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Robustness of a Perceptually Lossless Medical Image Coder: Interpolation

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Abstract—Perceptually lossless medical image coding is an alternative for compressing medical images. It provides a solution to the challenge of delivering clinically critical information in the shortest time possible. In this paper, an investigation of the robustness of the perceptually lossless image coder is carried out by applying bilinear, biquadratic and bicubic standard and centered B-spline interpolation filters. In order to evaluate the visual performance, a subjective assessment was conducted consisting of 30 medical images and 6 image processing experts. Here, the perceptually lossless medical image coder was compared to the state-of-the-art JPEG-LS compliant LOCO and NLOCO image coders. Current results have shown that overall, there were no perceivable differences of statistical significance when the medical images were enlarged by a factor of 2.

I. INTRODUCTION

Medical imaging technologies offers the benefits of faster and accurate diagnosis. These imaging modalities include Computed Tomography (CT) [1], Magnetic Resonance Imaging (MRI) [2] and Digital Radiography (DR) [3] and so forth. In addition, when coupled with the advances of digitisation, they offer the advantages of permanent storage and fast transmission to any geographical location with relative ease. However, for medical images, there is a need for effective compression algorithms that alleviate the taxing burden of both large storage space and transmission bandwidth requirements, especially for applications such as Telemedicine [4] and Tele-mammography [5].

Compression algorithms generally fall into two broad categories [6], namely, reversible (lossless) and irreversible (lossy) compression. Reversible compression algorithms are highly desired due to a property, which enables them to retain all information without any loss during the encoding/decoding stage. They are, however, limited in compression ratio gains [7]. In contrast, irreversible compression algorithms trade off image integrity for greater compression ratio gain. An alternative is perceptually lossless image coding (PLIC), which offers the best of both worlds - having greater compression ratio gain without any loss in visual fidelity. Its effectiveness for compressing medical images was demonstrated in [8].

Image interpolation/enlargement is a common image processing operation used in medical imaging for critical diagnosis. In this paper, the robustness of a perceptually lossless medical image coder (PLMIC) presented in [8] is investigated for interpolated medical images using B-spline filters. Among

various interpolation methods, it has been shown that B-spline interpolation offers superior cost-performance tradeoff over other medical interpolation algorithms [9], [10]. It is important to reiterate that the objective of this paper is to examine the robustness of the PLMIC, in terms of interpolation, i.e. Is the compressed medical image perceptually lossless to the original? Hence, perceptual enhancement and evaluation of interpolation algorithms for medical imaging is not the focus of the paper. A subjective assessment was conducted using the 30 medical images found in [8] and assessed with 6 image processing experts. A comparison is made against two benchmark coders: the state-of-art JPEG-LS compliant LOCO and NLOCO coder [11] with $d=2$, where d represents the maximum pixel difference between the compressed and original image. Current results show that there were no visible differences of statistical significance for 5 out of 6 assessments for interpolation by a factor of 2.

This paper is organized as follows. In section II, B-spline interpolators for medical images are briefly reviewed. Section III presents the layout of the subject assessment and discusses the results. Finally, a conclusion is drawn in Section IV.

II. B-SPLINE INTERPOLATION

In this section, the underlying B-spline principals for the interpolation of medical images are briefly reviewed. For more details, the reader is referred to [12], [13], [14].

A. B-spline Kernel [14]

1) *General Kernel Expression*: The B-spline of degree n is denoted by $\beta^n(x)$, which can be derived by the $n + 1$ times repeated convolution of a B-spline of degree 0,

$$\begin{aligned}\beta^n(x) &= \beta^{n-1} * \beta^0 \\ &= \underbrace{\beta^0 * \beta^0 * \dots * \beta^0}_{n+1}\end{aligned}\quad (1)$$

where $\beta^0(x)$ is centered normalized rectangular pulse,

$$\beta^0(x) = \begin{cases} 1, & |x| < \frac{1}{2} \\ \frac{1}{2}, & |x| = \frac{1}{2} \\ 0, & |x| > \frac{1}{2} \end{cases}\quad (2)$$

Thus, the linear B-spline could also be referred to B-spline with degree 1,

$$\beta^1(x) = \begin{cases} 1 - |x|, & 0 \leq |x| < 1 \\ 0, & 1 \leq |x|. \end{cases} \quad (3)$$

