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THE INFLUENCE OF NOISE CORRUPTION TO IMAGE WATERMARKING IN DCT DOMAIN

Rastislav Lukáč — Marek Čandík *

In this paper we propose some results from noise corruption of digital watermarked images. The discrete cosine transformation (DCT) domain was used for embedding a watermark into the image. The quality of extracted watermarks was tested through subjective criteria and two well-known objective criteria such as the mean absolute error (MAE) and the mean square error (MSE). We have focused on the influence of Gaussian noise and impulse noise on the quality of extracted watermarks and also on the influence of some filters that were used to suppress the proposed corruption.

Keywords: digital watermarking, DCT, noise corruption, Gaussian noise, impulse noise, digital filters, average filter, L-filter, median filter, adaptive LUM FTC filter.

1 INTRODUCTION

Digital watermarking [1, 3, 7], the art of hiding information into image (generally - multimedia) data in a robust and invisible manner, has gained great interest over the past few years. One reason for the large interest in digital watermarking methods is its high commercial potential for applications such as copyright protection, authentication, labeling and monitoring. The watermark is given by a binary number and every watermark is represented by a two-dimensional function. According to the type of features, the watermarking algorithm can be divided into two classes. The first, the watermark can be embedded into a spatial domain done by intensity values of the luminance, while the second class includes techniques based on frequency coefficients given by transformations such as wavelets or discrete cosine transform (DCT). In this paper we considered the frequency domain given by DCT. We choose to work in this frequency domain for the following reasons:

- DCT has good energy compaction capability,
- it is feasible to incorporate the human visual system characteristics in this domain,
- the sensitivity of human visual system to the DCT basis images has been extensively studied resulting in a default JPEG quantization table.

It is acknowledged that hidden information can be decoded without quality losses. However, the image transmission over the information channel corrupts useful information. On that account, we consider real applications *ie* the watermark extraction from noised images since in this way we model the influence of the information channel.

In this paper, we propose some practical results from extraction of corrupted watermarked images. As shown in Fig. 1, four possibilities can be observed. This paper is focused on noise and filter influence as shown in Fig. 1b–d, on that account the ideal situation (Fig. 1a) was excluded. Concerning the character of DCT watermarking process, it will be interesting to observe the quality of extracted images under the influence of additive Gaussian noise in comparison with the influence of dotted noise *ie* impulse noise. To suppress the Gaussian noise, two filters such as non-adaptive average filter and adaptive constrained order-statistic L-filter were used. In the case of impulse noise, the well-known median filter (example of non-adaptive filter) and adaptive LUM (a lower-upper-middle) smoother with fixed threshold control (LUM FTC) were used.

To evaluate the influence of noise corruption and filtering methods, we propose amount of figures and tables. In tables, the well-known MAE and MSE objective criteria were used, however we insist that these criteria be applied to binary watermarks.

2 WATERMARKING

A watermark is a piece of hidden information within a digital signal. To achieve maximum protection of intellectual property with watermarked media, several requirements must be satisfied [1, 8]:

- Imperceptible — the watermark should be imperceptible, not to affect the viewing experience of the image or the quality of signal.

* Department of Electronics and Multimedial Communications, Technical University of Košice, Park Komenského 13, 041 20 Košice, Slovakia, E-mail: lukacr@tuke.sk, candik@tuke.sk

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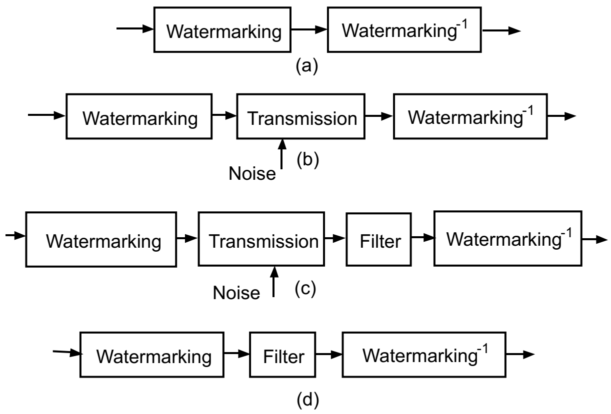

Fig. 1. Analysis of watermarked image transmission (a) ideal situation (b) transmission of hidden information over noised information channel (c) filter reconstruction of noised watermarked images (d) filter influence to noise-free watermarking process

- Undeletable — the watermark must be difficult or even impossible to remove by a hacker, at least without obviously degrading the host signal.

