e-ISSN 1607-3274 Радіоелектроніка, інформатика, управління. 2022. № 2
p-ISSN 2313-688X Radio Electronics, Computer Science, Control. 2022. № 2

UDC 004.056

EFFECTIVENESS OF STEGO IMAGE CALIBRATION VIA FEATURE VECTORS RE-PROJECTION INTO HIGH-DIMENSIONAL SPACES

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ABSTRACT

Context. The topical problem of sensitive information protection during data transmission in local and global communication systems was considered. The case of detection of stego images formed according to novel steganographic (embedding) methods was analyzed. The object of research is special methods of stego images features pre-processing (calibration) that are used for improving detection accuracy of modern statistical stegdetectors.

Objective. The purpose of the work is performance analysis of applying special types of image calibration methods, namely divergent reference techniques, for revealing stego images formed according to adaptive embedding methods.

Method. The considered divergent reference methods are aimed at search an appropriate transformation for cover and stego images features that allows increasing Euclidean distance between them. This can be achieved by re-projection of estimated features into a high-dimensional space where cover and stego features may have higher inter-cluster distances. The work is devoted to analysis of such methods, namely by applying the inverse Fast Johnson-Lindenstrauss transform for estimation preimages of cover and stego images features. The transform allows considerably decreasing computation complexity of features calibration procedure while providing a fixed level of relative positions changes for cover and stego images features vectors, which is of particular interest in steganalysis.

Results. The dependencies of detection accuracy, namely Matthews correlation coefficient, on cover image payload and dimensionality of estimated preimages for feature vector were obtained. The case of usage state-of-the-art HUGO, S-UNIWARD, MG and MiPOD embedding methods for message hiding into a cover image was considered. Also, the variants of stego image features pre-processing by full access to stego encoder for a steganalytic as well as limited a prior information about used embedding method were analyzed.

Conclusions. The obtained experimental results proved effectiveness of proposed approach in the most difficult case of limited a prior information about used embedding method and low cover image payload (less than 10%). The prospects for further research may include investigation of applying special methods for features preimages estimation in a high-dimensional space for improving detection accuracy for advanced embedding methods.

KEYWORDS: digital image steganalysis, adaptive embedding method, image calibration, dimensionality reduction.

ABBREVIATIONS

ASM is an adaptive steganographic method;
CI is a cover image;
CNN is a convolutional neural network;
DI is a digital image;
DR is the divergent reference calibration method;
FJLT is the Fast Johnson-Lindenstrauss transform;
GMM is the Gaussian Mixture model;
HPF is a high-pass filter;
JLL is the Johnson-Lindenstrauss lemma;
MCC is the Matthews correlation coefficient;
SD is a stegdetector;
SI is sensitive information.

NOMENCLATURE

Δ_p is a cover image payload;

$\rho_{ij}(\cdot)$ is a cost function for estimation CI alteration due to individual stego bit hiding into $(i,j)^{th}$ pixel of CI;

u, v, w are weights;

$C(\cdot)$ is an image calibration operator;

C is the set of three-elements cliques for four-pixels adjacency directions;

$\mathbf{D}$ is an array of differences between adjacency pixels values;

$D(X,Y)$ is an empirical distortion estimation function;

$\Im$ represents brightness range for 8-bits grayscale image;

k is the number of parameters for the SPAM model;

$\mathbf{M}$ is a binary message to be embedded;

$\mathbf{M}^a$, $\mathbf{M}^b$ are adjacency matrices for Markov model by scanning grayscale image from left-bottom to right-top and from right-top to left-bottom directions respectively;

$\mathbf{M}^c$, $\mathbf{M}^d$ are adjacency matrices for Markov model by scanning grayscale image from left-top to right-bottom and from right-bottom to left-top directions correspondingly;

P_e is the detection error;

P_{FA} is the probability of false alarm during detection (assignment cover image as stego one);

P_{MD} is the probability of missed detection (assignment of stego image as cover one);

T is a threshold;

$\mathbf{X}$ is a cover image;

$\mathbf{Y}$ is a stego image;

$\Pr(a)$ is the probability of event a.

INTRODUCTION

Ensuring the reliable protection of sensitive information, which is processed in the critical information infrastructure of public institutions and private organizations, is extremely important and urgent task today. Particular attention is paid to counteracting to SI

DOI 10.15588/1607-3274-2022-2-16

leakage during data exchange in communication systems, in particular the detection of latent (steganographic) transmission of SI embedded in multimedia cover files, such as digital images [1, 2]. The solution of this problem is significantly complicated by the widespread usage of attackers the advanced adaptive steganographic methods. The feature of these methods is the minimization of cover image statistical parameters alteration during message embedding, which leads to a significant reduction of modern stegdetectors accuracy.

The object of study is methods for revealing of stego images according to modern ASM. These methods are based on analysis of differences between statistical, spectral and structural parameters of the current DI and available examples of cover or stego images.

