Paper

A Robust Watermarking Method for Copyright Protection of Digital Images using Wavelet Transformation

Yasuhiko Dote*, Member, Muhammad Shafique Shaikh*, Non-member

A multiresolution wavelet transformation based robust watermarking method is introduced. The coefficients of watermark are embedded into those of host image at different transformation level using a secret key. Watermark is extracted using the same key and by inverse transformation at each level. Finally, the watermark is estimated by taking mean value of the obtained watermarks. The introduced method is tested on gray and color images with added Gaussian, salt and pepper, Speckle, and JPEG noises. Correlation coefficients are used to compare the embedded and extracted watermarks. Comparison result with an earlier work is presented.

Keywords : Copyright protection, watermarking, digital image, wavelet transform

1. Introduction

In the age of Internet technology and due to availability of multimedia computing facilities, protection of intellectual property rights has become a serious issue. In particular it is true for image and video data that can be easily stolen or altered. Conventionally, to identify the source a painting is signed by the artist, an identity card is stamped by a seal, and a paper money is embossed by a portrait [1]. Borrowing the same idea the digital information may be embedded with a watermark. Digital watermarks may comprise of copyright or authentication codes or a legend. An efficient watermark should have features, like, unobtrusive, discreet, easily extracted and robust to incidental and intentional distortions.

In the academic literature, several techniques have been developed for watermarking. Detailed reviews are given in [2][3][4]. Current techniques for watermarking of digital images can be grouped into two classes: transform domain methods [5][6][7], which embed the data by modulating the transform domain coefficients, and spatial domain techniques [8][9].

It is found in the literature that multi-resolution wavelet-based fusion algorithms are superior to other image merging techniques [7]. The localization of the watermark at high resolution provides the ability to identify distinct regions of the watermarked image, which have undergone tampering, and global spreading of the watermark at low resolutions within the host image makes it robust to large-scale signal distortions [10]. We utilize multilevel wavelet decomposition and present a technique to embed the watermark using a secret key in each of the resolution levels and test the method on gray and color images under noisy conditions.

Section 2 describes novel multilevel watermarking method. Similarity measure is presented in Section 3. We discuss our simulation results for gray and color images in Sections 4 and 5, respectively. Section 6 concludes our paper.

* Department of Computer Science and Systems Engineering, Muroran Institute of Technology, 27-1, Mizumoto-cho, Muroran, 050-8585, Japan.
(e-mail,dote@csse. muroran-it.ac.jp)

2. Novel Multilevel Watermarking Method

In the presented method we use binary watermark comprised of $N \times N$ arrays of ones and zeros. For simplicity, we adopt the notation scheme used in [6] with some modifications. It is assumed that the size of the watermark in relation to the host image is small. We use $f(m,n)$ to denote the host image and $w(p,q)$ the watermark; where m and n denote the image dimension and p and q represent the watermark size. A general view of watermarking method is shown in Fig. 1. The watermark embedding and retrieval method [11][12] is described in the following subsections.

2·1 Watermark Embedding The presented watermark-embedding scheme is comprised of following two steps.

Step I: The host image and watermark are transformed into the wavelet domain. The number of levels (L) of discrete wavelet transformation (DWT) depends on the size of the watermark. The DWT of the host image produces three detail images, *i.e.*, horizontal, vertical, and diagonal details at each resolution level, and an approximation of the image at L^{th} level. The detail coefficients of the host image and watermark are denoted by $f_{k,l}(m,n)$ and $w_{k,1}(p,q)$, respectively, where $k=1,2,3$ and $l=1,\ldots,L$ We perform 1st level DWT for the watermark.

Step II: Let's denote the number of coefficients in k details of l level of DWT of the host image as $s_{k,l}$ and that of watermark as $t_{k,1}$. We randomly select $s_{k,l}$ using a secret key for watermark embedding and denote it as $r_{k,l}(p,q)$. Therefore, for every level l:

1. Add the watermark coefficients $w_{k,1}(p,q)$ to the $f_{k,l}(m,n)$ at locations pointed at by $r_{k,l}(p,q)$.
2. Inverse transform and feed marked image to the next level of embedding.

