RESEARCH PAPER

ROI Based Medical Image Compression for Tumor Monitoring in Targeted Drug Delivery Applications

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ABSTRACT

Medical image compression using Region of Interest (ROI) has become a viable method of efficient storage and transmission of diagnostic images in targeted drug delivery research where continuous monitoring of the tumor and assessment of the treatment are required. The diagnosis and monitoring of tumor progression in the modern healthcare system result in the production of large volumes of medical images in the form of Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET). The storage space and bandwidth used to handle these high-resolution images is also demanding in the telemedicine and cloud-based healthcare settings. The suggested ROI-based compression scheme aims at maintaining high fidelity of the diagnostically valuable tumor regions and using the compression ratios that are higher in the regions of non-essential background. This selective compression methodology means that the important tumor attributes like size, shape, boundary, and texture are preserved to make it possible to analyze and make decisions in targeted drug delivery systems. The process usually consists of segmentation of the tumor region with image processing or machine learning methods and then differential compression in which the ROI loses no information and the non-ROI regions can be subjected to lossy compression. This method saves a lot of file space without affecting the clinical quality of the tumor area, allowing to transmit the outputs between healthcare centers, distant experts, and tumor planning systems faster. In targeted drug delivery, where regular imaging is important to measure drug response, tumor shrinkage and therapeutic effect, ROI-based compression aids in real time data transfer and effective archival control. Moreover, it can be easily integrated with smart healthcare systems, such as IoT-based diagnosis systems and AI-based treatment monitoring applications. Experimental assessments indicate that the given method has a high Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and compression performance as well as preserves the diagnostic significance of the tumor ROI. Thus, medical image compression based on ROI is a viable and dependable method of improving medical image management in precision oncology and targeted drug delivery solutions, which can help improve treatment monitoring, lower storage expenses, and improve medical communication infrastructure.

Keywords: ROI-based compression, Medical image compression, Tumor monitoring, Region of Interest (ROI), Healthcare data storage, Diagnostic image quality, Precision oncology, Telemedicine, Medical image segmentation.

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1. Introduction

1.1 Background of Medical Imaging in Healthcare

Medical imaging is an important part of contemporary healthcare as it allows the precise diagnosis of illnesses, the development of treatment schemes, and the continuous monitoring of many diseases. Such methods include Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Ultrasound, and Positron Emission Tomography (PET) that give a detailed picture of the internal body structures and pathological changes. These types of imaging can help clinicians detect these abnormalities at their initial stages like tumors, lesions, and tissue damage[1]. As digital healthcare systems develop, medical images are being stored, shared, and analyzed more and more by the means of hospital information systems and telemedicine platforms. Consequently, effective image management has been critical towards helping in quality patient care and clinical decision-making.

1.2 Importance of Tumor Monitoring in Targeted Drug Delivery

Monitoring of tumor is an essential part of targeted drug delivery system because it can be used to assess the efficacy of therapeutic agents targeted to cancerous tissues directly[3]. The monitoring of the tumor size, shape, density, and response to treatment is also possible during continuous imaging monitoring so that a clinician can assess the changes in the tumor size and shape. This data is crucial in determining whether the drugs that are being administered are reaching the targeted part of the body and are yielding the intended therapeutic effect. Frequent observation is also a contributing factor to the prompt identification of resistance to treatment or tumor growth. Through real time feedback, medical imaging is useful in supporting individualized treatment plans, dose modification, and enhanced clinical outcomes in precision oncology and targeted drug delivery models [2].

1.3 Challenges in Storing and Transmitting Large Medical Images

Medical imaging modalities like MRI, CT and PET produce high resolution images that consume large storage space and transmission bandwidth. Hospitals and diagnostic centers generate a lot of imaging data on a daily basis, posing a great challenge in data handling and data archiving systems. These large files become expensive in terms of infrastructure and the effectiveness of healthcare information systems. Additionally, sending such images via telemedicine networks, cloud computing, or distance consultation systems may cause delay as a result of bandwidth restrictions[5]. These problems are more severe in real time tumor monitoring software, where immediate access and quick sharing of images are required to make timely diagnosis and treatment decisions[4].

