ARTICLE IN PRESS

Computers and Electrical Engineering xxx (2013) xxx–xxx

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

Dynamic stochastic resonance-based improved logo extraction in discrete cosine transform domain ☆

Rajib Kumar Jha [a,*], Rajlaxmi Chouhan [b], Kiyoharu Aizawa [c]

[a] Dept. of Electrical Engineering, Indian Institute of Technology, Patna, India
[b] Dept. of E & ECE, Indian Institute of Technology, Kharagpur, WB, India
[c] Dept. of Information & Communication Engineering, The University of Tokyo, Japan

ARTICLE INFO

Article history:
Available online xxxx

ABSTRACT

In this paper, a dynamic stochastic resonance (DSR) technique is used for blind watermark extraction in discrete cosine transform (DCT) domain. The watermark embedding has been done on mid-band DCT coefficients. DSR has been used to improve the robustness of the extraction algorithm by utilizing the degradation introduced during attacks. DSR is an iterative process that tunes the coefficients of the possibly attacked watermarked image so that the effect of noise is suppressed and hidden information is enhanced. Resilience of this technique has been tested in the presence of various attacks. An adaptive optimization procedure has been adopted for the selection of bistable parameters to achieve maximum correlation coefficient under minimum computational complexity. Using the proposed technique, robust extraction of watermark is obtained without trading-off with visual quality of the watermarked image. When compared with the plain DCT-based technique, DSR-based technique has been found to give remarkable performance.

1. Introduction

Traditionally considered as a nuisance, noise has been recently found to be used to improve signal detection performance. Recent studies have convincingly shown that in non-linear systems, noise can induce more ordered regimes that cause amplification of weak signals and increase the signal-to-noise ratio. In the context of images, a concept of physics called 'Dynamic stochastic resonance' (DSR) that uses noise to improve the performance of a system [1], has been recently used for various image processing applications such as image enhancement [2–11] edge detection [12], de-noising [13] and watermarking [14–17]. Most of the de-noising algorithms try to remove or suppress noise from the noisy images. On the contrary, in DSR, internal noise itself is utilized to suppress noise in the image and therefore can be used in image detection and enhancement.

Ye et al. [2] have used SR phenomenon for line detection from noisy images based on Radon transform in 2003. Similarly, stochastic resonance for sine detection was explored by Zozor et al. [4] in 2002. A noise-enhanced non-linear detector for detection of signal has been reported by Rousseau et al. [5] in 2007. A constructive action of noise for impulsive noise removal from noisy images has been reported by Histace et al. [13] in 2006. Recently, a stochastic resonance based technique in wavelet and fourier domain for the enhancement of unclear diagnostic ultrasound and MRI images respectively has been reported [7,8]. These methods can readily enhance the image by fusing a unique constructive interaction of noise and signal,

☆ Reviews processed and recommended for publication to Editor-in-Chief by Associate Editor Dr. Jose M. Alcaraz Calero.

* Corresponding author. Tel.: +91 06122552010.
E-mail addresses: jharajib@gmail.com (R.K. Jha), rajlaxmi.chouhan@gmail.com (R. Chouhan), aizawa@hal.t.u-tokyo.ac.jp (K. Aizawa).

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http://dx.doi.org/10.1016/j.compeleceng.2013.07.024

and enable improved diagnosis over conventional methods. Recently non-dynamic and dynamic stochastic resonance is used for enhancement of dark and low contrast images by Jha et al. [10,18].

A novel watermarking scheme based on stochastic resonance was reported in 2006 by Guangchun et al. [14]. An aperiodic stochastic resonance signal processor based on bistable dynamic mechanism is proposed for detecting binary PAM signals and DCT watermarking in 2008 by Sun et al. [15]. However, no background related to exact selection of parameters for application of DSR phenomenon was discussed. Some new techniques are established for watermark detection and extraction using stochastic resonance and dynamic stochastic resonance by Jha et al. [18,19].

Digital watermarking techniques exist both in spatial and transform domains. Generally, spatial domain techniques are simple and require less computation but are quite fragile to attacks than transform domain techniques. Various transforms such as discrete cosine transform (DCT), discrete wavelet transforms (DWT) and singular value decomposition (SVD) have been employed for watermarking in literature [20–23]. One of the main approach used by many researchers while embedding a binary logo is to use a pseudorandom sequence in spread-spectrum fashion [24,25]. The main drawbacks of these extraction methods are that when the watermarked image is corrupted by strong attacks such as JPEG compression, addition of uniform noise, salt & pepper noise, and filtering, watermark extraction becomes quite difficult. Also, it is a common observation that watermark amplification factor controls the perceptual quality of the watermarked image and robustness. Greater the value of amplification factor, better is the robustness but the visual quality of the logo becomes poor.

The rest of the paper is organized as follows. Section 2 discusses the basic concept of dynamic stochastic resonance. Section 3 uses the combined dynamic stochastic resonance with discrete cosine transform for watermark extraction. Mathematical discussion of selection of dynamic stochastic resonance parameters are discussed in Section 4. Section 5 discusses the proposed algorithm. Experimental results, observations and discussions are elaborated in Sections 6–8 respectively. Finally conclusions are drawn in Section 9.

Key Contribution: Most of the existing watermarking techniques suggest that good robustness can be achieved only at the cost of perceptual quality of the watermarked image. However, in this paper, a novel DSR-based technique has been proposed for robust extraction of logo in DCT domain without any loss of perceptual quality of watermarked image. To overcome the need of robustness-transparency trade-off, in this paper, a smaller value of amplification factor has been used as per the requirements to suit visual quality, while robustness is achieved by application of DSR. The proposed technique selects bistable parameters by maximization of SNR and optimizes these parameters to ensure that extracted logo has significant visual quality. The parameters corresponding to SNR maximization has the property of enhancing signal information (hide logo) as well as to reduce noise present in the form of attacks. Therefore the proposed technique provides two process simultaneously such as signal extraction as well as noise reduction. We have extended the applicability of DSR on watermarked images (to make it a subthreshold signal) by imposing condition on parameter b so that the watermarked image can be accepted as an input for this logo extraction technique (Section 4).

