

Fusion of Two Typical Quantitative Steganalysis Based on SVR

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Abstract—For the LSB steganography, a fusion method is proposed to fuse two typical quantitative steganalysis methods based on support vector regression (SVR). This paper first gives some main factors influencing the errors of structural steganalysis and weighted stego image steganalysis, viz. the local variance and saturation. Then, the estimated embedding ratios of above two methods, the local variance, the histogram of local variance and saturation are fed to the SVR to train the fusion rule which is used to fusing these two methods. Experimental results show that the proposed fusion method can estimate the embedding ratio with higher accuracy than the individual method.

Index Terms—steganalysis, fusion, embedding ratio, local variance, support vector regression

I. INTRODUCTION

Steganography is the art of hiding the very presence of communication by embedding secret message into innocuous looking covers, such as digital images [1]. Contrarily, one of the main goals of steganalysis is to detect the stego object generated by steganography. Steganography and steganalysis have been the key technologies of multimedia information security [2], [3]. Technically, steganography is considered broken when the mere presence of secret message can be established [1]. However, in order to extract the secret message, the investigators need more details of stego object, such as the length of secret message and the modification ratio of samples [4], [5]. Steganalysis that can estimate the length of secret message or the modification ratio of samples is called as quantitative steganalysis [6]. The estimation of the secret message's length or the modification ratio can not only be used to distinguish the stego objects, but also help to the estimation of stego positions and the search of stego key [4], [5], [7].

Nowadays, there have been many quantitative steganalysis methods for different steganography methods.

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For example, for the popular least significant bit (LSB) replacement, researchers have proposed many corresponding quantitative steganalysis methods, such as RS (regular and singular groups) method [8], DIH (difference image histogram) method [9], SPA (sample pair analysis) method [10], WS (weighted stego image) method [11] and some improved variant of them. For multiple least significant bit planes replacement, LSB matching, $\pm K$, stochastic modulation, JSteg, F5, OutGuess and so on, some relevant quantitative steganalysis methods also have been designed. And some researcher presented to design quantitative steganalyzers from the features in blind steganalysis [12], [13]. Additionally, some researches on error analysis of quantitative steganalysis have been published. In 2005, Rainer Böhme proposed multiple regression models as a method for quantitative evaluation of the accuracy in quantitative steganalysis with respect to various moderating factors [14]. In 2006, on the basis of the results in [14], Rainer Böhme and Andrew D. Ker presented a rationale for a two-factor model for sources of error in quantitative steganalysis, and analyzed the effects of some factors on the two error components [15]. In 2007, Andrew D. Ker derived the error distribution of the least squares steganalysis for cover images [16]. In the past 2011, the authors of this paper used the support vector regression to learn the prediction function of the estimation error of the SPA method [17].

The above works drive the further researches on quantitative steganalysis. But, we all know that for different images, different quantitative steganalysis methods will obtain different results. We know that fusion of multiple results or features would generate more accurate results [18], [19]. Therefore, we try to fuse the existing quantitative steganalysis methods to estimate the embedding ratio more accurately. In this paper, we consider the main factors influencing the estimation errors of the structural steganalysis and weighted stego image steganalysis, and use the support vector regression to fuse these two typical quantitative steganalysis. The experimental results verify the validity of the proposed fusion method.

II. STRUCTURAL STEGANALYSIS AND WEIGHTED STEGO IMAGE STEGANALYSIS

A. Structural Steganalysis

In the structural steganalysis, the estimation equation of embedding ratio is derived from the probabilities of that the structure of each pixel group transfers to various structures and some statistical characteristics of the cover images. The RS method and SPA method for LSB embedding are two typical structural steganalysis methods. This section will take the SPA method proposed by Dumitrescu *et al.* as an example to briefly introduce the principle of structural steganalysis.

