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Effectiveness of stego images pre-processing with spectral analysis methods

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ABSTRACT

Early detection of sensitive data leakage during message transmission in communication systems is topical task today. This is complicated by applying of attackers to advanced steganographic methods. Feature of such methods is sensitive information embedding into innocuous (cover) files, such as digital images. This drastically reduces effectiveness of modern stegdetectors based on applying of signature and statistical steganalysis methods. There are proposed several approaches for improving detection accuracy of stegdetectors that are based on image pre-processing (calibration). These methods are aimed at estimation parameters either of stego, or cover images from current analysed image. The first group of calibration methods requires prior information about features of used embedding methods to minimize detection error. In most cases, this information is limited that decrease effectiveness of such calibration methods. The second group of calibration methods is of special interest today due to extensive set of proposed methods for advanced image denoising techniques. Nevertheless, practical usage of such methods requires carefully adjustment of parameters. This restricts fast re-training of stegdetector for revealing stego images formed according to unknown embedding methods.The promising approach for estimation cover image parameters from current (noisy) images is based on applying of novel methods of spectral analysis, namely sparse and redundant representation of signals. Feature of these methods is ability to adjust parameters of basic functions to statistical parameters of analysed set of image. This allows improving effectiveness of stegdetectors without necessity to re-tune theirs parameters for new set if images. The paper is aimed at performance analysis of stego images pre-processing with usage of advanced methods of spectral analysis. The analysis was performed for state-of-the-art HUGO embedding methods by usage of standard ALASKA dataset. Based on obtained results, it was revealed that applying of proposed methods allows improving detection accuracy up to 6 % even in case of absence prior information about used embedding methods and low cover image payload, e.g. less than 10 %. Nevertheless, practical usage of these methods for image calibration requires further improvement of dictionary learning procedure, namely decreasing its computation complexity by processing images with high resolution.

Keywords: Digital image; steganalysis; statistical stegdetectors; wavelet transform; sparse representation

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INTRODUCTION

Early detection of sensitive information leakage in state and corporate networks is topical task today. In most cases, the leakage is performed with usage of steganographic communication systems [1].

Feature of such systems is concealing even the fact of unauthorized message transmission by data hiding into innocuous files like digital images (DI).

Novel steganographic methods for message hiding into a cover image (CI) are based on applying adaptive techniques for both pixels pre-selection, and theirs brightness adjustment for minimization of cover statistical features alterations. This considerably reduces accuracy of widespread stegdetectors (SD) that are aimed at revealing of ad-hoc alterations of CI parameters (signatures) caused by message hiding.

Proposed methods for improving performance of modern SD are based on development of advanced image pre-processing (calibration) functions. These functions are aimed at revealing and extraction weak alterations of CI cause by message hiding. The majority of proposed calibration functions utilize either advanced denoising methods, or huge ensembles of high-pass filters. These methods tend to be ineffective in practical scenarios due to “aggressive” character of image denoising (removal both intrinsic and introduced noises) and laborious pre-selection of ensemble elements to minimize detection error. Therefore, development of novel calibration methods for reliable detection of CI alterations under limited prior information about used embedding method is needed.

The work is aimed at performance analysis of novel spectral methods for calibration of stego images formed by adaptive embedding methods(AEM). These methods are based on design of image decomposition functions with usage of available prior information about signals features that is of special interest for digital image steganalysis.

RELATED WORKS

Proposed methods for improvement of used SD are based on applying cover rich models and artificial neural networks. The formed approach is based on usage of ensemble of CI models to improve accuracy of revealing alterations caused by message hiding. The example of such approach usage is SRM group of models [2]. These models are based on CI context suppression by applying of extensive set of high-pass filters (HPF). This allows decreasing detection error for modern embedding methods, such as UNIWARD methods [3], by the cost of time-consuming selection of an appropriate HPF.

The second approach has been proposed to overcome mentioned limitations, namely by adjustment of convolutional networks parameters by the backpropagation methods. The novel convolutional neural networks SR-Net [4], Zhu-Net [5] and GB-Ras [6] fully utilize mentioned method that allows achieve similar or even better detection error for wide range of embedding methods in comparison with SD based on cover rich models. Still, achieving of high detection accuracy by usage this approach requires both increasing depth of neural network to improve generalization ability, and network tuning on huge dataset. This is time-consuming operations that limit fast re-training of SD to detect unknown embedding methods.

The alternative methods for digital image calibration are based on estimations parameters of stego or cover images. This is achieved by applying of ad-hoc transformations which either “emphasize” distortions caused by message hiding, or estimate parameters of CI from current (noisy) images. The methods form the first group can be realized by message re-embedding into analyzed image [7], or image pre-noising [8]. The effectiveness of such approaches relies on utilization prior information about embedding procedure that may be unrealistic cases for real steganalysis scenarios.

The recent progress of development of advanced methods for estimation CI parameters from a noisy image makes these methods attractive candidates for next-generation SD. Still, performance of such methods considerably depends on statistical parameters of used samples of cover and stego images. This decreases effectiveness of such approach for usage with new sets of digital images. For overcome this limitation we propose to use novel methods of spectral analysis, namely sparse and redundant representation of signals, that makes possible incorporating information about features of CI into a process of decomposition functions (dictionary) construction. Despite promising features of such methods for digital image steganalysis, there is no information about effectiveness of this approach for AEM. The paper is aimed at filling this gap by performance analysis of usage modern methods of DI spectral analysis for improving SD performance during processing of stego image formed according to AEM.

THE SCOPE OF THE RESEARCH

The paper is aimed at performance analysis of stego images pre-processing with usage of advanced methods of spectral analysis.

To achieve this aim it is proposed to solve the following tasks:

1) to review features of adaptive embedding methods for digital images;

2) to review modern methods for digital images spectral analysis, namely sparse and redundant representation;

3) to compare performance of proposed method and state-of-the-art rich models for digital images.

The object of study is methods for detection of stego images formed according to AEM.

The subject of study is methods for revealing and extraction alterations of cover images caused by message embedding by AEM.

NOTATIONS

The calligraphic font is used for sets and collections, while vectors or matrices are always in boldface. We supposed that a stego image $\mathbf{Y}$ is created from a grayscale cover image $\mathbf{X}$ with size $M{\cdot}N$ pixels and k=8 bits color depth. The stego data is represented as a binary message $\mathbf{M}$ with K bits length.

ADAPTIVE EMBEDDING METHODS FOR DIGITAL IMAGES

The feature of novel embedding methods is representation of message embedding process as optimization task of minimization cover image $\mathbf{X}$ distortion during message $\mathbf{M}$ hiding [9]:

$$D(\mathbf{X},\mathbf{Y}) = \sum_{i,j} \rho_{i,j}(\mathbf{X},\mathbf{Y}) \xrightarrow{|\mathbf{M}|=const} \min. \qquad (1)$$

where: $D(\mathbf{X},\mathbf{Y})$ – empirical function for estimation alteration of cover image $\mathbf{X}$ during forming of stego image $\mathbf{Y}$; $\rho(\cdot)$ – cost function of cover image pixel parameters distortions by embedding of a single bit.

