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ANALYSIS OF 3D MEDICAL IMAGE COMPRESSION

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ABSTRACT

In recent years, the market for digital images has increased as we see the rise in multimedia technology. There is an immense amount of data when it comes to digital information. Where as in medical field, image compression plays a significant role. The fundamental purpose of image compression is to represent an image of an appropriate quality with a minimum number of bits. Many of the advanced medical imaging technologies are 3D images like CT, MRI are important in biomedical field. The advances in communication engineering are also enjoyed by modern medical field such as telemedicine. The work addressed in this review is dedicated to applying the most popular image compression methods available. We focus on 3D medical image compression in this analysis. The 3D images are in demand for storage and archiving services as well as for transmission over the network due to their enormous file size. And the storage of 3D images in the medical field for remote area diagnosis is now more common. Understanding and analyzing the methods used for medical image compression are the main goal of this paper.

Keywords: Image-Compression; Lossless; Lossy; Redundancy; Parameters; Transforms; DWT; DCT.

I. INTRODUCTION

In recent decades, the production of knowledge managed by computers in the internet, digital and high-definition television technologies id growing exponentially. The storage and transfer of the digital image portion of multimedia systems is also a significant issue. High-quality images need a significant amount of space and transmission band width, which is to compress the data of digital image so that storage space and transmission time can be decreased if the existing technology is unable to manage this problem technically and economically. The compression of the image may be possible since redundant information consists of the image. The redundancy and irrelevant reduction of information can also achieve compression. Whereas redundancy and irrelevant reduction of information can also achieve compression. Whereas redundancy means that the human visual system may not be able to see a repeat of the portion of an image that can be omitted from the image to minimize the size of an image.

Medical imaging research focuses on the interaction of all sources of radiation with tissue. Medical images have very large sizes and numbers, and the compression of medical images reduces storage space and costs and increases the speed of transmission so that the data can be processed on the server and distributed to users based on requirements. The primary aim of medical compression is to minimize the large-scale image that consists of large volumes of data due to its high size that can be processed and transmitted during critical diagnosis [1].

Medical images have various file formats, such as Bitmap image (BMP), Tagged image file format (TIFF) and portable network graphics (PNG). A special type of file format in medical images is called digital imaging communications in medicine (DICOM) which is most commonly used. The DICOM is the most popular file format in medical imaging because it contains information not only about the image but also the patient, such as the patient ID.

Each image has a background and a foreground detail. The background region includes information that can be compromised during compression or can be ignored. The object captured during imaging is depicted by the data in the foreground field. This type of information cannot be compromised by compression, especially for medical images. This foreground information region is called the region of interest (ROI). Segmentation techniques are preferred to identify the ROI. Non-ROI techniques can sometimes be used to preserve each and every information foreground and background of the medical image or normal image at that time.

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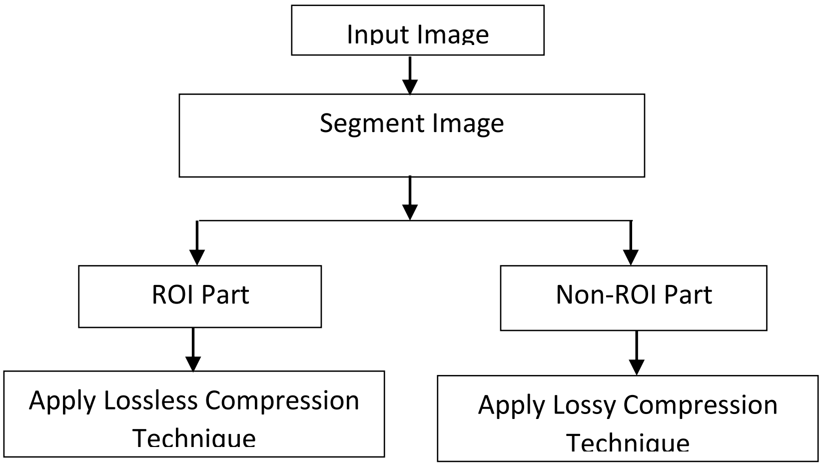

Figure 1. Image Segmentation based on ROI and Non-ROI

In many clinical and scientific applications, 3D medical images are used. Due to their large file size the 3D images are in demands for storage and archiving resources. Image compression is typically used to remove unimportant data before sending the image to clouds to reducing data traffic. The storage of 3D images is now more common in the field of remote area diagnostics. where specialists might not be present to diagnose or provide the patient with the necessary care at such a location that this 3D image compression may work due to reducing the size of image as well as reducing transmission bandwidth and expense.

