Accepted Manuscript

A visual quality evaluation method for telemedicine applications

Karim M. Nasr, Maria G. Martini

PII: S0923-5965(17)30110-8
DOI: http://dx.doi.org/10.1016/j.image.2017.06.003
Reference: IMAGE 15237

To appear in: *Signal Processing: Image Communication*

Received date : 21 November 2016
Revised date : 11 April 2017
Accepted date : 7 June 2017

Please cite this article as: K. Nasr, M. Martini, A visual quality evaluation method for telemedicine applications, *Signal Processing: Image Communication* (2017), http://dx.doi.org/10.1016/j.image.2017.06.003

A Visual Quality Evaluation Method for Telemedicine Applications

Karim M. Nasr [1] and Maria G. Martini [2]

1. University of Surrey, Guildford, GU2 7XH, United Kingdom
2. Kingston University London, Penrhyn Road, Kingston upon Thames, KT1 2EE, United Kingdom

k.nasr@surrey.ac.uk, m.martini@kingston.ac.uk

***Abstract*—We present a new approach for image and video quality evaluation in telemedicine applications, relying on analyzing the quality of a pre-known reduced size logo embedded in an unused part of the medical ultrasound frame. The method is tested using two different objective metrics, namely: the Peak Signal to Noise Ratio (PSNR) and the Structural SIMilarity index metric (SSIM). Comparisons with subjective results in terms of Differential Mean Opinion Scores (DMOS) are also presented. We show that the presented method, not needing the original frame to predict the quality, achieves a high correlation with subjective results (more than 0.9) for the different quality metrics used. We also present relationships between the quality derived via the logo and via the original frame and we assess the overhead in data transmission resulting from the compressed logo data and its protection overhead.**

***Index Terms*—Visual quality evaluation, medical ultrasound, objective quality metrics, subjective quality metrics, medical quality of service/experience, wireless telemedicine**

1. INTRODUCTION

Recently, there has been a large interest in electronic and mobile healthcare applications making use of advances in multimedia content processing and emerging high data rate wireless transmission standards [1-6]. Quality of Service / Quality of Experience (QoS/QoE) is an important aspect in assessing the validity and reliability of multimedia telemedicine applications [6-11]. There is therefore a need to develop efficient and accurate image and video quality assessment (IQA/VQA) methodologies that enable a physician or a medical specialist to have enough confidence to use the medical data (*e.g.* a medical ultrasound scan) for diagnosis purposes even after processing and transmission over wireless channels which are prone to errors and may introduce degradations. Example use cases include remote medical tele-consultation in an accident scenario where medical ultrasound data is being transmitted from a remote location (*e.g.*an ambulance in an accident site) to a medical expert in a hospital as addressed by the Concerto project [12-13].

Traditionally, subjective or objective and hybrid approaches [7, 12-21] are used to assess the quality of an image or a video. Subjective quality assessment for healthcare applications relies on medical experts or trained users visually analysing and rating the images or videos on a scale of 1(bad) to 5(excellent), often by comparing them with the originals. A Mean Opinion Score (MOS) of the image or video being assessed, or Differential MOS (DMOS) with respect to the original, is obtained. Subjective testing is considered the ultimate approach for quality evaluation. However, to make such an assessment, an adequate number of experts is needed and experiments have to be carried out, which make this process time consuming and expensive. Objective quality metrics are alternative measures relying on algorithms or statistical analysis to automatically quantify the perceived quality of the image or video by comparing some features of the original and processed image or video (*e.g.*, impairments introduced by lossy compression or artefacts and degradations due to transmission). Examples of objective metrics include the mean square error (MSE), the peak signal to noise ratio (PSNR) and the structural similarity index metric (SSIM). Hybrid metrics aim at combining the two methods of assessment. This is normally achieved by correlating the results obtained from subjective and objective tests and by making use of the experience obtained from previous subjective tests to obtain an objective figure of merit for new sets. The main drawback of objective methods is that the quality score obtained is not always well correlated with the subjective experienced quality.

In general, the original image or video is needed for the quality assessment (Full Reference (FR) approach), while this may not be available or practical in real time telemedicine applications. Objective quality assessment methods can be in fact classified as Full Reference (FR), Reduced Reference (RR) and blind or No Reference (NR) categories. Unlike FR methods, which require access to the original image or video frames as references for quality assessment, RR methods only need partial information in the form of some extracted features of the original to be sent as ancillary data. NR methods are more challenging and are normally designed for specific types of pre-known distortions. NR Image/Video Quality Assessment (IQA/VQA) generally rely on feature extracting and feature learning based methods. A good overview of such techniques can be found in [34, 35].

Some approaches to blind quality assessment proposed the use of watermarking as in [21]. This approach may not be suitable for medical applications as it introduces unwanted artefacts into the region of interest (ROI) of the medical image or video frame of interest which may affect the sought after medical information for diagnosis purposes. A recent work considers a white image ("static pattern") and compares the original frame (at the transmitter) and the received frame (at the receiver) with it, assessing then the difference [25]. While the correlation with subjective results is reasonable, this is not high enough for medical images. All NR and RR techniques reported in the literature vary in complexity and processing requirements [34, 35] and may not particularly answer the needs in a telemedicine application.

In this paper, we present a reduced reference image and video quality assessment method targeting ultrasound telemedicine and mobile healthcare applications. The proposed method does not need extracted features from the original image/video for quality assessment, does not introduces unwanted artefacts into the region of interest, and achieves a high accuracy in quality estimation.

The paper is organized as follows: In Section 2, we describe the new approach. In Section 3, we introduce the main materials and methods used for our investigations. In section 4, we compare objective metric results obtained from the proposed approach with their full reference (FR) counterparts and we present relationships linking the two sets of metrics. In Section 5, we present comparisons of the metrics obtained from the new method with subjective tests based on Differential Mean Opinion Score for HEVC sequences. Finally, Section 6 concludes the paper.

2. THE PROPOSED LOGO BASED METHOD

2.1 Method description

The proposed method exploits the black unused areas in a medical ultrasound image or video frame. This approach relies on inserting a pre-known reference ultrasound image of smaller size ("logo") in an unused black area of the original frame of interest.

The reference logo frame is known in advance and is representative of a typical ultrasound frame of the medical organ of interest. There is therefore no need to acquire the original full frame for quality evaluation and this method could hence be considered "No-Reference" from this point of view. A small overhead is however associated to the transmission of the logo instead of the black area, hence we refer to this method as reduced reference.

During processing and transmission through the communication channel (for instance a wireless channel), the logo will undergo the same effects and degradations as the original frame or region of interest (ROI) in the frame. Possible pre-processing functions applied to the logo include compression, interleaving to randomize the effect of bursty errors during transmission and insertion of error correction coding and redundancy data for protection in a similar way to the ROI or the whole original frame.

At the receiving end, analysis is done on the pre-known logo part to determine objectively its quality. The obtained logo quality is highly correlated to the overall target frame of interest as will be shown below and subsequently the system reports the quality of the overall frame and informs the medical experts of the figure of merit, hence enabling them to judge the validity of the received ultrasound frame before diagnosis.

Once the quality evaluation process is concluded, the logo part can be discarded and replaced back by black pixels or voxels to minimize any possible distraction to the medical experts examining the original frame for diagnosis purposes. It is also possible to replace the logo area at this final stage by the quality evaluation value indicating a pass or fail.

Several tests were performed by the authors to decide on a suitable logo size in a typical ultrasound frame. It was found that a representative logo of one sixteenth the size of the original frame (or a quarter of each dimension of the main frame) is adequate to obtain high correlation coefficient values (more than 0.9) between the quality of the original frame and the logo under varying noise and compression conditions, as will be presented in the following section.

An illustration of the proposed method is presented in Fig. 1 and Fig. 2.