The function $D(\mathbf{X},\mathbf{Y})$ (1) should include estimation of CI alterations caused both single bits embedding, and non-linear interaction of alterations caused by separate bits hiding [9]. Nevertheless, design of a function that including both features is non-trivial task. This is caused by necessity of analysis of pixels brightness changes combinations that become intractable even for short messages **M** (about 100 bits) [9].Consequently, the simplified function $\rho(\cdot)$ that estimates only CI distortions caused by a single bit hiding is used in most cases.

The paper is aimed at analysis of novel HUGO embedding method [10].

The method is based on minimization of CI distortion under constrain of fixed message length [10]:

$$\min_{\pi} E_{\pi}\left(D\right)=\sum\nolimits_{Y\in \Upsilon}\pi\left(\mathbf{Y}\right)\cdot D\left(\mathbf{X},\mathbf{Y}\right), \qquad (2)$$
$$wrt.\left|M\right|=-\sum\nolimits_{Y\in \Upsilon}\pi\left(\mathbf{Y}\right)\cdot\log\left(\pi\left(\mathbf{Y}\right)\right).$$

where: $\mathbf{Y}$ – a stego image sampled from the set of all stego images Υ; π – probability distribution of selection of some stego image from the set Υ; $E_{\pi}(D)$ – averaging operator for function $D(\cdot)$ over distribution π; $H(\pi)$ – entropy function over distribution π.

Filler et al [10] proposed to use adjacency matrix $\mathbf{C}_{kl}\left(\mathbf{X}\right)$ for estimation of CI distortions during message hiding. This makes possible numerical solving of eq. (2) in the following form:

$$D\left(\mathbf{X},\mathbf{Y}\right)=\sum\nolimits_{c\in C}\sum\nolimits_{(k,l)\in\Im}\omega_{k,l}\mathbf{H}^{c}_{(k,l)}\left(\mathbf{Y}\right),$$

where: $\Im=\left\{0,1,...,2^{k}-1\right\}$ – brightness range of cover and stego image with k-bits color depth; $C=\left\{\rightarrow,\leftarrow,\uparrow,\downarrow\right\}$ – set of scanning directions during co-occurrence matrix $\mathbf{C}_{k,l}$ estimation; $\omega_{k,l}>0$ – weights.

For instance, matrix **H** in the case of row-wise image processing and left-to-right pixels scanning can be calculated as [10]:

$$\begin{gathered}\mathbf{H}^{\rightarrow}_{(k,l)}\left(\mathbf{X},\mathbf{Y}\right)=\left(N\cdot\left(M-2\right)\right)^{-1}\cdot\\ \cdot\sum\nolimits_{i,j}\left|\left[\left(\mathbf{D}^{\rightarrow}_{i,j},\mathbf{D}^{\rightarrow}_{i,j+1}\right)\left(\mathbf{Y}\right)=\left(k,l\right)\right]_{I}-\right. \qquad (3)\\ \left.-\left[\left(\mathbf{D}^{\rightarrow}_{i,j},\mathbf{D}^{\rightarrow}_{i,j+1}\right)\left(\mathbf{X}\right)=\left(k,l\right)\right]_{I}\right|,\\ \left(\mathbf{D}^{\rightarrow}_{i,j},\mathbf{D}^{\rightarrow}_{i,j+1}\right)\left(\mathbf{X}\right)=\left(k,l\right)\Leftrightarrow\\ \Leftrightarrow\left(\mathbf{D}^{\rightarrow}_{i,j}\left(\mathbf{X}\right)=k\right)\wedge\left(\mathbf{D}^{\rightarrow}_{i,j+1}\left(\mathbf{X}\right)=l\right).\end{gathered}$$

Matrix **H** for other types of cliques C can be calculated in a way similar to eq. (3) [10].

STEGO IMAGES CALIBRATION WITH USAGE OF SPECTRAL ANALYSIS METHODS

Modern paradigm of digital image steganalysis is based on applying pre-processing methods for revealing weak alterations of CI caused by message hiding. In most cases, these methods are based on applying of extensive set of HPF to analyzed image and further statistical analysis of obtained residuals [2]. Despite high detection performance of formed SD, practical usage of this approach is limited. This is caused by necessity of time-consuming tuning of HPF ensemble that limits fast re-training of used SD to revealing of unknown embedding methods. Decreasing of computation complexity of this operation requires laborious pre-selection and tuning of the ensemble's elements by processing of cover/stego images and, respectively, access to stego encoder that may by unavailable in real cases. Therefore, development of fast calibration methods that preserve high detection accuracy under limited prior information about used embedding method is topical task today.

Modern approaches to stego images calibration can be divided into next groups [11]:

- Parallel reference – these methods lead only to a shift of the feature vectors for cover and stego images, which does not increase the accuracy of the SD;
- Divergent reference (DR) – aimed at enhancing the differences between cover and stego images by increasing the distance between the respective feature vectors;
- Eraser – leads to decreasing of distance between feature vectors for cover and stego images;
- Cover estimate (CE) – aimed at estimation of statistical characteristics of a cover image by analysis of available (noised) images. This leads to negligible changes of feature vectors for CI by providing considerable changes of features for stego image.
- Stego estimate (SE) – aimed at detection and extraction alterations caused by message hiding into a CI. In this case, applying of these methods leads to insignificant alterations of stego images features, and drastically changes of CI features.

As mentioned before, majority of modern approaches to image calibration is related to SE-methods. Also, special interest is taken on DR-methods that are based on estimations preimages of

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feature vectors for cover and stego images from higher-dimensional space [12]. Nevertheless, practical application of such methods requires usage of stego images examples for estimation mutual positions of feature vectors for cover and stego images. This may be inappropriate for real situation when steganalytics have to reveale stego images formed by unknown steganographic methods (zero-day problem).

The alternative approach to image calibration is based on applying of CE-methods for estimation of cover image's statistical parameters from current (noised) images. Performance analysis of such methods [13] showed promising results for advanced denoising methods. However, such methods tend to "aggressive" processing of digital images by removing considerably part of intrinsic noises. This decreases differences between results of calibration for cover and stego images, especially in case of low cover image payload (less than 10 %). Therefore, it is required novel CE-methods for selective suppression of image intrinsic noise. One of promising approach for solving this task is applying of spectral analysis methods, namely sparse and redundant representation.

A common approach to spectral analysis of digital images is the use of wavelet transform, in particular two-dimensional discrete wavelet transform (2D-DWT).

