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ORIGINAL RESEARCH

Investigation on automated surveillance monitoring for human identification and recognition using face and iris biometric

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Abstract
Nowadays, Biometric system automatically identifies the unique feature of an individual for better evaluation and verification in recognition systems. Face and iris recognition in biometric identification systems is considered as most accurate procedure with higher recognition rate. CCTV surveillance plays a major role in human recognition and identification with the help of intelligent systems. The biometric system combined with CCTV output analyzes the data with/without human intervention. This paper presents an approach of human identification with recognition using facial and iris biometric from lower resolution images. Also, Lower resolution in image clarity is a major constraint in recognizing the individuals from distance with biometric values. To overcome problem in individual recognizing, the combination of Gabor and Legendre filter is combined. The use of hybrid log-Gabor–Legendre (LGL) filter improves the recognition pattern of face and iris in multi-spectral images. After log Gabor–Legendre filtration, two new techniques such as phase quadrant method for iris and LGBPHS method for face are used to improve recognition pattern. Hence, a framework comprising of feature recognition using LGL filter and similarity comparison using score level fusion is proposed. A series of stages enhances well the recognition performances using the proposed solution. Experiments established the validity against existing linear techniques for facial and iris image recognition pattern from CCTV cameras for automated human identification and verification.

Keywords Log-Gabor filter · Face and iris · Recognition · Identification · Surveillance monitoring

1 Introduction

There is need of human recognition and verification schemes due to widespread of automated verification identity systems. Since, each area is equipped with surveillance cameras, the use of biometric identify systems is made inbuilt in such systems to improve the automated verifications (Pravinthraja and Umamaheswari 2011). Iris and facial recognition are considered as the best choices since facial recognition is non-invasive and iris recognition is most accurate one (Jain et al. 1999; Mansfield et al. 2001). On the other hand, the issue in resolving the biometric recognition is still needs to be addressed, since the accuracy of face is affected mostly by illumination, expression and pose (Zhao et al. 2000). Facial recognition in many applications seems robust with all these variations. The iris recognition is considered to be less accurate, since the user has to be co-operative. In advance, the image of iris should be of high quality, since iris image with larger pupil and off center (Kumar and Srinivasan 2013) is rejected at the acquisition phase. Consequently, many attempts are made for acquiring the iris that should not delay the recognition and verification and not to irritate the user. The accuracy of iris recognition is also affected by change in shape of iris due to disease. This results in poor identification of iris in automated identification systems. The enroll failure rate or the rejection rate of poor quality image would tend to increase in these cases.

These problems are resolved or the impact of these problems can be reduced through fusion of several biometric recognition systems. This includes iris and face recognition in the proposed system. The overall error rate is reduced due to fusion of several classified results (Hong and Jain 1998). Therefore, spoof attacks can be reduced using this fusion process. The population coverage of the fused method gets larger

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coverage than standalone recognition systems. The people with several disabilities are captured with other biometric identities. The combining of classifier uses increases the processing speed of the recognizing systems. However, combining classifier further makes the user to be captured with more biometric identities. This identity has to be captured previously in the database for accurate classification. The acquisition stage with more biometric identities increases the processing duration and space. The combination of iris and face helps in simultaneous acquisition of these biometric images. This combination creates no additional inconvenience. The face recognition with iris reduces the enroll failure rate, though either the iris or the facial are dissimilar and not the both images.

The combination of the biometric identities increases the work done to classify the instances (Kittler et al. 1998; Skurichina and Duin 2002). Hence, to improve the work done by the system, additionally; the use of Log-Gabor filter is employed during the phase of acquisition. Gabor features is effective in extracting the discriminate information for a biometric system that includes iris (Daugman 2007) and face (Serrano et al. 2010). This achieves a trade-off between the spectral and spatial resolution during brain cortex mimics (Daugman 2002).The typical recognition approach of Log-Gabor iris recognition is shown in Fig. 1. The region of iris is segmented from the eye and then normalized to form a rectangle of fixed size. This is done usually before the encoding phase that creates iris code (Daugman 2004) using phase-quadrant wavelet Log-Gabor encoding technique.

Log-Gabor face recognition system is done through analytical and holistic approaches as shown in Fig. 2. While the analytical approach computes local response of iris image

Fig. 1 Iris recognition

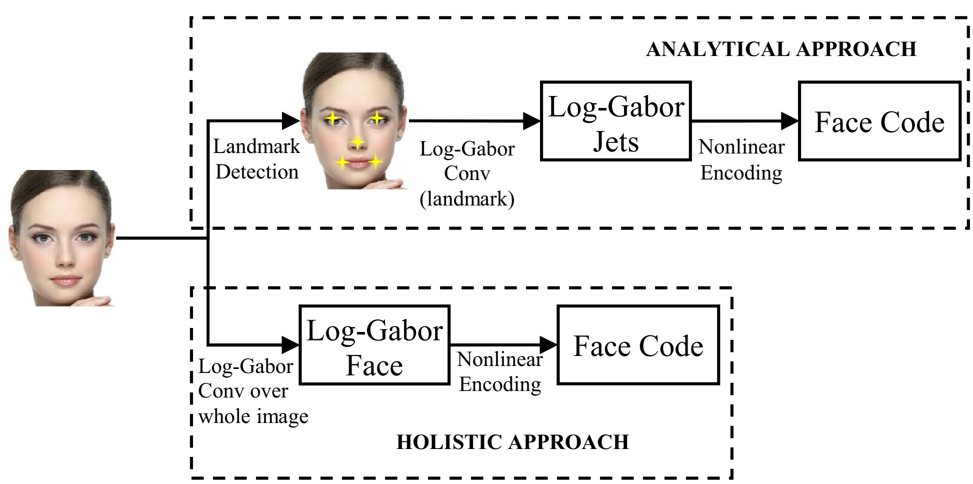
using discrete wavelet—Log-Gabor filter in a discrete set of locations. The holistic approach uses global response characteristics processed subsequently using encoding techniques (Nguyen et al. 2011a). This paper uses holistic approach as they relate closely with the aligned iris techniques that makes the proposed technique a more practical one.

In spite of the superior performance in recognition process than linear methods like PCA and LDA (Daugman 2007; Serrano et al. 2010), the Log-Gabor-based filters are not conventionally deployed for feature domain high resolution. The main confrontation that avoids feature high resolution domain that contains the iris and facial image in applying successfully over Log-Gabor encoding is the nature of non-linearity during encoding procedure. This includes phase-quadrant technique (Daugman 2004) for iris and Local Gabor Binary Pattern Histogram Sequence technique (Liu and Wechsler 2002), Gabor Fisher Classifier technique (Liu and Wechsler 2002) and Kernel PCA technique (Liu 2004) for face.

