# An adaptive Watermarking Approach for Medical Imaging Using Swarm Intelligent

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***Abstract***

*In this paper we present a secure patient medical images and authentication scheme which enhances the security, confidentiality and integrity of medical images transmitted through the Internet. This paper proposes a watermarking by invoking particle swarm optimization (PSO) technique in adaptive quantization index modulation and singular value decomposition in conjunction with discrete wavelet transform (DWT) and discrete cosine transform (DCT). The proposed approach promotes the robustness and watermarked image quality. The experimental results show that the proposed algorithm yields a watermark which is invisible to human eyes, robust against a wide variety of common attacks and reliable enough for tracing colluders.*

***Keywords:***

## 1. Introduction

Data integrity and protection is one of the important areas of privacy protection in hospital. Digital radiological modalities in modern hospitals have led to the producing a variety of a vast amount of digital medical files. Therefore, for the medical image, the authenticity needs to ensure the image belongs to the correct patient, the integrity check to ensure the image has not been modified, and safe transfer are very big challenges. Moreover with the necessity to exchange these medical images among hospitals, the issues of their unified network protocols and different security settings in the data transfer arise. Also, when a digital medical image is opened for diagnosis, it is important that an automated framework exists to verify the authenticity and integrity of the image itself. Medical staff and patients get access to the system through the organizational network and terminals that are considered as reasonably secure. In order to implement telemedicine among the geographically separated medical organizations, public network is used to connect the foreign medical service provider. Moreover, medical images transmission between hospitals and exchanging the patients' data such as images and diagnostic reports between physicians via networks, cause complicated network protocol, image compression and security problems. Hospital Information System (HIS) and Picture Archiving and Communication System (PACS) have been established to provide security solutions to ensure confidentiality, integrity, and authentication [4].

Digital watermarking [2, 3, 15, 16] has been extensively researched and regarded as a potentially effective means for protection copyright of digital media in recent years, since it makes possible the embedding of secret information in the digital content to identify the copyright owner. Digital watermarking describes methods and technologies that allow hidden information, for example, a sequence of numbers or recognizable pattern in digital media, such as images, video and audio [15]. The basic idea behind digital watermarking is to embed a watermark signal into the host data with the purpose of copyright protection, access control, broadcast monitoring etc. A watermark can be a tag, label or digital signal. A host may be multimedia object such as audio, image or video. Watermarking techniques can be classified into different groups according to domain, visibility [1]. In medical applications, because of their diagnostic value, it is very important to maintain the quality of images. Therefore, algorithms which generally embed watermarks into coefficient of different sub-bands with different coefficients are not acceptable. They are not robust to common signal processing. For this matter, the development of a new algorithm that can satisfy both invisibility and robustness is needed. Improvements in performance of watermarking schemes can be obtained by several methods. One way is to make use of artificial intelligence techniques by considering image watermarking problem as an optimization problem [4].

In this paper, we design an adaptive watermarking scheme in medical imaging based on swarm intelligence [9]. The watermark bits are embedded on singular value vector of each embedding block within low frequency sub-band in the hybrid DWT-DCT domain. One quantization parameter is determined by exploiting the characteristics of HVS [12], the other quantization parameter is optimized through PSO algorithm. These two quantization parameters are combined for ensuring the final adaptive quantization steps are optimal for all embedding blocks and reaching better trade of between the imperceptibility and robustness of the digital watermarking system. In adaptive watermark scheme the quantization step that used in determining the embedding watermark is changed for every image. For a single image the quantization step is not fixed but it change its value through PSO training procedure till reaching the best quantization step and hence best locations for watermark bits to be embedded. This work compared with work in [6] that used a fixed quantization step in the embedding process.

The remainder of this paper is organized as follows. Section (2) reviews the swarm intelligence and DWT-SVD based watermarking. Section (3) discusses the proposed watermarking scheme in details including the watermarking embedding and extracting processes. Section (4) shows the experimental results. Conclusions are discussed in Section (5).

