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Improving Digital Watermarking Fidelity Using Fast Neural Network for Adaptive Wavelet Synthesis

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Abstract. *This paper introduces a new adaptive algorithm for digital watermark embedding in wavelet domain. The proposed algorithm performs adaptive mother wavelet synthesis based on a low frequency component energy maximization. The algorithm is based on an orthogonal neural network. We demonstrate that the presented adaptive method can improve both the correlation between an extracted watermark and an embedded watermark, as well as the fidelity of an image. The proposed algorithm is applied to improve well known wavelet based embedding algorithms.*
Keywords: *digital image watermarking, wavelet synthesis, neural networks.*

1. Introduction

Nowadays, most information is stored and processed in digital form on computers. Digital content can be easily copied, modified and distributed over the Internet. As a result, copyright protection and ownership authentication of digital content becomes a serious concern [1]. Digital Watermarking has emerged as one of possible solutions for improvement of copyright protection and ownership identification [2].

Digital watermarking is the process of embedding visible or invisible, additional information into digital data. This information can prove an author's ownership or can be used to trace the illegal use of the data. Digital watermarks can be embedded into every form of digital content in multiple ways, however in this article only blind invisible watermarking of still images [1] is considered.

Digital watermarking in the wavelet domain gained much popularity in recent years [3]. Many algorithms for embedding watermarks in wavelet domain have been developed [4, 5, 6, 7, 8, 9, 10]. In all of these algorithms very little attention is paid to proper wavelet filter selection. Adaptive mother wavelet selection is sometimes considered only as a method to protect wavelet based watermarks against unauthorised detection [3, 11, 12, 13]. Proper choice of a wavelet filter bank (mother wavelet) can have significant influence on image fidelity and watermark detection. According to [14], it is impossible to identify a single mother wavelet which gives best results in terms of image fidelity. The most suitable mother wavelet depends on image properties, as well as the embedding algorithm. Therefore, a neural network–based algorithm for best wavelet base selection which maximizes energy in low frequency components has been developed. Using this algorithm, the mother wavelet based on a cover image is synthesized. The watermark is embedded using well known wavelet–based watermarking algorithms.

The article is organized as follows. In Section 2, watermark embedding algorithms are briefly presented. In Section 3, adaptive algorithm for wavelet synthesis is described. Experimental results of proposed algorithm are provided in section 4. The conclusions are given in Section 5.

2. Watermark embedding

To explain the idea behind the new adaptive algorithm presented here, it is useful to briefly review the traditional model of watermarking. In subsection 2.1, some watermarking system's basic components, that will be relevant in proposed adaptive algorithm, are highlighted. In subsection 2.2, a new adaptive algorithm is discussed in detail.

2.1. Traditional approach to watermark embedding

All watermarking systems use the same generic scheme. Fig. 1 shows such a generic scheme of watermarking [15]. A digital watermark w is embedded into host data d (an image) using an arbitrarily chosen embedding technique. Embedding, means changing some parameters of the host data in order to hide the digital watermark. As a result of embedding, watermarked data *wd* is obtained. Next, extraction algorithm is applied in order to extract the watermark *ew* from the watermarked data *wd*.

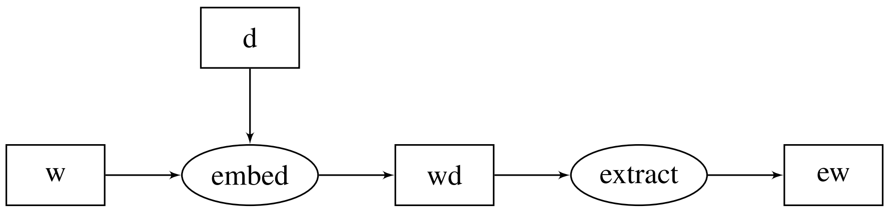

Figure 1. Generic scheme of watermark embedding and extraction algorithm

In this paper, imperceptible watermarking is considered, which means that the host data *d* and the watermarked data *wd* should be as close as possible with respect to a chosen fidelity measure. As the fidelity measure Peak Signal-to-Noise Ratio (PSNR) has been used:

$$PSNR = 10 \cdot \log_{10} \frac{255^2}{\frac{1}{NM} \sum_{i=0}^{N} \sum_{j=0}^{M} \left(d_{ij} - wd_{ij} \right)^2} , \tag{1}$$

where N, M – image dimensions; d_{ij} – a single element of the host data; wd_{ij} – a single element of watermarked data. The higher the PSNR, the higher the fidelity. A watermarking algorithm should also maximize the correlation *Cor* between embedded watermark *w* and extracted watermark *ew*. Correlation is defined as

$$Cor = \frac{w \cdot ew}{|w||ew|} , \tag{2}$$

where $\cdot$ denotes dot product. The higher the correlation, the smaller the difference between an embedded and an extracted watermarks. It should be noted that there is a trade-off between the fidelity and the correlation and it is challenging to create a watermarking system which guarantees high correlation between embedded and extracted watermarks and fidelity at the same time [1].

The correlation and the fidelity can be improved when the watermark is not embedded in space domain, but the host data is first transformed using an invertible transform. The watermark is then embedded in a transform domain. There are many transforms which can be used in digital watermarking, like Fourier transform, cosine transform, wavelet transform etc. Wavelet transform–based watermarking seems to be the most promising, especially for recent compression standards [15]. When considering wavelet transform–based watermarking the generic scheme from Fig. 1 takes form shown in Fig. 2. Host data d is transformed by applying multilevel (3-5 levels) wavelet transform. As a result, transformed data D is obtained. Watermark w is embedded into the transformed data D, producing watermarked data in the wavelet domain wD. Next, inverse transform is applied to wD, which results in obtaining watermarked data wd. In order to extract the watermark from the watermarked data, wd must be transformed into the wavelet domain and watermark ew can be extracted from wD.

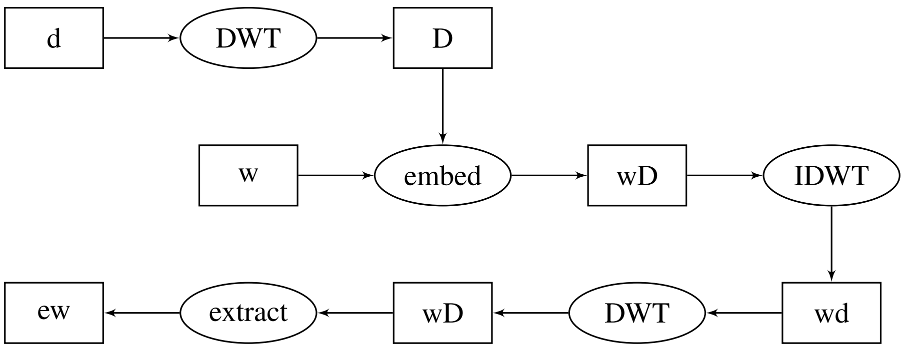

Figure 2. Generic scheme of watermark embedding in the wavelet transform domain

2.2. New adaptive algorithm for watermark embedding

When considering wavelet transform–based image watermarking, a mother wavelet (see Fig. 2) should be selected carefully, in order to maximize both the fidelity and the correlation. To achieve this goal, an adaptive algorithm of mother wavelet synthesis, which adapts the mother wavelet shape to the characteristics of the host data, is proposed. The transform is not optimized directly to maximize both PSNR and *Cor*. Instead, the neural network is used to synthesize the mother wavelet which maximizes the energy of low frequency component. The synthesized mother wavelet is then used in the watermarking algorithm shown in Fig. 2. The detailed discussion of the wavelet synthesis algorithm is given in the following section. The complete adaptive watermark embedding scheme is given as follows:

1. Using algorithm from section 3, synthesize the mother wavelet which maximizes low frequency component.
2. Perform the wavelet transform of the host data d using the mother wavelet obtained in 1.
3. Embed the watermark w using one of the DWT-based embedding algorithms. In this article, the following embedding algorithms were chosen: Corvi – Nicchiotti method [4], Dugad–Ratakonda – Ahuja method [5], Kim – Moon method [6], Wang – Su – Jay Kuo method [7], Xia – Boncelet – Arce method [8], Xie – Arce method [9], Zhu – Xiong – Zhang method [10].
4. Compute the inverse transform using the synthesized mother wavelet obtained in 1.

3. Adaptive wavelet synthesis

The wavelet synthesis is performed using the fast neural network [16] with topology based on the orthogonal a lattice structure [17]. In order to adaptively synthesize the mother wavelet, an objective function for the neural network must be defined. This function is minimized during training of the network. In this paper, wavelet synthesis based on desired energy distribution between low–pass and high–pass filters is used [18]. This criterion is applied to maximize energy of the signal's low frequency component.

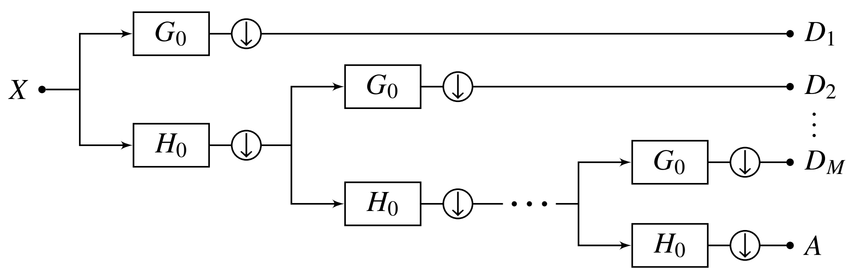

Figure 3. Multiresolution analysis

Fig. 3 shows a diagram of multiresolution analysis of one–dimensional input signal X. H_0 and G_0 are low–pass and high–pass filters respectively. $\circledDownarrow$ represents signal decimation (removing every other sample). $D_1, D_2, \ldots, D_M$ are detail signals and A is the approximation signal. Wavelet–based watermarking algorithms perform multilevel analysis of an input image (usually from 3 to 5). This implies, that synthesized wavelet should have identical energy distribution on each level of signal analysis. Therefore, energy distribution criterion is applied on subsequent levels of multiresolution analysis. This can be written as

$$\frac{E(D_1)}{E(A) + \sum_{i=2}^{M} E(D_i)} = \frac{E(D_2)}{E(A) + \sum_{i=3}^{M} E(D_i)} = \cdots = \frac{E(D_M)}{E(A)} = P \quad , \tag{3}$$

where $E(\cdot)$ denotes energy of a signal, M denotes the number of multiresolution analysis levels and P is the expected energy proportion between low–pass and high–pass components of the signal. In the proposed approach it is assumed that P approaches 0. For smooth input signals, like images, the above method leads to synthesis of smooth wavelets.

4. Experimental results

Proposed scheme was tested using twenty different images of two types – 10 pictures and 10 textures – taken from the SIPI Image Database [19] (see Fig. 4). To train the network using these images, each image had to be converted to a training set, consisting of 512 vectors, each vector being a row of an image. For each such set adaptive 4–tap, 6–tap and 8–tap wavelets with highest possible energy compaction for 4 levels of multiresolution analysis were synthesized. Fig. 5 shows comparison between the Daubechies 4 wavelet and example of synthesized adaptive 4–tap wavelet.

Synthesized wavelets were then used in the watermark embedding process. Seven different wavelet–based methods of watermark embedding were selected to carry out the experiments: Corvi–Nicchiotti method [4], Dugad–Ratakonda–Ahuja method [5], Kim–Moon method [6], Wang–Su–Jay Kuo method [7], Xia–Boncelet–Arce method [8], Xie–Arce method [9], Zhu–Xiong–Zhang method [10]. In further text methods will be denoted by their principal author's name. Wavelets were synthesized using software created by the authors. Watermark generation, embedding and extraction was performed using software created by Peter Meerwald [20].

