AN ADAPTIVE DISCRETE WAVELET TRANSFORM METHOD OF GRAYSCALE IMAGES

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Abstract

In this paper, a modified discrete wavelet transform method with a hierarchical adaptation to the signal size is developed to enhance wavelet-compression performance: reduction of the bit rate, enhancing the quality of reconstruction, and the reduction of computational complexity. The method is based on adaptive padding alignment wavelet-coefficients to an approximation coefficient sequence of a certain wavelet-decomposition level for forming an even length sequence. The presence or absence of the alignment wavelet-coefficients is determined by the binary values of the alignment vector components. A comparative efficiency evaluation, of the methods of one-dimensional and two-dimensional rational (or integer) wavelet-transform with and without a hierarchical adaptation to the image size, is presented. It is found that the developed method provides a gain in terms of compression coefficients, peak signal-to-noise ratio and computational complexity.

Keywords*:* Discrete wavelet-transform, Adaptation to the signal size, Image compression.

1. Introduction

Improving the efficiency of information processing is a challenge for many applications. Practically, the increasing productivity of hardware and software allows us to solve this problem only partly. Currently, one of the ways to enhance the efficiency of the multimedia data processing is the application of methods based on multi-resolution representation. Multi-resolution representation is a hierarchical structure, the first level which contains sufficient information for the coarse (low resolution) reconstruction of media-data [1]. When adding information for each subsequent level of detail increases as the media would not be fully restored with full resolution. The processing algorithms of multi-resolution representation based on wavelet transform, are simple enough and efficient in implementation.

Modern dyadic wavelet-transform has the important properties that are absent in the other transforms: a large set of basic wavelet-functions with different ratio of the frequency and temporal resolution, energy compactness, simultaneous local spatial and scale relationship of large / small values of wavelet coefficients [1-6]. The efficiency of hardware-software implementation of discrete wavelet transform is limited to the requirements of input signal samples number, which must be equal to 2^{Dn}, where D is the signal dimension and n is a natural number. This is due to using iterative binary scaling of wavelet-transform result that ensures the equality between the wavelet coefficients number and the input signal samples number. If the input signal samples number is not equal to 2^{Dn}, the signal is extended out of its boundaries by symmetrical, asymmetrical or periodical extension methods. This leads to an increase in the number of wavelet-coefficients, reducing the efficiency of wavelet transform and the deterioration of wavelet-compression performance. In this regard, the actual task is to enhance the adaptation degree of wavelet-transform to the size of the processed signal.

This work is aimed to develop a modified method of wavelet-transform with adaptation to the signal size in order to improve wavelet-compression performance: bit rate decrease, reconstruction quality enhancement, and computational complexity reduction.

2. Basic Principle

2.1 Discrete Wavelet Transform (DWT).

For an original signal $\vec{x} = (x(0),...,x(n),...,x(N-1))$ of time sample length $N = 2^J$, where J is a positive integer or signal resolution of $\vec{x}$, the one-dimensional DWT is computed using the hierarchical algorithm of Mallat [1], which uses the relationship between the adjacent scale DWT coefficients and linear filtering operation. Thus, when representing DWT in terms of filter bank, which is defined as a set of subband filters, the transform coefficients (approximation $s_j(k)$ and wavelet $d_j(k)$ coefficients at the resolution 2^j) of the current scale j $(1 \le j \le J)$ are computed on the basis of approximation $s_{j-1}(k)$ coefficients of the previous scale $j-1$ using the relations:

$$s_j(k) = \varphi(h_\varphi, s_{j-1}(k)) = \sum_{l=-\lfloor L/2 \rfloor}^{\lfloor L/2 \rfloor} h_\varphi(l) s_{j-1}((2k+l) \bmod N_{j-1}), \qquad \dots (1)$$

