Image watermarking method in multiwavelet domain based on support vector machines

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ABSTRACT

A novel image watermarking method in multiwavelet domain based on support vector machines (SVMs) is proposed in this paper. The special frequency band and property of image in multiwavelet domain are employed for the watermarking algorithm. After performed single-level multiwavelet decomposition on each image block of an image, a mean value modulation method, which modulates mean value relationship of multiwavelet coefficients in two approximation sub-bands, is used for carrying watermark embedding. The mean value modulation method can more effectively reduce image distortion than that of conventional single coefficient. At watermark detector, SVMs is used to learn the mean value relationship. Due to good learning ability of SVMs, watermark can be correctly extracted under several different attacks. The experimental results show proposed algorithm is robust to common attacks such as JPEG, low-pass filtering, noise addition, rotation and scaling, etc.}

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1. Introduction

A field of rapidly increasing interest during the last few years has been multimedia data protection. It emerges from the fact that many innovative techniques for digital data transfer, storage, and processing have been recently developed and used. Attackers of the stored/transferred data intend to present copyrighted material, such as digital image, audio, and video, as their own property. Digital watermarking technique provides efficient tool for ensuring that product ownership of these multimedia is preserved even if multimedia data is processed by such attackers. Two main requirements for an acceptable watermarking technique are imperceptibility and robustness (Voyatzis and Pitas, 1999). Imperceptibility refers to perceptual quality of the data being protected. For image data, watermark should be invisible and over all image types. The digital watermark should also be robust to image processing. Ideally, the amount of signal distortion necessary to remove the watermark should degrade desired image quality to a point of becoming commercially valueless. Usually, a tradeoff between watermark imperceptibility and robustness is necessary. These watermark techniques are applied either in the spatial domain (Bender et al., 1996; Nikolaidis and Pitas, 1998) or in some image transform domain (e.g., DCT, DFT, DWT Cox et al., 1997; Barni et al., 1998; Pereira and Pun, 2000; Xia et al., 1998). Pervious works have shown that transform domain techniques are typically more robust to noise, common image processing, compression when compared with spatial domain techniques.

In recent years, efforts have been made to take advantage of machine learning techniques for watermark embedding and extraction. Yu et al. (2001) proposed a digital watermarking method in spatial domain based on artificial neural networks (ANNs), where employing multi-layer perceptrons (MLPs) calculated adaptively its thresholds. Shieh et al. (2004) presented a watermarking optimization scheme based on genetic algorithms (GAs), where GAs was applied to find optimal frequency bands for watermark embedding. Sakr et al. (2005) proposed an adaptive image watermarking algorithm based on dynamic fuzzy inference system. Chang et al. (2005) proposed a fuzzy-ART based adaptive digital watermarking approach in DCT domain. Chang et al. (2009) presented a robust DWT-based copyright verification scheme with fuzzy-ART, which combines DWT, fuzzy-ART and the quantization process.

Support vector machines (SVMs), as a new class of machine learning methods based on statistical learning theory, can overcome over-fitting weakness of neural networks. Moreover, according to Vapnik’s structure risk minimization principle (Vapnik, 2001), it is important that SVMs can well improve generalization ability of learning machine, and its learning algorithm is essentially a convex optimization problem which can avoid to fall into local optimal solution (Burges, 1998; Smola and Schölkopf, 1998; Schölkopf et al., 2000). Due to these advantages, introducing SVMs into watermarking scheme is magnetic. Lyu and Farid (2002) used...
SVM to classify watermarked images according to high order statistical model of natural image. Fu et al. (2004) proposed an SVM-based watermarking method in which the difference of intensity level of pixels's blue components was used to train the SVM. Tsai and Sun (2007) proposed a color image watermarking approach in spatial domain based on SVM, where watermark extraction was considered as a binary classification problem. Fu and Peng (2007) presented a sub-sampling based image watermarking algorithm in wavelet domain, where using support vector regression modeled relationship between coefficients in randomly selected coefficient set and corresponding coefficients in other positions. Wang et al. (2008) presented an image watermarking approach using SVM to resist desynchronization attacks.