We propose hence to use the quality evaluated on the logo based on a full reference objective metric as an estimation of the quality of the full frame.

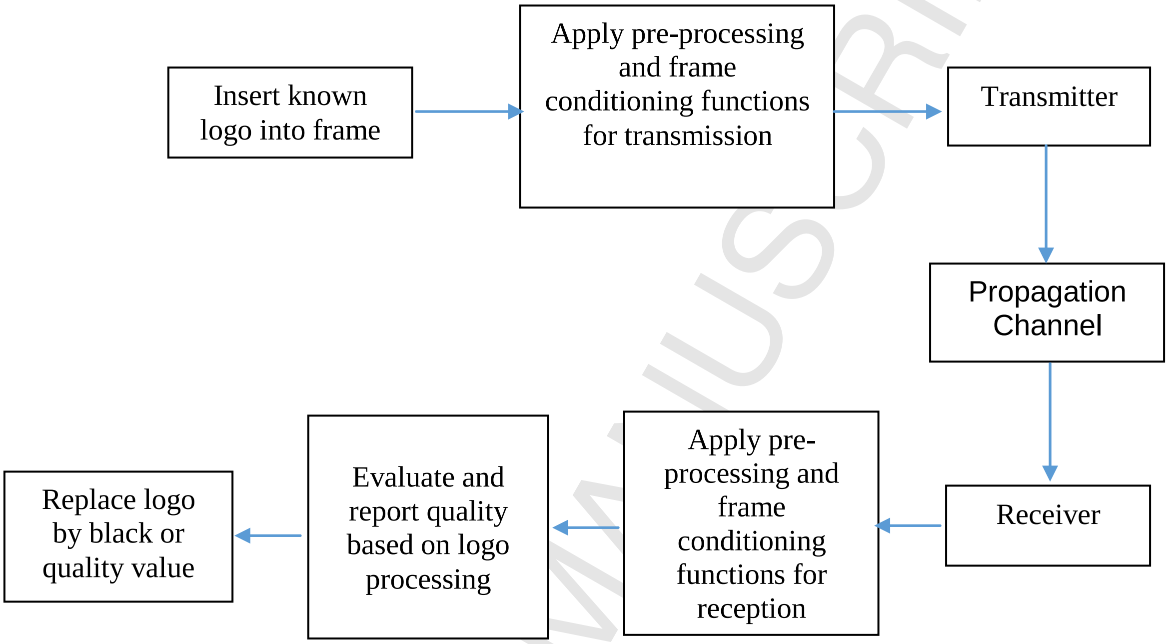
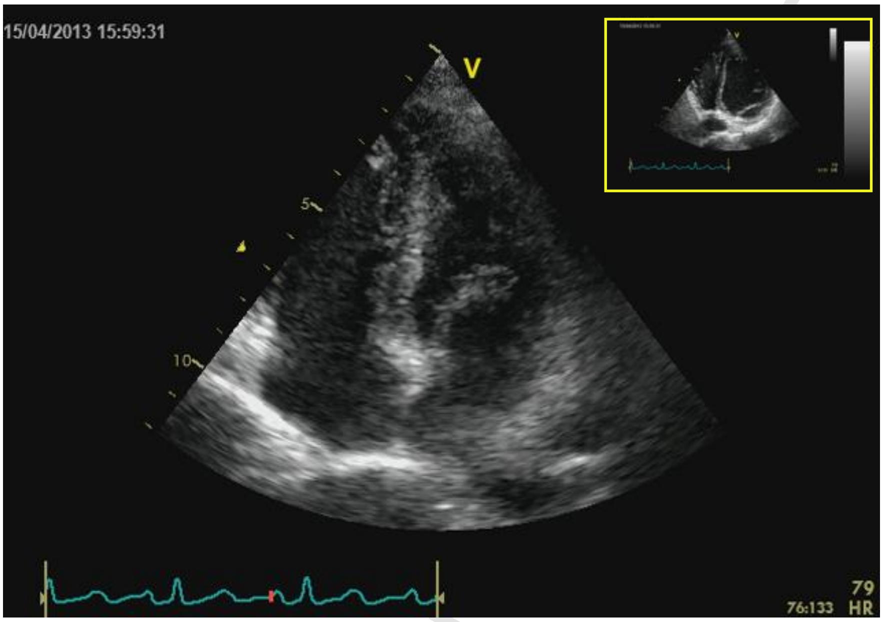


Fig. 1 Block diagram of the proposed method



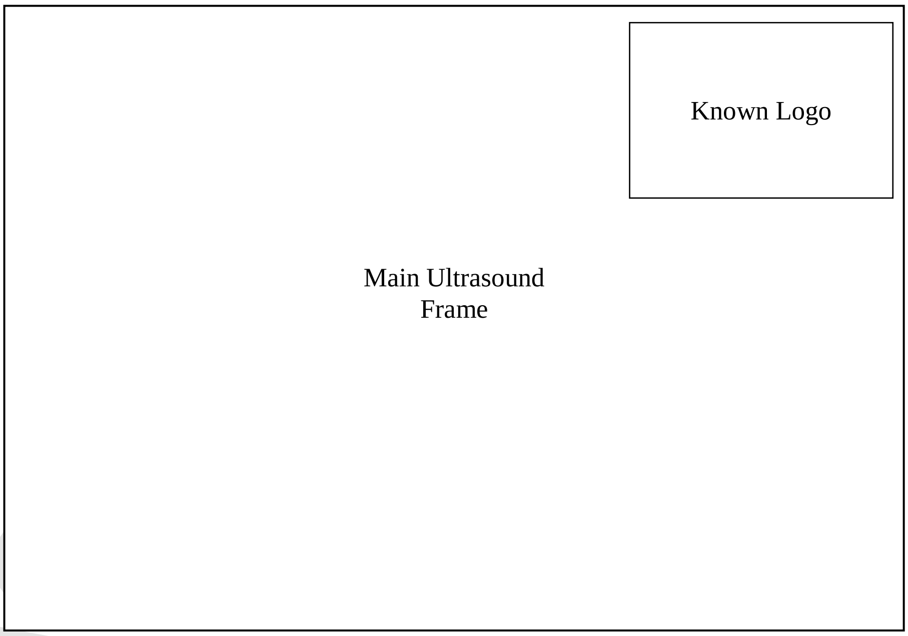


Fig. 2. A typical ultrasound frame with an inserted logo

2.2 Objective full reference metrics

The proposed metric can be obtained for instance based on the following objective quality metrics.

1) The first metric we use is the Peak Signal to Noise Ratio (PSNR) defined as:

$$PSNR = 20\, log_{10}\left(\frac{2^D - 1}{\sqrt{MSE}}\right) \qquad in\ dB, \tag{1}$$

where *D* is the bit depth and *MSE* is the Mean Square Error given by:

$$MSE = \frac{1}{LW}\sum_{i=1}^{L-1}\sum_{j=1}^{W-1}[|I(i,j) - I'(i,j)|^2], \tag{2}$$

where *I* is the original uncompressed and distortion free image frame of size $L \times W$ and *I'* is the modified image frame after being compressed or subjected to other form of processing or distortion.

2) The second metric we use is the Mean Structural SIMilarity (MSSIM), which is designed to improve the accuracy with respect to PSNR and MSE metrics and is shown to perform better than PSNR for medical ultrasound images [29]. SSIM relies on combining the luminance, contrast and structure comparison of two image window blocks *x* and *y* of the whole image and is defined as:

$$SSIM\ (x,y) = \left(\frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}\right)\left(\frac{2\sigma_{xy} + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}\right), \tag{3}$$

where μ is the average, σ^2 is the variance and σ_{xy} is the covariance of the luminance values in the window blocks. C_1 and C_2 are two small value variables to stabilize the division. MSSIM is a quality measurement over the entire image frame as follows:

$$MSSIM = \frac{1}{M}\sum_{j=1}^{M} SSIM(x_j, y_j)\,, \tag{4}$$

where *M* is the total number of windows applied to the frame.

