

Optimal DWT-SVD Domain Image Watermarking Using Multi-Objective Evolutionary Algorithms

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Abstract

In this paper, we present an optimal Discrete Wavelet Transform-Singular Value Decomposition (DWT-SVD) based image watermarking scheme using Pareto-based Multi-Objective Evolutionary Algorithm (MOEA). After decomposing the cover image into four bands, we apply the SVD to each band, and the singular values of each sub-band of the host image are modified by different scaling factors to embed the watermark image. Modifications are optimized using a fast Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) to obtain the highest possible robustness without losing the transparency. Since the same watermark with proper scaling factors is embedded in 4 blocks, it is extremely difficult to remove or destroy the watermark from all frequencies. Experimental results show improvement both in transparency and robustness under a wide range of attacks.

1. Introduction

Nowadays, all kinds of digitized information can be touched through network, including text, audio, image, video etc. Especially with the booming development of Internet, it is more convenient for communications and information transfer. But, besides all of these advantages, there are many undesired issues, one of which is pirates of digital works. As we all know, illegal distribution, copy and modification to digital works have seriously violate the commercial advantages of many corporations. Digital watermarking has been proposed as a way to resolve this problem since 1990's. Watermarking is to embed some information into the protected data with little quality difference between the watermarked data and the original data. From the other side whenever we need, the watermark should be able to be extracted from the watermarked data, even when the input data have been processed for some purposes. Watermarking technique is thought to be able to achieve the goals for copyright protection and authentication of

digital media and should have some characters. In most multimedia applications, three desired attributes for a watermarking scheme are *invisibility (transparency), robustness and high capacity*. Invisibility refers to the degree of distortion introduced by the watermark and its affect on the viewers or listeners. Robustness is the resistance of an embedded watermark against intentional attacks, and normal audio/visual processes such as noise, filtering, resampling, scaling, rotation, cropping and lossy compression. Capacity is the amount of data that can be represented by the embedded watermark.

Watermarks can be embedded in the spatial domain or the transform domain. The early watermarking schemes are most designed in spatial domain. Since some signal transformation methods provide good frequency distribution character, they are more suitable for watermark embedding and thus get more research. In general, three kinds of transformation are more often used in watermarking, DCT [1], DFT [2], DWT [3]. Due to the excellent time/frequency decomposition ability, DWT domain watermarking is getting more attentions.

In all frequency domain watermarking schemes, there is a conflict between robustness and transparency. If the watermark is embedded in perceptually most significant components, the scheme would be robust to attacks but the watermark may be difficult to hide. On the other hand, if the watermark is embedded in perceptually insignificant components, it would be easier to hide the watermark but the scheme may be less resilient to attacks. In the proposed scheme, we used a fast Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) [5] to obtain Pareto-front and optimize scaling factors (SFs) in watermark embedding process in the DWT-SVD domain with respect to two conflicting requirement: transparency and robustness to different attacks. This new method gives successful results comparing to known method in [4] that use experimental scaling factors. As we know, watermarks inserted in the lowest frequencies (LL sub-band) are resilient to one group of attacks, and watermarks embedded in highest frequencies (HH sub-band) are resilient to another group

of attacks. In our scheme since the same watermark with proper scaling factors is embedded in 4 blocks, it is extremely difficult to remove or destroy the watermark from all frequencies.

The rest of paper is organized as follows: In section 2, DWT-SVD domain watermarking technique is described. Section 3 explains the basic concepts of Non-dominated Sorting Genetic Algorithm and demonstrates the proposed method for embedding the watermark in the DWT-SVD domain with MOEA. Then, in section 4, some experimental results are given to show the validation of the proposed scheme. Finally, conclusions are given in section 5.

2. DWT-SVD domain watermarking

DWT is considered to be a powerful signal process and analysis tool, especially for the character in time/frequency domain. DWT decomposes an image into four coefficient sets, i.e., LL, LH, HL, HH. In DWT-based watermarking, the DWT coefficients are modified to embed the watermark data. Because of the conflict between robustness and transparency, the modification is usually made in HL, LH, and HH sub-bands.

Any matrix $A \in \mathbb{R}$ of size $(m \times n)$ can be decomposed into 3 matrices, $A = USV^T$, where U and V are orthogonal matrices, i.e. $UU^T = I$, and $VV^T = I$, where $S = \text{diagonal}\{\lambda_i \geq 0, i = 1, 2, \dots, n\} \in \mathbb{R}$ of size $(m \times n)$, are the singular values of A or the square roots of the eigenvalues of AA^T and $A^T A$. The columns of U are called the left singular vectors of A or the eigenvectors of AA^T and the columns of V are called the right singular vectors of A or the eigenvectors of $A^T A$. This decomposition is known as the *Singular Value Decomposition (SVD)* of A , and can be written as:

$$A = \sum_{i=1}^r \lambda_i U_i V_i^T \quad (1)$$

where r is the rank of matrix A . It is important to note that each singular value specifies the luminance of an image layer while the corresponding pair of singular vectors specifies the geometry of the image layer.