The decompositions coefficients of 2D-DWT for grayscale image $\mathbf{U}$ with size $N \times M$ (pixels) can be calculated using following formulae [14]:

$$\mathbf{U}_{x,y} = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1} \mathbf{W}_{xy}^{A}\left(\mathbf{U}_{x,y}\right)\cdot\varphi_x\cdot\varphi_y + $$
$$+\mathbf{W}_{xy}^{H}\left(\mathbf{U}_{x,y}\right)\cdot\psi_x\cdot\varphi_y + \mathbf{W}_{xy}^{V}\left(\mathbf{U}_{x,y}\right)\cdot\varphi_x\cdot\psi_y$$
$$+\mathbf{W}_{xy}^{D}\left(\mathbf{U}_{x,y}\right)\cdot\psi_x\cdot\psi_y,$$
$$\mathbf{W}_{xy}^{k} = \left\langle \mathbf{U}_{xy}, \boldsymbol{\psi}_{xy}^{k}\right\rangle =$$
$$= \frac{1}{MN}\cdot\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\sum_{k\in\{A,H,V,D\}} \mathbf{U}_{xy}\cdot\boldsymbol{\psi}_{xy}^{k},$$

where: $\psi, \varphi -$ wavelet and corresponding scaling functions respectively; $\mathbf{W}_{xy}^{A}, \mathbf{W}_{xy}^{(H,V,D)} -$ approximation and detailing coefficients of image; $\langle\cdot,\cdot\rangle -$ dot product.

The image denoising using 2D-DWT is based on thresholding of corresponding decompositions coefficients, for example [14]:

$$T_{hard}\left(x,T\right) = \begin{cases} x, & |x| \ge T, \\ 0, & |x| < T. \end{cases}$$
$$T_{hard}\left(x,T\right) = \max\left(1 - \frac{T}{|x|}, 0\right),$$

where: $T_{hard}, T_{soft} -$ functions for hard and soft thresholding respectively; $T > 0 -$ the threshold.

These threshold functions can be used to process the decomposition coefficients either a single (level-dependent threshold), or several (global threshold) decomposition levels. Note that wavelet functions are configured to process signals with specified statistical properties, such as smoothness of the functions, the finite value of signal elements variance etc. This decrease effectiveness of this approach, especially in case of processing noised signal with non-stationary distribution of noise.

To overcome this limitation, methods for constructing of sparse and redundant systems of functions (SRS) based on the results of signal sample analysis were proposed. These methods are based on the formation of a sparse representation of signals in terms of $M-$element approximation [15] – using only the biggest $M\left(M > 0\right)$ signal decomposition coefficients. The approach allows forming systems of decomposition functions depending on the available parameters of cover and stego images.

The problem of SRS development for $M-$elemental approximation of a set of signals $\left\{\mathbf{y}_i\right\}_{i=1}^{M}$ can be presented as a solution of the following optimization problem [15]:

$$\min_{\mathbf{A},\left\{\mathbf{x}_i\right\}_{i=1}^{M}} \sum_{i=1}^{M} \left\|\mathbf{x}_i\right\|_0, \left\|\mathbf{y}_i - \mathbf{A}\mathbf{x}_i\right\|_2 \le \varepsilon, \varepsilon \ge 0, \tag{4}$$

where: $\mathbf{y}_i -$ current train signal; $\mathbf{x}_i -$ vector of i^{th} decomposition coefficients for the signal $\mathbf{y}_i$ by usage of fixed SRS; $\mathbf{A} -$ matrix of decomposition functions formed by concatenation elements of the basis functions (column vectors).

One of the common methods of building a matrix $\mathbf{A}$ is the block-coordinate relaxation MOD (Method of optimal directions) method proposed by Engan [16]. The method allows solving the initial problem in an iterative way – at the k^{th} step we use the estimate $\mathbf{A}_{(k-1)}$ from the previous step, and solve M problems P_0^{ε} to minimize the error of reconstruction of each element of the train sample $\mathbf{y}_i$. In the next step, the obtained decomposition matrix

$\mathbf{X}_{(k)}$ is used to adjust the elements of the matrix $\mathbf{A}_{(k)}$ using the least squares [16]:

$$\mathbf{A}_{(k)} = \arg\min_{\mathbf{A}} \left\| \mathbf{Y} - \mathbf{A}\mathbf{X}_{(k)} \right\|_F^2 = \\ = \mathbf{Y}\mathbf{X}_{(k)}^{\mathrm{T}} \left(\mathbf{X}_{(k)} \mathbf{X}_{(k)}^{\mathrm{T}} \right)^{-1} = \mathbf{Y}\mathbf{X}_{(k)}^{+}, \tag{5}$$

where $\|\cdot\|_F -$ Fresenius norm. These steps are repeated until the criterion of convergence of the solution is achieved (providing an $M-$elemental approximation of the training signals). The limitation of the MOD method is the relatively large number of optimization steps in the case of processing signals whose parameters are drastically change from used training set [15, 17]. This is caused by low convergence of the optimization problem (4) due to the optimization of all elements of the matrix $\mathbf{A}$ at each step of the algorithm [15]. To overcome this limitation, the K-SVD method was proposed by Acharon et al. [15] for iterative definition of dictionary $\mathbf{A}$.

Unlike the MOD method, the K-SVD method is based on the sequential definition of each dictionary element (matrix $\mathbf{A}$ columns [18]. For example, the determination of $j_0 -$ atom is done by fixing other elements of the matrix $\mathbf{A}$ and using only the $\mathbf{a}_{j_0}$ column of the matrix when processing the training set $\mathbf{X}$. This is achieved by modifying expression (5) as follows [18]:

$$\left\| \mathbf{Y} - \mathbf{A}\mathbf{X} \right\|_F^2 = \left\| \mathbf{Y} - \sum_{j=1}^{M} \mathbf{a}_j \mathbf{x}_j^{\mathrm{T}} \right\|_F^2 = \\ = \left\| \left(\mathbf{Y} - \sum_{j \neq j_0} \mathbf{a}_j \mathbf{x}_j^{\mathrm{T}} \right) - \mathbf{a}_{j_0} \mathbf{x}_{j_0}^{\mathrm{T}} \right\|_F^2, \tag{6}$$

where: $\mathbf{x}_j^{\mathrm{T}} -$ corresponds j^{th} row of matrix $\mathbf{X}$.

