An Efficient Method for Deformed Iris Recognition by Extracting Hybrid Features

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Abstract: ***Iris being one of unique feature to identify human, thus iris recognition has become one of the most authenticated and reliable system in the field of security. Main drawback that influences its efficiency is deformation of iris pattern caused by pupil dilation and contraction. In most state-of-the-art, only local iris texture features are used to overcome this problem. In this paper new algorithm is proposed to recognize deformed iris by utilizing simultaneously both geometric and photometric features contained in low pass and band pass regions. Non sub sampled contour let transform (NSCT), is used to eliminate noise and integrate the directional boundary information in different band pass sub bands, using SURF features in maxima image(created using 16 band pass sub bands) and ordinal features in low pass sub bands , matching score is generated . These scores are then used to classify deformed iris image with the iris images present in the database using KNN classifier.***

Keywords: KNN Classifier, Iris Recognition

1. Introduction

Identification and authentication of any individual is becoming more important in recent days. In the modern world where computers and electronics devices are more extensively used and the population of the world is increasing, there is a need for highly accurate and secured practical authentication technology. Traditional techniques such as user name, passwords, keys, ID cards, hardware token based systems are not reliable and secure in many of the security zones. Thus there is an increasing need for automatic reliable authentication process in modern society. In the recent few years biometric identification has proven to be more reliable means of verifying the human identity. Biometric refers to a science of analyzing human physiological or behavioral characteristics for security purposes and the word is derived from the Greek words bios means life and metrikos means measure. The Biometric characteristics cannot be faked, forged, guessed and stolen easily. One need not remember his/her biometric traits. Biometric identification techniques use inherent physical or behavioral characteristics which are unique among all individuals. The behavioral biometrics are signature, voice, keystroke, gait etc., and physiological biometrics are fingerprint, face, palm print, iris, retina, ear, DNA etc. Among the physiological biometrics, iris is an important feature of the human body and it has the characters of uniqueness and stability. Iris recognition technology is now a day's more advantageous in the field of information security and verification of individuals in the areas such as controlling access to security zones, verification of passengers at airports, stations, computer access at defense establishments, research organization, data base access control in distributed systems etc. Iris recognition systems are currently being deployed in many countries for airline crews, airport staffs, national ID cards and missing children identification etc.

The human iris is a visible color ring bounded by the pupil (the dark opening) and white sclera, as depicted in Fig. 1. The size of the iris varies from person to person with a range of 10.2 to 13.0 mm in diameter, an average size of 12 mm in diameter, and a circumference of 37 mm [5].

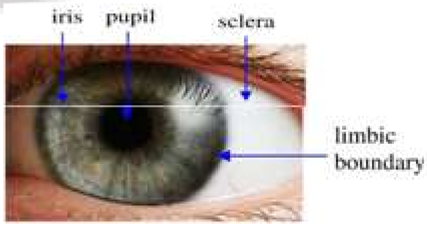


Figure 1: Anterior surface of the iris

The human eye is sensitive to visible light. Increasing illumination on the eye causes the pupil of the eye to contract, while decreasing illumination causes the pupil to dilate. Visible light causes specular reflections inside the iris ring. On the other hand, the human retina is less sensitive to near infra-red (NIR) radiation in the wavelength range from 800 nm to 1400 nm, but iris detail can still be imaged with NIR illumination.

As the muscles surrounding a pupil contract or relax, the size of the pupil changes to regulate the amount of light entering into an eye. Therefore, illumination variations will cause significant changes in pupil size. In the daily illumination environment, pupil diameter usually varies from 1.5mm to 7mm.As a result; the changes lead to iris deformation dramatically and introduce large intra-class difference. Thus, iris recognition under unrestricted illumination conditions is an extremely challenging problem.

Irises from different people may be captured in different size, and even for irises from the same eye, the size may change due to illumination variations and changes of the camera-to-eye distance. Such elastic deformation in iris texture will affect the matching results. Daugman [15] represented the iris using a fixed parameter interval in a doubly dimensionless pseudo polar coordinate system, normalized the iris into an image of a fixed size. In experiments, we counter-clockwise unwrap the annular iris to a rectangular texture block with a fixed size. The normalization not only reduces to a certain extent the distortion of the iris caused by pupil movement but also simplifies subsequent processing.

