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Discrete Shearlet Transform and Lempel-Ziv Welch Coding for Lossless Fingerprint Image Compression

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Abstract: Image compression is a crucial task in image processing and in the process of sending and receiving files. There is a need for effective techniques for image compression as the raw images require large amounts of disk space to defect during transportation and storage operations. The most important objective of image compression is to decrease the redundancy of the image which helps in increasing the storage capacity and then efficient transmission. This study introduces a system for lossless image compression that is built to work on fingerprint image compression. It uses lossless compression to take care of the first image during processing. However, there is a serious problem which is the low ratio of compression. In order to make the ratio higher, there are five lossless compression techniques used in this study which are Elias Gamma Coding (EGC), Huffman Coding (HC), Arithmetic Coding (AC), Run-Length Encoding (RLE) and Lempel Ziv Welch (LZW). With these techniques, there are three types of transforms are used; they are Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), and Discrete Shearlet Transform (DST). The results conclude that discrete shearlet transform with the Lempel-Ziv Welch coding technique outperforms the other lossless compression techniques and its Compression Ratio (CR) is 3.678023.

Keywords: Discrete Shearlet Transform, Discrete Wavelet Transform, Discrete Cosine Transform, Arithmetic Coding, Huffman Coding, Elias Gamma Coding, Lempel-Ziv Welch, Run Length Encoding, Compression Ratio, Fingerprint Image

Introduction

Compression methods are the most needed to lower the mind volume required for the picture. The certain compressing system is of two kinds, lossy and lossless. In lossless, the first picture is strictly reconstructed after the decompression whereas, lossy may lose some information from the picture data. Comparatively, lossless gives more accuracy to Khandwani and Ajmire (2018).

Compression is used in information transfer applications, with the main goal being speed. of the transmission depends on the number of bits transmitted, which determines the time required for the encoder to push the encoded message and, in turn, the time required for the decoder to recover the main ensemble in an information storage application by Borowiec and Welnicki (2018).

A compression management service requires the dataset to have a primary allocation so that the mechanisms determine whether a knowledge compression operation should be applied to the info for a current data replication operation supported by the compression ratios. In response to determining that data compression should be applied to the info, the info compression operation is performed and therefore, the compressed data is replicated to the second processing system. In response to determining that data compression should not be applied, the info is replicated without compression. Compression is often classified as lossy or lossless by Khandwani and Ajmire (2018); Araki *et al*. (2017).

Low-level compression ratios are presented via lossless compression by Rusyn *et al*. (2016). The initial acts of this compressed file are reconstructed using lossless compression, which preserves information. Consequently, information remains unchanged during the compression and decompression procedures. Since the decompression procedure reconstructs the original information, these types of compression techniques are known as reversible compressions by Arora and Saini (2015).

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Biometrics is a widely utilized technique for access control in a variety of application fields, including e-commerce, healthcare, security, and the military, in addition to cell phones and autos. The basic concept is to match a given number with a reference value that, generally speaking, represents an individual in certain physiological and/or behavioral traits that are particular to each and every human being. The most widely used biometric systems nowadays are based on fingerprint scanning, face and/or voice recognition, iris scanning, hand geometry, and finger vein detection, however, the most recent ones rely on a variety of factors by Sawalha and Awajan (2014). These days, biometric identification systems are widely used and difficult to use in many places where very high security is required. The system is said to have numerous benefits using biometrics, including unique, strong, and high privilege on its own for personal identity because it is thought that each person's biometric cannot be shared, stolen, or lost Ahmad *et al*. (2017).

There is a problem in storing and transferring the biometric data. The problem is related to size and speed. Therefore, the data should be saved or preserved in order to be stored and transferred with appropriate size and speed. Time delays result from the significant growth in data, which causes delays in getting the necessary information. Accurate information is obtained due to the erroneous findings that large data sets provide when assessing data similarity. The goal of this study is to create a more lossless biometric signal compression technique that will protect and maintain transmission time and space. The goal of the lossless compression method is to lower the compressed output bit rate without causing any data distortion. The importance of this study is to build an improved lossless biometric signal compression. In addition, to seek for the order of a work that is approved by using discrete shearlet transform. This is done by applying lossless compression techniques of the types of techniques exemplified by huffman coding, arithmetic coding, run length encoding, Elias gamma coding, and lempel ziv welch. The data are better preserved and maintained by lempel ziv Welch. The approach and its best results are based on compressing data by using discrete shearlet transform with lempel-ziv welch coding.

Lossless fingerprint image compression using Huffman coding, arithmetic coding for lossless compression and discrete transforms such as discrete wavelet transform, discrete cosine transform and discrete shearlet transform is made by Kadim *et al*. (2020), A new technique for multispectral fingerprint biometric systems based on image compression and employing wavelet decomposition and Huffman coding has been introduced by Sharma *et al*. (2020), fingerprint image compression using sparse representation and enhancement with Wiener2 Filter is a method developed by Joseph and Joseph (2015). Radhika *et al*. (2022) made the fingerprint compression algorithm based on singular value decomposition in sparse representation; (Murthy *et al*., 2022) made the fingerprint compression algorithm based on sparse representation and (Saikrishna and Sreenivasulu, 2015) made the fingerprint compression algorithm based on singular value decomposition in sparse representation.

Materials and Methods

This section includes a comparison and explanation of the work, as well as the suggested combination for biometric signal compression that uses three different transforms and five different compression algorithms to provide the best results.

Problem Formulation

One of the biggest problems that face biometric signal compression is the outcome of the decompression. In previous works, the compression techniques provided either a good compression ratio, but with a major decline in the reconstructed signal or an average compression ratio in order to provide a better-reconstructed signal. In order to solve this compression problem and make it better, one must design an effective technique for removing different types of redundancy from a given format of data. Methods for compressing data can be used to generate a different sequence of symbols with fewer bits overall and decompression methods can be used to restore the original string.