The solution of this optimization problem is aimed at minimizing the error matrix $\mathbf{E}_{j_0}$ by updating the values $\mathbf{a}_j$ and $\mathbf{x}_j^{\mathrm{T}}$:

$$\mathbf{E}_{j_0} = \left(\mathbf{Y} - \sum_{j \neq j_0} \mathbf{a}_j \mathbf{x}_j^{\mathrm{T}} \right) \to \min, \tag{7}$$

The optimal values $\mathbf{a}_j$ and $\mathbf{x}_j^{\mathrm{T}}$ that minimize the values $\mathbf{E}_{j_0}$ (7) correspond to matrices with a rank of one. These matrices are approximated $\mathbf{E}_{j_0}$ and can be obtained by singular decomposition of the error matrix (7). However, in most cases, this approach to solving the optimization problem (5) leads to a decrease in the degree of "sparseness" of the vector $\mathbf{x}_j^{\mathrm{T}}$. This violates the conditions of the problem – estimation of dictionary $\mathbf{A}$ that provides the most sparse representation of a given train samples. To overcome this limitation, it was proposed to use only a separate column of the matrix $\mathbf{E}_{j_0}$, which corresponds to the $j_0 -$element of the desired dictionary $\mathbf{A}$.

The projection operator of the matrix (7) in the subspace $\mathbf{P}_{j_0}$ is proposed to obtain $j_0 -$column of the matrix $\mathbf{E}_{j_0}$. The operator can be represented as a matrix multiplied on the right by the matrix $\mathbf{E}_{j_0}$ to zeroing all other columns. The matrix $\mathbf{P}_{j_0}$ has the size of M rows (the number of elements in the test sample of signals) and M_{j_0} columns (the number of elements of the sample that requires the use of $j_0 -$ element of the dictionary $\mathbf{A}$).

Denote $\left(\mathbf{x}_{j_0}^{R}\right)^{\mathrm{T}} = \mathbf{x}_{j_0}^{\mathrm{T}} \mathbf{P}_{j_0}$ as the result of applying the operator $\mathbf{P}_{j_0}$ to the error matrix $\mathbf{E}_{j_0}$. Then the approximation of the product $\mathbf{E}_{j_0}\mathbf{P}_{j_0}$ by a matrix having a single rank can be obtained by applying a singular decomposition. The approximating matrix is used to update of both the atom $\mathbf{a}_{j_0}$ and the decomposition coefficients of the current vector $\mathbf{x}_{j_0}^{\mathrm{T}}$.

It should be noted that the calculation of all components of the singular decomposition $\mathbf{E}_{j_0}\mathbf{P}_{j_0}$ is redundant, because only the approximation matrix with a rank of one is required. Therefore, to speed up the calculations, similar to the MOD method, the block-coordinate method using the least squares algorithm can be used. The vector $\mathbf{x}_{j_0}^{\mathrm{T}}$ can be updated by solving the following optimization problem with fixed values $\mathbf{a}_{j_0}$ [18]:

$$\min_{\mathbf{x}_{j_0}^{R}} \left\| \mathbf{E}_{j_0}\mathbf{P}_{j_0} - \mathbf{a}_{j_0} \left(\mathbf{x}_{j_0}^{R}\right)^{\mathrm{T}} \right\|_F^2 \Rightarrow \\ \Rightarrow \mathbf{x}_{j_0}^{R} = \frac{\mathbf{P}_{j_0}^{\mathrm{T}} \mathbf{E}_{j_0}^{\mathrm{T}} \mathbf{a}_{j_0}}{\left\| \mathbf{a}_{j_0} \right\|_2^2}.$$

Then in a similar way it is possible to update the value of the vector $\mathbf{a}_{j_0}$ [18]:

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$$\min_{\mathbf{x}_{j_0}^R} \left\| \mathbf{E}_{j_0} \mathbf{P}_{j_0} - \mathbf{a}_{j_0} \left(\mathbf{x}_{j_0}^R \right)^{\mathrm{T}} \right\|_F^2 \Rightarrow$$
$$\Rightarrow \mathbf{a}_{j_0} = \frac{\mathbf{P}_{j_0}^{\mathrm{T}} \mathbf{E}_{j_0}^{\mathrm{T}} \mathbf{x}_{j_0}^R}{\left\| \mathbf{x}_{j_0}^R \right\|_2^2}.$$

The K-SVD method is characterized by high accuracy of dictionary $\mathbf{A}$ estimation while providing a given degree of sparseness of decomposition vectors and accuracy of signal reconstruction [15, 18]. Therefore, this method was investigated in the work to build a dictionary $\mathbf{A}$ from a given set of CI.

Further feature extraction from pre-processed images may be performed using standard SPAM model [19]. The calculation of SPAM features starts by computation the difference array **D** by processing an image in row-wise and column-wise orders.

For example, the array **D** for the case of row-wise processing and left-to-right pixels scanning of grayscale image **U** with size $M{\cdot}N$ pixels can be calculated as [19]:

$$\mathbf{D}_{i,j}^{\rightarrow} = \mathbf{U}_{i,j} - \mathbf{U}_{i,j+1},$$
$$\mathbf{U} \in \Im^{M \cdot N}, i \in [1; M], j \in [1; N-1].$$

The first-order SPAM features F_1 are used for modeling array **D** with first-order Markov process [19].

Likewise, the second-order SPAM features F_2 are taken for modeling difference array **D** with second-order Markov process [20]:

$$\mathbf{M}_{u,v}^{\rightarrow} = \Pr\left(\mathbf{D}_{i,j+1}^{\rightarrow} = u \,|\, \mathbf{D}_{i,j}^{\rightarrow} = v \right), \quad (8)$$
$$u, v \in [-T; T], T \in \mathrm{N}.$$
$$\mathbf{M}_{u,v,w}^{\rightarrow} = \Pr\left(\mathbf{D}_{i,j+2}^{\rightarrow} = u \,|\, \mathbf{D}_{i,j+1}^{\rightarrow} = v, \mathbf{D}_{i,j}^{\rightarrow} = w \right), \quad (9)$$
$$u, v, w \in [-T; T], T \in \mathrm{N}.$$

If mentioned probability is equal to zero, then we obtain $\mathbf{M}_{u,v}^{\rightarrow} = 0$ and $\mathbf{M}_{u,v,w}^{\rightarrow} = 0$ as well.

For decreasing dimensionality of SPAM-features, the assumption that statistics in natural images are symmetric with respect to mirroring and flipping [19] is used. Thus, we can separately averaging matrices for horizontal, vertical and diagonal directions to form the final features:

$$F_{1\ldots k} = \left(\mathbf{M}^{\rightarrow} + \mathbf{M}^{\leftarrow} + \mathbf{M}^{\uparrow} + \mathbf{M}^{\downarrow} \right) \big/ 4,$$
$$F_{(k+1)\ldots 2k} = \left(\mathbf{M}^{a} + \mathbf{M}^{b} + \mathbf{M}^{c} + \mathbf{M}^{d} \right) \big/ 4.$$

Note that F_1 and F_2 features for other scanning directions, namely $c \in \{\leftarrow,\uparrow,\rightarrow,\downarrow\}$, can be estimated in the same way to eq. (8)-(9). Number of parameters for the first-order SPAM model is $k_{SPAM}=(2T+1)^2$, while for the second-order one – $k_{SPAM}=(2T+1)^3$.

