

# Introducing a Novel Method to Digital Image Watermarking in Multiwavelet Domain Based on LS-SVM

Fatemeh Adim

Designation : MSc of Software, Organization : Islamic Azad University Sari branch, Email ID : fe\_adim@yahoo.com

Sajjad Tavassoli

Designation : Faculty member, Organization : Islamic Azad University Sari branch, Email ID Tavassoli\_5@yahoo.com

**Abstract** — In the past decade, digital watermarking have been considered as an important tool for protecting digital data. Due to the high value of images, in recent years, particular attention has paid to image watermarking. A novel image watermarking method in multiwavelet domain based on least square support vector machines (LS-SVMs) is proposed in this paper. In proposed method, according to the special structure and property of image in multiwavelet domain, watermark bits are embedded into multiwavelet approximation sub-bands of image blocks, and a mean value modulation method is employed to modulate their multiwavelet coefficients. In order to robustly extract watermark, LS-SVMs is used to learn mean value relationship between these approximation sub-bands. Due to powerful learning ability and good generalization ability of LS-SVMs, watermark can be correctly recovered under several different attacks.

**Keyword** — Image watermarking, Multiwavelet domain, LS-SVM

## 1. INTRODUCTION

The rapid expansion of digital networks in the last decade has made it easy the transmission, distribution and access to digital products. The consequence of this development is reproduction and unauthorized use of the products that has caused a great loss of the companies producing them. Copyright laws violations have made large financial losses to the digital industries such as imaging worldwide in the recent years. Cryptography techniques can not prevent unauthorized use of digital products more because sooner or later you have to decode the encrypted product for user. However, the user is able to copy or reproduce the product illegally.

In the late twentieth century, Digital watermarking has been considered as a complement to traditional methods to protect the rights of owners of the digital products that followed by extensive research in this area. Although the valuable works have been done by researchers funded by manufacturers of digital products but still there are a lot of unresolved issues about the effective use of digital watermarking which have developed the common grounds for further researches and development of systems for Digital watermarking. So, in addition to defending the rights of owners, versatile and valuable uses of digital watermarking have been proposed.

In general, digital watermarking hides a signal called watermark in the data such as audio, video and digital video to take a variety of purposes. Using digital watermarking has expanded rapidly in recent years to the point where it seems that in the near future, most digital products will be equipped with hidden information Which may contain information to protect the rights of producers, tracking delinquent customers, authentication, intelligent tracking of delivery and etc [1].

SVM is a novel machine learning method introduced by Vapnik in the early 1990s [2]. SVM has been successfully applied to numerous classification and pattern recognition problems. SVM-based classifier is built to minimize the structural misclassification risk, whereas conventional classification techniques often apply minimization of the empirical risk. Vapnik constructed the standard SVM to separate training data into two classes. The goal of the SVM is to find the hyperplane that maximizes the minimum distance between any data point as described in reference [2]. This method in comparison with methods such as neural networks or genetic algorithms has a stronger mathematical basis and several applications of this method has shown its good quality. The standard SVM is solved using quadratic programming methods. However, these methods are often time consuming and are difficult to implement adaptively. So we will be faced with costly computation. Least squares support vector machines (LS-SVM) is capable of solving both classification and regression problems and is receiving more and more attention because it has some properties that are related to the implementation and the computational method. For example, training requires solving a set of linear equations instead of solving the quadratic programming problem involved in the original SVM. In this regard, in 1999 the method of least squares was designed to support vector machines by Suykens and Vandewalle [3].

In recent years, efforts have been made to take advantage of machine learning techniques for image watermark.

Tsai and Sun [4] proposed a color image watermarking technique based on SVM, where watermark extraction was considered as a binary classification problem. Wang et al. [5] proposed an image watermarking approach using SVM to resist against common image processing attacks such as median filtering, noise adding and JPEG compression, etc and desynchronization attacks such as rotation, translation, scaling and row or column removal, etc. Tsai et al. [6] proposed an SVD- based image watermarking scheme in wavelet domain using support

vector regression (SVR) and particle swarm optimization (PSO). The design concept of the proposed technique is to employ the DWT and the singular value decomposition (SVD) to enhance the robustness of existing SVD-based methods. Tseng et al. [7] presented a robust lossless watermarking technique based on  $\alpha$ -trimmed mean algorithm and SVM. In this method, SVM is trained to memorize relationship between the watermark and the image-dependent watermark other than embedding watermark into the host image. While needing to authenticate the ownership of the image, the trained SVM is used to recover the watermark and then the recovered watermark is compared with the original watermark to determine the ownership. Wang et al. [8] a robust color image watermarking scheme based on quaternion Fourier transform and LS-SVM, which has good visual quality. Ghouti et al. [9] proposed a blind watermarking algorithm using balanced multiwavelet transform. The latter transform achieves simultaneous orthogonality and symmetry without requiring any input prefiltering. Therefore, considerable reduction in computational complexity is possible