There are many approaches to SVD watermarking. One of them is to apply SVD to the whole cover image, and modify all the singular values, i.e., add the watermark to the all the singular values. Embedding a watermark in the SVD domain results in very little perceptual difference and the largest of singular values changes very little for most common attacks.

Assume the size of visual watermark is $n \times n$, and the size of the cover image is $2n \times 2n$.

2.1. Watermark embedding

1. Using DWT, decompose the cover image A into 4 sub-bands: LL, HL, LH, and HH.
2. Apply SVD to each sub-bands image: $A^k = U^k S^k V^{kT}$, $k = 1, 2, 3, 4$, where k denotes LL, HL, LH, and HH bands, and λ_i^k , $i = 1, \dots, n$ are the singular values of S^k .
3. Apply SVD to the visual watermark: $W = U_W S_W V_W^T$, where, λ_{wi} , $i = 1, \dots, n$, are the singular values of S_W .
4. Modify the singular values of the cover image in each sub-band with the singular values of the visual watermark: $\lambda_i^{*k} = \lambda_i^k + \alpha_k \lambda_{wi}$, $i = 1, \dots, n$, and $k = 1, 2, 3, 4$.
5. Obtain the 4 sets of modified DWT coefficients: $A^{*k} = U^k S^{*k} V^{kT}$, $k = 1, 2, 3, 4$.
6. Apply the inverse DWT using the 4 sets of modified DWT coefficients to produce the watermarked cover image.

2.2. Watermark extraction

1. Using DWT, decompose the watermarked (and possibly attacked) cover image A_d^* into 4 sub-bands: LL, HL, LH, and HH.
2. Apply SVD to each sub-band image: $A_d^{*k} = U_d^{*k} S_d^{*k} V_d^{*kT}$, $k = 1, 2, 3, 4$, where k denotes the attacked LL, HL, LH, and HH bands.
3. Extract the singular values from each sub-band: $\lambda_{dwi}^k = (\lambda_{di}^{*k} - \lambda_i^k) / \alpha_k$, $i = 1, \dots, n$, and $k = 1, 2, 3, 4$.
4. Construct the four visual watermarks using the singular vectors: $W^k = U_W S_{dW}^k V_W^T$, $k = 1, 2, 3, 4$.

3. Pareto-based multi-objective evolutionary algorithm

3.1. Background on multi-objective optimization

Multi-objective optimization differs from single-objective ones in the cardinality of the optimal set of solutions. Single-objective optimization techniques are aimed towards finding the global optima. In case of multi-objective optimization, there is no such concept of a single optimum solution. This is due to the fact that a solution that optimizes one of the objectives may not have the desired effect on the others. As a result, it is not always possible to determine an optimum that corresponds in the same way to all the objectives under consideration. Decision making under such situations thus require some domain expertise to choose from multiple trade-off solutions depending on the feasibility

of implementation. Due to the conflicting nature of the objective functions, a simple objective value comparison cannot be performed to compare two feasible solutions in a multi-objective problem. Most multi-objective algorithms thus use the concept of dominance to compare feasible solutions.

Definition 1. Dominance and Pareto-optimal set

In a minimization problem with M objectives, a feasible solution vector \vec{x} is said to dominate another feasible solution vector \vec{y} (or \vec{y} is dominated by \vec{x}) if:

1. $\forall i \in \{1, 2, \dots, M\} \quad f_i(\vec{x}) \leq f_i(\vec{y})$ and
2. $\exists j \in \{1, 2, \dots, M\} \quad f_j(\vec{x}) < f_j(\vec{y})$

If the two conditions are not hold, \vec{x} and \vec{y} are said to be non-dominated with respect to each other. The set of all non-dominated solutions obtained over the entire feasible region constitutes the Pareto-optimal set. The surface generated by the Pareto-optimal solutions in the objective space is called the Pareto-front or Pareto-surface.

Multi-objective evolutionary algorithms which use non-dominated sorting and sharing have been mainly criticized for their (i) $O(MN^3)$ computational complexity (where M is the number of objectives and N is the population size), (ii) non-elitism approach, and (iii) the need for specifying a sharing parameter. In this paper, we use a fast non-dominated sorting based multi-objective evolutionary algorithm (NSGA-II) [5] which alleviates all the above three difficulties.

