Cover Selection Steganography Via Run Length Matrix and Human Visual System

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Abstract
A novel approach for steganography cover selection is proposed, based on image texture features and human visual system. Our proposed algorithm employs run length matrix to select a set of appropriate images from an image database and creates their stego version after embedding process. Then, it computes similarity between original images and their stego versions by using structural similarity as image quality metric to select, as the best cover, one image with maximum similarity with its stego. According to the results of comparing our new proposed cover selection algorithm with other steganography methods, it is confirmed that the proposed algorithm is able to increase the stego quality. We also evaluated the robustness of our algorithm over steganalysis methods such as Wavelet based and Block based steganalyses; the experimental results show that the proposed approach decreases the risk of message hiding detection.

Keywords: Steganography; Cover Selection; Run Length Matrix; Image Texture Features; SSIM.

1. Introduction

Steganography is a security technique to disguise messages in a media called cover, which is the object to be used as the carrier for embedding a hidden message. Many different types of objects have been employed as carriers, for example images, audio and video. The object which is carrying a hidden message, is called stego [1-3].

Steganography methods can be categorized into two groups: spatial-domain and transform-domain. In spatial domain methods, the secret messages are embedded in the image pixels directly. LSB [4] technique is a famous method in this group. In transform-domain methods, messages are embedded into coefficients obtained after applying a transform on the original image. Techniques such as the Discrete-Cosine Transform (DCT) [5,6,7], Discrete Fourier Transform (DFT) [8], Wavelet Transform (DWT) [9,10] and Contourlet transform [11,12,13] belongs to this category [14]. In steganography, one prefers to hide information as much as possible in a cover with a distortion as little as possible. Selection of a suitable cover plays an important role to achieve these goals, i.e. increasing payload and decreasing detectability. Different image cover selection methods have been suggested in the literature. Image cover selection technique proposed in [14] is concentrated in textured similarity. This technique replaces some blocks of a cover image with similar secret image blocks. The enhanced version of this method in [15], uses statistical features of image blocks and their neighborhood. In [16], some scenarios are discussed with a steganographer having complete or partial knowledge or no knowledge about steganalysis methods. In addition, some measures for cover selection are introduced. Another cover selection method is introduced in [17] based on computation of the steganography capacity as a property of images.

In this paper, we will exploit the textured characteristics of images to elicit suitable images from a large database as proper covers. Then, in order to generate the stego version of images, we embed a secret message into the selected images. Finally, we use Structural Similarity Measurement (SSIM), which is based on Human Visual System (HVS), instead of PSNR and MSE to measure the similarity between each selected image and its stego. Then, the image with maximum SSIM is selected as the best cover. Analysis of results showed that the proposed cover selection method extracts the best image with high payload and little distortion.

Rest of this paper is organized as follows. Section 2 explains Run Length Matrix and its

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features. In Section 3, we introduce several visual perceptual measures based on HVS. Our proposed approach is explained in Section 4. Experimentations and results are presented in Section 5. Finally, Section 6 concludes the paper.

2. Run Length Metrics and Texture Features

Texture is one of the most used characteristics in image analysis, and is applicable to a wide variety of image processing problems. In image processing, “texture” is related to repeated pixels in an image, producing a pattern. Texture is arranged in two categories: deterministic (regular), and statistical (irregular) textures. Deterministic texture is created by repetition of a fixed geometric shape such as a circle or square. Statistical textures are created by changing patterns with fixed statistical properties. Statistical textures are represented typically in term of spatial frequency properties. The human visual system is less sensitive to distortion in complex texture patterns compared to simple texture patterns. As a consequence, images with complex textures are preferred in information hiding [18], and selection of secure cover from an image database is an important phase in steganography methods. Some of the texture features used in this work are extracted from run length matrix [18,19]. In this section, we introduce these texture features.

