Proceedings Paper:

Ma, YuanYuan, Luo, Xiangyang, Li, Zhenyu et al. (2 more authors) (2019) Feature selection method for image steganalysis based on weighted inner-inter class distance and dispersion criterion. In: Proc. ACM Turing Celebration Conference - China. ACM.

https://doi.org/10.1145/3321408.3321572

Feature Selection Method For Image Steganalysis Based on Weighted Inner-Inter Class Distance and Dispersion Criterion

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ABSTRACT

In order to improve the detection of hidden information in signals, additional features are considered as inputs for steganalysers. This research study proposes a feature selection method based on Weighted Inner-Inter class Distance and Dispersion (W2ID) criterion in order to reduce the steganalytic feature dimensionality. The definition of W2ID criterion and an algorithm determining the weight for the W2ID criterion based on the frequency statistical weighting method are proposed. Then, the W2ID criterion is applied in the decision rough set α-positive domain reduction, producing the W2ID-based feature selection method. Experimental results show that the proposed method can reduce the dimension of the feature space and memory requirements of Gabor Filter Residuals (GFR) feature while maintaining or improving the detection accuracy.

CCS CONCEPTS

• **Management of Computing and Information System** → *Security and Protection*; • **Pattern Recognition** → *Applications; Signal processing*.

KEYWORDS

Steganalysis, Feature selection, W2ID criterion, Reduction, Steganalysis-α method

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ACM TURC '19, May 17–19, 2019, Chengdu

ACM ISBN 978-1-4503-9999-9/18/06...$15.00

ACM Reference Format:
Yuanyuan Ma, Xiangyang Luo, Zhenyu Li, Yi Zhang, and Adrian G. Bors. 2019. Feature Selection Method For Image Steganalysis Based on Weighted Inner-Inter Class Distance and Dispersion Criterion. In *Proceedings of ACM Turing Celebration Conference (ACM TURC '19).* ACM, New York, NY, USA, 5 pages.

1 INTRODUCTION

Steganalysis aims to detect hidden information in image, audio, video, text, 3D object and other multimedia cover. It is designed to counteract against to steganography which is a technology that hides messages in multimedia [3]. After more than 20 years of development, the research on steganalysis has made significant progress [1, 14]. The key point of steganalysis is to identify statistical differences between features extracted from cover-signals and stego-signals. However, traditional steganalytic methods no longer work when the information is hidden by image adaptive steganography methods, such as those from [4]. Existing steganalytic methods require ever larger feature sets and enormous memory and computation power.

Recently, steganalytic feature reduction methods have been proposed such as those based on Genetic or Particle Swarm Optimization algorithm and the integrated classifier [2, 12]. Other feature selection methods use the mutual information to select complementary features [5, 6]. Principal Component Analysis (PCA) is also used by several methods [10, 11] in order to reduce the feature dimensions while aiming to maintain the accuracy of the steganalyser. In previous work, we have conducted a series of related studies on feature selection for steganalysis[7, 8]. A feature selection method for image steganalysis based on decision rough set α-positive region reduction is proposed to reduce feature dimension [9]. Nevertheless, the steganalytic detection accuracy using the selected feature set by this method can be improved.

In order to solve the problems above, this paper proposes Weighted Inner-Inter class Distance and Dispersion (W2ID) criterion. The W2ID criterion is applied to the decision rough set α-positive domain reduction, defining a steganalytic feature selection method, which is expected to further improve the detection accuracy while reducing the feature dimension.

Section 2 describes the proposed feature selection algorithm based in W2ID criterion. In Section 3 we provide the experimental results, and in Section 4 we provide the conclusions of this paper.

2 FEATURE SELECTION BASED ON W2ID CRITERION

In this section, we propose a feature selection method using the W2ID criterion as a criterion for the ability of features to distinguish stego-signals from cover-signals. Then we propose an algorithm for estimating the weights in W2ID criterion based on the frequency statistical weighting method.

