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High Bit-Depth Medical Image Compression with HEVC

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***Abstract*—Efficient storing and retrieval of medical images has direct impact on reducing costs and improving access in cloud based health care services. JPEG 2000 is currently the commonly used compression format for medical images shared using the DICOM standard. However, new formats such as HEVC can provide better compression efficiency compared to JPEG 2000. Furthermore, JPEG 2000 is not suitable for efficiently storing image series and 3D imagery. Using HEVC, a single format can support all forms of medical images. This paper presents the use of HEVC for diagnostically acceptable medical image compression, focusing on compression efficiency compared to JPEG 2000. Diagnostically acceptable lossy compression and complexity of high bit-depth medical image compression are studied. Based on an established medically acceptable compression range for JPEG 2000, this paper establishes acceptable HEVC compression range for medical imaging applications. Experimental results show that using HEVC can increase the compression performance, compared to JPEG 2000, by over 54%. Along with this, new method for reducing computational complexity of HEVC encoding for medical images is proposed. Results show that HEVC intra encoding complexity can be reduced by over 55% with negligible increase in file size.**

***Index Terms*—Computational Complexity Reduction, DICOM, HEVC, Intra coding, Irreversible Compression, JPEG 2000, Medical Image Compression**

I. Introduction

Cloud based health care service offer several benefits such as storage of, and access to, medical imaging data and electronic medical records in real time. Real time access to medical imaging will lower the distribution costs, reduce the duplication of medical imaging, and reduce the cost of medical image storage infrastructure. Medical images have to be stored at very high quality and efficient compression algorithms will have a direct impact on lowering costs. For example, four sets of PET-CT medical images of one patient may require 4+ GB of storage space. Efficient compression of medical images has a direct impact on reducing costs and improving access on ubiquitous and heterogeneous mobile devices.

Digital Imaging and Communications in Medicine (DICOM), a medical imaging standard [1] is currently used for sharing medical images across applications. DICOM specifies JPEG and JPEG 2000 (J2K) for reversible (lossless) and irreversible (lossy) compression of medical images. Medical image series (a set of related images of a single body part) are compressed in DICOM as individual images without exploiting any temporal redundancy in the image series. The High Efficiency Video Coding (HEVC) standard offers significant performance improvements over standards such as H.264/AVC and JPEG/J2K [2], [3], [4] and can provide significant compression savings for medical image applications. While it is desirable to use lossless compression for medical images, lossy compression that does not affect the diagnostic accuracy may be acceptable. Koff *et al*. reported an acceptable range of irreversible compression ratios (ICR) of JPEG and J2K for 2D medical images of various DICOM modalities and anatomical body parts [5].

A key contribution of this paper is the establishment of acceptable irreversible compression ratio range for both HEVC Intra and Inter encoding of medical images. In this study, the focus is on comparing the irreversible compression performance of HEVC-Intra and HEVC-Inter with J2K. Compression performance was evaluated for the diagnostically acceptable compression ratio ranges established by Koff *et al*. [5]. Results show that using HEVC for medical image compression reduces storage and bandwidth needs by up to 54% compared to DICOM images using J2K compression. Another contribution of this paper is a new method for reducing computational complexity of lossless HEVC encoding for medical images. Results show that HEVC intra encoding complexity can be reduced by over 55% with negligible increase in file size.

This paper is an extension of the work presented at the IEEE International Conference on Consumer Electronics [6], [7]. The work is extended with in-depth experimentation, use of larger data sets, and use of images with more modalities and body parts, and development of a methodology to establish acceptable irreversible compression and reducing computational complexity of HEVC Intra coding for medical images. The paper is organized as follows: section-II provides

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overview of few widely used video and image coding standards along with related research; section III and IV present HEVC irreversible compression evaluation method and its results, whereas section V and VI present the computational complexity reduction method and its results. Finally, observations and conclusion are presented in sections VII to VIII respectively.

II. Overview of Video/Image Coding Standards

Medical images are commonly represented in DICOM format and in many cases, are image series. In digital video coding, a picture (a medical image) from a video sequence (a medical image series) is represented by three components: Luma (Y component), that represents the brightness of the medical content at each pixel location whereas other two chroma components (commonly known as U and V components) represent the color difference at each pixel in the picture. Each picture (medical image) is represented by 3 rectangular arrays consisting of Y, U and V components.

H.264, a widely used hybrid video coding standard has block based coding structure and it segments each medical image into several macro blocks of size 16x16 pixels. Each Marco-block consists of 16x16 Luma and two 16x16 chroma component arrays for a 4:4:4 YUV scheme. In this case each component array is of equal size. Other YUV schemes includes 4:2:2, wherein chroma samples are half the width but same height as Y component and 4:2:0 wherein both chroma components have half width and height as of Y. For medical images which are mostly grayscale images normally the YUV format of 4:0:0 is recommended. Macro blocks are further segmented into blocks of various sizes ranging from 16x16 to 4x4 [8]. H.264 predicts each block as per the encoder settings and the residual is obtained by computing the difference between the actual source and predicted block.