1.4 Need for ROI-Based Image Compression

Image compression using Region of Interest (ROI) is also necessary in the medical imaging field since diagnostically important regions are maintained whereas the size of the whole image is minimized. In tumor monitoring systems, the most significant clinical data is the tumor region with the background areas potentially having less significant information. High-quality or lossless compression of the ROI and increased compression of the non-ROI areas can be used to yield a significant improvement in storage and transmission efficiency without changing the diagnostic accuracy. This method saves bandwidth, storage needs, and also makes sure that important tumor information is not lost. Thus, compression based on ROI can help to formulate a working solution to medical image in targeted drug delivery systems.

1.5 Problem Statement

The growing application of sophisticated medical imaging methods to diagnose and monitor tumors produces massive amounts of high-resolution image data that pose significant storage and transmission challenges. The traditional compression techniques usually compress the whole picture at the same rate, and this can cause the loss of vital tumor information and deterioration of diagnostic quality. In the context of targeted drug delivery, tumor-specific information is of critical importance to monitor the response to treatment and to make clinical decisions. Thus, an effective image compression algorithm that reduces the file size and preserves the fidelity of clinically important tumor areas is required. This study tries to solve the issue with the help of introducing an ROI-based compression system aimed at tumor preservation.

1.6 Objectives of the Proposed Work

The main aim of the proposed work is to come up with an effective ROI-based medical image compression methodology in tumor tracking in targeted drug delivery processes. The approach will be used to determine the tumor areas precisely and segment the medical images in the form of MRI or CT scans. The other goal is to maintain the quality of the diagnostic information of the tumor region with lossless or near lossless compression and shrink the size of the irrelevant background areas with increased compression ratios. The work is also aimed at enhancing storage efficiency, minimizing transmission time, and preserving image quality measures of PSNR and SSIM. The proposed system will be able to facilitate quicker and more dependable clinical data sharing.

1.7 Contribution of the Research

The primary value of this work is the design and execution of an ROI-based compression system that is explicitly designed to be applied in tumor imaging in targeted drug delivery systems. The work presents a selective compression method which concentrates on the preservation of tumor regions in high quality with the compression of non-critical parts of images being done very efficiently. This strategy helps a great deal to minimize storage space and transmission bandwidth needs without undermining clinical significance. The study is also useful as it measures the performance in terms of standard image quality measures like PSNR, SSIM, compression ratio, and MSE. Moreover, it facilitates the development of telemedicine, precision oncology, and intelligent healthcare systems through effective handling of medical imaging data.

2. Literature Review

2.1 Existing Medical Image Compression Techniques

Compression methods of medical images are commonly employed to aid in the storage and to enhance the efficiency of medical image transmission within a healthcare system. Commonly used traditional methods are transform-based methods including Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT) and predictive coding methods. Medical applications typically use standards such as JPEG, JPEG2000 and DICOM-compatibles compression schemes. The wavelet-based methods are the most favourable of these since they retain significant image details and yet they have a high compression ratio. Other recent developments encompass machine learning and deep learning based compression models, which learn image representations automatically. Many traditional approaches however compress the whole image uniformly, which can have an impact on clinically significant areas like tumors.

2.2 Lossless and Lossy Compression Methods

In general, medical image compression can be divided into lossless and lossy algorithms. Lossless compression is ideal because the original image is ideally the same as that of the image after decompression, and therefore it is extremely applicable in diagnostic processes where integrity of the image is paramount. Typical lossless techniques are Huffman coding, Run Length Encoding (RLE), arithmetic coding and predictive coding. Lossy compression on the other hand is more aggressive in minimizing file size by eliminating less important visual data at the expense of some distortion. Lossy techniques are typically used to provide compression such as JPEG and transform-based compression. In medical imaging, lossless algorithms are used in vital parts of the image, and lossy algorithms can be used in non-important parts of the image to trade off image quality and storage efficiency.