2.1 Feature Selection Framework

Based on the W2ID criterion and the decision rough set α-positive region reduction, we propose a new feature selection method for image steganalysis. The proposed algorithm, firstly constructs a feature matrix based on the features extracted from the cover and stego images, and adds a decision attribute column in order to generate the corresponding decision table. Afterwards, based on the feature matrix, the algorithm measures the attribute separability for each feature component using the W2ID criterion. Based on the values provided by the W2ID criterion, the feature components are sorted in descending order. From this ordering, the algorithm selects that candidate feature subset which fulfils the positive region non-reduced criterion based on the decision rough set α-positive region reduction[9]; This algorithm removes those feature components which do not fulfill the attribute independence requirement and are redundant or fulfil same separation tasks as other features already selected[9]. Then it leads to selecting decision rough set α-positive region reduction subsets. Finally, select one subset with the high detection accuracy and low feature dimensionality from these decision rough set α-positive region reduction remained subsets. The diagram of the W2ID-based method is given in Figure.1.

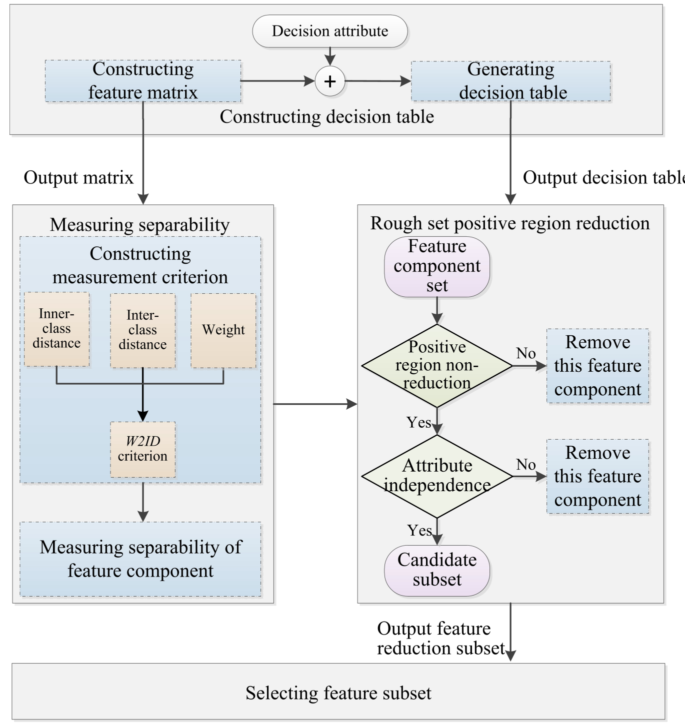

Figure 1: The diagram for the W2ID-based method.

2.2 W2ID criteron

In the following we introduce how to calculate the W2ID criterion. In pattern recognition, the distances between two classes represents the inter class distance and the distances between the data samples within a class represents the inner class distance. Two classes are better separated by minimizing the inner class distance and maximizing the inter class distance. In addition, the dispersion degree is also a concept, which can be used to measure the inconsistent distribution between the two classes in the feature space. A larger dispersion degree can also be the basis for separating two classes from each other in the feature space.

We use the attribute separability measurement

$$ASM\left(f_i\right) = \left|\frac{\mu_c\left(f_i\right) - \mu_s\left(f_i\right)}{\sigma_c\left(f_i\right) + \sigma_s\left(f_i\right)}\right| \tag{1}$$

to represent the degree of inner-inter class distance, where μ_c and μ_s represent the centers of feature component f_i in the cover image set and stego image set, respectively. $\mu_c\left(f_i\right) - \mu_s\left(f_i\right)$ is considered as the inter-class distance of f_i of the cover image and stego image sets, respectively. $\sigma_c\left(f_i\right)$ and $\sigma_s\left(f_i\right)$ represent inner-class distances of f_i of the cover image and stego image sets, respectively. The related theorem of the attribute separability measurement has been described in detail in [9]. Since $\frac{\sigma_c(f_i)}{\sigma_s(f_i)}$ and $\frac{\sigma_s(f_i)}{\sigma_c(f_i)}$ can represent the dispersion of the feature component between the cover and stego image set, consider new equation

$$g\left(f_i\right) = \frac{1}{2} \times \left(\frac{\sigma_c\left(f_i\right)}{\sigma_s\left(f_i\right)} + \frac{\sigma_s\left(f_i\right)}{\sigma_c\left(f_i\right)}\right) = \frac{\sigma_c^2\left(f_i\right) + \sigma_s^2\left(f_i\right)}{2\sigma_c\left(f_i\right)\sigma_s\left(f_i\right)} \tag{2}$$