H.264 has two prediction modes such as (i) intra picture prediction and (ii) inter picture prediction. In order to remove spatial redundancies, intra picture prediction uses selectable position dependent linear combinations of neighboring sample values to form a prediction block. H.264 intra uses various block sizes such as 16x16, 8x8, and 4x4 for luma block prediction and 16x16, 16x8 or 8x8 chroma block prediction. H.264 has 9 intra prediction modes for 4x4 luma blocks and 4 modes for 16x16 luma and 8x8 chroma blocks. Prediction process generates residual values by subtracting original block from predicted block. Thereafter an integer transform is applied to residual and scalar quantization is applied to the transformed residual (Max QP parameter value is 52). Quantization is followed by zigzag scan prior to entropy coding of residual. H.264 uses two variants of entropy coding such as Context Adaptive Variable Length Coding (CAVLC) and Content Adaptive Binary Arithmetic Coding (CABAC), these methods outperform VLC in achieving compression.

Inter picture prediction is used to reduce temporal redundancies. Blocks of pixels from previously coded pictures are used to form a prediction. The residual signal encoded in each frame is the difference between a given block and the predicted block. H.264 supports lossy and lossless compression. Lossy compression process includes the block linear transformation, quantization and entropy coding of the blocks whereas lossless encoding skips transformation and quantization. Besides H.264, JPEG 2000 is also widely used for medical image compression.

Instead of block based encoding of images as seen in H.264, JPEG 2000 partitions the original medical image into rectangular non-overlapping tiles, which are independently compressed into distinct images. Each tile component are applied DC level shift by subtracting the sample values with 2^{p-1} precision quantity (p is precision). The tiles may undergo either irreversible or reversible forward discrete wavelet transformation (DWT) that may be used for lossy and lossless coding. DWT is used to transform the tile component into different transform levels that is sub-bands with coefficient describing the direction of spatial frequency characteristics of the original tile component. Transformed tiles are quantized using scalar quantization resulting into loss of precision. Quantization is normally used for lossy encoding. The binary symbols of Quantized tiles undergo arithmetic coding (entropy) wherein the symbols are compressed into 18 different coding symbols. [9][10].

The main structure of HEVC is similar to H.264 as both of them include spatial and temporal prediction, transform, quantization and entropy coding. However, HEVC achieves significant compression gains over H.264 and J2K due to refinement in its coding tools such as more prediction modes for luma and chroma components and larger range of block sizes. HEVC dynamically divides the picture into coding units (CU) and supports a wide range of Coding Unit (CU) sizes, such as Prediction Units (PU) ranging from 4x4 to 64x64 pixels and Transform Units (TU) ranging from 4x4 to 32x32 pixels. HEVC uses 33 angular directional intra prediction modes plus planar and DC and provides improved Intra compression performance. In case of J2K, each tile component are applied DC level shift by subtracting the sample values with 2^{p-1} precision quantity (p is precision). This HEVC coding tools results better match of prediction blocks during intra and/or inter prediction. HEVC [3] supports lossless compression mode up to Coding Unit (CU) level. The HEVC main profile bypasses the process of transform, quantization, and in-loop filtering in order to achieve lossless compression. In the lossless mode, HEVC still uses Inter prediction, Entropy coding and Intra prediction to exploit temporal, statistical and spatial redundancies. Due to new coding tools and approach, it's meaningful to compare the performance of HEVC with

TABLE I
ACCEPTABLE IRREVERSIBLE COMPRESSION RATIO RANGE ESTABLISHED BY KOFF ET AL. FOR JPEG & J2K [5]

Anatomical Region / Modality	CR/DR (Cr)	CT (Cr)	US (Cr)	MR (Cr)
Body	20-30	JPEG-10-15 J2K 10	8-12	16-24
Chest	20-30	10-15	-	-
Neuro	-	JPEG 8-12 J2K 8	-	16-24
Breast	-	-	-	16-24

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other widely used image coding method such as J2K.

In reference to medical image compression, prior work evaluates the compression performance of 8-10 bit medical images [11], [12] and HEVC Main Still Picture Profile was used for encoding [12] whereas this paper evaluates the use of HEVC Range Extension Profiles, which support YUV format 4:0:0 and compression of high bit depth images (10+ bpp). Zhou *et al*. reported that HEVC lossless coding can reduce the bitrate by up to 13% in comparison to near-lossless coding of HEVC using a quantization parameter of 0 [11]. Sanchez *et al*. had compared the performance of HEVC lossless compression of medical images with their proposed sample wise differential pulse code modulation method and achieved bit-rate savings up to 15% [12]. The Image dataset used for their study consisted of images of DICOM modalities such as Magnetic Resonance (MR), Computed Tomography (CT) and Angiography [12]. Panayides *et al*. evaluated the compression performance of HEVC with MPEG-2, H.263, MPEG-4, and H.264/AVC for ultrasound videos and showed HEVC gains as much as 33.2% compared to H.264/AVC and their Despeckle HEVC filter achieves bit-rate savings of 43.6% compared to standard nonfiltered HEVC [13]. Koff *et al*. studied irreversible compression of medical images and established a diagnostically acceptable irreversible compression ratio (ICR) range of JPEG & J2K for medical images of various modalities and body parts [5]. Table I shows the compression range limits established by Koff *et al*. for medical images of commonly used modalities such as Computed Radiography (CR), Computed Tomography (CT), Ultrasound (US) and Magnetic Resonance (MR) [5]. The study shows that acceptable J2K ICR range varies by image modality and anatomical body part.

