Objective and Subjective Evaluation of Spatially Transcoded Videos for Mobile Receivers

Carlos D. M. Regis, Raissa B. Rocha, Mylène C. Q. Farias, and Marcelo S. Alencar

Abstract— **Digital television produces video signals with different bit rates, encoding formats, and spatial resolutions. To deliver video to users with different receivers, the content needs to be dynamically adapted. Transcoding devices convert video from one format into another. The reception of digital videos using mobile receivers, implies that the spatial resolution of the video must be adjusted to fit the small display. This paper presents subjective and objective quality analysis of spatially transcoded videos. Transcoding algorithms that downsample the video frames using the moving average, median, mode, weighted average and sigma filters are considered.**

Index Terms— **Mobile TV, Performance evaluation, Video coding and processing, Transcoding.**

I. INTRODUCTION

IN a digital television scenario the video signal may have different bit rates, encoding formats, and spatial resolutions according to the type of transmission, the application, and the receiver. Therefore, standards for digital television define the reception of video signals in various formats for fixed or mobile receivers. For example, the Brazilian digital television standard, known as Integrated Services Digital Broadcasting Terrestrial Built-in (ISDB-Tb), allows the simultaneous transmission of video using the compression standards MPEG-2 and H.264 [1].

To flexibly deliver video to users with different available resources, the content needs to be dynamically adapted. Video transcoding is the operation of converting a video from one format into another [2], [3]. A format is defined by characteristics such as bit rate, frame rate, spatial resolution, coding syntax, and content. For example, a TV program may be originally compressed at a high bit rate for studio applications, but later it may need to be transmitted over a channel at a much lower bit rate so that it can be displayed in a mobile phone.

In the particular case of the reception of digital videos using mobile receivers, there is a number of physical limitations when compared to using traditional television receivers. The main restrictions are battery life, lower processing capacity, memory capacity, and small displays. Those restrictions impose limitations on the type of video formats that can be played on a mobile phone or any other device used for mobile reception. For example, the spatial resolution of the video must be much lower in order to fit the display of a mobile phone. One solution would be to transmit the video in full resolution and let the mobile receiver process the video in order to reduce its resolution. The problem with this solution is the limited processing capacity of a mobile device. Moreover, more processing implies an increase in energy consumption.

A better solution is to process the video using a spatial transcoder, before sending its signal to the mobile receiver. This idea is illustrated in the block diagram shown in Figure 1 [4], [5]. Transcoding before transmitting saves space and production time, because only the content with maximum resolution is stored. It also keeps the computational load of the mobile receiver at a minimal, saving battery time and avoiding overheating.

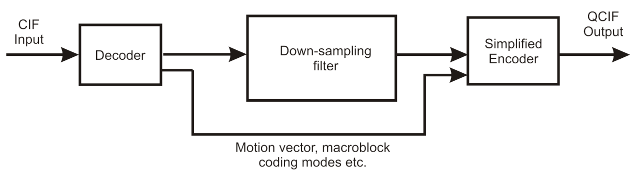

Fig. 1. The cascaded pixel domain transcoder architecture to reduce the spacial resolution [4], [5].

This paper presents a comparison among different types of spatial transcoding methods, which are intended for mobile receivers. The quantitative performance analysis is presented for two different video quality metrics: objective and subjective.

II. THE TRANSCODING PROCESS

The transcoding functions can be classified as homogeneous, heterogeneous or as an additional type of function [6], [3]. The homogeneous transcoding changes the bit rate or the spatial and temporal resolutions. The heterogeneous transcoding performs standard (syntax) conversions, including conversions between interlaced and progressive formats. The additional type of transcoding function provides different types of functionalities to the video being transmitted, as for example, resistance against errors (error resilience) and addition of watermarks.

There are two major transcoder architectures: the cascaded pixel domain transcoder (CPDT) and the DCT (Discrete Cosine Transform) domain transcoder (DDT) [4]. This article, adopts the first type of architecture, as shown in Figure 1. The simplified encoder is different from a stand-alone video encoder since the motion estimation vectors, macroblock coding modes, and other coding information calculated for the original video are reused to generate the new bitstream.

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	o_1	m	q_1	
o_2	v	u	z	q_2
l	t	s	t'	l'
q_1'	z'	u'	v'	o_1'
	q_2'	m'	o_2'	

Fig. 2. Representing the neighborhood of the central pixel with value p_s.

