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Wavelet Based Medical MRI Compression Using ROI And Comparing RGB And Ycbcr Color Spaces

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Abstract:
Region Of Interest (ROI) coding is a feature provided by some modern image coding systems that allows to the compressor to assign higher priority to certain regions of the image (ROIs) over the rest of the image. After a preprocessing step remove the mean, select region of interest indvidualy in RGB, transform RGB to YCbCr color space, the DWT is applied and followed by bisection method include thresholding, the quantization, dequantization, the Inverse Discrete Wavelet Transform (IDWT), YCbCr to RGB transform of mean recovering. To obtain the best PSNR, encoding algorithm is used for compressing the input medical image in to three matrices and forward to DWT block a coresponding (m×n) vector containg the maximum possible run of zeros at its end. In the last step decoding algorithm is used to decompress the image using IDWT to get three matrices of medical image.

Key words: *Region of interest, MRI, RGB, YCbCr transform, Block-based DWT, Transform coding*

1.Introduction

Nowadays, problems arise when handling large-sized images (i.e. medical images such as MRI, CT images) of 10, 50, 100 or more Megabytes, due to the amount of time required for transmitting and displaying, this time being even worse when a narrow bandwidth transmission medium is involved (i.e. dial-up or mobile network), because the receiver must wait until the entire image has arrived. To solve this issue, progressive transmission schemes are used. These schemes allow the image sender to encode the image data in such a way that it is possible for the receiver to perform a reconstruction of the original image from the very beginning of transmission. Despite this reconstruction being, of course, partial, it is possible to improve the reconstruction on the fly, as more and more data of the original image are received. In the progressive transmission of region of interest [1-3], we want not only to reconstruct the image as we receive image data, but also to be able to select which part or parts of the emerging image we think are relevant and want to receive first, and which part or parts are of no interest.

When an image is synthesized from its transform coefficients, each coefficient contributes only to a specific region in the reconstruction. Thus, one way to code a ROI with greater fidelity than the rest of the image would be to identify the coefficients contributing to the ROI, and then to encode some or all of these coefficients with greater precision than the others.

When an image is to be coded with a ROI, some of the transform coefficients are identified as being more important than the others. The coefficients of greater importance are referred to as ROI coefficients, while the remaining coefficients are known as background coefficients. Noting that there is a one-to-one correspondence between transform coefficients and quantizer indices, we further define the quantizer indices for the ROI and background coefficients as the ROI and background quantizer indices, respectively. With this terminology introduced, we are now in a position to describe how ROI coding fits into the rest of the coding framework [4-6].

We will focus now on the aspects of the large-sized images. A good example is medical imaging. A Computed Tomography (CT) and MRI were composed in the 70's, of a couple of images of, say 100 kilobytes, while nowadays a complete 3D image of 500 frames of 512×512 pixels sizing more than 500 megabytes is common practice. Intensive use of CT and MRI produces a huge output of terabytes, information that must be processed and stored, and later retrieved and displayed when physicians make their diagnosis [3]. In figure 1 we can find a good example in our reference image. Sending this image using a modem can take several times, even if it has been compressed.

To solve this problem we can use progressive transmission schemes able to provide compression (for storage and transmission) and efficient visualization (reconstruction). On the one hand, using conventional "sequential" transmission, an image cannot be shown until complete transmission ends. Even if complete transmission is not required, the obtained image usually is useful until most of the data have been not received, as we can see on figure 2.

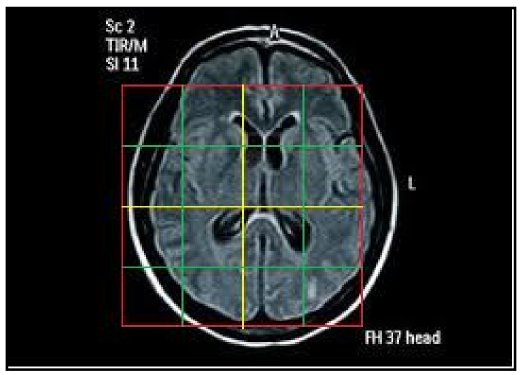


Figure 1: Example of large image size 190×268

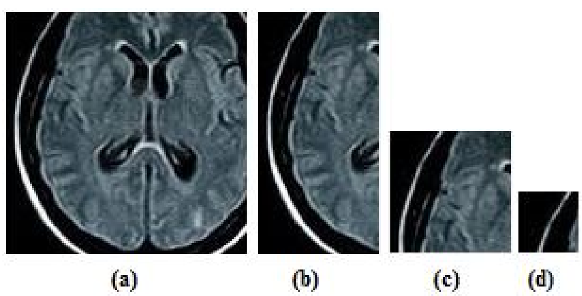


Figure 2: Reconstruction of reference ROI image (a) size 128×128 (b) 64×128 (c) size 64×64 and (d) size 32×32

