IJCCS (Indonesian Journal of Computing and Cybernetics Systems)
Vol.x, No.x, July xxxx, pp. 1~5
ISSN (print): 1978-1520, ISSN (online): 2460-7258
DOI: 10.22146/ijccs.xxxx

Two-Step Iris Recognition Verification Using 2D Gabor Wavelet and Domain-Specific Binarized Statistical Image Features

Sri Mulyana*[1], Moh. Edi Wibowo[2], Arie Kurniawan[3]
[1,2]Department of Computer Science and Electronics, FMIPA UGM, Yogyakarta, Indonesia
[3]Master Program in Computer Science, FMIPA UGM, Yogyakarta, Indonesia
e-mail: ***[1]smulyana@ugm.ac.id** , [2]mediw@ugm.ac.id, [3]ariekurniawan1997@ugm.ac.id

Abstrak

Iris merupakan salah satu fitur biometrik yang kredibel karena tekstur iris mempunyai properti yang kompleks. Namun adanya kontak lensa berjenis colored menjadikan iris tidak lagi kredibel dalam sistem iris recognition. Kontak lensa colored merupakan salah satu spoofing dalam biometrik yang mana dapat menggelapkan identitas seseorang. Untuk mencegah spoofing terjadi perlu adanya verifikasi dua langkah dalam sistem iris recognition. Verifikasi pertama dilakukan untuk mendeteksi kontak lensa colored, sedangkan verifikasi kedua dilakukan untuk recognition atau matching identitas seseorang. Adapun metode ekstraksi yang digunakan adalah Domain Spesific Binarized Statistical Image Features (DSBSIF) dan Gabor Wavelet. Sedangkan metode untuk mendeteksi kontak lensa adalah Support Vector Machine (SVM) dan matching adalah Haming Distance (HD). Penelitian ini melakukan eksperimen single feature dan fusion feature dari metode DSBSIF dan Gabor Wavelet untuk verifikasi dua langkah iris recognition tersebut. Hasil yang didapatkan menyatakan bahwa single fitur DSBSIF mendapatkan akurasi yang paling tinggi yaitu 99,86% untuk verifikasi pertama dan 95,34% untuk verifikasi kedua. Hasil tersebut lebih unggul dari hasil ketika menggunakan single fitur Gabor Wavelet dengan selisih 5,01% untuk verifikasi pertama dan 0,25% untuk verifikasi kedua. Sedangkan selisih antara single fitur DSBSIF dan fusion fitur adalah 0,36% untuk verifikasi pertama dan 0,25% untuk verifikasi kedua.

Kata kunci— *Iris Recognition, Spoofing, BSIF, Gabor Wavelet*

Abstract

The Iris is one of the most reliable biometric features due to its complex textural properties. However, using coloured contact lenses renders the iris unreliable in iris recognition systems. Colored contact lenses are one of the spoofing methods in biometrics that can conceal a person's identity. To prevent spoofing, a two-step verification process is needed in the iris recognition system. The first verification step is to detect colored contact lenses, while the second is to recognize or match a person's identity. The feature extraction methods used are Domain Specific Binarized Statistical Image Features (DSBSIF) and Gabor Wavelet. The method for detecting contact lenses is Support Vector Machine (SVM), and matching is performed using Hamming Distance (HD). This study conducted experiments using single features, feature fusion, and hybrid feature extraction methods combining DSBSIF and Gabor Wavelet for two-step iris recognition verification. The results indicate that the hybrid feature extraction method of DSBSIF and Gabor Wavelet achieved the highest accuracy of 99.95% for the first verification and 95.40% for the second verification. These results are 0.02 and 0.31 percentage points better, respectively than previous methods in the first and second verifications.

Keywords— *Iris Recognition; Spoofing; DBSIF; Gabor Wavelet*

Received June 1st,2012; Revised June 25th, 2012; Accepted July 10th, 2012

1. INTRODUCTION

The Iris is a reliable biometric feature for identifying a person [1]. Singh and colleagues have stated that iris texture possesses highly distinctive features and remains invariant throughout an individual's lifetime [2]. Furthermore, Krishnan [3] noted that fields such as airport security, criminal investigation, and others also employ Iris recognition, which is believed to exhibit unique patterns in each individual. Iris recognition was first pioneered by Daugman [4], who reported that in his study of 9.1 million individuals, no two irises exhibited identical textures.