## 2. Preliminaries

### 2.1 Swarm Intelligence

Swarm intelligence is aimed at collective behavior of intelligent agents in decentralized systems. Although there is typically no centralized control dictating the behaviour of the agents, local interactions among agents often cause a global pattern to merge. Most of the basic ideas are derived from the real swarms in the nature, which includes ant colonies, bird flocking, honeybees, bacteria and microorganisms. Swarm models are population-based and the population is initialized with a population of potential solutions. These individuals are then manipulated over many several iterations using several heuristics inspired from the social behavior of insects in an effort to find the optimal solution [3, 4, 13, 14].

The concept of particle swarms, although initially introduced for simulating human social behaviors, has become very popular these days as an efficient search and optimization technique. Particle swarm optimization (PSO) [17], does not require any gradient information of the function to be optimized, uses only primitive mathematical operators and is conceptually very simple. PSO has attracted the attention of a lot of researchers resulting into a large number of variants of the basic algorithm as well as many parameter automation strategies. The canonical PSO model consists of a swarm of particles, which are initialized with a population of random candidate solutions [17]. They move iteratively through the d-dimension problem space to search the new solutions, where the fitness, *f*, can be calculated as the certain qualities measure. Each particle has a position represented by a position-vector $\vec{x}_i$ (i is the index of the particle), and a velocity represented by a velocity-vector $\vec{v}_i$. Each particle remembers its own best position so far in a vector $\vec{x}_i^{\#}$, and its *j*-th dimensional value is $x_{ij}^{\#}$. The best position-vector among the swarm so far is then stored in a vector $\vec{x}^*$, and its *j*-th dimensional value is $x^*_j$. During the iteration time t, the update of the velocity from the previous velocity to the new velocity is determined by Eq. (1). The new position is then determined by the sum of the previous position and the new velocity by Eq. (2).

$$v_{ij}(t+1) = \begin{cases} wv_{ij}(t) + c_1 r_1 (x_{ij}^{\#}(t) - x_{ij}(t)) \\ +c_2 r_2 (x_j^*(t) - x_{ij}(t)) \end{cases} \quad (1)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1). \quad (2)$$

where w is called as the inertia factor which governs how much the pervious velocity should be retained from the previous time step , $r_1$ and $r_2$ are the random numbers, which are used to maintain the diversity of the population, and are uniformly distributed in the interval [0, 1] for the *j*-th dimension of the *i*-th particle. $c_1$ is a positive constant, called as coefficient of the self-recognition component, $c_2$ is a positive constant, called as coefficient of the social component. From Eq. (1), a particle decides where to move next, considering its own experience, which is the memory of its best past position, and the experience of its most successful particle in the swarm. In the particle swarm model, the particle searches the solutions in the problem space with a range [$-s$, $s$] (if the range is not symmetrical, it can be translated to the corresponding symmetrical range). In order to guide the particles effectively in the search space, the maximum moving distance during one iteration must be clamped in between the maximum velocity [$-v_{max}$, $v_{max}$] given in Eq.(3):

$$v_{ij} = sign(v_{ij}) min(|v_{ij}|, v_{max}). \quad (3)$$

The value of $v_{max}$ is $p$ x $s$, with $0.1 \leq p \leq 1.0$ and is usually chosen to be $s$, i.e. $p = 1$. The end criteria are usually one of the following: maximum number of iterations, number of iterations without improvement, or minimum objective function error.

### 2.2. DWT-SVD Based Watermarking

Wavelet transform is obtained by calculating inner product of data to be transformed, with the translated and scaled mother wavelet function chosen for transform. Value of an inner product is express the resemblance of the mother wavelet in a certain translation and scaling state, with the data. Product result of each translation and scaling state is named as wavelet coefficient of certain translation and scaling state. DWT process is realized by filtering data that will be transformed, by various low pass and high pass filters and down scaling the results. Decomposition level is the unit (number) of the above process. Every decomposition level forms four band data called *LL*, *HL*, *LH* and *HH* sub-bands. This process can be continued up to reach desired level [6].

In past years, a singular value decomposition SVD-based watermarking technique and its variations have been proposed [5-10]. The core idea behind these approaches is to find the SVD of the cover image or each block of the cover image, and then modify the singular values to embed the watermark. There are two main properties to employ SVD method in digital watermarking scheme:

- The singular values of an image have very good stability, that is, when a small perturbation is added to an image, its singular values do not change significantly.

- Singular values represent intrinsic algebraic image properties.

