Surf and Sift Descriptors Using Wavelet Transforms for Iris Recognition

Mohammed Kamal Majeed[1]* and Rahib Abiyev[2]
[1]*Tishk International University/ faculty of Engineering/ Computer Engineering/ Erbil, Iraq.*
[2]*Near East University/ faculty of Engineering/ Computer Engineering/ Nicosia, Cyprus*
[1]*moxammad.kamal@gmail.com*, [1]*mohammed.kamal@tiu.edu.iq*
[2]*rahib.h.abiyev@gmail.com*, [2]*rahib.abiyev@neu.edu.tr*

Abstract

Iris recognition is a well-known accurate biometric technology and major research area in pattern recognition and computer vision available today. It targets human recognition through the person's iris recognition without human intervention. In many areas iris recognition plays well such as bioinformatics, machine vision, pattern recognition, etc., and it is one of the popular subjects still. Finding of features to identify an iris, which is a small black part of an eye, is a difficult problem in iris recognition. Many methods and algorithms have been proposed on feature extraction, which include aspects like statistical features, level of invariance and robustness.

In this article, a traditional SURF and SIFT algorithms are tested for iris recognition. To improve the performance of these algorithms, we passed the input through different domains from the real time. Through applying the Gabor Wavelet Transform (GWT) or Discrete Wavelet Transform (DWT)to the input iris images, a denser and more clear images obtained compared to those by the traditional SURF and SIFT. Thus the simulations of the proposed approaches of using Gabor Wavelet Transform or Discrete Wavelet Transform on SURF and SIFT algorithms gives better results compared to the traditional algorithms.

Keywords: *Iris recognition; Discrete wavelet transform; Scale-invariant feature transform; Gabor wavelet transform; Speeded-up robust features.*

1- Introduction

Biometric systems use either physical or behavioral characteristics of the user to recognize the authorized user. There are many biometric techniques like finger prints, walking, iris and face recognition which are more secure than traditional authentication systems like hardware tools such as smart cards or passwords, due to not being easily modeled, shared or forgotten. It's also known that biometric systems are more stable (Maghiros et al., 2005; Miyazawa et al., 2008). Among all Biometric systems iris authentication is special. It's true that all biometric systems have the uniqueness property. But iris is special, even genetically twins or the same person's right and eye irises, differ from each other and has different patterns (Daugman, 2003; Daugman, 2009). For the first time in 1936 an ophthalmologist in the name of Frank Burch proposed the basics of getting benefit from iris patterns as a way to recognize individuals (Shah et al., 2014). Later in 1985, both ophthalmologists, Leonard and Safir, showed the unique values for irises (Shah et al., 2014). They both awarded a patent in 1987 for finding the basics of iris

ISSN: 2233-7857 IJFGCN

identification. In 1993 Dr. John Daugman developed the first algorithm on automate identification of human iris.

After Daugman's automate identification system, (Wildes et al., 1996; Wildes, 1997) created a significant iris recognition system which became very popular. Wildes segmented the iris, first by detecting the edges of the eye image and then finding the iris boundaries and circular pupil through applying circular Hough transform. A large amount of the later works on iris segmentation developed from Wildes algorithms with the use of coarse-to-fine strategy. Through applying Laplacian of Gaussian filter in different scales Wildes extracted unique features from the iris images. For the verification, he used normalized correlation to utilize template matching. Wildes' approach is the base for later coming works in segmentation side but with a variation and enhancement in the algorithm, while Daugman's wavelet-based approach is the mother for most upcoming feature extraction schemes with variations and changes.

Many other algorithms have been developed later. Lim (Lim et al., 2001), uses wavelet transform to analyze and find the high level of stability and distinctiveness between iris patterns, and uses weight vector initialization and the winner selection as competitive learning method. Sanchez (de Martin-Roche et al., 2001), proposes a scale invariant and rotation technique using fine-to-coarse approximations to extract iris's important keypoints at separate scale levels based on discrete dyadic wavelet transform zero-crossing representation. Before extracting features, a pre-processing step is done to the eye image to isolate the iris part to work on it. (Ma et al., 2002), developed a fast algorithm by forming a fixed length feature vector through using a bank of gabor filters to capture global and local iris features. The weighted Euclidean distance of each iris decides on the matching between two irises as (Vatsa et al., 2002) explains. (Ismail et al., 2015) used Contrast Limited Adaptive Histogram Equalization (CLAHE) before applying Speeded Up Robust Features (SURF) in which it gets a faster matching process for the recognition. (Ali et al., 2016) has used SURF for keypoint detection with many different feature matching techniques including Contrast-limited adaptive histogram equalization (CLAHE), histogram equalization (HE) and adaptive histogram equalization (AHE) at different levels for finding which best fits with SURF and enhances iris image recognition. (Rathgeb et al. 2019) has discussed the advantages and significance of using SIFT and SURF descriptors on iris recognition.