Wavelet Compression

Wavelet based image compression were its wavelet coding schemes combine excellent compression efficiency with possibility of embedded represtation. Wavelets are the mathematical functions that divides information into various frequency comeponents and later study those component with their resolution that matches its scale. Few of the coding schemes that are emerged are Embedded Zero tree Wavelet (EZW), Encoding by set partiotoning in Hierarchical Trees (SPHIT) [2].

II. LITERATURE SURVEY

In 2017, Qingzhu Wang, et al presents tensor compressive sensing to simultaneously encrypted and compress a 3D sequence as tensor rather than several 2D images. The proposed method preserves the intrinsic structure of tensor-based 3D image sequences and achieves a balanced compression ratio, decryption accuracy and security. In this paper the simultaneous compression and encryption system is presented based on improved TCS and 3D Lorenz components which can encrypted and decrypted 3D images as a tensor. The performance of the proposed method tested on Lung CT sequences in the Lung Image Database Consortium. The security of the proposed method meets the requirements of the standard encryption technology [10].

In 2018, M.A.P. Manimekalai, et al presents the hybrid LZW and CHE (clipped histogram equalization) based image compression techniques. The proposed method was preprocessed by means of median filter. Then processed image split into region of interest (ROI) and non-region of interest (Non-ROI) by means of deep convolution networks with jacquard distance. The ROI part is compressed by hybrid Lempel-Ziv-Welch and clipped histogram equalization (CHE). The non-ROI is compressed using the enhanced zero tree wavelet (EZW). The experimental evaluation is conducted on MRI -brain, nuro, skull full and MRI-Tumor images. The performance of the proposed method provided a great result when match with the existing method [16].

In 2019, Khalid M. Hosny, et al presents Legendre moments nd differential evolution. The successful use of orthogonal Legendre moments in image compression is motivated to introduce new method. The proposed method has two stages. First is image transformation using Legendre moments to generates the Legendre coefficients. Second is differential evolution optimization is used to select proper coefficients according to the optimization cost function. The performance of the proposed method is tested on Axial view of MRI knee, abdomen CT and sagittal view of knee. Overall found that the application leads to higher compression ratio as well as quality reconstructed images [8].

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In 2019, Shuai liu, et al presents a fast MRI image compression method based on fractal. In this proposed method the 3D MRI images are converted into 2D images sequences, then range and domain block are classified based on inherent spatiotemporal similarity of 3D objects. The residual compensation mechanism is introduced to achieve compression of MRI images with high decompression quality. A Huffman coding based on integer squared quantization threshold is performed on regions with finer threshold. To obtain stream data is transmitted with original data. The performance of the proposed method significantly improved when compared with other traditional method [9].

In 2020, Matina Ch. Zerva, et al presents the extension of the 3D wavelet difference reduction (3D-WDR) method that employs mean co-located pixel difference (MCPD) to estimate the optimal number of slices to be efficiently compressed in volumetric object. The proposed method achieved a high compression ratio and just a limited amount of loss of information that can be within a reasonable range. Used an publicly available datasets named as cancer image archive (TCIA). The performance of the proposed method is improved with respect to PSNR value. The visual perception of an image is retained is very close to the original image [17].

In 2020, S. UmaMaheswari et al presents an adaptive image compression technique which has non-redundant tetromino basis functions and a fast filter bank technique. The proposed method is based on Haar wavelet-based transform the tetrolet transform is made. The major advantage of wavelet-based image compression is, able to process multi scale analysis due presence of frequency spectra. And the multi-resolution property of wavelet is used to get image details. Haar transform is performed on input image. And new details are obtained. After that matching tiles are selected. In this proposed method mainly three images are selected for test i.e., MRI, CT, and normal images. The performance of the proposed method is high as compared to other existing methods [18].

