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## SURF AND SIFT DESCRIPTORS USING WAVELET TRANSFORMS FOR IRIS RECOGNITION

## A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES OF NEAR EAST UNIVERSITY

By MOHAMMED KAMAL MAJEED

In Partial Fulfillment of the Requirements for the Degree of Master of Science in Computer Engineering

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## Mohammed Kamal Majeed: SURF AND SIFT DESCRIPTORS USING WAVELET TRANSFORMS FOR IRIS RECOGNITION

Approval of Director of Graduate School of Applied Sciences

Prof. Dr. Nadire CAVUS

We certify this thesis is a satisfactory for the award of degree of Master of Science in Computer Engineering

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To my family...

#### 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 thesis, 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; discrete wavelet transform

#### ÖZET

Iris tanıma, günümüzde mevcut olan tanınma ve bilgisayar görüslerinde tanınmış doğru biyometrik teknoloji ve büyük araştırma alanıdır. İnsan müdahalesi olmadan kişinin iris tanıma yoluyla insan tanıma hedefler. Birçok alanda iris tanıma biyoinformatik, makine görme, örüntü tanıma, vb. gibi iyi çalışmaktadır ve hala popüler olan konulardan biridir. İris tanımadaki temel problemlerden biri, gözün küçük bir siyah kısmı olan bir iris tanımlamak için belirlenen özelliklerin bulunmasıdır. İstatistiksel özellikler, değişmezlik düzeyi ve sağlamlık gibi özellikleri içeren özellik çıkarma konusunda birçok yöntem ve algoritma önerilmiştir.

Bu tezde, iris tanıma için geleneksel bir SURF ve SIFT algoritmaları test edilmiştir. Bu algoritmaların performansını artırmak için, girdiyi farklı alanlardan gerçek zamanlı olarak geçirdik. Gabor Dalgacık Dönüşümü (GWT) veya Ayrık Dalgacık Dönüşümü'nün (DWT) giriş iris görüntülerine uygulanmasıyla, geleneksel SURF ve SIFT ile karşılaştırıldığında daha yoğun ve daha net görüntüler elde edilir. Bu nedenle, Gabor Dalgacık Dönüşümü veya Ayrık Dalgacık Dönüşümü'nün SURF ve SIFT algoritmalarında kullanılması için önerilen yaklaşımların simülasyonları, geleneksel algoritmalara kıyasla daha iyi sonuçlar vermektedir.

*Anahtar Kelimeler:* ıris tanıma; ayrık dalgacık dönüşümü; sabit ölçek öznitelik dönüşümü; gabor dalgacık dönüşümü; hızlandırılmış dayanıklı özellikler

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### LIST OF ABBREVIATIONS

2D:	Two Dimensional
<b>2D-DWT:</b>	Two Dimensional Discrete Wavelet Transform
3D:	Three Dimensional
DoG:	Difference of Gaussian
DWT:	Discrete Wavelet Transform
HL:	High pass Low pass sub-band
HH:	High pass High pass sub-band
kNN:	k-Nearest Neighbor
LL:	Low pass Low pass sub-band
LH:	Low pass High pass sub-band
LoG:	Laplacian of Gaussian
SURF:	Speeded-Up Robust Features
SIFT:	Scale-Invariance Feature Transform
GWT:	Gabor Wavelet Transform
LoG:	Laplacian of Gaussian
LoG:	Laplacian of Gaussian

## CHAPTER 1 INTRODUCTION

#### 1.1. Overview

As time passes, conventional authentication methods starting to be changed and replaced with the automated personal identifications which are based on biometric authentication systems. For user authentication, biometric systems uses either physical or behavioral characteristics of the user. There are many bio metric Technics like finger prints, walking, iris and face recognition.

In the reliability point of view, traditional authentication systems like hardware tools as an example smart cards or passwords these systems are more reliable sources of authentication. Biometric systems are unlike passwords or smart cards which are traditional, 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 has 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, 2004).

Image and signal processing techniques are the pillars of biometric systems. Many feature extracting algorithms have been proposed working on images such as fuzzy logic, wavelet transform, Scale Invariant Feature Transform, SURF, neural network, etc.

#### 1.2. Related Work

Due to its high reliability and not changing through whole life, iris recognition is viewed as one of the most possible approach in image processing. From what's seen in an iris appearance is highly randomized pattern with highly data rich structures that are totally different from one person to another or between monocular twins (Flom and Safir, 1987). So, iris of a person is unique, doesn't change and remains as it's through the person's whole life (Wildes et al., 1994). Moreover, the reaction of human iris is so sensitive to light that it changes its size and shape accordingly. This property makes it extremely difficult for a person to fake or copy (Boles and Boashash, 1998). We also should mention that, the protection of one's body mechanism for iris makes it difficult to be changed without risk. Hence, the most accurate and reliable person identification among biometric identification systems is iris (Yampolskiy et al., 2008).

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 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 (Sanchez-Avila, 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 (Christel-LoFc et al., 2002) explains.

Iris recognition developed more and more. Due to its accuracy, Uniqueness patterns, and stability with age, it's been used in many world wide applications such as ATMs, National Border Controls, Secure financial transaction, control of access to privileged information and internet, and many other applications.

#### 1.3. Iris Recognition

Iris is a highly protected internal organ which can be visible externally. Iris recognition is a kind of biometric systems which includes both identification and authentication of a person through iris patterns with using pattern-recognition techniques. Due to its pattern uniqueness, It is known to be one of the finest biometric technologies exist today.

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 pre-processing, keypoint extraction, and classification and feature matching, as its seen in Figure 1.1. The following section describes the steps.



Figure 1.1: The four general steps in iris recognition.

#### 1.3.1. Iris 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.

#### 1.3.2. Iris pre-processing

Iris preprocessing step is applied to make the iris detection stabilized, and get better feature extraction. Iris pre-processing composed of many different processes depending on the application, such as; alignment (translation, rotation, scaling), contrast adjustment, edge detection and illumination correlation. Also segmentation of the iris images can be done in this step. (Abiyev and Altunkaya, 2007; Abiyev et al., 2008; Rahib and Koray, 2009) proposes a fast algorithm for the localization of the inner and outer boundaries of the iris region which is done by used Neural Network (NN). 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.

#### 1.3.3. 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).

#### 1.3.4. 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.

#### **1.4. Problem Definition**

Our problem statement is as follows: an input iris image is taken to be checked, the iris image then observed if it's available or identifiable in the enrolled iris database.

