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Image forgery detection by semi-automatic wavelet soft-Thresholding with error level analysis

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ABSTRACT

In this paper a method for detection of image forgery in lossy compressed digital images known as error level analysis (ELA) is presented and it's noisy components are filtered with automatic wavelet soft-thresholding. With ELA, a lossy compressed image is recompressed at a known error rate and the absolute differences between these images, known as error levels, are computed. This method might be weakened if the image noise generated by the compression scheme is too intense, creating the necessity of noise filtering. Wavelet thresholding is a proven denoising technique which is capable of removing an image's noise avoiding altering other components, like high frequencies regions, by thresholding the wavelet transform coefficients, thus not causing blurring. Despite its effectiveness, the choice of the threshold is a known issue. However there are some approaches to select it automatically. In this paper, a lowpass filter is implemented through wavelet thresholding, attenuating error level noises. An efficient method to automatically determine the threshold level is used, showing good results in threshold selection for the presented problems. This automatic threshold level can be fine tuned by a parameter k. Standard test images have been doctored to simulate image tampering, error levels for these images are computed and wavelet thresholding is performed to attenuate noise. Results are presented, confirming the method's efficiency at noise filtering while preserving necessary error levels. The main contribution of this paper is the investigation of Daubechies wavelets with semi-automatic soft-thresholding in order to highlight forgeries in images. These results can be further extended by expert systems to classify and identify forgeries.

1. Introduction

We propose the application of a method given by Kovesi (1999) to Error Level Analysis (ELA) (Krawetz, 2007). In Kovesi (1999) magnitude of response vectors of *log Gabor* filters is estimated by application of the Rayleigh distribution. Kovesi's method is expanded in this paper and applied to ELA. This application allows for efficient and automatic separation of noise from signal in error level images, since noise in ELA tends to mimic spatial features in the image. An additional k parameter can be used to fine tune results.

Standard benchmarking images such as the cameraman, farm, lena and peppers, are originally taken from a lossless compression format, TIFF, in 512x512 resolution and converted to a lossy compression format, JPEG, to simulate originally acquired images, i.e., from a camera. These images are then doctored to represent forgeries. Error levels are computed and the noise in them are removed using wavelet thresholding with its threshold automatically determined by the method presented in Kovesi (1999). A summary of the method is presented in Fig. 1.

The results achieved show that the ELA technique is indeed very effective in detecting the forgeries and despite the noisy images generated in the ELA process, filtering through wavelet thresholding with automatic thresholding selection proved to be an effective approach in denoising, making easier to detect the

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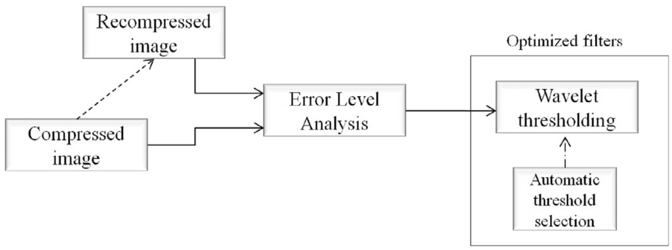

Fig. 1. Summary and work flow of the method.

forgeries. Therefore, the proposed method has its validity attested and could be used to diminish the attempts to moral rights by helping forensic professionals to detect a forged image.

The rest of this paper is organized as follows: Section 2 presents an introduction to current literature on image forgery detection and wavelet thresholding; Section 3 summarizes application of error level analysis, detailing the application of error level analysis, presenting standard test images, their doctored versions for this paper and the associated error levels; Section 4 presents the process of wavelet thresholding, a scheme for automatic threshold selection and this paper's contribution; Section 5 presents results obtained by the automatic wavelet thresholding; ultimately, in Section 6, steps of the method are enumerated, its efficiency discussed and future works addressed.

2. Image forgery detection and wavelet thresholding

Since late years, even before 1990, altering images digitally has become a disseminated practice, much due to the personal computer popularization. For example, the number of tampered pictures, by definition images where part of its original content has been some way altered, removed or combined with other images, synthetic textures or even computer rendered graphics (Lin, He, Tang, & Tang, 2009), reached 10% of all photos published in the United States around the year 1989 (Amsberry, 2009).

