TKK Reports in Information and Computer Science

Espoo 2010 TKK-ICS-R34

# USING MULTIPLE RE-EMBEDDINGS FOR QUANTITATIVE STEGANALYSIS AND IMAGE RELIABILITY ESTIMATION

Yoan Miche, Patrick Bas and Amaury Lendasse

Aalto University
School of Science
and Technology

TKK Reports in Information and Computer Science
Espoo 2010 TKK-ICS-R34

# USING MULTIPLE RE-EMBEDDINGS FOR QUANTITATIVE STEGANALYSIS AND IMAGE RELIABILITY ESTIMATION

**Yoan Miche, Patrick Bas and Amaury Lendasse**

Aalto University School of Science and Technology
Faculty of Information and Natural Sciences
Department of Information and Computer Science

Aalto-yliopiston teknillinen korkeakoulu
Informaatio- ja luonnontieteiden tiedekunta
Tietojenkäsittelytieteen laitos

Distribution:
Aalto University School of Science and Technology
Faculty of Information and Natural Sciences
Department of Information and Computer Science
PO Box 15400
FI-00076 AALTO
FINLAND
URL: http://ics.tkk.fi
Tel. +358 9 470 01
Fax +358 9 470 23369
E-mail: series@ics.tkk.fi



ISBN 978-952-60-3249-8 (Print)
ISBN 978-952-60-3250-4 (Online)
ISSN 1797-5034 (Print)
ISSN 1797-5042 (Online)
URL: http://lib.tkk.fi/Reports/2010/isbn9789526032504.pdf

TKK ICS
Espoo 2010

**Abstract:** The quantitative steganalysis problem aims at estimating the amount of payload embedded inside a document. In this paper, JPEG images are considered, and by the use of a re-embedding based methodology, it is possible to estimate the number of original embedding changes performed on the image by a stego source and to slightly improve the estimation regarding classical quantitative steganalysis methods. The major advance of this methodology is that it also enables to obtain a confidence interval on this estimated payload. This confidence interval then permits to evaluate the difficulty of an image, in terms of steganalysis by estimating the reliability of the output. The regression technique comes from the OP-ELM and the reliability is estimated using linear approximation. The methodology is applied with a publicly available stego algorithm, regression model and database of images. The methodology is generic and can be used for any quantitative steganalysis problem of this class.

**Keywords:** Steganography, Steganalysis, OP-ELM, Quantitative Steganalysis, Re-embedding, Inner Image Difficulty

# CONTENTS

# 1 INTRODUCTION

The classical goal of steganalysis is to detect whether a document (considered to be images, here) has been tampered with or not. While this detection is important, one can wish to obtain more information about the actual payload present in the image. This problem is addressed by quantitative steganalysis: it estimates the embedded payload, usually by estimating directly the number of embedding changes that have been made to the image in the first place. An initial approach to this has been proposed in [6, 13]. Such a problem has been addressed recently for example by the use of classical blind steganalysis features such as [5]: the knowledge of the stego algorithm is supposed to be given, following Kerckhoff's principles [8] — or inferred by some usual means of blind steganalysis [11, 12] for example —, and the problem of payload estimation comes down to a regression problem, with the output being the payload to predict and inputs being the blind steganalysis features. In a recent paper, this regression has been achieved through the use of Ordinary Least Squares (OLS) and Support Vector Regression (SVR) [13].

In such a setup, it is assumed that one can use the identified stego algorithm in order to train an OLS or SVR model, for example on a known dataset. Such a model can then be used on new unknown images (the intercepted images on a specific channel) to estimate a possible embedded payload.

Although this usually leads to a good estimation, it is interesting to also have a confidence interval on such estimation, which gives information on the quality of the estimation as well as the possible "difficulty" of the considered image (reliability), i.e. the reliability of the output.

This problem of image reliability is important for future steganography. Indeed, in the case where a specific image is known to be "difficult", a steganographer will prefer using it, knowing that it is more likely to be misclassified or have a payload estimation that is unreliable. In [14], the authors propose to estimate the embedding capacity of the image beforehand, in order to embed the payload into the possibly most appropriate images. Such an approach, combined with reliability estimation can lead to more secure steganography. For example, the estimation of the difficulty of the image could be a starting point to perform batch steganography by embedding a payload function of the difficulty of the image.

This idea of image difficulty was first related to the error in steganalysis in the work of Böhme [2]. In this paper, the authors define a two-error model for the quantitative steganalysis setup, with a *within-image* error and a *between-image* one. The between-image error relates to the possible inaccurate assumptions made on the cover image and is thus related to images as a whole.

The within-image error is highly related to the concept of difficulty used in this paper and attempts to take into account the errors caused by the possible dependencies between a cover image and the message embedded in it.

In the original paper, the authors illustrate through the use of numerous types of steganalysis on a LSB replacement steganography scheme that the between-image error and the within-image error are quite different in nature: the between-image error follows rather closely that of a Student's $t$ distribution, while the within-image error is similar to a Gaussian one. It also seems that some of the steganalysis schemes tested by the authors are more prone to one type of error than the other.

The within-image error is related in [2] to a measure of the local variance of the image, introduced in the paper and computed over the original image. The concept of difficulty and the measure for it proposed in section 2 are tightly related to the within-image error and uses multiple repetitions of steganography with different messages on the same image. One main difference here is that a blind approach is used to determine it, i.e. it is assumed that the original image is not available and it is only possible to rely on the intercepted suspicious image.

