Image and Vision Computing 27 (2009) 1497–1503

Contents lists available at ScienceDirect

Image and Vision Computing

journal homepage: www.elsevier.com/locate/imavis

Using noise inconsistencies for blind image forensics

Babak Mahdian *, Stanislav Saic

The Institute of Information Theory and Automation of the ASCR, Pod Vodárenskou věží 4, 182 08 Prague 8, Czech Republic

ARTICLE INFO

Article history:
Received 3 October 2007
Received in revised form 30 January 2009
Accepted 2 February 2009

Keywords:
Image forensics
Digital forgery
Image tampering
Image segmentation
Noise inconsistency

ABSTRACT

A commonly used tool to conceal the traces of tampering is the addition of locally random noise to the altered image regions. The noise degradation is the main cause of failure of many active or passive image forgery detection methods. Typically, the amount of noise is uniform across the entire authentic image. Adding locally random noise may cause inconsistencies in the image's noise. Therefore, the detection of various noise levels in an image may signify tampering. In this paper, we propose a novel method capable of dividing an investigated image into various partitions with homogenous noise levels. In other words, we introduce a segmentation method detecting changes in noise level. We assume the additive white Gaussian noise. Several examples are shown to demonstrate the proposed method's output. An extensive quantitative measure of the efficiency of the noise estimation part as a function of different noise standard deviations, region sizes and various JPEG compression qualities is proposed as well.

1. Introduction

In today's digital age, due to the advent of low-cost, high-performance computers, more friendly human computer interfaces, and the availability of many powerful and easy to control image processing and editing software packages, digital images have become easy to manipulate and edit even for non-professional users. Without a doubt, image authenticity is significant in many social areas and plays a crucial role in peoples lives. For instance, the trustworthiness of photographs has an essential role in courtrooms, where they are used as evidence. Every day newspapers and magazines depend on digital images. Today, we face the problem of digital image forgeries even in the scientific literature. There are articles containing results presented by images which were significantly affected and changed by a tampering process.

Existing digital forgery detection methods are divided into active [1–3] and passive (blind) [4–9] approaches. The blind approach is regarded as the new direction and interest in this field has over the last few years rapidly increased. In contrast to active approaches, blind approaches do not need any explicit priori information about the image. They work in the absence of any digital watermark or signature. Blind approaches have not yet been thoroughly researched by many.

A commonly used tool to conceal traces of tampering is the addition of locally random noise to the forged image regions. Typically, the amount of noise in an authentic image is uniform across the entire image. Adding locally random noise may cause inconsistencies in the image's noise. Therefore, detection of various noise levels in an image may signify tampering. In this paper, we will propose a simple method capable of dividing an investigated image into various segments of different noise levels. In other words, we introduce a segmentation method amounting to the detecting of changes in noise standard deviations.

Noise degradation is the main cause of failure of most existing blind forgery detection methods. These methods are able to work correctly only when the amount of present noise is small. For example, in copy-move forgery (in this type of forgery, a part of the image is copied and pasted into another part of the same image with the intention of hiding an object or a region of the image [4,10]), additive noise causes duplicated regions to not match exactly. This causes a significant decrease in the performance of copy-move forgery detection methods. The same can be observed in the resampling detection methods (resampling is almost always needed when two or more images are spliced together to create a high quality and consistent forged image [5,6]). Here, the noise degradation causes lose of detectable correlation among neighboring pixels. This correlation is brought into the signal by interpolation step. Furthermore, when two or more images from different sources are spliced together, the forged image may then contain several regions with various noise levels as well.

The rest of the paper is organized as follows. The next section summarizes previously published papers concerned with the topic of this paper. Following on from that, some basic notations are given to build up the necessary mathematical background. Then, the proposed method is explained and each step of the method discussed in detail. Section 4 contains experiments to demonstrate the outcomes of the proposed method. In Section 5, important properties of the method and obtained results are discussed. The last section summarizes the work that has been done in this paper.

