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Research Article

Effect of Different Places in Applying Laplacian Filter on the Recovery Algorithm in Spatial Domain Watermarking

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Abstract: Generally, Laplacian filter is used to make an image more defined and enhanced. In this study, a comparison is toke place between the effects of different places of performing Laplacian filter on the power of the watermark recovery in spatial domain image watermarking. This filter is applied in two different places in the watermark recovery algorithm; before performing the watermark recovery and before take the correlation in the middle of recovery algorithm. The distinction between the watermark and UN water marked parts of the image are increased by this filter. Thus, watermark could recover significantly better by recovery algorithm. We intend to determine which of these places is more appropriate to apply this filter. A typical correlation based method is used as a representative of spatial domain watermarking methods. Several experiment are done to compare the effect of different places in applying proposed filter on quality of extracted watermark in correlation based watermarking algorithm.

Keywords: Correlation based watermarking, digital image watermarking, Laplacian filter, spatial domain watermarking

INTRODUCTION

In recent years, with the expansion of Internet, it becomes very easy to transmit and distribute digital media. Therefore, there is the high demand for financial and intellectual property protection methods for digital data. The watermarking has been proposed as an appropriate proposal for this problem. The purpose of the watermark is to embed some extra information about the digital data without visibly modifying it (Kasmani and Naghsh-Nilchi, 2008).

In the design of the watermarking algorithm always, there is a conflict between robustness and imperceptibility. The imperceptibility means that how much the embedded information makes reductions in signal quality; and the robustness is the ability of the watermark to remain readable after innocent or malicious signal processing operations on the watermarked image. These parameters are incompatible with each other and they should be set to meet the requirements of the application (Kasmani *et al*., 2009; Kasmani and Naghsh-Nilchi, 2008).

Generally, watermarking methods could be categorized into the spatial domain or the transform domain. The watermark information is embedded directly in the pixels of the host image in the spatial domain techniques. These methods are not robust to image common image processing operation (Kasmani and Sharifi, 2014; Potdar *et al*., 2005). Although some methods, e.g., (Depovere *et al*., 1998) utilized the filters capability to better extract the watermark. Transform domain watermarking schemes benefit properties of the transform domain to embed the watermark. These methods usually use the Discrete Cosine Transform (DCT) (Chu, 2003; Lin and Chen, 2000) and the Discrete Wavelet Transform (DWT) (Hsieh *et al*., 2001). These methods typically bring higher image fidelity and more robustness to image manipulations.

Many researchers have tried to improve the performance of algorithms watermarking. Several of these researchers investigate on finding suitable locations for watermark embedding and others have studied the enhancement algorithm to increase power of watermark retrieval algorithms.

In the first methods, there are an attempt to use human visual system characteristics to choose appropriate for resistance and transparency. These methods are commonly used in frequency domain watermarking techniques. These method utilize a perceptually optimal quantization matrix (Watson, 1994), Just Noticeable Difference (JND) (Chou and Li, 1995), wavelet filter (Watson *et al*., 1997) and Human Visual System (HVS) (Kutter and Winkler, 2002;

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Levický and Peter, 2004), for probing the most suitable coefficients to embed the watermark information.

However, in the second methods, there is an attempt at providing a method to make watermark information visible to the watermark recovery algorithms. As a result, these approaches could increase the resistance watermarking algorithms.

An improved detector is proposed for detection based on thresholds extracted by statistic rules on which the method relies (Fotopoulos and Skodras, 2002). Applying blurring filters to a watermarked image before executing watermark detection can increase the possibility of detection (Braudaway and Mintzer, 2003). Since blurring filters, suppress the high spatial frequencies, they generally distort the image quality. However, for a watermark that has dominant low frequency content, the application of a blurring filter can serve to improve the statistical environment for watermark detection and thereby improves the detection probability. Since the content of image might interfere with the watermark, especially in the low-frequency parts, the reliability of the detector could be improved by applying matched filtering before correlation (Depovere *et al*., 1998). This decreases the influence of the original image to the correlation. Therefore, the watermark could easily be extracted from watermarked image.