$$d_j(k) = \psi(h_\psi, s_{j-1}(k)) = \sum_{l=-\lfloor L/2 \rfloor}^{\lfloor L/2 \rfloor} h_\psi(l) s_{j-1}((2k+l) \bmod N_{j-1}), \qquad \dots (2)$$

where $\varphi(\cdot)$ and $\psi(\cdot)$ are the linear convolution functions of approximation coefficient sequence and finite impulse responses of low-pass scaling-filter h_φ and high-pass wavelet-filter h_ψ respectively; $J = \log_2 N$ is the maximum possible number of decomposition levels of the original signal $\vec{x}$; $s_0(k) = x(k)$; $k = \overline{0, 2^{J-j} - 1} = 0,..., N_j - 1$; $N_j = N/2^j$ is the number of approximation or wavelet coefficients at scale j; $\bmod N_{j-1}$ is the modulo N_j to account the signal boundaries of finite length, $\lfloor \ \rfloor$ is the floor operation.

Fig.1 demonstrates the features of the standard one-dimensional wavelet-transform structure without adaptation

For two-channel biorthogonal filter bank ensuring the original signal reconstruction and consisting of $\{h_\varphi, \tilde{h}_\varphi, h_\psi, \tilde{h}_\psi\}$, the relationship between two low-pass biorthogonal filters h_φ and $\tilde{h}_\varphi$, also between two high-pass biorthogonal filters h_ψ and $\tilde{h}_\psi$, has the following form due to the well-known biorthogonal relations and perfect reconstruction conditions:

$$h_\psi(l) = (-1)^l \tilde{h}_\varphi(l), \quad \dots (3)$$

$$\tilde{h}_\psi(l) = -(-1)^l h_\varphi(l), \quad \dots (4)$$

where $\{h_\varphi, h_\psi\}$ and $\{\tilde{h}_\varphi, \tilde{h}_\psi\}$ are pairs of biorthogonal filters for decomposition (analysis) and reconstruction (synthesis) of signals, respectively.

Moreover, in this case, the following biorthogonal relations will be true:

$$\sum_l h_\varphi(l) = \sum_l \tilde{h}_\varphi(l) = \sqrt{2}, \qquad \sum_l h_\psi(l) = \sum_l \tilde{h}_\psi(l) = 0, \qquad \sum_l h_\varphi(l)\tilde{h}_\varphi(l+2k) = \delta_{k0},$$

$\sum_l h_\psi(l)\tilde{h}_\psi(l+2k) = \delta_{k0}$, $\sum_l \tilde{h}_\varphi(l) h_\psi(l+2k) = 0$, $\sum_l h_\varphi(l)\tilde{h}_\psi(l+2k) = 0$, where $2k$ is the shift at even number of points; $\delta_{k0} = \begin{cases} 1 \ if \ \ k = 0, \\ 0 \ if \ \ k \ne 0 \end{cases}$ is the Kronecker symbol or two integer variables function.

The forward and inverse integer lifting wavelet-transforms [5, 6] for one decomposition level have the following form:

$$\begin{cases} a_0(k)=s_{j-1}(2k), \qquad b_0(k)=s_{j-1}(2k+1), \\ b_i(k)=b_{i-1}(k)-\left\lfloor \sum_l p_i(l)a_{i-1}(k-l)+\frac{1}{2}\right\rfloor, \\ a_i(k)=a_{i-1}(k)+\left\lfloor \sum_l u_i(l)b_i(k-l)+\frac{1}{2}\right\rfloor, \\ s_j(k)=a_I(k)/K,\ d_j(k)=Kb_I(k), \end{cases} \qquad \ldots (5)$$

$$\begin{cases} a_I(k)=Ks_j(k),\ b_I(k)=d_j(k)/K, \\ a_{i-1}(k)=a_i(k)-\left\lfloor \sum_l u_i(l)b_i(k-l)+\frac{1}{2}\right\rfloor, \\ b_{i-1}(k)=b_i(k)+\left\lfloor \sum_l p_i(l)a_{i-1}(k-l)+\frac{1}{2}\right\rfloor, \\ s_{j-1}(2k)=a_0(k), \qquad s_{j-1}(2k+1)=b_0(k), \end{cases} \qquad \ldots (6)$$