HEVC intra coding tools achieves greater compression efficiency [6], [11]-[13] but it comes with higher computational cost [7]. Hence the second goal of this paper is to exploit the structure and similarity of medical images in order to reduce the Intra HEVC coding complexity. Methods for complexity reduction come at a cost of reduced compression efficiency and the goal is to minimize such cost. Wang *et al*. show average of 54% saving in encoding time for HEVC test sequences with RD performance loss of 1.0% in all Intra High Profile compared with HEVC reference software 10 [14]. Correa *et al*. had earlier studied HEVC encoding decision using data mining for HEVC test sequences and showed Computation Complexity Reductions (CCR) of 50% at a cost of 0.56% in terms of Bjontegaard Delta (BD) rate [15]. Ruiz *et al*. proposed fast partitioning algorithm for HEVC Intra frame coding using machine learning, which show gains up to 30% with negligible loss of coding efficiency [16]. All the above mentioned studies on complexity reduction were carried out for standard 8 bits per pixel HEVC test sequences and HM 10.0 was mainly used for the study. The second goal of this paper is complexity reduction for high bit-depth medical images. The proposed model for computational complexity reduction is evaluated for medical images of more DICOM modalities and body parts.

While we know that HEVC offers better compression performance than J2K, we do not know what level of HEVC compression could be diagnostically acceptable. We answer this question by using the established ICR bounds of J2K images. The first part of the paper discusses the evaluation of HEVC ICR bounds with a widely used medical image coding standard that is J2K. We compare with J2K because diagnostically acceptable ICR bounds of 10 and 12-bit J2K images are readily available for comparison [5].

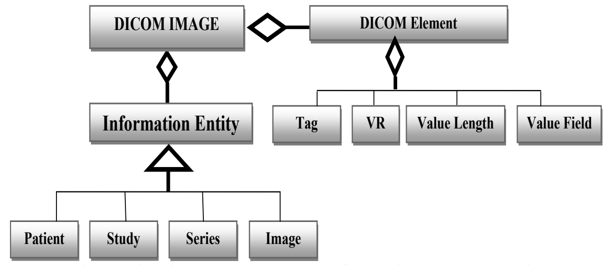

Fig. 1. Relationship between DICOM Information Entities and Elements

III. HEVC BOUNDS FOR MEDICALLY ACCEPTABLE IRREVERSIBLE COMPRESSION

A. DICOM standard and Medical Image Dataset

The Medical images used in this study were DICOM images. DICOM is a medical imaging standard which enables interoperability between heterogeneous medical applications and devices [1]. The core part of the standard includes information entities, modules, file format, and a networking protocol. A DICOM medical image file normally contains medical image data and meta data included as Information Entities (IE) describing attributes such as patient, study, series, and image [1]. IE is an aggregation of several DICOM elements or DICOM attributes. Each DICOM element is an aggregation of four fields: a tag, a data type called value representation (VR), value length, and the value field. The relationship diagram depicting the association between DICOM objects is shown in Fig. 1. A DICOM tag is made up of group and element number fields; for example, the tag with group number 0028 is an image pixel group. These group tags are used to obtain the image configuration information that is

TABLE II
DICOM IMAGE PIXEL GROUP TAGS

DICOM Image Tags	Description
Samples per pixel (0028,0002)	Number of color channels.
Photometric interpretation (0028,0004)	Monochrome1 / Monochrome2. Defines whether zeroes be interpreted as black or white.
Planar configuration (0028,0006)	Shows how color channels are arranged in the pixel data buffer.
Bits Allocated (0028,0100)	Defines how much space in bits is allocated in the buffer for every sample.
Bits Stored (0028, 0101)	Defines how many of the bits allocated are actually used.
High Bit (0028, 0102)	Defines how the bits stored are aligned inside the bits allocated.
Number of Frames (0028,0008)	Defines the total no. of frames in the image.

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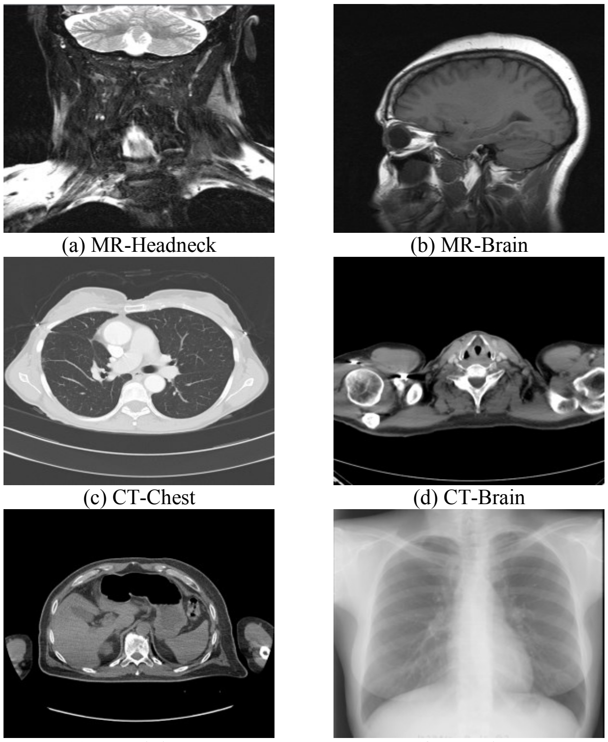

(a) MR-Headneck (b) MR-Brain (c) CT-Chest (d) CT-Brain (e) CT-Abdomen (f) CR-Chest

Fig. 2. Sample medical images of various DICOM modalities and body parts used in this study.

required for image compression. A few commonly used image pixel group tags are defined in Table II.