2. Iris Recognition

Iris is circular thin diaphragm, located between the human eye lens and the cornea. The task of Iris is controlling the light amount enters the eye pupil. It's also important to know that iris works for blind person, stable with age, not changing though age and it's also impossible to alter surgically. So it's a living Password with you, can't be copies, altered or forgotten (Dong et al., 2008). The formation of an iris is at first six months after birth while the stability of an iris starts just after one year after birth, then through the life it remains the same without any change in the patterns. Complex iris patterns hold unique information which is used for personal recognition. (Daugman, 2003). The image acquisition and recognition process can work on a different variations of input images such as; a 3D laser scans, 2D iris image, and Stereo 2D images. There are four core steps in iris recognition systems which are; Iris Image acquisition, iris preprocessing, keypoint extraction, and classification and feature matching, as its seen in Figure 1 The following section describes the steps

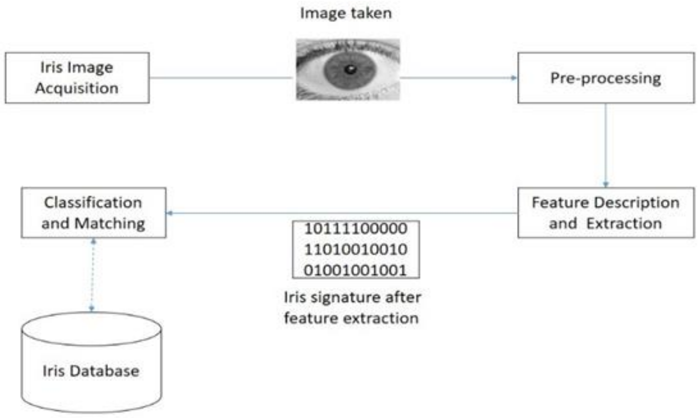

Figure 1. feature extraction process.

2.1. Image acquisition

Capturing a high quality iris image without letting the human operator notified is still a major challenge. This is because of the small size of iris which is (approximately 1 cm in diameter), also the sensitivity of human and their care for their eyes and the iris accordingly, requires a careful engineering.

2.2. Iris pre-processing

Iris preprocessing step is applied to make the iris detection stabilized, and get better feature extraction. Iris preprocessing composed of many different processes depending on the application, such as; alignment (translation, rotation, scaling), contrast adjustment, edge detection and illumination correlation. At first, the iris part of the eye is extracted from the image, and then it goes through normalization and enhancement of the iris part, after all it will be represented as a data set.

2.3. Feature description and extraction

After features or keypoints are detected and described, the feature extraction is an essential step in iris recognition, because it extracts specific features and keypoints which solid, stable and discriminative. Some of the algorithms which are used in feature extraction are: SIFT (Lowe, 2004) and SURF (Bay et al., 2006).

2.4. Feature matching

The recognition process is happened in feature matching. The iris image's feature vector which will be extracted from feature extraction will be compared to the iris database to obtain matching points. Different Matching algorithms are available nowadays, k-Nearest Neighbor (k-NN) classifier and hamming distance are two examples of them. Between two bit patterns, the amount of the same bits is known as Hamming Distance. While k-Nearest Neighbor) classifier compares performance result based on separate k values for the neighbor number (k) parameter of each system. In Feature matching, we will compare either the result of two iris images patterns are generated from the same iris images or not.

3. Materials

In digital image analysis and processing using feature extraction is very common, which uses a voting procedure for finding the shapes of the objects within the classes available. In fact, a base for having a good iris recognition system is having a good feature extraction technique. Proper selection and extraction of features lead the Iris recognition system to be good system while improper selection of keypoints could bring a wrong classification of the iris images.

3.1. Scale-Invariant Feature Transform (SIFT)

SIFT Algorithm (Lowe, 2004) developed by D. Lowe in 2004. It is a feature extraction algorithm for extracting invariant features from iris images which are then used for feature matching and recognizing the iris inside a database of iris images of the same objects. The extracted features are not affected by rotations, image scale, noise, and changing of illuminations. We simply say it's invariant to such changes. Different scales in an image are detected with different windows sizes to obtain the keypoints in In SIFT algorithm. Larger corners of the image have to be detected with large windows to obtain the keypoints, while detecting small corners of the image are easier. That's why scale-space kernels is used here which gives different σ values to different types of images, such for fade iris images Laplacian of Gaussian (LoG) has a different σ values. So, LoG is simply a blob detector which works according to the variation of σ on different scales of the iris images. Accordingly, σ is the scaling parameter. Gaussian kernel outputs high value for small corners which has low σ values, and fits well for larger corners which has high σ values. We come to the conclusion that across the scale and space we can find local maxima, which provides us a set of (x, y, σ) values that proves, a potential feature point of (x, y) at σ scale. Due to being costly, LoG has not been used in SIFT algorithm, instead of that Difference of Gaussians (DoG) is used that's the Gaussian blurring of an iris image with couple σ, let it be σ and $k\sigma$. Here is the algorithm for DoG in the equations of (1) and (2).