From the many traditional image quality assessment algorithms, Gabor model is developed for content images by Daugman (1985). Also the result of Gabor is highly consistent with HVS response by naked eyes. Further for better signal representation, Gaussian distribution with log scale representation is used in Log Gabor filter technique (Field et al. 1987). Log Gabor filter is also used in various shape identification purposes. So that we choose log Gabor in our proposed system. But one drawback is, it simply worked on sinusoidal plane wave with Gaussian distribution. To standardize the work (Massot and Hérault 2008), we use Euler transform as Legendre filter. Legendre filter works on polynomial degree standard. Also there is two main reasons to use lo Gabor model. First, it does not have DC component. So content of image is not delivered. i.e. day or night image must feature must not change. Second is, it provides bandwidth as needed. Bandwidth can be tuned as per the need. Whereas gabor has fixed bandwidth.

The conventional feature high resolution domain framework in Gunturk et al. (2003), Nguyen et al. (2011a),

Fig. 2 Face recognition



Jia and Gong (2005) are unable to resolve the nonlinear features of Gabor features. The proposed method improves further the performance of recognizing the feature high resolution domain approaches applied over biometrics. Thus, a framework is proposed that enable the features of high resolution domain in nonlinear features such as Gabor phase quadrant for iris and LGBPHS (Liu and Wechsler 2002) for face. In this paper a framework is developed that fused face and iris verification system at final stage that overcomes the inherent difficulties in standalone classifiers. The results of the proposed combined classifier are compared with the individual classifier results of face and iris. To avoid non-linearity in the encoding, Log-Gabor features for both iris and LGBPHS (Liu and Wechsler 2002) for face is deployed in the proposed technique.

The outline of the paper is as follows: Sect. 2 gives recent survey on biometrics and extraction process, Sect. 3 includes the proposed framework for automated surveillance. Section 4 evaluates the proposed method with existing technique and Sect. 5 concludes the paper with future work.

2 Literature review

In the research article (An et al. 2019), mostly used Gabor filter and Legendre wavelet filter are used feature selection in CASIA, UBIRIS datasets. This result shows that Legendre wavelet filter increase its accuracy than Gabor wavelet filter. The face recognition in Zhang et al. (2019) uses normalization feature methods. Adaptive pose alignment (APA) is used to recognize the pose of face by deep representation using softmax or ArcFace using softmax and effective normalization feature. The fusion method for the sparse representation in Tadic et al. (2020) multiplication fusion is applied. Here, it does not require artificial weights. Correlation error, classification error and score is obtained. Next two step face recognition with help of original training samples and training samples can achieve most perfect face recognition. The circular Gabor filter (Dargan et al. 2019a, b, c) with fuzzifying parameters and filter achieved additional selectivity. Circular objects and deformed circular objects are extracted efficiently with resistance to noise and degrading of images is achieved.

The deep learning survey in Dargan et al. (2019a, b, c) studied about its basic and advanced design, also discussed about new techniques. The Classical and conventional machine learning algorithms with its advancement is discussed. The real time applications with deep learning features are also discussed. The survey on biometric system in Kumar et al. (2019) is a deep literature work on unimodal, multimodal biometric techniques with feature extraction, classifiers, datasets, and reliability. The various classical methods, taxonomies, influential methods are justified in this article based on biometric parameters. Classifiers and its comparison are discussed in Gupta et al. (2020) with characters of gurmukhi and recognizing numerals. The various classifiers algorithms such as linear-SVM, K-NN, RBFSVM, decision tree, Naive bayes algorithm, neural networks, random based forest classifiers are studied. In study result, random forest classifiers produce the result better than other classifier algorithms.

The 2D-images used by feature based method in Chabra et al. (2020) such as speeded up robust features (SURF) and and scale invariant feature transform (SIFT) are implemented. With these, decision tree and random forest has been experimented. Accuracy is improved. Two types of image extractor using image feature is implemented in Dargan et al. (2019a, b, c). They are oriented fast and rotated brief (ORB) and scalar invariant feature transform (SIFT) are used. The ORB detects the picture using fast key and SIFT is used to analysis the image based on orientation scales. K-means clustering used in all the descriptors. Locality preserving algorithm is further used in dimensionality reduction. It is a biometric text based on handwriting of individual. In this paper in Dargan et al. (2019a, b, c) it employs machine learning and pattern recognition algorithm for framework generation. Here, author's segments the characters prior and the state of art job is presented for devanagiri script. Four extraction methods of zoning, diagonal, transition and peak extent features are used. Then classification process is done using K-NN and linear SVM are used with accuracy. To reduce the image noise, the authors in the Kumar and Jindal (2018) introduced new method of CLAHE algorithm (Contrast Limited Adaptive Histogram Equalization). They also increase the image contrast. The two model such as Red–Green–Blue (RGB) and Hue Saturation-Value (HSV) uses histogram with modification. CLAHE first identify red part and stick to it and next stage HSV color model is suggested.

Automatic face recognition plays important role (Kumar et al. 2018) in face recognition, facial expression; head pose estimation, human computer interaction. The digital images of humans are detected using its location and size of image in the digi print. This is one type of computer technology. This review explains techniques about face recognition. The classifier using random forest algorithm for the face detection is suggested in paper (Arora et al. 2018). Here they recognize the emotions in the face images. Japanese female facial emotions are considered as experimental results. It can be also used in electroencephalogram with interfaces of computers in real time. Hybrid approach of gradient filter, PCA, PSO has been implemented for facial recognition and it performs better than existing algorithms.

3 Proposed log-Gabor–Legendre framework

The iris and face systems uses Log-Gabor–Legendre filter that computes the global response by convolving entire image with the filter. The images are encoded further using non-linear methods such as phase-quadrant approach for iris recognition and local Gabor binary pattern histogram sequence (LGBPHS) approach for face recognition. The non-linear approaches computes the global response values of normalized iris and facial image using LGL wavelet filters before encoding with phase quadrant and LGBPHS (Fig. 3).