Iris recognition is one of the major matters in recognition systems. It's important to work on algorithms that has better performances in recognizing the sample input image. Iris recognition as mentioned before is one of the most accurate systems and has the best security so ever, because even two identical persons from birth doesn't have the same pattern of iris, moreover the iris pattern of right eye of each single person is different from the iris pattern of the right eye. The most difficult process in iris recognition is to recognize the iris images inside a wild environment: because iris is so small that can't be seen far away, iris shapes and right or left looking of the person are also differ from time to time.

Under controlled environments iris recognition algorithms have a good performance, but still with increasing number of samples in a database the performance alters down, this issue

makes the recognition and performance still stay unsolved and make the researchers still work to have better algorithms with better performances. The proposed approach, works on increasing the performance of recognition rate over the traditional algorithms.

Since the algorithms nowadays which are used for different recognition applications work according to the scope and task of iris system, there are two basic classes for iris recognition (Lawrence, 1997; Azade et a., 2014; Abiyev and Altunkay, 2008);

- 1. Checking the validity of an individual inside a large iris database.
- 2. Identifying or recognizing an individual in a real time like systems used for tracking.

In this thesis, we specifically work on the first point. Our aim is to provide a better performance in recognizing each sample input which are valid in the iris database.

#### **1.5. Thesis Organization**

The flow of the thesis is like this; Chapter one provides an introduction about iris. It covers the iris recognition, and has the contributions of the thesis work.

Chapter 2, contains the detail of the feature extraction algorithms that we have used and the proposed approach. The Discussion about the properties and working mechanisms of these feature descriptors are valid here.

Chapter 3, contains a detailed methodology on which we have worked on and the explanation of the proposed approaches. It also has the feature extraction algorithms and the transformation algorithms were also discussed.

In chapter 4 we have discussed the simulations results separately. This chapter also concludes the best result among all results.

Chapter 5 has the work conclusions and recommendations for future work.

#### **CHAPTER 2**

#### FEATURE EXTRACTION ALGORITHMS

#### 2.1. Overview

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.

After getting an input image, both segmentation and normalization are applied to extract the iris images from the database as mentioned in (Masek, 2003). During segmentation algorithm the iris part is localized from eye images and their eyelids, eyelashes are all isolated from it as well. Through using circular Hough transform algorithm in segmentation step iris region and pupil part are located, also through using linear Hough transform the eyelids are detected. The eliminating of the eyelashes are done with a maintained thresholding. Then the iris region is unwrapped and normalized with the help of Daugman's rubber sheet model (Daugmn, 2002) to form a fixed dimensional rectangular block. Now the iris template is ready for feature extraction.

#### 2.2. 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. Figure 2.1 shows four steps in SIFT algorithm for keypoint description and feature extraction.



Figure 2.1: SIFT features extraction process.

#### 2.2.1. Scale-space local extrema detection

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. Scale-space kernels gives different  $\sigma$  values to different types of images, such for fade iris images Laplacian of Gaussian (LoG) has a different  $\sigma$ values. So, LoG is simply a blob detector which works according to the variation of  $\sigma$  on different scales of the iris images. Accordingly,  $\sigma$  is the scaling parameter. Gaussian kernel outputs high value for small corners which has low  $\sigma$  values, and fits well for larger corners which has high  $\sigma$  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,  $\sigma$ ) values that proves, a potential feature point of (x, y) at  $\sigma$  scale.



**Figure. 2.2:** A scale space construction example of SIFT algorithm. Showing 3 successive octaves and, per each octave there is 6 scales (Alonso-Fernandez et al., 2009).

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  $\sigma$ , let it be  $\sigma$  and  $k\sigma$ . Here is the algorithm for DoG.

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

with the Gaussian kernel:

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

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

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

So, various scales (octaves) of the iris image as its seen from the Gaussian Pyramid, undergoes this procedure as shown in Figure 2.3.



Figure 2.3: Gaussian pyramid (Lowe, 2004).

After Differential of Gaussian has found, iris images are observed for the local maximum and local minimum over the scale and space. For example, a sample input point or pixel in a iris image will be compared to all its neighbors which are 26 pixels or points, that's 8 neighbors, 9 pixels from the previous scale and 9 pixels in the next scale. Accordingly we will get local maximum or local minimum keypoints. A pixel is said to be local maximum when the pixel's value is bigger than the values o all neighbor pixels around and it will be known as minimum when its values is smaller than the other pixels around. So the found keypoint is the best possible keypoint observed in that scale as shown in Figure 2.3.



Figure 2.4: Scale space for keypoint (Lowe, 2004).

#### 2.2.2. Keypoint localization

After the possible keypoints have found, it will be observed to be made more accurate or be taken out and removed, to make a keyoint have more accurate results they should be refined. For the refining process of keypoints, Taylor Series Approximation is used to check the precise position of the keypoints in the scale space. Keypoints below the Taylor Series threshold level will be removed. For the edge problem Difference of Gaussians is used, accordingly the edges need to be removed, for this purpose, a procedure is applied very similar to Harris corner detector that talks about a principal curvature which is computed using a 2x2 Hessian matrix (H). According to Harris corner detector one eigenvalue for any edge is bigger than the other eigenvalue. So we come up with a function that, if a keypoint ratio was larger than the determined threshold value, that keypoint is goint to be rejected. This way we get robust and strong keypoints, while we get rid of any low-contrast keypoints or edge keypoints.

#### 2.2.3. Orientation assignment

With giving image rotation invariance to each keypoint we get orientation assignment. The scale is the base for determining the gradient magnitude and direction of the neighborhood pixels around the keypoint positions. So, the 360 degree range of orientation is covered with an orientation histogram of 36 bins. Gaussian-weighted circular window is used to calculate the weight of this 36 bins and its gradient magnitude with  $\sigma$  equal to 1.5 times the scale of keypoint. The histogram's uppermost peak and all other peaks which are over 80% are part

of the orientation. This will generate keypoints with different directions but having the same scale and position. This will lead to the stability of matching.

#### 2.2.4. Keypoint descriptor

Around each keypoint a neighborhood of 16x16 scale pixels are taken. These pixels then divided into 16 subregions of 4x4 size. An 8 bin of orientation histogram is formed for each sub-block. Overall, a 128 bin are achieved. Also to create keypoint descriptors, the values are assigned as vectors from the Figure 2.5 it shown obviously.



Figure 2.5: SIFT keypoint descriptor (Lowe, 2004).

To gain robustness against illumination changes, rotation etc. some procedures are applied. Figure 2.6 shows distinctive keypoints detected in iris image.



Figure 2.6: SIFT keypoints detected in an iris image.