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y),$$

with the Gaussian kernel:

$$G(x, y, \sigma) = \frac{1}{2\Pi\sigma^2} e^{-(x^2+y^2)}/(2\sigma^2) \tag{1}$$

The difference-of-Gaussian is separated by a factor k, resulting in the following definition:

$$\begin{aligned} D(x, y, \sigma) &= L(x, y, k\sigma) - L(x, y, \sigma) \\ &= (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y). \end{aligned} \tag{2}$$

3.2. Speeded-Up Robust Features

Bay et al., developed SURF (Speeded-Up Robust Features) algorithm in 2006 from ETH Zurich (Bay et al., 2006). SURF algorithm is a robust keypoint detector of local features in a face image. It is a developed version of SIFT and Hessian blob detectors integer approximation to the determinant is calculated with integral images.

As we have mentioned In SIFT algorithms, DoG was used instead of LoG for scale-space step. SURF goes one step more by approximating LoG with Box filters. Figure 2 shows approximation demonstration. This approximations biggest advantage is that, with the support of integral images the box filter convolution will be easy calculated, and parallel calculation can be done for different scales. Also, for both position and scale, SURF depends on the Hessian matrix.

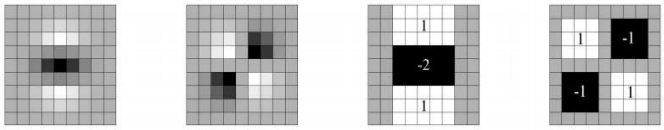

Figure 2. The box filters of approximations of Gaussian second order partial derivative.

3.3. 2D-Discrete Wavelet Transform

Functionally, the two dimensional of discrete wavelet transform (2D-DWT) is composed of a single dimensional analysis but for two dimensional signal (Wickerhauser, 1996). Thus it works on a single dimension at a time. It examines the columns and rows of an input image in separate time. It works on the rows first by convolving the low and high pass kernels (filters) of the iris image. After that two new images are formed, one image has the set of detailed row coefficients while the other contains a set of coarse row coefficients. Then kernels are convolved for the analysis of columns for each new image, such the number of different images become four which are then called sub-images or sub-bands. The next step is defining H as columns and rows which are convolved with high pass filter, while defining L as columns and rows which are convolved with a low pass filter. For example, the production of HL sub-band or sub-image is through low pass filter and high pass filters on the rows and the columns respectively. Figure 3 describes the whole procedure.

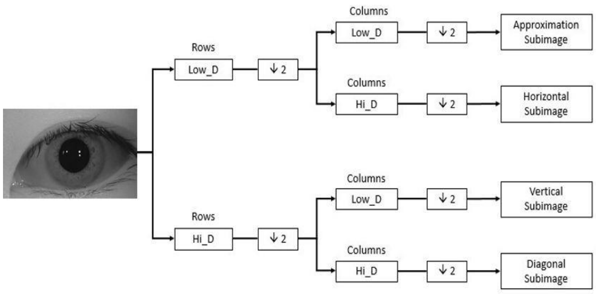

Figure 3. 2D-DWT, The working of high and low pass filters separately on columns and rows to form four different sub-images.

3.4. Gabor Wavelet Transform (GWT)

Dennis Gabor first developed Gabor functions as a signal detecting tool in a noisy environment. Gabor functions (Gabor, 1946; Swati et al., 2013) showed the availability of a "quantum principle" for information; in order no signal can conquer less than certain minimal area in it, the conjoint time-frequency domain must be quantized for 1D signals. Gabor decomposition is well-known for its sensitivity in the orientation and scaling for directional microscope. Images contain curves have low level feature map intensity, because of having some low-level salient features. Gabor wavlet filter is resulted from a modulation of sinusoidal plane wave on Gaussian kernel function as seen in (3).

$$\psi_g\ (u,v) = \exp\left(-\pi^2\left(\frac{(u'-f)^2}{a^2}+\frac{v'^2}{\beta^2}\right)\right)$$

$$u' = \ u\,cos\theta + \ v\,sin\theta,$$

$$v' = \ v\,cos\theta \ - \ u\,cos\theta$$

(3)

where f is the dominant frequency of the sinusoidal plane wave, α is the sharpness of the Gaussian along the major axis parallel to the wave, θ is the anticlockwise rotation of the Gaussian and the envelope wave, and β is the sharpness of the Gaussian minor axis perpendicular to the wave.

3.5. Iris Databases

The proposed approach has been applied on two different databases of irises which are CASIA (BIT) and UBIRIS (Proença, 2005). For each of the dataset experiments of the CASIA database, we have set a train gallery set which is composed of 5 randomly chosen iris images and the test or probe set which are the remaining iris 5 as well. For the case of UBIRIS, we have a set of two randomly chosen iris images as training gallery set and test or probe set which is composed of two images as well. All the iris subjects here in the two databases possess separate conditions such as (directions, orientation, illumination, noises …etc.). Training gallery set iris images do not exist in the probe set. Iris images from the test set are matched against the gallery set images one by one, accordingly scores and results are merged, thus decision will be made. Both of the stated databases have different properties to test and asses our proposed approach, and both contain iris images with many noises such as hair, side view, part seen images …etc.

