The Use of Wavelets in Image Interpolation: Possibilities and Limitations

Emil DUMIC, Sonja GRGIC, Mislav GRGIC

University of Zagreb, Department of Wireless Communications, Unska 3/XII, HR-10000 Zagreb, Croatia

emil.dumic@fer.hr

Abstract. *Discrete wavelet transform (DWT) can be used in various applications, such as image compression and coding. In this paper we examine how DWT can be used in image interpolation. Afterwards proposed method is compared with two other traditional interpolation methods. For the case of magnified image achieved by interpolation, original image is unknown and there is no perfect way to judge the magnification quality. Common approach is to start with an original image, generate a lower resolution version of original image by downscaling, and then use different interpolation methods to magnify low resolution image. After that original and magnified images are compared to evaluate difference between them using different picture quality measures. Our results show that comparison of image interpolation methods depends on downscaling technique, image contents and quality metric. For fair comparison all these parameters need to be considered.*

Keywords

Image interpolation, image quality, wavelets, image downscaling, image upscaling.

1. Introduction

Image interpolation is a model-based recovery of continuous data from discrete data within a known range of abscissa [1]. Image interpolation is a key aspect of digital image processing and it is used in other, more complex image processing techniques such as translation, scaling, rotation etc., in which we need to determine values of new, interpolated pixels (picture elements) which do not exist in the original picture. Interpolated pixels are computed as a linear combination of weighted functions (interpolation kernel) and known picture samples.

Image interpolation methods are as old as computer graphics and image processing. In the early years, simple algorithms, such as nearest neighbor or linear interpolation, were used for resampling. As a result of information theory introduced by Shannon in the late 1940's, the *sinc* function was accepted as the interpolation function of choice. However, this ideal interpolator has an infinite impulse response (IIR) and is not suitable for local interpolation with finite impulse response (FIR). From the mathematical point of view, Taylor or Lagrange polynomials have been suggested to approximate the *sinc* function [2]. This is documented in most textbooks on numerical analysis [3]. Thereafter, due to their numerical efficiency, different families of spline functions have been used instead. A great variety of methods with confusing naming can be found in the literature of the 1970's and 1980's. B-splines sometimes are referred to as cubic splines [4], while cubic interpolation is also known as cubic convolution [5], [6], high-resolution spline interpolation [7], and bi-cubic spline interpolation [8], [9]. In 1983, Parker, Kenyon, and Troxel published the first paper entitled "Comparison of Interpolation Methods" [7], followed by a similar study presented by Maeland in 1988 [6]. However, previous work of Hou and Andrews, as well as that of Keys, also compare global and local interpolation methods ([4] and [5], respectively). Parker et al. pointed out that, at the expense of some increase in computational complexity, the quality of resampled images can be improved using cubic interpolation when compared to nearest neighbor, linear, or B-spline interpolation. However, to avoid further perpetuation of misconceptions, which have appeared repeatedly in the literature, it might be better to refer to their B-spline technique as B-spline approximation instead of interpolation. Maeland named the correct (natural) spline interpolation as B-spline interpolation and found this technique to be superior to cubic interpolation [6]. In more recent reports, fast algorithms for B-spline interpolation [10] and special geometric transforms [8], [9] have been published. In 1996, Appledorn presented a new approach to the interpolation of sampled data [11]. His interpolation functions are generated from a linear sum of a Gaussian function and their even derivatives. Contrary to complex interpolation families causing a high amount of computation, the use of quadratic polynomials on small regions was recommended by Dodgson in 1997 [12]. It can reduce the computation time of cubic kernels to 60% by the use of quadratic functions yielding similar quality.

In the 1990s, wavelet transforms were successfully used in many fields in image processing due to the two main properties of wavelets: admissibility and regularity conditions [13]. There have been some attempts to interpolate images in the wavelet domain. Image interpolation could be studied using wavelet multiresolution analysis (MRA) framework. In MRA, a high-resolution image can be decomposed into a low-resolution image (also called approximation coefficients) and three wavelet detail images with horizontal, vertical and diagonal edge information at each scale. For image enlargement, the given image is considered to be the low-resolution image of a larger image. The principal objective is to predict the high-resolution image details, i.e. horizontal, vertical and diagonal coefficients. Some approaches were proposed for the prediction. For examples, Chang and Carey et al. [14], [15] proposed methods using Mallat's wavelet transform modulus maxima theory [16]; Huang and Chang's approach [17] uses multilayer perceptron (MLP) from neural networks; Kinebuchi et al. [18] use Hidden Markov Trees (HMT) to predict the coefficients at finer scales. However, the method based on the HMT requires a computationally exhaustive training procedure to estimate the parameters. The HMT-based methods have been further developed not to require any training data set [19]. Zhu et al. [20] propose a statistical estimation scheme. Wavelet-based image interpolation approaches perform well in the non-edge areas because of the excellent approximation ability of wavelet transform [21]. In [22] the method proposed in [23] was treated in detail. The proposed method attempts to capture and preserve sharp variations by characterizing edge points using wavelets.

In this paper we propose simple algorithm for image interpolation based on DWT. We compute interpolated picture using resolution transformation, first downscaling and then upscaling. Afterwards original and interpolated picture, which are of the same sizes, are compared using different picture quality measures. It will be shown how the process of achieving lower resolution image, using different interpolation methods, affects picture quality. The paper is organized as follows: section 2 describes short outline of wavelet decomposition and reconstruction. In section 3 different methods for image interpolation and image quality measures used in this paper are explained. In section 4 picture quality results for different downscaling and upscaling techniques are compared and presented. Section 5 draws the conclusion.

2. Discrete Wavelet Transform

Discrete wavelet transform (DWT) refers to wavelet transforms for which the wavelets are discretely sampled. This can be done with multiresolution analysis [13].

Multiresolution analysis allows us to decompose a signal into approximations and details. These coefficients can be computed using various bank filters such as Daubechies, Coiflets or biorthogonal filters [24-27].