Ensuring high accuracy of stego images detection requires usage enormous ensembles of high-pass filters in order to detect weak (anomalous) changes in statistical, spectral and structural parameters of the CI, caused by stegodata embedding. The high complexity of the formation of these ensembles to minimize a stego image detection error in the case of limited a priori data about used ASM determines the urgency of the problem of finding pre-processing (calibration) methods of DI that can reliably detect weak distortions of CI.

The subject of study is methods for DI calibration aimed at detecting weak changes of image's parameters alterations caused by message hiding according to ASM.

Given the mentioned limitations of usage ensembles of HPF to detect stego images formed according to the advanced ASM, it is of interest to investigate the effectiveness of special calibration methods usage. In particular, there is presented limited information in the literature about calibration methods aimed at increasing the distance between the multidimensional vectors (statistical parameters) of cover and stego images [3]. These methods allow increasing the differences between the statistical parameters of the cover and formed stego images without the need to use compute-intensive procedures for high-frequency filtering of a DI in order to extract components that are usually used for message hiding.

The purpose of the work is performance analysis of applying special types of image calibration methods to improve the detection accuracy for stego images formed according to ASM.

1 PROBLEM STATEMENT

For a given set of cover $\mathbf{X}_i$ and stego $\mathbf{Y}_i$ images $\left(\mathbf{X}_i, \mathbf{Y}_i\right) \in \Im^{M \cdot N}$, $i \in [1; Q]$ the task of stegdetector training can be presented as the optimization problem [4, 5]:

$$P_e = \min_{P_{FA}} \left(P_{FA} + P_{MD}\left(P_{FA}\right)\right) / 2 . \quad (1)$$

Solving of (1) is done under constrain of applying to images a predefined image calibration transformation $C(\cdot)$: $\Im^{M \cdot N} \to \Im^{M \cdot N}$.

DOI 10.15588/1607-3274-2022-2-16

Selection of calibration transformation $C(\cdot)$ should be done according to known a priori information about used embedding method. Nevertheless, this information is limited or even absent in most cases. Therefore, the choice of appropriate transformation $C(\cdot)$ that allows solving problem (1) in case of limited a priori information about steganographic method remains an open question.

The work is devoted to performance analysis of usage special types of image calibration methods that are based on image's vectors (statistical features) preimages estimation into a high-dimensional space in order to emphasize differences between features of cover and stego images.

2 REVIEW OF THE LITERATURE

The feature of advanced methods for message embedding into a cover image is preserving minimal impact on cover's statistical features [4, 5]. This is achieved by carefully selection of cover's pixels to be altered with usage of empirical functions D(**X**,**Y**) for estimation cover image alterations. Detection of these alterations is non-trivial task due to limited information about used functions D(**X**,**Y**). Therefore, special attention is paid on images pre-processing (calibration) methods that allow revealing mentioned alterations for further analysis.

One of most effective methods for image calibration was proposed for SRM statistical model of a cover image [6]. Feature of such methods is usage of redundant set of HPF for image's context suppression. Despite high detection accuracy, practical usage of SRM-based models is limited due to high computation complexity and necessity to update set of HPF for minimization stego image detection error for each embedding method.

Further evolution of SRM-based model is applying of modern convolutional neural networks for learning appropriate filters (convolutional kernels) during SD tuning [7, 8]. Applying of well-known backpropagation method allows considerable reducing time-consuming manual selection of an appropriate HPF for minimization of detection error. In spite of CNN's high detection accuracy, they remain vulnerable to differences between statistical features of training and testing sets of DI (domain adaptation problem). Therefore, applying of computation-intensive transfer learning methods is required for prevention negative impact of this problem.

Given mentioned limitation of modern methods for DI calibration, it is of interest to use special types of image calibration methods, namely the divergent reference methods [3]. These methods are aimed at increasing the distance between the distributions of statistical parameters of cover and stego images by applying of an appropriate transformation for features vectors. Modern approaches to the design of such calibration methods require usage of a priori data about statistical parameters of cover and stego images in order to choose an appropriate transformation method [8, 9]. As a result, the presence of complete / partial overlap of clusters of vectors (statistical features) of cover/stego images leads to a significant reduction in the effectiveness of such calibration methods. To overcome this limitation, we proposed to use methods for image's vectors (statistical features) preimages estimation from a high-dimensional space while preserving theirs relative positions. Therefore, the work is devoted to performance analysis of such approach to image calibration for improving performance of modern SD.

3 MATERIALS AND METHODS

The development of effective and computationally cheap image calibration methods requires review and classification of known approaches to solving this problem. This allows establishing the advantages and identifies limitations in the practical application of known calibration methods.

The classification of modern calibration methods for digital images was proposed in the work [3]:

1. Parallel reference – usage of calibration methods leads only to a parallel shift of vectors for cover and stego images, which does not increase the accuracy of the SD;
2. Divergent reference – aimed at enhancing the differences between cover and stego images by increasing distance metric between these vectors;
3. Eraser – as a result of usage of such methods the distance between vectors of cover/stego images considerably decreases, up to their full alignment;
4. Cover estimate – are aimed at estimation features of cover images from the current (noised) image. Correspondingly, applying of such methods preserves minimal changes of cover's images, while leads to considerable changes of stego ones;
5. Stego estimate – are aimed at detection and extraction image's alterations caused by message hiding. Therefore, usage of such methods preserves minimal changes of stego images, while features of cover image are changed significantly.