In the SPA method, the digital image is represented by the succession of samples, a sample pair means a two-tuple composed of two pixel values. Let D_n ($0 \leq n \leq 2^b - 1$) denote the multiset of the sample pairs whose values differ by n . Let C_m ($0 \leq m \leq 2^{b-1} - 1$) denote the multiset of the sample pairs whose values differ by m in the first $(b-1)$ bits (i.e., by right shifting one bit and then measuring the difference) where b is number of bits used to store the value of a pixel. Let $X_{2m+1} = D_{2m+1} \cap C_{m+1}$, $Y_{2m+1} = D_{2m+1} \cap C_m$, $0 \leq m \leq 2^{b-1} - 2$, and $X_{2^b-1} = \emptyset$, $Y_{2^b-1} = D_{2^b-1}$. Then, when $1 \leq m \leq 2^{b-1} - 1$, the multiset C_m can be partitioned into four trace submultisets X_{2m-1} , X_{2m} , Y_{2m} and Y_{2m+1} . When $m = 0$, the multiset C_0 can be partitioned into two trace submultisets X_0 and Y_1 . Clearly, C_m is closed for LSB replacement, but its trace submultisets are not but convert reciprocally under the LSB embedding operations.

Let $\pi = (\pi_1, \pi_2) \in \{(0,0), (1,0), (0,1), (1,1)\}$ denote the modification pattern where the bit 1 in the first (or second) element of π denotes that the LSB of the first (or second) pixel value in a sample pair is flipped, the bit 0 denotes the unchanged case. Then when modifying the sample pairs in a trace submultiset of C_m by the same modification pattern, the modified sample pairs will transfer to the same trace submultiset. When modifying the sample pairs in a trace submultiset of C_m by different modification patterns, the modified sample pairs will transfer to different trace submultisets of C_m . Dumitrescu *et al.* analyzed the occurred modification pattern when the sample pairs transfer between two trace submultisets of C_m , and gave the probability of that the modification pattern occurs based on the following assumption:

(a) The message bits are randomly embedded into the LSB plane of the cover object, so the embedded message is uncorrelated with the cover bits replaced, and the probability of that the modification pattern π occurs is

$$\rho(\pi) = (1 - p/2)^{2-\pi_1-\pi_2} (p/2)^{\pi_1+\pi_2}. \quad (1)$$

where p is the ratio of the length of the embedded message in bits to the total number of samples in an image.

As a convention in sequel, when Z denote the multiset of the original (clean) sample pairs, let Z' denote the multiset of the sample pairs after LSB embedding.

According to the modification pattern which must occur when the sample pairs transition from a trace submultiset

to another one and the probability that the modification pattern occurs, the cardinalities of the trace submultisets X_{2m-1} and Y_{2m+1} can be described by the functions with respect to the embedding ratio and the cardinalities of C_m , D'_{2m} , X'_{2m-1} and Y'_{2m+1} . Then for each $m \in [0, 2^{b-1} - 2]$, one can derive a quadratic equation to estimate the embedding ratio based on the following assumption:

(b) For original images, if the absolute difference between two samples' values of a sample pair is odd, then it about equally probable that the larger component's LSB of this sample pair is 0 or 1. Namely,

$$|X_{2m+1}| \approx |Y_{2m+1}| \quad (2)$$

where $|A|$ denotes the cardinality of multiset A .

In order to improve the accuracy, the literature [10] summed the quadratic equations for different m to obtained more robust quadratic equations to estimate the embedding ratio. And the literature [10] suggested to summed the quadratic equations over $m \in [0, 30]$.

B. Weighted Stego Image Steganalysis

The weighted stego image steganalysis was first proposed by Fridrich *et al.* for LSB replacement [11]. In the weighted stego image steganalysis for LSB replacement, a weighted stego image is constructed by correcting each pixel with a weight due to that one can model the LSB replacement as modifying each pixel with the same range averagely. Then, when the constructed weighted stego image is closest to an estimated cover image in the sense of squared Euclidean distance, the corresponding weight in the weighted stego image is the estimation of embedding ratio. This section will briefly introduce the weighted stego image steganalysis method first proposed by Fridrich *et al.*

In the WS method, a grayscale cover image with size of $n = M_x \times N_x$ is represented by a set of integers in the range $[0, 255]$, viz. $X = \{x_i\}_{i=1}^n$. The value of x_i after flipping its LSB is denoted as $\bar{x}_i = x_i + 1 - 2(x_i \bmod 2)$. The stego image of LSB embedding with embedding ratio p is denoted as $S = \{s_i\}_{i=1}^n$. For the given stego image S , Fridrich *et al.* constructed a weighted stego image with a weight parameter as follows:

$$S^{(q)} = \{s_i^{(q)}\}_{i=1}^n \quad (3)$$

where $s_i^{(q)} = s_i + (\bar{s}_i - s_i)q/2$, $0 \leq q \leq 1$. It was proved that when the squared Euclidean distance between the weighted stego image and the cover image is minimal, the corresponding value of weight parameter q is equal to the embedding ratio based on the assumption (a). Because the cover image pixel values x_i are not available for detection, Fridrich *et al.* estimated the embedding ratio based on the following assumption:

(c) One can use a function of s_i and its neighbors to estimate the value of x_i .