System Architecture

In order to maximize data transmission and minimize storage space while maintaining the quality of the input data, a lossless biometric signal compression technique will be employed in this study. Making the output data clearly similar to the input data is the goal. The goal of the system is to maintain the biometric signal's quality. Let us take an example where it is known in advance that the images will only be compressed into JPEG using the DCT technique and the default matrix. Furthermore, assume that there won't be any significant compression of the image that goes above the quality factor.

In order for the suggested approach to work, twenty original, uncompressed fingerprint photographs in various sizes must be introduced. Prepressing is the technique used by the system to determine the image's dimensions (16×16) and then convert it from the RBG image to grayscale to make the image easier to work with. The compression is done by applying different transforms to these images such as Discrete Wavelet Transform (DWT),

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Discrete Cosine Transform (DCT), and Discrete Shearlet Transform (DST). The zigzag scan method can then cause a change in the two-dimensional matrix to become one-dimensional. Moreover, arithmetic coding, run length encoding, huffman encoding, Elias gamma encoding, and lempel ziv welch encoding are employed as examples of lossless compression techniques. The block diagram in Fig. 1 demonstrates the steps of the suggested procedure in order.

Image Preprocessing

The grayscale input image is preprocessed using entropy coding to enhance the efficiency of lossless compression. In order to convert an input image map into a more compressed format, our approach begins with a Counted Array (CA), whose rows and columns are the same size (16×16). Then converted from (RGB) to (grayscale) in Fig. 2 by Hussein *et al*. (2019). While (grayscale) ways to convert a full-color image to grayscale, grayscale algorithms utilize an equivalent basic three-step process:

1. Perceive the red, youthful, and melancholy consequences of a pixel
2. Use flowery math to show those numbers into one gray value
3. Replace the first red, growing, and blue finishes with the unusual gray power

When describing grayscale algorithms, I'm going to focus on step 2-using math to turn color values into a grayscale value. So, when you see a formula like this:

$$Gray = (Red + Green + Blue) / 3 \tag{1}$$

When the intensity in the *red* channel is denoted by *red*, the intensity in the *green* channel by *Green*, and the intensity in the blue channel by *blue*. Recognize that the particular code to implement such an algorithm seems like Yuan *et al*. (2016).

Image Transformation

Three different transformation techniques are utilized in this step to compress data. They are called as follows: Discrete cosine transform by Zhang *et al*. (2018), discrete wavelet transform by Panapakidis and Dagoumas (2017), and discrete shearlet transform by Cao *et al*. (2017). Transformation is mostly used to compress the signal's energy into fewer samples than those of the time domain term. Typically, when we talk about "image transform," we're talking about a class of unitary matrices that are used to repress images. A discrete set of basis arrays known as "basis images" can be used to extend an image. Unitary matrices have the ability to produce these basic images.

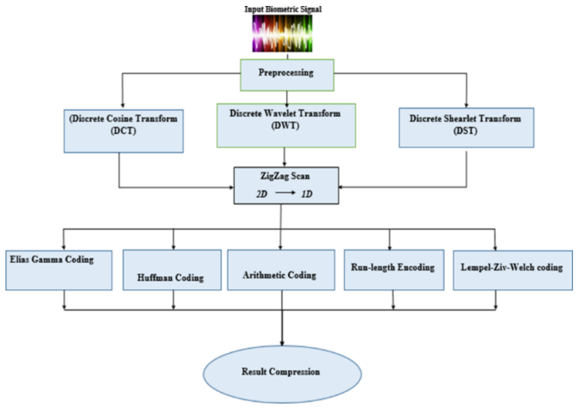

Fig. 1: Architecture of the proposed method

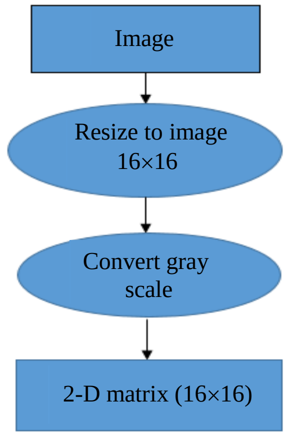

Fig. 2: Image preprocessing

Zigzag Scan

In the third stage, use a zigzag scan to change the matrix from two dimensions to one dimension. The process of ordering the conversion of two-dimensional arrays to one-dimensional arrays requires an increase in frequency (both horizontal and vertical), which in turn causes a decrease in coefficient change, the zigzag scan is shown by Hussein *et al*. (2019).

Lossless Compression Techniques

There are five lossless compression techniques used in this study which are Elias Gamma Coding (EGC) by Trotman and Lilly (2018), Huffman Coding (HC) by Khaitu and Panday, (2018) Arithmetic Coding (AC) by Sarkar *et al*. (2017), Run-Length Encoding (RLE) by Gupta *et al*. (2017) Lempel Ziv Welch (LZW) (Sangeetha *et al*., 2017).

Compression Ratio

Compression Ratio: This is the first size of the compressed database system's volume.

Also, a reference to, power is a phrase from computer science that can be used to describe how much a knowledge compression approach reduces the size of the data representation. The following is the definition of the compression ratio using Eq. (2) by Joshua *et al*. (2016):

$$CR = \frac{size \quad of \; original \quad image \quad data}{size \quad of \; compressed \quad image \quad data} \tag{2}$$

Compression Time

Compression time = represents the time period through the compression procedure.

Speed = number of uncompressed bits that will be handled in one second shown by Kodituwakku and Amarasinghe (2010).