EXPERIMENTS

Performance analysis of statistical SD by image noising was performed on packet of 10,000 grayscale images sampled from standard ALASKA dataset [21]. The test images were resized to the fixed resolution of 512·512 pixels.

The case of message embedding into CI with HUGO method was considered. The CI payload Δ_p was changed in the following range – 3 %; 5 %; 10 %; 20 %; 30 %; 40 %; 50 %.

The SD was trained with usage of spectral features extracted with considered 2D-DWT and dictionary learning approaches. Classification of extracted features to the classes of cover and stego images was performed with usage of Random Forest classifier [22]. The SD was tested according to cross-validation procedure by minimization of detection error P_e [22]. The dataset was divided 10 times into training (50 %) and testing (50 %) subsets during cross-validation.

Also, the case of applying the standard SPAM [19] statistical models of CI was considered. These models are based on applying the second-order Markov chain model to estimate correlation of adjacent pixels brightness.

Training of SD with usage of extracted spectral features can be performed in various modes by combination features of initial and calibrated images.

According to the performance evaluation [23], the following types of features allow minimizing detection of stego images for wide set of embedding methods:

1. Linearly transformed features of calibrated image – correspond to the difference between features of calibrated and unprocessed images:

$$\mathbf{F}_{DF} = \mathbf{F}_{calib} - \mathbf{F}_{nc}. \quad 10)$$

2. Cartesian calibrated features – corresponds to the case of merging features of unprocessed and calibrated images:

$$\mathbf{F}_{CC} = [\mathbf{F}_{nc}; \mathbf{F}_{calib}]. \quad (11)$$

where $\mathbf{F}_{nc}$ and $\mathbf{F}_{calib}$ are features extracted from initial and calibrated images correspondingly.

Also, performance of SD considerably depends on available information about features of used embedding method [24].

Emulation of the cases of presence or absence of prior information about used AEM can be done using following index [25]:

$$F_\alpha = \frac{\left|\left\{(\mathbf{X},\mathbf{Y}):(\mathbf{X}_i,\mathbf{Y}_i), i \in S_{train}\right\}\right|}{\left|S_{train}\right|} \cdot 100\%,$$

where: F_α is the fraction of pairs of cover-stego images features used for SD training; S_{train} – set of digital images used during training of stegdetector; $\mathbf{Y}_i$ – stego images formed from cover $\mathbf{X}_i$.

The F_α parameter varies from 0% (steganalytics cannot create a stego image for any cover image) to 100 % (steganalytics have access to stego encoder and can create a stego image for arbitrary cover image). In most situations, steganalytics have partial information about used embedding methods – only type of embedding algorithm can be guessed, while ability to estimate its parameters is limited. This case can be emulate by sampling of F_α value from uniform distribution $U(0;100)$. Therefore, these cases of F_α =0 %, F_α=100% and F_α sampled from uniform distribution were considered during performance evaluation of spectral methods for image calibration.

Calibration of test images calibration was performed using wavelet-filtering methods and image restoration using dictionary learning. The Wavelet filtering was done using three-level 2D-DWT with Haar wavelet as basis function. The cases of decompositions coefficients thresholding using global threshold as well as level-dependent thresholding were investigated. The global threshold was estimated as median of absolute values of decompositions coefficients, while level-dependent threshold were calculated according to Birgé-Massart strategy [26].

Dictionary learning for test images was performed using considered K-SVD method [18]. Given the high computational complexity of this method in the processing of digital images with large size (more than 256x256 pixels), the images from the training sample were divided into elements (tiles) of a fixed size of 8x8 and 16x16 pixels.

Evaluation of SD detection accuracy was performed with usage of Matthews Correlation Coefficient *MCC*. The coefficient is used to estimate the degree of correlation of the (true) labels of the classes of the studied images with output of SD [27]:

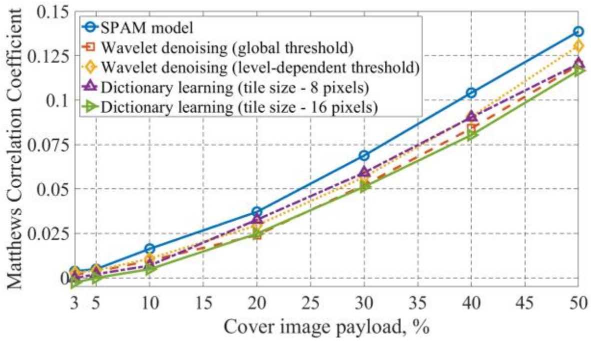
$$MCC = \frac{P_{TP} \cdot P_{TN} - P_{FP} \cdot P_{FN}}{\sqrt{N_{MCC}}},$$

$$N_{MCC} = (P_{TP} + P_{FP}) \cdot (P_{TP} + P_{FN}) \cdot$$
$$\cdot (P_{TN} + P_{FP}) \cdot (P_{TN} + P_{FN}),$$

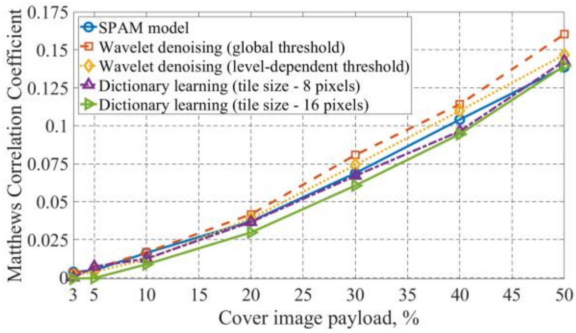
where: P_{TP} – the probability of correct classification of stego images; P_{TN} – the probability of correct classification of cover images; P_{FP} – the probability of incorrect classification of cover images as stego ones; P_{FN} – the probability of incorrect classification of stego images as cover ones.

The value of the *MCC* varies from (-1) that corresponds to the case of incorrect classification of stego images as cover ones and vice versa, to (+1) that relates to correct classification of both cover and stego images. The value *MCC*=0 is the special case that corresponds to the situation of assigning the analyzed image to the classes of cover or stego images randomly (P_{FN}=P_{FP}).