Table 1. Impulse noise — image Einstein

Noise	I2		I5	
	MAE	MSE	MAE	MSE
W1	0.293	74.645	0.402	102.411
W2	0.270	68.731	0.405	103.345

Table 2. Impulse noise — image Lena

Noise	I2		I5	
	MAE	MSE	MAE	MSE
W1	0.281	71.719	0.421	107.267
W2	0.281	71.594	0.406	103.469

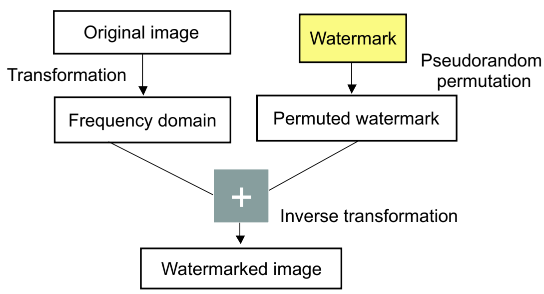

Fig. 2. Algorithm of watermarking

- Statistically undetectable – A pirate should not be able to detect the watermark by comparing several watermarked signals belonging to the same author.
- Robustness – The watermark should survive the use of loss-free compression techniques and signal processing operations (signal enhancement, geometric image operations, noise, filtering, *etc*).

Watermarking in frequency domain uses selected discrete transformations (DCT, wavelet) for embedding the hidden information into the spectral coefficients. The schematic algorithm of watermarking in frequency domain is shown in Fig. 2 and the algorithm for extraction of the watermark is shown in Fig. 3.

Our experiments have been performed on well-known 8 bit gray-scale static test images Einstein (Fig. 5a) and well-known Lena, both with a size of 256 × 256 image points. However, for place saving visual examples for image Einstein are presented only. As watermarks were employed two binary images with a size of 64 × 64 pixels that are shown in following figures (Fig. 4).

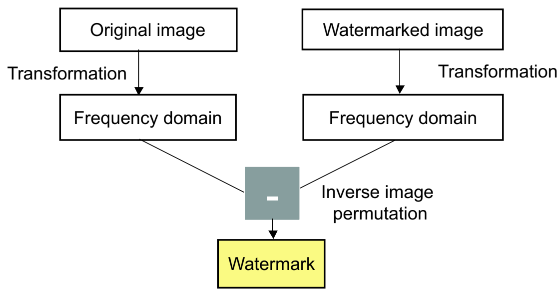

Fig. 3. Algorithm of the extraction of watermark

The used watermarks include heavy lines and objects since just binary images with heavy objects are preferred in watermarking process. Thus, for an ideal situation the watermarking extraction is performed without the loss of performance.

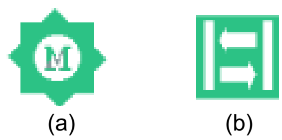

Fig. 4. Used watermark with size 64 × 64 pixels (a) W1, (b) W2

3 NOISE MODELS

To illustrate the degree of damage, 2 % (I2) and 5 % (I5) impulse noise and two types of Gaussian noise with variance $\sigma = 5$ (denoted as G5) and $\sigma = 10$ (G10) were used.

