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Performance Analysis for Medical Imaging using Fractal Image Compression

Shreya Tiwari[1], Dr. Rachana Dubey[2], Dr. Sadhna K. Mishra[3]
M. Tech Scholar, Department of CSE, LNCT, Bhopal (India)1
Professor, Department of CSE, LNCT, Bhopal (India)2
Head & Professor, Department of CSE, LNCT, Bhopal (India)3

Abstract: *The reason for increasing data storage and great rate transmission due to recent developments in the area of information technology that have contributed to the genesis of a massive amount of information every moment. For instance, text, image, audio, video data is mostly passed from person to person or from place to place in a digital form. It is often desirable to store data or transmits it for saving disk space, reducing the time needed for communication or the time needed for data transfer, and more. In this work we present the enhanced image compression model for medical imaging and improve the performance than existing system, our model gives better result in the form of numerical result value*.

Keywords: *Image Segmentation, Image Compression, Medical Imaging, Magnetic Resonance Imaging*.

1. INTRODUCTION

Medical imaging has become one of the most active and rapidly evolving fields in medical research and clinical diagnosis. Medical images display the internal structure of the human body in an intuitive form, providing clinicians with intuitive and accurate basic information on anatomy, pathology and function. Typical imaging modalities include magnetic resonance imaging (MRI), computer-assisted tomography (CT), ultrasound (US), computer-assisted X-ray (CR), digital subtraction angiography (DSA). With continuous advancement of medical imaging technology, especially the resolution of imaging devices, the amount of medical image data will continue to grow. Existing bandwidth conditions are difficult to meet the real-time transmission requirements of large data volumes. To meet effective storage and transmission of medical images, it is not only necessary to expand storage space and transmission bandwidth, but also to study how to efficiently compress medical data. Therefore, it is necessary to implement effective compression of various medical images using an image compression algorithm. Medical image compression methods are generally classified into lossless compression and lossy compression. Lossless compression provides medical diagnostics with image information of the same quality as the original image. However, the compression ratio of lossless compression is usually low, which is difficult to meet the actual transmission requirements of medical images. Lossy compression provides a higher compression ratio by losing some information. Increase in compression inevitably brings a certain degree of degradation to medical images. In the future of telemedicine applications, lossless compression will be difficult to provide a low bit rate required for image transmission, while relying on lossy compression to achieve real-time transmission of images. At present, lossy compression technology for medical images has become a research hotspot at domestic and international, and its research goal is to improve the reconstruction quality of images as much as possible under a given code rate [1].

Hospitals and medical research centers are currently moving toward a digitalized diagnosis and treatment environment. These environmental changes have made the security of the usage, management, and transmission of digital medical images extremely important. In response, the standard format Digital Imaging and Communications in Medicine (DICOM) was created as a storage standard for medical images based on the Transmission Control Protocol/Internet Protocol as a foundation for communication to ensure a consistent format for storing, processing, printing, and transmitting medical images and data between facilities.

Using the DICOM standard, medical devices from different manufacturers within a network can be used to transmit and use medical images. This enables patients, physicians, and medical research units to share relevant medical images through internet image servers to conduct real-time, convenient disease diagnosis, treatment, and research. However, it cannot be ignored that in such a convenient environment, stored data may be susceptible to attacks, tampering, or misplacement during transmission or storage for diagnosis and treatment.

2. MEDICAL IMAGE SEGMENTATION

Medical image segmentation, identifying the pixels/voxels of anatomical or pathological structures from background biomedical images, is of vital importance in many biomedical applications, such as computer-assisted diagnosis, radiotherapy planning, surgery simulation, treatment, and follow-up of many diseases. Typical medical image segmentation tasks include brain and tumor segmentation [12], cardiac segmentation, liver and tumor segmentation, cell and subcellular structures, multi-organ segmentation and lung and pulmonary nodules [13], vessel segmentation, etc., and thus can deliver crucial information about the objects of interest. While semantic segmentation of medical images involves labeling each pixel/voxel with the semantic class, instance segmentation (such as cell segmentation) extends semantic segmentation to discriminate each instance within the same class. Recently, deep learning methods have achieved impressive performance improvements on various medical image segmentation tasks and set the new state of the art. Numerous image segmentation algorithms have been developed in the literature and have made great progress on the designs and performance of deep network models.

