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An Artificial Intelligent Technique for Robust Digital Watermarking in Multiwavelet Domain

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***Abstract*—**In this paper, an artificial intelligent technique for robust digital image watermarking in multiwavelet domain is proposed. The embedding technique is based on the quantization index modulation technique and the watermark extraction process does not require the original image. We have developed an optimization technique using the genetic algorithms to search for optimal quantization steps to improve the quality of watermarked image and robustness of the watermark. In addition, we construct a prediction model based on image moments and back propagation neural network to correct an attacked image geometrically before the watermark extraction process begins. The experimental results show that the proposed watermarking algorithm yields watermarked image with good imperceptibility and very robust watermark against various image processing attacks.

***Keywords*—**Watermarking, Multiwavelet, Quantization index modulation, Genetic algorithms, Neural networks.

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I. Introduction

WITH the great spread of the Internet networks and the rapid development of digital multimedia technologies, digital contents can be readily shared via Internet networks and easily used, processed, and transmitted. However, there is the problem that digital contents can be copied without any loss and distributed without the approval of an author. Therefore, it is an important issue to protect the intellectual property rights of digital multimedia contents.

Digital watermarking is one of the most popular approaches considered as a tool for providing the copyright protection of digital multimedia contents. In a desired image watermarking system, the watermark should be robust to content preserving attacks including common image processing operations and geometrical distortions. Common image processing does not modify only the image but may also modify the watermark as well. Thus, the watermark may become undetectable after intentional or unintentional image processing attacks and many methods are proposed to resist this kind of attacks [1], [2].

Geometrical distortions mostly cause a watermarking detector to fail to detect the existence of watermark in the watermarked image. Similarly, there also have been many kinds of methods for resisting geometrical distortions, such as the transform-based scheme [3] and the feature-based scheme [4, 5] etc.

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In previous work, [1] Chen and Wornell proposed a class of embedding methods called quantization index modulation (QIM) that achieves probably good rate-distortion-robustness performance. In general, the watermark must be embedded in invisible way to avoid degrading the perceptual quality of the host image. To overcome this difficulty, many researches exploited the characteristics of the human visual system to compromise between the invisibility and robustness of the embedding algorithm. In [2], Li et al. proposed watermarking techniques for digital images. The watermark is embedded into the wavelet coefficients after the singular value decomposition of the image is computed. In order to satisfy the requirements on the invisibility and robustness of the embedded watermark, the human visual system is used to develop a perceptual mask for optimizing the watermark strength in the embedding process.

Another way to achieve the main requirements of watermarking schemes is to make use of artificial intelligence techniques. The image watermarking problem can be viewed as an optimization problem. Therefore, it can be solved by optimization algorithm such as neural network (NN), genetic algorithms (GA) or support vector machine (SVM). In recent years, a number of artificial intelligence watermarking techniques for digital images has been reported. In recent years, the application of neural networks to digital watermarking mainly includes determining the watermark strength and improving watermark detection. In [4], Gao and Jiang proposed a novel robust grayscale image watermarking scheme against geometric attacks in wavelet transform domain. The watermark robustness is improved through embedding the perceptually significant part of watermark information into the low-frequency part of the cover image coefficients. The back propagation neural network is utilized to construct the forecasting model which can be used to correct the attacked image geometrically. Wang et al. [5] proposed an image watermarking scheme in spatial domain and applied classification techniques based on SVM to improve the performance of conventional methods. Huang *et al.* [6] proposed a novel blind watermarking technique in wavelet transform domain. The artificial neural network is applied to memorizing the relation between the watermark signal and the corresponding watermarked image. Thus the watermark can be recovered exactly from the watermarked image without the original and the watermark images. Chen *et al.* [7] proposed a new robust public watermarking algorithm. The watermark is embedded repeatedly in different coefficients of the discrete cosine transform domain using a proper embedding threshold below the perceptible threshold. Moreover the neural network is applied to extract the watermark.

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Several gray level watermarking schemes based on mutiwavelet were proposed recently. Ghouti et al. [8] introduced a robust watermarking algorithm using balanced multiwavelet transform. The watermark embedding scheme is based on the principles of spread-spectrum communications to achieve higher watermark robustness. In [9], Kumsawat et al. proposed a new digital image watermarking algorithm in the discrete multiwavelet transform (DMT) domain. The embedding technique is based on the parent-child structure of the transform coefficients called the triple tree. The watermark is a binary pseudo-random noise sequence and this algorithm does not require the original image in the watermark extraction.

