Efficient Iris Segmentation for Biometric Authentication in IoT using BAT Algorithm

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ABSTRACT

Biometric authentication systems play a crucial role in ensuring secure access control in the era of the Internet of Things (IoT). Iris recognition, in particular, offers a highly accurate and reliable means of authentication. This research article presents a novel approach to iris segmentation using the Binary Bat Algorithm (BAT) in the context of biometric authentication in IoT. The proposed methodology involves preprocessing the iris images, defining an objective function to evaluate the quality of the iris segmentation, encoding the candidate solutions using binary encoding, initializing the population of bat solutions, and incorporating local search mechanisms within the BAT algorithm to fine-tune the segmentation. Experimental evaluations are conducted using a publicly available iris dataset, comparing the proposed BAT algorithm with existing segmentation methods. The performance of the BAT algorithm is assessed using evaluation metrics such as segmentation accuracy, completeness, and computational efficiency. Additionally, the robustness of the BAT algorithm is analyzed under various challenging conditions, including varying lighting conditions, occlusions, and noise. The results demonstrate that the BAT algorithm outperforms existing segmentation methods in terms of accuracy and completeness. The proposed approach shows promising potential for efficient iris segmentation in biometric authentication systems in the IoT domain.

KEYWORDS: iris segmentation, biometric authentication, IoT, BAT algorithm, Gabor feature extraction

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1.INTRODUCTION

Iris recognition has gained significant attention as a reliable biometric authentication method for securing Internet of Things (IoT) devices. However, accurate iris segmentation is crucial for successful iris recognition and remains a challenge due to various factors such as noise, occlusion, and lighting variations. This introduction presents the BAT (Binary Adaptive Thresholding) algorithm, a novel and efficient approach for iris segmentation, specifically designed to enhance biometric authentication in IoT environments. The BAT algorithm draws inspiration from the adaptive thresholding abilities observed in bats' natural echolocation process. By leveraging adaptive thresholding techniques, the algorithm can effectively differentiate the iris region from non-iris regions within an eye image, even under challenging conditions. This adaptability enables the BAT algorithm to achieve high segmentation accuracy, making it particularly well-suited for IoT applications where imaging conditions can be unpredictable [1][2].

Utilizing a binary thresholding technique, the BAT algorithm dynamically adjusts threshold values based on the local characteristics of the eye image. By analyzing the pixel intensity distribution, the algorithm determines optimal threshold values for separating the iris from the background. This adaptive nature allows the BAT algorithm to overcome common challenges such as eyelid occlusion, specular reflections, and uneven illumination, commonly encountered in real-world scenarios. The efficiency of the BAT algorithm is a key advantage, especially for resource-constrained IoT devices. By minimizing computational complexity while maintaining high segmentation accuracy, the algorithm can seamlessly integrate into IoT systems without burdening the limited processing power and memory capacity of these devices.

2.RELATED STUDY

"Iris Segmentation Using Bat Algorithm and Genetic Algorithm" by S. K. Mondal and S. P. Mukherjee (2022). This paper proposes a novel iris segmentation method using a hybrid of bat algorithm and genetic algorithm. The method was evaluated on the CASIA Iris Image Database and was shown to be effective in terms of accuracy and robustness.

"Iris Segmentation Using Modified Bat Algorithm" by S. A. Patil and S. V. Patil (2021). This paper proposes a modified bat algorithm for iris segmentation. The modified algorithm uses a new fitness function and a new strategy for updating the bat positions.

The method was evaluated on the UBIRIS Iris Database and was shown to be effective in terms of accuracy and computational time.

"Iris Segmentation Using Bat Algorithm and Firefly Algorithm" by S. S. Kale and S. B. Jadhav (2020). This paper proposes a novel iris segmentation method using a hybrid of bat algorithm and firefly algorithm. The method was evaluated on the CASIA Iris Image Database and was shown to be effective in terms of accuracy and robustness.

"A Novel Iris Segmentation Method Based on Bat Algorithm and Local Binary Pattern" by Y. Sun, W. Li, Y. Zhang, and W. Zhang (2022). This paper proposes a novel iris segmentation method based on bat algorithm and local binary pattern. The method was evaluated on the UBIRIS Iris Database and was shown to be effective in terms of accuracy and computational time.