The decompression process involves inversely compressing the compressed image first, then applying lossless inverse compression techniques like huffman, Elias gamma, arithmetic, run length, and Lempel Ziv Welch decoding. The output is then converted from one dimension to two dimensions using an inverse zigzag scan and inverse transforms like inverse Discrete Wavelet Transform (DWT), inverse Discrete Cosine Transform (DCT), and inverse Discrete Shearlet Transform (DST) are applied to obtain the reconstructed image. Lossless image compression is shown when the difference between the reconstructed and uncompressed (original) images is equal to zero.

Results and Discussion

This section presents a selection of the experimental evaluation's findings, comprising a number of experiments carried out to determine and evaluate the precision and resilience of the method suggested in the section before.

Research Requirements

Dataset

Because there aren't many publicly accessible fingerprint datasets, the studies are carried out using the benchmarked CASIA fingerprint (CASIA-fingerprintv5) database by Francis-Lothai and Bong (2015) the database contains 20,000 fingerprint images of 500 subjects. The fingerprint images of CASIA-fingerprintv5 were captured using a URU4000 fingerprint sensor in one session. The CASIA-FingerprintV5 volunteer pool consists of employees, wait staff, graduate students, and others. Every volunteer provided 40 fingerprint images, five for each of his eight fingers (thumb, second, third, and fourth on the left and right). Significant intra-class variances were produced by asking the volunteers to spin their fingers at different pressure levels. All fingerprint images are 8-bit gray-level BMP files and the image resolutions are 328×356. In the next stage, you will insert twenty different-sized photos into a 16×16 canvas based on the determined rate of changes. Afterward, the images are transformed from RGB to grayscale using the discrete cosine, discrete wavelet, and discrete shearlet the three types of transformations included in the proposed system.

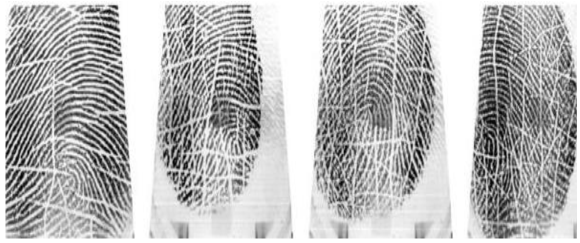

Fig. 3: Sample of fingerprint images

Software Used

A software development environment called MATLAB, which provides high-performance numerical calculation, data analysis, visualization, and application development tools, has been used to construct the recommended system. The image processing toolbox supplies an overall set of reference-gauge algorithms and workflow apps for image processing, analysis, ideation, and algorithm expansion. There are several options available, including zigzag scanning, lossless compression, image segmentation, and preprocessing. Figure 3 shows a sample of fingerprint images. In the preprocessing step, our images are converted from the two-dimension matrix into the one-dimension matrix.

Hardware Used

The system has been implemented using the laptop computer with the following specifications:

- Processor: Intel (R), core (TM) i5-5200U CPU@2.20 GHZ @ 2.20GHz
- Installed memory (RAM): 4 GB
- System kind: 64-bit OS, x64-based processor

Experimental Results

In this section, three different transformations and five different technique sets are used to evaluate performance; the primary method of picture processing is the final image compression approach. When saving or transferring an image, compression is mostly necessary. By doing this, the bits per pixel are decreased:

- Discrete cosine transform is used with twenty images of a biometric fingerprint with algorithms such as Huffman coding, arithmetic coding, Elias gamma coding, run length encoding, and Lempel Ziv Welch coding. It is expected through this study to get a high compression ratio, with fewer bits and less time
- Discrete wavelet transform is used with twenty images of a biometric fingerprint with algorithms such as Elias gamma coding, huffman coding, arithmetic coding, run length encoding, and lempel ziv welch coding. It is expected through this study to get a high compression ratio, with fewer bits and less time

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- Discrete shearlet transform is used with twenty images of a biometric fingerprint with algorithms such as huffman coding, arithmetic coding, Elias gamma coding, run length encoding, and Lempel Ziv Welch coding. It is expected through this study to get a high compression ratio, with fewer bits and less time

The First Experiment

The first kind of fingerprint compression technique in the most recent databases will guarantee a notable reduction in the amount of memory needed. Moving the image from one place to another will speed up the information retrieval process. Because the fingerprint picture is provided with maintained quality without degrading system performance, the receiving side will be able to use the maximum amount of data available for user authentication and will achieve improved recognition reliability. In this experiment, there are three operations to find out the compression ratio and the time that is spent. Therefore, the purpose of this study is to. Find out which conversion is better in terms of time, bit rate, and compression ratio by using DCT-zigzag-elias gamma coding, DWT-zigzag-elias gamma coding, and DST-zigzag-elias gamma coding.

Table 1 shows the results of the application for compression of fingerprint images. In order to present the advantages of this study, the table was compared with another study that used the same dataset. The comparison was performed with images of fingerprints. The testing was performed with 20 grayscale fingerprint images. The image compression process uses three types of transformations: Discrete shearlet transform, discrete wavelet transform, and discrete cosine transform. The proposed approach resizes the images of different sizes in accordance with the measured rate of (16×16) and then converts them from (RGB) to (grayscale). Afterwards, the image enters the algorithm (Elias Gamma coding). The average compression ratio of the images was better in the discrete shearlet transform with (Elias Gamma coding) which is estimated as 1.34570005. In the discrete wavelets transform with (Elias Gamma Coding), the ratio is 1.1055135. Discrete cosine transform with (Elias Gamma Coding) is 0.725369. As for the time when implementing the algorithm (EGC), the average time in all images with discrete shearlet transform was 0.4874254, discrete wavelet transform was 0.0699518 and discrete cosine transform was 0.1091524. As for the bit rate when implementing the algorithm (EGC), the average bit rate in all images with discrete shearlet transform was 5.9564736, discrete wavelet transform was 6.9498048 and discrete cosine transform was 9.871485.