2. Dynamic stochastic resonance

In order to exhibit stochastic resonance (SR), a system should possess three basic properties: *a non-linearity in terms of threshold*, *a sub-threshold signal* like signal with small amplitude and *a source of additive noise*. This phenomenon occurs frequently in bistable systems or in systems with threshold-like behavior [1]. The general behavior of SR mechanism shows that at lower noise intensities the weak signal is unable to cross the threshold, thus giving a very low SNR. For large noise intensities the output is dominated by the noise, also leading to a low SNR. But, for moderate noise intensities, the noise allows the signal to cross the threshold giving maximum SNR at some optimum additive noise level.

2.1. Mathematical formulation of DSR for binary watermark extraction

A classic one-dimensional non-linear dynamic system that exhibits stochastic resonance is modeled with the help of Langevin equation of motion given in [26] in the form of Eq. (1) given below.

$$m\frac{d^2x(t)}{dt^2} + \gamma\frac{dx(t)}{dt} = -\frac{dU(x)}{dx} + \sqrt{D}\xi(t) \tag{1}$$

This equation describes the motion of a particle of mass m moving in the presence of friction, γ. The restoring force is expressed as the gradient of some bistable potential function $U(x)$. In addition, there is an additive stochastic force $\xi(t)$ with intensity D. $U(x)$ is a bistable quartic potential given in Eq. (2). D is the noise variance and $\xi(t)$ is an additive zero mean stochastic fluctuation (noise).

$$U(x) = -a\frac{x^2}{2} + b\frac{x^4}{4} \tag{2}$$

Here, a and b are positive bistable double-well parameters. The double-well system is stable at $x_m = \pm\sqrt{\frac{a}{b}}$ separated by a barrier of height $\Delta U = \frac{a^2}{4b}$ when the $\xi(t)$ is zero.

Addition of a periodic input signal $[B\sin(\omega t)]$ to the bistable system makes it time-dependent whose dynamics are governed by Eq. (3).

$$\frac{dx(t)}{dt} = -\frac{dU(x)}{dx} + B\sin(\omega t) + \sqrt{D}\xi(t) \tag{3}$$

where B and ω are the amplitude and frequency of the periodic signal respectively. It is assumed that the signal amplitude is small enough so that in the absence of noise it is insufficient to force a particle to move from one well to another.

Substituting $U(x)$ from Eq. (2) into Eq. (3).

$$\frac{dx(t)}{dt} = \left[ax - bx^3\right] + B\sin(\omega t) + \sqrt{D}\xi(t) \tag{4}$$

In the absence of periodic force the particle fluctuates around its local stable states. The rate of transition of particle (r_k) between the potential well under the noise-driven switching is given by Kramer's rate [26] as in Eq. (5).

$$r_k = \frac{a}{\sqrt{2}\pi} exp\left[-\frac{2\Delta U}{D}\right] \tag{5}$$

When a weak periodic force is applied to the unit mass particle in the potential well, noise-driven switching between the potential wells takes place and synchronized with the average waiting time, $T_k(D) = \frac{1}{r_k}$, between two noise-driven inter-well transitions that satisfies the time-scale matching between signal frequency ω and the residence times of the particle in each well [1]. That is

$$2T_k(D) = T_\omega \tag{6}$$

where T_ω is the period of the periodic force.

The most common quantifier of stochastic resonance is signal-to-noise ratio. For a symmetric bistable system, SNR is obtained as [1].

$$SNR = \pi\left(\frac{Bx_m}{D}\right)^2 r_k \tag{7}$$

Substituting the value of r_k from Eqs. (5)–(7) we get

$$SNR = \left[\frac{a}{\sqrt{2}\pi}\pi\left(\frac{Bx_m}{D}\right)^2\right] exp\left(-\frac{a}{2\sigma_0^2}\right) \tag{8}$$

The SNR expression for dynamic stochastic resonance as derived in [2] is given below.

$$SNR = \left[\frac{4a}{\sqrt{2}(\sigma_0\sigma_1)^2}\right] exp\left(-\frac{a}{2\sigma_0^2}\right) \tag{9}$$

Here σ_1 is the standard deviation of the added noise in the stochastic resonance based system and σ_0 is the internal noise standard deviation of the original bistable system.

In the current watermark extraction scenario, a watermark (binary logo) can be considered to be a weak signal as it is statistically invisible when embedded in the cover image. The signal apart from the watermark can be considered noise. When the watermarked image is attacked, the extraction of watermark becomes difficult. Here, stochastic fluctuation (noise) can be given to the transformed coefficients of the attacked watermarked image so that its distribution varies in such a way that at some optimum noise density, the coefficient can jump from noisy state to enhanced state. The result is that the embedded watermark coefficients get enhanced and watermark would be easily extracted.

Dynamic stochastic resonance is exhibited by a double well potential valley denoted by parameters a and b. These parameters denote the stability of such a system. The transformed coefficients (in the present context, the DCT coefficients) of a watermarked image are destabilized in the sense that their distribution becomes random due to external attacks applied on watermarked image. The application of DSR involves correlation of these double-well parameters a and b with properties of these random coefficients, such as standard deviation. The result is a system that tends towards stability. Thus an unstable system becomes stable at optimum values of bistable system parameters a and b. This mechanism has been tested on DCT coefficients of different attacked images.

3. Proposed mathematical formulation of dynamic stochastic resonance in DCT domain

Mathematical formulation of dynamic stochastic resonance based extraction of digital watermark has been discussed here. 2-D discrete cosine transform is applied to the input image. Let us consider the 2-D spatial representation of an image $I(x,y)$ in an actual physical space (x,y) where the function will be image pixel value. After applying the 2-D discrete cosine transform to image $I(x,y)$, $I'(u,v)$ is obtained.

