British Journal of Mathematics & Computer Science
4(19): 2781-2798, 2014

SCIENCEDOMAIN *international*
www.sciencedomain.org

A Review of Wavelet-Based Image Processing Methods for Fingerprint Compression in Biometric Application

B. S. Emmanuel[1*], M. B. Mu'azu[1], S. M. Sani[1] and S. Garba[1]

[1]*Department of Electrical and Computer Engineering, Ahmadu Bello University, Zaria, Nigeria.*

Received: 10 June 2014
Accepted: 09 July 2014
Published: 20 July 2014

Review Article

Abstract

A data compression algorithm is a signal processing technique used to convert data from a large format to one optimized for compactness. Huge volumes of fingerprint images that need to be transmitted over a network of biometric databases are an excellent example of why data compression is important. The cardinal goal of image compression is to obtain the best possible image quality at a reduced storage and transmission bandwidth costs. In this paper, a review of different methodological approaches to fingerprint image compression based on the wavelet algorithm is conducted. From the survey of the existing wavelet-based image compression methods, the problems that have been identified include: the limitation of WSQ standard to a compression ratio of 15:1 which could be improved with better algorithm. High complexity of image encoding process of the existing techniques is also a problem. Most of the existing methods require the generation of codebooks or lookup tables which require additional computational cost for implementation. Additionally, significant degradation in the biometric features of fingerprint at compression ratio higher than 15:1 remains a major challenge. Therefore, the investigation of an efficient compression method that can significantly reduce fingerprint image size while preserving its biometric properties (the core, ridge endings and bifurcations) is justified.

Keywords: Wavelet transform, image compression, quantization, entropy coding, fingerprint.

1 Introduction

Images contain large amount of information that requires huge storage space and large transmission bandwidth. Image data processing and storage attract cost and the cost is directly proportional to the size of data. In spite of the advancements made in mass storage and processing capacities, these have continued to fall below capacity requirements of application systems [1]. Therefore, it is advantageous to compress an image by storing only the essential information needed to reconstruct the image. An image can be thought of as a matrix of pixel (or intensity) values and in order to compress it, redundancies must be exploited. Image compression is the general term for the various algorithms that have been developed to address these problems.

**Corresponding author: sbemmanuel@yahoo.com;*

A compression algorithm is used to convert data from a large format to one optimized for compactness. Data compression algorithms are categorized into two, namely; lossless and lossy compression techniques. A lossless technique guarantees that the compressed data is identical to the original data whereas in lossy compression technique, images are compressed with some degree of data loss or degradation while still retaining its essential features. This distinction is important because lossy techniques are much more effective at compression than lossless methods. Huge volumes of fingerprint images that need to be stored and transmitted over a network of biometric databases are an excellent example of why data compression is important. The cardinal goal of image compression is to obtain the best possible image quality at a reduced storage, transmission and computation costs.

1.1 General Concept of Image Compression System

An image compression system involves three fundamental image coding stages, namely:

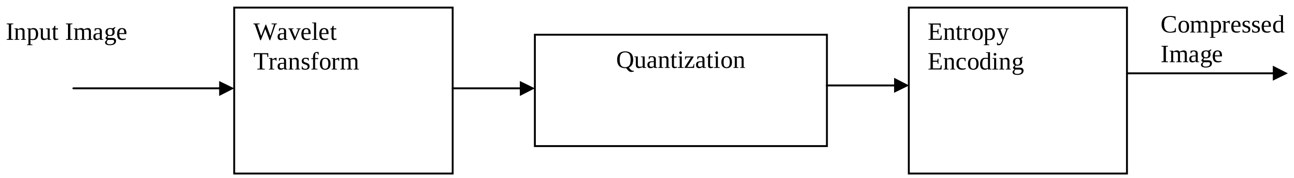
(i) Transformation;
(ii) Quantization; and
(iii) Entropy Coding.

The transformation which is achieved through suitable mathematical transformation technique (such as Fourier and Wavelet transforms) is applied to the image with the aim of converting it into a different domain where the compression will be easier. In the transform domain, correlation level can be lowered, and the energy can be concentrated in a small portion of the transformed image. The quantization, which can either be vector or scalar quantization or their variations, is the stage that is mostly responsible for the 'lossy' character of the system. It entails a reduction in the number of bits used to represent the pixel values of the transformed image (also called transform coefficients). Coefficients of low contribution to the total energy or the visual appearance of the image are coarsely quantized (represented with a small number of bits) or even discarded, whereas more significant coefficients are subjected to a finer quantization (represented with more bits). At the entropy coding stage, further compression is achieved with the aid of some entropy coding scheme such as Huffman, run-length, arithmetic coding etc. where the non-uniform distribution of the symbols in the quantization result is exploited so as to assign fewer bits to the most likely symbols and more bits to unlikely ones. This results in a size reduction of the resulting bit-stream on the average and the conversion that takes place at this stage is lossless [2-3].

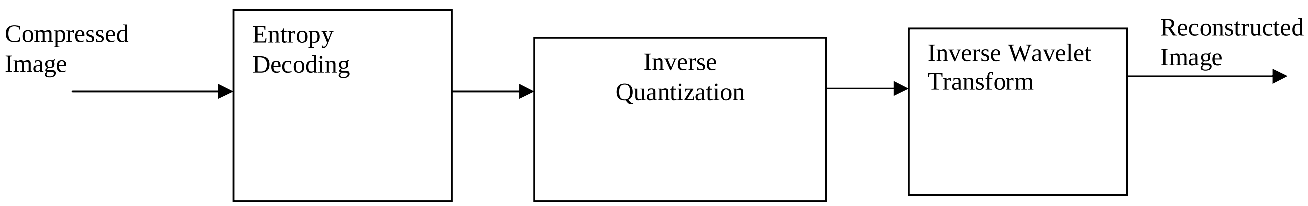
In specific terms, fingerprint image compression algorithm using wavelet transform method is implemented in two parts, namely [3]:

(i) Image encoding for converting image to optimized bit stream; and
(ii) Image decoding for reconstructing the image from optimized bit stream.