In this paper, a methodology applicable to any stego algorithm is proposed in order to devise a confidence interval on the provided estimation of the original embedding rate, by using re-embeddings on the considered image. Using this methodology, it is possible to obtain:

- A better estimate of the original embedding rate used on an intercepted suspicious image which is tantamount to the number of embedding changes or the initial number of non-zero AC coefficients;

- An estimate of the original number of non-zero AC coefficients of the genuine image (and hence, from the embedding rate and this, the number of embedding changes);

- An estimated confidence interval on the embedding rate and on the number of non-zero AC coefficients;

- Using the confidence interval, a measure of the "difficulty" of the image.

Follows a description of the methodology, in section 2, and a set of experiments on 700 images in section 3.

## 2 METHODOLOGY

The following methodology is described for a single image, for the sake of simplicity of notations.

In the following, the embedding rate is defined as the ratio $R$ between the number of embedding changes $E$ and the number of non-zero AC coefficients $A$: $R = \frac{E}{A}$.

Assume that we have intercepted an image $I_o$ coming from a suspicious source, as in Figure 2, with a payload embedded $P_o$, which will be in the following assimilated to the number of embedding changes $E_o$ performed on $I_o$.

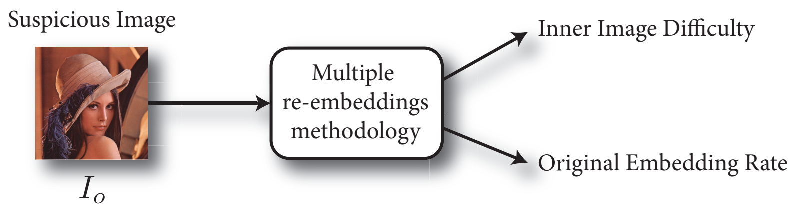


Figure 1: Suspicious image $I_o$ with unknown payload $P_o$, assimilated to the number of embedding changes made in the image $E_o$, by a stego algorithm $S$. The proposed methodology gives an estimate of $E_o$ and of the inner image difficulty.

According to Kerckhoffs' principle [8], the stego algorithm $S$ can be considered known; if not, it can be devised by the means of blind steganalysis, using multi-class classifiers [5], for example.

A model $\mathcal{M}$ that estimates the embedding rates $R$ is first trained on a given training set for which the embedding rates are known. This model is supposed to be available in the following.

## 2.1 Re-embedding concept

In this paper we propose to use the re-embedding idea to embed again some information inside the considered image $I_o$. The rationale here is to assume that the reliability of the estimation of the initial embedding rate is function of the reliability after multiple re-embeddings. Multiple such re-embedding with different sizes provide images with a larger embedding rate, of which a part is known. The global idea of the re-embedding and its use in this paper is illustrated in Figure 2.1.

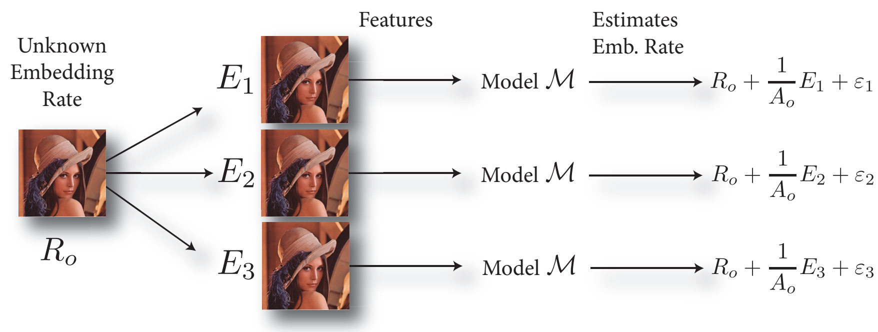


Figure 2: The Re-embedding concept: the original image $I_o$ supposedly having a payload with embedding rate $R_o$ is duplicated $N$ times ($N = 3$ here) and payloads with number of embedding changes $E_i$ are embedded in it. Features are extracted from each duplicate image (with additional embedding changes) and the previously built model $\mathcal{M}$ is used on these features to devise the final embedding rate $\hat{R}_i$.

Consider the intercepted image $I_o$; the idea is to make a known amount $E_i$ of new embedding changes to $I_o$. This process is repeated $N$ times $\{E_i, 1 \leq i \leq N\}$ on the image $I_o$, in order to obtain a set of images $\{I_i, 1 \leq i \leq N\}$ for each of which $E_i$ re-embedding changes are performed.

After this re-embedding procedure, the actual embedding rate for image $I_i$ is approximated as

$$R_i = \frac{E_o + E_i}{A_o} = R_o + \frac{1}{A_o} E_i, \tag{1}$$

with $E_o$ and $A_o$ the number of embedding changes and the number of non-zero AC coefficients in the considered image $I_o$, respectively (the sender of the suspicious image $I_o$ has caused $E_o$ embedding changes). It is assumed in this context that the number of non-zero AC coefficients $A$ might vary due to an embedding. Some stego algorithms attempt to not modify this quantity, though.

In order to illustrate that Eq. 1 is a good approximation for low $E_o$ and $E_i$, let us introduce two additional notations: the total number of pixels in the image $I$, $N_{\text{pix}}(I)$ and the *real* total number of embedding changes $E_i^{\text{tot}}$, measured between the original "clean" image $I$ and the image $I_i$ for which re-embedding with $E_i$ embedding changes has been performed.

If the stego algorithm $S$ is assumed to modify directly LSBs of pixels for each embedding change to perform (no matrix encoding, for example), it is possible to estimate the probability $P_{\text{pix}}$ of a pixel to be modified by both the first embedding (by the sender) and the re-embedding. Using these notations, it is straightforward,

$$P_{\text{pix}} = \frac{E_o}{N_{\text{pix}}(I)} \times \frac{E_i}{N_{\text{pix}}(I)}. \tag{2}$$

Figure 3 illustrates the validity of the approximation made by Eq. 1, for small $E_o + E_i$ (the experiment uses the nsF5 algorithm [15, 7]and Fridrich's extended DCT calibrated features [5]). Note that the plot of $E_o + E_i - P_{\text{pix}}(E_o + E_i)$ would be barely distinguishable from that of $E_o + E_i$ here, due to $P_{\text{pix}} \ll 1$. This is the case when the assumptions on $E_o$ and the range of $E_i$ made in this paper are met: "low" $E_o$ (compared to $N_{\text{pix}}$) and a controlled small range for $E_i$. In the event of a careless steganographer ($E_o$ exceptionally large) for example, this result might not hold as well as here.

