Visually Lossless Compression of Dental Images

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***Abstract*—It has become a standard practice to use images in medicine. Due to increasing resolution, their size often occurs to be large and, then, necessity to compress them efficiently before storage and/or transmission arises. Since compression ratio of lossless compression is frequently limited, one has to apply lossy compression. Then, a problem of providing an acceptable quality to retain diagnostic value of compressed data appears. This paper deals with analyzing opportunities to perform this in non-iterative way for dental medical images for two versions of a coder based on discrete cosine transform (DCT) – AGU and AGU-M. It is demonstrated that mean squared error (MSE) and MSE modified with taking into account peculiarities of human vision system (MSE_{HVS}) of distortions due to lossy compression can be predicted before starting compression itself. Then, a desired quantization step (QS) for AGU or scaling factor (SF) for AGU-M can be adjusted to provide a desired quality. Regression uses statistics of alternating current (AC) DCT coefficients calculated in 300…500 8x8 pixel blocks to predict output metrics using fitting curves in preliminary obtained scatter-plots.**

Keywords—lossy compression; dental image; metric prediction

I. Introduction

Medical disgnostics applies different types of images nowadays [1, 2]. A great amount of images is obtained, analyzed, and stored. Many of them are transferred via telecommunication links in telededicine applications [3]. In addition to total amount of acquired images, their size is often quite large - it is hundreds of kB or even exceeds 1 MB [4] – see file sizes in [5]. This leads to problems in both image storage (computer memory has a limited space) and image transmission (due to a limited bandwidth of communication lines and/or limited time of data transferring). In both cases, one needs to have efficient methods for medical image compression [6, 7].

One way is to apply lossless (reversible) compression for which no losses (distortions) are introduced. Then, valuable (diagnostic) information is preserved (not lost). However, attained values of compression ratio (CR) for such image standard formats as TIFF, GIF, PNG, etc., are usually less that 3:1. Such values often do not satisfy practical needs. Then, lossy (irreversible) compression has to be considered [7, 8]. The corresponding methods provide larger CRs but introduce losses that, under certain conditions, can be acceptable for practice. To understand what is acceptable, numerous studies have been carried out (see [1, 8-10] and references therein). For some types of medical images, even CR of about 40:1 for JPEG and 50:1 for JPEG2000 are considered acceptable [9] whilst smaller CR values (14:1, 12:1 or even smaller) are recommended for other types of data.

In general, the following has been understood by both medical imaging specialists and researchers dealing with other applications of image compression. First, acceptable or recommended CR depends upon a set of factors where the most important are (medical) image type, is an image subject to compression grayscale or color, is there noise in an image and how intensive it is, etc. [1, 7-14]. Simple structure images can be compressed without negative consequences with a larger CR [14, 15], color images are compressed with a larger CR than grayscale if component correlation is taken into account [11], noise presence decreases CR and leads to the use of specific approaches in lossy compression since it possesses specific denoising effect [13, 16]. Second, performance of lossy compression sufficiently depends upon a method used. Many more or less known techniques are based on discrete cosine transform (DCT) as JPEG or more advanced coders as AGU and AGU-M [13, 15, 17] that considerably outperform JPEG. Other employ wavelet [18] or other [19] transforms. In fact, one needs a (visually lossless) compression method that provides a larger CR with producing distortions that are invisible (cannot be noticed by visual inspection) and, thus, do not result in reduction of image diagnostic value.

Here we come to visually lossless compression that depends upon application. In this paper, we consider dental grayscale images for which there is an obvious tendency to growing up the number and volume of acquired images. We show that it is possible to extend for them the approach earlier proposed in our papers [20-22]. Empiric recommendations concerning setting the scaling factor (SF) for the coder AGU-M to provide invisibility of introduced distortions are given in [20]. The ways to predict mean squared error (MSE) of introduced losses and to provide their acceptable level for AGU have been proposed in [21, 22]. Further advances have been done in [23] where it has been shown that other than MSE quality metrics can be predicted as well. Note that many visual quality metrics have thresholds of distortion invisibility determined in [24].