In addition, for a number of reasons, some of those are intended to deceive the viewer in ways that hurt legal and moral principles guaranteed by law, creating a number of issues. The advent of powerful tools with that purpose turns the detection in a very difficult process even for professionals.

The techniques for image forgery are many, (Lin, He, Tang, & Tang, 2009) names a few, such as, simple cutting and pasting, known as cloning (Ng & Chang, 2004), matting for perfect blending (Chuang, Agarwala, Curless, Salesin, & Szeliski, 2002; Sun, Jia, keung Tang, & yeung Shum, 2004), graph cut for finding optimal composition boundaries (Kwatra, Schödl, Essa, Turk, & Bobick, 2003; Li, Sun, Tang, & Shum, 2004), texture synthesis (Bugeau & Bertalmío, 2009; Kwatra, Schödl, Essa, Turk, & Bobick, 2003; Sun, Yuan, Jia, & Shum, 2005) and variational approaches for synthesis of new content (Bertalmío, Sapiro, Caselles, & Ballester, 2000; Bugeau & Bertalmío, 2009; Bugeau, Bertalmío, Caselles, & Sapiro, 2010; Pérez, Gangnet, & Blake, 2003).

For that reason, techniques for detection of tampered images have attracted the attention of the scientific community, current image forgery detection is achieved through either active or passive (blind) approaches. Active approaches depend on the usage of watermarks or signatures (Huynh-The, Banos, Lee, Yoon, & Le-Tien, 2016; Loganathan & Kaliyaperumal, 2016; Mishra, Agarwal, Sharma, & Bedi, 2014; Verma, Jha, & Ojha, 2015). On the other hand, passive approaches do not need any explicit *a priori* information about the image, constituting a new direction of great interest in the field of image forensics (Bourouis, Mashrgy, & Bouguila, 2014; Guo, Liu, & Wu, 2013; Mahdian & Saic, 2009; Uliyan, Jalab, Wahab, Shivakumara, & Sadeghi, 2016). However, considering current art, there is no complete solution to automatically and blindly determine image forgeries (Lin, He, Tang, & Tang, 2009).

Passive blind image forensics are well documented, featuring surveys such as Farid (2009b); Ng, Chang, Lin, and Sun (2006). Current methods dwell on detecting cloning, which is essentially cutting and pasting in an image (Fridrich, Soukal, & Lukás, 2003; Popescu & Farid, 2004a); resampling, originated from processes of resizing, rotating or stretching portions of pixels (Kirchner, 2008; Mahdian & Saic, 2007; Popescu & Farid, 2004b; Prasad & Ramakrishnan, 2006); splicing or matting, the process of combining two or more images into a single composite, usually taking care to match borders (Farid, 1999; Ng & Chang, 2004) and statistical analysis, where statistical properties of natural images are exploited to detect image manipulation (Bayram, Avcibas, Sankur, & Memon, 2005; 2006; Farid & Lyu, 2003; Lin, He, Tang, & Tang, 2009; Mahdian & Saic, 2009).

Error level analysis is a passive blind image forensic method created by Krawetz (2007), although sometimes related to others authors due to failures in recent art (Farid, 2009a; Grigoras & Smith, 2013; Zhao, Shih, & Shi, 2011) to properly cite and acknowledge the original author of this method. This technique takes advantage of lossy compression schemes of tampered images to detect forgeries.

Lossy compression schemes perform a trade off between data quality and compressed data size, at first, this might seem as a drawback to a forensic analyst due to the loss of evidence associated with the trade off, however, different quality levels in an image are evidence themselves.

An original image possesses an unique quality level, a property originated both from its acquisition and compression scheme. When such an image is tampered, either through cloning, splicing or matting, the original content is combined with foreign content, which will possess different quality levels, being the original content usually already compressed and the foreign uncompressed.

ELA works by taking an image compressed with a lossy compression scheme, intentionally recompressing at a known error rate and then computing the absolute difference between the first image and its recompression.

This difference between images are the error levels associated with the original pixels, these error levels, seen as an amount of change, are directly associated with compression loss.

If the amount of change is small, the pixel has reached its local minima for error at the determined error rate, hence it is likely to be already compressed, on the other hand, if there is a large amount of change, then the pixels were not at their local compression minima and are likely to be foreign (Krawetz, 2007).