Similarly, the quadratic B-spline with degree 2 is,

$$\beta^2(x) = \begin{cases} \frac{3}{4} - |x|^2, & 0 \leq |x| < \frac{1}{2} \\ \frac{1}{2} (\frac{3}{2} - |x|)^2, & \frac{1}{2} \leq |x| < \frac{3}{2} \\ 0, & \frac{3}{2} \leq |x|. \end{cases} \quad (4)$$

And the cubic B-spline with degree 3 is,

$$\beta^3(x) = \begin{cases} \frac{3}{2} - |x|^2 + \frac{|x|^3}{2}, & 0 \leq |x| < 1 \\ \frac{1}{6} (2 - |x|)^3, & 1 \leq |x| < 2 \\ 0, & 2 \leq |x|. \end{cases} \quad (5)$$

B. B-spline Representation [12]

Given a discrete sequence $f[k] \in l_2$, where l_2 denotes the square summable vector space, its underlying continuous function is approximated by $f(x)$,

$$f(x) = \sum_{k=-\infty}^{+\infty} c[k] \beta^n(x - k), \quad c \in l_2 \quad (6)$$

where $c[k]$ denotes the coefficients in space whose basis functions are made up of a series of shifted functions of $\beta^n(x)$. The $c[k]$ in Eq. (6), which is not the same as signal values $f[k] \in l_2$, can be obtained by filtering $f[k]$,

$$c[k] = (b^n)^{-1} * f[k] \quad (7)$$

where $(b^n)^{-1}$ represents the impulse response of analysis basis function of degree n ,

$$\begin{aligned} b^n[k] &= \beta^n(x)|_{x=k} \xrightarrow{Z} B^n(z) \\ (b^n)^{-1}[k] &\xrightarrow{Z} \frac{1}{B^n(z)} \end{aligned}$$

However, the cardinal kernel allows to use the exact signal values, $f[k] \in l_2$, as the expansion coefficients:

$$\begin{aligned} f(x) &= \sum_{k=-\infty}^{+\infty} ((b^n)^{-1} * f)[k] \beta^n(x - k) \\ &= \sum_{k=-\infty}^{+\infty} f[k] \eta^n(x - k) \end{aligned} \quad (8)$$

Here, the cardinal kernel can be obtained by filtering the kernel $\beta^n(x)$,

$$\eta^n(x) = \sum_{k=-\infty}^{+\infty} (b^n)^{-1}[k] \beta^n(x - k) \quad (9)$$

A well-known property of function $\eta^n(x)$ is that it converges to $\text{sinc}(x)$ as the degree tends to infinity [9].

C. Scaled Conversion [15]

Given the sequence $s[k]$, the scaled representation of the $s^n(x)$, denoted by $s_\Delta^n(x) := s^n(x/\Delta)$, can be derived by resampling $s^n(x)$ with step size Δ . And the scaled space S_Δ^n is defined as,

$$S_\Delta^n = \left\{ s_\Delta^n(x) = \sum_{k=-\infty}^{+\infty} c_\Delta[k] \beta_\Delta^n(x - k\Delta), |c_\Delta| \in l_2 \right\} \quad (10)$$

where $\beta_\Delta^n(x) := \beta^n(x/\Delta)$.

Similarly, we have the equivalent scaled cardinal spline representation ,

$$s_\Delta^n(x) = \sum_{k=-\infty}^{+\infty} s_\Delta[k] \eta^n(x/\Delta - k) \quad (11)$$

Actually, the scaled polynomial spline s_Δ^n is the approximation of s_1^n in space S_Δ^n .

Particularly, when Δ is the power of 2, a multiresolution pyramid for reduction and expansion respectively can be constructed [16]. Furthermore, centered pyramid can be constructed by shifting the the basis functions of coarser level one-half pixel with respect to grid on finer level [17].