Thus, in this paper, we analyze possibility to predict quality for dental images compressed in a lossy manner by AGU and

AGU-M coders that outperform JPEG and JPEG2000 according to rate/distortion characteristics [15]. The novelty of our study consists in demonstration of opportunity to predict visual quality metrics that characterize quality of compressed images more adequately than conventional MSE. An advantage of our approach is that such a prediction is very fast and it allows setting quantization step (QS) or SF adaptively depending upon image content and complexity.

II. DCT-Based Compression and Its Basic Properties

Most of modern methods of lossy image compression employ orthogonal transforms [15] that are able to represent data sparsely. DCT and wavelets are, in general, compete in this sense. Advantages of DCT-based compression that we will use consists in the following. First, advanced DCT-based coders as AGU [17] and its modification AGU-M [13, 15] perform better than the standard JPEG2000 [15]. Compared to the standard JPEG, AGU and AGU-M have the following differences. They use two-dimensional (2D) DCT in 32x32 pixel blocks and employ bit-plane coding of quantized DCT coefficients. In addition, embedded deblocking is applied to images after decompression. AGU uses uniform quantization whilst AGU-M employs frequency dependent quantization steps that are determined by SF and special table of size 32x32. CR is controlled by QS for AGU and by SF for AGU-M. Larger QS or SF values result in a larger CR for any given image. To produce approximately the same quality of compressed image, SF for AGU-M should be about 1.6 times smaller than QS for AGU.

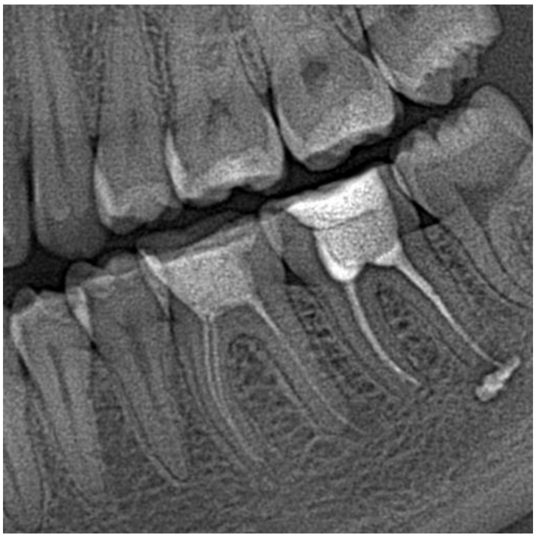
Let us present examples of aforementioned dependences. Two 512x512 pixel fragments of large size dental image have been compressed (Fig. 1). These fragments differ by their complexity where the first fragment (dental1_part23) is less complex (contains less textures, edges, and details) and the second one (dental2_part13) has more higher contrast details. MSE of introduced losses and CR as functions of QS for AGU coder are presented in Fig. 2. Similarly, the dependences for AGU-M on SF are given in Fig. 3. Analysis of the plots shows the following. The dependences of MSE on QS and MSE on SF for the considered fragments behave in a specific manner. For small QS or SF, MSE is larger for simpler structure fragment (see the plots in Fig. 2,a and 3,a). In turn, for larger QS or SF, MSE is larger for the fragment in Fig. 1,a. MSE of introduced losses for a given fragment for AGU and AGU-M are almost the same for QS=SF. The dependences of MSE on QS and SF grow faster for small QS and SF.

CR for a given QS or SF is smaller for the more complex fragment (see the plots in Fig. 2,b and 3,b), especially if QS or SF are large enough. Meanwhile they are almost the same for QS<10 and SF<10.

These results show that quality of a compressed image characterized by MSE sufficiently depends on QS or SF but it also depends upon image characteristics.

Let us also analyze quality of compressed image in terms of visual quality metrics. Good metrics that are well suited for grayscale images are PSNR-HVS and PSNR-HVS-M expressed as $PSNR-HVS=10log_{10}(255^2/MSE_{HVS})$ and $PSNR-HVS-M=10log_{10}(255^2/MSE_{HVS-M})$ (both in dB) where MSE_{HVS} and MSE_{HVS-M} are specific MSEs that take into account peculiarities of HVS. PSNR-HVS and MSE_{HVS} take into account the fact that distortions in low spatial frequencies are more important and visible compared to distortions in high spatial frequencies. PSNR-HVS-M and MSE_{HVS-M}, in addition to previous property, take into account masking effect of texture (distortions in textural regions and less visible than in homogeneous ones). Recall that MSE and MSE_{HVS} are approximately equal if distortions have properties close to additive white Gaussian noise.

