Steganalysis for LSB Matching by Counting Image Blocks with the Same Gray Level

Zhao Y.R., Ping X.J., Wang R., Zheng E.G.
Zhengzhou Information Science and Technology Institute, Zhengzhou, Henan, China
zhaoyanrong1983@126.com

***Abstract*—The steganalysis for the least significant bit (LSB) matching is a hot and difficult topic. Some bit plane/s might be changed during the LSB matching steganograpy. Huang *et al.* proposed a method based on the differences in the least two bit planes of an image and the results show good performance to uncompressed images. In this paper, we make some improvements by introducing Median Filter and sum image. The Median Filter, which is effective to remove random noise in an image, is useful for decreasing the noise brought by embedding based on the additive noise steganography model. The sum image is the same as a low-pass filter to an image in some degree. With Median Filter and sum image together, the influence to a stego image is more than a cover image so the differences can be used for discriminating. Extensive experimental results show that the new detectors in our improved method perform better than the old ones, especially to uncompressed images.**

Keywords-LSB matching; steganalysis; gray level; Median Filter; sum image

I. INTRODUCTION

Steganography is the art and science of secret communication, as the opposite side of which, steganalysis is to detect the existence of hidden message. The least significant bit (LSB) matching is the counterpart of the LSB replacement but it is more difficult to detect. Many steganalysis methods have been proposed for the recent years. Harmsen *et al*. used the histogram characteristic function center of the mass (HCFC) for the detection of additive noise based steganography [1]. Ker improved the work for detection in grayscale images by extending the HCFC to calibrated histogram characteristic function center of the mass (CHCFC) and adjacency histogram characteristic function center of the mass (ACHFC) [2]. Huang *et al*. presented a method by counting alteration rate of the number of 3×3 blocks with the same gray level in the least two significant bit planes of an image [3]. In [4], Zhang *et al*. described the amplitudes of local extrema (ALE) as detectors with good performance in NRCS, in which the images are rich in high frequency noise [5]. Some improvements have been made on ALE [6][7][8].

There are also many other methods for attacking LSB matching steganography. However, it is still a hard work to detect the existence of the hidden message when the embedding rate is very low especially to uncompressed images. Our method is done for the detection to uncompressed images based on Huang's work. Get the filtered image by Median Filter. Take the least two, three and four significant bit planes of an image and its filtered image to make some new images. Count the alteration rate of the number of image blocks with the same gray level in all overlapped blocks with certain size of the new images. The horizontal sum image is also introduced for further improvement. A 12-D feature vector is applied for detection. Extensive experimental results show that the improved detectors outperform the previous ones, especially to never compressed images. The rest of this paper is organized as follows. A brief introduction to the previous work is given in section II. Then our improvements are presented in section III. Extensive experimental results are shown in section IV. A conclusion is made in section V.

II. PRELIMINARIES

LSB matching is known as the second method of LSB steganography besides LSB replacement. Rather than simply replace the LSB with the desired message bit, the corresponding pixel value is randomly incremented or decremented, thereby removing the asymmetry of odd and even pixels. Specifically, LSB matching can be described by:

$$I_s = \begin{cases} I_c + 1, & \text{if } b \neq \mathrm{LSB}(I_c) \text{ and } (k > 0 \text{ or } I_c = 0) \\ I_c - 1, & \text{if } b \neq \mathrm{LSB}(I_c) \text{ and } (k < 0 \text{ or } I_c = 255) \\ I_c, & \text{if } b = \mathrm{LSB}(I_c) \end{cases} \quad (1)$$

Where I_c (resp. I_s) denotes a pixel value in a cover image (resp. stego image), b is the secret message sequence to be hidden, and k is an i.i.d. random variable with uniform distribution on $\{-1,+1\}^2$.

Given an image $I(i,j)$ with size of $M \times N$, it is composed of eight one-bit planes from I_0 to I_7, in which I_0 is the least significant bit plane and I_7 is the most important one. With the least two significant bit planes, we have a new image:

$$f_1(i,j) = I_0(i,j) + I_1(i,j) \times 2 \quad (1 \le i \le M, 1 \le j \le N) \quad (2)$$

There are four different gray levels in $f_1(i,j)$ from 0 to 3. Then we divide $f_1(i,j)$ into 3×3 overlapped blocks and classify all the blocks to four different types according to the gray level/s they contain:

S_1: the nine pixels in every block with the same gray level in all blocks.