Multiwavelet constitutes a new concept, which has been added to wavelet theory. The main advantage of using multiwavelet is that it is possible to construct multiwavelet bases possessing several desirable properties at the same time, for example orthogonality, symmetry, short support and a high number of vanishing moments (Cotronei et al., 1998; Strela et al., 1999; Geronimo et al., 1994; Xia et al., 1996; Hardin and Roach, 1998). Recently, a few works of multiwavelet watermarking were reported. Zhang et al., 1994; Xia et al., 1996; Hardin and Roach, 1998). Recently, a few works of multiwavelet watermarking were reported. Zhang et al., 1994; Xia et al., 1996; Hardin and Roach, 1998). Recently, a few works of multiwavelet watermarking were reported. Zhang et al., 1994; Xia et al., 1996; Hardin and Roach, 1998).

Multiwavelet is very similar to wavelet but has some important differences (Cotronei et al., 1998; Strela et al., 1999). 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 \( \Phi(t) = [\phi_1(t), \phi_2(t), \ldots, \phi_r(t)]^T \), called a multi-scaling function. In the same way, we can define a multiwavelet function using a set of \( r \) wavelet functions as \( \Psi(t) = [\psi_1(t), \psi_2(t), \ldots, \psi_r(t)]^T \).

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. Finally, conclusions are drawn in Section 5.

2. Multiwavelet transform

Fig. 1. (a) Multiwavelet filter banks using one level decomposition. (b) Multiwavelet sub-bands of 2-dimensional image using one level decomposition.
information in each dimension separately. Fig. 1(b) shows all multiwavelet sub-bands of an image under one level decomposition. Here, each sub-band corresponds to low-pass and high-pass filters used in vertical and horizontal directions. For examples, sub-band labeled by $L_1 H_2$ corresponds to data obtained by applying high-pass filter on horizontal direction and taking its second channel, then applying low-pass filter on vertical direction and taking its first channel. In multiwavelet sub-bands, $L_1 L_1, L_1 L_2, L_2 L_1$ and $L_2 L_2$ are “low-low-pass” sub-bands, which represent an approximation of original image. Fig. 2(a) shows all sub-bands 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. The special structure and property will be used to design a new watermark embedding algorithm. 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.

Some common multiwavelets are as follows:

- GHM: This multiwavelet was introduced by Geronimo, Hardin and Massopust. Both scaling functions are symmetric and multiwavelet functions are symmetric-antisymmetric (Geronimo et al., 1994). It has approximation order of two.
- CL: This multiwavelet was introduced by Chui and Lian (1995) and has approximation order of two.
- SA4: Shen et al. showed how to create symmetric-antisymmetric orthonormal multiwavelets scalar wavelets (Shen et al., 2000). Then, they obtained the SA4 multiwavelet with length 4 from Daubechies orthonormal scalar wavelets.
- BiGHM2: This a biorthogonal multiwavelet with length 2. Strela suggested a method to design biorthogonal multiwavelets with desired approximation order from ordinary multiwavelets (Strela, 1998). Using this method, BiGHM2 multiwavelet was developed based on GHM multiwavelet.

3. Proposed watermarking method

3.1. 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, $L_1 L_1, L_1 L_2, L_2 L_1$ and $L_2 L_2$, 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 $W = HS = w_1, \ldots, w_n, w_{n+1}, \ldots, w_{N}$, where $m = m_1 \times m_2$. Let $I$ be original image with size $M \times N$. 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, $k = 1, 2, \ldots, \lceil M \times N \rceil/(16 \times 8)$. For each image block $I_k$, we perform one level multiwavelet decomposition, and then obtain its four “low-low-pass” sub-bands, $L_1 L_1, L_1 L_2, L_2 L_1$ and $L_2 L_2$.