In this paper, we propose an image watermarking method based on the discrete multiwavelet transform for the application of copyright protection. In our algorithm, the imperceptibility and robustness of an existing image watermarking technique is enhanced through GA optimization and NN. Finally, we have compared our experimental results with the results of previous work.

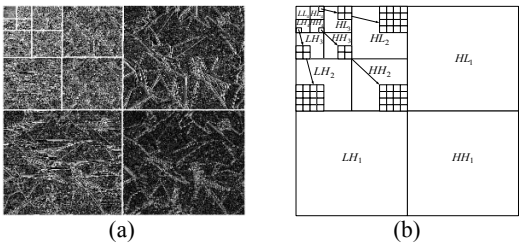
This paper is organized as follows: in Section II, the preliminaries of multiwavelet transform and multiwavelet tree are introduced. Watermarking in the DMT domain with genetic algorithm optimization and neural network training are described in Section III. In Section IV, the experimental results are shown. The conclusions of our study can be found in Section V.

II. Preliminaries

A. Multiwavelet Transform and Multiwavelet Tree

In recent years, discrete multiwavelet transformations have gained a lot of attention in signal processing applications. The main motivation of using multiwavelet is that it is possible to construct multiwavelets that simultaneously possess desirable properties such as orthogonality, symmetry and compact support with a given approximation order [10]. A scalar wavelet cannot possess all these properties at the same time. Thus, multiwavelets offer the possibility of superior performance for image processing applications, compared with scalar wavelets. Multiwavelet transform coefficients have the property that the related coefficients in different scales are located at the same orientation and location in the multiwavelet hierarchical decomposition. Figure 1(a) illustrates a four-level multiwavelet decomposition of the EM1 image.

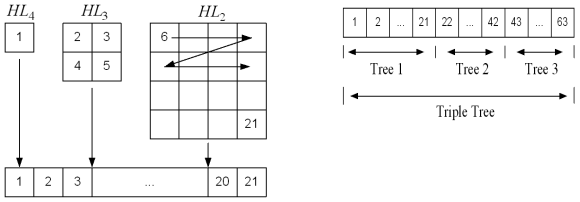
With the exception of the highest frequency subbands, every coefficient at a given scale can be related to a set of coefficients at the next finer scale of similar orientation. The coefficient at the coarse scale is called the parent, and all coefficients corresponding to the same spatial location at the next finer scale of similar orientation are called children. For the four-level multiwavelet hierarchical subband decomposition, the parent-child dependencies are shown in Fig. 1(b). For a given parent, the set of all coefficients at all finer scales of similar orientation corresponding to the same location are called descendants. Multiwavelet trees descending from a single coefficient in the subband HH_4 , HL_4 and LH_4 is shown in Fig. 1(b).



(a) (b)

Fig. 1 (a) Four-level multiwavelet decomposition of EM1 image and (b) the parent-child dependencies of multiwavelet trees

Without significant loss of generality, we shall focus on watermarking still images with 256 gray levels of size 512×512 pixels. To trade off between the invisibility and robustness of the watermark, the high-energy subband (LL_4) is not used. Furthermore, the coefficients in high-frequency subbands (LH_1 , HL_1 and HH_1) are not used since they often contain low energy coefficients.



(a) (b)

Fig.2 (a) A group of multiwavelet coefficients in each tree and (b) the example of triple tree

In other subbands, we group the coefficients corresponding to the same spatial location together. Figure 2(a) shows an example of a group with one coefficient from HL_4 , 4 coefficients from HL_3 , and 16 coefficients from HL_2 . The coefficients of the same group correspond to various frequency bands of the same spatial location and the same orientation. The total number of groups is equal to the sum of the number of coefficient in LH_4 , HL_4 and HH_4 , each of which has 32×32 coefficients. There are a total of $3 \times 32 \times 32 = 3072$ groups. We denote each group of multiwavelet tree by Tg_m , where $m = 1, 2, ..., 3072$.

III. Proposed Method

In this section, we first give a brief overview of the watermark embedding and watermark extracting processes in the DMT domain. We then describe the GA optimization of our proposed method.

