LOCAL CORRELATION PATTERN FOR IMAGE STEGANALYSIS

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ABSTRACT

Correlation of pixels is the most important information used for image steganalysis. Current methods often consider some special types of relationships among neighboring pixels. In this paper, we propose a general descriptor to consider the correlation of pixels comprehensively. We consider the correlation of pixels in an adjacency pattern as a local correlation pattern (LCP). The LCP descriptor is proposed to embrace different local correlation patterns and represent each pattern by mapping the relative values of pixels in the pattern to a numerical value. Then, histograms of LCP values are taken as features for steganalysis. The LCP descriptor also can be used for describing the correlation of elements in the residual image obtained by image filtering. Experiments show that our constructed feature set based on the LCP descriptor outperforms a state-of-the-art method on detecting three popular steganographic algorithms.

***Index Terms*—** Steganography, steganalysis, local correlation, LCP

1. INTRODUCTION

For image steganalysis, effective feature sets extracted in the spatial domain are almost all based on the correlation of neighboring pixels. Pixels in a meaningful image are not randomly distributed, they have strong dependence in a local region and such dependence may be weaken by the data hiding operation. Based on modeling the correlation of pixels, many methods achieved good performances on detecting a wide spectrum of steganographic algorithms. In [1], the authors firstly modeled the dependency of adjacent pixels as a Markov process. Thereafter, so many famous methods are derived from the Markov framework. Zou et al. [2] proposed to predict the current pixel by neighboring pixels and then use Markov chain to model the thresholded prediction-error image. Pevny et al. [3] developed a special Markov model named SPAM which subtracts gray values of adjacent pixels in certain direction, and took the joint probabilities of differences as features. Today, to reduce the impact of image content and get more robust features, many methods focus on modeling the correlation of neighboring elements in the residual image obtained by image high-pass filtering [4–7].

While describing the correlation of pixels (here we also call an element in the residual image as a pixel), current methods often use co-occurrence matrices of neighboring pixels along one or more of the following four directions: horizontal, vertical, diagonal or minor diagonal. However, co-occurrences of pixels along these directions are just some special types of relationships of neighboring pixels. There should be more kinds of correlations exist in a local region of an image, associating with the number of pixels and the way they are adjacent to each other (or more generally, their relative positions). Even the very famous “Rich Models” [5] only considered the diversity of image residuals but ignored the diversity of adjacency patterns of pixels.

In this paper, we formulate a general description of various types of correlations among pixels. In a local region, for a certain number of neighboring pixels, they are adjacent to each other in many different patterns and each adjacency pattern corresponding to a kind of local correlation. We consider the correlation of pixels in an adjacency pattern as a local correlation pattern (LCP). The LCP descriptor is proposed to represent such pattern by mapping the relative values of pixels in each adjacency pattern to a numerical value. And, histograms of LCP values are then taken as features for steganalysis. The LCP descriptor not only considers the correlations of pixels in linear directions often used in current methods, but also the correlations of pixels in many other nonlinear directions. This is very meaningful since current new steganographic algorithms tend to embed messages in texture and noisy regions that are hard to model in linear directions. The LCP descriptor also can be used for describing the correlation of neighboring elements in the residual image obtained by image filtering. Since there are too many kinds of LCPs and image filters, we also propose to select subsets of features according to their diversity and individual performances.

The remainder of the paper is organized as follows: In Section 2, we analyze the adjacency patterns of pixels in a local region and propose the LCP descriptor. In Section 3, we demonstrate how to construct a feature set for steganalysis based on the LCP descriptor. The experimental results are presented in Section 4. Finally, conclusions are drawn in Section 5.

2. LCP DESCRIPTOR

To consider the correlation of pixels in a local region, the first step is to decide the number of pixels involved and their relative positions. Since pixels in closer proximity have stronger dependencies, in this paper, we mainly consider pixels connected to each other in a small local region. We will analyze the cases from simple to complex.

Two pixels have four different adjacency patterns: horizontal, vertical, diagonal and against diagonal. Three pixels have more diverse adjacency patterns, as shown in Fig. 1 (each small box denotes a pixel). Further, more pixels correspond to more and varied patterns.

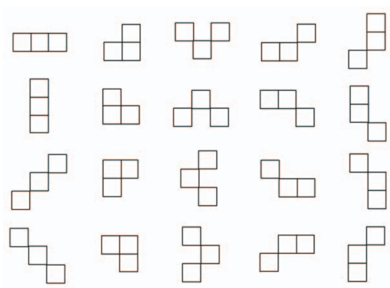

Fig. 1. Adjacency patterns of three pixels.