The schematic representation of the mutual positions of vectors corresponding to cover/stego statistical features by applying of considered calibration methods is shown in Fig. 1.

The calibration methods that relates to parallel reference and eraser cases are rarely used today due to considerable decreasing of stegdetector performance. The image calibration methods based on applying of ensembles of HPF are related to the stego estimation case due to detection and extraction of DI alterations caused by message hiding [10–12]. On the other hand, cover estimation calibration methods are not widely adopted in SD today due to theirs "aggressive" characters – removing both internal noise and alterations caused by message hiding [13].

In general, current researches of stego images calibration methods is aimed at finding methods belonging to the DR case (Fig. 1) – the search of methods that enhance the differences between features of cover/stego images, namely to cluster corresponding multidimensional vectors in different parts of the feature space. Therefore, these calibration methods make it possible to use simple (linear) methods of features classification and preserving low detection errors.

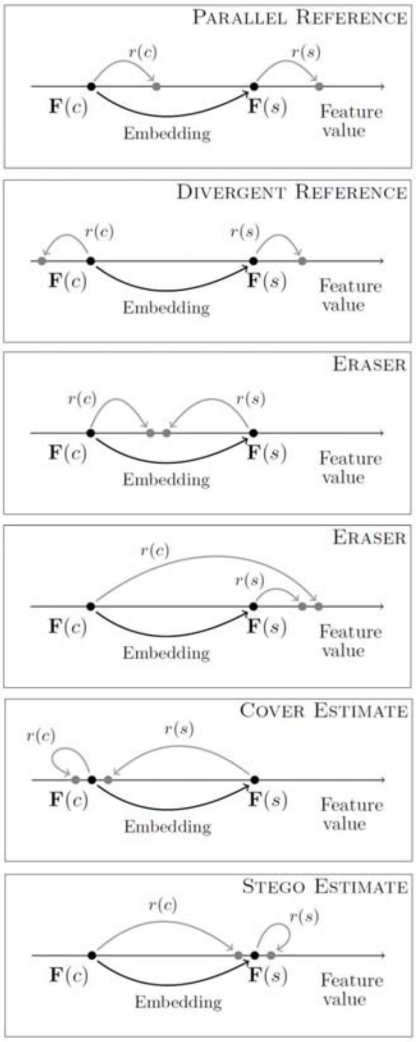


Figure 1 – Schematic representation of cover and stego images features shift caused by calibration methods applying. According to paper [3]

The DR-based calibration methods can be implemented by projections of the corresponding vectors from current to a higher dimension space. Thus, despite the relatively small differences between these vectors in the current space, their preimages from a higher dimension space may have significantly greater differences.

Therefore, it is represent the interest to investigate performance of modern methods for vectors re-projection into a higher dimension space. These methods can be represented as "inversion" of the well-known dimensionality reduction techniques that are aimed at preserving relative location of features. One of the most known methods for solving this task is based on Johnson-Lindenstrauss lemma concerning low-distortion embeddings of points from high-dimensional into low-dimensional Euclidean space [14]. The feature of JLL is preservation of projected clusters relevant structure that makes it promising method for wide range of dimensionality reduction technique. Also, the JLL is based on construction the projection matrix that can be

DOI 10.15588/1607-3274-2022-2-16

inverted with usage of Moore-Penrose method [15]. Therefore, the JLL can be adapted for the estimation of cover and stego images feature vectors preimages that take special interest for improving SD performance.

By the Johnson-Lindenstrauss lemma [16], n points in Euclidean space can be projected from the original d dimensions down to lower $k = O(\varepsilon^{-2}\cdot\log n)$ dimensions while just incurring a distortion of at most ($\pm\varepsilon$) in their pairwise distances, where $0<\varepsilon<1$. Based on the JLL, Alion and Chazelle [17, 18] proposed the Fast Johnson-Lindenstrauss transform for a low-distortion embedding of l_p^d into l_p^k (p equals 1 or 2).

The FJLT is based on preconditioning of a sparse projection matrix with a randomized Fourier transform. Note that we will only consider the l_2 case (p = 2) because of processing two-dimensional matrices of pixels brightness. For the l_1 case, please refer to [17].

The FJLT is denoted as $\mathbf{\Phi}_{JLT}$=FJLT(n, d, ε), that can be obtained as a product of three real-valued matrices:

$$\mathbf{\Phi}_{JLT} = \mathbf{P}_{JLT} \cdot \mathbf{H}_{JLT} \cdot \mathbf{D}_{JLT},$$

where matrices $\mathbf{P}_{JLT}$ and $\mathbf{D}_{JLT}$ are random and matrix $\mathbf{H}_{JLT}$ is deterministic [17, 18], namely:

– Matrix $\mathbf{P}_{JLT}$ is a k-by-d matrix whose elements P_{ij} are drawn independently from Normal distribution N(0, q^{-1}) with zero-mean and variance q^{-1} with probability q, and equal zeros with probability (q–1), where

$$q = \min\left\{c \log^2 n/d, 1\right\}$$

for a large enough constant c.