3.1 Impulse noise

The mathematical model of impulse noise [9] is expressed as

$$x_{ij} = \begin{cases} rnd & p_{md} \\ o_{ij} & 1 - p_{md} \end{cases} \tag{1}$$

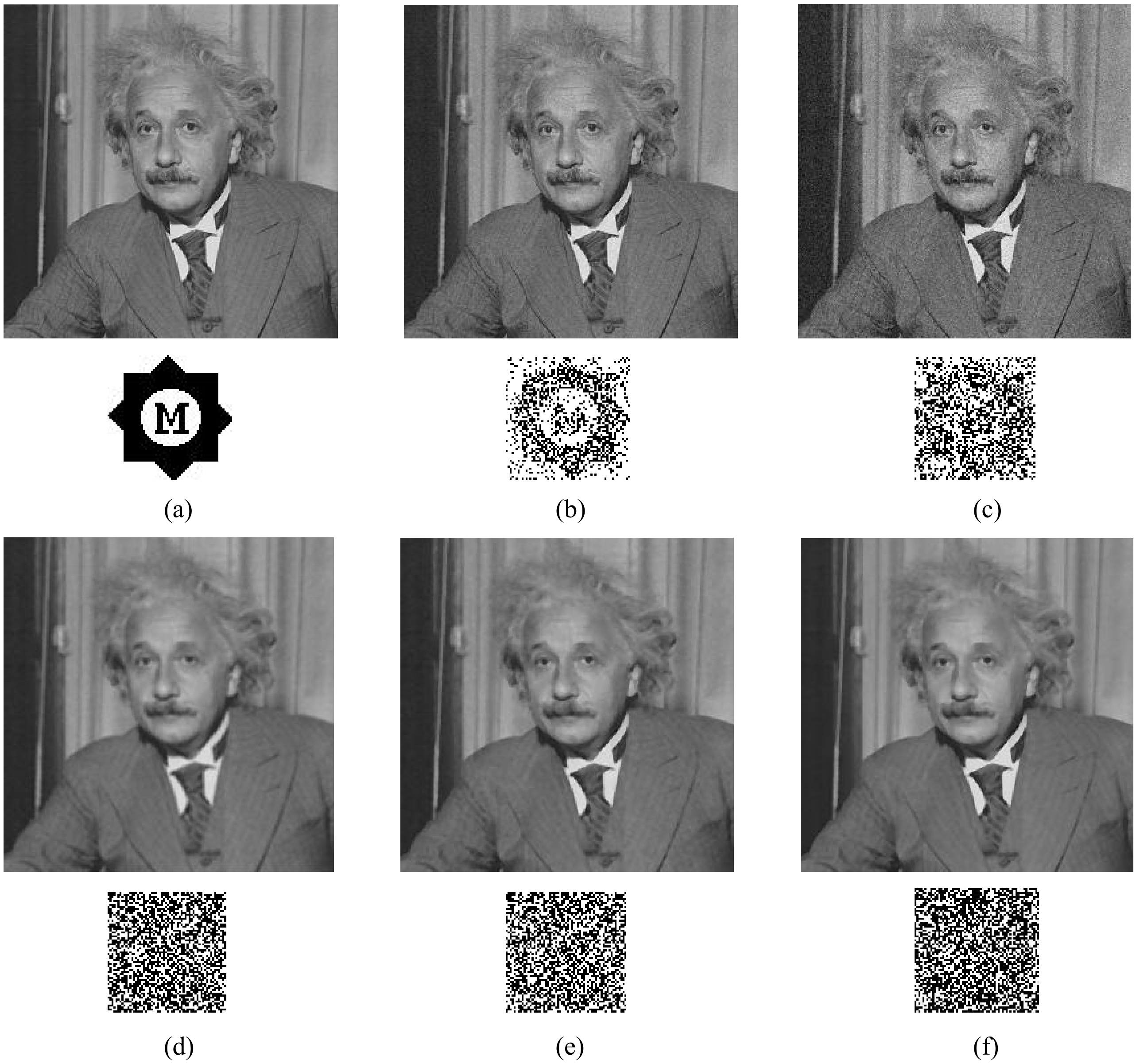

Fig. 5. Processed images and their corresponding watermarks: (a) – original image Einstein, (b) – Gaussian noise $\sigma = 5$, (c) – Gaussian noise $\sigma = 10$, (d) – Gaussian noise $\sigma = 5$ suppressed by average filter, (e) – Gaussian noise $\sigma = 5$ suppressed by L-filter, (f) – original passed through L-filter

where o_{ij} represents an image element of the original image on the position destined by i^{th} row and j^{th} column, x_{ij} is a sample from the corrupted (noised) image, rnd denotes, in the case of 8 bits/pixel quantization, the random value between 0 and 255 including both extreme values.