* Corresponding author. Tel.: +420 266052211; fax: +420 284680730.
E-mail addresses: mahdian@utia.cas.cz (B. Mahdian), ssaic@utia.cas.cz (S. Saic).

0262-8856/$ - see front matter
doi:10.1016/j.imavis.2009.02.001

2. Related work

Numerous works exist that deal with noise presence in signals. For instance, image denoising belongs to the most popular and active areas in signal processing and has been intensively studied in both image processing and computer vision literature [11,12]. On the other hand, to our knowledge, there exists only one blind forgery detection method based on the image's noise properties which does not use any a priori information about the image or source camera.

Popescu and Farid have proposed in [13] a method based on estimating the noise variances of overlapping blocks which tile the entire investigated image. The method uses the second and fourth moments of the analyzed block to estimate the noise variance. The proposed method assumes white Gaussian noise and a non-Gaussian uncorrupted image. The kurtosis of the original signal is assumed to be known, which is mostly not true in practice. But, as the authors suggest, this can be overcome by estimating the original kurtosis from a region of the image that is believed to be unadulterated.

In this paper, we propose a blind forgery detection method based on local noise level inconsistencies. Our aim is to also be able to detect small regions corrupted by local noise (often the forgery creator modifies only a small part of the image). The local noise estimation is based on tiling the high pass diagonal wavelet coefficients at the highest resolution with non-overlapping blocks. The noise standard deviation in each block is estimated using a widely used median-based method ([12]). Once the noise standard deviation of each block is estimated, it is used as the homogeneity condition to segment the investigated image into several homogenous sub-regions. This is carried out by a simple regions-merging segmentation technique.

3. Noise inconsistencies analysis

In this section, we introduce a method capable of dividing the investigated image into various homogenous segments according to the noise level. We will assume the white Gaussian noise.

We will define the problem in the following way. Given an image containing an arbitrary number of isolated regions of unknown location and shape with different noise levels, our task is to determine the presence of such regions and to localize them.

It is obvious that the noise variance can vary spatially. So, there are several variance values on different image segments. The noise variance values as well as the segments' sizes and locations are unknown. We assume the following non-stationary model:

$$f_n(x,y) = f(x,y) + n(x,y), \tag{1}$$

where $f(x,y)$ is the uncorrupted signal and $n(x,y)$ the white Gaussian noise $n(x,y)$ with variance σ^2 which can spatially vary. We assume that σ^2 is a piecewise constant function.

The proposed method is based on a few main steps:

- wavelet analysis,
- tiling sub-band HH_1 with non-overlapping blocks,
- blocks noise variance estimation,
- blocks merging.

Each step is explained separately in the following sections.

3.1. Wavelet transform

In recent years, wavelet analysis has been demonstrated to be a powerful way for performing tasks concerned with image noise [11,12]. In the first step of the proposed method, a one-level wavelet decomposition [14,15] of the investigated image is carried out.

3.2. Non-overlapping blocks

The HH_1 sub-band gives the diagonal details of the image the highest resolution. Our method begins with tiling this sub-band by non-overlapping blocks B_i of $R \times R$ pixels. Blocks are assumed to be smaller than the size of the corrupted regions, which have to be detected. The total number of non-overlapping blocks for an image of $M \times N$ pixels is $r = \lfloor \frac{M}{R} \rfloor \times \lfloor \frac{N}{R} \rfloor$.

Alternatively, an operator can manually divide the image into different portions whose integrities are in question and where we wish to strengthen our evidence. An ROI can be identified by one of the forgery detection techniques capable of localizing the tampering as well (for example [4,10,6]).

3.3. Noise level estimation

In this section, the noise level of each block created in the previous step is estimated. Numerous methods have been proposed so far to perform the noise level estimation in digital images. Generally, these methods can be divided into following groups: block-based, smoothing-based and gradient-based.