The implementation of each of the parts of the proposed algorithm is in three stages. They are Discrete Wavelet Transform (DWT)/Inverse DWT, Scalar quantizer/Scalar dequantizer and Entropy encoder/decoder. This is depicted in Fig. 1.1.



(a) Wavelet Encoder



(b) Wavelet Decoder

Fig. 1.1. Block diagram of a wavelet transform based image compression system

1.2 Overview of Biometric Application System

Biometrics system is an emerging technology that deals with automatic identification of individuals, based on their physiological and behavioral characteristics. The biometric traits must satisfy universality, uniqueness, permanence, accessibility and collectivity [4]. The physiological biometrics are fingerprint, hand scan, iris scan, facial scan, retina scan, etc., and behavioral biometrics are voice, signature etc. [5]. The main advantage of biometric methods is the capability for identity verification [6]. The methods for human identity authentication based on biometrics using the physiological and behavioural characteristics of a person have been evolving continuously and seen significant improvement in performance and robustness over the last few years. However, most of the systems reported perform well in controlled operating scenarios, and their performance deteriorates significantly under real world operating conditions, and far from satisfactory in terms of robustness and accuracy [5]. To address these challenges, and satisfy the requirements of new and emerging biometric applications, there is a need for the development of improved algorithms for efficient lossy fingerprint image compression. This is because computer systems have provided the capability for the acquisition of massive volumes of biometric fingerprint data, and it is reasonable to develop computational techniques to help extract, store in compact form and derive meaningful patterns and structures from these data in order to address the problem of data overload. Additionally, data mining processes for law enforcement, immigration services, and forensic applications can immensely benefit from the proposed technique. This is the primary focus of this research work.

1.3 Characteristics of Fingerprint Image

Fingerprint is the biometric features of a finger. The development of these features is congenital and maintains uniqueness among the population [4]. A fingerprint usually appears as a series of dark lines that represents the high peaking portion of the friction ridge skin, while the valleys between these ridges appear as white space and are the low shallow portion of the friction ridge skin. Minutia is the term used to describe the location and direction of the ridge endings and bifurcations along a ridge path. The upper most point on the inner most ridge of the fingerprint image is known as core [5]. The fingerprint has been used for personal identity verification for more than a century, and is the most widely used in biometrics today [7]. Fingerprint images are digitized at a resolution of 500 pixels per inch (ppi) with 256 levels of gray-scale information per pixel. A single fingerprint is about 700,000 pixels and needs about 0.6 Mbytes for storage. A pair of hands, then, requires about 6 Mbytes of storage [8-9]. This huge storage requirement by fingerprint images impacts adversely on the efficiency of biometric application systems. The only way to improve on these resource requirements is to compress these images, such that they can be cost-effectively stored, transmitted and then reconstructed without compromising the essential biometric features such as the fingerprint's core, ridge endings and bifurcations. These features are shown in Fig. 1.2.

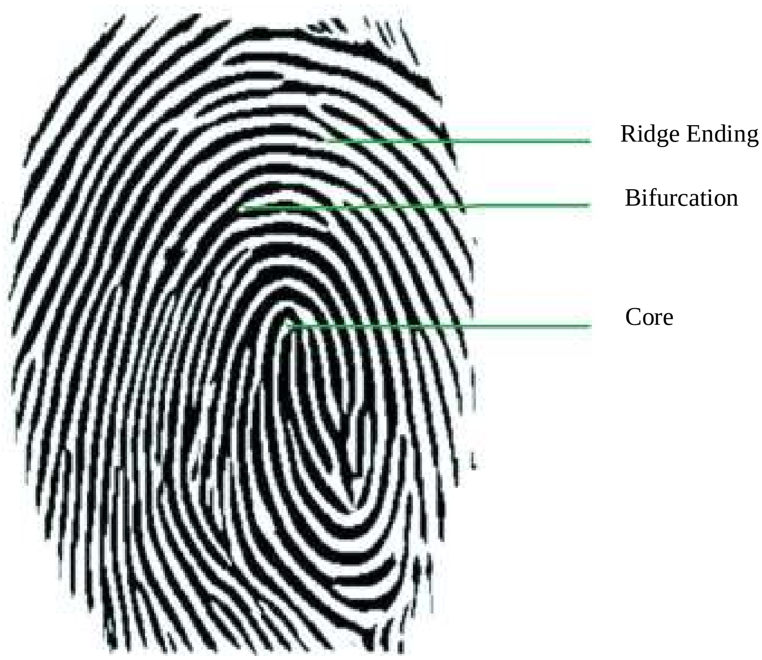


Fig. 1.2. Biometric features of a fingerprint image

1.4 Overview of Fingerprint Image Compression Techniques and Standards

The efficiency of the application of wavelet transform on image coding was significantly boosted by the introduction of embedded zero-tree wavelet (EZW) algorithm introduced by Shapiro [10]. The algorithm has since undergone significant improvements in the set partitioning in hierarchical trees (SPIHT) introduced by Said and Pearlman [11]. The EZW and SPIHT performed better than JPEG with most images. However, they both produced blurring effect on feature pattern of fingerprint images which renders the data useless for biometric application. Wavelet Scalar Quantization (WSQ) is a compression standard developed specifically for the compression of fingerprint images to improve the capability of preserving the fingerprint features for biometric pattern recognition. A compression ratio limit of 15:1 is specified for WSQ fingerprint compression standard [12]. In other words, its performance becomes unsatisfactory at compression ratio higher than 15:1 [13-14]. The embedded block coding with optimized truncation of embedded bit-streams (EBCOT) by Taubman [15] have resulted in modern wavelet image compression and coding techniques. As a matter of fact, the latest Joint Photographic Expert Group (JPEG 2000) image coding standard was developed based on the EBCOT algorithm [3,16]. The EBCOT-based JPEG2000 as a robust general-purpose compression standard has the limitation of not being able to adequately preserve the crucial biometric features of fingerprint images at high compression ratio and it has the problem of complex algorithm implementation. The JPEG was the earlier version of JPEG2000 standard and it was based on discrete cosine transform technique while the JPEG 2000 was based on wavelet transform technique [2-3,16].