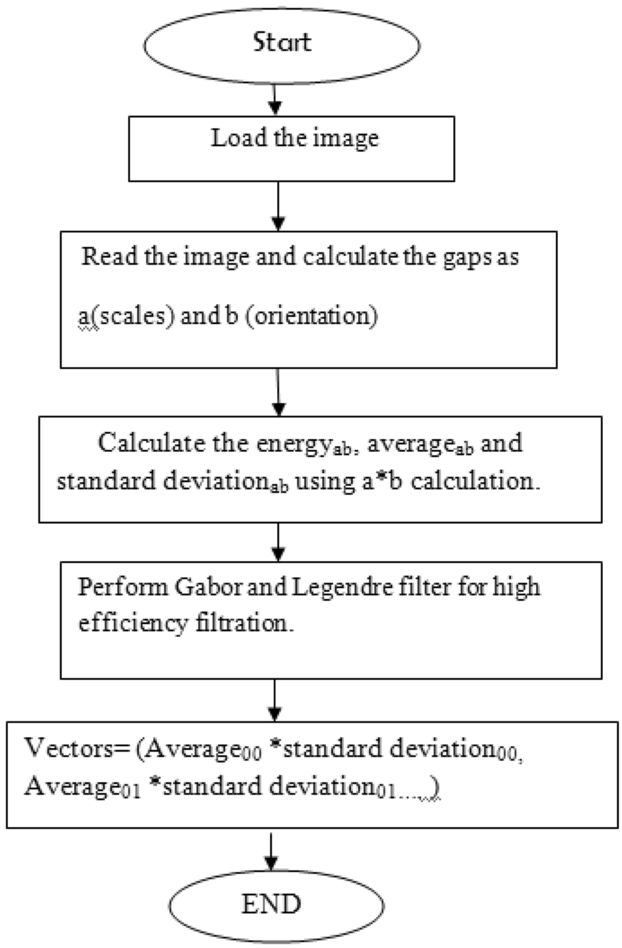


Fig. 3 Flow diagram for LGL filtration

The LGL filter is linear with nonlinear methods of encoding techniques results from phase quadrant method for iris and LGBPHS method for face. Hence, feature HR domain is carried out in Log-Gabor response than final encoding features. The LGL response represents a complex 2D LGL form. The observation on the non-linear origin, a framework is proposed and applied over feature HR domain through nonlinear Log-Gabor features as shown in Fig. 4.

3.1 Face recognition

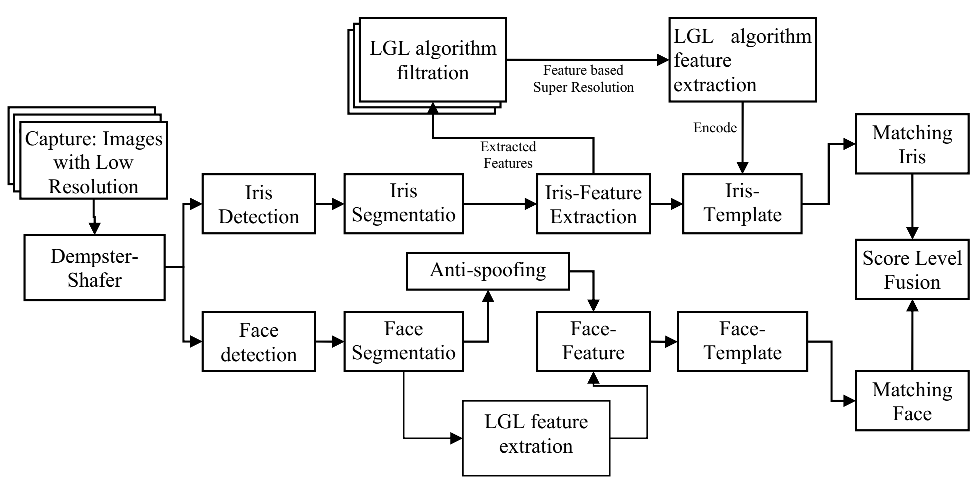
3.1.1 Acquisition and segmentation

The face detection module locates the reference points and presents a pseudo-front pose. Viola-Jones algorithm (Lee et al. 2013) is implemented for localization of pertinent regions in facial image. The pose of the face is corrected before it proceeds with recognition process. Here, illumination correction is done through smoothening filters and the ratio between the corrected and smoothened image is computed. This provides a light-invariant representation of facial image. The pixel value of each image is divided using neighborhood mean value or square mask (n × n) size. The correction process produces quality indices that reject the biometric samples that poor support recognition.

3.1.2 Anti-spoofing detection

3D geometric invariants are adopted for facial structure estimation. Once this is done, the technique finds the distance between the reference points of the face. Though the reference points might subject to change, however, certain points tend to remain the same. These geometric invariants are applied with anti-spoofing technique that applies the principle in reverse direction. A set of 5 points are exploited from the face that includes right eye, left eye, nose tip and extreme right and left of the lips. The co-planarity constraint for these five sets is strongly violated. The spoofing

Fig. 4 Framework of the proposed LGL system



technique estimates the invariants when the face position changes. When the face position is changed, the spoofing detection estimates the geometric invariants invariant relative to reference points identified. If invariant holds, point corresponds to the co-planarity and if this is not the case, then the face is said to be spoofed. Otherwise if the reference points are coplanar and the facial points are guaranteed, the captured image is said to be real. The anti-spoofing determines the matrix determinants ration that is fast and a straightforward technique.

3.1.3 Template selection

The CCTV camera captures maximum number of frames for maximum recognition accuracy. Here, the selection strategy is based on entropy selection that saves the computational complexity. The normalization procedure is avoided and that improves the frame quality after the face localization. The correlation between the all facial pairs are acquired from frames and the correlation index over interval [−1,1] is normalized to [0,1] that sum up to unity. The difference algorithm in Keys (1981) for best facial selection is treated as a localized correlation index version and this is used for similarity measurement.

Probability distribution on whole sample set calculates the entropy. Then, the module for selection removes an individual sample at a time over entire set and recalculates the remaining set is calculated for its entropy. A difference value between the entropy (before) and entropy (after) is taken for sample elimination. Entire samples in the set is captured and extracted to produce minimum difference. This is removed permanently and then the process repeats. The sample that is remaining at final is considered as best sample and submitted over to the next stage.

