Iris Image Compression Utilizing the FBI Compression Algorithm

Ariel Gonzalez¹, Melissa Martinez¹, & Aarón Ortega¹

Dr. Helmut Knaust 1

July 23, 2013

 $^{1}\mathrm{Department}$ of Mathematics, University of Texas at El Paso, El Paso, TX

Abstract

Iris imaging for biometric identification is starting to gain recognition across different fields. Therefore, a need for efficient iris image compression algorithms with optimal resolution will ensue. The basis for our research is the Federal Bureau of Investigations use of the Wavelet Scalar Quantization (WSQ) algorithm for fingerprint images. We adjust this algorithm, derived from the JPEG-2000 standard, to work well with iris images. Our algorithm entails a discrete wavelet transform, a quantization scheme for further image compression, and an inverse method for image retrieval. We experiment with various wavelet transforms such as Haar, Daubechies- 6, and Cohen Daubechies-Feauveau 9/7 filters, in order to gauge the compression proficiency of the wavelet and quantization process. To quantify the quality of our results, we evaluate the Peak Signal-to-Noise Ratio (PSNR) measure for the different wavelet transforms. Our modified FBI algorithm yields effective results when applied to iris images. Our procedure generates iris images that retain a considerable amount of detail of the iris pattern and texture and at the same time exhibit excellent compression results.

1 Introduction

During the 20th century, the Federal Bureau of Investigation (FBI) established an Integrated Automated Fingerprint Identification System (IAFIS) composing of human fingerprints. In 1996, the FBI had around 200 million inked fingerprint cards that were in need of digitization [2]. In order to achieve this feat the FBI developed the Wavelet Scalar Quantization (WSQ) algorithm. The algorithm facilitated storage requirements and procedural information exchange between agencies. With technological advances in recent years, various groups have sought to expand this algorithm to new types of biometric identification, such as the human iris, palm print, voice, signature, and gait [6]. The iris texture and complex pattern on its anterior surface offer an extremely valid biometric cue for human recognition [8]. The iris has great variation among individuals, even among monozygotic twins; random events during gestation influence an individuals iris pattern [8]. The outline of the iris is not easily altered by environmental factors, such as lacerations or infections, so the form remains consistent over time [3]. Like fingerprints, human irises have very similar features when comparing between individuals, so the difference in iris pattern between two people is hard to find. In using the iris for personal identification, computer systems need to store images of irises with as much detail as possible. Therefore, during image compression, the texture and pattern of each iris has to be conserved for successful use of the image for human recognition. Since the FBI produced an exclusive algorithm to compress fingerprint images for optimal detail preservation, we decided to adjust this algorithm and apply it for iris image compression.

2 Methodology

For this research, we used the Wolfram Mathematica software to produce a modified version of the FBI WSQ algorithm and to implement a quantization method. Ruch and Van Fleet, as previously mentioned, give us the compression standard for the FBI fingerprint algorithm [9, 10].

2.1 Discrete Wavelet Transformation

First, we applied a normalization procedure to the image

$$\tilde{A}_{i,j} = \frac{A_{i,j} - \mu}{R}$$

where A denotes the original image with \tilde{A} being its normalization, $R = \frac{1}{128} \max\{M_1 - \mu, \mu - m_1\}$, M_1 and m_1 represent the maximum and minimum elements of A, and μ is the mean of the elements of A. Normalization of an image/matrix changes the range of pixel values ideally starting from zero and ending at 255 to span as equally as possible around zero, with some values being positive and some being negative; this later helps in

the quantization to set a range of values in the transform, straddling around zero, to zero in order to increase the compression factor. The compression ratio is defined by dividing the entropy of the original image by the entropy obtained when the imaged is transformed and quantized. Entropy measures the amount of bit information a system needs for data storage. Second, we employed the (9,7) Cohen-Daubechies-Feauveau Filter Pair (CDF97) [10]. The conditions to utilize the wavelet transform are as follows

a.
$$n$$

b. $2^{n}|r$
c. $2^{n}|c$

where n is the number of iterations, r is the number of rows, c is the number of columns.

