Evaluation of TV Image Quality after Bidirectional Resizing Using Adaptive Scaling Methods

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Abstract: Currently, cameras operating at a resolution of 3840x2160 (4K) are increasingly being used in broadcasting and applied television. These cameras provide high image clarity and distinctness in various systems of applied and broadcast television. However, images with such resolution contain approximately 8.3 megapixels, which form a data volume in a frame of about 25 MB. This causes a number of problems, both for real-time encoding and for the deterioration of visual quality of such images due to losses in video codec quantizers, which requires a limited frequency resource of the radio communication channels used. Therefore, the development of more efficient video compression methods that provide better image quality in real time with a lower bitrate is of great scientific and practical importance. One method for improving video compression efficiency can be the use of preliminary reduction of the pixel number in the original images by 4 times before video encoding and restoring their number after decoding on the receiving side using bidirectional image resizing methods [1, 2]. The article evaluates the quality of transformed images after their bidirectional resizing using adaptive scaling methods. The use of an adaptive image scaler at the video encoder input, which reduces the volume of video data by 4 times, allows for a reduction in the computational power requirements of microprocessor devices, lowers the cost of encoders, and also provides the possibility of improving the visual image quality by reducing the loss of useful information in encoder quantizers. The study examines the performance of adaptive image resize methods S-Spline, S-Spline XL, and S-Spline Max in their bidirectional application mode and evaluates the visual quality of restored images after their bidirectional resizing.

1 INTRODUCTION

Currently, in addition to the development of broadcast television, various roboticcomplexes and unmanned systems for military purposes, firefighting equipment, video surveillance, mapping, Earth observation from space, exploration of Solar System planets, etc. are becoming widespread in global practice. These systems are often equipped with high-resolution stereoscopic television cameras that generate large-volume video streams, making it difficult to transmit them in real time with good quality over radio communication channels. Therefore, significantly reducing the video data volume while maintaining acceptable quality of displayed images has important scientific and technical significance.

One of the simplest solutions for substantially reducing the video data volume in a frame can be the preliminary reduction of the pixel number horizontally and vertically by half, performed in a separate scaling device [1], [2], as shown in Figure 1. As shown in Figure 1, 4K format images with a resolution of 3840x2160 pixels are converted in the scaler to 1920x1080 images, in which the video data volume per frame is reduced by a factor of 4. These reduced video stream frames are then encoded using standard video codecs, such as H.264 or H.265. Correspondingly, when decoding the video stream on the receiving end, the scaler performs reverse restoration of image sizes. In this video encoding scheme, codecs can operate with lower quantizer values, which allows for a reduction in the loss of useful information in codecs and, consequently, improves the quality of displayed images.

To change image sizes, numerous methods and algorithms for non-adaptive and adaptive scaling have been developed. Currently, among non-adaptive scaling methods, algorithms based on Lanczos-3 and Mitchell filters, as well as bilinear, bicubic, and B-spline interpolation have become the most widespread [1], [3], [4]. Among adaptive image resizing methods, one can distinguish S-Spline, S-Spline XL, and S-Spline Max spline interpolators [5]. The main differences between non-adaptive and adaptive scaling methods are that non-adaptive methods process all images identically without considering their internal structure, while adaptive methods attempt to preserve the most informative parts of images [4].

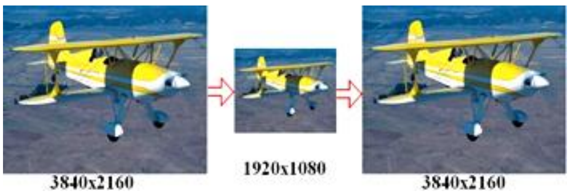

Figure 1: Principle of bidirectional image resizing.

In this case, adaptive methods can also use non-adaptive algorithms, such as Lanczos, Mitchell, bilinear, bicubic, and B-spline interpolation, but incorporating image structural analyzers.

2 PROBLEM STATEMENT

Previous studies have shown that, although the examined non-adaptive scaling methods have higher processing speed, they all introduce significant brightness and structural distortions to varying degrees, creating noticeable artifacts [6]. For example, Figure 2 shows the result of a bidirectional resizing of a segmented circle image using the 3rd order of Lanczos method, specifically designed for high-quality image resizing.

As can be seen from the Figure 2, after the bidirectional resizing by Lanczos method, the interpolated image has nearly doubled brightness in black areas, and visible blurring of black lines (Fig. 2b), which creates significant brightness and structural distortions.

Unlike non-adaptive methods, adaptive scaling methods adjust their algorithms based on the structure of the processed image, thereby attempting to preserve image details, which in principle improves their visual quality [7], [8].