3.2. NSGA-II

NSGA-II is a fast and elitist non-dominated sorting based multi-objective evolutionary algorithm (with $O(MN^2)$ computational complexity). It proposes a fast non-dominated sorting approach by incorporating a better bookkeeping strategy that reduces the complexity involved in the non-dominated sorting procedure in every generation. NSGA-II uses an elite-preserving strategy as well as an explicit diversity preserving mechanism [5]. In NSGA-II the offspring population Q_t is first created by using the parent population P_t , based on mating and mutation processes, these two populations are combined forming a new population of $2N$ dimension (R_t). Then nondominated sorting is used to classify the entire population R_t . To preserve diversity, a density metric called *Crowding Distance* is used. The different steps of the algorithm are described below:

- Step1: A random population is initialized.
- Step2: Objective functions for all objectives and constraint are evaluated.
- Step3: Front ranking of the population is done based on the dominance criteria.
- Step4: Crowding distance is calculated.

- Step5: Selection is performed using crowded binary tournament selection operator.
- Step6: Crossover and mutation operators are applied to generate an offspring population.
- Step7: Parent and offspring populations are combined and a non-dominated sorting is done.
- Step8: The parent population is replaced by the best members of the combined population.

In Step 3, each solution is assigned a non-domination rank (a smaller rank to a better non-dominated front). In Step 4, for each i -th solution of a particular front, density of solutions in its surrounding is estimated by taking average distance of two solutions on its either side along each of the objective. This average distance is called the crowding distance. Selection is done based on the front rank of an individual and for solutions having same front rank, selection is done on the basis of their crowding distances (larger, the better). To create new offspring, simulated binary crossover (SBX) operator [6] and polynomial mutation operator [7] are used. In Step 8, initially solutions of better fronts replace the parent population. When it is not possible to accommodate all solutions of a particular front, that front is sorted on the basis of crowding distance and as many individuals are selected on the basis of higher crowding distance, which makes the population size of the new population same as the previous population.

Due to its low computational requirements, elitist features and constraint handling capacity, NSGA-II has been successfully used in many applications. It proved to be better than many other multi-objective optimization GAs.

3.3. Optimization of SFs using NSGA-II

We want to find the optimal performance of our digital image watermarking algorithm in terms of transparency and robustness against different attacks. We do that by using the algorithm NSGA-II. We define two objective functions F_1 and F_2 which are minimization functions. The objective function F_1 is for transparency and the objective function F_2 is for robustness. The goal is to obtain the minimization of both functions simultaneously. Recall from section 2 (part 2.1) that we modify the singular values of the cover image in each sub-band with the singular values of the visual watermark: $\lambda_i^{*k} = \lambda_i^k + \alpha_k \lambda_{wi}$. Here the coefficients α_k 's (SFs) are parameters that can be adjusted and we use from them to minimize our objective functions. We run the algorithm NSGA-II on parameters α_k 's and objective functions to find the appropriate values for α_k 's that minimize the objective functions F_1 and F_2 . Next we explain how we obtain the

objective functions F_1 and F_2 for transparency and robustness as follows.

1) The Objective Functions F_1 for Transparency:

For this objective function we calculate the two dimensional correlation values between the cover image (I) and watermarked cover image (I_w) ($corr_I = corr(I, I_w)$) by this formula:

$$corr_I = \frac{\sum_{i=1}^M \sum_{j=1}^N [(I(i,j) - \bar{I})(I_w(i,j) - \bar{I}_w)]}{\sqrt{(\sum_i \sum_j (I(i,j) - \bar{I})^2)(\sum_i \sum_j (I_w(i,j) - \bar{I}_w)^2)}} \quad (2)$$

where \bar{I} and \bar{I}_w are the mean of the value in I and I_w respectively. The objective function F_1 will be $F_1 = -(corr_I)$ that we need to minimize it.

2) The Objective Functions F_2 for Robustness:

Recall the watermarks are computed from the attacked watermarked images using the extraction procedure given in section 2. The robustness of the watermarking algorithm is evaluated using Mean Square Error (MSE), thus the second objective function to be minimized is $F_2 = MSE$. The MSE can be defined as:

$$MSE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N ((W(i,j) - W^*(i,j))^2) \quad (3)$$

where W is original watermark, W^* is extracted watermark, M , N are the width and height of the watermark.

4. Experimental results

We have tested our new scheme through seven experiments. The chosen attacks that we consider are rotation, rescaling, cropping, sharpening, Gaussian noise, JPEG compression, and median filtering. Fig. 1 shows the 256x256 gray scale cover image Lena, the 128x128 gray scale visual watermark Cameraman, the watermarked Lena, and the watermarks constructed from the 4 sub-bands.

For the NSGA-II, we adopted real-numbers encoding and the following parameters setting: Population size (N) = 150; Generations = 90; Probability of crossover (P_c) = 0.9; Probability of mutation (P_m) = 1/num var (num var = number of decision variables); Distribution index for crossover (η_c) = 20; Distribution index for mutation (η_m) = 20; Tour size = 2; Pool size = 75. The population is the set of candidate values for the coefficients α_k 's that we try to adjust them during 90 generations of NSGA-II to minimize our objective functions and each individual is a vector with four elements.