Gray level Run length matrix: A gray-level run is a set of consecutive pixels having the same gray-level value. The number of pixels in the run is called Length of run. Run length features encode textural information related to the number of times each gray-level is repeated. Four run length matrix QRL are defined for four directions: 0◦, 45◦, 90◦ and 135◦. Element (i, j) in QRL illustrates the number of times a gray-level i appears in the image with run length j. Dimension of each QRL matrix is Ng * Nr array, where Nr and Ng are the largest possible run length and highest possible gray level value in the image, respectively. Many numerical texture features can be computed on the basis of run length matrix. The four features [19] of run length statistics used in this work are as follows:

Short Run Emphasis (SRE) measures the distribution of short runs. The SRE is highly dependent on the occurrence of short runs and is expected to be large for coarser images.

$$SRE = \frac{\sum_{i=1}^{Ng} \sum_{j=1}^{Nr} \left(\frac{Q_{RL}(i,j)}{j^2}\right)}{\sum_{i=1}^{Ng} \sum_{j=1}^{Nr} Q_{RL}\,(i,j)} \qquad (1)$$

Long-Run Emphasis (LRE) is a measure of distribution of long runs. It is small for coarser images.

$$LRE = \frac{\sum_{i=1}^{Ng} \sum_{j=1}^{Nr} (Q_{RL}(i,j) j^2)}{\sum_{i=1}^{Ng} \sum_{j=1}^{Nr} Q_{RL}(i,j)} \qquad (2)$$

Gray Level Non Uniformity (GLNU) shows the similarity of gray level values throughout an image. When runs are uniformly distributed among the gray levels, GLNU takes small values. Large run length values have a high contribution in this metric, because of existence of square. It is expected to be large for coarser images.

$$GLNU = \frac{\sum_{i=1}^{Ng} \left[\sum_{j=1}^{Nr} Q_{RL}(i,j)\right]^2}{\sum_{i=1}^{Ng} \sum_{j=1}^{Nr} Q_{RL}(i,j)} \qquad (3)$$

Run Length Non Uniformity (RLN) emphasizes on the similarity of the length of runs throughout the image. The RLN is expected to be small if the run lengths are alike throughout the image.

$$RLN = \frac{\sum_{j=1}^{Nr} \left[\sum_{i=1}^{Ng} Q_{RL}(i,j)\right]^2}{\sum_{i=1}^{Ng} \sum_{j=1}^{Nr} Q_{RL}(i,j)} \qquad (4)$$

3. Visual Specification Based on the Structural Similarity Measurement

Image quality assessment is an important field of signal processing. The MSE and PSNR are the most commonly used quality metrics. These are used widely because they are simple and easy to be calculated, but are not well correlated with human perception of quality [20,21]. Recently, various efforts have been made into the development of quality assessment methods that take advantage of known characteristics of the Human Visual System (HVS). Quality assessment (QA) algorithms based on HVS predict visual quality by comparing a distorted signal against a reference, typically by modeling the human visual system. These measurement methods consider HVS characteristics in an attempt to incorporate perceptual quality measures. SSIM, Structural Similarity Metric [22], is a quality measure which separates the task of similarity measurement between two images into three comparisons: luminance, contrast and structure [22,23,24]. Its value lies on the interval [0,1]. The steps of SSIM measurement are presented in Figure 1 [24]. Local structural similarity between two images x and y, is defined in Equation 5; l, c, and s represent luminance, contrast and structure, respectively.

$$S(x,y) = l(x,y).c(x,y).s(x,y) \quad (5)$$

where

$$l(x,y) = \frac{2\,\mu_x\,\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}\; c(x,y) = (\frac{2\,\sigma_x\,\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2})$$

$$S(x,y) = (\frac{\sigma_{xy} + C_3}{\sigma_x\,\sigma_y + C_3})$$

and x and y are original, and distorted signals, respectively. "Original" form of signal (x) is free of any distortions, and is therefore assumed to have perfect quality. μ_x and μ_y are the local sample means of x and y, respectively. σ_x and σ_y are the local sample standard deviations of x and y, and σ_{xy} is the sample cross correlation of x and y. The parameters C1, C2 and C3 are small positive constants which stabilize each term, so that near-zero sample means, variances, or correlations do not lead to numerical instability. The properties of SSIM are being symmetry, boundedness and unique maximum as follows:

Symmetry: *S(x,y) = S(y,x)*

Boundedness: *S(x,y) <= 1*

Unique maximum: *S(x,y) = 1* if and only if *x=y*

We have used the primitive similarity measure proposed in [22,23] as quality evaluation criterion between stego and cover image for selecting the secure cover. This measure helps us to select the best cover from an image database.