– Matrix $\mathbf{H}_{JLT}$ is d-by-d normalized Hadamard matrix with the elements as

$$H_{ij} = d^{-1/2}(-1)^{\langle i-1, j-1\rangle},$$

where $<i,j>$ is the dot-product of the m-bit vectors of (i,j) expressed in binary format.

– Matrix $\mathbf{D}_{JLT}$ is a d-by-d diagonal matrix, where each diagonal element D_{ii} is drawn independently from {–1, +1} with probability 0.5.

Therefore, the FJLT output is a k-by-d matrix, where d is the original dimension number of the data and k is the lower dimension number, which is set to be ($c'\varepsilon^{-2}\log n$). Here, n is the number of data points, ε is the distortion rate, and c' is a constant. Given any data point $\mathbf{X}$ from a d-dimension space, it is intuitively mapped to the data point $\mathbf{X}'$ at a lower k-dimension space by the FJLT and the distortion of their pairwise distances could be estimated with JLL [17, 18].

We considered usage of standard SPAM statistical model of DI for estimation images statistical features. The SPAM model is based on usage Markov chains theory for estimation cross-correlation of adjacent pixels brightness [19]. The calculation of SPAM-features starts by computation the difference array $\mathbf{D}$ by processing an image in row- and column-wise orders. For example, the array $\mathbf{D}$ for the case of row-wise processing (left-to-right pixels scanning) of the grayscale image $\mathbf{U}$ with size $M\cdot N$ pixels can be calculated as [19]:

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

Then, the array $\mathbf{D}$ is modelled with usage of first-order and second-order Markov processes that produces $\mathbf{F}_1$ and $\mathbf{F}_2$ features respectively [19]. For the considered example, it leads to:

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

If probabilities $\Pr\left(\mathbf{D}_{i,j}^{\rightarrow} = v\right)$ or $\Pr\left(\mathbf{D}_{i,j+1}^{\rightarrow} = v, \mathbf{D}_{i,j}^{\rightarrow} = w\right)$ are equal to zero, corresponding values $\mathbf{M}_{u,v}^{\rightarrow}$ and $\mathbf{M}_{u,v,w}^{\rightarrow}$ equal to zero as well. The same approach can be used for estimation $\mathbf{F}_1$ and $\mathbf{F}_2$ features for other scanning directions, namely $c \in \{\rightarrow, \leftarrow, \uparrow, \downarrow\}$.

Finally, estimated features $\mathbf{F}_1$ and $\mathbf{F}_2$ are averaged for decreasing dimensionality of SPAM-features. This procedure is based on the standard 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:

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

Number of parameters for the first-order SPAM model is $k=(2T+1)^2$, while for the second-order one – $k=(2T+1)^3$.

4 EXPERIMENTS

Performance analysis of proposed method for images features DR-calibration was performed on ALASKA dataset [20]. The sub-set of 10,000 grayscale images with size 512·512 pixels was pseudo randomly chosen from the dataset. The case of message embedding into CI with usage of advanced adaptive embedding methods HUGO [21], S-UNIWARD [22], MG [23] and MiPOD [24] was considered. The CI payload Δ_p was changed in the following range – 3%, 5%, 10%, 20%, 30%, 40%, 50%.

The feature of considered embedding methods is minimization of total cost by a binary message $\mathbf{M} \in \{0,1\}^K$ hiding into a cover grayscale image X [25]:

$$D(\mathbf{X}, \mathbf{Y}) = \sum\nolimits_{i,j} \rho_{i,j}(\mathbf{X}, \mathbf{Y}) \xrightarrow{|\mathbf{M}|=const} \min. \qquad (2)$$

DOI 10.15588/1607-3274-2022-2-16

Ideally, cost function ρ(·) in (2) can estimate both CI alteration due to changing of individual pixel, and non-linear interaction between these changes [25]. The former estimation can be done with usage of widespread statistical models of CI [1], while the latter one requires compute-intensive analysis of pixels changes combinations that becomes intractable even for short messages **M** (about 100 bits) [25]. Therefore, the simplified function ρ(·) that estimate only CI distortions caused by individual stego bit embedding is used in most real cases.

The HUGO embedding method is based on minimization of CI distortion under constrains of message length by alteration of pixels brightness levels [21]. On the other hand, the S-UNIWARD method uses similar approach by manipulation of CI decomposition coefficients, obtained after two-dimensional discrete wavelet transformation [22]. In contrast, the MG and MiPOD embedding methods use Gaussian Mixture model for estimate statistical features of CI intrinsic noises [23, 24]. Usage of GMM allows both estimation alterations of CI statistical features caused by message hiding, and tracking of expected detection accuracy for formed stego images.