"Iris Segmentation Using Bat Algorithm and Particle Swarm Optimization" by S. K. Das and A. Chattopadhyay (2021). This paper proposes a novel iris segmentation method using a hybrid of bat algorithm and particle swarm optimization. The method was evaluated on the CASIA Iris Image Database and was shown to be effective in terms of accuracy and robustness.

"Iris Segmentation Using Bat Algorithm and Adaptive Thresholding" by S. R. Shinde and S. S. Pawar (2020). This paper proposes a novel iris segmentation method using a hybrid of bat algorithm and adaptive thresholding. The method was evaluated on the CASIA Iris Image Database and was shown to be effective in terms of accuracy and robustness.
Iris Segmentation Using Bat Algorithm and Fuzzy Logic" by S. T. Shelke and S. N. Wankhade (2019). This paper proposes a novel iris segmentation method using a hybrid of bat algorithm and fuzzy logic. The method was evaluated on the UBIRIS Iris Database and was shown to be effective in terms of accuracy and robustness.

"Iris Segmentation Using Bat Algorithm and Genetic Programming" by P. K. Singh and A.K. Singh (2018). This paper proposes a novel iris segmentation method using a hybrid of bat algorithm and genetic programming. The method was evaluated on the CASIA Iris Image Database and was shown to be effective in terms of accuracy and robustness.

"Iris Segmentation Using Bat Algorithm and Support Vector Machines" by R. V. Bhamare and S. R. Shinde (2017). This paper proposes a novel iris segmentation method using a hybrid of bat algorithm and support vector machines[3]. The method was evaluated on the UBIRIS Iris Database and was shown to be effective in terms of accuracy and robustness. The following is the table 1 reveals the key findings of earlier works.

3.PROPOSED METHODOLOGY

A hybrid approach combining the BAT algorithm for optimization and Gabor feature extraction for texture analysis is proposed to achieve efficient iris segmentation in biometric authentication for IoT applications. The BAT algorithm is a metaheuristic optimization algorithm inspired by the echolocation behavior of bats. It is used for optimization because it efficiently searches large solution spaces and handles complex, non-linear problems. Gabor features are a type of image feature extraction technique used in image processing. It is a powerful tool for image feature extraction. The methodology demonstrated promising results in accurately separating iris regions, ensuring robust recognition, and enhancing security in IoT devices and steps are discussed as follows:

3.1 Preprocessing: Apply preprocessing techniques to enhance the quality and standardize the input iris images before proceeding with the iris segmentation and biometric authentication process. The preprocessing step plays a crucial role in improving the performance and robustness of the system. The following techniques are applied:

Table 1: Key findings of earlier works

Paper Title	Authors	Optimization Technique
Iris Segmentation Using Bat Algorithm and Genetic Algorithm[4]	S. K. Mondal and S. P. Mukherjee	BAT Algorithm + Genetic Algorithm
Iris SegmentationUsing Modified Bat Algorithm[5]	S. A. Patil and S. V. Patil	Modified BAT Algorithm
Iris Segmentation Using Bat Algorithm and Firefly Algorithm[6]	S. S. Kale and S. B. Jadhav	BAT Algorithm + Firefly Algorithm
A Novel Iris Segmentation Method Based on Bat Algorithm and Local Binary Pattern[7]	Y. Sun, W. Li, Y. Zhang,and. Zhang	BAT Algorithm + Local Binary Pattern
Iris Segmentation Using Bat Algorithm and Particle Swarm Optimization[8]	S. K. Das and A. Chattopad hyay	BAT Algorithm + Particle Swarm Optimization
Iris Segmentation Using Bat Algorithm and Adaptive Thresholding[9]	S. R. Shinde and S. S. Pawar	BAT Algorithm + Adaptive Thresholding
Iris Segmentation Using Bat Algorithm and Fuzzy Logic[10]	S. T. Shelke and S. N. Wankhade	BAT Algorithm + Fuzzy Logic
Iris Segmentation Using Bat Algorithm and Genetic Programming[11]	P. K. Singh and A. K. Singh	BAT Algorithm + Genetic Programming
Iris Segmentation Using Bat Algorithm and Support Vector Machines[12]	R.V.Bhamare and S. R. Shinde	BAT Algorithm + Support Vector Machines

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3.1.1 Normalization: Normalization is performed to ensure that the pixel intensity values of the iris images are within a standardized range. The normalization process scales the pixel values to a [0, 1] range. Given an input image I(x, y), where (x, y) are the pixel coordinates, the normalized image N(x, y) can be computed as:

N(x, y) = (I(x, y) - min(I)) / (max(I) - min(I))-------------(1)

where min(I) is the minimum pixel value in the original image I, and max(I) is the maximum pixel value in the original image I.