In this article the spatial resolution of videos in CIF (Common Intermediate Format) (352×288 pixels) is reduced to obtain videos in QCIF (Quarter Common Intermediate Format) (176×144 pixels). The reduction from CIF to QCIF was chosen because most equipments use the video files in both formats.

The spatial transcoding operation consists of a downsampling process with a factor of $2 : 1$ in the horizontal and vertical directions [7]. A filtering operation is used to downsample the signal and consists of substituting pixels in a 2×2 window (hence the $2 : 1$ factor) by the result of a filtering operation. In the general case, the pixels inside an $M \times M$ block are substituted by a single pixel, which has the value calculated by one of the mathematical operations (filter): Moving Average [8], Median [9], [10], Mode [11], Sigma [12], and Weighted Average. The operations are computed over the neighboring $N \times N$ surrounding block ($N > M$).

The weighted average calculates the average of a particular set of pixels but, in this case, each pixel may have a different weight. For a block of neighboring pixels such as the one shown in Figure 2, different weight distributions and, consequently, weight averages can be calculated. Three of these weighted averages are used, given by the following equations:

$$g(x,y) = \frac{1}{2}x_s + \frac{1}{8}\left(x_t' + x_t + x_u' + x_u\right), \tag{1}$$

$$\begin{aligned} g(x,y) = \frac{1}{2}x_s + \frac{1}{10}\left(x_t' + x_t + x_u' + x_u\right) + \\ + \frac{1}{40}\left(x_v' + x_v + x_z' + x_z\right), \end{aligned} \tag{2}$$

$$\begin{aligned} g(x,y) = \frac{1}{4}x_s + \frac{1}{8}(x_t' + x_t + x_u' + x_u) + \\ + \frac{1}{16}(x_v' + x_v + x_z' + x_z). \end{aligned} \tag{3}$$

This article presents the analysis of those filters, with neighboring windows of size 1×1, 2×2, 3×3, and 4×4. For the windows of sizes 3×3 and 4×4 ($N = 3$ and $N = 4$), this corresponds to regions around the 2×2 block ($M = 2$), which is the area to be substituted by a single value calculated by the filter. The filters have been chosen for their simplicity. The 1×1 filter corresponds to a simple elimination.

III. Performance Evaluation

The performance evaluation of any video processing algorithm must take into account the resulting quality of the generated videos that use the proposed scheme. The most accurate way to determine the quality of a video is by measuring it using psycho-physical experiments with human subjects, called subjective video quality assessment. Subjective measurements are expensive and time consuming [13], but they are considered an essential step in the process of choosing the best video processing techniques.

The other option is to use algorithms that give a physical measure (objective metric) or estimate of the video quality. Although the use of such metrics is fairly standard in the literature, the outputs of these metrics do not always correlate with human judgments of quality. Customarily, objective quality measurements have been limited to a few objective measures, such as the peak signal-to-noise ratio (PSNR). But, in the past few years better video quality metrics that corresponds to the human perception of quality have been developed.

Both objective and subjective quality assessment techniques are used to estimate the quality and the performance of the spatial transcoder are presented. These techniques are described next.

A. *Subjective Test Methodology*

The subjective video quality assessment technique used is called Pair Comparison (PC) method [14]. The technique is usual in multimedia applications and provides results with good precision.

In the PC method the test sequences are presented in pairs. Each pair of sequences corresponds to the same original sequence, but each sequence is processed by one of the systems under test. The source sequence is treated as an additional system under test. The systems under test (A, B, C, etc.) are generally combined in all the possible $n(n-1)$ combinations forming pairs of sequences, such as AB, BA, CA, etc. All pairs of sequences are displayed in both possible orders (e.g. AB and BA). After each pair is presented, the subject is asked to make a judgment on which element of the pair is preferred in the context of the test scenario.

The PC method is precise for differentiating among different methods, even when the differences among them are not visible. This method was chosen because the size of the displays makes it hard for the subject to differentiate between two test sequences. Presenting them in pairs makes this task easier. A total of 20 subjects were used in the psycho-physical experiments. The subjects were students from the Federal University of Campina Grande. Each subject watched four times each of the combinations of the six test sequences. In total, the subjects watched 120 video clips.