There are three categories of methods to handle iris deformation. The first one is image preprocessing. Daugman [5] proposed to linearly stretch the circular iris area into a rectangle image. Yuan et ale [14] described the relationship of iris collagen fibers between different iris sizes by employing a meshwork model. Wei et al [13] applied a Gaussian function to normalize deformation of iris texture nonlinearly. However, precise mathematical model of iris deformation does not exist. Even after image preprocessing, deformed iris images are still highly different. Thus the second kind of methods is to extract robust features. Sun et ale [11] made use of qualitative iris texture representation which is robust to deformation to a certain degree. Ortiz et ale [16] implemented dilation-aware enrollment to improve recognition accuracy. To address heavy deformation, robust matching strategies can be our third resort. Under a Bayesian model, Thornton et ale [12] utilized maximum a posteriori probability (MAP) parameters of training iris images for matching deformed patterns. The approach in [8] estimated iris deformation as a bunch of hidden variables and designed a graph model. Zhang et ale [17] showed perturbation-enhanced local and global feature fusion method for robust iris recognition. Although there are lots of deformed iris image matching methods, it remains a challenging problem and deserves further study.

In [5] and [10], multi-channel filters were utilized to extract multi-scale and multi-orientation iris features. It is mentioned that discriminating features are contained in different frequency bands. Inspired by this work, we propose a novel algorithm using bandpass geometric features and low pass Ordinal features for deformed iris image matching.

Two kinds of iris features are extracted in different subbands and then fused for deformed iris image matching are classified using KNN classifier. In the flowchart shown in Figure 5, a normalized iris image is decomposed into low pass and bandpass subbands by nonsubsampled contourlet transform (NSCT) [4] in the beginning. And then key points and aligned Ordinal features are extracted in different subbands, separately. At last, two kinds of features are fused for final matching and are classified. The details of the proposed method can be seen in Section 4.1.

There are three main contributions of our work. First, due to the shift-invariant, multi-scale and multi-direction properties of NSCT, smooth iris texture contours are extracted effectively. Second, deformed iris images are easily aligned by the locations of key points extracted from the subbands where iris texture edges are strengthened. Lastly, diverse features in different subbands are separately extracted and then fused, which can make use of various advantages of different subbands. The remainder of this paper is organized as follows. Section 2 reviews the background of the proposed algorithm. Section 3 gives the motivation of the algorithm. The technical details of the proposed algorithm are described in Section 4. Experimental results on iris database are presented in Section 5. Finally, Section 6 gives discussion and conclusion.

2. Background

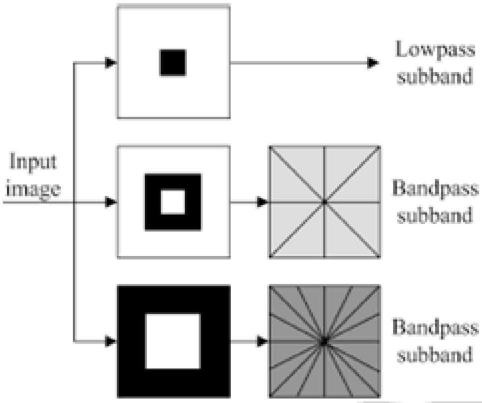
2.1 Nonsubsampled Contourlet Transform

The Contourlet transform is an extension of the wavelet transform which uses multi scale and directional filter banks. Here images are oriented at various directions in multiple scales, with flexible aspect ratios [6]. The Contourlet transform effectively captures smooth contours images which are the dominant feature in natural images. The main difference between Contourlet and other multi scale directional systems is that the Contourlet transform allows for different and flexible number of directions at each scale, while achieving nearly critical sampling. In addition, the Contourlet transform uses iterated filter banks, which makes it computationally efficient. The Contourlet transform (Do and Vetterli, 2004) is a multidirectional and multi scale transform that is constructed by combining the Laplacian pyramid with the Directional Filter Bank (DFB) proposed. Due to down samplers and up samplers present in both the Laplacian pyramid and the DFB, the Contourlet transform is not shift-invariant. The structure consists in a bank of filters that splits the 2-D frequency plane in the subbands illustrated in Fig. 3. This transform can thus be divided into two shift-invariant parts: (1) a Nonsubsampled pyramid structure that ensures the multi scale property and (2) a Nonsubsampled DFB structure that gives directionality.