In our method, the most widely used technique for estimating the standard deviation of the noise on a wavelet component is employed. Wavelet-based noise estimation is a special case of gradient-based methods for noise estimation, where the gradient amplitudes are obtained from the wavelet decomposition.

It has been shown in [12] that the standard deviation of noise can be robustly estimated from the first decomposition level diagonal sub-band HH_1 using the following median based estimator:

$$\hat{\sigma} = \frac{median(|HH_1|)}{0.6745}. \tag{2}$$

The median measurement is insensitive to isolated outliers of potentially high amplitudes. Often $median(|HH_1|)$ is denoted as $MAD(HH_1)$ where MAD stands for median absolute deviation. This estimator is very popular and generally provides robust and precise outcomes.

3.4. Blocks merging

Once the noise standard deviation of each block is estimated, $\hat{\sigma}_i,\ i = 1 \cdots r$, we divide the noisy image, f_n, into several connected homogenous sub-regions $R_1 \cup R_2 \cup \cdots \cup R_n$. The homogeneity condition is the noise standard deviation. To achieve this, we group blocks $B_i,\ i = 1 \cdots r$, using a simple region merging technique [16–18].

The region merging algorithm expands the blocks into neighboring blocks using $\hat{\sigma}_i$. It starts with individual blocks and iteratively merges similar neighboring ones. The similarity is based on a selected similarity threshold T. The core of the merging method is the following:

- Give a unique label to each block.
- In a predefined order, examine the neighboring regions and decide if the absolute value of difference of their standard deviation of noise is smaller than the selected threshold ($|\hat{\sigma}_i - \hat{\sigma}_j| < T$). If so, then give these neighbors the same label and estimate the new created region's $\hat{\sigma}_i$.
- Continue until no more merging operations are possible.

The output of this step is a map showing partitions with similar standard deviation of noise.

4. Experimental results

In the first part of this section, to demonstrate the method's outcomes, we apply it to several examples. An experimental version of the proposed method was implemented in Matlab. Here, test images have resolution of 1200×800. Parameters of the method were set to $M = 40$, $N = 40$ (blocks of size 40×40) and $T = 1$ (similarity threshold). All experimental results were obtained using the Daubechies wavelet db8. In all experiments, the mean of additive Gaussian noise is zero and intensity levels are in the range 0–255.

Shown in Figs. 1(a), 2(a) and 3(a) are the noise-free test images. Figs. 1(b), 2(b) and 3(b) show the noise-corrupted regions. Outcomes of the method are shown in Figs. 1(c)–(h), 2(c)–(h) and 3(c)–(h) for Gaussian noise with standard deviations $\sigma = 1$, 3, 5, 7, 10 and 15. The largest detected homogenous region is denoted by the black color. Colors denoting other regions with the homogenous noise standard deviation are assigned randomly.