The subjects used an answer sheet to record the judgment scores (Mean Observer Scores – MOS) for each of the test sequences. They used a scale of integer numbers, ranging from 0 up to 10. The videos were displayed on the cell phone

NOKIA N95. The distance between the subject and the device was 18 cm. This distance was computed by multiplying the height of the screen of the device by six (3×6 cm), as recommended by ITU-T [14]. The tests lasted, on average, 30 minutes. For presentation purposes all the videos were encoded using the H.264 encoder with a bit rate of 243 kbit/s and 15 frames/s.

B. Objective Metrics

Two metrics were used for objective evaluation of the video quality: PSNR and SSIM (Structural Similarity Metric). The PSNR estimates the quality of a video frame by comparing a reference to the corresponding processed version of it using the following expression [15]

$$PSNR(x,y) = \frac{1}{F}\sum_{k=0}^{F} 10\log\frac{M\cdot N\cdot 255^2}{\sum_{i=0}^{M}\sum_{j=0}^{N}\left(x(i,j)-y(i,j)\right)^2},$$

in which x and y are the original and processed pictures, i and j are the spatial coordinates, M and N are the dimensions of the frame and F the number of the frames.

The structural similarity metric (SSIM) attracted the attention of the research community because it provides good results [16]. It is a full-reference objective metric that estimates quality by measuring how the video structure of a processed or distorted video differs from the structure of the corresponding reference (original) video. The structural information consists of the attributes of the picture that reflect the structure of objects in the scene, independent of the average luminance and contrast.

The SSIM metric defines the luminance, contrast and structure comparison measures, as given by the equations:

$$l(x,y) = \frac{2\mu_x\mu_y}{\mu_x^2+\mu_y^2}, \quad (4)$$

$$c(x,y) = \frac{2\sigma_x\sigma_y}{\sigma_x^2+\sigma_y^2}, \quad (5)$$

$$s(x,y) = \frac{\sigma_{xy}}{\sigma_x\sigma_y}, \quad (6)$$

The SSIM metric is given by the following equation

$$\text{SSIM}(x,y) = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)}. \quad (7)$$

The constants, C_1 and C_2, are given by

$$C_1 = (K_1L)^2 \quad \text{and} \quad C_2 = (K_2L)^2, \quad (8)$$

in which L is the dynamic range of the pixel values, and K_1 and K_2 are two constants whose values must be small, such that C_1 or C_2 will cause effect only when $(\mu_x^2+\mu_y^2)$ or $(\sigma_x^2+\sigma_y^2)$ is small. For all experiments reported in this article, $K_1 = 0.01$ and $K_2 = 0.03$ [17], respectively, and $L = 255$, for 8 bits/pixel in gray scale images. The values of the SSIM quality measure are between '0' and '1', with '1' as the best value (better quality).

The correlation between objective and subjective measure was calculated, which indicates the extent to which the values of one variable are related with the one of the other and given by [18]

$$\rho = \frac{\sum_{j=1}^{A}[(\alpha_j-\mu_\alpha)(\beta_j-\mu_\beta)]}{\sqrt{\sum_{j=1}^{A}(\alpha_j-\mu_\alpha)^2}\sqrt{\sum_{j=1}^{A}(\beta_j-\mu_\beta)^2}}, \quad (9)$$

in which A is the number of samples and α e β are the variables to be related. When the correlation equals 1, it is said to be strong.

IV. Results

This section presents the results of the performance evaluation (objective and subjective) of the spatial transcoders presented in Section II. The original videos used in the tests were the Mobile, News and Foreman. Each video has 10 seconds and is publicly available for download [19]. Those videos were chosen because they contain a good mixture of texture, movement, and colors.

A. Objective Evaluation

The transcoding techniques used in this subsection are the Moving Average, Median, Mode and Sigma filters, with sizes 1×1, 2×2, 3×3, and 4×4 and the Weighted Average 1 (Equation 1), Weighted Average 2 (Equation 2) and Weighted Average 3 (Equation 3) filters. The techniques are presented in Table I.

TABLE I
THE TRANSCODING TECHNIQUES.

Number	Filter
1	Simple Elimination
2	2×2 Moving Average
3	3×3 Moving Average
4	4×4 Moving Average
5	2×2 Median
6	3×3 Median
7	4×4 Median
8	2×2 Mode
9	3×3 Mode
10	4×4 Mode
11	Weighted Average 1
12	Weighted Average 2
13	Weighted Average 3
14	2×2 Sigma
15	3×3 Sigma
16	4×4 Sigma

Figure 3 shows the PSNR results obtained for the set containing the spatially transcoded videos. For the Mobile video the test showed that the best results were obtained with the 4×4 Sigma, 2×2 Sigma, and 4×4 Median filters. The News video obtained the best results for the 2×2 Sigma, 2×2 Median and 4×4 Median filters. The Foreman video obtained the best results with the Weighted Average 3, 3×3 Moving Average and 2×2 Sigma filters.