where $p_i(l)$ and $u_i(l)$ are the coefficients of prediction $b_{i-1}(k)$ and refinement $a_{i-1}(k)$ on the nearest neighboring coefficients at the i's lifting-step respectively; $a_i(k)$ and $b_i(k)$ are approximation and wavelet coefficients at the i's lifting-step respectively; $\lfloor \cdot \rfloor$ is the floor operation; $i=\overline{1,I}$; I is the number of the lifting-steps for the use of wavelet-functions; K is the scaling coefficient.

Wavelet-transform of two-dimensional signals (images) can be implemented as a sequence of one-dimensional transform over image rows and columns.

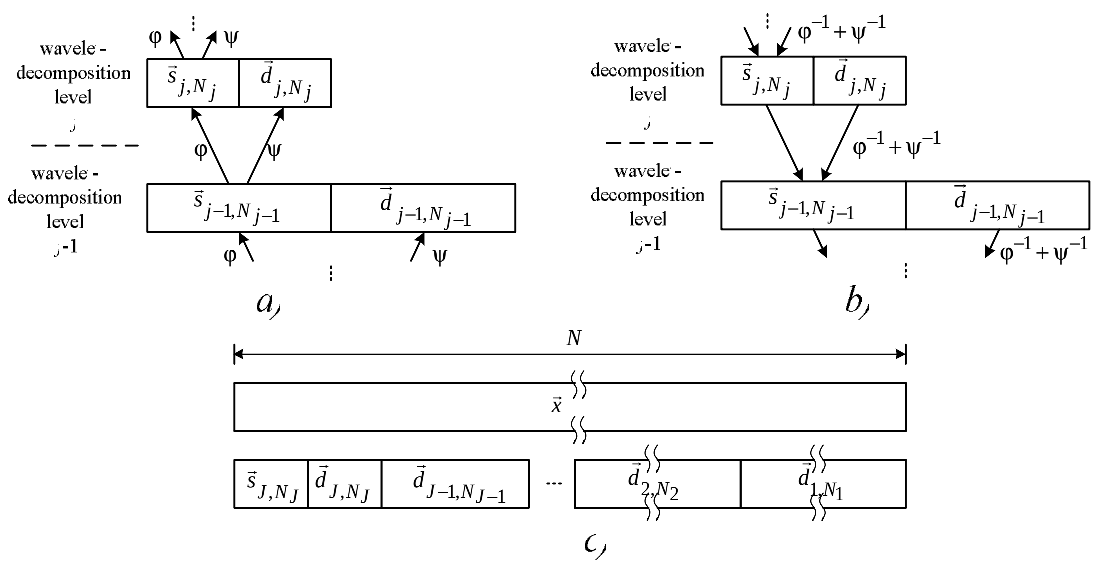

Fig. 1 The standard one-dimensional wavelet-transform structure without adaptation
a) The forward wavelet transform; b) The inverse wavelet transform; c) The sequence of approximation and wavelet coefficients

3. Proposed Methods

3.1 Rational Wavelet Transform with a Hierarchical Adaptation to the Signal Size.

For processing signals with an arbitrary length, a method is suggested which is called *rational DWT with adaptation to the number of signal samples at each decomposition level*.