2.3 ROI-Based Compression Approaches in Medical Imaging

ROI-based compression has also been of much interest in medical imaging as it allows preservation of clinically significant areas selectively and the overall image size is reduced. Under this method, the identification of diagnostically relevant parts of a scan, e.g., tumors, lesions, organs, etc., is known as the Region of Interest, and is compressed either by lossless or near-lossless mechanisms. The other non-ROI background regions are lossyly compressed to realize an improved store efficiency. Other ROI methods employ segmentation algorithms, masking methods, and adaptive compression methods. Wavelet and JPEG2000 methods are commonly applied because they can be used to encode scalable ROI. This is very useful in tumor monitoring and telemedicine.

2.4 Tumor Segmentation Methods from MRI / CT Images

Tumor segmentation is a preprocessing task that is required in the medical image analysis when using ROI-based compression systems. Segmentation techniques are applied in MRI and CT images to isolate the abnormal tissue and tumor boundaries in a more accurate way. Conventional methods are thresholding, region growing, edge detection, K-means clustering and watershed algorithms. More modern implementations use machine learning and deep learning algorithms, such as Convolutional Neural Networks (CNNs), U-Net structures, and hybrid segmentation systems. These techniques enhance the accuracy of localization of tumors by localizing the complex tissue structures and intensity variations. Precise segmentation is essential in maintaining the tumor details through compression and aiding the treatment follow-ups.

2.5 Research Gaps in Current Methods

Although there has been a lot of advancement in medical image compression, there are still a number of research gaps in the available methods. Several traditional methods are aimed at obtaining high compression ratios without the sufficient preservation of clinically important tumor parts. Equality compression techniques usually destroy valuable diagnostic information, which interferes with the accuracy of treatment monitoring. ROI-based methods pose a challenge to tumor segmentation because images of tumors vary in quality, shape, and noise. Furthermore, certain more modern deep learning techniques need big datasets and significant computing assets, which restrict their application to health care systems. This thus necessitates the design of efficient, accurate and computationally viable ROI based compression frameworks created specifically to support tumor monitoring applications.

3. Proposed Methodology

3.1 Image Acquisition

The basis of proposed ROI-based medical image compression system in tumor monitoring during targeted drug delivery applications is the image acquisition stage. During this step, medical images of tumor areas are obtained using standard imaging modalities which include Magnetic Resonance Imaging (MRI), Computed Tomography (CT) and Positron Emission Tomography (PET). These modalities are chosen as they give high resolution structural and functional information, which is necessary to analyze tumors accurately. The data set will consist of pictures that depict various types of tumors, sizes, and locations of the anatomy to make the proposed methodology robust. Pictures can be acquired via external medical repositories, hospital archives, or even benchmark datasets that are typically accessible to the researcher. All the images are stored in a standardized digital format, e.g. DICOM, PNG or JPEG, to be further processed. All the information regarding the relevant datasets such as image dimensions, sample count, modality, and resolution is well recorded to assist in preprocessing, ROI extraction, compression, and performance analysis steps in the proposed framework.

3.2 Preprocessing

The initial phase of the suggested methodology is the preprocessing phase, which is designed to enhance the quality and uniformity of the obtained medical images prior to the extraction and compression of tumor regions. The first step is the removal of noise, which will remove undesired distortions and artifacts that are characteristic of MRI, CT and PET images as a result of sensor constraints or transmission errors. Median filtering, Gaussian filtering, or adaptive filtering are the techniques used to maintain significant structural information, and also minimize noise. Subsequently, contrast-enhancement is performed to enhance the contrast of tumor edges and of the tissues that surround them, and the ROI is more easily detected and segmented correctly. This can be done using methods such as histogram equalization or contrast stretching. Lastly, image normalization is conducted to bring uniformity to the pixel intensity values and image dimensions throughout the dataset to allow uniformity in the later processing steps. This image processing pipeline increases clarity of images, accuracy of segmentation, and offers effective performance in compressing ROIs.