A novel image watermarking method in multiwavelet domain least based on support vector machines (LS-SVMs) is proposed in this paper. In proposed method, the special structure and property of image in multiwavelet domain are employed to design a new watermarking algorithm. Accordingly, watermark bits are embedded into multiwavelet approximation subbands of image blocks and a mean value modulation method is employed to modulate their multiwavelet coefficients. During watermark extraction, LS-SVMs is used to learn mean value relationship between these approximation subbands, and then perform watermark extraction. Due to powerful learning ability and good generalization ability of LS-SVMs, watermark can be correctly extracted under several different attacks.

The main features of the proposed method as follows:

- The special structure of the image in multiwavelet domain and concentrating property of energy in approximation sub-bands are used to design a new watermark embedding algorithm. The concentrating property of energy can tolerate more image distortions.
- It is known from statistical theory that mean value of samples has a smaller variance than single sample. So, when we embed a watermark bit into a set of multiwavelet coefficients, the mean value modulation technique can greatly reduce the effect of severe image distortion on single watermark bit.
- Because learning ability and generalization performance of LS-SVMs are superior to that of traditional neural networks, such as MLPs and radial basis function, it can more effectively improve robustness of watermarking algorithm under different attacks.

- It does not require original image for watermark extraction.

This paper is organized as follows. We describe some fundamental concepts of multiwavelet transform in Section 2. In Section 3, proposed watermarking approach is discussed in detail. Simulation results are presented in Section 4 and finally, conclusions are presented in Section 5.

### 3. MULTIWAVELET TRANSFORM

Multiwavelet is very similar to wavelet but has some important differences [10, 11]. Specially, multiwavelet has two or more scaling and wavelet functions, while wavelet has only an associated scaling function  $\phi(t)$  and wavelet function  $\psi(t)$ . Usually, a set of  $r$  scaling functions can be written as a vector notation  $\phi(t) = [\phi_1(t), \phi_2(t), \dots, \phi_r(t)]^T$ , called a multiscaling function. In the same way, we can define a multiwavelet function using a set of  $r$  wavelet functions as  $\psi(t) = [\psi_1(t), \dots, \psi_r(t)]^T$ . In this paper, we use multiwavelet with multiplicity  $r = 2$ . In multiwavelet analysis, multi-scaling function and multiwavelet function should satisfy the following two-scale equations.

$$\phi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} H_k \phi(2t - k) \quad (1)$$

$$\psi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} G_k \phi(2t - k) \quad (2)$$

Here,  $\{H_k\}$  and  $\{G_k\}$  are matrix filters, i.e.,  $\{H_k\}$  and  $\{G_k\}$  are  $r \times r$  matrixes for each integer  $k$ . Because matrix elements in these filters can provide more degrees of freedom than a traditional scalar wavelet, this brings an opportunity to simultaneously achieve orthogonality, symmetry, and high order of approximation. Fig. 1(a) shows multiwavelet filter banks, which need for input rows. Thus, a method for vectorization of scalar input, called preprocessing approach, should be used [12].

For accomplishing multiwavelet transform of an image, tensor product approach is used by applying one-dimensional algorithm in each dimension separately. Fig. 1(b) shows all multiwavelet subbands of an image under one level decomposition. Here, each subband corresponds to low-pass and high-pass filters used in vertical and horizontal directions. For examples, subband labeled by  $L_1H_2$  corresponds to data obtained by applying high-pass filter on horizontal direction and taking its second channel, then applying lowpass filter on vertical direction and taking its first channel. In multiwavelet sub-bands  $L_1L_1$ ,  $L_1L_2$ ,  $L_2L_1$  and  $L_2L_2$  are “low-low-pass” sub-bands, which represent an approximation of original image. Fig. 2(a) shows all subbands of Boat image under single-level decomposition by using scalar wavelet, while Fig. 2(b) shows all sub-bands of Boat image under single-level decomposition by using

multiwavelet. From Fig. 2, we see that image in multiwavelet domain has different structure of frequency band compared with that in wavelet domain. Besides, four “low-low-pass” sub-bands in multiwavelet domain concentrate more energy of an image. In this paper, we will randomly select two approximation sub-bands, and employ a mean value modulation approach to modulate mean value relationship of their multiwavelet coefficients in order to embed watermark information.

