Iris Data Compression Based on Hexa-Data Coding

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A R T I C L E   I N F O

A B S T R A C T

Iris research is focused on developing techniques for identifying and locating relevant biometric features, accurate segmentation and efficient computation while lending themselves to compression methods. Most iris segmentation methods are based on complex modelling of traits and characteristics which, in turn, reduce the effectiveness of the system being used as a real time system. This paper introduces a novel parameterized technique for iris segmentation. The method is based on a number of steps starting from converting grayscale eye image to a bit plane representation, selection of the most significant bit planes followed by a parameterization of the iris location resulting in an accurate segmentation of the iris from the original image. A lossless Hexadata encoding method is then applied to the data, which is based on reducing each set of six data items to a single encoded value. The tested results achieved acceptable saving bytes performance for the 21 iris square images of sizes 256x256 pixels which is about 22.4 KB on average with 0.79 sec decompression average time, with high saving bytes performance for 2 iris non-square images of sizes 640x480/2048x1536 that reached 76KB/2.2 sec, 1630 KB/4.71 sec respectively, Finally, the proposed promising techniques standard lossless JPEG2000 compression techniques with reduction about 1.2 and more in KB saving that implicitly demonstrating the power and efficiency of the suggested lossless biometric techniques.

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1. Introduction

Human beings have distinctive and unique physical characteristics and traits, referred to as biometric features. Those traits and characteristics are either obvious (i.e., easily recognizable) or hidden and may need further processing to extract them. Data and information extracted from

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biometric features can be used in many applications, such is identity verification and authentication. Automatic identification of an individual's biometric features can be a reliable replacement for other traditional methods such as the use of identification numbers, keys and passwords, which can be very inefficient and insecure from time to time [1].

Biometric identification involves actions taken to identify an individual based on their intrinsic and distinctive traits. Biometric data are obtained and converted to a form that can be used to correlate distinctive traits in a database against a real time sample to make an accurate and fast decision. Among many other biometric acquisition techniques being investigated, biometric data extracted from the iris is getting increased attention from the research community due to its accuracy and applicability to be used in real time systems [1,2]. One of the reasons behind its accuracy is because of its structure stability and sustainability over the long period of a human's lifetime. Iris recognition is considered the most accurate method compared to other known modalities such as fingerprints, voice, facial and palm vein biometrics that developed a traffic sign classification system using convolutional neural networks (CNN) trained with a learning approach. The method involves training the CNNs to learn features and classify RGB-D images, and the initial classification results are presented in their paper [3,4].

Biometric data extracted from the iris representing the annular region between the pupil and the sclera has extremely rich and unique information. In order to extract this unique information, iris segmentation is an important processing step. The importance of iris segmentation lies in specifying (identifying) an accurate and precise boundary of the iris region which leads later on to a reliable extraction of features [5,6], where Designing a fast and reliable iris segmentation algorithm for less constrained iris images is crucial in building a robust iris recognition system. Although one of the powerful iris segmentation mechanisms is available, it consumes a significant portion of the computational time in localizing the rough position of the iris center and eyelid boundaries, as highlighted by Ling et al. [5]. The goal of Boureau and his team's work is threefold. Firstly, they aim to establish the relative importance of each step of mid-level feature extraction through a comprehensive cross-evaluation of various types of coding modules (such as hard and soft vector quantization and sparse coding) and pooling schemes (by taking the average or the maximum). Secondly, their approach achieves state-of-the-art performance or better on multiple recognition benchmarks. Lastly, they aim to contribute to the advancement of recognition tasks in computer vision [6]. Improper segmentation methodology can increase the probability of false or incorrect extraction of features around discriminative/impeded areas which leads to a reduction in the performance of the recognition system. Typically, the shape of the iris region is specified by sclera and pupil. Since the iris in its normal state may be impeded by eyelashes, eyelids (upper and lower) and light reflections, it is crucial that the process of iris segmentation involves localization processes of the impeded areas and disposal of other environmental changing factor such as shadows and reflections [7].

Effective iris recognition requires high quality biometric data extraction, while real time recognition systems based on biometric data can consume considerable amount of time. Therefore, a reliable iris segmentation method incorporated with data compression can play a vital rule on balancing both aspects and improve the overall performance of the recognition system [8]. Since biometric data need to be stored in a digital form and need to be present during live iris scanning to be compared with stored biometric data, image compression is considered a vital step for the overall efficiency of the iris recognition system. This is even more relevant for data stored in a database over the Internet or in the cloud, as such configuration

would consume most of the system's bandwidth [2,9]. Image compression in principle is used to reduce redundant and uncorrelated data which both help in removing less relevant features [10]. Thus, compressing iris images while maintaining relevant biometric features and characteristics can lead to increased recognition and overall system performance [2].

This paper introduces a novel effective lossless iris compression technique of hexa-coding two levels base for grayscale images, along exploiting a new segmentation of optimized circular feature extraction scheme that efficiently separate (isolate) the iris (Region Of Interest) from Non-Region Of Interest. The rest of this paper is organized as follows. Section 2 discusses iris segmentation issues, Section 3 illustrates our proposed iris segmentation method, Section 4 describes lossless compression of iris data by the Hexadata method while Section 5 describes the decompression steps. Section 6 describes experimental results and finally a discussion and conclusions are presented in Section 7.

2. Iris Segmentation Issues

Within iris recognition and segmentation research studies, it can be seen that there are significant number of different approaches [3]. Each one suggests different methods that convey certain levels of accuracy and reliability [4]. In this paper, we focus on a new segmentation methodology that precisely isolates ROI (Region of Interest) from non-ROI parts while providing reliability and accuracy.

