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A NOVEL METHOD OF MEDICAL IMAGE ENCRYPTION BY APPLYING THE MULTISCALE TRANSFORM-BASED IMAGE COMPRESSION: A REVIEW

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Abstract

The use of cloud computing and its countless applications has experienced rapid development in recent years. In the form of images, video and audio, a cloud can contain vast amounts of multimedia data. Cloud computing systems confront problems in terms of data security, message integrity, user authentication and compression. Multimedia data requires plenty of space for storage. Consequently, to minimize data size, multimedia data compression is required. Compression methods are very reliable, giving advantages to organizations in the cloud that deal with metasized data. Compressing vast volumes of information contributes to superior cloud storage usage. The main objective of this paper is to propose a new architecture that performs joint medical image compression and image encryption in the cloud, comprising multiscale transformations, public key cryptography and suitable encoding techniques. In image compression, multiscale transforms play a leading role, and wavelet, bandelet, curvelet, ridgelet and contourlet transforms are those discussed in this paper. In terms of time and frequency domains, wavelet transforms give robust localization.

Keywords: *Cloud Computing, Data, Encryption, Image, Security, Protection, Compression methods.*

I. INTRODUCTION

Cloud computing is the fastest-growing internet technology around today, arguably. A cloud can be called a collection of hardware, networks, storage, services, and interfaces in cloud

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computing that combine to provide different computing aspects as a service. In order to use the cloud, it is unnecessary to instal hardware or software: cloud applications may instead be used as utilities as and when needed [1].

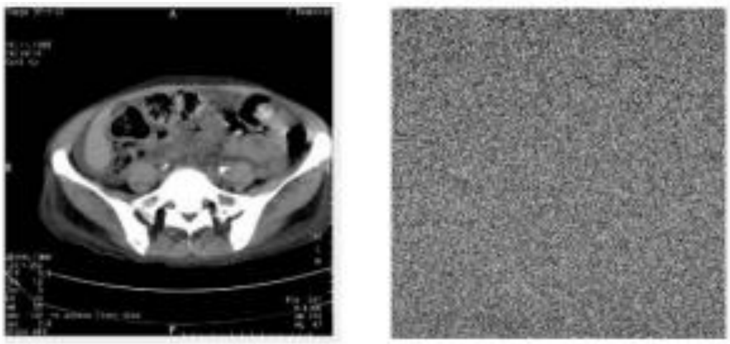

Figure 1: Illustrates the Real Images and Encrypted Image [2]

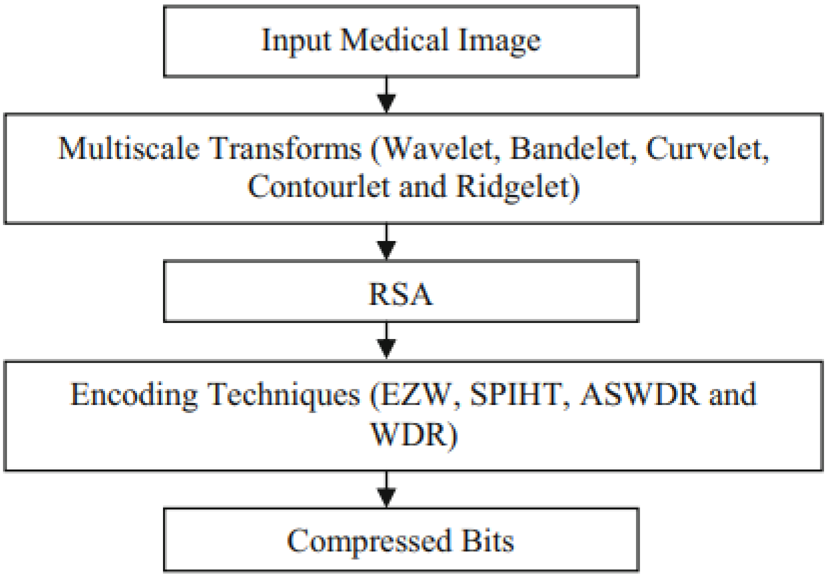

Figure 2: Illustrates the outline of the proposed method

$$E(x) = \frac{1}{N}\sum_{i=1}^{N} x_i$$

$$D(x) = \frac{1}{N}\sum_{i=1}^{N} (x_i - E(x))^2$$

$$cov\ (x,y) = \frac{1}{N}\sum_{i=1}^{N} (x_i - E(x))\ (y_i - E(y))$$

$$r_{xy} = \frac{cov\ (x,y)}{\sqrt{D(x)}\sqrt{D(y)}}$$

$$\sqrt{D(x)}\ \neq 0, \sqrt{D(y)} \neq 0$$

$$NPCR = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} D(i,j) \times 100\ \%$$

$$UACI = \left[\sum_{i=1}^{M} \sum_{j=1}^{N} \frac{|C1(i,j) - C2(i,j)|}{255} \right] \times \frac{100\%}{M \times N}$$

$$D(y) = \frac{1}{K} \sum_{i=1}^{K} (y_i - E(y))^2$$

The correlation coefficient is another essential constraint to ensure that how much efficient is the encryption algorithm [3].

$$r_{x,y} = \frac{C(x,y)}{\sqrt{D(x)}.\sqrt{D(y)}}$$

Where $C(x,y), D(x)$ and $D(y)$ can be evaluated by using the following equations [4].

$$C(x,y) = \frac{\sum_{i=1}^{K} (x_i - E(x))(y_i - E(y))}{K}$$

$$D(x) = \frac{1}{K} \sum_{i=1}^{K} (x_i - E(x))^2$$

$$D(y) = \frac{1}{K} \sum_{i=1}^{K} (y_i - E(y))^2$$

II. LITERATURE REVIEW

A study was conducted by Devadoss et al on near-lossless medical image compression using block BWT-MTF and hybrid fractal compression techniques. A medical image compression model is proposed in this paper for efficient medical image transmission using block BWT-MTF with Huffman encoding and hybrid fractal encoding. Medical image diagnosis requires careful examination of essential portions of the image. A minor loss in the critical portion leads to incorrect perception in medical image compression. By using region-based compression that results in the lossless compression of the appropriate area where the salient information are stored and lossy compression in the remaining region, the proposed compression scheme would remove this hindrance[5].

III. DISCUSSION AND CONCLUSION

For medical image compression and encryption in the cloud, a new architecture is introduced in this paper. The output of multiscale transformations, encoding methods and the supporting compression encryption algorithm are successfully described in this work. It is found that, with all encoding methods, the bandelet transform achieves favorable results, clearly enhancing the results of image compression and encryption compared to other transformations. The transformation of the bandelet is based on the picture and the warped wavelet geometric flow. The benefit of the transformation of the bandelet is that it can acquire the warped base adaptive to the edge direction of the picture. In addition, with all multiscale transforms, it is known that the SPIHT and ASWDR encoding techniques produce high PSNR and low MSE values. It is, therefore, concluded that the transformation of the bandelet produces excellent results in the compression and encryption of joint medical images.

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