This study used publicly available and de-identified medical DICOM [17], [18]. The images used in this experiment are of three modalities: Magnetic Resonance Imaging (MR), Computed Tomography (CT) and, Computed Radiography (CR). The data set covered five anatomical body parts: abdomen, brain, breast, chest and Headneck. Out of the images used in the study, MR-Headneck (wherein "MR" represents Modality and Headneck represents the body part), MR-Brain, MR-Breast, CT-Chest, CT-Brain, and CT-Abdomen are image series whereas CR-Chest image has a single image. The DICOM images are grayscale images with 10-12 bpp depth. Images selected for this study are of 10-12 bpp because our method for establishing HEVC ICR bounds relies on J2K ICR bounds established by Koff *et al* for 10-12 bpp images [5]. Sample images from the data set are shown in

TABLE III
DICOM MODALITY AND ANATOMICAL BODY PARTS OF THE MEDICAL IMAGES USED IN THIS EXPERIMENT

BODY PART / DICOM MODALITY	ABDOMEN	BRAIN	BREAST	CHEST	HEAD NECK
Computed Tomography (CT)	X	X	-	X	-
Computed Radiography (CR)	-	-	-	X	-
Magnetic Resonance Imaging (MR)	-	X	X	-	X

'X' indicates that the image modality + body part combination was used for the study

Fig. 2. The images used in this study were of similar modality as used by Koff *et al*. [5]. The combination of modality and body part of images used in this experiment are shown as cross marked in Table III.

B. *Bounds for Irreversible Compression*

Koff *et al*. carried out diagnostic accuracy assessments with radiologists using the Just Noticeable Difference (JND) technique, to establish the Irreversible compression ranges acceptable for medical diagnosis [5]. These ICR ranges are shown in Table. I. In this study, the J2K compression ratios which fall within the irreversible compression range established by Koff *et al*. are used to establish the compression comparison with HEVC [5] and the irreversible compression performance of J2K and HEVC are compared for equivalent quality, measured using Structural Similarity Index (SSIM) and Peak Signal to Noise Ratio (PSNR). Razaak *et al*. evaluated the performance of seven video quality metrics for HEVC compressed ultrasound video sequences and found that structural similarity index metrics show good correlation with the subjective evaluation done by medical experts [19]. Hence the quality equivalence between J2K and HEVC was established on the basis of equivalent SSIM and PSNR [5], [19]. The study presented in this paper establishes an irreversible compression range for medical images compressed using HEVC-Intra and Inter coding modes.

C. *Method*

The compression method comprises of two processes (i) image format conversion and (ii) image compression. Firstly, the ImageJ [20] tool was used to convert DICOM image series into raw medical images (YUV (4:0:0) format). The irreversible J2K compression was carried out for these medical images using ffmpeg [21]. The compression level flag was varied from 0 to 30 in order to match the compression ratios with the ones established by Koff *et al*. Secondly, to compare the HEVC compression performance with J2K, HEVC HM reference software 16.6 was used to carry out HEVC encoding in intra and inter modes [22].

For intra encoding, high-throughput-RExt profile was used and "Intraperiod" encoder parameter was set to 1. In this case, all the frames were encoded as Intra (I) frames. HEVC Inter coding was used to evaluate the benefits of temporal predictive coding for medical image series, which is not supported in Motion JPEG and J2K. For inter encoding, main-RExt profile was used and the "Intraperiod" parameter was set to -1. This configuration results in the first frame being

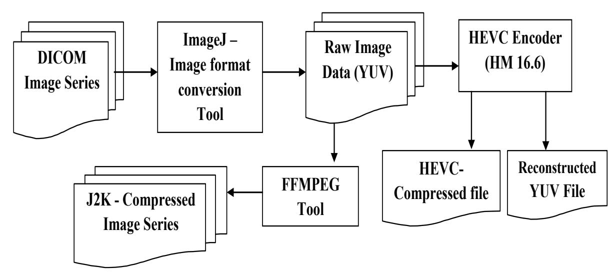

Fig. 3 Overview of the proposed method

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encoded as an I-frame and the remaining coded as bi-directionally predicted B-frames. The HEVC lossy encoding of high bit depth medical images was carried out by varying the quantization parameter, in order to match the PSNR and SSIM values of HEVC with J2K. The above mentioned experimental method is depicted in Fig. 3.

IV. RESULTS

The irreversible compression ratio (ICR) plots of HEVC-Intra and Inter encoding of medical images of various modalities and body parts are shown in Fig.4-7. The figures show quality (PSNR or SSIM) values plotted on Y axis and compression ratio on X axis. Each figure shows quality vs. compression ratio plots for J2K and HEVC encoding of medical images. These plots show how the HEVC ICR is derived for a given J2K ICR limit using PSNR and SSIM as measures of equivalent quality. Fig. 4 and 5 show the mapping between ICR of HEVC-Intra and J2K for equivalent PSNR and SSIM quality for medical images of various modality and body parts whereas Fig. 6 and 7 shows same for HEVC-Inter and J2K. The title of each graph represents image and the graph related properties. As for example, the title of the 1st graph shown in Fig. 5 is "MR HeadNeck-3 / J2K - HEVC Intra / Cr - Mean SSIM / f-26 / 336 x 384 / 12 bpp ," wherein "MR HeadNeck" means image modality and body part examined, "J2K–HEVC Intra" represents the two variables, for which data points are plotted in the graph, "Cr–Mean SSIM" represents the titles of X and Y axis, "f-26" represents the total no of frames in the image series, "336 x 384" is the image resolution in pixels and "12 bpp" is image bit depth.