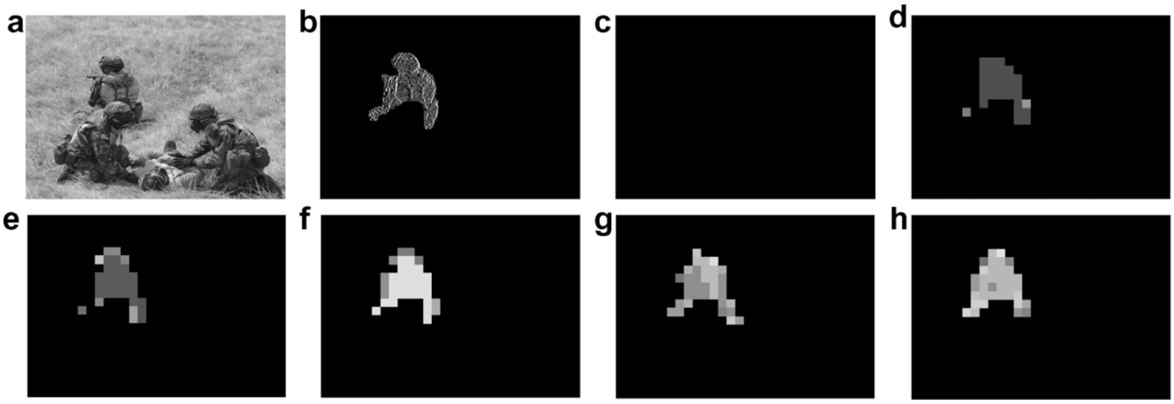

Fig. 1. Shown are the test image (a), AWGN corrupted region (b) segmented image for Gaussian noise with standard deviation $\sigma = 1$ (c), $\sigma = 3$ (d), $\sigma = 5$ (e), $\sigma = 7$ (f), $\sigma = 10$ (g) and $\sigma = 15$ (h).

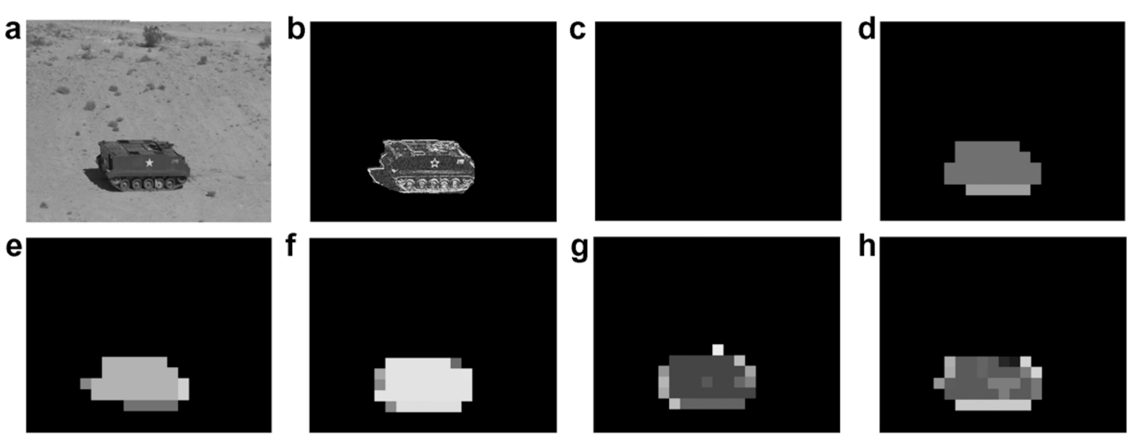

Fig. 2. Shown are the test image (a), AWGN corrupted region (b) segmented image for Gaussian noise with standard deviation $\sigma = 1$ (c), $\sigma = 3$ (d), $\sigma = 5$ (e), $\sigma = 7$ (f), $\sigma = 10$ (g) and $\sigma = 15$ (h).

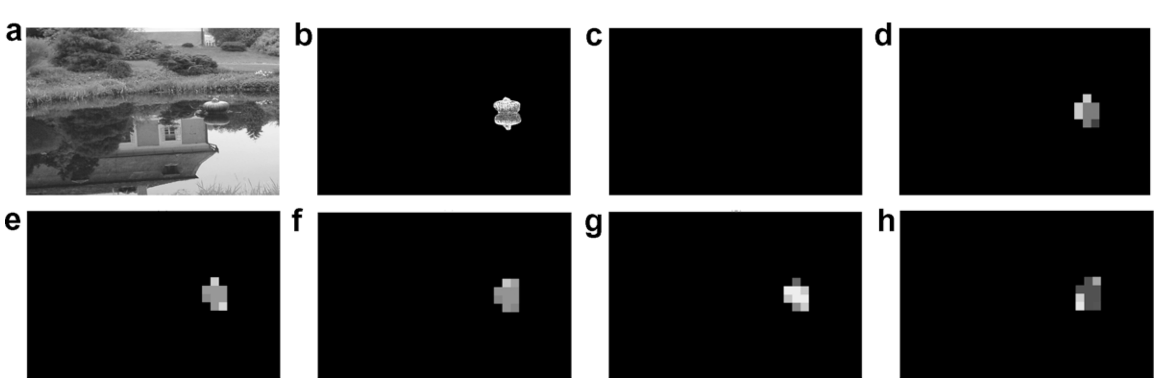

Fig. 3. Shown are the test image (a), AWGN corrupted region (b) segmented image for Gaussian noise with standard deviation $\sigma = 1$ (c), $\sigma = 3$ (d), $\sigma = 5$ (e), $\sigma = 7$ (f), $\sigma = 10$ (g) and $\sigma = 15$ (h).