In addition, the absolute error made by the approximation of Eq. 1 versus the number of re-embedding changes $E_i$ is depicted on Figure 4 for one image (the behavior is the same for all 700 images used in this paper). Consequently, the larger $E_i$, the more probable it is that some "overlap" happens, between the initial embedding changes $E_o$ and the re-embeddings $E_i$, which is expected from Eq. 2.

The rationale in this paper is that the sender is not careless about the embedding rate used and that the number of re-embedding changes $E_i$ are controlled in a certain range. With these assumptions, Eq. 1 is a reasonable approximation.

Then, in the very same way as that of the quantitative steganalysis, it is possible to obtain an estimation of the $R_i$, using a previously trained regression model $\mathcal{M}$. Denoting $\mathbf{X}_i = (x_i^1, \ldots, x_i^d)$ the $d$-dimensional feature vector extracted for image $I_i$, one gets the predicted embedding rate $\hat{R}_i = \mathcal{M}(\mathbf{X}_i)$.

From Eq. 1 comes

$$\hat{R}_i = R_o + \frac{1}{A_o} E_i + \varepsilon_i, \tag{3}$$

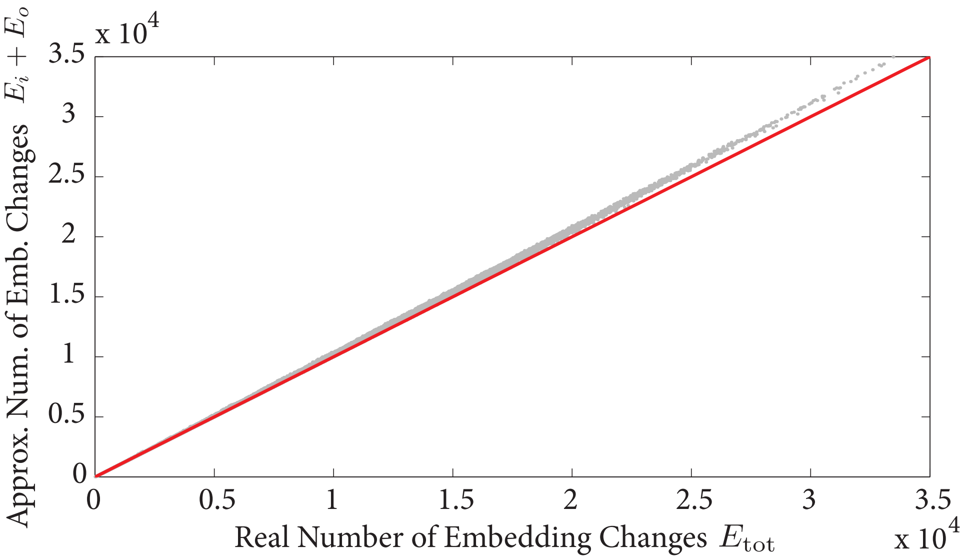


Figure 3: Approximated number of total embedding changes by Eq. 1, $E_o + E_i$, versus the *real* total number of embedding changes $E_{\text{tot}}$. The solid line denotes the case where $(E_o + E_i) = E_{\text{tot}}$ exactly. The plot of $E_o + E_i - P_{\text{pix}}(E_o + E_i)$ is not distinguishable from that of $E_o + E_i$ and is not depicted here. This experiment uses the nsF5 stego algorithm [15, 7].

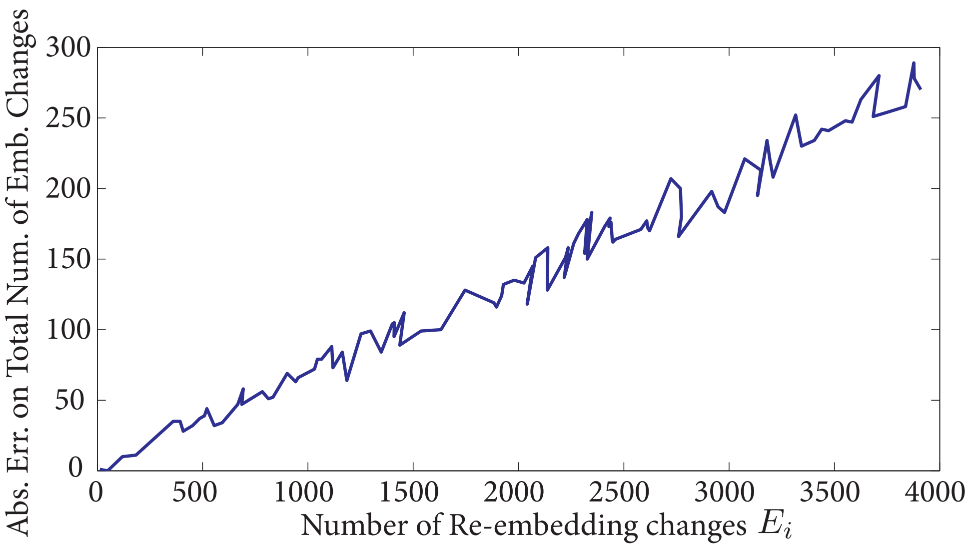


Figure 4: Absolute Error on the total number of embedding changes $\text{abs}(E_{\text{tot}} - (E_o + E_i))$ versus the number of re-embedding changes $E_i$.

with $\varepsilon_i$ the error made in the estimation of $R_i$. It is assumed in the following that the $\varepsilon_i$ are independent from each other and from the $E_i$, for simplicity.

