DOI: https://doi.org/10.15276/aait.03.2021.5
UDC 004[056.5+932.2]

Effectiveness of stego images pre-noising with fractional noise for digital image steganalysis

Dmytro O. Progonov
ORCID: https://orcid.org/0000-0002-1124-1497; progonov@gmail.com
National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", 37, Peremogy Ave. Kyiv, 03056, Ukraine

ABSTRACT

Counteraction to sensitive data leakage in cyber-physical systems is topical task today. Solving of the task is complicated to widely usage by attackers of novel steganographic methods for sensitive data embedding into innocuous (cover) files, such as digital images. Feature of these embedding methods is minimization of cover image's parameters alterations during message hiding. This negatively affects detection accuracy of formed stego images by state-of-the-art statistical stegdetectors. Therefore, advanced methods for detection and amplification of cover image's parameters abnormal changes caused by data embedding are needed. The novel approach for solving of mentioned task is applying of image pre-processing (calibration) methods. These methods are aimed at estimation parameters either of cover, or stego images from current analysed image. The majority of known calibration methods are based on cover image content suppression by utilization of extensive set of high-pass filters. This makes possible close to state-of-the-art detection accuracy by the cost of time consuming preselection of appropriate filters. Therefore, this approach may be inappropriate in real cases, when fast re-train stegdetector for revealing of stego images formed by unknown embedding methods is required. For overcoming this limitation, we proposed to calibrate an image by amplification of alterations caused by message hiding. This can be realized by data re-embedding into images or their pre-noising. The effectiveness of such approach was proved for wide range of modern embedding methods in the case of message re-embedding. The paper is aimed at performance analysis of image calibration by pre-noising, namely by using of non-stationary fraction noise. The performance analysis of proposed solution was performed for novel HUGO and MG adaptive embedding methods on standard VISION dataset. According to obtained results, we may conclude that applying of proposed solution allows achieving close to state-of-the-art detection accuracy for HUGO embedding method and low (less than 10 %) cover image payload. Also, low computation complexity of proposed solution makes it an attractive alternative to novel cover rich models based stegdetectors. Nevertheless, solution's performance concedes effectiveness of novel stegdetectors for medium (less than 20 %) and high (more 25 %) cover image payload for MG embedding method.

Keywords: Digital image; steganalysis; statistical stegdetectors; fractional noise

***For citation*: Progonov D. O. Effectiveness of stego images pre-noising with fractional noise for digital image steganalysis. *Applied Aspects of Information Technology*. 2021; Vol.4 No.3: 261–270. DOI: https://doi.org/10.15276/aait.03.2021.5**

INTRODUCTION

Protection of critical information infrastructure became topical task in last years. Special interest is taken on improving security of cyber-physical systems (CPS) involved in processing of sensitive data [1]. Widespread usage of global communication systems for data exchanging between CPS creates new threats for sensitive data protection, such as unauthorized transmission using covert channels.

Modern methods for covert (steganographic) communication are aimed at message embedding into innocuous (cover) files, such as digital images (DI), by preserving low level of cover's features alteration [2, 3]. Detection of formed stego images requires usage of either statistical models [4], or convolutional neural networks [5, 6]. Despite high detection accuracy, excessive computation-complexity makes these approaches inappropriate for practical usage, especially in case of detection unknown embedding methods. Therefore, development of advanced steganalysis methods capable to reliably detection of stego images even under limited prior information about used embedding method is topical task.

One of promising approaches for solving mentioned task is DI pre-processing (calibration) for emphasizing weak alterations caused by message hiding [7]. This allows increasing stego-to-cover ratio that improves overall performance of stegdetectors (SD). Nevertheless, search of effective methods for DI calibration under condition of limited a prior knowledge about used embedding methods remains open problem.

The work is aimed at performance analysis of special type of DI calibration, based on image pre-noising with fractional noise for emphasizing weak alterations of cover images (CI).

RELATED WORKS

Feature of modern advanced embedding methods (AEM) is minimal alteration of CI statistical parameters as well as perceptual quality during message hiding [2, 3]. This leads to considerable reducing of CI features changes that negatively impact on performance of modern SD.

For overcoming this limitation of known SD, it was proposed to include additional pre-processing step (calibration) during DI analysis by stegdetector. The calibration is aimed at increasing stego-to-cover ratio that can be achieved by estimations parameters of either cover, or stego images [8].

The first approach is aimed at estimation of CI parameters from current (noised) image with usage of DI statistical models, such as Markov Random Fields, multiscale models etc. The well-known example of such approach usage is SRM models [9]. These models are based on CI context suppression by extensive set of high-pass filters. This allows drastically improving detection accuracy for wide range of modern embedding methods, such as HUGO [10], UNIWARD [11] etc., by the cost of time-consuming selection of an appropriate filter.

The second approach to DI calibration is based on measuring the expected level of CI distortions by message hiding according to known embedding method. In practice, this approach may be implemented by message re-embedding into DI or image pre-noising. The effectiveness of such approach was shown in the works [12, 13], by usage of either known embedding methods, or widespread types of DI noises (thermal and shot noises).

The message re-embedding approach relies on utilization prior information about embedding procedure that may be unrealistic cases for real steganalysis scenarios. The DI pre-noising approach does not require information about used embedding method that makes such approach a promising candidate for increasing performance of modern SD.

Nevertheless, modern methods for DI calibration via pre-noising include only widespread thermal and shot noises for modelling possible image alteration during in-camera processing. Therefore, device and environment dependent effects, such as dispersion of noise parameters, are not included into used model. The paper is aimed at filling this gap by performance analysis of usage the fractional noises for pre-processing of stego image formed according to AEM.

THE SCOPE OF THE RESEARCH

The paper is aimed at performance analysis of digital image calibration by preliminary noising with fractional noises for revealing stego images formed according to AEM.