In 2020, Dr.K.Prabavathy, et al presents a hybrid method based on evaluation on SPIHT algorithm. The SOIHT is an image compression algorithm correlated with DWT and applies the principle of self-similarity across plane as it is been implemented by EZW. The proposed method was tested on scan images and x-ray images. The proposed method provides the better results which are approvingly efficient in terms of various different matrices [19].

In 2020, N.N. Kulkarni, et al presents ROI based Lossless compression using integer wavelet transform and Run-length coding. The proposed method is evaluated on MRI images. In this proposed method the preprocessing were done for filtering an image using various image processing tools. Then segmentation is done to obtain ROI and Non-ROI region. Once the ROI part is extracted then further compression process takes place. By an experimental result it concluded the better result in terms of CR, PSNR, and MSE. And it has less complexity and takes less time for encoding and decoding process [20].

III. TYPES OF IMAGE COMPRESSION TECHNIQUES

Image compression technique is classified into two types. One is lossy image compression and other one is lossless image compression [3].

A. Lossy Image Compression

When we reconstruct information from compressed data, we may get something close to, but not exactly the same as the original one. In lossy compression techniques, compression is used to improve throughput but at a loss of quality.

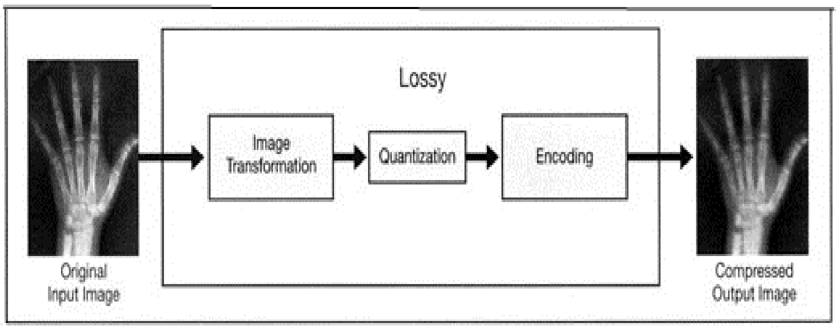

Figure 2. lossy medical image compression

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Why lossy coding:

Bandwidth: In India we have bandwidth issues in rural places. To speed up the initial arrival of the images we need to prefer the lossy image coding.

Storage Costs: storage cost of medical image is expensive also the image modalities become more complex.

B. Lossless Image Compression

The reconstructed image is same as original image but the compression ratio is less. This method or scheme can be used for the application where no loss of any information is compromised as we can see in medical field where we can't make compromise with any information of an image because bit of information more important in medical application to diagnose a patient.

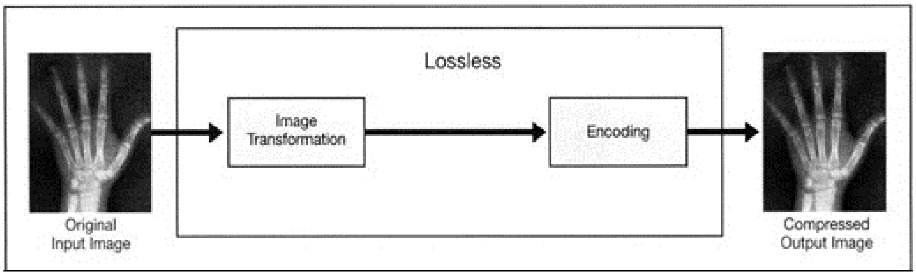

Figure 3. Lossless Medical Image Compression

IV. HOW ACHIEVES A COMPRESSION?

Redundancy plays an important role in achieving compression. By minimizing the redundancy of the image, we can achieve a compression that removes redundant information from the image [4].