The logo-based metrics we propose (QL_{PSNR} and QL_{MSSIM}) can be evaluated based on the two objective quality metrics above. Other objective quality metrics can be evaluated by applying the same methodology. The logo-based metric represents a good estimation of the actual quality of the full image/video sequences as will be shown in Section 4.

3 Materials and Methods

3.1 Medical data-set considered

The performance of the objective VQA metrics is evaluated on nine original medical ultrasound videos, with a frame resolution of 640 x 416. Each video sequence has 100 frames, encoded at 25 frames per second (fps). Of the nine ultrasound videos, three videos are related to the heart and liver each, two for kidney, and one video is related to the lung. An example frame of each medical video sequence used in the tests is shown in Fig. 3

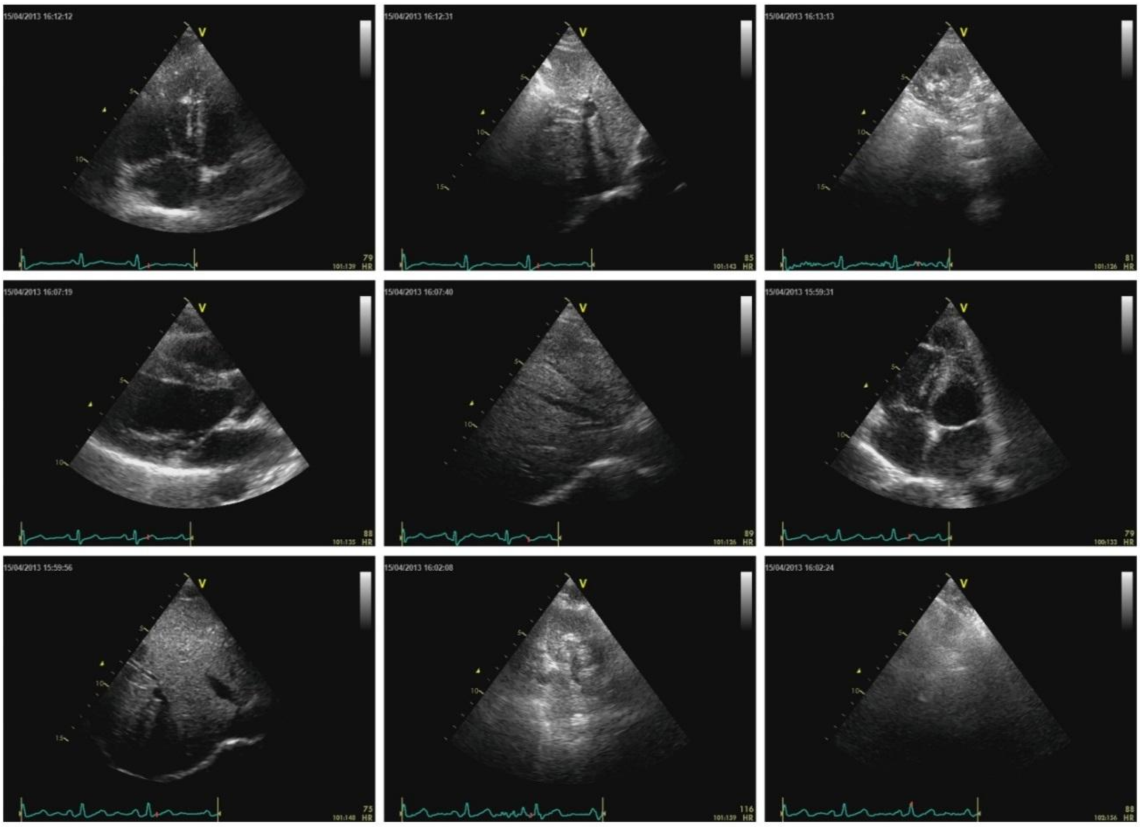


Fig. 3 An example frame of the nine ultrasound video sequences used for validation

3.2 Summary of tests

We first investigated the impact of varying the Gaussian noise level on the logo quality estimation. This was followed by an investigation of the impact of JPEG 2000 compression with nine different compression ratios as examples of degradation that can impact the quality of the ultrasound frame.

For the evaluation of the impact of HEVC compression, the sequences were compressed at eight different Quantization Parameter (QP) levels using the HM reference software provided by the Joint Collaborative Team on Video Coding (JCT-VC) team [37]. For further details and the description of the conditions of the subjective tests, the reader is referred to [29]. The results of these investigations are presented in Section 4. Finally, we compared objective HEVC results and subjective test results in Section 5.

4 Analysis and Numerical Results for Objective Tests

In this section, several objective quality metrics are compared for the logo and the main frame to demonstrate the validity of the proposed method under varying noise and compression conditions as examples of degradation or distortions that can affect the medical ultrasound frames. Correlation figures are obtained and relationships linking logo and main frame metrics are presented. The compression and redundancy overheads will be also discussed.

4.1 Comparison of the Metrics on logo and main frame with varying Gaussian Noise Levels

Different tests were performed on the raw ultrasound main frames. A logo size of 160 × 104 pixels, which is a quarter of each dimension of the main frame or one sixteenth of the size of the original frame total number of pixels, was selected as the most suitable in terms of size and obtained correlation coefficient values (> 0.9) among those tested. This logo size was selected to fill as much as possible the black (top right unused region) of the frame which results in good correlation values as will be shown below.

For these tests, we used one pre-known frame of the medical organ in question (e.g. heart) as a logo that was inserted in each of the nine tested sequences. Averaging was then done to obtain a single value for the logo quality and the main frame quality at different noise levels.

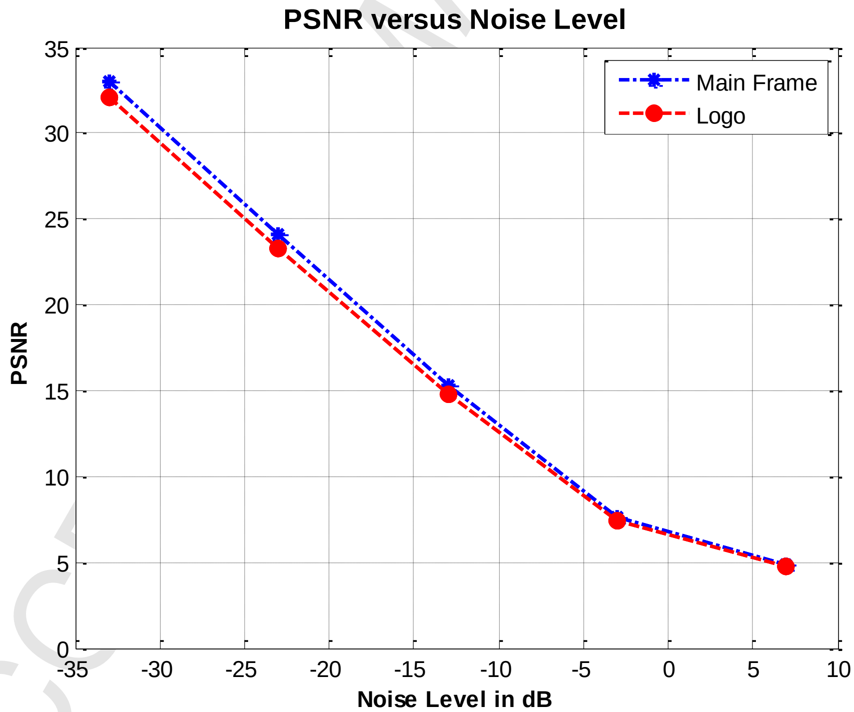
Results of the considered quality metrics evaluated on the logo and on the main frame with varying Gaussian noise levels are shown in Fig. 4 (a) for PSNR and (b) for MSSIM. Nine medical sequences were tested as detailed in [29]. Fig. 5. shows an example of the XY relationships between the main frame and logo metrics in the case of Gaussian noise. It is concluded that high correlation coefficient values (> 0.9) are obtained with the selected logo size for all the metrics. Table I summarizes the correlation coefficient values for all the cases.