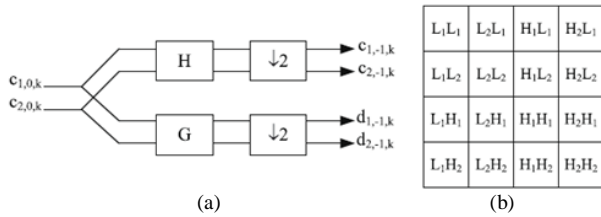


Fig. 1. (a) Multiwavelet filter banks using one level decomposition. (b) Multiwavelet sub-bands

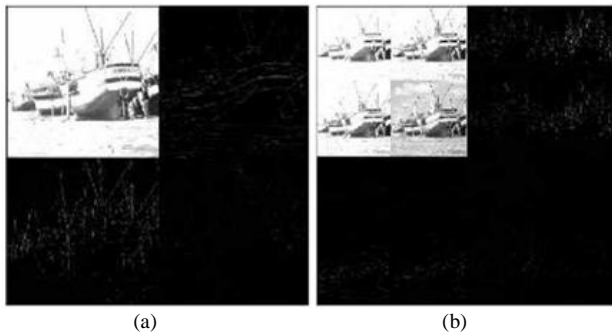


Fig. 2. Single-level decomposition of Boat image for (a) scalar wavelet and (b) multiwavelet

## 4. PROPOSED WATERMARKING METHOD

### 4.1. Watermark Embedding

In this paper, block-wise strategy will be employed to divide host image into non-overlapping image blocks, and watermark information will be hid in “low-low-pass” sub-bands of these image blocks. From Fig. 2(b), we can know that after one level multiwavelet decomposition, four “low-low-pass” sub-bands of an image block,  $L_1L_1$ ,  $L_1L_2$ ,  $L_2L_1$  and  $L_2L_2$  represent its approximation and concentrate its most energy. By applying the special structure and property, we present a new watermark embedding algorithm, where two sub-bands among “low-low-pass” sub-bands of every image block are selected as embedding positions, and a mean value modulation approach is employed to modulate mean value relationship of their coefficients in order to embed watermark information. To enhance security, the selection of sub-bands is random and is controlled by a secret key  $K$ . During embedding watermark, only one watermark bit is embedded into every image block. From view of watermark modulation, the mean value modulation approach modulates each watermark bit into a coefficient set of selected two “low-low-pass” sub-bands, whereas traditional watermarking approach modulates each watermark bit into a single coefficient. The mean value modulation technique is based on the

statistical principle: Given a set of samples, mean value of samples has a smaller variance than that single sample. The effect of severe image distortion on single watermark bit can be reduced greatly. Therefore, mean value modulation technique is more robust than single coefficient modulation technique.

In this paper, watermark  $W$  consists of two components, reference information  $H$  with length  $n$  and owner signature  $S$  of a binary logo image with size  $m_1 \times m_2$ . The reference information  $H$  is used to train SVMs during watermark extraction. Thus, watermark to be embedded can be represented by  $W = HS = w_1, \dots, w_n, w_{n+1}, \dots, w_{n+m} = h_1, h_2, \dots, h_n, s_1, s_2, \dots, s_{m_1 \times m_2}$ , where  $m = m_1 \times m_2$ . Let  $I$  be original image with size. The watermark embedding process is described as follows:

**Step 1.** Multiwavelet transforming. We partition original image  $I$  into non-overlapping image blocks with size  $16 \times 8$ . Let  $I_k$  denotes  $k$ th image block. For each image block  $I_k$ , we perform one level multiwavelet decomposition, and then obtain its four “low-low-pass” sub-bands,  $L_1L_1$ ,  $L_1L_2$ ,  $L_2L_1$  and  $L_2L_2$ .

