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Medical Image Compression based on ROI using Integer Wavelet Transform

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Abstract— Medical imaging refers to techniques and processes used to create images of various parts of the human body for diagnostic and treatment purposes within digital health. With the increased use of digital images in clinical settings, it has become necessary to use various compression methods, both lossless and lossy, in order to reduce their cost of storage or transmission. While lossy compression alternatives allow high compression rates, there are legal limitations that such images including MRI, ultrasound, X-Ray and CT-Scan should be stored in a format without loss of information. This work proposes a digital image compression mechanism compatible with the Digital Imaging and Communications in Medicine (DICOM) standard that takes advantage of the IDWT capabilities to preserve the diagnostic quality of the regions of interest, through lossless encoding, while the rest of the image, composed of zones less relevant, is compressed with for JPEG compression. The results, in terms of Compression Ratio, MSE and PSNR are found to be quite satisfactory both quantitatively and qualitatively.

Keywords- *Compression, JPEG, ROI, Wavelet Transform, Segmentation, DICOM, PSNR.*

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I. INTRODUCTION

In the area of medicine, large volumes of information are generated annually through the acquisition of digital images, such as Computed Tomography (CT) or Magnetic Resonance Imaging (MRI), among others. Due to the growing trend towards image digitization and filmless removal within medical institutions, image compression becomes a key aspect of image storage and communication systems (known as PACS, by Picture Archiving and Communication Systems) and for teleradiology or telemedicine, among other applications.

In the particular case of the Argentine legislation, according to the law 26,529 art. 18, "patients' rights in their relationship with health professionals and institutions" establish custody for a minimum period of 10 years, "this term is computed from the last performance recorded in the medical history and expired the same, depositary shall dispose of it in the manner and manner determined by the regulations. "[1]. This information about the studies of a patient should be stored properly and also remain online at all times, since physicians need to be able to access them easily from anywhere to diagnose and analyze the evolution of any pathology.

Although there is currently no legislation that establishes standards for medical image compression, health institutions often resort to the use of lossy compression algorithms for the storage of already diagnosed studies in order to reduce their storage space.

Several technological initiatives have been proposed to optimize the handling of this information, such as the design of new compression standards, or the development of DICOM (Digital Imaging and Communicating Medicine), as a standard for the transmission and storage of medical images [2-3].

In the present work we analyze these techniques as a whole and propose the development of a solution that allows incorporating the benefits of each one of them and their most recent extensions. It presents a storage mechanism compatible with the DICOM standard that takes advantage of the capabilities of the IDWT standard to introduce a Region of Interest (ROI), allowing lossless compression of the area of greatest diagnostic importance within the image and with a loss moderate the remaining region.

A. Characteristics of Medical Image Compression

Commonly used digital modalities (such as MRI, CT, computerized radiographs, mammograms, etc.) may require a high cost of storage and infrastructure. For this reason, these types of images become ideal candidates for compression, in order to improve the utilization of existing resources and increase the capacity of transmission through the network used. Some of these modalities, due to their volumetric characteristics, have a certain similarity between the successive cuts or cross sections that compose each study, similarly to what happens between frames of a video, as well as color properties (gray scale, high contrast), number of homogeneous zones and secondary information (context). These characteristics can be exploited in search of compression mechanisms especially suitable for this type of images, without danger of affecting the diagnostic capacity [4].

Compression techniques are based on reducing the redundancy present in the data. Typically, a lossless compression algorithm can achieve compression factors of no more than 2: 1, on average. If it is desired to increase the compression rate, then it will be necessary to apply techniques that exploit even more the spatial (intraframe redundancy) and temporal (interframe redundancy) characteristics of the images with volumetric characteristics [5]. Another strategy with great compression potential is based on the definition of an ROI, so that the area of the image belonging to such a region can be compressed using a lossless algorithm in order to recover the original data without alteration and the external area to through a lossy or irreversible algorithm, which can equally achieve results with visually indistinguishable quality decrease.

The MJ2 format is based on efficiency of the JPEG 2000 still image compression algorithm and consists of one or more image sequences compressed individually by said encoder

(intraframe coding), allowing random access to any frame and reducing the complexity of the algorithm. This method is mainly used in environments where scalability, high quality, lossless compression and fault tolerance are needed [6].