ELA's absolute differences are computed across all spatial frequencies in an image. This causes the error levels to mimic the spatial frequencies of the pixels they represent. That is, low frequency regions, regions where the tonal transition is smooth, such as uniform skies or skin, will present lower amounts of change while high frequency regions, where the tonal transition is abrupt, such as fur, grass or hair, will present higher amounts of change.

These fluctuations might confuse a forensic analyst, since both high frequency and foreign content will present high amounts of change. Regarding this problem, a windowed absolute differences scheme is presented in literature (Farid, 2009a) to compensate the fluctuations created by both low and high frequencies.

Error levels are noisy by essence since the absolute differences are computed across all spatial frequencies in the image. This causes the error levels to mimic the distribution of the spatial frequencies present in the image, increasing the difficulty in the interpretation of error levels.

Noise, as any sharp changes in an image's intensity, implies in high-frequency components, thus, lowpass filtering is a common application of noise removal in image analysis

(Seul, O'Gorman, & Sammon, 2000). Several convolution based methods of noise attenuation are present in image analysis literature such as de Araujo, Constantinou, and Tavares (2016); Bernardes et al. (2010); Dugad and Ahuja (1999); Fernández, Salinas, and Puliafito (2005); Gilboa, Member, Sochen, and Zeevi (2004); Gonzalez and Woods (2001); Lim (1990); Nodes and Gallagher Jr. (1982); Salinas and Fernández (2007); Sun, Gabbouj, and Neuvo (1994), however, the greatest downside of these methods is the blurring of images.

On the other hand, Wavelets thresholding is a process that uses a forward wavelet transform, filters the noise by thresholding the resulting coefficients and then applying the inverse transform to recover the image. It is able to effectively remove noise components without interfering with other signal components present in an image, that is, without causing blurring (Donoho, 1993).

Although its success in image processing, determining the most adequate threshold level is a current issue because the thresholding might affect components other than noise. With this issue in focus in recent wavelet thresholding literature, several automatic and adaptive methods are proposed to determine the threshold, such as Chen, Lei, Ji, and Sun (2007); Deivalakshmi and Palanisamy (2016); Ju, Shijing, and Jiantao (2010); Kovesi (1999); Liu, Szeliski, Kang, Zitnick, and Freeman (2008); Madeiro, Cortez, Oliveira, and Siqueira (2007); Poornachandra (2008); Yong and Qiang (2010); Zhang, Wong, and Zheng (2002), to cite a few.

3. Error level analysis

Error level analysis (ELA) is a passive blind image forensic method created by Krawetz (2007) which takes advantage of the lossy compression schemes of tampered images to identify its forgery. The original quality level of a image is a unique feature itself, thus, any alteration process leaves its traces behind also in it. Briefly, ELA works by using an image compressed by a lossy scheme and recompressing it with a known error rate, then, it computes the absolute difference between the analyzed image and the recompressed one. Formally, ELA is described as follows.

Error levels, $ELA(n_1, n_2)$ where n_1 and n_2 are row and column indices, can be represented by

$$ELA(n_1, n_2) = |X(n_1, n_2) - X_{rc}(n_1, n_2)| \, , \tag{1}$$

for each color channel, where X is the image suspected of forgery and X_{rc} is the recompressed image. Total error levels are error levels averaged across all color channels, as in

$$ELA(n_1, n_2) = \frac{1}{3}\sum_{i=1}^{3} |X(n_1, n_2, i) - X_{rc}(n_1, n_2, i)| \, , \tag{2}$$

where $i = 1, 2, 3,$ for a RGB image.

This difference between images are the error levels associated with the original pixels, these error levels, seen as an amount of change, are directly associated with compression loss. If the amount of change is small, the pixel has reached its local minima for error at the determined error rate. However, if there is a large amount of change, then the pixels are not at their local minima and are likely to be foreign (Krawetz, 2007).