To obtain the FBI fingerprint compression standard, we performed one iteration to each assigned section of the image previously transformed, beginning with the entire normalized image. Each iteration transforms the designated image into four sections, a blur, the vertical edges, the horizontal edges, and the diagonal edges, in which all the edges are extracted from the chosen image to generate the blur. The first iteration is constructed by multiplying biorthogonal filter pair matrices on the left and right of the normalized image matrix. The filter matrices are biorthogonal, meaning when CDF1 is multiplied by the transpose of CDF2, or vice versa, the resulting matrix is the identity matrix (a square unit matrix of size m x m with ones on the main diagonal and zeros elsewhere). The filters are symmetric: the filters have an odd number of values and the filter entries are symmetric about the center. The top half of the CDF1 filter has length 9 and the bottom half has length 9.

(h3	h2	hl	h0	-h1	-h2	-h3	-h4	0	0	0	h4	۱	(h3	h2	h1	h0	-h1	-h2	-h3	0	0	0	0	0
0	h4	h 3	h2	hl	h 0	-h1	-h2	-h3	- h 4	0	0		0	0	h3	h2	h1	h0	-h1	-h2	-h3	0	0	0
0	0	0	h4	h 3	h2	hl	h 0	-h1	-h2	-h3	-h4		0	0	0	0	h3	h2	h1	h0	-h1	-h2	-h3	0
-h3	-h4	0	0	0	h 4	h3	h2	hl	h 0	-h1	-h2		-h3	0	0	0	0	0	h3	h2	h1	h 0	-h1	-h2
-h1	-h2	-h3	-h4	0	0	0	h4	h3	h2	hl	h0		-h1	-h2	-h3	0	0	0	0	0	h3	h2	h1	h0
hl	h 0	-h1	-h2	-h3	- h 4	0	0	0	h4	h 3	h2		h1	h 0	-h1	-h2	-h3	0	0	0	0	0	h3	h2
0	g3	g2	g1	g0	-g1	-g2	-g3	0	0	0	0		g4	g3	g2	g1	g0	-g1	-g2	-g3	-g4	0	0	0
0	0	0	g3	g2	g1	g0	-g1	-g2	-g3	0	0		0	0	g4	g3	g2	g1	g0	-g1	-g2	-g3	-g4	0
0	0	0	0	0	g3	g2	g1	g0	-g1	-g2	-g3		-g4	0	0	0	g4	g3	g2	g1	g0	-g1	-g2	-g3
-g2	-g3	0	0	0	0	0	g3	g2	g1	g0	-g1		-g2	-g3	-g4	0	0	0	g4	g3	g2	g1	g0	-g1
g0	-g1	-g2	-g3	0	0	0	0	0	g3	g2	g1		g0	-g1	-g2	-g3	-g4	0	0	0	g4	g3	g2	g1
g2	g1	g0	-g1	-g2	-g3	0	0	0	0	0	g3 ,)	g 2	g1	g0	-g1	-g2	-g3	-g4	0	0	0	g4	g3)
				((a) C	DF1	L										((b) (DF:	2				

Figure 1: Generalized 12 X 12 Filler Matrices

The entries of each filter matrix are determined by a process outlined by Van Fleet [10]. After the first iteration, the following iterations are constructed using the same process; the following iterations are done on a particular segment of the formerly transformed image. The conditions to apply the wavelet transform we produced utilizing the FBI WSQ algorithm is for a value of n = 5.

0	1	4	7	8	19	20	23	24	52	53
2	3									
5		6	9	10	21	22	25	26		
11		12	15	16	27	28	31	32		
13		14	17	18	29	30	33	34		
35		36	39	40	51	1	1	1	54	55
37		38	41	42	-					
43		44	47	48						
45		46	49	50						
56					57				60	61
58					59				62	63

After we constructed and ran an iris wavelet quantization (IWQ) transform, we obtained the wavelet compression standard that the FBI employs for optimal compression.

