Steganalysis of LSB matching for Images with High Noise

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Abstract

This paper proposed a new steganalysis method against least significant bit (LSB) matching for images with high noise component which is considered more difficult for steganalysis than images with low noise component. First we calculate the sum of curvature of images histogram as discriminative feature which will reduce after LSB matching. Then, the calibration mechanism is introduced to reduce the steganalytic difficulty caused by the image variety. Experimental results show that the proposed method is efficient to detect the LSB matching steganography on image with high noise and has superior results compared with other recently proposed algorithms.

Keywords: Steganalysis, Information Hiding, Information Security, LSB matching, Curvature

1. Introduction

Steganography embed secret information into carrier which will not do a lot of distortion. Compared with the traditional cryptography, Steganography conceals the fact that secret information is communicated and is a safer security communication mechanism. Steganalysis aims to expose the presence of hidden data. Generally speaking, the steganographic system is considered broken if an algorithm can judge whether a given image contains a secret message or not[1]. In this paper, we concentrate on the detection of spatial domain LSB matching steganography in gray images with high noise.

LSB matching which embeds message in spatial domain of image is the archetype of many kinds of steganography method. The embedding strategy of LSB matching can be described as follows: if the LSB of the image pixel matches the secret data bit, the pixel will be unchanged; otherwise, the pixel will be added or subtracted by one at random[2]. Due to the stochastic mechanism, LSB matching maintains more statistical properties than LSB replacement which is other spatial domain steganography. LSB matching makes card square detection, RS detection, SPA detection, DIH detection methods which are efficient to LSB replacement failure [3-5]. Facts prove that detection of LSB matching is more difficult than that of LSB replacement.

The key of steganalysis is to find the difference between cover and stego images which is named feature extraction in pattern recognition. If the difference has statistically significance, the difference can make as a sign to distinguish the two types.

Harmsen [6] exploit the histogram characteristic function (HCF) to detect of steganography in color images. Ker [7] improved Harmsen's method through: (i) introduce a calibration mechanism by using a downsample technology, and (ii) substitute the usual intensity histogram for the adjacency histogram to compute the histogram characteristic function, which is referred to as the AD-HCF method. AD-HCF has significant improvements results compared with Harmsen's method. Xiao [8] utilizes the run-length histogram (RLH) to extract the feature which catches dependence among pixels that are not adjacent to each other. They find that the run length histogram of images will "shrink", i.e. the number of runs with long length in an image will decrease and the number of runs with short length will increase after LSB matching. Pevny [9] exploit first-order and second-order Markov chains to modeling the differences between adjacent pixels in natural images. They postulate that deviations from this model are due to steganographic embedding. The features for steganalyzer are the subsets of sample transition probability matrices.
Perhaps surprisingly, steganalysis of LSB matching for images with high noise (such as uncompressed images) is much more difficult than that for images with low noise component (such as JPEG-compressed images) [10-12]. There are some papers of steganalysis for decompressed images. Luo[13] presented a quantities method to reliably estimate the length of spatial modifications in those gray-scale JPEG stegos by using data fitting technology. Zhang[14] presented an efficient steganalyzer that exploits the fact that the noise residuals in the DCT domain are rather concentrated on zero and very sensitive to LSB matching. But the literature does contain a few detectors for LSB matching in uncompressed images. Zhang[15] find that the sum of the absolute differences between local extrema and their neighbors in the intensity histogram of stego images will be smaller than cover images. Cancelli[16] improved this algorithm to (i) reduce the noise associated with border effects in the histogram, and (ii) extend the analysis to amplitudes of local extrema in the 2D adjacency histogram. This algorithm is referred to as the ALE method.