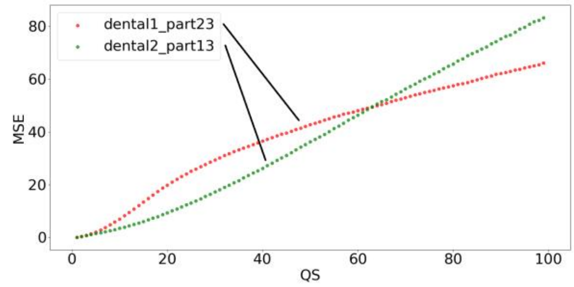
a



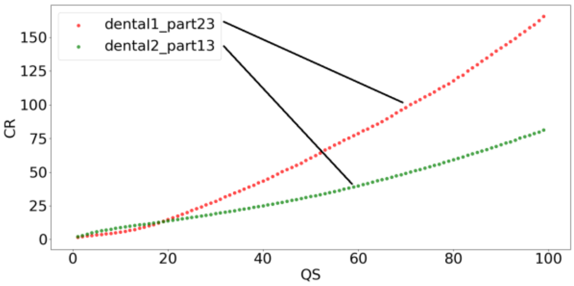
b

Fig. 1. Two test fragments of different complexity: dental1_part23(a), dental2_part13 (b)

The plots of MSE_{HVS} and MSE_{HVS-M} on QS for the coder AGU are presented in Fig. 4. Similarly, the plots of MSE_{HVS} and MSE_{HVS-M} on SF for the coder AGU-M are given in Fig. 5.

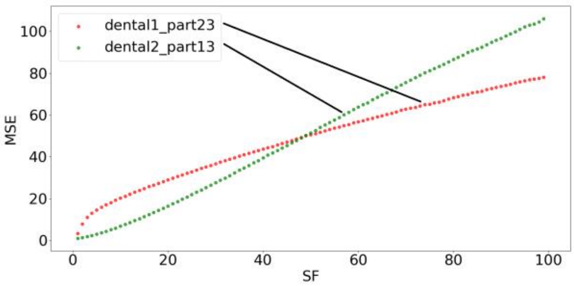


a

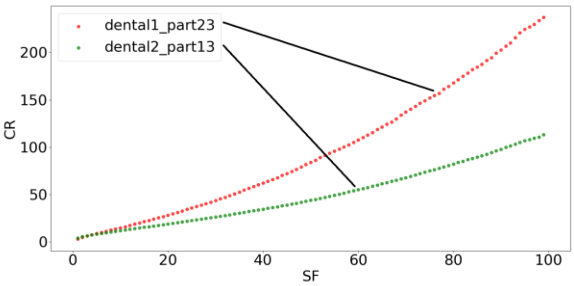


b

Fig. 2. Dependences of MSE and CR on QS for two test images for AGU



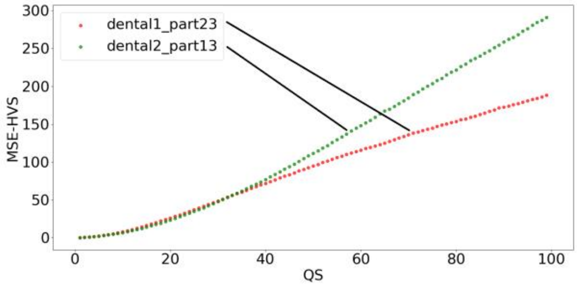
a



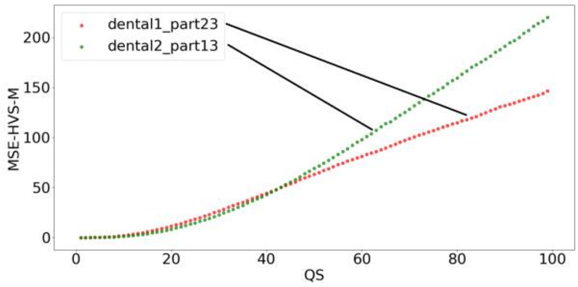
b

Fig. 3. Dependences of MSE and CR on SF for two test images for AGU-M

The first observation is that the curves for both test fragments behave almost the same for QS<40 and SF<40, i.e. just for QS and SF values that are of interest for our application. Second, MSE_{HVS} and $MSE_{HVS\text{-}M}$ seem to be approximately proportional to QS and SF for the coders AGU and AGU-M, respectively.

