Evaluation of Feature Selection Measures for Steganalysis

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Abstract. Steganalysis has attracted researchers attention overwhelmingly in last few years which discriminate stego images from non-stego images. The performance of a Steganalysis depends not only on the choice of classifier but also on features that are used to represent the image. Features extracted from images may contain irrelevant and redundant features which makes them inefficient for machine learning. Relevant features not only decrease the processing time to train a classifier but also provide better generalization. In this paper, kullback divergence measure, chernoff distance measure and linear regression are used for relevant feature selection. The performance of steganalysis using different measures used for feature selection is compared and evaluated in terms of classification error and computation time of training classifier. Experimental results show that Linear regression measure used for feature selection outperforms other measures used for feature selection in terms of both classification error and compilation time.

Keywords: Steganalysis, Feature Selection, Linear Regression, Kullback Divergence, Chernoff Distance Measure.

1 Introduction

Information hiding techniques have gained enormous popularity among researchers due to increasing threats for security, especially after 9/11 incident. Research community is involved in study of methods of secure communication as well as methods of detection of the covert communication between the two parties. Steganography is commonly used technique for data hiding in carrier signals. The carrier signal undergoes modification once the data to be sent is embedded using some technique. Images are often used as a carrier because of their extensive availability with high resolution of pixels. In recent years, detecting the presence of hidden messages has posed significant challenges to research community [2, 3, 4, 6, 10, 17]. Steganalysis is art of discriminating such suspicious signals from a large number of inoffensive signals over a communication channel. Several techniques for steganalysis were proposed in literature [4, 11, 18]. Since the data hiding may involve different image formats, different embedding algorithms, and various steganographic keys, steganalysis turns out to be more difficult and challenging task. Recently, Farid [2, 3] used wavelet-like decomposition to build higher-order statistical models of natural images in terms of mean, variance, skewness, and kurtosis of coefficients of wavelet subbands as features and employed classifier to discriminate between stego and non-stego images. However, the resultant features may contain noisy,

irrelevant or redundant features which makes them inefficient for machine learning. In fact, the presence of irrelevant and redundant features may deteriorate the performance of the classifier and requires high computation time and other resources for training and testing the data. Hence, in order to enhance the performance of steganalysis in terms of accuracy and time required to detect, there is need to identify a set of relevant features.

Feature selection is used to remove such noisy, irrelevant, and redundant features. There are two major approaches to feature selection: filter and wrapper approach [5, 7, 8]. Most filter methods employ statistical characteristics of data for feature selection which requires less computation. It independently measures the importance of features without involving any classifier. Since, the filter approach does not take into account the learning bias introduced by the final learning algorithm, it may not be able to select the most relevant set of features for the learning algorithm. On the other hand, wrapper methods tend to find features better suited to the predetermined learning algorithm resulting in better performance. But, it tends to be computationally more expensive since the classifier must be trained for each candidate subset.

Feature ranking approaches have been widely investigated for feature selection [12, 14, 15] in literature. Since in most of feature ranking approaches features are evaluated using statistical characteristics of the data, different feature ranking methods measure different characteristics of data. Therefore, the informative features selected by different ranking methods may be different. Another disadvantage associated with feature ranking methods is that they ignore the correlation among the features because of their univariate approach. Hence the selected features subset may have low discriminatory capacity and increased redundancy. In literature to remove redundancy a forward/backward feature selection method or its combinations are used with a measure that selects relevant and non redundant features. Among the most widely used filter methods [6] for feature selection, there are techniques based on statistical separability measures which allow one to select a suitable subset of features by assigning the degree of interclass separability associated with each subset considered. In particular, Kullback Divergence, Chernoff distance measures and linear regression are commonly employed by research community. In this paper, we compare and evaluate these measures to determine relevant features for steganalysis.

Our work is organized as follows: Feature extraction using higher order statistical model is included in section 2. A brief introduction of separability measures employed for features selection techniques are discussed in section 3. Experimental results on a database of natural images are shown in section 4 and section 5 contains conclusions.

2 Feature Extraction Using Higher Order Image Statistics

Although the presence of embedded message is most often not detectable to the human eye, but it may nevertheless changes the statistics of an image. The distortions in the resulting stegoimages can be analyzed by comparing the statistical properties of both cover and stegoimages [18, 19]. In literature, techniques [19, 20] are available to detect such changes based on first order statistical distributions of intensity or transform coefficients. The disadvantage of this analysis is that simple counter-measures that match first order statistics are likely to thwart detection. Farid [2] has pointed out that steganalysis based on higher-order statistical models may detect stegoimages. It has been

observed across a large number of natural images that there exist strong higher-order statistical regularities within a wavelet-like decomposition. The embedding of a message may significantly change the statistics of image and thus becomes detectable.