Now DSR is applied to the $I'(u,v)$, DCT coefficients as follows:

$$I'(u,v)_{DSR} = \sqrt{\frac{2}{M}}\sqrt{\frac{2}{N}}\sum_{u=0}^{M-1}\sum_{v=0}^{N-1} DSR\left(\alpha_u\alpha_v I'(u,v) cos\frac{(2x+1)u\pi}{2M} cos\frac{(2y+1)v\pi}{2N}\right)$$

Please cite this article in press as: Jha RK et al. Dynamic stochastic resonance-based improved logo extraction in discrete cosine transform domain. Comput Electr Eng (2013), http://dx.doi.org/10.1016/j.compeleceng.2013.07.024

where the DSR operation can be shown in differential equation form as given in Eq. (4). Here the noise term $\sqrt{D}\xi(t)$ and the input term $B\sin(\omega t)$ is replaced by DCT coefficient of $I(x,y)$, i.e., $I'(u,v)$. In Eq. (4), the DSR is produced by the noise term $\sqrt{D}\xi(t)$, whereby the maximization of the SNR occurs at double well parameters $a = 2\sigma_0^2$ (as described in Section 4).

We now computationally implement the DSR in digital images. We need to solve the stochastic differential equation given in Eq. (4) using the stochastic version of Euler–Maruyama's method [27] which gives the iterative discrete equation as follows:

$$x(n+1) = x(n) + \Delta t\left[(ax(n) - bx^3(n)) + Input\right] \tag{10}$$

Note that $Input = B\sin(\omega t) + \sqrt{D}\xi(t)$ denotes the sequence of input signal and noise, with the initial condition being $x(0) = 0$. This assumption can be done keeping in view that the attacked watermarked image contains hidden data as well as degradation due to attack. The transform coefficients where data is hidden can be viewed as containing signal (image information) as well as noise. The final stochastic simulation is obtained after certain number of iterations. Here, Δt is the sampling time and is experimentally taken as 0.005.

Image can be inverted back into spatial domain using

$$I'(x,y) = \sqrt{\frac{2}{M}}\sqrt{\frac{2}{N}}\sum_{u=0}^{M-1}\sum_{v=0}^{N-1}\alpha_u\alpha_v I'_{DSR}(u,v)\cos\frac{(2x+1)u\pi}{2M}\cos\frac{(2y+1)v\pi}{2N}$$

4. Selection of parameters for watermark extraction

This section describes one of our key contributions – the approach for selection of double well system parameters a and b.

4.1. Selection of a

SR is produced by Eq. (10) after proper selection of the double well parameters a and b. These double well parameters can be obtained by maximization of the SNR expression.

For SNR maximization, we differentiate Eq. (9) with respect to a and equate to zero. Out of two parameters a and b of the dynamic stochastic resonance, any one can be selected for proper discussion of DSR. We have selected parameter a here for our discussion.

$$\frac{d(SNR)}{d(a)} = \left[\frac{1}{\sqrt{2}(\sigma_0\sigma_1)^2}\right]\exp\left(-\frac{a}{2\sigma_0^2}\right) - \left[\frac{a}{\sqrt{2}(\sigma_0\sigma_1)^2}\right]\left(\frac{1}{2\sigma_0^2}\right)\exp\left(-\frac{a}{2\sigma_0^2}\right) = 0$$

This gives $a = 2\sigma_0^2$ for maximum SNR. Thus SNR has maximum value at an intrinsic property a of the dynamic double well system. The other parameter b can be obtained using parameter a.

4.2. Selection of b

To ensure that the input signal is subthreshold, we have derived a condition for the value of parameter b. As shown in Eq. (1), the restoring force is expressed as the gradient of some bistable potential function $U(x)$. We have arrived at the maximum possible value of such a additive periodic signal so that the bistable potential well is still stable. Let R=$B\sin\omega t$ be the periodic signal.

$$R = -\frac{dU(x)}{dx} = -ax + bx^3, \quad \frac{dR}{dx} = -a + 3bx^2 = 0$$

implying $x = \sqrt{\frac{a}{3b}}$. Finding R at this value gives maximum force as $\sqrt{\frac{4a^3}{27b}}$.

Therefore,

$$B\sin\omega t < \sqrt{\frac{4a^3}{27b}}$$

Since our desire is to obtain a maximal signal, we let the sine term attain its maximum value, i.e., unity.

$$1 < \sqrt{\frac{4a^3}{27b}} \tag{11}$$

Therefore, for weak input signal $b < \frac{4a^3}{27}$.

Therefore, the values of these parameters for maximizing correlation coefficient or signal-to-noise ratio (in a general sense) are taken to be $a = 2\sigma_0^2$ and $b < (4a^3)/27$.

5. Proposed algorithm

The proposed DSR-based extraction algorithm on DCT values for robust watermark detection has been described in this section. The pivotal step in the algorithm is application of DSR to DCT coefficients of a possibly tampered/attacked watermarked image. As discussed in Section 2, this step requires addition of additive noise. However, degradation introduced in the watermarked image due to various noises, geometrical, compression and filtering attacks can itself be modeled as noise. The DCT coefficients of the attacked watermark image can be considered to have already incorporated the image information as well additive noise attack. Even if there is no attack, the DCT coefficients of the watermarked image can be intuitively viewed to have gaussian distribution. We have therefore used this internal noise of the attacked watermarked image for improving robustness instead of adding external noise in the DSR step and therefore the term Input in Eq. (10) has been replaced with midband DCT coefficients of attacked image. The scheme proposed in this paper is a blind one as it does not require the original cover image during watermark extraction.

Since embedding of watermark consists of block-DCT transformation ensure that the size of the cover image is large enough to embed the watermark. The watermark is a binary image and consists of only ones and zeros. Since one bit of the watermark shall be embedded in one 8×8 block of DCT coefficients, the maximum allowable size of watermark is $(M \times N)/(blocksize)^2$, where M and N are respectively the height and width of the cover image. In case the watermark is smaller than this size, pad the remaining bits with 1's to create a watermark of size $(M \times N)/(blocksize)^2$. The middle frequency bands (midband) of DCT are chosen for embedding so that they can avoid the most visual important parts of the image (low frequencies) without over-exposing themselves to removal through compression and noise attacks (high frequencies). In this paper, we have chosen seven midband coefficients for watermark embedding (as shown in Fig. 1).