### 2.2 Confidence interval estimation

Since both quantities $\hat{R}_i$ and $E_i$ are known, the confidence interval and the estimation of the original embedding rate $\hat{R}_o$ can then be obtained by solving the linear system

$$\frac{E_o}{A_o} + \frac{1}{A_o}\mathbf{E} = \hat{\mathbf{R}}, \tag{4}$$

with $\hat{\mathbf{R}} = (\hat{R}_1, \ldots, \hat{R}_N)^T$ the vector holding the estimations made by model $\mathcal{M}$ and $\mathbf{E} = (E_1, \ldots, E_N)^T$ the vector of the embedding changes performed.

This system is solved in a Least Squares sense, by minimizing $\| \ \varepsilon \ \|^2$, where $\varepsilon = (\varepsilon_1, \ldots, \varepsilon_N)^T$, which comes down to the problem

$$\min_{\alpha,\beta} \left\| \alpha + \beta \cdot \mathbf{E} - \hat{\mathbf{R}} \right\|^2, \tag{5}$$

with $\alpha = \frac{E_o}{A_o}$ and $\beta = \frac{1}{A_o}$. This is solved by a classical pseudo-inverse formulation.

The constant term in the minimization problem is the original rate $R_o$ for which we will obtain "an estimate" $\hat{R}_o$ , along with a confidence interval on the value $\hat{R}_o$, denoted $\left[\hat{R}_o^{\mathrm{INF}}, \hat{R}_o^{\mathrm{SUP}}\right]$. This confidence interval is obtained using the Matlab® function `regress`, which uses a Student's $t$ score, as described in [4]: $\hat{R}_o^{\mathrm{INF}}$ is obtained by

$$\hat{R}_o^{\mathrm{INF}} = \hat{R}_o - t_{\alpha/2,\nu}\hat{\sigma}\left(\hat{R}_o\right), \tag{6}$$

where $t_{\alpha/2,\nu}$ is the $t$ score (inverse Student $t$ cdf) with parameter $\alpha/2$ (for a $100(1-\alpha)\%$ confidence interval) with $\nu$ degrees of freedom (here $\nu = N-2$), and $\hat{\sigma}(\hat{R}_o)$ is the estimated standard deviation of $\hat{R}_o$. The upper bound $\hat{R}_o^{\mathrm{SUP}}$ is computed similarly, and the confidence interval for the first order term also (please refer to [4] for the derivations). One can also obtain the number of non-zero AC coefficients $A_o$ when solving the system, and hence recover the original number of embedding changes $E_o$.

This is illustrated on a set of images in the experiments section 3.

### 2.3 Estimation of the inner image difficulty

The inner difficulty of the image can be represented as the variation of the predictions for a given original embedding rate $E_o$ when the embedding key, or the embedded message fluctuates (similarly to [2]). Note that this variation is solely due to the characteristics of the cover image. Consequently our rationale is to measure the image difficulty as the standard deviation of the error performed for various embeddings on this image (no re-embeddings).

That is, for a genuine image $I$, $L$ different embeddings are performed with different number of embedding changes $\{E_i^{\mathrm{O}}, 1 \leq i \leq L\}$. The error $\varepsilon_{\mathrm{i}}^{O}$ between the estimated value of the embedding rate $\hat{R}_i^{\mathrm{O}}$ (by model $\mathcal{M}$) and the true value $R_i^{\mathrm{O}}$ is then defined as $\varepsilon_{\mathrm{i}}^{O} = R_i^{\mathrm{O}} - \hat{R}_i^{\mathrm{O}}$.

The standard deviation of this quantity over the $L$ different realizations is the proposed measure of the inner image difficulty $D$ for image $I$:

$$D_I = \mathrm{std}\left(\varepsilon^O\right), \tag{7}$$

with $\varepsilon^O = \left(\varepsilon_1^O, \ldots, \varepsilon_L^O\right)^T$.

In order to show that the estimated confidence interval gives information on the inner image difficulty, through the re-embeddings, the quantity $D_I$ inherent to each image $I$, is compared to the width of the estimated confidence interval for $\hat{R}_o$.

A dependence between the two proves the width of the estimated confidence interval can be used as an indicator of the image difficulty measured by $D_I$.

Note that the calculation of $D_I$ for an image requires the use of the genuine image, which is not accessible in practice. In the following, these $L$ embeddings on the cover image are referred to as "original embeddings".

The following section presents results for this methodology with publicly available algorithms and images.

# 3 RESULTS

For the following experiments, 700 images picked at random from the BOWS2 database have been used [1], with $L = 100$ repetitions for the estimation of the image difficulty $D_I$ and $N = 1500$ repetitions for the re-embeddings.

For each of the 700 images, initial embedding rates (supposed to be the embedding rate in the intercepted suspicious image) uniformly selected between 0 and 30% are used.

Re-embeddings follow the same range of rates, leading to final embedding rates $R_i$ between 0 and about 50% for the $I_i$. The stego algorithm used in the experiments is nsF5 [15, 7].

In this paper, the model $\mathcal{M}$ used for the regression is an OP-ELM [10] (the toolbox from `http://www.cis.hut.fi/projects/eiml` was used), which is a feedforward neural network using random projections. It has the advantage of performing very well (with similar performances to state of the art Machine Learning techniques such as Support Vector Machines) while keeping a rather low computational time. The OP-ELM optimizes the Mean Square Error. Default parameters (Linear, Sigmoid and Gaussian kernels, 300 maximum number of kernels) have been used for the experiments.