The HEVC ICR range, its corresponding mean QP search range along with standard deviation and space savings is shown in Table IV and V for the test images of specific modality-body part. The HEVC ICR range for each image modality and body part was computed by taking the longest common sub sequence of compression ratios across all related test images grouped by the same class (modality + body part).

As shown in Table IV, the ICR range of MR-Brain Modality shows the lowest compression ratio increased from 16 (J2K) to 29 (HEVC Intra- PSNR) and at the same time, the highest compression ratio also increased from 24(J2K) to 35 (HEVC Intra-PSNR). This example is shown in bold-italics in Table IV.

In comparison to the other images used in the experiment, for MR-Headneck the increase in ICR range in comparison to J2K for equivalent SSIM quality (shown in the fourth column of Table IV) is the lowest. One main reason for the low ICR increase in case of MR-Headneck images is due to presence of complex anatomical structural details in the image (refer Fig. 2a). In lossy mode, the encoding of this complex anatomical structure leads to a larger loss of structural information as indicated by lower SSIM. HEVC-Intra results show higher space savings in comparison to J2K for all modalities and the results are shown within parenthesis in 3rd and 4th column of Table IV. The space savings achieved is up-to 54% in case of PSNR and up to 50% for SSIM based results.

Similarly, Fig. 6 & 7 shows the correlation between ICR of HEVC-Inter and J2K for equivalent PSNR and SSIM values. As shown in Table V, for MR-Brain Modality, the lowest compression ratio for HEVC-Inter increased to 29 from 16 (J2K) and at the same time, the highest compression ratio also increased from 24 (J2K) to 33 (HEVC-Inter). HEVC-Inter shows increase in ICR in comparison to J2K for MR-Headneck, MR-Brain and CT-Abdomen images and the space saving results are shown within parenthesis in third and fourth column of Table V. The space savings achieved is up-to 51% in case of PSNR and up to 50% for SSIM based results.

For CT-Chest and CT-Brain modalities evaluated, the ICR correlation could not be established in absence of equivalent PSNR and SSIM quality points. The Third graph shown in fig. 6 depicts this scenario for CT-Chest sample. As shown in this plot, the acceptable J2K ICR range for CT-Chest is 10-15 Cr (plotted in yellow color) and the corresponding max and min PSNR is 63.67 and 60.28 dB, Moreover for these PSNR quality points, HEVC–Inter has no equivalent PSNR points, because the max PSNR is 59.45 dB and compression ratio is 23.29 (for QP = 0). Similar result was observed for SSIM, wherein the min and max SSIM for J2K is 0.78 & 0.92 (for 10-15 Cr) whereas HEVC-Inter yields max SSIM of 0.62 and

TABLE IV
PROPOSED HEVC-INTRA ICR RANGE, QP SEARCH RANGE AND SPACE SAVINGS FOR HIGH BIT DEPTH MEDICAL IMAGES.

DICOM Modality - Body Part examined	ICR range of J2K (Koff et el[5])	HEVC-Intra ICR , derived on basis of equal PSNR quality [QP search range ± SD] (related % decrease in file size)	HEVC-Intra ICR , derived on basis of equal SSIM quality [QP search range ± SD] (related % decrease in file size)
MR-Headneck	16-24	26 – 30 [10-14 ± 4] (38 - 47)	18 – 27 [8-12 ± 6] (9 - 40)
MR-Brain	***16-24***	***29-35*** [13-18 ±2] ***(45-54)***	***29-32*** [14-17 ± 4] ***(45 to 50)***
CT-Abdomen	10	13 [4 ± 1] (23)	12 [4 ± 1] (17)
CT-Chest	10-15	16 – 18[5-8 ± 8] (38 – 44)	15 – 18 [5-7 ± 8] (33 – 44)
CT-Brain	8-12	11 – 14[5-9 ± 8] (27 – 43)	12 – 14 [5-9 ± 9] (33 – 43)
CR-Chest	20-30	27 – 38 [8-11 ±1] (26 – 47)	26- 34 [8-10 ± 1] (23 – 41)

TABLE V
PROPOSED HEVC-INTER ICR RANGE, QP SEARCH RANGE AND SPACE SAVINGS FOR HIGH BIT DEPTH MEDICAL IMAGES.

DICOM Modality - Body Part examined	ICR range of J2K (Koff et el[5])	HEVC-Inter ICR , derived on basis of equal PSNR quality [QP search range ± SD] (related % decrease in file size)	HEVC-Inter ICR , derived on basis of equal SSIM quality [QP search range ± SD] (related % decrease in file size)
MR-Headneck	16-24	26 to 30 [7-11 ± 5] (38 - 47)	17 to 28 [8-12 ± 3] (6 to 42)
MR-Brain	***16-24***	***29-33 [11-15 ± 2] (44 to 51)***	***29-32 [10-14 ± 3] (44 to 50)***
CT-Abdomen	10	13 [1 ± 1] (23)	12 [1 ± 1] (17)