3.2 Feature extraction and matching

The spatial correlation between two images with its mean value M_1 and M_2 for each pixel intensities is calculated as:

$$s(M_1, M_2) = \frac{\sum_{i=0}^{n-1}\sum_{j=0}^{m-1}\left(M_1(i,j)-\overline{M}_1\right)\left(M_2(i,j)-\overline{M}_2\right)}{\sqrt{\sum_{i=0}^{n-1}\sum_{j=0}^{m-1}\left(M_1(i,j)-\overline{M}_1\right)^2\sum_{i=0}^{n-1}\sum_{j=0}^{m-1}\left(M_2(i,j)-\overline{M}_2\right)^2}} \tag{1}$$

In recognition procedure, correlation is adopted locally over the sub-regions ofM_1 and M_2. Each sub-region maximizes the correlated coefficient s, i.e. searched and that extends to a narrow window over M_2. The global correlation, S is the sum of local maxima and that achieves better accuracy during recognition.

$\left(M_1(i,j)-\overline{M}_1\right)$ Difference between the located sample locations of M_1 sub-region.

$\left(M_2(i,j)-\overline{M}_2\right)$ Difference between the located sample locations of M_2 sub-region.

To improve the recognition performance, pre-calculation is taken place. During verification, the user with a specific identity is claimed using an identification protocol. This matches the facial image matched against the stored images in gallery. For registered user identity in gallery stores more images. When a query image is complied, a comparison of all images is done and that calculates the correlation indices. The final values are arranged in descending order and the identity with more images is retained in the first positions. If gallery possesses only a single image per user, the first identity retrieved is returned.

Consistently, global spatial correlation value/similarity measured value is then normalized to [0, 1] range and then subtracted from 1 to get transformed to a distance in the equivalent range.

3.3 IRIS recognition

3.3.1 Acquisition and segmentation

In eye images, the acquisition capture procedure includes maintaining the frontal pose that avoids off-axis problem. The user is captured until he/she reaches the camera at the closest. The segmentation algorithm is devised to undercontrol the acquisition conditions and computational time.

- *Preprocessing* The eye image with many details like pores, lashes etc. interfere negatively and hinders segmentation. A pasteurization filter, which moves the entire image into a square window is applied. The image is applied pixel by pixel and then the histogram is computed for the iris region contained and the maximum frequency value is then substituted.
- *Pupil location* Canny filtering is applied on preprocessed image with 10 different thresholds. A fixed step is chosen that explore uniformly in its permissible range. Adaptive threshold techniques applied over other specific range that completely explores the iris region. This forms a circular region with the threshold values and the iris is perfectly circular. If the pupil are not perfect circle then approaches search for possible elliptical shapes and the same techniques is applied over it.

The noise erroneously affects the results of elliptical fitting algorithms and fast circle detection is carried out with Taubin's algorithm (Lin et al.2007). The extraction of real pupil boundary is done through voting procedure that includes summing up the two different measures in De Marsico et al. (2010a, b) i.e. separability and homogeneity. The circle possessing the uppermost score is treated as the perfectly circular that approximates better hepupil.

- *Linearization*: This is done in order of performing limbus location, where the image is transformed first to polar from Cartesian coordinates. Pixel with maximum distance from the center of pupil circle is the starting points for the transformation no fan image.
- *Limbus location*: For the polar image, a median filter is applied and weighted difference is calculated for the columns corresponding to θ_i on horizontal axis that ranges overρ_j on the vertical axis.

$$\begin{aligned}\Delta\left(\rho_j,\theta_i\right) &= \gamma\left(\dot{M},\rho_j,\theta_i\right)\cdot\ddot{M}\\ \ddot{M} &= \left(\dot{M}\left(\rho_j+\delta,\theta_i\right)-\dot{M}\left(\rho_j-\delta,\theta_i\right)\right)\end{aligned} \tag{2}$$

where $\dot{M}$ is the polar co-ordinate.

$$\gamma\left(\dot{M},\rho_j,\theta_i\right)=\begin{cases} & if\ \dot{M}\left(\rho_j+\delta,\theta_i\right)-\dot{M}\left(\rho_j-\delta,\theta_i\right)>0\\ 1 & \text{and}\\ & \min\left(\dot{M}\left(\rho_j+\delta,\theta_i\right)-\dot{M}\left(\rho_j-\delta,\theta_i\right)\right)>g\\ 0 & \qquad otherwise\end{cases} \tag{3}$$

The points are identified with greater positive variation indicating the transition from darker to lighter zone. The first inequality chooses the point with positive gradient and the next one prescribes darker pixel by ruling out the points between iris and pupil by. This exceed the threshold level of $g \in [0,255]$ or ($g=50$). Points that exploit (2) over θ_i in M structures the limbs. The outliers are discarded in polar space and the limbus point lies on line and has a constant ρ component.

3.3.2 Feature extraction and matching

The extraction is done through Cumulative SUM algorithm (DeMarsico et al. 2012). The method analysis the local gray levels variations and robust under controlled iris conditions. The algorithm is then applied over polar image and involves the following procedure:

Step 1 Normalized iris image is divided in to cell regions, where cumulative sum is calculated.

Cell region with 3×10 pixels with mean gray value is treated as the typical value for the cell region with subsequent calculations.

Step 2 Vertical and Horizontal grouping of cell regions (4 cells); There presented values are computed over each groups.

Step 3 Cumulative sums calculation over each group:

Thus by comparing, iris code for each group is obtained with 2 cumulative sums.

IF Value 1 or 2 is assigned for a cell: value contributes for an upward or downward slope.

Else value 0 assigned.

Iris code Matching is calculated through hamming distance.

4 Proposed LGL filtration and extraction

In this proposed methodology, log Gabor based Legendre Wavelet filter is designed in the same manner to which the Wavelet filter is developed. However, the Legendre Wavelet filter is developed based on the order of its polynomial, so we only consider the Legendre Wavelet at its first order of its polynomial. The Legendre with log Gabor Wavelet filter is a linear filter used for texture analysis. It studies about specific frequency present in certain direction in image localized area of analysis. The more contemporary researchers prove about frequency representation and orientation representation in wavelet filter is similar to human visual systems. Though there is no evidence frequency and orientation idea. Researchers consider they are most fitted for texture identification and discrimination.

In domain of spatial ability, function of Gaussian kernel with Euler transform of 2D Log Gabor Legendre (LGL) filter modulated with sinusoidal wave and constructed based on degree of polynomial. The algorithm for LGL 2D filter is shown below. First algorithm initialize the function arrays for 2D LGL arguments as a,b,c,d. After initialization size of filter is 2D and verified with number scale variables and orientation variables. Next step is to create LGL filter using array. Then the array is initialize in cells a,b. Further the value of variables is declared. Loop with values a,b with m,n is assigned. Finally LGL array with i,j dimension is assigned to filter. Finally LGL filter is constructed as a*b of scale 'c' and 'd' orientation. The filter size is initialized using a*b products value.