In Table 1 and Table 2 the evaluation is shown of extracted watermarks from watermarked images that were degraded by impulse noise. For simple understanding, a block diagram of the processing chain is displayed in Fig. 1b. Visual quality of watermarks can be compared in Fig. 6a and Fig. 6b. In both cases *ie* in the cases of 2 % and 5 % impulse noise, separately, the watermark extraction is highly corrupted, useful information is lost.

3.2 Additive Gaussian noise

The above mentioned block diagram (Fig. 1b) is used again. However, in the case of additive Gaussian noise (Fig. 5b,c), a random value with Gaussian distribution for a zero mean and characterised variance is added to each image point. It is evident that the increase in the variance goes hand in hand with the extension of the random interval, *ie* with a larger degree of damage.

Mathematical model of the additive Gaussian noise can be expressed as

$$f(x) = \frac{1}{\sigma\sqrt{2pi}} \exp\Big(-\frac{1}{2}\big(\frac{x-\mu}{\sigma}\big)^2\Big) \qquad (2)$$

where σ is the variance, μ is the mean and x is an image point. Clearly, small values are added with large probability, whereas large values are added with small probability. Usually, the following noise generator is preferred:

$$x = \sqrt{-2\ln(r_1)}\cos\big(\pi(2r_2 - 1)\big) \qquad (3)$$

where r_1 and r_2 are random values with uniform distribution.

Table 3. Gaussian noise — image Einstein

Noise	$\sigma = 5$		$\sigma = 10$	
	MAE	MSE	MAE	MSE
W1	0.286	72.839	0.395	100.730
W2	0.265	67.610	0.389	99.298

Table 4. Gaussian noise — image Lena

Noise	$\sigma = 5$		$\sigma = 10$	
	MAE	MSE	MAE	MSE
W1	0.288	73.337	0.383	97.555
W2	0.270	68.917	0.371	94.691

Table 5. Original images passed through MF

Image	Lena		Einstein	
	MAE	MSE	MAE	MSE
W1	0.378	96.497	0.467	119.158
W2	0.406	103.532	0.461	117.539

In the case of Gaussian noise, the evaluating of extracted watermarks is presented in Table 3 and Table 4. Extracted watermarks with corresponding degraded images are show in Figs. 5b,c.

However, visual comparison between the impulse noise corruption and the degradation by the additive Gaussian noise reveals that Gaussian noise has a considerably smaller influence on watermark extraction in comparison with the impulse noise.

In the next section, some adaptive and non-adaptive filtering algorithms for noise suppression will be provided. These filters are used not only in noisy environments as shown in Fig. 1c, however, in the case of degraded images the filter influence will be examined in the case of original watermarked images (Fig. 1d), too.

4 USED FILTERS

To suppress the impulse noise, two filters, *ie* the well-known median (MF) and adaptive LUM smoother with fixed threshold control (LUM FTC) are used. In the case of Gaussian noise, a simple average filter (AF) and adaptive constrained L-filter were preferred, since both filters provide a robust estimate in the environments corrupted by additive Gaussian noise.

4.1. Median filter

Consider an input set $W = \{x_1, x_2, \ldots, x_N\}$ centered around the central sample $x^* = x_{(N+1)/2}$. Note that N is a window size. Thus, filter output is represented by a central sample from an ordered input set. Mathematically, MF is defined as follows [2, 6]:

$$y = \text{med}\{W\} \qquad (4)$$

$$= x_{((N+1)/2)} \qquad (5)$$

where y is the filter output, med is a median operator, that requires an ordering of input samples and a choice of central sample $x_{((N+1)/2)}$ from an ordered set. Moreover, $x_{(.)}$ denotes an ordered sample, *ie* an order statistic, where $x_{(1)} \le x_{(2)} \le \cdots \le x_{(N)}$.