In general, the watermark can be scaled by a scaling factor *SF* which is used to control the strength of the watermark. It is found that the scaling factor is set to be constant in some SVD-based studies. However, many argued that considering a single and constant scaling factor may not be applicable [7]. The larger the *SF*, the more the distortion of the quality of the host image (transparency) and the stronger the robustness. On the other hand, the smaller the *SF*, the better the image quality and the weaker the robustness [5]. SVD decomposes an $M$ x $N$ real matrix $A$ into a product of three matrices $A = USV^T$ , where $U$ and $V^T$ are $M$ x $N$ and $N$ x $N$ orthogonal matrices, respectively. $S$ is an $N$ x $N$ diagonal matrix. The elements of $S$ are only nonzero on the diagonal and are called the *SV*s of $A$.

## 3. An Adaptive Watermarking Approach for Medical Imaging using Swarm Intelligent

The watermark can be embedded into the host image by three steps. First, DWT is performed on the host image. Second, the low performed on DCT. Then a set of final quantization steps are modeled both the characteristics of the DCT domain human visual masking and particle swarm optimization of each block to ensure a high perceptual quality of watermarked image and a low bit error rate of the detected watermark. Finally, watermark is embedded into the singular values vector of each block by adaptive and optimized quantization steps. PSO helps search proper basic step of each block in order to optimize watermark embedding process. It is a difficult for determining the proper values of multiple basic quantization steps. In some cases, the choice of them may be based on some general assumption. Therefore, an efficient and optimal algorithm is required for achieving both invisibility and robustness. Here we use PSO to automatically determine these values without making any assumption. It is done using three essential components:

1. *Solution representation and initialization:* Each particle in the swarm represents a possible solution to the problem and hence consists of a set of

basic step of each block. In this work we randomly generate each particle value in the initial swarm.

2. *Fitness function:* The watermarked image transparency and robustness should be measured in order to formulate a proper fitness function. We adopt the same fitness function used in [9]:

$$f_i = \lfloor \frac{m}{\sum NC_i(w'_i, w)} - NC(I'_0, I_0) \rfloor^{-1} \quad (4)$$

where NCi denotes 2-D normalized correlation ,and m represents number of attacking methods

3. *PSO training operation*: The canonical PSO algorithm with inertia weight *w* is used.

### 3.1. Watermarking Embedding Process

Suppose the host medical image I0 has size $M$ x $N$ that is decomposed in $j$ levels DWT, we obtain the low frequency sub-band $LL_j$ and three high frequency sub-bands, $HL_j$ , $LH_j$ , $HH_j$ . To take the advantage of low frequency coefficients which have a higher energy value and robustness against various signal processing, the DCT is only performed on low frequency coefficient $LL_j$. The embedding watermark procedure is described in details as shown in algorithm (1). We have to note that final quantization parameter $\delta_i$ is estimated for each block and is determined as a combination of two quantization steps one come from Human Visual System (HVS) by using luminance mask $M^L{}_i$ and texture mask $M^T{}_i$. The other quantization step determined by PSO training. When PSO procedure converge it give a basic quantization step $\delta_{i0}$ that used to formulate the final quantization step $\delta_i$ according to following equation

$$\delta_i = \lfloor log2^{M_i^L \times M_i^T} \times 1000 \rfloor / 1000 + \delta_{i0} \quad (5)$$

### 3.2 Watermarking Extraction Process

The watermark extracting process is the inverse of embedding procedure that neither needs the host image signal nor any other side information. Suppose the watermarked image is $I'_0$ that is decomposed in $j$ levels DWT, we obtain low frequency sub-band $LL'_j$. Transform each block to the frequency coefficient by DCT, then we compute $N's_i$ for each block and quantize it by optimal final quantization step $\delta_i$ which derived during embedding process. The extraction watermark procedure can be described in details as shown in algorithm (2).