**Step 2.** Selecting embedding positions. We select randomly two sub-bands from four “low-low-pass” sub-bands ( $L_1L_1$ ,  $L_1L_2$ ,  $L_2L_1$  and  $L_2L_2$ ) of every image block, which is controlled by a secret key  $K$ . For  $k$ th image block, its two randomly selected sub-bands are simply denoted by  $L_1^k$  and  $L_2^k$ . The coefficient sets  $C_1^k$  and  $C_2^k$  of  $L_1^k$  and  $L_2^k$  can be expressed as follows:

$$C_j^k = c_j^k(i) \mid i = 1, 2, \dots, 64, j = 1, 2 \quad (3)$$

**Step3.** Calculating mean values. For each sub-band  $L_j^k$  of  $k$ th image block, mean value  $AVG_j^k$  of its coefficient set ( $C_j^k$ ) is calculated as follows:

$$AVG_j^k = \frac{1}{64} \sum_{i=1}^{64} |c_j^k(i)|, j = 1, 2 \quad k = 1, 2, \dots, m \quad (4)$$

where  $c_j^k(i)$   $i$ th coefficient in  $C_j^k$ .

**Step 4.** Watermark embedding. A mean value modulation technique which modulates mean value relationship between two sub-bands, is employed to performing watermark embedding. The mean value modulation technique can be performed as follows. For image block  $I_k$ ,  $k = 1, \dots, n + m$ :

- 1) If  $w_k = 1$ , then we decrease absolute value of each coefficient in coefficient set  $C_1^k$  and meanwhile increase absolute value of each coefficient in coefficient set  $C_2^k$  so that  $AVG_1^k < AVG_2^k$ .
- 2) If  $w_k = 0$ , then we increase absolute value of each coefficient in coefficient set  $C_1^k$  and meanwhile



decrease absolute value of each coefficient in coefficient set  $C_2^k$  so that  $AVG_1^k \geq AVG_2^k$ .

**Step 5.** Last, each image block is reconstructed by applying inverse multiwavelet transform and then all image blocks are combined into final watermarked image  $I'$ .

After watermark embedding, there is some mean value relationship between selected “low-low-pass” sub-bands of these image blocks. In order to more robustly extract embedded watermark, we will use LS-SVMs to learn the mean value relationship.

#### 4.2. WATERMARK EXTRACTION

In this paper, watermark extraction is regarded as a binary classification problem, and LS-SVM is used to realize watermark extraction. The reasons of using LS-SVMs are as follows:

From watermark embedding procedure described above, we can see that embedded watermark bit (1 or 0) corresponds to some mean value relationship ( $AVG_1^k < AVG_2^k$  or  $AVG_1^k \geq AVG_2^k$ ) between two randomly selected approximation sub-bands. So, according to Eq. (4), there is a nonlinear function relationship between watermark bit  $w_k$  and all coefficients in  $C_1^k$  and  $C_2^k$  i.e.,

$w_k = f(c_1^k(1), c_1^k(2), \dots, c_1^k(64), c_2^k(1), c_2^k(2), \dots, c_2^k(64))$ . Because LS-SVMs has powerful nonlinear mapping ability, it can be used to learn the nonlinear relationship.

It is well known that watermarked image may suffer from different signal processing operations or attacks, such as JPEG lossy compression, additive noise, filtering, etc. From view of transform domain, this results in the change of multiwavelet coefficients of an image after attacking. So, it is required that watermark detector should have high ability to resist the noises. For this reason, we choose LS-SVMs as watermark detector, and improvement of the robustness of watermarking algorithm will benefit from good generalization ability of LS-SVMs.

From embedding procedure described above, we know that two classes of watermark information, reference information and owner signature, are embedded into watermarked image. Firstly, we extract their multiwavelet coefficients in “low-low-pass” subbands from the image blocks in which reference information are embedded, and the coefficients are used to train LS-SVMs in order to learn some mean value relationship hind in them. Finally, using well-trained LS-SVMs extracts watermark information from the image blocks in which owner signature is embedded. Likewise, using same secret key  $K$  controls the selection of “low-low-pass” subbands, and two selected sub-bands are denoted by  $L_1^k$  and  $L_2^k$ . Here, watermark can be extracted from

tested image without original image. The watermark extraction process is described as follows:

**Step 1.** Multiwavelet transforming. Input image  $\hat{I}$  is partitioned into non-overlapping image blocks with size  $16 \times 16$ , and then these image blocks are decomposed into multiwavelet domain as in the embedding process, respectively.