The decomposition of image is possible by using separable quadrature mirror filters (QMFs). Thus, the frequency space is divided into multiple scales and orientations. This can be accomplished by applying separable lowpass and highpass filters along the image axes generating a vertical, horizontal, diagonal, and lowpass subband. The diagonal, horizontal, and vertical subband at scale $i = 1, 2, \dots, n$ are represented as $D_i(x, y)$, $H_i(x, y)$, and $V_i(x, y)$ respectively. Subsequent scales are obtained by recursively filtering the lowpass subband. Farid [2,3] pointed out that using above decomposition the statistical model containing the mean, variance, skewness and kurtosis of the subband coefficients for each orientation and scales can be obtained for $i = 1$ to n . This characterizes the basic coefficient distributions statistically. The second set of statistics is based on the errors in an optimal linear predictor of coefficient magnitude. It is pointed out [2,3] that the subband coefficients of the image are correlated to their spatial, orientation and scale neighbors. Taking this into account, $V_i(x, y)$, a vertical band at scale i , can be represented in terms of neighboring pixels in spatial domain as:

$$V_i(x, y) = w_1 V_i(x-1, y) + w_2 V_i(x+1, y) + w_3 V_i(x, y-1) + w_4 V_i(x, y+1) \\ + w_5 V_{i+1}(x/2, y/2) + w_6 D_i(x, y) + w_7 D_{i+1}(x/2, y/2) \quad (1)$$

Where w_k denotes scalar weighting values. In more compact form, it can be expressed as

$$V = Qw, \quad (2)$$

Where $w = (w_1, w_2, \dots, w_7)^T$, the vector V contains the coefficient magnitudes of $V_i(x, y)$ strung into a column vector and the columns of the matrix Q contain the neighboring coefficient magnitudes as specified in (1) also strung out in column vectors. To determine coefficients of quadratic error function is defined [2,3] as

$$E(w) = [V - Qw]^2 \quad (3)$$

This error function $E(w)$ can be minimized by differentiating equation (3) and substituting it equal to zero yields:

$$w = (Q^T Q)^{-1} Q^T V \quad (4)$$

From the above, order statistics such as the mean, variance, skewness, and kurtosis can be evaluated. Similarly, the above procedure can be repeated to get the subbands $H_i(x, y)$, $D_i(x, y)$. Since, there are four statistics and linear predictor for three subband are computed for $(n-1)$ levels, we have total $12(n-1)$ error statistics and $12(n-1)$ coefficient statistics. Thus, these $24(n-1)$ statistics altogether will form a feature vector of the image.

3 Forward Feature Selection Techniques

Feature ranking is commonly used to determine a subset of relevant features. However, the disadvantage of feature ranking method is that they ignore the correlations between features. Hence the features selected may contain redundant information. Some of the methods suggested in literature for removing redundancy are Chernoff distance measure, Kullback divergence measure [14] and linear regression [16].

In order to obtain a quantitative measure of how separable are two classes, a distance measure can be easily extracted from some parameters of the data. A very important aspect of probabilistic distance measures is that a number of these criteria can be analytically simplified in the case when the class conditional p.d.f.s $p(X_i | C_i)$ follows multivariate normal distribution. In literature, for multivariate normal distribution for two classes, KD and CD measures are given as follows [14]:

$$J_k^d = \frac{1}{2}(\mu_k^2 - \mu_k^1)^T ((\Sigma_k^1)^{-1} + (\Sigma_k^2)^{-1}) (\mu_k^2 - \mu_k^1) + \frac{1}{2} \text{tr} \left((\Sigma_k^1)^{-1} \Sigma_k^2 + (\Sigma_k^2)^{-1} \Sigma_k^1 - 2I_k \right) \quad (5)$$

$$J_k^c = \frac{1}{2} \beta (1 - \beta) (\mu_k^2 - \mu_k^1)^T [(1 - \beta) \Sigma_k^1 + \beta \Sigma_k^2]^{-1} (\mu_k^2 - \mu_k^1) + \frac{1}{2} \log \frac{|(1 - \beta) \Sigma_k^1 + \beta \Sigma_k^2|}{|\Sigma_k^1|^{1-\beta} |\Sigma_k^2|^\beta} \quad (6)$$

where μ_k^i is a mean vector and Σ_k^i is a covariance matrix of k -dimensional data for class C_i , $i = 1, 2$. The regression analysis considers the relations between the selected features which minimizes redundancy. While using regression analysis for data a multiple regression model is considered because there can be many features which could affect the presence or absence of stegoimage. A multiple regression model with a target variable y and multiple variables X is given by [16]:

$$y = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_n X_{ni} + \xi_i, \quad i = 1, 2, \dots, n \quad (7)$$