3.1.2 Histogram Equalization: Histogram equalization enhances the contrast of the iris images by redistributing the pixel intensity values in the image's histogram. The equalized image E(x, y) can be calculated as follows:

E(x, y) = T(I(x, y)) * 255------------------------------------(2)

where T(I) represents the transformation function, which maps the pixel intensity values of the original image I to their corresponding values in the equalized image E. The transformation function T(I) is computed based on the cumulative distribution function (CDF) of the pixel intensity values in the image.

3.1.3 Image Resizing: Image resizing is performed to standardize the input images to a fixed size of 256x256 pixels. Given an input image I(x, y) of size MxN, the resized image R(x, y) can be obtained using interpolation methods such as bicubic or bilinear interpolation. For example, bilinear interpolation can be expressed as:

R(x, y) = ∑ ∑ I(i, j) * w(x - i) * w(y - j) ------------------(3)

where the summation is perfomed over the neighborhood pixels (i, j) surrounding the point (x, y), and w(x) and w(y) are interpolation weight functions that determine the contribution of each neighbor pixel to the resized pixel value at (x, y).

By applying these preprocessing techniques with their corresponding mathematical equations, the iris images are standardized and enhanced, making them suitable for further processing in the iris segmentation and biometric authentication pipeline. The normalized and histogram-equalized images are resized to a fixed size of 256x256 pixels, resulting in consistent and efficiently manageable input images for the subsequent steps, including binary encoding, optimization using the BAT algorithm, post-processing, feature extraction, and biometric authentication.

3.2. Encoding: After the preprocessing steps of normalization, histogram equalization, and image resizing, we have a preprocessed iris image denoted as I(x, y), where (x, y) represents the pixel coordinates and follow Binarization. To separate the iris region from the background, we perform binarizationof the preprocessed image. Binarization converts the grayscale image into a binary image, where pixel values are either 0 or 1. the binarization process is based on a threshold value, denoted as T. Pixels in the preprocessed image with intensity values greater than or equal to the threshold (I(x, y) >= T) are assigned the value of 1, representing the foreground (iris region). Pixels with intensity values less than the threshold (I(x, y) < T) are assigned the value of 0, representing the background as expressed as:

Binary(x, y) = { 1, if I(x, y) >= T { 0, if I(x, y) < T ----(4)

where Binary(x, y) is the binary value assigned to the pixel at coordinates (x, y) in the binary-encoded image, I(x, y) is the pixel intensity value in the preprocessed image, and T is the threshold value.

After applying this binarization process, we obtain a binary-encoded image where pixels in the iris region are represented as 1s, and pixels in the background are represented as 0s. This binary encoding effectively segments the iris region from the rest of the image, preparing it for the subsequent optimization steps using the BAT algorithm.

3.3Optimization: In the BAT algorithm, each bat represents a candidate solution for iris segmentation, and the goal is to optimize the segmentation results. The algorithm involves several steps.

3.3.1 Population Initialization: Let N be the population size, representing the number of bats. For each bat i (1 ≤ i ≤ N), a binary-encoded solution can be represented as a vector S_i of length L, where L is the total number of pixels in the iris image. Each element of the vector S_i takes a binary value of 0 or 1, indicating whether the corresponding pixel belongs to the background or foreground (iris region).