The OP-ELM model $\mathcal{M}$ is used on the 274 DCT-based features extracted from image $I_o$ [5] augmented by the number of non-zero DCT coefficients of the image $I_o$.

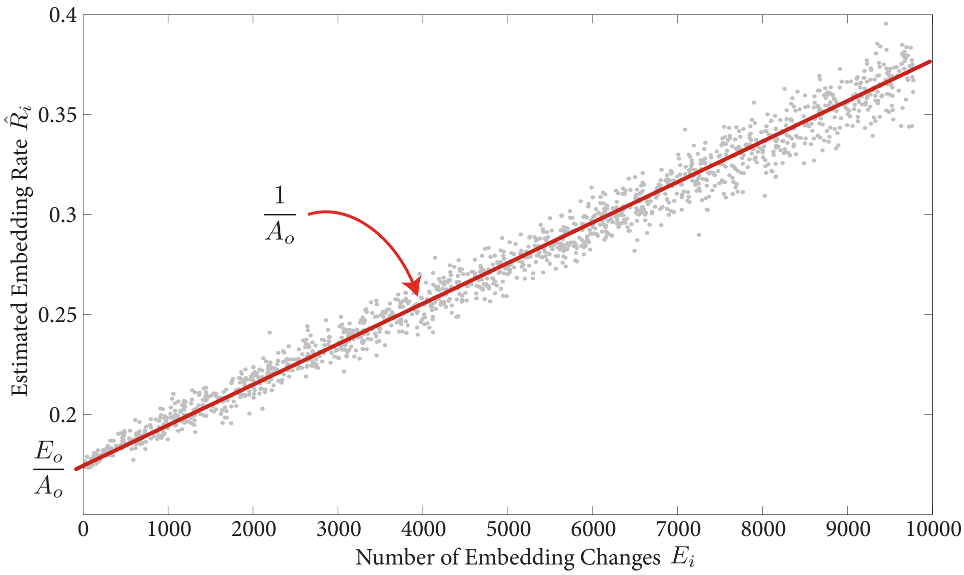


Figure 5: Plot of the estimated embedding rate $\hat{R}_i$ versus the number of embedding changes $E_i$, for one image. From Eq. 5, the slope gives the $\beta = \frac{1}{A_o}$ term while the value for $E_i \longrightarrow 0$ gives the $\alpha = \frac{E_o}{A_o}$ term.

### 3.1 Estimation of the original embedding rate $\hat{R}_o$

First, Figure 5 illustrates the solution of Eq. 5 for one image only (the behavior is the same for all images): by solving the linear system in a Least Squares sense, the values of $\beta = \frac{1}{A_o}$ (the slope) and $\alpha = \frac{E_o}{A_o}$ (estimated embedding rate for $E_i \longrightarrow 0$) are devised. Here, all $N = 1500$ values obtained for each re-embedding are plotted.

In order to show that the minimization problem is correctly solved for the whole range of embedding rates and for all 700 images, Figure 6 represents the estimated value of the original embedding rate $\hat{R}_o$ versus the real value $R_o$. The actual Normalized Mean Square Error (NMSE) for the 700 images in this figure using the re-embeddings is 0.0330, while using the same model $\mathcal{M}$ directly on each image (classical quantitative steganalysis, no re-embedding) leads to a 0.0346 NMSE in this case.

Hence, using this methodology on the 700 images yields on average an improvement of 5% of the NMSE for quantitative steganalysis.

It can be noted that the OP-ELM already performs very well [9] and the nsF5 stego problem is easy enough, hence the difficulty to improve "radically" the performances obtained in the first place.

To investigate the influence of the number of re-embeddings $N$, a variable number of re-embeddings has been used to establish Figure 7. It illustrates the evolution of the NMSE using the re-embedding approach, with a varying number of re-embeddings $N$. It is interesting to note that the error decreases dramatically with the number of re-embeddings $N$ in the beginning, until the improvement becomes statistically insignificant, beyond $N = 1000$.

In fact, once there are enough samples (equations) in the system to solve Eq. 4, new re-embeddings (and hence, new equations in the system) do not provide sufficient additional information for the regression problem. Hence

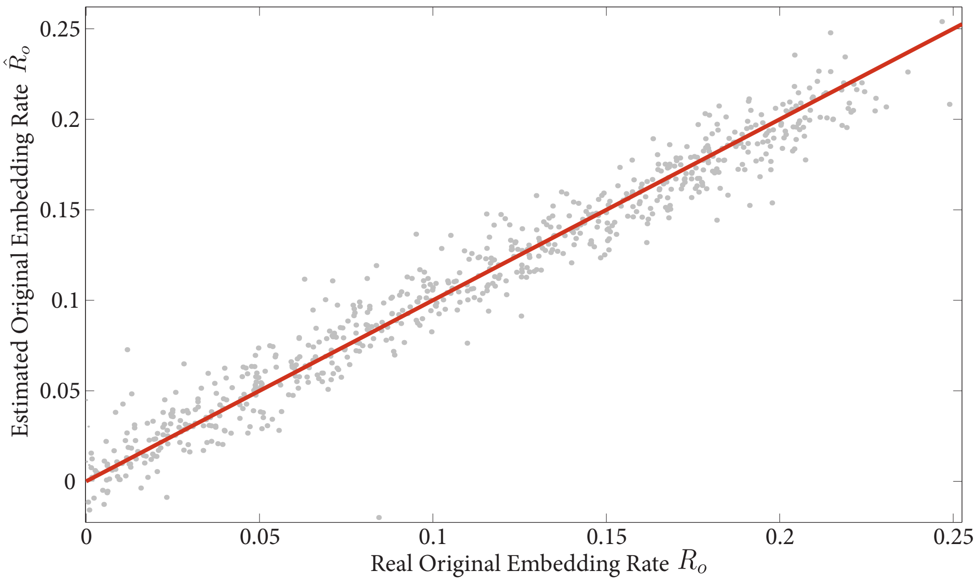


Figure 6: Plot of the estimated original embedding Rate $\hat{R}_o$ through the re-embeddings versus the original $R_o$, for all 700 images.