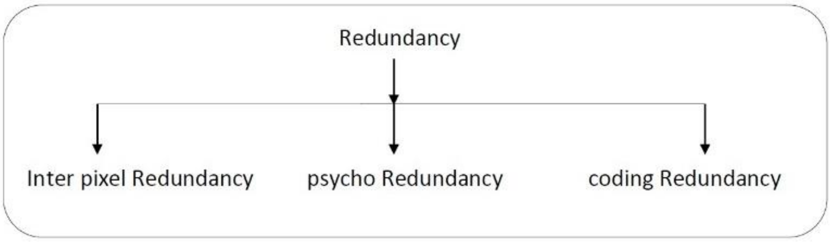

Figure 4. Types of Redundancies.

Inter pixel redundancy: it takes advantage of the fact that the image most often contains highly correlated pixels, large regions with the same or almost same pixel values.

Psycho visual redundancy: Elimination of psycho-visual redundant data results in a loss of quantitative information; it is commonly referred to as quantification.

Coding Redundancy: A code is a set of symbols used to describe a collection of events or a body of knowledge. Compression can be generated using a number of variable length code systems, such as Huffman coding and arithmetic coding.

V. EVALUATION PARAMETERS FOR THE ANALYSIS OF COMPRESSION

The performance evaluation is needed to check the efficiency of the compression. Mean square error (MSE), peak signal noise ratio (PSNR) and compression ratio (CR) are widely used measurements. In addition to those which need to be checked, the quality of the reconstructed image is validated by metrics such as Normalized Cross-Correct (NCC), Normalized Absolute Error (NAE), average difference (AD), structural content (SC), Laplacian mean square error (LMSE) [5].

Mean Square Error (MSE):

The MSE characterized the collective squared error between the flattened image and the inventive image [6]. it is defined as the difference between the reconstructed image and the original image [6]. It is used to measure the error between the original image and reconstructed image.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[y(i,j)-x(i,j)]^2 \quad (1)$$

Peak signal noise ratio (PSNR):

It is used to calculate the accuracy of the images that are being reconstructed. It is used to calculate the efficiency of the image loss measurement [7]. PSNR distinguishes the relationship between the initial image and the noise and the decoded image.

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{255^2}{\mathrm{MSE}}\right) \quad (2)$$

Compression ratio (CR):

By comparing the memory occupied by the compressed image to that of the original image, this discards the capacity of the proposed compression algorithm. The higher the compression ratio, the more effective the compression with an indicative [6].

$$\mathrm{CR} = \frac{\text{Size of original image}}{\text{Size of compressed image}} \quad (3)$$

Structural similarity index method (SSIM):

The SSIM is a novel method of measuring the similarity between original image and the reconstructed image [8].

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_1^2 + \mu_2^2 + c_1)(\sigma_1^2 + \sigma_2^2 + c_2)} \quad (4)$$

Speed Ratio (SR) Indicator:

SR=TS/TC (5)

Where TS is the time required to adopt the traditional MRI fractal image compression method. TC is the time required by the method [9].

Normalized Cross-Correlation (NCC):

It measures the similarity between the original image and the reconstructed image. The higher the value of NCC closer to 1 indicates the efficiency of the compression [5].

$$NCC = \sum_{i=1}^{m}\sum_{j=1}^{n}\frac{X(i,j) \times Y(i,j)}{X(i,j)^2}. \quad (6)$$

Normalized Absolute Error (NAE):

The value of NAE should be low for the reconstructed image which indicates the compression capability [5].

$$\mathrm{NAE} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(X(i,j) - Y(i,j))}{\sum_{i=1}^{m}\sum_{j=1}^{n}X(i,j)}. \quad (7)$$

Average difference (AD):

It measures the difference between the original image and the reconstructed image. Ideally it should be zero; a compression algorithm should have low values of the AD [5].

$$\mathrm{AD} = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}[X(i,j) - Y(i,j)]. \quad (8)$$

Structural content (SC):

If SC consists higher value than it indicates that the poor quality of reconstructed image [5].

$$SC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(X(i,j))^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}(Y(i,j))^2}. \quad (9)$$

Laplacian Mean Square Error (LMSE):