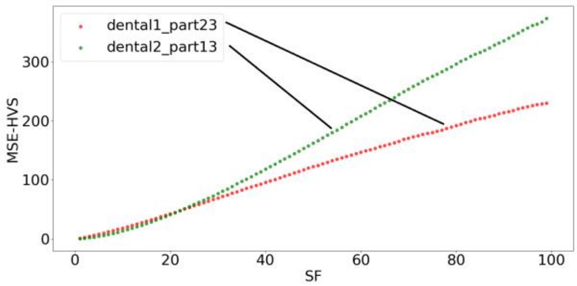


a

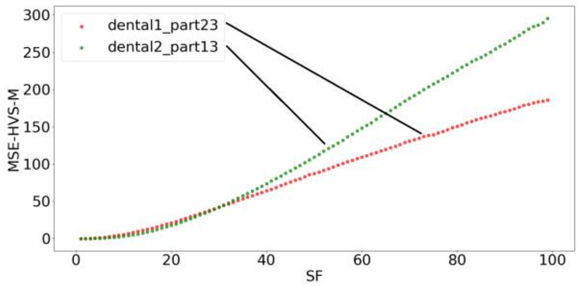


b

Fig. 4. Dependences of MSE_{HVS} and MSE_{HVSM} on QS for two test images for AGU



a



b

Fig. 5. Dependences of MSE_{HVS} and MSE_{HVSM} on SF for two test images for AGU-M

Thus, our first task is to provide a desired value of a metric that characterizes quality of a compressed image. It is worth recalling here that there are approximate threshold values for several metrics that define invisibility threshold for images distorted in different manner [24]. For example, it is supposed that MSE should be about 20 (PSNR about 35 dB) while

MSE_{HVS-M} should be about 4 to provide PSNR-HVS-M about 42 dB.

III. Prediction Based on Regression

If one needs to provide a desired value of a used metric in lossy image compression, several approaches are possible. One way is to apply iterative compression with multiple compression/decompression, metric calculation and changing of QS or SF in respective manner [15]. This method produces quite accurate results but some problems arise. A first problem is that such a compression requires several iterations and, thus, considerable time. A second problem is that the number of iterations before starting them is unknown and, thus, compression time is unknown, too.

This can be impractical. Then, another, less accurate but much faster approach is possible. It presumes fast calculation of a desired QS based on analysis of statistics of DCT coefficients [21, 22]. In these papers, it has been shown that MSE of introduced losses for JPEG with uniform quantization and some other DCT-based coders is approximately equal to $QS^2/12$ for small QS. It has been also demonstrated [26] that many compression parameters including MSE, PSNR and CR considerably depend on percentage of zeros P_0 of quantized DCT coefficients. As the result, MSE has been expressed as $MSE = (QS^2/12) f(P_0)$ where the function $f(P_0)$ has been obtained in advance. By "in advance", we mean that this function is known before starting image compression. It is obtained by regression (see details below). Then, having the dependence $MSE = (QS^2/12) f(P_0)$ and having distribution of AC DCT coefficients that allows calculating P_0, it is easy to determine QS to provide a desired MSE_{des}.

P_0 for a given image has to be determined for a limited number of 8x8 pixel blocks. In fact, it is calculated very quickly as $N_0/63N_{bl}$ where N_0 denotes the total number of AC DCT coefficients the amplitudes of which are smaller than QS/2 and N_{bl} denotes the number of considered image blocks (it is enough to have 300…500 blocks for this purpose).