**Step 2.** Training LS-SVMs

We construct a training set  $D$  from image blocks in which reference information  $h_0, h_1, \dots, h_n$  has been embedded:

$$D = (x_k, y_k) \in R^{16} \mid k = 1, 2, \dots, n$$

$$= ((c_1^k(1), c_1^k(2), \dots, c_1^k(64), c_2^k(1), c_2^k(2), \dots, c_2^k(64)), h_k) \mid k = 1, 2, \dots, n$$
(5)

where  $c_1^k(i)$  and  $c_2^k(i)$  are  $i$ th coefficients of sub-bands  $L_1^k$  and  $L_2^k$  of  $k$ th image block respectively and  $h_k$  is desired output, ( $k=1, 2, \dots, n$ ).

The “RBF” kernel of SVMs is selected as follows:

$$K(x, x_k) = \exp(-\|x - x_k\|^2 / \sigma^2)$$
(6)

Here,  $\sigma$  is the width parameter of “RBF” kernel.

The optimal model is the following:

$$\begin{cases} \text{Minimize} & \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y_i y_j K(x_i, x_j) - \sum_{i=1}^n \alpha_i \\ \text{Subject to} & \sum_{i=1}^n \alpha_i y_i = 0 \leq \alpha_i \leq C, \quad i = 1, \dots, n \end{cases}$$
(7)

where  $\alpha_i (i=1, \dots, n)$  are training parameters, and  $C$  is the penalty parameter. Assume that optimal solution is  $\alpha = (\alpha_1, \dots, \alpha_n)$ , and then decision function can be expressed by

$$y = f(x) = \text{sign} \left( \sum_{i=1}^n \alpha_i y_i K(x, x_i) + b \right)$$
(8)

**Step 3.** Watermark extraction. From image blocks in which owner signature is embedded, we can construct input set

$$D' = \hat{x}_k = (c_1^k(1), c_1^k(2), \dots, c_1^k(64), c_2^k(1), c_2^k(2), \dots, c_2^k(64)) \mid k = 1, \dots, m$$

Then, by using well-trained LS-SVMs in Eq. (8), we can calculate their corresponding outputs

$$\hat{y}_k \mid k = 1, \dots, m \text{ i.e:}$$

$$\begin{cases} \hat{y}_k = f(\hat{x}_k) & k = 1, 2, \dots, m \\ \hat{x}_k = (c_1^k(1), c_1^k(2), \dots, c_1^k(64), c_2^k(1), c_2^k(2), \dots, c_2^k(64)) \in D' \end{cases}$$
(9)

Thus, embedded owner signature is obtained by

$$s_k = \begin{cases} 1 & \text{if } \hat{y}_k = 1 \\ 0 & \text{if } \hat{y}_k = -1 \end{cases} \quad k = 1, 2, \dots, m_1 \times m_2$$
(10)

**Step 4.** Finally, one-dimensional sequence  $s_1, s_2, \dots, s_{m_1 \times m_2}$  of owner signature is converted into a two-dimensional logo watermark image  $W'$ .

## 5. EXPERIMENTAL RESULT

In our experiments, we use some standard images with size  $512 \times 512$ , such as "Lena", "Peppers", "Boat", shown in Fig. 3. Some necessary parameters used in proposed watermarking method are determined as follows. Firstly, "RBF kernel" is employed as our kernel function, which shows better performance than other kernel functions, such as "Polynomial kernel" and "Linear kernel", according to testing results for watermarked image under different attacks. Here, we set width parameter  $\sigma = 10000$  for RBF kernel and penalty parameter  $C=50$  for SVMs. Secondly, GHM multiwavelet is used in the experiments. Thirdly, reference information  $(H=h_1, h_2, \dots, h_n)$  is a pseudo-random binary sequence which is generated from a Gaussian distribution with zero mean and unit variance, where  $n=512$ . Finally, a binary logo image with size  $32 \times 16$  is used for owner signature, shown in Fig. 4.