ELA's absolute differences are computed across all spatial frequencies in an image. This causes the error levels to mimic the spatial frequencies of the pixels they represent. That is, low frequency regions, regions where the tonal transition is smooth, such as uniform skies or skin, will present lower amounts of change while high frequency regions, where the tonal transition is abrupt, such as fur, grass or hair, will present higher amounts of change. These fluctuations might confuse a forensic analyst, since both high frequency and foreign content will present high amounts of change. Regarding this problem, a windowed absolute differences scheme is presented in literature (Farid, 2009a) to compensate the fluctuations created by both low and high frequencies.

Figs. 2,3,4,5 present the cameraman, farm, lena and peppers images, respectively. Exhibited in these figures are the original and doctored images. ELA is presented for the doctored images in the 512x512 resolution. Fig. 2 shows ELA's weakness in gray-scale images, since the level of information is lower, so are the precision of error levels, thus, error levels created by high frequency components and error levels created by different qualities are indistinguishable. This problem is not present in any of the color images.

4. Automatic wavelet threshold selection

Wavelet thresholding, also known as wavelet shrinkage, is the process of converting a signal to a time-scale domain through a forward wavelet transform, wavelet coefficients are then thresholded according to a certain criteria and the reverse wavelet transform converts the wavelet coefficients back to the time-space domain of the image.

Wavelets have proved very efficient at separating signal and noise, although no particular wavelet has been shown to be more effective at denoising than others, however, threshold choice is a delicate issue. Here is presented a short review of the method described in Kovesi (1999) to automatically determine the threshold.

In Kovesi (1999), the Rayleigh distribution is utilized for estimation of the magnitude of response vectors in *log Gabor* filters, considering 2D Gaussian noise in the complex plane. This distribution is defined by

$$R(x) = \frac{x}{\sigma_g^2} e^{\frac{-x^2}{2\sigma_g^2}} \, , \tag{3}$$

where σ_g^2 is the variance of the 2D Gaussian distribution which describes the position of the filter's response vectors. The mean of this distribution is

$$\mu_r = \sigma_g \sqrt{\frac{\pi}{2}} \, , \tag{4}$$

and the variance is

$$\sigma_r^2 = \frac{4-\pi}{2}\sigma_g^2 \, . \tag{5}$$

Threshold choice is then a matter of choosing a value which is a scale of the standard deviation beyond the mean noise, as in

$$T = \mu_r + k \cdot \sigma_r \, , \tag{6}$$

where k controls how beyond the noise's mean is the standard deviation.

A reliable estimate of the mean of noise amplitude distribution can be determined by

$$E(A_N) = \frac{1}{2}\sqrt{\frac{-\pi}{ln(\frac{1}{2})}} \cdot median \, , \tag{7}$$

where A_N is the $N'th$ wavelet transform of the image. Smallest scales of A_N provide the best result, since they contain the most noise, further discussion can be seen in Kovesi (1999). In fact, noise power is elevated at small scales (Xu, Weaver, Healy, & Lu, 1994), at it can be seen in the wavelet decomposition of the cameraman error levels, in Fig. 6. That shows the wavelet scales decomposition, it is clear that at small scales seen in the smaller images in the upper left side the noise is greater than the larger scales.

The noise mean μ_r is effectively equal to $E(A_N)$ and the variance, σ_r can be calculated by combining Eq. 5 with

$$\sigma_g = \frac{E(A_N)}{\sqrt{\frac{\pi}{2}}} \, , \tag{8}$$

Fig. 2. Figure a) shows the original cameraman image, b) shows the forgery, with a zeppelin in the background and c) shows ELA for the doctored image.