The emergence of colored contact lenses has become a significant challenge in iris recognition. These lenses are worn directly on the cornea and can alter the iris patterns, leading to failures in the matching process of Iris recognition [5]. However, as research into the effects of colored contact lenses has advanced, there have been claims that such lenses represent a form of spoofing in iris recognition systems [6], [7]. Presentation attack, or spoofing, refers to attempts to deceive biometric systems by presenting fake or altered biometric traits, such as using colored contact lenses to mimic another person's iris pattern. [8]. Overall, the design of colored contact lenses adheres to the manufacturer's specifications. This means that presentation attacks can be conducted by identifying manufacturer-specific design patterns to facilitate identity spoofing

Multi-Scale Line Tracking (MSLT) is the initial approach for detecting contact lenses based on the offset lines between the contact lens and the Iris. [9]. However, this method is ineffective as not all outer lines of the contact lens are clearly visible, resulting in inaccurate detection. The second approach is texture-based. The Binarized Statistical Image Features (BSIF) method has been proven accurate and reliable in detecting colored contact lenses, having been validated in [5]–[7], [10] with accuracy above 90%. Similar texture-based studies were conducted by Kulkarni [11] using the Weber Local Descriptor (WLD) and by Gragnaniello using the Scale-invariant Local Descriptor (SID) [1]. However, the study by Doyle and Bowyer [6] used BSIF as the feature extraction method, which is not optimal for capturing complex patterns in contact lenses with certain textures.

In iris recognition, several methods are employed, including the 2D Gabor Wavelet proposed by Daugman [4], the Integer Wavelet Transform (IWT) by Singh [2] and the Global Neighborhood Structure (GNS) [12]. Although the Gabor wavelet was proposed in 2004, its use in iris recognition feature extraction is still employed by [13], [14]. However, the research conducted by Liu [14] performed an experiment using the 2D Gabor wavelet and proved that the 2D Gabor method is inefficient in representing iris texture features in images with significant variations. Using images captured by the iPhone 5 and Samsung Galaxy S4, the 2D Gabor method showed very poor performance with an accuracy of only 59%.

Convolutional Neural Network (CNN) is an algorithm used for image classification or image recognition; this method recognizes an image by trying to imitate the human visual cortex network [29]. However, the CNN model training process requires large computational resources and a long time. Support Vector Machine (SVM) is one of the computationally efficient and accurate algorithms in iris recognition. Research conducted by [28] has demonstrated that SVM performs exceptionally well in iris recognition, achieving an accuracy of 99.3%. However, the performance of SVM heavily depends on the selection of an appropriate kernel function. This process often requires extensive experimentation and validation to identify the kernel that best fits the data.

This study will conduct a two-step verification process in iris recognition. The first step involves detecting colored contact lenses. This process aims to prevent individuals wearing colored contact lenses from entering the matching process, as these lenses alter the natural texture of the iris and constitute spoofing in iris recognition systems. The first verification step is crucial to anticipate and prevent using Iris templates obtained while wearing colored contact lenses, which could lead to matching failures. The second verification step is matching two irises: the iris template and the iris being identified. This step is performed only if no colored contact lenses are detected. The second verification step serves to authenticate an individual. Research involving fusion and hybrid features is rarely conducted, and these two-step verifications represent a novel integration of two research areas: detecting colored contact lenses and iris recognition.

The feature extraction methods employed in this study are Domain-Specific Binarized Statistical Image Features (DSBSIF), proposed by Czajka [15] as an improvement over the BSIF method for Iris recognition [16]. The 2D Gabor Wavelet feature extraction method is also utilized, first introduced by Daugman and still in use for iris recognition today [13], [14]. This study will conduct experiments on feature fusion and hybrid feature extraction between DSBSIF and Gabor Wavelet. Feature fusion involves combining features from two or more methods to obtain more detailed information [17]. Hybrid feature extraction, inspired by the BSIF method [16], involves combining several convolution kernels to enhance image processing analysis, [18]. as [18] has shown that varying kernels can improve performance and accuracy. Support Vector Machine (SVM) is employed for modelling the detection of colored contact lenses, while Hamming Distance is used to match two irises: the template Iris and the identifier Iris.

Accuracy is employed to evaluate the performance of the methods used in this study. The performance of each stage, namely the detection of colored contact lenses and the matching process, will be measured. Both methods will be tested at each stage.

2. METHODS

This section will discuss architecture, or design method used. The portrayal of the stages used in this study is shown in Figure 1.