Performance evaluation of considered calibration methods was done in several stages. At the first stage, the case of SD training by full awareness of steganalytics about used embedding method (F_α=100 %) was considered. The dependency of *MCC* on cover image payload by stego images generation according to HUGO embedding methods and usage of $\mathbf{F}_{DF}$ (10) and $\mathbf{F}_{CC}$ (11) features for the case of F_α=100 % are presented at Fig. 1.



a



b

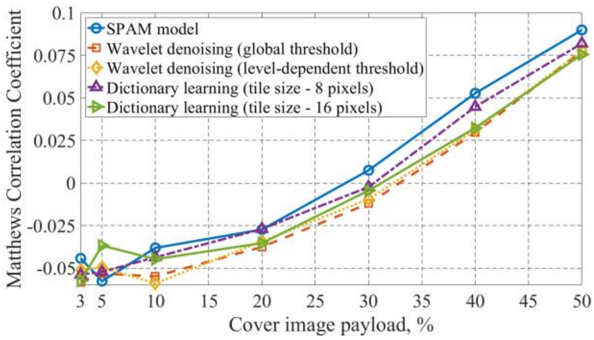
Fig. 1. **The dependency of Matthews correlation coefficient on cover image payload for stego images generated by HUGO embedding method and usage of $\mathbf{F}_{DF}$ (a) and $\mathbf{F}_{CC}$ (b) features for F_α=100 % and applying of spectral calibration methods**

***Source:* compiled by the authors**

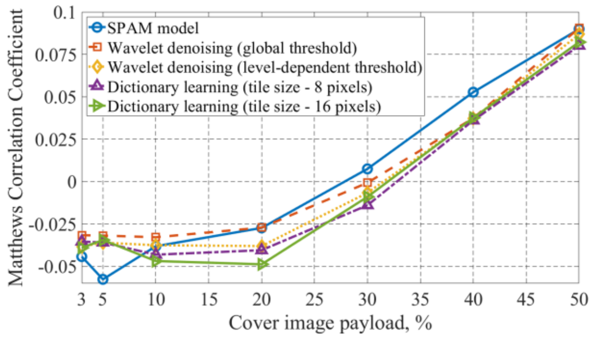
Applying of $\mathbf{F}_{CC}$ (11) features allows improving values of MCC in comparison with standard SPAM model (Fig. 1a), especially for the huge CI payload (more than 20 %). This is achieved by usage of wavelet-filtering with global thresholding, while applying of considered dictionary learning methods leads to increasing of *MCC* only for the low cover image payload (less than 10 %). This can be explained by usage of relatively small tiles during dictionary **A** learning that cannot effectively suppress alterations spreaded over the whole CI for the high Δ_p value.

On the other hand, applying of $\mathbf{F}_{DF}$ (10) features (Fig.1a) does not improve *MCC* values in comparison of SPAM model for considered calibration methods. This can be explained by negligible differences between $\mathbf{F}_{nc}$ and $\mathbf{F}_{calib}$ features that decreases effectiveness of $\mathbf{F}_{DF}$ features usage.

For comparison, the dependency of *MCC* on cover image payload by stego images generation according to HUGO embedding methods and usage of $\mathbf{F}_{DF}$ (10) and $\mathbf{F}_{CC}$ (11) features for the case of F_α sampled uniformly from interval (0;100) are presented at Fig. 2.



a



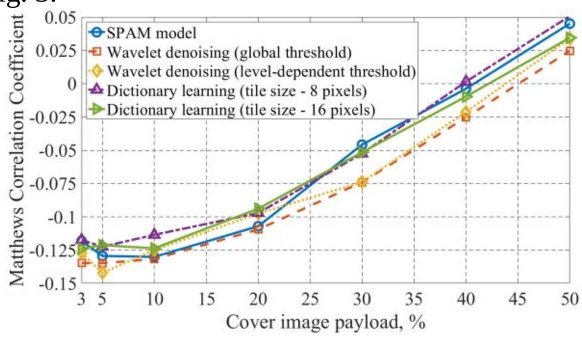
b

Fig. 2. **The dependency of Matthews Correlation Coefficient on cover image payload for stego images generated by HUGO embedding method and usage of $\mathbf{F}_{DF}$ (a) and $\mathbf{F}_{CC}$ (b) features for F_α~U(0;100) and applying of spectral calibration methods**

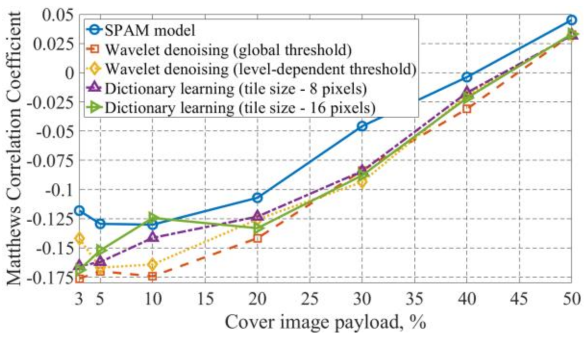
Source: **compiled by the authors**

Note that performance of proposed dictionary learning approach overcomes corresponding results for wavelet-filtering methods under limited prior information about used embedding method (Fig. 2). The biggest gain is achieved for the most difficult case of extra low CI payload (less than 5 %) and usage of $\mathbf{F}_{DF}$ (10) features (Fig.2a). On the other hand estimated values of *MCC* for the $\mathbf{F}_{CC}$ (11) features are much lower (Fig. 2b) that can be explained by decreasing differences between features of initial and calibrated images by preserving of doubled dimensionality of feature vectors.

The most interest case is stego image revealing under absence of prior information about used embedding method (zero day problem). the dependency of *MCC* on cover image payload by stego images generation according to HUGO embedding methods and usage of $\mathbf{F}_{DF}$ (10) and $\mathbf{F}_{CC}$ (11) features for the case of F_α=0 % are presented at Fig. 3.



a



b

Fig. 3. **The dependency of Matthews Correlation Coefficient on cover image payload for stego images generated by HUGO embedding method and usage of $\mathbf{F}_{DF}$ (a) and $\mathbf{F}_{CC}$ (b) features for F_α=0% and applying of spectral calibration methods**

Source: **compiled by the authors**

Obtained results (Fig. 3) proved conclusions made for the previous case (Fig. 2) – applying of dictionary learning based image calibration and $\mathbf{F}_{DF}$ (10) features allows increasing *MCC* values for the case of low (less than 10 %) and middle (less than 20 %) cover image payload in comparison with wavelet-filtering case.

On the other hand, usage of $\mathbf{F}_{CC}$ (11) features leads to drastically reducing of *MCC* values in the whole range of Δ_p index. These results are obtained for both wavelet-filtering and dictionary learning methods (Fig. 3b). This is explained by insignificant changes of features for initial and calibrated images that is "mask out" by doubled dimensionality of $\mathbf{F}_{CC}$ features in comparison with $\mathbf{F}_{DF}$ ones.

DISCUSSIONS

Dependency of SD performance by usage of spectral methods for image calibration considerably depends on amount of available prior information about used AEM. This is proved by values of MCC for HUGO embedding methods for the case of stegdetector by cover and stego images calibration with spectral methods and variation of F_α index (Table).