In most cases, selection of cover image pixels to be used during message embedding (2) is performed by heuristic rules. These rules assess noise level in a local neighborhood of $(i,j)^{th}$ pixel [25] that allows achieving close to state-of-the-art security of formed stego images and preserving computation effective optimization methods for cost estimation.

The stegdetector was tested according to cross-validation procedure by minimization of detection error P_e (1) [26]. The dataset was divided 10 times into training (70%) and testing (30%) sub-sets during cross-validation for estimation averaged values of P_e. The SD includes ensemble classifier with Fisher Linear Discriminant base learner [26] trained with second-order SPAM model [19] with threshold parameter T=3, leading to 686 features.

The SD performance significantly depends on fraction F_α of cover-stego images features pairs utilized during training stage [27]:

$$F_\alpha = \frac{\left|\left\{(\mathbf{X},\mathbf{Y}):(\mathbf{X}_i,\mathbf{Y}_i), i\in S_{train}\right\}\right|}{\left|S_{train}\right|}\cdot 100\%, \qquad (3)$$

where S_{train} – set of images used during training of stegdetector; $\mathbf{Y}_i$ – stego images formed from the i^{th} cover image $\mathbf{X}_i$.

The F_α parameter varies from 0% (absent of cover-stego images pairs in training set) to 100% (training set consists only from cover-stego images pairs). The former case corresponds to the situation when steganalytic does not have access to stego encoder and may use only collected stego images. The latter one relates to the situation when steganalytics have access to stego encoder and they can generate a stego image for any CI.

The Matthews correlation coefficient was used as performance metric for trained SD [28]:

$$MCC = \frac{P_{TP}\cdot P_{TN} - P_{FP}\cdot P_{FN}}{\sqrt{N_{MCC}}}, \qquad (4)$$

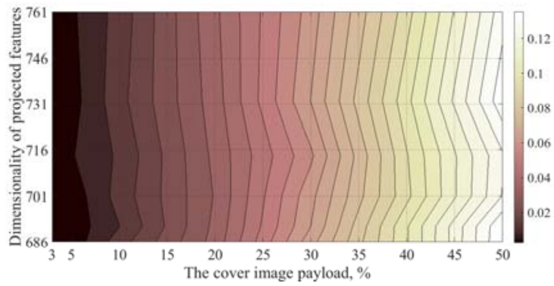
$$N_{MCC} = \left(P_{TP}+P_{FP}\right)\cdot\left(P_{TP}+P_{FN}\right)\times$$
$$\times\left(P_{TN}+P_{FP}\right)\cdot\left(P_{TN}+P_{FN}\right),$$

where P_{TP}, P_{TN} are probabilities of correct classification of stego and cover images; P_{FP}, P_{FN} are probabilities of false alarm (misclassification of cover image as a stego one) and miss detection (misclassification of stego image as a cover one). The value of MCC index (4) varies from (–1), which corresponds to the case of incorrect classification of cover images as stego ones and vice versa, to (+1), which corresponds to the correct classification of both cover and stego images. The special case is value MCC = 0, which corresponds to the case of assigning the studied image to cover/stego images classes randomly (P_{FP}= P_{FN}).

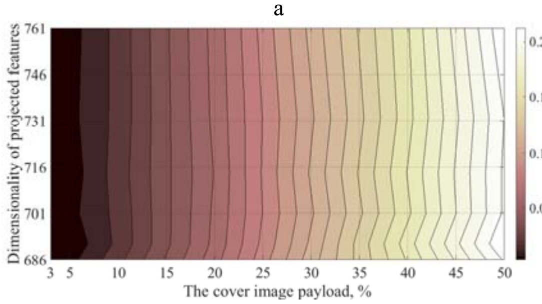
The estimated features were calibrated with usage of inverse FJLT by increasing of features dimensionality up to 10% in comparison with initial SPAM features – from 686 to 761 with step of 5. The transformation matrix **T** for estimation preimages of features was performed with usage of Moore-Penrose procedure [29]. Due to stochastic nature of FJLT, the SD performance was estimated by 10 times generation of transformation matrix T and using of median values of detection error P_e (1).

5 RESULTS

After testing of stegdetector trained with initial and projected SPAM features the dependencies of MCC values on CI payload were plotted. The dependencies of MCC mean values on cover image payload for considered embedding methods HUGO, S-UNIWARD, MG and MiPOD for the case F_α=100% are presented at Fig. 2–3.