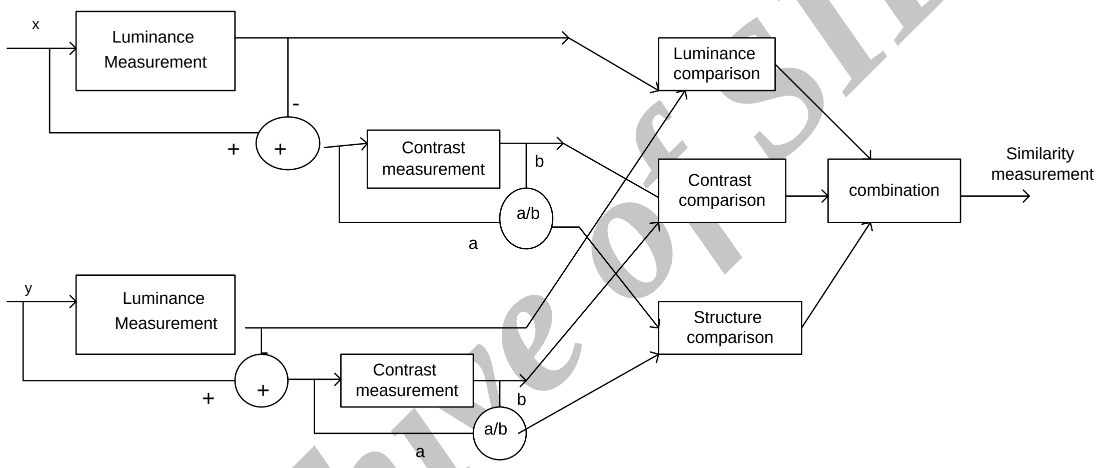


Figure1. Structural Similarity Measurement (SSIM) System [24]