The Second Experiment

The second kind, which uses a technique for fingerprint compression in current databases, guarantees a notable reduction in the amount of memory needed. The time it takes to receive the information will be shorter in situations when the image needs to be moved. As a result, the receiving side will be able to use the maximum data available for user authentication and will obtain higher recognition reliability because the fingerprint image is sent with retained quality without slowing down the system's performance. In this experiment, there are three operations to find out the compression ratio and the time that is spent. Therefore, the purpose of this study is to. Find out which conversion is better in terms of time, Bit Rate, and compression ratio by using DST-zigzag-Huffman coding, DWT-zigzag-Huffman coding, and DCT-zigzag -huffman coding.

Table 1: Discrete cosine transform, discrete wavelet transform, and discrete shearlet transform with Elias gamma coding

		DCT-zigzag-EGC			DWT-zigzag-EGC			DST-zigzag-EGC		
No.	Image	Run time (sec)	Bit rate	C. ratio	Run time (sec)	Bit rate	C. ratio	Run time (sec)	Bit rate	C. ratio
1	Fingerprint	0.0482560	10.8984380	0.734050	0.0863900	7.3281250	1.0916840	0.3723030	6.2421880	1.2816020
2	Fingerprint	0.0500760	10.0585940	0.795340	0.0506360	6.9765630	1.1466970	0.3631570	6.0407370	1.3243420
3	Fingerprint	0.6730200	11.8867190	0.047062	0.0628760	8.0898440	0.9888940	0.4849340	6.4575890	1.2388520
4	Fingerprint	0.0715240	8.7187500	0.917563	0.0840740	6.6835940	1.1969610	0.3786790	5.6746650	1.4097750
5	Fingerprint	0.0452420	9.3398440	0.856545	0.0552370	6.6523440	1.2025840	0.3495660	5.8521210	1.3670260
6	Fingerprint	0.1350320	10.0585940	0.795340	0.0828760	7.0039060	1.1422200	0.3501110	5.8521210	1.3670260
7	Fingerprint	0.0557250	11.8867190	0.673020	0.0467480	7.8710940	1.0163770	0.3626230	6.0407370	1.3243420
8	Fingerprint	0.0869080	8.7187500	0.917563	0.0573550	6.8476560	1.1682830	0.6077020	5.5078130	1.4524820
9	Fingerprint	0.0553290	10.8984380	0.734050	0.0573040	7.4765630	1.0700100	0.3551550	6.2421880	1.2816020
10	Fingerprint	0.1207900	9.3398440	0.856545	0.0982560	6.7968750	1.1770110	0.5291090	5.8521210	1.3670260
11	Fingerprint	0.0852740	10.0585940	0.795340	0.0998290	7.1718750	1.1154680	0.3608010	6.0407370	1.3243420
12	Fingerprint	0.1143930	11.8867190	0.673020	0.0877850	7.7929690	1.0265660	0.5153100	6.0407370	1.3243420
13	Fingerprint	0.1064090	8.7187500	0.917563	0.0931060	7.2890630	1.2890630	0.5832680	5.5078130	1.4524820
14	Fingerprint	0.0650880	10.8984380	0.734050	0.0687620	7.7187500	1.0364370	0.5077160	6.2421880	1.2816020
15	Fingerprint	0.0889150	9.3398440	0.856545	0.0994450	6.7812500	1.1797240	0.6601980	5.8521210	1.3670260
16	Fingerprint	0.0661820	10.0585940	0.795340	0.1065040	8.4570310	0.9459580	0.6514710	6.0407370	1.3243420
17	Fingerprint	0.1405470	8.7187500	0.917563	0.0788700	7.2890630	1.0975350	0.5325080	5.5078130	1.4524820
18	Fingerprint	0.0544890	11.8867190	0.673020	0.0674250	8.2968750	0.9642180	0.6161890	6.0407370	1.3243420
19	Fingerprint	0.1072730	9.3398440	0.856545	0.0666080	6.6250000	1.2075470	0.8177330	5.8521210	1.3670260
20	Fingerprint	0.0125760	4.7187500	0.695364	0.0487790	7.6406250	1.0470350	0.3499760	6.2421880	1.2816020
Average	Fingerprint	0.1091524	9.8714850	0.725369	0.0699518	6.9498048	1.1055135	0.4874254	5.9564736	1.3457001

Table 2 shows the results of the application for compression of fingerprint images. In order to present the advantages of this study, the table was compared with another study that used the same dataset (Kadim *et al*., 2020). The comparison was performed with images of fingerprints. The testing was performed with 20 grayscale fingerprint images. The image compression process uses three types of transformations: Discrete shearlet transform, discrete wavelet transform, and discrete cosine transform. The proposed approach resizes the images of different sizes in accordance with the measured rate of (16×16) and then converts them from (RGB) to (grayscale). Afterwards, the image enters the algorithm (Huffman coding). The average compression ratio of the images was better in the discrete shearlet transform with (Huffman coding) which is estimated as 2.2330555. The discrete wavelet transform with (Huffman coding) was 1.610216. Discrete cosine transform with (Huffman coding) was 1.606742. As for the time when implementing the algorithm (Huffman coding), the average time in all images with discrete shearlet transform was 2.936313, discrete wavelet transform was 0.10406960 and discrete cosine transform was 0.2242184. As for the bit rate when implementing the algorithm (Huffman coding) the average bit rate in all images with discrete shearlet transform was 3.589481, discrete wavelet transform was 4.9921875 and discrete cosine transform was 6.22453.