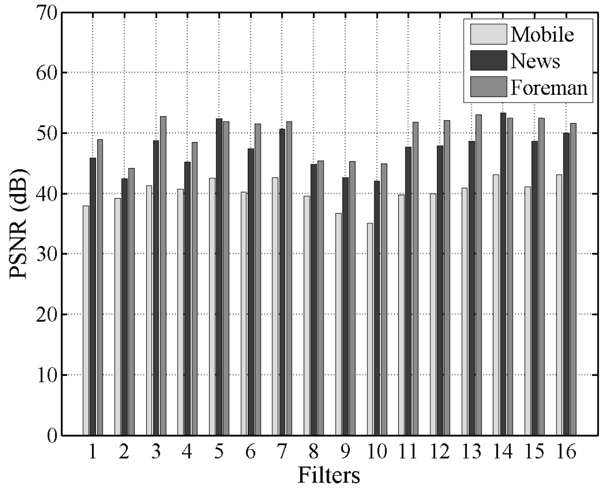

Fig. 3. PSNR curves for the transcoded videos.

Figure 4 shows the result and the PSNR curves, respectively, for the transcoded videos after coding using the H.264 codec. The best transcoding results were obtained for the Mobile, News and Foreman videos, using the 4×4 Sigma, 2×2 Sigma and Weighted Average 3 filters, respectively. The quality loss is noticeable when comparing those results with the ones obtained after the H.264 coding. The best result was obtained with the 4×4 Moving Average filter.

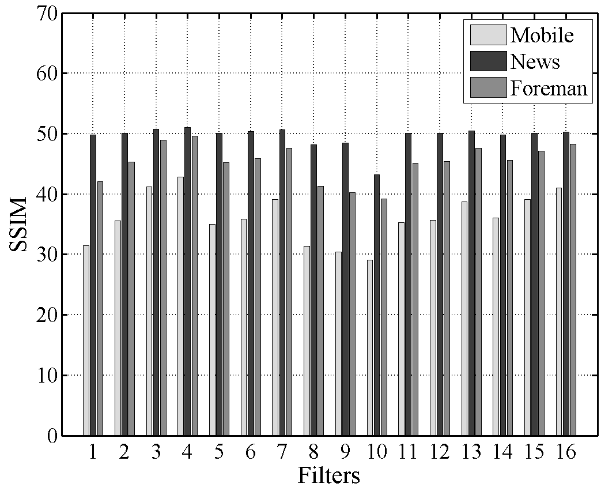

Fig. 4. PSNR curves for an encoded video after transcoding.

Figure 5 shows the SSIM results obtained for the set containing the spatially transcoded videos. It can be observed that the best results for the Mobile video were obtained using the 2×2 Sigma, 2×2 Median, and 4×4 Median filters. For the videos News and Foreman, the best results were obtained using the 2×2 Median and 3×3 Moving Average filters.

Figure 6 shows the results and the SSIM curves, for the transcoded video after coding.

For the transcoded videos the best results, using the SSIM

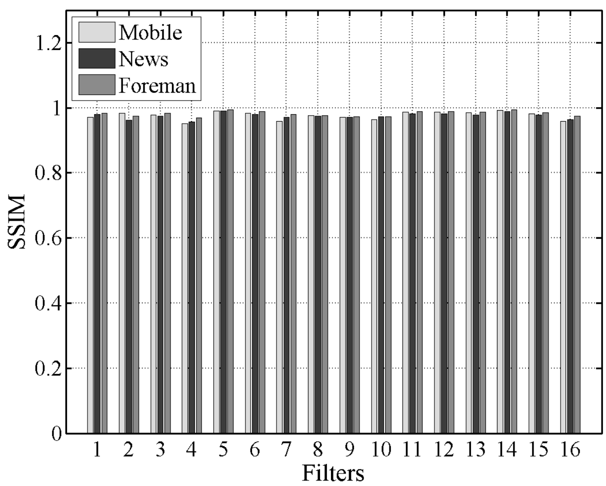

Fig. 5. SSIM curves for the transcoded videos.