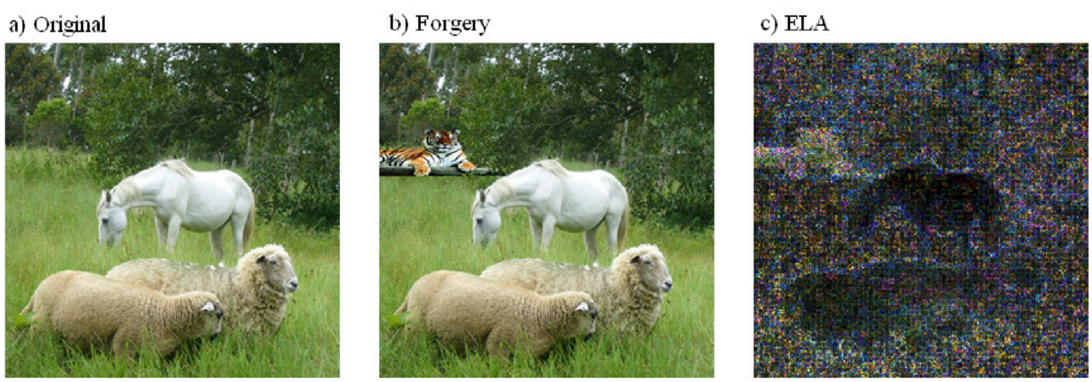

Fig. 3. Figure a) shows the original farm image, b) shows the forgery, with a tiger in the background and c) shows ELA for the doctored image.

Fig. 4. Figure a) shows the original lena image, b) shows the forgery, with a flower on her hat and contrast enhanced eyes and lips and c) shows ELA for the doctored image.

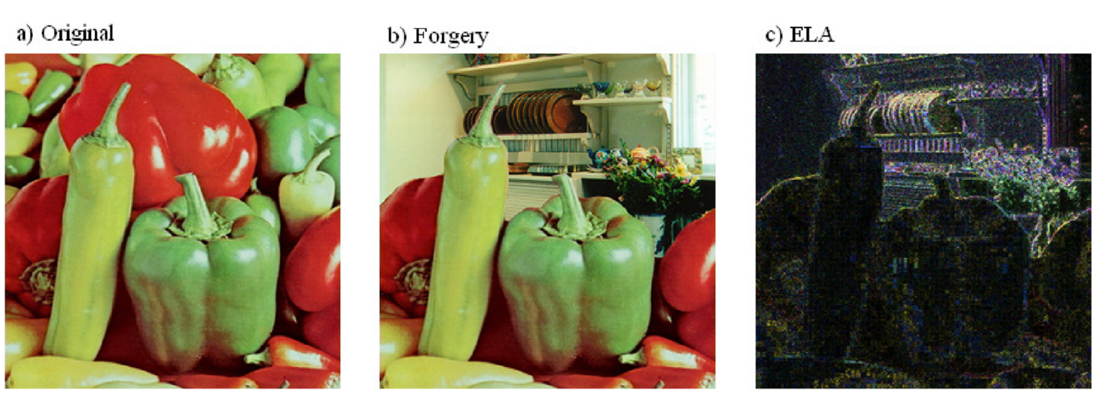

Fig. 5. Figure a) shows the original peppers image, b) shows the forgery, with a kitchen on the background and c) shows ELA for the doctored image.