5.1. Algorithm for watermark embedding

The conventional algorithm for binary logo embedding is as follows:

- **Step 1** The cover image is transformed into DCT coefficients.
- **Step 2** Two uniformly distributed, highly uncorrelated, zero-mean, two-dimensional pseudorandom sequences (PN_0 and PN_1 sequence) of the size of DCT matrix are generated for each bit of the watermark using two different known seeds. The PN_0 sequence is used to embed the zero watermark bit and PN_1 is used to embed watermark bit one.
- **Step 3** Embed the pseudorandom sequences PN_0 and PN_1 in the selected normalized mid-band DCT coefficients for one bit with a watermark amplification factor α. If we denote W_i as DCT coefficients matrix of, then embedding is done according to the Eqs. (12) and (13).
  If the watermark bit is 0

$$I_i = W_i + \alpha PN_0 \tag{12}$$

If the watermark bit is 1,

$$I_i = W_i + \alpha PN_1 \tag{13}$$

- **Step 4** Apply the inverse block DCT to the modified coefficients to produce the watermarked image.
- **Step 5** PSNR between the cover image and watermarked image is calculated.

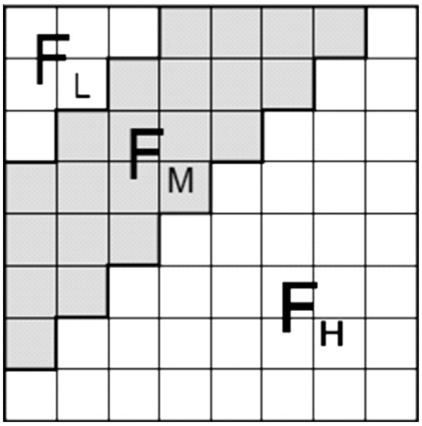


Fig. 1. F_M denotes mid-frequency band in an 8×8 DCT block. Last seven midband values have been chosen in this paper for watermark embedding.

Note: It should be ensured that the selection of α should be (low enough) such that PSNR is greater than 30 dB. This would ensure that the perceptual transparency of the watermarked image is very good and there is no degradation in its visual quality.

5.2. Proposed DSR-based algorithm for robust watermark extraction

The proposed DSR-based algorithm for improved robustness in binary logo extraction is as follows:

- **Step 1** Apply 8×8 block DCT transformation to the watermarked image. For performance evaluation of the scheme, this step can be preceded by attack on the image. This attack can be a noise attack, geometrical distortion, enhancement, filtering or compression attack. Since watermark was embedded only in midband DCT values of the cover image, midband coefficients of attacked image are selected for further DSR-based enhancement.
- **Step 2 Application of DSR to the midband DCT coefficients of a possibly tampered watermarked image**
  (a) Initialize

$$x(0) = 0, \quad a = 2\sigma_0^2, \quad b = m \times \frac{4a^3}{27} \tag{14}$$

  Value of bistable system parameter a is initialized following the condition of maximizing SNR for a DSR system (as discussed in Section 3), while m is a number less than 1 to ensure subthreshold condition of the signal.
  (b) Using iterative equation given in Eq. (10) compute tuned midband DCT coefficients.
  (c) **Adaptive Optimization** Extract the watermark bits (using steps explained further in Step 3) from this enhanced coefficient set after $(n+1)$th iteration. To make the algorithm adaptive, correlation coefficient (ρ) is computed for output after every iteration. If ρ no longer increases and starts decreasing, that value of iteration is taken as optimum number. The value of parameter a is fixed and depends on the statistics (variance) of the DCT data set. Optimization of parameters b and Δt has been done to obtain best results by initializing some values of factors m, Δt and n and then varying each of these parameters with respect to each other to reach highest correlation values while keeping the other three parameters constant. In this way, optimized values of $b, \Delta t$ and n can be obtained which later becomes a part of the adaptive iterative process.
- **Step 3** Extraction of bits from this enhanced data sets
  (a) Regenerate the pseudorandom sequences (PN_0 and PN_1) using the same seed used in the watermark embedding procedure.
  (b) Calculate the correlation between the DSR-enhanced set of DCT coefficients as obtained from **Step 2** and the generated pseudorandom sequences (PN_0 and PN_1). If the correlation with PN_0 is found to be greater than that with PN_1, the extracted watermark bit is set to 0. In case correlation with PN_1 is greater, the extracted watermark bit is set to 1.
  (c) Reconstruct the watermark image using the extracted watermark bits, and obtain the efficiency of extraction by computing correlation coefficient (ρ) between the original and extracted watermarks.

6. Experimental results

Results obtained from the proposed DSR-based adaptive DCT algorithm have been displayed and analyzed. The cover image is a grayscale 512×512 and four of the many test images have been shown in Fig. 2 Results shown for *Lena* and *Boat* images (Fig. 2a and b) have been displayed. Original watermark is 20×50 binary logo (Fig. 3e). Robustness against various attacks like salt & pepper noise (density 0.04), Gaussian noise (variance 0.04), speckle noise (variance 0.04), rotation (10°), cropping (35% pixel area), scaling, histogram equalization, low-pass filtering (averaging 11×11 neighborhood), high-pass filtering (Sobel) and JPEG compression (Quality = 10) have also been established. Watermarked image have been shown in Fig. 3a and b respectively and the respective extracted watermark using DSR in the absence of attack is shown in

(a) Lena (b) Boat (c) Barbara (d) Baboon

Fig. 2. Cover images used for testing the proposed DSR-based watermark extraction technique.