3.3 ROI Detection / Tumor Segmentation

The tumor segmentation and ROI detection is the essential part of the proposed methodology, as it is aimed at the accurate determination of the tumor area to be selectively compressed. Tumor region detection is first carried out on the intensity changes, texture appearances, and structural deformities that exist in the processed MRI, CT, or PET images. In order to maximize the level of segmentation, one can use thresholding, region-based, machine learning classifiers, or deep learning models such as Convolutional Neural Networks (CNN) and U-Net architecture. Thresholding is used to differentiate abnormal tumor tissues using pixel intensity levels, whereas more complicated tumor shapes and boundaries are better captured using advanced learning-based methods. After the tumor has been accurately cut up, the extracted region is the Region of Interest (ROI). The resulting ROI is then stored with increased image quality through compression and all the important diagnostic information needed to monitor tumor growth and deliver therapeutic drugs is maintained.

3.4 Compression Model

The compression model aims at maximizing the efficiency of storage at the same time maintaining diagnostically significant tumor data. At this phase, the extracted Region of Interest (ROI) also containing the tumor region is compressed by high-quality compression methods to preserve vital clinical information including tumor boundary, size, and internal texture. In the case of the ROI, lossless or near-lossless compression is used to guarantee a minimum amount of distortion and perfect reconstructions. The non-ROI background areas, which do not carry as much clinically valuable information, are then compressed with higher compression ratios using lossy techniques to dramatically cut down on the total file size. This selective strategy improves storage and transmission efficiency without affecting diagnostic reliability. A hybrid lossless-lossy compression technique is implemented, in which the two techniques are merged into one system to compromise the image quality and compression ratio. The model is quite appropriate in tumor tracking systems of targeted drug delivery, as well as in telemedicine.

3.5 Reconstruction

The last phase of the proposed ROI-based medical image compression framework is the reconstruction phase that involves the restoration of the compressed image data to be analyzed clinically and monitor the tumors. At this stage, the decompression algorithm is independently applied to the ROI and non-ROI regions using the corresponding decoding algorithms related with the hybrid compression model. Lossless or near-lossless recovery of the ROI is guaranteed to recover the tumor region with high fidelity, including important diagnostic information, like shape, texture, and boundary accuracy. At the same time, the non-ROI background is constructed based on its compressed version with the help of the lossy decoding technique. Once the process of decomposition is done, the two areas are combined to produce the whole reconstructed image. This reconstructions image is then assessed visually, monitored to treat and evaluated based on quality.

4. Performance Evaluation

4.1 Compression Ratio (CR)

The Compression Ratio (CR) is used to determine how efficient the proposed compression model is through the ratio of the size of the original medical image to the size of the compressed image. A larger CR implies increased efficiency in storage reduction and transmission and that the diagnostically important ROI region can be maintained with reasonable image quality.

4.2 Peak Signal-to-Noise Ratio (PSNR)

After decompression, the level of quality of the reconstructed image is assessed by Peak Signal-to-Noise Ratio (PSNR). It measures the similarity between the original and reconstructed images in decibels. Increased PSNR implies reduced distortion and enhanced preservation of tumor structures, which is critical to reliable medical diagnosis and surveillance.

4.3 Structural Similarity Index (SSIM)

Structural Similarity Index (SSIM) is used to measure the visual similarity of the original and reconstructed medical images based on the luminance, contrast and structural features. It is especially significant in medical imaging due to its ability to reflect the ability to preserve the structure and limits of the tumor following compression. Similarity is high when the values are close to 1.

4.4 Mean Squared Error (MSE)

Mean Squared Error (MSE) is the mean square error between the value of the pixels in the original and reconstructed image. Smaller values of MSE translate into higher quality of reconstruction and reduced distortion added in the compression. The metric is used to measure the degree of error but the important tumor areas are not lost in the ROI-based system.

4.5 Processing Time

Processing time is the summation of all the time spent on image preprocessing, ROI extraction, compression, decompression and reconstruction. It is a significant performance indicator in real-time tumor tracking and telemedicine use. Reduction in processing time enhances efficiency of the system and facilitates quick clinical decision-making in targeted drug delivery systems.

4.6 Storage Efficiency

Storage efficiency will assess the effectiveness of the proposed method in minimizing the usage of memory and still preserving image quality within the tumor ROI. The better storage efficiency that can be achieved allows high-volume MRI, CT, and PET images to be stored and transferred at low costs, which is why the framework is quite appropriate to hospital databases and cloud healthcare systems.