This work was supported by National Natural Science Foundation of China (No. 60970142).

978-1-4244-5900-1/10/$26.00 ©2010 IEEE

S_2 : the nine pixels in every block with two different gray levels in all blocks.

S_3 : the nine pixels in every block with three different gray levels in all blocks.

S_4 : the nine pixels in every block with four different gray levels in all blocks.

When embedding some secret message sequence into an image, it is much more possible that the blocks would change from S_1 to S_i $(2 \le i \le 4)$ than from S_i $(2 \le i \le 4)$ to S_1. Define $/S_1/$ as the number of S_1 and it will reduce during the embedding process. Embedding a random sequence into an image by LSB matching, we can obtain $/S_1^*/$. Denote (3) to avoid setting an appropriate threshold.

$$K = \frac{/S_1/ - /S_1^*/}{/S_1/} \tag{3}$$

III. THE PROPOSED IMPROVEMENTS

In this paper, the Median Filter is introduced to remove random noise in an image. Taking the secret message brought by LSB matching as additive noise, it is a good way to decrease the impact on an image by Median Filter. The $/S_1^*/$ in Huang's work denotes the number of the blocks with the same gray level in an embedded image while we denote $/S_1^{*'}/$ as the number of S_1 of a filtered image. We know that $/S_1^{*'}/$ is usually higher than $/S_1/$, which leads to the difference $/S_1/ - /S_1^{*'}/$ always being minus. To avoid this problem, change (3) to (4).

$$K' = \left| \frac{/S_1/ - /S_1^{*'}/}{/S_1/} \right| \tag{4}$$

Denote K' as the alteration rate of the number of the blocks with the same gray level in all overlapped blocks. $\left| /S_1/ - /S_1^{*'}/ \right|$ of an image becomes larger when some secret sequence is embedded. The higher the embedding rate is, the larger it will be. Comparing with a stego image, $/S_1/$ is larger while $\left| /S_1/ - /S_1^{*'}/ \right|$ is smaller of a cover image so the conclusion can be drawn that:

$$K_c' < K_s' \tag{5}$$

Where K_c' is of a cover image and K_s' is of a stego image, which holds true usually. Choose 200 images randomly from UCID for test [9]. Embed a random sequence by LSB matching at the embedding rate 100%. The results of K_c' and K_s' are in Fig. 1, which can prove our conclusion.

We find that K_c' is usually lower than K_s' in Fig. 1. Moreover, combine $/S_1/$ and K' together with 200 images for test the same from UCID and give the results in Fig. 2. It is noted that the 2-D feature vector is useful to discriminate cover and stego images.

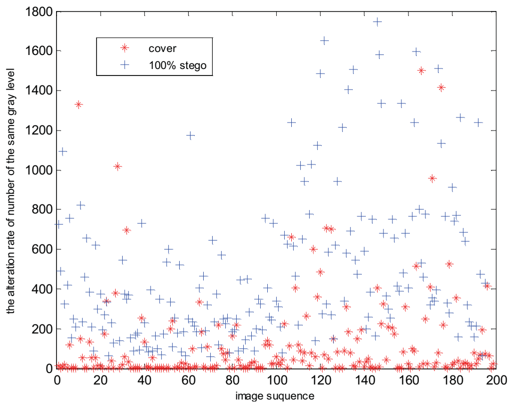


Figure 1. K_c' and K_s' of 200 images from UCID

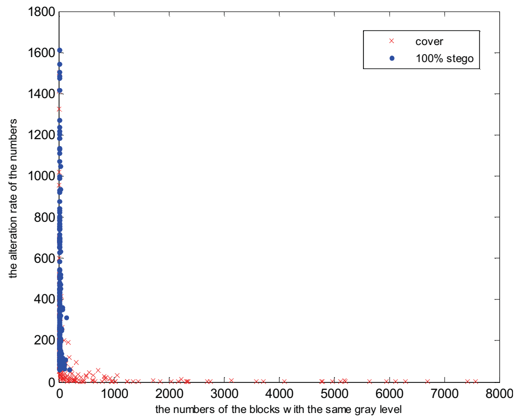


Figure 2. 2-D feature vector of 200 images from UCID

The correlation between pixels in an image goes stronger with the bit plane from I_0 to I_7, however, it might become weaker if some secret message sequence is embedded. There are only two different gray levels from 0 to 1 in the least significant bit plane, in which the random noise is excessive. While we make the least three and four significant bit planes to another two new images:

$$f_2(i,j) = I_0(i,j) + I_1(i,j) \times 2 + I_2(i,j) \times 4 \quad (1 \le i \le M, 1 \le j \le N) \tag{6}$$

$$f_3(i,j) = I_0(i,j) + I_1(i,j) \times 2 + I_2(i,j) \times 4 + I_3(i,j) \times 8 \quad (1 \le i \le M, 1 \le j \le N) \tag{7}$$

There are eight different gray levels from 0 to 7 in $f_2(i,j)$ and sixteen from 0 to 15 in $f_3(i,j)$. The gray levels increase a lot and $/S_1/$ in 3×3 overlapped blocks may be very low so we instead 2×2 overlapped blocks of 3×3.

The calibration Ker proposed plays like a low-pass filter to an image. Sum image is the same so horizontal sum image is introduced, which is defined as:

$$I_{sum}(i,j) = I(i,j) + I(i,j+1) \quad (1 \le i \le M, 1 \le j \le N-1) \tag{8}$$

Based on all above analysis, we present our tests for the following steps.

(1) For any given image $I(i,j)$, get $I_{sum}(i,j)$ by (8) and their least two, three and four significant bit planes by (2), (6) and (7). There are six images: $f_1(i,j)$, $f_{1sum}(i,j)$, $f_2(i,j)$, $f_{2sum}(i,j)$, $f_3(i,j)$ and $f_{3sum}(i,j)$.

(2) Denote $D_i\ i=1,2$ as the numbers of 3×3 overlapped blocks with the same gray level in $f_1(i,j)$ and $f_{1sum}(i,j)$. Denote $D_i\ i=3\sim 6$ as the numbers of 2×2 overlapped blocks with the same gray level in $f_2(i,j)$, $f_{2sum}(i,j)$, $f_3(i,j)$ and $f_{3sum}(i,j)$.

(3) Have $I(i,j)$ and $I_{sum}(i,j)$ filtered by Median Filter and get $D_i^{'}\ i=1\sim 6$ of the filtered images the same as $I(i,j)$ and $I_{sum}(i,j)$.

(4) Count $K_i^{'}: i=1\sim 6$ by (4). Use the 12-D feature vector $D_i: i=1\sim 6$ and $K_i^{'}: i=1\sim 6$ for detection.

IV. THE EXPERIMENTAL RESULTS

In this section, we present our experimental results of the improved method. First, we describe the image sets used in our experiments.

UCID: There are 1338 uncompressed color images with size of 512×384. Choose 1000 images randomly.

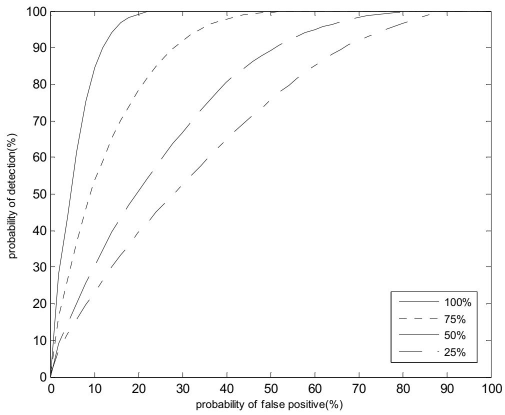
Camera [10]: There are 3164 uncompressed images with size of 512×512 caught from different cameras. Choose 3000 images randomly.

NRCS: The 3185 images are very high resolution TIF files (mostly 2100×1500) and appear to be scanned somewhere. Choose 3000 images randomly and resample to 700×500.