A. Watermark Embedding Algorithm

1. Generate a seed by mapping a signature or text through a one-way deterministic function. The seed is used as the secret key (K) for watermarking.

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2. Generate a permuted watermark W using the secret key, where $W = \{w_i\}$ for $i = 1, 2, ..., N_w$; $w_i \in \{+1, -1\}$, and N_w is the length of watermark.

3. Transform the original image into four-level decomposition using the DMT. Then, create multiwavelet trees and rearrange them into 3072 groups.

4. To increase the watermarking security, we order the groups Tg_m in a pseudorandom manner. The random numbers can be generated using the secret key K. We further combine the coefficients of every three groups together to form "a triple tree: Tt_i", for $i = 1, 2, ..., 1024$. Each watermark bit could be embedded into one triple tree.

5. For watermark embedding, we select the first N_w triple trees, which have the largest mean values. Then, the watermark sequence $\{w_i\}$ is embedded into the selected triple trees by quantization index modulation technique. The quantization function is given as follows:

$$Tt_i' = \begin{cases} \lfloor Tt_i / S_j \rfloor \cdot S_j + 3S_j / 4 & if\ w_i = +1 \\ \lfloor Tt_i / S_j \rfloor \cdot S_j + S_j / 4 & if\ w_i = -1 \end{cases} \quad (1)$$

, where $\lfloor x \rfloor$ rounds to the greatest integer smaller than x, Tt_i and Tt_i' denote the triple tree of the original image and the corresponding watermarked image respectively. The variable S_j, for $j = 1, 2, 3$, denotes the quantization steps corresponding to the orientation of horizontal, vertical and diagonal of DMT subband, respectively. A large S_j makes the watermark robust, but it will destroy the original quality of the image. Thus, the value of S_j should be as large as possible under the constraint of imperceptibility.

6. In order to improve both quality of watermarked image and robustness of the watermark, this work employs the genetic algorithm to search for the quantization steps. The details of GA optimization process will be described in details in Section III.

7. Pass the modified DMT coefficients through the inverse DMT to obtain the watermarked image.

B. Watermark Extracting Algorithm

1. Transform the watermarked image into four-level decomposition using the DMT. Then, create the multiwavelet trees and rearrange them into 3072 groups.

2. We order the groups in a pseudorandom manner by a similar secret key which was used in the embedding process. Then, combine every 3 groups to form a triple tree Tt_n, for $n = 1, 2, ..., 1024$.

3. Let $\tilde{T}t_i$ denote the first N_w triple trees, which have the largest mean values. The embedded watermark can be extracted from $\tilde{T}t_i$ by using the following rule:

$$\tilde{w}_i = \begin{cases} +1 & if\ \ \tilde{T}t_i - \lfloor \tilde{T}t_i / S_j \rfloor \cdot S_j \geq S_j / 2 \\ -1 & if\ \ \tilde{T}t_i - \lfloor \tilde{T}t_i / S_j \rfloor \cdot S_j < S_j / 2 \end{cases} \quad (2)$$

4. After extracting the watermark, we used normalized correlation coefficients (NC) to quantify the correlation between the original watermark and the extracted one.

C. Genetic Algorithm Optimization

The goals of an effective digital watermarking, such as imperceptibility, robustness and data capacity usually conflicts [11]. In order to minimize such conflicts, this work employs the genetic algorithms to search for optimal parameters. This allows the system to achieve optimum performance. For the optimization process, GA is applied in the watermark embedding. The parameters to be searched for are three quantization steps S_1, S_2 and S_3. The objective function of searching process is computed using factors that both related to robustness and imperceptibility of watermarked image. Details of GA are described as follows:

Chromosomes in GA represent desired parameters to be searched [12]. Number of chromosomes used in this work is 30. The encoding scheme is binary string with 32 bit resolutions for each chromosome. The parameter S_j is then represented by chromosome with length of 96 bits. The objective function uses both a universal quality index (UQI) [13] and normalized correlation as performance indices. UQI is used as output image quality performance index due to its role of imperceptibility measure. Similarly, NC is used as a watermark detection performance index because of its role of robustness measure. An objective value W can be calculated from (3):

$$W = \delta_{UQI} \times UQI + \delta_{NC} \times NC \quad (3)$$

where δ_{UQI} and δ_{NC} are weighting factors of UQI and NC, respectively. These weighting factors represent the significance of each index used in GA searching process. In this work, a ranking selection is chosen for selection mechanism. The crossover and mutation probability is fixed at 0.7 and 0.05, respectively.