#### 2.3. Speeded-Up Robust Features

Bay et al., developed SURF (Speeded-Up Robust Features) algorithm in 2006 from ETH Zurich (Bay et al., 2006). SURF is one of the best algorithms for detecting keypoints of a

local features in an iris image. It is a developed version of Shift-Invariant Feature Transform (SIFT).

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 2.7 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 2.7: The box filters of approximations of Gaussian second order partial derivative.

In order to get orientation assignment, wavelet responses are used in both vertical and horizontal directions for a size 6 neighborhood multiplied by the scale in which the keypoint is detected. Afterwards, Proper Gaussian weights will also be applied to it. Then, the estimation of the main orientation is obtained in a sliding orientation window of 60° through the calculation of the summing of all responses within. A good point is that, simply at any scale, integral images can be used to find wavelet response. Many applications don't require rotation invariance, so looking for this orientation is not required, accordingly, the processing speeds increases. SURF also provides one more method called Upright-SURF or U-SURF which is faster and is strong up to  $\pm 15^\circ$ . Figure 2.8 shows distinctive SURF keypoints of an iris image.



Figure 2.8: SURF keypoints detected in an iris image.

Feature description is performed by taking a 20sX20s neighborhood size around each keypoint where s is the size. Division happens to it and 4x4 subregions are formed as shown in Figure 2.9. For each of the subregions a vertical and horizontal wavelet responses are taken and a vector is formed according to the following formula  $v = (\sum d, \sum d, \sum |dx|, \sum |dy|)$ . Thus, from the forming vector, there are total of 64 dimensions of SURF feature descriptors. This will lead to higher the speed of computation and matching, and lower the dimension, so we get better feature distinctiveness.



Figure 2.9: The demonstration of descriptor building (Bay et al., 2006).

For distinctive underlying keypoints, another development has been done which is using trace of Hessian Matrix or simply sign of Laplacian. It doesn't require any additional computations cost because has already been done during detection. In the reverse situation, sign of the Laplacian differentiates the blobs which are bright from the dark backgrounds.

During the feature matching, only features are compared to each other in case of having the same type of background as shown in Figure 2.10. So this will make the matching process faster without affecting the descriptor's performance negatively.



Figure 2.10: The fast index for matching.

So in every step, a lot of features are added to the SURF and this improves the speed of the process in SURF. We have to mention that, in handling images with blurring and rotation SURF is very good, but at handling illumination and viewpoint variation, it's not that much good.

In both SURF and SIFT, the matching process between the keypoints of two images are by identifying their nearest neighbors (k-NN) which is shown in Figure 2.11. But sometimes, the first and second closest-matches are very close to each other, which is because of noise or maybe other reasons. At these situations, the first closest-distance to second-closest distance ratio of is taken into consideration.



Figure 2.11: Example of point matching result.

#### 2.4. Wavelet Transform

#### 2.4.1. 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 2.12 describes the whole procedure.



Figure 2.12: 2D-DWT, The working of high and low pass filters separately on columns and rows to form four different sub-images.

As we can see from the image below in Figure 2.13. that each sub-image give different information. The (LL) approximation sub-image is one of the image approximations in which all high frequency textures have been taken away. In the the horizontal (LH) sub-image high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while high frequency textures have been eliminated along the rows while h



Figure 2.13: 2D-DWT transform on iris image.

#### 2.4.2. Gabor Wavelet Transform

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.

In fact a moderated function of Gaussian kernel with a wave of sinusoidal plane forms Gabor wavelet filter. (1)

$$\psi_g(x, y) = \frac{f^2}{\eta \gamma \pi} \exp(\beta^2 y'^2 - a^2 x'^2) \exp(2\pi j f x')$$

$$x' = x \cos \theta + y \sin \theta,$$
 (1)  
$$y' = y \cos \theta - x \sin \theta,$$

Where *f* defined to be the sinusoidal plane wave's central frequency, The Gaussians anticlockwise rotation is defined by  $\theta$  and the  $\alpha$  is defined as the envelope wave, which is the Gaussians sharpness along the major axis parallel to the wave and the Gaussian minor axis' sharpness perpendicular to the wave defined by  $\beta$ . For keeping the ratio of sharpness and frequency constant  $\gamma = f/\alpha$  and  $\eta = f/\beta$  is defined. (2) Defines the 2D Gabor wavelet which has Fourier transform.

$$\psi_g(u,v) = \exp\left(-\pi^2 \left(\frac{(u'-f)^2}{\alpha^2} + \frac{v'^2}{\beta^2}\right)\right)$$
$$u' = u\cos\theta + v\sin\theta,$$
$$v' = v\cos\theta - u\sin\theta.$$
(2)

Iris recognition can be one of the best applications that can be described with GWT algorithm, since, vision applications and systems are what GWT was mainly developed for. For the first time in 1980 Daugman used GWT in the vision area and applications, he also developed the first automatic iris recognition system (Swati et al., 2013). The Gabor filters are used to extract the phase features which are known as Iris Code from iris images.

GWT describes an input image both by spatial relations and spatial frequency structure. Using 8 orientations and 5 scales in the convolving of an input image with Gabor filters, will result in capturing the whole frequency spectrum, and the complexity of the response is always seen. In Figure 2.14, the phase and the magnitude responses are shown on an input image using Gabor filter.



Figure 2.14: the above eye is the original image iris, first five rows are the magnitude and the second five rows are phase of the Gabor kernels at one scale and eight orientations.
### **CHAPTER 3**

### METHODOLOGY

#### 3.1. Overview

Iris recognition is a pattern recognition task that is implemented specially on iris images. Iris recognition is a challenging and difficult task for image processing and analysis. Despite its wide spread usage, most of iris recognition methods suffer from challenges like rotation, illumination, pose etc... The core task of this thesis work is to investigate the means by which the recognition performance can be enhanced and speeded up. Therefore, image transformation approach is used as a pre-processing stage before the feature extraction stage. Also image segmentation can be done in the preprocessing step to speed up the recognition performance as well (Abiyev, 2003) because an eye image doesn't only contain the iris alone, it also has pupils, eyelids, sclera etc. There is segmentation to localize and extract the iris region from the eye and all the other parts of the eye (Rahib and Koray, 2009).

To extract salient features from iris image, a feature based algorithm is used. The motivation behind this is the demonstration of the iris image in a very compact way. This fact mainly gains attention and importance when we want to make the system as accurate as possible. Feature based techniques are based on detecting distinctive keypoints on an iris image and defining its feature vector in a well-organized way. However, using these algorithms alone does not result in a good recognition performance, so choosing suitable approach is extremely critical for increasingl performance and the recognition rate. So, we perform transformations on images before extracting features from them.