Curve fitting of the XY relationships allows the estimation of the main frame quality metric value for a corresponding value of the logo metric and vice versa. The following relationships linking the different quality metrics in the case of noise are obtained from curve fitting:

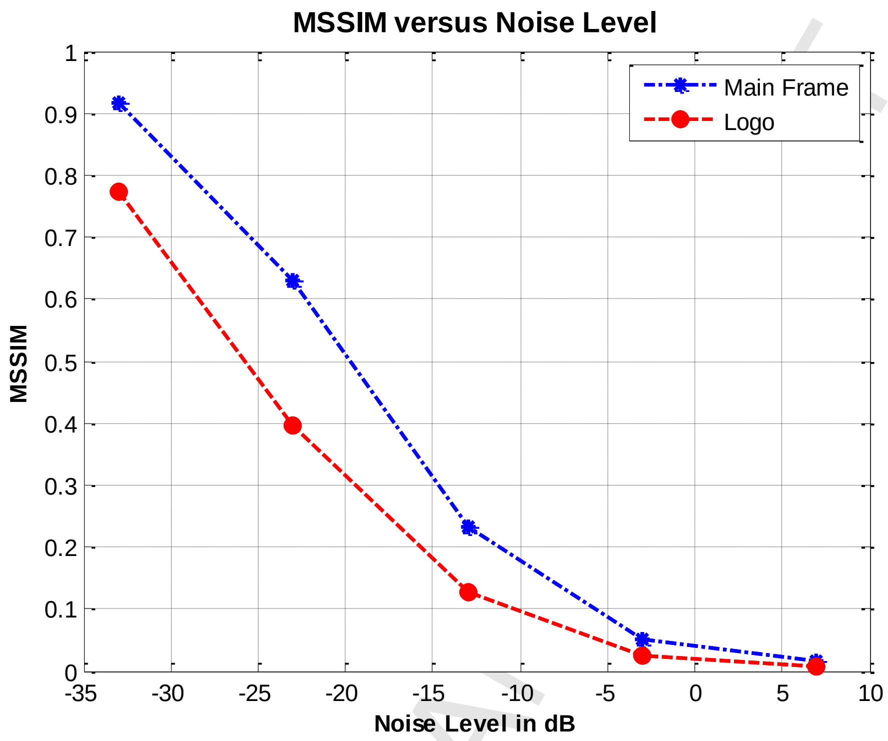
$$QL_{PSNR} = 0.9989\, PSNR_{Main\,Frame} + 0.01435 \quad , \qquad (5)$$

$$QL_{MSSIM} = 0.8136\, MSSIM_{Main\,Frame} - 0.03464, \qquad (6)$$

The R-square and Spearman rank goodness of fit values were above 0.9 for all studied cases as shown in Table 1.

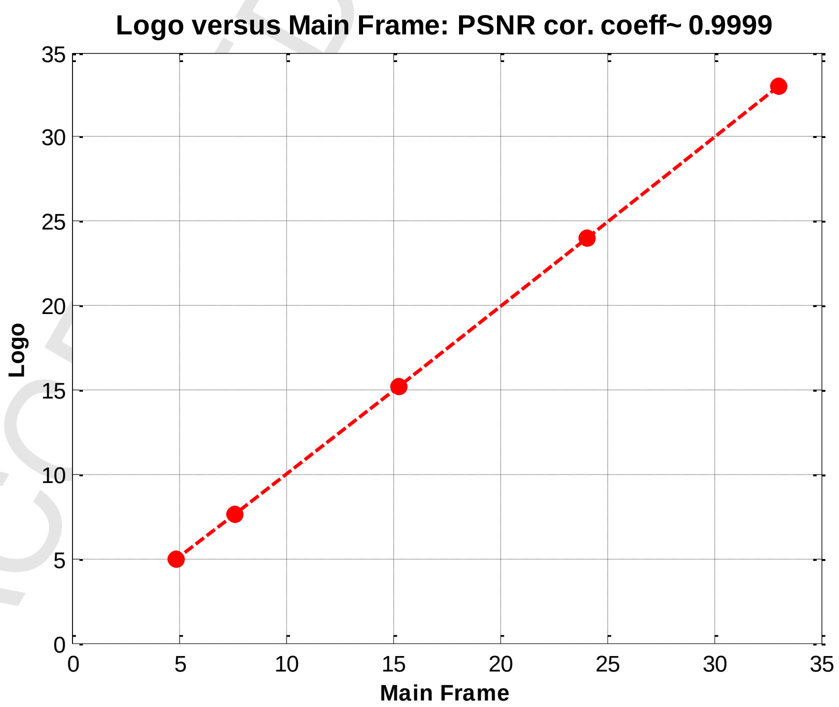


(a)PSNR for main frame and logo

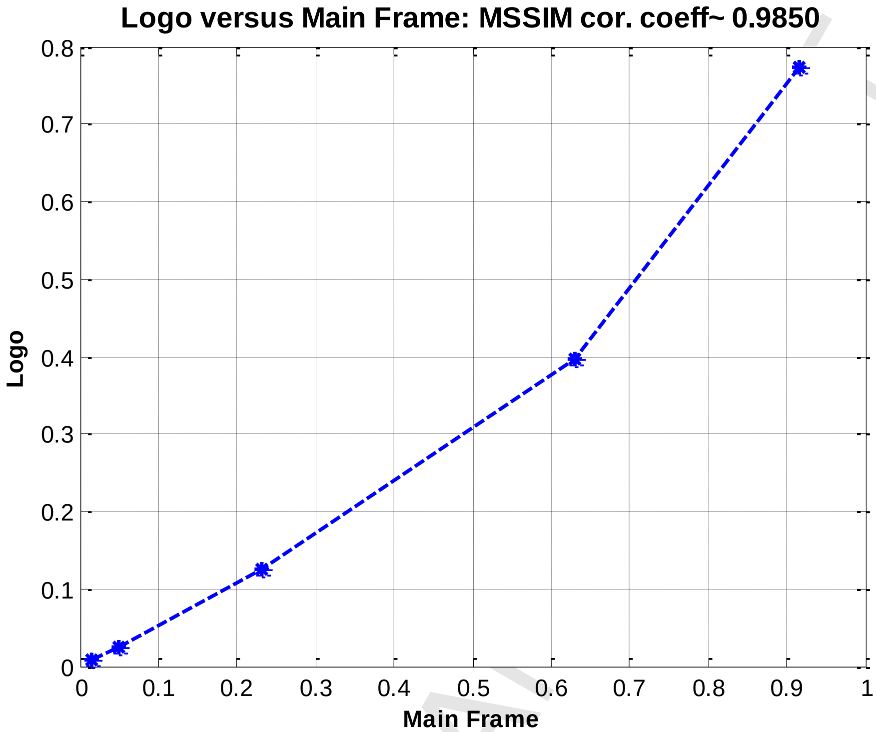


(b) MSSIM Noise results for main frame and logo

Fig. 4. Results of different metrics versus Gaussian noise



(a) XY relationship of main frame and logo PSNR with noise



(b) XY relationship of main frame and logo MSSIM with noise

Fig. 5. XY relationships in the case of noise

4.2 Comparison of the Metrics on logo and main frame for JPEG2000 compression with different Compression Ratios

Different tests were performed to evaluate the effect of compression on the obtained quality metrics for the main frame and the logo. JPEG2000 compression was selected as an example of a compression standard. The logo size was again a quarter of the main frame size. For these tests, we used one pre-known frame of the medical organ in question (e.g. heart) as a logo that was inserted in each of the nine tested sequences. Averaging was then done to obtain a single value for the logo quality and the main frame quality at different compression ratios.