The forward rational wavelet-transform with a hierarchical adaptation to the signal size can be defined by the following recursive expression:

$$\begin{cases} \begin{cases} \vec{s}_{j,N_j} = \varphi\left(h_\varphi, \vec{s}_{j-1,N_{j-1}}\right) & if \quad \lfloor N_{j-1}/2 \rfloor \cdot 2 = N_{j-1}, \\ \vec{s}_{j,N_j} = \varphi\left(h_\varphi, \vec{\tilde{s}}_{j-1,(N_{j-1}+1)}\right) & if \quad \lfloor N_{j-1}/2 \rfloor \cdot 2 \neq N_{j-1}, \end{cases} \\ \begin{cases} \vec{d}_{j,N_j} = \psi\left(h_\psi, \vec{s}_{j-1,N_{j-1}}\right) & if \quad \lfloor N_{j-1}/2 \rfloor \cdot 2 = N_{j-1}, \\ \vec{d}_{j,N_j} = \psi\left(h_\psi, \vec{\tilde{s}}_{j-1,(N_{j-1}+1)}\right) & if \quad \lfloor N_{j-1}/2 \rfloor \cdot 2 \neq N_{j-1}, \end{cases} \end{cases} \quad \ldots (7)$$

where $\tilde{s}_{j-1}(k) = \begin{cases} s_{j-1}(k) & if \quad 0 \le k < N_{j-1}, \\ s_{j-1}(k-q) & if \quad k = N_{j-1} \end{cases}$ is the value of the k^{th} element in the vector $\vec{\tilde{s}}_{j-1,(N_{j-1}+1)} = \left(\tilde{s}_{j-1}(0),\ldots,\tilde{s}_{j-1}(k),\ldots,\tilde{s}_{j-1}(N_{j-1})\right)$ at the level $j-1$, associated with the values of elements in the vector $\vec{s}_{j-1,N_{j-1}} = \left(s_{j-1}(0),\ldots,s_{j-1}(k),\ldots,s_{j-1}(N_{j-1})\right)$; $\tilde{s}_{j-1}(N_{j-1}) = \tilde{s}_{j-1}(N_{j-1}-q)$ is the alignment wavelet-coefficient; q is a parameter for taking into consideration the boundary artifacts; $N_{j-1}/2$ is the number of approximation coefficients $s_j(k)$ at the resolution level j;

$N_j = \begin{cases} N_{j-1}/2 & if \quad \lfloor N_{j-1}/2 \rfloor \cdot 2 = N_{j-1}, \\ (N_{j-1}+1)/2 & if \quad \lfloor N_{j-1}/2 \rfloor \cdot 2 \neq N_{j-1} \end{cases}$ is the number of approximation coefficients at the resolution level j; $N_0 = N$.

Consequently, forward wavelet-transform with a hierarchical adaptation to the signal size forms a sequence of approximation and detail coefficients with an insignificant extension $\sum_{j=1}^{J} N_j \ge N$, but $\sum_{j=1}^{J} N_j - N < J$.

The inverse rational wavelet-transform with a hierarchical adaptation to the signal size can be defined by the following recursive expression:

$$\vec{s}_{j-1,N_{j-1}} = \varphi^{-1}\left(\tilde{h}_\varphi, \vec{s}_{j,N_j}\right) + \psi^{-1}\left(\tilde{h}_\psi, \vec{d}_{j,N_j}\right) \quad \ldots (8)$$

if $\begin{cases} N_{j-1} = 2N_j & if \quad A_j = 0, \\ N_{j-1} = 2N_j - 1 & if \quad A_j = 1, \end{cases}$

where $\varphi^{-1}(\cdot)$ and $\psi^{-1}(\cdot)$ are the linear convolution functions of approximation and detail coefficient and finite impulse responses of low-pass $\tilde{h}_\varphi$ and high-pass $\tilde{h}_\psi$ filters, respectively;

$A_j = \begin{cases} 0 & if \quad \lfloor N_{j-1}/2 \rfloor \cdot 2 = N_{j-1}, \\ 1 & if \quad \lfloor N_{j-1}/2 \rfloor \cdot 2 \neq N_{j-1}, \end{cases}$ is an even (two) multiplicity indicator (or the value of the alignment vector element of low-pass subband size of level ($j-1$)) at the resolution level j.