Iris segmentation is a necessary step in any iris recognition system. Our proposed method detaches ROI from non-ROI areas. While the former represents the iris itself, the latter refers to impeded areas such as containing the eyelids or eyelashes. ROI and non-ROI implicitly classify an image region into major and minor regions in terms of meaningful features where each region is compressed separately by the proposed lossless Hexadata algorithm.

Normally, depending on the image intensity utilization and properties, image segmentation algorithms can be categorized under two bases:

- **Discontinuity based segmentation**: also called boundary segmentation, in which the segregation process is based on searching for abrupt intensity changes and exploiting the edge detection convolution concept of gradient base. Although this method has been characterized by its popularity, simplicity and speed, in the case of iris segmentation it is very challenging to clearly detect edges especially in detailed or noisy images [6].
- **Continuity based segmentation**: also referred to as region segmentation, in which the segregation process is based on connectivity or continuity patterns of intensity in neighbouring pixels following predefined criteria. This approach is characterized by its complexity, expensive, and can be affected by segmentation parameters that involve threshold values either set globally or locally, seed value, and homogeneity measure [7]. Since there is not a universal segmentation solution that can reliably and seamless work well for all images, utilizing one segmentation approach over others is dependent on the characteristics or features of the problem being considered, for more details see [8].

The practical issues of iris segmentation are related to overcoming thresholding techniques or how to yield convenient, reliable and effective methods of segmentation.

3. Proposed Iris Segmentation Technique

This paper introduces a new parameterisation technique by using a small number of coefficients to overcome the limitations of the thresholding techniques. The processes are divided into two steps namely segmentation and compression enabling robust iris segmentation with efficient storage and transmission. The proposed iris segmentation technique starts by loading an original 8-bit grey scale uncompressed image I of size $N \times N$ of the eye. A bit-plane slicing coding technique is applied which simply translates the input image I into its binary representation, i.e., convert I into binary images $(I_1, I_2, \ldots, I_s)$ ranging from the lowest to highest order bit-plane as shown in Figure 1, where I_x represents the xth bit of I.
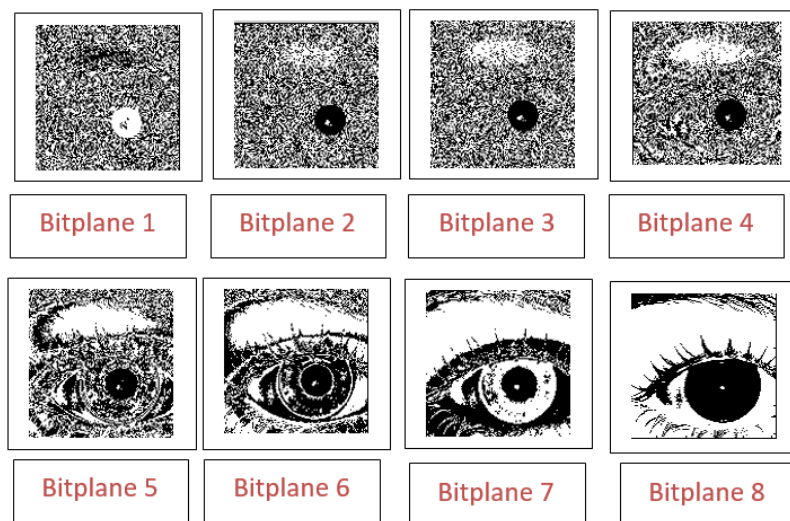

Figure 1: Bit-plane slicing image into its binary
representation

By examining the results of the bit plane slicing from Figure 1, it is clear that the least significant bits (LSB) in the range between I_1 to I_4 are noticeably noisy and much less useful for the segmentation process and therefore will be neglected. In contrast, the most significant bits (MSB) ranging from I_5 to I_8, and specifically I_8 represent most useful information and are thus, obvious candidates to exploit for precise iris segmentation.

In order to separately and equally divide and quantize each bit of our selected bit plane samples, uniform scalar quantization is applied to quantize bit plane I_8 as shown in Figure 2. This step ensures that the range of the quantized image values (I_{8Q}) is between 0 and 1. Furthermore, utilizing the image complement on the result (I_{8QC}) certainly would allow efficient segmentation due to visibility enhancement and clarity of regions of interest.

At this point, we parameterize the iris region segmentation process based on circle optimization. Start by finding the initial coordinates of the centre point (x_c, y_c) of the quantized image I_{8QC} which represents the average position based on the weighted sum of intensities and the position along both directions (i.e., the sum of all position in each direction multiplied by the image

intensity then divided by the sum of image intensities), followed by a guess of the initial radius r of the iris using the computed centre values above, formulated as:

$$(x - x_c)^2 + (y - y_c)^2 = r^2 \qquad\qquad (1)$$

Where (x_c, y_c) correspond to the average (mean) of horizontal and vertical coordinates of the eye image, and r corresponds to the radius of a circular based object. Lastly, optimize the iris region of the circular object implicitly based on the centre and radius using the Equation (1) above. The fitting function is based on maximizing the iris region (radius) which simply maximizes the white connected pixels within the circular base compared to foreground using the simplex method. Figure 2 shows a complete block diagram that illustrates the proposed segmentation process.
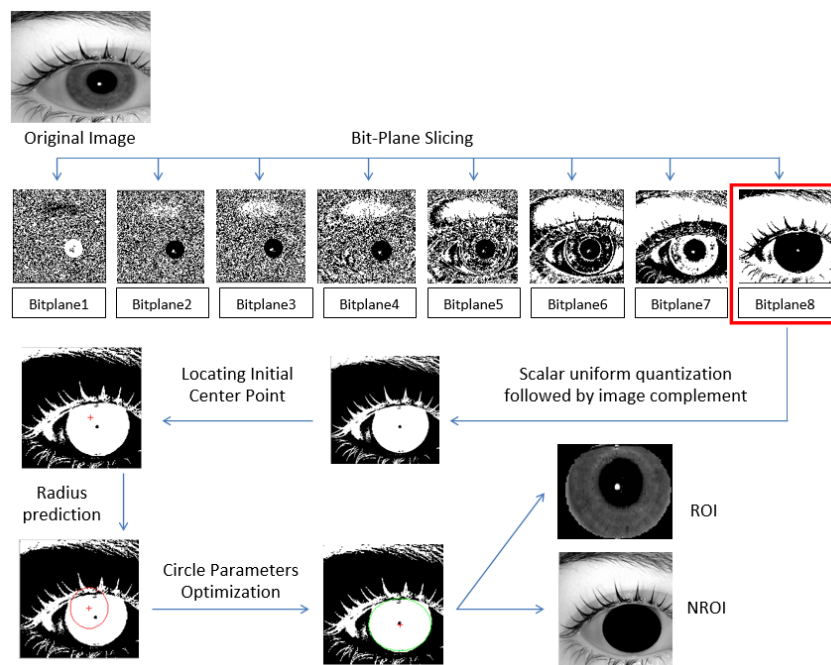