To prevent the value of $g\left(f_i\right)$ from being too large, we use the logarithm of $g\left(f_i\right)$ to measure the dispersion. Considering that $ASM\left(f_i\right)$ and $\ln g\left(f_i\right)$ may play different roles in the separability measurement, we propose the W2ID criterion assigning the weights to the two component parts:

$$Wscore(f_i) = w_1 \times \left|\frac{\mu_c\left(f_i\right) - \mu_s\left(f_i\right)}{\sigma_c\left(f_i\right) + \sigma_s\left(f_i\right)}\right| + w_2 \times \ln \frac{\sigma_c^2\left(f_i\right) + \sigma_s^2\left(f_i\right)}{2\sigma_c\left(f_i\right)\sigma_s\left(f_i\right)} \tag{3}$$

where $0 \le w_1, w_2 \le 1$, $w_1 + w_2 = 1$. A larger $Wscore(f_i)$ can leads better separability of the steganalytic feature component by choosing those feature minimizing the inner-class distances and maximizing the inter-lass distance and dispersion.

2.3 Weight determination algorithm

This section describes the algorithm selecting the weights for equations (3), balancing the W2ID criterion. The proposed algorithm relies on a threshold τ which will monitor the frequencies of features selected according to the conditions for $ASM(f_i)$ and $g(f_i)$ from equations (3), respectively. By considering the difference between the numbers of feature components which fulfil $ASM(f_i) > \tau$ and $\ln g(f_i) > \tau$, we propose the Weight Determination Algorithm to determine the weights of $ASM(f_i)$ and $\ln g(f_i)$ for the W2ID criterion. Based on the frequency statistical weighting method, the selection of weights w_1 and w_2 characterizing equation (3), which will ensure better separability between the cover and stego classes, is made according to the Algorithm 1.

Algorithm1:	Weight Determination Algorithm
Input:	Steganalytic feature with different payloads;
Output:	The weight of each item in the W2ID criterion;
Step1:	The defining components of W2ID criterion are $ASM(f_i)$ and $\ln g(f_i)$.
Step2:	Determine the conditions that need to be met. $ASM(f_i) > \tau$ and $\ln g(f_i) > \tau$, where τ is a threshold which can be used to remove redundant information.
Step3:	Count the frequency of feature components that meet the condition. The frequencies of feature components under n payloads satisfying $ASM(f_i) > \tau$ and $\ln g(f_i) > \tau$ are counted as $(z_1, \cdots, z_n)$ and $(z'_1, \cdots, z'_n)$, respectively. Then the two frequency sums are $z = \sum_{j=1}^{n} z_j$, $z' = \sum_{j=1}^{n} z'_j$;
Step4:	Calculate the total frequency. $Z = z + z' = \sum_{j=1}^{n} (z_j + z'_j)$;
Step5:	Determine the weight. The weight of $ASM(f_i)$ is w_1, $w_1 = \frac{z}{Z}$, $(0 \le w_1 \le 1)$; The weigh of $\ln g(f_i)$ is w_2, $w_2 = \frac{z'}{Z}$, $(0 \le w_2 \le 1)$.