### **3.2. The Proposed Approach**

The proposed approach contains details of the stages taken in carrying out the simulations. All the images are transformed using DWT or GWT. We proposed two approaches using SIFT and SURF. In first 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 3.1 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 3.1: 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 3.2 describes steps of 2-scales transformation using DWT-SURF.



Figure 3.2: 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 3.3 and 3.4 shows the same procedure with SIFT algorithm.



Figure 3.3: block diagram of 1-scale of DWT-SIFT.



Figure 3.4: block diagram of 2-scales 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 3.5 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 sample of class or it does not.



Figure 3.5: The block diagram of 1-scale of GWT-SURF and GWT-SIFT.

### **CHAPTER 4**

# **RESULTS AND DISCUSSIONS**

#### 4.1. Overview

Simulation results of the base line recognition performance for both iris databases of CASIA and UBIRIS are presented. MATLAB R2015a software package was used to apply the simulations. In each simulation category we have done, we have given a short discussion and a simple observation drawing about. At the end, we have discussed the results generally.

#### 4.2. Simulation Setup

The proposed approach have been pplied on two different databases of irises which are CASIA (Zhaofeng et al., 2008) 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.

Different number of subjects were used to test our approach which is a general way to test. Through choosing randomly different subjects each time, we run our program 10 times. After each experiment finished, scores will be fused and compared. During all of the experiments, the database for the iris images is divided into two separated classes; probe (test) and gallery (train) set. In the experiments of the CASIA database, gallery set is composed of 5 images for each subject and the rest is in probe set. Various extraction algorithms were applied with the proposed approaches such as (SIFT and SURF) and different transform algorithms were used such as (GWT, DWT ...). With DWT, we only applied the filter of (db5), because it gives the best result among other dbs (Ameen, 2017).

In the coming section we will explain the detail of the two iris databases we have used and their performance results according to our proposed approach will be explained accordingly, also comparisons will take place in the explanation with some conventional iris recognition algorithms.



(a) gallery irises



(b) probe irises

Figure 4.1: Different iris poses of two subjects from CASIA iris images,

We have applied different types of conventional algorithms with our approached algorithm on the same iris databases, then a comparison of the results were taken out.

# 4.3. Databases Used

# 4.3.1. The CASIA iris database

CASI (Zhaofeng et al., 2008) 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 imageswhich 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. Below in the Figure 4.2 a complete set of 120 subjects' iris images has been shown.



Figure 4.2: Iris sample set from CASIA database, contains 12 subjects, 10 per each person.

### 4.3.2. The 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 is exist 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.



Figure 4.3: Sample set of iris images for UBIRIS database, each sample is composed of 4 images.

# 4.4. Results for the CASIA Iris Database

4.4.1. Results for CASIA iris database with DWT

• Results for CASIA iris database using SURF

With SURF we have tested 10 to 100 subjects, the average recognition rate was 68.59% and the range of correctly classified different number of subjects have been displayed in the below in Figure 4.4.

With the increasing in number of subjects, the performance of every algorithms are decreasing.



Figure 4.4: Performance of SURF using CASIA iris database.

At first, 1-scale transformation was applied on iris images, using db5 transformation filter. Performance results can be seen in Figure 4.5.As its obvious, the performance of the proposed approach was not good enough because after transformation, SURF couldn't extract enough features to describe iris images. For cA (Approximate), there was 0 SURF points for all images in test and train sets. So we had to use cH (Horizontal), cV (Vertical) and cD (Diagonal) sub-images of DWT output.



Figure 4.5: Recognition performance of CASIA database after applying 1-scale DWT-SURF.

After applying 1-scale transformation, 2-scales transformation was applied on images with the same filter that we used in 1-scale transformation. Performance of 2-scales transformation is charted in Figure 4.6.



Figure 4.6: Recognition performance of CASIA database after applying 2-scales DWT-SURF.

For DWT algorithm it can be concluded that there is approximately ~1% difference between 1-scale and 2-scales transformation. One can observe the differences from Figure 4.7. which shows the range performance of 1-scale and 2-scales transformations.



Figure 4.7: Average performance of CASIA database after applying 1-scale and 2-scales DWT-SURF.

We have mentioned the performance of the proposed approach, and charted each of SURF, SURF-DWT (1s) and SURF-DWT(2s). Now we tabulate them in order the comparison be seen with numbers. The average of each of the algorithms that are seen in the Table 4.1. for SURF, SURF-DWT(1s) and SURF-DWT(2s) are 68.59%, 75.63% and 75.64% respectively. We see that there is not much difference between 1 scale and 2 scale DWT algorithms.

Table 4.1: Recognition performance of CASIA database after applying SURF, 1-scale

# of Subjects	SURF	SURF-DWT(1s)	SURF-DWT(2s)
10	90.60	87.60	88.20
20	83.40	87.70	87.60
30	75.53	81.00	80.93
40	69.05	76.50	76.45
50	64.04	73.68	73.52
60	63.90	73.03	72.97
70	61.29	71.34	71.26
80	59.00	69.90	69.85
90	59.06	67.91	67.95
100	59.98	67.60	67.62

and 2 scale DWT.

### • Results for CASIA iris database using SIFT

SIFT algorithm performance rate doesn't get affected by size of subjects. As shown in Figure 4.6 for 10 subjects recognition rate is 100% while for 100 subjects it is 92.65%. Overall average of SIFT using CASIA database is 95.58%. The recognition percentage for the following SIFT charts start from 95 - 100 vertically, so we numbered it throug 95 and above. Horizontally we have numbered according to the number of subjects, starting from 10 to 100 subjects respectively.



Figure 4.8: Performance of SIFT using CASIA iris database.

With 1-scale transformation with DWT, the performance of proposed approach is  $\sim 2\%$  different form SIFT as shown in the Figure 4.9. The rate of recognition varies with number of subjects, as number of subjects increase recognition rate decreases. The average of DWT-SIFT is 97.33%.



Figure 4.9: Recognition performance of CASIA database after applying 1-scale DWT.

In 2-scales transformations using DWT, the performance is ~1% different from 1-scale transformation as it's seen in the charts below. Figure 4.10. and Figure 4.11., clarify average performance difference between them.



Figure 4.10: Recognition performance of CASIA database after applying 2-scales DWT-SIFT.

As a conclusion, there is approximately more than  $\sim 1\%$  and less than  $\sim 2\%$  difference between 1-scale and 2-scales transformation on CASIA iris images using SIFT.