Table. **The values of Matthews Correlation Coefficient for HUGO embedding methods for the case of stegdetector by cover and stego images calibration with spectral methods and variation of F_α index**

Stego images detection method		Cover image payload		
		Δ_P=5 %	Δ_P=20 %	Δ_P=50 %
F_α=100 %				
SPAM model		0.0049	0.0371	0.1386
Wavelet (global thresh)	$\mathbf{F}_{DF}$	0.0036	0.0287	0.1255
	$\mathbf{F}_{CC}$	0.0057	0.0436	0.1587
Wavelet (level thresh)	$\mathbf{F}_{DF}$	0.0041	0.0295	0.1306
	$\mathbf{F}_{CC}$	0.0039	0.0390	0.1468
Diction. learning (16x16 pixels)	$\mathbf{F}_{DF}$	-0.0001	0.0248	0.1166
	$\mathbf{F}_{CC}$	-0.0003	0.0298	0.1394
$F_\alpha \sim U(0;100)$				
SPAM model		-0.0576	-0.0273	0.0899
Wavelet (global thresh)	$\mathbf{F}_{DF}$	-0.0616	-0.0415	0.0770
	$\mathbf{F}_{CC}$	-0.0384	-0.0319	0.0917
Wavelet (level thresh)	$\mathbf{F}_{DF}$	-0.0495	-0.0343	0.0778
	$\mathbf{F}_{CC}$	-0.0360	-0.0380	0.0868
Diction. learning (16x16 pixels)	$\mathbf{F}_{DF}$	-0.0367	-0.0353	0.0755
	$\mathbf{F}_{CC}$	-0.0344	-0.0487	0.0822
F_α=0 %				
SPAM model		-0.1294	-0.1071	0.0451
Wavelet (global thresh)	$\mathbf{F}_{DF}$	-0.1337	-0.1010	0.0312
	$\mathbf{F}_{CC}$	-0.1831	-0.1447	0.0282
Wavelet (level thresh)	$\mathbf{F}_{DF}$	-0.1421	-0.0976	0.0341
	$\mathbf{F}_{CC}$	-0.1669	-0.1256	0.0323
Diction. learning (16x16 pixels)	$\mathbf{F}_{DF}$	-0.1213	-0.0939	0.0345
	$\mathbf{F}_{CC}$	-0.1521	-0.1331	0.0331

Source: **compiled by the authors**

Let us note that reducing of MCC values by decreasing of F_α index closely connected with performance of used statistical model and ability of used classifier to estimate separation hyperplane between classes. Since these parameters are fixed for considered case, we can estimate performance of spectral calibration methods itself (Table). Note that effectiveness of $\mathbf{F}_{CC}$ (11) features are constantly reducing by decreasing of F_α index that is related to minimizing of differences between features of initial and calibrated images by preserving high (doubled) dimensionality of feature vector. On the other hand, applying of $\mathbf{F}_{DF}$ (10) features allows detect mentioned differences by preserving fixed dimensionality of feature vector that improve classifier performance for the most difficult case of F_α =0 %.

It should be noted that applying of wavelet-filtering methods has considerable limitations for the considered HUGO embedding method (Table). This is related to the differences in processing of noise components used for message hiding – wavelet-filtering is aimed at suppression these components at whole, while message embedding try to minimize changes of components statistical features. In contrast, dictionary learning methods allows improving image calibration due to estimation of CI parameters from the current (noisy) images. This preserves high detection accuracy without necessity to estimate parameters of cover image's noise components.

CONCLUSION

The paper is aimed at performance analysis of stego images pre-processing with usage of state-of-the-art and advanced methods of spectral analysis. The case of applying the wavelet-filtering and dictionary learning methods for calibration of stego images formed according to HUGO embedding method was considered.

Based on obtained results, it was revealed that performance of modern spectral methods for image calibration hardly depends on amount of available prior information about used embedding method. This leads to significant decreasing of Matthews correlation coefficient for SD based on images wavelet-filtering up to 40 %, especially in case of low cover image payload, e.g. less than 10 %.

On the other hand, applying of advanced dictionary learning methods allows improving detection accuracy up to 6 % in most difficult cases of absence prior information about used embedding methods and low cover image payload. Still, practical usage of the method requires decreasing of computation complexity of dictionary formation procedure, especially in case of processing images with high resolution.

REFERENCES

1. Legezo, D. "MontysThree: Industrial espionage with steganography and a Russian accent on both sides". SecureList. Available from: https://securelist.com/montysthree-industrial-espionage/98972/. [Accessed on October 8, 2020].

2. Fridrich, J. & Kodovsky, J. "Rich models for steganalysis of digital images". *IEEE Trans. Inf. Forensics Secur.* 2012; Vol. 7 Iss. 3: 868–882. DOI: https://doi.org/10.1109/TIFS.2012.2190402.

3. Holub, V., Fridrich, J. & Denemark, T. "Universal distortion function for steganography in an arbitrary domain". Eurasip J. Inf. Secur. 2014; Vol. 1. DOI: https://doi.org/10.1186/1687-417X-2014-1.

4. Boroumand, M., Chen, M. & Fridrich, J. "Deep residual network for steganalysis of digital images". *IEEE Trans. Inf. Forensics Secur.* 2019; Vol. 14 Iss. 5: 118–1193. DOI: https://doi.org/10.1109/TIFS.2018.2871749.

5. Zhang, R., Zhu, F., Liu, J. & Liu, G. "Efficient feature learning and multisize image steganalysis based on CNN". Cornell University Library. ArXiv preprint depository. 2018. – Available from: https://arxiv.org/pdf/1807.11428.pdf.

6. Rubio, A. M., Grisales, J. A. A. & Soto, R. T. "GBRAS-Net: A convolutional neural network architecture for spatial image steganalysis". *IEEE Access.* 2021; Vol. 9: 14340–14350. DOI: https://doi.org/10.1109/ACCESS.2021.3052494.

7. Yoan, M., Bas, P. & Amaury, L. "Using multiple re-embeddings for quantitative steganalysis and image reliability estimation. TKK reports in information and computer science". *Department of Information and Computer Science.* Aalto University. 2010. 19 p. ISBN 978-952-60-3250-4.

8. Progonov, D. O. "Effectiveness of stego images pre-noising with fractional noise for digital image steganalysis". *Applied Aspects of Information Technology*. 2021; Vol. 4 Issue 3: 261–270. DOI: https://doi.org/10.15276/aait.03.2021.5.

9. Sedighi, V., Cogranne, R. & Fridrich, J. "Content adaptive steganography by minimizing statistical detectability". *IEEE Trans. Inf. Forensics Secur.* 2015; Vol. 11: 221–234. DOI: https://doi.org/10.1109/TIFS.2015.2486744.

10. Filler, T. & Fridrich, J. "Gibbs construction in steganography". *IEEE Trans. Inf. Forensics Secur.* 2010; Vol. 5: 705–720. DOI: https://doi.org/10.1109/TIFS.2010.2077629.

11. Kodovsky, J. & Fridrich, J. "Calibration revisited". *Proceedings of the 11th ACM workshop on Multimedia and security.* 2009. p. 63–74. DOI: https://doi.org/10.1145/1597817.1597830.