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

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

2) to review models of fractional noise generation with specified parameters;

3) to analyse detection accuracy of stego image revealing with usage of proposed pre-noising approach;

4) 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 increasing stego-to-cover ratio to be used in steganalysis of advanced AEM.

NOTATIONS

The calligraphic font is used for sets and collections, while vectors or matrices are always in boldface. During investigation, 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 binary message $\mathbf{M}$ with K bits length.

ADAPTIVE EMBEDDING METHODS FOR DIGITAL IMAGES

The feature of AEM is minimization of total cost of cover image $\mathbf{X}$ distortion during message $\mathbf{M}$ hiding [14]:

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

where $\rho(\cdot)$ – cost function of cover image pixel parameters distortions by embedding of a single bit.

Ideally, function $\rho(\cdot)$ in (1) can estimate both CI alteration caused by single bit embedding, and non-linear interaction between these changes [14]. The former one can be performed with usage of widespread statistical models of CI [2]. The latter one requires time-consuming analysis of pixels changes combinations that becomes intractable even for short messages $\mathbf{M}$ (about 100 bits) [14]. Therefore, the simplified function $\rho(\cdot)$ that estimates only CI distortions caused by a single bit hiding is used in most real cases.

Frequently, the selection of pixels to be used during message embedding (1) is performed by heuristic rules that assess noise level in a local neighborhood of $(i,j)^{th}$ pixel [14]. This allows achieving state-of-the-art empirical security of formed stego images while preserving low computational complexity of cost $\rho(\cdot)$ estimation.

The paper is aimed at analysis of state-of-the-art HUGO [10] and MG [15] embedding methods.

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

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

where: $\mathbf{Y}$ – a stego image sampled from the set of all stego images Υ;

ISSN 2617-4316 (Print)
ISSN 2663-7723 (Online)

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 numerical solving of eq. (2) by using adjacency matrix $\mathbf{C}_{kl}(\mathbf{X})$ for estimation of CI distortions during message hiding:

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

where: $\Im = \{0,1,...,2^k-1\}$ – brightness range of cover and stego image with k-bits color depth;

$C = \{\rightarrow,\leftarrow,\uparrow,\downarrow\}$ – 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]:

$$\mathbf{H}^{\rightarrow}_{(k,l)}(\mathbf{X},\mathbf{Y}) = (N\cdot(M-2))^{-1}\cdot \\ \cdot\sum_{i,j}\left|\left[\left(\mathbf{D}^{\rightarrow}_{i,j},\mathbf{D}^{\rightarrow}_{i,j+1}\right)(\mathbf{Y})=(k,l)\right]_I - \\ -\left[\left(\mathbf{D}^{\rightarrow}_{i,j},\mathbf{D}^{\rightarrow}_{i,j+1}\right)(\mathbf{X})=(k,l)\right]_I\right|, \\ \left(\mathbf{D}^{\rightarrow}_{i,j},\mathbf{D}^{\rightarrow}_{i,j+1}\right)(\mathbf{X})=(k,l)\Leftrightarrow \\ \Leftrightarrow\left(\mathbf{D}^{\rightarrow}_{i,j}(\mathbf{X})=k\right)\wedge\left(\mathbf{D}^{\rightarrow}_{i,j+1}(\mathbf{X})=l\right). \tag{3}$$

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

In contrast to HUGO method, the MG embedding methods is aimed at minimization both CI distortion and statistical detectability of formed stego image [15]. It is achieved by usage of locally-estimated multivariate Gaussian model of CI noises. The model allows deriving the closed-form expression of SD performance as well as capturing the non-stationary character of natural images [15].

The stego image creation pipeline for MG methods consists of several steps [15].

Firstly, image context is suppressed using denoising filter F_{dn}:

$$\mathbf{r} = \mathbf{X} - F_{dn}(\mathbf{X}).$$

Secondly, the variance σ_l^2 of obtained residuals **r** is measured with linear model:

$$\mathbf{r}_l = \mathbf{G}\mathbf{a}_l + \xi, l\in[1;M\cdot N].$$

For MG method the simplified estimation of variance σ_l^2 is used [15]:

$$\sigma_l^2 = \left\|\mathbf{r}_l - \mathbf{G}\left(\mathbf{G}^T\mathbf{G}\right)^{-1}\mathbf{G}^T\mathbf{r}_l\right\| \Big/ \left(p^2-q\right), q\in\mathrm{N}.$$

where $\mathbf{r}_l$ – residuals evaluated within $p\cdot p$ block surrounding the l^{th} pixel of CI.

Thirdly, embedding changes β_l, $l\in[1; M\cdot N]$ that minimizes deflection coefficient ζ^2, is estimated:

$$\zeta^2(\beta_l) = 2\sum_{l=1}^{M\cdot N}\beta_l^2\sigma_l^{-4} \xrightarrow{\sum_{l=1}^{M\cdot N} H_4(\beta_l)=const} \min, \\ H_4(z) = -2z\log(z) - (1-2z)\log(1-2z). \tag{4}$$

The deflection coefficient ζ^2 (4) is used as a measure of divergence between cover and stego images distributions [15].

The optimization problem (4) can be solved using Lagrange multiplier method [15]. Then, change rate β_l and Lagrange multiplier λ_L can be determined by numerical solving of next equations [15]:

$$\beta_l^2\sigma_l^{-4} = \frac{1}{2\lambda_L}\ln\left(\frac{1-2\beta_l}{\beta_l}\right), l\in[1;M\cdot N].$$

Then, estimated β_l is converted to corresponding cost ρ_l of stego bit hiding in l^{th} pixel of CI:

$$\rho_l = -\ln(\beta_l - 2). \tag{5}$$

Finally, a message **M** is embedded into CI using syndrome-trellis codes with pixel costs determined according to eq. (5).