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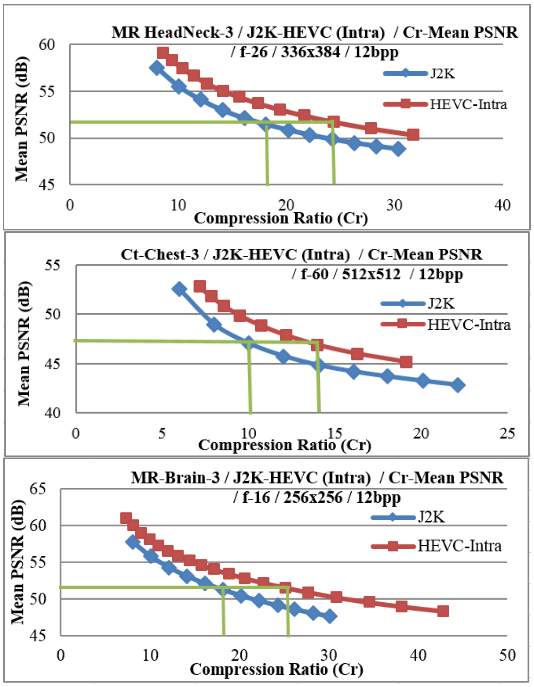

Fig. 4 Graphs of medical images of various modalities showing ICR correlation between HEVC-Intra and J2K for equivalent PSNR quality.

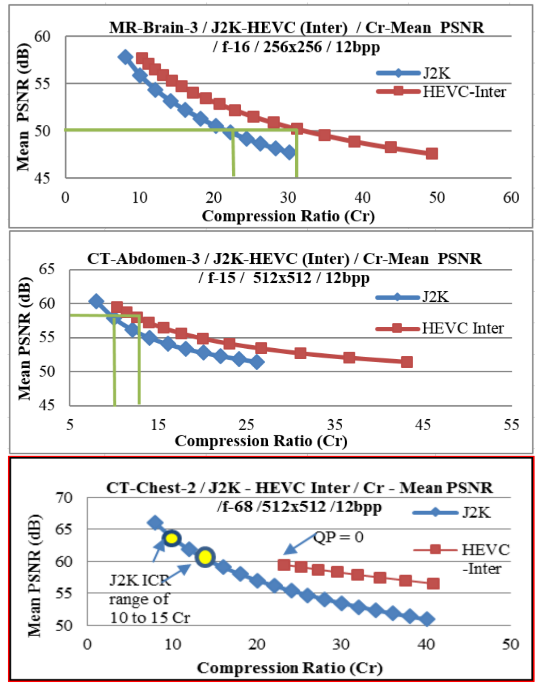

Fig. 6 Graphs of medical images of various modalities showing ICR correlation between HEVC-Inter and J2K for equivalent PSNR quality.

Min Cr of 23.29 (for QP =0). Thus, for acceptable ICR range of J2K, the corresponding min PSNR and SSIM is greater than max PSNR and SSIM of HEVC-Inter. Similar result was observed for ¾ of CT-Chest & Brain samples. Hence for CT-Chest & Brain samples, HEVC-Inter compress more but at cost of acceptable quality.

The HEVC compression benefit comes with a cost. The higher computational complexity of HEVC increases the encoding time. The predictable structure of medical images can also be exploited to reduce encoding complexity. The

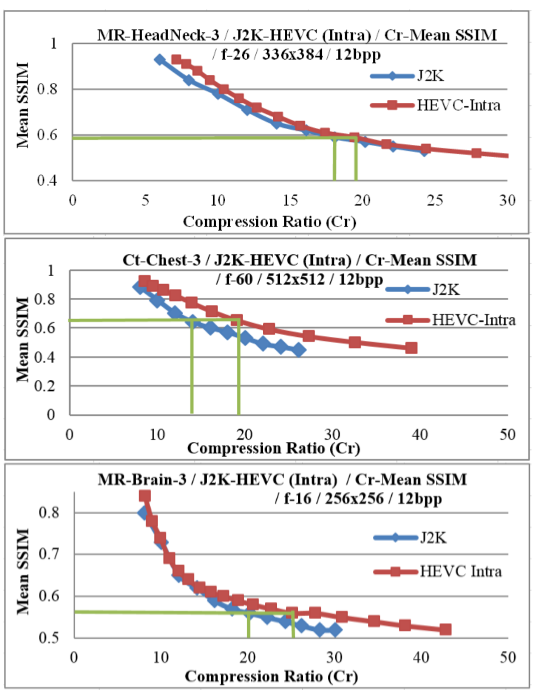

Fig. 5 Graphs of medical images of various modalities showing ICR correlation between HEVC-Intra and J2K for equivalent SSIM quality

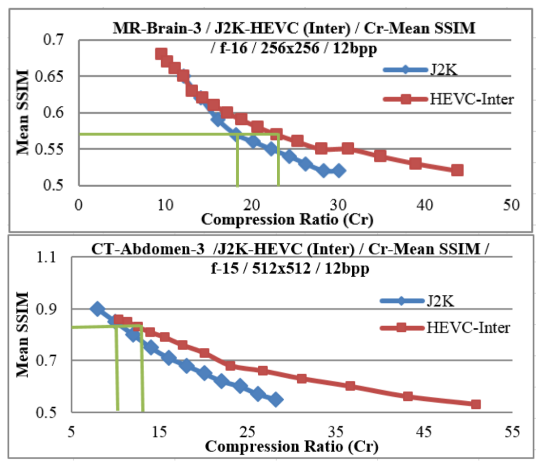

Fig. 7 Graphs of medical images of various modalities showing ICR correlation between HEVC-Inter and J2K for equivalent SSIM quality.

second part of this paper presents a method for computational complexity reduction of HEVC intra coding for medical images. Preliminary results from this approach were reported in [7]. The following section presents the CCR method and its performance for medical images of several modalities and body parts.