We denote the watermarked image after L times of embedding as $\tilde{f}(m,n)$.

2·2 Watermark Retrieval The watermark retrieval is comprised of following two steps.

Step I: The watermark is extracted from the marked image by applying the inverse procedure at each resolution level. Let's denote the detail coefficients of $\tilde{f}(m,n)$ for every l level of wavelet decomposition as $\tilde{f}_{k,l}(m,n)$. We need host image and the

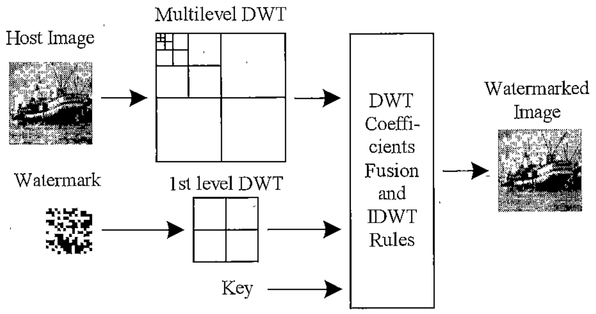


Fig. 1. Proposed watermarking method.

secret key to generate $r_{k,l}(p,q)$ for extraction of the watermark. Therefore, for every level l:

1. Subtract the host detail coefficients $f_{k,l}(m,n)$ from those of noisy marked image, $\tilde{f}_{k,l}(m,n)$, only from the locations pointed at by $r_{k,l}(p,q)$. Store the residual marked image for further processing in next step.
2. Inverse transform the extracted watermark coefficient and residual watermarked coefficients for 1st level and l level respectively. The extracted watermark is denoted by $\hat{w}_l(p,q)$. Feed the residual marked image to the next level of watermark extraction.

Step II: Estimate the watermark by averaging the extracted watermarks $\hat{w}_l(p,q)$ and normalize it for binary values.

3. Similarity Measure

In order to find out similarity between embedded and extracted watermarks first we observe the host and the marked images perceptually. We calculate correlation coefficients between them at different signal to noise ratio (SNR) values.

The correlation coefficient, ρ, used for similarity measurement, and SNR are defined as

$$\rho(w,\hat{w}) = \frac{\sum_{i=1}^{N} w_i \hat{w}_i}{\sqrt{\sum_{i=1}^{N} w_i^2}\sqrt{\sum_{i=1}^{N} \hat{w}_i^2}} \quad \cdots\cdots (1)$$

$$\mathrm{SNR}(w,\hat{w}) = 10\log_{10}\frac{\sum_{i=1}^{N} w_i^2}{\sum_{i=1}^{N}(w_i - \hat{w}_i)^2} \quad \cdots\cdots (2)$$

where N is the number of pixels in watermark, and w and $\hat{w}$ are the original and extracted watermarks, respectively.

4. Simulation Results and Discussion for Water-marking of Gray Images

For simulation of the presented watermarking method we chose six 256x256 gray intensity images, *i.e. bird, cameraman, fishingboat, goldhill, rice,* and *tire*, and two 16×16 binary watermarks where one is randomly generated while the other has English text, ICLMIT, as shown in Fig. 2. Haar wavelet is used in our simulation. We selected up to 5th level of DWT for host image and level 1st for the watermark since the size of detail coefficients are same at these levels although it is not the requirement of the method. The dimensions of transformed components of host image, $f_{k,l}(m,n)$, and watermark, $w_{k,1}(p,q)$, are shown in Tables 1 and 2, respectively.

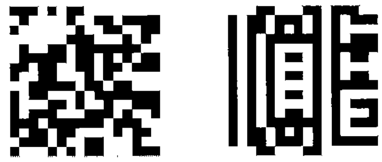


Fig. 2. Random (left) and text (right) watermarks.