The differences between JPEG2000 and WSQ standards are in their wavelet transform decomposition structures and the scanning order of the quantized coefficients in their entropy coding stage. In wavelet decomposition, JPEG 2000 applies Mallat's algorithm or the pyramidal approach with Cohen Daubechies Feauveau (CDF), a variant Daubechies wavelet filters, while WSQ uses a fixed wavelet packet basis with the same CDF wavelet filter. WSQ uses raster scanning order, while JPEG2000 uses vertical bitplane scanning order [2]. More significantly, both standards are based on CDF wavelets and have been adopted as fingerprint compression standards. It is noteworthy that JPEG 2000 is designed for general-purpose compression with significant flexibility. It has the disadvantage of complex algorithm implementation and high computation cost [17]. The next sections describe the relevant theoretical concepts of image coding.

2 Review of Fundamental Concepts

This sections presents the review of the theoretical concepts for wavelet based fingerprint image analysis. There are different methods for the analysis of image signals. The most well-known approach is the signal spectral analysis using Fourier Techniques and the most recent method is wavelet multi-resolution analysis [16,18-19]. Fourier Series (FS) is Joseph Fourier's original work which involved the representation of a periodic function as a finite, weighted sum of sinusoids that are integer multiples of the fundamental frequency of the analysis signal [20]. These frequencies are said to be harmonically related or simply harmonics. Continuous Fourier Transform (FT) is an extension of Fourier series to non-periodic functions. Any continuous aperiodic function can be represented as an infinite sum (integral) of sinusoids. Discrete Time Fourier Transform (DTFT) is an extension of FT to discrete sequences where the discrete function is also represented with an infinite sum (integral) of sinusoids. The frequency representation of DTFT is not discrete but continuous. Discrete Fourier Transform (DFT) is an extension of DTFT, where the frequency variable is also discretized. Fast Fourier Transform (FFT) is mathematically identical to DFT, however, it has a more significantly efficient implementation. Given an N-sampled signal sequence, the number of computations for DFT is N^2 whereas the number of computations for FFT is $N \log_2 N$ [16].

In Fourier analysis, any periodic signal x(t) whose fundamental period is T_0, can be represented as a finite and discrete sum of complex exponentials (sines and cosines) that are integer multiples of ω_0, the fundamental frequency. This method is referred to as Fourier Series and it is given by [16,20]:

$$x(t) = \sum_{k=-\infty}^{\infty} c_k e^{j\omega_0 kt} \quad (1)$$

$$c_k = \frac{1}{T_0} \int_{t_0}^{t_0+T_0} x(t) e^{-j\omega_0 kt} dt \quad (2)$$

Where,

x(t) = Original signal
c_k= Amplitudes of frequency components
ω_0 = Fundamental frequency
T_0 = Fundamental period

A non-periodic continuous time signal can also be represented as an infinite and continuous (not integer multiples of ω) sum of complex exponentials. This method is known as Fourier Transform and it is given by [16,20]:

$$X(\omega) = F\big(x(t)\big) = \int_{-\infty}^{\infty} x(t)e^{-j\omega t}dt \tag{3}$$

The Inverse Fourier Transform is given by:

$$x(t) = F^{-1}\big(X(\omega)\big) = \int_{-\infty}^{\infty} X(\omega)e^{j\omega t}d\omega \tag{4}$$

Furthermore, the DFT applies to discrete time signals, where the spectrum is also made discrete. It should be noted that in DTFT, the spectrum is continuous. Therefore, for an N-point signal x[n], the Discrete Fourier Transform is mathematically given by [16,20]:

$$X[k] = \sum_{n=0}^{N-1} x[n]e^{-j\frac{2\pi k}{N}}, \qquad 0 \leq k \leq N-1 \tag{5}$$

$$x[n] = \frac{1}{N}\sum_{k=0}^{N-1} X[k]e^{j\frac{2\pi}{N}nk}, \qquad 0 \leq n \leq N-1 \tag{6}$$

Where,

$X[k]$ = Discrete Fourier Transform of $x[n]$
$x[n]$ = Inverse DFT
k = Frequency index
n = index of signal array

X[k] represents how much of the sinusoid at frequency k(2π/N) exists in the original signal x[n], or in other words, how much of this frequency shall be used in reconstructing the original signal.

For image analysis and synthesis, Discrete Fourier Transform in Two Dimensions (2-D) and its inverse can be easily extended from One Dimensional (1-D) DFT. 2-D DFT of an image function f(x, y) of size MxN is given by [21]:

$$f(u,v) = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\, e^{-j2\pi(\frac{ux}{M}+\frac{vy}{N})} \tag{7}$$

f(x, y) can be obtained from 2-D Inverse DFT

$$f(x,y) = \frac{1}{MN}\sum_{u=0}^{M-1}\sum_{v=0}^{N-1} f(u,v)\, e^{j2\pi(\frac{ux}{M}+\frac{vy}{N})} \tag{8}$$

Where,

v = Column index of the transformed array
u = Row index of the transformed array
x = Column index of the image array
y = Column index of the image array

A different way to understand the Fourier technique is as a method for transforming our view of a signal from a time-based representation to a frequency-based one. For many signals, Fourier analysis is extremely useful because the signal's frequency content is of great importance. However, Fourier method has a serious drawback especially in the analysis of non-stationary signal. In transforming to the frequency domain, time or spatial information is lost [2,19].

In an effort to correct the deficiency of Fourier Transform, Dennis Gabor adapted the Fourier transform to analyse only a small section of the signal at a time, a technique called windowing the signal [22]. Gabor's adaptation, called the Short-Time Fourier Transform (STFT), maps a signal into a two-dimensional function of time and frequency.