Figure 2. The proposed segmentation methodology

4. The Lossless Hexadata Compression Methodology

The outcomes from our proposed segmentation method is literally two integer data matrices that represent ROI and non-ROI parts of the original image. In order to increase recognition performance, these two integer matrices can be further compressed as lossless to reduce its size while maintaining its segmentation properties. Among many lossless compression techniques available in the research community, a novel method to perform lossless data compression was demonstrated by Siddeq and Rodrigues in 2019 [11,12], a technique that is selected and applied in this paper.

The novelty of the compression technique is that data presented in an array are divided into groups of 6 items, each of which is then converted into a single floating-point value through

equations involving the use of multi-level hierarchical key sets [13,14]. The algorithm starts by generating two levels of keys, the first level consisting of three keys RK1, RK2 and RK3 while the second level consisting of two keys RK4 and RK5. The key generation algorithm uses two variables to compute the keys: the first variable is M which is the maximum value in the data. The second one is a scaling factor whose value is equal or greater than 1 (F >= 1). The key generation method is highlighted as follows:

Pseudo-Code for the Key Generator Algorithm

M = max(Q)/2;   //max value of data matrix Q

RK1 = 1   //set first 0 < key <=1

RK2 = RK1 + M + F;   //where F >=1 is an integer scaling factor

RK3 = F*M*(RK1 + RK2); //where * is the dot multiplication operator

RK4 =random;   //second level random key

RK5 =random;   //second level random key

As a default value for F, RK4 and RK5 in this research are set to F=1, RK4=1 and RK5=0.9706 (i.e. RK5 generated by a random number generator), because the floating point in RK5 plays an essential role to reconstruct the six original values. Figure 3 illustrates the data flow for lossless Hexadata compression [10].

Original data (size *n*)

d1 d2 d3 d4   d5 d6 d7   d8 d9 d10 d11 … etc.

RK1 RK2 RK3   RK1 RK2 RK3   RK1 RK2 RK3

coded data at first level (size *n/3*)

e1   e2   e3 … etc.

RK4   RK5
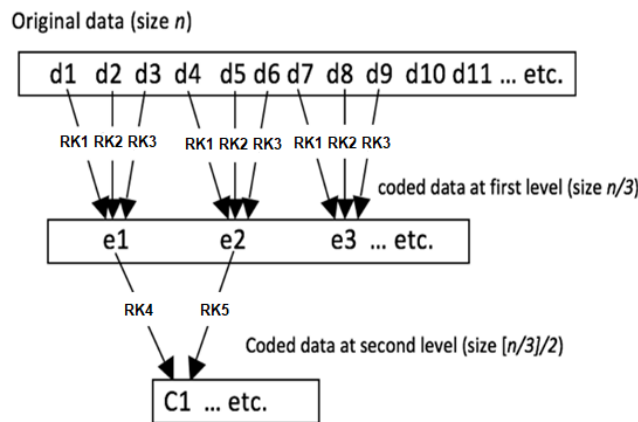
Coded data at second level (size [*n/3*]/2)

C1 … etc.

Figure 3. The structure of the lossless Hexadata
compression steps.

To illustrate the encoding steps assume we have the following sample input iris data that can be represented in two ways:

Q = [65, 64, 63, 67, 100, 60, 61, 60, 68, 67, 66, 69, 70, 69, 68, 67, 68, 69]

Q_Δ= [1, 1, -4, -33, 40, -1, 1, -8, 1, 1, -3, -1, 1, 1, 1, -1, -1, 69]

Where the size of data matrix Q is 18 and Q_Δ is the difference between two consecutive entries in Q. The keys for the first level are generated from the key generator algorithm above: RK1=1, RK2=52 and RK3=2550. The keys for the second level are between 0 and 1: RK4=1 and RK5=0.9706. The encoded data as illustrated in Figure 3 (intermediate and final encoding) are calculated from Equation (2) for level i encoding and Equation (3) for level j encoding [13,14]:

$$e(i) = RK1 \times d(n) + RK2 \times d(n+1) + RK3 \times d(n+2) \tag{2}$$

$$C(j) = RK4 \times e(p) + RK5 \times e(p+1) \tag{3}$$

Where $e(i)$ is the intermediate encoded output from the original data matrix and $C(j)$ is the final encoded output from previous encoded data $e(i)$. Thus, the encoded output from Equations (2) and (3) for matrices Q and Q_Δ are:

For matrix Q:

$e = [164043, 158267, 176581, 179449, 177058, 179553]$

$C = [317656.9502, 350754.1994, 351332.1418]$

Recalculating e and C for Q_Δ, it is possible to increase the compression ratio as follows. The new keys generated for matrix Q_Δ are: RK1=1, RK2=35, RK3=1330, RK4=1 and RK5=0.9706, and the new outputs from Equations (2) and (3) are:

For matrix Q_Δ:

$e = [-5284, 37, 1051, -1434, 1366, 91734]$

$C = [-5248.0878, -340.8404, 90403.0204]$

The difference between option 1 (for matrix Q) and option 2 (for matrix of data differences Q_Δ) is the number of bits in the final output C. If we were to compress the output of option 1 we would need a total number of bits of 120 or more, while in option 2 the total number of bits is 96 or less. For this reason, in this research we will always use option 2 to compress and encode iris data; that is, we will use not the original data but the matrix of differences.