Fig. 2 shows Pareto-front for two objective functions F_1 and F_2 by NSGA-II. Using Pareto-front, for different

applications depending on which one is more important, the robustness or the transparency, proper SFs can be obtained easily as we discussed before.

Using Pareto-front, when the transparency is as important as the robustness, optimal scaling factors are obtained as follow:

$$\alpha_1 = 5.2652511 \times 10^{-1}, \quad \alpha_2 = 1.1070060 \times 10^{-2}$$

$$\alpha_3 = 3.0724224 \times 10^{-2}, \quad \alpha_4 = 2.3149145 \times 10^{-2}$$

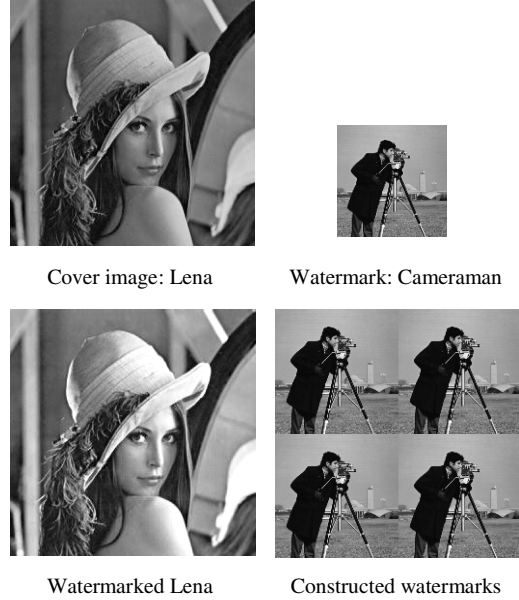


Figure 1. Watermark embedding/extraction

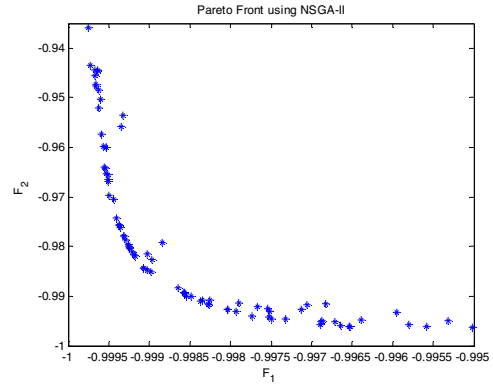













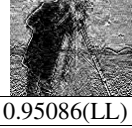


Figure 2. Pareto-front (optimal solutions) obtained by NSGA-II after 90 generations

Table 1 shows the best quality watermarks extracted from the 4 bands for both the optimal SFs obtained by our algorithm and non-optimal experimental SFs that has been used in the previous paper [4]. The numbers below the images indicate the Pearson product moment

correlation between the original vector of singular values and extracted vector of singular values for each subband. The Pearson correlation coefficient is a dimensionless index that ranges from -1.0 to 1.0, and reflects the extent of a linear relationship between two data sets. The observer is also able to evaluate the quality of constructed watermarks subjectively through a visual comparison with the reference watermark and can also see that the quality of constructed watermarks by our algorithm is better than the previous result in [4].

Table 1. Comparison of the constructed watermarks with best quality between optimal SFs by our scheme and non-optimal experimental SFs in [4].

	NSGA-II	experimental SFs [4]
Rotation (20°)		
	0.901 (LL)	0.3509(HL)
Rescale (256→128→256)		
	0.99924 (LL)	0.90281(LL)
Crop on both sides		
	0.9997 (HH)	0.9913(HH)
Sharpening (3X3)		
	0.964 (LL)	0.74834(HL)
Gaussian Noise (0,0.01)		
	0.9952 (LL)	0.79346(LL)
JPEG (quality= 35)		
	0.9996 (LL)	0.99692(LL)
Median filtering (3X3)		
	0.9987 (LL)	0.95086(LL)

5. Conclusions

In this paper, we proposed a hybrid approach to obtain an optimal watermarking algorithm based on a combination of a fast elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) and DWT-SVD approach. We used from NSGA-II to obtain Pareto-front and optimize scaling factors in watermark embedding process in the DWT-SVD domain with respect to two conflicting requirements: transparency and robustness against different attacks. This new method gives successful results comparing to known method in [4] that use experimental scaling factors. It is known that watermarks inserted in the lowest frequencies (LL sub-band) are resistant to one group of attacks, and watermarks embedded in highest frequencies (HH sub-band) are resistant to another group of attacks. Since the same watermark with proper scaling factors is embedded in 4 blocks, it is extremely difficult to remove or destroy the watermark from all frequencies.

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