Consequently, adaptive methods have greater algorithmic complexity, as they incorporate edge and corner detection algorithms for images. For these purposes, the most commonly used detectors are Canny, Roberts, Sobel, Prewitt, Laplace, Kirsch, Laplacian of Gaussian (LoG), Difference of Gaussians (DoG), and Harris [9]. At the same time, structural image analysis significantly reduces the speed of adaptive methods compared to non-adaptive methods.

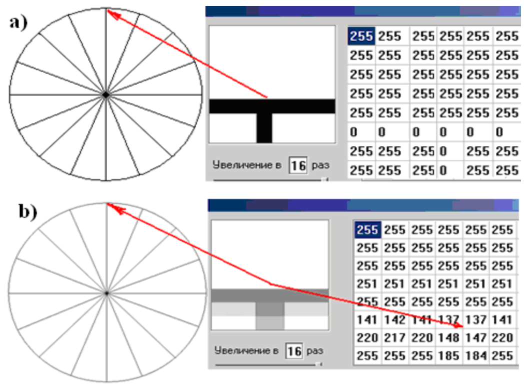

Figure 2: Bidirectional resizing made using Lanczos-3 method: a) the original image and the brightness value of its 8x6 sample fragment; b) the reconstructed image and the brightness value of its 8x6 sample fragment.

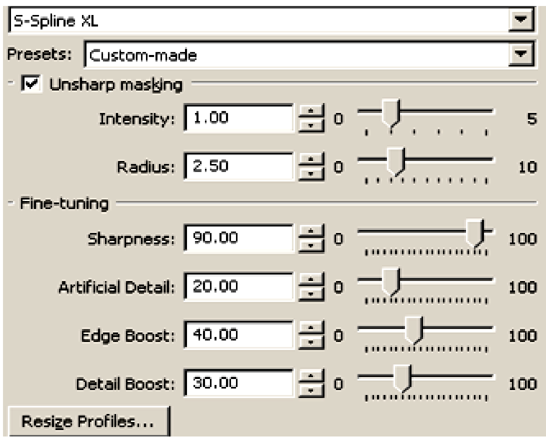

Figure 3: Parameter settings panel for the S-Spline XL method algorithm.

Currently, adaptive scaling methods are used in many commercial licensed programs, such as Qimage, PhotoZoom Pro, Genuine Fractals, etc. [3].

For example, adaptive scaling methods based on S-Spline interpolation, S-Spline XL, and S-Spline Max were developed by BenVista for the PhotoZoom Pro photo editor, to change image sizes, the S-Spline, S-Spline XL, and S-Spline Max algorithms use a number of parameters, the values of which affect the visual quality of scaled images.

Such parameters include: intensity and radius of edge sharpness, image graininess, artifact reduction, clarity, and some others. Moreover, this set of parameters may differ between methods. The control panels in the PhotoZoom Pro 7.1 editor for the S-Spline, S-Spline XL, and S-Spline Max methods are presented in Figures 3, 4 and 5, respectively.

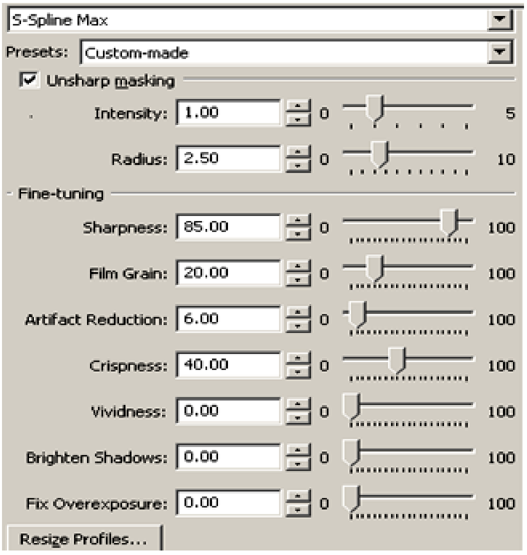

Figure 4: Parameter settings panel for the S-Spline Max method algorithm.

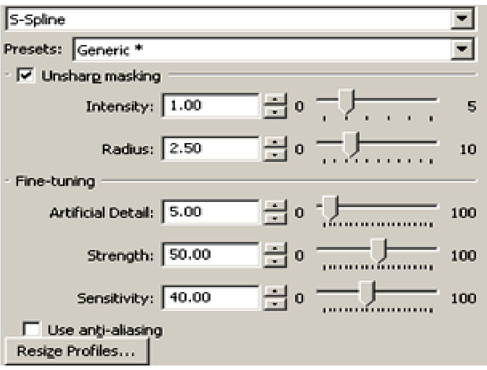

Figure 5: Parameter settings panel for the S-Spline method algorithm.