When comparing the original image, the quality of the edges in the reconstructed image is reflected. The higher the LSME value, the poorer the quality of the reconstructed image [5].

$$LMSE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}[L(X(i,j)) - L(Y(i,j))]^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}[L(X(i,j))]^2} \quad (10)$$

VI. COMPRESSION METHODS

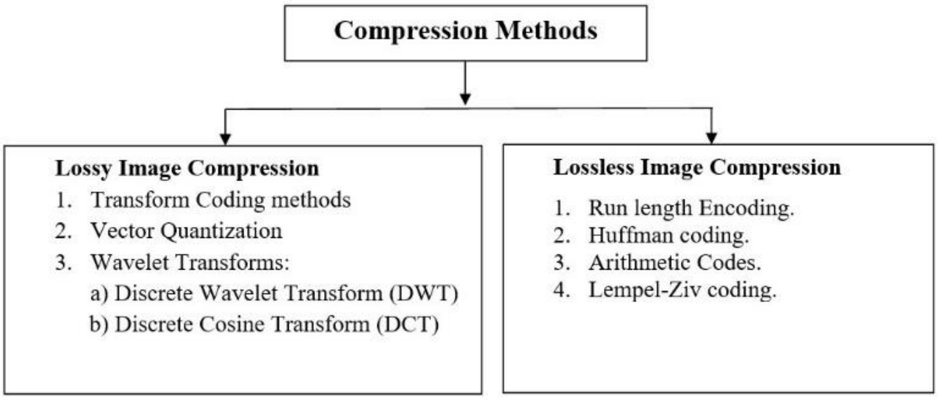

Figure 5. Types of Compression Methods.

A. Lossy image compression methods:

1. Transform coding method: It starts by partitioning the original input image into small blocks (usually like 8x8). The transform coefficient is calculated for each block, converting the original 8x8 pixel array values into a coefficient array contains the information needed to quantify and encode the image with a small amount of distortion [10].

2. Vector Quantization: it is a classical quantization technique for image compression; it works by dividing a large set of values into groups with almost the same number of points closest to them. Every group represented by its central value. It is also used for loss data correlation and density estimation. Methodology depends on a competitive learning model [11].

3. Wavelet transform: signals are nothing but wavelets which are local in time and scale and have irregular shape. A wavelet has limited duration that has average value zero. It has great advantage of being able to separate the fine details in a signal [10].

i. Discrete wavelet transforms (DWT): it produces no redundant image representation; it provides spatial and spectral localization of image formation compared to other multi-scale representation. The use of the DWT image is decomposed into a sequence of different spatial resolution images. This method is well suited for compressing images. The goal is to store image data in a small space [10].

ii. Discrete cosine transforms (DCT): it transforms the signal from spatial representation to frequency representation. The image is represented as a sum of sinusoid of varying magnitudes and frequencies. In the image compression technique, the less important frequencies are discarded during the quantization process, and the most important frequencies are still used to retrieve the image during the decompression process [12].

B. Lossless image compression methods:

1. Run-length coding: this technique is more efficient only if the data consists of long runs of repeated characters or symbols while compressing data [11]. In other words, it replaces a series of two or more characters that are the same and a number that represents the length of the run, followed by original character [13].

2. Huffman coding: the symbol that occurs more frequently will have a shorter codeword than the symbols that occur less frequently. Also, the two symbols that occur less frequently have the same maximum code-word length [11]. Here, the fixed length codes are replaced by the variable length codes.

3. Arithmetic coding: it is more efficient when the size of the alphabet is small or the probabilities of the symbol are highly skewed. The generation of code words for the sequence of symbols is well organized than the generation of a separate codeword for each symbol in sequence. It provides a better compression ratio than the Huffman code [11].

4. Lempel-Ziv coding: it is dictionary-based coding. The dictionary-based coding may be static or dynamic. In static the dictionary is fixed while coding and decoding processes. Mainly used for GIF image formats [13].

VII. IMAGE COMPRESSION SYSTEM

In general, the compression system model consists of two distinct structural blocks: the encoder and the decoder. The encoder generates a stream of code from the original input data. After the channel is transmitted, the decoder generates the reconstructed output data [14].