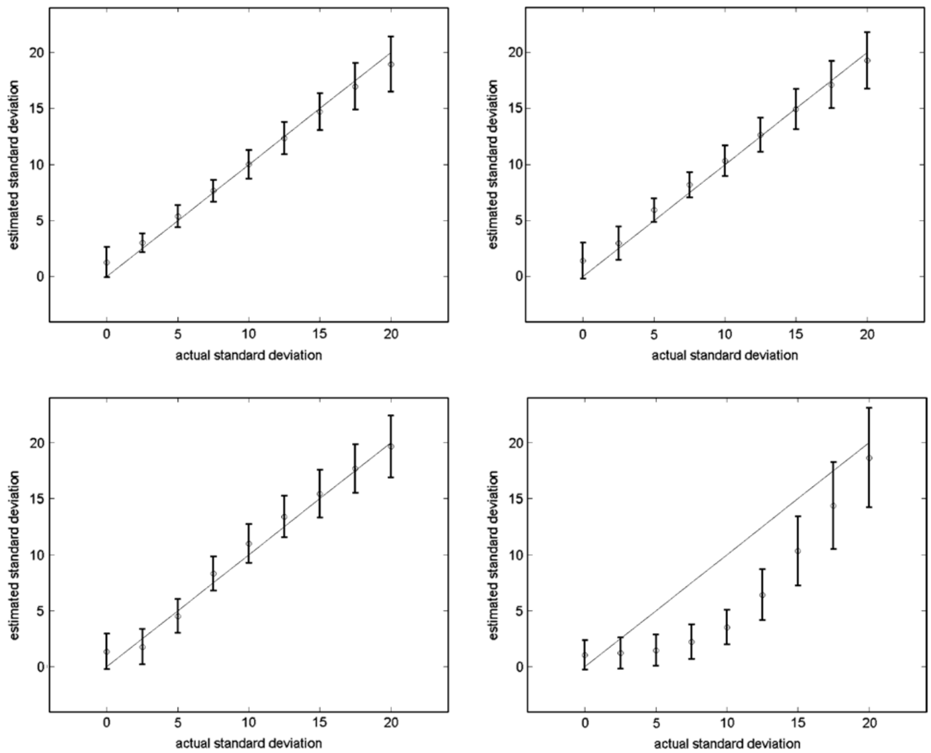

Fig. 4. Shown are average estimated standard deviations of noise and standard deviations of estimates, plotted against the true values of the noise standard deviations. These estimates were obtained from the 1000 randomly chosen blocks of size 16×16. Blocks were obtained from the green channel of 1000 color images of size 1600×1200 (one block from each image). Estimates are shown for pure noise-corrupted images (top-left), compressed noise-corrupted images JPEG 95 (top-right), JPEG 90 (bottom-left) and JPEG 70 (bottom-right).