However, the scarcity of high-quality annotated training data has been a significant challenge for medical image segmentation. The strong generalization capabilities of most cutting-edge segmentation models, which are usually deep and wide networks, highly rely on large-scale and high-quality pixel-wise annotated data, which are often unavailable for clinical and health care tasks. In fact, it is an expensive and time-consuming process to manually annotate medical images at pixel-level since it requires the knowledge of experienced clinical experts. The scarcity of annotated medical imaging data is further exacerbated by the data differences in patient populations, acquisition parameters and protocols, sequences, vendors, and centers, which may result in obvious statistical shifts. Thus, it is even challenging to collect a sufficiently large number of training data due to the heterogeneous nature of medical imaging data and the strict legal and ethical requirements for patient privacy. The data scarcity problem is much more severe for emerging tasks and new environments, where quick model employment is expected. However, only a limited amount of annotations with limited quality are available. Therefore, the high cost of pixel-level labeling and the privacy and security of data hinder the model training and their scalability to novel images of emerging tasks and new environments, which subsequently hamper the application of deep segmentation models in real-world clinical and health care usage. Thus, learning strong and robust segmentation models from limited labeled data and readily available unlabeled data is crucial for the successful application of deep learning models in clinical usage and health care.

Figure 1: A taxonomy of medical image segmentation under limited supervision [12].

3. RELATED WORK

[1] Current compression methods for MRI images with high compression ratio cause loss of information on lesions, leading to misdiagnosis; compression methods for MRI images with low compression ratio does not achieve the desired effect. Therefore, a fast fractal-based compression algorithm for MRI images is proposed in this paper. First, three-dimensional (3D) MRI images are converted into a two-dimensional (2D) image sequence, which facilitates the image sequence based on the fractal compression method. Then, range and domain blocks are classified according to the inherent spatiotemporal similarity of 3D objects. By using self-similarity, the number of blocks in the matching pool is reduced to improve the matching speed of the proposed method. Finally, a residual compensation mechanism is introduced to achieve compression of MRI images with high decompression quality.

[2] Fractal image compression is a lossy technique to compress the image in a coded form instead of pixels and is differentiated by its long encoding time with a high compression ratio, resolution independent, fast decoding, and self-similarity. The main purpose of this paper is to present a comparative performance study of the three coding schemes of fractal compression for grayscale medical images based on fixed partition. The first two coding schemes are based on the pixel-pattern measure and the third scheme is a proposed method based on the fractal dimension for complexity measure of range and domain blocks. The comparative study included encoding time, peak signal to noise ratio, and compression ratio, as a result, has been accomplished.

[3] This paper explores a unique neural network FIC that is capable of increasing neural network speed and image quality simultaneously. An artificial intelligence technique similar to a neural network is used to reduce the search space and encoding time for images by employing a neural network algorithm known as the “back propagation” neural network algorithm. Initially, the image is divided into fixed-size and domains. For each range block its most matched domain is selected, its range index is produced and best matched domains index is the expert system's input, which reduces matching domain blocks in sets of results. This leads in the training of the neural network. This trained network is now used to compress other images which give encoding a lot less time. During the decoding phase, any random original image, converging after some changes to the Fractal image, reciprocates the transformation parameters. The quality of this FIC is indeed demonstrated by the simulation findings.

[4] This work proposed an effective strategy for multimodal medical picture fusion based on a hybrid approach of NSCT and DTCWT. The experimental study’s input multimodality medical images included computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET). A suggested approach employs a convolutional network to generate a weight map that incorporates pixel movement information from dual or more multimodality medical pictures. To provide greater visual comprehension by humans, the medical picture fusion method is performed on a multi-scale basis using medical image pyramids. Additionally, a local comparison-based method is employed to adaptively alter the fusion mode for the decomposed coefficients. The proposed fusion methodologies result in the highest-quality fused multimodal medical pictures, the lowest processing period, and the finest visualization in terms of visual quality and objective assessment standards.

[5] The importance of image security in the field of medical imaging is challenging. Several research works have been conducted to secure medical healthcare images. Encryption, not risking loss of data, is the right solution for image confidentiality. Due to data size limitations, redundancy, and capacity, traditional encryption techniques cannot be applied directly to e-health data, especially when patient data are transferred over the open channels. Therefore, patients may lose the privacy of data contents since images are different from the text because of their two particular factors of loss of data and confidentiality. Researchers have identified such security threats and have proposed several image encryption techniques to mitigate the security problem. However, the study has found that the existing proposed techniques still face application-specific several security problems. Therefore, this paper presents an efficient, lightweight encryption algorithm to develop a secure image encryption technique for the healthcare industry. The proposed lightweight encryption technique employs two permutation techniques to secure medical images. The proposed technique is analyzed, evaluated, and then compared to conventionally encrypted ones in security and execution time.

[6] Among several applications, medical image semantic segmentation is one of the core areas of active research to delineate the anatomical structures and other regions of interest. It has a significant contribution to healthcare and provides guided interventions, radiotherapy, and improved radiological diagnostics. The underlying article provides a brief overview of deep convolutional neural architecture, the platforms and applications of deep neural networks, metrics used for empirical evaluation, state-of-the-art semantic segmentation architectures based on a foundational convolution concept, and a review of publicly available

medical image datasets highlighting four distinct regions of interest. The article also analyzes the existing work and provides open-ended potential research directions in deep medical image semantic segmentation.