(a) Watermarked Lena Image, PSNR=48.79 dB (b) Watermarked Boat Image,PSNR=49.07 dB (c) Watermarked Barbara Image, PSNR=48.58 dB (d) Watermarked Baboon Image, PSNR=48.21 dB

(e) Grayscale watermark (f) Extracted from Lena image, ρ=1.0000 (g) Extracted from Boat image, ρ=0.9985 (h) Extracted from Barbara image, ρ=1.0000 (i) Extracted from Baboon image, ρ=0.9985

Fig. 3. (a)–(d) Watermarked images, (e) is the original watermark and (f)–(i) are the extracted watermarks from untampered watermarked images (without attack).

Fig. 3f and g. Extracted watermarks obtained from the proposed adaptive DSR–DCT and those obtained from plain DCT (without DSR) have been displayed in Figs. 4–7, showing attacked watermarked images and extracted watermarks the aforementioned techniques. Table 1 shows correlation values obtained from the proposed technique and non DSR-based DCT technique for four cover images. Adaptive optimization of bistable system parameters have been performed for all types of attacks and graphs obtained using optimization on Gaussian noise attack of zero mean and variance 0.04 have been displayed in Fig. 9

7. Observations

Striking features of the proposed technique have been noted and discussed in this section.

7.1. Adaptive parameter optimization results

Initially assumed values are $m = 0.001$, $\Delta t = 0.0015$ and $n = 100$. So, for 100 iterations, $\Delta t = 0.0015$, correlation coefficient (ρ) is obtained for different values of m. The value of m for which maximum value of ρ is obtained is the optimum value of m. Experimentation on watermarked image corrupted by Gaussian noise of zero mean and variance 0.04 shows that the value of a was found to be 0.2191. Optimized value of m is 0.051. With this optimized m and 100 iterations, value of Δt is optimized in a similar manner by selecting that value of Δt for which maximum value of ρ is obtained. Optimized Δt is found to be 0.025. An adaptive process to optimize number of iterations similarly shows that number of iterations required for Gaussian noise attack is 55.

Graphs of correlation coefficient (ρ) versus noise variance (or equivalently a) shows that maximum correlation occurs at $a = 0.2206$. This is nearly equal to value of a obtained by maximizing SNR of a general DSR system. Graphs of correlation versus all bistable parameters a, b, Δt and n shows a converging resonant nature of the DSR process – i.e. increasing till a particular value, reaching a peak for an optimum value and then decreasing beyond that value. This confirms the fact the DSR is a converging phenomenon tending towards stability at convergence. This is one such example of result obtained when *Lena* image is subjected to Gaussian noise attack. Different results would be obtained for different attacks on different images.

7.2. Quality of watermarked image

As it can be inferred from the visual quality and PSNR of the watermarked image (Fig. 3a–d), there is no perceptual degradation in the quality of watermarked image for $\alpha = 5$ and the embedded watermark is perceptually and statistically invisible.

7.3. Quality of extracted watermark

With $\alpha = 5$, correlation of extracted watermark with original watermark without any noise attack is 1.0000 and 0.9985 (Fig. 3f and g). When tested for watermarked images corrupted by noise attacks (Gaussian, salt & pepper and speckle), geometrical attacks (rotation, cropping, scaling), filtering (low and high-pass), histogram equalization and JPEG compression, the DSR-based proposed technique reaches very high correlation values. The plain DCT-based technique is dependent on value of α for robustness. Although better robustness could be achieved using higher values of α, this leads to degradation

(a) Salt & Pepper (b) DSR-DCT (c) DCT (d) Gaussian (e) DSR-DCT (f) DCT
(g) Speckle (h) DSR-DCT (i) DCT (j) Rotation (k) DSR-DCT (l) DCT
(m) Cropping (n) DSR-DCT (o) DCT (p) Scaling (q) DSR-DCT (r) DCT
(s) Histogram Equalization (t) DSR-DCT (u) DCT (v) Low-pass filtering (w) DSR-DCT (x) DCT

Fig. 4. Attacked images and extracted logo for the proposed DSR–DCT technique and existing DCT-based technique.

(a) High-pass filtering (b) DSR-DCT (c) DCT (d) JPEG Compression (e) DSR-DCT (f) DCT

Fig. 5. Attacked images and extracted logo for the proposed DSR–DCT technique and existing DCT-based technique.

of perceptual quality of the watermarked image. It is therefore observed that for good perceptual quality of the watermarked image, remarkably better visual quality of the extracted watermark is obtained using the proposed DSR-based technique (as shown in Figs. 4, 5, 6 and 7) than that obtained without using DSR.

Table 1 shows correlation coefficient values for various attacks and are found to be consistently very high for the DSR-based technique. The DCT-based technique is found to give poor robustness under attacks (unacceptably low robustness to Gaussian noise attack, rotation, scaling, filtering and JPEG compression attacks). Correlation coefficients obtained using DSR-based technique show remarkable improvement in value for all the attacks. Although histogram equalization and cropping do not found to deteriorate extracted watermark much, DSR based output is found to be higher than all those obtained without applying DSR.

Fig. 6. Attacked images and extracted logo for the proposed DSR–DCT technique and existing DCT-based technique.

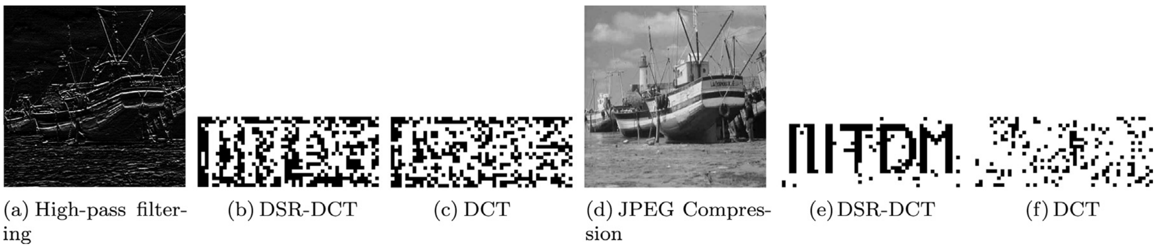


Fig. 7. Attacked images and extracted logo for the proposed DSR–DCT technique and existing DCT-based technique.