Figure 2: Wavelet Transform Scheme with 64 bands.



Figure 3: Wavelet Transform of Iris Image

2.2 Encoding the Subband Quantization

The wavelet transform has so far allowed for the image to remain lossless, however, the quantization reserved in the WSQ algorithm will advertently produce a lossy compression. In the transform, the image has been divided into subbands W^k , where $k = 0, 1, \ldots$, 63 indicated the corresponding bands, but from this point bands 60 through 63 will be discarded, i.e. quantized to contain all zero entries. The remaining bands will be subject to quantization using the following piecewise step function

$$f(W_{i,j}^{k}, Q_{k}, Z_{k}) = \begin{cases} \left[\frac{W_{i,j}^{k} - Z_{k}/2}{Q_{k}}\right] + 1, & W_{i,j}^{k} > \frac{Z_{k}}{2} \\ 0, & -\frac{Z_{k}}{2} \le W_{i,j}^{k} \le \frac{Z_{k}}{2} \\ \left[\frac{W_{i,j}^{k} + Z_{k}/2}{Q_{k}}\right] - 1, & W_{i,j}^{k} < -\frac{Z_{k}}{2} \end{cases}$$
(1)

where, respectively, $Q_k, Z_k \in \mathbb{R}^+$ denote the bin width, range of values that are quantized to an integer, and the zero bin width, range of values to be quantized to zero, of a particular band W^k [9]. The value $W_{i,j}^k$ is the specific entry in the band W^k that will be mapped by the function f. However, before Q_k and Z_k are defined, some parameters must be introduced.



Figure 4: The quantization function f for subband W^0 .

2.2.1 Defining Quantization Parameters

The characteristics which make an iris, much like a fingerprint, a viable biometric identifier are localized in the center region of the image. Additionally, as an image is captured it will include unnecessary information in the sclera and outer eye boundaries, thus affecting the compression [2]. In effect, a subband variance, σ_k^2 , is computed in a subregion of each band in order to deal with such issues. The subregion dimensions, with band dimensions X_k and Y_k , are defined as

$$\tilde{X}_k = \left\lfloor \frac{3X_k}{4} \right\rfloor \qquad \tilde{Y}_k = \left\lfloor \frac{7Y_k}{16} \right\rfloor$$

to be the width and height, respectively, and

$$\tilde{I}_{0,k} = \left\lfloor \frac{\tilde{X}_k}{8} \right\rfloor \qquad \qquad \tilde{J}_{0,k} = \left\lfloor \frac{9\tilde{Y}_k}{32} \right\rfloor$$
$$\tilde{I}_{1,k} = \tilde{I}_{0,k} + \tilde{X}_k - 1 \qquad \qquad \tilde{J}_{1,k} = \tilde{J}_{0,k} + \tilde{Y}_k - 1$$

will be the indices used for the variance computation. The variance is defined as

$$\sigma_k^2 = \frac{1}{\tilde{X}_k \tilde{Y}_k - 1} \sum_{i=\tilde{I}_{0,k}}^{\tilde{I}_{1,k}} \sum_{j=\tilde{J}_{0,k}}^{\tilde{J}_{1,k}} (W_{i,j}^k - \mu_k)^2$$

where μ_k is the mean of the subband k. Additionally, as in the FBI standard for the fingerprint compression, we will target an overall lossy bit rate, r, of 0.75 bits per pixel since at this value typical images achieve an average 15:1 compression [2].