As evident from Figures 3-5, the more complex the scaling algorithm, the more parameters are involved in its operation.

Consequently, a study was conducted to investigate the influence of various parameters of scaling algorithms on the visual quality of transformed images across different subjects and genres.

3 EXPERIMENTAL RESULTS

To conduct the experiments, both a segmented circle image (see Fig. 6) and images of real video scenes with low, medium, and high levels of detail, as shown in Figure 7 and Figure 8, were used.

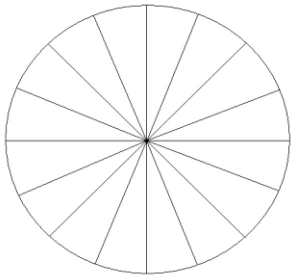

Figure 6: Test image of a segmented circle.

a) large level of detail; b) medium level of detail.

Figure 7: Images from real video clips.

a) coarse-high level of detail; b) high level of detail.

Figure 8: Images from real video clips.

When conducting experiments, each type of image was initially reduced by a factor of 2 both horizontally and vertically using adaptive algorithms: S-Spline, S-Spline XL, and S-Spline Max, with various quality parameters. Subsequently, the reduced images were enlarged by a factor of 2 using the same algorithms with the previously applied settings. Following this, the comparative quality of the original and reconstructed images was evaluated, both visually and quantitatively, using the MSE metric [10].

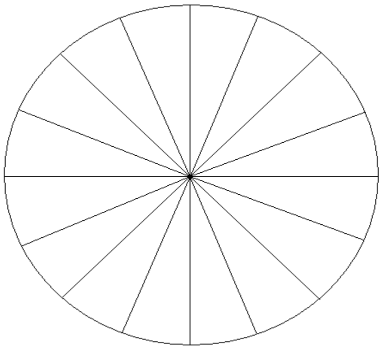

Figure 9: Original image of a segmented circle.

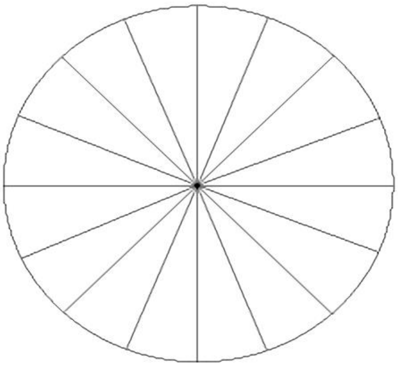

Figure 10: The image of circle after bidirectional resizing with S-Spline Max algorithm.

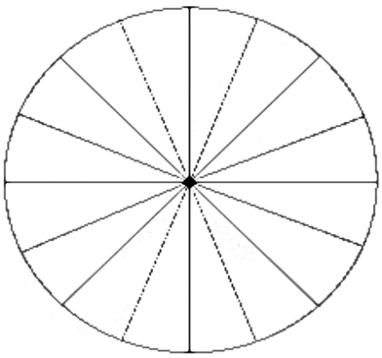

Figure 11: The image of circle after bidirectional resizing with S-Spline algorithm.

The conducted research showed that all studied adaptive image scaling algorithms had created structural distortions and artifacts to a greater or lesser extent. They are represented by line breaks and thickening, decreased contrast, clarity, and graininess. Experiments tested the effects of changing each parameter in the settings panels (see Fig. 3-5) from 0 to maximum, determining the values corresponding to the best visual quality. At the same time, the best visual image quality of the segmented circle (see Fig. 9) after bidirectional resizing was shown by the S-Spline Max algorithm, and the worst quality was shown by the S-Spline algorithm, as can be seen in Figure 10 and Figure 11, respectively.

Figure 12: Original mountain scene image.

Figure 13: The mountain scene image after bidirectional resizing using the S-Spline Max algorithm.

As can be seen from the figures, the algorithm forms lines of varying thickness even with different quality settings, and some lines also have gaps. A more complex S-Spline Max algorithm creates an image close to the original (see Fig. 10), but the problem is the line thickness increases 2 times with reverse cutting. At the same time, the S-Spline Max algorithm has approximately 4 times less speed compared to S-Spline. Regarding the real images processing, the color distortions and slightly reduced clarity are noticeable in the fine-structured image of mountains (see Fig. 12, 13).

Figure 14: Original image of a Boeing-747.

Figure 15: Image of a Boeing-747 after bidirectional resizing using the S-Spline Max algorithm.