Figure 4. Test images. The first two columns show normal pictures, the last two columns show textures

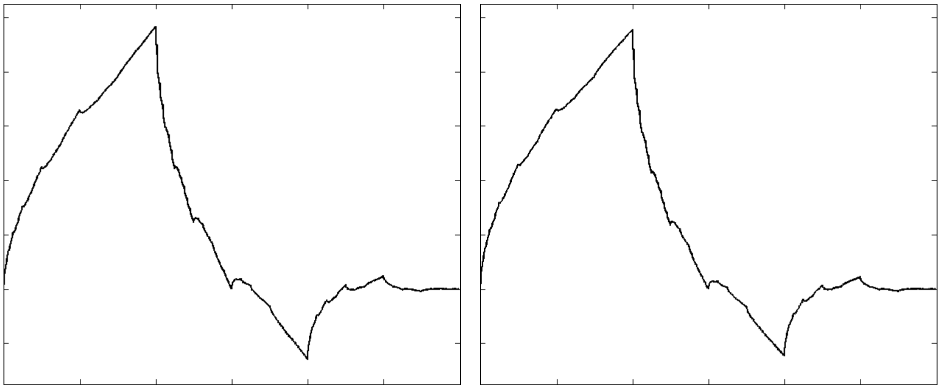

Figure 5. a) Daubechies 4 wavelet (on the left); b) adaptive 4–tap wavelet synthesized for Lena image (on the right)

Table 1. Example results of watermark embedding using 4–tap wavelets

Embedding method	Daubechies		Adaptive	
	correlation	PSNR	correlation	PSNR
Corvi	0.822000	37.143282	0.912000	37.365253
Dugad	0.777778	27.398078	0.888889	27.553811
Kim	0.995137	37.718645	0.996075	37.793631
Wang	0.989457	32.748372	0.990520	32.912993
Xia	0.998683	21.042080	0.998905	21.109084
Xie	1.000000	42.097722	0.975000	42.095117
Zhu	0.996526	30.580313	0.995784	30.826689

For each of the test images, watermark was embedded using each of the selected methods. Embedding was done using both Daubechies wavelets and synthesized adaptive wavelets, to compare their performance. Table 1 shows example results of watermark embedding. First column shows name of the embedding method. Following two columns show results of watermark embedding with Daubechies wavelets. The remaining two columns show results for synthesized adaptive wavelets. Correlation column shows correlation *Cor* between the original watermark that was embedded in the image and watermark that was extracted from the watermarked image (ideally this would be 1). PSNR is the Peak Signal–to–Noise Ratio between original image and the watermarked image (the higher its value the better). Results in Table 1 show, that for Corvi, Dugad, Kim, Wang and Xia methods, both correlation and PSNR were improved by using adaptive wavelets. For Xie method, both correlation and PSNR have decreased, while for Zhu method correlation was decreased, but PSNR was increased by using adaptive wavelets. This shows that although adaptive wavelets can improve watermarking process, they do not bring improvement to all of the embedding methods. This is caused by the fact, that wavelet synthesis is based only on the image data. Adaptive algorithm doesn't take into account neither watermark that is to be embedded nor the embedding algorithm itself. These tests were carried out for all twenty images, each image tested for 4–tap, 6–tap and 8–tap wavelets, which gives a total of sixty tables.

Tables 2–7 present summary of these tests. Tables 2, 3 and 4 present summary results of the experiments for textures, while tables 5, 6 and 7 present summary results obtained for standard pictures. Tables 2 and 5 show results for 4–tap wavelets, tables 3 and 6 show results for 6–tap wavelets, while tables 4 and 7 show results for 8–tap wavelets. Each table shows summary results for 10 images of a given class. First column in each table is the embedding method. Following four columns show, respectively, the number of cases where: both correlation and PSNR were improved by using adaptive wavelets, only correlation was improved (PSNR was decreased), only PSNR was improved (correlation was decreased) and both PSNR and correlation were decreased.