Feature extraction is performed with further algorithm steps as follows. First half of algorithm gives normalized image as output; now normalized image is processed for feature extraction. It checks iris and face image are in grey scale. If it is gray scale, then the image feature is extracted in filter and returned. Consider an example, LGL filter vector is 2, face is 12*12, iris is 12*12 then size of image is 12*12*4 = 576. Let choose down sample factor as, 4*4 = 16. Final image size is 576/16 = 36. Down sampling factor is used to reduce the size of image.

The Scale and orientation (a*b) value is assumed as 1.In LGL closely look at further increase in filter size. Now the normal gabor filter with LGL filtered iris image is shown below using MATLAB in Fig. 5.

Algorithm 1 :

Initialize : Scales c, orientation d, row size a, column size b.
Set LGL parameters p1=p2=1,a1=a2=b1=1 as one.

1. Compute b1=b2=2n-1.
2. Set maximum value max =0.50
3. For i=1, do with c as,
4. Compute c= max/ $\sqrt{2}^{i-1}$
5. For j=1; do d as,
6. Compute Θ_c using J-1 /d.
7. // LGL FILTRATION

Compute gaussain and euler process parallel to extract
// Gobar filter //

$$f(a,b) = \sum_{i=0}^{b-1}\sum_{j=0}^{a-1} \frac{(a(i,j)-a')(b(i,j)-b')}{\sqrt{\sum_{i=0}^{b-1}\sum_{j=0}^{a-1}(a(i,j)-a')\sum_{i=0}^{b-1}\sum_{j=0}^{a-1}(b(i,j)-b')}}$$

Legendre filter

$$x' = \left(x - \frac{a+1}{2}\right)\cos(\gamma_c) + \left(y - \frac{b+1}{2}\right)\sin(\gamma_c)$$

$$y' = -\left(x - \frac{a+1}{2}\right)\sin(\gamma_c) + \left(y - \frac{b+1}{2}\right)\cos(\gamma_c)$$

8. // 2D LGL //

$$lgl(filter) = \sqrt{(a1+0.5)(b1+0.5)}\ \ 2^{\frac{p1+p2}{2}} \times ka(2^k x' - n)kb(2^k x' - n)e^{i2\pi(a1c1 \times b1d1)}\ ;$$

Stop for loop;

Return lgl array(i,j);

end

9. // Feature extraction //

Determine the array size

For (i=1;j=1;++)
Filter the image using lgl array i,j images feature
End

Select the down sampling for extraction
Normalization is performed for extracted image with mean ,variance.
Return normalized result.
End.

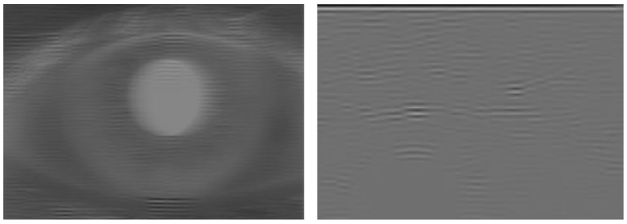


Fig. 5 **a** LGL output a = b = 20, **b** Gabor output

4.1 Feature high resolution domain approach

This section gives the observation in spatial domain since it uses, *D*, *B* and *W* parameters, here, *x* be the HR facial image and y be the iris image, hence the relation between *x* and *y* is defined as:

$$y(i) = [D(i)B(i)W(i)x + n(i)]$$

The observation model is transformed from spatial to feature domain (Fig. 6). The non-linear Log-Gabor-legendre features that includes phase-quadrant features for iris and LGBPHS technique for face of HR image, *H* and LR image *h*, is signified as,

$$\text{Face}: \begin{array}{l} H_{\mathrm{Re,Im}} = sign\left(G_{\mathrm{Re,Im}}\right) \\ h^{(i)}_{\mathrm{Re,Im}} = sign\left(\left(g^{(i)}_{\mathrm{Re,Im}}\right)\right) \end{array} \tag{4}$$

$$\text{Iris}: \begin{array}{l} H_{\mathrm{Re,Im}} = L^{*}\left(G_{\mathrm{Re,Im}}\right) \\ h^{(i)}_{\mathrm{Re,Im}} = L^{*}\left(\left(g^{(i)}_{\mathrm{Re,Im}}\right)\right) \end{array} \tag{5}$$

where $G_{\mathrm{Re,Im}}$ and $g^{(i)}_{\mathrm{Re,Im}}$ are considered as the complex-2D Log-Gabor-Legendre features of HR iris and faces.

The Low Resolution iris and faces details are given by,

$$G = x\left(\exp\left(-\left[\log\left(\frac{\rho}{f_0}\right)\right]^2 \Big/ 2\sigma_\rho^2\right).\exp\left(-\left[\left(\theta-\theta_0\right)^2\right] \Big/ 2\sigma_\theta^2\right)\right) \tag{6}$$

$$g^{(i)}_{\mathrm{Re,Im}} = x^{(i)}_{\mathrm{Re,Im}}\left(\exp\left(-\left[\log\left(\frac{\rho}{f_0}\right)\right]^2 \Big/ 2\sigma_\rho^2\right).\exp\left(-\left[\left(\theta-\theta_0\right)^2\right] \Big/ 2\sigma_\theta^2\right)\right) \tag{7}$$

where $\rho$and θ- polar coordinates, f_0—Filter center frequency, θ_0- orientation angle, σ_ρ- scale band width and σ_0- angular bandwidth.

From, Eq. (7), it is observed that the log-Gabor–Legendre function is symmetrical with log-axis in spite of the linear frequency. This yields much more effective image representation. In fact, the tail is featured in the linear axis higher frequency, which is correlated with the amplitude fall-out of images. The lower frequency redundancy in reduced further and that achieves effective frequency spectrum coverage. Also, the DC-component of Log-Gabor-Legendre filter is considered zero and hence each filter bank's bandwidth is enlarged. The required total number of overall filters is reduced w.r.t to standard Gabor filters.