In the quantization process q is defined as a global parameter, which determines the general compression, has rate control over the bin widths, and assures a final entropy value not bigger than r [7, 1]. It is given by

$$q = \gamma^{-1} 2^{r/S-1} \left[\prod_{k \in K} \left(\frac{\sigma_k}{P_k} \right)^{1/m_k} \right]^{-1/S}$$

$$\tag{2}$$

where the loading factor, $\gamma = 2.5$, is a parameter that specifies the number of standard deviations of data that are being coded, $S = \sum_{k \in K} \frac{1}{m_k}$ where m_k is the ratio of the image size to the k^{th} subband size and $P_k = qQ_k$ [1, 4]. Before using (2), the following must be noted. First, if $\sigma_k^2 < 1.01$, set $Q_k = 0$ in order to prevent an overflow in the bin. Second, if $Q_k > 2\gamma\sigma_k$ then the bit rate for each subband will be negative since, according to FBI standard, Q_k can also be defined as $Q_k = \frac{2\gamma\sigma_k}{2^{r_k}}$, where r_k is the assigned bit rate of the k^{th} subband [11, 2]. Therefore, an appropriate measure for (1) can be found below.

1. Initialize:

(a) j= 0;
(b)
$$\mathbf{K}^{0} = \{k \mid 0 \le k \le 59 \land \sigma_{k}^{2} \ge 1.01\}$$

2. Iterate on j to calculate q:

(a)
$$S^{j} = \sum_{k \in K^{j}} \frac{1}{m_{k}}$$

(b) $q^{j} = \gamma^{-1} 2^{r/S^{j}-1} \left[\prod_{k \in K^{j}} \left(\frac{\sigma_{k}}{P_{k}} \right)^{1/m_{k}} \right]^{-1/S^{j}}$

3. Exclude bands that would contribute theoretically nonpositive bit rates:

(a)
$$G^{j} = \left\{ k \in K^{j} \mid \frac{P_{k}}{q^{j}} \ge 2\gamma\sigma_{k} \right\}$$

(b) If $G^{j} \neq \emptyset$
i. $K^{j+1} = K^{j} \setminus G^{j}$
ii. $j++;$
iii. repeat step 2
else
i. $q = q^{j}$
ii. $K=K^{j}$
iii. continue

4. Calculate bin widths:

If
$$k \in K^0$$

 $Q_k = \frac{P_k}{q}$
else
 $Q_k = 0$
5. Exit

The iterative procedure, developed by Brislawn and Bradley, allows for proper bit allocation by disregarding any band with a negative bit rate when defining q [2]. Q_k will still be computed for all bands and used for quantization, since they contribute useful information for quantization purposes.

2.2.2 Bin Widths

The bits for each subband in the image are allocated using the following bin widths

$$Q_{k} = \begin{cases} \frac{1}{q}, & 0 \le k \le 3\\ \frac{10}{q A_{k} \ln(\sigma_{k}^{2})}, & 4 \le k \le 59 \end{cases}$$

and $Z_k = 1.2 Q_k$. The A_k 's are set weights used to improve or degrade a band; each of which was set by the FBI's specification [7].

Table 1: Quantizing Weights

Subband	A_k
4-51	1.00
53, 55, 58, & 59	1.08
52 & 56	1.32
54 & 57	1.42

2.3 Dequantization Function

The resulting quantization process, while lowering entropy, reduces the variation between neighboring $W_{i,j}^k$ and thus final detail, and as such causes the lossless of the final image. Furthermore, the non-invertible ceiling and floor functions augment the difficulty. Following the FBI algorithm, a constant value for all subbands $C \in (0, 1)$ encompasses the function as measure for the latter issues. As specified, C= 0.44 will be used for iris images as well [9]. The dequantization function is defined as

$$d(y, Q_k, Z_k) = \begin{cases} (y - C)Q_k + Z_k/2, & y > 0\\ 0, & y = 0\\ (y + C)Q_k - Z_k/2, & y < 0 \end{cases}$$

with y being the quantized entry of the k^{th} band. Noticeably zero values remain unchanged; however, in recollection, all bits have been modified in the process so there are no means of returning to their initial value.