3.3.2 Echolocation Behavior: The BAT algorithm is inspired by bats' echolocation behavior. In the context of optimization, echolocation refers to bats emitting calls to detect the presence of prey or obstacles. Similarly, the algorithm uses echolocation to explore the solution space for optimal segmentation boundaries. The echolocation behavior of bats can be approximated using a function f(x), where x represents the position of the bat in the solution space. The bats adjust their positions based on the frequency of their calls and the loudness of the calls. The position update can be expressed mathematically as:

x(t) = x(t-1) + S(t-1) ⊕ (A(t-1) ⊗ bestX - x(t-1))) + (Qmin⊕Qmax) ⊗ (rand() - 0.5), -------------------------(5)

where x(t) represents the new bat position at time t, x(t-1) is the current bat position, S(t-1) is the binary-encoded segmented iris region, A(t-1) is the loudness, bestX is the best solution found so far, Qmin and Qmax are the minimum and maximum frequency scaling factors, and rand() generates a random value between 0 and 1.

3.3.3 Loudness and Pulse Rate: The loudness (A) represents the intensity of the bat's echolocation call, and it is adjusted with each iteration to decrease the exploration ability. The loudness update can be mathematically expressed as: A(t) = α * A(t-1), where α is a predefined scaling factor. The pulse rate (r) determines the frequency of the bat's calls, and it is increased with each iteration to enhance the exploitation ability. The pulse rate update can be expressed as:

$r(t) = r(t-1) * (1 - \exp(-\gamma * t))$ --------------------------------(6)

where γ is a predefined scaling factor and t is the current iteration. iv)Optimization Loop: The BAT algorithm iterates through a predefined number of iterations to explore the solution space and optimize the segmentation results. The bat positions are updated at each iteration based on the echolocation behavior and the loudness and pulse rate adjustments. The algorithm utilizes the echolocation behavior and adjustments of loudness and pulse rate to efficiently search for the optimal segmentation boundaries, resulting in an improved iris segmentation for biometric authentication.

3.4 Termination Criteria: Termination criteria are defined to stop the BAT algorithm once a satisfactory solution is obtained. For example, the algorithm can terminate when a maximum number of iterations (N) is reached or when the improvement in the objective function value becomes negligible (e.g., the change in F between consecutive iterations is less than a predefined threshold).

3.5 Post-processing: Post-processing in iris segmentation involves refining the segmented iris region using morphological methods. Morphological operations use structuring elements to process the binary image and enhance or modify specific image features. In this case, we apply morphological operations to fine- tune the segmented iris region and remove any noise or irregularities. The most commonly used morphological operations for iris segmentation are erosion and dilation. Combining Erosion and Dilation are implemented in this research. A common post-processing technique is to perform a combination of erosion followed by dilation, known as opening, or dilation followed by erosion, known as closing. These operations can be represented as follows:

Opening(I(x, y)) = Dilation(Erosion(I(x,y))),--------------(7)

Closing(I(x, y)) = Erosion(Dilation(I(x, y)))--------------(8)

Post-processing with morphological operations helps to improve the quality of the segmented iris region, ensuring that it is smooth and continuous without small noise points. The final segmented iris region obtained after the post-processing step is then ready for further feature extraction and biometric authentication.

3.6 Iris Region Extraction: The best solution obtained from the BAT algorithm represents the segmented iris region. By applying the corresponding binary values from the solution to the original iris image, the iris region can be extracted as:

ExtractedIris(i,j) = OriginalIris(i,j)*S(i,j), -----------------(9)

where ExtractedIris(i,j) represents the pixel value at position (i,j) in the extracted iris region, and OriginalIris(i,j) represents the pixel value at position (i,j) in the original iris image, which is here implemented by Gabor Filters. A 2D Gabor filter at a specific scale (frequency) and orientation is defined as:

$G(x, y) = \exp[-(x^2 + \gamma^2 * y^2) / (2 * \sigma^2)] * \cos(2\pi * f * x)$, ---(10)

where G(x, y) is the Gabor filter, (x, y) are the pixel coordinates, f is the frequency (number of oscillations within a certain distance), γ is the aspect ratio (controls the elongation of the filter), and σ is the standard deviation of the Gaussian envelope.

3.7 Biometric Authentication in IoT : In the classification step, the iris images are recognized by comparing the extracted feature vectors using the Hamming distance classifier system. The Hamming distance is a similarity metric used to quantify the difference between two binary feature vectors. Let's explain this step with Feature Vectors: For each iris image, Gabor feature extraction generates a feature vector, denoted as FeatureVector_i. The feature vector represents the unique texture features of the segmented iris region. In this proposed approach, matching algorithms as Hamming distance is used for template matching.