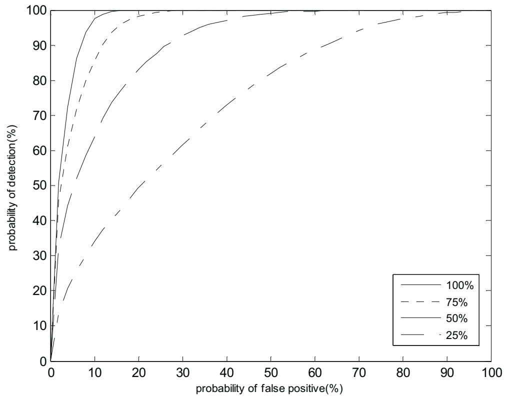
All the images used are converted to grayscale and embedded secret sequence at the embedding rates 100%, 75%, 50% and 25% by LSB matching. In the test, about 0.3% cover images and 0.5% stego images at most, of which the numbers of the blocks with the same gray level are zeros, are treated as stego images. Choose 20% randomly for train and the rest for test. The fisher linear discriminator (FLD) is applied for 20 times to obtain the mean performance. The receiver operating characteristic (ROC) curves are given in different database in Fig. 3. To well demonstrate the superior performance, some other experimental results are also reported in Table I, in which ER is the embedding rate, the AUC means the value of the area under the ROC curve, FP_50 and FP_80 are the false positive (FP) results when the true positive (TP) are at 50% and 80%.

From Fig.3 and Table I, it is noted that the improved method shows good performance in UCID and Camera than NRCS because images in different database may have some effect on the performance so the results among the three database have large differences. Images in the former two database are uncompressed but in the latter are of too much high frequency noise. Even images in UCID and Camera are all uncompressed, there are still some differences of the performance in the two database.

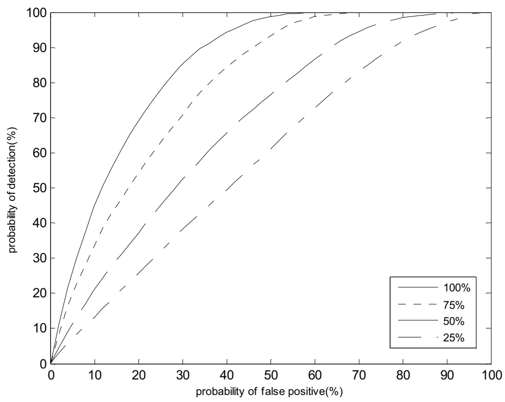
We compare the improved method with CHCFC and AHCFC proposed by Ker and Huang's work in UCID. The ROC curves at the embedding rates 100% and 50% are given in Fig. 4 and the AUC and FP_50 and FP_80 are reported in Table II and III.



(a)ROC cuvers in UCID



(b) ROC cuvers in Camera

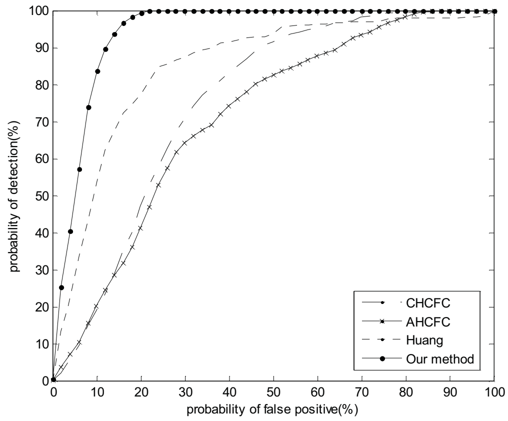


(c) ROC cuvers in NRCS

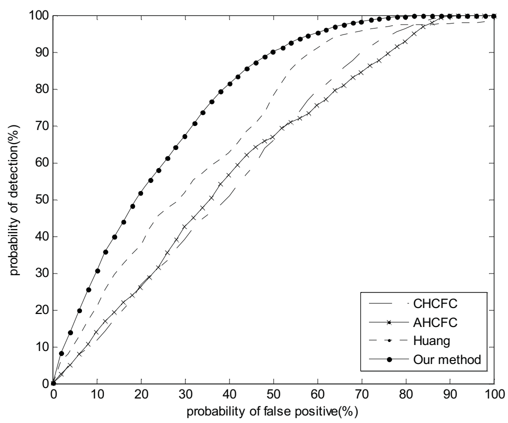
Figure 3. ROC curves in different database at different embedding rates