Since MSE_{HVS-M} is more adequate than MSE in characterizing visual quality of compressed images, we are interested in analyzing an opportunity to predict MSE_{HVS-M}. We have obtained the scatter-plot of MSE_{HVS-M} on QS for the coder AGU presented in Fig. 6. Each point of this scatter-plot corresponds to one test image (20 test images totally) compressed with one value of QS (from 1 to 40 with step equal to 1). As it is seen, points are placed in a compact manner where their divergence increases with larger QS. The tendency of MSE_{HVS-M} increasing if QS increases is obvious.

Due to compactness of the scatter-plot, it is easy to fit a curve describing the dependence of MSE_{HVS-M} on QS (one example is shown in Fig. 6). Nowadays there are standard tools to carry out this task as, for example, Matlab or Excel. There are also standard criteria to characterize quality of fitting [27]. They are goodness-of-fit R^2 (this parameter should approach unity or, at least, exceed 0.9) and root mean square eror (RMSE) that should be as small as possible.

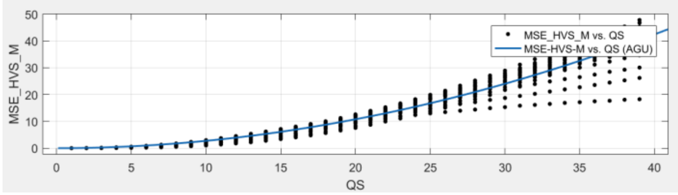


Fig. 6. Scatter-plot of MSE_{HVS-M} on QS for lossy compression of grayscale images for the coder AGU

We have got, at least, three good approximations:

$$MSE_{HVS-M}=0.02896\times QS^{1.976}, \quad (1)$$

$$MSE_{HVS-M}=0.02505\times QS^2+0.077\times QS-0.7803, \quad (2)$$

$$MSE_{HVS-M}=42.49\times\exp(-((QS-45.79)/21.56)^2). \quad (3)$$

Brief analysis of these expressions shows that MSE_{HVS-M} is approximately proportional to QS^2. For all three expressions given above, R^2 values are practically the same and equal to 0.95, i.e. high enough. RMSE values are equal to 2.89, 2.88, and 2.91, i.e. all three approximations (1) – (3) are almost equally well. Then, other factors have to be taken into account in choosing the best approximation. To our opinion, approximation (1) is the best since it produces MSE_{HVS-M} very close to zero for QS=0 and all the values are positive (in opposite to approximation (2)).

Having this approximation, a desired QS can be calculated as

$$QS = (MSE_{HVS-M\,des}/0.02896)^{1/1.976} \approx (MSE_{HVS-M\,des}/0.02896)^{1/2}$$

where $MSE_{HVS-M\,des}$ is the desired MSE_{HVS-M}. For example, if $MSE_{HVS-M\,des}$=4, QS has to be about 12.

Consider now the data for the coder AGU-M. The scatter-plot and one example of the fitted curve are represented in Fig. 7. The mein observations are the same as in the previous case. The obtained approximations are the following:

$$MSE_{HVS-M}=0.1195\times SF^{1.698}, \quad (4)$$

$$MSE_{HVS-M}=0.0275\times SF^2+0.5307\times SF-2.161, \quad (5)$$

$$MSE_{HVS-M}=61.4\times\exp(-((SF-44.92)/22.73)^2). \quad (6)$$

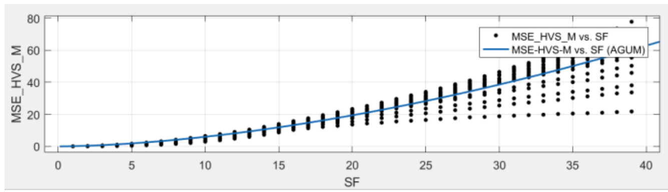


Fig. 7. Scatter-plot and approximating curves for the sum of two exponentials (a) and the fifth order polynomial (b)

The obtained values of R^2 are smaller than in the previous case and they are about 0.91 whilst all RMSE are about 6. To our opinion, the approximation (4) is the best and

$$SF = (MSE_{HVS-M\,des}/0.1195)^{1/1.698}.$$

Then, to provide $MSE_{HVS-M\,des}$=4, SF should be about 8. These results are in good agreement with averaged dependences presented in Fig. 16 in [15] for SNR-HVS-M_{des}about 42 dB that corresponds to $MSE_{HVS-M\,des}$=4 for 8-bit representation of processed images (this is just the case for dental medical images).