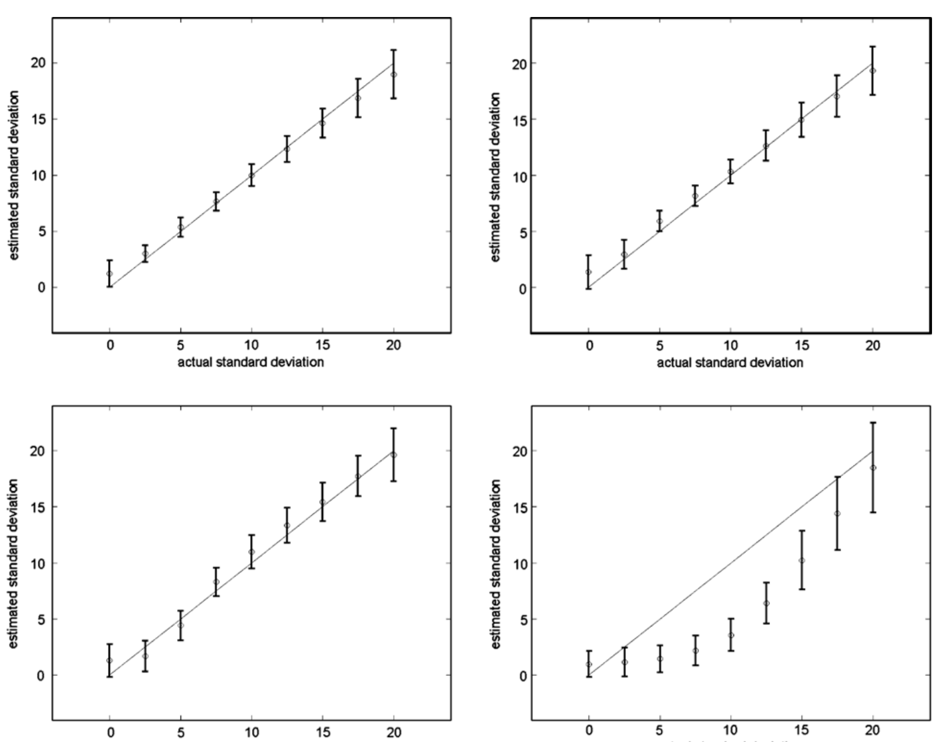

Fig. 5. Shown are average estimated standard deviations of noise and standard deviations of estimates, plotted against the true values of the noise standard deviations. These estimates were obtained from the 1000 randomly chosen blocks of size 32×32. Blocks were obtained from the green channel of 1000 color images of size 1600×1200 (one block from each image). Estimates are shown for pure noise-corrupted images (top-left), compressed noise-corrupted images JPEG 95 (top-right), JPEG 90 (bottom-left) and JPEG 70 (bottom-right).