Tables 2 and 3 show correlation coefficient obtained for different values of α with and without using DSR on DCT coefficients on various attacks. It can be observed that for even for small values of α, reasonable robustness is obtained using DSR.

7.4. Comparison with existing SR-based techniques

Table 4 shows comparison of *PSNR* between original watermark and extracted watermark (on *Lena* image) for the proposed technique and those obtained using existing stochastic resonance-based techniques [14,15]. Values displayed are for attacks – Gaussian noise (zero mean, variance 0.01), salt & pepper noise (density 2.5%), cropping 50%, histogram equalization, Gaussian filtering (5×5) and JPEG compression (Quality = 10). It is apparent that higher performance is delivered by the proposed adaptive DCT–DSR technique.

Table 1
Correlation coefficient (ρ) obtained for using the proposed DSR-based technique and plain DCT technique (n is the iteration count, α was taken as 5).

PSNR	Lena Image 48.79 dB			Boat Image 49.07			Barbara Image 48.58			Baboon Image 48.21		
	DSR–DCT		DCT	DSR–DCT		DCT	DSR–DCT		DCT	DSR–DCT		DCT
Attacks	ρ	n	ρ	ρ	n	ρ	ρ	n	ρ	ρ	n	ρ
Without attack	1.0000	30	1.000	0.9974	35	0.9906	0.9998	30	0.9998	1.000	33	0.9998
Salt & pepper (density = 0.04)	0.8612	25	0.5419	0.7083	25	0.4998	0.8015	30	0.5142	0.8891	40	0.5135
Gaussian noise (var. = 0.04)	0.7105	55	0.3947	0.7452	30	0.1581	0.7532	45	0.4216	0.6583	38	0.4234
Speckle noise (var. = 0.04)	0.9323	25	0.7003	0.5998	35	0.2451	0.8488	28	0.6812	0.7215	40	0.5811
Rotation (5 °)	0.4562	90	0.0146	0.0284	100	0.0359	0.5308	95	0.0460	0.5135	100	0.0312
Crop (35 %)	0.9974	35	0.9653	0.8569	30	0.8562	0.9242	32	0.9240	0.8511	40	0.8200
Scale(2:1:2)	0.6063	75	0.5057	0.9185	42	0.2521	0.7787	50	0.3044	0.8155	45	0.3842
HE	0.9998	20	0.9948	0.9596	25	0.9593	0.9681	22	0.9544	0.9806	20	0.9600
LPF (7 × 7)	0.6804	60	−0.1520	0.5594	65	0.0340	0.6501	60	−0.2134	0.5912	65	−0.2010
HPF (Sobel)	0.6032	110	−0.4842	−0.4557	75	−0.2412	0.5433	75	0.2131	0.6055	90	−0.3130
JPEG (quality = 10)	0.8564	120	0.0133	0.8883	50	0.1095	0.8086	60	0.2033	0.4345	80	0.1135

Table 2
Correlation coefficient (ρ) obtained using the proposed DSR-based technique for different values of α on *Lena* image.

α	2	4	6	8	10	15
Salt & pepper noise (With DSR)	0.5433	0.7983	0.8685	0.8522	0.8788	0.8865
Salt & pepper noise (Without DSR)	0.1250	0.4915	0.5510	0.5855	0.5965	0.6032
Scaling (With DSR)	0.5532	0.5915	0.6533	0.6819	0.7011	0.7356
Scaling (Without DSR)	0.1135	0.3156	0.5258	0.5515	0.6104	0.6356
LPF (With DSR)	0.1156	0.5906	0.6806	0.6914	0.7155	0.7286
LPF (Without DSR)	0.0135	−0.0311	0.0911	0.1056	0.1135	0.2035
JPEG (With DSR)	0.3312	0.6013	0.8584	0.8015	0.8610	0.8251
JPEG (Without DSR)	0.0135	0.0133	0.1056	0.1563	0.1815	0.2122

Table 3
Correlation coefficient (ρ) obtained using the proposed DSR-based technique for different values of α on *Boat* image.

α	2	4	6	8	10	15
Salt & pepper noise (With DSR)	0.6531	0.8431	0.8861	0.8915	0.8923	0.9056
Salt & pepper noise (Without DSR)	0.2709	0.3987	0.5574	0.5818	0.5933	0.6983
Scaling (With DSR)	0.6011	0.6063	0.6165	0.7523	0.8156	0.8803
Scaling (Without DSR)	0.2521	0.4058	0.5534	0.5895	0.6234	0.6550
LPF (With DSR)	0.5504	0.6044	0.6855	0.6964	0.7591	0.8022
LPF (Without DSR)	−0.0463	0.0157	0.0149	0.0356	0.0467	0.0567
JPEG (With DSR)	0.8085	0.8583	0.8695	0.9012	0.9115	0.9203
JPEG (Without DSR)	0.0155	0.1040	0.1346	0.1890	0.2056	0.2963