The Third Experiment

The third kind, which uses a technique for fingerprint compression in current databases, guarantees a large reduction in the amount of memory needed. The time it takes to receive the information will be shorter in situations when the image needs to be moved. As a result, the receiving side will be able to use the maximum data available for user authentication and will obtain higher recognition reliability because the fingerprint image is sent with retained quality without slowing down the system's performance. In this experiment, there are three operations to find out the compression ratio and the time that is spent. Therefore, the purpose of this study is to. Find out which conversion is better in terms of time, Bit Rate, and compression ratio by using DCT-Zigzag-Arithmetic coding, DWT-zigzag-arithmetic coding, and dst-zigzag-arithmetic coding.

Table 3 shows the results of the application for compression of fingerprint images. In order to present the advantages of this study, the table was compared with another study that used the same dataset by Kadim *et al*. (2020). The comparison was performed with images of fingerprints. The testing was performed with 20 grayscale fingerprint images. The image compression process uses three types of transformations: Discrete shearlet transform, discrete wavelet transform, and discrete cosine transform. The proposed approach resizes the images of different sizes in accordance with the measured rate of (16×16) and then converts them from (RGB) to (grayscale). Afterwards, the image enters the algorithm (Arithmetic coding). The average compression ratio of the images was better in the discrete shearlet transform with (Arithmetic coding) which is estimated as 2.238244. In discrete wavelet transform with (arithmetic coding) was 1.541135. The discrete cosine transform with (Arithmetic coding) was 1.2245625. As for the time when implementing the algorithm (Arithmetic coding), the average time in all images with discrete shearlet transform was 0.2618996, discrete wavelet transform was 0.00284105 and discrete cosine transform was 0.059867. As for the bit rate when implementing the algorithm (arithmetic coding) the average bit rate in all images with discrete shearlet transform was 3.581166, discrete wavelet transform was 4.742193 and discrete cosine transform was 6.611915.

Table 2: Discrete cosine transform, discrete wavelet transform and discrete shearlet transform with huffman coding

		DCT-zigzag-Huffman			DWT-zigzag-Huffman			DST-zigzag-Huffman		
No.	Image	Run time (sec)	Bit rate	C. ratio	Run time (sec)	Bit rate	C. ratio	Run time (sec)	Bit rate	C. ratio
1	Fingerprint	0.1076050	7.085938	1.128997	0.046402	5.105469	1.566947	2.575806	3.761719	2.1266870
2	Fingerprint	0.0004460	6.125000	1.306122	0.050083	4.792969	1.669112	2.632253	3.640067	2.1977620
3	Fingerprint	1.0348660	7.730469	0.110895	0.085046	5.558594	1.439213	2.759323	3.891183	2.0559300
4	Fingerprint	0.1411040	5.667969	1.411440	0.092782	4.867188	1.643660	3.034746	3.419643	2.3394260
5	Fingerprint	0.1252040	6.074219	1.317042	0.046832	4.500000	1.777778	2.642272	3.526786	2.2683540
6	Fingerprint	0.3295580	6.539063	1.223417	0.096439	4.824219	1.658300	2.615668	3.526786	2.2683540
7	Fingerprint	0.1160580	7.730469	1.034866	0.064108	5.519531	1.449398	3.036293	3.640067	2.1977620
8	Fingerprint	0.1751160	5.667969	1.411440	0.074387	4.738281	1.688376	2.941868	3.319196	2.4102220
9	Fingerprint	0.1364790	7.085938	1.128997	0.093833	5.171875	1.546828	3.105105	3.761719	2.1266870
10	Fingerprint	0.1966440	6.074219	1.317042	0.143938	4.609375	1.735593	2.983461	3.526786	2.2683540
11	Fingerprint	0.2227070	6.539063	1.223417	0.169227	4.875000	1.641026	2.663626	3.640067	2.1977620
12	Fingerprint	0.2444760	0.244476	1.034866	0.166914	4.945313	1.617694	2.961277	3.640067	2.1977620
13	Fingerprint	0.2079680	5.667969	1.411440	0.146447	4.863281	1.644980	3.007320	3.319196	2.4102220
14	Fingerprint	0.1663320	7.085938	1.128997	0.082970	5.230469	1.529500	2.679832	3.761719	2.1266870
15	Fingerprint	0.2519160	6.074219	1.317042	0.164593	4.523438	1.768566	3.261506	3.526786	2.2683540
16	Fingerprint	0.1574030	6.539063	1.223417	0.215059	5.570313	1.436185	2.998280	3.640067	2.1977620
17	Fingerprint	0.3327120	5.667969	1.667969	0.090517	4.761719	1.680066	3.108334	3.319196	2.4102220
18	Fingerprint	0.1161220	7.730469	1.034866	0.079790	5.527344	1.447350	3.056447	3.640067	2.1977620
19	Fingerprint	0.2786500	6.074219	1.317042	0.107562	4.562500	1.753425	3.285200	3.526786	2.2683540
20	Fingerprint	0.1430020	7.085938	1.128997	0.0644630	5.296875	1.510324	3.377642	3.761719	2.1266870
Average	Fingerprint	0.2242184	6.224530	1.606742	0.1040696	4.9921875	1.610216	2.936313	3.589481	2.2330555

Table 3: Discrete cosine transform, discrete wavelet transform and discrete shearlet transform with arithmetic coding