In the next step, we will compute the probability of the output C. The following sample will illustrate the probability process in an easy to visualize way. Assume input values as:

$$Q = [60, 60, 60, 60, 60, 60, 61, 61, 61, 61, 61, 61, 62, 70, 70, 69, 68, 69]$$

After differences are computed, the new values are:

$$Q_\Delta = [0, 0, 0, 0, 0, -1, 0, 0, 0, 0, 0, -1, -8, 0, 1, 1, -1, 69]$$

With RK1=1, RK2=70, RK3=4968, RK4=1 and RK5=0.9706 (from the key generator algorithm). After applying Equations (2) and (3) to Q_Δ the output will be:

$$C = [-4821.9408, -4821.9408, 337605.9732]$$

In the final coded output C we found (-4821.9408) repeated twice, this means the source data for this output is the same. In this case the probabilities for output are:

output	Source data
-4821.9408	0, 0, 0, 0, 0, -1
337605.9732	-8, 0, 1, 1, -1, 69

Indeed, the sequence $[0,0,0,0,0,-1]$ is repeated in data matrix Q_Δ. This source data represents an additional key which is used for encoding and thus must be kept for decoding. By the same token, the five keys generated by the key generator are used for encoding as defined by Equations (2) and (3). In this way, we can say that the output C is encrypted by 6 types of keys which would be extremely difficult to decode without those keys. If one of those keys is lost or damaged, then the image is unrecoverable.
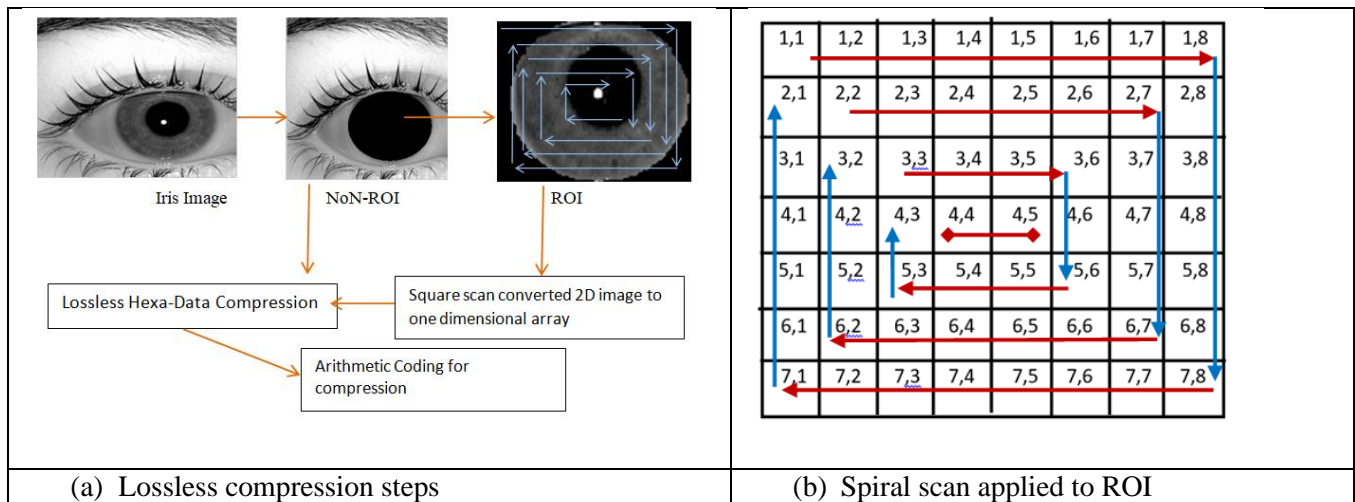

| (a) Lossless compression steps | (b) Spiral scan applied to ROI |

Figure 4: (a) Steps in the algorithm, (b) Converting matrix 7x8 to one dimensional array, by spiral scan algorithm.

Figure 4 depicts the steps of the Hexadata compression and spiral scan to the iris ROI and the pseudo-code below illustrates the method.

Pseudo-Code for Lossless Iris Encoding

I = **read_image**(image)

BW = **edge_detect_iris**(I)

P = **predicted_iris_frame**(BW,I)   //detect iris ROI

Q = **spiral_scan**(P)   //ROI as one-dimensional array

Qd = **difference_matrix**(Q)   //matrix of differences

Qde = **hexacoding**(Qd)   //encode ROI

B = **non_ROI_to_1d**(I,P);   //background to 1D array, row wise

Be = **hexacoding**(B)   //encode non-ROI background

Ar = **arithmetic_coding**(Qde,Be)   //arithmetic coding of all data

save_encoded_data(Ar)   //save compressed data

Pseudo-Code for Square Scan Algorithm:

Set start point index (i=1, j=1)

Set end point index (P1=(Row size /2), P2=(Column size /2))

While (i<=P1 and j<=P2)

  Row1=**read_index**(i,1 i,2 i,3 i,n)

  Column1=**read_index**(i+1,n i+2,n i+3,n k,n)

  Row2=**read_index**(k,n-1 k,n-2 k,n-3 k,j)

  Column2=**read_index**(k-1,j k-2,j k-3,j i+1,j)

  Update new start point index as (i=i+1, j=j+1)

Our choice of using arithmetic coding as opposed to other methods say, Huffman coding are three-fold. First, the compression ratio of arithmetic coding is efficient in comparison to Huffman, i.e., arithmetic coding has a higher compression ratio than Huffman. Second, arithmetic coding provides convenience of adaptation of the frequency or probability tables, provided that the same tables are used for coding and decoding, which is our case. Finally, arithmetic coding needs less memory and can be applied to huge amounts of data represented as a single array [8][9].