As a category of Blind Embedding Watermark, Hafiz proposed an approach to blind watermark detection/decoding for spread spectrum by using of Independent Component Analysis theory (Malik *et al*., 2005). It uses the theory of Independent Component Analysis (ICA) and detects the watermark with a blind source separation method. The watermark information is considered as noise for the watermarked image in its spatial domain. This noise is magnified before detection and then recovers the watermark information by adjusting the extracted data from the frequency domain according to the global minimum method (Pan *et al*., 2004). A preprocessing method is proposed that exploit a combination of noise boosting and filtering to facilitate recovering the watermark from watermarked image in the DCT-based watermarking algorithm (Kasmani *et al*., 2009; Kasmani and Sharifi, 2014).

In this study, a comparison is made between effects of different places of applying Laplacian filter on increasing power of correlation based watermark recovery algorithms in the spatial domain methods. In order to compare, this filter is applied before executing watermark extraction procedures and before comparing the correlation between the extracted block and pseudo random noise, in the correlation based method. Different Experiments are done to show that which of these places is appropriate for applying Laplacian filter in the spatial domain based watermarking.

MATERIALS AND METHODS

Laplacian filter: In this study, Gonzales definition is used for Laplacian filter (Gonzalez and Woods, 2002). Because the Laplacian is a derivative operator, its use highlights gray-level discontinuities in an image and deemphasizes regions with slowly changing gray levels. This will tend to produce images that have grayish edge lines and other discontinuities, all superimposed on a dark, featureless background. Background features can be "recovered" while still preserving the sharpening effect of the Laplacian operation simply by adding the original and Laplacian images.

In this study a special implementations of the Laplacian is used:

$$\nabla^2 f = 8f(x,y) - \begin{bmatrix} f(x-1,y-1) + f(x-1,y) \\ +f(x-1,y+1) + f(x,y-1) \\ +f(x,y+1) + f(x+1,y-1) \\ +f(x+1,y) + f(x+1,y+1) \end{bmatrix} \qquad (1)$$

This equation can be implemented using the mask shown in Eq. (2):

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \qquad (2)$$

Correlation based watermarking using block processing in the spatial domain:

Watermark embedding algorithm: The watermark embedding process is represented in Fig. 1, followed by a detailed explanation:

Step 1: Divide the host image into 16×16 blocks.

Step 2: Re-formulate the watermark image into a vector of zeroes and ones.

Step 3: Generate two uncorrelated pseudorandom sequences by a key. One sequence is used to embed the watermark bit 0 (PN_0) and the other sequence is used to embed the watermark bit 1 (PN_1). Number of elements in each of the two pseudorandom sequences must be equal to the number of block.

Step 4: Embed the two pseudorandom sequences, PN_0 and PN_1, with a gain factor α in the 16×16 blocks of the host image. If we donate X as the matrix of the block, then embedding is done as Eq. (3):

$$X' = \begin{cases} X + \alpha * PN0 & watermark\_bit = 0 \\ X + \alpha * PN1 & watermark\_bit = 1 \end{cases} \qquad (3)$$

Watermark extracting procedure: The typical correlation based algorithm is a blind watermarking algorithm and thus the original host image is not required to extract the watermark. Extraction algorithm is the same as embedding one and filtering is used before applying it to better separate watermark information from host image. The watermark extraction