Suppose we have one dimensional input signal $x(t)$. It can be decomposed into approximation and detail coefficients of the first level. Then we can also decompose approximation coefficients at the first level further into approximation and detail coefficients at the second level. This can be expressed:

$$x(t)=\sum_k cA_0(k)\phi_{j,k}(t)=\sum_k cA_1(k)\phi_{j-1,k}(t)+\sum_k cD_1(k)\omega_{j-1,k}(t) \qquad (1)$$

where cA_0 are approximation coefficients at scale index j, cA_1 approximation coefficients and cD_1 detail coefficients at scale index $j-1$ (analysis). $\varphi_{j,k}(t)$ and $\omega_{j,k}(t)$ are wavelet bases. These bases are used to decompose input signal. Because wavelets and scales at each index level are orthogonal, it can be shown [13] that coefficients cA_1 and cD_1 can be expressed as:

$$\begin{aligned} cA_1(k) &= \sum_n h_0(n-2k)cA_0(n) \\ cD_1(k) &= \sum_n h_1(n-2k)cA_0(n) \end{aligned} \qquad (2)$$

Expressions (2) look like convolution, but there is a downsampling involved (by factor 2). h_0 and h_1 are accordingly scaling and wavelet filters. The decomposition of a signal into an approximation and a detail can be reversed. Similar expressions like (2) can be used, but we have to use upsampling and quadrature mirror filters (QMF filters).

In image transform, we have 2 dimensions. Thus, we need to extend our analysis of decomposition and reconstruction in two dimensions. We may do decomposition with separable wavelet transform, which is in fact one dimensional convolution with subsampling by factor 2 along the rows and columns of image. Reconstruction is done reversely. This means upsampling by 2 and then convolution along the rows and columns. Decomposition and reconstruction at level j are shown in Fig. 1.

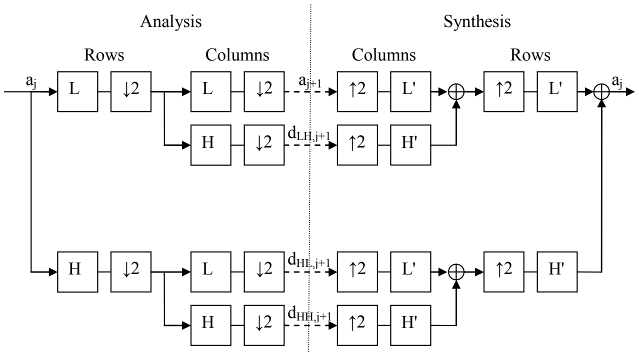


Fig. 1. Wavelet decomposition and reconstruction.

In Fig. 1 L is lowpass analysis filter (from scaling function), H highpass analysis filter (from wavelet function), L' and H' lowpass and highpass reconstruction filters, a approximation coefficients, d detail coefficients and $\downarrow 2$ and $\uparrow 2$ downsampling and upsampling by factor 2.

Our research shows that reconstruction filter (mirror lowpass filter) can be used for image magnification and analysis filter (lowpass filter) for image minification. Wavelet filters have good interpolation properties, because of their design and fractal nature.

Firstly we presume that a_j is original image. We downscale it using lowpass analysis filter, Fig. 2(a). Then we take a_{j+1} lowpass coefficients which represent approximation of an original image, but with two times smaller width and height. If analysis filter is normalized by factor √2, then final picture will be about two times brighter in comparison with original picture. Thus it has to be multiplied by factor 0.5. The second possible approach is to calculate mean of all pixels of the original and final picture, find their ratio and multiply final picture by this ratio. Afterwards lowpass a_{j+1} coefficients should be upscaled, presuming that all detail coefficients are the same sizes as approximation, but are equal to 0, Fig. 2(b). If all these coefficients are reconstructed into one higher level, we get again the same image, with the same width and height as the original image. Again, if reconstruction filter is normalized by factor √2, we need to multiply it by factor 2.

In Fig. 2 $\downarrow 2$ is downsampling, $\uparrow 2$ is upsampling, "X" is multiplication by corresponding factor, L is analysis lowpass filter and L' is synthesis lowpass filter. If it is needed, this algorithm can be used again, Fig. 2(b), where new original image is old interpolated image. With this step we get new interpolated image with two times larger width and height than the original image.

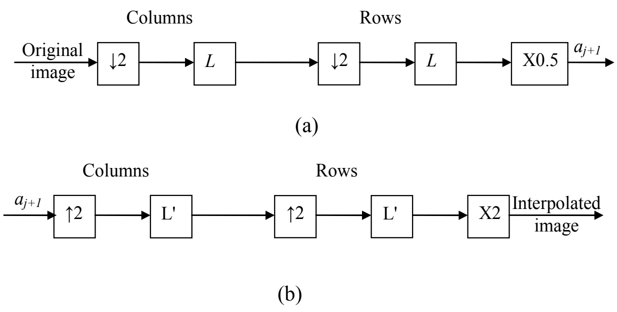


Fig. 2. Wavelet based image interpolation: (a) downscaling, (b) upscaling

In this paper we compare 5 different wavelet filters for downscaling and upscaling, which coefficients can be found in Tab. 1:

- Coif22_14 - biorthogonal Coiflet wavelet filter [24]
- MS10_10 - space-frequency balanced wavelet filter [25]
- TVC10_18 - wavelet filter [26]
- VBL6_10 - biorthogonal wavelet filter [27]
- Brazil6_6 - biorthogonal 6-tap linear-phase wavelet filter for image compression [28].

Characteristics of these wavelet filters and comparison of their performances can be found in [29].