Tables 2–7 show that in 42.8% to 47.2% of cases adaptive wavelets lead to improvement of both correlation and PSNR. Correlation improvement together with PSNR decreasing occurred in 18.5%–28.5% of cases. PSNR improvement with correlation decreasing occurred in 10%–20% of cases. In 11.4%–27.1% of cases both correlation and PSNR have decreased. Therefore, wavelet–based watermarking using adaptive wavelets synthesised for the cover image can lead to improvement of both correlation and PSNR. Increased correlation makes detection of an embedded watermark more reliable, while increased PSNR makes differences between original and watermarked image less visible.

5. Conclusions

In this paper, we have proposed a new adaptive algorithm for digital watermark embedding in wavelet domain, in order to enhance two coefficients: correlation of an extracted watermark with an embedded watermark as well as PSNR

Table 2. Texture watermarking improvement by using adaptive 4–tap wavelets

	PSNR and correlation	correlation only	PSNR only	none
Corvi	3	4	3	0
Dugad	5	0	3	2
Kim	3	4	3	0
Wang	7	0	2	1
Xia	5	4	0	1
Xie	4	1	1	4
Zhu	7	1	2	0
total	34	14	14	8

Table 3. Texture watermarking improvement by using adaptive 6–tap wavelets

	PSNR and correlation	correlation only	PSNR only	none
Corvi	5	1	3	1
Dugad	5	3	0	2
Kim	5	2	0	3
Wang	4	4	1	1
Xia	3	5	0	2
Xie	4	2	2	2
Zhu	5	3	1	1
total	31	20	7	12

Table 4. Texture watermarking improvement by using adaptive 8–tap wavelets

	PSNR and correlation	correlation only	PSNR only	none
Corvi	7	2	0	1
Dugad	3	3	0	4
Kim	1	2	1	6
Wang	6	0	4	0
Xia	0	4	2	4
Xie	6	1	0	3
Zhu	7	2	1	0
total	30	14	8	18

Table 5. Picture watermarking improvement by using adaptive 4–tap wavelets

	PSNR and correlation	correlation only	PSNR only	none
Corvi	4	4	1	1
Dugad	7	0	2	1
Kim	4	1	4	1
Wang	4	3	3	0
Xia	4	2	3	1
Xie	3	0	1	6
Zhu	6	3	1	0
total	32	13	15	10

Table 6. Picture watermarking improvement by using adaptive 6–tap wavelets

	PSNR and correlation	correlation only	PSNR only	none
Corvi	6	1	2	1
Dugad	5	2	0	3
Kim	4	2	2	2
Wang	3	1	2	4
Xia	7	2	0	1
Xie	2	3	0	5
Zhu	3	2	2	3
total	30	13	8	19

Table 7. Picture watermarking improvement by using adaptive 8–tap wavelets

	PSNR and correlation	correlation only	PSNR only	none
Corvi	8	1	1	0
Dugad	2	1	0	7
Kim	3	3	3	1
Wang	5	1	2	2
Xia	2	7	1	0
Xie	5	0	0	5
Xhu	7	2	1	0
total	32	15	8	15

of the watermarked image. Experiments have shown that the algorithm which utilizes the adaptive mother wavelet selection, based on the low frequency component energy maximization, improves both above mentioned coefficients in 45% average, and deteriorates both coefficients only in 19.25% average. This means that adaptive mother wavelet synthesis can be used to improve watermark embedding algorithms.

Further development of proposed methods should extend wavelet synthesis algorithm in such a way, that it takes into account not only the cover image, but also the watermark and the embedding method. Different fidelity measures can be considered to improve the algorithm performance.

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