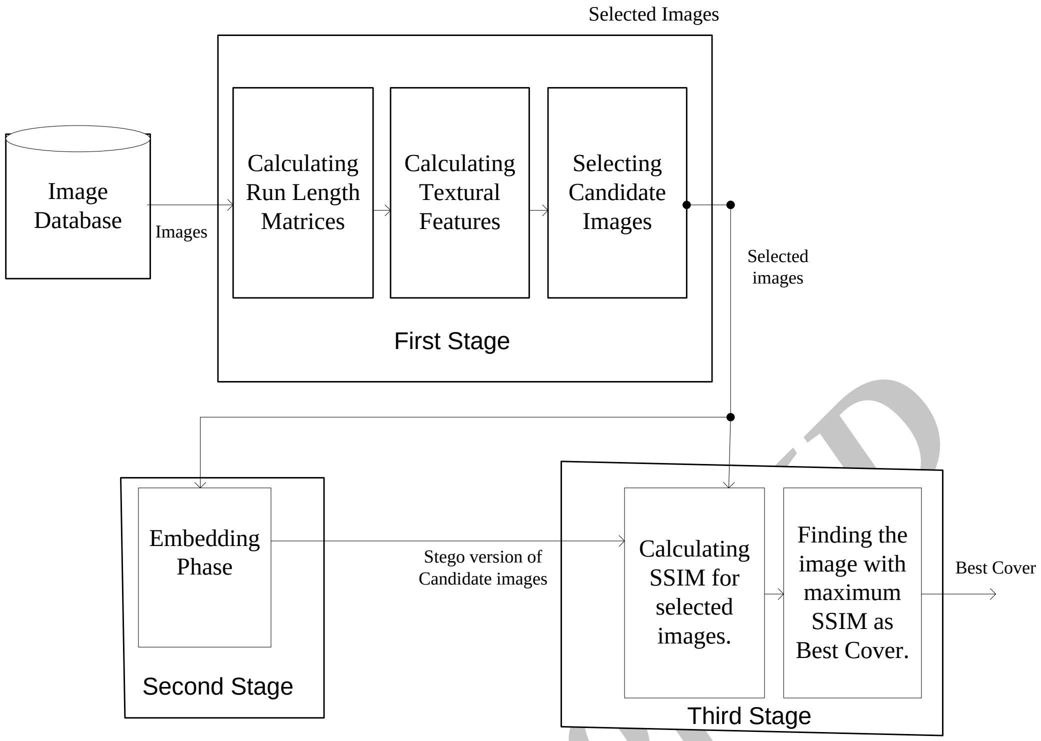


Figure 2. Block diagram of proposed algorithm

4. The Proposed Algorithm

The block diagram of proposed algorithm is shown in Figure 2. This algorithm contains three stages. In the first stage, the run-length matrix for each image in the database is calculated and then, texture features SRE, LRE, GLNU and RLN are calculated to select a set of image candidates which are suitable to be served as covers. In the second stage, data are embedded into the selected images using DWT steganography method. Consequently, the stego version of the selected images is formed. In the third stage, the best cover is extracted from the set of selected images by using SSIM measure. The proposed cover selection algorithm is described as follows:

Input: Image database

Output: Best cover

Step 1. Calculate Run length matrix in 4 directions 0°, 45°, 90° and 135° for each image of the database.

Step 2. Compute SRE, LRE, GLNU and RLN features for each image using run-length matrix.

Step 3. Select images with maximum SRE, GLNU, RLN and minimum LRE from database.

Step 4. Use DWT steganography embedding algorithm and then hide data in the images found in Step 3.

Step 5. Compute Structural Similarity (SSIM) between the original and stego versions of images obtained in Steps 3 and 4, respectively.

Step 6. Select the image having maximum similarity with its stego version (Step 5) as the best cover.

5. Experimental Results

All experiments were performed on a PC with core 2.35 GHZ processor and 4GB main memory. In order to evaluate our approach, we used the USC-SIPI Texture Database [27].

In this section, we illustrate the influence of our cover selection method on stego quality. Then, we evaluate the robustness of our method against steganalysis attacks.

A. Textural and SSIM Evaluations

We extracted the textural features for each image of database using run length matrix in 4 directions: 0°, 45°, 90° and 135° to obtain the selected images as candidate covers, and then, selected the best cover based on SSIM. The textured features are SRE, LRE, GLNU and RLN.

The selected images, were selected based on textured features that are shown in Figure 3. As it can be seen in Figure 3, results of using different textured measures might be identical images. The results of computing texture features for selected images (shown in Figure 3) are depicted in Tables 1 to 6.

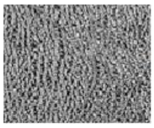
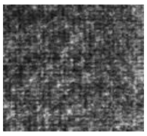
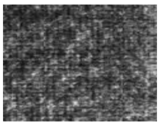
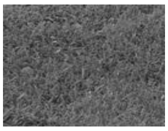
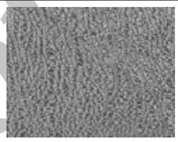
	MAXIMUM SRE	MINIMUM LRE	MAXIMUM GLNU	MAXIMUM RLN
	Pic 1	Pic 2	Pic 3	Pic 4
QRL_0				
	Pic 1	Pic 2	Pic 5	Pic 4
QRL_{45}				
	Pic 5	Pic 2	Pic 4	Pic 4
QRL_{90}				
	Pic 4	Pic 2	Pic 6	Pic 4
QRL_{135}				

Figure 3. Candidate images based on textur features

After extracting candidate images based on texture features, random binary data are created and embedded into the selected pictures by using DWT steganography method [6]. As a result, several stego version of images with different payloads are obtained. It should be noted that the embedding process can be carried on by any steganography method including Contourlet, and Wavelet. Tables 1 to 6 contain original candidate images in Figure 3 with their stego versions, values of texture features, and SSIM between each selected image and its stego. The best cover, which maximizes SSIM, is depicted in Figure 4. The results of experiments confirm that the images with high SRE, GLNU and RLN and less LRE are good candidates for the best cover because they preserve the quality after embedding data.