The locally-estimated multivariate Gaussian model allows accurately measuring local distortions of CI caused by message hiding [15]. This makes possible achieving state-of-the-art empirical security of formed stego images without taking compute-intensive statistical models.

MODERN METHODS OF DIGITAL IMAGES STEGANALYSIS

Modern paradigm in digital image steganalysis is usage of image pre-processing with extensive set of high-pass filters and further statistical parameters extraction from obtained residuals [9]. This approach shown outstanding result for detection of stego images formed according to both widespread and advanced EM. On the other hand, necessity of time-consuming pre-selection of appropriate high-pass filters limits fast adaptation of already trained SD to revealing of unknown embedding methods. Also, such pre-selection requires a priori information about features of EM that may by unavailable in real situations. Therefore, the topical task is development of advanced calibration techniques that is able to preserve high detection accuracy even under limited a priori information about embedding process.

For solving mentioned task, it is proposed to increase stego-to-cover ratio by amplification of negligible changes of CI. In most cases, these changes are noise-like that allows using pre-noising methods for image calibration. In the work [13], the effectiveness of such approach was shown by usage of Gaussian and Poisson noises that models thermal and shot noises of natural images.

Further feature extraction from pre-processed images may be performed using well-known SPAM model [16]. The model allows estimating correlation features of calibrated DI without any additional processing. Let us describe this model in details.

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 [16]:

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

The first-order SPAM features F_1 are used for modeling array **D** with first-order Markov process [16]. For the considered example, it leads to:

$$\mathbf{M}^{\rightarrow}_{u,v} = \Pr\left(\mathbf{D}^{\rightarrow}_{i,j+1} = u \mid \mathbf{D}^{\rightarrow}_{i,j} = v\right), \qquad (6)$$
$$u,v \in [-T;T], T \in \mathrm{N}.$$

If probability $\Pr\left(\mathbf{D}^{\rightarrow}_{i,j} = v\right)$ is equal to zero, then $\mathbf{M}^{\rightarrow}_{u,v} = 0$ as well.

The second-order SPAM features F_2 are taken for modeling difference array **D** with second-order Markov process [17]. Similarly to eq. (6), we obtain:

$$\mathbf{M}^{\rightarrow}_{u,v,w} = \Pr\left(\mathbf{D}^{\rightarrow}_{i,j+2} = u \mid \mathbf{D}^{\rightarrow}_{i,j+1} = v, \mathbf{D}^{\rightarrow}_{i,j} = w\right), \qquad (7)$$
$$u,v,w \in [-T;T], T \in \mathrm{N}.$$

Similarly to F_1 features, $\mathbf{M}^{\rightarrow}_{u,v,w}$ is equal to zero if $\Pr\left(\mathbf{D}^{\rightarrow}_{i,j+1} = v, \mathbf{D}^{\rightarrow}_{i,j} = w\right) = 0$.

Both features F_1 and F_2 for other scanning directions, namely $c \in \{\leftarrow,\uparrow,\rightarrow,\downarrow\}$, can be estimated in the same way to eq. (6)-(7).

For decreasing dimensionality of SPAM-features, the assumption that statistics in natural images are symmetric with respect to mirroring and flipping [16] is used. Thus, we can separately averaging matrices for horizontal, vertical and diagonal directions to form the final features:

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

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

IMAGE CALIBRATION VIA PRE-NOISING

The wide range of modern image denoising approaches utilizes the standard assumption about influence of thermal and shot noises during in-camera image processing [17]. They correspond to stationary stochastic processes that can be accurately modeling using well-known Gaussian and Poisson distributions. This allows using methods from statistical analysis, namely Wiener filters, for effectively suppression such kind of noises.

On the other hand, mentioned assumption does not cover cases of influence the non-white (Gaussian) noises during in-camera processing. Such noises may rise due to fluctuating occupancies of traps in semiconductors, namely pixels cells [18]. This leads to appearance of "colored" or fractional noises which power spectrum concentrates over specific frequency range:

$$S(\mathbf{U}) \propto 1/f^{\beta_f},$$

where: **U** – inputted grayscale image;
$\beta_f \in (0;2)$ – frequency scaler.

The case of β_f=0 corresponds to white Gaussian noise, while β_f =2 relates to Brownian noise. In most cases β_f =1 is used that corresponds to pink noise.

Practically, mentioned fractional noise may be modelled using Perlin method [19], namely pre-generated white Gaussian noise and further applying of $1/f^{\alpha}$ filter to its Fourier spectrum. This allows fast generation of multidimensional fractional noise with predefined scaler parameter α.

Message hiding to cover image leads to introducing of non-stationary noises. These noises may be approximated by well-known Gaussian or Poisson distribution [13]. Nevertheless, it is represent the interest to apply the fractional noises for improving accuracy of cover alterations caused by message hiding.

EXPERIMENTS

Performance analysis of statistical SD by image noising was performed on VISION 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 HUGO and MG methods was considered. The CI payload Δ_p was changed in range – 3 %, 5 %, 10 %, 20 %, 30 %, 40 %, 50 %.

The SD includes Random Forest classifier [21] trained with second-order SPAM model [16].

Practical application of SPAM-features requires theirs pre-processing before using in a classifier.

The modern methods of feature pre-processing for DI steganalysis can be divided into next groups [8, 12]:

1. Non-calibrated features – corresponds to the case of feature extraction from unprocessed image:

$$\mathbf{F}_{nc} = F_e(\mathbf{U}). \quad (8)$$

2. Features of calibrated image – corresponds to features obtained after image noising:

$$\mathbf{F}_{noise} = F_e(C(\mathbf{U})). \quad (9)$$

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

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

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

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

Today, non-calibrated features (8) are rarely used due to theirs negligible differences for cover and stego images [2]. On the other hand, Cartesian calibrated features (11) are widely used for SD performance improving since they preserve features for both initial and calibrated DI [9]. The calibrated (9) and linearly transformed (10) features do not get much attention today [12]. Therefore, performance analysis of stegdetector by usage of these features takes special interest.