It is seen from Fig. 2 that the approximation and detail coefficients sequence may include additional aligning wavelet-coefficients, and the presence or absence of which is determined by the alignment vector components $\vec{A} = (A_J,\ldots,A_j,\ldots,A_1)$ which consists of the binary values (0 – there is no alignment, 1 – there is an alignment). The alignment vector is automatically constructed in a decoder according to the values N and J.

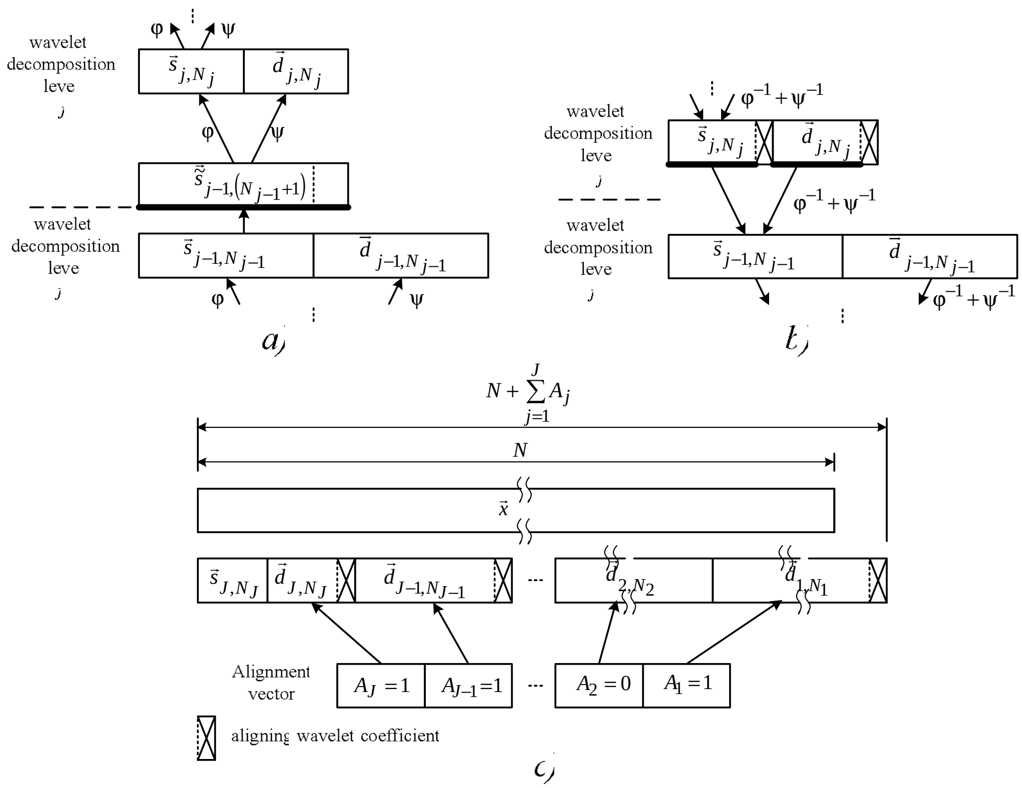

Fig. 2 The one-dimensional wavelet transform structure with adaptation
a) The forward wavelet transform with adaptation; b) The inverse wavelet transform with adaptation;
c) The result of adaptive wavelet transform is a sequence of approximation and detail coefficients with the alignment wavelet coefficients

3.2 Integer Wavelet Transform with a Hierarchical Adaptation to the Signal Size.

For lossless compression of signals with an arbitrary length, a method is suggested which is called *integer DWT with adaptation to the number of signal samples at each level*.