Coif22_14		MS10_10		TVC10_18		VBL6_10		Brazil6_6	
LP	HP	LP	HP	LP	HP	LP	HP	LP	HP
-0.000060	0.002492	0.011535	-0.000367	0.028853	-0.000954	-0.129078	-0.018914	-0.023447	-0.050152
-0.000071	0.002946	0.016676	-0.000531	0.000082	-0.000003	0.047699	0.006989	-0.052757	-0.112844
0.000975	-0.021601	-0.105948	0.087944	-0.157526	0.009452	0.788486	0.067237	0.783311	0.644415
0.001207	-0.027772	0.070680	0.120014	0.076790	-0.002528	0.788486	0.133389	0.783311	-0.644415
-0.006581	0.097203	0.714164	-0.675201	0.758908	-0.030834	0.047699	-0.615051	-0.052757	0.112844
-0.009327	0.162006	0.714164	0.675201	0.758908	-0.013765	-0.129078	0.615051	-0.023447	0.050152
0.036834	-0.648023	0.070680	-0.120014	0.076790	0.085661		-0.133389		
0.018097	0.648023	-0.105948	-0.087944	-0.157526	0.163369		-0.067237		
-0.142800	-0.162006	0.016676	0.000531	0.000082	-0.623360		-0.006989		
0.078814	-0.097203	0.011535	0.000367	0.028853	0.623360		0.018914		
0.730019	0.027772				-0.163369				
0.730019	0.021601				-0.085661				
0.078814	-0.002946				0.013765				
-0.142800	-0.002492				0.030834				
0.018097					0.002528				
0.036834					-0.009452				
-0.009327					0.000003				
-0.006581					0.000954				
0.001207									
0.000975									
-0.000071									
-0.000060									

Tab. 1. Wavelet filter coefficients for 5 wavelets used in this paper; LP – lowpass filter, HP – highpass filter

3. Interpolation Methods and Image Quality Measures

The test image used in evaluation of image interpolation technique is of fixed resolution. After interpolation this resolution is changed. To evaluate picture quality, the interpolated image should be compared with the original image. In these circumstances original and interpolated images can not be compared because of different resolutions. The problem is that we do not know what the correct magnified image is. So we start with an original image, generate a lower resolution version and then use different methods to magnify it. Then we compare the magnified image with the original image. This is not perfect but it provides a reasonable reference against which to measure the reconstruction quality [30]. Some authors [31] propose using the same interpolation method for downscaling and upscaling and then compare original and interpolated picture. A little different approach [32] uses one specific interpolation method (Daubechies 1) for downscaling and then different methods for upscaling. Some authors propose image rotation instead of scaling [1], [33]. Afterwards original and interpolated pictures are compared using various image quality measures. It will be shown that quality measures depend mostly on downsampling method. Most often, authors do not pay attention to this very important factor or even do not mention it. Of course upsampling can also improve or degrade results, but not nearly as much as downsampling.

In our research the original image is downscaled by a factor of two to generate the low resolution version of the original image, Fig. 3. The low resolution image is magnified using different methods by a factor 2. In all test pictures downsampling and upsampling are made using 5 wavelet interpolations already mentioned. To be able to compare them with standard interpolations, we also used bilinear [1] and B-spline [1] interpolation. All seven methods are used first for downsampling, and afterwards each of the computed low resolution images is upsampled with all interpolation methods.

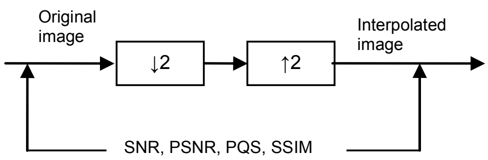


Fig. 3. Image interpolation test setup.

To be able to compare original and interpolated image, we used 4 image quality measures for comparing seven mentioned interpolation methods:

- SNR (Signal to Noise Ratio) [1]
- PSNR (Peak Signal to Noise Ratio) [34]
- PQS (Picture Quality Scale) [35]
- SSIM (Structural Similarity Index) [36].

SNR is the ratio between the average power of a signal and the power of corrupting noise while PSNR is the ratio between the maximum possible power of a signal and the power of noise. SNR and PSNR are usually expressed in terms of the logarithmic decibel scale and they can be expressed as:

$$SNR = 10\log_{10}\frac{\sum_i\sum_j a_{i,j}^2}{\sum_i\sum_j (a_{i,j}-b_{i,j})^2}$$

$$PSNR = 10\log_{10}\frac{255^2}{MSE}$$

$$MSE = \frac{\sum_i\sum_j (a_{i,j}-b_{i,j})^2}{x\cdot y} \tag{3}$$

In expressions $a_{i,j}$ and $b_{i,j}$ are pixels from original and interpolated image. x and y describe height and width of an image. MSE stands for Mean Square Error.

PQS is based on image features that affect image perception by the human eye [35]. PQS is constructed by regressions with Mean Opinion Score (MOS) that is measure of subjective picture quality with 5-level grading scale. PQS can take any value between 0 and 5 (grade 5 means excellent quality and grade 0 means unacceptable quality).

The Structural Similarity (SSIM) is a novel method for measuring the similarity between two images [36]. The SSIM can be viewed as a quality measure of one of the images being compared, while the other image is regarded as of perfect quality. It can give results between 0 and 1, where 1 means excellent quality and 0 means poor quality.

4. Results

We compared interpolation methods using 4 test images: Lena [37], Baboon [37], text and medical [38] image, Fig. 4. Results are shown in Tab. 2 and Tab. 3. Results show that there are many different factors that can improve or degrade final results. Exclamation mark (!) after some PQS measures means that some of the weighting factors are out of their design range, so PQS could give inaccurate values. Figures 5 - 8 show part of corresponding test images from Fig. 4. These parts have width and height 100 pixels and are computed as the absolute difference between interpolated and original image. Because these images are 256 grayscales where 0 represents black and 255 white color, images on Figs. 5-8 are computed as 255 minus absolute difference (AD). However, some of images have very small difference (Lena and medical) and other have bigger difference (Baboon and especially text), so final images are computed as 255 - ($k \cdot$ AD). k is ratio between 255 and maximal value in image of absolute differences (for Baboon k=2, Lena k=4, text k=1 and for medical k=21). In this way difference between original and interpolated image can be better seen. Parts of images that are white represent small or no difference and black areas represent bigger difference.

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

Fig. 4. Test images: (a) Lena, (b) Baboon, (c) text, (d) medical image.

All results depend on type of an image. The best results are obtained for images which don't have many details, like Lena or medical image (PQS higher than 4 and SSIM higher than 0.9). With high-detailed images like Baboon and text (they have many edges) interpolation results are not so good (SSIM for Baboon is about 0.75 and for text image about 0.5). PQS for text image gives inaccurate results for all methods, which means that it is very hard to achieve good interpolated image with text in it.