Assume that the spatial observation model is made inbuilt in the feature HR domain,

$$g^{(i)}_{\mathrm{Re,Im}} = [D(i)B(i)W(i) + n(i)]x^{(i)}_{\mathrm{Re,Im}} \times\left(\exp\left(-\left[\log\left(\frac{\rho}{f_0}\right)\right]^2 \Big/ 2\sigma_\rho^2\right).\exp\left(-\left[\left(\theta-\theta_0\right)^2\right] \Big/ 2\sigma_\theta^2\right)\right) \tag{8}$$

where *D* Down sampling, *B* Blur, *W* Wrap and *n* noise degradation.

This filter helps in providing HR pixels in feature domain and once this is formed, the iris image is sent further for other process.

4.2 Fusion matching

The fusion matching adopts confidence values between the iris and face systems that fuses the respective returned distances. The two returned values for face is $\varphi_f$and for iris it is φ_i.

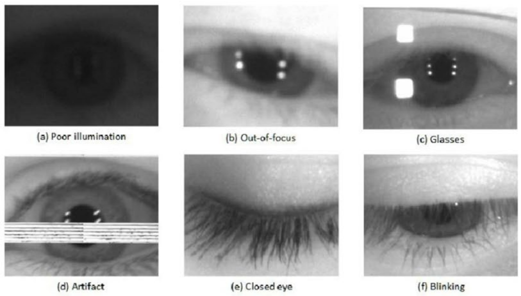
$$d = \frac{\varphi_f}{\varphi_f + \varphi_i}\cdot d_f + \frac{\varphi_i}{\varphi_f + \varphi_i}\cdot d_i \tag{9}$$

where $\frac{\varphi_f}{\varphi_f+\varphi_i}\cdot d_f$ represents the confident value of the facial image. $\frac{\varphi_f}{\varphi_f+\varphi_i}\cdot d_f$ represents the confident value of the iris image.

φ_f and $\varphi_i$indicates the function applied over the galleries. These are considered as the weights assigned over the distances for producing the weighted sum corresponding to global distance.

5 Dataset

Experimental verification for face and iris is conducted on MBGC dataset (B. Gunturk et al. 2003). This evaluates the proposed framework validity over 628 NIR iris video of 129 individuals against 8589 NIR HR iris images. The resolution of iris (still) image is 220 pixels across the iris boundary diameter and resolution of portal videos is only 90 pixels



(a) MBGC iris dataset with various iris patterns [22]

(b) MBGC Face dataset with various Facial patterns

Fig. 6 **a** Iris. **b** Face

across iris diameter. The Fig. 7 shows the degradation factors that reduces the iris image quality. The training dataset has 10 iris still images and a single video sequence. Also, for testing remaining nine video sequences over each identity is matched with the high resolution image.

The frames of each video are evaluated for quality purpose. The quality metrics (Nguyen et al. 2011b) evaluate each frame quality that includes illumination variation, focus, motion blur and **off angle appearance**. These are fused together with the help of Dumpster-Shafer theory. This theory improves the overall score of quality (Nguyen et al. 2011b) of each individual frame. However, the optimal frames may vary for a different database. For face, videos over MBGC dataset focus on confines eyes for recognizing the iris. The faces in videos contain facial images very rarely and it is ideal to use low resolution (LR) imagery. The entire dataset has 3482 h images for 129 individuals. The face images (visible) at high quality (2616 × 3904) are captured. The facial image (high quality) is set as a reference image, while other 10 visible facial (high quality) images of each identity is degraded using Gaussian blurring, warping and then down sampled to 40 × 40 pixels. Thus 10 LR sequences of 32 frames are formed. Initial five images are used for training and other 5 are used for testing.

For both face and iris images, LGL feature are extracted from each image sequence with a single identity. The identities are extracted using global convolution of normalized image in sync with LGL filter. The LGL features are combined with feature HR domain approach that generates HR feature. Consequently, the HR resolved features of iris images are encoded through nonlinear techniques. In this paper, phase-quadrant for iris image, and LGBPHS for facial image is used. The final features are matched with the HR images in database and the similarity scores of different points of face

Fig. 7 Comparisons between linear and nonlinear features in feature HR domain: **a** Iris, **b** Face

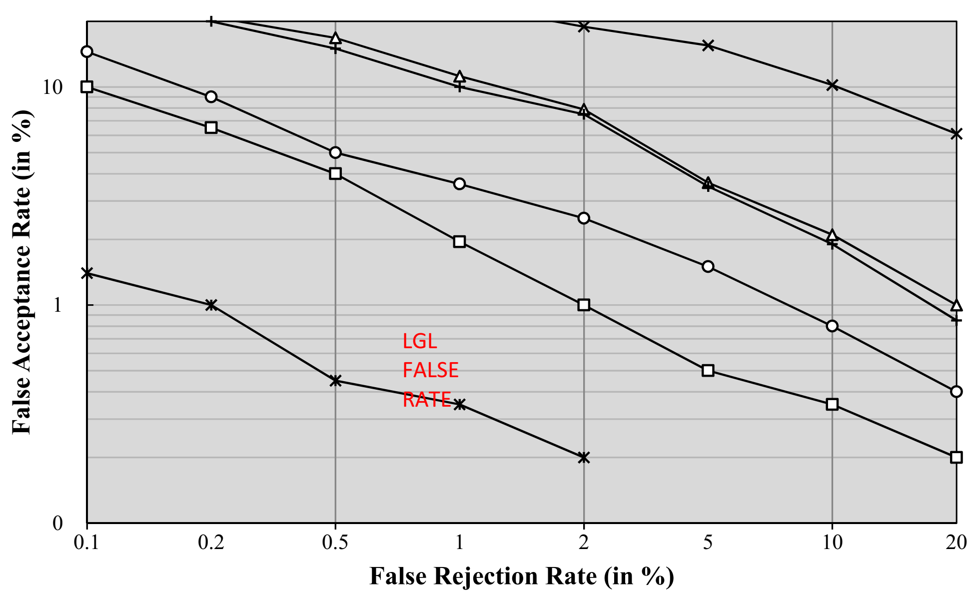


Table 1 False rejection rate (in %) of iris

FRR (%)—*in log scale					
2D LGL	LDA	PCA	2D LGL SR	LDA HR	PCA HR
10	25	42	1.4	14.5	24
6.5	21	36	1	9	20
4	16.8	31	0.45	5	15
1.95	11.2	24	0.35	3.59	10
1	7.89	18.9	0.2	2.5	7.5
0.5	3.64	15.5	0	1.5	3.5
0.35	2.1	10.2	0	0.8	1.9
0.2	1	6.1	0	0.4	0.85

Table 2 False rejection rate (in %) of face

FRR (%)—*in log scale					
LGL-LGBPHS	LDA	PCA	LGL-LGBPHS HR	LDA HR	PCA HR
45	60	60	17	50	60
44	60	60	14	47	60
41	60	60	9.5	46	52
26	45	60	5	41	48
15	42	57	1.9	28	45
8.7	33	54	0	19.5	24
2	15	42	0	8.5	15
0	5	28	0	4	12
0	2	5	0	0	5
0	0	3	0	0	1

and iris patterns are noted. Detection Error Trade Off plots from the similarity scores are used to prove the effectiveness of iris and facial recognition of different approaches. Experiments are conducted in order to compare the performance of the proposed framework based feature HR domain using linear features with pixel domain techniques. The experimental results are presented in following sections.