The STFT method can analyze a non-stationary signal in the time domain through a segmented algorithm. STFT processes the signal with a sliding window having constant length in time or space. Through a moving window process, the original signal is broken up into a set of segments, and each segment is processed by the conventional Fast Fourier transform (FFT) algorithm. In the end, all the results in frequency domain are summed up [23]. The problem with the STFT has to do with the width of the window function that is used. To be technically correct, this width of the window function is known as the support of the window. If the window function is narrow, it is said to be compactly supported [16,19].

In the STFT analysis, the signal to be transformed is decomposed in segments which usually overlap each other, to reduce artifacts at the boundary. FFT is then applied to each segment and the results are summed. STFT can be expressed as [24]:

$$STFT\{x[n]\}(m,\omega) = X(m,\omega) = \sum_{n=-\infty}^{\infty} x[n]\omega[n-m]e^{-j\omega n} \tag{9}$$

Where,

$$X(m,\omega) = \text{STFT of signal } x[n]$$

$$\omega[n] = \text{Window function}$$

However, the accuracy of this method is limited by its fixed analysis window size. The drawback is that sudden breaks appear between windowed segments. This is more obvious in a visual image. It is known as blocking effect [22]. Windowing of signal became an important concept because of the limitation, Heisenberg's uncertainty principle imposed on data analysis. The uncertainty principle deals with the concept of time-frequency resolution. The principle states that with high time resolution, a poor frequency resolution is achieved and with high frequency resolution, a low time resolution is realized [19]. So when using STFT, once the window size has been chosen, the time frequency resolution is fixed. Thus a window could be analyzed with good time resolution or frequency resolution but not with both [19].

In order to overcome the limitation of STFT, one must change the window size at several different values, thus, achieving a multi-resolution analysis. The Heisenberg's principle is still satisfied but the time or spatial resolution enhances at high frequencies while the frequency resolution enhances at low spatial or time resolution. Wavelet analysis represents such method. It is a signal windowing technique with variable-sized regions. It is a new idea in signal processing. Instead of analysing cosine waves that go on forever or get chopped off, the new building blocks are wavelets. These are little waves that start and stop. A long signal is broken into a basis of possible signals, called wavelets. The wavelets come from a single function w(x) by shifting and scaling [16,18]. Amplitudes or coefficients of transformation are processed and reconstructed to recover a synthesis signal. Redundant coefficients are discarded to achieve compression. One major advantage afforded by wavelets is the ability to perform local analysis, that is, to analyse a localized area of a large signal. Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques miss, aspects like trends, breakdown points, discontinuities in higher derivatives, and self-similarity. This is because it gives a different view of data than those presented by traditional techniques. Wavelet analysis can often compress a signal without appreciable degradation. The summary of the advantages of wavelet analysis and Fourier analysis, as well as, its variants is shown in Table 1.0.

Table 1.0. Comparison between the properties of Fourier and wavelet analyses

Criteria		**DFT/FFT**	**STFT**	**DWT**
1.	Applications	Periodic and aperiodic signal pattern recognition and trends	Pattern recognition, trends and compression for non-stationary signal with mild discontinuities	Localization characterization, pattern recognition, trends and compression for non-stationary signal with sharp discontinuities
2.	Sliding Window	No windowing	Fixed-size windowing	Variable-size windowing
3.	Analysis	Frequency representation/Spectra analysis	Time-Frequency representation	Multi-resolution analysis
4.	Uncertainty Principle	Do not satisfy	Do not satisfy	Satisfy
5.	Input signal	Best suited for stationary signals	Best suited for non-stationary signals with mild discontinuities	Best suited for non-stationary signals with sharp discontinuities
6.	Number of Computation (N samples)	DFT = N^2 Computations FFT = N $\log_2$ N Computations	STFT = N $\log_2$ N Computations	DWT = N Computations

It is for these obvious reasons that wavelet technique has been adopted as the preferred tool for fingerprint image compression in this research work. The wavelet transform provides for space-frequency multi-resolution analysis. The first step in the protocol for a wavelet transform is to determine a mother wavelet. The mother wavelet is also known as wavelet prototype or basis. There are many types of mother wavelets and each one has its own application. Once a mother wavelet is decided, it is translated through the signal using the mathematical technique, called convolution. The windowing technique is used by changing the scale of the wavelet. This is basically, the dilation and compression of the wavelet when translated. The idea behind dilation and compression is that if the wavelet is compressed it represents high frequency and if it is dilated, it has a slow rate of change, that is, low frequency. As wavelet is translated and dilated multiple times through the signal, the wavelet quantifies how well it correlates to the topology of the signal. The correlation of the signal receives a value of how well it matches the signal. If there is a high correlation, the transform reports high value at a particular scale and position in time. If there is no correlation, the transform reports low index value of correlation. The term mother wavelet gets its name due to two important properties of the wavelet analysis. First, the term wavelet means a small wave and smallness refers to the condition that this window function is of finite length (compactly supported). The wave refers to the condition that this function is oscillatory. Secondly, the term mother implies that the functions with different region of support that are used in the transformation process are derived from one main function, or the mother wavelet. In other words, the mother wavelet is a prototype for generating the other window functions. In the next section, the various types of mother wavelets or wavelet prototypes are presented.

2.1 Wavelet Bases or Prototypes

Even though, wavelet analysis is the preferred techniques for image signal compression, there are different types of wavelets and their qualities vary according to several criteria. The main criteria include: support of wavelet and scaling functions; the symmetry, the number of vanishing moments; the regularity, the orthogonality or biorthogonality. Some of the wavelet prototypes include: Haar, Daubechies; Coiflet, Symlet, Mexican-Hat, Morlet, Biorthogonal wavelets etc [22].