TABLE I. AUC AND FP IN DIFFERENT DATABASE AT DIFFERENT EMBEDDING RATES

Database	ER	AUC	FP_50	FP_80
UCID	100%	0.9447	0.0521	0.0941
	75%	0.8776	0.0887	0.2054
	50%	0.7631	0.1939	0.3931
	25%	0.6809	0.2792	0.5435
Camera	100%	0.9711	0.0198	0.0583
	75%	0.9546	0.0239	0.0795
	50%	0.9003	0.0514	0.1707
	25%	0.7346	0.2094	0.4822
NRCS	100%	0.8462	0.1115	0.2586
	75%	0.7885	0.1742	0.3627
	50%	0.6832	0.2883	0.5371
	25%	0.5833	0.3988	0.8002



(a) ROC curves at the embedding rate 100%



(b) ROC curves at the embedding rate 50%

Figure 4. ROC curves of different methods at different embedding rates

TABLE II. THE VALUES OF AUC AND FP AT EMBEDDING RATE 100%

Method	AUC	FP_50	FP_80
CHCFC	0.7581	0.2065	0.3657
AHCFC	0.7131	0.2295	0.4581
Huang	0.8495	0.0976	0.2096
Our method	0.9459	0.0506	0.0876

TABLE III. THE VALUES OF AUC AND FP AT EMBEDDING RATE 50%

Method	AUC	FP_50	FP_80
CHCFC	0.6091	0.3888	0.6043
AHCFC	0.6073	0.3587	0.6421
Huang	0.6872	0.2901	0.5144
Our method	0.7648	0.1919	0.3857

It is obvious that our improved method performs better to never compressed images than other methods in UCID from the results in Fig.4, Table II and III. Comparing at different embedding rates, the higher the embedding rate is, the better the performance will be.

V. CONCLUSION

In this paper, we have made some improvements based on Huang's work for attacking LSB matching steganography and evaluated the performance in different image database. The main points of our improved method are the Median Filter and horizontal sum image. Median Filter is introduced to remove the random noise embedded to an image and count the difference for feature obtained. The horizontal sum image effects like a low filter to an image in some degree so it plays a positive role in improving the performance. Extensive experimental results have shown that the 12-D feature vector is more effective for detection to uncompressed images.

However, it is still a hard work when the embedding rate is very low. Furthermore, there are some differences of the performance in different database. More work should be done to improve the performance at very low embedding rates and in different database.

REFERENCES

[1] Harmsen J and Pearlman W A, "Steganalysis of additive noise modelable information hiding," Proc. of the SPIE, Security, Steganography, and Watermarking of Multimedia Contents VI. San Jose, CA, 2003:131-142.

[2] Ker A D, "Steganalysis of LSB Matching in Grayscale Images," IEEE Signal Processing Letters, 2005, 12(6):441-444.

[3] Huang F, Li B and Huang J, "Attack LSB Matching Steganography by Counting Alteration Rate of the Number of Neighbourhood Gray Levels," Proc. of IEEE ICIP2007, Vol.1, pp.401-404, 2007.

[4] Zhang Jun, Cox Ingemar J and Doerr Gwenael, "Steganalysis for LSB Matching in Images with High-frequency Noise," Proceeding of the IEEE MMSP2007, pp. 385-388.

[5] The USDA NRCS Photo Gallery[DB/OL]. [2008-9-14]. http://photogallery.nrcs.usda.gov.

[6] Giacomo Cancelli, Gwenaël Doërr, Ingemar J. Cox and Mauro Barni, "Detection of ±1 LSB Steganography Based on the Amplitude of Histogram Local Extrema," in IEEE International Conference on Image Processing, pp. 1288-1291, October 2008.

[7] Yunkai Gao, Xiaolong Li, Bin Yang and Yifeng Lu, "Detecting LSB Matching By Characterizing the Amplitude of Histogram," Proceeding of of the IEEE ICASSP2009, pp. 1505 - 1508.

[8] Jun Zhang, Yuping Hu and Zhibin Yuan, "Detection of LSB Matching Steganography using the Envelope of Histogram," Journal of Computers, Vol. 4, No. 7, July 2009, pp. 646-653.

[9] G. Schaefer, M. Stich. UCID – An Uncompressed Colour Image Database[R]. UK: Nottingham Trent University, 2003.

[10] G. Doërr. Image database for steganalysis studies. http://www. adastral.ucl.ac.uk/gwendoer/steganalysis.