B. Characteristics of the DICOM Standard

The DICOM format is a standard created by the National Electrical Manufacturers Association for the handling, transmission, storage and printing of digital medical images [7]. This format also defines which algorithms can be used for image compression, as well as the way in which each one must be parameterized according to the type of image to be stored (if loss is allowed, ROI, etc.).

The original definition of DICOM consists of 16 parts [8]. Among its definitions, part 10 is the most interesting in this work, since it includes both a communication protocol and a file format.

Typically, DICOM files consist of a header (which stores patient data, methodology used, image dimensions, among others) and its contents (which may have one or more data elements). The data in the file can be compressed in order to reduce its size. Compressed images can be generated using an algorithm without loss or variants with loss of techniques known as JPEG or Run Length Encoding, among others. The compression format is indicated by the Transfer Syntax Unique Identification attribute. This value not only describes the structure of the data, but also the order in which the bytes are to be interpreted. For example, they can be read in Little Endian or Big Endian format. In order to ensure compatibility with the standard and with other systems already established, it is desirable that the compression algorithms used be supported by DICOM.

C. Developed Compression Tool

The objective of this work is to provide a tool through which it is possible to create DICOM files for the storage of MRI, CT and other monochrome modalities, parameterizing those attributes that have effect on the compression. These attributes may be common to all techniques used, for example the number of bits transmitted per bitrate of the resulting or particular images of the strategy such as the number of frames per second for MPEG-4 compression , percentage of loss out of ROI for JPEG-2000, among others.

With respect to the definition of an ROI, it can be specified through a set of coordinates or as a binary mask of the same size as the image. If not supplied, the images are completely compressed without loss. There are three alternatives to ROI coding: Tiling, CodeBlock Selection and Coefficient Scaling (called the Maxshift algorithm in the JPEG-2000 standard) [9]. For simplicity reasons, it was decided to restrict the definition of ROI to rectangular binary masks. Therefore, implementation was developed using the Code Block Selection method, which is more efficient for this type of regions. This is because the definition, by means of different geometric or curvilinear forms, requires the division into small blocks and can render the coding inefficient, since a discrete wavelet transform (DWT) process is applied to each one of them.

The rest of the paper is arranged as follows. The image compression techniques are discussed in section II wile the proposed methodology has been introduced in section III. The simulations and results are presented in section IV while the conclusion is given in section V.

II. IMAGE COMPRESSION TECHNIQUES

The compression techniques can be grouped into two large classes: a) Compression techniques without loss of information and b) Compression techniques with loss of information. In the first class, the compressed images are regenerated without errors, that is, they are the same as the original. However, in the second, the reconstructed images are more or less different from the original image.

In each classification there are strategies or compression algorithms that stand out, which are presented in the following subsections along with their characteristics.

I. Techniques of image compression without loss of information

In this classification, images are considered to be based on entropy, a technique that encodes the data without needing to know the nature of these, are general purpose and where the reconstructed image is exactly the same as the original image. These techniques are notable because they employ statistical methods, based on Shannon's theory that allows lossless compression. Some of these techniques are: Run-length encoding (RLE)[10], Huffman coding, arithmetic coding and Lempel-Ziv[11].

II. Image compression techniques with loss of information

In this classification, the reconstructed image or sequence is more or less different from the original image. They are used mainly when the images have redundant information that can be removed or reduced, for example, the color of the sky in a photo is usually uniform and blue. In these techniques, it is sometimes also interesting to code the brightness level of a sample (luminance or component Y) and the color differences (blue, red and green chrominances, or components C_b, C_r, C_g).

The reduction is done using source encoding techniques [12], which encode the data based on the characteristics and properties of their images, allow high compression rates and are generally for specific purposes. Some techniques that stand out are: 1) Codification by transformation, 2) Quantization Vector and 3) Fractal Compression.

III. PROPOSED METHODOLOGY

The proposed work can be obtained by integer wavelet transform followed by JPEG algorithm. Fig. 1 shows the general architecture of the proposed system.

The proposed image compression and reconstruction architecture addressed in this paper involves the following steps.