Haar wavelets are the simplest and first to be invented in the wavelets family. Although, wavelets are advanced topic but the Haar wavelets are elementary [18]. Therefore, there is the need to turn to better wavelet bases or prototypes or functions. The new wavelets are more sophisticated. Popular among them are the Daubechies and Coiflet wavelet functions. Most Daubechies wavelets are not symmetrical. For some, the asymmetry is very pronounced. The regularity property increases with the order of wavelet function. Regularity means that the iterated wavelet filter converges to a continuous function. The Daubechies wavelet analysis is orthogonal. Coiflet wavelet function, on the other hand, was developed to fix the symmetry limitation of Daubechies wavelet. The coiflet wavelet and scaling functions are much more symmetrical than that of Daubechies [9,22]. The symmetry property of a wavelet matrix is given by its product with its transpose to obtain an identity matrix. This property guarantees a perfect reconstruction of signal in the transformation domain.

2.2 Discrete Wavelet Transform (DWT)

Discrete wavelet transform (DWT) filter is used for reliable fingerprint image transformation. The DWT is recognised for its capability of space-frequency decomposition of images, energy compaction of low frequency subbands, and space localization of high frequency subbands [1,16]. DWT decomposes a discrete image signal into bands that vary in spatial frequency and orientation.

In DWT, a space-frequency representation of the digital image signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cutoff frequencies at different scales. For a discrete sampled signal sequence f(x), where integer x = 0, 1, 2 ... m-1. There is m number of samples in the sequence.

The scaling function $w_{\emptyset}(j_o, k)$ and wavelet function $w_{\Psi}(j, k)$ are given by [16]:

$$w_{\varphi}(j_o, k) = \frac{1}{\sqrt{m}} \sum_x f(x) \varphi_{j_o,k}(x) \quad (10)$$

$$w_{\Psi}(j, k) = \frac{1}{\sqrt{m}} \sum_x f(x) \Psi_{j,k}(x) \quad (11)$$

Note that $\frac{1}{\sqrt{m}}$ is a normalizing term. This is to ensure that the energy of the signal in the two transformation domain remains the same.

The inverse discrete wavelet transform (IDWT) is given by [16]:

$$f'(x) = \frac{1}{\sqrt{m}} \sum_k w_{\varphi}(j_o, k)\, \varphi_{j_o,k}(x) + \sum_{j=j_o}^{\infty} \sum_k w_{\Psi}(j, k) \Psi_{j,k}(x) \quad (12)$$

Where:

$f(x)$= Original signal sequence
$f^{'}(x)$= Reconstructed signal sequence
$\varphi_{j_o,k}(x)$= Scaling parameter
$\Psi_{j,k}(x)$= wavelet parameter

Equations (10) and (11) can be called forward discrete wavelet transform while equation (12) is the inverse discrete wavelet transform. Every mathematical transformation involves the original signal, the transformed signal and the transformation kernel. In this case, the transformation kernels are $w_{\emptyset}(j_o, k)$ and $w_{\Psi}(j, k)$. Note that for a more efficient computational implementation of DWT, fast wavelet transform (FWT) algorithm is used. The number of FWT computations for N-sampled sequence is equal to N [16,19].

2.3 Wavelet Transform in Two Dimensions

For analytic transformation of image signal, a two-dimensional (2-D) discrete wavelet transform is used which can easily be extended from a one-dimensional (1-D) wavelet transform. To achieve this, one 2-D scaling function, $\varphi(x, y)$, and three 2-D wavelets: Ψ^H(x, y), Ψ^V(x, y), and Ψ^D(x, y) are required. Each is the product of 1-D scaling function φ and corresponding 1-D wavelets φ as shown [21]:

$$\varphi(x, y) = \varphi(x)\varphi(y) \quad (13)$$

$$\Psi^H(x, y) = \Psi(x)\varphi(y) \quad (14)$$

$$\Psi^V(x, y) = \varphi(x)\Psi(y) \quad (15)$$

$$\Psi^D(x, y) = \Psi(x)\Psi(y) \quad (16)$$

Equation (13) defines the separable scaling function, $\varphi(x, y)$. Equations (14) to (16) define the wavelet functions that measure the functional variations of intensity or grayscale for images along different directions: Ψ^H defines variation along columns (horizontal edges); Ψ^V defines variation along rows (vertical edges); Ψ^D defines variation along diagonals.

Given separable 2-D scaling and wavelet functions, 2-D DWT can be defined. First, we define the scaled and translated or shifted basis functions are defined as follows [21]:

$$\varphi_{j,m,n}(x,y) = 2^{\frac{j}{2}}\varphi(2^j x - m, 2^j y - n) \quad (17)$$

$$\Psi^i{}_{j,m,n}(x,y) = 2^{\frac{j}{2}}\Psi^i(2^j x - m, 2^j y - n), \;\; i = \{H,V,D\} \quad (18)$$

Where, i = directional wavelet index

Therefore, 2-D DWT of function f(x, y) of size MxN is given by [21]:

$$w_\varphi(j_0,m,n) = \frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\, \varphi_{j_0,m,n}(x,y) \quad (19)$$

$$w^i{}_\Psi(j,m,n) = \frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\, \Psi^i{}_{j,m,n}(x,y), \;\; i = \{H,V,D\} \quad (20)$$

Where,

$j_0 = $ Arbitrary starting scale ($j_0 = 0$)
$w_\varphi(j_0,m,n) = $ Approximation coefficients for f(x, y) at scale j_0
$w^i{}_\Psi(j,m,n) = $ Horizontal, vertical and diagonal details coefficients at scales $j \geq j_0$

$$M = N = 2^j, for\ j = 0,1,2,\dots,j-1$$

$$m,n = 0,1,2,\dots,2^j - 1$$

Given w_φ and $w^i{}_\Psi$, f(x, y) can be obtained from 2-D Inverse DWT as follows [21]:

$$f(x,y) = \frac{1}{\sqrt{MN}}\sum_m\sum_n w_\varphi(j_0,m,n)\, \varphi_{j_0,m,n}(x,y) + \frac{1}{\sqrt{MN}}\sum_{i=H,D,V}\sum_{j=j_0}^{\infty}\sum_m\sum_n w^i{}_\Psi(j,m,n)\, \Psi^i{}_{j,m,n}(x,y) \quad (21)$$

It should be noted that since image signal has two dimensional data structure, 2-D DWT is implemented for fingerprint image transformation.