Along with type of features used for SD training, stegdetectors performance significantly depends on fraction F_α of pairs of cover-stego images features utilized by training stage [22]:

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

where: 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% (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 real situation when steganalytics do not have access to stego encoder and may use only captured 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 fractional noise was generated using known Perlin method [19]. The scaler parameter β_f was varied from 0.25 to 1.00 with step 0.25. The amplitude A_n of generated fractional noise was rescaled to one (A_n=1) or two (A_n=2) brightness level that corresponds to distortions caused by message embedding.

The SD was tested according to cross-validation procedure by minimization of detection error P_e [21]. The dataset was divided 10 times into training (50 %) and testing (50 %) sub-sets during cross-validation.

Performance analysis of proposed stego image calibration methods was done in several stages. At the first stage, it was compared detection accuracy of stego images by using of considered SPAM as well as state-of-the-art maxSRMd2 statistical models. The dependency of detection error P_e on cover image payload by stego images generation according to HUGO and MG embedding methods and variation of F_α are presented at Fig. 1.

It should be noted considerable decreasing of error P_e by usage of nodel maxSRMd2 model (Fig. 1) – the improving of detection accuracy varies from 15 % for F_α=100 % to 7 % for F_α=0 %. The most influence of this decreasing has only single EDGE filter of maxSRMd2 model, while other filters have negligible influence on achieved detection accuracy.

As it was mentioned, the case of F_α=100% corresponds to the situation when steganalytic has full access to stego encoder. This case is quite unrealistic in real situations, especially when attackers apply (previously) unknown embedding methods. Therefore, we paid special attention to the case of F_α = 0 %, when steganalytic was able to include stego images generated for unknown CI.

On the second stage, we considered performance of SD by pre-noising with fractional noise a stego image generated by HUGO embedding method. The relative detection accuracy indicator P_Δ was used for estimating difference of P_e error for initial (processing of non-calibrated images) and considered cases:

$$P_\Delta = P_e^{SPAM} - P_e^{calib}.$$

Positive values of the P_Δ index correspond to the case, when applying of proposed approach (image pre-noising) allows improving detection accuracy. The negative ones relates to the case of decreasing SD performance in comparison with initial (non-calibrated) case.

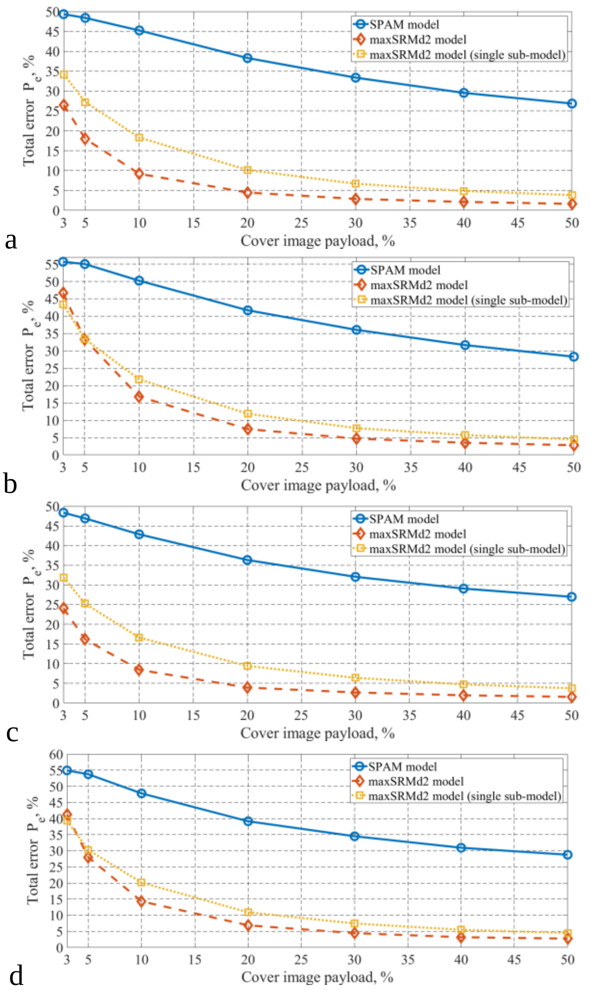

Fig. 1. **The dependency of detection error P_e on cover image payload for stego images generated by:**
a – HUGO (F_a=0%); b – a – HUGO (F_a=1000%); c – MG (F_a=0%); d – a – MG (F_a=1000 %) embedding methods
Source: **compiled by the author**

The dependency of detection error P_e on cover image payload by stego images generation according to HUGO embedding methods and image pre-noising with fractional noise with amplitude A_n=1 are presented at Fig. 2.

It should be noted that images pre-noising allows reduce detection error up to 4 % for the most difficult case – the low cover image payload (less than 10 %, Fig. 2). This makes proposed approach comparable with effectiveness of more computation-intensive sub-model of maxSRMd2 model (Fig.1b). Further increasing of cover image payload leads to considerable decreasing of detection accuracy (up to 8 %, Fig 2) that negatively impact on effectiveness of proposed approach.