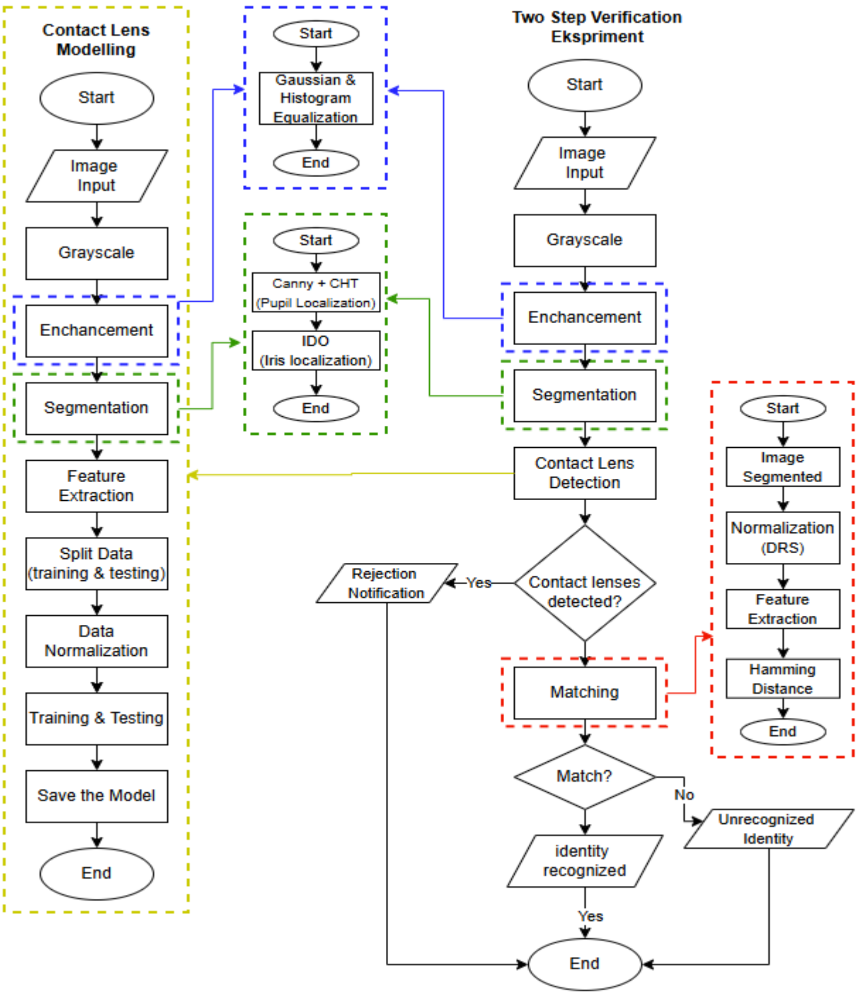

Figure 1 System arcitechture

This study is conducted in two stages including contact lens detection modeling and iris recognition. The architecture of the proposed system design is shown in Figure 1. The contact lens detection modeling part is a sub-process of the two-step verification. Starting from image input, enhancement, segmentation, colored contact lens detection process, and matching process. The following is a detailed explanation of these processes.

2.1 Acquisition

This study utilizes secondary data from IIITD, obtained by request from the website http://iab-rubric.org/. IIITD is a dataset collected by the Image Analysis & Biometric Lab, CSE Department, IIT Jodhpur, Rajasthan, India. Two types of sensors were employed to capture the images: Cogent and VistaFA2E. The total dataset comprises 2005 records, including 1000 eye data without contact lenses and 1005 eye data with colored contact lenses.

2.2 Enchancement

Image enhancement involves improving image quality to enhance the interpretation or perception of information within the image. The primary objective of image enhancement is to modify image attributes to meet specific requirements, such as noise reduction or sharpening specific areas [1]. The image enhancement techniques employed in this study are Gaussian filtering and histogram equalization, as described in equations (1) and (2).

1. Gaussian Filter

$$\mathrm{G(x,y)} = \frac{1}{2\pi\sigma^2} e^{\frac{(x-x_0)^2 + (x-x_0)^2}{2\sigma^2}} \tag{1}$$

2. Histogram Equalization

$$s_k = T(r_k) = \sum_{j=0}^{k} \frac{n_j}{n} - (L-1) \tag{2}$$

2.3 Segmentation

The segmentation process consists of two steps: pupil localization and Iris localization. In the pupil localization process, the initial step is global thresholding, which is the most suitable method because the pupil inherently has the darkest color compared to the iris and sclera. Equation (3) represents the global thresholding formula

$$g(x,y) = \begin{cases} 1, & f(x,y) \geq T \\ 0, & f(x,y) < T \end{cases} \tag{3}$$

Where g(x,y)$g(x,y)$ is the output of global thresholding, f(x,y)$f(x,y)$ is the input image, and TT is the threshold. The result of global thresholding will undergo dilation, which serves for hit-or-miss transformation. Subsequently, edge detection is performed using Canny Edge Detection to identify objects in the image, a method proposed by Husain [2]. Three stages must be completed to perform the Canny edge detection operation.

1. Noise Reduction

Several methods can be used for noise reduction, and one commonly employed method at this stage is the Gaussian filter. The equation for the Gaussian filter is provided in equation (1).

2. Gradient Calculation

Detecting pixel intensity by calculating the gradient of the image using edge detector operators. The formula for calculating the gradient is provided in equation (4).

$$|G| = \sqrt{I_x^2 + I_y^2}, \theta(x,y) = \arctan\left(\frac{I_y}{I_x}\right) \tag{4}$$

3. Non-maximum Supression
   This process iterates through all points in the gradient intensity matrix and identifies pixels with the maximum value in the edge direction.
4. Double Thresholding
   The process involves verifying whether the results from the previous step meet the threshold criteria. In this process, there are two thresholds: the lower threshold (minimum) and the upper threshold (maximum).
5. Hystresis
   If the double threshold selects a range of values, hysteresis involves matching these values. If the intensity value does not match the hysteresis criteria, it is set to 0; if it matches, the value remains unchanged.