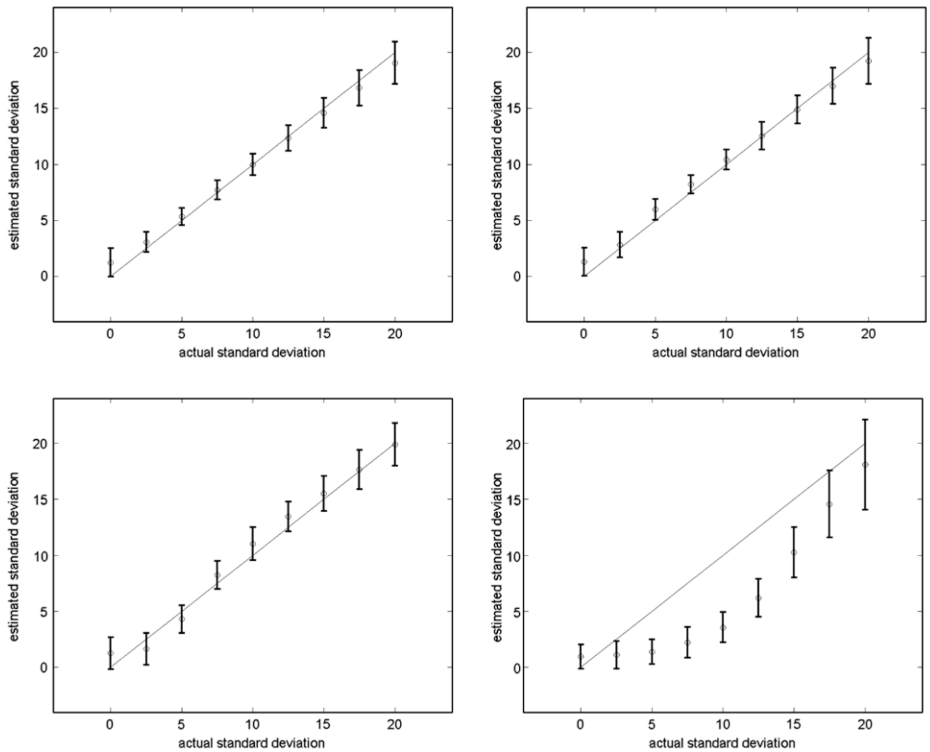

Fig. 6. Shown are average estimated standard deviations of noise and standard deviations of estimates, plotted against the true values of the noise standard deviations. These estimates were obtained from the 1000 randomly chosen blocks of size 64 × 64. Blocks were obtained from the green channel of 1000 color images of size 1600 × 1200 (one block from each image). Estimates are shown for pure noise-corrupted images (top-left), compressed noise-corrupted images JPEG 95 (top-right), JPEG 90 (bottom-left) and JPEG 70 (bottom-right).

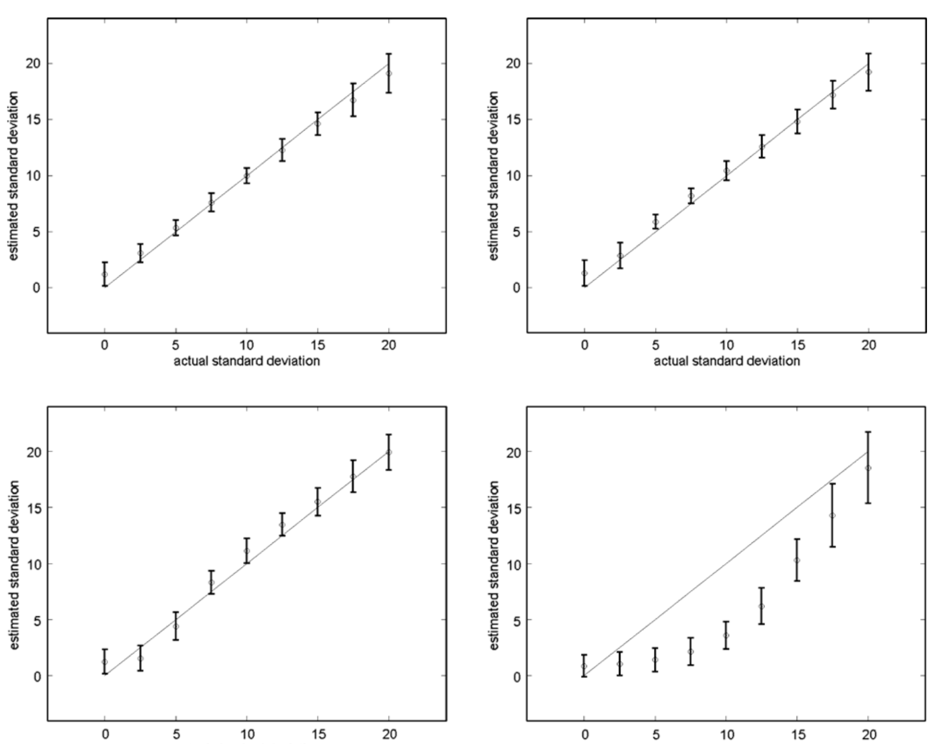

Fig. 7. Shown are average estimated standard deviations of noise and standard deviations of estimates, plotted against the true values of the noise standard deviations. These estimates were obtained from the 1000 randomly chosen blocks of size 128 × 128. Blocks were obtained from the green channel of 1000 color images of size 1600 × 1200 (one block from each image). Estimates are shown for pure noise-corrupted images (top-left), compressed noise-corrupted images JPEG 95 (top-right), JPEG 90 (bottom-left) and JPEG 70 (bottom-right).