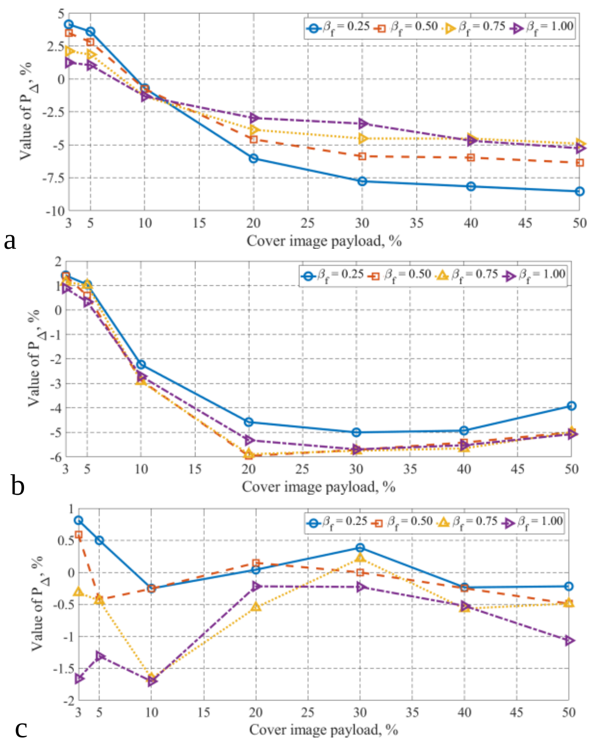

Fig. 2. **The dependency of detection error P_e on cover image payload by pre-noising (A_n=1) of stego images generated by HUGO method and usage of $\mathbf{F}_{noise}$ (a), $\mathbf{F}_{DF}$ (b) and $\mathbf{F}_{CC}$ (c) features**
Source: **compiled by the author**

The biggest "gain" of detection accuracy is achieved by usage of $\mathbf{F}_{noise}$ (up to 4 %) and $\mathbf{F}_{DF}$ (up to 1.5 %) features, while Cartesian calibrated features $\mathbf{F}_{CC}$ do not allow considerably improving detection accuracy. Also, increasing of fractional noise scaler β_f leads to decreasing of efficiency of proposed approach – this can be explained that added distortion is transformed from Gaussian noise to pink noise which energy is more localized in frequency subband.

For comparison, it was considered the case of increasing amplitude of adding noise from A_n=1 or A_n=2. The dependency of detection error P_e on cover image payload by stego images generation according to HUGO embedding methods and image pre-noising with fractional noise with amplitude A_n=2 are presented at Fig. 3.

Increasing of added noise's amplitude A_n allows additionally improving detection accuracy up to 1 % for $\mathbf{F}_{noise}$ features (Fig. 3a) and 0.5 % for $\mathbf{F}_{CC}$ features (Fig. 3c) in the case of low cover image payload (less than 10 %). On the other hand, increasing of noise's amplitude leads to corresponding increasing of detection error for the middle (less than 20 %) and high (more 25 %) cover image payload for all considered types of features (Fig. 3).

ISSN 2617-4316 (Print)
ISSN 2663-7723 (Online)

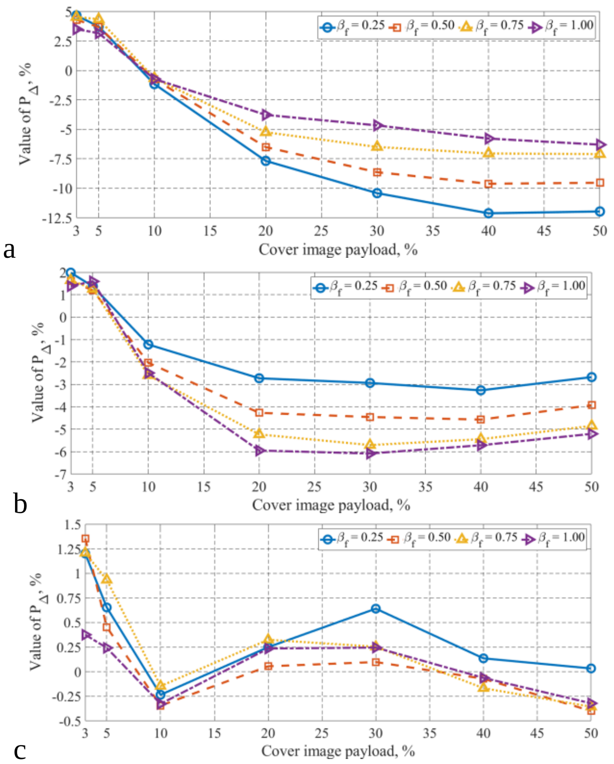

Fig. 3. **The dependency of detection error P_e on cover image payload by pre-noising (A_n=2) of stego images generated by HUGO method and usage of $\mathbf{F}_{noise}$ (a), $\mathbf{F}_{DF}$ (b) and $\mathbf{F}_{CC}$ (c) features**
Source: **compiled by the author**

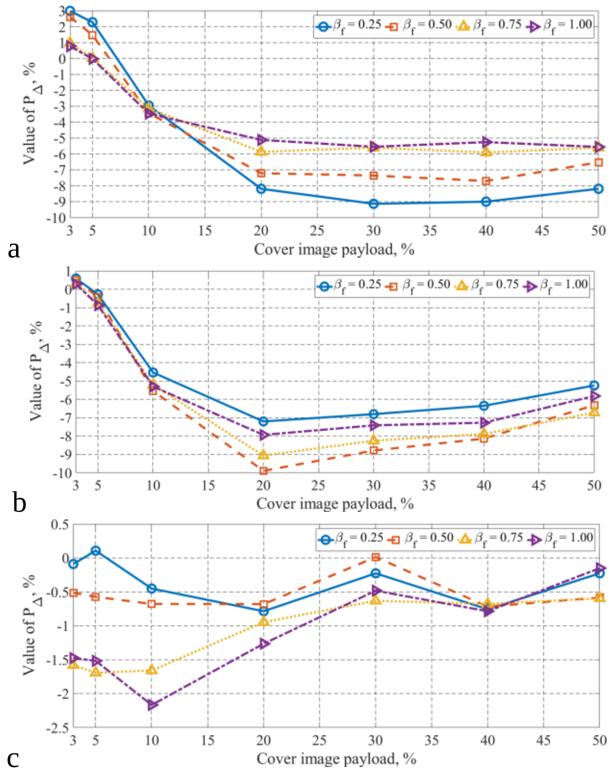

Fig. 4. **The dependency of detection error P_e on cover image payload by pre-noising (A_n=1) of stego images generated by MG method and usage of $\mathbf{F}_{noise}$ (a), $\mathbf{F}_{DF}$ (b) and $\mathbf{F}_{CC}$ (c) features**
Source: **compiled by the author**

On the third stage, we considered performance of SD by pre-noising with fractional noise a stego image generated by advanced MG embedding method. The dependency of detection error P_e on cover image payload by stego images generation according to MG embedding methods and image pre-noising with fractional noise with amplitude A_n=1 are presented at Fig. 4.