2.4 Review of Similar Works

The following show a critical review of some similar research works undertaken by some researchers.

Khalifa [25] presented an image compression model using wavelet decomposition with multi-resolution codebook encoder. The algorithm decomposed an image into desired resolution level using Daubechies wavelet. The resulting low frequency sub-images are quantized using Dual Pulse Code Modulation (DPCM). While the high frequency sub-images are quantized by vector quantization using a multi-resolution codebook. Huffman coding was used as entropy coding scheme. Due to the codebook generation, the computation cost of the algorithm is high. Additionally, Huffman coding is a less optimal image coder compared to arithmetic coder.

Li and Bayoumi [26] proposed multi-level parallel high speed architecture for Embedded Block Coding with Optimized Truncation (EBCOT) tier-1 in JPEG2000. Discrete wavelet transform (DWT) filters were used to decompose the image tiles into corresponding coefficients. The transform coefficients were quantized using scalar quantization to form code blocks which were entropy coded by EBCOT algorithm. The architecture adopted three levels of parallelism to increase throughput at the level of bit-planes, scanning passes and coding bits. The method achieved faster throughput than the existing EBCOT architectures. However, the complexity of the algorithm implementation also increased as a result of the EBCOT architecture implemented in a three-level parallelism.

Sudhakar and Jayaraman [27] proposed a fingerprint compression scheme to obtain improved quality and higher compression ratio through multiwavelet transform. Embedded coding of multiwavelet coefficients was achieved through Set Partitioning in Hierarchical Trees Algorithm (SPIHT). According to Sudhakar et al (2006), for better performance in compression, filters used in wavelet transform have the property of orthogonality, symmetry, short support and higher approximation order which scalar wavelets do not satisfy simultaneously. Hence, the need for multiwavelets, which possess more than one scaling filters. Orthogonal wavelet filters used are not as efficient as biorthogonal wavelet because of the requirement for perfect image reconstruction.

Hsin et al. [28] proposed a hybrid algorithm using SPIHT and EBC (embedded block coding) to encode low frequency and high frequency wavelet coefficients, respectively; the intermediate coding results of low frequency coefficients are used to facilitate the coding operation of high frequency coefficients. Experimental results showed that the coding performance can be significantly improved by the hybrid SPIHT-EBC algorithm. According to Hsin et al. [28], one of the advantages of hybrid SPIHT-EBC coding is that the well-defined hierarchical structure across wavelet subbands and energy clustering within each wavelet subband can be taken into account to facilitate the image compression task. The SPIHT coding method does not perform well in the preservation of an acceptable quality of biometric fingerprint patterns.

Chang et al [29] proposed two methods to improve computational efficiency of parallel context formation of EBCOT, that is, sample-parallel pass-type context formations (SPPD) and column-based pass-parallel coding (CBPC) methods. In this technique, DWT was used to decompose the image and then scalar quantized. The resulting code blocks were encoded with the proposed EBCOT methods. According to Chang et al (2007) EBCOT is a two-tiered architecture. Tier-1 is a context-based adaptive arithmetic coder, which is composed of a context formation (CF) engine and a binary arithmetic coder (BAC). Tier-2 is responsible for rate-distortion optimization and bit stream formation. The proposed methods achieved greater computation efficiency. However, EBCOT algorithm is not amenable to simple implementation.

Rawat and Meher [30] proposed a hybrid scheme combining Kohonen's Self Organizing Feature Map (SOFM) based Vector Quantization (VQ) coding and Set Partitioning in Hierarchical Trees (SPIHT) coding for effective compression of images. First, the input image is decomposed using biorthogonal wavelet transform. Subsequently, the decomposed image is compressed using SPIHT encoding, which results in bit stream. The resulted bit stream is then fed to the SOFM based VQ coding for further compression. The SOFM algorithm generates a codebook corresponding to the input bit stream and based on the generated codebook compression is achieved. The reconstructed image quality achieved after decoding is of desirable quality. However, the vector quantization method used in this algorithm is very complex and require the generation of codebook which can increase computational cost.

Ashok et al. [1] proposed an algorithm for fingerprint image compression based on wave atoms decomposition. This method was used for sparse representation of fingerprint images since they belong to a category of images that oscillate smoothly in varying directions. In the proposed method, 2-dimentional wave atoms decomposition was applied on the original image in order to efficiently capture coherence of the fingerprint images along and across the oscillations (Ashok et al. [1]). Wave atoms decomposed coefficients with values close to zero are discarded without significant degradation in image quality. An appropriate global threshold is used to achieve desired transmission rate after which significance map matrix and significant coefficients are generated. Significance map is a matrix of binary values that indicates the presence or absence of significant coefficient at specific location. According to Ashok et al. [1] the significance map is divided into non-overlapping blocks of 4x4 and they are quantized using K-means vector quantization scheme. The significant coefficients are quantized using a uniform scalar quantizer. Quantized significance map and significant coefficients are encoded using an arithmetic entropy scheme. The model was reported to achieve better peak signal to noise ratio (PSNR) than the wavelet scalar quantization (WSQ) standard. However, the global thresholding strategy used for image de-correlation is not optimal. Level-dependent thresholding is more robust and efficient.

Kumar et al. [31] proposed a SPIHT based fingerprint compression algorithm. The set partitioning in hierarchical trees (SPIHT) is a modified version of the embedded zerotree wavelet method. It used DWT decomposition of image signal using biorthogonal and orthogonal properties of wavelets. The method achieved a compression ratio of 20:1. The SPIHT problem is the inability to preserve featured pattern of fingerprint images.