Where $\beta_0, \beta_1, \dots, \beta_n$ are constants estimated by observed values of X and class label y and is estimated by normal distribution having mean zero and a variance σ^2 .

The error sum of squares SSE which is sum of the squared residuals is given by

$$SSE = \sum_{n=0}^n (y_i - \text{predicted } y_i) \quad (8)$$

A large value of SSE means that the regression is predicted poorly. The total sum of squares is given by

$$SSTO = \sum_{n=0}^n (y_i - \bar{y}) \quad (9)$$

Where $\bar{y}$ is the average of y_i . In a regression model the choice of features which best explains the class label depends on the value of $\mathcal{R}^2$ given by

$$\mathcal{R}^2 = 1 - \frac{SSE}{SSTO} \quad (10)$$

4 Experimental Setup and Results

We prepared a database of 1500 natural images taken from different sources i.e *www.1000pictures.com*, *www.1000wallpapers.com*. All the images were in JPEG format. The image resolutions were ranging from 800×600 to 1600×1200 . We first resized each one of these images to 640×480 pixels images and embedded message images of six different resolutions 256×256 , 128×128 , 64×64 , 32×32 , 16×16 , and 8×8 into cover image using OUTGUESS [19].

We have created 1000 non-stego images and 1000 stego images. Features are extracted from each one of the grey images using Haar wavelet. Each image is represented in terms of 72 statistics for four level wavelet decomposition. To remove redundancy from the selected pool of features three methods are compared: kullback divergence measure, chernoff distance measure and linear regression. For chernoff distance features are selected using 3 different values ranging from 0.1 to 0.9 with an increment of 0.4. We have used the following classifiers to evaluate the performance of the feature selection methods: naive Bayes Classifier (naivebc), Logistics linear classifier (loglc), Fisher linear classifier (fisherc), Nearest mean classifier (nmc), Normal Density based classifier-Independent features (udc), Normal Density based linear classifier (ldc), Normal Density based quadratic classifier (qdc). Classification error is computed using ten cross-validation. All the simulations are done using matlab. Tables 1-3 show the minimum classification error achieved with different classifiers along with the number of features for different measures. For chernoff distance measure the minimum classification error achieved for optimal value of β is shown in Tables 1-3. The best results in each category are indicated in bold. We observe the following from Tables 1-3:

1. The minimum classification error is achieved with linear regression for all classifiers and for different size of embedding.
2. The number of features required to obtain minimum classification error is significantly smaller using linear regression in comparison to baseline, kullback divergence measure and chernoff distance measure using all classifiers and different size of embedding.
3. The performances of ldc, fisherc and loglc are comparable and better than other classifiers in terms of classification error for all sizes of embedding used in experiments.

Table 1. Comparative results of classification error and minimum number of features for Size 8×8 and 16×16

	Size= 8×8							Size= 16×16						
	Baseline	JD		JC		Linear		Baseline	JD		JC		Linear	
	ErrAll	fea	ErrJD	beta	ErrJC	fea	ErrLin	ErrAll	fea	ErrJD	beta	ErrJC	fea	ErrLin
Ldc	0.3170	67	0.3045	38,,9	0.2985	23	0.2905	0.3210	39	0.3040	38,,5	0.2985	24	0.2680
Fisherc	0.3240	67	0.3045	46,,9	0.3000	24	0.2905	0.3160	34	0.3045	38,,5	0.2955	20	0.2910
Naivebc	0.5605	64	0.4705	16,,9	0.4430	2	0.4360	0.5390	27	0.4660	21,,9	0.4350	4	0.3860
Udc	0.4900	65	0.4860	22,,5	0.4875	9	0.4260	0.5025	55	0.4945	37,,9	0.4930	9	0.3855
Qdc	0.5000	37	0.4735	35,,5	0.4670	7	0.3445	0.5090	31	0.4760	24,,5	0.4675	7	0.3085
Nmc	0.4990	47	0.4970	52,,1	0.4950	4	0.4165	0.5020	3	0.4975	1,,1	0.4975	1	0.4090
Loglc	0.3090	63	0.3005	44,,1	0.2960	24	0.2935	0.3065	34	0.2995	44,,1	0.2985	18	0.2670