In an image, take a non-edge pixel as the center, its 8 immediate connected pixels form a set, denoted as N_8. The center and every two pixels from the set N_8 compose an adjacency pattern of three neighboring pixels. And so is the center with three or even more pixels from N_8, compose adjacency patterns of four or more pixels. That means, each adjacency pattern corresponds to a selection of pixels from a set of neighboring pixels without regarding the order. Such a selection is also called a combination in terms of combinatorics. The number of combinations of n pixels taken k at a time is denoted by nC_k. Adjacency patterns of three neighboring pixels correspond to $n = 8, k = 2$ and the total number is $nC_k = 28$. We found that some kinds of combinations correspond to the same adjacency pattern. Eliminate duplications, the final number of different adjacency patterns of three pixels is twenty, as shown in Fig. 1.

For each adjacency pattern of three pixels, the joint probability matrix of pixels may reflect their correlation well. However, this matrix is too large to compute and useless for steganlaysis, because most of its elements reflect the image content rather than the stego information. Actually, steganalysis only cares about the relationships among pixels not the exact values of pixels. Then we only need to consider the relative values of pixels. Taking one as reference and subtracting it from the other two pixels to get two differences (relative values). Then these three pixels' correlation can be reflected by the dependence of the two differences. In practice, the obtained differences often need to be truncated. Because it is believed that the adjacent pixels with small differences have higher correlation. Compared to the irregular sharp edges, they are more proper for steganalysis. However, truncation inevitably results in loss of information. Employing quantization to the differences may let us able to model the dependencies among pixels with larger differences. In fact, truncation and quantization have appeared for the first time in [1], and then widely used in many steganalytic systems.

Based on above analysis, we can derive the general LCP descriptor. Let x_r be a pixel in an image, S be a set of n elements which are neighbors of x_r in a certain local region. S_k^m is a subset of S, where k is the number of elements chosen from S, m indicates the mth selection since there are many selections of k elements from S. The ith element of S_k^m is denoted as x_i. The total number of S_k^m is nC_k and each S_k^m corresponds to a specific type of adjacency pattern. We consider the correlation of pixels in an adjacency pattern as a local correlation pattern (LCP). Then, the LCP descriptor is defined in the following:

$$LCP\left(x_r, S_k^m\right) = \sum_{i=1}^{k} f\left(\frac{x_i - x_r}{q}\right)(\beta - \alpha + 1)^{i-1}$$

where

$$S_k^m \subseteq \{x_1, \cdots, x_n\}, \quad m = 1, 2, \cdots, \begin{pmatrix} n \\ k \end{pmatrix}$$
$$q > 0, \quad \alpha \in \mathbb{Z}_{\leq 0} \quad n, k, \beta \in \mathbb{Z}_{>0}$$
$$f(x) = \begin{cases} 0 & if\ x < \alpha \\ \beta - \alpha & if\ x > \beta \\ [x] - \alpha & otherwise \end{cases}$$

The above LCP function essentially encodes a local correlation pattern to a number with a specific radix, and this number reflects the correlation among x_r and the elements in S_k^m. This strategy is very similar with the very famous LBP used widely in computer vision [8]. The center x_r of the local region is taken as a reference, and the difference between x_r and a member of S_k^m is then quantized as the input of function $f(x)$. $f(x)$ is used to round up and truncate the input. The quantization and truncation are similar as defined and explained in [5], but, instead of using a single threshold, we use α and β as the bounds of the truncation and also to determine the radix of the encoded number. Here we present a definite form of $f(x)$, however, as a general descriptor, $f(x)$ is not restricted to this form.

After calculating the LCP value for each pixel in an image, the normalized histograms of LCP values are taken as features for steganalysis, defined as:

$$H_{k,m}(u) = \frac{1}{Z} \left| \left\{ (i,j) \,\middle|\, LCP\left(x_{i,j}, S_k^m\right) = u \right\} \right|,$$
$$u = 0, \cdots, U - 1.$$

where U is the upper bound of LCP value and the symbol $x_{i,j}$ denote the value of the pixel in position (i, j) in an image. i is the horizontal coordinate and j is the vertical. Z is the sum of all histograms, used to normalize the features. Note that each S_k^m corresponds to a kind of LCP hence yielding a subset of features. The final feature set is the fusion of all subsets, covers correlations of pixels in many kinds of adjacent patterns.