In Table 5 the influence is shown of median filtering on watermarked images. Although a median filter is more a robust filter in the environments corrupted by impulse noise, considerable blurring (Fig. 6e) is introduced into an image. Thus, edges and small signal features, *ie* high frequency elements are removed and watermark extraction (Fig. 6e) is performed without preservation of hidden information.

Table 6. MF applied on noised image Einstein

Noise	I2		I5	
	MAE	MSE	MAE	MSE
W1	0.466	118.846	0.473	120.714
W2	0.643	118.099	0.464	118.411

Table 7. MF applied on noised image Lena

Noise	I2		I5	
	MAE	MSE	MAE	MSE
W1	0.395	100.606	0.408	103.905
W2	0.417	106.271	0.434	110.629

Table 8. Original images passed through LUM FTC

Image	Lena		Einstein	
	MAE	MSE	MAE	MSE
W1	0.041	10.335	0.042	10.708
W2	0.042	10.584	0.033	8.529

Table 9. LUM FTC applied on noised image Einstein

Noise	I2		I5	
	MAE	MSE	MAE	MSE
W1	0.090	22.910	0.140	35.735
W2	0.063	16.062	0.123	31.439

Table 10. LUM FTC applied on noised image Lena

Noise	I2		I5	
	MAE	MSE	MAE	MSE
W1	0.077	19.611	0.125	31.813
W2	0.080	20.420	0.125	31.937

Likewise, in Table 6 and 7 is evaluated the quality of watermarks extracted from noisy watermarked images. However, like in the case of noise free watermarked images, useful information is lost (Fig. 6c) since the reconstruction process by the MF introduces blurring, although all impulses are removed. From results (Table 5–7, Fig. 6c,e) it is evident that a median filter can not be used for noise suppression in watermarked images.

4.2 LUM FTC

As the second filter used for impulse noise suppression the excellent adaptive LUM smoother with fixed threshold control was chosen that was presented in [4, 9]. This adaptive nonlinear filter is distinguished by an excellent balance between noise removing and signal-details preservation. The output of adaptive LUM FTC is given by

$$y^* = y_s \,, \tag{6}$$

where s (for 3×3 filter window $1 \le s \le 5$) is a sum of comparators c_k whose output is defined by

$$\begin{aligned} \text{IF} \quad d_k \ge Tol_k \quad &\text{THEN} \quad c_k = 1 \\ &\text{ELSE} \quad c_k = 0 \end{aligned} \tag{7}$$

In equation (7) $d_{(k)}$ represent absolute differences between the central sample x^* and traditional LUM smoother outputs y_k [9] defined by

$$y_k = \text{med}\{x_{(k)}, x^*, x_{(N-k+1)}\}\,, \tag{8}$$

for all k *ie* $1 \le k \le (N+1)/2$. Thus, in every location of a running window the output of adaptive LUM smoother is determined by the most appropriate smoothing level y_k corresponding to the sum s of comparator outputs. Note that for 3×3 LUM FTC the following sub-optimal thresholds were obtained: {0, 10, 15, 30, 30} [4].

The performance of the LUM FTC filter was successfully tested in various smoothing applications. As shown in Table 8–10 and Fig. 5d,f, the watermark extraction from images that were processed by LUM FTC filter is well performed and useful information is well legible. It is a outcome of accurate smoothing properties of LUM FTC since this filter produces minimal blurring. In addition, LUM FTC provides excellent estimates of processed pixels.

In the case of watermark extraction from noisy watermarked images, excellent results were obtained, too.

4.3 Average filter

Average filter (AF), also called a mean filter, belongs to a class of linear filters. Although the median is a nonlinear filter, there exists an interesting analogy between MF and AF, and thus, these filters can be expressed as [2]

$$L(\beta) = \sum_{i=1}^{N} |x_i - \beta|^\gamma \tag{9}$$

where the median of $W = \{x_1, x_2, \dots, x_N\}$ can be defined as the value β minimising $L(\beta)$ in (9) when $\gamma = 1$. The sample average minimizes the same expression for $\gamma = 2$.