3.5.1. CASIA Database

CASIA (BIT) database is one of the good databases available so far, which we have used for assessing our proposed approach. We have used 100 different subjects (persons), 10 iris images per subject, a total of 1000 iris images. OKI's was used to capture the iris images which is a hand-held iris sensor. To change intra-class and light variation a lamp with two modes of on/off have been used close to the subject, also rotation has been made during creating the database. It is obvious that iris images are captured in two sessions on different passing of time.

3.5.2. UBIRIS Database

UBIRIS images are incorporating with many noise factors, due to less constrained image acquisition environments. Accordingly, this will show the robustness of iris recognition methods through the evaluation. Variations in illuminations, rotation and several other noises are existing in this database. We have 400 iris images and 100 subjects. In the Figure 4.3 below a sample iris set of images are shown from the UBIRIS database. In this database we have used images which have different levels of noise, we have also edited the size and resolution of the images inside the database and decreased it, thus letting our algorithms recognize images even in bad cases.

4. The proposed approach

In first approach, SURF or SIFT was used as a feature extraction algorithm, but before extracting features input iris images were transformed using DWT. DWT outputs four different sub-images.

Figure 4 shows 1-scale transformation of input images, and features are extracted from output sub-images using SURF or SIFT defined as (DWT-SURF, DWT-SIFT). All keypoint features that are extracted from SURF or SIFT will be stored. Then, each corresponding feature of keypoints will be compared using kNN to get a score (that defines the number of matched keypoints). Then, summation of scores are stored. At last decision will be made based on the highest score, which will define if a subject belongs to a particular class or no.

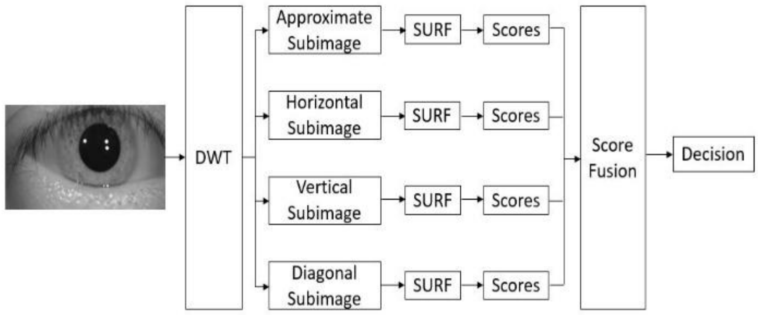

Figure 4. The block diagram of proposed approach for DWT-SURF.

In 2-scales transformation, after applying 1-scale transformation, DWT was applied as a second scale on approximate sub-image, which produces four sub-images. Scores of all eight sub-images will be fused and decision will be made based on results. Figure 5 describes steps of 2-scales transformation using DWT-SURF.

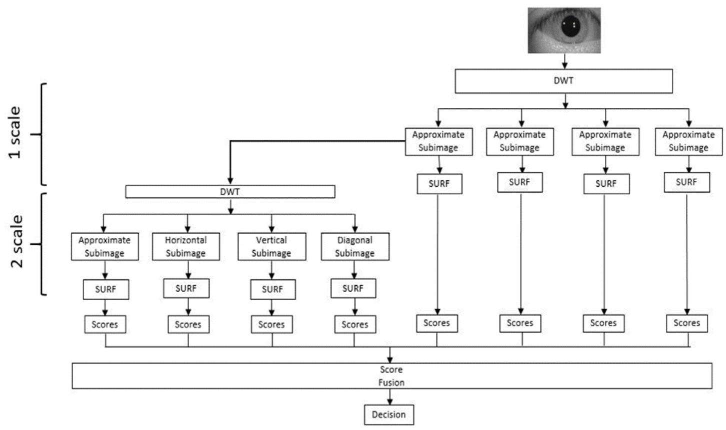

Figure 5. The block diagram of 2-scales of DWT-SURF.

The same scenario has been applied but SIFT have been used instead of SURF to extract features from iris images. Below in Figures 6 shows the same procedure with SIFT algorithm.

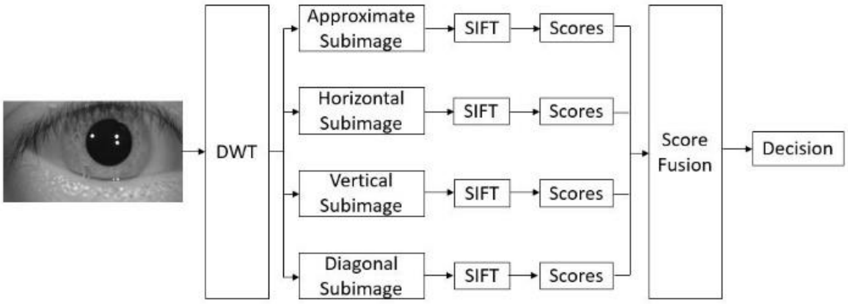

Figure 6. block diagram of 1-scale of DWT-SIFT.