**Algorithm 1** The watermark embedding process

Segment the $LL_j$ into non-overlapping blocks $A_i$ of Size $w \times w$ , $i$=1,2,..., $M$

**for** Each block $A_i$ **do**

transformed to a frequency coefficient using DCT transform, and then compute the singular values vector of each frequency coefficient block $A_i$ by SVD according to the following equation:

$$DCT(A_i) = \bigcup_i \sum_i V_i^T \tag{6}$$

**end for**

Compute $N_i^s = \|s_i\| + 1$ and quantize by adaptive quantization step $\delta_i$

$$N_i = \lfloor \frac{N_i^s}{\delta_i} \rfloor i = 1, 2, ..., M \tag{7}$$

where $S_i = (\sigma_{i1}, \sigma_{i2}, ..., \sigma_{iw})$, $S_i$ denotes a vector formed by the singular values of the frequency coefficient block $A_i$.

**for** Embed each watermark bit **do**

Applying scrambling mechanism on original watermark, here we use Arnold transform [11] then modify integer number $N_i$according to the following equation

$$N_{iw} = \begin{cases} N_i + 1, & \text{if } (mod(N_i, 2), W_i) = (1, 1) or (0, 0) \\ N_i, & \text{otherwise} \end{cases} \tag{8}$$

**end for**

Compute the value $N_{iw}^s = \sigma_i \times N_{iw} + 0.5$ and the modified singular values:

$$(\sigma_{i1}, \sigma_{i2}, ..., \sigma_{iw}) = (\sigma_{i1}, \sigma_{i2}, ..., \sigma_{iw}) \times (\frac{N_{iw}^s}{N_i^s}) \tag{9}$$

Compute the watermarked block $A_i'$ with modified singular values. The watermarked low frequency sub-band $LL_j'$ is reshaped through $A_j'$ performed on Inverse Discrete Cosine Transform (IDCT), then the watermarked image $I_0'$ is obtained utilizing Inverse Discrete Wavelet Transform (IDWT).

**Algorithm 2** The watermark extracting process

Segment the $LL_j'$ into non-overlapping blocks $A_i'$ of size $w \times w$, $i = 1, 2, ..., M$. Transform each block $A_i$ to the frequency coefficient by DCT, then compute $N' s_i = \|s_i'\| + 1$ and quantize it by optimal final quantization step $\delta_i$ , where $s_i'$ denotes a vector formed by the singular values of the frequency coefficient block $A_i'$.

$$N_i' = \lfloor \frac{N' s_i}{\delta_i} \rfloor, i = 1, 2, ..., M \tag{10}$$

Extract watermark bits according to the following equation:

$$W_i' \begin{cases} 1, & \text{if } mod(N_i', 2) = 0; \\ 0, & \text{else } mod(N_i', 2) = 1. \end{cases} \tag{11}$$

Reshape the original binary watermark image by performing inverse extended Arnolded scrambling on watermark image according to the extracted watermark bits.

## 4. Experimental Results and Discussion

In this section, some experimental results are demonstrated to show the effectiveness of the proposed digital watermarking scheme. In our simulation study, we assume a group of five medical professionals, which are x-ray images of size 512*x*512. The length of the watermark is 32*x*32 binary bits set. The proposed algorithm is developed in MATLAB7.6 environment. The embedding strength is more or less proportional to the perceptual sensitivity to distortions for using adaptive quantization step size. In order to resist the normal signal processing and other different attacks, we wish the quantization step to be as high as possible. However, because the watermark directly affects the host image, it is obvious that the higher the quantization step, the lower the quality of the watermarked image will be. In other words, the robustness and the imperceptibility of the watermark are contradictory to each other. The experiments compare the performance of proposed scheme with scheme mentioned in [6], which considered as a non-blind watermarking method used a fixed scaling factor (SF) in DWT-SVD domain for watermark embedding. In the simulation results our designed method is referred to adaptive method while the other method we compared with is referred as a fixed method indicated by scaling factor value(S).

The results of our simulations are depicted in Fig 1, which shows the original and watermarked images, also it shows difference image that represent the absolute difference between original image and watermarked image.

The PSNR values used for quality comparison between the original and the watermark images are utilized in Table (1). This table compare the results of PSNR values come from our designed technique against DWT-SVD with fixed SF [6].