5. The Hexadata Decompression Steps

The decompression algorithm is very fast in reconstructing the original image. Thee algorithm starts by applying Equation (3) to the source data table (see previous section). From [10,13] to recompute the output according to the source data table example we have:

Output	Source data
-4821.9408	0, 0, 0, 0, 0, -1

337605.9732	-8, 0, 1, 1, -1, 69

Select the compressed output C and search for it in the source data table. If found, the relative source data represents the original iris data. Of course, there is the possibility of no option (output not found), because all the output probabilities available in the source data table are from the compression stage. Note that the size of source-data table depends on the probability of the repeated Hexadata. Figure 5 illustrates the Hexadata decompression steps.
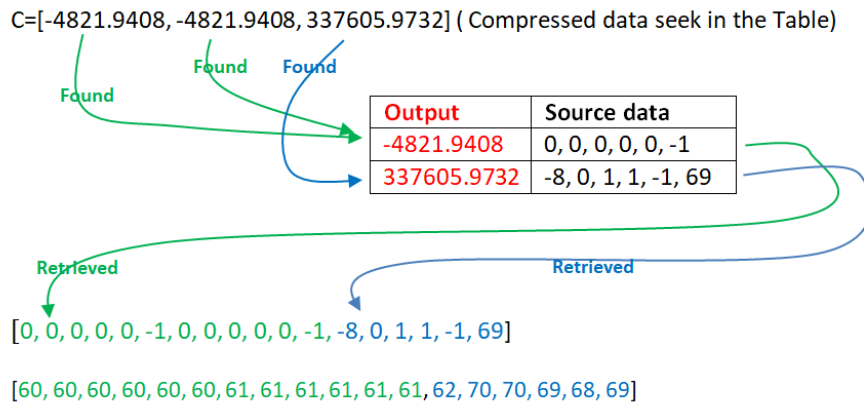
Figure 5. Decompression steps to reconstruct original
Iris data

Finally, the iris data are replaced in the exact location according to the spiral scan algorithm to recover the original Iris image, which is then combined with the background image (non-ROI region) to reconstruct the original complete iris image.

6. Experimental Results

The Lossless Hexadata encoding and decoding applied to different types on greyscale Iris images, by using MATLAB language using an Intel core i7-3740QM @ 2.7MHz computer. The results show that our algorithm successfully compress and decompress those images as showed in Figure 6. Also Table 1 shows the compressed size and execution time for each image.

Table 1. LOSSLESS IRIS DATA COMPRESSED BY HEXA-DATA COMPRESSION

Image name	Uncompressed image Size KB	Image dimensions	Size after Compression KB	Time execution (Decompression) (sec.)
SIMGR_3000	300	(640 x 480)	224	2.2

SIMGR_3001	65	(256 x 256)	39.8	0.82
SIMGR_3002	65	(256 x 256)	41.4	0.79
SIMGR_3003	65	(256 x 256)	42.7	0.83
SIMGR_3004	65	(256 x 256)	44.7	0.96
SIMGR_3005	65	(256 x 256)	43.0	0.83
SIMGR_3006	65	(256 x 256)	44.5	0.78
SIMGR_3007	65	(256 x 256)	42.6	0.92
SIMGR_3008	65	(256 x 256)	42.8	0.87
SIMGR_3009	65	(256 x 256)	32.7	0.93
SIMGR_3010	65	(256 x 256)	42.5	0.79
SIMG_4000	3000	(2048 x1536)	1370	4.71
SIMG_4001	65	(256 x 256)	33.6	0.77
SIMG_4002	65	(256 x 256)	43.0	0.87
SIMG_4003	65	(256 x 256)	42.3	0.91
SIMG_4004	65	(256 x 256)	41.2	0.76
SIMG_4005	65	(256 x 256)	40.5	0.79
SIMG_4006	65	(256 x 256)	37.9	0.78
SIMG_4007	65	(256 x 256)	44.7	0.88
SIMG_4008	65	(256 x 256)	43.2	0.87
SIMG_4009	65	(256 x 256)	43.8	0.79