2.4 Inverse Wavelet Transformation

The dequantization procedure initiates the image decompression process. During this scheme, the dequantized image needs to be run through an inverse wavelet transform procedure to retrieve an image similar to the original. The inverse wavelet transform we use follows the same general process as our IWQ transform, except we reverse the order of the commands; we multiply the transpose of the CDF1 filter matrix on the left and the CDF2 filter matrix on the right of the dequantized image matrix. The first iteration of the inverse wavelet transform multiplies the two filters on the left and right of the smallest section of the dequantized image. All iterations after the first multiply the two filters to the designated section of the previously transformed image. At the end of our inverse IWQ transform, we obtained the normalized image once again, with slight differences in image quality that we measured with the Peak Signal-to-Noise Ratio (PSNR), taking the entropy of the original normalized image against the entropy of the normalized image after dequantization and the inverse wavelet transform. The PSNR measure for image compression determines the quality of reconstruction.

After applying the inverse wavelet transform, we denormalized the resulting image to obtain the original image, again with slight differences in image quality measured with the PSNR, comparing the entropy of the original image against the entropy of the image after denormalization. The formula for denormalization is as follows

$$B_{i,j} = R\tilde{B}_{i,j} + \mu$$

where R and μ are as previously defined, \hat{B} is the image before denormalized, and B is the denormalized image.

3 Results

We used a modified form of the FBI fingerprint algorithm, the Iris Wavelet Quantization (IWQ) algorithm. For comparison, we used the Haar and Daubechies-6 wavelets with their quantize function and a step-quantize process for the JPEG 2000 in order to find the efficiency of the IWQ algorithm. The Haar wavelet transform is the simplest wavelet transform that we compared to our CDFBI transform. The Haar wavelet transform uses the Haar matrix, which has the following form and filter:

$\left(\frac{1}{\sqrt{2}}\right)$	$\frac{1}{\sqrt{2}}$	0	0	0	0	0	0	0	0
0	0	$\frac{1}{\sqrt{2}}$	$\frac{1}{\sqrt{2}}$	0	0	0	0	0	0
0	0	0	0	$\frac{1}{\sqrt{2}}$	$\frac{1}{\sqrt{2}}$	0	0	0	0
0	0	0	0	0	0	$\frac{1}{\sqrt{2}}$	$\frac{1}{\sqrt{2}}$	0	0
0	0	0	0	0	0	0	0	$\frac{1}{\sqrt{2}}$	$\frac{1}{\sqrt{2}}$
$\frac{1}{\sqrt{2}}$	$-\frac{1}{\sqrt{2}}$	0	0	0	0	0	0	0	0
0	0	$\frac{1}{\sqrt{2}}$	$-\frac{1}{\sqrt{2}}$	0	0	0	0	0	0
0	0	0	0	$\frac{1}{\sqrt{2}}$	$-\frac{1}{\sqrt{2}}$	0	0	0	0
0	0	0	0	0	0	$\frac{1}{\sqrt{2}}$	$-\frac{1}{\sqrt{2}}$	0	0
0	0	0	0	0	0	0	0	$\frac{1}{\sqrt{2}}$	$-\frac{1}{\sqrt{2}}$

Figure 5: Wavelet Transform Scheme with 64 bands.

The Haar wavelet transform multiplies an r x r (the number of rows) Haar matrix to the left of the image matrix, and multiplies the transpose of a c x c (the number of columns) Haar matrix to the right of the image matrix. This process helps obtain the blur and the vertical, horizontal, and diagonal edges of an image. With each iteration, the Haar wavelet transform repeats the process only to the blur attained from the previous iteration [10].

The Daubechies-6 (D6) wavelet transform has the same general procedure as the Haar wavelet transform, in that it multiplies an $r \ge r$ D6 filter matrix to the left of the image matrix, and multiplies the transpose of a c $\ge r$ C D6 filter matrix to the right of the image matrix.