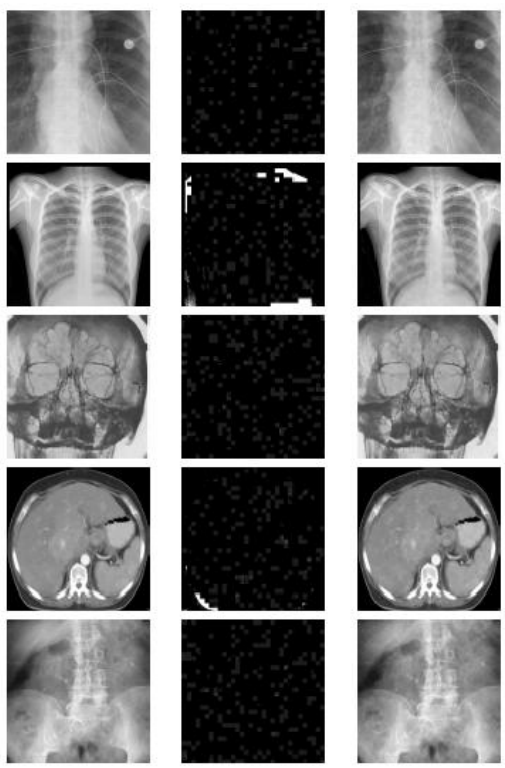

**Figure 1. From Left to Right Host Image, Difference Image, Watermarked Image**

**Table 1: PSNR Values**

| Image | Ad | (SF=20) | (SF=50) |
|---|---|---|---|
| Chest-1 | 51.69 | 56.74 | 48.95 |
| Chest-2 | 52.28 | 58.25 | 52.30 |
| Skull | 51.53 | 59.46 | 51.63 |
| Liver | 52.24 | 62.18 | 55.73 |
| Kidney | 51.54 | 54.08 | 46.17 |

**Table 2: Robustness Against JPEG Compression**

| Method | QF | Ch-1 | Ch-2 | Sk | Li | Kd |
|---|---|---|---|---|---|---|
| **Ad** | 50 | 0.99 | 0.90 | 0.99 | 0.88 | 0.99 |
| **S=20** | | 0.99 | 0.98 | 0.97 | 0.84 | 0.98 |
| **S=50** | | 0.99 | 0.99 | 0.99 | 0.82 | 0.99 |
| **Ad** | 40 | 0.99 | 0.91 | 1.00 | 0.87 | 0.99 |
| **S=20** | | 1.00 | 0.99 | 0.99 | 0.81 | 0.99 |
| **S=50** | | 1.00 | 1.00 | 1.00 | 0.81 | 1.00 |
| **Ad** | 30 | 0.84 | 0.69 | 0.83 | 0.67 | 0.85 |
| **S=20** | | 0.99 | 0.99 | 0.99 | 0.84 | 0.99 |
| **S=50** | | 1.00 | 1.00 | 1.00 | 0.82 | 1.00 |

The listed results are affected by value of *c1*, *c2*, inertia weight *W* used in PSO update positions, many experiments has been performed and we specify *c1* = 1.2, *c2* = 1.8, *w* which decrease from 0.9 to 0.4 during iteration sequence. This setting of W allow PSO to explore a large area at the start of the simulation run (when the inertia weight is large) and refine the search later by using a smaller inertia weight. Also number of epochs is an important factor to get proper quantization step which is seated in this work = 40 To investigate the robustness of watermark schemes, each watermarked image is attacked using JPEG compression, Gaussian noise, Salt and Pepper noises, Gaussian filter, median filter, and geometrical attacks like image cropping and scaling. The watermarking scheme should be robust to signal processing attacks. Normalized Correlation (NC) is adopted for the evaluating the robustness of the watermarking scheme. Without any image attacks, the NC value is 1. In other words, the watermark can be completely extracted. Tables (2)-(5) show the detailed values of NC for different types of attack that is performed on tested images. All tables show the results of our procedure against DWT-SVD fixed method with different SF value. These simulated results show how the adaptive method improve the performance of DWT-SVD with fixed SF methods in some cases but even it seems worse in other cases but our designed procedure is blind that does not require the original image in order to extract the watermark and this is the common case in exchanging medical images via internet. Our procedure try to compromise between the robustness and imperceptibility using PSO optimization procedure while DWT-SVD with fixed SF perform that by manually change SF value.