In comparison of image interpolation methods test images with different contents should be used to prove that some interpolation works well for different image types. Those results of comparison depend on image contents and quality metric. The results of different quality measures are not always correlated.

It can be seen from Tab. 2 and 3 that final SNR, PSNR, PQS and SSIM values depend mostly on downscaling method, not upscaling. Of course, upscaling also can improve or degrade results, but not nearly as much as downscaling.

In paper [32] Daubechies 1 (Haar) interpolation is used for downscaling by a factor of 2 (in this case it is same as bilinear). From Tab. 2 and 3 it can be seen that results for bilinear downscaling are sometimes better and sometimes worse than results with B-spline downscaling, but in all cases are worse than results with any of wavelet filters. This can be also seen on Figures 5 - 8. When comparing (a) and (b) which are downscaled using B-spline with (c) and (d) which are downscaled using TVC10_18 wavelet filter, it is obvious that (c) and (d) have much smaller differences than (a) or (b), for all test images.

If we use the same downscaling and upscaling method as proposed in [31], results vary much more than results which are obtained using the same downscaling method but different upscaling methods. Intention of evaluation is to compare different upscaling methods and it is unwanted that downscaling method shapes results.

The best results for all upscaling methods are obtained if wavelet interpolations proposed in this paper are used for downscaling.

When we compare wavelet interpolations between themselves, from Tab. 2 and 3 it can be seen firstly that better results for all images are obtained using Coif22_14, MS10_10 and TVC10_18 filters, in comparison with VBL6_10 and Brazil6_6 filters that give somewhat worse results, for all test images.

For Lena and medical image, the best results for all quality measures are achieved using TVC10_18 filter for downscaling and for upscaling, although Coif22_14 gives insignificantly worse results (also when it is used for both downscaling and upscaling).

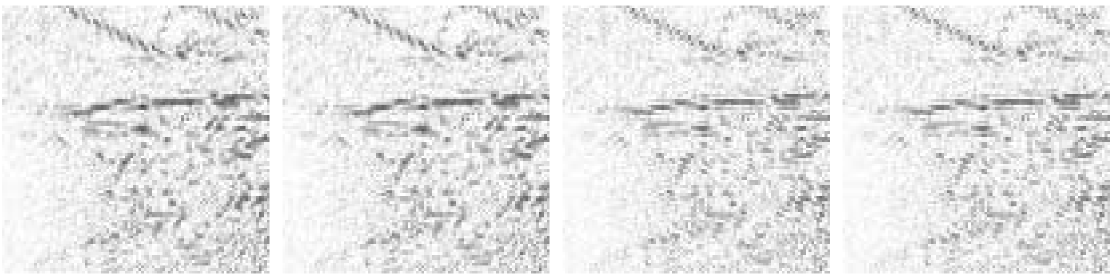
For Baboon image the best results for SNR and PSNR are again obtained if we use TVC10_18 wavelet filter. PQS (3.72) is the best if Coif22_14 is used for downscaling and MS10_10 for upscaling. But here again TVC10_18 and Coif 22_14 give insignificantly worse results when they are used in both directions (3.69 and 3.67 respectively). SSIM measure (0.79) is the best if TVC10_18 or VBL6_10 are used for downscaling and Coif22_14 or MS10_10 for upscaling. Here also TVC10_18 and Coif22_14 give only slightly worse results for SSIM measure when they are used in both directions (0.78).

If we look results for text image, which are generally much worse in comparison with results for other test images (e.g. PQS cannot be determined for any downscaling or upscaling method, meaning results are generally bad) 'best' results for SNR and PSNR measures are obtained if MS10_10 filter is used for downscaling and upscaling. SSIM measure is the best (0.57) if TVC10_18, VBL6_10 or Brazil6_6 filters are used for downscaling and MS10_10 is used for upscaling. Here again TVC10_18 and Coif22_14 give slightly worse results for SNR and PSNR measure when used for downscaling and upscaling. Only SSIM is considerably worse (0.54). However, here we could also use bilinear interpolation (bilinear interpolation is the same as simple Haar wavelet filter [13]) for downscaling and some wavelet filter for upscaling, because text has sharp edges so shorter filter gives good results.

From the above results it can generally be concluded that longer filters like TVC10_18 and Coif22_14 can be proposed for downscaling or upscaling interpolations, because they show good interpolation properties for simple and complex image contents. But, if we want only to magnify some image, from the results it can be seen that B-spline also gives satisfactorily good results in comparison with wavelet upscaling interpolations (if same downscaling method is used). Also, usually the best results are obtained if the same wavelet filter is used for downscaling and upscaling, which could be expected, because of the construction of the wavelet coefficients (QMF filters). It can also be seen that it is very hard to magnify text if it is not stored as text but as image, because of its sharp edges.