There are a number of advantages in using proposed algorithm. The first advantage is that it restricts search space to several proper images based on texture features, which are suitable candidates for the best cover. Another advantage is quality assessment based on human visual system. Consequently, the extracted image with highest SSIM is the best cover among all images in database, since it preserves the structural specifications of image and influences the least distortion after embedding data into image. Additionally, as it can be seen in Table 7, the proposed method is able to preserve the quality of stego compared to traditional steganography methods such as DWT and Contourlet.

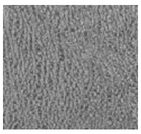


Figure 4. Best picture with maximum SSIM

Table 1. Textured feature for Cover candidate Pic 1

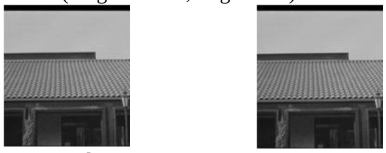
	SRE	LRE	GLNU	RLN	SSIM (Original Pic 1, stego Pic 1) = 0.6539
0	0.316	7.023	12524.215	23028.2831	
45	0.291	7.100	21475.359	36995.59	
90	0.284	7.254	21273.273	35067.147	
135	0.278	7.447	25918.064	39218.90	Original Pic 1 Stego Pic 1

Table 2. Textured feature for cover candidate Pic 2

	SRE	LRE	GLNU	RLN	SSIM (Original Pic 2, Stego Pic 2) = 0.7069
0	0.2288	6.4966	14244.798	31772.291	
45	0.233	6.4339	17285.013	34125.173	
90	0.2305	6.5691	9182.1280	24146.1759	
135	0.2275	6.5104	19904.8591	36749.9546	Original Pic 2 Stego Pic 2

Table 3. Textured feature for cover candidate Pic 3

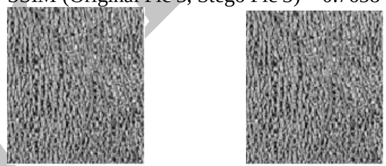
	SRE	LRE	GLNU	RLN	SSIM (Original Pic 3, Stego Pic 3) = 0.7658
0	0.20031	11.1264	70969.650	36409.807	
45	0.2080	10.998	83860.266	38540.7957	
90	0.1959	10.9636	42386.300	30032.533	
135	0.2076	11.0405	76185.050	37038.2771	Original Pic 3 Stego Pic 3

Table 4.Textured feature for cover candidate Pic 4

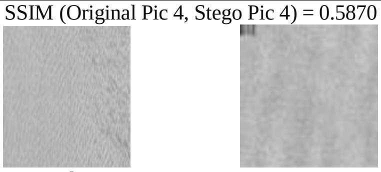
Pic4	SRE	LRE	GLNU	RLN	SSIM (Original Pic 4, Stego Pic 4) = 0.5870
0	0.0995	11.7041	56333.207	120284.371	
45	0.09946	11.705	63884.576	126287.319	
90	0.09925	11.721	66351.635	114841.102	
135	0.0993	11.711	60150.5370	126585.202	Original Pic 4 Stego Pic 4

Table 5. Textured feature for cover candidate Pic 5

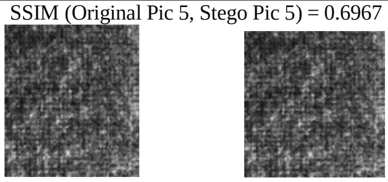
	SRE	LRE	GLNU	RLN	SSIM (Original Pic 5, Stego Pic 5) = 0.6967
0	0.2797	6.7079	61145.671	95578.7526	
45	0.28156	6.6517	86087.757	112300.071	
90	0.28619	6.6502	48889.245	84681.3921	
135	0.2853	6.6180	77996.164	106393.578	Original Pic 5 Stego Pic 5