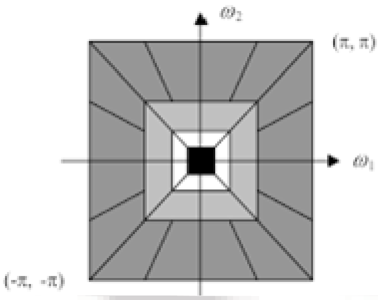
Multiscale decomposition step of the NSCT is realized by shift-invariant filter banks satisfying Bezout identical equation (perfect reconstruction (PR)), not LP of CT. Because of no downsampling in pyramid decomposition, there is no frequency aliasing in low-pass subband, even the band width is larger than $\pi/2$. Hence, the NSCT has better frequency characteristic than CT. The two-level NSCT decomposition is shown in Fig. 2.

The multi scale property of the NSCT is obtained from a shift-invariant filtering structure that achieves subband decomposition similar to that of the Laplacian pyramid [3]. This is achieved by using two-channel non sub sampled 2-D filter banks. Figure 2a and b illustrates the Nonsubsampled pyramid (NSP) decomposition with J = 3 stages. The ideal pass band support of the low-pass filter at the jth stage is the region [-(Π /2j), (Π /2j)]2. Accordingly, the ideal support of the equivalent high-pass filter is the complement of the low-pass, i.e., the region [(-Π /2j-1), (Π/2j-1)]2 \ [(-Π /2j), (Π /2j)]2. The filters for subsequent stages are obtained by up sampling the filters of the first stage. This gives the multi scale property without the need for additional filter design.

The core of NSCT is non-separable two-channel NSFB. It is easier and more flexible to design the needed filter banks, which leads to an NSCT with better frequency selectivity and regularity than the CT counterparts. Based on mapping approach and ladder structure fast implementation, NSCT frame elements are regularity, symmetry, and the frame is close to tight frame



(a) NSFB structure that implements the NSC



(b) Frequency partitioning obtained with the proposed structure

Figure 2: Two-level NSCT decomposition

2.2 Daugman's Rubber Sheet Model

The most common normalization method in the literature was proposed by Daugman[15] . The Daugman's rubber sheet model transforms a segmented iris region, represented in the Cartesian coordinates system, into a fixed length and dimensionless polar coordinate system using the pupil center as a reference point. The method maps each point (x,y) in the Cartesian domain to a point (r,□) in polar coordinates, as shown in Fig 3.

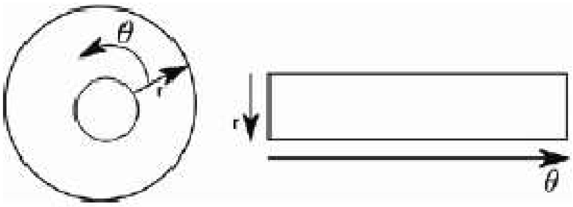


Figure 3: Rubber sheet model conversion

The mapping equations, where r represents the radial distance on the unit interval [0;1] and □θ□is an angle interval [0,2π], are

$$x(r,\theta) = (1-r)\, x_p + r x_i(\theta) \quad (1)$$
$$y(r,\theta) = (1-r)\, y_p + r y_i(\theta) \quad (2)$$

where

$$x_p(\theta) = x_{p0}(\theta) + r_p \cos(\theta) \;,\; x_i(\theta) = x_{i0}(\theta) + \cos(\theta)$$
$$y_p(\theta) = y_{p0}(\theta) + y_p \cos(\theta) \;,\; y_i(\theta) = y_{i0}(\theta) + y_i \cos(\theta)$$

and (x_{p0}, y_{p0}) are the coordinates of the pupil's center, (x_{i0}, y_{i0}) are the coordinates of the iris's center, (x_p, y_p) are the coordinates of the pupil boundary, and (x_i, y_i) are the coordinates of the iris boundary along the θ direction.