Table 2. Comparative results of classification error and minimum number of features for sizes 32×32 and 64×64

	Size= 32×32						Size= 64×64					
	Baseline	JD	JC		Linear		Baseline	JD	JC		Linear	
	ErrAll	fea	ErrJD	beta	ErrJC	fea	ErrAll	fea	ErrJD	beta	ErrJC	fea
Ldc	0.3155	54	0.3075	44,,1	0.3005	23	0.3095	60	0.3090	43,,1	0.2990	37
Fisherc	0.3210	51	0.3085	36,,9	0.3015	21	0.3260	25	0.3130	37,,1	0.3020	19
Naivebc	0.5385	19	0.4675	13,,9	0.4375	2	0.5325	6	0.4725	15,,5	0.4420	2
Udc	0.4985	38	0.4865	29,,5	0.4850	9	0.5035	43	0.4925	47,,9	0.4895	11
Qdc	0.5035	23	0.4650	22,,1	0.4595	2	0.5025	26	0.4705	17,,5	0.4620	11
Nmc	0.5030	72	0.4910	5,,5	0.4925	4	0.5015	46	0.4960	2,,1	0.4940	4
Loglc	0.3025	60	0.2965	66,,5	0.2975	17	0.3135	66	0.3010	39,,9	0.2965	25

Table 3. Comparative results of classification error and minimum number of features for Size 128×128 and 256×256

	Size= 128×128						Size= 256×256					
	Baseline	JD	JC		Linear		Baseline	JD	JC		Linear	
	ErrAll	fea	ErrJD	beta	ErrJC	fea	ErrAll	fea	ErrJD	beta	ErrJC	fea
Ldc	0.3195	64	0.3170	42,,1	0.3015	27	0.2900	67	0.2820	55,,9	0.2675	24
Fisherc	0.3355	69	0.3130	45,,5	0.3075	22	0.3360	67	0.2770	46,,9	0.2730	20
Naivebc	0.5085	25	0.4900	29,,5	0.4430	2	0.4360	64	0.4330	22,,5	0.4125	4
Udc	0.4955	69	0.4915	35,,5	0.4910	11	0.4780	65	0.4765	71,,5	0.4710	9
Qdc	0.5015	56	0.4875	34,,1	0.4730	12	0.4745	37	0.4605	25,,5	0.4555	7
Nmc	0.4985	22	0.4945	25,,5	0.4950	2	0.4970	47	0.4865	45,,5	0.4930	1
Loglc	0.3190	70	0.3190	41,,1	0.3020	22	0.2835	63	0.2795	43,,5	0.2695	18

Fig. 1. Variation of Computation time (a) 8×8 (b) 128×128

The training time of different classifiers using features selected to achieve minimum classification error using linear regression measure and using baseline (all features) for two (8×8 and 128×128) sizes of embedding are shown in Figure 1. It can be observed from Figure 1 that the training time required using features selected by linear regression measure is very small in comparison to training time of classifier using baseline (all features) for all sizes of embedding used in experiments. The time difference observed is more in case of logc classifier.

5 Conclusions

The performance of a classifier depends on the choice of features and classifier for any pattern recognition system. Features based on higher order statistics are extracted from

stego and non-stego images using wavelet decompositions. Feature extracted from image may contain irrelevant and redundant features which makes them inefficient for machine learning. Hence, relevant features which provide minimum classification error are selected using kullback divergence measure, chernoff distance measure and linear regression. The performance of steganalysis using different measures used for feature selection is compared and evaluated in terms of classification error and computation time of training classifier. Experimental results show that classification error with features selected using linear regression is less in comparison to other measures used for feature selection. Also the relevant features selected using linear regression is much smaller in size in comparison to other measures with all classifiers. Hence linear regression measure used for feature selection outperforms other measures in terms of training computation time of a classifier. To improve the performance of the Steganalysis, future work could include the following: (i) identifying the type of Steganography algorithm used for embedding the secret message, (ii) To locate, retrieve and analyze the embedded message to infer the information hidden in image.

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