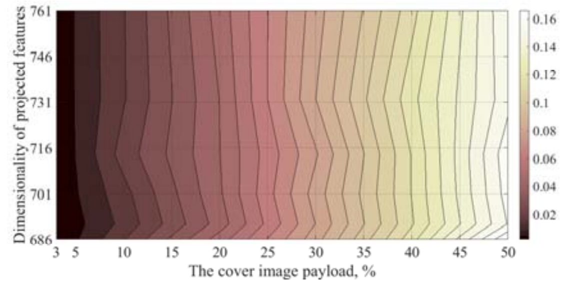
a



b

Figure 2 – The dependencies of Matthews correlation coefficient mean values on cover image payload for HUGO (a) and S-UNIWARD (b) embedding methods for the case F_α=100% on ALASKA dataset

DOI 10.15588/1607-3274-2022-2-16



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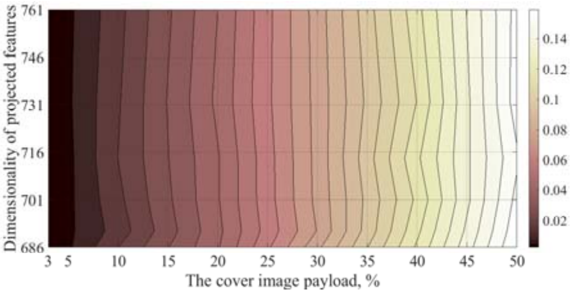
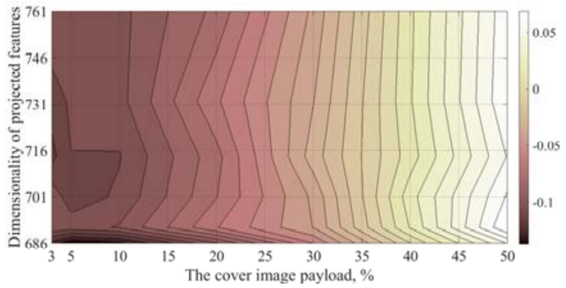


b

Figure 3 – The dependencies of Matthews correlation coefficient mean values on cover image payload for MG (a) and MiPOD (b) embedding methods for the case F_α=100% on ALASKA dataset

Usage of inverse transformation matrix $\mathbf{T}_{inv}$ leads to negligible changes of *MCC* index ($\Delta MCC < 10^{-3}$) for all considered embedding methods (Fig. 2–3). Therefore, we may conclude that usage of DR-features based on features projection into high-dimensional space does not allow improving detection accuracy of SD.

For comparison, the dependencies of MCC mean values on cover image payload for considered embedding methods HUGO, S-UNIWARD, MG and MiPOD for the case F_α=0% are presented at Fig. 4–5.



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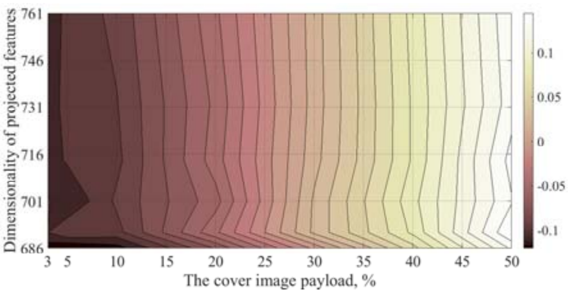
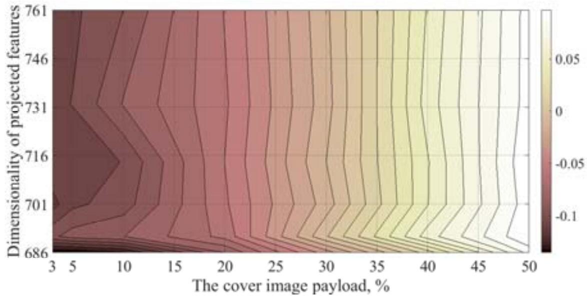


b

Figure 4 – The dependencies of Matthews correlation coeffi cient mean values on cover image payload for HUGO (a) and S-UNIWARD (b) embedding methods for the case F_α=0% on ALASKA dataset.



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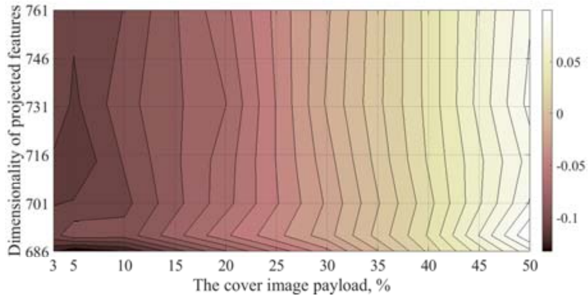

b

Figure 5 – The dependencies of Matthews correlation coefficient mean values on cover image payload for MG (a) and MiPOD (b) embedding methods for the case F_α=0% on ALASKA dataset.

In contrast to the previous case (Fig. 2–3), projection of SPAM-features into high-dimensional space allows improving values of *MCC* index (Fig. 4–5) even by negligible changes of inverse transformation matrix $\mathbf{T}_{inv}$ size. The biggest impact on *MCC* values was obtain for low (less than 10%) and medium (less than 20%) cover image payload – increasing dimensionality of used features allows increasing *MCC* index up to 0.04 for advanced MG (Fig. 5a) and MiPOD (Fig. 5b) embedding methods. On the other hand, changing of *MCC* for high cover image payload (more than 20%) by usage of inverse transformation matrix $\mathbf{T}_{inv}$ is much smaller ($\Delta MCC \le 2 \cdot 10^{-2}$).