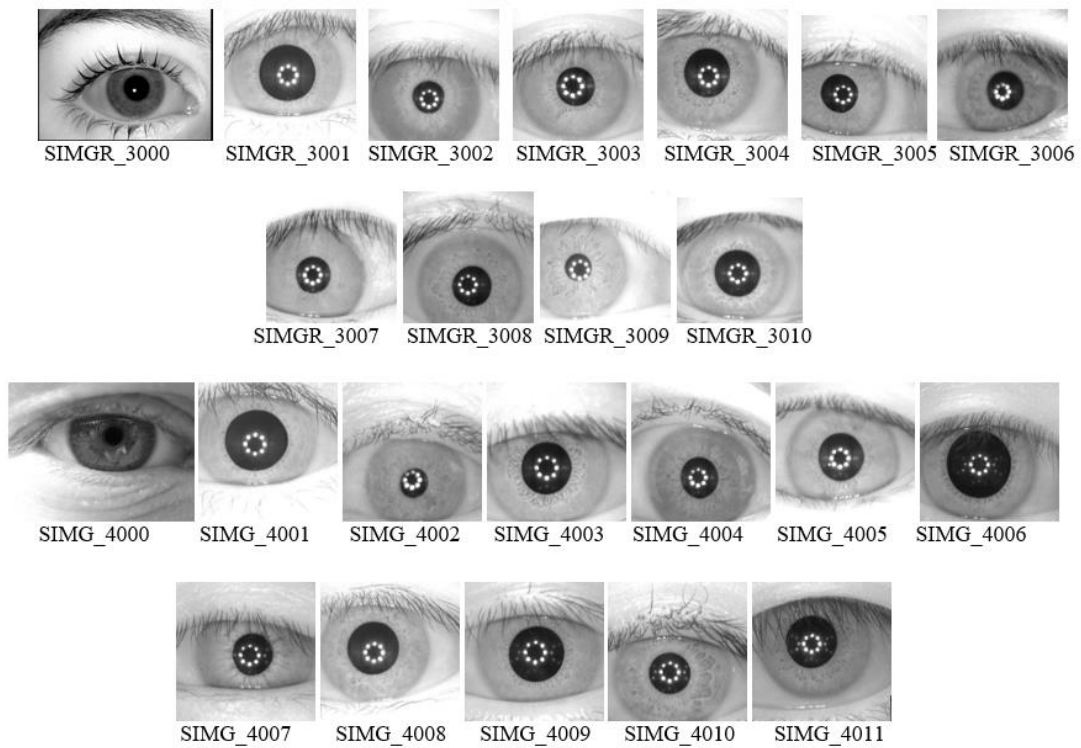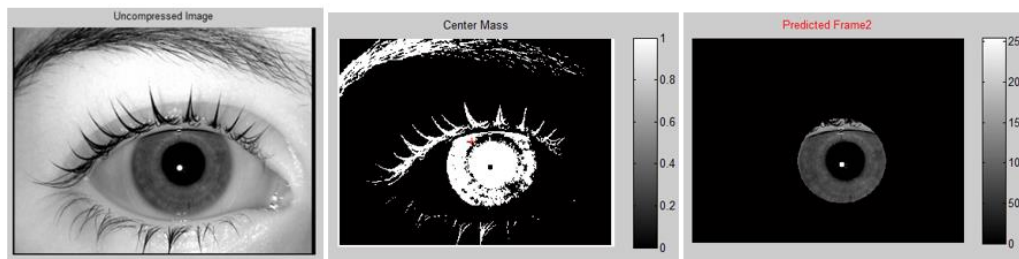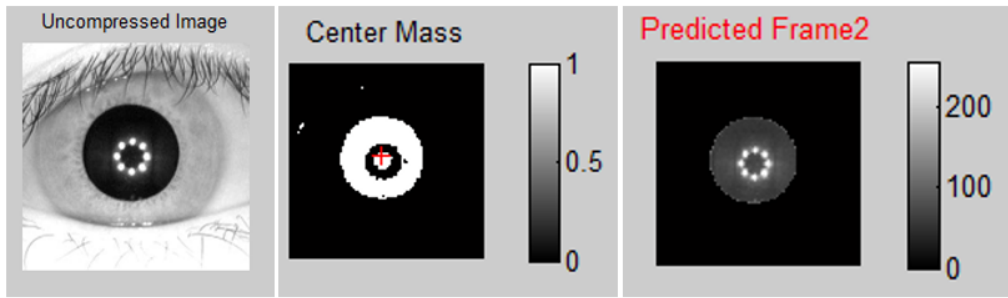| SIMG_4010	65	(256 x 256)	45.1	1.2
SIMG_4011	65	(256 x 256)	44.1	1.09

Figure 6. Set of IRIS images collected from Baghdad
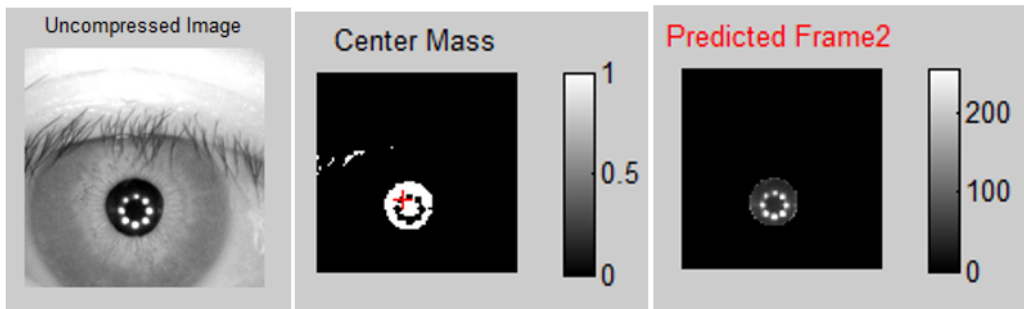University's database for test