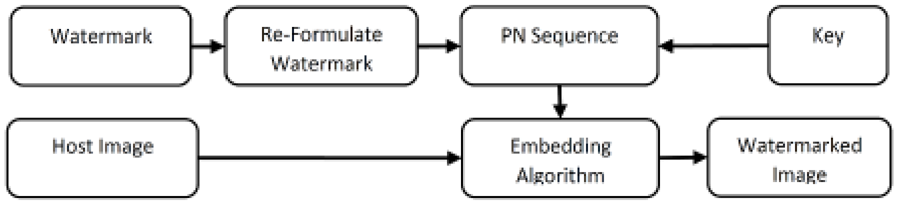
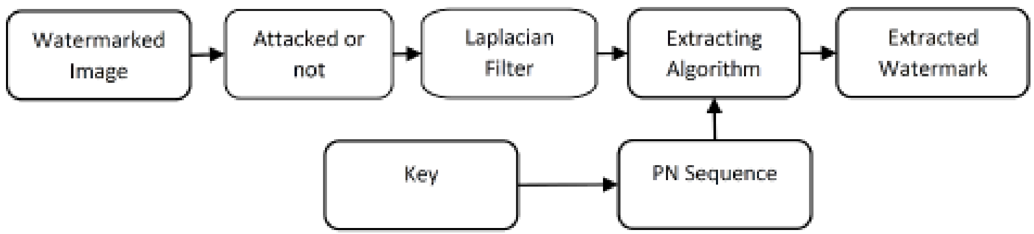
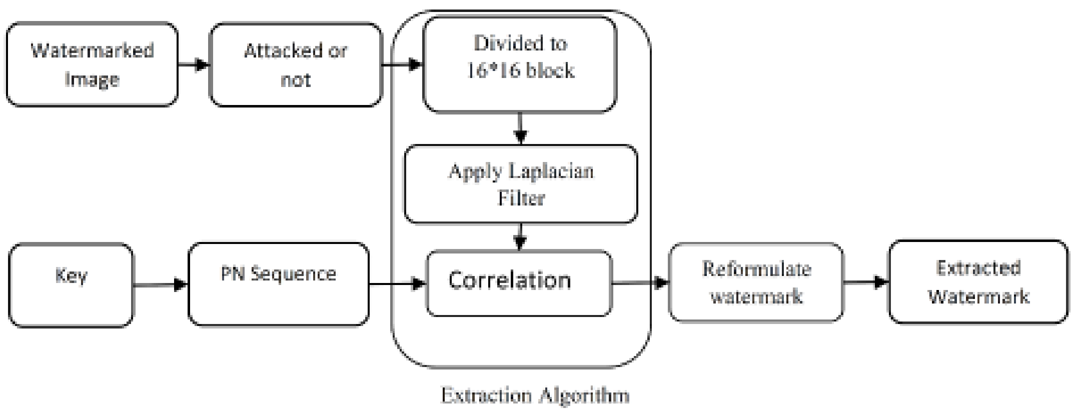


Fig. 1: The watermark embedding process



(a)



(b)

Fig. 2: (a) the watermark extracting with applying Laplacian before preforming extracting algorithm, (b) the watermark extracting process with applying Laplacian in the middle of extracting algorithm

procedure is shown in Fig. 2 and described in details in the following steps:

Step 1: Applying proposed filter as shown in the Eq. of (2) for Laplacian filter, on the watermarked image.
Step 2: Divide watermarked image that could be attacked or not into 16×16 blocks.
Step 3: Regenerate the two pseudorandom sequences (PN_0 and PN_1) using the same key which used in the watermark embedding procedure.
Step 4: For each block in the watermarked image calculate the correlation between the element and the two generated pseudorandom sequences (PN_0 and PN_1). If the correlation with the PN_0 was higher than the correlation with PN_1, then the extracted watermark bit is considered 0, otherwise the extracted watermark is considered 1.
Step 5: The scrambled watermark is reconstructed using the extracted watermark bits.

RESULTS AND DISCUSSION

To compare the efficiency of the proposed filter on correlation based methods, three standard gray-scale images with different contents of size 512×512 are used in our experiments, as shown in Fig. 3a to c. Pepper is used as a representation of image with low spatial frequency and Barbara as a representation of image with average spatial frequency and Baboon as a representation of image with high spatial frequency. In this experiment, a 32×32 binary image, as shown in Fig. 3d is taken as the watermark of images. The effect of the Laplacian filters is investigated by measuring imperceptible and robustness of watermarked image. For the imperceptible capability, a quantitative index,

(a) (b) (c) (d)

Fig. 3: (a) the original pepper image, (b) the original Barbara image, (c) the original Baboon image and (d) the original watermark

Peak Signal-to-Noise Ratio (PSNR), is employed to evaluate the difference between an original image O and a watermarked image. For the robust capability, the Mean Absolute Error (MAE) measures the difference between an original watermark W and the corresponding extracted one. If a method has lower MAE, it is more robust. The PSNR and the MAE are, respectively, defined by Eq. (4) and (5); respectively:

$$\mathrm{PSNR}\left(\mathrm{O},\overline{\mathrm{O}}\right) = 10\log_{10}\frac{255\times 255}{\dfrac{\sum_{i=0}^{I-1}\sum_{j=0}^{J-1}\left(\left\|\mathrm{O}_{ij}-\overline{\mathrm{O}}_{ij}\right\|\right)^{2}}{\mathrm{I}\times\mathrm{J}}} \tag{4}$$

$$MAE(W,\hat{W}) = \frac{\sum_{i=0}^{S-1}\left\|w_i-\hat{w}_i\right\|_1}{|W|} \tag{5}$$

where, $\|.\|_1$ and $|.|$ stand for the L1 norm and the number of components of a vector, respectively.