4. EXPERIMENTAL RESULT

Fractal image compression (FIC) is a method of lossy compression, attempting to construct an approximation of the original image. The major task of this method is to examine similarities between large and small parts of images. FIC is utilized in various image processing applications, such as image retrieval, feature extraction, image signature, multi-resolution medical image processing, and texture segmentation. It has important advantages, such as high compression ratio and fast image reconstruction. Also, its multi-resolution property is one of the advantages achieved by decoding the image to get lower or higher resolutions than the original image. The widely used fractal features in the applications of image processing are texture segmentation of images, image retrieval system, and fractal dimension (FD) based texture segmentation of images. In FIC, the main implication is a fast encoding time and a high CR of the image, which is possible through variable size partition of range blocks known as quadtree partition. An FD is a measure, comparing how a fractal pattern of grayscale medical image changes with the scale. Usually, the image data discretized in computer applications for further processes. The covering method of the pixel mostly used in the FD estimation of the fractal binary image. In this binary image, the foreground values represented by 1 (white), while the background represented by 0 (black). It is found that the low FD value-based blocks contained fewer textures. So that the domain blocks could not cover the high FD value-based range block. On the other side, the range blocks might be covered by the domain blocks of high FD value by reducing the amount of texture in that domain blocks. The FIC method is to improve the encoding time of grayscale medical and non-medical images by using efficient parallel hardware architecture and for an agricultural image by using the statistical loss. A fast FIC method based on feature extraction by transforming the problem from the image domain to the vector domain and, a new local binary feature resembles local binary patterns based method to reduce the search space. In another method, accelerate the encoding process by reducing the full searching scope of similarity matching by using the coefficient of variation feature was adopted. A novel approach for FIC was proposed by calculating the affine parameters based on the approximation of the scaling parameter.

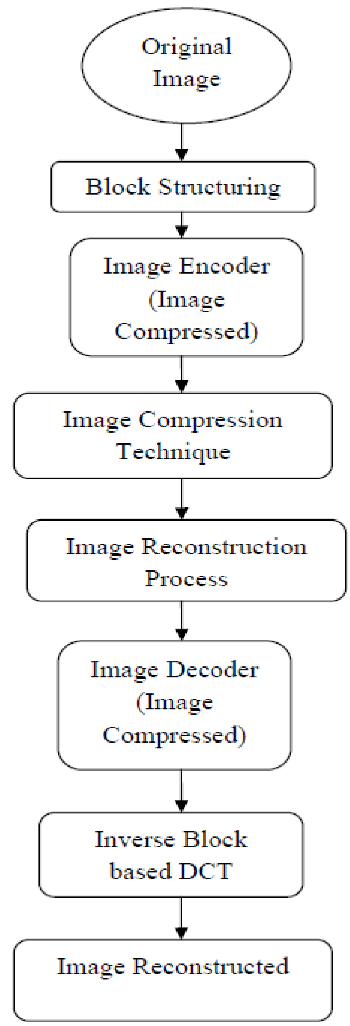

Figure 2: Proposed model of medical science image compression.

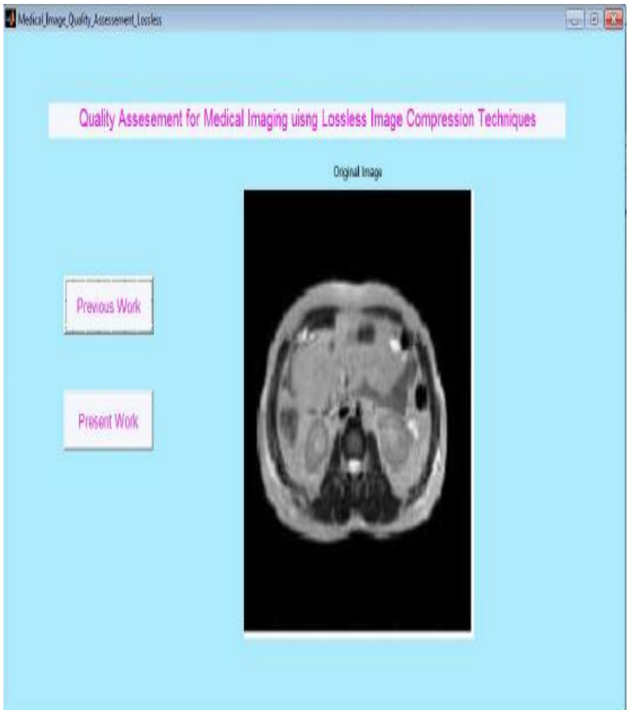

Figure 3: This is the original input image-2 with select for the experimental process using previous work.