Figure 4.11: Average performance of CASIA database after applying 1-scale and 2-scales DWT-SIFT.

Previously we have mentioned the performance and the chart figure of each of SIFT, SIFT-DWT (1s) and SIFT-DWT(2s). Now we tabulate them in order the comparison be seen with numbers. The average of each of the algorithms that are seen in the Figure 4.11. above for SIFT, SIFT-DWT(1s) and SIFT-DWT(2s) are 99.56%, 97.33% and 98.70% respectively.

**Table 4.2:** Recognition performance of CASIA database after applying SIFT, SIFT with both 1-scale and 2 scale DWT.

# of Subjects	SIFT	SIFT-DWT(1s)	SIFT-DWT(2s)
10	99.80	99.40	99.40
20	99.90	98.90	99.60
30	99.86	98.60	99.30
40	99.70	98.25	99.04
50	99.60	97.32	99.00
60	99.60	97.07	98.91
70	99.51	96.69	98.55
80	99.37	96.00	97.87
90	99.18	95.62	97.72
100	99.10	95.42	97.60

#### 4.4.2. Results for CASIA iris database with GWT

#### Results for CASIA iris database using SURF

The performance of our proposed approach was completely different when GWT was applied on iris images before extracting features from it. At first, with 1-scale transformation, GWT outputs sub-images in complex and SURF doesn't work properly with complex, so our proposed approaches performed well using both Magnitude and Phase. Figure 4.12. is showing the performance of GWT-SURF.



Figure 4.12: Recognition performance of CASIA after applying 1-scale GWT-SURF

The performance of proposed approach using Magnitude and Phase of transformed images is ~27% higher than the conventional SURF algorithm. The performance of recognition of our proposed approach decreases less compared to SURF itself 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 4.13 and Figure 4.14.



**Figure 4.13:** Overall recognition performance of SIFT, DWT-SIFT (1-scale), DWT-SIFT (2scales), and GWT-SIFT on CASIA database.

Previously we have mentioned the performance and the chart figure of each of SIFT, SIFT-DWT (1s) and SIFT-DWT(2s). Now we tabulate them in order the comparison be seen with numbers. The average of each of the algorithms that are seen in the Table 4.3. for SIFT, SIFT-DWT(1s) and SIFT-DWT(2s) are 99.56%, 97.33% and 98.70% respectively.

# of subjects	SIFT	SIFT-DWT(1s)	SIFT-DWT(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

**Table 4.3:** Recognition performance of CASIA database after applying SIFT, SIFT withboth 1-scale and 2 scale DWT and GWT-SIFT.



**Figure 4.14:** Overall recognition performance of SURF, DWT- SURF (1-scale), DWT- SURF (2-scales), and GWT- SURF on CASIA database.

Previously we have mentioned the performance of each of SURF, SURF-DWT (1s) and SURF-DWT(2s) and GWT-SURF, we also have charted each them. Now we tabulate them in order the comparison be seen with numbers. The average of each of the algorithms that are seen in the Table 4.4. for SURF, SURF-DWT(1s) and SURF-DWT(2s) and GWT-SURF are 68.59%, 75.63%, 75.64% and 95.01% respectively.

# of subjects	SURF	SURF-DWT(1s)	SURF-DWT(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

**Table 4.4:** Recognition performance of CASIA database after applying SIFT, SIFT withboth 1-scale and 2 scale DWT and GWT-SURF.

Adding a preprocessing stage increases performance of our proposed approach but at the same time it increases computation time especially with GWT since there is more subimages than DWT so the time for computing GWT sub-images are higher than DWT sub-images. Number of keypoints detected using DWT or GWT are higher than SIFT or SURF only.

#### 4.5. Results for the UBIRIS Database

#### 4.5.1. Results for UBIRIS database with DWT

# • Results for UBIRIS database using SURF

With SURF, 10 to 100 subjects were tested, the average recognition rate was 91.67%. The average of correctly classified different number of subjects are shown in Figure 4.15. Performance of SURF decreases when number of subjects are increased.



Figure 4.15: Performance of SURF using UBIRIS database.

The same steps that were performed on CASIA database, was performed on UBIRIS database. At first 1-scale transformation was applied on images, using transformation filter. Result is shown in the figure 4.16. Performance of the algorithm was not good because after transformation, SURF couldn't extract enough features to describe iris images. For cA (Approximate), there was 0 SURF points for all iris images in train and test sets. So we had to use cH (Horizontal), cV (Vertical) and cD (Diagonal) sub-images of DWT.



Figure 4.16: Recognition performance of UBIRIS database after applying 1-scale DWT-SURF.

2-scales of transformations were applied on images with the same filter that we used in 1scale transformation. Performance of 2-scale transformation is charted in Figure 4.17.



Figure 4.17: Recognition performance of UBIRIS database after applying 2-scales DWT-SURF

For DWT algorithm on UBIRIS database there is approximately no difference between 1 scale and 2-scales transformations. One can observe the performance differences from Figure 4.18 which is totally same to each other.



Figure 4.18: Performance of UBIRIS database after applying 1-scale and 2-scales DWT-SURF.

Previously we have mentioned the performance and the chart figure of each of SURF, SURF -DWT (1s) and SURF -DWT(2s). Now we tabulate them in order the comparison be seen with numbers. The average of each of the algorithms that are seen in the Table 4.5. for SURF, SURF -DWT(1s) and SURF -DWT(2s) are 91.67%, 65.77% and 65.77% respectively.

# of Subjects	SURF	SURF -DWT(1s)	SURF -DWT(2s)
10	96.00	83.50	83.50
20	98.00	69.75	69.75
30	95.33	68.83	68.83
40	95.87	66.00	66.00
50	94.00	65.10	65.10
60	93.25	65.33	65.33
70	88.14	62.14	62.14
80	87.50	61.62	61.62
90	85.28	57.50	57.50
100	83.30	57.90	57.90

**Table 4.5:** Recognition performance of UBIRIS database after applying SURF, SURF with both 1-scale and 2 scale DWT.

# • Results for UBIRIS Database using SIFT

SIFT algorithm performance rate changes when size of subject's decreases. As shown in Figure 4.19, for 10 subjects recognition rate is 100% while for 100 subjects it is 92.65%. Overall average of SIFT on UBIRIS database is 95.58%.



Figure 4.19: Performance of SIFT using UBIRIS database.

The same steps were performed that was performed before on CASIA database. At first 1scale transformation was applied on iris images, using transformation filter. Result is charted in the Figure 4.20. Performance of our proposed approach was not good because after transformation, SURF couldn't extract enough features to describe iris images. For cA (Approximate), there was 0 SURF points for all images in test and train sets. So we had to use cH (Horizontal), cV (Vertical) and cD (Diagonal) sub-images of DWT.