The watermarked image O is obtained following the completion of the watermark embedding procedure. The watermark information is embedded with PSNR 30, 35 and 40 dB, respectively in the watermarked images. Then Laplacian filter which is described in above Section are performed on these watermarked images which may be attached by the method presented in this section. MAE between the original W and the extracted watermark W' is calculated for different PSNRs. The performance of the Laplacian filter is compared with the default results when no processing is done on the correlation based watermarking algorithm. To compare the robustness of this filter, the algorithm is tested by several attacks, including JPEG compression, image scaling, adding Salt and Pepper noise, Gaussian filtering. The presented method is implemented using MATLAB.

Visual comparison: The Table 1 shows visual comparisons between the effects of different places in applying Laplacian filter on the extracted watermark in the correlation based watermarked. These results have been obtained for Pepper's image which watermarked with PSNR 40. As shown in the Table 1, although applying the Laplacian filter before correlation improve the reliability of watermark recovery of typical correlation based watermarking method, But, preforming the Laplacian filter before running extraction slightly is better than it. This improvement in the case of noise addition attack is more significant than the others. From these experimental results, we could find that the applying Laplacian filter before running extraction is more appropriate.

Results for the pepper image: In the second experiment, the results of applying Laplacian filter on Pepper image as a representation of image with low spatial frequency are shown. The goal of this section is to show the effect of proposed filter on a typical low spatial frequency image. As it is shown in the Table 2, results are significantly increased by applying the Laplacian filter in both of places for in compare with normal extraction. Applying Laplacian filter before recovery algorithms is more successful to the attacked image with jpeg compression and a Blurring attacks. However, in the noise addition and resize attacks, utilizing Laplacian filter before calculating the correlation better improves the results. As it shown in this table, preforming Laplacian filter before recovery algorithm shows better improvement in the values of MAE. For example, in jpeg compression attack on image with PSNR 40 as a high imperceptible watermarked image, MAE preforms 0.035 much better than utilized this filter before calculating the correlation and in the case of Blurring attack improvement is 0.05 in term of MAE. Therefore, for low spatial frequency, utilizing the Laplacian before running extraction is more suitable than preforming it before calculating the correlation.

Results for the Barbara image: In the third experiment, the results of applying Laplacian filters on

Table 1: Visual comparison between the extracted watermark from the peppers watermarked image with PSNR = 40

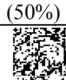
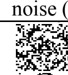
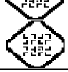
	Attack				
	Attack free	Jpeg compression (50%)	Scaling (50%)	Salt and pepper noise (10%)	Blurring (Gaussian with h = 5 and σ = 1)
Without filtering					
Laplacian before extraction					
Laplacian before correlation					

Table 2: Comparison in term of MAE between the extracted watermark from the peppers watermarked image with diffrent methods

Pepper image	PSNR	Attack: Attack free	Jpeg compression (50%)	Scaling (50%)	Salt and pepper noise (10%)	Blurring (Gaussian with h = 5 and σ = 1)
Without filtering	30	0.0107	0.1055	0.2285	0.1973	0.2910
	35	0.0381	0.2051	0.2959	0.3154	0.3389
	40	0.1045	0.3428	0.3662	0.4316	0.4092
Laplacian before extraction	30	0	0.0029	0.0498	0.0273	0.0459
	35	0	0.0449	0.0947	0.0928	0.0898
	40	0.0020	0.1838	0.2207	0.2207	0.1768
Laplacian before correlation	30	0	0.0049	0.0381	0.0225	0.0654
	35	0	0.0537	0.0850	0.0879	0.1152
	40	0.0020	0.2178	0.2148	0.2148	0.2246

Table 3: Comparison in term of MAE between the extracted watermark from the Barbara watermarked image with diffrent methods

Barbara image	PSNR	Attack: Attack free	Jpeg compression (50%)	Scaling (50%)	Salt and pepper noise (10%)	Blurring (Gaussian with h = 5 and σ = 1)
Without filtering	30	0.0186	0.1338	0.2793	0.1914	0.3213
	35	0.0879	0.2734	0.3428	0.3311	0.3721
	40	0.1982	0.3984	0.3867	0.4258	0.4209
Laplacian before extraction	30	0.0049	0.0332	0.0879	0.0635	0.0957
	35	0.0254	0.1240	0.1816	0.1514	0.1895
	40	0.0771	0.2646	0.2852	0.2695	0.2881
Laplacian before correlation	30	0.0049	0.0420	0.0762	0.0566	0.1270
	35	0.0273	0.1328	0.1719	0.1445	0.2285
	40	0.0713	0.2695	0.2803	0.2607	0.3105