Applying of fractional noise for calibration of stego images formed according to MG method (Fig. 4) leads to similar results obtained for HUGO method (Fig. 2) – increasing of detection accuracy for low cover image payload range. Nevertheless, obtained "gain" of detection accuracy for MG method is smaller than for HUGO one – up to 3 % for $\mathbf{F}_{noise}$ features and about 0.5% for $\mathbf{F}_{DF}$ features. Usage of Cartesian calibrated features $\mathbf{F}_{CC}$ does not allow considerably improving detection accuracy (Fig. 4c).

As it was for HUGO method (Fig. 2), increasing of frequency scaler β_f leads to decreasing of efficiency of proposed approach for MG method (Fig. 4) that may be explained by moving to "bandpass" pink noise instead of "widepass" Gaussian one.

For comparison, the case of usage the noise's amplitude A_n=2 was considered for MG embedding method. The dependency of detection error P_e on cover image payload by stego images generation according to MG embedding methods and image pre-noising with fractional noise with amplitude A_n=2 are presented at Fig. 5.

Usage of amplified fractional noise (Fig. 5) allows negligibly improving detection accuracy in comparison with previous case (Fig. 4). Nevertheless, obtained "gain" does not exceed 1 % that considerably less than results obtained for sub-model of modern maxSRMd2 model (Fig. 1).

DISCUSSIONS

Obtained results of detection accuracy for stego images formed according to state-of-the-art adaptive embedding methods proved effectiveness of image pre-noising with fractional, Gaussian and Poisson noises digital image calibration [13]. The Gaussian and Poisson noises were generated according to recommendation of work [13], e.g. by estimations of theirs parameters with sliding windows of size 3·3 pixels.

The comparison of detection accuracy changes by usage of considered models and embedding methods are given in Table.

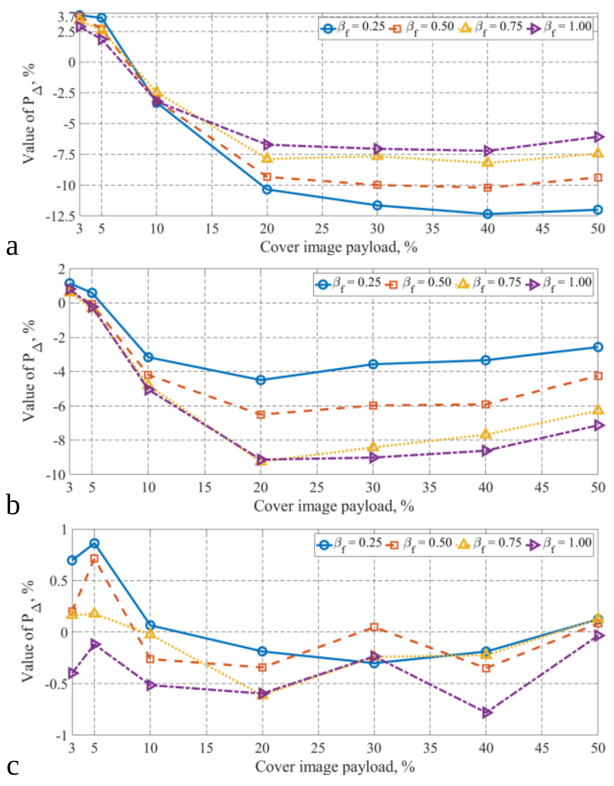

Fig. 5. **The dependency of detection error P_e on cover image payload by pre-noising (A_n=2) of stego images generated by MG method and usage of $\mathbf{F}_{noise}$ (a), $\mathbf{F}_{DF}$ (b) and $\mathbf{F}_{CC}$ (c) features**

Source: **compiled by the author**

Detection accuracy improvement for HUGO embedding method by image pre-noising is less than by usage of image pre-filtering by EDGE filters of maxSRMd2 model (Table). Among considered types of noises, the biggest improvement is achieved by usage of Gaussian noise for low cover image payload (up to 5 %), while for middle and high payload fractional noise allows obtaining less values of detection error.

For MG embedding methods, we obtained the similar results – usage of image pre-filtering allows considerably improve detection accuracy in comparison with pre-noising case (Table). The Poisson noise allows achieving smaller detection error levels for low cover image payload, while for middle and high payload better results are obtained for fractional noise.

It should be noted that applying of $\mathbf{F}_{noise}$ features allows considerably improve detection accuracy in all considered cases for image pre-noising in comparison with $\mathbf{F}_{DF}$ and $\mathbf{F}_{CC}$ features (Table). This can be explained by increasing cross-distance between SPAM features of cover and stego images after pre-noising, despite absolute values of such difference is small.