Once the iris object is detected, the Circular Hough Transform (CHT) is applied for iris localization. The CHT operates by mapping the edges of the image to the eye, derived from calculating the first derivative of intensity values. Each edge point contributes a circle radius (r) and centre (xc, yc) to an accumulator array. Subsequently, a voting procedure is employed to identify the largest peak in the resulting accumulator array within the parameter space, corresponding to the circle best defined by the edge points [3]. The CHT equation is provided in equation (5).

$$(\mathrm{x}_i - a)^2 + (\mathrm{y}_i - b)^2 = r^2 \tag{4}$$

Points a and b represent the edge detection results from the Canny Edge Detection, where r is the predefined radius, while xi and yi denote the radial distances from points a and b. Once the pupil is localized, the subsequent step involves approximating the iris using the Integro-Differential Operator (IDO) method. This method was proposed by John Daugman [4]. IDO has been proven reliable in approximating the iris based on the circular pupil [5]. Equation (6) presents the IDO formula.

$$Max(r, x_0, y_0) \left| G_\sigma(r) * \oint_{(r,x_0,y_0)} \frac{I(x,y)}{2\pi r}\, ds \right| \tag{5}$$

I(x,y) represents the grayscale input image, G_σ(r) is the smoothing function, and ds is the counter represented by (x_0, y_0) as the centre and r as the radius. The operator seeks the maximum circular path that is blurred by incrementally increasing the radius.

2.4 Feature Extraction

In this study, feature extraction is performed at each stage, including detecting colored contact lenses and the recognition process. Specifically, modelling for detecting colored contact lenses and matching for recognition is conducted. The feature extraction method currently considered reliable for contact lens detection is the Binarized Statistical Image Features (BSIF) [6]. This has been confirmed in further research, [7] where BSIF was shown to outperform Local Binary Patterns (LBP) for detecting colored contact lenses when used with Support Vector Machines (SVM). Additionally, enhancements to BSIF, such as Domain Specific BSIF and Discrete Wavelet Transform, have demonstrated superior performance compared to the original BSIF in detecting colored contact lenses [8].

The BSIF method combines the image with a specific filter or kernel to generate binary values. These binary values within each kernel are summed to produce image intensity values. After convolving all pixels in the image, the resultant image is represented using a histogram, which is then employed for feature extraction.The features obtained from Domain-Specific BSIF will be combined with the 2D Gabor Wavelet, as proposed by [13], and [14] in their research for iris recognition feature extraction.

The 2D Gabor wavelet results from convolution with a 2D kernel derived from sinusoidal orientation modulated by a 2D Gaussian function [11]. How the 2D Gabor wavelet work begins the convolution between the input image and the Gabor filter. The convolution output undergoes quantization, then converted into 8-bit binary values. This conversion process transforms decimal values into 8-bit binary values. The size of the binary output is the image size multiplied by 8 (bits).

2.5 Hybrid Kernel

Hybrid kernel refers to the combination of multiple kernels or convolution methods to enhance image analysis and processing. This approach aims to leverage the strengths of each kernel used, thereby producing richer and more accurate feature representations [12].

2.6 Feature Fusion

The feature fusion approach can produce images with improved representational capabilities.

2.7 Iris Normalisation

In image processing, normalization is adjusting the range of intensity values. The purpose of normalization is to convert the input image into a range of intensity values commonly used for processing. In this study, normalization transforms the image from polar (circular) to Cartesian (rectangular) coordinates. The method employed for normalization is the Daugman Rubber Sheet Model.

2.8 Support Vector Machine

This study employs a Support Vector Machine (SVM) for modelling contact lens detection. SVM is a machine learning method that operates on the Structural Risk Minimization (SRM) principle, aiming to find the optimal hyperplane that separates two classes in the input space. SVM can be utilized for classification tasks, such as handwriting detection, object recognition, voice identification, and more. [13].

2.9 Hamming Distance

This study utilizes Hamming Distance as the matching algorithm for the iris recognition process. Hamming Distance is a matching method that compares two-bit strings of equal length and calculates the distance through substitution. By using Hamming Distance on two-bit strings of the same length, it can be determined whether the two patterns originate from the same iris or different irises. Before applying the Hamming Distance, the binary feature vector is first digitized, as the Hamming Distance algorithm requires binary feature vectors for its operation. The Hamming Distance can be computed using the XOR function, as shown in Equation 6.

$$HD = \frac{1}{N} \sum_{i=1}^{n} X_i \otimes Y_i \tag{6}$$

2.10 Evaluation

This study evaluates performance metrics using accuracy rates. Each stage (colored contact lens detection and matching) will have its performance measured. Both methods will be tested at each stage. Performance evaluation will be conducted in two steps as follows:

1. Contact Lens Detection Accuracy

   To measure the performance of contact lens detection, we can use equation 7.

$$Akurasi = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

Where TP (true positive) represents the number of correct detections of contact lenses, TN (true negative) denotes the number of correct detections without contact lenses, FP (false positive) indicates the number of incorrect detections of contact lenses, and FN (false negative) signifies the number of incorrect detections without contact lenses.