The rubber-sheet model is a linear mapping function. It accounts for scale and translation variants. The rotation variants addressed in the matching stage by selecting the best match among the n-shift iris template comparisons since rotation of an iris in the Cartesian coordinates is equivalent to a shift in the polar coordinates. The selection of reference points which can be the center of the pupil or the iris or a virtual center.

3. Motivation

Iris recognition accuracy is commonly affected by iris deformation caused by illumination changes, emotion, and medical condition and so on. When iris images are acquired in different illumination environments, pupil dilation and contraction generate serious iris elastic deformation, which leads to large intra-class difference. As shown in Figure 4, the iris images are from CASIA-Iris-Lamp Database [1].

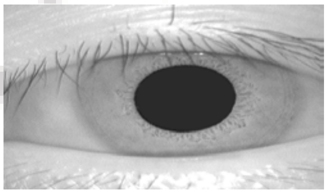


Figure 4: Deformed iris image

Usually, iris images are registered and recognized at different time, even by different devices. The changes of environment illumination make heavily deformed iris images ubiquitous in iris recognition so as to decrease recognition accuracy significantly. Thus in this paper we propose a deformed iris recognition method using bandpass geometric information and lowpass Ordinal features to solve this problem. This method decomposes iris images into different subbands and extracts different features based on the unique characteristics of subbands. The geometric features extracted in bandpass subbands based on key point detection are used to align deformed iris images and then alignment information is taken into account to help local Ordinal feature extraction in lowpass subbands. Furthermore, fusion of key point features and aligned Ordinal features is applied and classified using KNN classifier to achieve better recognition performance.

4. Technical Details

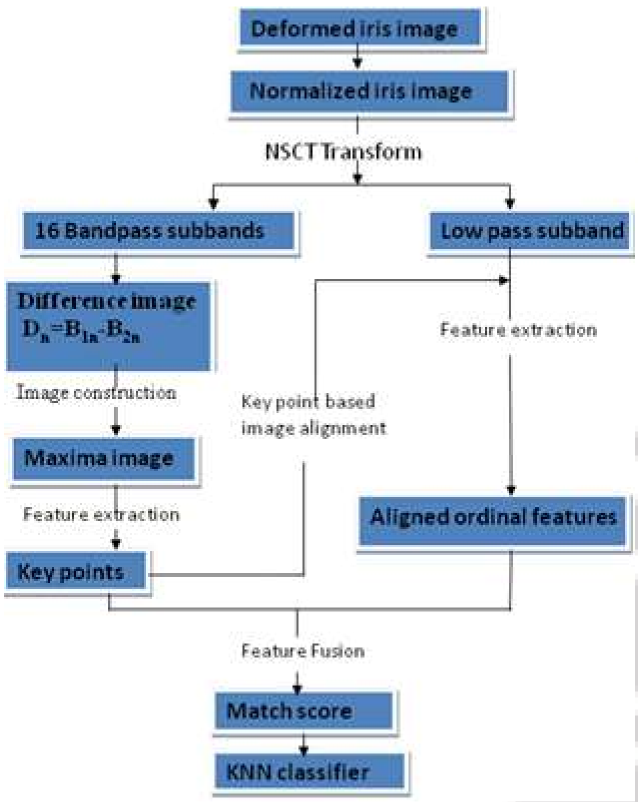


Figure 5: Flowchart of proposed system

4.1 Framework of proposed method

A novel deformed iris image matching method using bandpass geometric information and lowpass Ordinal features is proposed to address deformed iris image matching problem. In our work, deformed iris image is converted into normalized iris image using Daugman's rubber sheet model and then non subsampled contourlet transform (NSCT) is implemented to decompose normalized iris images for its multi-scale, multi-direction and shift-invariant properties. We find out that bandpass subbands contain smooth and strengthened iris texture boundaries, which makes bandpass subbands suitable to extract key points for deformed image alignment. Meanwhile, lowpass subbands contain less noise and less high-frequency information, thus they are suitable to extract local iris features. There are four main Blocks in the framework of the proposed method shown in Figure 5.