6 DISCUSSION

Providing reliable detection of stego images formed according to advanced ASM requires utilization of huge ensembles of HPS [7]. This complicates tuning of stegdetectors due to necessity to time-consuming preselection of HPS for minimization detection errors. Proposed method of DR-calibration for analyzed images allows improving detection accuracy by search an appropriate transformation for increasing distance between clusters of estimated features for cover and stego images. In general case, the DR-calibration requires utilization of prior information about used embedding method for estimation mutual positions of these clusters. This makes such methods in appropriate candidates for real cases when steganalytics have limited or even no access to stego encoder.

Proposed DR-calibration method is based on inverse FJLT for estimations preimages of cover/stego statistical features from high-dimensional space. Usage of this method allows preserving similar detection accuracy for the case when steganalytics have full access to stego encoder (Fig. 2) and they can embed a payload for an arbi-

DOI 10.15588/1607-3274-2022-2-16

trary cover image. On the other hand, applying of inverse transformation matrix $\mathbf{T}_{inv}$ estimated by inverse FJLT allows improving detection accuracy ($\Delta MCC \leq 4 \cdot 10^{-2}$) in most difficult case of limited a prior information about used embedding method (Fig. 3) – the value F_α=0% (3) corresponds to the case of limited ability of steganalytics to form stego images for an arbitrary cover image.

Despite revealed effectiveness of applying of inverse FJLT, practical application of such method may require compute-intensive pre-processing step. This is connected with stochastic nature of transformation matrix $\mathbf{T}$ generation by FJLT [18] – the probability of successful generation (matrix T preserves mutual location of features clusters corresponds to cover/stego images) is at least 2/3. This is arisen from the features random projection by JLL and could be amplified to (1–δ) for any δ>0, if we repeat the construction O(log(1/ δ)) times [17].

Additional increasing of detection accuracy by usage of proposed approach can be achieved by preselection of generated inverse transformation matrix $\mathbf{T}_{inv}$ by the criterion of preserving same or increasing inter-distance between clusters of preimages for cover/stego images features. This can be achieved by corresponding increasing of procedure duration that may be critical for some applications, like fast re-tuning of SD.

Therefore, we may conclude that usage of proposed inverse FJLT allows improving detection accuracy for the most difficult cases of limited a prior information about embedding method (F_α=0%) and low cover image payload (less than 10%).

The future research directions may include comparative analysis of other methods for estimation features preimages in high-dimensional space, such as kernel principal component analysis (kernel-PCA) [30], multidimensional scaling [31], matrix completion scheme [32] to name a few. Also, it is represent the interest to estimate performance of proposed DR-calibration method in case of processing real digital images that characterized by high variability of statistical and spectral features.

CONCLUSIONS

The topical problem of improving accuracy for modern stegdetectors in case of processing stego images formed by adaptive embedding methods was considered. The case of applying special types of stego image calibration techniques was investigated.

The scientific novelty of obtained results is performance analysis of special types of digital image calibration, namely divergent reference methods. There is proposed to use inverse Fast Johnson-Lindenstrauss Transform that allows estimating preimages for image's feature from high-dimensional space for increasing Euclidean distances between features clusters correspond to cover/stego images. Proposed approach allows improving detection accuracy for novel embedding methods in the most difficult cases of limited a prior information about embedding method (F_α=0%) and low cover image payload (less than 10%). This allows improving performance of statistical stegdetectors for revealing stego images formed according to advanced embedding methods.

The practical significance of obtained experimental results is estimations of stego images detection error by usage of inverse FJLT. These results allow establishing achievable detection accuracy by usage of DR-based stego image calibration methods for state-of-the-art adaptive embedding methods HUGO, S-UNIWAR, MG and MiPOD.

Prospects for further research are to investigate effectiveness of special methods for features preimages estimation in high-dimensional space as well as performance analysis of DR-based stego image calibration methods by processing of real digital images that characterized by high variability of statistical features.

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Received 22.02.2022.
Accepted 20.03.2022.

УДК 004.056

ЕФЕКТИВНІСТЬ МЕТОДІВ ПОПЕРЕДНЬОЇ ОБРОБКИ СТЕГАНОГРАМ, ЗАСНОВАНИХ НА ВИЗНАЧЕННІ ПРООБРАЗУ ВЕКТОРІВ СТАТИСТИЧНИХ ПАРАМЕТРІВ ЗОБРАЖЕНЬ У ПРОСТОРІ ВИЩОЇ РОЗМІРНОСТІ

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АНОТАЦІЯ

Актуальність. Розглянуто актуальну проблему захисту конфіденційної інформації під час передачі даних у локальних та глобальних системах зв'язку. Досліджено випадок виявлення стеганограм, сформованих згідно новітніх адаптивних стеганографічних методів. Об'єктом дослідження є спеціальні методи обробки статистичних параметрів стеганограм, що використовуються для підвищення точності роботи сучасних статистичних стегодетекторів. Метою роботи є аналіз ефективності застосування спеціальних методів попередньої обробци цифрових зображень для підвищення точності виявлення стеганограм, сформованих з використанням адаптивних стеганографічних методів.