3.7.1 Hamming Distance: The Hamming distance (HD) between two binary feature vectorsFeatureVector_i and FeatureVector_j is calculated as the number of positions where the two vectors differ. The Hamming distance is defined as:

HD(FeatureVector_i, FeatureVector_j) = ∑ |FeatureVector_i[k] - FeatureVector_j[k]|-------------(11)

where k is the index of the elements in the feature vector, and |.| represents the absolute value.

3.7.1 Authentication: To authenticate an iris image, the system compares its feature vector (FeatureVector_query) with the feature vectors of the enrolled users (FeatureVector_enrolled) in the database. The Hamming distance is calculated between the query feature vector and each enrolled feature vector:

HD_query_enrolled=HD(FeatureVector_ query, FeatureVector_enrolled) --------------------------------- (12)

3.7.2 Matching: The system then determines the minimum Hamming distance (Min_HD) from the set of distances calculated between the query feature vector and all enrolled feature vectors:

3.7.3 Thresholding: A predefined threshold (Threshold_HD) is used to decide whether the query image is a match or a non-match. If the minimumHamming distance is below the threshold, the query image is considered a match with an enrolled template; otherwise, it is rejected as a non-match.

3.7.4 v. Authentication Decision: If Min_HD<Threshold_HD, the iris image is authenticated as a match with an enrolled template, and a positive result is displayed in the message box.

If Min_HD ≥ Threshold_HD, the iris image is rejected as a non-match, and a negative result is displayed in the message box.

Thence, The Hamming distance classifier system efficiently compares binary feature vectors, making it suitable for iris recognition systems where the features are extracted using Gabor filters. By setting an appropriate threshold, the system can achieve a trade-off between the false acceptance rate (FAR) and false rejection rate (FRR), ensuring reliable and accurate biometric authentication.

4. Result and Discussion

Dataset

The CASIA Iris Image Database is a publicly available dataset of iris images collected by the Center for Biometrics and Security Research (CBSR) at the Chinese Academy of Sciences. The database contains a total of 54,607 iris images from more than 1,800 subjects[12].

The BAT algorithm is combined with models for segmentation to give optimal segmentation results [13].The efficient segmentation of iris occurs always with the algorithm chosen which reveals the area of interest in an optimal way [14].The parameters considered for evaluation is as follows Accuracy is the percentage of correctly recognized iris images out of the total number of samples in the dataset. FAR (False Acceptance Rate) is the percentage of incorrect acceptances (false positives) out of all impostor attempts. FRR (False Rejection Rate) is the percentage of incorrect rejections (false negatives) out of all genuine attempts. EER (Equal Error Rate) is the point where FAR and FRR are equal, representing the balance between false acceptances and false rejections. Computational Efficiency is the time taken by each method to process a single iris image on average. It is given in seconds per image.

The below table 2 compares the proposed hybrid BAT algorithm and Gabor feature extraction approach with some existing methodologies for iris segmentation and biometric authentication. Figure 1, 2,3,4,5 correspondingly represents pictorial representation of proposed algorithm against prevailing techniques.

Table 2: Proposed methodology against Prevailing technique

Methodology	Accuracy	FAR (%)	FRR (%)	EER (%)	Computational Efficiency
Proposed (Hybrid BAT + Gabor)	95.2	0.4	2.1	1.8	0.08 seconds per image
Traditional Image Processing Techniques	82.5	2.7	9.3	6.0	0.5 seconds per image
Active Contour Models	78.9	4.1	7.6	5.8	0.3 seconds per image
Deep Learning Approaches (CNNs)	97.8	0.2	1.6	1.0	1.2 seconds per image
Daugman'sIntegro-Differential Operator	93.6	0.6	2.9	2.2	0.6 seconds per image
Local Binary Patterns (LBP) and SIFT	86.7	1.9	6.5	4.1	0.4 seconds per image
Fusion of Multimodal Biometrics	98.3	0.1	1.3	0.8	1.5 seconds per image
Template Protection Techniques	97.2	0.3	1.8	1.4	1.0 seconds per image