2. Matching Accuracy

To measure the accuracy performance of matching, it is essential to understand the False Acceptance Rate (FAR) and False Failure Rate (FFR). The False Acceptance Rate (FAR) measures the likelihood that a biometric security system incorrectly recognizes an unauthorized user as authorized, meaning it mistakenly identifies a different individual. On the other hand, the False Failure Rate (FFR) measures the likelihood that the system fails to recognize an authorized user, meaning it incorrectly rejects a legitimate individual. [14]. Equations 8 and 9 provide the calculations for FAR and FFR, respectively.

$$FAR = \frac{FP}{TN + FP} \tag{8}$$

$$FFR = \frac{FN}{TP + FN} \tag{9}$$

The values of FP and TN for FAR are obtained from inter-class comparisons. These inter-class comparisons involve matching between different individuals. Meanwhile, the values of FN and TP for FFR are derived from intra-class comparisons. Intra-class comparisons involve matching within the same individual.To measure the overall performance of iris recognition, Equation 10 can be utilized.[14]

$$Akurasi = 100 - \frac{FAR + FFR}{2} \tag{10}$$

Based on Equation 16, the False Acceptance Rate (FAR) is calculated using Equation 8, while the False Failure Rate (FFR) is derived from Equation 9.

3. RESULTS AND DISCUSSION

3.1 Contact Lens Detection

Contact lens detection is the first stage of the verification process. The methods used for modeling contact lens detection are illustrated in Figure 2

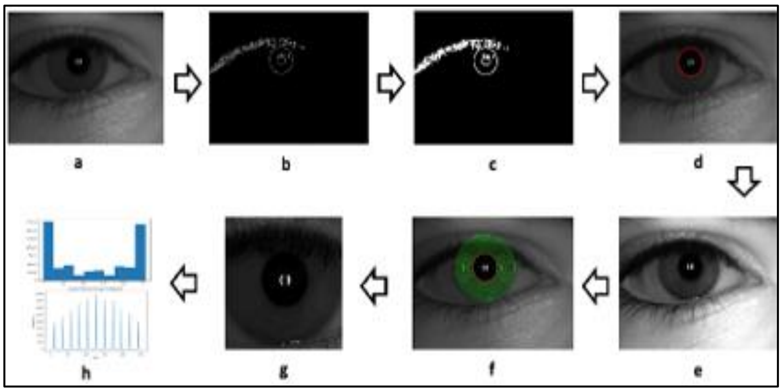

Figure 2. a) image input. b) global threshold. c) dilation. d) pupil localisation (CHT). e) histogram equalization. f) Iris locatisation (IDO). g) cropping. h) feature extraction (BSIF + 2D Gabor)

Figure 2. illustrates the input image captured using a near-infrared camera. Figure 2.b displays the result after applying the global thresholding method and edge detection using the Canny algorithm. To enhance the thickness of faintly visible lines in Figure 2.b, a dilation technique is applied, as shown in Figure 2.c. Subsequently, the pupil circle's location is identified using a voting method with Circular Hough Transform (CHT), as depicted in Figure 6.d.

The subsequent step involves enhancing the quality of the input image through histogram equalization, as illustrated in Figure 2.e, and approximating the iris circle using the IDO method, as shown in Figure 2.f. Once the iris position is successfully identified, the next step is the image cropping process, as depicted in Figure 2.g, followed by feature extraction, as demonstrated in Figure 2.h.

Based on the explanation of Figure 2 above, there are threshold values and hyperparameters required for the contact lens detection process, including the threshold for segmentation and the hyperparameters for SVM. Research conducted by Vachroni [15] has identified optimal threshold values, specifically 13, 15, 16, 17, 18, 19, and 20. Meanwhile, the most optimal SVM hyperparameters consist of a linear kernel with a C value of 100. For the Domain-Specific BSIF kernel, the most optimal configuration is 5x5 12-bit. Therefore, this study employs these configurations. Table 1 presents the experimental results.

Table 1 BSIF and 2D Gabor Wavelet Experiments

No	Methods	Training Accuracy(70%)	Testing Accuracy(30%)
1	BSIF	100%	99,86%
2	Gabor	100%	94,85%
3	Fusion Bsif + Gabor	100%	99,50%
4	**Hybrid BSIF + Gabor**	**100%**	**99,95%**

Table 1 represents the combination of experiments conducted. The results indicate that the hybrid feature extraction method combining Domain-Specific BSIF and 2D Gabor Wavelet achieves the highest accuracy of 99.95%. Based on Table 1, the hybrid feature extraction of DSBSIF and Gabor achieves an accuracy of 99.95%, Therefore, the hybrid feature extraction of Domain-Specific BSIF and 2D Gabor Wavelet will be used for the first verification stage, which is contact lens detection.

3.2 Matching Iris

Iris matching is the second stage of the verification process. The methods used in the iris matching process are illustrated in Figure 10.