Table 1. Wavelet decomposed host image components.

l	$h_{1,l}(m,n)$	$h_{2,l}(m,n)$	$h_{3,l}(m,n)$
1	128×128	128×128	128×128
2	64×64	64×64	64×64
3	32×32	32×32	32×32
4	16×16	16×16	16×16
5	8×8	8×8	8×8

Table 2. Wavelet decomposed watermark components.

l	$w_{1,l}(p,q)$	$w_{2,l}(p,q)$	$w_{3,l}(p,q)$
1	8×8	8×8	8×8

The decomposed watermark coefficients were embedded into those of the host image using steps I to II of the presented watermark embedding method. The host and marked images using *random* and *text* watermarks are shown in Fig. 3. There is no perceptual distortion in these images, which means that our scheme has satisfied the first criteria.

Although perceptually we do not find any difference in the host and marked images but some degradation might have occurred in the process of watermark embedding. In order to find the degradation we calculated the peak signal to noise ratio (PSNR) between the host and marked images and compared our result with that of [13]. For this comparison we use the same formula that is used in [13], *i.e.*,

$$RMSE = \sqrt{\frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[\hat{f}(m,n) - f(m,n)\right]^2}$$

where (M,N) is the size of host image, f, and that of marked image $\hat{f}$, and RMSE represents root-mean-square error. The related measure of PSNR (in dB) is computed using

$$\mathrm{PSNR} = 20\log_{10}\left[\frac{255}{\mathrm{RMSE}}\right]$$

for the 8-bit (0-255) image.

The PSNR values are calculated using a watermark scaling factor, α, for the range 0.1 to 1.0. Table 3 shows that our scheme gave better result as compare to that of [13]. Average improvement in PSNR is found as 63.

For rest of the simulation we computed the SNR using Eq. (2) and did not the use the scaling factor, α.

To verify the robustness of the presented method the marked images were distorted by adding *Gaussian, salt & pepper,* and *Speckle* noises, and were subjected to lossy *joint photographic experts group* (JPEG) compression that is widely used for digital

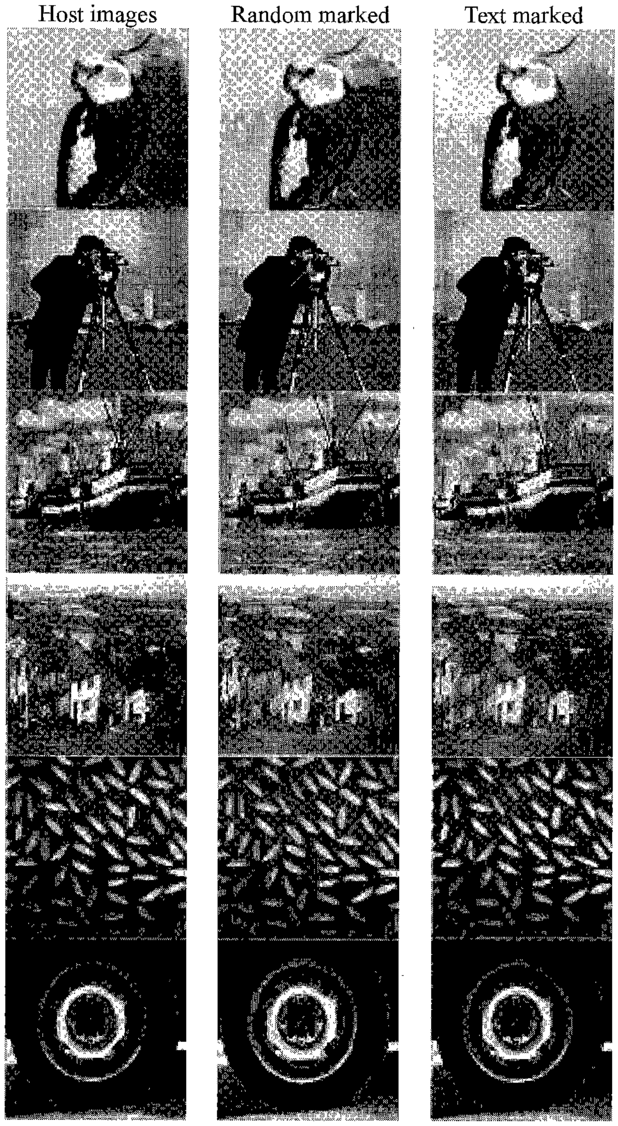


Fig. 3. Host and random and text watermarked images.