Table 4: Comparison in term of MAE between the extracted watermark from the Baboon watermarked image with diffrent methods

Baboon image	PSNR	Attack: Attack free	Jpeg compression (50%)	Scaling (50%)	Salt and pepper noise (10%)	Blurring (Gaussian with h = 5 and σ = 1)
Without filtering	30	0.0000	0.0449	0.2432	0.1475	0.3027
	35	0.0381	0.1602	0.3379	0.3018	0.3730
	40	0.0977	0.2500	0.3809	0.3691	0.4043
Laplacian before extraction	30	0.0000	0.0186	0.1201	0.0352	0.1309
	35	0.0156	0.0918	0.2188	0.1563	0.2314
	40	0.0430	0.1963	0.2949	0.2412	0.2949
Laplacian before correlation	30	0.0000	0.0234	0.1152	0.0381	0.1494
	35	0.0127	0.1094	0.2227	0.1416	0.2559
	40	0.0439	0.2158	0.2959	0.2354	0.3193

Barbara as a representation of image with average spatial frequency. The goal of this section is to show the effect of proposed filter on a typical average spatial frequency image. As it is shown in the Table 3, results are significantly improved by convolution of the Laplacian filter with the Barbara image in both places in compare with normal extraction. Convolving Laplacian filter before recovery algorithms is more successful to the attacked image with jpeg compression and a Blurring attacks. However, in the noise addition and resize attacks, apply filter before calculating the correlation better improves the results. As it shown in this table, applying Laplacian filter before recovery algorithm shows better improvement in the values of MAE. For example, in blurring attack on image with PSNR 40 as a high imperceptible watermarked image, MAE performs 0.025 much better than applying this filter before calculating the correlation. Therefore, for average spatial frequency, convolving the Laplacian before running extraction is more appropriate than performing it before calculating the correlation.

Results for the baboon image: In the fourth experiment, the results of applying Laplacian filter on Baboon image as a representation of image with high spatial frequency are shown. In this section, we concentrate to show the effect of proposed filter on a typical high spatial frequency image. As it is shown in the Table 4, results are significantly improved by convolution of the Laplacian filter with the Baboon image in both places in compare with normal recovery method. Convolving Laplacian filter before recovery algorithms is more successful to the attacked image with jpeg compression and blurring attacks and slightly in the scaling attack. However, in the noise addition attack, preform filter before calculating the correlation better improves the results slightly. As it shown in this table, convolving Laplacian filter before extraction algorithm shows better improvement in the values of MAE. For example, in blurring attack on image with PSNR 40 as a high imperceptible watermarked image, MAE performs 0.025 much better than applying this filter before calculating the correlation and in jpeg compression this value is 0.02 better than the other method. Therefore, for high spatial frequency, convolving the Laplacian before running recovery is more appropriate than convolving it before calculating the correlation.

CONCLUSION

The dissimilarity between watermarked part and un water marked part of host image is increased by Laplacian filter. Then, this enhanced watermarked image is used as the input image in the watermark extraction's process. In this study, a comparison between the effects of different places on convolving Laplacian filter with the watermarked image in increasing the power of watermark recovery algorithms is investigated. The Laplacian filter is convolved with watermarked image in two places; before executing recovery algorithm and in the middle of recovery algorithm and before calculates the correlation. Several experiments are done to show that which of these places is more suitable for improving power of spatial domain watermarking method. Effectiveness of the methods is tested by comparing its result with each other in the term of MAE. The watermark is extracted after common image processing attacks with lower MAE value by performing Laplacian filter before recovery algorithm. Especially, increasing in performance is become more noticeable in case of enhancement operations with blurring filter and jpeg compression. In high spatial frequency image, improvement is better than low and average frequency images. However, results of performing Laplacian filter before take the correlation is better than applying filter before executing recovery algorithm, in the case of resizing and salt and pepper noise. Therefore, we suggest to use Laplacian filter before running watermark recovery algorithms in the spatial domain watermarking algorithm.

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