D. Neural Network Training

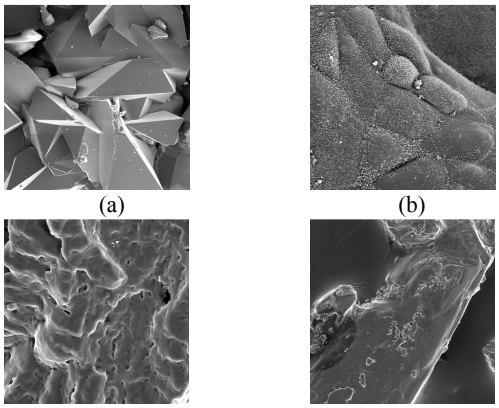
The back-propagation neural network (BPNN) is one type of supervised learning neural network. It is a potential tool in many signal processing applications [14]. In this paper, a robust image watermarking scheme against geometric attacks based on neural networks is proposed. In the process of getting prediction model using BPNN, the original image is geometrically transformed, such as rotation, scaling and translation, to generate the training samples. Then, the eigenvectors of every training sample image, which is the Tchebichef image moments [15], are computed to use as the input of BPNN training. In the meantime, the corresponding geometric transformation parameters R, S, Tx and Ty, which denote the values of rotation, scaling, translation in x-

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axis and translation in *y*-axis respectively, are viewed as the target of BPNN training. We construct a three-layer BPNN with 5, 20 and 1 neurons in the input, hidden and output layers respectively. The activation function in the hidden layer is a sigmoid function, but the output neuron uses the linear activation function. Levenberg-Marquardt algorithm is used to increase the training speed and makes the training avoid getting into local minimum. The training error is set to 0.001 and the number of maximum learning iteration is set to be 4500. The training is finished when either training error is smaller than 0.001 or the iteration is reached to the maximum iteration number. After training, neural network can memorize the characteristics of the learning samples, and predict a new output due to its adaptive capability. Therefore, the watermarked image undergone rotation, scaling, and translation transformations can be inverted to its original size and orientation for watermark detection.

IV. Experimental Results and Discussions

To evaluate performance of the proposed watermarking scheme, experiments were conducted using four electron microscope images. The images are illustrated in Fig.3. They are all gray level images with standard dimension 512×512 pixels. We use a binary "SIP SUT" logo with 16×32 pixels as a visually recognizable watermark. The original binary watermark and permutated watermark images are shown is Fig. 4(a) and 4(b), respectively.



(a) (b) (c) (d)

Fig. 3 Original images used in experiments (a) EM1, (b) EM2, (c) EM3 and (d) EM4

A. Result of Genetic Algorithm Optimization and Neural Network Training

Figure 5 shows the convergence of GA optimization at 30 generations of the EM1 image. The results of optimal parameters S_1, S_2 and S_3 from GA searching using 4 test images are shown in Table I. These parameters are optimally varied to achieve the most desirable ones for original images with different characteristics. Figure 6 shows the mean square error in each step when the BPNN is trained using the EM1 image.



(a) (b)

Fig. 4 (a) Original watermark and (b) permuted watermark

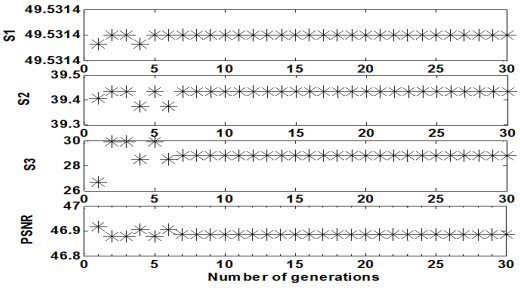


Fig. 5 S_1, S_2, S_3 and $PSNR$ from GA optimization process of the EM1 image

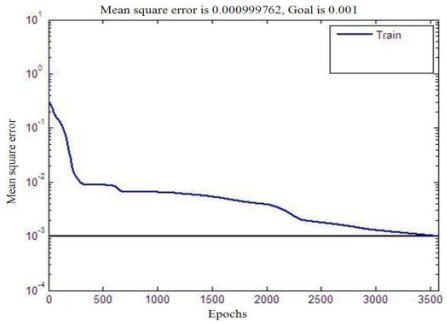


Fig. 6 Training curve of BPNN

B. Imperceptibility Test Results

We test the output image quality by watermarking the original images with the resulting parameters from GA. Then, we use the peak signal to noise ratio ($PSNR$) to compare the image quality between the original and the watermarked images. By using the proposed algorithm, the watermark is almost imperceptibility to the human eyes, as shown in Table I.