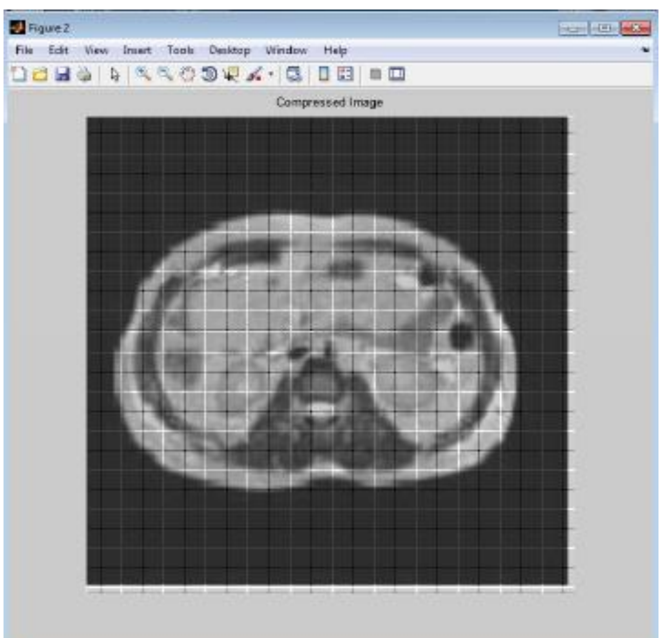

Figure 4: This figure shows that the compressed output using of previous work for input image-2.

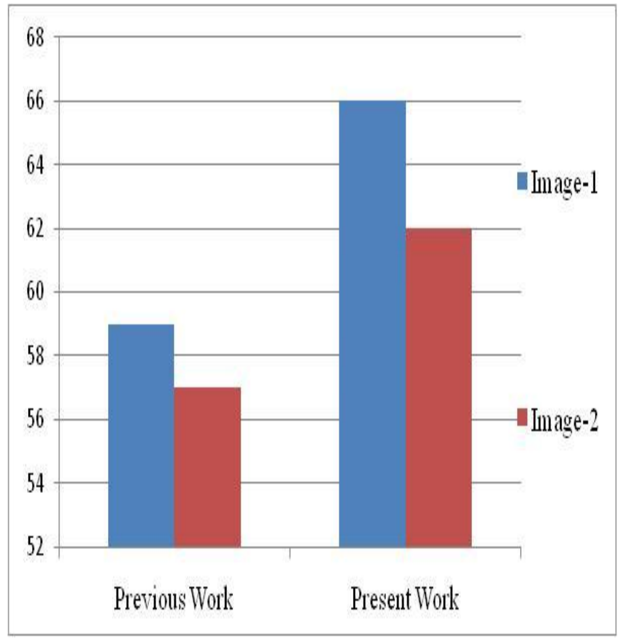

Figure 5: The above figure represent that the comparative study between the previous work and resent work for the input image-1 and input image-2 with performance parameters PSNR.

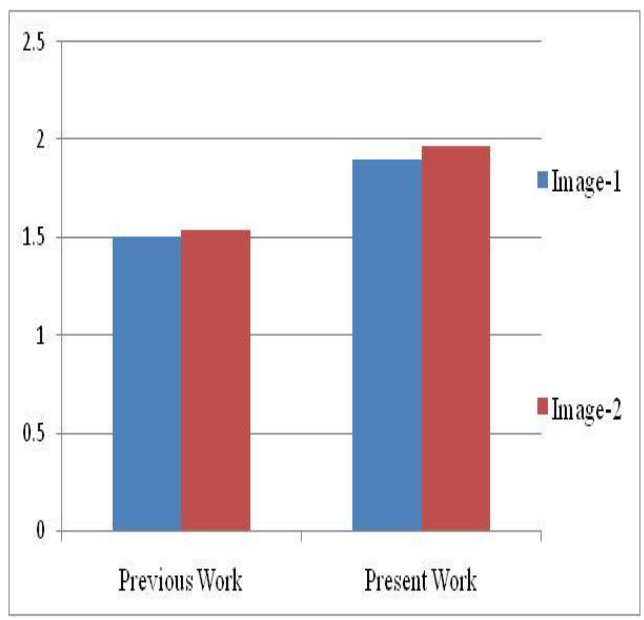

Fig 6: The above figure represent that the comparative study between the previous work and resent work for the input image-1 and input image-2 with performance parameters compression ratio.

5. CONCLUSION

Medical diagnosis systems play a vital role in recent year especially after witnessing dramatic pandemic concerns around the world. Image segmentation plays a vital role in the field of auxiliary medical diagnosis. The method with a better segmentation effect can significantly promote the accuracy of medical diagnosis and improve the efficiency of diagnosis. The comparative study of all the methods under the given criterion, it is clear that the our present work gives better image quality and compression rate than existing techniques, the proposed methods not only speed-up the block mapping process but also preserves the significant visual quality.

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