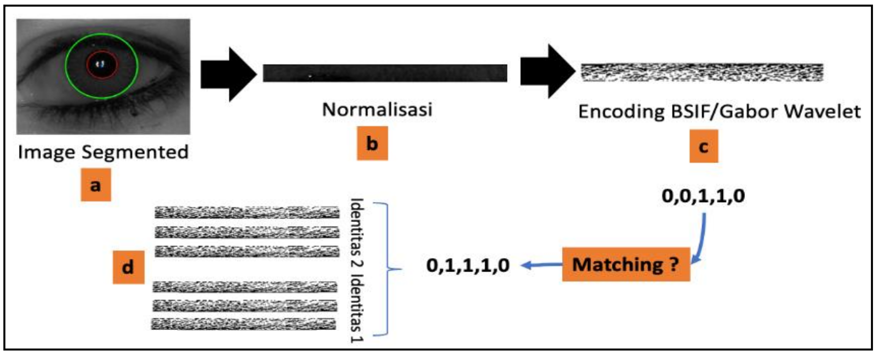

Figure 3 Matching Process

Starting with Figure 3.a, representing the segmentation result, the Region of Interest (ROI) is normalized, as shown in Figure 3.b. Normalization involves transforming the image from polar (circular) to Cartesian (rectangular) coordinates. After normalization, the next step is iris encoding. As previously mentioned, this encoding converts the image into binary form or its binary feature representation. Subsequently, these features are matched using Hamming Distance.

The contact lens detection model with the highest accuracy in the first stage, as shown in Table 1, is utilized in the two-step iris recognition verification process. The performance evaluation of BSIF and Gabor Wavelet in identifying individuals at this stage employs the False Acceptance Rate (FAR) and False Failure Rate (FFR). To determine whether individuals are the same or different based on the extracted BSIF and Gabor features, this study uses Hamming Distance.

To identify the best method, this study will conduct experiments using single features, feature fusion, and hybrid features, as outlined in Table 2. This study will use values ranging from 0.3 to 0.45 for the matching threshold. Table 2 presents the best matching process results in this experimental research.

Table 2 Best result of matching process

No	Method	BSIF	Gabor	Threshold	FAR	FFR	Accuracy(%)
1	BSIF	5x5	-	0,39	1.49	7.83	95.34%
2	Gabor	-	7x7	0.39	1.47	8.63	94.94%
3	Fusion bsif + gabor	5x5	14x14	0.37	2.54	7.13	95.17%
4	**Hybrid BSIF + gabor**	**5x5**	**9x9**	**0.43**	**1.81**	**7.38**	**95.40%**

Table 2 presents the best results from each representation method, whether single-feature Domain-Specific BSIF, 2D Gabor Wavelet, feature fusion, or a hybrid of the two methods. Based on the experiments, hybrid feature extraction achieves higher accuracy than single and fusion features. This study also experiments with 5x5 kernels for BSIF and 7x7, 9x9, and 14x14 kernels for Gabor. The results of these experiments are included in the appendix. The optimal threshold is determined to be 0.43. The threshold selection in this experiment is based on the work of Daugman, the pioneer of Iris Recognition, who stated in his research that the standard matching threshold is 0.329 [4]. Therefore, this study selects a threshold range of 0.3 to 0.45 for matching.

The best results indicate that the hybrid feature extraction combining Domain-Specific BSIF and 2D Gabor Wavelet achieves an accuracy of 95.40%. Below is an analysis of how this accuracy of 95.40% was obtained.

a) Data Sample

As explained in Subsection 2.1 on data collection, the dataset for irises without contact lenses consists of 1,000 samples from 100 individuals (subjects). The matching process involves only samples without contact lenses.

b) Number of *pairs*

The number of pairs refers to the total number of matching pairs, whether they are from the same individual (intra-class) or different individuals (inter-class). Below is the equation for calculating the number of pairs.

$$pairs = \frac{n\,(n-1)}{2} = \frac{1000 * 999}{2} = 499{,}500$$

Where *n* is the total number of contact lens sample data; therefore, the total number of pairs generated is 499,500. Each individual has 10 sample data points. However, there is an individual with only 8 samples (individual 42). Additionally, individuals 20 and 21 have 11 samples each. Using Python tools, the number of intra-class pairs is calculated as 2,003, and the number of inter-class pairs is 494,997.

c) FAR, FFR, and Accuracy

The False Acceptance Rate (FAR) measures how often the system incorrectly recognizes different individuals. In contrast, the False Failure Rate (FFR) measures how often the system fails to recognize the same individual. Accuracy, on the other hand, is a cumulative measurement derived from FAR and FFR. Below are the detailed results of the hybrid feature extraction combining. The values for FAR, FFR, and Accuracy are as follows:

$$FAR = \frac{FP}{TN + FP} = \frac{8983}{486014 + 8983} = 0{,}018 \rightarrow 1{,}8\%\ (Wrong)$$

$$FFR = \frac{FN}{TP + FN} = \frac{148}{1855 + 148} = 0{,}073 \rightarrow 7{,}3\%\ (Wrong)$$

$$Accuracy = 100 - \frac{FAR + FRR}{2} = 100 - \frac{1{,}8 + 7{,}3}{2} = 95{,}4\%$$

Domain-Specific BSIF and 2D Gabor Wavelet: True Positive (TP) = 1,855, True Negative (TN) = 486,014, False Positive (FP) = 8,983, and False Negative (FN) = 148.

To determine the computational time of the methods used, Table 3 presents the resulting computational times.

Tabel 1 The computational time of the model.