The forward integer wavelet-transform with a hierarchical adaptation to the signal size can be defined by the following recursive expression:

$$\begin{cases} \begin{cases} \vec{s}_{j,N_j} = \varphi_I\left(\vec{s}_{j-1,N_{j-1}}, \vec{d}_{j,N_j}\right) & if \ \lfloor N_{j-1}/2 \rfloor \cdot 2 = N_{j-1}, \\ \vec{s}_{j,N_j} = \varphi_I\left(\tilde{\vec{s}}_{j-1,N_{j-1}}, \vec{d}_{j,N_j}\right) & if \ \lfloor N_{j-1}/2 \rfloor \cdot 2 \neq N_{j-1}, \end{cases} \\ \begin{cases} \vec{d}_{j,N_j} = \psi_I\left(\vec{s}_{j-1,N_{j-1}}\right) & if \ \lfloor N_{j-1}/2 \rfloor \cdot 2 = N_{j-1}, \\ \vec{d}_{j,N_j} = \psi_I\left(\tilde{\vec{s}}_{j-1,N_{j-1}}\right) & if \ \lfloor N_{j-1}/2 \rfloor \cdot 2 \neq N_{j-1}, \end{cases} \end{cases} \quad \ldots (9)$$

where φ_I and ψ_I are integer lifting wavelet transforms for computing the approximation and detail coefficients.

The inverse integer wavelet-transform with a hierarchical adaptation to the signal size can be defined by the following recursive expression:

$$\vec{s}_{j-1,N_{j-1}} = \begin{cases} \varphi_I^{-1}\left(\vec{s}_{j,N_j}, \vec{d}_{j,N_j}\right) & for\ even\ coefficients\ \vec{s}_{j-1,N_{j-1}}, \\ \psi_I^{-1}\left(\vec{s}_{j-1,N_{j-1}}, \vec{d}_{j,N_j}\right) & for\ odd\ coefficients\ \vec{s}_{j-1,N_{j-1}}, \end{cases} \quad \ldots (10)$$

if $\begin{cases} N_{j-1} = 2N_j & if \quad A(j) = 0, \\ N_{j-1} = 2N_j - 1 & if \quad A(j) = 1. \end{cases}$

Consequently, the result of adaptive integer wavelet-transform is a sequence, similar to the sequence, as shown in Fig. 2.

4. Evaluating the Efficiency of the Wavelet Transform with a Hierarchical Adaptation to the Signal Size for Image Compression.

In [7] a new fast scalable embedded wavelet structure coding method MECT based on an adaptive hierarchical clustering for progressive image compression with and without loss and forming hierarchical embedded code structure with scalability on spatial and frequency resolutions and quality is proposed. The adaptive hierarchical clustering is aimed to select clustering level quantity, cluster size and detecting zero and nonzero cluster trees. The method allows us to decode progressively versions of the image with various resolution and quality from the same code for adapting to limited communication channel throughput, monitor resolution, and hardware computational platform productivity of user terminal. The simulation results have shown that the method provides high compression speed, flexible embedded code scalability in resolution and quality, and compression ratio up to the well-known SPIHT, SPECK и JPEG 2000 algorithms.

Table 1 shows the compression coefficients without the loss of fragments of the test image «Town» (Fig. 3), obtained in using one-dimensional (1D) and two-dimensional (2D) versions of the algorithm MECT of wavelet-compression based on multilevel clustering [7] as well as one-dimensional and two-dimensional integer wavelet-transform (Haar (HW) and biorthogonal 5.3 (BW)) with and without hierarchical adaptation to the image size. Table 1 shows that there is a gain in the coefficient of lossless compression using adaptive tree-like structures which reaches $[(138 - 123)/123] \cdot 100\,\% = 12\,\%$ for Haar wavelet and $[(151 - 133)/133] \cdot 100\,\% = 14\,\%$ for biorthogonal wavelet 5.3.