C. Robustness Test Results

To investigate robustness of the watermark, watermarked images are attacked by various common image operations and geometric distortions. Then, we perform watermark extraction process and compute the normalized correlation (NC). Since our system is a multi-bit watermarking system, the bit error rate (BER) is a very useful measure of performance. We first examine the robustness against common signal processing such as, median filtering, JPEG compression and JPEG2000 compression. The watermark detection results are shown in Table II, Fig. 7 and Fig.8. It shows that the watermark can be detected under most of the common signal processing attacks which were included in this study.

TABLE I
THE RESULTS OF PARAMETERS USING GA OPTIMIZATION PROCESS FROM VARIOUS IMAGES

Images	S_1	S_2	S_3	*PSNR*	*UQI*
EM1	49.53	39.43	28.81	46.88	0.9730
EM2	49.49	35.80	25.06	48.19	0.9931
EM3	24.14	35.58	29.59	50.28	0.9992
EM4	45.88	39.68	25.28	47.27	0.9846

TABLE II
NC AND BER VALUES FROM COMMON IMAGE OPERATIONS OF THE EM1-EM4 IMAGE (AVERAGE)

Attack method	*NC*	*BER* (%)
3 × 3 Median filtering	0.9589	5.66
JPEG Quality 20%	0.9420	8.00
JPEG Quality 50%	0.9986	0.19
JPEG Quality 80%	1.0000	0.00
JPEG Quality 90%	1.0000	0.00
JPEG2000 (1:10)	1.0000	0.00
JPEG2000 (1:20)	0.9986	0.19
JPEG2000 (1:30)	0.9591	5.66
JPEG2000 (1:40)	0.9462	7.42

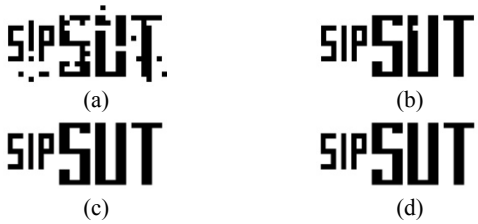


Fig. 7 Robustness to JPEG Compression of various quality factors (a) 20%, (b) 50%, (c) 80% and (d) 90%.

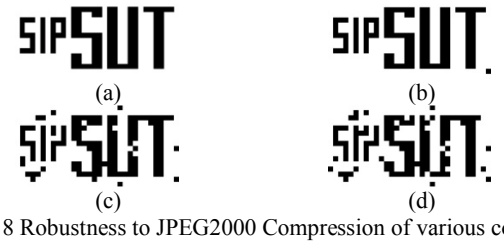


Fig. 8 Robustness to JPEG2000 Compression of various compression ratios (a) 1:10, (b) 1:20, (c) 1:30 and (d) 1:40.

Next, we test the robustness with respected to geometrical attacks such as, rotation, scaling and translation. The examples of different types of geometric attacks to the watermarked image are shown in Fig. 9. Before watermark detection is performed, the back propagation neural network is utilized to memorize the relations between a geometric distortions and the corresponding watermarked image to correct the attacked image geometrically. The experiment results are shown in Fig. 10 and Table III.

Finally, the results obtained from our proposed method are compared with the method based on multiwavelet-tree quantization in [9]. For a fair comparison, the quality of the watermarked EM1 image (PSNR around 38 dB) and embedding capacity (watermark 512 bits) for both schemes must be the same. The comparison results are listed in Table IV and we can see that the proposed method is very robust to various attacks and yields significant more robust watermark than the method in [9] does.