No	Method	Verif 1 CT	Verif 2 CT	CT Total
1	Single Fitur	2,29s	1,85s	4,14s
2	Fusion BSIF + gabor	3,28	2,12s	5,40s
3	Hybrid BSIF + gabor	2,95s	1,98s	4,93s

Table 3 presents a comparison of the computational times for single feature, feature fusion, and hybrid feature methods. Unsurprisingly, the single-feature method achieves the fastest computational time, as it only involves computing a single method. When compared to the hybrid method, the single-feature approach is faster by 0.79 seconds. However, the hybrid method is 0.37 seconds faster than the fusion method. While both hybrid and fusion methods involve computing two methods, the hybrid method is quicker because the result of the first method is directly convolved with the second method. In contrast, the fusion method requires two parallel convolution processes followed by a concatenation step.

4. CONCLUSIONS

Based on the results of the conducted research, it can be concluded that the analysis of a two-step iris recognition verification achieves an accuracy of 99.95% for the first step, which involves contact lens detection using an SVM classifier, and 95.40% for the second step, which utilizes Hamming distance with a hybrid feature extraction of DBSIF and Gabor Wavelet. Furthermore, the experimental results demonstrate that the hybrid feature extraction of DBSIF and Gabor Wavelet outperforms single-feature and fusion-feature approaches, such as DSBSIF and Gabor, which achieved accuracies of 95.34%, 94.94%, and 95.17%, respectively.

By utilizing DBSIF feature extraction, this study successfully implements Presentation Attack Detection (PAD) in the first verification step with an accuracy of 99.95% and recognition in the second verification step with an accuracy of 95.40%. Compared to previous studies, this research achieves an accuracy improvement of 0.02% for contact lens detection and 0.31% for the matching process.

Consequently, this study demonstrates the advantage of identity verification without the risk of spoofing.Based on the research findings and conclusions, this study obtained a relatively low accuracy in the matching process or the second step. Therefore, the author recommends that future research explore alternative methods to enhance matching accuracy.

REFERENCES

[1] D. Gragnaniello, G. Poggi, C. Sansone, and L. Verdoliva, “Using iris and sclera for detection and classification of contact lenses,” Pattern Recognit. Lett., vol. 82, pp. 251–257, Oct. 2016, doi: 10.1016/j.patrec.2015.10.009.

[2] G. Singh, R. K. Singh, R. Saha, and N. Agarwal, “IWT Based Iris Recognition for Image Authentication,” Procedia Comput. Sci., vol. 171, pp. 1868–1876, 2020, doi: 10.1016/j.procs.2020.04.200.

[3] K. Gopala Krishnan and P. T. Vanathi, “An efficient texture classification algorithm using integrated Discrete Wavelet Transform and local binary pattern features,” Cogn. Syst. Res., vol. 52, pp. 267–274, Dec. 2018, doi: 10.1016/j.cogsys.2018.07.015.

[4] J. Daugman, “How Iris Recognition Works,” IEEE Trans. Circuits Syst. Video Technol., vol. 14, no. 1, pp. 21–30, Jan. 2004, doi: 10.1109/TCSVT.2003.818350.

[5] D. Yadav, N. Kohli, J. S. Doyle, R. Singh, M. Vatsa, and K. W. Bowyer, “Unraveling the Effect of Textured Contact Lenses on Iris Recognition,” IEEE Trans. Inf. Forensics Secur., vol. 9, no. 5, pp. 851–862, May 2013, doi: 10.1109/TIFS.2014.2313025.

[6] J. S. Doyle and K. W. Bowyer, “Robust Detection of Textured Contact Lenses in Iris Recognition Using BSIF,” IEEE Access, vol. 3, pp. 1672–1683, 2015, doi: 10.1109/ACCESS.2015.2477470.

[7] M. R. Dronky, W. Khalifa, and M. Roushdy, “Using residual images with BSIF for iris liveness detection,” Expert Syst. Appl., vol. 182, p. 115266, Nov. 2021, doi: 10.1016/j.eswa.2021.115266.

[8] M. Fang, N. Damer, F. Boutros, F. Kirchbuchner, and A. Kuijper, “Cross-database and cross-attack Iris presentation attack detection using micro stripes analyses,” Image Vis. Comput., vol. 105, p. 104057, Jan. 2021, doi: 10.1016/j.imavis.2020.104057.

[9] B. Kumar, A. Nigam, and P. Gupta, “Fully Automated Soft Contact Lens Detection from NIR Iris Images,” in Proceedings of the 5th International Conference on Pattern Recognition Applications and Methods, 2016, pp. 589–596. doi: 10.5220/0005702005890596.

[10] M. R. Dronky, W. Khalifa, and M. Roushdy, “Impact of segmentation on iris liveness detection,” in 2019 14th International Conference on Computer Engineering and Systems (ICCES), Dec. 2019, pp. 386–392. doi: 10.1109/ICCES48960.2019.9068147.