**Table 3: Robustness for Noise Addition Attacks**

| kind of attack | Method | Ch-1 | Ch-2 | Sk | Li | Kd |
|---|---|---|---|---|---|---|
| Guassian Var=0.001 | Adaptive | 0.99 | 0.86 | 0.99 | 0.81 | 0.99 |
| Var=0.01 | | 0.54 | 0.47 | 0.55 | 0.40 | 0.56 |
| Var=0.001 | Fixed(SF=20) | 0.92 | 0.86 | 0.94 | 0.70 | 0.93 |
| Var=0.01 | | 0.65 | 0.54 | 0.60 | 0.44 | 0.65 |
| Var=0.001 | Fixed(SF=50) | 0.98 | 0.96 | 0.98 | 0.76 | 0.98 |
| Var=0.01 | | 0.82 | 0.73 | 0.77 | 0.63 | 0.82 |
| Salt and pepper den=0.001 | Adaptive | 0.99 | 0.92 | 0.99 | 0.89 | 0.99 |
| den=0.01 | | 0.84 | 0.75 | 0.90 | 0.72 | 0.90 |
| den=0.001 | Fixed(SF=20) | 0.98 | 0.98 | 0.99 | 0.86 | 0.98 |
| den=0.01 | | 0.77 | 0.73 | 0.82 | 0.67 | 0.78 |
| den=0.001 | Fixed(SF=50) | 0.99 | 0.99 | 0.99 | 0.83 | 0.99 |
| den=0.01 | | 0.92 | 0.91 | 0.93 | 0.74 | 0.92 |

**Table 4: Robustness for Noise Filtration**

| kind of attack | Method | Ch-1 | Ch-2 | Sk | Li | Kd |
|---|---|---|---|---|---|---|
| Guass Filter $5 \times 5$ | Adaptive | 1.0 | 0.99 | 0.99 | 0.91 | 0.99 |
| $7 \times 7$ | | 1.0 | 0.94 | 1.0 | 0.91 | 1.0 |
| $5 \times 5$ | Fixed(SF=20) | 1.0 | 1.0 | 1.0 | 0.85 | 1.0 |
| $7 \times 7$ | | 1.0 | 1.0 | 1.0 | 0.85 | 1.0 |
| $5 \times 5$ | Fixed(SF=50) | 1.0 | 1.0 | 1.0 | 0.91 | 1.0 |
| $7 \times 7$ | | 1.0 | 1.0 | 1.0 | 0.91 | 1.0 |
| Median Filter $3 \times 3$ | Adaptive | 0.99 | 0.91 | 0.98 | 0.88 | 0.99 |
| $5 \times 5$ | | 0.94 | 0.77 | 0.92 | 0.74 | 0.99 |
| $3 \times 3$ | Fixed(SF=20) | 0.94 | 0.81 | 0.87 | 0.82 | 0.93 |
| $5 \times 5$ | | 0.87 | 0.74 | 0.80 | 0.77 | 0.89 |
| $3 \times 3$ | Fixed(SF=50) | 0.99 | 0.94 | 0.97 | 0.81 | 0.94 |
| $5 \times 5$ | | 0.98 | 0.90 | 0.95 | 0.79 | 0.97 |

**Table 5: Robustness for Geometric Attack**

| kind of attack | Method | Ch-1 | Ch-2 | Sk | Li | Kd |
|---|---|---|---|---|---|---|
| Scaling 25% | Adaptive | 0.99 | 0.83 | 0.97 | 0.69 | 0.99 |
| 50% | | 1.0 | 0.90 | 0.99 | 0.88 | 1.0 |
| 25% | Fixed(SF=20) | 1.0 | 0.99 | 0.99 | 0.87 | 0.99 |
| 50% | | 0.99 | 0.99 | 0.97 | 0.83 | 0.99 |
| 25% | Fixed(SF=50) | 1.0 | 1.0 | 1.0 | 0.83 | 0.99 |
| 50% | | 0.99 | 0.99 | 0.99 | 0.82 | 0.99 |
| Cropping 25% | Adaptive | 0.97 | 0.93 | 0.97 | 0.90 | 0.97 |
| 35% | | 0.91 | 0.87 | 0.90 | 0.83 | 0.90 |
| 25% | Fixed(SF=20) | 0.37 | 0.36 | 0.29 | 0.44 | 0.36 |
| 35% | | 0.63 | 0.32 | 0.49 | 0.50 | 0.57 |
| 25% | Fixed(SF=50) | 0.39 | 0.39 | 0.33 | 0.45 | 0.39 |
| 35% | | 0.67 | 0.42 | 0.53 | 0.54 | 0.60 |

Fig (2) shows some of the simulated attacks in this work. It shows the extracted watermark from our work in first row followed with extracted watermark come from DWT-SVD with fixed SF in the next two rows.