Метод. Розглянуто використання методів, спрямованих на збільшення евклідової відстані між векторами (статистичними параметрами) зображень-контейнерів та стеганограм шляхом визначення прообразів даних векторів з багатовимірних

DOI 10.15588/1607-3274-2022-2-16

просторів вищої розмірності. Для вирішення даної задачі запропоновано використовувати зворотнє перетворення Джонсона-Ліденштрауса. Запропонований метод дозволяє суттєво зменшити обчислювальну складність процедури попередньої обробки досліджуваних зображень при забезпеченні фіксованого рівня змін взаємного положення векторів, які відповідають зображенням-контейнерам та стеганограмам, що становить особливий інтерес при проведенні стегоаналізу.

Результати. Отримано залежності точності виявлення стеганограм, а саме коефіцієнта кореляції Метьюза, від ступеня заповнення зображення-контейнеру стегоданими при використанні запропонованого методу обробки зображень, а також формування стеганограм згідно новітніх стеганографічних методів HUGO, S-UNIWARD, MG та MiPOD. Визначено досяжні межі точності виявлення стеганограм при застосуванні запропонованого методу у найбільш складному випадку обмеженості апріорних даних щодо використаного стеганографічного методу.

Висновки. Результати проведених експериментальних досліджень підтвердили ефективність запропонованого підходу навіть у найбільш складному випадку проведення стегоаналізу, а саме обмеженості апріорних даних щодо використаного стеганографічного методу та низького ступеня заповнення зображення-контейнеру стегоданими (менше 10%). Подальший інтерес становить порівняльний аналіз ефективності використання спеціалізованих методів визначення прообразів векторів (статистичних параметрів) досліджуваних зображень з метою підвищення точності виявлення стеганограм, сформованих згідно новітніх стеганографічних методів.

КЛЮЧОВІ СЛОВА: стегоаналіз, цифрові зображення, адаптивні стеганографічні методи, методи попередньої обробки зображення, методи зменшення розмірності багатовимірних векторів.

УДК 004.056

ЭФФЕКТИВНОСТЬ МЕТОДОВ ПРЕДВАРИТЕЛЬНОЙ ОБРАБОТКИ СТЕГАНОГРАМ, ОСНОВАННЫХ НА ОПРЕДЕЛЕНИИ ПРООБРАЗОВ ВЕКТОРОВ СТАТИСТИЧЕСКИХ ПАРАМЕТРОВ ИЗОБРАЖЕНИЙ В ПРОСТРАНСТВЕ ВЫСШЕЙ РАЗМЕРНОСТИ

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АННОТАЦИЯ

Актуальность. Рассмотрена актуальная проблема защиты конфиденциальной информации при передаче данных в локальных и глобальных системах связи. Исследован случай обнаружения стеганограмм, сформированных согласно новейшим адаптивным стеганографическим методам. Объектом исследования являются специальные методы обработки статистических параметров стеганограмм, направленные на повышение точности работы современных стегодетекторов. Целью работы является анализ эффективности применения специальных методов предварительной обработки цифровых изображений для повышения точности обнаружения стеганограмм, сформированных с использованием адаптивных стеганографических методов.

Метод. Рассмотрено использование методов, направленных на увеличение евклидового расстояния между векторами (статистическими параметрами) изображений-контейнеров и стеганограмм, путем определения прообразов данных векторов из пространств более высокой размерности. Для решения данной задачи предложено использовать обратное преобразование Джонсона-Линденштрауса. Предложенный метод позволяет существенно уменьшить вычислительную сложность процедуры предварительной обработки исследуемых изображений при обеспечении фиксированного уровня изменений взаимного положения векторов, соответствующих изображениям-контейнерам и стеганограммам, что представляет особый интерес при проведении стегоанализа.

Результаты. Получены зависимости точности обнаружения стеганограмм, а именно коэффициента корреляции Мэтьюса, от степени заполнения изображения-контейнера стегодаными при использовании предложенного метода обработки изображений, а также формирования стеганограмм согласно новейшим стеганографическим методам HUGO, S-UNIWARD, MG и MiPOD. Определены достижимые границы точности обнаружения стеганограмм при применении предлагаемого метода в наиболее сложном случае ограниченности априорных данных относительно использованного стеганографического метода.

Выводы. Результаты проведенных экспериментальных исследований подтвердили эффективность предлагаемого подхода даже в наиболее сложном случае проведения стегоанализа, а именно ограниченности априорных данных относительного использованного стеганографического метода и низкой степени заполнения изображения-контейнера стегоданными (менее 10%). Дальнейший интерес представляет сравнительный анализ эффективности применения специализированных методов определения прообразов векторов (статистических параметров) изучаемых изображений с целью повышения точности обнаружения стеганограмм, сформированных согласно новейшим стеганографическим методам.

КЛЮЧЕВЫЕ СЛОВА: стегоанализ, цифровые изображения, адаптивные стеганографические методы, методы предварительной обработки изображения, методы уменьшения размерности многомерных векторов.

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DOI 10.15588/1607-3274-2022-2-16