Results of the different quality metrics with varying compression ratios are shown in Fig. 6 (a) for PSNR and (b) for MSSIM. Fig. 7 shows the XY relationships between the main frame and logo metrics in the case of JPEG2000 compression.

It is concluded that high correlation coefficient values (> 0.9) are obtained with the selected logo size for all the metrics. Table I summarizes the correlation coefficient values for all the cases.

The following relationships linking the different quality metrics in the case of JPEG2000 compression are obtained from curve fitting:

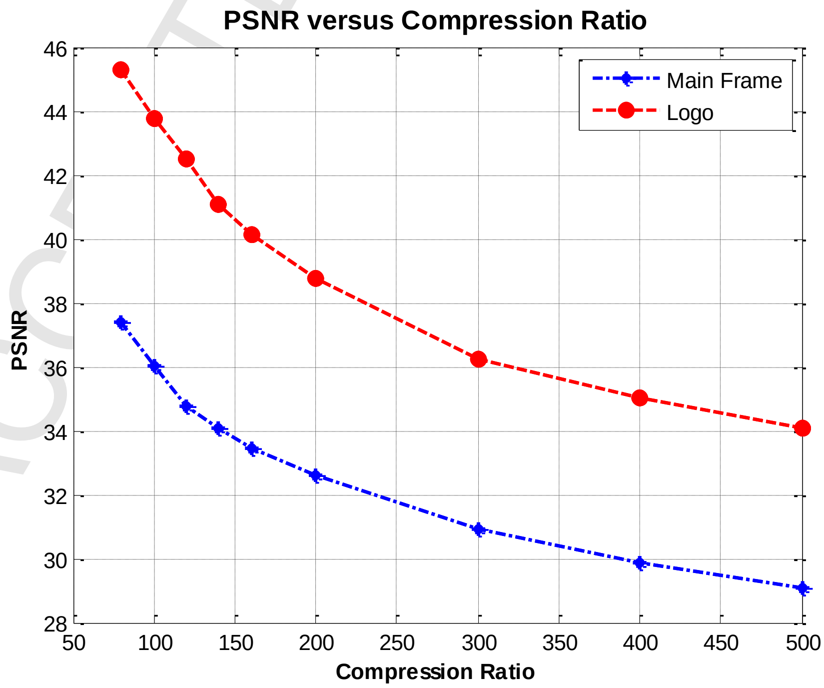
$$QL_{PSNR} = 1.415\ PSNR_{Main\ Frame} - 7.256\ , \qquad (7)$$

$$QL_{MSSIM} = 0.5621\ MSSIM_{Main\ Frame} + 0.4442, \qquad (8)$$

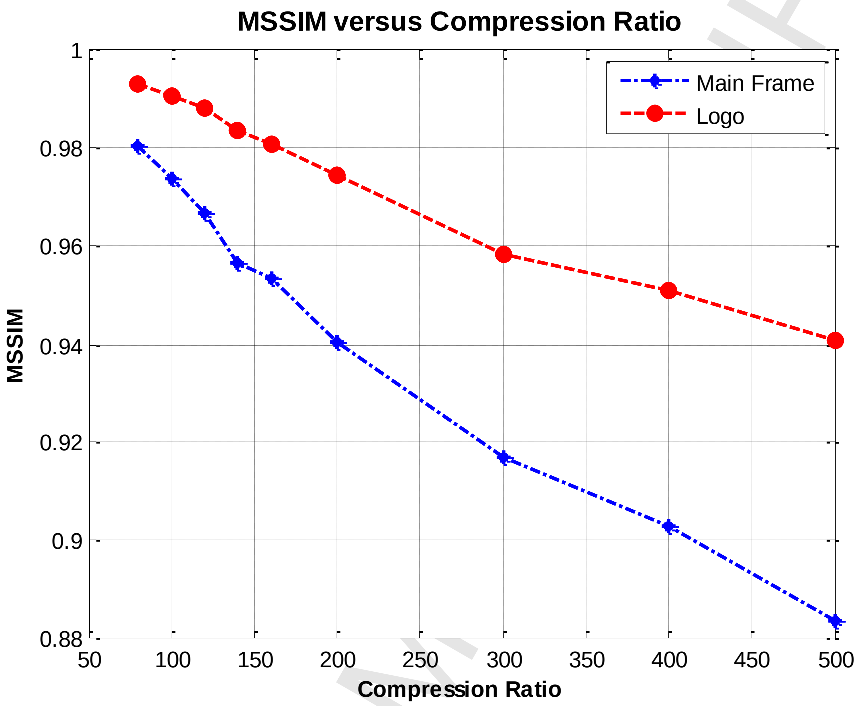
The R-square and Spearman rank goodness of fit values were above 0.9 for all studied cases as shown in Table 1.

Table 1 Summary of Correlation Coefficients and Goodness of Fit for Studied Cases

Degradation	Average PSNR	R Square Goodness of Fit	Spearman Rank	Average MSSIM	R Square Goodness of Fit	Spearman Rank
Gaussian Noise	0.9999	0.9931	1	0.9850	0.9604	0.9703
Compression	0.9975	0.9944	0.9951	0.9972	0.9937	0.9945