**Step 2.** Selecting embedding positions. We select randomly two sub-bands from four “low-low-pass” sub-bands ($L_1 L_1, L_1 L_2, L_2 L_1$ and $L_2 L_2$) 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 $L^k_1$ and $L^k_2$. The coefficient sets $C^k_1$ and $C^k_2$ of $L^k_1$ and $L^k_2$ can be expressed as follows, respectively,

\[
C^k_j = \{c^k_j(i) | i = 1, 2, \ldots, 8\}, \quad j = 1, 2, \quad (3)
\]
Step 3. Calculating mean values. For each sub-band $L^k_i$ of $k$th image block, mean value $AVG^k_j$ of its coefficient set $C^j_k$ is calculated as follows:

$$AVG^k_j = \frac{1}{8} \sum_{i=1}^{8} |c^i_j|, \quad j = 1, 2, \quad k = 1, \ldots, m, \quad (4)$$

where $c^i_j$ is $i$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 carry out watermark embedding. The mean value modulation technique can be performed as follows. For image block $L^k$, $k = 1, \ldots, n + m$,

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 $AVG^1_k > AVG^2_k$.

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

Remark 1. 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 SVMs to learn the mean value relationship.

3.2. Watermark extraction

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

1. From watermark embedding procedure described above, we can see that embedded watermark bit (1 or 0) corresponds to some mean value relationship ($AVG^1 < AVG^2$ or $AVG^1 > AVG^2$) 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., $w_k = f(c^1_1(1), c^1_2(2), \ldots, c^1_7(8), c^2_1(1), c^2_2(2), \ldots, c^2_7(8))$. Because SVMs has powerful nonlinear mapping ability, it can be used to learn the nonlinear relationship.
2. 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. The changes can be viewed as the case that these coefficients are polluted by different type noises. So, it is required that designed watermark detector should have high ability to resist the noises. From view of machine learning, the ability actually is generalization ability of learning algorithm. For the sake of the reason, we choose SVMs as watermark detector, and improvement of the robustness of watermarking algorithm will benefit from good generalization ability of 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” sub-bands from the image blocks in which reference information are embedded, and the coefficients are used to train SVMs in order to learn some mean value relationship hind in them. Finally, using well-trained 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” sub-bands, 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 $I$ is partitioned into non-overlapping image blocks with size $16 \times 8$, and then these image blocks are decomposed into multiwavelet domain as in the embedding process, respectively.

Step 2. Training SVMs.

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

$$D = \{(x_k, y_k) \in \mathbb{R}^{16 \times 8} \times \{1, 2, \ldots, n\} \mid y_k = \{(c^1_1(1), c^1_2(2), \ldots, c^1_7(8), c^2_1(1), c^2_2(2), \ldots, c^2_7(8)), h_i\} \mid k = 1, 2, \ldots, n\}, \quad (5)$$

where $c^i_j$ is $i$th coefficients of sub-bands $L^i_k$ and $L^2_k$ of $k$th image block respectively ($i = 1, 2, \ldots, 8$), and $h_i$ is desired output, $k = 1, 2, \ldots, n$.

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

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

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

(iii) The optimal model is the following:

$$\text{Minimize} \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j y_i y_j K(x_i, x_j) - \sum_{i=1}^{n} x_i$$

s.t. $\sum_{i=1}^{n} x_i y_i = 0, \quad 0 \leq x_i \leq C, \quad i = 1, \ldots, n \quad (7)$

where $x_i$ ($i = 1, \ldots, n$) are training parameters, and $C$ is the penalty parameter. Assume that optimal solution is $x = (x_1, \ldots, x_n)$, and then decision function can be expressed by

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

Step 3. Watermark extraction. From image blocks in which owner signature is embedded, we can construct input set $D' = \{x_k = (c^1_1(1), c^1_2(2), \ldots, c^1_7(8), c^2_1(1), c^2_2(2), \ldots, c^2_7(8)) \mid k = 1, \ldots, m\}$. Then, by using well-trained SVMs in Eq. (8), we can calculate their corresponding outputs $\{\hat{y}_k | k = 1, \ldots, m\}$, i.e.,

$$\begin{cases} \hat{y}_k = f(\hat{x}_k), & k = 1, \ldots, m \\ \hat{x}_k = (c^1_1(1), c^1_2(2), \ldots, c^1_7(8), c^2_1(1), c^2_2(2), \ldots, c^2_7(8)) \in D' \end{cases} \quad (9)$$