In second approach, SURF or SIFT was used as a feature extraction algorithm, but before extracting features input iris images were transformed using GWT. GWT outputs eight different sub-images in each scale.

Figure 7 shows gabor wavelet transformation of input images, and features are extracted from output sub-images using SURF or SIFT defined as (GWT-SURF, GWT-SIFT). All keypoint features that are extracted from SURF or SIFT will be stored. Then, each corresponding feature of keypoints will be compared using kNN to get a score (that defines the number of matched keypoints). Then, summation of scores are stored. At last decision will be made based on the highest score, which will define if a subject belongs to a particular sample of class or it does not.

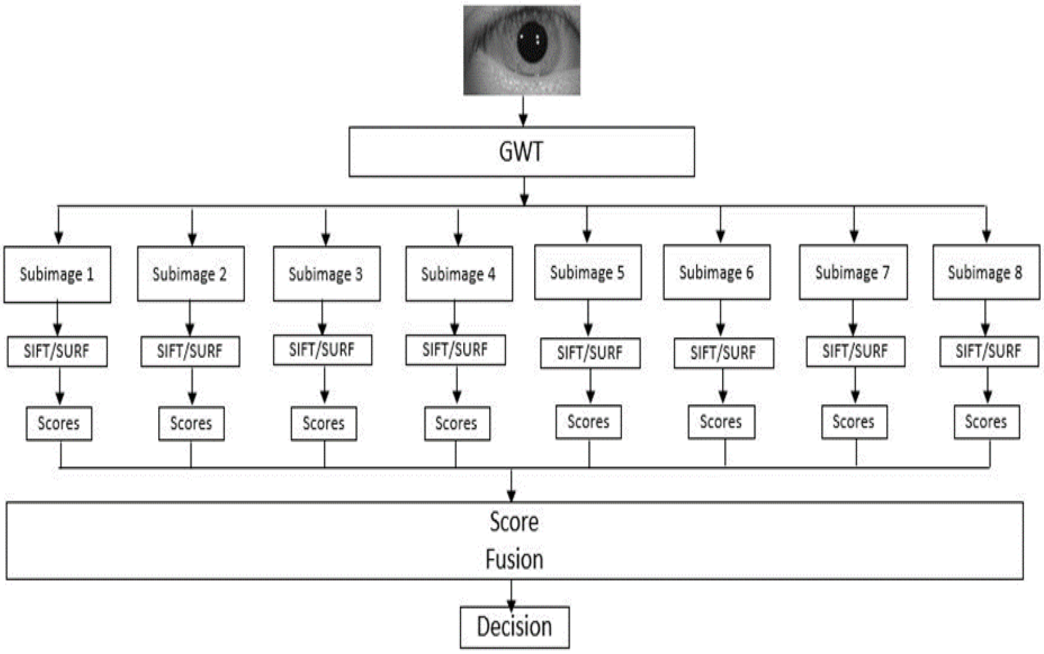

Figure 7. The block diagram of 1-scale of GWT-SURF and GWT-SIFT.

5. Results

For our tests we have used MATLAB language and MATLAB R2017 program, which is a programming platform that makes it simple to work on computational mathematics using

International Journal of Future Generation Communication and Networking
Vol. 13, No. 4, (2020), pp. 2361-2373

MATLAB language.

5.1. CASIA Database

The performance of proposed approach using Magnitude and Phase of transformed images with SIFT is not very much higher than the conventional SIFT algorithm which is 0.67%, while GWT-SURF is ~27% higher than the conventional SURF algorithm. The performance of recognition of our proposed approach decreases less compared to SURF and SIFT themselves with increasing number of subjects. The overall recognition performance rate for different number of subjects for SURF, SIFT, and proposed approaches are shown in Figure 8 and Figure 9, and shown in detail in the tables of 1 and 2.