Krishnaiah et al. [32] proposed 5/3 discrete wavelet transform (DWT) for fingerprint image compression and reconstruction with the SPIHT algorithm. Experimental results were obtained using 9/7 and 5/3 wavelet transforms for different types of fingerprint images. The experimental results showed that the proposed method, that is, 5/3 wavelet transforms approach consistently outperforms 9/7 wavelet transforms approach on fingerprint images for lossless image compression, in terms of compression ratio (CR), Mean square error (MSE), Peak Signal to noise ratio (PSNR), Encoding time, decoding time and transforming time or decomposition time. This is a lossless compression algorithm and the compression ratio that can be achieved lossless technique is less than 5:1.

Muhsen et al. [33] proposed a methodology for lossy fingerprint compression using wavelet and optimal re-quantization approach. 9/7 wavelet transform was used to decompose the image to form coefficients which were optimally re-quantized using generated codebook. The output stream of coding symbols were entropy coded using run-length encoding scheme. However, in this scheme the generation of codebook required additional computational resources for implementation.

Gangwar [34] presented a fingerprint image compression technique using the Haar wavelet transform for image decomposition. Elimination of redundancies was presented to achieve reduced computation and storage costs. However, this technique fell below international image compression standard as it excluded vital stages of quantization and entropy coding of a typical image encoder.

Shakhakarmi [35] performed an experiment that employed different wavelets to deploy cascaded filter banks to achieve fingerprint image decomposition and reconstruction. Significantly, the multiscale analysis of 2D fingerprint image at stage-4, produced a better result for wavelet filters in comparison to the result obtained with Fast Fourier Transform (FFT) and Discrete Cosine Transform (DCT) based filters. The inefficiency of FFT and DCT for image compression has been established as they produced blocking artifacts. A comparative study with these techniques is not rigorous enough for accurate judgement.

Libert et al. [17] conducted a study to compare the effects of WSQ and JPEG 2000 compression on 500 pixel per inch (ppi) fingerprint imagery at a typical operational compression rate of 0.55 bpp (bits per pixel), corresponding to an effective compression ratio of approximately 15:1. More significantly, the study revealed that while JPEG 2000 exhibited a small advantage over WSQ with respect to PSNR comparison, frequency spectrum comparison shows that WSQ is better tuned to the preservation of fingerprint features than JPEG 2000. However, JPEG 2000 is considerably more stable over multiple compression cycles. WSQ compression ratio is limited to 15:1 while JPEG2000 does not adequately preserve the minutia features of fingerprint at compression ratio higher than 20:1.

Shanavaz and Mythili [36] presented a technique for evolution of wavelet lifting coefficients for fingerprint image compression to enhance computation efficiency. In this work wavelets were evolved with resized and cropped images. Cropped images performed better in wavelet lifting coefficients. It adopted the SPIHT coder which required the use of codebooks and produced blurring effect in fingerprint images at higher compression ratio.

Islam et al. [9] investigated Coiflet-type wavelet-based fingerprint image decomposition using wavelet packets. For all Coiflet-type wavelets, different global thresholding values were used at constant decomposition level 3. It was found out that Coiflet5 achieved better compression for the same image using wavelet packets than wavelets. In this study, global threshold strategy was adopted and it is less robust compared to level dependent threshold strategy.

Singla et al. [37] conducted a comparative study of wavelet-based compression on medical images. The performances of Haar, Daubechies, Coiflet and Biorthogonal wavelets were compared. The comparison was based on different parameters to measure the image quality and the methods' compression ratio. The study showed that Coiflets transform produced higher compression rate for ultrasound and mammography images compared to other wavelets using PSNR quality measure. However, the mean squared error was not determined to evaluate the extent of degradation or distortion in the images.

3 Conclusion

In this paper, a review of different methodological approaches to fingerprint image compression based on the wavelet algorithm is conducted. From the survey of the existing wavelet-based image compression methods, the problems that have been identified include: the limitation of WSQ standard to a compression ratio of 15:1 which could be improved with better algorithm. High complexity of image encoding process of the existing techniques is also a problem. Most of the existing methods require the generation of codebooks or lookup tables which require additional computational cost for implementation. Additionally, significant degradation in the biometric features of fingerprint at compression ratio higher than 15:1 remains a major challenge. Therefore, the signal processing capability to efficiently process fingerprint images in transform domain, quantize and encode them for optimized compression to achieve cost-effective data storage and transmission in biometric systems has become a priority. The use of biorthogonal coiflet wavelets to achieve superior performance in terms of better rate-distortion, better perceptual quality and lower computational complexity over the standard CDF 9/7 wavelet is therefore recommended.

Competing Interests

Authors have declared that no competing interests exist.

References

[1] Ashok J, Shailaja TV, Somayajula SPK. Wave atoms decomposition based fingerprint image compression. IJCSNS. 2010;10(9):57-61.

[2] Strang G, Nguyen T. Wavelets and filter banks. Wellesley-Cambridge Press, Massachusetts, USA; 1996.

[3] Usevitch BE. A tutorial on modern lossy wavelet image compression: Foundations of JPEG 2000. IEEE Signal Processing Magazine. 2001;22-35.

[4] Kazi MM, Mane AV, Manza RR, Kale KV. Comparison of fingerprint enhancement techniques through mean square error and peak-signal to noise ratio. IJCSE. 2011;3(1):266-270.

[5] George JP, Abhilash SK, Raja KB. Transform domain fingerprint identification based on DTCWT. International Journal of Advanced Computer Science and Applications (IJACSA). 2012;3(1):190-195.

[6] Villegas OV, Domínguez HO, Sanchez VG, Maynez LO, Orozco HM. Biometric human identification of hand geometry features using discrete wavelet transform. In Olkkonen H, (Ed). Discrete Wavelet Transforms – Biomedical Applications. 2006;251-266.

[7] Rajkumar R, Meetei TC, Begum SA, Hemachandra K. Fingerprint enhancement and its features purification. Journal of Computing. 2012;4(5):78-82.