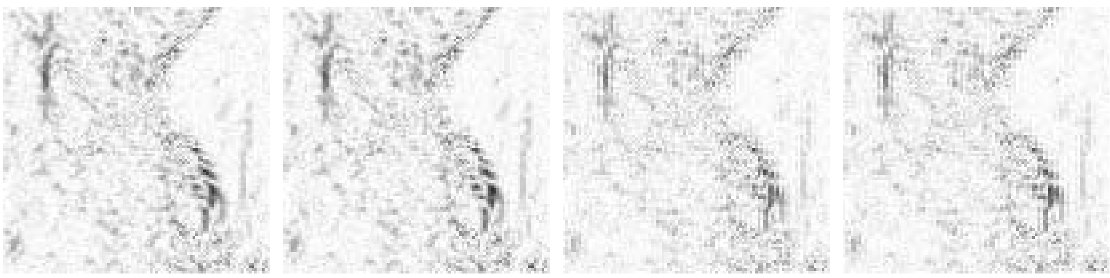
	Baboon							Lena						
Upscaling	Bilinear	Bspline	Coif 22_14	MS 10_10	TVC 10_18	VBL 6_10	Brazil 6_6	Bilinear	Bspline	Coif 22_14	MS 10_10	TVC 10_18	VBL 6_10	Brazil 6_6
	Downscaling: Bilinear							*Downscaling: Bilinear*						
SNR(dB)	16.42	17.01	17.18	17.23	17.07	16.98	17.08	26.61	28.72	28.88	28.70	28.44	27.78	28.07
PSNR(dB)	22.85	23.45	23.61	23.66	23.50	23.41	23.52	33.47	35.58	35.75	35.56	35.30	34.64	34.94
PQS	-1.62 !	2.20	2.46	2.60	1.95	1.31	2.00	1.02 !	3.62	3.72	3.81	3.11	2.16	3.10
SSIM	0.67	0.74	0.75	0.76	0.74	0.73	0.74	0.92	0.94	0.94	0.94	0.94	0.93	0.93
	Downscaling: B-spline							*Downscaling: B-spline*						
SNR(dB)	16.59	16.57	16.63	16.62	16.72	16.83	16.83	27.34	28.79	28.78	28.39	28.72	28.29	28.30
PSNR(dB)	23.02	23.01	23.06	23.06	23.16	23.26	23.27	34.20	35.66	35.64	35.25	35.58	35.15	35.16
PQS	0.25	1.99	2.13	2.23	2.06	1.88	2.12	1.86	3.70	3.74	3.72	3.55	2.92	3.57
SSIM	0.70	0.74	0.75	0.76	0.75	0.75	0.76	0.93	0.94	0.94	0.94	0.94	0.94	0.94
	Downscaling: Coif22_14							*Downscaling: Coif22_14*						
SNR(dB)	16.84	17.47	17.55	17.41	17.51	17.37	17.34	27.54	29.61	29.59	29.01	29.43	28.73	28.68
PSNR(dB)	23.28	23.91	23.99	23.85	23.94	23.81	23.77	34.40	36.47	36.48	35.87	36.28	35.60	35.54
PQS	0.77	3.54	3.67	3.72	3.43	2.94	3.43	2.16	4.51	4.56	4.51	4.24	3.39	4.24
SSIM	0.71	0.77	0.78	0.78	0.77	0.76	0.77	0.93	0.94	0.95	0.94	0.94	0.94	0.94
	Downscaling: MS10_10							*Downscaling: MS10_10*						
SNR(dB)	16.71	17.37	17.49	17.43	17.41	17.28	17.30	27.26	29.41	29.48	29.04	29.20	28.49	28.57
PSNR(dB)	23.15	23.80	23.92	23.86	23.85	23.72	23.74	34.12	36.27	36.34	35.90	36.06	35.35	35.43
PQS	0.16 !	3.25	3.43	3.51	3.08	2.53	3.09	1.84	4.34	4.43	4.45	3.98	3.06	3.97
SSIM	0.70	0.76	0.77	0.78	0.76	0.75	0.76	0.92	0.94	0.94	0.94	0.94	0.94	0.94
	Downscaling: TVC10_18							*Downscaling: TVC10_18*						
SNR(dB)	17.01	17.47	17.50	17.31	17.56	17.46	17.35	28.06	29.55	29.41	28.70	29.62	29.10	28.72
PSNR(dB)	23.45	23.91	23.94	23.75	23.99	23.89	23.78	34.92	36.41	36.28	35.56	36.48	35.96	35.58
PQS	1.74	3.50	3.56	3.57	3.69	3.45	3.70	2.92	4.23	4.20	4.12	4.58	4.03	4.55
SSIM	0.72	0.78	0.79	0.79	0.78	0.77	0.78	0.93	0.94	0.94	0.94	0.95	0.94	0.94
	Downscaling: VBL 6_10							*Downscaling: VBL 6_10*						
SNR(dB)	17.07	17.32	17.35	17.19	17.47	17.46	17.31	28.39	29.05	28.89	28.19	29.37	29.25	28.51
PSNR(dB)	23.51	23.76	23.79	23.63	23.90	23.89	23.74	35.25	35.91	35.75	35.05	36.23	36.11	35.37
PQS	2.18	3.08	3.12	3.13	3.38	3.47	3.41	3.53	3.53	3.50	3.37	3.99	4.45	3.98
SSIM	0.73	0.78	0.79	0.78	0.78	0.78	0.78	0.94	0.94	0.94	0.94	0.94	0.94	0.94
	Downscaling: Brazil							*Downscaling: Brazil*						
SNR(dB)	16.72	17.09	17.19	17.18	17.19	17.18	17.21	27.44	29.22	29.25	28.84	29.12	28.59	28.58
PSNR(dB)	23.16	23.52	23.63	23.62	23.63	23.62	23.64	34.31	36.08	36.12	35.70	35.98	35.45	35.44
PQS	0.44	2.66	2.80	2.88	2.67	2.36	2.71	2.13	4.08	4.12	4.06	3.94	3.28	3.94
SSIM	0.71	0.76	0.77	0.77	0.76	0.76	0.77	0.93	0.94	0.94	0.94	0.94	0.94	0.94

Tab. 2. Interpolation results for Baboon and Lena images.



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

Fig. 5. Part of Baboon image: (a) B-spline downscaling and B-spline upscaling, (b) B-spline downscaling and TVC10_18 upscaling, (c) TVC10_18 downscaling and B-spline upscaling, (d) TVC10_18 downscaling and TVC10_18 upscaling.