Fridrich *et al.* also tried to analyze the influence of the local variance and saturation on the estimation error, and improved the accuracy from these aspects.

III. FUSION OF STRUCTURAL STEGANALYSIS AND WEIGHTED STEGO IMAGE STEGANALYSIS BASED ON SVR

A. Factors Influencing Error of Quantitative Steganalysis

From the description in Section II, it can be seen that the accuracy of quantitative steganalysis mainly influenced by the statistical characteristics about cover image. In [14] and [15], Böhme and Ker have modeled the error distribution of quantitative steganalysis, and analyzed the effects of some statistical features on the accuracy by experiments. In this subsection, we will discuss these factors by analyzing the influence of them to the assumptions in Section II.

For the structural steganalysis and weighted stego image steganalysis, the two-factor error model in [15] shows that there are two critical parts to derivation of the methods, viz. the assumption (a) which causes the within-image error due to the correlation between the message and the cover image and the assumptions (b) and (c) which cause the between-image error. And in [16], Ker pointed out that the within-image error is generally of much smaller magnitude than between-image error, unless the embedded payload is very large, and its mean is very close to 0. And because the steganalyst usually can not own the knowledge of message bits' distribution, it is impossible to predict the correlation between the message and the cover image. Therefore, this paper will only consider the between-image error of quantitative steganalysis.

From the description in Section II, it can be seen that the between-image error of the structural steganalysis is mainly caused by the assumption (b), and the between-image error of the weighted stego image steganalysis is mainly caused by the assumption (c). Actually, the assumptions (b) and (c) are seriously influenced by the noise level and outliers of the images. Among many measurement of the image's noise level and outlier, the local variance and the saturation are two popular metrics used to measure the image's noise level and outlier. And the results in [14] and [15] have showed that besides the size of image, the between-image error of quantitative steganalysis is influenced significantly by the local variance and saturation. Thus, the local variance and saturation will be considered when fusing above two typical quantitative steganalysis methods.

(1) Saturation

The saturation of an image denotes the proportion of saturated pixels (i.e., maximum or minimum intensity) in this image. The experimental results in [15] denote that the accuracy of quantitative steganalysis is influenced by the saturation likely more complicated.

(2) Local Variance

In [14], the local variance of an image has been regarded as the most influential factor for detection accuracy among a number of statistical image characteristics. The

local variance of an image can be computed as follows:

$$v_{\text{loc}} = \frac{\sum_{k=1}^{M-1} \sum_{l=1}^N (c_{k,l} - c_{k+1,l})^2 + \sum_{k=1}^M \sum_{l=1}^{N-1} (c_{k,l} - c_{k,l+1})^2}{2MN - (M + N)} \quad (4)$$

where M and N denote the height and width of image respectively.

In order to capture more information of the image's texture, the histogram of the local variance of pixels will also be considered. The local variance of the pixel $c_{k,l}$ is defined as follows:

$$v_{k,l} = \frac{(c_{k,l} - c_{k-1,l})^2 + (c_{k,l} - c_{k,l-1})^2 + (c_{k,l} - c_{k+1,l})^2 + (c_{k,l} - c_{k,l+1})^2}{4} \quad (5)$$

Then the histogram of the local variance of pixels is denoted as $\{h(v)\}_{v=0}^{v=255 \times 255 \times 4}$, where $h(v)$ is the ratio of pixels whose local variance is v to the total number of pixels. In this paper, the bins $h(0), h(1), \dots, h(9)$ will be used for the fusion of different quantitative steganalysis methods.

B. Fusion of Steganalysis Methods Based on SVR

This subsection will describe the method to fuse different quantitative steganalysis methods based on SVR (see Figure 1). This fusion method supposes that we have a set of cover images and some sets of stego images with different embedding ratios which will be used as training data. We use the existing quantitative steganalysis methods to estimate the embedding ratios of the training images, and extract the statistical features of them, such as the local variance, histogram of local variance and saturation. Then some standardization parameters will be computed from the features extracted from the cover training images and used to standardize the features extracted from the cover and stego training images. The standardized features, the embedding ratios estimated by the existing methods and the targets which are set as the actual embedding ratios will be fed to the SVR to train the corresponding model which actually is the fusion rule of the adopted quantitative steganalysis methods.