2. Methodology

The block diagram of DWT based medical image compression/ decompression with region of inerest (ROI) model shown in figure 3. This method is dedicated to lossy medical image compression DWT based and two phases of compression/decompression. The input to the system is a medical image and the output is the ROI compressed one. The compression technique is built with several steps and each will be explained in details [3,5].

Before the RGB to YCbCr transformation, manually select the ROI of images shown in figure 2 [7-8]. The RGB to YCbCr transformation is the mean value of three plane images R, G and B are removed and the almost signal energy of the new transformed YCbCr image is contained in the Y plane.

In the encoder, before the quantizer indices for the various subbands are transform coded, the ROI quantizer indices are scaled upwards by a power of two (i.e., by a left bit shift). This scaling is performed in such a way as to ensure that all bits of the ROI quantizer indices lie in more significant source coding. Source coding is to represent information in bits, with the natural aim of using a small number of bits [9-10].

The "information" is denoted by a real column vector $x \in \mathbb{R}^2$or a sequence of such vectors. A vector might be formed from pixel values in an ROI image; *K.N* pixels can be arranged as a sequence of *K* vectors of length *N*. The vector length *N* is defined such that each vector in a sequence is encoded independently. Transform codes are easy to apply at any rate and even with very large values of *N*. An invertible linear transform of the source vector *x* is computed, producing *y =Tx*. Each component of *y* is called a transform coefficient. The *N* transform coefficients are then ROI quantized independently of each other by *N* scalar quantizers. The reconstruction process is straightforward: The coefficients are unpacked, rearranged, de-quantized (multiplied by the respective quantization values), and the inverse DWT applied to recover the original m×n pixel values. This recovery will be more or less close to the original values depending on the number of coefficients discarded in the codification steps. During decoding, a quantizer q is a mapping from a source alphabet $\mathbb{R}^N$to a reproduction code. It can be decomposed into two operations $q = \beta.\alpha$. The ROI lossy encoder $\alpha\mathbb{R}^N \to \mathcal{L}$ is specified by a partition of $\mathbb{R}^N$ into partition cells $S_t = \{x \in \mathbb{R}^2 \mid \propto (x) = i\}, i \in \mathcal{L}$ and the reproduction decoder is $\beta: \mathcal{L} \to \mathbb{R}^N$.

The ROI set can be chosen to correspond to transform coefficients affecting a particular region in an image or subset of those affecting the region. This ROI coding technique has a number of desirable properties. First, the ROI can have any arbitrary shape and be disjoint. Second, there is no need to explicitly signal the ROI set, since it can be deduced by the decoder from the ROI shift value and the magnitude of the quantizer indices.