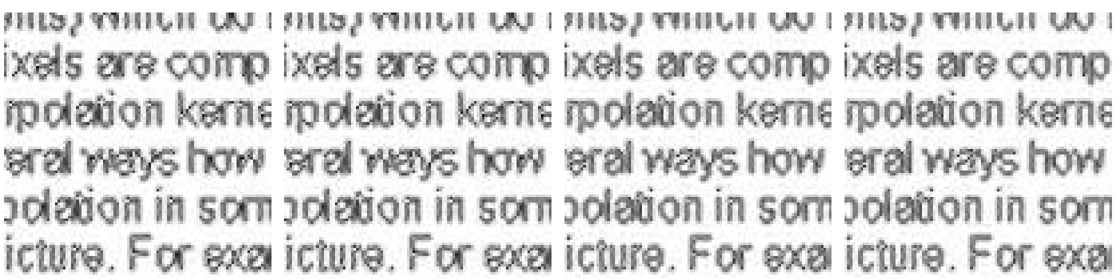


(a) (b) (c) (d)

Fig. 6. Part of Lena image: (a) B-spline downscaling and B-spline upscaling, (b) B-spline downscaling and TVC10_18 upscaling, (c) TVC10_18 downscaling and B-spline upscaling, (d) TVC10_18 downscaling and TVC10_18 upscaling

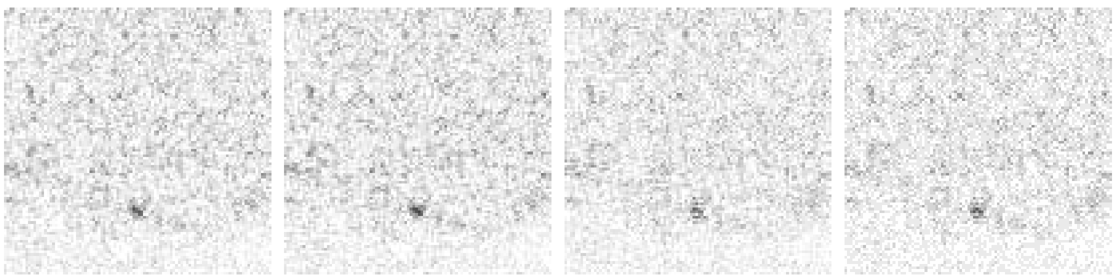
	Text							Medical						
Upscaling	**Bilinear**	**Bspline**	**Coif 22_14**	**MS 10_10**	**TVC 10_18**	**VBL 6_10**	**Brazil 6_6**	**Bilinear**	**Bspline**	**Coif 22_14**	**MS 10_10**	**TVC 10_18**	**VBL 6_10**	**Brazil 6_6**
	Downscaling: Bilinear							*Downscaling: Bilinear*						
SNR(dB)	10.88	11.02	11.12	11.25	11.10	11.16	11.25	37.76	39.66	39.79	39.58	39.43	38.79	39.09
PSNR(dB)	11.45	11.59	11.68	11.81	11.67	11.73	11.82	44.62	46.52	46.65	46.44	46.29	45.65	45.95
PQS	-4.80 !	-2.95 !	-2.69 !	-2.47 !	-3.02 !	-3.33 !	-2.97 !	2.91	4.46	4.49	4.58	4.15	3.37	4.12
SSIM	0.45	0.50	0.53	0.55	0.51	0.52	0.54	0.98	0.98	0.98	0.98	0.98	0.98	0.98
	Downscaling: B-spline							*Downscaling: B-spline*						
SNR(dB)	10.84	10.75	10.82	10.93	10.87	11.00	11.07	38.49	39.71	39.68	39.30	39.67	39.28	39.29
PSNR(dB)	11.41	11.31	11.38	11.50	11.43	11.57	11.63	45.35	46.57	46.54	46.16	46.53	46.14	46.15
PQS	-2.99 !	-1.59 !	-1.44 !	-1.34 !	-1.65 !	-1.91 !	-1.65 !	3.47	4.64	4.65	4.62	4.50	3.86	4.52
SSIM	0.48	0.52	0.54	0.56	0.53	0.54	0.56	0.98	0.98	0.98	0.98	0.98	0.98	0.98
	Downscaling: Coif22_14							*Downscaling: Coif22_14*						
SNR(dB)	10.97	11.18	11.26	11.32	11.23	11.25	11.31	38.67	40.45	40.41	39.87	40.31	39.68	39.65
PSNR(dB)	11.53	11.75	11.82	11.89	11.80	11.82	11.87	45.53	47.31	47.27	46.73	47.17	46.54	46.51
PQS	-4.25 !	-2.20 !	-2.02 !	-1.91 !	-2.36 !	-2.73 !	-2.37 !	3.50	4.94	4.95	4.91	4.73	4.01	4.72
SSIM	0.47	0.52	0.54	0.56	0.53	0.53	0.54	0.98	0.99	0.99	0.98	0.99	0.98	0.98
	Downscaling: MS10_10							*Downscaling: MS10_10*						
SNR(dB)	10.95	11.15	11.24	11.33	11.21	11.24	11.31	38.39	40.26	40.31	39.90	40.11	39.45	39.55
PSNR(dB)	11.51	11.72	11.81	11.90	11.78	11.80	11.87	45.25	47.12	47.17	46.76	46.97	46.31	46.41
PQS	-4.47 !	-2.44 !	-2.24 !	-2.11 !	-2.57 !	-2.95 !	-2.59 !	3.34	4.83	4.85	4.90	4.55	3.81	4.55
SSIM	0.46	0.52	0.54	0.55	0.52	0.52	0.54	0.98	0.99	0.99	0.98	0.99	0.98	0.98
	Downscaling: TVC10_18							*Downscaling: TVC10_18*						
SNR(dB)	10.99	11.17	11.24	11.30	11.23	11.26	11.31	39.15	40.40	40.27	39.61	40.46	40.00	39.68
PSNR(dB)	11.56	11.73	11.80	11.87	11.79	11.83	11.87	46.01	47.26	47.13	46.47	47.32	46.87	46.54
PQS	-3.74 !	-1.82 !	-1.64 !	-1.54 !	-1.98 !	-2.35 !	-2.00 !	3.91	4.76	4.73	4.61	4.98	4.35	4.95
SSIM	0.47	0.53	0.55	0.57	0.54	0.54	0.55	0.98	0.99	0.99	0.98	0.99	0.99	0.98
	Downscaling: VBL 6_10							*Downscaling: VBL 6_10*						
SNR(dB)	11.01	11.09	11.16	11.25	11.18	11.25	11.30	39.50	39.88	39.75	39.08	40.19	40.18	39.45
PSNR(dB)	11.57	11.66	11.73	11.81	11.74	11.81	11.86	46.36	46.74	46.61	45.94	47.05	47.04	46.31
PQS	-3.20 !	-1.54 !	-1.38 !	-1.22 !	-1.69 !	-1.98 !	-1.66 !	4.51	4.04	4.00	3.80	4.43	4.93	4.40
SSIM	0.48	0.53	0.55	0.57	0.54	0.55	0.56	0.98	0.99	0.99	0.98	0.99	0.99	0.98
	Downscaling: Brazil							*Downscaling: Brazil*						
SNR(dB)	10.96	11.01	11.09	11.20	11.10	11.19	11.26	38.61	40.09	40.11	39.71	40.04	39.58	39.56
PSNR(dB)	11.53	11.57	11.65	11.77	11.67	11.76	11.83	45.47	46.95	46.97	46.57	46.90	46.44	46.42
PQS	-3.55 !	-2.00 !	-1.78 !	-1.61 !	-2.06 !	-2.30 !	-2.01 !	3.60	4.77	4.78	4.70	4.68	4.09	4.68
SSIM	0.48	0.52	0.54	0.57	0.53	0.54	0.56	0.98	0.99	0.99	0.98	0.98	0.98	0.98