3. FEATURE SET CONSTRUCTION BASED ON LCP

The LCP descriptor can be used for describing the correlation of pixels in the original image or filtered image (residual image). Histograms of each kind of LCP can be taken as a subset of features for steganalysis. This is a general framework for generating correlation based features. But, in practice, to construct an effective feature set based on LCP, we need to make a selection of subsets of features since there are too many kinds of LCPs and image filters, and the dimensionality of the final feature set should be taken into account. In this section, we will give an example of feature set construction using LCP descriptor.

3.1. Selection of LCPs

Since the strength of the dependency among pixels drops quickly with the increase of their mutual distances, we choose to use a small size of local region: 3×3. Therefore, the number of elements in S is 8 ($n = 8$), with the central pixel as the reference. As introduced above, S_k^m is a combination of k elements taken from S, corresponding to one kind of LCP. A subset of features is obtained by calculating the histograms of each kind of LCP within the entire image. The dimensionality of each subset $\mathrm{D} = (\beta - \alpha + 1)^k$ grows exponentially as the values of k and $\beta - \alpha$ increase. With consideration of the feature dimensionality and the performance, we choose to use $k = 2, 3, 4, 5, 8$ and set different α and β according to the values of k, as shown in Table 1. It is worthy to mention that when $k = 8$, $\alpha = 0$ and $\beta = 1$, the LCP is just local binary pattern (LBP)[8]. And, in [6], features generated from LBP have been proved to be more powerful than those from co-occurrence matrix for steganalysis. Here we did not use $k = 6, 7$ because when $k = 6, 7$ with $\alpha = 0$ and $\beta = 1$, the LCPs and their performances are similar with the performance when $k = 8$, and if $k = 6, 7$ with larger range of α and β, the feature dimensionality would be too high.

From Table 1, we can see that there are too many kinds of LCPs ($M = 8C_k$ is the number of LCPs at a certain k). To decrease the number of LCPs, we first eliminate the duplicates since some combinations correspond to the same adjacent pattern. Then, the new number of LCPs (M') is shown in the next-to-last row in Table 1.

In the next step, we merge the symmetrical LCPs based on the assumption that the statistics of natural images do not change after rotating right angles or flipping by mirror. For example as shown in Fig. 2, 8 LCPs (with $k = 3$) can be converted to each other by rotating or mirroring them. We take symmetrical LCPs as one kind of LCP while calculating their histograms to get a subset of features. This operation can not only reduce the number of LCPs but also increase the statistical robustness. After this, the number of LCP (M'') is shown in the last row in Table 1.

Table 1. Parameters and properties of feature subsets.

k	2	3	4	5	8
(α, β)	$(-4, 4)$	$(-3, 3)$	$(-2, 2)$	$(-1, 1)$	$(0, 1)$
D	81	343	625	243	256
M	28	56	70	56	1
M'	20	45	62	54	1
M''	5	9	12	9	1

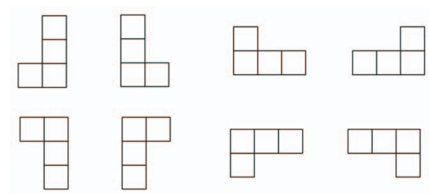

Fig. 2. The eight symmetrical LCPs

We see that now the total number of LCPs is $5+9+12+9+1 = 36$ and the dimension of the union of all feature sets is $5 \times 81 + 9 \times 343 + 12 \times 625 + 10 \times 243 + 1 \times 256 = 13,678$. To further reduce the dimensionality, we have investigated the individual performances of these LCPs on detecting LSBMR [9], as shown in Fig. 3. Note that, for different values of k, the LCP feature sets have different dimensionalities, we should compare LCPs within the same value of k.

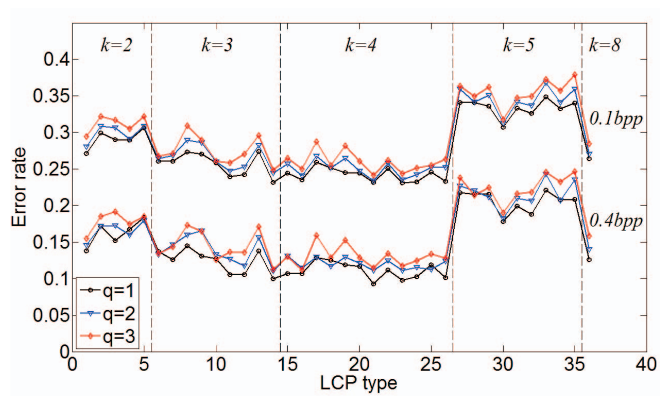

Fig. 3. Performances of different LCP feature sets on detecting LSBMR. Payloads: 0.1 and 0.4 bpp (bit per pixel). Database: BOSSbase v1.01.