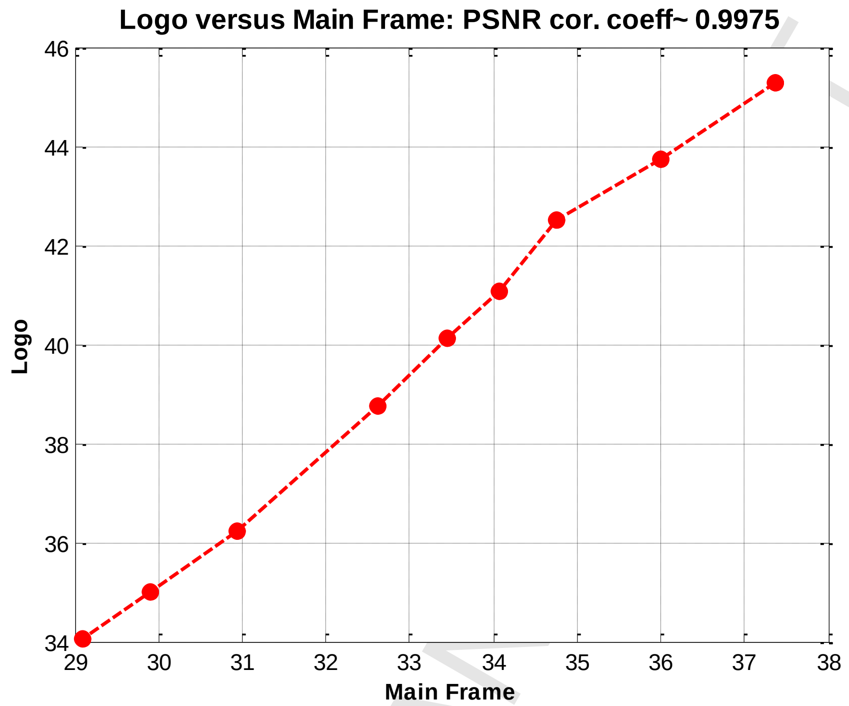


(a)PSNR compression results for main frame and logo

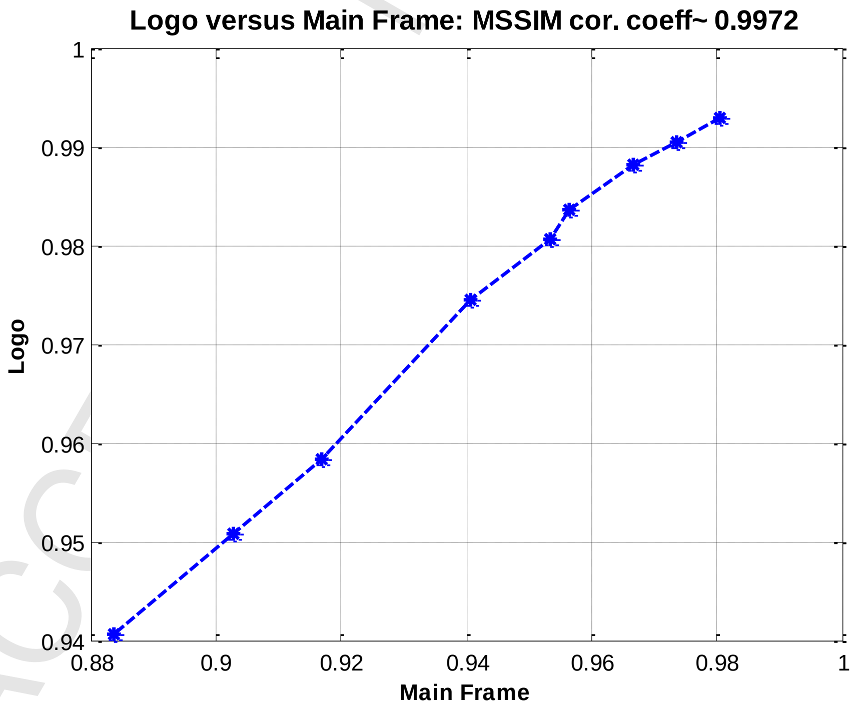


(b) MSSIM compression results for main frame and logo

Fig. 6. Different metrics versus compression ratio



(a) XY relationship of main frame and logo PSNR with compression



(b) XY relationship of main frame and logo MSSIM with compression

Fig. 7. XY relationships of the metrics in the case of compression

4.3 Overheads

Table 2 presents an example of the size of a compressed ultrasound frame with and without the added logo, for different JPEG 2000 compression ratios (CR) for a raw portable pixmap format (ppm) frame of 798.735 kbits. The associated overhead is also reported. It is shown that the overhead due to the logo in the compressed frame is negligible for all the studied cases and is lower than the overheads of RR methods reported in literature (*e.g.* [22, 23]).

Table 2 JPEG2000 Frame Size (bits) for Different Compression Ratios

CR	15	20	30	100	500
Size of Main Frame only in bits	52750	39377	26158	7776	1662
Size of Main frame with logo in bits	52793	39410	26190	7813	1674
Overhead in bits	43	33	32	37	12
Percentage overhead	0.081	0.083	0.122	0.475	0.722

4.4 Tests with HEVC Sequences

Nine different medical ultrasound videos sequences compressed using High Efficiency Video Coding (HEVC) [22-24] were tested using the new technique. The ultrasound sequences were related to different organs (*e.g.* heart, liver, lungs). Eight different quantization parameter (QP) levels (27 to 41 in steps of 2) of the HEVC encoder were tested for each sequence [29]. Tests were first carried out to obtain the average correlation coefficients of the logo with main frame objective metrics. This was then followed by a comparison of subjective Differential Mean Opinion Scores (DMOS) results with objective logo metrics as will be shown in the next section.

The results of the individual and average correlation coefficient between the logo metrics (QL_{PSNR} and QL_{MSSIM}) and the corresponding average main frame metrics are summarized in Table III. The obtained Spearman rank for the tested cases is 1. An example of the MSSIM XY relationships for the logo and the main frame for each of the nine tested sequences are shown in Fig. 8. It is concluded that, similar to the cases investigated in the previous section, high correlation coefficients (> 0.9) are obtained for HEVC video sequences for the different objective metrics.

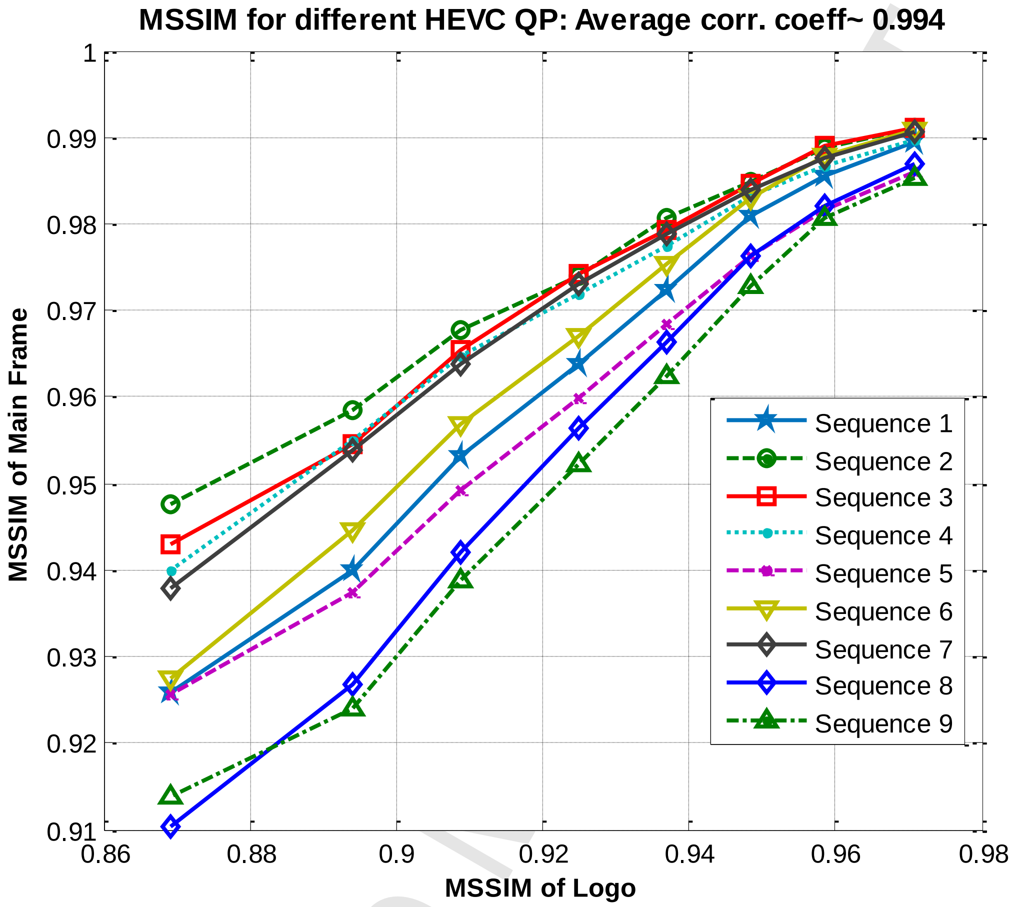


Fig. 8. XY relationships of MSSIM metric for the main frame versus logo for the different tested HEVC compressed sequences

Table 3 Summary of Correlation Coefficient Values for HEVC Objective Tests (Logo and Main Frame)

Metric	PSNR	MSSIM
Sequence 1	0.9995	0.9956
Sequence 2	0.9993	0.9945
Sequence 3	0.9990	0.9931
Sequence 4	0.9992	0.9924
Sequence 5	0.9995	0.9968
Sequence 6	0.9993	0.9944
Sequence 7	0.9992	0.9908
Sequence 8	0.9994	0.9956
Sequence 9	0.9985	0.9940
Average Correlation Coefficient	**0.9992**	**0.9941**
Standard deviation	**0.0002**	**0.0017**

If we were to use five sequences (Sequences 1, 2, 4, 6, 9) selected at random (instead of the nine sequences used above) to train the logo quality estimation system, the maximum error in the estimated main frame quality for the other four sequences would be approximately 0.5% for PSNR and 0.3% for MSSIM.