Figure 4.20: Recognition performance of UBIRIS database after applying 1-scale DWT-SIFT.

2-scales transformation was applied on iris images using the same filter that was used in 1scale transformation. Performance of 2-scales transformation is charted in Figure 4.21.



**Figure 4.21:** Recognition performance of UBIRIS database after applying 2-scales DWT-SIFT.

For DWT algorithm it can be concluded that there is approximately ~3% difference between 1scale and 2-scales transformation. One can observe the range of performance differences from Figures 4.22.



Figure 4.22: Range performance of UBIRIS database after applying 1-scale and 2-scales DWT-SIFT.

Previously we have mentioned the performance and the chart figure of each of SIFT, SIFT-DWT (1s) and SIFT-DWT(2s). Now we tabulate them in order the comparison be seen with numbers. The average of each of the algorithms that are seen in the Table 4.6. for SIFT, SIFT-DWT(1s) and SIFT-DWT(2s) are 95.58%, 86.95% and 89.73% respectively.

# of Subjects	SIFT	SIFT-DWT(1s)	SIFT-DWT(2s)
10	100.0	100.0	100.0
20	98.25	95.75	96.75
30	95.50	92.50	94.67
40	96.62	91.50	93.12
50	95.90	91.00	92.30
60	95.91	82.00	86.33
70	94.07	81.14	84.93
80	94.25	81.18	85.69
90	92.67	78.28	82.77
100	92.65	76.10	80.75

 Table 4.6: Recognition performance of UBIRIS database after applying SIFT, SIFT with both 1-scale and 2 scale DWT.

# 4.5.2. Results for UBIRIS database with GWT

#### • Results for UBIRIS Database using SURF

The performance of our proposed approach was completely different when GWT was applied on iris images before extracting features from it. At first 1-scale transformation was used.

GWT outputs vectors in complex and SURF doesn't work properly with complex, so Magnitude, Phase and both of them were used in the proposed approach. Performance of proposed approach is listed in Table 4.23.



Figure 4.23: Recognition performance of UBIRIS database after applying 1-scale GWT-SURF.

# • Results for UBIRIS database using SIFT

The performance of proposed approach was not as expected using DWT, but using GWT it differs around ~3% which is much better than conventional SIFT only, as listed in Table 4.7. Overall average recognition rate of SIFT is 95.58%. On the other hand recognition rate of SIFT after applying GWT as a transformation is 98.70%.



Figure 4.24: Recognition performance of UBIRIS database after applying 1-scale GWT-SIFT.

The overall recognition performance rate for different number of subjects for SURF, SIFT, and proposed approaches are shown in Figure 4.25 and Figure 4.26.



**Figure 4.25:** Overall recognition performance of SIFT, DWT-SIFT (1-scale), DWT-SIFT (2scales), and GWT-SIFT on UBIRIS database.

Previously we have mentioned the performance and the chart figure of each of SIFT, SIFT-DWT (1s) and SIFT-DWT (2s). Now we tabulate them in order the comparison be seen with numbers. The average of each of the algorithms that are seen in the Table 4.7. for SIFT, SIFT-DWT (1s), SIFT-DWT (2s) and GWT-SIFT are 95.58%, 86.95%, 89.73% and 98.70% respectively.

**Table 4.7:** Recognition performance of UBIRIS database after applying SIFT, SIFT with both 1-scale and 2 scale DWT and GWT-SIFT

# of subjects	SIFT	SIFT-DWT(1s)	SIFT-DWT(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



**Figure 4.26:** Overall recognition performance of SURF, DWT- SURF (1-scale), DWT- SURF (2scales), and GWT- SURF on UBIRIS database.

Previously we have mentioned the performance and the chart figure of each of SURF, SURF with both 1-scale and 2 scale DWT and GWT-SURF. Now we tabulate them in order the comparison be seen with numbers. The average of each of the algorithms that are seen in the Table 4.8. for SIFT, SIFT-DWT (1s) and SIFT-DWT (2s) and GWT-SURF are 91.67%, 65.77%, 65.77% and 95.87 respectively.

# of Subjects	SURF	SURF -DWT(1s)	SURF -DWT(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

 Table 4.8: Recognition performance of UBIRIS database after applying SURF, SURF

 with both 1-scale and 2 scale DWT and GWT-SURF

Size of iris images affects overall performance iris recognition system and computation time. Since the size of CASIA images are bigger than UBIRIS images so performance of our proposed approach is higher and at the same time computation time is also higher. Especially, with GWT since there is more sub-images than DWT so the time for computing GWT sub-images are higher than DWT sub-images.

#### 4.6. Results for Different Sizes of Gallery Set

Experiments from the simulation have been applied on different number of tests and trains for different number of subjects. The number of subjects vary from 1 to 9 (1,2,3,4,5,6,7,8,9) for CASIA database while it changes from 1 to 3(1,2,3) for UBIRIS database. For example, 1 subject from gallery of CASIA and the rest, which is 9, will be in probe set, or 1 subject of UBIRIS database and the rest which are 3 will be probe. Our proposed approaches were applied and tested on both of the CASIA and UBIRIS databases.

The following sections are dedicated for the brief results of the experiments.

#### 4.6.1. Results for UBIRIS database

In general, for UBIRIS database the performance of the proposed approaches which are GWT-SURF and GWT-SIFT are higher and better compared to those of SURF and SIFT.

# • Results using SIFT

In this experiment we used SIFT as a feature extraction algorithms and the results show that, GWT-SIFT outperforms DWT-SIFT and SIFT. The difference between GWT-SIFT and SIFT is approximately ~3%. The difference of recognition performances are shown in Figure 4.27.



Figure 4.27: The performance of SIFT, DWT-SIFT and GWT-SIFT using UBIRIS with different number of images per subjects.

### • Results using SURF

In this experiment SURF was used as a feature extraction algorithm and the results show that, GWT-SURF outperforms both SURF and DWT-SURF. The difference between GWT-SURF and SURF is approximately ~4%. The detailed differences of recognition performances are shown in Figure 4.28.



Figure 4.28: The performance of SURF, DWT-SURF, and GWT-SURF using UBIRIS with different number of subjects.

### 4.6.2. Results for CASIA iris database

In general with CASIA database, the performances of GWT-SURF and GWT-SIFT are higher and better compared to those of DWT-SURF, DWT-SIFT, SURF, and SIFT.