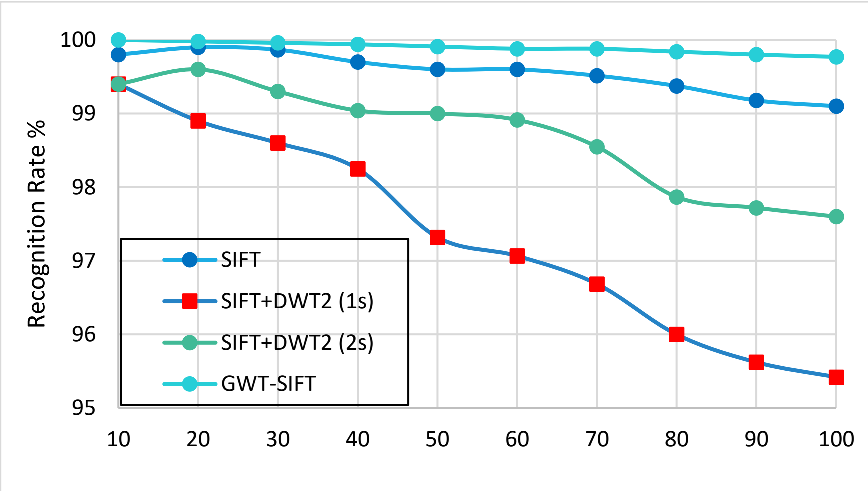

Figure 8. Overall recognition performance of SIFT, DWT-SIFT (1-scale), DWT-SIFT (2scales), and GWT-SIFT on CASIA database.

Table 1. Recognition performance of CASIA database after applying SIFT, SIFT with both 1-scale and 2 scale DWT and GWT-SIFT.

# of subjects	SIFT	SIFT-DWT2(1s)	SIFT-DWT2(2s)	GWT- SIFT
10	99.80	99.40	99.40	100.0
20	99.90	98.90	99.60	99.98
30	99.86	98.60	99.30	99.96
40	99.70	98.25	99.04	99.94
50	99.60	97.32	99.00	99.91
60	99.60	97.07	98.91	99.88
70	99.51	96.69	98.55	99.88
80	99.37	96.00	97.87	99.84
90	99.18	95.62	97.72	99.80
100	99.10	95.42	97.60	99.77

ISSN: 2233-7857 IJFGCN

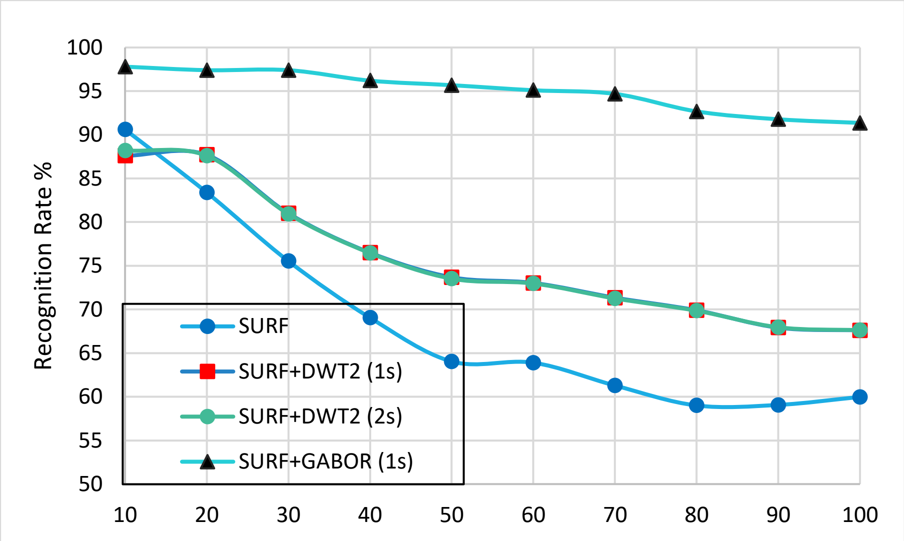

Figure 9. Overall recognition performance of SURF, DWT- SURF (1-scale), DWT- SURF (2-scales), and GWT- SURF on CASIA database.

Table 2. Recognition performance of CASIA database after applying SIFT, SIFT with both 1-scale and 2 scale DWT and GWT-SURF.

# of subjects	SURF	SURF-DWT2(1s)	SURF-DWT2(2s)	GWT-SURF
10	90.60	87.60	88.20	97.80
20	83.40	87.70	87.60	97.40
30	75.53	81.00	80.93	97.40
40	69.05	76.50	76.45	96.20
50	64.04	73.68	73.52	95.68
60	63.90	73.03	72.97	95.10
70	61.29	71.34	71.26	94.69
80	59.00	69.90	69.85	92.68
90	59.07	67.91	67.96	91.78
100	59.98	67.60	67.62	91.36

5.2. UBIRIS Database

The performance of proposed approach using Magnitude and Phase of transformed images with SIFT is higher than the conventional SIFT algorithm by 5%, while GWT-SURF is ~13% higher than the conventional SURF algorithm. The performance of recognition of our proposed approach decreases less compared to SURF and SIFT themselves with increasing number of subjects. The overall recognition performance rate for different number of subjects for SURF, SIFT, and proposed approaches are shown in Figure 10 and Figure 11, and shown in detail in the tables of 3 and 4.