2. Proposed methods

2.1. Effect on the histogram by LSB matching

Denote a grayscale image as \( I \) and write \( I(i, j) \) for the intensity of the image at location \((i, j)\). We define the histogram of an image as \( h(n) = \lfloor |I(i, j)| I(i, j) = n \rfloor \). At the embedding rates of \( p \), the LSB matching can be modeled as adding an independent additive noise to the image\[17\], and the effects of LSB matching on image histogram can thus be formulated as follows.

\[
\begin{align*}
  h_i(n) &= (1 - \frac{P}{2})h_i(n) + \frac{P}{4}h_i(n-1) + \frac{P}{4}h_i(n+1), \quad n \in \{2 \ldots 253\}, \\
  h_i(0) &= (1 - \frac{P}{2})h_i(0) + \frac{P}{4}h_i(1), \\
  h_i(1) &= (1 - \frac{P}{2})h_i(1) + \frac{P}{4}h_i(0) + \frac{P}{4}h_i(2), \\
  h_i(254) &= (1 - \frac{P}{2})h_i(254) + \frac{P}{4}h_i(253) + \frac{P}{4}h_i(255), \\
  h_i(255) &= (1 - \frac{P}{2})h_i(255) + \frac{P}{4}h_i(254)
\end{align*}
\]

Under this situation, LSB matching will be deduced as low pass filter on the histogram with the kernel of \([p/4, 1-p/2, p/4]\), if histogram boundary is ignored. Namely, histogram will be smoothed by the LSB matching.

2.2. Feature Extraction From Histogram

Curvature is utilized to evaluate the smoothness of the histogram. After connect the peak of image histogram, we will get a discrete curve which has 256 ordered points. If the histogram was smoothed by LSB matching, the curvature of this discrete curve is likely to descend as well. In this paper, we calculate the sum of curvature of histogram, which is denoted as \( SCH \), to describe the smoothness of histogram.

Fig. 1 shows a part of discrete curve obtained by connecting the peak of image histogram, the order is marked as \( \{h_i\}^{255}_{i=0} \), where \( h_i \) stands for the peak of image histogram. The curvature of peak of image histogram at point \( h_i \) which is denoted as \( CH_i \) is calculated as follows \[18\].

\[
CH_i = \frac{2\Delta h_i \cdot h_i \cdot h_{i+1}}{d_i d_{i+1} d'} = (d_i + d_{i+1} + d') \ast (d_{i+1} + d - d') \ast (d_i + d' - d_{i+1}) \ast (d_i + d_{i+1} - d') \ast /8d_i d_{i+1} d'
\]
To calculate the above formula, we should configure the horizontal distance between two adjacent bins with a value. Due to the histogram is not normalized, we reduce impact of image size by giving a dynamic value determined by the image size to the bins distance. In this paper, square root of the number of pixels is used.

![Histogram diagram](image)

**Figure 1.** Schematic drawing of calculate curvatures of the

We define:

\[
SCH = \sum_{i=1}^{254} CH_i
\]  

(3)

Using \( SCH_c \) and \( SCH_s \) to denote the \( SCH \) of the cover and stego images, because smoothed by the LSB matching, respectively, we have

\[ SCH_c \leq SCH_s \]  

(4)

We calculate the value of \( SCH \) from 3,162 uncompressed images which downloaded from NRCS and their stego version as shown in Fig.2 (only 400 pairs are given for better visual). Apparently, the value of \( SCH \) obtained from stego images are smaller than that obtained from cover images.

![Graph](image)

**Figure 2.** Values of SCH before and after embedding by LSB matching for NRCS

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2.3. Calibration mechanism

Natural images are highly various, so the features extracted from these images are very unstable. To deal with this problem, we choose to use calibration mechanism. Generally speaking, if we embed a image twice, the influence of the first embedding on image is greater than the second one. Therefore, with a pending image, we first embed message in each pixel of the image to get a calibrated image. Then, SCH are calculated from both pending image and the corresponding calibrated image. The final feature (named as calibrated feature) is the ratio of two SCHs.

Fig.3 shows the calibrated feature extract from 3162 cover image and their stego versions. Compared with uncalibrated feature shown in Fig. 2, the calibrated feature gains better separability.

2.4. Description of Algorithm

The flowchart of this steganalysis method is summarized as follows:

1) Get $SCH_d$ from detect image $I_d$
2) Get $SCH_c$ from the calibrated image $I_c$ which uses the proposed calibration mechanism.
3) Calculate final feature which is the ratio of $SCH_d$ and the $SCH_c$.