Thus, embedded owner signature is obtained by

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

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

In our experiments, original images are some standard gray-scale 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” (see Eq. (6)) 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 $\sigma = 290$ for RBF kernel and penalty parameter $C = 500$ for SVMs. Secondly, GHM multiwavelet is used in the experiments. Thirdly, reference information $(H = h_1, h_2, \ldots, h_n)$ is a pseudo-random binary sequence which is generated from a Gaussian distribution with zero mean and unit variance, where $n = 1024$. Finally, a binary logo image with size $32 \times 32$ is used for owner signature, shown in Fig. 5(a).

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 $I'$. For robustness, *Bit Error Rate* (BER) measures difference between original watermark $W$ and extracted watermark $W'$. It should be noted that the larger PSNR, the better imperceptibility. If a method has a lower BER, it is more robust.

4.1. Test results for imperceptibility

According to the parameters given above, we run proposed watermark embedding algorithm on tested images. Fig. 4 shows watermarked versions of Lena image with PSNR = 42.179 dB, Peppers image with PSNR = 42.026 dB, and Boat image with PSNR = 42.381 dB, respectively. We can see that all watermarked images are not distinguishable from their original ones, which demonstrate good imperceptibility of proposed watermarking method.

4.2. Test results for robustness

In attack free case, we extract watermark images from watermarked images using proposed watermark extraction algorithm, respectively. Fig. 5(b)–(d) show these extracted watermark images from watermarked Lena, Peppers and Boat image, respectively, and all results are with BER = 0. 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, low-pass filtering, median filtering, salt&peppers noise, Gaussian noise, image scaling, image cropping, rotation, respectively. Then, we perform watermark extraction process and compute their BER outputs. Here, we only show experimental results obtained on standard Boat image. In experiments, we will compare several machine learning methods, including Tsai’s method (Tsai and Sun, 2007), Zhang’s method (Zhang et al., 2002) and Li’s method (Li et al., 2005), because these methods have good performance which outperforms that of conventional watermarking methods. Tsai’s method is a color image watermarking algorithm in spatial domain based on support vector machines (Tsai and Sun, 2007). Here, we will implement the algorithm on gray-scale image according to same idea. Li et al. (2005) used support vector regression (SVR) for watermark embedding and extracting in spatial domain. Zhang’s method is a watermarking method, and use neural net-
works to extract the watermark (Zhang et al., 2002). For fair comparison, parameters of algorithms in Tsai’s method, Li’s method and Zhang’s method are decided experimentally to get watermarked image with similar PSNR value.

For JPEG compression, watermarked images are compressed by JPEG with quality factor 80 and 50, respectively. Fig. 6(a) and (f) show JPEG compression versions of watermarked Boat image with quality factor 80 and 50, respectively. The watermarks which are extracted from Fig. 6(a) and (f) by proposed method with BER = 0.0946 and 0.2215, are shown in Fig. 6(b) and (g), respectively. Fig. 6(c) and (h) are extracted watermarks by Zhang’s method with BER = 0.0983 and 0.3658, respectively. Fig. 6(d) and (i) are the extracted watermarks by the Tsai’s method with BER = 0.1025 and 0.3871 respectively. Fig. 6(e) and (j) are extracted watermarks by Li’s method with BER = 0.2643 and 0.4157, respectively. The comparable results in terms of BER under JPEG compression are listed in Table 1. It is evident that proposed method is more robust against JPEG compression attack than Tsai’s method, Li’s method and Zhang’s method.