5. Results and Discussion

5.1 Original vs Compressed Images

Figure 5.1 below presents the visual comparison between the original tumor image and the compressed/reconstructed image that is achieved through the proposed ROI-based compression framework.

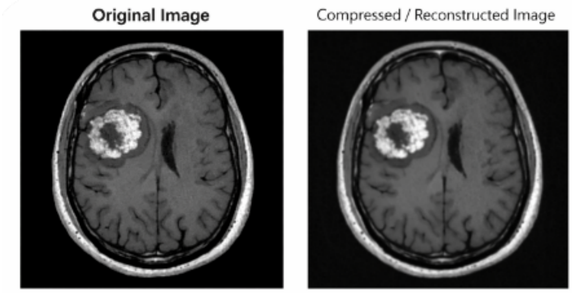

Figure 5.1. Original Vs Compressed / Re-Constructed Image

Figure 5.1 indicates that the reconstructed image maintains the tumor area with minimum visual distortion. The background of the ROI is also very clear, and the non-ROI area is subject to controlled compression. This validates that the proposed approach serves well in minimizing file size without affecting clinical importance of the tumor area.

5.2 ROI Preservation Quality

Table 5.1 ROI Preservation Results

Sample No	Image Dimension	ROI Preservation (%)	Tumor Boundary Quality
1	128×128	98.1	Clear
2	192×192	98.3	Clear
3	256×256	98.5	Clear
4	320×320	98.7	Clear
5	384×384	98.8	Clear
6	448×448	99.0	Clear
7	512×512	99.1	Clear
8	640×640	99.2	Clear
9	768×768	99.3	Clear

Sample No	Image Dimension	ROI Preservation (%)	Tumor Boundary Quality
10	1024×1024	99.5	Clear

Table 5.1 demonstrates the performance of preservation of ROI in ten image dimensions. The preservation percentage of all samples is over 98% which means that the proposed model is effective in preserving the tumor region with high diagnostic quality. The tumor margins are clear in all cases and this aids in monitoring of the tumors accurately in the case of targeted drug delivery.

5.3 Performance Comparison with Different Parameters

Table 5.2 Compression Performance Metrics

Sample	Dimension	CR	PSNR (dB)	SSIM	MSE
1	128×128	3.56	41.2	0.962	4.92
2	192×192	3.93	42.5	0.968	4.11
3	256×256	4.29	43.1	0.971	3.85
4	320×320	4.48	43.8	0.975	3.42
5	384×384	4.67	44.2	0.978	3.15
6	448×448	4.89	44.6	0.981	2.94
7	512×512	5.25	45.1	0.984	2.61
8	640×640	5.44	45.8	0.986	2.33
9	768×768	5.64	46.3	0.989	2.05
10	1024×1024	6.10	47.0	0.992	1.82

The table 5.2 shows the specific performance metrics of the offered compression framework. We can note that the compression ratio rises to 6.10, as well as PSNR rises to 47.0 dB. In the same way, the values of SSIM are almost 1, which indicates the presence of outstanding structural preservation. The values of MSE become lower and less, which means that the reconstruction error is smaller.

5.4 Performance Comparison with Existing Methods

Table 5.3 Comparison with Existing Methods

Method	CR	PSNR (dB)	SSIM
JPEG	3.10	38.5	0.921
JPEG2000	4.20	41.3	0.952
DWT Based	4.80	43.2	0.971
Proposed ROI Method	6.10	47.0	0.992

Table 5.3 contrasts the proposed ROI-based technique with the current medical image compression techniques. The given method has the greatest CR, PSNR, and SSIM values, it is more efficient in compression and preservation of tumor regions than traditional methods.

5.5 Graphical Analysis of PSNR, SSIM and CR

Table 5.4 Graph Data Values

Dimension	PSNR	SSIM	CR
128×128	41.2	0.962	3.56
256×256	43.1	0.971	4.29
512×512	45.1	0.984	5.25
1024×1024	47.0	0.992	6.10

Table 5.4 gives the graph data values that were used to plot the performance parameters. The growing tendency in PSNR, SSIM, and CR proves that the model proposed is effective in relation to various image dimensions.