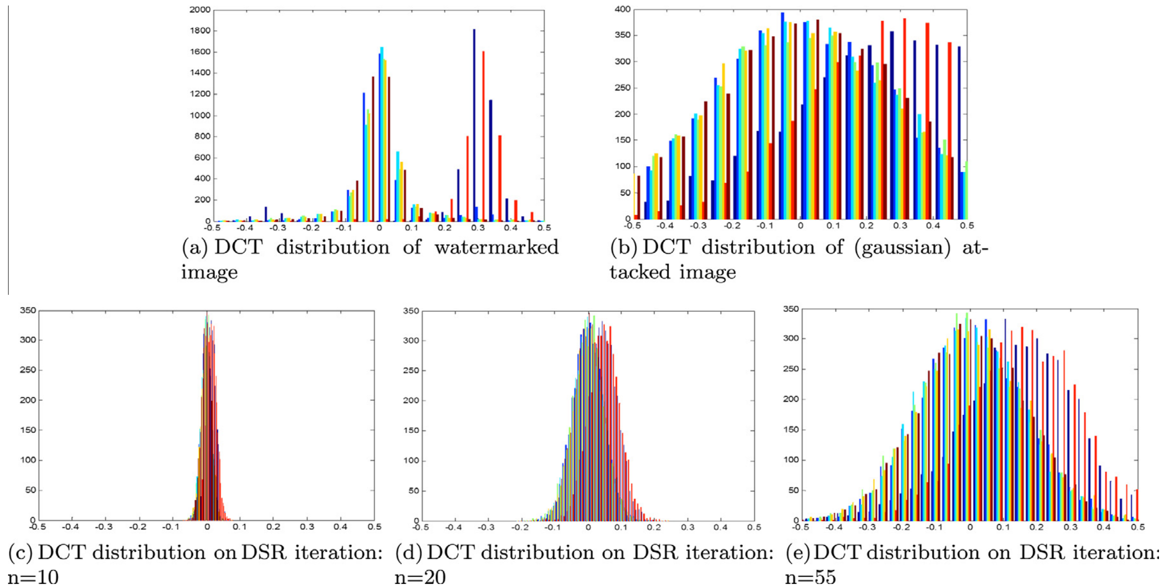
Table 4
Peak signal-to-noise ratio (in *db*) between original and extracted watermarks obtained for proposed and existing techniques.

Attack	Proposed DSR–DCT technique	Wu et al. method [14]	Sun et al. method [15]
Gaussian noise	21.55	18.92	19.56
Salt & pepper noise	21.64	17.87	20.41
Cropping	30.00	28.55	29.02
Histogram equalization	30.00	28.55	29.03
Gaussian filter	30.00	28.35	29.51
JPEG 10	29.55	22.05	27.54

8. Discussion

8.1. Mechanism of dynamic stochastic resonance on DCT coefficients for improvement of robustness

The basic mechanism of DSR for improvement of robustness is attributed to the way DSR iterations modify the distribution of midband (of an 8 × 8 block) DCT coefficients of the attacked watermarked image. It is observed that the distribution of each of the seven midband values is Gaussian-like in nature and centered about two clearly distinguishable peaks. The first peak corresponds to first and seventh (extreme) midband coefficients while the other peak corresponds to intermediate



(a) DCT distribution of watermarked image

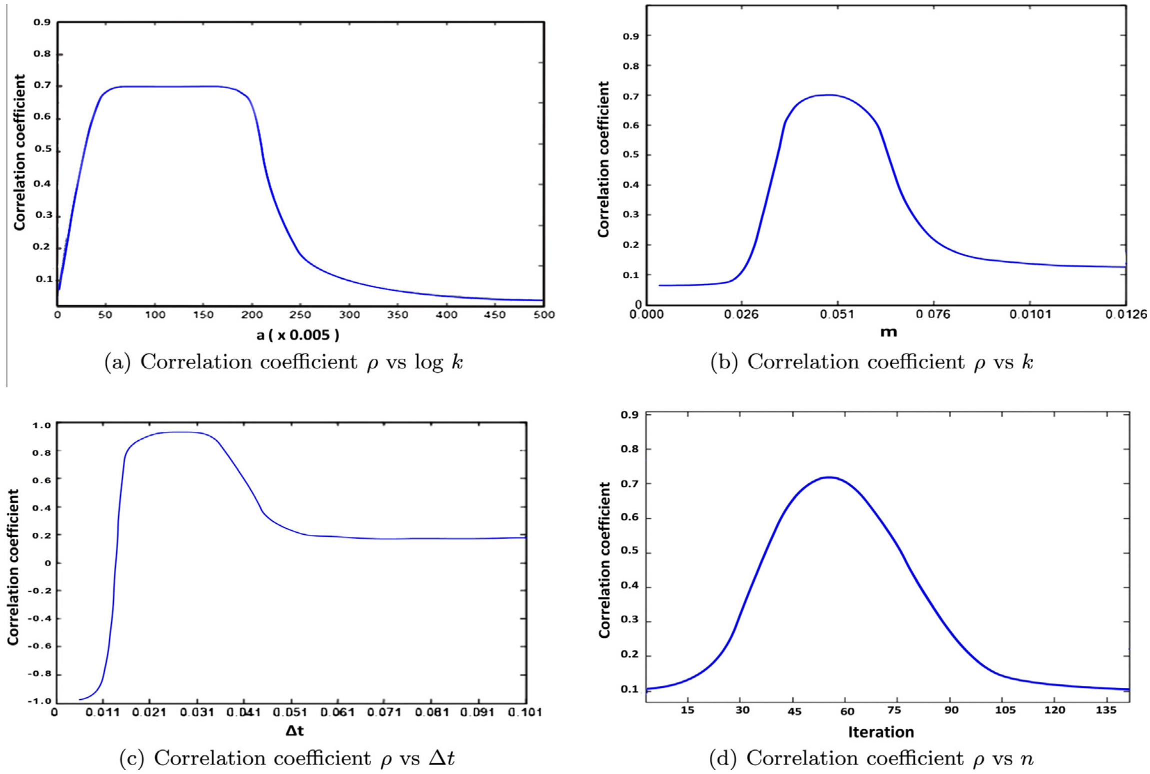
(b) DCT distribution of (gaussian) attacked image

(c) DCT distribution on DSR iteration: n=10

(d) DCT distribution on DSR iteration: n=20

(e) DCT distribution on DSR iteration: n=55

Fig. 8. (a) Midband DCT coefficient distribution of a normal watermarked image. (b) Midband DCT coefficient distribution of an attacked watermarked image. (c), (d) and (e) Midband DCT coefficients distribution after applying DSR for 10, 20 and 55 iterations respectively.