6 Evaluation of log-Gabor–legendre framework

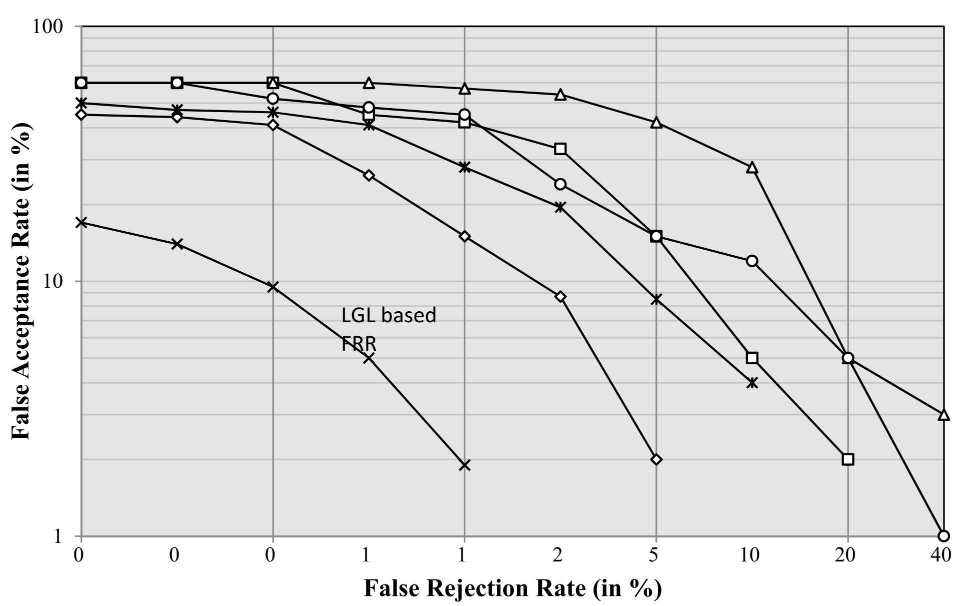
6.1 Linear vs. Nonlinear features

The linear features include PCA and LDA for iris (Field et al. 1987) and face (Daugman 1985) is employed over feature HR domain. An advantage of retaining non-linear Log-Gabor-Legendre features over linear techniques like PCA and LDA is established. With neglecting the HR features, Log-Gabor-Lengdre outperforms the features of LDA and PCA in its recognition performance for both face and iris. This is shown in Fig. 7. An improvement could be seen in the recognition performance of all the three techniques in terms of feature HR domain.

A superior discrimination of the LGL features are clearly evident from the fact that non-HR LGL technique performs well when compared with HR-PCA and HR-LDA for both face and iris modalities. Further, the performance is improved by adding HR pixels to the LGL filter that benefits the recognition performance of LGL features that provides more discriminative results than LDA and PCA approaches.

Employing nonlinear LGL based feature in featured HR domain framework capitalizes the boosting performance in

Fig. 8 Comparisons between Linear and Nonlinear features in feature HR domain:(**a**) Iris (**b**) Face



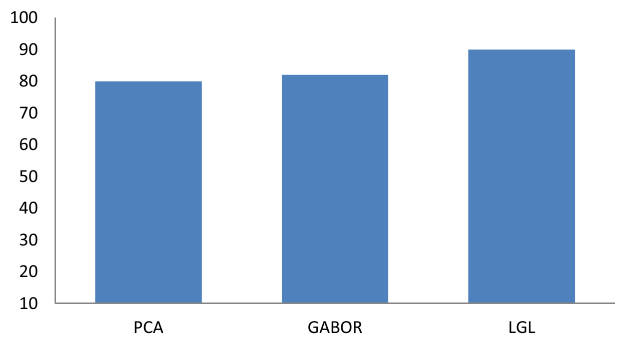


Fig. 9 Accuracy of LGL

recognition pattern that is obtained through the discriminate property and featured HR domain approach of LGL filter (Tables 1 and 2).

The Fig. 8 illustrated the comparison between the linear and non-linear features in Feature HR domain. The linear feature includes LDA and PCA (Field et al. 1987) and non-linear Log-Gabor phase quadrant for (a) Eyes and LGBPHS for (b) Face.

7 Accuracy of proposed LGL model

This proposed LGL method works better than simple Gabor or PCA method. The Fig. 9 shows accuracy chart for proposed system.

As per the above result, Gabor filter with Legendre filter fused to extract the image features similar to original image feature or training templates. The combination two filters improve the efficiency of filter techniques. It also improves the extraction and matching very accurately. In this article, existing Gabor and PCA has an average recognition of 82% with 30.54 s but proposed takes only 1.99 s to combine two filters and recognize at 90%. Here it's noted that less time to recognize the face and iris in image. Due to recognizing iris, it's very clear identification accuracy is highly improved.

8 Conclusion

Feature HR domain is presented for improving the performance of recognition in biometric automated systems in comparison with existing pixel HR domain. The proposed technique uses direct high resolution features for classification and incorporates specific biometric model knowledge of iris and face. The proposed method improves further the performance of feature HR domain through framework that enable feature HR domain with nonlinear/ LGL features. Thus, by employing nonlinear LGL features, the framework boosts the performance of recognition by capitalizing the recognition performance using feature HR domain approach and high LGL features property. Finally, the paper demonstrated the framework over two biometrics i.e. iris and face that demonstrated parallel recognition performance in both biometric modalities. In future, the research can be applied over recognition and identification in real time streaming systems. Also, further enhancement can be carried out based on noise reduction while applying filters.