1. Load the Medical image as input.

2. Using a Global thresholding method, apply threshold to remove background i.e. the ROI & Non-ROI regions are separated from background (BG)
3. Select ROI, and separate out ROI and Non-ROI.
4. ROI region is encoded using IWT with high bpp.
5. Non-ROI region is encoded using JPEG compression with low bpp.
6. Merge the two encoded regions (ROI and Non-ROI) to get the ROI based compressed image.

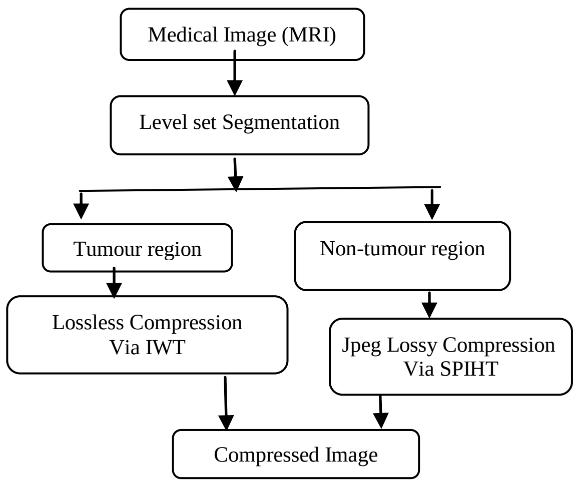

Fig. 1. Flowchart for proposed work

7. To perform Non-ROI compression i.e. compression without any particular selection of region, apply SPIHT on the binary image, obtained in step (2).
8. Get the Non-ROI based compressed image.
9. Compare the quality of ROI based compressed image with Non-ROI based compressed image obtained in previous steps in terms of PSNR and compression ratio.
10. Repeat the same process to applying on more images.

A. Segmentation for ROI and NON-ROI

The first phase is to acquire the MRI image and then apply the pre-processing steps. There are various methods which come under this step; we will be dealing with only grey scale image and filters. Basically pre-processing is done to remove noise and blurring as well as a ringing effect in order to get the enhanced and much clear image for our purpose. The filter which has been used is a high pass filter. As the image samples are required for medical purpose, the high pass filter has to be passed with mask for better image. In order to achieve this, a Sobel operator is used.

1) Level Set Function

The Level Set Function [13] is used here to make the image under consideration robust towards noise condition, aptitude in extracting curved objects with complex topology and its clean numerical framework of multidimensional implementation. With the initialization of level function we generate the initial region of image as a rectangle. Level set evolution and object detection is further divided in three categories i.e. dilate marker, erode marker and Gradient Magnitude. The first two are subjected to the Morphological Reconstructions (Mask, Marker) from which binary image is extracted.

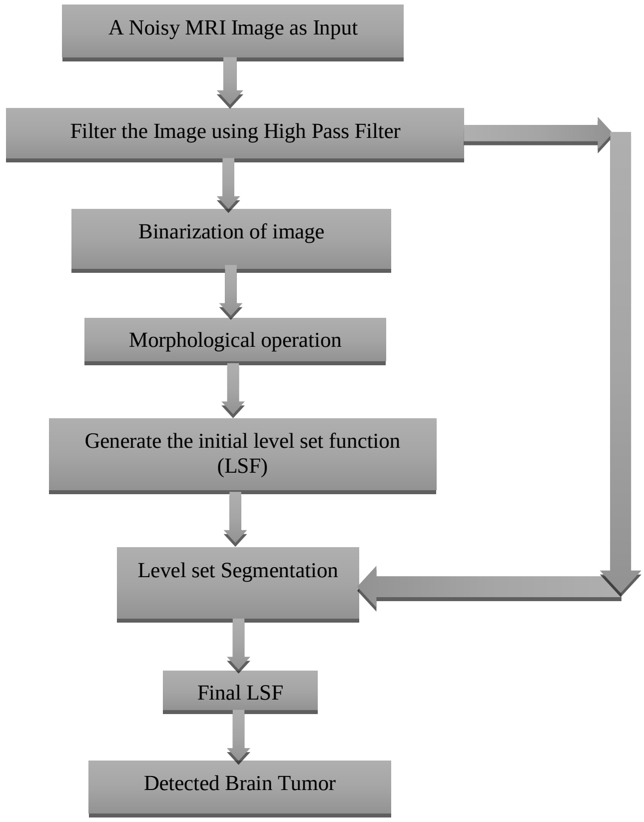

Fig. 2. Flow chart of segmentation for ROI

Algorithm:

1. Acquire image and convert it to gray (if it is not already) because operations (which are to be used) are not possible on RGB.
2. High Pass filter the gray scale image for noise removal.
3. Enhance image for intensity.
4. Convert enhanced image to binary image (tumor region will have high intensity so it would be binary 1 and other will binary 0 in binary image).
5. Perform morphological operations on binary image to remove unwanted regions and to identify tumors regions.
6. Detected regions are not fine-tuned due to morphological operations. Hence, we use the binary image as level set function and apply level set evolution on high pass filtered image. This will output the detected tumor in MRI brain image.

A compression algorithm of images using the Wavelet Transform is now discussed. The Wavelet transform is a convenient tool for multiresolution analysis of signals and in particular is naturally adjusted to the compression of images by adapting the required bandwidth automatically. This algorithm studies the characteristics of the images in shades of gray to exploit important aspects of the human visual system. The human eye is less sensitive to high spatial frequencies (edges of an image) than to low spatial frequencies (textures of an image). The method used consists in coding with few bits the coefficients representing high frequencies and with more bits the coefficients of low frequencies.

B. Compression of Images

One of the most widely used algorithms for image compression is JPEG. The algorithm divides the image into blocks of 8x8 pixels using in each one the Discrete Cosine Transformation (DCT). The disadvantage of this is that the

image compressed reveals the blocks and cannot take advantage of the correlation between blocks. A compression algorithm essentially consists of three steps: transformation, quantification, and coding.

1) Wavelet Transform

For the choice of a particular wavelet, the following properties:

- Compact support: Filters must be finite FIR.
- Rational coefficients: they allow to avoid the operations of floating point.
- Smoothness: if the wavelet is not smooth the error will be easy to detect visually.
- Length of filters: short filters are preferable, but there is a trade-off between these and the softness since it is proportional to the length of the filters.
- Quantification: One problem that impedes efficient coding is the fact that the coefficients of the transform can have arbitrary values. The purpose of quantification is to restrict the values of the coefficients to a limited number of possibilities.
- Coding: The coding step involves reversibly replacing the string of input symbols of the quantizer by a bit stream.

The two main categories are fixed length and variable length encoding. In a fixed length encoder each symbol is replaced with the same number of bits. It is therefore essential to use a good quantifier. An example is the Lloyd-Max algorithm. A more powerful variant uses variable-length encoding. The idea is to assign the shortest words to the most frequent symbols. Suppose a code word k_i has probability p_i with:

$$p_i \Sigma_i = 1 \tag{1}$$

The content of information or entropy is now given by H_{p_i} where, $i = -\Sigma \log 2$. And this is the theoretical minimum amount of bits required by code word. The problem is that H is not necessarily a natural number. Variable-length encoders (or entropic encoders) try to approach as much as possible to this minimum. The two most popular methods are Huffman and arithmetic coding. It should be borne in mind that these encoders are only optimal is the case where the probabilities pi are known. In practice one usually has to estimate p_i obviously, the position of the coefficients that were set to zero has to be coded as well. This can be done with Run Length coding, which is usually followed by entropic coding of the lengths of the runs.

2) JPEG Compression

JPEG stands for Joint Photographic Experts Group. JPEG is a committee of experts ISO / IEC and ITU-T, to share their experience and analyze the problem of digital image coding. This group has created several standards for image coding, the most recent being the JPEG2000 that is based on wavelet transformations, but this chapter will focus on the first one they developed and is commonly referred to as the acronym of the group. The formal name of this standard is ITU-T Recommendation T.81 or ISO / IEC IS 10918-1. This compression standard has been the most widely used so far. Uses the discrete cosine transform (DCT) to perform a compression with losses taking advantage of the deficiencies of the human eye. The sequence of operations performed by a JPEG compressor are as follows:

- Transformation of the color space.
- Splitting the image into blocks of 8×8 pixels.
- Application of the discrete cosine transform (DCT) to each block.