We finally choose to use the LCPs shown in Fig. 4, with consideration of their diversity and individual performances.

And we only use the quantization step $q = 1$ for each kind of LCPs, since for $q = 1, 2, 3$, the performances are close. The dimensionality of the final LCP feature set is $5 \times 81 + 4 \times 343 + 5 \times 625 + 3 \times 243 + 1 \times 256 = 5887$.

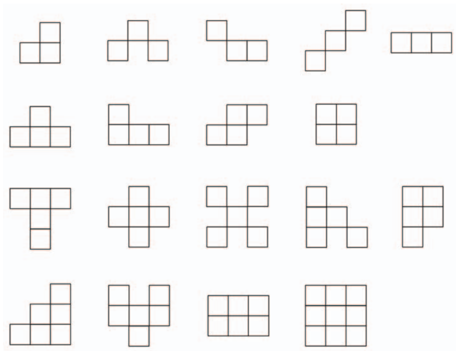

Fig. 4. The selected LCPs.

3.2. LCP on filtered image

Our proposed LCP descriptor also can be used for extracting features from the filtered image. The correlation of elements in filtered image is often more useful for steganalysis [5] since specially designed filters can suppress the image content and make the stego signal more prominent. Many kinds of filters can be used to generate residual images. Since this paper do not focus on the design of filters, we just consider the most effective filters reported in [5]. The selected five filters are: '2nd' spam12hv, '3rd' minmax22v, '3rd' spam14hv, 'EDGE3x3' minmax24 and SQUARE11. The details for these filters and their naming rules can be found in [5].

4. EXPERIMENTS

The image database is BOSS V1.01 [10], which is composed of 10,000 images with the size of 512×512. We carry out experiments on detecting three popular steganographic algorithms in spatial domain: LSB matching revisited (LSBMR) [9], HUGO [11] and S-UNIWARD [12], with payloads of 0.10, 0.20, 0.30 and 0.40 bpp (bit per pixel). For each cover or stego image, selected LCP features are respectively extracted from the original image and its five filtered images, and then merged together to a 35322-dimensional ($6 \times 5887 = 35322$) feature set.

After feature extraction, we train the classifier (steganalyzer) on the training set using ensemble classifiers [13] and report the performance of the steganalyzer on testing set using the minimum detection error rate under equal priors:

$$P_E = \min_{P_{FA}} \frac{1}{2} \left(P_{FA} + P_{MD} \right),$$

averaged over ten random 50%/50% splits of the database, where P_{FA} and P_{MD} are the probabilities of false alarm and missed detection.

We compared our feature set with Rich Models [5], which is the most famous state-of-the-art steganalytic feature set. The results of all experiments are summarized in Table 2. We can find out that our LCP feature set outperforms Rich Models on detecting all the three steganographic algorithms. Although the improvement seems modest, we believe that further improvement can be achieved via careful selection of LCPs together with more kinds of image filters, and this will be our future work. Another advantage of our feature set is that it can be extracted very fast, about 0.42 second for each 512×512 image, while Rich models need 4.8s (using the C++ source code released by the authors [14]. The running environment: Intel Xeon E5620, 16GB memory, Windows Server 2008).

Table 2. Detection errors on three steganographic algorithms.

Algorithm	Payload (bpp)	Rich Models (34671D)	**LCP features (35322D)**
LSBMR	0.10	0.1862	**0.1758**
	0.20	0.1261	**0.1143**
	0.30	0.0930	**0.0865**
	0.40	0.0724	**0.0660**
HUGO	0.10	0.3719	**0.3641**
	0.20	0.2745	**0.2673**
	0.30	0.1977	**0.1886**
	0.40	0.1436	**0.1350**
S-UNIWARD	0.10	0.4182	**0.4063**
	0.20	0.3271	**0.3142**
	0.30	0.2638	**0.2510**
	0.40	0.2194	**0.2037**

5. CONCLUSIONS

As a preliminary investigation on enlarging the diversity of correlation based features through introducing LCP descriptor, our feature set demonstrated the effectiveness and prospect of this approach. There are more possible extensions for LCP. For distortion function based adaptive steganography, it can directly utilize the prior-knowledge of the distortion function, which is analogues to the procedure of maxSRM [15]. The LCP descriptor and the selection of LCPs also need further study to provide a framework for more theoretical guidance.

6. ACKNOWLEDGMENTS

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