Table 6. Textured feature for cover candidate Pic 6

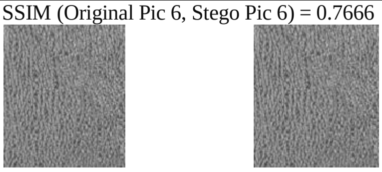
	SRE	LRE	GLNU	RLN	SSIM (Original Pic 6, Stego Pic 6) = 0.7666
0	0.2178	10.348	56395.577	33272.359	
45	0.2261	9.9992	37138.731	27639.546	
90	0.2186	10.378	54113.767	32695.715	
135	0.2303	10.625	99762.5456	40307.402	Original Pic 6 Stego Pic 6

Table 7. Stego Visual Quality in proposed Algorithm

STEGANOGRAPHY METHODS	SSIM
PROPOSED COVER SELECTION + DWT STEGANOGRAPHY	0.7666
PROPOSED COVER SELECTION + CONTOURLET STEGANOGRAPHY	0.8612

B. Steganalysis Results

We evaluated the robustness of the proposed algorithm against steganalysis attacks such as Wavelet-based and Block-based steganalysis methods introduced in [25] [26]. They used nonlinear support vector machine classifier in training and testing phases. To make image cover database used in training and testing phases, we collected 800 JPEG images from Internet including Washington University image database [28]. All of the images were converted to grayscale with size of 512*512. Descriptions of these steganalysis methods are as follows:

1- Wavelet-based steganalysis (WBS) in [25] produces a model for clean images and then, it computes the distance between each image and its clean image model. It uses statistics such as mean, variance and skewness, extracting from each Wavelet sub-band of cover to detect a stego from clean image. Totally, 24 features are employed for classification.

2- Block-Based steganalysis (BBS) in [26] divides image blocks into multiple classes and defines a classifier for each class to determine whether a block is from a cover or stego image. Consequently, the steganalysis of the whole image can be conducted by fusing steganalysis results of all image blocks through a voting process.

Table 8. Detection Rate (%) of steganalses against our method composed with DWT embedding

Payload Rate (bits)	Embedding in DWT		Cover Selection and DWT Embedding	
	WBS	BBS	WBS	BBS
2000	60	59	55	55
5000	65	65	59	57
10000	67	66	60	62

Table 9. Detection Rate (%) of steganalses against our method composed with Contourlet embedding

Payload Rate (bits)	Embedding in Contourlet		Cover Selection and Contourlet Transform Embedding	
	WBS	BBS	WBS	BBS
2000	56	55	49	48
5000	58	59	51	50
10000	62	61	55	53

We created three stego databases with payloads of 2000, 5000 and 10000 bits for each steganography algorithm (DWT, Contourlet). Size of each stego database is 800. So, each pair of stego-cover databases includes 1600. We selected 1000 images for training phase and 600 images for testing, randomly. To evaluate the robustness of our proposed method against steganalyses, random subsets of images are selected; percentage of its average true detection (both stego and cover) over these random subsets is named accuracy of each method. The average detection accuracy of Wavelet-based and Block-based steganalyses over steganography techniques are represented in Tables 8 and 9. The results show that the proposed cover selection algorithm improved the robustness of DWT and Contourlet steganography against steganalysis attacks.

6. Conclusions

We proposed a new Cover selection approach for secure steganography using textural features of run-length matrix and structural similarity metric. According to textural features of run length matrix, suitable images are extracted as candidate covers. Through using SSIM, algorithm selects one image as the best cover among suitable images. This quality assessment method, SSIM, takes advantage of known characteristics of the human visual system.

New proposed cover selection algorithm results on preserving higher quality in stego with equal payload in comparison with traditional steganography methods. Additionally, we applied our suggested cover selection method to steganography methods such as DWT and Contourlet embedding. The results showed the robustness of our composed method against steganalysis attacks in comparison with DWT and Contourlet steganography methods.

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