The performance of proposed watermarking method is investigated by measuring its imperceptibility and robustness. For imperceptibility, Peak Signal to Noise Ratio (PSNR) is employed to evaluate difference between original images  $I$  and watermarked image  $I'$ . It is defined as

$$PSNR = 10 \times \log \frac{255^2 \times M \times N}{\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (I'(x,y) - I(x,y))^2} \quad (11)$$

where  $I$  and  $I'$  denote the host image and the watermarked version of  $I$ , respectively and  $M$  and  $N$  are digital image dimensions.  $I(x,y)$  and  $I'(x,y)$  is original pixel value and its corresponding watermarked pixel value, respectively.

The higher PSNR value for  $I$  and  $I'$  indicates a watermarking method has higher transparent capability. In other words, the method produces few differences between  $I$  and  $I_w$  after it embeds a watermark in the original image  $I$ .

For robustness, Bit Error Rate (BER) measures difference between original watermark  $W$  and extracted watermark  $W'$ .

$$BER = \frac{B}{M \times N} \quad (12)$$

where  $B$  is the number of erroneously detected bits,  $M \times N$  is the watermark image dimensions.

It should be noted that the larger PSNR, the better imperceptibility. If a method has a lower BER, it is more robust.

Following, the results of the implementation of the program will be fully studied then some attacks on each of the three watermarked images applied and BER values will be got for each of the extracted watermark images.

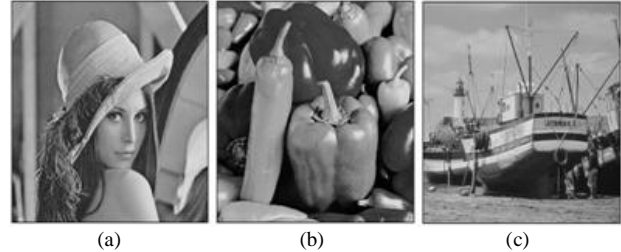


Fig. 3. (a) The original Lena image, (b) The original Peppers image, (c) The original Boat image.



Fig. 4. The original watermark image

### 5.1. Test Result for Imperceptibility

According to the parameters given above, we run proposed watermark embedding algorithm on tested images. Fig. 5 shows watermarked versions of Lena image with PSNR = 44.39 dB, Peppers image with PSNR = 43.61 dB, and Boat image with PSNR = 43.29 dB, respectively. We can see that all watermarked images are not distinguishable from their original ones, which demonstrate good imperceptibility of proposed watermarking method.

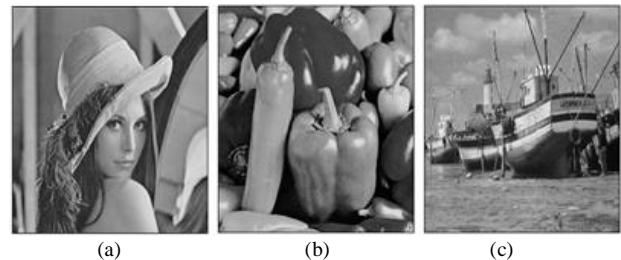


Fig. 5. (a) The watermarked Lena, (b) The watermarked Peppers image, (c) The watermarked Boat image

### 5.2. Test Result for Robustness

In attack free case, we extract watermark images from watermarked images using proposed watermark extraction algorithm, respectively. Fig. 6(a)–(c) show these extracted watermark images from watermarked Lena, Peppers and Boat image, respectively. For Lena and Peppers image, BER=0 and for Boat image, BER=0.0020. So, we can extract accurately watermark images in no attack case.

To investigate robustness of watermarking method, watermarked images first are attacked by using JPEG compression, median filtering, average filtering, salt &

peppers noise and image rotation. Then we perform watermark extraction process and compute their BER outputs. The result in terms of BER are listed in Table 1.

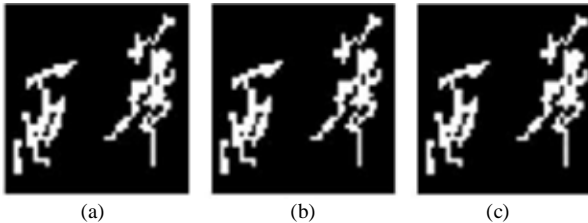


Fig. 6. (a)-(c) The extracted watermark images (a) From watermarked Lena Image, (b) From watermarked Peppers image, (c) From watermarked Boat image