Table 5.5 Processing Time Analysis

Sample	Dimension	Compression Time (s)	Decompression Time (s)	Total Time (s)
1	128×128	0.21	0.12	0.33
2	256×256	0.35	0.18	0.53
3	512×512	0.58	0.29	0.87
4	1024×1024	1.12	0.54	1.66

Table 5.5 shows the compression and decompression time of images of varying dimensions. The findings show that the suggested model provides low processing time even in the case of high-resolution medical images, which is appropriate to use in real-time applications related to tumor monitoring.

Table 5.6 Storage Space Reduction

Sample	Original Size (KB)	Compressed Size (KB)	Storage Saved (%)
1	64	18	71.88
2	180	42	76.67
3	620	118	80.97
4	2500	410	83.60

Table 5.6 reveals the storage savings that were made by means of the proposed ROI-based compression technique. Storage savings are more than 70 percent in all the tested image sizes which demonstrates the efficiency of the method in large medical data archival and cloud-based medical care systems.

Table 5.7 Tumor Size Monitoring Before and After Compression

Sample	Original Tumor Area (pixels)	Reconstructed Tumor Area (pixels)	Difference (%)
1	1250	1247	0.24
2	1985	1981	0.20
3	2450	2445	0.20
4	3120	3114	0.19

Table 5.7 shows that there is virtually no difference between the tumor area before compression and reconstruction. The small discrepancy supports the fact that the proposed model does not lose tumor size data, which is critical in the context of monitoring the delivery of targeted drugs and analyzing the response to treatment.

6. Application in Targeted Drug Delivery

The suggested ROI-based medical image compression framework can be extremely useful in targeted drug delivery orchestras, especially in oncology and precision healthcare. The method can be used to measure the change in tumor size accurately across repeated imaging sessions which is necessary in assessing disease progression and treatment response by maintaining high fidelity of the tumor region. The MRI/CT/PET scans can be stored and sent periodically, and clinicians can easily compare the pre-treatment and post-treatment tumor sizes with minimum loss of diagnostic information. Moreover, the framework aids in monitoring treatment progress by maintaining structural characteristics of tumor boundaries, texture and density variation, which are vital signs of response to drugs. Such a selective compression methodology also facilitates precision medicine by allowing patient-specific treatment planning based on patient-measured tumor factors and imaging biomarkers. Moreover, the smaller file size and enhanced transmission rates mean that the system is extremely applicable to the telemedicine and the use of cloud healthcare, where medical images should be exchanged among hospitals, specialists, and remote diagnostic centers in a short period of time. The suggested procedure thus enables real-time clinical decision-making, effective healthcare data handling, and constant monitoring of the tumor in sophisticated targeted drug delivery systems.

7. Conclusion

Overall, the ROI-based medical image compression framework is a viable and practical solution to efficient tumor monitoring in the targeted drug delivery system. The paper shows that the selective compression of the tumor area maintains important diagnostic information like tumor size, clarity of boundaries and structural integrity of the tumor, and also the overall image size is considerably smaller. The performance analysis validates the enhanced compression ratio, high PSNR, high SSIM values and high storage efficiency with respect to various image dimensions. The key advantage of ROI compression is that it can preserve clinically significant areas of high quality and reduce storage and transmission needs, and thus is quite applicable to telemedicine and cloud-based healthcare systems. Clinically, the suggested strategy will help to assess response to treatment correctly, continuously monitor tumor progression, and make better decisions in precision oncology. Moreover, it improves interaction among healthcare providers as it allows spreading images faster and storing data more effectively. The framework can be developed further as future scopes with AI-based automatic identification of ROI, which will allow full localization and segmentation of tumors to be fully automated. Compression efficiency and reconstruction quality can also be enhanced by the integration of deep learning-based compression models. Moreover, real-time implementation within hospital settings and integration with IoT-enabled healthcare networks can facilitate continuous remote patient monitoring, smart diagnostics, and high-tech targeted drug delivery solutions in the next-generation smart healthcare applications.

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