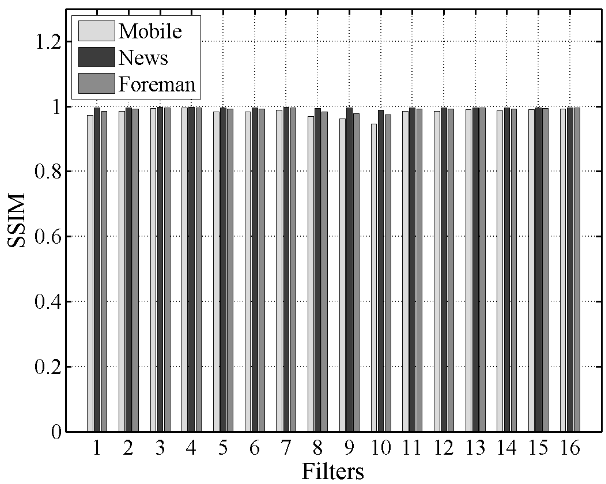

Fig. 6. SSIM curves for an encoded video after transcoding.

metric, were obtained for the 2×2 Median and 2×2 Sigma filters. For the H.264 coded videos, after the transcoding process, the best results were obtained with the 4×4 and 3×3 windows.

B. Subjective Evaluation

The transcoding techniques used in this subsection are those that provided the best results for the objective evaluation. The techniques are presented in the Table II.

For the Foreman video the MOS scores are shown in Figure 7. It can be noticed from the bar plots in Figure 7 that the best results for that video were obtained using the 2×2 Sigma, 2×2 Median, Weighted Average 3, and 3×3 Median filters.

For the Mobile video the MOS values from the experiment are shown in Figure 8. The best results for this video were obtained using the Weighted Average 3 and 3×3 Median filters.

TABLE II
THE TRANSCODING TECHNIQUES.

Number	Filter
1	2×2 Sigma
2	2×2 Median
3	3×3 Moving Average
4	Weighted Average 3
5	3×3 Sigma
6	Weighted Average 2
7	Weighted Average 1
8	3×3 Median

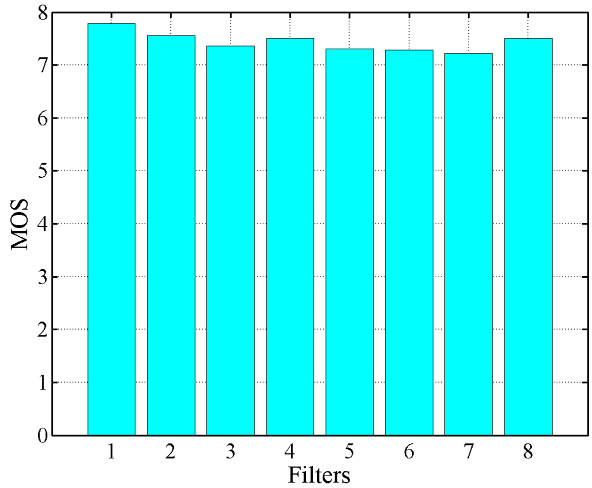

Fig. 7. MOS bar graph obtained for the Foreman video.

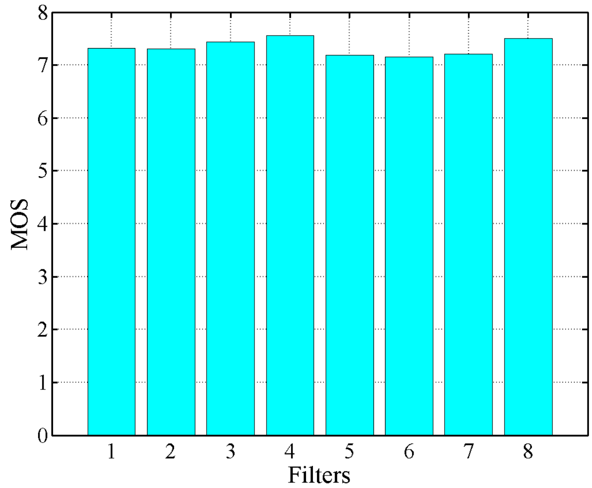

Fig. 8. MOS bar plot obtained for the Mobile video.