12. Progonov, D. O. "Effectiveness of stego image calibration via feature vectors re-projection into high-dimensional spaces". *Radio Electronics, Computer Science, Control.* 2022; Vol. 2 (61).

13. Progonov, D. O. "Detection of stego images with adaptively embedded data by component analysis methods". *Advances in Cyber-Physical Systems.* 2021; Vol. 6 No. 2: 146–154. DOI: https://doi.org/10.23939/ acps2021.02.146.

14. Mallat, S. "A wavelet tour of signal processing: the sparse way". 3rd ed. *Academic Press.* 2008. 832 p. ISBN: 978-0123743701.

15. Elad, M. "Sparse and redundant representations: from theory to applications in signal and image processing". *Publ. Springer.* 2010. 396 p. ISBN: 978-1441970107.

16. Engan, K., Aase, S. O. & Hakon Husoy, J. "Method of optimal directions for frame design", *International Conference on Acoustics, Speech and Signal Processing.* Phoenix. IEEE. USA. 1999. DOI: https://doi.org/10.1109/ICASSP.1999.760624.

17. Eldar, Y. C. & Kutyniok, G. "Compressed sensing: theory and applications". 1st ed. *Cambridge University Press.* 2012. 558 p. ISBN: 978-1107005587.

18. Aharon, M., Elad, M. & Bruckstein, A. "K-SVD: An algorithm for designing overcompletes dictionaries for sparse representation". *IEEE Transactions on Signal Processing.* 2006; Vol. 54(11): 4311–4322. DOI: https://doi.org/10.1109/TSP.2006.881199.

19. Pevny, T., Bas, P. & Fridrich, J. "Steganalysis by subtractive pixel adjacency matrix". *IEEE Trans. Inf. Forensics Secur.* 2010; Vol. 5: 215-224. DOI: https://doi.org/10.1109/TIFS.2010.2045842.

20. Gonzalez, R., Woods, R. Digital Image Processing. 4th ed. *Pearson Press.* 2017. 1192 p. ISBN 978-0133356724.

21. Cogranne, R., Giboulot, Q. & Bas, P. “The ALASKA steganalysis challenge: a first step towards steganalysis”. *Proceedings of the ACM Workshop on Information Hiding and Multimedia Security,* New York. 2019. p. 125–137. DOI: https://doi.org/10.1145/3335203.3335726.

22. Kodovsky, J. & Fridrich, J. “Ensemble classifiers for steganalysis of digital media”. *IEEE Trans. Inf. Forensics Secur*. 2012; Vol. 7: 432–444. DOI: https://doi.org/10.1109/TIFS.2011.2175919.

23. Progonov, D. & Lucenko, V. “Steganalysis of adaptive embedding methods by message re-embedding into stego images”. *Information Theories and Applications*. 2020; Vol. 27 Iss. 4: 3–24.

24. Fridrich, J. “Steganography in digital media: principles, algorithms, and applications. *Cam-bridge: Cambridge University Press*. 2009; 437 p. ISBN 978–0–521–19019–0. DOI: https://doi.org/10.1017/CBO9781139192903.

25. Progonov, D. “Performance of statistical stegdetectors in case of small number of stego images in training set”. *IEEE Int. Conf. “Problems of Info communications Science and Technology”*. Kharkiv: Ukraine. 2020. DOI: https://doi.org/10.1109/PICST51311.2020.9467901.

26. Birgé, L. & Massart, P. “From model selection to adaptive estimation”. *Festschrift for Lucien Le Cam: Research Papers in Probability and Statistics*. Ed.: Torgersen, E., Pollard, D., Yang, G. *Springer-Verlag*. 1997. p. 55–88.

27. Chicco, D. & Jurman, G. “The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation”. *BMC Genomics*. 2020; Vol. 21. DOI: https://doi.org/10.1186/s12864-019-6413-7.

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Ефективність попередньої обробки стеганограм з використанням методів спектрального аналізу

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АНОТАЦІЯ

Забезпечення раннього виявлення витоку конфіденційних даних під час передачі повідомлень у інформаційно-комунікаційних системах є актуальною та важливою задачею сьогодні. Вирішення даної задачі ускладнюється застосуванням зловмисниками новітніх стеганографічних методів для вбудовування повідомлень до файлів, що циркулюють в комунікаційних мережах, зокрема цифрових зображень. Внаслідок цього суттєво знижується точність роботи поширених типів стегодетекторів, заснованих на використанні методів сигнатурного та статистичного стегоаналізу. Для підвищення точності роботи сучасних стегодетекторів було запропоновано декілька підходів, заснованих на попередній обробці досліджуваних зображень. Дані підходи спрямовані на оцінку статистичних параметрів сформованих стеганограм, або ж зображень-контейнерів за результатами обробки досліджуваного зображення. Запропоновані методи попередньої обробки стеганограм потребують використання апріорних даних щодо особливостей використаного стеганографічного методу. Це обмежує їх застосування у реальних випадках, коли дані відомості є обмеженими або навіть відсутніми. Внаслідок цього особлива увага приділяється методам попередньої обробки, спрямованих на оцінку параметрів зображень-контейнерів, зокрема шляхом використання новітніх методів зниження впливу шумів. Проте забезпечення малих значень помилки класифікації стеганограм потребує ретельного налаштування параметрів даних методів, що обмежує можливість швидкого переналаштування стегодетектору для виявлення нових типів стеганографічних методів. Перспективним підходом до оцінки параметрів зображення-контейнеру за наявними (зашумленими) зображеннями є використання новітніх методів спектрального аналізу сигналів, зокрема методів побудови надлишкових систем функцій для розрідженого представлення сигналів. Особливістю даних методів є врахування статистичних параметрів досліджуваних сигналів при побудові системи функцій для проведення декомпозиції сигналів. Це дозволяє підвищити ефективність роботи стегодетекторів без необхідності їх повторного налаштування при обробці нових пакетів зображень. Метою даної роботи є дослідження ефективності методів попередньої обробки стеганограм при використанні новітніх методів спектрального аналізу. Дослідження проводилося для випадку формування стеганограм згідно адаптивного стеганографічного методу HUGO з використання тестових зображень зі стандартного пакету ALASKA. За результатами аналізу отриманих даних виявлено, що використання запропонованого методу попередньої обробки стеганограм дозволяє суттєво (до 6%) підвищити точність виявлення стеганограм у порівнянні з поширеними типами стегодетекторів навіть у найбільш складному випадку слабкого заповнення зображення-контейнеру стегоданими (менше 10%) та відсутності апріорних даних щодо використаного стеганографічного методу. Проте практичне використання запропонованого методу потребує подальшого вдосконалення методів побудови надлишкових систем функцій, зокрема зниження їх високої обчислювальної складності у випадку обробки зображень з високою роздільною здатністю.

Ключові слова: цифрові зображення; стегоаналіз; статистичні стегодетектори; вейвлет-аналіз; розріджене представлення сигналів.

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