(a) Correlation coefficient ρ vs log k

(b) Correlation coefficient ρ vs k

(c) Correlation coefficient ρ vs Δt

(d) Correlation coefficient ρ vs n

Fig. 9. (a)–(d) Optimization results of correlation coefficient versus bistable parameters a, m, Δt and iteration count n respectively (for Gaussian noise attack). Note that in (a) Maximum correlation wrt a occurs at $a = 0.2206$ when value of a is varied. From (b)–(d), optimum m, Δt and n are found to be 0.051, 0.025 and 55 iterations (a)–(d) Graphs showing variation of correlation coefficient with respect to bistable system parameters.

midband coefficients (Fig. 8a). When this watermarked image is subjected to attack, the distribution of DCT coefficients changes to a very broad and convex curve with the two lobes merged and nearly indistinguishable (Fig. 8b). This distribution does not allow robust extraction of the hidden data. When DSR is applied to such a data set, its distribution varies (as shown

Fig. 8c–e) in a manner such that its variance increases gradually with iterations while maintaining its Gaussian shape. With DSR iterations, distribution of each of the midband coefficient throughout each 8×8 DCT block set is observed to increase in variance. After optimum number of iterations, it is observed that the two peaks are reasonably separated. This tuning of midband coefficients due to DSR phenomenon leads to enhancement of hidden data and therefore watermark bits can be extracted more accurately. Beyond optimum iteration number, the distribution becomes too flat again leading to ambiguity regarding extraction of hidden watermark bits.

8.2. Role of internal noise in DSR

Dynamic stochastic resonance is exhibited by a double-potential valley denoted by parameters a and b. These parameters denote the stability of such a system. The transformed coefficients (DCT coefficients) of an attacked watermarked images are destabilized in the sense that their distribution becomes random due to degradation introduced by noise attacks, geometrical distortion or compression attacks. The application of DSR involves tuning of these random transform coefficients with the properties of double-well parameters a and b. Thus an unstable system becomes stable at optimum values of bistable system parameters a and b. Application of DSR on these coefficients helps in extracting the hidden data more efficiently.

The double well with two stable states can be used to suggest two states of an image – one in which its over-all energy is low and one in which it is high. The transition from one state to another can be modeled by addition of weak noise (or in our case, the attacking noise). In the current proposed watermark extraction scenario, a watermark can be considered to be a weak signal as it is statistically invisible when embedded in the cover image. The signal apart from the watermark can be considered as noise. When the watermarked image is attacked, watermark extraction becomes difficult. Here, stochastic fluctuation (noise) can be given to the transformed coefficients of the attacked watermarked image so that its distribution varies in such a way that at some optimum noise density, the coefficient can jump from noisy state to enhanced state. The result is that the embedded watermark coefficients (hidden data) get enhanced and therefore a well-marked peak in correlation coefficient between the original watermark and the extracted watermark is obtained. This denotes accurate extraction of the watermark in those coefficients where it was embedded.

Thus, the most pivotal step in the algorithm is application of DSR to DCT of a tampered/attacked watermarked image. As discussed in Section 2, this step requires addition of additive noise. However, degradation introduced in the watermarked image due to various noise, geometrical, compression and filtering attacks can itself be modeled as noise. The DCT values of the attacked watermark image can be considered to have already incorporated the image information as well additive noise attack. We have therefore used this internal noise of the attacked watermarked image for improving robustness instead of adding external noise in the DSR step and therefore the term Input in Eq. (10) has been replaced with DCT coefficient of attacked image. By initializing bistable system parameters, the DCT coefficients are tuned using the iterative DSR equation. Optimization selection of parameters has been discussed in Section 5.2.

8.3. Computational complexity

On an Intel Core2 Duo CPU 3.25GB of RAM, one iterative step including calculation of performance to ensure adaptive process on the DCT coefficients takes around 0.05 second. If the average optimum number of iterations is nearly 55, therefore average computation cost can be considered around 2.75 s.

9. Conclusions

An optimization-based adaptive DSR algorithm for blind Logo extraction in DCT domain has been proposed and analyzed. The most striking feature of the proposed technique is that it produces tremendous improvement in accuracy of watermark extraction even when embedding is done using a low amplification factor α. This means that a very robust extraction is possible without compromising with the perceptual quality of the watermarked image even in the presence of severe noise attacks. Improvement in robustness is achieved due to rearrangement of the distribution of DCT data by an iterative DSR procedure. The noise introduced during attacks is itself utilized in the DSR iterations to suppress the effect of noise on watermark extraction. An optimization of bistable double-well system parameters is used to ensure that maximum correlation coefficient is obtained at minimum computational complexity. Robustness has been evaluated against various noise attacks, geometrical distortions, filtering, enhancement and JPEG compression attacks and the DSR-based technique is found to give remarkable improvement in robustness of the extracted watermark.

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Please cite this article in press as: Jha RK et al. Dynamic stochastic resonance-based improved logo extraction in discrete cosine transform domain. Comput Electr Eng (2013), http://dx.doi.org/10.1016/j.compeleceng.2013.07.024

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Rajib Kumar Jha received his B.Tech. in ECE from UIET Kanpur, India. He obtained his M.Tech. and Ph.D. degree from IIT Kharagpur. Since July 2006–April 2013 he was working as an Assistant Professor in IIITDM Jabalpur and IIT Ropar. Presently he is Assistant Professor at IIT Patna. He has received the prestigious National award for Best M.Tech. Thesis in 2003.

Rajlaxmi Chouhan is currently a Research Scholar at Indian Institute of Technology Kharagpur, India. Her research interests include image enhancement, watermarking, and stochastic resonance-based image processing applications. Miss Chouhan received the National award for Best M.Tech. Thesis in Electronics and Electrical Engineering from ISTE, New Delhi, India in 2012. She is a graduate student member of IEEE.

Kiyoharu Aizawa received B.E., M.E. and Dr.E. in electrical engineering from the University of Tokyo in 1983, 1985, 1988 respectively. He is currently a Professor at the Department of Information and Communication Engineering, the University of Tokyo. He received IBM Japan Science Prize 2002. He serves as Editor-in-Chief of ITE Journal and serves Associate Editor of IEEE Trans. Image Processing.

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