1	h 5	h4	h3	h2	h1	h0	0	0	0	0	0	0
I	0	0	h5	h4	h3	h2	h1	h0	0	0	0	0
	0	0	0	0	h 5	h4	h3	h2	h1	h0	0	0
	0	0	0	0	0	0	h 5	h4	h3	h2	h1	h0
I	h1	h0	0	0	0	0	0	0	h 5	h4	h3	h2
I	h3	h2	h1	h0	0	0	0	0	0	0	h 5	h4
	-h0	h1	-h2	h3	-h4	h5	0	0	0	0	0	0
I	0	0	-h0	h1	-h2	h3	-h4	h5	0	0	0	0
I	0	0	0	0	-h0	h1	-h2	h3	-h4	h5	0	0
	0	0	0	0	0	0	-h0	h1	-h2	h3	-h4	h5
I	-h4	h5	0	0	0	0	0	0	-h0	h1	-h2	h3
Į	-h2	h3	-h4	h5	0	0	0	0	0	0	-h0	h1

Figure 6: Wavelet Transform Scheme with 64 bands.

In the same way as the Haar transform, with each iteration, the D6 wavelet transform repeats the method only to the blur taken from the previous iteration [10]. Our CDFBI wavelet transform is derived from the JPEG2000 (CDF97WLT) wavelet transform. The

CDF97WLT takes biorthogonal filter pairs, multiplies an r x r CDF1 filter matrix to the left of the image matrix, and multiplies the transpose of a c x c CDF2 filter matrix to the right of the image matrix. As previously mentioned with the Haar and D6 wavelet transforms, the fundamental CDF97WLT repeats this formula only to the blur taken from the former transformation with each iteration [10].

Algorithm	Compression Factor	Peak to Noise Ratio
IWQ	9.00	28.5240
JPEG 2000	9.00	30.1596
Daubechies-6	9.00	29.6029
Haar	9.00	26.7875

Table 2: Fingerprint Image

rable o. mis mage	Table	3:	Iris	Image
-------------------	-------	----	------	-------

Algorithm	Compression Factor	Peak to Noise Ratio
IWQ	7.00	40.9632
JPEG 2000	7.00	39.7877
Daubechies-6	7.00	38.7083
Haar	7.00	37.2152

As you can see in Table 2, the IWQ algorithm, with the same compression, has a lower PSNR than the JPEG 2000. On the other hand, in Table 3, the IWQ, with the same compression factor has a higher PSNR than the other three algorithms used. This proves that the IWQ algorithm retains more details with a higher compression of the images, which gives high efficiency to the image processing of irises. While modifying the quantization, we found that at a compression factor of 20.10 the PSNR is at 34.97, which is a good amount of details retained. At this point, our standards of the details that have to be retained are only preliminary and they are only based on the definition of the PSNR of good quality.

4 Conclusion

The ISQ algorithm was more efficient when applied to iris images rather than on fingerprints. The reason found was due to the cloudiness of some areas in the irises, as opposed to the many edges found in the fingerprint images. A few tweaks are needed in the quantization process of the IWQ to generalize the algorithm since some of the iris images were not able to go through the process.

With the compression wavelet and the quantization we have done, the resulting image is lighter and more blurry than the original. In lighter colored irises, human perception cannot tell much of a difference between the original picture and the compressed and quantized picture. The darker colored irises, human perception is able to see the obvious differences, and this allows for a better visual determination if the transformed image kept the amount of detail desired for a successful compression and quantization of the important features of a given iris.



Figure 7: Original Iris Image



Figure 8: Iris Image after IWQ algorithm



Figure 9: Haar Wavelet Transform on Iris Image

In comparing between the Haar wavelet transform and our IWQ transform with the same compression rate, the human eye is able to see major differences between the two. After the iris images were run through the entire Haar wavelet transform process, we produced a pixelated image. The pixelated image may be a result of the Haar filter. The Haar filter is a very simple filter consisting of positive and negative 12, and may cut out a substantial amount of rows and columns when multiplied by an image matrix. The resulting pixelated image seems to smooth out ridges and lines within the iris, especially the ridges and lines on the outside edge of the iris and the area around the pupil.