		DCT-zigzag-Arithmetic			DWT-zigzag-Arithmetic			DST-zigzag-Arithmetic		
No.	Image	Run time (sec)	Bit rate	C. ratio	Run time (sec)	Bit rate	C. ratio	Run time (sec)	Bit rate	C. ratio
1	Fingerprint	0.020266	7.074219	1.1308670	0.0159440	5.070313	1.577812	0.1847580	3.753348	2.131430
2	Fingerprint	0.115566	6.539063	1.2234170	0.0187430	4.785156	1.671837	0.1945090	3.631696	2.202827
3	Fingerprint	0.021796	7.718750	1.0364370	0.0302420	5.566406	1.437193	0.2387770	3.882254	2.060658
4	Fingerprint	0.020351	5.664063	1.4124140	0.0359180	4.843750	1.651613	0.1638670	3.411830	2.344782
5	Fingerprint	0.035178	6.066406	1.3187380	0.0181270	4.472656	1.788646	0.1570780	3.518415	2.273751
6	Fingerprint	0.159072	6.535156	1.2241480	0.0480390	4.785156	1.671837	0.2274590	3.518415	2.273751
7	Fingerprint	0.021150	7.722656	1.0359130	0.0557830	5.515625	1.450425	0.2919290	3.632254	2.202489
8	Fingerprint	0.046056	5.660156	1.4133890	0.0183440	4.722656	1.693962	0.3220200	3.311384	2.415908
9	Fingerprint	0.035363	7.078125	1.1302430	0.0184540	5.156250	1.551515	0.2609540	3.752790	2.131747
10	Fingerprint	0.051085	6.062500	1.3195880	0.0467130	4.609375	1.735593	0.2605690	3.518415	2.273751
11	Fingerprint	0.058825	6.535156	1.2241480	0.0573550	4.871094	1.642342	0.2234050	3.631696	2.202827
12	Fingerprint	0.125544	7.722656	1.0359130	0.0576740	4.996094	1.601251	0.3040880	3.631696	2.202827
13	Fingerprint	0.068600	5.664063	1.4124140	0.0587030	4.058703	1.643660	0.2953910	3.311384	2.415908
14	Fingerprint	0.033278	7.078125	1.1302430	0.0189790	5.226563	1.530643	0.2629210	3.752790	2.131747
15	Fingerprint	0.065691	6.062500	1.3195880	0.0460780	4.492188	1.780870	0.5446360	3.518415	2.273751
16	Fingerprint	0.036561	6.531250	1.2248800	0.0836830	5.582031	1.433170	0.2674910	3.631696	2.202827
17	Fingerprint	0.124694	5.660156	1.4133890	0.0313570	4.722656	1.693962	0.2734260	3.311384	2.415908
18	Fingerprint	0.019741	7.722656	1.0359130	0.0248900	5.515625	1.450425	0.2097470	3.632254	2.202489
19	Fingerprint	0.113106	6.066406	1.3187380	0.1388450	4.558594	1.754927	0.2657480	3.518415	2.273751
20	Fingerprint	0.025424	7.074219	1.1308670	0.0298400	5.292969	1.511439	0.2892190	3.752790	2.131747
Average	Fingerprint	0.059867	6.611915	1.2245625	0.0426856	4.742193	1.541135	0.2618996	3.581166	2.238244

Table 4: Discrete cosine transform, discrete wavelet transform and discrete shearlet transform with run length encoding

		DCT-zigzag-RLE			DWT-zigzag-RLE			DST-zigzag-RLE		
No.	Image	Run time (sec)	Bit rate	C. ratio	Run time (sec)	Bit rate	C. ratio	Run time (sec)	Bit rate	C. ratio
1	Fingerprint	0.0003520	6.656250	1.201878	0.0004070	4.9687500	1.6100630	0.0008420	2.6651790	3.001675
2	Fingerprint	0.0109020	4.343750	1.841727	0.0002950	4.7812500	1.6732030	0.0008530	2.5803570	3.100346
3	Fingerprint	1.1034480	7.250000	0.000353	0.0016890	5.3125000	1.5058820	0.0014460	2.7544640	2.904376
4	Fingerprint	0.0005960	5.312500	1.505882	0.0081040	4.6250000	1.7297300	0.0008160	2.4241070	3.300184
5	Fingerprint	0.0008190	5.687500	1.406593	0.0004180	4.4062500	1.8156030	0.0008000	2.5000000	3.200000
6	Fingerprint	0.0026880	6.125000	1.306122	0.0058590	4.7187500	1.6953640	0.0008140	2.5000000	3.200000
7	Fingerprint	0.0006950	7.250000	1.103448	0.0014990	5.3750000	1.4883720	0.0009120	2.5803570	3.100346
8	Fingerprint	0.0027440	5.312500	1.505882	0.0015190	4.6875000	1.7066670	0.0077550	2.3526790	3.400380
9	Fingerprint	0.0006420	6.656250	1.201878	0.0009490	5.0625000	1.5802470	0.0052460	2.6651790	3.001675
10	Fingerprint	0.0029750	5.687500	1.406593	0.0039350	4.4687500	1.7902100	0.0054420	2.5000000	3.200000
11	Fingerprint	0.0069370	6.125000	1.306122	0.0030630	4.8437500	1.6516130	0.0011040	2.5803570	3.100346
12	Fingerprint	0.0038150	7.250000	1.103448	0.0032310	4.9375000	1.6202530	0.0053280	2.5803570	3.100346
13	Fingerprint	0.0037980	5.312500	1.505882	0.0053520	4.7812500	1.6732030	0.0031220	2.3526790	3.400380
14	Fingerprint	0.0027860	6.656250	1.201878	0.0023900	5.2500000	1.5238100	0.0021210	2.6651790	3.001675
15	Fingerprint	0.0062100	5.687500	1.406593	0.0027920	4.1875000	1.9104480	0.0085900	2.5000000	3.200000
16	Fingerprint	0.0043310	6.125000	1.306122	0.0043930	4.9062500	1.6305730	0.0095860	2.5803570	3.100346
17	Fingerprint	0.0043430	5.312500	1.505882	0.0032890	4.4375000	1.8028170	0.0024570	2.3526790	3.400380
18	Fingerprint	0.0004720	7.250000	1.103448	0.0036390	4.8437500	1.6516130	0.0020660	2.5803570	3.100346
19	Fingerprint	0.0046980	5.687500	1.406593	0.0031790	4.4062500	1.8156030	0.0054440	2.5000000	3.200000
20	Fingerprint	0.1430020	7.085938	1.128997	0.0008190	5.0937500	1.5705520	0.0028690	2.6651790	3.001675
Average	Fingerprint	0.0653127	5.805860	1.272766	0.0028411	4.8046875	1.6722915	0.0033807	2.5439733	3.150724