In this paper, the local variance, histogram of local variance and saturation will be combined to be a feature vector with 12 dimensions. And for each dimension of the feature vector, the preprocessing method [20] is adopted to standardize it so as to improve the performance of regression. This preprocessing is to find the maximum feature value and minimum feature value of each dimension from all of the cover training set, then standardize the local variance, the histogram of local variance and the saturation as follows:

$$\tilde{v}_{\text{loc}} = \frac{v_{\text{loc}} - v_{\text{loc},\min}}{v_{\text{loc},\max} - v_{\text{loc},\min}} \quad (6)$$

$$\tilde{h}(v) = \frac{h(v) - h_{\min}(v)}{h_{\max}(v) - h_{\min}(v)} \quad (7)$$

$$\tilde{s} = \frac{s - s_{\min}}{s_{\max} - s_{\min}} \quad (8)$$

where $v_{loc,min}$ and $v_{loc,max}$ are the minimum and maximum local variances, $h_{min}(v)$ are the minimum and maximum bin value of the pixel's local variance v , s_{min} and s_{max} are the minimum and maximum saturations over all cover training images.

On the basis of the SVR model trained with the training sets, for a given image, the results of the adopted quantitative steganalysis methods will be fused as follows:

- 1) Estimate the embedding ratio of it by the adopted quantitative steganalysis methods;
- 2) Extract the local variance, the histogram of local variance and the saturation from the given image;
- 3) Standardize the extracted features by maximum and minimum feature values obtained from the cover training images;
- 4) Feed the embedding ratios estimated by the adopted quantitative steganalysis methods (viz. the SPA method and WS method), the standardized local variance, histogram of local variance and saturation to the obtained SVR model, viz. the fusion rule, to obtain the final estimated embedding ratio.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The proposed fusion method is evaluated on the following experimental setup (The tool used was Advanced Batch Converter 3.8.20, and the interpolation filter was bilinear.):

- 1) Download 3000 originally very high resolution color images in format "tiff" from <http://photogallery.nrcs.usda.gov>, and partition them to 15 groups averagely;
- 2) Convert them to grayscale images in format "bmp", and crop the 15 groups of cover images to leave 128×128 pixels, 256×128 pixels, 256×256 pixels, 384×256 pixels, 384×384 pixels, 512×384 pixels, 512×512 pixels, 640×512 pixels, 640×640 pixels, 768×640 pixels, 768×768 pixels, 896×768 pixels, 896×896 pixels, 1024×896 pixels, 1024×1024 pixels;
- 3) From each group cropped, select 150 images and put them into the cover training set, put the residual 50 images into the cover test set;
- 4) Embed the pseudo-random messages into the LSB of the cover images with the embedding ratio $p \in \{0.05, 0.1, 0.15, 0.2, \dots, 1.0\}$ to generate 21 sets of stego images.
- 5) Utilize the horizontal and vertical adjacent pixel pairs in the SPA method.

In our experiments, we select the v -SVR with radial basis function kernel as the training tool. The proposed fusion method is called as the SPA_WS_SVR method because it fusing the results of the SPA and WS methods based on SVR, and compared with the SPA method and WS method before fusing.

Figure 2 shows the mean of the estimation errors of the proposed fusion method, the SPA method and the WS method. It can be seen that the fusion method can estimate the embedding ratios with the errors' mean closer to 0 significantly except that the actual embedding ratio is close to 0 or 1. Figure 3 shows that in the aspect of the

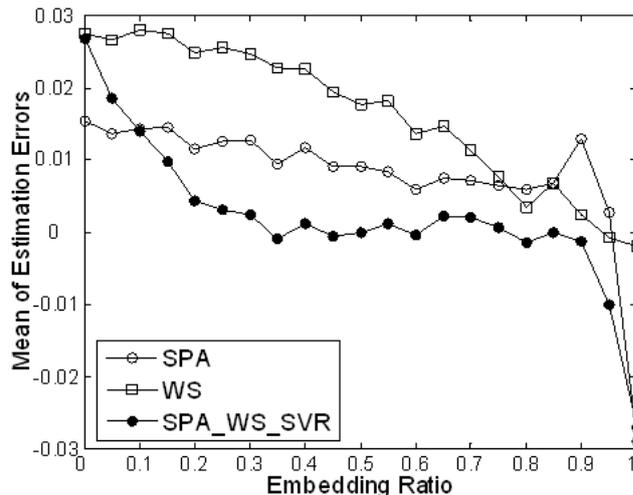


Figure 2. Mean of the estimation errors of the fusion method denoted by SPA_WS_SVR, SPA method and WS method.