D. Discrete B-spline Representation

The discrete B-spline kernel of degree n at scale m is denoted as $b_m^n(k)$, which is obtained by directly sampling the n th-continuous B-splines at the step m :

$$b_m^n[k] = \beta^n(x)|_{x=k/m}, \quad \forall k \in Z, \quad (12)$$

the centered B-spline kernel is obtained by shifting $\frac{1}{2}$ after sample at step m ,

$$q_m^n[k] = \beta^n(x)|_{x=(k+\frac{1}{2})/m}, \quad \forall k \in Z \quad (13)$$

E. Implementation

The above one-dimensional signal processing is carried out successively along the rows and columns of an image. For more detail, the reader is referred to the references [13], [15], [17].

III. ROBUSTNESS EVALUATION

A. Assessment Apparatus and Conditions

The experiment was conducted in a room with minimal ambient light, allowing only an experiment supervisor and one expert assessor so as to prevent contamination of the results. Two calibrated Barco 10-bit 20.8-inch medical grade LCDs were placed next to each other. Each screen has the maximum resolution of 1536 x 2048 pixels (3 mega-pixels). This setup attempts to emulate the conditions of a standard radiological examination room. In total there were 6 image processing experts, who have experience in picture quality assessment tasks. Image processing experts, while may not be capable of making a diagnosis, have the advantage of being able to critically assess picture quality.

TABLE I: The combinations of B-spline interpolation.

Type	Description
E2C1	Enlarged 2 times, centered B-Spline degree 1.
E2C2	Enlarged 2 times, centered B-Spline degree 2.
E2C3	Enlarged 2 times, centered B-Spline degree 3.
E2S1	Enlarged 2 times, standard B-Spline degree 1.
E2S2	Enlarged 2 times, standard B-Spline degree 2.
E2S3	Enlarged 2 times, standard B-Spline degree 3.
E4C1	Enlarged 4 times, centered B-Spline degree 1.
E4C2	Enlarged 4 times, centered B-Spline degree 2.
E4C3	Enlarged 4 times, centered B-Spline degree 3.
E4S1	Enlarged 4 times, standard B-Spline degree 1.
E4S2	Enlarged 4 times, standard B-Spline degree 2.
E4S3	Enlarged 4 times, standard B-Spline degree 3.

B. Assessment Design

A double-blind experiment[18] was conducted. The PLMIC is evaluated against two benchmark coders, the JPEG-LS compliant LOCO and NLOCO [11] with $d=2$. To simplify the discussion, the letters B, A and C are used to denote the aforementioned three coders, respectively. Hence, there was initially 30 images, composed of CT, CR and MRI images, to be encoded by each coder, yielding 90 images. These 90 images were then subjected to the two types of B-spline interpolators, standard and centered; enlarged by a factor of 2 and 4 with polynomial degrees 1, 2 and 3, respectively. Each of these combinations were labeled accordingly in Table I. Thus, in total there were 1080 images. To simplify and prevent systematic errors, the assessment was partitioned into sessions from the categories specified in Table I. Hence, there was 12 sessions for each viewer. Each session was held at different times, so as to minimise fatigue.

In each of the 12 sessions, each viewer was to assess 30 pairs of medical images. These pairs of medical images were randomly selected and displayed side by side. There were 9 possible combinations of presenting the image pairs, being A vs A, B vs B, C vs C, A vs B, B vs A, A vs C, C vs A, C vs B and B vs C. This approach eliminates the systematic error associated with the scanning effect [18]. In this experiment, the 2-staged Forced Choice (2SFC) was employed [8] in assessing each pair of medical images. The first stage asks, “Are the two images identical?”, if not, “Which image in the pair is preferred, Left, Right or Either?” (Fig. 1).

C. Results and Analysis

This paper analyses the results for the ‘identical’ selection. Two statistical models are employed to analyse the results of the assessment. The first model ascertains the ‘identicalness’ or rate of correctly identifying an image as identical when it is displayed on either sides of the screens. This also provides a rough indication of the reliability of the assessors. The second model determines if there are any visible differences of statistical significance when a compressed image is displayed with a the original image, e.g., Is A vs B seen as identical?