In noise addition experiments, noising method generates 10% noises to degrade watermarked images. Fig. 7(a) shows watermarked image corrupted by noise addition. Four watermarks recovered by proposed method, Zhang’s method, Tsai’s method and Li’s method respectively, are exhibited in Fig. 7(b)–(e). Table 1 shows experimental results in terms of BER under noise addition attack. The results clearly show that proposed method yields better robustness than Zhang’s method, Tsai’s method and Li’s method.

For median filtering, Fig. 7(f) shows watermarked Boat image after median filtering. Watermarks extracted by proposed method, Zhang’s method, Tsai’s method and Li’s method respectively, are shown in Fig. 7(g)–(j). The comparable results in terms of BER under median filtering are listed in Table 1. The results clearly show that proposed method outperforms other three methods. Some other quantity results are tabulated in Table 1. From these visual comparisons and quantity results, it is verified that proposed method has good visual quality and high robustness against JPEG compression, low-pass filtering, median filtering, salt&peppers noise, Gaussian noise, image scaling, image cropping, rotation, etc. According to Table 1, proposed method possesses better robustness than Zhang’s method, Tsai’s method and Li’s method. The main advantages of proposed method are from the following

![Fig. 5](image1.png)

- (a) The original watermark image.
- (b)(d) The extracted watermark images by using the proposed method under attack free case: (b) From watermarked Lena image; (c) From watermarked Peppers image; (d) From watermarked Boat image.

![Fig. 6](image2.png)

- (a) The watermarked image compressed by JPEG with quality factor 80; (b) Extracted watermark by the proposed method; (c) Extracted watermark by Tsai’s method; (d) Extracted watermark by Li’s method; (e) Extracted watermark by Zhang’s method; (f) The watermarked image compressed by JPEG with quality factor 50; (g) Extracted watermark by the proposed method; (h) Extracted watermark by Tsai’s method; (i) Extracted watermark by Li’s method; (j) Extracted watermark by Zhang’s method.

![Fig. 7](image3.png)

- (a) The watermarked image corrupted by noise addition; (b) Extracted watermark by the proposed method; (c) Extracted watermark by Tsai’s method; (d) Extracted watermark by Li’s method; (e) Extracted watermark by Zhang’s method; (f) The watermarked image is corrupted by median filtering; (g) Extracted watermark by the proposed method; (h) Extracted watermark by Tsai’s method; (i) Extracted watermark by Li’s method; (j) Extracted watermark by Zhang’s method.
reasons. (1) From viewpoint of watermark modulation fashion, proposed method uses a mean value modulation technique to embed one watermark bit, whereas other three methods modulate directly single coefficient or pixel. It is well known that mean value of samples has a smaller variance than single sample. So, the mean value modulation technique can more effectively reduce image distortion than that of single coefficient. (2) The special concentrating property of energy of "low-low-pass" sub-bands in multiwavelet domain can tolerate more image distortions. (3) When watermarked images suffer from different attacks, it can be viewed that they are corrupted by different type noises. Because SVMs have powerful learning ability and good generalization performance, robustness of watermarking algorithm is improved greatly. In addition, SVMs can avoid some drawbacks of neural networks in theory.

5. Conclusions

Combining both multiwavelet and support vector machine, we present a novel blind image watermarking approach in this paper. The special structure and property of image in multiwavelet domain are applied to design the watermarking algorithm, and a mean value modulation technique is employed to modulate a set of multiwavelet coefficients in approximation sub-bands. The mean value modulation technique can efficiently reduce effects of image distortion when suffering from different attacks. In order to robustly extract watermark, 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 SVMs, watermark can be exactly recovered unless watermarked image is attacked severely. The experimental results show that proposed method possesses significant robustness against several attacks.

In recent years, except multiwavelet, a number of new techniques have been added into image multiscale geometric analysis in wavelet theory, such as ridgelet, curvelet, wedgelet, contourlet, etc. These new techniques hold different good properties compared with wavelet, and can more effectively capture some features of image, for example, line-like, curve-like, wedge-like, contour-like features. Our further work is that introducing the techniques into image watermarking solves a challenging issue for resisting affine attacks.

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