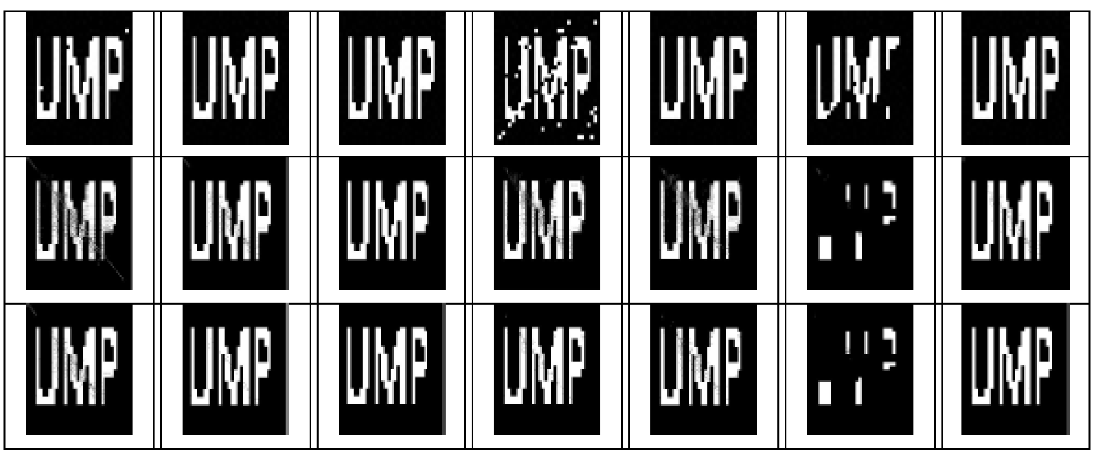

**Figure 2. From Top to Bottom Extracted Watermarks using three methods. From Left to Right Extracted Watermarks after Different Types of Attack.**

Using HVS to determine one quantization parameter and PSO to determine the other in an optimal way provide a great improvement in NC value. Fig (3) shows such improvement in performance, the experiment was performed on all five images but the following figure shows the improvement for chest-1 image only.

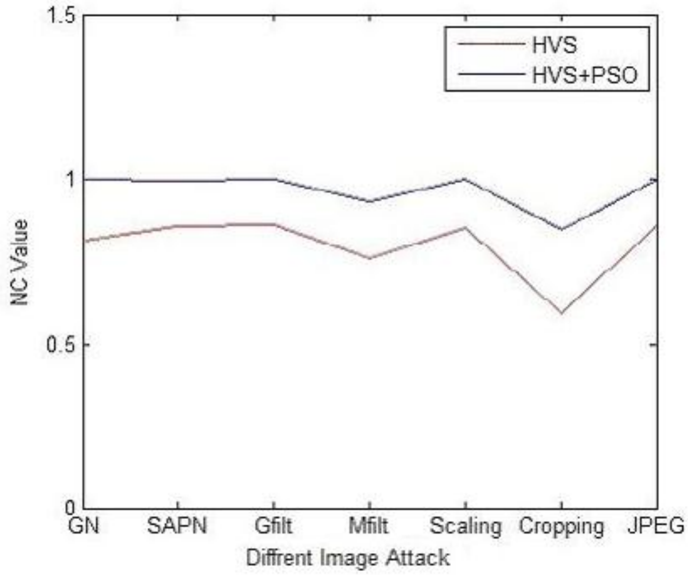


**Figure 3. NC Value Comparison between HVS only and PSO+HVS**

## 6. Conclusion

This paper introduced a robust watermarking approach for protecting medical images using swarm intelligent technique. PSO approach is used to get basic quantization steps which are optimally varied to achieve the most suitable locations for various images with different frequency characteristics. The experimental results reveal that our method can improve the quality of the watermarked image and increase the robustness of the embedded watermark against various attacks.

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