Table 3. Performance evaluation.

α	*PSNR (dB)* [13]	*PSNR (dB)*	*Improvement (%)*
0.1	27.11	92.32	341
0.2	20.98	86.30	411
0.3	17.41	82.77	475
0.4	14.81	80.28	542
0.5	12.70	78.34	617
0.6	11.36	76.75	676
0.7	10.48	75.41	720
0.8	9.60	74.25	773
0.9	8.69	73.23	843
1.0	7.79	72.32	928

image storage and communication by Internet community. For our method we suppose that the correlation coefficient, ρ, of about 0.75 or above is assumed as an acceptable value. The obtained correlation coefficient for Gaussian, salt and pepper, Speckle, and JPEG noises are shown in Figs. 4, 5, 6, and 7, respectively. It was

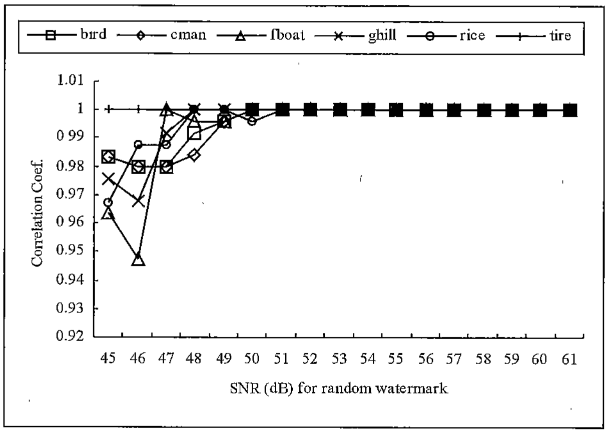


Fig. 4. Result for additive Gaussian noise using random watermark on marked images.

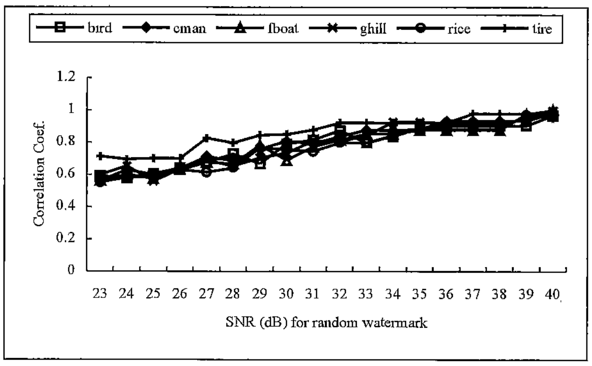


Fig. 5. Result for additive salt and pepper noise using random watermark on marked images.

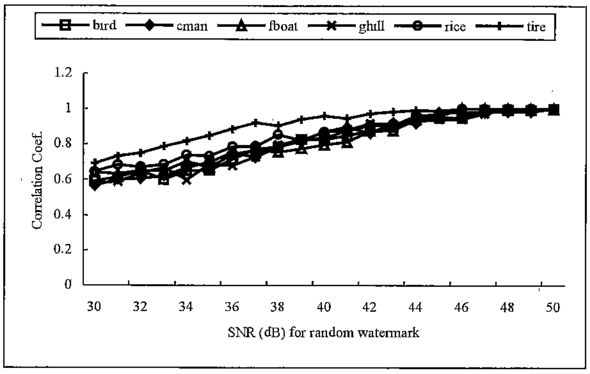


Fig. 6. Result for additive Speckle noise using random watermark on marked images.

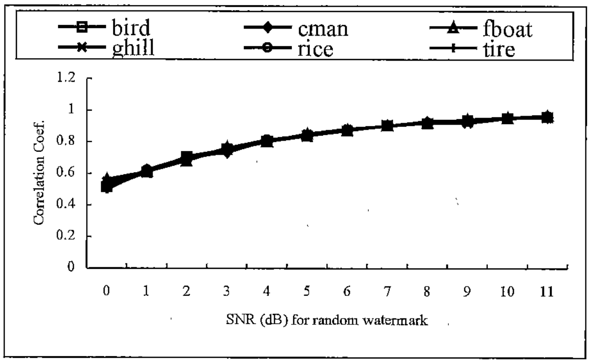


Fig. 7. Result for additive JPEG noise using random watermark on marked images.

observed that t ρ pattern for test watermark followed the pattern of random watermark.