5 SUBJECTIVE TESTS INVESTIGATIONS AND RESULTS

A group of four medical experts and 16 viewers with no medical expertise provided DMOS results for the nine HEVC sequences and eight different QP levels. Medical experts assess the sequences based on diagnostic quality while non-experts assess the sequences from a visual quality perspective. The subjective test results were obtained using the double stimulus continuous quality scale (DSCQS) as recommended in ITU-R-BT.500-11 [36,29]. Differential Mean Opinion Score (DMOS) results were then computed as summarized in Table 4. These subjective results were then compared with the logo objective metrics using PSNR and MSSIM metrics. An example of comparative results for the different tested sequences is shown in Fig. 9 for the case of logo MSSIM metric. Individual and average logo correlation coefficients were finally obtained as shown in Table 5. It is concluded that high correlation coefficients (> 0.9) between the logo metrics and DMOS subjective results are obtained. The highest average correlation value is obtained using the logo MSSIM metric.

Table 4. Summary of DMOS results for the different sequences and different quantization parameters

QP	Sequence 1	Sequence 2	Sequence 3	Sequence 4	Sequence 5	Sequence 6	Sequence 7	Sequence 8	Sequence 9
27	5.55	5.55	9.72	4.16	6.94	5.55	5.55	9.72	8.33
29	11.11	6.94	2.77	5.55	8.33	6.94	11.11	9.72	13.88
31	13.88	18.05	15.27	13.88	11.11	13.88	9.72	18.05	19.44
33	23.61	23.61	33.33	19.44	23.61	15.27	20.83	27.77	33.33
35	33.33	31.94	37.50	25.00	36.11	26.38	27.77	34.72	51.38
37	43.05	37.50	48.61	33.33	44.44	40.27	34.72	50.00	62.50
39	50.00	51.38	61.11	41.66	62.50	45.83	50.00	61.11	76.38
41	62.50	59.72	72.22	51.38	66.66	52.77	66.66	66.66	84.72

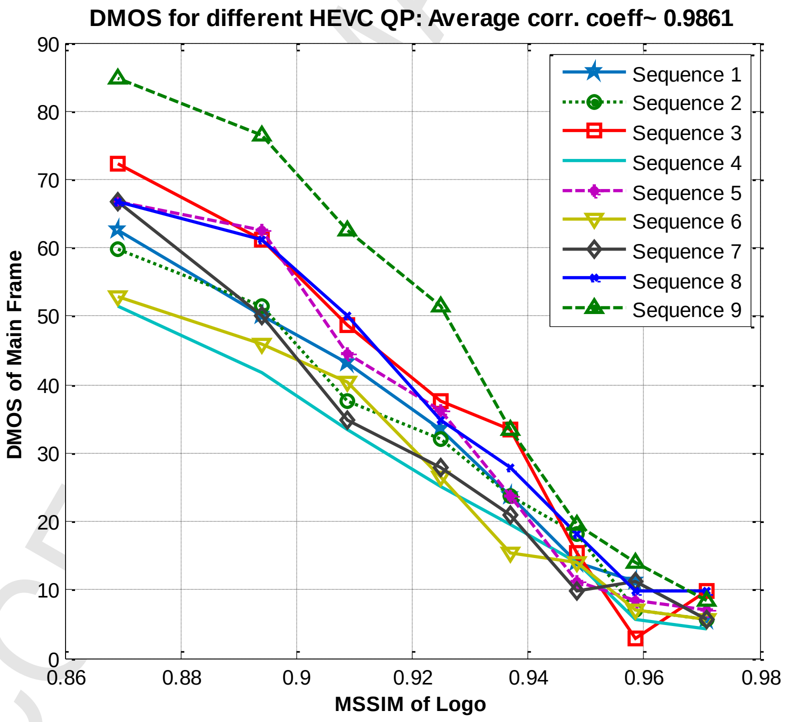


Fig. 9. XY relationships of subjective DMOS results versus QL_{MSSIM} metric for different HEVC compressed sequences

Table 5 Summary of Correlation Coefficient values for HEVC Subjective tests (Logo and DMOS)

Metric	**QL_{PSNR}**	**QL_{MSSIM}**
Sequence 1	0.9867	0.9953
Sequence 2	0.9861	0.9915
Sequence 3	0.9720	0.9761
Sequence 4	0.9857	0.9961
Sequence 5	0.9729	0.9792
Sequence 6	0.9711	0.9817
Sequence 7	0.9549	0.9861
Sequence 8	0.9797	0.9842
Sequence 9	0.9873	0.9845
Average Correlation Coefficient	**0.9774**	**0.9861**
Standard deviation	**0.0101**	**0.0065**

If we were to use five sequences (Sequences 2, 3, 4, 7, 8) selected at random (instead of the nine sequences used above) to train the logo quality estimation system using the subjective test results, the maximum error in the estimated quality for the other four sequences would be approximately 2.5% for PSNR and 0.6% for MSSIM. It is concluded that the MSSIM metric gives the smallest error in the estimation of quality.

A comparison of Video Quality Assessment (VQA) metrics for HEVC in medical ultrasound was presented in [29, 30]. The average QL_{MSSIM} correlation results obtained above are comparable to the SSIM, the Video Information Fidelity (VIF) [31] and the Universal Quality Index (UQI) [32] metric results reported in [29] and better than VQM [33] metric results also reported in [29]. We highlight that while the metrics considered in [29] require the original image as reference, this is not required by the method presented in this paper.

6. CONCLUSIONS

A new method for image and video quality assessment (IQA/VQA) of medical ultrasound applications was presented. The new technique relies on inserting a pre-known reduced size logo with the same characteristics (i.e. similar organ of interest and layout) as the original frame of interest. The logo is inserted in a redundant or unused part of the original frame for quality evaluation purposes. Tests have shown that high correlation of the quality metrics (> 0.9) is achieved when the logo size is a quarter in each dimension (i.e. one sixteenth) of the main frame size. The effect of noise and compression were evaluated for PSNR and MSSIM. It was shown that the overhead due to the logo in the compressed image is negligible for the tested JPEG2000 frames. HEVC objective and subjective test results revealed high correlation coefficient values between the logo and the used metrics. The MSSIM metric gives the best correlation results.

The presented technique can be extended and applied to other medical applications such as CT, MRI and X-ray frames and to other image and video applications where a logo can be inserted in a redundant area of the frame without affecting the main content.

ACKNOWLEDGMENTS

This work was supported in part by the European Union's Seventh Framework Programme under grant agreement No. 288502 'CONCERTO'.

REFERENCES

[1] J. E. Cabral and Y. Kim, "Multimedia systems for telemedicine and their communications requirements," *IEEE Commun. Mag.*, July1996, pp. 20–27.

[2] A. Panayides, M.S. Pattichis, C.S. Pattichis, and A. Pitsillides, "A Tutorial for Emerging Wireless Medical Video Transmission Systems [Wireless Corner]," *IEEE Antennas & Propagation Magazine*, Vol. 53, No. 2, April 2011, pp. 202-213.

[3] A. Panayides, Z. Antoniou, Y. Mylonas, M. S. Pattichis, A. Pitsillides, and C. S. Pattichis, "High-resolution, low-delay, and error-resilient medical ultrasound video communication using H.264/AVC over mobile WiMAX networks," *IEEE J. Biomed. Health Informat.*, Vol.17, No. 3, May 2013, pp. 619–628.

[4] M. Martini, "Wireless broadband multimedia health services: current status and emerging concepts." *IEEE 19th International Symposium on Personal, Indoor and Mobile Radio Communications*, Cannes, Sep 2008.