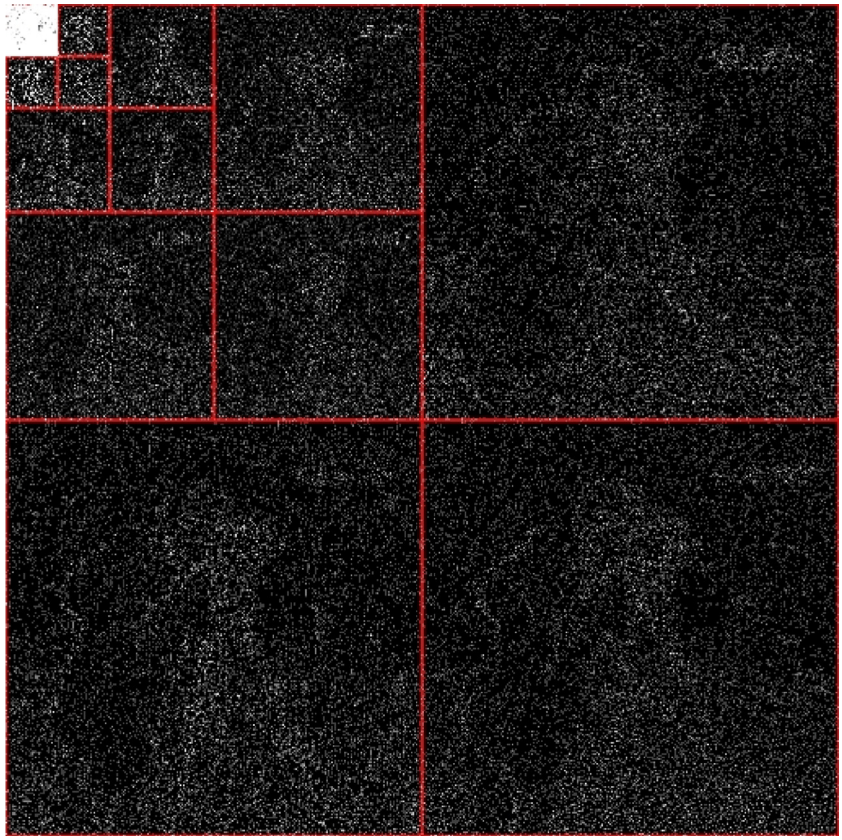

Fig. 6. Wavelet decomposition of the cameraman error levels, showing greater noise power in small scales.

resulting in

$$\sigma_r = \frac{(4-\pi)\cdot E(A_N)}{\pi}\,. \tag{9}$$

This statistical approach to the estimation of the threshold, T, through Eq. 6, proves successful in removing noise from wavelet transforms.

4.1. Threshold selection with Daubechies Wavelet

Instead of log-Gabor wavelets using Kovesi's method we argue for the application of Daubechies wavelets in image forensics with ELA. Our approach is summarized as follows.

After ELA is performed, median value is calculated for each color channel (R,G,B) of the image. A Daubechies wavelet transform is applied to each channel of the image. A threshold value is then calculated for each color channel using Eq. 6. Transformed image is soft-thresholded on all channels. Inverse Daubechies wavelet transform is applied, obtaining denoised image.

5. Results

Soft-thresholding is utilized to ensure avoiding the introduction of frayed edges, typical of wavelet thresholding. The standard test images have been wavelet shrinked with the automatic threshold selection described in the previous section. The orthogonal Daubechies wavelet with a vanishing moment of four was used for the wavelet transforms.

For the cameraman image, results are presented in Fig. 7. Despite ELA's failure to distinguish between the low resolution error levels in the gray scale image, the noise removal results are adequate. The value of the k scale factor used for this image was 4.

For the farm image, results are presented in Fig. 8. Overall noise has been greatly attenuated and the tiger stands out from the background. However, high frequency spatial characteristics of the image such as the vegetation increase error levels throughout the entire image.

For the lena image, results are presented in Fig. 9. The image's interpretation is difficult due to error levels created from the high frequency features such as the fur, however, the flower stands out. Minor modifications such as the contrast enhanced eyes and lips are not distinguishable.

For the peppers image, results are presented in Fig. 10. This image presents the best results in both noise removal and error level identification. The kitchen at the background completely stands out, canceling the peppers at the front.

6. Conclusion

This paper presents the not well known method Error Level Analysis, correctly identifying its original author despite omission in recent literature, and investigates the usage of wavelet transforms in error level noise removal. A method to automatically select a threshold level is used, from Kovesi (1999), showing good results in this application. A limitation of ELA is its application is limited to images subjected to lossy compression.

Standard images such as the cameraman, farm, lena and peppers, are doctored to represent forgeries. These images are then studied with error level analysis and compared with the error level analysis of lower resolutions of these same images. It's noted that ELA fails to process gray scale images due to low resolution of error levels but graciously succeeds in color images.

Afterwards, noise removal is performed, through wavelet thresholding, transforming the images from the time-space representation to time-scale, filtering the noise through wavelet's coef-

Fig. 7. Cameraman image error level analysis after automatic wavelet thresholding.