The basic idea in this technique is to use a discrete Fourier transform to match the image with a set of transform coefficients. A quantization process is applied on these coefficients, where a significant number of the coefficients usually have small values that are insignificant, which can be eliminated by a process known as quantization, resulting in the loss of information, although this does not imply an appreciable distortion of the image. In this way a reduced number of image data is obtained, to which a lossless coding technique is usually applied to improve the results.

The discrete cosine transform (known as DCT) is most often used for image compression because of its ability to package information, as it packs most of the information into the smallest number of coefficients; DCT also minimizes the visibility of the boundaries between sub-pictures. The coefficients in this technique are calculated from equation 2.

$$T_{ij} = \begin{cases} \sqrt{\frac{1}{n}} \cos \frac{(2j+1)\pi i}{2n} & i = 0, 0 \leq j < n \\ \sqrt{\frac{2}{n}} \cos \frac{(2j+1)\pi i}{2n} & 0 < i < n, 0 \leq j \leq n \end{cases} \tag{2}$$

IV. SIMULATION AND RESULTS

The simulation and results have been presented in this section. Two of the error metrics used to compare the various image compression techniques are the:

- Mean Square Error (MSE)
- Peak Signal to Noise Ratio (PSNR)

The MSE is the cumulative squared error between the compressed and the original image the mathematical formula is:

$$MSE = \frac{1}{MN} \sum_{y=1}^{M} \sum_{x=1}^{N} [I(x,y) - I'(x,y)]^2 \tag{3}$$

The PSNR is a measure of the peak error between the compressed and the original image the mathematical formula is:

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$$PSNR = 20\log_{10}\frac{(255)^2}{MSE} \quad (4)$$

where $I(x,y)$ is the original image, $I'(x,y)$ is the approximated version (which is actually the decompressed image) and M, N are the dimensions of the images. A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR.