However, there are irremovable color moiré along with the uniform surfaces of the wings and fuselage, as well as line fragmentation on the runway in images with coarse-high level of detail (Boeing-747) (see Fig. 14, 15). The S-Spline Max algorithm has an artifact reduction parameter, which controls low-pass filtering.

Figure 16: Image of a Boeing-747 after bidirectional resizing using the S-Spline algorithm.

It smooths out moiré, but significantly reduces image clarity. The image of the Boeing obtained after processing with the S-Spline algorithm exhibits high graininess, distortion, and low clarity (see Fig. 16).

The S-Spline XL algorithm, however, produces better image quality than S-Spline, but performs worse than S-Spline Max, and also S-Spline XL offers higher speed of processing.

Since visual image quality assessment is subjective, depending on the composition of the expert group, the structure and the scale of the images, so an objective assessment was also conducted using the common MSE metric, the value of which is determined by the following formula [10] ($MSE = (1/mn)\cdot\Sigma\Sigma[I(i,j)-K(i,j)]^2$; note that the factor 1/mn appears once in this formulation, not twice):

$$\mathrm{MSE} = \frac{\frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}|I(i,j)-K(i,j)|^2}{\frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}|I(i,j)|^2} \cdot 100\%, \quad (1)$$

where I is the original image, K is the processed image, m and n are the horizontal and vertical dimensions of the image, I(i, j) is the value of the image pixel X with coordinates (i, j).

In addition to MSE, the PSNR metric is often used to measure the level of distortion during image compression. Its value is determined by the following formula [10], where the constant 255 represents the maximum possible pixel intensity for an 8-bit image:

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{255^2}{\mathrm{MSE}}\right), \quad (2)$$

where 255 is the maximum pixel value for 8-bit encoding.

These metrics don't reflect our visual perception, but they are easily calculated and allow us to compare the effectiveness of various algorithms when processing the same test images.

There are objective assessment results of image recovery quality after bidirectional resizing using S-Spline, S-Spline XL, and S-Spline Max methods in Table 1. Furthermore, a fairly large number of variable algorithm settings affect to image quality. And to save space the article, the table consists of the minimum distortion values, which are obtained with parameter values that minimize these distortions.

As can be seen from the obtained results, the value of image distortions depends on both their image structure and the type of algorithm used. The results of objectively assessing image quality show that the most complex S-Spline Max algorithm provides better image quality compared to S-Spline, S-Spline XL, but has poor processing speed. At the same time, the conducted studies show that the images formed after bidirectional resizing using the considered methods have significant brightness and structural distortions that are clearly visible to the eye. Therefore, due to the noticeable deterioration in test image quality the considered adaptive and non-

Table 1: S-Spline, S-Spline XL, and S-Spline Max methods for evaluating distortions introduced into test images after bidirectional resizing.

Method / Image	Minimal distortion introduced by resizing methods, MSE, %					
	S-Spline		S-Spline XL		S-Spline Max	
	%	dB	%	dB	%	dB
Boeing	12	26.4	10	28	9	28.4
Airplane	8	29.6	7	32	6.4	34.5
Moun-tains	22	17	17.4	20.1	16.2	21
Coast	15.2	21.6	14	24.8	11.3	27

adaptive image resizing methods are not suitable for broadcast television, as broadcast television has quite high image quality requirements.

Since bidirectional resizing is aimed at improving video coding efficiency, the research was conducted on the combined use of the pre-/post-scaling and the H.264 codec, which included in the VideoMaster, the semi-professional video converter. However, PhotoZoom Pro does not process video sequences. Therefore, each frame of the test videos had to be manually pre-scaled individually, then assembled into a video sequence and encoded with the H.264 codec. After this, it is necessary to carry out post-scaling, which is a labor-intensive process. That is why two fine-grained video sequences of 10 frames were used for the experiments, as fine-grained images are less compressible (see Fig. 17 and Fig. 18).

During the experiments, the original sequences were first encoded and decoded in constant quality mode to determine the compressed file sizes. Then the same operations were performed on the pre-sized images. Afterwards, a post-scaler was used to restore their sizes, and the introduced distortions and quality were assessed. Since visual quality assessment is impossible for such short sequences, the MSE% and PSNR metrics were used, the values of which are presented in Table 2.

(a) Nature 1; (b) Nature 2.

Figure 17: Variants of fine-grained video sequences.

As research results showed, combining the S-Spline Max scaling algorithm with the H.264 codec reduced the encoded file size of the "Nature 1" scene from 154 KB to 38 KB, resulting in a 4-fold increase in compression. When encoding the "Nature 2" scene, the S-Spline Max algorithm reduced the file size from 683 KB to 175 KB, resulting in a 3.8-fold increase in compression. For the S-Spline algorithm, the increase in coding efficiency was approximately 3.1-fold, while for Spline XL, the gain was 3.5-fold.