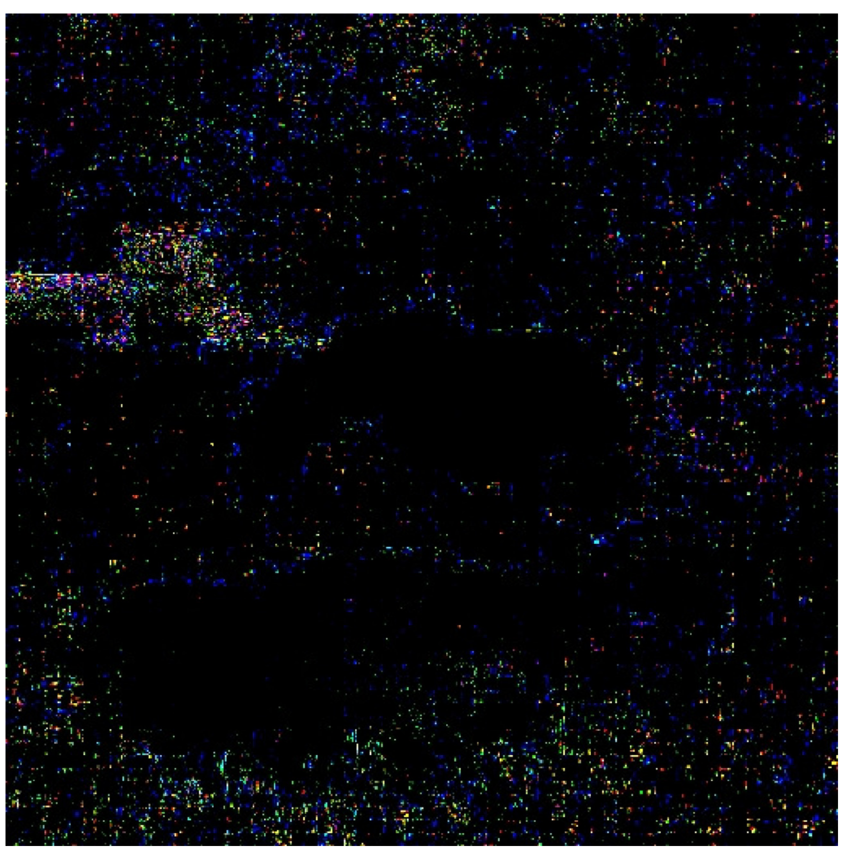

Fig. 8. Farm image error level analysis after automatic wavelet thresholding.

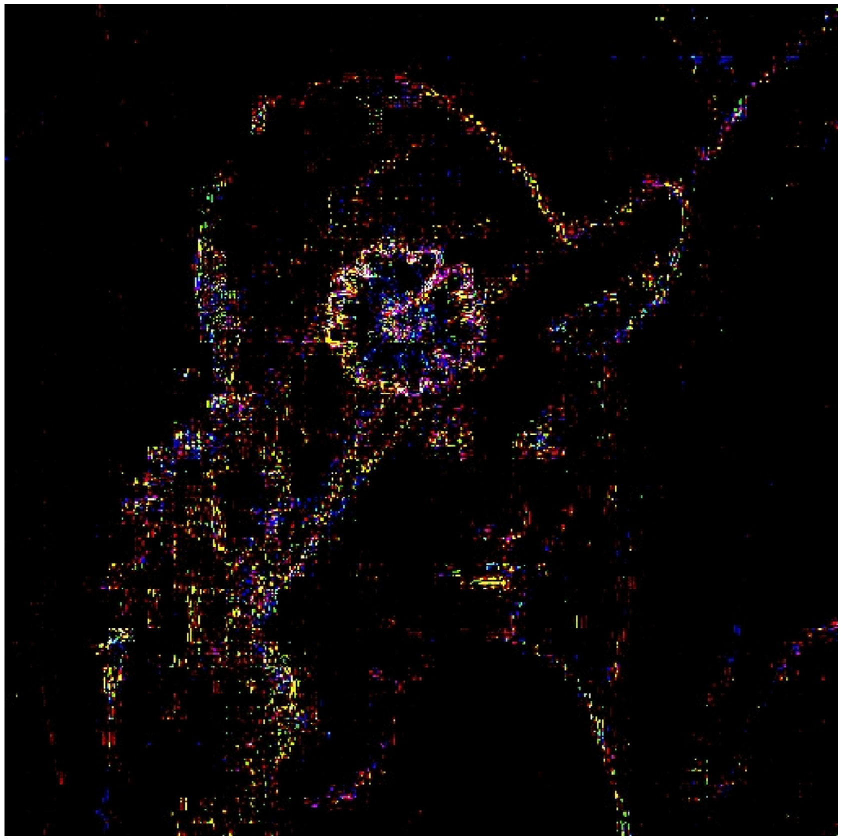

Fig. 9. Lena image error level analysis after automatic wavelet thresholding.