Thus, in the first model (TABLE II), for E2C1, the rate of correctly identifying A vs A, B vs B and C vs C as identical was 83.30%, 87.00% and 77.80%. Taking the average of these gives the baseline for the rate of correct identification at 82.70%. The second model checks for statistical significance

Fig. 1: The 2-Stage Forced Choice Assessment Method.

over the 95% confidence interval with a two-tail z-score [19] given by

$$Z = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}},$$

where, as shown in TABLE II, μ_0 represents the baseline for ‘identicalness’ and $\sigma/\sqrt{n}$ is the standard deviation. $\bar{X}$ denotes the rate of identifying A vs B, A vs C and B vs C as identical. If $|Z| \leq 1.96$, then there are no perceivable differences of statistical significance. For example, in E2C1, the baseline is 0.827. The percentage of observed identical count of A vs B is 0.858. The resulting z-score is 1.120, which is less than or equal to 1.96. Therefore, in E2C1, there were no perceivable differences of statistical significance for images compressed by the PLMIC in comparison with the corresponding originals.

For the A vs B category as shown in Fig. 2, when the images were enlarged by a factor of 2, 5 out of 6 assessments showed that there were no perceivable differences of statistical significance between the two coders. It is also interesting to note the results E2S2 and E2S3 for A vs C, where differences can be seen. When enlarged by 4 times, however, there were only 2 assessments for category A vs B, E4C3 and E4S1, that did not have any perceivable differences of statistical significance. Overall, there is evidence that show that differences of statistical significance were not visible for 2 times interpolation (Fig. 3) and more visible for 4 times interpolation (Fig. 4). Finally, it is also important to note that the interpolation algorithm themselves can introduce distortions into the pictures. While statistical differences have been observed in compressed images, it is unclear if these differences were the result of compression or interpolation operations. This is a matter to be addressed in future investigations.

IV. CONCLUSION

Perceptually lossless medical image coding offers an alternative solution for compression digital medical images. The robustness of a PLMIC [8], under interpolation operations, has been evaluated at enlargement factors of 2 and 4 with the center and standard B-spline filters [17], [12]. Current results have shown that at 2 times magnification, 5 out of 6 assessments

TABLE II: Calculation of the z-scores and the rate of correct identification for each category.

Session	Response as Identical			Standard Deviation ($\sigma/\sqrt{n}$)	Baseline (μ_0)	Response as Identical ($\bar{X}$)			Z-Score / Is Identical		
	A vs A	B vs B	C vs C			A vs B	A vs C	B vs C	A vs B	A vs C	B vs C
E2C1	0.833	0.870	0.778	0.028	0.827	0.858	0.880	0.762	1.120 / Yes	1.896 / Yes	2.334 / No
E2C2	0.826	0.909	0.842	0.027	0.859	0.892	0.882	0.720	1.235 / Yes	0.878 / Yes	5.249 / No
E2C3	0.882	0.85	0.842	0.029	0.858	0.819	0.829	0.737	1.376 / Yes	1.028 / Yes	4.198 / No
E2S1	0.900	0.893	0.714	0.028	0.836	0.828	0.861	0.781	0.276 / Yes	0.895 / Yes	1.931 / Yes
E2S2	0.900	0.895	0.808	0.030	0.867	0.823	0.769	0.726	1.459 / Yes	3.244 / No	4.646 / No
E2S3	0.889	0.867	0.867	0.028	0.874	0.804	0.800	0.843	2.486 / No	2.690 / No	1.084 / Yes
E4C1	0.833	0.810	0.818	0.032	0.820	0.709	0.808	0.598	3.467 / No	0.371 / Yes	6.942 / No
E4C2	0.808	0.895	0.667	0.034	0.790	0.678	0.717	0.511	3.253 / No	2.104 / No	8.115 / No
E4C3	0.800	0.867	0.790	0.032	0.819	0.759	0.700	0.658	1.828 / Yes	3.639 / No	4.916 / No
E4S1	0.826	0.722	0.833	0.033	0.794	0.744	0.801	0.674	1.526 / Yes	0.218 / Yes	3.674 / No
E4S2	0.800	0.826	0.778	0.034	0.801	0.694	0.686	0.583	3.173 / No	3.400 / No	6.432 / No
E4S3	0.769	0.889	0.75	0.034	0.803	0.670	0.692	0.594	3.904 / No	3.272 / No	6.154 / No

(a) A (b) B (c) C

Fig. 3: Centered Bi-cubic interpolation by a factor of 2.

(a) A (b) B (c) C

Fig. 4: Centered Bi-cubic interpolation by a factor of 4.