Table 1. Apply attacks watermarked Lena, Peppers and Boat image

Attacks	Extracted watermark from Lena image (BER)	Extracted watermark from Peppers image (BER)	Extracted watermark from boat image (BER)
JPEG QF=80	0.1016	0.1218	0.1465
JPEG (QF=50)	0.1035	0.1325	0.1426
Median filtering	0.1055	0.1152	0.1582
Average filtering	0.0967	0.1014	0.1572
Salt & peppers noise(2%)	0.0938	0.1168	0.1416
Rotate 90	0.1182	0.1097	0.0938
Rotate 270	0.0957	0.1089	0.1211

## 6. CONCLUSIONS

Combining both multiwavelet and support vector machine, we present a novel blind image watermarking method in this paper. The mean value modulation technique that is applied in this method, can efficiently reduce effects of image distortion when suffering from different attacks. In order to robustly extract watermark, LS-SVMs is used to learn mean value relationship between watermark and coefficients in multiwavelet sub-bands. Due to powerful learning ability and good generalization ability of LS-SVMs, watermark can be correctly recovered under several different attacks. The experimental results show that proposed method possesses significant robustness against several attacks.

Drawback of the proposed image watermarking scheme are related to the computation time for LS-SVM training. Future work will focus on eliminating this drawback. In addition, to extend the proposed idea to color image watermarking is another future work.

## ACKNOWLEDGMENT

This work was accepted in 9<sup>th</sup> Symposium on Advances in Science & Technology (9<sup>th</sup> SASTech ), National Conference on science and Computer Engineering, Mashhad, Iran, 2014.

## REFERENCES

[1] Ingemar. J.Cox, Matthew. L.Miller, Jeffrey. A.Bloom, Jessica. F and Ton. K, Digital watermarking and

Steganography. 2nd Ed., The Morgan Kaufmann Series in Multimedia Information and Systems, 2008.

- [2] Vapnik. V, The Nature of Statistical Learning Theory, New York, SpringerVerlage , 1995.
- [3] Suykens. J.A.K and Vandewall. J, Least Squares Support Vector Machine Classifiers, Neural Processing Letters 9, 293-3000, 1999.
- [4] Tsai. H-H and Sun. D-W, Color image watermark extraction based on support vector machines, Information Sciences, Vol. 177, 550-569, 2007.
- [5] Wang. X-Y, Yang. H-Y and Cui Ch-Y, An SVM-based robust digital image watermarking against desynchronization attacks, Signal Processing, Vol. 88, No. 9, 2193-2205, 2008.
- [6] Tsai. H-H, Jhuang. Y-J, Lai. Y-Sh, An SVD-based image watermarking in wavelet domain using SVR and PSO, Applied Soft Computing Vol. 12, No. 8, 2442-2453, 2012.
- [7] Tsai. H-H, Tseng. H-C and Lai. Y-S, Robust lossless image watermarking based on  $\alpha$ -trimmed mean algorithm and support vector machine, journal of Systems and Software, Vol. 83, No. 6, 1015-1028, 2010.
- [8] Wang. X-Y, Wang. Ch-P, Yang H-Y and Niu. P-P, A robust blind color image watermarking in quaternion Fourier transform domain, Journal of Systems and Software, Vol. 86, No. 2, 255-277, 2013.
- [9] Ghouti. L, Bouridane. A, Ibrahim. M.K and Boussakta. S, Digital image watermarking using balanced multiwavelets, IEEE Transactions on Signal Processing, Vol. 54, No. 4, 1519-1536, 2006.
- [10] Contronei. M, Montefuscon. L.B and Puccio. L, Multiwavelet analysis and signal processing, IEEE Transactions on Circuits and Systems II: Analog and Digital Signal Processing, Vol. 45, No. 8, 970-987, 1998.
- [11] Strela. V, Heller. P.N, Strang. G, Topiwala. P and Heil. C, The application of multiwavelet filterbanks to image processing, IEEE Transactions on Image Processing, Vol. 8, No. 4, 548-562, 1999.
- [12] Hardin. D.P and Roach D.W, Multiwavelet prefilters I: Orthogonal prefilters preserving approximation order  $p \leq 2$ , IEEE Transactions on Circuits System II: Analog and digital processing, Vol. 45, No. 8, 1106-1112, 1998.

## AUTHOR'S PROFILE



Fatemeh Adim, Msc of software



Sajjad Tavassoli, Faculty member of Islamic Azad University Sari branch