One can argue that RMSE values for the obtained approximations are too large and, thus, prediction is not accurate enough. However, analysis of fitting results show that the largest errors take place for QS>30 and SF>25, i.e. for such values that introduced distortions are visible and such lossy compression is not acceptable in our case. Besides, in the future, we plan to consider some ways to improve prediction accuracy.

IV. Other Compression Results

One can be interested in CR values provided by lossy compression with the recommended parameters. The coder AGU with QS=12 for 20 considered test fragments has produced CR values from 6.2 to 24.2 where $MSE_{HVS\text{-}M}$ varied from 1.78 to 4.52. Thus, accuracy of providing the desired $MSE_{HVS\text{-}M}$ about 4 is quite high and the produced CR values are large enough.

Similarly, the CR values for the coder AGU-M with SF=8 have been analyzed for the considered test fragments. The largest reached CR=31.3 whilst the smallest CR=8.9. This means that CR depends on image content (complexity) considerably. $MSE_{HVS\text{-}M}$ varied from 1.53 to 4.12.

The compressed images are presented in Fig. 7a and Fig. 7b. Comparing them to the corresponding images in Fig. 1, we can state that no visible distortions are introduced. Besides, to confirm preservation of diagnostically important information (details), Fig. 7c and 7d. show magnified fragment before and after compression. As it can be seen, no differences can be detected.

The smallest CR has been observed for the highly textural test fragment in Fig. 8 where original and compressed images are given. To our opinion, no difference can be seen.

Comparing the results for AGU and AGU-M, we can state that AGU-M produces slightly larger CR for given quality or slightly better quality for a given CR.

Average time for compressing 512x512 pixel fragment using CPU Intel(c) Core (c) i7-4710 HQ 2.5 GHz takes less than 1.32 seconds for AGU and less than 1.33 seconds for AGU-M. Decompression takes approximately the same time.

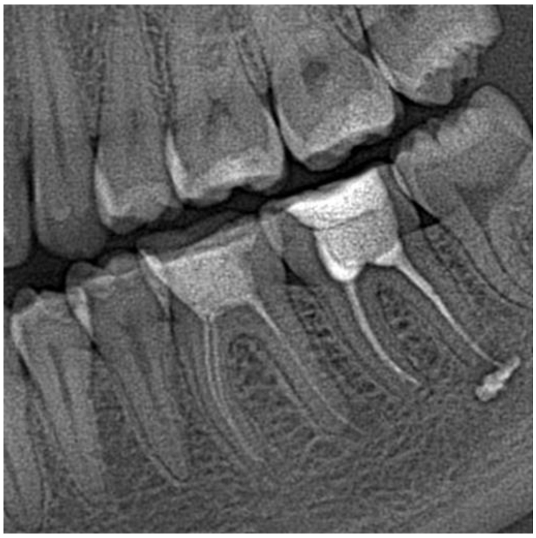
V. Conclusions

Peculiarities of lossy compression applied to dental images have been considered. It has been shown that compression parameters (CR and metrics that characterize image quality) depend upon image properties sufficiently. A general way to introduce distortions that are “invisible” is introduced for two DCT based coders – AGU and AGU-M. The recommendations concerning QS or SF setting are given. It is shown that the attained values of CR can be quite large: they can reach 30 and even more and this is considerably greater that CR values usually recommended for JPEG (about 10) for compressing medical images. Meanwhile, CR values are individual for each image (or its fragment) – from 8.9 to 31.3 for the considered set of test images.

Note that compression with a desired quality can be done without iterations, i.e. quite quickly.

We expect that the proposed approach can be modified for 3D version of the AGU coder and it can be also generalized for other methods of lossy compression based on DCT.

a



b

c

d

Fig. 7. Test fragments for which SF=8, CR=12.5 (a), SF=8, CR=10.6 (b); magnified fragment of treated tooth before (c) and after (d) compression

a

b

Fig. 8. Dental2_part00 – a) clear, b) SF=8, CR=8.9

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