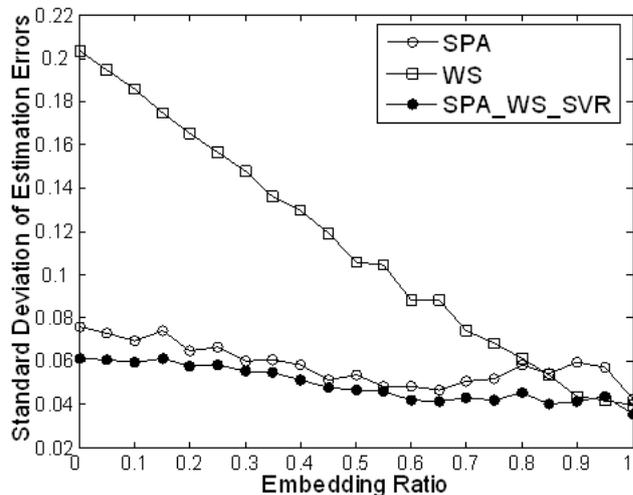


Figure 3. Standard deviation of the estimation errors of the fusion method, SPA method and WS method.

standard deviation of estimation errors, the fusion method will reduce the standard deviation to about 80% of that the best methods before fusing can achieve.

Additionally, the absolute means of the estimation errors given in Figure 4 further show that except that the embedding ratio is close to 1, the fusion method can estimate the embedding ratios with small absolute biases.

In a word, the experimental results demonstrate that the fusion method owns higher accuracy than the individual quantitative steganalysis methods as a whole.

V. CONCLUSION

Based on the support vector regression, this paper proposed a method to fuse the existing structural steganalysis and weighted stego image steganalysis methods for LSB replacement. The proposed fusion method considered two main factors—local variance and saturation pixel ratio—which influence the estimation errors significantly. Then, the fusion rule was approximately fitted by the support vector regression on the training set. For the given