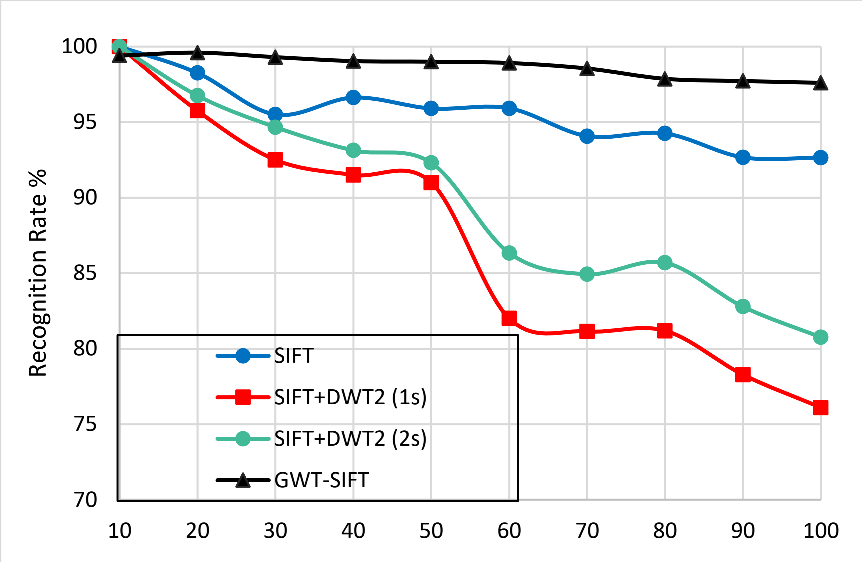

Figure 10. Overall recognition performance of SIFT, DWT-SIFT (1-scale), DWT-SIFT (2scales), and GWT-SIFT on UBIRIS database.

Table 3. Recognition performance of UBIRIS database after applying SIFT, SIFT with both 1-scale and 2 scale DWT and GWT-SIFT.

# of subjects	SIFT	SIFT-DWT2(1s)	SIFT-DWT2(2s)	GWT-SIFT
10	100.0	100.0	100.0	99.40
20	98.25	95.75	96.75	99.60
30	95.50	92.50	94.68	99.30
40	96.62	91.50	93.12	99.04
50	95.90	91.00	92.30	99.00
60	95.91	82.00	86.33	98.91
70	94.07	81.14	84.92	98.55
80	94.25	81.18	85.69	97.87
90	92.67	78.28	82.78	97.72
100	92.65	76.10	80.75	97.60

ISSN: 2233-7857 IJFGCN

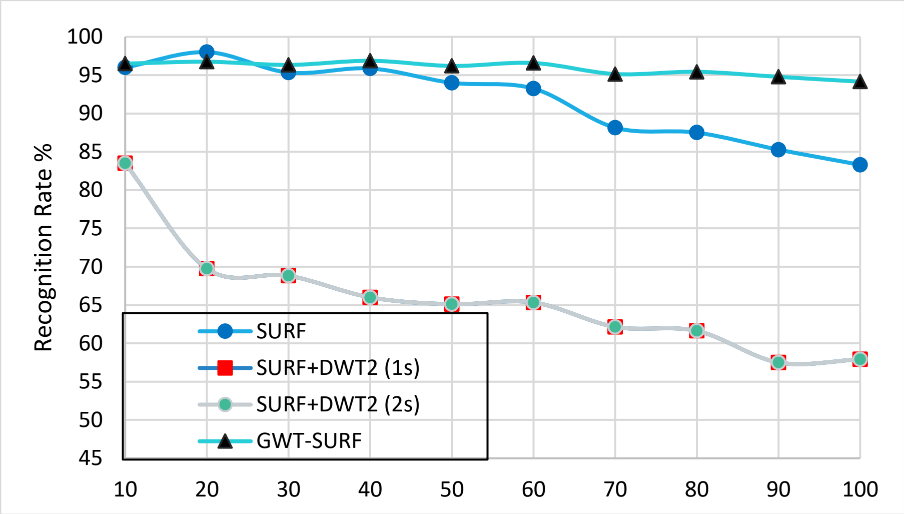

Figure 11. Overall recognition performance of SURF, DWT-SURF (1-scale), DWT- SURF (2scales), and GWT- SURF on UBIRIS database.

Table 4. Recognition performance of UBIRIS database after applying SURF, SURF with both 1-scale and 2 scale DWT and GWT-SURF

# of Subjects	SURF	SURF -DWT2(1s)	SURF -DWT2(2s)	GWT-SURF
10	96.00	83.50	83.50	96.50
20	98.00	69.75	69.75	96.75
30	95.33	68.83	68.83	96.33
40	95.87	66.00	66.00	96.87
50	94.00	65.10	65.10	96.20
60	93.25	65.33	65.33	96.58
70	88.14	62.14	62.14	95.14
80	87.50	61.62	61.62	95.43
90	85.28	57.50	57.50	94.78
100	83.30	57.90	57.90	94.15

6. Conclusion

Here, SURF or SIFT are feature extraction algorithms used for iris recognition. However, after SURF or SIFT are successfully applied for the feature detection and description, two approaches are proposed to improve the results. The first approach is based on DWT with SURF or SIFT namely DWT-SURF or DWT-SIFT. The second approach is based on GWT with SURF or SIFT namely GWT-SURF or GWT-SIFT. The DWT or GWT is applied to the image as a preprocessing stage before conventional SURF or SIFT algorithm. The recognition results obtained using this technique show substantial improvements, especially, in the recognition performance.