We notice in Fig. 4 that ρ remain above 0.96 in most of the cases and then reach the value 1 and maintains it for SNR 46.0 dB and above for all the images. The correlation coefficients are well above the set criteria. This means that our method sustained the degradation caused by the Gaussian noise of the given variance.

For the used range of salt and pepper noise, ρ started increasing from 0.5 and reached its maximum value 1 gradually, as shown in Fig. 5. It crosses the desired criteria of 0.75 at about 24 dB SNR that is an acceptable value. Hence, the presented scheme coped with the degradation caused by *salt and pepper* noise of the used density.

For Speckle noise, we observe in Fig. 6 that correlation coefficients, ρ, increase gradually from 0.6 to 1 for SNR of 30 dB and above, it reached 0.75, the criteria, at about 35 dB SNR, which is an acceptable value.

Lossy JPEG compression technology is commonly used in the Internet community for image storage and communication. We subjected the watermarked images to lossy JPEG compression to see the effect on extracted watermarks for quality factors from 0 to 100. We observe in Fig. 7, that the correlation coefficient increases gradually from 0.5 to 1. Quality factor of 75 is widely used for Jpeg. We observe that ρ remain well near 1.0 in all cases for the quality factor 75 (i.e. SNR=8 dB) and above.

Therefore we can say that the proposed method coped with the additive *Gaussian, salt and pepper, Speckle,* and *JPEG* noises of different intensity for the given gray level images and watermarks.

5. Simulation Results and Discussion for Water-marking of Color Images

In the case of true color images first we converted the color space of the images from RGB to YCbCr, where Y represents the luminance and Cb and Cr denote the chrominance values with respect to blue and red colors, respectively. For watermarking we used only the luminance, Y, values of the images and selected up to 5th level of DWT. We tested our scheme on six color images *e.g. hitte, lily, magi12, pianorso, portofino,* and *trees,* that are freely available on Internet, with *random* and *text* watermarks as shown in Fig. 2. After embedding the transformed watermark's coefficient into those of luminance of color images we inverse transformed the YCbCr values and then converted them to true color images. The original and watermarked color images were found to be visibly similar, hence, we say that the embedding of watermark in color images using presented scheme did not alter the visible shape of the images.

In order to confirm the robustness of presented scheme on color images we inflicted the marked images with *Gaussian, salt and pepper, Speckle* and *JPEG* noises. Correlation coefficients, ρ, obtained from the original and extracted watermarks from noisy images are shown Figs. 8, 9, 10, and 11.

For Gaussian noised images, we notice in Fig. 8 that ρ remain above 0.90 in most of the cases which is well above the criteria.

In case of *salt and pepper* noise ρ increased gradually from 0.5 to 1.0, as shown in Fig. 9, except for *hitte* image.

In Fig. 10 we observe that ρ followed the same pattern for all images and reached the criteria of 0.75 except in the case of *lily*

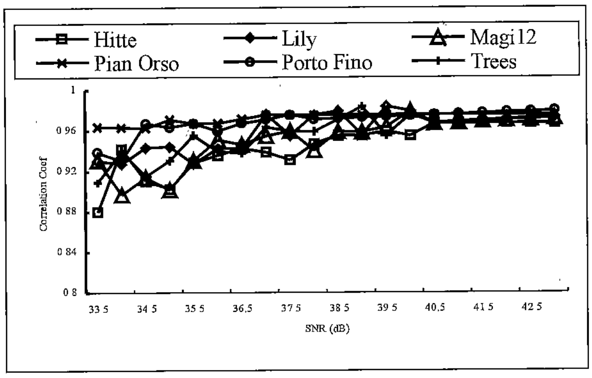


Fig. 8. Result for additive Gaussian noise using random watermark on marked color images.