The Fourth Experiment

The fourth kind, which uses a technique for fingerprint compression in current databases, guarantees a notable reduction in the amount of memory needed. The time it takes to receive the information will be shorter in situations when the image needs to be moved. As a result, the receiving side will be able to use the maximum data available for user authentication and will obtain higher recognition reliability because the fingerprint image is sent with retained quality without slowing down the system's performance. In this experiment, there are three operations to find out the compression ratio and the time that is spent. Therefore, the purpose of this study is to. Find out which conversion is better in terms of time, bit rate, and compression ratio by using dct-zigzag run-length encoding, dwt-zigzag-run length encoding, and dst-zigzag-run length encoding.

Table 4 shows the results of the application for compression of fingerprint images. In order to present the advantages of this study, the table was compared with another study that used the same dataset. The comparison was performed with images of fingerprints. The testing was performed with 20 grayscale fingerprint images. The image compression process uses three types of transformations: Discrete shearlet transform, discrete wavelet transform, and discrete cosine transform. The proposed approach resizes the images of different sizes in accordance with the measured rate of (16×16) and then converts them from (RGB) to (grayscale). Afterwards, the image enters the algorithm (RLE). The average compression ratio of the images was better in the discrete shearlet transform with (RLE) which is estimated as 3.150724. In discrete wavelet transform with (RLE) was 1.6722915. Discrete cosine transforms with (RLE) was 1.272766. As for the time when implementing the algorithm (RLE), the average time in all images with discrete shearlet transform was 0.00338065, discrete wavelet transform was 0.0145625 and discrete cosine transform was 0.06531265. As for the bit rate when implementing the algorithm (RLE) the average bit rate in all images with discrete shearlet transform was 2.5439733, discrete wavelet transform was 4.8046875 and discrete cosine transform was 5.80586.

The Fifth Experiment

The fifth kind, which uses a technique for fingerprint compression in current databases, guarantees a notable reduction in the amount of memory needed. The time it takes to receive the information will be shorter in situations when the image needs to be moved. As a result, the receiving side will be able to use the maximum data available for user authentication and will obtain higher recognition reliability because the fingerprint image is sent with retained quality without slowing down the system's performance. In this experiment, there are three operations to find out the compression ratio and the time that is spent. Therefore, the purpose of this study is to. Find out which conversion is better in terms of time, bit rate and compression ratio by using DCT-zigzag-lempel ziv welch coding, DWT-zigzag-lempel ziv welch coding and DST-zigzag-lempel ziv welch coding.

Table 5 shows the results of the application for compression of fingerprint images. In order to present the advantages of this study, the table was compared with another study that used the same dataset. The comparison was performed with images of fingerprints. The testing was performed with 20 grayscale fingerprint images. The image compression process uses three types of transformations: Discrete shearlet transform, discrete wavelet transform, and discrete cosine transform. The proposed approach resizes the images of different sizes in accordance with the measured rate of (16×16) and then converts them from (RGB) to (grayscale). Afterwards, the image enters the algorithm (LZW). The average compression ratio of the images was better in the discrete shearlet transform with (LZW) which is estimated as 3.678023. In discrete wavelet transform with (LZW) 3.301732. Discrete cosine transforms with (LZW) was 1.713832. As for the time when implementing the algorithm (LZW), the average time in all images with discrete shearlet transform was 0.09939985, discrete wavelet transform was 0.0145625 and discrete cosine transform was1.713832. As for the bit rate when implementing the algorithm (LZW) the average bit rate in all images with discrete shearlet transform was 2.18125, discrete wavelet transform was 2.4171875 and discrete cosine transform was 4.732617.

Table 6 shows the average of all results in tables from Tables 1-5 and also shows the comparison with the average results by Kadim *et al*. (2020).

Analysis

1. The compression ratio in LZW is higher with a discrete shearlet transform and is estimated as 3.678023
2. Discrete shearlet transform is the better transform in EGC and is calculated as 1.34570005, Huffman coding is 2.2330555, arithmetic coding is 2.238244, RLE is 3.150724 and LZW is 3.678023
3. LZW coding is better than RLE. LZW equals 3.678023
4. The arithmetic coding is better than huffman coding. Arithmetic coding is calculated as 2.238244
5. The huffman coding is better than EGC. Huffman coding is 2.2330555
6. The way that is better for image compression is the discrete shearlet transform with zigzag scan-LZW. In this way, the achieved compression ratio is 3.678023. In addition, the running time in sec. is calculated as 0.09939985

Table 5: Discrete cosine transform, discrete wavelet transform, and discrete shearlet transform with Lempel Ziv Welch coding