The following Figure 7 shows sample of segmentation, predicted Iris data (ROI), separated from background image (non-ROI).
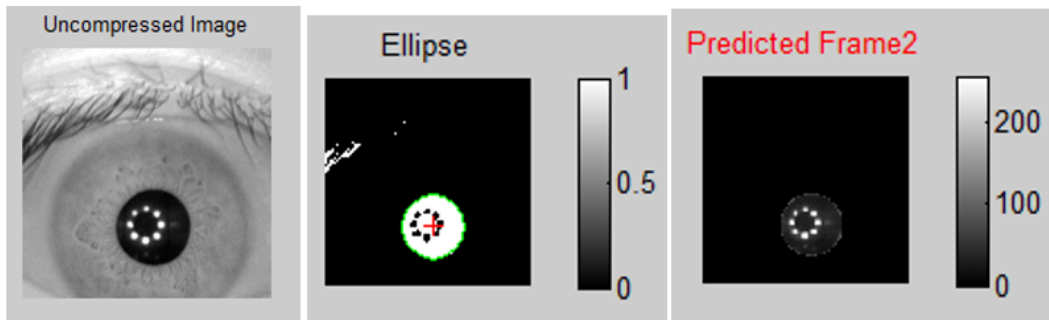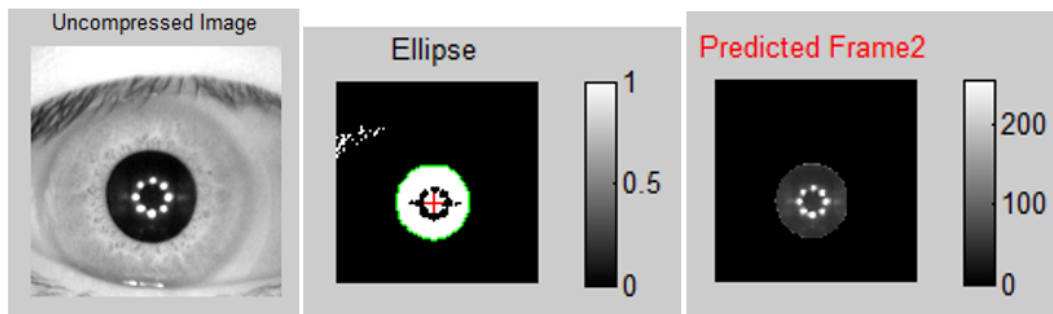

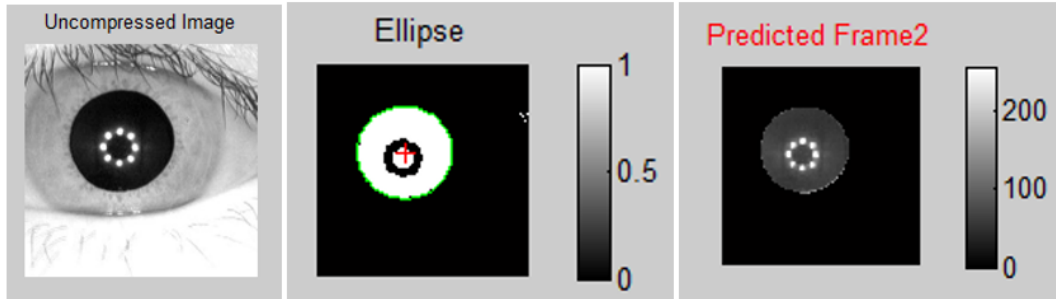(a) Lossless iris SIMGR_3000.bmp

(b) Lossless iris SIMGR_3001.bmp

(c) Lossless iris SIMGR_3002.bmp

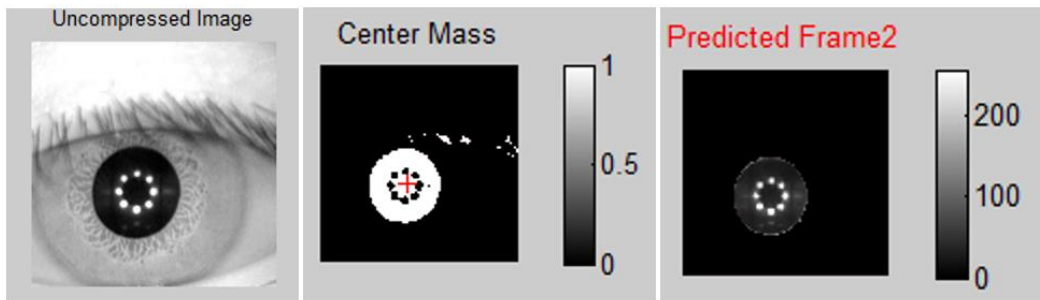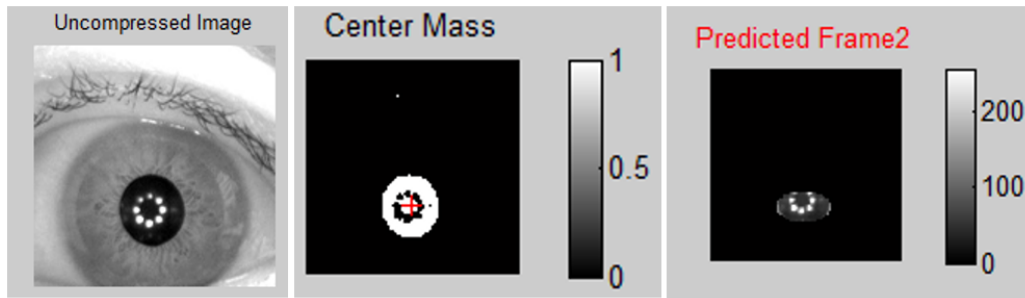(d) Lossless iris SIMGR_3008.bmp
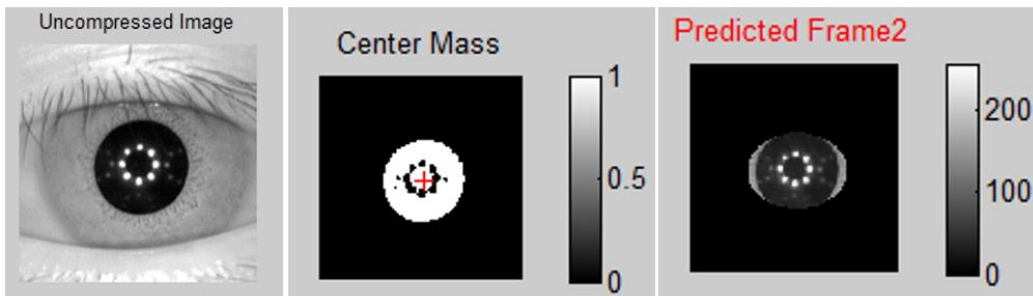