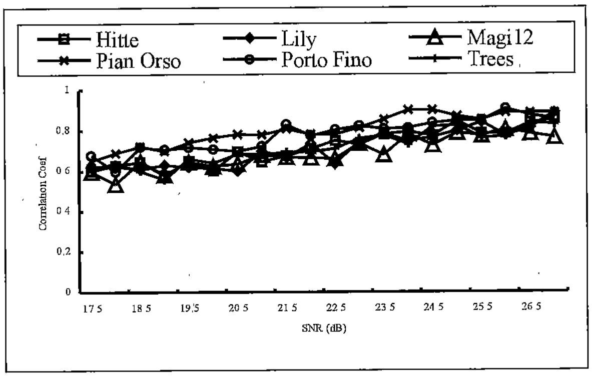


Fig. 9. Result for additive salt and pepper noise using random watermark on marked color images.

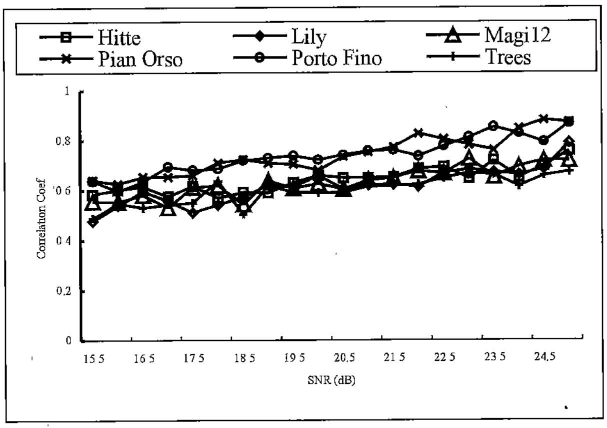


Fig. 10. Result for additive Speckle noise using random watermark on marked color images.

and *portofino* images.

In case of JPEG compression we found that ρ increased gradually from 0.6 to 1.0 and met the criteria.

Observing the overall results obtained from affecting the marked color images with *Gaussian, salt and pepper, Speckle* and *JPEG* noises we may say that the presented scheme coped with the additive noises in most of the cases and achieved the criteria of 0.75. The results obtained from simulation for *text* watermark were approximately the same as those for *random* watermark.

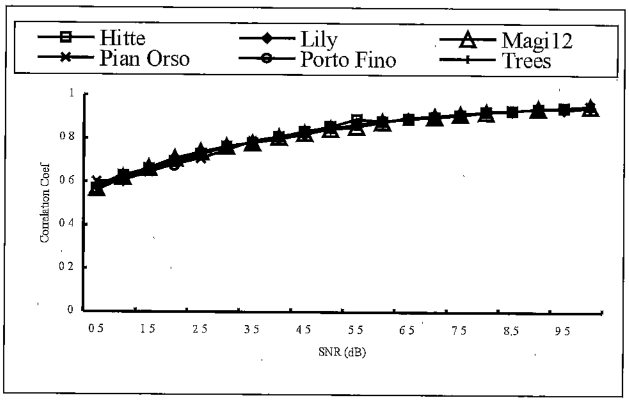


Fig. 11. Result for additive JPEG noise using random watermark on marked images.

6. Conclusion

We presented a watermarking method using discrete wavelet transformation and a *random* and a *text* watermark for simulation. The watermarks thus embedded were found perceptually non-obstructive in gray level and color images. The presented method was found better when compared with an earlier work. We tested the robustness of the proposed method by adding four standard noises to the marked images. We extracted the watermarks from the noisy images to an acceptable degree of correlation. Therefore, we say that our method has coped with the added noise and is robust.

In future, we intend to test our watermarking scheme using other kinds of noise and filtering techniques.