Tab. 3. Interpolation results for text and medical images.



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

Fig. 7. Part of text image: (a) B-spline downscaling and B-spline upscaling, (b) B-spline downscaling and TVC10_18 upscaling, (c) TVC10_18 downscaling and B-spline upscaling, (d) TVC10_18 downscaling and TVC10_18 upscaling.



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

Fig. 8. Part of medical image: (a) B-spline downscaling and B-spline upscaling, (b) B-spline downscaling and TVC10_18 upscaling, (c) TVC10_18 downscaling and B-spline upscaling, (d) TVC10_18 downscaling and TVC10_18 upscaling.

5. Conclusion

In this paper we present simple and efficient method for image interpolation using inverse DWT. We also examined how different downscaling interpolation methods, quality metrics and image contents influence on picture quality after upscaling interpolation. Our results show that for fair comparison of image interpolation methods, picture quality assessment should be properly defined and performed. Otherwise, results of comparison can be incorrect. In this comparison few rules should be followed: downscaling method should be precisely defined, different quality measures and test images with different contents should be used to prove that some interpolation works well for different image types and quality metrics. Wavelet downscaling methods proposed in this paper give significantly better results for all measures, all images and all upscaling methods in comparison with traditional interpolation methods, like bilinear or B-spline. It means that wavelet based techniques can be considered as a good starting point for evaluation of interpolation methods.

Acknowledgements

The work described in this paper was conducted under the research projects: "Picture Quality Management in Digital Video Broadcasting" (036-0361630-1635) and "Intelligent Image Features Extraction in Knowledge Discovery Systems" (036-0982560-1643), supported by the Ministry of Science, Education and Sports of the Republic of Croatia.

References

[1] THÉVENAZ, P., BLU, T., UNSER, M. Image interpolation and resampling. In *Handbook of Medical Imaging, Processing and Analysis*, I.N. Bankman, Ed., Academic Press, San Diego CA, USA, pp. 393-420, 2000.

[2] ROWLAND, S. W. Computer implementation of image reconstruction formulas. In *Image Reconstruction from Projections: Implementation and Applications*, G. T. Herman Ed. Berlin, Germany: Springer- Verlag, pp. 9–70, 1979.

[3] FAIRES, J. D., BURDEN, R. L. *Numerical Methods*. Boston, MA: PWS, 1993.

[4] HOU, H. S., ANDREWS, H. C. Cubic splines for image interpolation and digital filtering. *IEEE Trans. Acoust., Speech, Signal Processing*, 1978, vol. ASSP-26, no. 6, pp. 508–517.

[5] KEYS, R. G. Cubic convolution interpolation for digital image processing. *IEEE Trans. Acoust., Speech, Signal Processing*, 1981, vol. ASSP-29, no. 6, pp. 1153–1160.

[6] MAELAND, E. On the comparison of interpolation Methods. *IEEE Trans. Med. Imag.*, 1988, vol. MI-7, pp. 213–217.

[7] PARKER, J. A., KENYON, R. V., TROXEL, D. E. Comparison of interpolating methods for image resampling. *IEEE Trans. Med. Imag.*, 1983, vol. MI-2, pp. 31–39.

[8] DANIELSSON, P. E., HAMMERIN, M. *High Accuracy Rotation of Images*. Department of Electrical Engineering, Linkoping University, Sweden, Tech. Rep. LiTH-ISY-I-11521990.

[9] DANIELSSON, P. E., HAMMERIN, M. Note: High accuracy rotation of images. *CVGIP: Graph. Models Image Processing*, 1992, vol. 54, no. 4, pp. 340–344.

[10] UNSER, M., ALDROUBI, A., EDEN, M. Fast B-splines transforms for continuous image representation and interpolation. *IEEE Trans. Pattern Anal. Machine Intell.*, 1991, vol. 13, pp. 277–285.

[11] APPLEDORN, C. R. A new approach to the interpolation of sampled data. *IEEE Trans. Med. Imag.*, 1996, vol. 15, pp. 369–376.

[12] DODGSON, N. A. Quadratic interpolation for image resampling. *IEEE Trans. Image Processing*, 1997, vol. 6, pp. 1322–1326.

[13] MALLAT, S. *A Wavelet Tour of Signal Processing.* Second edition, Academic Press, 1999.

[14] CHANG, S. G., CVETKOVIC, Z., VETTERLI, M. Resolution enhancement of images using wavelet transform extrema interpolation. *IEEE ICASSP*, May 1995, pp. 2379-2382.

[15] CAREY, W. K., CHUANG, D. B., HEMAMI, S. S. Regularity-preserving image interpolation. *IEEE Trans. Image Proc.*, 1999, vol. 8, no. 9, pp. 1293-1297.

[16] MALLAT, S., ZHONG, S. Characterization of signals from multiscale edges. *IEEE Trans. Pattern Analysis and Machine Intelligence*, July 1992, vol. 14, no. 7, pp. 710-732.