Another definition of AF can be expressed as

$$y^* = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{10}$$

or

$$y^* = \sum_{i=1}^{N} w_i x_i \tag{11}$$

where γ^* is a filter output, N is a window size and $w_1 = w_2 = \dots = w_N = 1/N$ are filter coefficients.

Although, the average filter is the maximum likelihood estimate of the signal level in the presence of additive Gaussian noise (Table 12-13), watermark reconstruction from watermarked images corrupted by Gaussian noise is catastrophic (Fig. 5d). Likewise in the case of original watermarked images shown in Table 11, useful hidden information is degraded by introducing of blurring. It is an outcome of the filter principle since a mean operator is used.

Table 11. Original images passed through AF

Image	Lena		Einstein	
	MAE	MSE	MAE	MSE
W1	0.482	122.955	0.495	126.317
W2	0.522	132.979	0.488	124.512

Table 12. AF applied on noised image Einstein

Noise	$\sigma = 2$		$\sigma = 10$	
	MAE	MSE	MAE	MSE
W1	0.487	124.200	0.484	123.516
W2	0.517	131.920	0.523	133.352

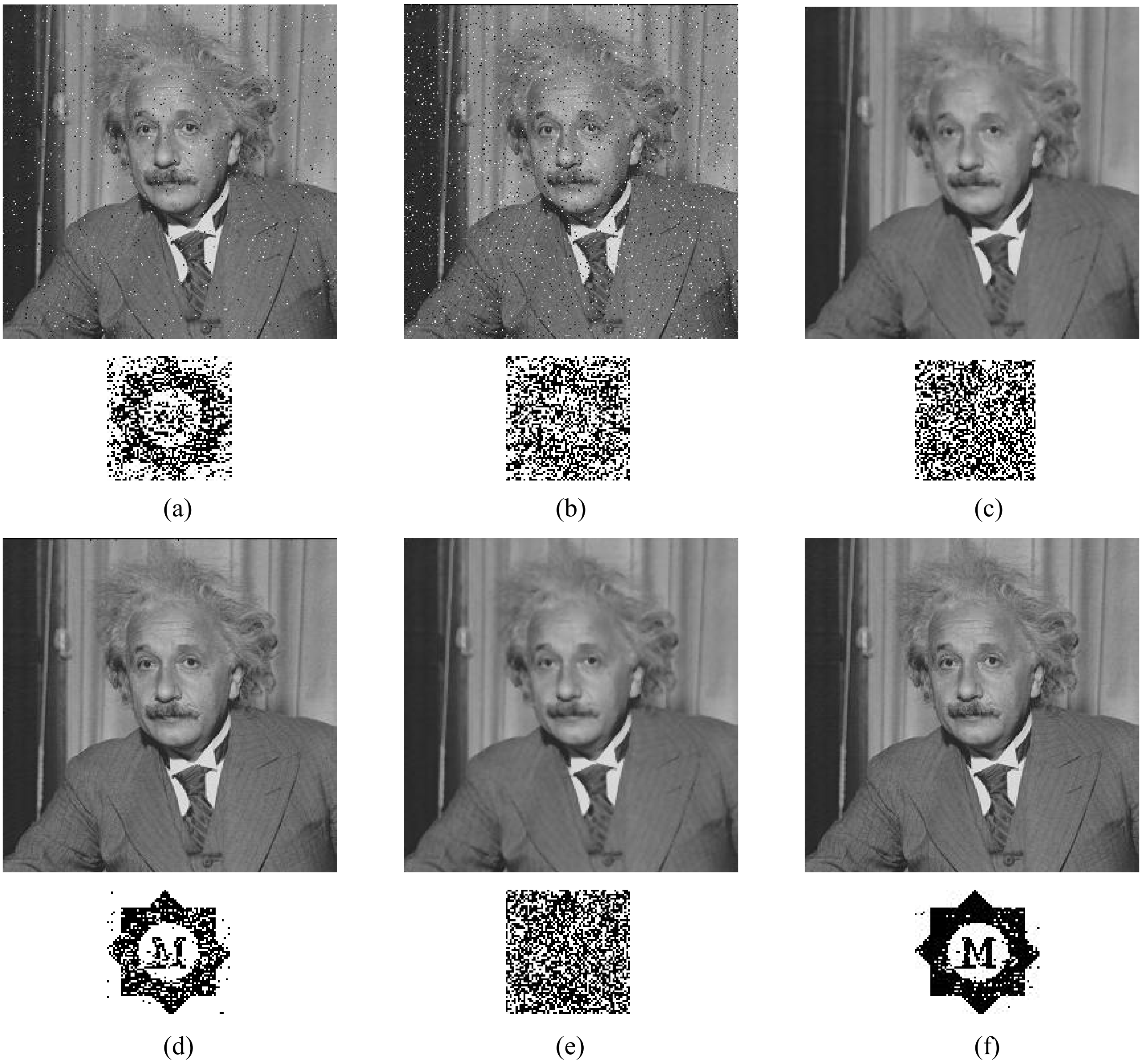

Fig. 6. Processed images and their corresponding watermarks: (a) – 2 % impulse noise – I2, (b) – 5 % impulse noise – I5, (c) – I2 noise suppressed by median filter, (d) – I2 noise suppressed by LUM FTC, (e) – original passed through MF, (f) – original passed through LUM FTC

Table 13. AF applied on noised image Lena

Noise	$\sigma = 5$		$\sigma = 10$	
	MAE	MSE	MAE	MSE
W1	0.498	126.877	0.488	124.325
W2	0.484	123.391	0.490	125.010

Clearly, from the proposed results it is evident that linear operators introduce blurring and thus it results in large modifications of intensity values.

Table 14. Original images passed through L-filter

Image	Lena		Einstein	
	MAE	MSE	MAE	MSE
W1	0.398	101.663	0.468	119.220
W2	0.425	108.263	0.4624	117.972

4.4 L-filter

An important generalization of the median filter is the L-filter [2]. In addition, previous MF and AF can be expressed as special cases of the L-filter. The output of

L-filter is given as a weighted sum of an ordered input set

$$y^* = \sum_{i=1}^{N} w_i x_{(i)} \tag{12}$$