1) Apply NSCT to a Normalize Iris image: This Block is further divide into …..steps
2) Normalized iris image is decomposed into subbands at three different levels by nonsubsampled contourlet transform (NSCT). The first level stands for the lowpass subband and the other two ones represent bandpass subbands in 8 orientations, thus 1 lowpass and 16 (8 x 2) bandpass subbands with the same size are obtained.
3) All the subbands are labeled as B_0, B_{1n}, B_{2n} (n = 1,2,... ,8), where B_0, is the lowpass subband, B_{1n}, B_{2n} (n == 1,2, ...,8) stand for the bandpass subbands with 8 orientations
4) The difference between two subbands is computed in each direction using $D_n == B_{1n} - B_{2n}$ (n == 1, 2... 8), where D_n is named as 'difference image' in the nth orientation. Thus 8 difference images are created .Now at each pixel location (i, j), M(i,j) == max(D_n(i,j)), is calculated to get maxima image M(i,j) Figure 6.

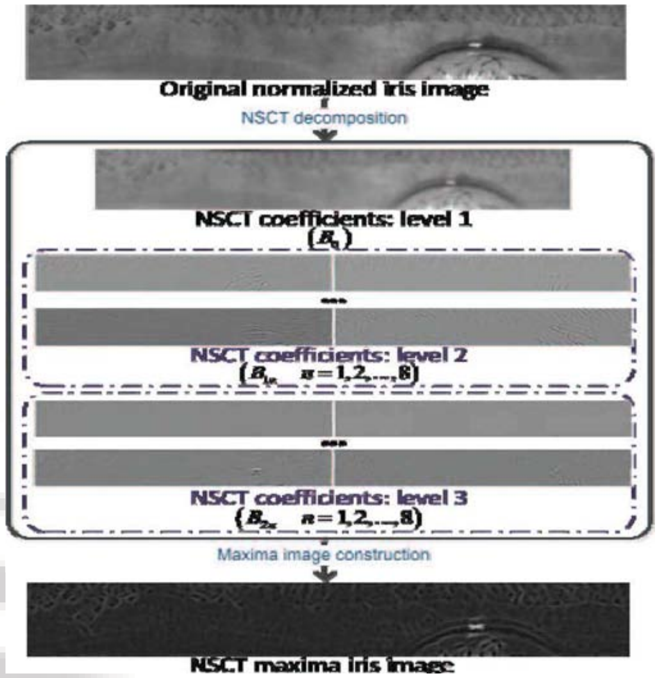


Figure 6: NSCT maxima iris image construction

1. Extraction of Key locations: To extract key points in the proposed method we have used maxima image M (i ,j) , because in maxima image the effect of noise is reduced and also boundaries of iris texture is enhance . In this block we have applied Speeded Up Robust Features (SURF) [2] to extract key locations. SURF is widely used to detect and match scale and rotation invariant interest points. In contrast to other existed key point matching algorithms (e.g. [7] [9]), SURF detects more scale and shift invariant key points faster and more accurately. The region of M (i, j) is split up regularly into smaller 4×4 square sub-regions. This preserves important spatial information. Then a 64-dimension feature for each key point is computed with the help of main orientation and gradient in scale space. Euclidean distance is taken to measure the similarity of key points from them.
2. Extraction of Ordinal Features: Ordinal features represent qualitative relationship between two pixels, instead of taking the real value of the two. For e.g. Two pixels 'A' and 'B' whether one is brighter or darker than another one. If one pixel is brighter than another one, it is encoded as '1'. Otherwise, it is encoded as '0'.

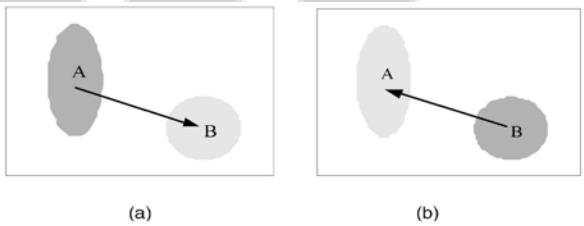


Figure 8: Ordinal measure of relationship between two regions. An arrow points from the darker region to the brighter one. (a) Region A is darker than B, i.e., A <B. (b) Region A is brighter than B, i.e., A> B.

Ordinal measures are robust to illumination changes, noise, etc. Sun et al [11] have used Ordinal measures to encode the qualitative relationship between different block regions in iris images. The locations of key points in band pass image are utilized to align Ordinal feature extraction in lowpass subband.