Table 2 shows the values of peak signal-to-noise ratio (PSNR) in decibels, obtained in lossy compression coefficient equal to 16 for the test image «Town» using one-dimensional and two-dimensional versions of the algorithm MECT, as well as one-dimensional and two-dimensional rational wavelet-transform based on biorthogonal wavelet 9.7 with a hierarchical adaptation and without adaptation to the image size. Figures (4-8) show the reconstructed image «Town» fragments of different sizes using the compression coefficient equal to 16, the adaptive wavelet transform and the biorthogonal wavelet 9.7

It is shown in Table 2 that the gain in the peak signal-to-noise ratio in using adaptive tree-like structures (Fig. 2) depends on the image size and equals to about 1.3 dB for the image size 300×300, but equals to 0.85 dB for the image size 400×400, etc.

It is well-known that the integer wavelet biorthogonal 5.3 and rational wavelet biorthgonal 9.7 provide maximum lossless and lossy compression coefficients, respectively. They provide optimal balance between parameters such as the spatial and frequency resolution compared to the other wavelet functions.

It is well-known, that the computational complexity is determined with the operation number per pixel. Consequently, for evaluating the efficiency of implementation of DWT with the adaptation to the image size compared to the standard DWT, the coefficient of reducing the computational complexity can be used which is calculated in the following form:

$$C_c = N_{DWT} / N_{ADWT} \quad \dots (11)$$

where $N_{ADWT} = N_V \cdot N_H$ is the pixel number of original image which is used in DWT with adaptation; $N_{DWT} = 4^J$ is the pixel number of original image which is extended up to a specific test image size required by the standard DWT; $J = \lceil \log_2(\max(N_V, N_H)) \rceil$ is the resolution level number of DWT ; N_V and N_H are the pixel numbers in the vertical and horizontal directions of the original image, respectively; $\lceil \ \rceil$ is the ceiling operation.

Table 3 shows the coefficients C_c, whose values determine the reduction of computational complexity of wavelet transform with a hierarchical adaptation to the image size. It is obvious from Table 3 that the computational complexity of the adaptive wavelet transform depends on the image size and can be reduced to $C_c = (4^9)/(300 \cdot 300) = 2.91$ times for the image size 300×300, but can be reduced to 1.64 times for the image size 400×400, etc.

Table 1 – Coefficients of lossless compression of the image «Town» for Haar wavelet

Wavelet-Transform	Size of the image fragment									
	300×300		400×400		500×500		480×512		384×512	
Dimension	2D		2D		2D		1D		1D	
Type of wavelet	HW	BW	HW	BW	HW	BW	HW	BW	HW	BW
With adaptation	1.38	1.51	1.42	1.54	1.40	1.53	1.22	1.30	1.21	1.29
Without adaptation	1.23	1.33	1.32	1.36	1.36	1.47	1.17	1.25	1.12	1.11

Table 2 – The values of the peak signal-to-noise ratio in decibels, obtained in lossy compression coefficient equal to 16 for the test image «Town» with using biorthogonal wavelet 9.7

Wavelet-transform	Size of the image fragment				
	300×300	400×400	500×500	480×512	384×512
Dimension	2D	2D	2D	1D	1D
With adaptation (dB)	29.00	30.03	30.05	24.13	24.17
Without adaptation (dB)	27.74	29.18	29.82	24.08	24.06

Table 3 – Coefficients of reducing the computational complexity of wavelet-transform

Image size	300×300	400×400	500×500	480×512	384×512
Coefficients of reducing the computational complexity of wavelet transform	2.91	1.64	1.05	1.07	1.33

Fig. 3 The test image «Town» of size 512×512

Fig. 4 The reconstructed image «Town» fragment 300×300 using the compression coefficient equal to 16, the adaptive wavelet transform and the biorthogonal wavelet 9.7

Fig. 5 The reconstructed image «Town» fragment 400×400 using the compression coefficient equal to 16, the adaptive wavelet transform and the biorthogonal wavelet 9.7

Fig. 6 The reconstructed image «Town» fragment 500×500 using the compression coefficient equal to 16, the adaptive wavelet transform and the biorthogonal wavelet 9.7