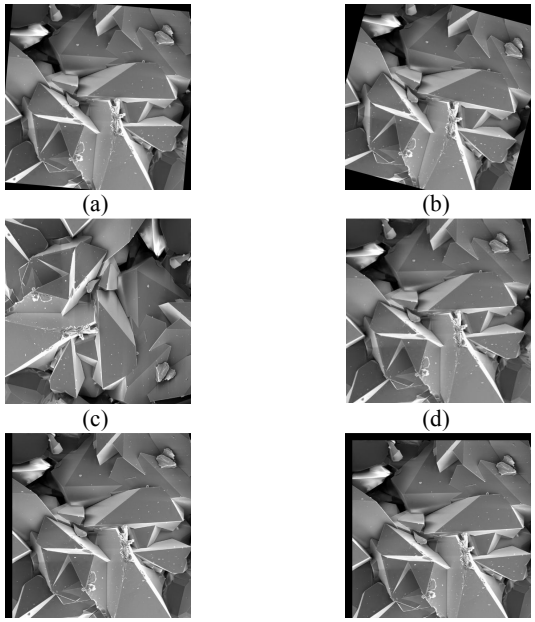


Fig. 9 Different type of attacks to watermarked image (a) rotation 5°, (b) rotation 15°, (c) rotation 90°, (d) scaling 200%, (e) Translation 20 pixels in x-axis and (f) Translation 20 pixels in x and y-axis

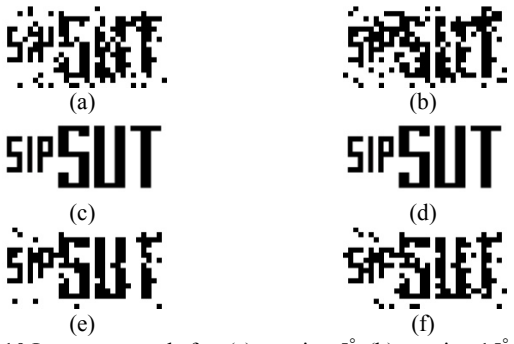


Fig. 10 Logo extracted after (a) rotation 5°, (b) rotation 15°, (c) rotation 90°, (d) scaling 200%, (e) Translation 20 pixels in x-axis and (f) Translation 20 pixels in x and y-axis

V. CONCLUSION

This paper proposed a digital image watermarking algorithm in the multiwavelet domain. The embedding technique is based on the quantization index modulation. In our optimization process, we use genetic algorithms to search for optimal parameters which are three quantization steps. These parameters are optimally varied to achieve the most suitable watermarked image. In addition, we construct a prediction model based on image moments and a back propagation neural network to geometrically correct the attacked image prior the watermark extraction. The experimental results demonstrate that the proposed algorithm is robust against common image processing attacks and geometrical distortions. Furthermore, the extracted watermark is visually recognizable in most cases.

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TABLE III
NC AND BER UNDER GEOMETRICAL ATTACKS OF THE EM1-EM4 IMAGE (AVERAGE)

Attack method	*NC*	*BER* (%)
Rotation 5	0.9065	12.69
Rotation 15	0.8779	16.21
Rotation 90	1.0000	00.00
Rotation -90	1.0000	00.00
Scaling 150%	1.0000	00.00
Scaling 200%	1.0000	00.00
Translation 5 pixels in x-axis	0.9775	3.12
Translation 5 pixels in y-axis	0.9763	3.32
Translation 20 pixels in x-axis	0.9648	4.84
Translation 20 pixels in y-axis	0.9546	6.25
Translation 20 pixels in x&y-axis	0.9256	10.15

TABLE IV
NC FROM SIGNAL PROCESSING ATTACKS OF THE EM1 IMAGE

Attack method	*NC*	
	Our	[9]
3 × 3 Median filtering	0.9585	0.5820
JPEG Quality 20	0.9420	0.4141
JPEG Quality 50	0.9986	0.9023
JPEG Quality 80	1.0000	0.9922
JPEG2000 (1:10)	1.0000	0.9610
JPEG2000 (1:20)	0.9986	0.7188
Rotation 5	0.9065	0.3867
Rotation 15	0.8779	0.4140
Scaling 150	1.0000	0.3633
Scaling 200	1.0000	0.3867
Translation 5 pixels in x-axis	0.9775	0.2266
Translation 20 pixels in x-axis	0.9648	0.2305

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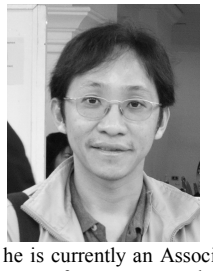
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