2.4 Separability Measurement based on W2ID Criterion

This section introduces the application of the W2ID criterion in separability measurement. Let T be a steganalytic feature matrix constructed by $f_i (1 \le i \le N)$, where f_i represents the ith steganalytic feature component. The $Wscore$ value of each feature component f_i in the feature matrix T is calculated based on the W2ID criterion. The calculation process is as Figure. 2:

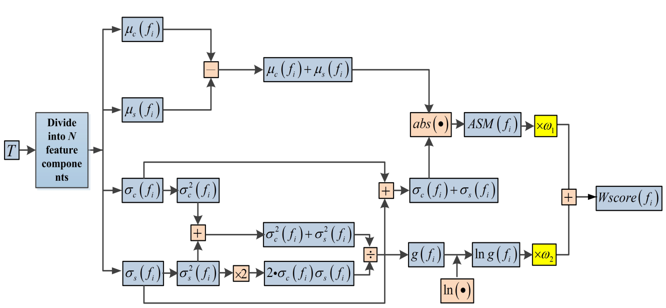

Figure 2: Calculation process of W2ID criterion

As shown in Figure. 2, an operator is put into an orange box, where $abs(\bullet)$ represents the absolute value of $\bullet$, and $\ln(\bullet)$ represents the natural logarithm value of $\bullet$. The data which involved in the operation is put into a blue box. μ_c and μ_s represent the means of feature component f_i in the cover image set and stego image set, respectively. $\sigma_c(f_i)$ and $\sigma_s(f_i)$ represent the standard deviations of f_i in the cover image and stego image sets, respectively. The weight for each item is put into a yellow box. Through the calculation procedure of this figure, the separability of every feature component in matrix T is measured.

3 EXPERIMENTAL RESULTS

In this section, after introducing the experimental settings, we analyze the selection of the weighting parameters w_1 and w_2 in the W2ID criterion.

3.1 Experimental Setting

The images used in the experiments are from of the BOSSbase-1.01 database[1] containing 10000 grayscale images, size 512×512. First, all the grayscale a PGM images are converted to JPEG grayscale images with quality factor 95. Second, the stego images with the payloads of 1.0, 0.25, 0.5, 0.8, 1.0 bpac (bits per nonzero AC DCT coefficient) are generated by the SI-UNIWARD [4] steganographic algorithm, which has good anti-detection performance. Then one group of cover images and five groups of stego images are considered. The steganalytic features are extracted from all the cover and stego images, using the GFR method [13]. A steganalysis feature database which includes 60000 feature sets are obtained.

In this paper we consider the Ensamble Classifier for steganalysis. The detection error P_E represents the sums of false negatives (missed detections) and false positives (false alarms). Average detection accuracy $\overline{P_A} = 1 - \overline{P_E}$ is used to evaluate the performance. 5000 pairs of images are used as the training set. 5000 pairs of cover and stego images are used as the testing set. The number of expected feature subsets is considered as 100.

3.2 Estimating the weights for feature selection

In the following we consider the GFR feature set [13] and we use Algorithm1 as described in Section 2.3 to determine the specific value of the w_1 and w_2 in the W2ID criterion. All given features in the training set have $ASM(f_i) < 10^{-4}$, when $\tau < 1 \times 10^{-4}$; and no feature in the training set has $\ln g(f_i) > 10^{-3}$, when $\tau > 1 \times 10^{-3}$. Then, the value of τ is set to $10^{-4} \le \tau \le 10^{-3}$ and the step is set to 10^{-4}. The results are shown in Table 1, where N_{ASM} is the number of feature components fulfilling the first requirement $ASM(f_i) > \tau$ and $N_{\ln g}$ is the number of feature components fulfil the requirement $\ln g(f_i) > \tau$.

According to Table 1, we have the frequency sums of two component part $z = 667068$, $z' = 277454$, respectively. Then total frequency $Z = z + z' = 944522$. $w_1 = \frac{z}{Z} = \frac{667068}{944522} \approx 0.75$, $w_2 = 1 - w_1 = 0.25$. Thus, the W2ID criterion is then specifically expressed as:

[1] P. Bas, T. Filler, T. Pevny, available: http://agents.fel.cvut.cz/stegodata/

Table 1: Statistics of Feature Components Fulfiling the Conditions of Algorithm 1 for Different Payloads.