Fig. 2: Graph of absolute Z-scores for different interpolators. The black horizontal line represents 1.96.

revealed no perceptible differences of statistical significance between PLMIC coded images and original images.

REFERENCES

- [1] Kak, A. C. and Slaney, M., *Principals of Computerized Tomographic Imaging*, IEEE Press, 1987.
- [2] R. Archarya, R. Wasserman, J. Stevens, and C. Hinojosa, "Biomedical Imaging Modalities: A Tutorial," *Computerized Medical Imaging and Graphics*, vol. 19, no. 1, pp. 3 – 25, 1995.
- [3] X. Cao and H. K. Huang, "Current Status and Advances of Digital Radiography and PACS," *IEEE Engineering in Medicine and Biology*, vol. 19, pp. 80 – 88, Sept. – Oct. 2000.
- [4] M. Krol, "Telemedicine," *IEEE Potentials*, vol. 16, pp. 29–31, Oct-Nov 1997.
- [5] E. O. Sheybani and R. Sankar, "ATMTN: a telemammography network architecture," *IEEE Transactions on Biomedical Engineering*, vol. 49, pp. 1438 – 1443, 2002.
- [6] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, Prentice Hall, Inc., second edition, 2002.
- [7] B. J. Erickson, A. Manduca, P. Palisson, K. R. Persons, F. Earnest, V. Savchenko, and N. J. Hangiandreou, "Wavelet Compression of Medical Images," *Radiology*, vol. 206, no. 3, pp. 599 – 607, 1998.
- [8] D. Wu, D.M. Tan, M. Baird, J. DeCampo, C. White, and H. R. Wu, "Perceptually Lossless Medical Image Coding," *IEEE Transactions of Medical Imaging*, vol. 25, no. 3, pp. 335 – 344, 2006.
- [9] T. Lehmann, C. Gönner, and K. Spitzer, "Survey: Interpolation methods in medical image processing," *IEEE Transactions on Image Processing*, vol. 18, no. 11, pp. 1049–1075, Nov. 1999.
- [10] T. Lehmann, C. Gönner, and K. Spitzer, "Addendum: B-spline interpolation in medical image processing," *IEEE Transactions on Image Processing*, vol. 20, no. 7, pp. 660–665, July 2001.
- [11] M. Weinberger, G. Seroussi, and G. Sapiro, "The LOCO-I Lossless Image Compression Algorithm: Principles and Standardization into JPEG-LS," *IEEE Transaction on Image Processing*, vol. 9, pp. 1309–1324, August 2000, Hewlett-Packard Laboratories Technical Report No. HPL-98-193R1, November 1998, revised October 1999.
- [12] M. Unser, A. Aldroubi, and M. Eden, "B-spline signal processing: Part i – theory," *IEEE Transactions on Signal Processing*, vol. 41, no. 2, pp. 821–832, Feb. 1993.
- [13] M. Unser, A. Aldroubi, and M. Eden, "B-spline signal processing: Part ii – efficient design and applications," *IEEE Transactions on Signal Processing*, vol. 41, no. 2, pp. 834–848, Feb. 1993.
- [14] M. Unser, "A perfect fit for signal and image processing," *IEEE Transactions on Signal Processing*, Nov. 1999.
- [15] M. Unser, A. Aldroubi, and M. Eden, "Enlargement or reduction of digital images with minimum loss of information," *IEEE Transactions on Signal Processing*, vol. 4, no. 3, pp. 247–258, March 1995.
- [16] M. Unser, A. Aldroubi, and M. Eden, "The l_2 polynomial spline pyramid," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 15, no. 4, pp. 364–379, April 1993.
- [17] P. Brigger, F. Müller, K. Illgner, and M. Unser, "Centered pyramids," *IEEE Transactions on Signal Processing*, vol. 15, no. 4, pp. 364–379, April 1993.
- [18] C. White, H. R. Wu, D. Tan, R. L. Martin, and D. Wu, *Experimental Design for Digital Image Quality Assessment*, Epsilon Publishing, 1st edition, 2004.
- [19] R. L. Scheaffer and J. T. McClave, *Probability and Statistics for Engineers*, Duxbury Press, Boston, Massachusetts, second edition, 1986.