Figure 10: Daubechies-6 Wavelet Transform on Iris Image

In evaluating the D6 wavelet transform and our iris wavelet transform with similar compression levels, there are differences in the shades of gray between the iris images, with the D6 image being slightly darker. The image created by the D6 transform seems to blur out some of the iris pattern in the area close to the pupil and the outer edges of the iris. The pattern and texture in between the two boundaries mentioned seems to maintain an appropriate amount of detail in terms of iris pattern and texture.



Figure 11: JPEG-2000 Wavelet Transform on Iris Image

In judging between the original JPEG-2000 wavelet transform and our IWQ transform with matching compression ratios, the resulting images produced by the JPEG-2000 transform have an obvious blur when compared to the images transformed by our wavelet. The blur is most obvious in the outer edges of the iris and the area around the pupil. In the area between the two margins, the blur produced by the JPEG-2000 transform shows less texture and less ridges within the iris images.

In conclusion, future research should concentrate on the quantization method of our constructed wavelet transform in order to compress the iris images further. In the quantization process, we were not able to achieve the optimal compression rate and PSNR that was attained by the FBI WSQ algorithm. Once the exact WSQ algorithm is replicated, future research should analyze its effectiveness on human irises. Also, further effort in

extracting the pupil in the wavelet transformation, since the pupil has unnecessary information needed for optimal iris image compression. In addition, extracting the pupil may help in producing a much crisper image quality in the area surrounding the pupil in the resulting dequantized and denormalized image.

References

- J. N. Bradley and C. M. Brislawn.: Proposed first-generation WSQ bit allocation procedure, in Proc. Symp. Criminal Justice Info. Services Tech., (Gaithersburg, MD), pp. Cll-C17, Federal Bureau of Investigation, Sept. 1993
- [2] C. M. Brislawn and J. N. Bradley.: The FBI Compression Standard for Digitized Fingerprint Images. SPIE 2847, Applications of Digital Image Processing XIX, 344 (1996).
- [3] E. Cho, R. D. Caytiles, and S. Kim.: New Algorithm Biometric- Based Iris Patter Recognition System: Basis of Identity Authentication and Verification. Journal of Security Engineering, Vol 8 Issue 5 (2011), pg. 585-598.
- [4] A. Gersho and R. M. Gray.: Vector Quantization and Signal Compression. No. 159 in Int'l. Series in Engineering & Computer Science, Norwell, MA: Kluwer Academic Publishers (1992).
- [5] S. Kasaei, M. Deriche, and B. Boashash.: A Novel Fingerprint Image Compression Technique using Wavelet Packets and Pyramid Lattice Vector Quantization. IEEE Transactions on Image Processing, Vol 12 Issue 11 (2002), pg. 1365-1378.
- [6] C. Kaucher.: Biometrics 101: Types of Biometrics. Biometrics Identity Management Agency. (2013) http://www.biometrics.dod.mil/References/Tutorial/3.aspx.
- [7] R. C. Kidd.: Comparison of Wavelet Scalar Quantization and JPEG for fingerprint image compression. Journal of Electric Imaging, Vol 4 Issue 1 (1995).
- [8] A. Ross.: Iris Recognition: The Path Forward. IEEE Computer Society 10 (2010), pg. 30-35
- [9] D. K. Ruch and P. J. Van Fleet.: Wavelet Theory: An Elementary Approach with Applications. John Wiley & Sons, Inc., Hoboken, NJ, USA. (2009).
- [10] P. J. Van Fleet.: Discrete Wavelet Transformations: An Elementary Approach with Applications. John Wiley & Sons, Inc., Hoboken, NJ, USA. (2008).
- [11] WSQ Gray-Scale Fingerprint Images Compression Specification (Version 3.1). Criminal Justice Information Services, Federal Bureau of Investigation, Washington DC, October 4, 2010.
- [12] "National Press Release." Federal Bureau of Investigation. FBI, 12 Feb 2008. www.fbi.gov/news/pressrel/press-releases/fbi-announces-contract-award-for-nextgeneration-identification-system