τ	0.1		0.25		0.5		0.8		1.0	
	N_{ASM}	$N_{\ln g}$	N_{ASM}	$N_{\ln g}$	N_{ASM}	$N_{\ln g}$	N_{ASM}	$N_{\ln g}$	N_{ASM}	$N_{\ln g}$
1×10^{-4}	15129	8493	15129	8493	17000	6633	17000	5144	16731	4417
2×10^{-4}	13309	7981	13309	7981	17000	6479	16691	5103	16711	4394
3×10^{-4}	11705	7429	13309	7981	17000	6479	16691	5103	16711	4394
4×10^{-4}	10427	6911	10427	6911	17000	6200	16607	5018	16670	4352
5×10^{-4}	9252	6424	9252	6424	15590	6067	16543	4970	16647	4327
6×10^{-4}	8110	5946	8110	5946	15260	5929	16458	4928	16621	4308
7×10^{-4}	6952	5465	6952	5465	14951	5823	16376	4897	16591	4280
8×10^{-4}	5863	4997	5863	4997	14687	5707	16301	4865	16556	4261
9×10^{-4}	4817	4529	4817	4529	14408	5552	16217	4822	16505	4249
1×10^{-3}	3950	4094	3950	4094	14128	5426	16000	4776	16444	4225
Number of selected features	89514	62269	89514	62269	157024	60145	164850	49586	166166	43185

Table 2: Comparison of Memory Cost Before and After Feature Reduction

Payloads	GFR memory cost (GB)	Selected feature set		Saving memory (GB)	Saving ratio
		Feature number	Memory cost(GB)		
0.1	0.4610	9985	0.2832	0.1778	38.57%
0.25	0.4610	12999	0.3242	0.1368	29.67%
0.5	0.4611	11850	0.2969	0.1642	35.61%
0.8	0.4615	7341	0.2051	0.2564	55.56%
1.0	0.4621	4005	0.1123	0.3498	75.70%

$$Wscore(f_i) = 0.75 \times \left| \frac{\mu_c(f_i) - \mu_s(f_i)}{\sigma_c(f_i) + \sigma_s(f_i)} \right| + 0.25 \times \ln \frac{\sigma_c^2(f_i) + \sigma_s^2(f_i)}{2\sigma_c(f_i)\,\sigma_s(f_i)} \tag{4}$$

3.3 Feature selection in GFR using W2ID-based method

The dimension of the GFR steganalytic feature proposed in [13] is 17000, including five sub-features, which capture the changes of image statistical feature from 5 different perspectives. We firstly consider the GFR features to conduct steganalysis. We then measure the $Wscore$ values of every feature component based on the W2ID criterion. According to $Wscore$ values and decision table, we use decision rough set α-positive region reduction to reduce the GFR feature. Finally, the accuracy of the resulting feature set is evaluated for image steganalysis.

In the plots of Figure. 3, we show the average detection accuracy of the initial GFR steganalysis feature set and after being reduced using the W2ID method when the bit embedded payloads in the images are 0.1, 0.25, 0.5, 0.8, 1.0. It can be observed that the proposed method significantly reduced the dimensionality of the steganalytic feature set, while improving also the stego-image detection accuracy.

The storage space of an original GFR steganalysis feature set is close to 0.5GB for 10000 images. In order to evaluate the memory requirement for the reduced steganalytic feature set, in Table 2 we provide the memory requirements when the reduced feature set achieves the same stego-image detection results as the case of the original steganalytic feature set GFR. From Table 2, it can be seen that the storage space of the GFR steganalysis feature after reducing the feature set size under different payloads is significantly reduced as well. For example, when the payload is 1.0, the required memory for storing the steganalytic feature set is reduced by 75.70%.

3.4 Comparison with Steganalysis-α method

Both the Steganalysis-α method [9] and W2ID-based method reduce the steganalysis feature based on decision rough set α-positive region reduction. However, the separability measure criteria for the two feature selection algorithms are different.

Table 3: Comparison with Steganalysis-α Method

Payloads	$\overline{P}_A$ (17000-D)	Steganalysis-α		Proposed	
		Number	$\overline{P}_A$	Number	$\overline{P}_A$
0.1	0.5168	15493	0.5169	15816	0.5214
0.25	0.5205	12739	0.5230	12999	0.5226
0.5	0.6572	13205	0.6579	13485	0.6582
0.8	0.9130	11605	0.9156	9533	0.9158
1.0	0.9661	10092	0.9697	9157	0.9700

It can be seen from Table 3 that both the Steganalysis-α method and the W2ID-based method can reduce the GFR image steganalytic feature set. From Table 3 it can be observed that the proposed W2ID criterion selects a smaller steganalytic set than the Steganalysis-α algorithm especially when embedding higher bit payloads, while also providing slightly better detection results.