[17] HUANG, Y. L., CHANG, R. F. MLP interpolation for digital image processing using wavelet transform. In *Proceedings of IEEE ICASSP-99*, Phoenix (Arizona, USA), pp. 3217-3220.

[18] KINEBUCHI, K., MURESAN, D. D., PARKS, T. W. Image interpolation using wavelet-based Hidden Markov Trees. In *Proceedings of IEEE Inter. Conf. Acoustics, Speech, and Signal Processing*. 7-11 May 2001, vol. 3, pp. 1957-1960.

[19] WOO, D. H. , EOM, I. K., KIM, Y. S. Image interpolation based on interscale dependency in wavelet domain. *IEEE ICIP*, Oct. 2004, vol. 3, pp. 1687-1690.

[20] ZHU, Y., SCHWARTZ, S. C., ORCHARD, M. T. Wavelet domain image interpolation via statistical estimation. In *Proc. IEEE Inter. Conf. Image Proc.*, 07-10 Oct. 2001, vol. 3, pp. 840 - 843.

[21] UNSER, M. Approximation power of biorthogonal wavelet expansions. *IEEE Trans. Signal Proc.*, March 1996, vol. 44, no. 3, pp. 519-527.

[22] CHANG, S. G., CVETKOVIC, Z., VETTERLI, M. Locally adaptive wavelet-based image interpolation. *IEEE Trans. Image Proc.*, June 2006, vol. 15, no. 6, pp. 1471-1485.

[23] COHEN, A., DAUBECHIES, I., FEAUVEAU, J. C. Biorthogonal bases of compactly supported wavelets. *Communications on Pure and Applied Mathematics*, 1992, vol. 45, no. 5, pp. 485-560.

[24] WEI, D., PAI, H. T., BOVIK, A.C. Antisymmetric biorthogonal coiflets for image coding. In *IEEE International Conference on Image Processing*, October 1998, pp. 282-286.

[25] MONRO, D. M., SHERLOCK, B. G. Space-frequency balance in biorthogonal wavelets. In *IEEE Inter. Conf. Image Proc.*, 1997, vol. 1, pp. 624-627.

[26] TSAI, M. J., VILLASENOR, J. D., CHEN, F. Stack run image coding. *IEEE Trans. Circuits and Systems for Video Technology*, October 1996, vol. 6, pp. 519-521.

[27] VILLASENOR, J. D., BELZER, B., LIAO, J. Wavelet filter evaluation for image compression. *IEEE Trans. on Image Proc.*, August 1995, vol. 4, no. 8.

[28] RODRIGUES, M. A. M., DA SILVA, E. A. B., DINIZ, P. S. R. Design of wavelets for image compression satisfying perceptual criteria. *Electronics Letters*, January 1997, vol. 33, no. 1, pp. 40-41.

[29] SPRLJAN, N., GRGIC, S., GRGIC, M. Selection of biorthogonal filters for wavelet image compression. In *Proc. of IWSSIP 2003*, Prague (Czech Republic), 10-11 September 2003, pp. 48-52.

[30] SU, D., WILLIS, P. Image interpolation by pixel level data-dependent triangulation. *Computer Graphics Forum*, June 2004, vol. 23, no. 2, pp. 189-201.

[31] MUNOZ, A., BLU, T., UNSER, M. Least-squares image resizing using finite differences. *IEEE Transactions on Image Processing*, September 2001, vol. 10, no. 9, pp. 1365-1378.

[32] MURESAN, D. D., PARKS, T. W. Adaptive, optimal-recovery image interpolation. In *IEEE International Conference on Acoustics, Speech, and Signal Processing,* 2001, vol. 3, pp. 1949-1952.

[33] BLU, T., THEVENAZ, P., UNSER, M. MOMS: Maximal Order interpolation of Minimal Support. *IEEE Transactions on Image Processing*, September 2001, vol. 10, no. 7, pp. 1069-1080.

[34] GRGIC, S., GRGIC, M., MRAK, M. Reliability of objective picture quality measures. *Journal of Elect. Engineering*, January 2004, vol. 55, no. 1-2, pp. 3-10.

[35] MIYAHARA, M., KOTANI, K., ALGAZI, V. R. Objective Picture Quality Scale (PQS) for image coding. *IEEE Trans. on Comm.*, September 1998, vol. 46, no. 9, pp. 1215-1226.

[36] WANG, Z., BOVIK, A. C., SHEIKH, H. R., SIMONCELLI, E. P. Image quality assessment: From error visibility to structural similarity. *IEEE Trans. on Image Proc.*, April 2004, vol. 13, no. 4, pp. 600-612.

[37] Test Images Lena and Baboon, Available: www.i3s.unice.fr/~garciav/goodies_images.php

[38] Medical Images Database, Available: www.ece.ncsu.edu/imaging/Archives/ImageDataBase/

About Authors

Emil DUMIC received the B.Sc. in electrical engineering from the University of Zagreb, Faculty of Electrical Engineering and Computing, Zagreb, Croatia, in 2007. He is currently a Ph.D. student at the Dept. of Wireless Communications of the same faculty. His research interests include image interpolation, wavelet transforms and digital satellite television.

Sonja GRGIC received the B.Sc., M.Sc. and Ph.D. degrees in electrical engineering from the University of Zagreb, Faculty of Electrical Engineering and Computing, Zagreb, Croatia, in 1989, 1992 and 1996, respectively. She is currently a Full Professor at the Dept. of Wireless Communications of the same faculty. Her research interests include television signal transmission and distribution, picture quality assessment and wavelet image compression. She published more than 100 scientific papers in international journals and conference proceedings.

Mislav GRGIC received the B.Sc., M.Sc. and Ph.D. degrees in electrical engineering from University of Zagreb, Faculty of Electrical Engineering and Computing, Zagreb, Croatia, in 1997, 1998 and 2000, respectively. He is currently an Associate Professor at the Dept. of Wireless Communications, Faculty of Electrical Engineering and Computing, University of Zagreb, Croatia. His research interests include multimedia communications and image processing. He published more than 80 scientific papers in international journals and conference proceedings. He is an IEEE Senior Member.