies between 53 dB to 60 dB for the signatures of 30 users when the watermarked image is not subjected to any attack, while in Table 2, it can be seen that the PSNR value of recovered watermarks (for 3 users) after the watermarked image is subjected to various attacks varies between 50 dB to 55 dB.

Even after subjecting the watermarked image to a JPEG compression ratio ranging between 90% to 30%, the watermark recovery is pretty good. For various noise ratios between 10% to 20%, the PSNR varies between 30 dB to 40 dB as shown in Table 2. For implementing the algorithm, MATLAB 7 on a 1.73 GHz Pentium M Processor with minimum 256 MB of RAM has been used. The results have been verified on various standard images like Lena, Peppers, Baboon and Elaine. Figures 2 and 3 show the effect of varying the embedding factor while Figures 4 and 7 show the effect of varying the decomposition level on various host images.

Table 1. Extracted Watermarks

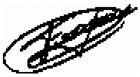
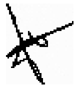
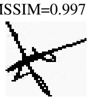
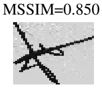
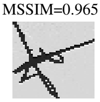
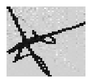
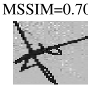
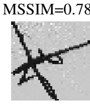
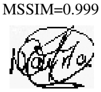
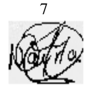
PSNR=54 **MSSIM=0.99886** 	**PSNR=53** **MSSIM=0.99826** 	**PSNR=54** **MSSIM=0.99909** 	**PSNR=54** **MSSIM=0.9983** 	**PSNR=55** **MSSIM=0.99995** 
PSNR=54 **MSSIM=0.99922** 	**PSNR=54** **MSSIM=0.99863** 	**PSNR=53** **MSSIM=0.99929** 	**PSNR=53** **MSSIM=0.99853** 	**PSNR=55** **MSSIM=0.99949** 
PSNR=59 **MSSIM=0.99949** 	**PSNR=54** **MSSIM=0.99969** 	**PSNR=54** **MSSIM=0.9994** 	**PSNR=54** **MSSIM=0.99914** 	**PSNR=57** **MSSIM=0.99998** 

Table 2. Extracted Watermarks after Simulation of Various Attacks

CROPPING	HISTOGRAM	MEDIAN	SALT & PEPPER	GAUSSIAN	SHARPENING	JPEG
PSNR=51 MSSIM=0.997 	PSNR=28 MSSIM=0.850 	PSNR=31 MSSIM=0.965 	PSNR=29 MSSIM=0.790 	PSNR=26 MSSIM=0.704 	PSNR=24 MSSIM=0.784 	PSNR=44 MSSIM=0.993 

(a) Signature 1

CROPPING	HISTOGRAM	MEDIAN	GAUSSIAN	SHARPENING	SALT & PEPPER	JPEG
PSNR=50 MSSIM=0.999 	PSNR=30 MSSIM=0.979 	PSNR=30 MSSIM=0.990 	PSNR=28 MSSIM=0.956 	PSNR=26 MSSIM=0.963 	PSNR=30 MSSIM=0.974 	PSNR=44 MSSIM=0.99 7 

(b) Signature 21

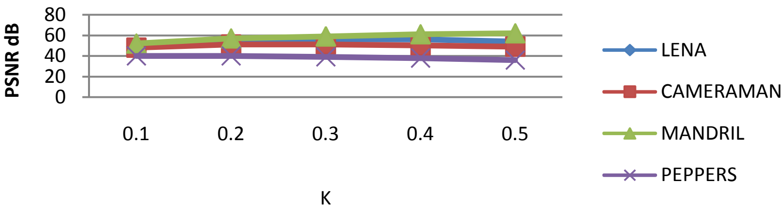


Fig. 2. PSNR versus embedding factor for various cover images

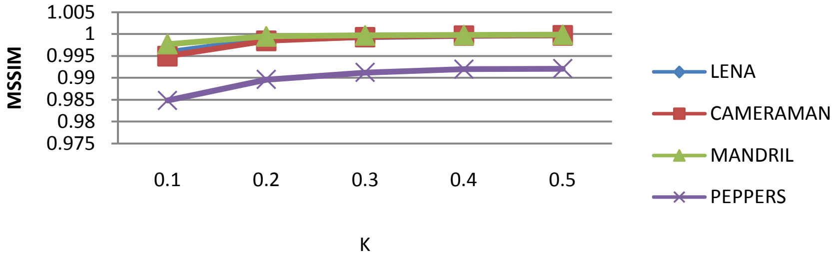


Fig. 3. MSSIM versus embedding factor for various cover images

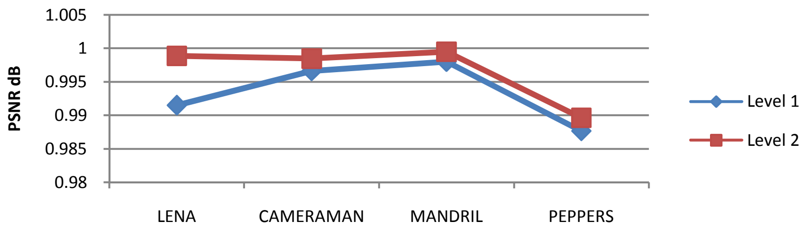


Fig. 4. PSNR versus decomposition level for various cover images

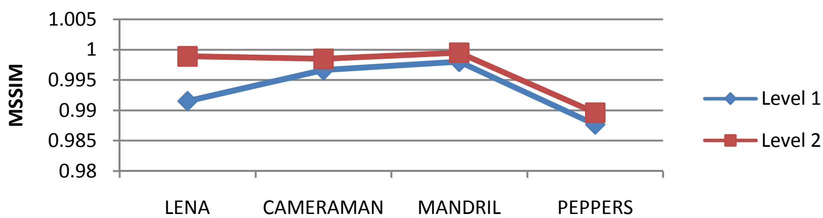


Fig. 5. MSSIM versus decomposition level for various cover images

Furthermore, the performance of the proposed algorithm has been tested for various values of embedding factor. The effect of embedding factor on PSNR and MSSIM has been presented in Tables 3 and 4 while Tables 5 and 6 show the effect of varying the decomposition level.

6 Conclusion

In this paper, a novel biometric watermarking scheme using LWT-SVD for offline handwritten signature has been proposed. The proposed technique shows superior results as compared to the existing technique. The work can be further expanded by incorporating the latest signature verification techniques so as to reduce the FAR or FRR of the proposed system and also amalgamate the two areas of biometric watermarking and signature authentication/ verification.

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