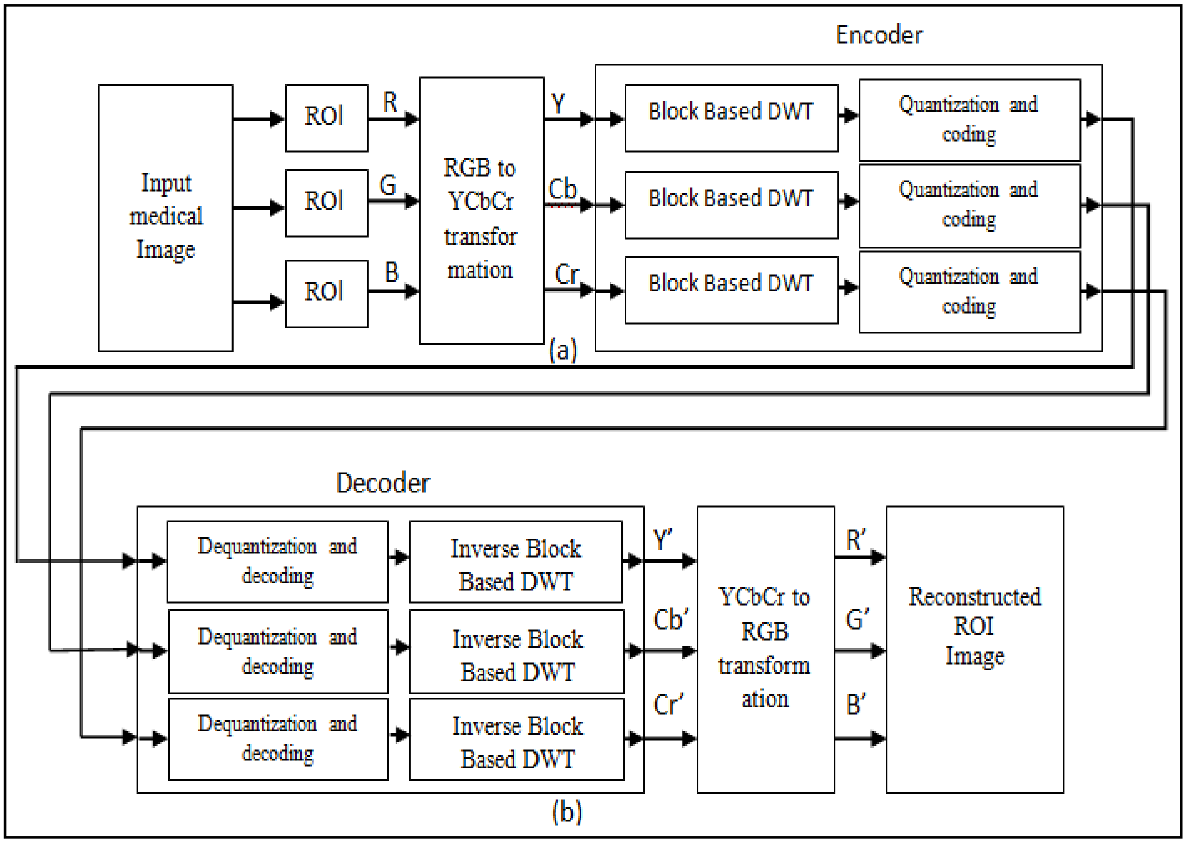


Figure 3: The block diagram of the proposed ROI algorithm

3.Measurements

Several quality measures can be found in open literature of the field. The mean square error (MSE) and the Peak signal to noise ratio (PSNR) are the most used measures.

Mean square error (MSE) is the some sort of average or sum of the squares of the error between two images. For M×N images u(m,n) and û(m,n), the least square error (LSE) is,

$$\text{LSE} = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}|u(m,n) - \hat{u}(m,n)|^2 \qquad (1)$$

and average LSE is called the Mean square error (MSE),

$$\text{MSE} = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}E[|u(m,n) - \hat{u}(m,n)|^2] \qquad (2)$$

Where u(m,n) and û(m,n) are the original and reconstructed intensities belonging to R, G and B plane. The PSNR is defined in decibels (dB) as,

$$\text{PSNR} = 10\log_{10}\frac{\sigma^2}{\text{MSE}} \qquad (3)$$

Where σ^2 is the variance of the original image. For medical image we used the relation given as

$$\text{PSNR} = 10 \log_{10}\left(\frac{\sigma^2 \times 3}{\text{MSE(R)}+\text{MSE(G)}+\text{MSE(B)}}\right) \quad (4)$$

Compression algorithm:

- Input: Medical image I(RGB)
- Break the input image into three matrices I(R), I(G) and I(B)
- Select region of interest of all three matrices
- Transformation of the I(R), I(G) and I(B) matrices into I(Y), I(Cb) and I(Cr)
- Perform DWT transform of sub-band I(Y), I(Cb) and I(Cr) separately
- Transform coder decomposes and quantizes the decomposition coefficients
- Output: Compressed medical image I(YCbCr)

Decompression algorithm:

- Input: Compressed medical image I(YCbCr)
- Inverse sub-band transform and dequantization of reproduction code
- IDWT is applied and get Î(Y), Î(Cb) and Î(Cr)
- Transformation of the Î(Y), Î(Cb) and Î(Cr) into Î(R), Î(G) and Î(B)
- Convert Î(R), Î(G) and Î(B) to Î(RGB)
- Output: Decompressed medical image Î(RGB)

4.Experiments

In our experiments, test images containing the medical images as shown in figure 4. The select ROIs are played an important factor for teleclinical diagnosis and progressive transmission in fast viewing or browsing the medical images. An approximation to the different ROI size k×l of reference images are shown in figure 5. The ROI sizes of 128×128 are the selected area of reference images shown in figure 5 (a), but the other ROI are the sub ROI of figure 5(a). In figure 5(b), 5(c) and 5(d) are two, four and sixteen equal ROI of figure 5 (a).

Reconstructions of each ROI are shown in figure 6. After that, as more and more data are used for the reconstruction.

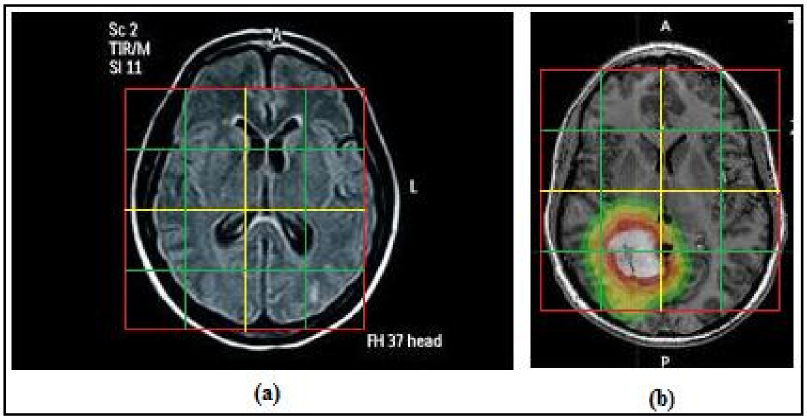


Figure 4: Reference medical test images with different size (a) 190×268 (b) 188×140

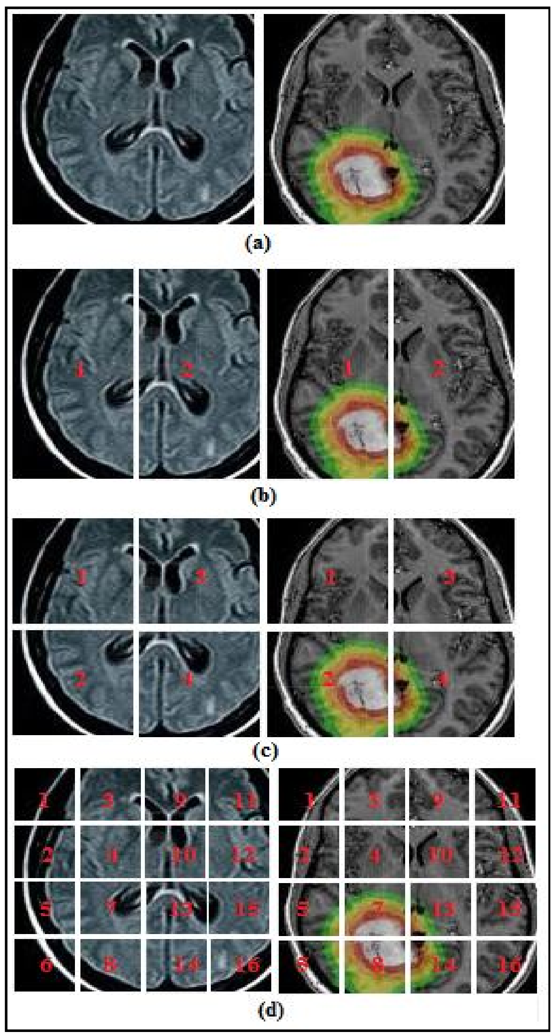


Figure 5: Reference image (a) ROI size 128×128,
(b) two equal ROI size 128×64 of image (a),
(c) four equal ROI size 64×64 of image (a),
(d) sixteen equal ROI size 32×32 o f image of image (a)