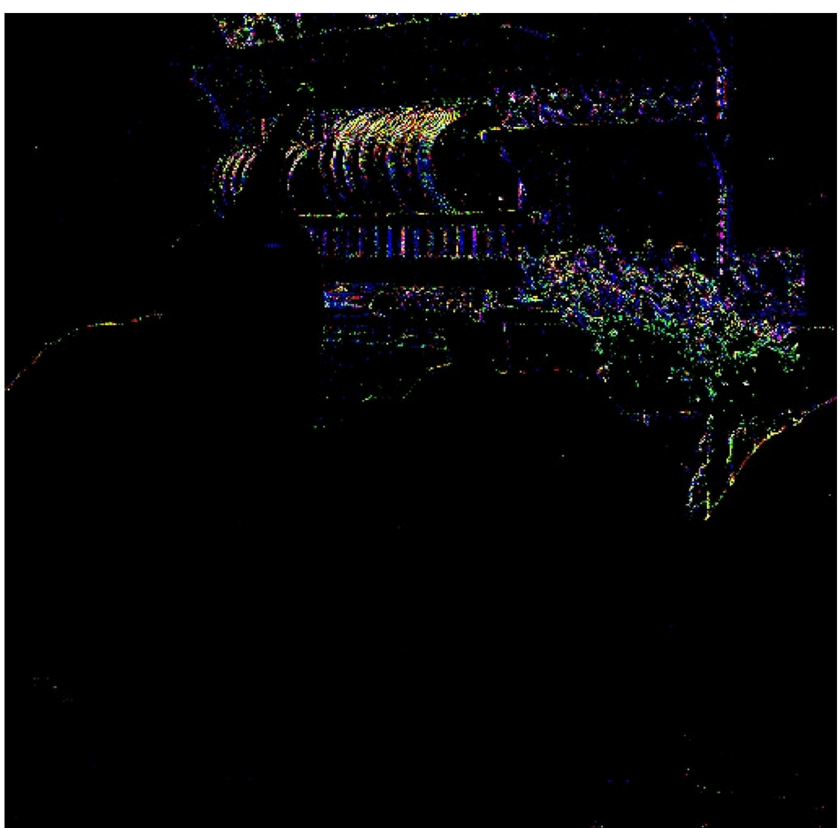

Fig. 10. Peppers image error level analysis after automatic wavelet thresholding.

ficients thresholding, where the threshold value is statistically calculated from the image, and performing the reverse wavelet transform on the image.

Empirically, results show the approach successfully attenuates noise and improves error levels, better identifying regions of the image where tampering has occurred. Daubechies wavelet transform achieves better results than log Gabor approach in ELA analysis. Despite providing a better estimate for a threshold value, the statistical approach for estimating this value is not ideal. This arises from the fact that error level analysis, by definition, creates a noise map from the image. Regions with greater noise tend to reflect forgeries, however, regions with high frequency components, such as hair or borders, also generate noise in ELA. The statistical approach used in this paper does not account for these high frequency components. Handling high frequency regions is proposed as future work.

Most work in literature of image forensics focus on active approaches such as Huynh-The, Banos, Lee, Yoon, and Le-Tien (2016); Loganathan and Kaliyaperumal (2016); Mishra, Agarwal, Sharma, and Bedi (2014); Verma, Jha, and Ojha (2015). Error level analysis (Krawetz, 2007) is by definition a passive approach since it does not use *a priori* information on the image under investigation. Despite having no prior information before the forgery, some information can be obtained from image data. This area is an interesting field for application of expert systems since it depends on information extraction, particularly those based on statistical methods. In this paper a direct statistical method was applied to calculate threshold level however other methods can be investigated, particularly Bayesian systems.

Discretion is necessary on the part of the forensic analyst when interpreting these results. Future work will focus in providing quantitative data to better automate the analysis of final results. These quantitative results should also enable the application of multi-objective optimization methods (Assunção, Colanzi, Vergilio, & Pozo, 2014). Another possibility for future work is the creation of expert systems which identify high frequency regions so a stronger thresholding can be applied to these regions. Application of other statistical methods, such as Bayesian systems, to the automatic calculation of threshold parameter is another direction of future research. Future work could also focus on training expert systems to automatically classify and identify forgeries in ELA images.

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