[8] Radunovic DP. Wavelets: From maths to practice. Springer-Verlag, Berlin, Germany; 2009.

[9] Islam MR, Bulbul F, Shanta SS. Performance analysis of Coiflet-type wavelets for a fingerprint image compression by using wavelet and wavelet packet transform. IJCSCS. 2012;3(2):79-87.

[10] Shapiro JM. Embedded image coding using zerotrees of wavelet coefficients. IEEE Transactions on Signal Processing. 1993;41(12):3445-3462.

[11] Said A, Pearlman W. A new fast and efficient image codec based on set partitioning. IEEE Trans. Circuits Syst. 1996;6:243-250.

[12] NIST. WSQ Fingerprint Image Compression Encoder/Decoder Compliance Guidelines, National Institute of Standards and Technology; 2011. Accessed from: http://nigos.nist.gov:8080/wsq/reference_images_v2.0_pgm.tar on March 2013.

[13] Onyshczak R, Youssef A. Fingerprint image compression and the wavelet scalar quantization specification. Technical Report, National Institute of Standards and Technology, U.S.A. 2000;1-32.

[14] CJIS. WSQ Gray-scale fingerprint image compression specification, Criminal Justice, Information Services Division, FBI, USA; 2000. Accessed from: https://www.fbibiospecs.org/docs/WSQ_Gray-scale_Specification_Version_3_1_Final.pdf in August 2011.

[15] Taubman D. High performance scalable image compression with EBCOT, IEEE Trans on Image Processing. 2000;9(7):1158-1170.

[16] Mallat S. A wavelet tour of signal processing: The sparse way, 3rd Edition. Elsevier Inc., Burlington MA, USA; 2009.

[17] Libert JM, Orandi S, Grantham JD. Comparison of the WSQ and JPEG 2000 Image Compression Algorithms on 500 ppi fingerprint imagery. NIST Interagency Report 7781; 2012. Accessed from: http://www.nist.gov/customcf/get_pdf.cfm?pub_id=910658 on April 2013.

[18] Strang G. Wavelets, American Scientist 82. Technical Report. 1994;250-255. Accessed from: www-math.mit.edu/~gs/papers/amsci.ps.gz in April 2012.

[19] Polikar R. The engineer's ultimate guide to wavelet analysis: The wavelet tutorial. Rowan University; 2001. Accessed from: http://users.rowan.edu/~polikar/WAVELETS /WTtutorial.html in May 2011.

[20] Polikar R. Processing of biological signals. Rowan University; 2004. Accessed from: http://engineering.rowan.edu/~polikar/CLASSES/ECE404 in May 2011.

[21] Gonzalez RC, Woods RE. Digital Image Processing, 3rd Edition. Pearson publishers; 2009.

[22] Misiti M, Misiti Y, Oppenheim G, Poggi JM. Wavelet toolbox for use with MATLAB; user guide. The Math Work, USA; 1996.

[23] Giurgiutiu V, Lingyu YuL. Comparison of short-time fourier transform and wavelet transform of transient and tone burst wave propagation signals for structural health monitoring. Proceedings of the 4th International Workshop on Structural Health Monitoring, Stanford University; 2003.

[24] Stranneby D. Digital signal processing: DSP and Applications. Newnes-Reed Educational and Professional Ltd, Oxford; 2001.

[25] Khalifa O. Wavelet coding design for image data compression. International Journal of Information Technology. 2005;2(2):118-128.

[26] Li Y, Bayoumi M. Three-level parallel high speed architecture for EBCOT in JPEG 2000. IEEE. 2005;5-8.

[27] Sudhakar R, Jayaraman S. Fingerprint compression using multiwavelets. International Journal of Information and Communication Engineering. 2006;2:2.

[28] Hsin HC, Lien JJ, Sung TY. A hybrid SPIHT-EBC image coder. International Journal of Computer Science. 2007;34:1.

[29] Chang CC, Chen SG, Chiang JC. Efficient encoder design for JPEG2000 EBCOT context formulation. 15th European Signal Processing Conference, EUSIPCO, Poznan. 2007;644-648 .

[30] Rawat CSD, Meher S. A hybrid coding scheme combining SPIHT and SOFM based vector quantization for effective image compression. European Journal of Scientific Research. 2009;38(3):425-440.

[31] Kumar C, Shekhar C, Das S, Bhandari S. Compression algorithm by using wavelets. International Journal of Engineering Science and Technology. 2010;2(10):4978-4982.

[32] Krishnaiah GC, Jayachandraprasad T, Prasad MNG. Evolved wavelets for improved fingerprint compression. IJCST. 2011;2(3):361-366.

[33] Mushen Z, Dababneh M, Al Nsour A. Wavelet and optimal re-quantization methodology for lossy fingerprint compression. International Arab Journal of Information Technology. 2011;8(4):383-387.

[34] Gangwar DK. Compression and development analysis on an image using Haar wavelet transform. IJATER. 2012;2(3):225-229.

[35] Shakhakarmi N. Quantitative multiscale analysis using different wavelets in 1D voice signal and 2D image. IJCSI International Journal of Computer Science. 2012;9:2. Accessed from: http://www.IJCSI.org on April 2013.

[36] Shanavaz KT, Mythili P. Faster techniques to evolve wavelet coefficients for better fingerprint image compression. International Journal of Electronics. 2012;100:5. Accessed from: http://www.tandfonline.com/doi/pdf/10.1080/00207217.2012.720944 on April 2013.

[37] Singla N, Sharma S. A Review on Wavelet based Compression using Medical Images. International Journal of Innovative Research in Computer and Communication Engineering, IJIRCCE. 2013;1(8):1649-1653.
Retrieved from: http://ijircce.com/upload/2013/october/7AReview.pdf in March 2014.

Peer-review history:
The peer review history for this paper can be accessed here (Please copy paste the total link in your browser address bar)
www.sciencedomain.org/review-history.php?iid=598&id=6&aid=5407