V. HEVC INTRA ENCODING COMPLEXITY REDUCTION FOR MEDICAL IMAGES

The second part of this study evaluates the performance of the proposed Computational Complexity Reduction (CCR) model for lossless-HEVC-intra encoding of medical images of various modalities. The objective of this work is to study whether the structure and content of medical images can be used to reduce encoding complexity. Another objective is to maximize complexity reduction while minimizing file size

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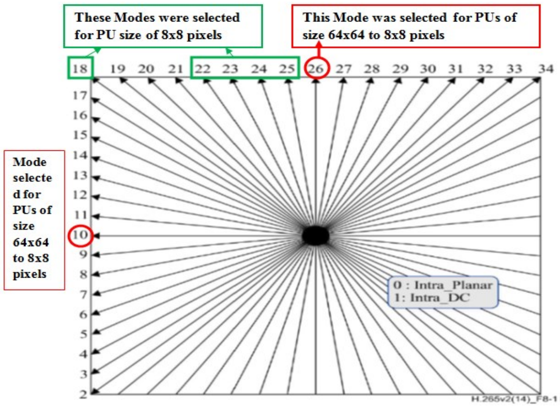

Fig. 8. Set of Angular Directional Intra Prediction modes that were selected for 95% times [4].

increase. The CCR model limits the HEVC coding tree depth and reduces the number of angular directional intra prediction modes evaluated during Rate Distortion (RD) optimization. The CCR model was trained with medical images of CR-chest modality [7] and is tested with images of different modality and body part as listed in Table III. These medical images are popularly used in related research [17], [18].

A. HEVC Coding features contributing to increase Computational Complexity.

HEVC compression gains in Intra coding are due to coding features such as (i) Higher Coding tree Depth, wherein each image (frame) is divided into coding units (CU) of various sizes. The size of these CUs can range from 64x64 to 8x8 pixels, (ii) use of large number of directional predictors, (iii) and use of variable size prediction units (PU) and transform units (TU), also enables a better match for prediction and transform of CUs. Furthermore, the size of a PU can also vary from 64 x 64 to 4 x 4 pixels in order to find a better PU match during prediction and TU size can vary from 32x32 to 4x4 pixels for efficient transformation of CU. For Intra prediction, there are 2 symmetric PU modes: 2N x 2N and NxN whereas for inter prediction, there are 8 asymmetric PU modes. The splitting of PU during intra or inter prediction is performed, when splitting results in better prediction and smaller residual. HEVC supports 33 angular directional intra prediction modes plus Planar and DC for reducing spatial redundancies by finding an optimal prediction match. In comparison to H.264, use of a large number of HEVC angular directional intra prediction modes results in increased computational complexity, as all these modes will be evaluated during RD optimization [2] [3]. Fig. 8 shows the 33 (modes 2 to 34) angular directional intra prediction modes, which may be evaluated during Intra prediction.

B. HEVC Intra Prediction

The HEVC intra prediction process is mainly divided into Rough Mode Decision (RMD) and Rate Distortion optimization. The full 35 Intra prediction modes are evaluated as a part of RMD and a set of 3 – 8 modes with lower Rate Distortion cost are selected for further evaluation. The optimal intra prediction mode and optimal PU size are determined in

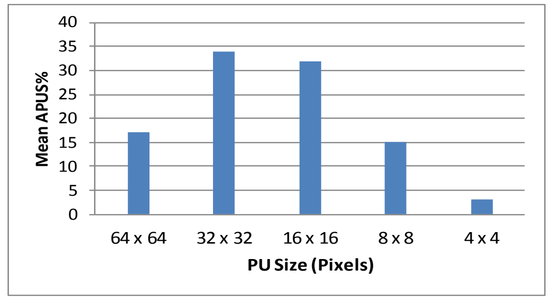

Fig. 9. Stage-I result: mean APUS% of each PU size across all CR-Chest training images [7]

the following stage. CU splitting and intra prediction mode selection is completely content dependent and is dynamically computed during runtime. Given that most commonly used medical images are grayscale with soft texture and less complex structural details, splitting of CU into smaller partitions may not be required. At the same time, evaluation of all 33 angular directional intra prediction modes may also not be required during intra prediction.

C. Computational Complexity Reduction Method

During Training phase the CCR experiment was divided into three stages. In Stage-I, the largest coding tree depth was determined for the training image set which included medical images of chest recorded in CR modality. A bound on the coding tree depth was determined by selecting the subset of PU sizes which cover at least 95% of the image area. Thereafter in Stage-II, for each PU size, a subset of angular directional intra prediction modes was selected. The angular directional intra prediction modes selected were the ones used for intra prediction in at least 95% of PUs of a given size. Finally, in Stage-III, the reduced depth and prediction modes established in the first two stages were implemented in an HEVC encoder (CCR-HEVC). The baseline complexity for performance comparison was obtained using the default HM reference software 16.4 [22]. The CCR results obtained by using the CCR-HEVC encoder during training phase, showed an average of 52.47% reduction in encoding time with a negligible penalty up to 0.22% in terms of increase in file size [7]. The CCR method is described as follows:

During Stage-I, the minimum subset of PU sizes, was found, which covers at least 95% of the image area (APUS %). The HEVC encoding was configured with RMD enabled and all the 33 angular directional intra prediction modes plus planar and DC were also enabled. After encoding the training images (CR-Chest images), the mean of the total pixel area for each PU size (APUS %) was computed among all training images. The Threshold Th_{apus} was set to 5% in order to eliminate the least used PU size. As shown in Fig. 9, PU size of 4x4 was least used (APUS% < Th_{apus}) and at the same time the pixel area jointly covered by all other PU sizes is greater than 95%. Therefore the coding tree depth was limited at PU size of 8x8 pixels. A part from these results, during Stage-I, the best angular directional intra prediction mode used for prediction of each PU was also noted [7].