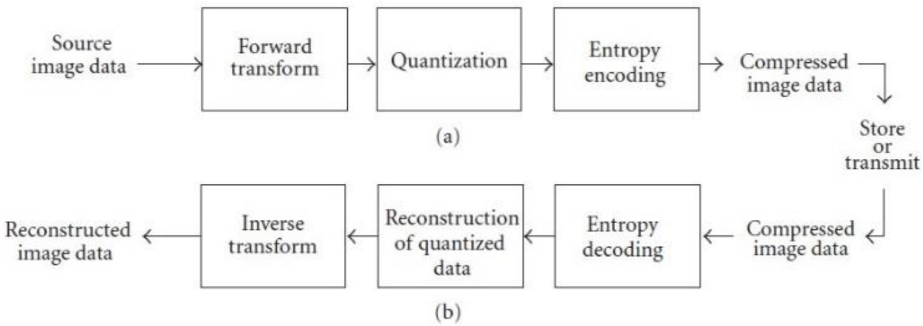

Figure 6. General block diagram of image compression system.

A typical encoder consists of three functional modules, shows in figure 3: a prediction module or forward module that performs spatial decorrelation, a quantization module that reduces the dynamic range of errors, and an entropy encoding module that reduces coding redundancy. When a lossless compression is required, the quantization step is omitted because it is irreversible operation [14].

VIII. MOST COMMON COMPRESSION TRANSFORMS

The mainly DCT and DWT are the two main compression transforms.

Discrete cosine transforms: baseline mode, which only supports lossy compression using DCT, is the most popular. The flow of process is shown in figure 4. The JPEG-baseline encoder starts with 8x8 block-based DCT, quantization, zigzag and entropy coding using Huffman table. The quality factor is determined using the quantification tables [14].

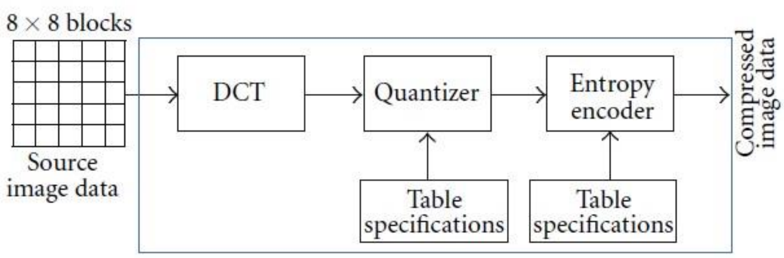

Figure 7. Block diagram of JPEG-baseline encoder.

For 3D images, usually 3D DCT has been computed on 8x8x8 or 16x16x16 cubes rather than on multiple frames due to memory and algorithm complexity. Cube based 3D DCT results in blocking artifacts, which destroys the edges of medical image [15].

Discrete wavelet transforms: the CCSDS-IDC (consultative committee for data systems-image data compression) consists two main functional parts: a DWT module that performs the decomposition of image data and a bit-plane encoder (BPE) that encodes the transformed data, as shown in figure 5.

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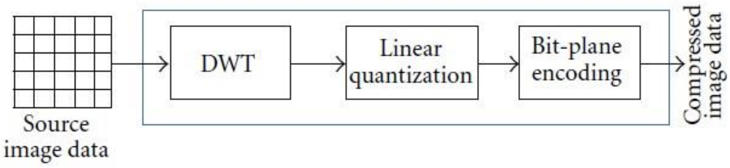

Figure 8. General diagram of the CCSDS-IDC encoder.

IX. CONCLUSION

This paper presents 3D medical image compression and the basic image compression techniques. we have discussed the types of image compression techniques available. The performance of compression technique is calculated by performance measures. why image compression is needed and how to achieve the compression. Different transformations and encoding methods. Also discussed some of the recent articles with methods they have applied. After study of all methods and articles, it is found that most of the image compression techniques or algorithm are available for 2D images and only few methods were found on 3D images. And many challenges are found for 3D medical image compression.

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