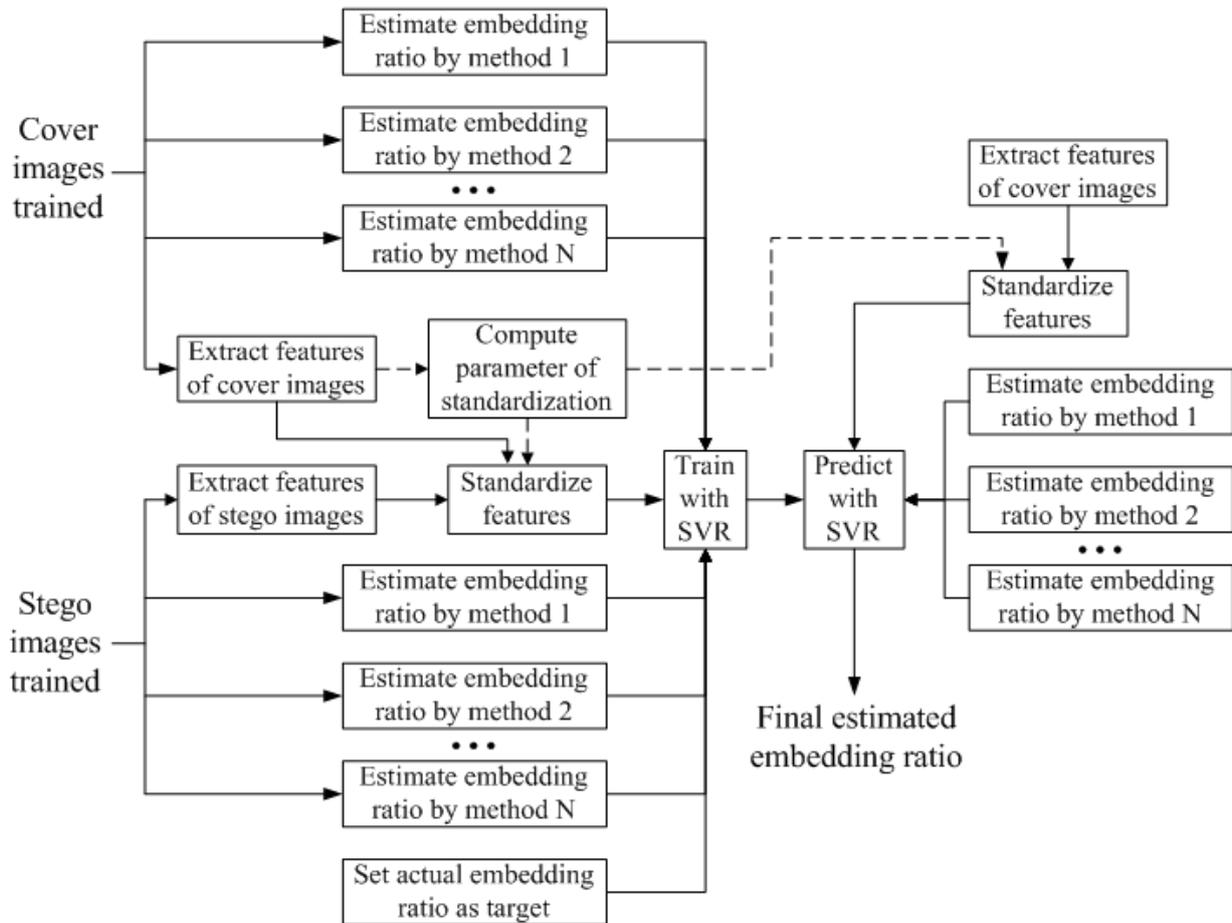


Figure 1. Diagram of the fusion method of different quantitative steganalysis methods based on SVR.

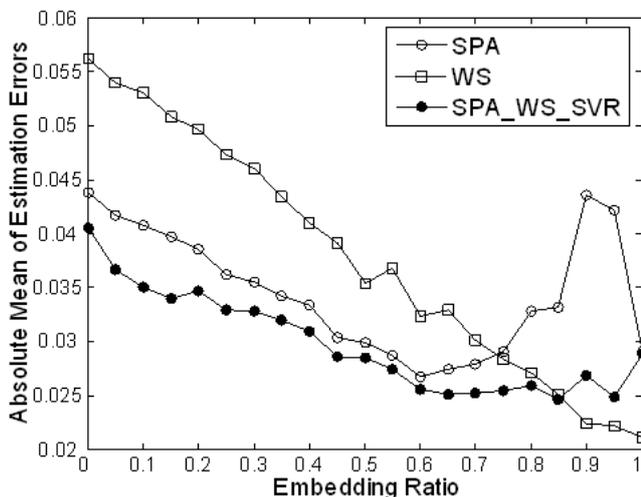


Figure 4. Absolute mean of the estimation errors of the fusion method, SPA method and WS method.

image, the estimated embedding ratios of the SPA and WS methods, the local variance, the histogram of local variance and saturation are fed to the fusion rule to obtain the final estimated embedding ratio. Experimental results show that the proposed fusion method can estimate the embedding ratio with higher accuracy as a whole.

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REFERENCES

- [1] J. Fridrich and M. Golijan, "Practical steganalysis of digital images—state of the art," in *Proc. of the SPIE, Security and Watermarking of Multimedia Contents IV, SPIE 4675*. San Jose, California: SPIE, Bellingham, Washington, 21 January 2002, pp. 1–13.
- [2] S. Lian, D. Kanellopoulos, and G. Ruffo, "Recent advances in multimedia information system security," *Informatica, Slovenian, Tech. Rep. 1*, 2009.
- [3] S. Lian and Y. Zhang, *Handbook of Research on Secure Multimedia Distribution*. Hershey, Pennsylvania: IGI Global (formerly Idea Group, Inc), 2009.
- [4] J. Fridrich, M. Golijan, and D. Soukal, "Searching for the stego-key," in *Proc. of the SPIE, Security, Steganography, and Watermarking of Multimedia Contents VI, SPIE 5306*. San Jose, California: SPIE, Bellingham, Washington, 18-22 January 2004, pp. 70–82.
- [5] J. Fridrich, M. Golijan, D. Soukal, and T. Holotyak, "Forensic steganalysis: determining the stego key in spatial domain steganography," in *Proc. of the SPIE, Security, Steganography, and Watermarking of Multimedia Contents VII, SPIE 5681*. San Jose, California: SPIE, Bellingham, Washington, 17-21 January 2005, pp. 631–642.