In the second part of this section, a quantitative measure of the efficiency of the noise estimation part of the algorithm based on various block sizes and image formats is carried out. Experimental results are obtained by applying the estimator to 1000 test blocks obtained randomly from 1000 color images (one block from each image) corrupted by additive Gaussian noise with various standard deviations ($\sigma = 0$, 2.5, 5, 7.5, 10, 12.5, 15, 17.5 and 20). Blocks were obtained from green channels. The size of test images was 1600×1200 pixels. Experiments were carried for blocks of sizes 16×16, 32×32, 64×64 and 128×128. The method was applied to each block separately. To analyze the behavior of the estimator with respect to the lossy compression JPEG, experiments were also carried out to jpeg compressed noise-corrupted images (most of image forgeries are in JPEG format). In these experiments, noise were added to the image before the JPEG compression has been done. Experiments were done for JPEG 95, JPEG 90 and JPEG 70.

Results of these quantitative experiments are shown by plots in Figs. 4–7. In these plots, each data point corresponds to average estimated standard deviations of noise and standard deviations of estimates, plotted against the true values of the noise standard deviations.

5. Discussion

Obtained results show that the proposed method makes it possible in a simple and blind way to divide an investigated image into various segments with homogenous noise level. The main drawback of the method is that authentic images also can contain various isolated regions with totally different variances. The method can denote these regions as inconsistent with the rest of the image. Therefore, a human interpretation of the output of the method is necessary. Because of these reasons, the proposed method is useful as a supplement to other forgery detection methods rather then a standalone forgery detector.

Typically, the proposed method is not able to find the corrupted regions, when the noise degradation is very small ($\sigma < 2$). However, please note that this is not a significant limitation. As was mentioned, our purpose was to develop a method capable of detecting forgeries where the random noise is the main cause of failure of other authentication methods. This occurs when the noise degradation is not small.

Compared to [13], the proposed method uses a more precise estimation of noise level. The main drawback of [13] is that in order to estimate the local noise variance of a single channel image, the local kurtosis values of the noiseless image need to be known. The estimation of this kurtosis brings numerical errors and decreases the performance.

The average run time of the implemented experimental version with parameters $M = 40$, $N = 40$ (blocks of size 40×40) and $T = 1$ for 1200×800 grayscale images on a 2.1 GHz processor and 512 MB RAM is 25 s (the most computational time belongs to the blocks merging step). It is important to note that the implemented experimental version was not optimized and it is possible to significantly improve the computational time.

The selected method's parameters were determined experimentally to yield a good tradeoff between the size of the detectable region and noise level estimation ability. But, generally, they can always be altered based on ROI size and image's properties by using results shown in Figs. 4–7. An interesting modification of the proposed method can be achieved by omitting the blocks merging step. The estimated noise standard variation can be directly shown as images on some convenient intensity scale. This can reduce the possible oversegmentation or undersegmentation effects of the blocks merging technique.

In this work, we have been concerned with gray-level images. There are several ways to adopt the presented method for RGB images. For instance, the method can be applied to each channel separately.

6. Conclusion

Image segmentation based on local noise standard deviation for blind image forensics purposes is considered in this work. The local noise estimation is based on tiling the high pass wavelet coefficients at the highest resolution with non-overlapping blocks. The noise standard deviation of each block is estimated using the widely used median-based method. Once the standard deviation of noise is estimated, it is used as the homogeneity condition to segment the investigated image into several homogenous subregions. The efficacy of the method in several examples is shown. An extensive quantitative measure of the efficiency of the noise standard deviation estimation as a function of different noise standard deviations, various JPEG compression qualities and various ROI sizes is also carried out.

The proposed method in combination with other blind image forensics techniques can be a very useful tool to detect the traces of tampering where the local noise is used to conceal the traces of tampering.

Acknowledgement

This work has been supported by the Czech Science Foundation under the Project No. GACR 102/08/0470.

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