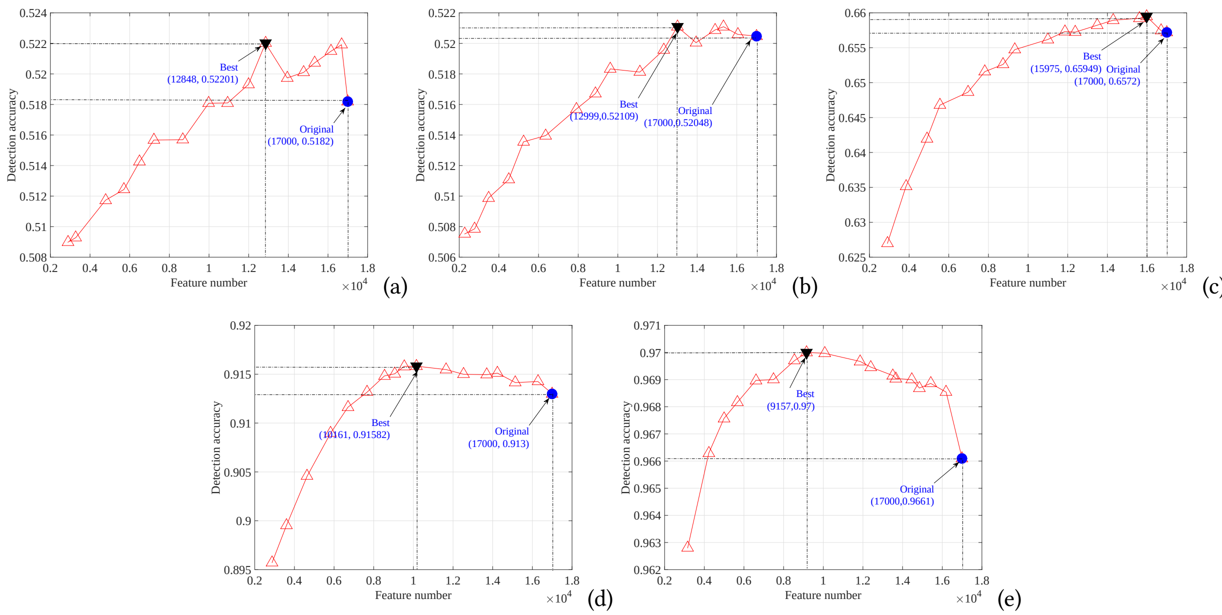

Figure 3: Detection accuracy of stego-images using the initial GFR feature set and after the feature reduction based on the W2ID method. For the best results indicated on the plots we specify the number of features and the detection accuracy achieved as well those corresponding to the original feature set.

4 CONCLUSIONS

In order to further reduce the dimension of high-dimensional steganalytic feature and improve the efficiency of steganalysis, this paper proposes a feature selection method based on W2ID criterion. This paper proposes to select the weights for two components of the W2ID criterion. The first component represents the inner-inter distance while the second component corresponds to the dispersion. Then, we apply the W2ID criterion into the decision rough set α-positive region reduction during feature selection. Finally, a series of feature selection experimental results show that the proposed method can improve the detection accuracy of the steganalysis detection algorithm based on the selected features, while significantly reducing the dimension and memory cost. In the future research work, we will continue to study how to evaluate the contribution of various steganalytic features.

5 ACKNOWLEDGMENTS

This work was supported in part by the National Natural Science Foundation of China (No. U1804263, U1636219, 61572052, 61602508, 61772549, and U1736214), the National Key R&D Program of China (No. 2016YFB0801303, 2016QY01W0105), the Science and Technology Innovation Talent Project of Henan Province (No. 2018JR0018).

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