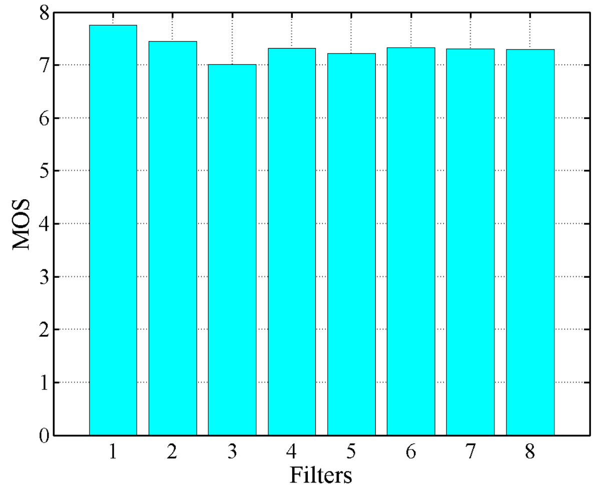

Fig. 9. MOS bar plot obtained for the News video.

For the News video the MOS gathered from the experiment are shown in Figure 9. The best results for this video were obtained using the 2×2 Sigma and 2×2 Median filters.

The correlation between the MOS and PSNR results for each transcoded video was calculated, resulting in a low correlation for the videos Foreman (ρ = 0.3721) and Mobile (ρ = 0.3209). The News video provided a somewhat higher correlation (ρ = 0.7745). As expected, the correlation between the MOS and SSIM values was higher. For the Foreman video the correlation was 0.5837, for the Mobile video it was 0.372, and for the video News the correlation was 0.8486. The News video provided the highest correlation considering both objective and subjective measures, which can be attributed to the lack of movement in the video.

Overall, the filters that presented the best results were the 2×2 Sigma, 3×3 Median, Weighted Average 3, and 2×2 Median. Thus, an evaluation of the processing time for each method has the potential to indicate which videos presented the best results.

C. Processing Time

Another important factor that should be considered when comparing different algorithms is the processing time, or computational complexity of the algorithm. Table III shows the processing time for each of the transcoding algorithms under test, to indicate the time spent as the filter window increases.

Table III shows that the Sigma and Mode filters demand longer processing times as compared to the Moving Average and the Weighted Average filters. This is why those techniques need to be compared. Also, the Median processing time is slightly higher than for the Average filter. Considering only the processing time, the best results were obtained for the filters: Weighted Average, 2×2 and 3×3 Moving Average, and 2×2 Median.

V. CONCLUSION

This article presented an analysis of the subjective and objective quality of spatially transcoded videos. The transcoder operation consisted of downsampling the video frames using Moving Average, Median, Mode, Weighted Average and Sigma filters with sizes 1×1, 2×2, 3×3, and 4×4.

TABLE III

PROCESSING TIME FOR A VIDEO.

Transcoding Method	Time(seconds)
Simple Elimination	0.47
2 × 2 Moving Average	1.30
3 × 3 Moving Average	1.13
4 × 4 Moving Average	3.89
2 × 2 Median	1.59
3 × 3 Median	5.00
4 × 4 Median	13.69
2 × 2 Mode	7.78
3 × 3 Mode	8.22
4 × 4 Mode	56.47
Weighted Average 1	0.75
Weighted Average 2	1.19
Weighted Average 3	3.42
2 × 2 Sigma	5.76
3 × 3 Sigma	12.06
4 × 4 Sigma	20.50

The objective quality evaluation of the transcoded videos used the PSNR and SSIM metrics. The PSNR results were considered satisfactory, and the filters 4×4 Median, 2×2 Sigma, and 2×2 Median produced the best results. The results obtained with the SSIM metric were also satisfactory, and the filters 2×2 Sigma and 2×2 Median showed the best results.

A subjective experiment was performed to obtain a more reliable quality assessment of the transcoded videos. The experiment was performed using the Pair Comparison (PC) method described in the ITU-T P.910 Recommendation [14]. The test sequences were displayed on the NOKIA N95 cell phone. Subjects used a scale of discrete numbers, ranging from 0 to 10 to inform their quality judgments (MOS).

The data gathered from the subjective experiment showed that all transcoded videos presented MOS values above 7, which is an acceptable subjective evaluation. The data also showed that the 2×2 Median and 2×2 Sigma filters provided the best results in terms of quality.

The computational complexity of the proposed transcoding algorithms was also tested. Considering only the processing time, the best results were obtained for the Weighted Average, 2×2 and 3×3 Moving Average, and 2×2 Median filters.