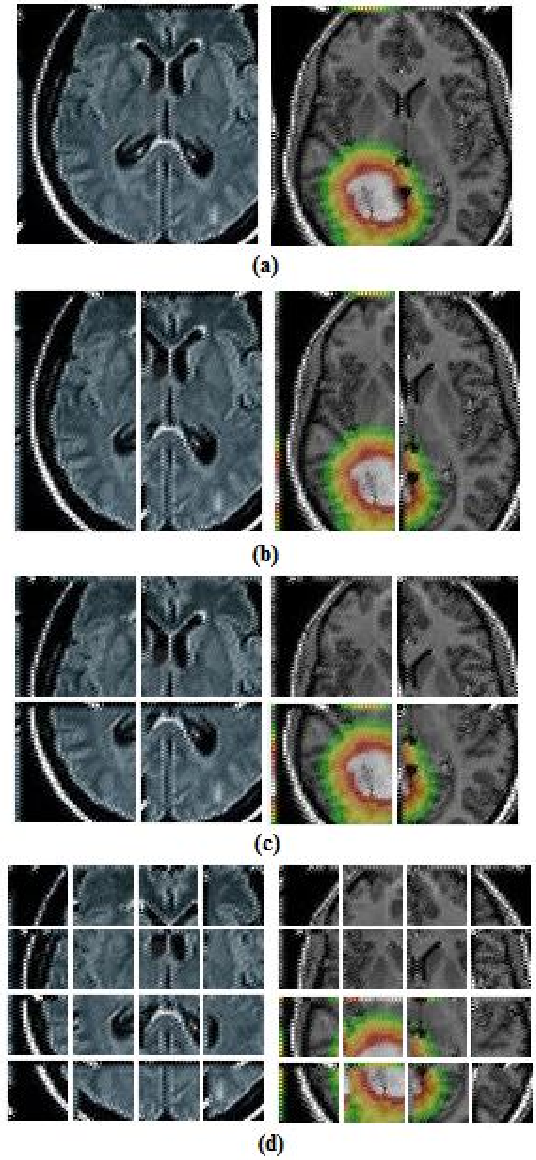


Figure 6: Reconstructed of reference ROI of image Figure 5

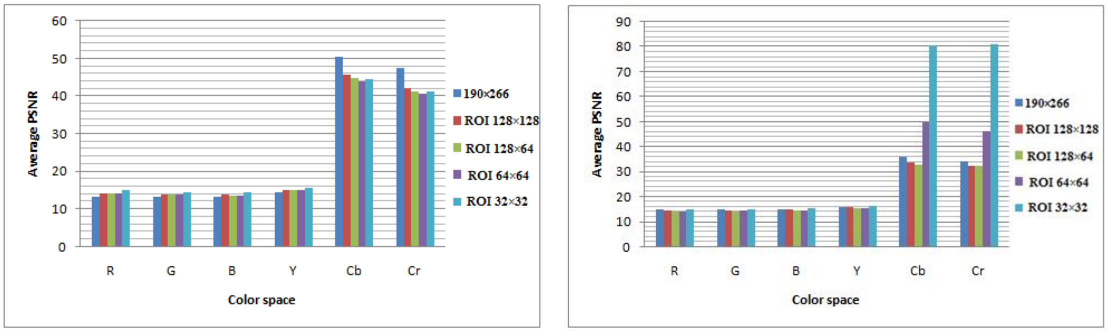
5.Result And Discussion

PSNR of each selected ROI of reference test image color spaces are shown in table 1. In this table, we show the PSNR of each ROI when images are divide into equal ROI size 128×128, 128×64, 64×64 and 32×32. If PSNR is high means that reconstructed image quality is better. So from the table it is observe that, by using dividing the image into equal different ROI we can increase the PSNR of image. The average PSNR of different ROI are shown in figure 7. From the figure 7(a), it is observe that, when we decrease the ROI size then average PSNR of RGB and Y color space are increased but in CbCr color space are decreased. In figure 7(b), it is observe that average PSNR is high if we divide the image into 16 equal ROI 32×32.