Table. **The P_Δ values for stegdetector by cover and stego images pre-noised with fractional (β_f=0.25), Gaussian and Poisson noises by F_a=0 %**

Stego images detection method		Cover image payload					
		Δ_P=5 %		Δ_P=20 %		Δ_P=50 %	
		mean	std	mean	std	mean	std
HUGO embedding method							
SPAM model		0.00	0.00	0.00	0.00	0.00	0.00
maxSRMd2 model, EDGE sub-model		12.22	1.63	29.81	0.28	23.83	0.21
Fract. noise (A_n=1)	$\mathbf{F}_{noise}$	4.14	0.43	-6.04	0.38	-8.54	0.37
	$\mathbf{F}_{DF}$	1.40	0.37	-4.58	0.45	-3.92	0.45
	$\mathbf{F}_{CC}$	0.81	0.71	0.04	0.43	-0.22	0.49
Fract. noise (A_n=2)	$\mathbf{F}_{noise}$	4.66	0.37	-7.67	0.33	-12.0	0.35
	$\mathbf{F}_{DF}$	1.98	0.63	-2.72	0.33	-2.68	0.43
	$\mathbf{F}_{CC}$	1.20	0.53	0.25	0.50	0.03	0.40
Gauss. noise	$\mathbf{F}_{noise}$	4.99	0.58	-8.86	0.51	-22.2	0.37
	$\mathbf{F}_{DF}$	1.18	0.78	0.36	0.39	-0.16	0.60
	$\mathbf{F}_{CC}$	1.70	0.99	0.41	0.48	0.13	0.50
Poisson noise	$\mathbf{F}_{noise}$	4.35	0.36	-10.8	0.35	-21.6	0.47
	$\mathbf{F}_{DF}$	0.48	0.42	-2.08	0.43	0.19	0.42
	$\mathbf{F}_{CC}$	0.67	0.97	-1.97	0.58	0.59	0.34
MG embedding method							
SPAM model		0.00	0.00	0.00	0.00	0.00	0.00
maxSRMd2 model, EDGE sub-model		15.65	1.14	28.23	0.46	24.28	0.15
Fract. noise (A_n=1)	$\mathbf{F}_{noise}$	2.98	0.39	-8.19	0.61	-8.19	0.50
	$\mathbf{F}_{DF}$	0.58	0.50	-7.21	0.76	-5.25	0.75
	$\mathbf{F}_{CC}$	-0.09	0.59	-0.79	0.52	-0.23	0.66
Fract. noise (A_n=2)	$\mathbf{F}_{noise}$	3.80	0.40	-10.4	0.42	-12.0	0.59
	$\mathbf{F}_{DF}$	1.14	0.53	-4.50	0.40	-2.58	0.32
	$\mathbf{F}_{CC}$	0.69	0.47	-0.19	0.41	0.12	0.54
Gauss. noise	$\mathbf{F}_{noise}$	4.49	0.44	-11.8	0.55	-22.0	0.54
	$\mathbf{F}_{DF}$	0.52	0.48	0.31	0.51	0.43	0.31
	$\mathbf{F}_{CC}$	0.85	0.71	-0.33	0.52	0.65	0.42
Poisson noise	$\mathbf{F}_{noise}$	4.90	0.52	-11.1	0.52	-21.5	0.39
	$\mathbf{F}_{DF}$	0.62	0.50	-0.06	0.42	0.06	0.60
	$\mathbf{F}_{CC}$	0.91	0.37	0.07	0.30	0.56	0.50

Source: **compiled by the author**

CONCLUSION

The paper is devoted to performance analysis of image calibration method based on pre-noising with fractional noise. The case of pre-processing stego images obtained for novel HUGO and MG adaptive embedding method is considered.

According to obtained results, we may conclude that image pre-noising with fractional noise allows achieving detection accuracy that is comparable with maxSRMd2 model results in the case of low (less than 10 %) cover image payload for HUGO embedding method. Proposed approach for middle (less than 20 %) and high (more 25 %) cover image payload is much less effective in comparison with considered state-of-the-art statistical model.

On the other hand, applying of proposed approach for MG embedding methods does not allow improving detection accuracy in comparison with state-of-the-art methods.

ISSN 2617-4316 (Print)
ISSN 2663-7723 (Online)

REFERENCES

1. Yaacoub, J.-P. A., Salman, O., Noura, H. N., Kaaniche, N., Chehab, A. & Malli, M. "Cyber-physical Systems Security: Limitations, Issues and Future Trends". *Microprocessors and Microsystems*. 2020; Vol. 77. DOI: https://doi.org/10.1016/j.micpro.2020.103201.

2. Fridrich, J. "Steganography in Digital Media: Principles, Algorithms, and Applications". Cambridge: *Cambridge University Press.* ISBN 978–0–521–19019–0. 2009. 437 p. DOI: https://doi.org/10.1017/CBO9781139192903.

3. Konachovych, G., Progonov, D. & Puzyrenko, O. "Digital Steganography Processing and Analysis of Multimedia Files". "Tsentr Uchbovoi Literatury" publishing (in Ukrainian). ISBN 978-617-673-741-4. Kyiv: Ukraine. 2018. 558 p.

4. Denemark, T., Sedighi, V., Holub, V., Cogranne, R. & Fridrich, J. "Selection-Channel-Aware Rich Model for Steganalysis of Digital Images". *IEEE Int. Workshop Inf. Forensics Secur.* Atlanta: USA. 2014. DOI: https://doi.org/10.1109/WIFS.2014.7084302.

5. Boroumand, M., Chen, M. & Fridrich, J. "Deep Residual Network for Steganalysis of Digital Images". *IEEE Trans. Inf. Forensics Secur.* 2018; Vol. 14 Issue 5: 1181–1193. DOI: https://doi.org/10.1109/TIFS.2018.2871749.

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*. ISBN 978-952-60-3250-4. 2010. 19 p.

8. Kodovsky, J. & Fridrich, J. "Calibration Revisited". *Multimedia and Security: 11th ACM workshop.* Princeton: USA. 2009. p. 63–74. DOI: https://doi.org/10.1145/1597817.1597830.

9. 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.

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. 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.

12. Progonov, D. & Lucenko, V. "Steganalysis of Adaptive Embedding Methods by Message Re-Embedding into Stego Images". *Information Theories and Applications*. 2020; Vol. 27 Issue 4: 3–24.