The spatially transcoded algorithms using the 2×2 Median and 2×2 Sigma filters produced the best results, both objectively and subjectively, and these techniques are the most appropriate to perform spatial transcoding. In particular, the 2×2 Median filter has the advantage of requiring less processing time.

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REFERENCES

[1] M. S. Alencar, *Digital Television Systems*. Cambridge Univerty Press, 2008.

[2] M. Bonuccelli, F. Lonetti, and F. Martelli, “Temporal transcoding for mobile video communication,” in *the second Annual International Conference on Mobile and Ubiquitous Systems: Networking and Services*. Citeseer, 2005, pp. 18–29.

[3] J. Xin, C.-W. Lin, and M.-T. Sun, “Digital video transcoding,” *Proceedings of the IEEE*, vol. 93, no. 1, pp. 84–97, Jan. 2005.

[4] J. Xin, M.-T. Sun, B.-S. Choi, and K.-W. Chun, “An HDTV-to-SDTV spatial transcoder,” *Circuits and Systems for Video Technology, IEEE Transactions on*, vol. 12, no. 11, pp. 998–1008, Nov 2002.

[5] Y.-R. Lee, C.-W. Lin, S.-H. Yeh, and Y.-C. Chen, “Low-complexity DCT-domain video transcoders for arbitrary-size downscaling,” *2004 IEEE 6th Workshop on Multimedia Signal Processing*, pp. 31–34, Sept.-1 Oct. 2004.

[6] I. Ahmad, X. Wei, Y. Sun, and Y.-Q. Zhang, “Video transcoding: an overview of various techniques and research issues,” *Multimedia, IEEE Transactions on*, vol. 7, no. 5, pp. 793–804, Oct. 2005.

[7] P. Yin, M. Wu, and B. Liu, “Video transcoding by reducing spatial resolution,” *International Conference on Image Processing*, vol. 1, pp. 972–975, 2000.

[8] T. Acharya and A. K. Ray, *Image Processing - Principles and Applications*. Hoboken, New Jersey, USA: John Wiley & Sons, Inc., 2005.

[9] M. Ahmad and D. Sundararajan, “A fast algorithm for two dimensional median filtering,” *Circuits and Systems, IEEE Transactions on*, vol. 34, no. 11, pp. 1364–1374, Nov 1987.

[10] A. Bovik, T. Huang, and J. Munson, D., “A generalization of median filtering using linear combinations of order statistics,” *IEEE Transactions on Acoustics, Speech and Signal Processing*, vol. 31, no. 6, pp. 1342–1350, Dec 1983.

[11] H. Wu and K. Rao, *Digital Video Image Quality and Perceptual Coding*. Boca Raton, FL, USA: CRC Press Taylor & Francis Group, 2006.

[12] R. Lukac, B. Smolka, K. Plataniotis, and A. Venetsanopoulos, “Generalized adaptive vector sigma filters,” *International Conference on Multimedia and Expo. ICME ’03.*, vol. 1, pp. I–537–40 vol.1, July 2003.

[13] T. H. Falk and W.-Y. Chan, “Performance study of objective speech quality measurement for modern wireless-voip communications,” *EURASIP Journal on Audio, Speech, and Music Processing*, p. 11 pages, 2009.

[14] ITU-T, “ITU-T Recommendation P.910, subjective video quality assessment methods for multimedia applications,” September 1999.

[15] Q. Huynh-Thu and M. Ghanbari, “Scope of validity of psnr in image/video quality assessment,” *Electronics Letters*, vol. 44, no. 13, pp. 800–801, 19 2008.

[16] R. de Freitas Zampolo, D. de Azevedo Gomes, and R. Seara, “Avaliação e comparação de métricas de referência completa na caracterização de limiares de detecção em imagens,” *XXVI Simpósio Brasileiro de Telecomunicações - SBrT 2008*, Sept. 2008.

[17] Z. Wang, L. Lu, and A. C. Bovik, “Video quality assessment using structural distortion measurement,” in *in Proc. IEEE Int. Conf. Image Proc*, 2002, pp. 65–68.

[18] J. Hu and J. Gibson, “New rate distortion bounds for natural videos based on a texture dependent correlation model in the spatial-temporal domain,” in *Communication, Control, and Computing, 2008 46th Annual Allerton Conference on*, Sept. 2008, pp. 996–1003.

[19] “YUV video sequences,” http://trace.eas.asu.edu/yuv/index.html, November 2008.

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