		DCT-zigzag-LZW			DWT-zigzag-LZW			DST-zigzag-LZW		
No.	Image	Run time (sec)	Bit rate	C. ratio	Run time (sec)	Bit rate	C. ratio	Run time (sec)	Bit rate	C. ratio
1	Fingerprint	0.008567	4.6875000	1.706667	0.0122440	2.3125000	3.459459	0.0853050	2.299107	3.479612
2	Fingerprint	0.046612	10.058594	1.706667	0.0107820	2.1875000	3.657143	0.0673890	2.205357	3.627530
3	Fingerprint	1.610063	4.9687500	1.011372	0.0123130	2.6250000	3.047619	0.0839080	2.370536	3.374765
4	Fingerprint	0.013031	3.6875000	2.169492	0.0168420	2.1875000	3.657143	0.0684880	2.058036	3.887202
5	Fingerprint	0.010049	4.0625000	1.969231	0.0089650	2.1875000	3.657143	0.0772440	2.174107	3.679671
6	Fingerprint	0.020713	5.0625000	1.580247	0.0176470	2.1875000	3.657143	0.0682940	2.133929	3.748954
7	Fingerprint	0.022663	3.8437500	2.081301	0.0079350	2.5625000	3.121951	0.0827650	2.223214	3.598394
8	Fingerprint	0.017418	3.8437500	2.081301	0.0077860	2.1250000	3.764706	0.1323720	2.031250	3.938462
9	Fingerprint	0.014056	4.6562500	1.718121	0.0103780	2.5000000	3.200000	0.0969020	2.281250	3.506849
10	Fingerprint	0.025669	4.0625000	1.969231	0.0288990	2.3437500	3.413333	0.1105330	2.138393	3.741127
11	Fingerprint	0.025254	4.4375000	1.802817	0.0220630	2.4375000	3.282051	0.0820070	2.205357	3.627530
12	Fingerprint	0.025514	5.0937500	1.570552	0.0236930	2.7187500	2.942529	0.1004370	2.218750	3.605634
13	Fingerprint	0.025742	3.7500000	2.133333	0.0220890	2.5312500	2.531250	0.1326640	2.040179	3.921225
14	Fingerprint	1.706667	4.6875000	0.015762	0.0110520	2.6250000	3.047619	0.0957900	2.290179	3.493177
15	Fingerprint	0.024267	3.9687500	2.015748	0.0194360	2.0937500	3.756813	0.1343840	2.129464	3.820896
16	Fingerprint	0.013066	4.3125000	1.855072	0.0229350	2.8437500	2.813187	0.1198320	2.209821	3.620202
17	Fingerprint	0.026160	3.8125000	2.098361	0.0101570	2.4062500	3.324675	0.0926390	2.008929	3.982222
18	Fingerprint	0.015144	4.9375000	1.620253	0.0036390	2.6250000	3.047619	0.0957510	2.205357	3.627530
19	Fingerprint	0.063992	4.0625000	1.969231	0.0080010	2.2187500	3.605634	0.1178690	2.120536	3.772632
20	Fingerprint	0.001099	6.6562500	1.201878	0.0143940	2.6250000	3.047619	0.1434240	2.281250	3.506849
Average	Fingerprint	1.713832	4.7326170	1.713832	0.0145625	2.4171875	3.301732	0.0993999	2.181250	3.678023

Table 6: Shows the average of all the tables

		Discrete cosine transform			Discrete wavelet transform			Discrete shearlet transform		
No.	Algorithm	Run time (sec)	Bit rate	C. ratio	Run time (sec)	Bit rate	C. ratio	Run time (sec)	Bit rate	C. ratio
1	EGC	0.10915240	9.871485	0.7253690	0.06995180	6.9498048	1.1055135	0.48742540	5.9564736	1.34570005
2	HC	0.22421840	6.224530	1.6067420	0.10406960	4.9921875	1.6102160	2.93631300	3.5894810	2.23305550
3	AC	0.05986700	6.611915	1.2245625	0.00284105	4.7421930	1.5411350	0.26189960	3.5811660	2.23824400
4	RLE	0.06531265	5.805860	1.2727660	0.01456250	4.8046875	1.6722915	0.00338065	2.5439733	3.15072400
5	LZW	1.71383200	4.732617	1.7138320	0.01456250	2.4171875	3.3017320	0.09939985	2.1812500	3.67802300

Conclusion

In this study, a new technique for image compression is presented. Image compression's primary objective is to lessen picture redundancy, which increases storage efficiency and capacity. It takes care of the initial image during processing by using lossless compression. However, there is a serious problem which is the low ratio of compression. In order to make the ratio higher, there are five compression techniques used in this study. These techniques are Huffman Coding (HC), Arithmetic Coding (AC), Elias Gamma Coding (EGC), Run-Length Encoding (RLE), and Lempel Ziv Welch (LZW). With these techniques, there are three types of transforms that are used; they are Discrete Cosine Transform (DCT), discrete Wavelet Transform (DWT), and Discrete Shearlet Transform (DST), in order to compress input images in four phases; namely preprocessing, image transformation, zigzag scan and lossless compression. Images are entered into the preprocessing step, where the suggested method resizes them to 16×16 according to the measured rate and then converts them from RGB to grayscale. Our method of approximation, utilizing the (DST) with LZW, outperforms the Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT). The comparison between the three types of transform is taken into consideration. As a result, one type of lossless compression developed by this study is achieved by the Discrete Shearlet Transform (DST) with (LZW) technique. The study's conclusions show that (DST) performs better than other lossless compression methods when using the lempel-ziv Welch coding approach and its Compression Ratio (CR) is 3.678023.

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Author's Contributions

Nahidah A. Kadim: Participated in all experiments, coordinated the data analysis, and contributed to the writing of the manuscript.

Shawkat K. Guirguis: Supervision.

Hend A. Elsayed: Participated in all experiments, coordinated the data analysis and contributed to the writing of the manuscript, designed the research plan, and organized the study.

Ethics

This article is original and contains unpublished material. There are no ethical issues involved.

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