ROI size		**MR1**						**MR2**					
		R	G	B	Y	Cb	Cr	R	G	B	Y	Cb	Cr
Full Size		**13.28**	**13.28**	**13.25**	**14.26**	**50.52**	**47.54**	**14.66**	**14.61**	**14.76**	**15.85**	**36.02**	**34.1**
128×128		**14.09**	**13.8**	**13.69**	**14.98**	**45.63**	**42.23**	**14.35**	**14.28**	**14.57**	**15.61**	**33.4**	**32.3**
128×64	1	13.96	13.6	13.44	14.72	43.86	40.89	13.7	13.68	14.22	15.07	31.26	30.57
	2	14.04	13.74	13.65	14.99	45.44	41.57	14.33	14.36	14.63	15.57	33.75	33.73
Average		**14**	**13.67**	**13.545**	**14.855**	**44.65**	**41.23**	**14.015**	**14.02**	**14.425**	**15.32**	**32.505**	**32.15**
64×64	1	13.99	13.58	13.4	14.85	43.93	40.34	14.29	14.29	14.29	15.49	60.53	62.96
	2	13.75	13.38	13.22	14.36	42.41	40.2	13.35	13.32	13.2	14.85	28.34	27.56
	3	15.16	14.82	14.73	16.09	46.78	42.34	15.18	15.18	15.18	16.32	79.05	64.06
	4	13.18	12.87	12.75	14.08	42.9	39.96	13.59	13.63	14.11	14.9	30.74	30.71
Average		**14.02**	**13.663**	**13.525**	**14.845**	**44.005**	**40.71**	**14.103**	**14.105**	**14.195**	**15.39**	**49.665**	**46.323**
32×32	1	13.5	13.07	12.87	14.41	43.76	40.74	12.44	12.44	12.44	13.7	147	147
	2	11.24	10.75	10.55	11.94	40.75	36.92	12.14	12.14	12.13	13.22	60.8	76.57
	3	16.66	16.58	16.54	17.91	48.71	44.41	16.55	16.55	16.55	17.86	147	147
	4	20.18	20.37	20.28	21.63	50.4	49.49	20.75	20.77	20.76	22.08	55.69	56.96

	5	10.12	9.813	9.689	10.74	41	37.66	11.09	10.94	11.91	12.33	27.49	29.21
	6	13.86	13.53	13.46	14.5	45.55	41.72	12.41	11.91	13.23	13.42	27.47	30.45
	7	17.15	16.84	16.75	18.23	45.1	43.69	15.96	15.6	16.77	17.93	27.77	25.2
	8	15.46	15.09	14.84	15.93	40.71	37.74	15.98	17.34	15.39	19.18	25.25	24.72
	9	13.11	12.71	12.62	14.01	45.67	40.31	18.03	18.03	18.03	19.31	147	147
	10	14.33	13.9	13.76	15.2	45.63	40.94	16.9	16.9	16.9	18.12	73.03	58.04
	11	16.65	16.08	15.95	17.29	43.78	39.39	14.51	14.51	14.51	15.41	147	147
	12	18.34	18.13	18.12	19.48	50.31	47.27	12.09	12.09	12.09	13.27	147	147
	13	12.98	12.69	12.58	13.94	44.72	40.59	18.8	18.79	18.68	20.68	30.07	30.55
	14	15.11	14.51	14.29	15.63	42.81	39.7	15.56	15.4	17.11	17.74	25.59	25.65
	15	18.61	17.68	17.27	19.13	43.6	41.39	15.53	15.53	15.53	16.27	147	147
	16	9.757	9.502	9.378	10.65	39.28	36.66	9.906	9.902	9.902	10.94	52.93	54.41
Average		**14.816**	**14.453**	**14.309**	**15.664**	**44.486**	**41.164**	**14.915**	**14.928**	**15.121**	**16.341**	**80.506**	**80.86**

Table 1: PSNR of MR1 and MR2 for different test medical images of RGB and YCbCr color space when images divides different equal ROI



(a) (b)

Figure 7: Average PSNR curve of (a) MR1 test image color spaces (b) MR2 test image color spaces, when image divide different ROI size.

There are important advantages in this scheme

- The reconstruction algorithm is pretty fast and has a straightforward implementation
- There is no redundancy in data transmission.
- Several (rectangular) ROIs can be selected at the same time if required.
- Once the ROIs are selected and their coordinates transmitted to the server, re-encoding the original image to transmit the ROIs progressively is NOT required.
- Already transmitted data are different from the new transmitted data to improve the quality of the ROIS.

7.Reference

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