Fig. 3. Acquired image

Fig. 4. Filtered image

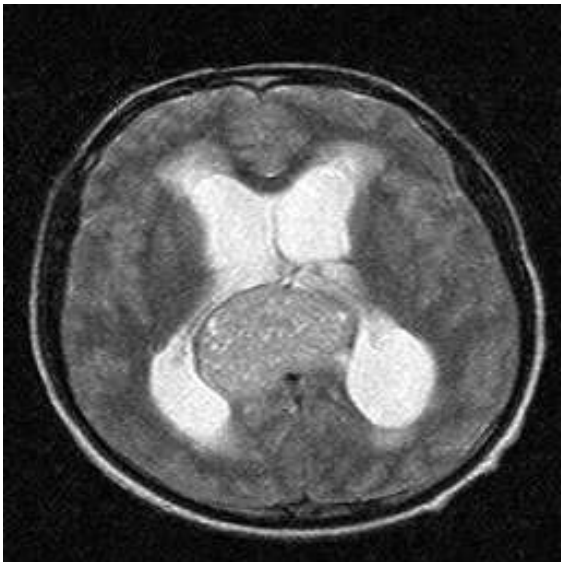

Fig. 5. Enhanced image

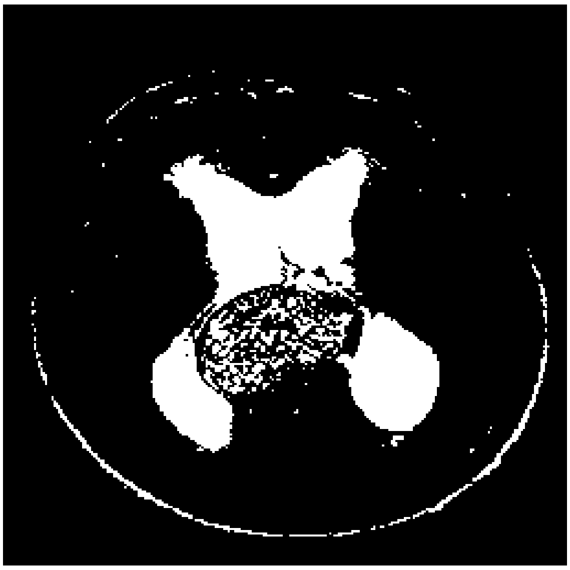

Fig. 6. Binary image

Fig. 7. Morphed image with detected Tumor region

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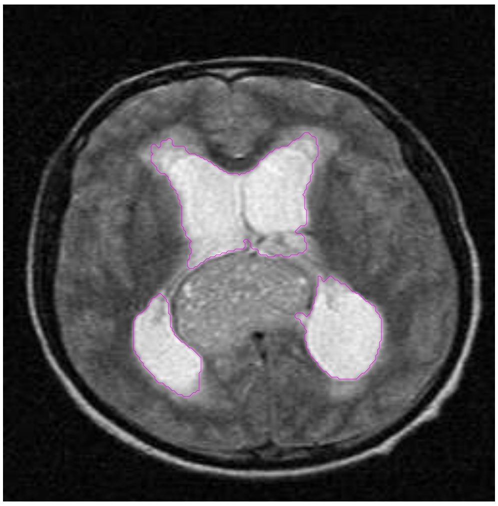


Fig. 8. Original image with initial tumor region

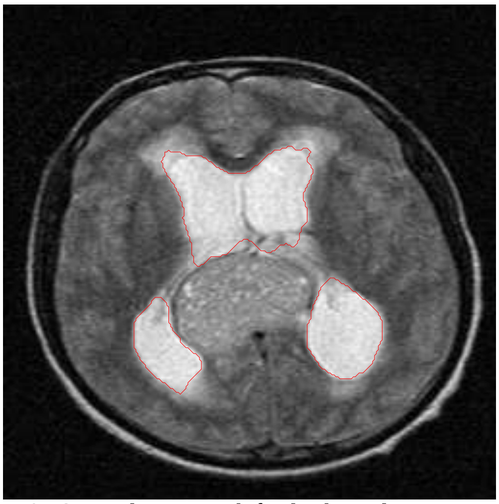
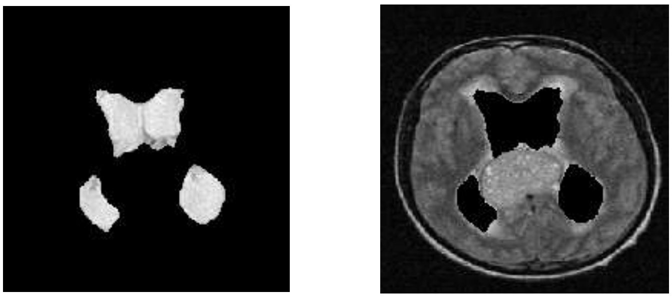
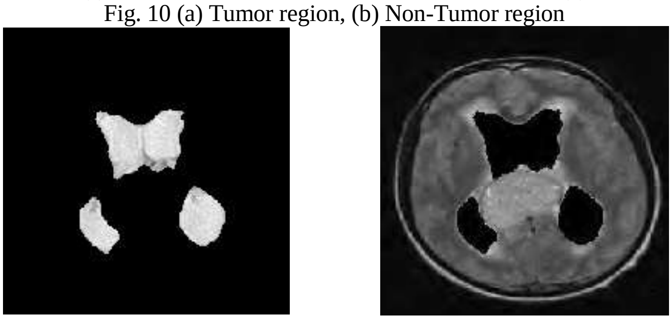


Fig. 9. Original image with final achieved tumor region



(a) (b)
Fig. 10 (a) Tumor region, (b) Non-Tumor region



(a) (b)
Fig. 11 (a) Reconstructed Tumor region, (b) Reconstructed Non-Tumor region

Table 1. Results

S. N.	Area (Pixels)	Mean	Variance
1	1012	211.3	337.1
2	3234	209.5	541.6
3	1528	214.4	270.6

The compression ratio, MSE and PSNR for the two cases i.e. for the original image with initial tumor region and the original image with the final achieved tumor region is shown in table 2.

Table 2:
Comparison of efficacy measures for the two cases

Method → Efficacy measures ↓	**Original image with initial tumor region**	**Original image with the final achieved tumor region**
Compression ratio	0.4412	0.2123
MSE	28.4016	4.4816
PSNR	81.7960	89.8152

V. CONCLUSION

This paper represents the medical image compression with lossy and loss less compression .The segmented region of Tumor is compressed via IDWT method and non-tumor region is compressed with JPEG compression. The receiver end decompress the respective region and further PSNR and MSE are calculated to evaluate the prototype.

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