(e) Lossless iris SIMGR_3010.bmp
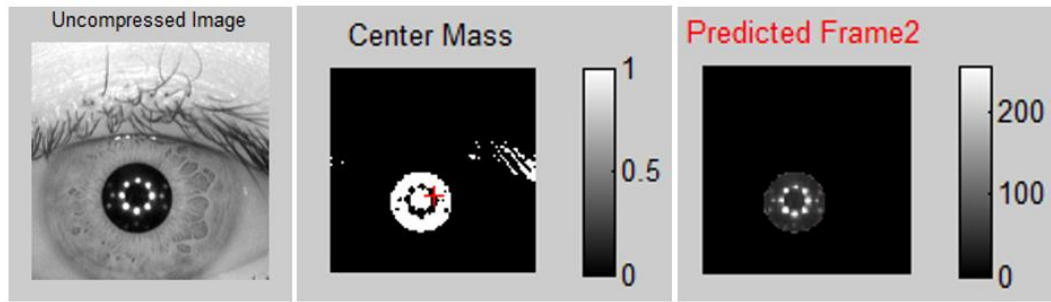
(f) Lossless iris SIMG_4001.bmp

(g) Lossless iris SIMG_4003.bmp

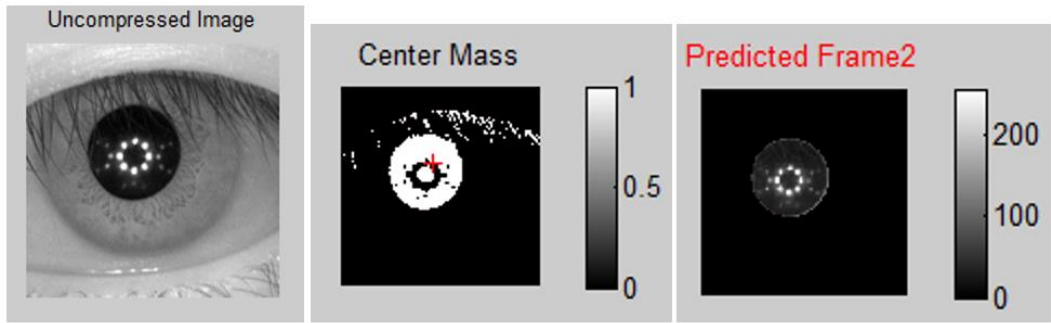(h) Lossless iris SIMG_4004.bmp

(i) Lossless iris SIMG_4009.bmp

(j) Lossless iris SIMG_4010.bmp

(k) Lossless iris SIMG_4011.bmp

Figure 7. (a – k) Set of ROI image predicted from
background image (non-ROI)

For a comparative analysis with the Hexadata method described above, the iris images are compressed by arithmetic coding, lossless 7zip compression and lossless JPEG2000 compression as shown in Table 2. Normally, lossless JPEG2000 is used to compress and store medical images, because it is necessary to store multiple images from a single patient. Additionally, significant information must store as lossless data for medical requirements; for example, accurate medical diagnosis [13]. For this reason, we used Lossless JPEG2000 as a guidance to compare with our proposed method.

Table 2. LOSSLESS IRIS DATA COMPRESSED BY HEXADATA WITH ARITHMETIC CODING, 7ZIP AND JPEG2000

Image name	Uncompressed image Size KB	Hexadata KB	Arithmetic Coding KB	Lossless 7zip KB	Lossless JPEG2000 KB
SIMGR_30	300	224	285	204	320

00					
SIMGR_30 01	65	39.8	55	40.1	60
SIMGR_30 02	65	41.4	56.5	38.5	62
SIMGR_30 03	65	42.7	58.1	38.1	68
SIMGR_30 04	65	44.7	59	39	69
SIMGR_30 05	65	43.0	57.8	37.8	67
SIMGR_30 06	65	44.5	60.5	40.5	60
SIMGR_30 07	65	42.6	55.3	35.3	65
SIMGR_30 08	65	42.8	56.8	36.8	66
SIMGR_30 09	65	32.7	45.4	31.7	61
SIMGR_30 10	65	42.5	56.3	38.4	68
SIMG_400 0	3000	1370	2860	1400	2600
SIMG_400 1	65	33.6	52.4	36.7	66
SIMG_400 2	65	43.0	57	40.5	62
SIMG_400 3	65	42.3	57.5	38.4	64
SIMG_400 4	65	41.2	56	39	66
SIMG_400 5	65	40.5	55.2	38.7	59

SIMG_400 6	65	37.9	60.4	40.1	60
SIMG_400 7	65	44.7	59.4	37.2	67
SIMG_400 8	65	43.2	55.	35	63
SIMG_400 9	65	43.8	59.1	40.4	62
SIMG_401 0	65	45.1	58.9	37.1	58

7. Conclusion

In this paper, we have proposed and demonstrated a novel method for optimized segmentation of circular based techniques by finding the best fitting of circular object centre and radius. Applying the method to the segmentation of iris data, it implies maximizing the white connected pixels within circular based compared to foreground using the simplex method. Furthermore, the techniques are implemented to run automatically without the need for a global threshold value due to exploiting bit plane slicing along with scalar quantization techniques to efficiently binarize the image. The iris image is classified into ROI (iris data itself) and non-ROI (background image) with a lossless Hexadata encoding technique being applied to compress both ROI and non-ROI data. The compression performance demonstrated in the experimental results shows the effectiveness of the proposed compression technique.

It is important to stress that the compression method lends itself as an encryption method by using six types of coding keys. Normally, the 6th key length is unknown, because it depends on the probabilities of image data. Furthermore, the proposed compression-encryption can be applied to live streaming in real time. The experimental results show that the proposed lossless Hexadata based iris image compression has better performance than arithmetic coding itself and lossless JPEG2000. On the other hand, while the lossless 7zip method provides higher compression ratios overall, our method has the advantage that it can be converted into a truly compression-encryption method. Research is under way from this perspective and results will be reported in the near future.

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