13. Progonov, D. O. "Influence of Digital Images Preliminary Noising on Statistical Stegdetectors Performance". *Radio Electronics, Computer Science, Control*. 2021; Vol. 1(56): 184–193.

14. 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.

15. Sedighi, V., Fridrich, J. & Cogranne, R. "Content-Adaptive Pentary Steganography Using the Multivariate Generalized Gaussian Cover Model". *Electronic Imaging, Media Watermarking, Security and Forensics.* San Francisco: USA. 2015. DOI: https://doi.org/10.1117/12.2080272.

16. 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.

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

18. Weissman, M. B. "1/f Noise and Other Slow, Nonexponential Kinetics in Condensed Matter". *Reviews of Modern Physics.* 1988; Vol. 60 Issue 2: 537–571. DOI: https://doi.org/10.1103/RevModPhys.60.537.

19. Perlin, K. "An Image Synthesizer". *Computer Graphics.* 1985; Vol. 19 (3): 287–296.

20. Shullani, D., Fontani, M., Iuliani, M., Al Shaya, O. & Piva, A. "VISION: a Video and Image Dataset for Source Identification". *Eurasip J. Inf. Secur.* 2017; Vol. 15. DOI: https://doi.org/10.1186/s13635-017-0067-2.

21. 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.

22. Progonov, D. "Performance of Statistical Stegdetectors in Case of Small Number of Stego Images in Training Set". *IEEE Int. Conf. "Problems of Infocommunications Science and Technology"*, Kharkiv: Ukraine. 2020. DOI: https://doi.org/10.1109/PICST51311.2020.9467901.

Conflicts of Interest: The author declares no conflict of interest

Received 14.01.2021
Received after revision 12.03 .2021
Accepted 17.03.2021

DOI: https://doi.org/10.15276/aait.03.2021.5
УДК 004.[056.5+932.2]

Ефективність попереднього зашумлення стеганограм з використанням фрактальних шумів в задачах стегоаналізу цифрових зображень

Дмитро Олександрович Прогонов
ORCID: https://orcid.org/0000-0002-1124-1497; progonov@gmail.com
Національний технічний університет України «Київський політехнічний інститут імені Ігоря Сікорського», просп. Перемоги, 37. Київ, 03056, Україна

АНОТАЦІЯ

Протидії витоку конфіденційних даних у кіберфізичних системах сьогодні приділяється особлива увага фахівців в галузі інформаційної та кібербезпеки. Вирішення даної задачі ускладнюється широким використанням зловмисниками новітніх стеганографічних методів вбудовування конфіденційних даних до файлів-контейнерів, зокрема цифрових зображень. Особливістю даних методів є мінімізація змін параметрів зображення-контейнеру під час приховання стегоданих. Це суттєво знижує ефективність виявлення сформованих стеганограм при використанні сучасних статистичних стегодетекторів. Тому розробка нових методів виявлення стеганограм, здатних локалізувати та підсилювати слабкі зміни параметрів зображень-контейнерів обумовлених прихованням повідомлень, є актуальною та важливою задачею. Одним з новітніх підходів до вирішення даної задачі є застосування методів попередньої обробки зображення (калібрування). Дані методи спрямовані на визначення параметрів зображення-контейнеру, або ж стеганограми за наявним (досліджуваним) цифровим зображенням. Більшість відомих методів калібрування засновані на зменшенні впливу зображення-контейнеру (контексту) шляхом застосування ансамблю високочастотних фільтрів. Це дозволяє суттєво підвищити точність виявлення стеганограм, проте потребує використання обчислювально складних методів підбору високочастотних фільтрів для придушення контексту. Внаслідок цього даний підхід може бути неефективним у реальних випадках, коли необхідна швидка адаптація стегодетекторів для виявлення стеганограм, сформованих згідно раніше невідомих методів вбудовування стегоданих. Для подолання даних обмежень були запропоновані методи калібрування зображень, спрямовані на підсилення спотворень, викликаних прихованням повідомлень. Дані методи засновані на повторному вбудовуванні повідомлень до досліджуваного зображення, або ж додаткового зашумлення зображень. Ефективність підходу на основі повторного вбудовування повідомлень була показана для широкого спектру сучасних стеганографічних методів. Дана робота присвячена дослідженню ефективності методів калібрування на основі попереднього зашумлення зображень, зокрема з використанням нестаціонарного фрактального шуму. Аналіз ефективності даного підходу був проведений для сучасних адаптивних стеганографічних методів HUGO та MG на стандартному пакеті зображень VISION. За результатами аналізу отриманих даних, виявлено, що додаткове зашумлення зображень дозволяє суттєво підвищити точність виявлення стеганограм для методу HUGO у випадку слабкого заповнення зображення-контейнеру стегоданими (менше 10 %). Вагомою перевагою запропонованого методу у порівнянні з сучасними статистичними стегодетекторами є його низька обчислювальна складність. Тим не менше, запропований метод суттєво поступається сучасним стегодетекторами у випадку середнього (менше 20 %) та сильного (більше 25 %) заповнення зображення-контейнеру стегоданими, зокрема у випадку використання стеганографічного методу MG.

Ключові слова: цифрові зображення; стегоаналіз; статистичні стегодетектори; фрактальний шум

ABOUT THE AUTHOR

Dmytro O. Progonov, PhD (Eng), Associate Professor, Associate Professor of the Department of Information Security. National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", 37, Peremohy Ave. Kyiv, 03056, Ukraine
ORCID: https://orcid.org/0000-0002-1124-1497; progonov @gmail.com
***Research field*:** Digital media steganalysis; digital image forensics; machine learning; advanced signal processing

Дмитро Олександрович Прогонов, кандидат технічних наук, доцент, доцент кафедри Інформаційної безпеки. Національний технічний університет України «Київський політехнічний інститут імені Ігоря Сікорського», просп. Перемоги, 37. Київ, 03056, Україна