In this paper, multi-lobe differential filters (MLDF) are applied to extract Ordinal features of iris images. A Gaussian kernel is taken as the basic element of MLDF [11], which is expressed as

$$\text{MLDF}=C_m \sum_{i=1}^{Nm} \frac{1}{\sqrt{2\pi}\delta_{mi}} \exp\frac{-(X-\mu_{mi})^2}{2\delta_{mi}^2} - C_n \sum_{j=1}^{Nn} \frac{1}{\sqrt{2\pi}\delta_{nj}} \exp\frac{-(X-\mu_{mj})^2}{2\delta_{nj}^2} \quad (3)$$

where μ and δ describe the size of each lobe. N_m and N_n stand for the numbers of positive and negative lobes, respectively. And CmNm = CnNn is necessary to ensure the zero Sum of MLDF.

To align a deformed iris image,SURF key points have been extracted and matched in the maxima images constructed by bandpass subbands and locations of there are;

1. Calculation of Matching Scores and Classification

Step 1-3 are common for training dataset and real dataset . The final matching score of two images is

$$S(p, q) = S_{OM}(p, q) + \lambda \times S_{SURF}(p, q) \quad (4)$$

where p and q stand for trained image and real image respectively different normalized iris images.

$S_{OM}(p, q)$ is the Hamming distance between aligned Ordinal features of p and q,

$S_{SURF}(p, q)$ is Euclidean distance between SURF features . λ is a weight value to determine the relative importance of two kinds of features.

With the help of matching score generated classification is carried out using KNN classifier.

5. Experiments

5.1 Databases

The iris databases used in this section for algorithm evaluation are CASIA-Iris-Lamp. Which will be abbreviated as Lamp in the following. There are more than 800 classes and each class contains about 20 images. A lamp was tum on/off when iris images were acquired, thus heavy iris deformation was introduced into the database. The ratio of pupil radius to iris radius varies from 0.19 to 0.67 in this database. Most iris images from this database are low-quality, for instance, defocus, occlusion by eyelashes and eyelids, deformation and so on.

$$\text{DI}=\frac{|m_1-m_2|}{\sqrt{(\delta_1^2+\delta_2^2)/2}} \quad (5)$$

where m_l and m_2 are two means of intra-class and inter-class distributions, and variances of the two distributions are δ_1^2 and δ_2^2.

Table 1: Experimental results on the CASIA database

Method	*Equal error rate (%)*	*Discriminating index*
proposed	2.05	5.8625

5.2. Experimental results

All the iris images from the datasets are linearly normalized. Deformed iris image is converted into normalized iris image by Daugman's rubber sheet model as shown in below figure 'a'. Normalized iris image is decomposed into low pass and bandpass subbands as shown in figure 'b' & 'c'. From 16 bandpass subbands difference image is obtained and maxima image is constructed as shown in figure 'd'.

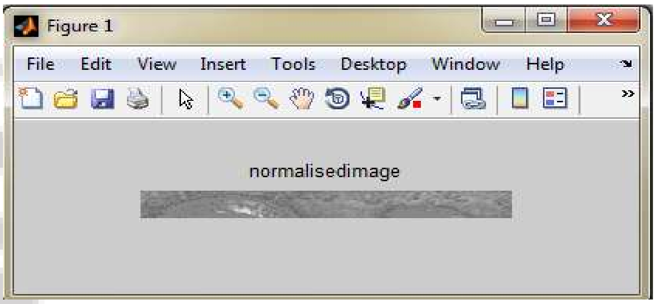


Figure 'a'

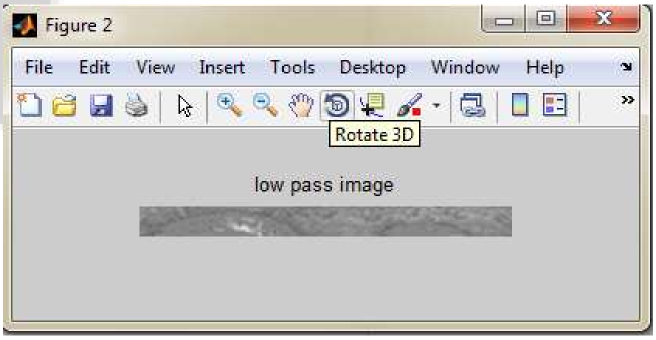


Figure 'b'