### • Results using SIFT

In this experiment SIFT was used as a feature extraction algorithm and the results show that, GWT-SIFT outperforms DWT-SIFT and SIFT. The difference between GWT-SIFT and SIFT is approximately ~8%. The difference of recognition performances are shown in Figure 4.29.



Figure 4.29: The performance of SIFT, DWT-SIFT and GWT-SIFT using CASIA with different number of subjects.

# • Results using SURF

In this experiment SURF was used as a feature extraction algorithm and the results show that, GWT-SURF outperforms DWT-SURF and SURF. The difference between GWTSURF and SURF is approximately ~26%. The differences of recognition performances are shown in Figure 4.30.



Figure 4.30: The performance of SURF, DWT-SURF and GWT-SURF using CASIA with different number of subjects.

#### 4.7. General Discussion of Results

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 using both CASIA and UBIRIS databases and but in case of computation time it was slower than SIFT or SURF.

Gabor Wavelets' directional selectivity in an important property that makes it appropriate for a large number of applications. Gabor wavelets is oriented in a way that in the desired direction it give excellent selectivity. Response to image features which are not aligned in the same direction is weak on the contrary for the features on the same direction very strong. A good success also comes from the properties which are Invariance to shifts and rotations. Local features of the iris images are captured accurately through space frequency analysis. Gabor wavelets extract maximum properties from local image regions though frequencyspace localization. Thus, Gabor wavelets is robust, insensitive to different variances in iris recognition through these properties and optimal local representation.

While DWT has limited directionality and it filters most of the textual information from the small size of images, as we have seen its effect on UBIRIS since all the images in this database were very small sized, but we don't see the same negative effect on CASIA database, since the images sizes are bigger according to the UBIRIS. This makes the DWT to decrease the performance of proposed approaches.

Our proposed approach was good in performance but for computation time since it adds a preprocessing stage it affects computation time.

Finally, it can be concluded that, image pre-processing on the acquired images before recognition stage, has a potential of increasing the recognition performance of iris recognition system, while increasing computation time.

### **CHAPTER 5**

# CONCLUSION AND FUTURE WORK

#### 5.1. Conclusion

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. Important developments in this field proves that in many of the iris recognition application areas the automated techniques perform better than human. Iris recognition encompasses many fields and study areas, such as pattern recognition, bioinformatics, and machine vision, and has become one of the hottest research areas. Finding of feature set to identify an iris which is small black part of an eye and variance which makes it difficult to recognize is an important step in the main problem fixing. Many methods and algorithms have been proposed on feature extraction, which include aspects like statistical features, level of invariance and robustness.

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.

### 5.2. Future Work

In this work, DWT or GWT is used with the conventional SIFT or SURF to propose two approaches for better performance of the mentioned algorithms for iris recognition. As a future work, the followings may be considered:

• In all the experiments, for the 1-scale and 2-scales, it is noticed that the performances of the proposed approach are close to each other. Hence, it can be applied for different scales, and the results may be compared to that of the SURF or SIFT.

• CASIA and UBIRIS databases were used in all of the experiments; more databases can be tested and the results may be compared with the proposed approach and conventional algorithms.

• We didn't do the preprocessing step for the iris images segmentation. The iris images which are taken from the databases can be segmented and then these algorithms can be applied.

#### REFERENCES

- Abiyev, R. H., & Altunkaya, K. (2007, October). Neural network based biometric personal identification. In Frontiers in the Convergence of Bioscience and Information Technologies, 2007. FBIT 2007 (pp. 682-687).
- Abiyev, R. H., & Altunkaya, K. (2008). Personal iris recognition using neural network. *International Journal of Security and its Applications*, 2(2), 41-50.
- Abiyev, R. H., & Altunkaya, K. (2009). Neural network based biometric personal identification with fast iris segmentation. *International Journal of Control, Automation and Systems*, 7(1), 17-23.
- Abiyev, R. H., & Kilic, K. I. (2011). Robust feature extraction and iris recognition for biometric personal identification. *In Biometric Systems, Design and Applications*. InTech.
- Alonso-Fernandez, F., Tome-Gonzalez, P., Ruiz-Albacete, V., & Ortega-Garcia, J. (2009, September). Iris recognition based on sift features. *In Biometrics, Identity and Security* (*BIdS*), 2009 International Conference on (pp. 1-8). IEEE.
- Ameen, M. M., & Eleyan, A. (2017). Score Fusion of SIFT & SURF Descriptors for Face Recognition Using Wavelet Transforms. *International Journal of Image, Graphics* and Signal Processing, 9(10), 22.
- Bastani, A. (2014). Iris Recognitionbasedon Wavelet Transform and Probabilistic Neural Network.
- 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)
- Boles, W. W., & Boashash, B. (1998). A human identification technique using images of the iris and wavelet transform. *IEEE transactions on signal processing*, *46*(4), 1185-1188.
- Daugman, J. (2003). The importance of being random: statistical principles of iris recognition. *Pattern recognition*, 36(2), 279-291.

- Daugman, J. (2009). How iris recognition works. In The essential guide to image processing (pp. 715-739).
- Martin-Roche, D., Sanchez-Avila, C., & Sanchez-Reillo, R. (2001, October). Iris recognition for biometric identification using dyadic wavelet transform zero-crossing. *In Security Technology, 2001 IEEE 35th International Carnahan Conference on* (pp. 272-277). IEEE.
- 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.
- Flom, L., & Safir, A. (1987). U.S. Patent No. 4,641,349. Washington, DC: U.S. Patent and Trademark Office.
- Gabor, D. (1946). Theory of communication. Part 1: The analysis of information. Journal of the Institution of Electrical Engineers-Part III: Radio and Communication Engineering, 93(26), 429-441.
- He, Z., Tan, T., Sun, Z., & Qiu, X. (2008, October). Robust eyelid, eyelash and shadow localization for iris recognition. *In Image Processing*, 2008. *ICIP 2008. 15th IEEE International Conference on* (pp. 265-268). IEEE.
- Kingsbury, N. (2001). Complex wavelets for shift invariant analysis and filtering of signals. *Applied and computational harmonic analysis*, 10(3), 234-253.
- Lawrence, S., Giles, C. L., Tsoi, A. C., & Back, A. D. (1997). Face recognition: A convolutional neural-network approach. *IEEE transactions on neural networks*, 8(1), 98-113.
- 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.
- Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. *International journal of computer vision*, 60(2), 91-110.
- 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).
- 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).
- Masek, L. (2003). Recognition of human iris patterns for biometric identification.
- Miyazawa, K., Ito, K., Aoki, T., Kobayashi, K., & Nakajima, H. (2008). An effective approach for iris recognition using phase-based image matching. *IEEE transactions* on pattern analysis and machine intelligence, 30(10), 1741-1756
- 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.
- Shah, N., & Shrinath, P. (2014). Iris Recognition System–A Review. *International Journal* of Computer and Information Technology, 3(02).
- Swati, S. D., & Deepak, G. (2013). Iris Recognition using Gabor. International Journal of Computer Technology and Applications, 4(1), 1.
- Tisse, C. L., Martin, L., Torres, L., & Robert, M. (2002, May). Person identification technique using human iris recognition. *In Proc. Vision Interface* (Vol. 294, No. 299, pp. 294-299).
- Wickerhauser, M. V. (1996). Adapted wavelet analysis: from theory to software. AK Peters/CRC Press.
- Wildes, R. P. (1997). Iris recognition: an emerging biometric technology. *Proceedings of the IEEE*, 85(9), 1348-1363.
- 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.
- 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.