[11] P. Kulkarni, “Textured Contact Lenses Detection in Iris Recognition Using Weber Local Descriptor (WLD),” JETIR, vol. 6, no. 1, 2019, [Online]. Available: . www.jetir.org

[12] R. Biswas, J. Uddin, and M. J. Hasan, “A New Approach of Iris Detection and Recognition,” Int. J. Electr. Comput. Eng., vol. 7, no. 5, p. 2530, Oct. 2017, doi: 10.11591/ijece.v7i5.pp2530-2536.

[13] N. Ahmadi, M. Nilashi, S. Samad, T. A. Rashid, and H. Ahmadi, “An intelligent method for iris recognition using supervised machine learning techniques,” Opt. Laser Technol., vol. 120, p. 105701, Dec. 2019, doi: 10.1016/j.optlastec.2019.105701.

[14] X. Liu, Y. Bai, Y. Luo, Z. Yang, and Y. Liu, "Iris recognition in visible spectrum based on multi-layer analogous convolution and collaborative representation," Pattern Recognit. Lett., vol. 117, pp. 66–73, Jan. 2019, doi: 10.1016/j.patrec.2018.12.003.

[15] A. Czajka, D. Moreira, K. Bowyer, and P. Flynn, "Domain-Specific Human-Inspired Binarized Statistical Image Features for Iris Recognition," in 2019 IEEE Winter Conference on Applications of Computer Vision (WACV), Jan. 2019, pp. 959–967. doi: 10.1109/WACV.2019.00107.

[16] J. Kannala and E. Rahtu, "BSIF: Binarized Statistical Image Features," 21st Int. Conf. Pattern Recognit. (ICPR 2012), 2012.

[17] B. Attallah, A. Serir, Y. Chahir, and A. Boudjelal, "Histogram of gradient and binarized statistical image features of wavelet subband-based palmprint features extraction," J. Electron. Imaging, vol. 26, no. 06, p. 1, Nov. 2017, doi: 10.1117/1.JEI.26.6.063006.

[18] A. Kumawat, S. Panda, V. C. Gerogiannis, A. Kanavos, B. Acharya, and S. Manika, "A Hybrid Approach for Image Acquisition Methods Based on Feature-Based Image Registration," J. Imaging, vol. 10, no. 9, p. 228, Sep. 2024, doi: 10.3390/jimaging10090228.

[19] S. Kaur and P. Kaur, "Review and Analysis of Various Image Enhancement Techniques," Int. J. Comput. Appl. Technol. Res., vol. 4, no. 5, pp. 414–418, May 2015, doi: 10.7753/IJCATR0405.1016.

[20] H. A. Biu, R. Husain, and A. S. Magaji, "An enhanced iris recognition and authentication system using energy measure," Sci. World J., vol. 13, no. 1, pp. 11–17, 2018.

[21] H. K. Rana, M. S. Azam, M. R. Akhtar, J. M. W. Quinn, and M. A. Moni, "A fast iris recognition system through optimum feature extraction," PeerJ Comput. Sci., vol. 5, p. e184, Apr. 2019, doi: 10.7717/peerj-cs.184.

[22] G. Gautam and S. Mukhopadhyay, "Challenges, taxonomy and techniques of iris localization: A survey," Digit. Signal Process., vol. 107, p. 102852, Dec. 2020, doi: 10.1016/j.dsp.2020.102852.

[23] M. I. A. Vachroni, "Deteksi Kontak Lensa Pada Mata Menggunakan Ekstraksi Ciri Domain Specific Binarized Statistical Image Features dan Discrete Wavelet Transform," University Gadjah Mada, 2022.

[24] S. Arivazhagan, L. Ganesan, and S. P. Priyal, "Texture classification using Gabor wavelets based rotation invariant features," Pattern Recognit. Lett., vol. 27, no. 16, pp. 1976–1982, Dec. 2006, doi: 10.1016/j.patrec.2006.05.008.

[25] K. L. Weiss et al., "Hybrid Convolution Kernel: Optimized CT of the Head, Neck, and Spine," Am. J. Roentgenol., vol. 196, no. 2, pp. 403–406, Feb. 2011, doi: 10.2214/AJR.10.4425.

[26] M. N. Ulwan, "Pattern Recognition pada Unstructured Data Teks Menggunakan Support Vector Machine dan Association," Universitas Islam Indonesia Yogyakarta, 2016.

[27] M. Abbasi, "Improving identification performance in iris recognition systems through combined feature extraction based on binary genetics," SN Appl. Sci., vol. 1, no. 7, p. 730, Jul. 2019, doi: 10.1007/s42452-019-0777-9.

[28] D. A. T. Muhamad Ilham Aji Vachroni , Raden Sumiharto, "Contact Lens Detection Using Domain Specific BSIF and Discrete Wavelet Transform," Khazanah Inform., vol. 9, no. 2, pp. 146–154, 2023, doi: https://doi.org/10.23917/khif.v9i2.20084.

[29] M. Omran and E. N. AlShemmary, "An Iris Recognition System Using Deep convolutional Neural Network," J. Phys. Conf. Ser., vol. 1530, no. 1, p. 012159, May 2020, doi: 10.1088/1742-6596/1530/1/012159.