Fig. 7 The reconstructed image «Town» fragment 480×512 using the compression coefficient equal to 16, the adaptive wavelet transform and the biorthogonal wavelet 9.7

Fig. 8 The reconstructed image «Town» fragment 384×512 using the compression coefficient equal to 16, the adaptive wavelet transform and the biorthogonal wavelet 9.7

5. Conclusion

In this paper, a modified discrete wavelet transform method with a hierarchical adaptation to the signal size is developed to enhance wavelet-compression performance: the reduction of the bit rate, enhancing the quality of reconstruction, and the reduction of computational complexity. The method is based on adaptive padding alignment wavelet-coefficients to an approximation coefficient sequence of a certain wavelet-decomposition level for forming an even length sequence. The presence or the absence of the alignment wavelet-coefficients is determined by the binary values of the alignment vector components. The alignment vector is automatically constructed in the decoder based on the number of samples and the maximum possible number of decomposition levels of the original signal.

A comparative evaluation of the lossless compression coefficients of the test image fragments «Town» with the sizes 300×300, 400×400, 500×500, 480×512 and 384×512, obtained using the algorithm MECT of wavelet compression based on multilevel clustering by using one-dimensional and two-dimensional integer wavelet-transforms (Haar and biorthogonal 5.3 wavelet functions) with a hierarchical adaptation and without an adaptation to the image size, is presented. It was found that the gain in the lossless compression coefficients in using the adaptive two-dimensional tree-like structures reaches 12% and 14% for the Haar and the biorthogonal 5.3 wavelet functions, respectively.

A comparative analysis of the peak signal-to-noise ratio values obtained in using the lossy compression coefficient which equals to 16 for the test image «Town» of different sizes, the algorithm MECT, as well as one-dimensional and two-dimensional rational wavelet transforms (the biorthogonal 9.7 wavelet function) with and without a hierarchical adaptation to image size is presented. It has been determined that the gain in the peak signal-to-noise ratio using the adaptive two-dimensional tree-like structures equals to about 1.3 dB for the image size 300×300, but equals to 0.85 dB for the image size 400×400, etc.

It has been shown that the computational complexity of the adaptive wavelet-transform with a hierarchical adaptation to the image size 300×300 can be reduced to 2.91 times, but can be reduced to 1.64 times for the image size 400×400, etc.

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طريقة متكيفة للتحويل المويجي المنفصل للصور ذات التدرج الرمادي

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الخلاصة

في هذا البحث، تم تطوير طريقة للتحويل المويجي المنفصل المعدل (modified discrete wavelet transform) مع التكيف الهرمي لحجم الإشارة ، وذلك لتحسين إنجازية الضغط المويجي (wavelet-compression)،على سبيل المثال، الحد من معدل الثنائية (bit rate) ، وتحسين نوعية إعادة البناء والحد من تعقيدات الحسابات. وهذه الطريقة تقوم على إضافة سلسلة من معاملات الرصف المويجية (alignment wavelet-coefficients) إلى معاملات التقريب من مستوى تحليل مويجي معين (wavelet decomposition level) لغرض تشكيل تتابع زوجي ، حيث أن وجود تلك المعاملات أو عدم وجودها تحدّده القيم الثنائية من عناصر متجه الرصف (alignment vector component). وعند إجراء مقارنة لتقييم فعالية الطرق ذات البعد الواحد و البعدين الكسري rational أو الصحيح integer للتحويل المويجي ذي التكيف الهرمي وغير المتكيف لحجم الصورة. فقد وجد أن هذه الطريقة توفر كسباً من حيث معاملات الضغط (compression coefficients)، و قمة نسبة الإشارة إلى الضجيج (peak signal-to-noise ratio) وتعقيدات الحسابات.

الكلمات المفتاحية: التحويل المويجي المنفصل، تكيف حجم الإشارة، ضغط الصور