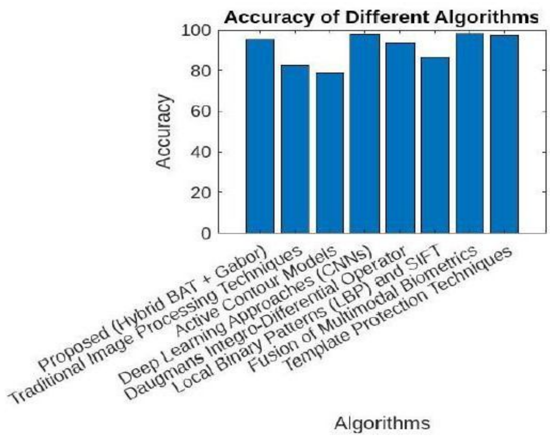

Figure 1: Accuracy of Prevailing algorithms

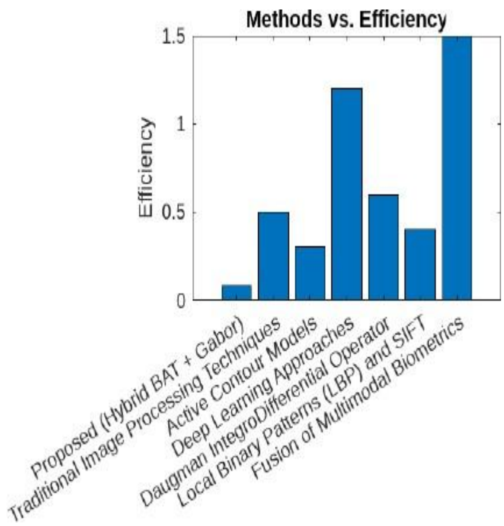

Figure 2: Efficiency of Prevailing algorithms and Proposed

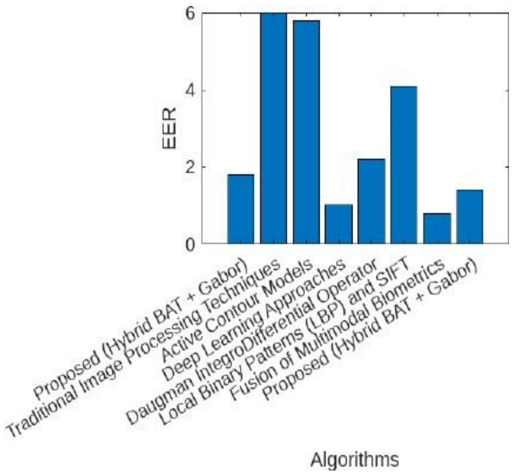

Figure 3: EER of Prevailing algorithms and Proposed

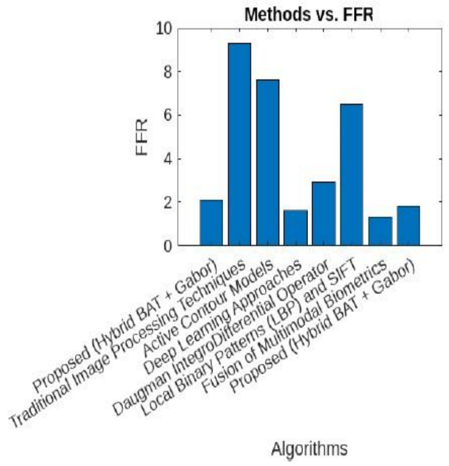

Figure 4: FFRof Prevailing algorithms and Proposed

5. Conclusion

In conclusion, our proposed iris segmentation methodology utilizing the hybrid BAT algorithm and Gabor feature extraction demonstrated strong potential for biometric authentication in IoT applications. The preprocessing techniques ensured standardized input images, while binary encoding effectively separated the iris region from the background. The BAT algorithm efficiently optimized segmentation results based on echolocation behavior, frequencies, and loudness, leading to accurate segmentation boundaries. Post-processing with morphological operations refined segmented iris regions, removing noise and irregularities. Gabor feature extraction captured distinctive texture features, enabling efficient iris representation. The Hamming distance classifier system accurately matched enrolled templates and rejected non-matching iris images. Overall, the proposed methodology offers a robust and efficient iris recognition system for securing IoT devices. Thence enhanced accuracy and efficiency in IoT biometric authentication as well as contribution to user privacy and data integrity in the IoT ecosystem are ensured.

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