(Manuscript received July 26, 2001, revised Jan,18, 2002)

References

(1) C. T. Hsu and J. L. Wu: "Hidden digital watermarks in images", *IEEE Trans. on Image Processing*, Vol. 8, No.1, pp. 58-68 (1999-1)

(2) N. Memon and P. W. Wong "Protecting digital media content", *Communications of the ACM*, Vol. 41, pp 35-43 (1998-7)

(3) F A P. Petitcolas, R. J. Anderson, and M. G Kuhn "Information hiding - a survey", *Proc. of the IEEE - Special Issue on Identification and Protection of Multimedia Information*, pp. 1062-1078 (1999-7)

(4) F. Hartung and M. Kutter "Multimedia watermarking techniques", *Proc. of IEEE - Special Issue on Identification and Protection of Multimedia Information*, pp 1079-1107 (1999-7)

(5) I. J. Cox, J. Killian, T Leighton, and T Shamoon: "Secure spread spectrum watermarking for multimedia", *Tech. Rep. 95-10*, NEC Research Institute (1995)

(6) J. Ohnishi and K Matsui: "Embedding a seal into a picture under orthogonal wavelet transform", *Proc. of Int. Conf. on Multimedia Comp. and Systems*, pp.514-521 (1996-6)

(7) D. Kundur and D. Hatzinakos. "A robust digital image watermarking method using wavelet-based fusion", *Proc. of IEEE Int. Conf. on Acoustics, Speech and Sig. Processing*, Vol 5, pp. 544-547 Seattle, Washington (1997-5)

(8) A. G. Bors and I. Pitas. "Image watermarking using DCT domain constraints", *Proc. of IEEE Int. Conf. on Image Processing*, Vol. 3, pp. 231-234 (1996)

(9) R. G. van Schyndel, A. Z Tirkel, and C. F Osborne: "A digital watermark", *Proc. of Int. Conf. in Image Processing*, Vol. 2, pp. 86-90, (1994)

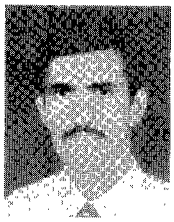
(10) D. Kundur and D. Hatzinakos: "Digital watermarking using multiresolution wavelet decomposition", *Proc. of IEEE Int. Conf. on Acoustics, Speech and Sig. Processing*, Vol. 5, pp 2969-2972, Seattle, Washington (1998-5)

(11) M. S. Shaikh and Y. Dote: "A robust multilevel watermarking method for digital images using multiresolution wavelet decomposition", *Proc. of 6th Online World Conf. on Soft Computing in Industrial Applications (WSC6)*, (http://vision fhg de/wsc6/), (2001-9)

(12) M. S. Shaikh and Y. Dote: "Watermarking of digital images using multilevel wavelet decomposition", *Proc. of 5th Online World Conf. on Softcomputing in Industrial Applications (WSC5)*, (http://wsc-virtual.hut.fi/), pp. 301-305 (2000-9)

(13) C. C. Wah: "Novel approach in watermarking of digital image", *Proc. of Int. Workshop on Soft Computing in Industry'99 (IWSCI'99)*, pp. 224-227, Muroran, Japan (1999-6)

Muhammad Shafique Shaikh (Non-member) received his B.Sc. and M.Sc. degrees in Electronics and Computer Technology from University of Sind, Pakistan, in 1983 and 1984, respectively. From 1985 to 1995 he worked in a Pakistan's space agency. He completed his M. Eng. In Computer Science and Systems Engineering at Muroran Institute Technology, Muroran, Japan, in 1999. Shaikh has completed his D. Eng. From the same institute in 2002. His research interests include signal and image processing, neural networks, and watermarking for digital images and videos.



Yasuhiko Dote (Member) received his BS degree from Muroran Institute of Technology, Muroran, Japan, in 1963. He completed the M. S. and Ph.D. at University of Missouri, Columbia, in 1972 and 1974, respectively. From 1963 to 1973, he has worked in Yaskawa Electric Manufacturing Co., Ltd., Japan. Presently, Dr. Dote is a Professor in Division of Computer Science and Systems Engineering, Muroran Institute of Technology, Japan. He has many research papers to his credit and has (co)-authored three books. He also has organized/chaired many national and international conferences. Dr. Dote's research interests include intelligent control, soft computing, and power electronics.