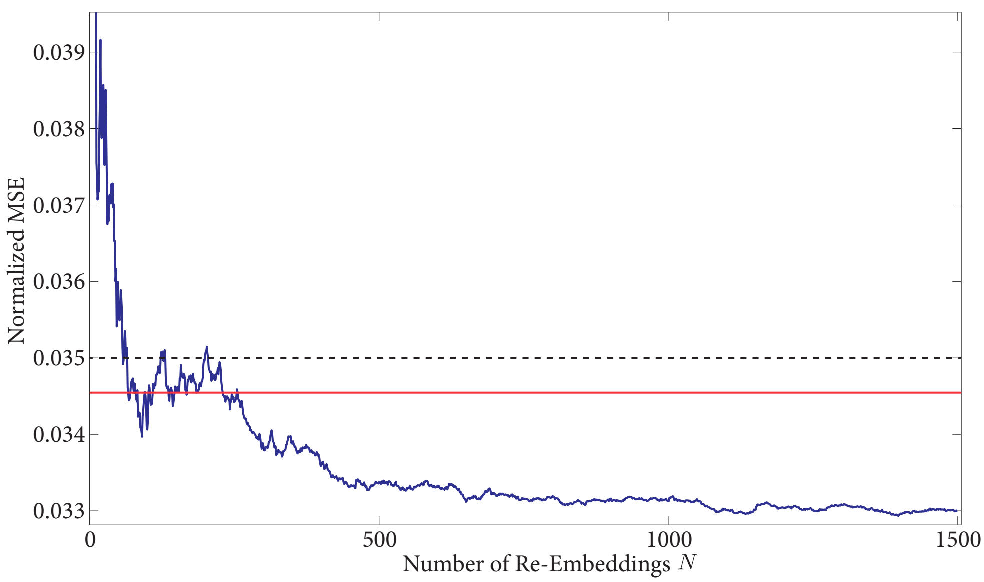


Figure 7: Plot of the Normalized Mean Square Error (NMSE) made on $\hat{R}_o$ versus the number of re-embeddings performed. The solid straight line gives the NMSE using the OP-ELM for classical quantitative steganalysis (no re-embedding), and the straight dashed line the NMSE for an OLS model.

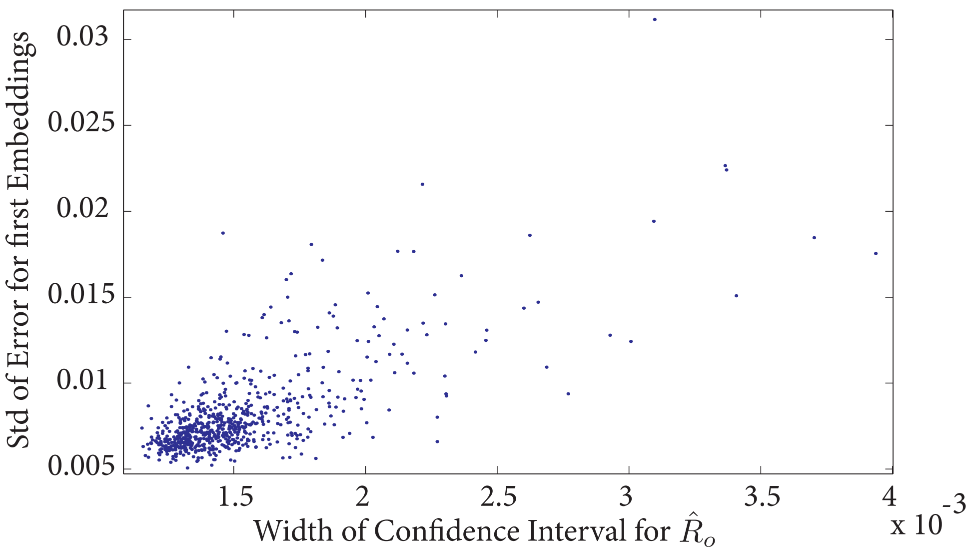


Figure 8: Plot of $D_I$, the standard deviation of the error made on the $L$ "original embeddings" $D_I = \text{std}\left(\varepsilon^O\right)$ versus the width of the estimated confidence interval $\hat{R}_o^{\text{SUP}} - \hat{R}_o^{\text{INF}}$.

the rather small improvement between 1000 and 1500 re-embeddings.

### 3.2 On the use of the width of the confidence interval

The confidence interval for the experiments has been set to 95% [3], and calculated using the Matlab©`regress` function [4].

Following results make use of the width of the confidence interval on the estimation of $\hat{R}_o$. The goal of this experiment is to establish a dependence between the estimated confidence interval $\left[\hat{R}_o^{INF}, \hat{R}_o^{\text{SUP}}\right]$ for the embedding rate $\hat{R}_o$ and the inner difficulty $D_I$ of the image $I$ considered, in the first place.

Figure 8 is a graph of the standard deviation of the error made on the "original embeddings" $D_I = \text{std}\left(\varepsilon^O\right)$ versus $\hat{R}_o^{\text{SUP}} - \hat{R}_o^{\text{INF}}$.

There appears to be a dependence between the "difficulty" (as estimated by the original embeddings), and the width of the confidence interval estimated by the re-embedding approach. Indeed, one can say that the larger is the estimated confidence interval for $\hat{R}_o$, the larger the probability of the error and therefore the more probable the image is a difficult one.