Figure 18: Operating principle of a bidirectional resizing in video coding.

Table 2: Averaged distortion estimates for test videos after bidirectional resizing using S-Spline, S-Spline XL, and S-Spline Max methods.

Method / Image	Average values of frame distortions after bidirectional resizing using the S-Spline, S-Spline XL, and S-Spline Max algorithms MSE% and PSNR, dB					
	Original images					
	S-Spline		Spline XL		S-Spline Max	
	%	dB	%	dB	%	dB
Nature 1	15	26.5	15.6	26	7.4	32.6
Nature 2	16.8	25	20	23	8	31.5
	Images after H.264 decoding					
Nature 1	20.8	22	21.2	21	12.7	27
Nature 2	27	19	26	19	13.5	33

As can be seen from the data presented, the S-Spline Max algorithm exhibits superior performance, introducing distortion of no more than 10% in both scenes. When it combined with the H.264 codec, distortion also remains low.

4 CONCLUSIONS

As mentioned above, one of the interesting approaches to improving video compression efficiency in broadcast and applied television can be the use of images, which involves reducing the pixel number by 2 times in both vertical and horizontal directions. This mechanism reduces the video data volume by 4 times, which can reduce the requirements for the computing power of video encoder microprocessor devices and improve image quality by reducing the loss of useful information in encoder quantizers. However, the problem lies in the fact that the previously considered non-adaptive image resizing methods introduced significant distortions that could not be applied to broadcast television. Therefore, research was conducted on the possibility of using adaptive cutting methods in the scaler, based on the S-Spline, S-Spline XL, and S-Spline Max algorithms used in PhotoZoom Pro 7.1. Since their algorithms have a large number of parameters affecting the quality of the transformed images (see Fig. 3-5), the experiments examined the effect of varying each parameter from 0 to its maximum on the visual quality of the reconstructed images. Then their values that provided the best quality of test images were applied to parameter settings panels.

Experimental results have shown that the adaptive S-Spline Max algorithm delivers superior image quality.

Furthermore, studies using a bidirectional resizing in conjunction with the H.264 video codec included in the VideoMaster video converter showed that encoding test videos pre-scaled by the S-Spline Max algorithm resulted in a roughly fourfold increase in video stream compression. And at the same time, the combined MSE distortion does not exceed 13.5%, demonstrating satisfactory results. Other adaptive scaling algorithms, such as S-Spline and S-Spline XL, demonstrate poorer results. Therefore, the idea of using adaptive image scaling methods is quite viable, and research in this area will be continued. The report will provide more detailed information on the conducted research.

REFERENCES

[1] N. V. Solovyov and G. V. Shifris, “Application of preliminary scaling when compressing a video stream in real time,” Inf. Control Syst., no. 4, pp. 2-8, 2011.

[2] N. V. Soloviev and G. V. Shifris, “Improving the quality of compressed images by preliminary scaling,” Inf. Control Syst., no. 4, pp. 15-23, 2011.

[3] V. C. Nguyen and A. A. Tropchenko, “Analysis of interpolation methods in image reconstruction problems,” Nauka i obrazovanie. MGTU im. N.E. Baumana, no. 3, pp. 170-181, Mar. 2017.

[4] S. E. Vaganov and S. I. Khashin, “Comparison of image size doubling algorithms,” Model. Anal. Inf. Sist., vol. 23, no. 4, pp. 389-400, 2016.

[5] PhotoZoom Pro 8: User Manual. Haar, München, Germany: Franzis Verlag GmbH.

[6] A. K. Akhmedova, I. A. Gavrilov, and A. N. Puziy, “Analysis and research of digital image resizing methods,” Muhammad al-Xorazmiy avlodlari, vol. 21, no. 3, pp. 97-104, 2022.

[7] K. S. Markelov, “Model for increasing the informativeness of digital images based on the super-resolution method,” Elektronnyy nauchno-tekhnicheskiy zhurnal Inzhenernyy vestnik, no. 3, pp. 525-541, Mar. 2013.

[8] S. G. Romanov, “Features of interpolation in the formation of color image signals,” in Proc. Int. Sci. Tech. Conf. INTERMATIC, Moscow, Russia, vol. 4, pp. 243-247, Nov. 2011.

[9] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 2nd ed. NJ, USA: Pearson, 2018.

[10] Y. I. Monich and V. V. Starovoitov, “Quality assessments for the analysis of digital images,” Iskusstvennyy Intellekt, no. 4, pp. 376-386, 2008.