where $w_1, w_2, \dots w_N$ are filter coefficients optimized according to [2]. There exist two approaches: the first is the constrained L-filter (sum of filter coefficients is equal to one) and the second is an unconstrained L-filter. In this paper was used the constrained L-filter.

In comparison with AF, better results (Table 14-16, Fig. 5e,f) were achieved by the constrained L-filter, however, extracted watermarks are not usable.

Table 15. L-filter applied on noised image Einstein

Noise	$\sigma = 5$		$\sigma = 10$	
	MAE	MSE	MAE	MSE
W1	0.454	115.565	0.489	124.575
W2	0.485	123.702	0.477	121.584

Table 16. L-filter applied on noised image Lena

Noise	$\sigma = 5$		$\sigma = 10$	
	MAE	MSE	MAE	MSE
W1	0.483	123.173	0.494	125.133
W2	0.506	128.867	0.481	122.643

5 CONCLUSION

This paper was focused on the noise and filter influence on watermarking extraction. The obtained results show that Gaussian noise degrades the extracted watermark less than the impulse noise. However, the blurring introduced by filters for Gaussian noise suppression destroys watermarked images and thus watermark reconstruction is catastrophic. On the other hand, for impulse noise suppression it is possible to find an appropriate filter *eg* LUM FTC that removes impulses only, whereas noise free samples will be invariant [4, 9] against the filter influence. Then the extracted watermarks present useful information.

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Rastislav Luk (Ing) received the Ing degree at the Technical University of Koice, the Slovak Republic, at the Department of Electronics and Multimedial Communications in 1998. Currently, he is with the Department of Electronics and Multimedial Communications at the Technical University of Košice. His research interest includes image filtering, impulse detection, neural network and permutations.

Marek andk (Ing) was born in Koice, Slovakia 1974. He graduated from the Technical University of Košice in 1997, then he started PhD study at the Department of Electronics and Multimedia Communications, Faculty of Electrical Engineering and Informatics, Technical University in Košice. His work includes digital image processing and transmission.