[5] R. S. H. Istepanian, N. Philip, M. G. Martini, N. Amso, and P. Shorvon,"Subjective and objective quality assessment in wireless tele-ultrasonography imaging", *in 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2008.

[6] RSH Istepanian, NY Philip, N.Y. and MG Martini, "Medical QoS provision based on reinforcement learning in ultrasound streaming over 3.5 G wireless systems", *IEEE Journal on Selected areas in Communications*, vol. 27., no. 4, pp.566-574.

[7] M. G. Martini, RSH Istepanian, M Mazzotti, and N Philip. "Robust multilayer control for enhanced wireless telemedical video streaming." *IEEE Transactions on Mobile Computing*, vol. 9, no. 1, 2010, pp 5-16.

[8] M. G. Martini and M. Mazzotti, "Quality driven wireless video transmission for medical applications", *28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, (EMBS'06)*, New York, August 2006.

[9] P. C. Cosman, R. M. Gray, and R. A. Olshen, "Evaluation Quality of Compressed Medical Images: SNR, Subjective Rating, and Diagnostic Accuracy", *Proc. IEEE*, Vol. 82, No.6, June 1994, pp.919-932.

[10] C. Delgorge, C. Rosenberger, G. Poisson, and P. Vieyres, "Towards a New Tool for the Evaluation of the Quality of Ultrasound Compressed Images", *IEEE Transactions on Medical Imaging*, 2006.

[11] E. Cavero, A. Alesanco, L. Castro, J. Montoya, I. Lacambra, and J. Garcia, "SPIHT-based echocardiogram compression: Clinical evaluation and recommendations of use*," IEEE J. Biomed. Health Inform.,*Vol. 17, No. 1,Jan. 2013, pp. 103–112.

[12] M.G. Martini, L. Iacobelli, C. Bergeron, C.T. Hewage, M. Mazzotti, P. Amon, J. Vehkapera, E. Piri, K. Savino, L. Bokor, "Real-Time Multimedia Communications in Medical Emergency - the CONCERTO Project Solution", *37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Milan, Italy, 25-29 Aug 2015.

[13] Concerto project webpage: http://ict-concerto.eu/twiki/bin/view/Concerto

[14] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," *IEEE Trans. Image Process.*, Vol. 13, No. 4, Apr. 2004, pp. 600–612.

[15] Z. Wang, G. Wu, H. R. Sheikh, E. P. Simoncelli, E. H. Yang, and A. C.Bovik, "Quality-aware images," *IEEE Trans. Image Process.*, Vol. 15, No. 5Jun. 2006, pp. 1680–1689.

[16] Z. Wang, H. R. Sheikh, and A. C. Bovik, "No-reference perceptual quality assessment of JPEG compressed images," in *Proc. IEEE Int. Conf. Image Process*., Rochester, NY, Sep. 22–25, 2002, pp. 477–480.

[17] Z. Wang and E. Simoncelli, "Reduced-reference image quality assessment using a wavelet-domain natural image statistic model," in *Proc.17th SPIE Annu. Symp. Electron. Imag.,* San Jose, CA, Jan. 2005.

[18] M. A. Saad, A. C. Bovik, and C. Charrier, "A DCT statistics-based blind image quality index," *IEEE Signal Process. Lett.*,Vol. 17, No. 6,Jun. 2010, pp. 583–586.

[19] M. A. Saad, A. C. Bovik, and C. Charrier, "Blind image quality assessment: A natural scene statistics approach in the DCT domain,"*IEEE Trans. Image Process*., Vol. 21, No. 8, Aug. 2012, pp. 3339–3352.

[20] Z. Wang and A. C. Bovik, "Reduced and no-reference visual quality assessment: The natural scene statistics model approach," *IEEE Signal Process. Mag.*, Vol. 29, No. 6, Nov. 2011, pp. 29–40.

[21] P. Campisi, M. Carli, G. Giunta and A. Neri, "Blind Quality Assessment System for Multimedia Communications using Tracing Watermarking," *IEEE Trans. on Signal Processing,*Vol. 51, No. 4, Apr. 2003, pp. 996–1002.

[22] M. Martini, B. Villarini, and F. Fiorucci, "A reduced-reference perceptual image and video quality metric based on edge preservation," *EURASIP J. Adv. Sig. Pr.*,Vol. 2012, No. 1, pp. 1–13, 2012.

[23] C. T. E. R. Hewage and M. G. Martini, "Reduced-Reference Quality Assessment for 3D Video Compression and Transmission," *IEEE Transactions on Consumer Electronics,*Vol. 57, No. 3, Aug. 2011.

[24] M.A.Saad, A.C. Bovik and C. Charrier, "Blind Prediction of Natural Video Quality", *IEEE Transactions on Image Processing,*Vol. 23, No. 3, Mar. 2014, pp. 1352-1365.

[25] M. Kourtis, H. Koumaras, F. Liberal, "Reduced-reference video quality assessment using a static video pattern*", Journal of Electronic Imaging*, vol 25, no 4, 2016.

[26] Information technology - High efficiency coding and media delivery in heterogeneous environments - Part 2: High efficiency video coding, ITU-T Rec. H.265 | ISO/IEC 23008-2, 2013.

[27] A. Panayides, Z. Antoniou, M. S. Pattichis, C. S. Pattichis, and A. G. Constantinides, "High efficiency video coding for ultrasound video communication in M-health systems," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.* , San Diego, CA, USA, Aug. 28–Sep. 1, 2012, pp. 2170–2173.

[28] H. Chen, G.Braeckman, S.M.Satti, P.Schelkens, A.Munteanu, "HEVC-based Video Coding with Lossless Region of Interest for Telemedicine Applications", *20th Int. Conf. on systems, Signals and Image Processing (IWSSIP)*, Jul. 2013, pp.129-132.

[29] M. Razaak, M.G. Martini, K. Savino, "A Study on Quality Assessment for Medical Ultrasound Video Compressed via HEVC",*IEEE J. Biomed. Health Inform.*, Vol. 18, No. 5, Sep. 2014, pp. 1552-1559.

[30] M. Razaak and M. G. Martini, "CUQI: cardiac ultrasound video quality index". *Journal of Medical Imaging*, SPIE, vol. 3, no 1, 2016.

[31] Y. Han, Y. Cai, Y. Cao, and X. Xu, "A new image fusion performance metric based on visual information fidelity," *Inf. Fusion*, Vol. 14, pp. 127–135, 2013.

[32] Z.Wang and A. C. Bovik, "A universal image quality index," *IEEE Signal Process. Lett.*,Vol. 9, No. 3, Mar. 2002, pp. 81–84.

[33] M. H. Pinson and S. Wolf, "A new standardized method for objectively measuring video quality," *IEEE Trans. Broadcast.*, Vol. 50, No. 3, Sep.2004, pp. 312–322.

[34] A.C.Bovik, "Automatic prediction of perceptual image and video quality", *Proc. IEEE*, Vo. 101, No. 9, 2013 pp 2008–2029.

[35] L. Liu, Y. Hua, Q. Zhao, H. Huang, and A. C. Bovik, "Blind image quality assessment by relative gradient statistics and adaboosting neural network," *Signal Processing: Image Communication*, Vol. 40, pp. 1–15, 2016.

[36] ITU-R BT, Recommendation 500-11, Methodology for the subjective assessment of the quality of television pictures," Int. Telecommun. Union, Geneva, Switzerland, Tech. Rep. BT.500-11, 2002

[37] http://www.itu.int/en/ITU-T/studygroups/2013-2016/16/Pages/video/jctvc.aspx

Highlights

- A new quality assessment method for medical ultrasound applications was presented.
- A pre-known logo is inserted in an unused part of the original frame.
- Objective and subjective test results show high correlation coefficient values.
- The new technique can be extended and applied to other medical applications.