Yampolskiy, R. V., & Govindaraju, V. (2008). Behavioural biometrics: a survey and classification. *International Journal of Biometrics*, 1(1), 81-113.

APPENDICES

## APPENDIX 1 SOURCE CODE

We have used matlab application 2015 for testing our application. The computers we have used were core i7 and has ram of 16 Gigabytes. We have many algorithms applied in matlab, here we will provide the source code for some of the algorithms.

## SURF(Speeded Up Robust Features) on Casia database for 10 sample.

tic clear all clc cd 'C:\Users\Esmer\Desktop\Master COde\Master COde' load rndMtrxCasia1000 NP = 10;NIP = 10;NTr = 5;NTs = NIP-NTr;avgScores=0; DB='Casia1000'; NoSubjs = 10;surfSize = 64; for x = 1:NoSubjs scoresList=0; for itr = 1:10clear memory clear Train clear Test clear classResults score = 0;c=1;

```
for perCounter = 1:NP;
  for imgPerCounter = 1:NTr;
                  [DB
                                           int2str(rndMtrxCasia1000(itr,
       im
             =
                          '\CsLamp
                                    ('
                                                                            (perCounter-
1)*NIP+imgPerCounter)) ').jpg'];
       trainImages = imread(im);
       trainPoints = detectSURFFeatures(trainImages);
[trainFeatures,trainPoints]=extractFeatures(trainImages,trainPoints,'Method','SURF','SURF
Size', surfSize);% extracting the feture points from trainPoints
       Train{c} = trainFeatures(:);
       c=c+1;
    end
  end
  c=1; for perCounter = 1:NP;
    for imgPerCounter = NTr+1:NIP;
       im
             =
                  [DB
                          '\CsLamp
                                      ('
                                           int2str(rndMtrxCasia1000(itr,
                                                                            (perCounter-
1)*NIP+imgPerCounter)) ').jpg'];
       testImages = imread(im);
       testPoints = detectSURFFeatures(testImages);
       [testFeatures,testPoints]
                                                                                       =
extractFeatures(testImages,testPoints,'Method','SURF','SURFSize',surfSize);
       Test{c} = testFeatures(:);
       c=c+1;
    end
  end
  rangeMin=1;
  rangeMax=NTr;
  for imagClassfCounter = 1:(NP*NTs);
    tsf = reshape(Test{1,imagClassfCounter},[],surfSize);
    for trainCounter = 1:(NP*NTr);
       trf = reshape(Train{1,trainCounter},[],surfSize);
       indexPairs = matchFeatures(trf,tsf);
```

```
60
```

```
if(size(indexPairs, 1) == 0)
         total = 0;
       else
         total = sum(sum(indexPairs));
       end
       classResults(:,trainCounter) = total;
    end
    [value,index] = max(classResults);
    if(index>=rangeMin && index<=rangeMax)
       score = score+1;
    end
    if(mod(imagClassfCounter,NTs) == 0)
       rangeMin = rangeMin+NTr;
       rangeMax = rangeMax+NTr;
       cond = true;
    end
  end
  scoresList(itr) = score;
end
avgScores(x) = mean(scoresList)*100/(NP*NTs);
end
avgScores = avgScores';
toc
```

## SIFT(Scale Invariant Feature Transform) on Casia database for 10 sample.

tic clear all clc cd 'C:\Users\mohammed.kamal\Desktop\Master code'

load rndMtrxUBIRIS400

NP = 10;

NIP = 4;

NTr = 2;

NTs = NIP-NTr;

avgScores=0;

DB='UBIRIS';

NoSubjs = 10;

siftSize=128;

for x = 1:NoSubjs

scoresList=0;

for itr = 1:10

clear memory

clear Train

clear Test

clear classResults

score = 0;

c=1;

for perCounter = 1:NP;

for imgPerCounter = 1:NTr;

im = [DB '\CsLamp (' int2str(rndMtrxUBIRIS400(itr, (perCounter-

1)\*NIP+imgPerCounter)) ').jpg'];

trainImages = single(imread(im));

[~,dtr] = vl\_sift(trainImages);

```
Train{c} = dtr(:);
      c=c+1;
    end
  end
  c=1;
  for perCounter = 1:NP;
    for imgPerCounter = NTr+1:NIP;
      im
                 [DB
                         '\CsLamp
                                     ('
                                          int2str(rndMtrxUBIRIS400(itr,
                                                                            (perCounter-
            =
1)*NIP+imgPerCounter)) ').jpg'];
       testImages = single(imread(im));
       [~,dts] = vl_sift(testImages);
       Test{c} = dts(:);
       c=c+1;
    end
  end
  rangeMin=1;
  rangeMax=NTr;
  for imagClassfCounter = 1:(NP*NTs);
    tsf = reshape(Test{1,imagClassfCounter},siftSize,[]);
    for trainCounter = 1:(NP*NTr);
       trf = reshape(Train{1,trainCounter},siftSize,[]);
       [matches, scores] = vl_ubcmatch(trf,tsf);
       classResults(:,trainCounter) = sum(sum(matches));
    end
    [value,index] = max(classResults);
```

```
if(index>=rangeMin && index<=rangeMax)
```

```
score = score+1;
```

end

```
if(mod(imagClassfCounter,NTs) == 0)
```

```
rangeMin = rangeMin+NTr;
```

```
rangeMax = rangeMax+NTr;
```

cond = true;

end

end

```
scoresList(itr) = score;
```

end

```
avgScores(x) = mean(scoresList)*100/(NP*NTs);
```

```
NP = NP + 10;
```

end

```
avgScores = avgScores';
```

toc