References

An Z, Deng W, Hu J, Zhong Y, Zhao Y (2019) APA: adaptive pose alignment for pose-invariant face recognition. Digital Object Identifier. https://doi.org/10.1109/ACCESS.2019.2894162

Arora M, Kumar M, Garg NK (2018) Facial emotion recognition system based on PCA and gradient features. Springer, Berlin

Chabra P, Kumar N, Kumar M (2020) Content-based image retrieval system using ORB and SIFT features. Neural Comput Appl 32(7):2725–2733

Dargan S, Kumar M (2019b) A comprehensive survey on the biometric recognition systems based on physiological and behavioral modalities. Elsevier, Amsterdam

Dargan S, Kumar M, Ayyagari MR, Kumar G (2019) A survey of deep learning and its applications: a new paradigm to machine learning. Arch Comput Methods Eng

Dargan S, Kumar M, Thakur K (2019) Writer identification system for pre-segmented offline handwritten Devanagari characters using k-NN and SVM, Soft Computing, 1–12 Methodologies and applications

Daugman JG (1985) Uncertainty relation for resolution in space, spatial frequency, and orientation optimized by two-dimensional visual cortical filters. J Opt Soc Am A Opt Image Sci 2:1160–1169

Daugman J (2002) Gabor wavelets and statistical pattern recognition. In: The handbook of brain theory and neural networks, pp 457–461. The Mit Press, Cambridge

Daugman J (2004) How iris recognition works. IEEE Trans Circuits Syst Video Technol 14(21–30):3

Daugman J (2007) New methods in iris recognition. IEEE Trans Syst Man Cybern Part B Cybern 37(5):1167–1175

De Marsico M, Nappi M, Riccio D (2010) Face: face analysis for commercial entities. In: 17th IEEE international conference on image processing (ICIP '10), Honk Kong, China, pp 1597–1600

De Marsico M, Nappi M, Riccio D (2010) ISIS: iris segmentation for identification systems. In: 20th international conference on pattern recognition (ICPR '10), Istanbul, pp 2857–2860

DeMarsico M, Nappi M, Riccio D (2012) ES-RU: an entropy based rule to select representative templates in face surveillance. Multimedia tools and applications, special issue on human vision and information theory. Springer Journal, published online November 08, 2012

Field DJ (1987) Relations between the statistics of natural images and the response properties of cortical cells. J Opt Soc Am A 4(12):2379–2394

Gunturk B, Batur A, Altunbasak Y, Hayes M, Mersereau R (2003) Eigenface-domain super-resolution for face recognition. IEEE Trans Image Process 12(5):597–606

Gupta S, Thakur K, Kumar M (2020) 2D-human face recognition using SIFT and SURF descriptors of face's feature regions. Springer, Berlin

Hong L, Jain AK (1998) Integrating faces and fingerprints for personal identification. IEEE Trans PAMI 20(12):1295–1307

Jain AK, Bolle RM, Pankanti S (1999) Biometrics: personal identification in a networked society. Kluwer, Dordrecht

Jia K, Gong S (2005) Multi-modal tensor face for simultaneous super-resolution and recognition. In: 10th IEEE international conference on computer vision, vol 2, pp 1683–1690

Keys R (1981) Cubic convolution interpolation for digital image processing. IEEE Trans Acoust Speech Signal Process 29(6):1153–1160

Kittler J, Hatef M, Duin RPW, Mates J (1998) On combining classifiers. IEEE Trans PAMI 20(3):226–239

Kumar M, Jindal SR (2018) Fusion of RGB and HSV colour space for foggy image quality enhancement. Springer, Berlin

Kumar VN, Srinivasan B (2013) Performance of personal identification system technique using iris biometrics technology. Int J Image Gr Signal Process 5(5):63

Kumar A, Kaur A, Kumar M (2018) Face detection techniques: a review. Artif Intell Rev 52(2):927–948

Kumar M, Jindal MK, Sharma RK, Jindal SR (2019) Performance evaluation of classifiers for the recognition of offline handwritten Gurmukhi characters and numerals: a study. Springer, Berlin

Lee Y, Micheals RJ, Filliben JJ, Phillips PJ (2013) Vasir: an open-source research platform for advanced iris recognition technologies. J Res Nat Inst Stand Technol 118:218

Lin F, Fookes C, Chandran V, Sridharan S (2007) Superresolved faces for improved face recognition from surveillance video. In: Lecture notes in computer science, vol 4642 LNCS, pp 1–10

Liu C (2004) Gabor-based kernel pca with fractional power polynomial models for face recognition. IEEE Trans Pattern Anal Mach Intell 26:572–581

Liu C, Wechsler H (2002) Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition. IEEE Trans Image Process 11:467–476

Mansfield T, Kelly G, Chandler D, Kan J (2001) Biometric product testing final report. Technical report, National Physical Laboratory of UK

Massot C, Hérault J (2008) Model of frequency analysis in the visual cortex and the shape from texture problem. Int J Comput Vis. 76(2):165–182

Nguyen K, Fookes C, Sridharan S, Denman S (2011a) Feature-domain super-resolution for iris recognition. In: 18th IEEE international conference on image processing, pp 3258–3261

Nguyen K, Fookes C, Sridharan S, Denman S (2011b) Quality-driven super-resolution for less constrained iris recognition at a distance and on the move. IEEE Trans Inf Forensics Secur 99:1

Pravinthraja S, Umamaheswari K (2011) Multimodal biometrics for improving automatic teller machine security. Bonfring Int J Adv Image Process 1:19

Serrano A, de Diego I, Conde C, Cabello E (2010) Recent advances in face biometrics with gabor wavelets: a review. Pattern Recognit Lett 31(5):372–381

Skurichina M, Duin RPW (2002) Bagging, boosting and the random subspace method for linear classifiers. Pattern Anal Appl 5(1):121–135

Tadic V, Odry A, Toth A, Vizvari Z, Odry P (2020) Fuzzified "circular gabor filter for circular and near-circular object detection". https://doi.org/10.1109/ACCESS.2020.2995553.

Zhang Y, Wang Q, Xiao L, Cui Z (2019) An improved two-step face recognition algorithm based on sparse representation. September 2019. https://doi.org/10.1109/ACCESS.2019.2940876

Zhao W, Chellappa R, Rosefeld A, Phillips PJ (2000) Face recognition: a literature survey. Technical report, Computer Vision Lab, University of Maryland