![Figure 4. The flowchart of this steganalysis method](image-url)
3. Experimental Results

The NRCS Photo Gallery, which includes 3,162 color images of artwork, is a classic image database in steganalysis. The original images are 24-bit, with dimensions of 1500*2000 and are uncompressed images. For experimental convenience, we covert them to 8-bit grayscale and all of the images were utilized as covers to generate stego images with LSB matching steganography. The message lengths take 100%, 75%, 50% and 25% of the maximal embedding length (i.e. one bit per pixel). Therefore, the image database consists of $3,162 \times (1+4) = 15,810$ cover and stego images.

In steganalysis, receiver operating characteristic curve (ROC) is classic performance evaluation standard, which describes the relationship between the detection probability and false-alarm probability. Chance line is defined as the straight line which is connect point (0,1) and point (1,1). The worst performance is that ROC curve is essentially coincident with chance line. The more far away from chance line, the higher the performance is. Therefore, the tested method achieves perfect performance when the curve is straight climb from point (0,0) to point (0,1), continue to point (1,1) at straight level.

Fig.5 shows the receiver operation characteristic (ROC) curve of our extracted feature on the image database at four secret message length $p=0.25, 0.5, 0.75, 1$ respectively.

We compare our method with the HCF COM, Runlength and ALE at the embedding rates of 100% and 75%. Note that HCF COM feature is a joint feature set which consists of conventional HCF COM, calibrated HCF COM, adjacency HCF COM and calibrated adjacency HCF COM. Due to the dimensions of the feature vectors from HCF COM, Runlength and ALE is multidimensional. So the C-support vector classification (C-SVC) of the LIBSVM with RBF kernel is introduced to classify cover and stego images. The training set of SVM contains 1,200 cover images and 1,200 corresponding stego images. Among the 1,200 stego images, images of four embedding rates, i.e. 100%, 75%, 50% and 25%, are equally included. The test image set is the rest of image database includes 1,962 cover images and stego images with four message lengths (i.e. $1,962 \times 4 = 4,648$ stego images). The tool “Cross-validation and Grid-search” was used to search the penalty parameter $C$ and kernel parameter $\gamma$ before the classifiers are trained. For NRCS, the parameter pairs $(C, \gamma)$ used in our experiment are listed in Table 1.

<table>
<thead>
<tr>
<th>Methods</th>
<th>$(C, \gamma)$</th>
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<tbody>
<tr>
<td>ALE</td>
<td>$(2048, 8)$</td>
</tr>
<tr>
<td>KER</td>
<td>$(32768, 0.001953125)$</td>
</tr>
<tr>
<td>Runlength</td>
<td>$(32768, 2)$</td>
</tr>
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Figure 5. ROC curves in the detection for different embedding rates: (a) 100%, (b) 75%, (c) 50%, and (d) 25%.
Note that the x-axes of Fig.6 and Fig.7 have been scaled to focus on regions of interest. As seen in Fig.6, performance of our method is close to the ALE[3] and superior to the HCF COM[4], Runlength[5] at the embedding rates of 100%. From Fig.7, our method is superior to the three classic methods at the embedding rates of 75%.

4. Conclusion and future work

Xia [19] proposed that features which exploit the histogram disturbance are better than other types' features to detect images with high noise. Through analysis the effects of LSB matching steganography on histogram, this paper proposed a feature base on the fact that SCH will decrease after LSB matching, it avoid feature of higher dimensionality, which troubled many steganalyzer especially those who use higher order statistics and learning method. Then, the calibration mechanism is introduced to reduce the negative effect of image content to the extracted feature. Experimental results show that the scheme is superior to some previous
methods such as HCF COM, Runlength and ALE which to aim at steganalysis for images with high noise. This paper is the first step that utilize geometrical characteristic to steganalysis for images, in our future research, we will increase dimension of feature vector, e.g. we can extend to the 2D adjacency histogram, which consider the correlation of pixels, we hope this will increase the detection performance.

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6. References