The performances of the two proposed approaches have been measured using widely used databases CASIA and UBIRIS. Different number of images per subjects, probes and gallery sets are defined. The proposed approach is found to perform well in iris recognition both on CASIA and UBIRIS iris databases. Results show better performance of the proposed approach to the conventional SURF and SIFT algorithms. In reference to the above observations, it is obvious that, using transformation on iris images before extracting features significantly improves the recognition rates of the studied iris recognition system. In general, the DWT-SIFT, GWT-SIFT outperforms the SIFT or SURF in terms of recognition performance.

References

[1] Maghiros, I., Punie, Y., Delaitre, S., Lignos, E., Rodriguez, C., Ulbrich, M., & Cabrera, M. (2005). Biometrics at the frontiers: Assessing the impact on society (No. EUR 21585 EN).

[2] Daugman, J. (2003). The importance of being random: statistical principles of iris recognition. Pattern recognition, 36(2), 279-291.

[3] Daugman, J. (2009). How iris recognition works. In The essential guide to image processing (pp. 715-739).

[4] Shah, N., & Shrinath, P. (2014). Iris Recognition System–A Review. International Journal of Computer and Information Technology, 3(02).

[5] Wildes, R. P. (1997). Iris recognition: an emerging biometric technology. Proceedings of the IEEE, 85(9), 1348-1363.

[6] Wildes, R. P., Asmuth, J. C., Green, G. L., Hsu, S. C., Kolczynski, R. J., Matey, J. R., & McBride, S. E. (1994, December). A system for automated iris recognition. In Applications of Computer Vision, 1994. Proceedings of the Second IEEE Workshop on (pp. 121-128). IEEE.

[7] Wildes, R. P., Asmuth, J. C., Green, G. L., Hsu, S. C., Kolczynski, R. J., Matey, J. R., & McBride, S. E. (1996). A machine-vision system for iris recognition. Machine vision and Applications, 9(1), 1-8.

[8] Lim, S., Lee, K., Byeon, O., & Kim, T. (2001). Efficient iris recognition through improvement of feature vector and classifier. ETRI journal, 23(2), 61-70.

[9] de Martin-Roche, D., Sanchez-Avila, C., & Sanchez-Reillo, R. (2001, October). Iris recognition for biometric identification using dyadic wavelet transform zero-crossing. In Proceedings IEEE 35th Annual 2001 International Carnahan Conference on Security Technology (Cat. No. 01CH37186) (pp. 272-277). IEEE.

[10] Ma, L., Wang, Y., & Tan, T. (2002, January). Iris recognition based on multichannel Gabor filtering. In Proc. Fifth Asian Conf. Computer Vision (Vol. 1, pp. 279-283).

[11] Vatsa, M., Singh, R., & Gupta, P. (2004, January). Comparison of iris recognition algorithms. In International Conference on Intelligent Sensing and Information Processing, 2004. Proceedings of (pp. 354-358). IEEE.

[12] Dong, W., Sun, Z., Tan, T., & Qiu, X. (2008, March). Self-adaptive iris image acquisition system. In Biometric Technology for Human Identification V (Vol. 6944, p. 694406). International Society for Optics and Photonics.

[13] Bay, H., Tuytelaars, T., & Van Gool, L. (2006, May). Surf: Speeded up robust features. In European conference on computer vision. Springer, Berlin, Heidelberg. (pp. 404-417)

[14] Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. International journal of computer vision, 60(2), 91-110.

[15] Proença, H., & Alexandre, L. A. (2005, September). UBIRIS: A noisy iris image database. In International Conference on Image Analysis and Processing (pp. 970-977). Springer, Berlin, Heidelberg.

[16] BIT. CASIA Iris Image Database [Online]. Available: http://biometrics.idealtest.org/. Last Accessed (July 2014).

[17] Ismail, A. I., Ali, H. S., & Farag, F. A. (2015, February). Efficient enhancement and matching for iris recognition using SURF. In 2015 5th national symposium on information technology: Towards new smart world (NSITNSW) (pp. 1-5). IEEE.

[18] Ali, H. S., Ismail, A. I., Farag, F. A., & El-Samie, F. E. A. (2016). Speeded up robust features for efficient iris recognition. Signal, Image and Video Processing, 10(8), 1385-1391.

[19] Rathgeb, C., Wagner, J., & Busch, C. (2019). SIFT-based iris recognition revisited: prerequisites, advantages and improvements. Pattern Analysis and Applications, 22(3), 889-906.