- [6] J. Fridrich, M. Golijan, D. Hoge, and D. Soukal, "Quantitative steganalysis of digital images: Estimating the secret message length," *ACM Multimedia Systems Journal, Special Issue on Multimedia Security*, vol. 9, no. 3, pp. 288–302, 2003.
- [7] A. D. Ker, "Locating steganographic payload via ws residual," in *Proc. of the Workshop on Multimedia and Security*. Oxford, United Kingdom: ACM, New York, NY, 22–23 September 2008, pp. 27–32.
- [8] J. Fridrich, M. Golijan, and R. Du, "Reliable detection of lsb steganography in color and grayscale images," in *Proc. of the Workshop on Multimedia and Security*. Ottawa, Ontario, Canada: ACM, New York, NY, 5 October 2001, pp. 27–30.
- [9] T. Zhang and X. Ping, "A new approach to reliable detection of lsb steganography in natural images," *Signal Processing*, vol. 83, no. 10, pp. 2085–2093, 2003.
- [10] S. Dumitrescu, X. Wu, and Z. Wang, "Detection of lsb steganography via sample pair analysis," *IEEE Transactions on Signal Processing*, vol. 51, no. 7, pp. 1995–2007, 2003.
- [11] J. Fridrich and M. Golijan, "On estimation of secret message length in lsb steganography in spatial domain," in *Proc. of the SPIE, Security, Steganography, and Watermarking of Multimedia Contents VI, SPIE 5306*. San Jose, California: SPIE, Bellingham, Washington, 18–22 January 2004, pp. 23–34.
- [12] T. Pevný, J. Fridrich, and A. D. Ker, "From blind to quantitative steganalysis," in *Proc. of the SPIE, Electronic Imaging, Security and Forensics of Multimedia Contents XI, SPIE 7254*. San Jose, California: SPIE, Bellingham, Washington, January 2002, pp. 0C01–0C14.
- [13] Y. Guo, X. Kong, X. You, and L. Li, "Universal methodology for developing quantitative steganalysis," *Chinese Journal of Electronics*, vol. 18, no. 3, pp. 455–459, 2009.
- [14] R. Böhme, "Assessment of steganalytic methods using multiple regression models," in *Proc. of the 7th Workshop on Information Hiding, LNCS 3727*. Barcelona, Spain: Springer Verlag, Berlin, June 2005, pp. 278–295.
- [15] R. Böhme and A. D. Ker, "A two-factor error model for quantitative steganalysis," in *Proc. of the SPIE, Security, Steganography and Watermarking of Multimedia Contents VIII, SPIE 6072*. San Jose, California: SPIE, Bellingham, Washington, 16–19 January 2006, pp. 59–74.
- [16] A. D. Ker, "Derivation of error distribution in least squares steganalysis," *IEEE Transactions on Information Forensics and Security*, vol. 2, no. 2, pp. 140–148, 2007.
- [17] C. Yang, F. Liu, and X. Luo, "Error correction of sample pair analysis based on support vector regression," in *Proc. of the 3rd International Conference on Multimedia Information Networking and Security*. Shanghai, China: IEEE, November 2011, pp. 633–636.
- [18] D. Wu, J. Cao, J. Wang, and W. Li, "Multi-feature fusion face recognition based on kernel discriminate local preserve projection algorithm under smart environment," *Journal of Computer*, vol. 7, no. 10, pp. 2479–2487, 2012.
- [19] H. Shi, H. Dong, L. Xu, C. Song, F. Zhong, and R. Su, "Multi-satellite monitoring sst data fusion based on the adaptive threshold clustering algorithm," *Journal of Computer*, vol. 7, no. 10, pp. 2593–2598, 2012.
- [20] X. Luo, F. Liu, C. Yang, and D. Wang, "Image universal steganalysis based on best wavelet packet decomposition," *Science China: Information Science*, vol. 53, no. 3, pp. 634–647, 2010.

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