The high correlation between the difficulty and the confidence interval is not very easy to notice on Figure 7 because of the non-uniform distribution of the samples along the abscissa. In order to overcome this visualisation drawback, a local average using the 30 nearest neighbors regarding the x-coordinate is computed, the y coordinate being computed by the average of y-coordinates the corresponding points. The result is depicted on Figure 9 where the relation between the estimated confidence interval and the difficulty of the images is straightforward.

Figure 9 shows the evolution of this average versus the width of the estimated confidence interval. In fact, if one considers the cloud of points of

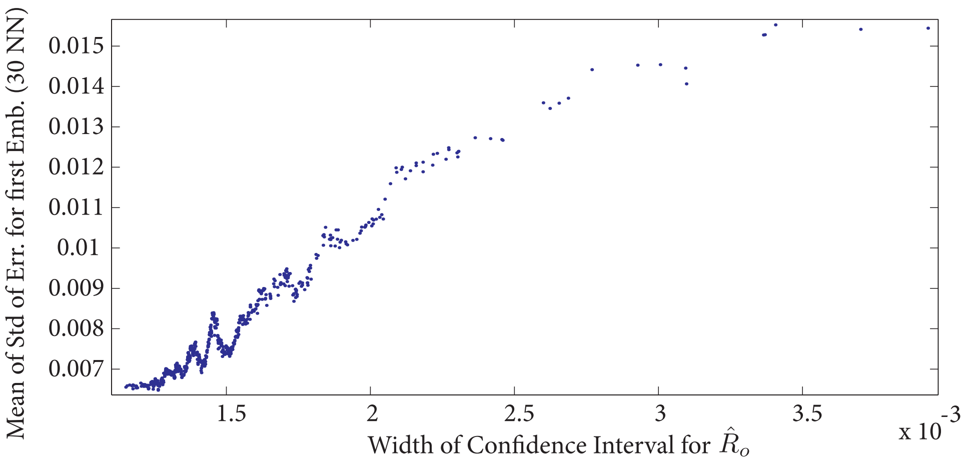


Figure 9: Plot of the mean of $D_I$ for the 30 nearest neighbors (with respect to $D_I$) versus the width of the estimated confidence interval.

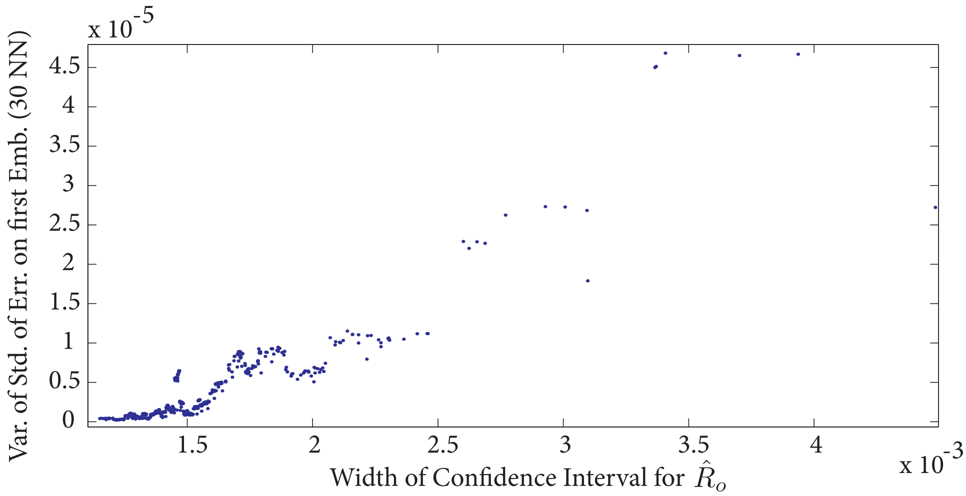


Figure 10: Plot of the variance of $D_I$ for the 30 nearest neighbors (with respect to $D_I$) versus the width of the estimated confidence interval.

Figure 8 as a "flat cone", Figure 9 plots the evolution of the center of the cone. It is then obvious that the larger the estimated confidence interval, the more difficult is the image to handle in steganalysis, in terms of the criterion $D_I$ (inner difficulty).

Finally, Figure 10 shows the evolution of the variance of $D_I$ for the 30 nearest neighbors for each image. The growth shows that the larger the confidence interval, the more difficult it is to have an accurate estimation of the difficulty. From Figures 9 and 10, we can conclude that the probability to get a large $D_I$ is increasing with respect to the width of the calculated confidence interval.

## 4 CONCLUSION

In this paper, an approach based on multiple re-embeddings is used to estimate in terms of quantitative steganalysis, the original embedding rate (and the number of embedding changes) in an intercepted image. The proposed methodology makes it possible to obtain a reliable estimation of this embedding rate — with a small improvement in terms of accuracy —, along with a confidence interval on this value.

The estimated confidence interval in turn enables the steganalyzer to measure the inherent difficulty of the image (reliability estimation), in terms of classical quantitative steganalysis. Through the width of this confidence interval, it becomes possible to rank the images of a database in terms of their probability of difficulty for quantitative steganalysis, without possessing the genuine images nor having any information on their being stego or genuine.

The proposed methodology has the advantage of being usable for any stego algorithm (given the assumptions made in section 2) and any regression model. Future work will apply this methodology to other stego algorithms (MMX, JPHS, Outguess, StegHide…), a larger image database and other regression models, such as SVR. Also, an analysis of the error $\varepsilon_i$ (in its relation to the embedding changes $E_i$ and on the assumed independence between the $\varepsilon_i$) could lead to a better modelisation and a more accurate estimation of the embedding rate and hence of inner image difficulty.