During Stage-II, RMD was disabled and RD Optimization

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TABLE VI
MAXIMAL SET OF ANGULAR DIRECTIONAL INTRA PREDICTION MODES FOUND DURING STAGE-II OF TRAINING PHASE

PU Size	Maximal set of angular directional intra prediction modes found during Stage-II (Training phase)
64x64	{10, 26}
32x32	{10, 26}
16x16	{0, 10, 26}
8x8	{0,1,10,18,22,23,24,25,26}

was run with all 33 modes + planar and DC. This exhaustive mode selection was carried out in order to find the best angular directional intra prediction mode for each PU. The mode data was used to determine the total usage of each angular directional intra prediction mode for all selected PU sizes. In the final step, for each PU size (selected during stage-I), the subset of angular directional intra prediction modes was selected, whose total combined usage was greater than Th_{adp}. The threshold Th_{adp} was set to 95% for the experiment. The results show that for large PU sizes (64x64, 32x32, 16x16), horizontal and vertical modes (10 and 26 as shown in Fig. 8) were selected for 95% of PUs whereas for 8x8 PU sizes; five additional vertical modes {18, 22, 23, 24, 25} (shown in Fig. 8) were also selected. This subset of angular directional intra prediction modes selected for each PU size during stage-II is shown in Table VI and these modes are circled in Fig. 8. The content of medical images is thus shown to reduce the number of angular directional intra prediction modes necessary for efficient compression.

The CCR-HEVC encoder was built on the basis of the PU size and angular directional intra prediction modes selected during Stage I and II. The CCR model was developed using mode training data from CR-Chest images and the results showed up to 52% reduction in encoding time with a negligible penalty of 0.22% increase in file size [7].

During testing phase, the CCR-HEVC encoder was evaluated for the medical image modalities and body parts as shown in Table III. The baseline results acquired by using default HEVC lossless encoder HM 16.4 were compared with the CCR results for these images. The experiment was run 2 times in lossless-Intra mode. The mean results of two runs shows up to 55% reduction in encoding time with negligible increase in compressed file size.

VI. RESULTS

The results for the computational complexity reduction experiment are shown in Table. VII. This table shows the mean % reduction in HEVC-Intra encoding time and resultant mean % increase in the compressed file size for medical images of various modality + body part. These CCR results acquired for each image modality and body part is compared with the baseline results, which was acquired by running the experiment using the default HEVC encoder. The Δ value between CCR and baseline results shows that encoding time reduces up to 55% with a penalty of up to 1.18% in terms of increase in compressed file size.

TABLE VII
CCR RESULTS FOR LOSSLESS HEVC –INTRA ENCODING OF MEDICAL IMAGES OF VARIOUS MODALITIES

DICOM Modality - Body Part examined	mean % reduction in encoding time (%)	mean % increase in compressed file size (%)
MR-Head-Neck	51.195	0.533
MR-Brain	52.146	0.583
MR-Breast	55.145	0.249
CT-Abdomen	53.035	0.655
CT-Chest	50.938	1.176
CT-Brain	50.915	0.784
CR-Chest	51.314	0.113

VII. OBSERVATION

HEVC ICR bounds : The results for the irreversible compression experiments shown in Fig. 4 to 7, clearly demonstrates increase in ICR range for all modalities in case of HEVC-Intra and for three modalities in case of HEVC-Inter. As shown in Table IV, for HEVC-Intra, on basis of PSNR quality all image modalities shows higher % reduction in file size and space saving up to 54% is measured for MR-Brain and lowest gains of 23% is measured for CT-Abdomen. Similarly for HEVC-Inter ICR results, MR-Brain shows highest % reduction in file size up to 50% and CT-Abdomen shows lowest % reduction in file size that is up to 17%. For all selected image modalities the ICR range extends over J2K for equivalent PSNR and SSIM quality. These results for HEVC-Intra are shown in Table IV whereas for HEVC- Inter, it is listed in Table V. The QP parameter with standard deviation recommended in Table IV and V may enable researchers to obtain a starting point to generate medically acceptable irreversible compression ratio within the recommended bounds and may speed up the compression process additionally.

CCR experiment results for test set of medical images are shown in Table VII. Medical test images of MR,CT,CR modalities shows similar gains in terms of reduction in encoding time as observed for training images and the gain varies from 55% for MR-Breast images to 51% for CT-Brain images. The penalty in terms of increase in file size is less than 1% for all image modalities and body part combination except for CT-Chest which shows penalty above 1%.

VIII. CONCLUSION

The study shows that using HEVC for medical image compression can reduce storage and bandwidth needs by up to 54% compared in comparison to J2K. The evaluation was limited to the diagnostically acceptable compression ranges established in prior studies. Even HEVC-Inter shows similar gains in terms of % reduction in file size. The ICR bounds established for HEVC are based on equivalent objective metrics and subjective assessments are necessary to determine subjective equivalence for the same objective distortion. The study also developed a method for computational complexity reduction in lossless Intra HEVC compression. Results show 55% reduction in computational complexity with negligible increase in file size. Using such complexity reduction

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approaches reduces the cost of HEVC encoding while retaining the compression benefits.

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