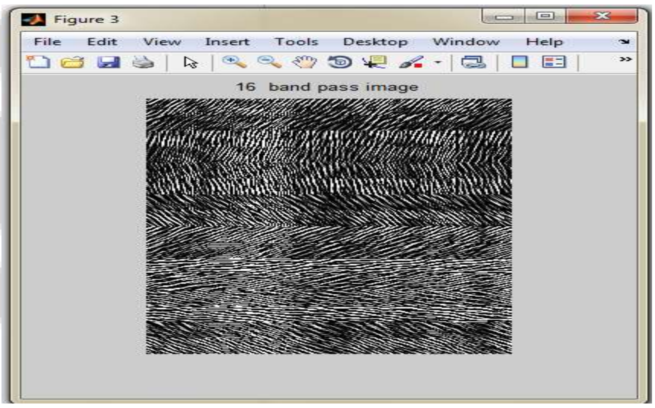
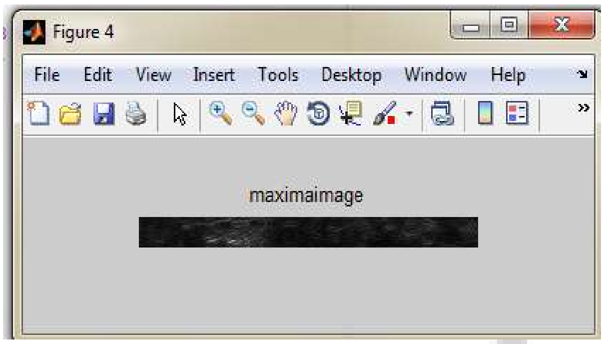
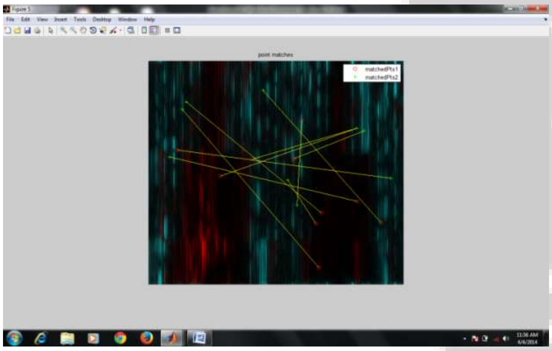


Figure 'c'

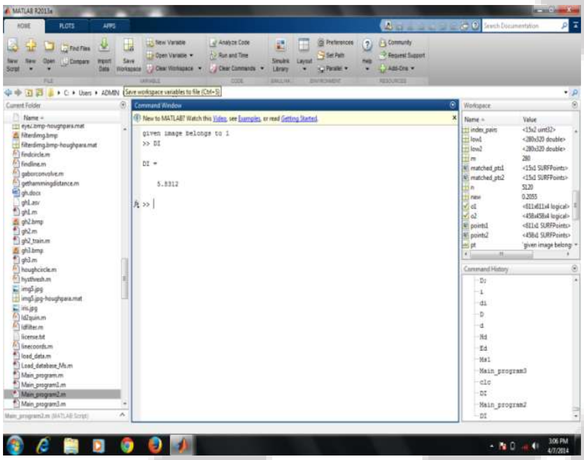


Figure'd'

SURF key points are extracted from maxima image as shown in below figure



By using the equation 5 we got the result of discriminating index of 5.8625



6. Discussion & Conclusion

In this work, we have utilized unique characteristic of NSCT. i.e. Minimum noise property of lowpass subband to extract ordinal features and stable property for alignment purpose, in bandpass subbands . The combinations of this property have led to extract hybrid features. The matching scores generated are used to classify deformed iris image to the iris database using KNN classifier. This algorithm is robust to deformation created by light. The experimental result shows that the proposed method is an effective approach which can reduce the error rates of deformed iris recognition. Since iris deformation is an important issue in iris recognition, we will continue to focus on deformation occurred due to other natural and environmental factors

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