## ACKNOWLEDGMENTS

The authors would like to thank Tomáš Pevný for his advices on addressing on the Quantitative Steganalysis problem.

## REFERENCES

[1] Patrick Bas and Teddy Furon. BOWS2 challenge: Break our watermarking scheme. ECRYPT European Network of Excellence, `http://bows2.gipsa-lab.inpg.fr/`.

[2] Rainer Böhme and Andrew D. Ker. A two-factor error model for quantitative steganalysis. In Edward J. Delp III and Ping Wah Wong, editors, *Proceedings of SPIE*, volume 6072, page 607206. SPIE, 2006.

[3] Samprit Chatterjee and Ali S. Hadi. Influential observations, high leverage points, and outliers in linear regression. *Statistical Science*, 1(3):379–393, 1986.

[4] Norman R. Draper and Harry Smith. *Applied Regression Analysis, 3rd edition*. Wiley-Interscience, 1998.

[5] Jessica Fridrich. Feature-based steganalysis for jpeg images and its implications for future design of steganographic schemes. In *Information Hiding: 6th International Workshop*, volume 3200 of *Lecture Notes in Computer Science*, pages 67–81, May 23-25 2004.

[6] Jessica Fridrich, Miroslav Goljan, Dorin Hogea, and David Soukal. Quantitative steganalysis of digital images: estimating the secret message length. *Multimedia systems*, 9(3):288–302, 2003.

[7] Jessica Fridrich, Tomáš Pevný, and Jan Kodovský. Statistically undetectable jpeg steganography: dead ends challenges, and opportunities. In *MM&Sec '07: Proceedings of the 9th workshop on Multimedia & security*, pages 3–14, New York, NY, USA, 2007. ACM.

[8] Auguste Kerckhoffs. La cryptographie militaire. *Journal des sciences militaires*, 9:5–38, January 1883.

[9] Yoan Miche, Patrick Bas, Amaury Lendasse, Christian Jutten, and Olli Simula. Reliable steganalysis using a minimum set of samples and features. *EURASIP Journal on Information Security*, 2009(1):1–13 (Article ID 901381), March 2009. http://www.hindawi.com/journals/is/2009/901381.html.

[10] Yoan Miche, Antti Sorjamaa, Patrick Bas, Olli Simula, Christian Jutten, and Aamaury Lendasse. OP-ELM: Optimally-pruned extreme learning machine. *IEEE Transactions on Neural Networks*, 21(1):158–162, January 2010.

[11] Tomáš Pevný and Jessica Fridrich. Towards multi-class blind steganalyzer for jpeg images. In *International Workshop on Digital Watermarking 2005*, volume 3710 of *LNCS*, pages 39–53, 2005.

[12] Tomáš Pevný and Jessica Fridrich. Multiclass blind steganalysis for jpeg images. In *SPIE Electronic Imaging*, volume 6072, page 60720O, 16-19 January 2006.

[13] Tomáš Pevný, Jessica Fridrich, and Andrew D. Ker. From blind to quantitative steganalysis. In Edward J. Delp III, Jana Dittmann, Nasir D. Memon, and Ping Wah Wong, editors, *Media Forensics and Security*, volume 7254, page 72540C. SPIE, 2009.

[14] Hedieh Sajedi and Mansour Jamzad. Secure steganography based on embedding capacity. *International Journal of Information Security*, 8(6), December 2009.

[15] Andreas Westfeld. F5-a steganographic algorithm. In *IHW '01: Proceedings of the 4th International Workshop on Information Hiding*, pages 289–302, London, UK, 2001. Springer-Verlag.

TKK REPORTS IN INFORMATION AND COMPUTER SCIENCE

| | | |
|---|---|---|
| TKK-ICS-R24 | Timo Honkela, Nina Janasik, Krista Lagus, Tiina Lindh-Knuutila, Mika Pantzar, Juha Raitio<br>Modeling communities of experts. December 2009. |
| TKK-ICS-R25 | Jani Lampinen, Sami Liedes, Kari Kähkönen, Janne Kauttio, Keijo Heljanko<br>Interface Specification Methods for Software Components. December 2009. |
| TKK-ICS-R26 | Kari Kähkönen<br>Automated Test Generation for Software Components. December 2009. |
| TKK-ICS-R27 | Antti Ajanki, Mark Billinghurst, Melih Kandemir, Samuel Kaski, Markus Koskela, Mikko Kurimo, Jorma Laaksonen, Kai Puolamäki, Timo Tossavainen<br>Ubiquitous Contextual Information Access with Proactive Retrieval and Augmentation. December 2009. |
| TKK-ICS-R28 | Juho Frits<br>Model Checking Embedded Control Software. March 2010. |
| TKK-ICS-R29 | Miki Sirola, Jaakko Talonen, Jukka Parviainen, Golan Lampi<br>Decision Support with Data-Analysis Methods in a Nuclear Power Plant. March 2010. |
| TKK-ICS-R30 | Teuvo Kohonen<br>Contextually Self-Organized Maps of Chinese Words. April 2010. |
| TKK-ICS-R31 | Jefrey Lijffijt, Panagiotis Papapetrou, Niko Vuokko, Kai Puolamäki<br>The smallest set of constraints that explains the data: a randomization approach. May 2010. |
| TKK-ICS-R32 | Tero Laitinen<br>Extending SAT Solver With Parity Constraints. June 2010. |
| TKK-ICS-R33 | Antti Sorjamaa, Amaury Lendasse<br>Fast Missing Value Imputation using Ensemble of SOMs. June 2010. |

ISBN 978-952-60-3249-8 (Print)
ISBN 978-952-60-3250-4 (Online)
ISSN 1797-5034 (Print)
ISSN 1797-5042 (Online)