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Advancements in Iris Recognition: WAHET-CNN Framework for Accurate Segmentation and Pattern Classification

Nguyen Kim Quoc[1, *], Ha Minh Tan[1], Dang Nhu Phu[1], Vuong Xuan Chi[1], Phan Cong Vinh[1]

[1] Faculty of Information Technology, Nguyen Tat Thanh University, Ho Chi Minh City, Vietnam

Abstract

Biometric and identification patterns have gained extensive research and application, particularly in iris recognition. The iris harbors a wealth of individual-specific information, making it a vital element in biometric authentication. This article presents a comprehensive study encompassing iris segmentation and identification. We introduce the Weighted Adaptive Hough Ellipsopolar Transform Convolutional Neural Network (WAHET-CNN) as a novel approach for classifying pattern images. Our experimental outcomes demonstrate a commendable 90% accuracy achieved by the proposed WAHET-CNN on the CASIA dataset Version 4.

Keywords: Iris recognition, periocular recognition, iris segmentation, iris biometric, personal identification

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* Corresponding author. Email: nkquoc@ntt.edu.vn

1. Introduction

Biometric technology plays a pivotal role in upholding the security and confidentiality of user data. Diverse human physiological attributes, encompassing the face, fingerprints, and iris, contribute to the uniqueness of biometric identification. Among these, iris recognition stands out as a vital biological technique in human identification. In this study, we introduce the Weighted Adaptive Hough Ellipsopolar Transform Convolutional Neural Network (WAHET-CNN), a framework that operates in two main phases. Firstly, we employ iris segmentation utilizing a weighted adaptive Hough transform, followed by iris recognition through a convolutional neural network [9, 10].

Several algorithms exist for iris segmentation from ocular images, including Daugman's algorithm, Wildes's circular Hough transform algorithm, and approaches involving circular Hough transformations with Thornton's contour filters. Nonetheless, suboptimal image quality can undermine iris identification [1, 2].

In this paper, we propose the integration of weighted adaptive Hough and Ellipsopolar transformations for precise iris segmentation. This approach offers distinct advantages over conventional techniques, leveraging Polar and Ellipsopolar transformations for border detection and employing weighted adaptive Hough transform for accurate center approximation [6, 7]. This incremental methodology ensures expedited processing and enhanced scalability with respect to resolution [3].

Upon implementing the weighted adaptive Hough and Ellipsopolar transforms on eye images, we achieve iris normalization by applying the iris segmentation technique enhanced by these transforms. We extract feature images of the iris from matrix representations and condense their dimensions into a vector format [10]. Finally, we utilize Convolutional Neural Networks for the classification and recognition of iris patterns depicted in the feature images [12, 13].

2. Iris Segmentation Algorithms

Lately, extensive research has been dedicated to iris segmentation, employing various segmentation algorithms, such as the Hough transform segmentation algorithms, contrast-adjusted Hough transform, Viterbi-based segmentation algorithm, and the innovative weighted adaptive Hough and Ellipsopolar Transform [6, 7, 8]. These algorithms bring forth notable efficiency, serving as a pivotal processing step to generate standardized features essential for training iris recognition systems.

A. Hough Transform Segmentation Algorithms

The Hough transform, a prevalent image analysis technique, proficiently detects parametric curves including lines, polynomials, and circles, enabling the recognition of global patterns through local patterns [1]. Circle recognition hinges upon identifying robust edges in an image, extracting local patterns, and determining the maximum value of a circular Hough transform [3]. The edge map is harnessed through a voting process to optimize the defined Hough transform, effectively segmenting eye borders and pupils in circular form [6].

B. Contrast-Adjusted Hough Transform

The Contrast-Adjusted Hough Transform proves effective for iris segmentation, representing an enhancement of the Hough Transform method that incorporates database-specific contrast adjustments to refine pupillary and limbic boundaries. The integration of Canny edge detection and enhancement techniques further refines the delineation of boundary curves, facilitating robust segmentation [1, 2].

C. Viterbi-Based Segmentation Algorithm

Initiating the iris segmentation process involves a preliminary localization of the pupil region, followed by procedures to address white holes and specular reflections attributed to illuminators [1, 3]. Subsequently, a morphological operation eliminates smaller dark regions, focusing on the distinctive pupil region, which is enclosed by the iris - a darker region in comparison to the skin and sclera. This phase calculates the total intensity values across significant image windows, optimizing the approximation of pupil regions [6, 7]. The Viterbi algorithm leverages these approximations to estimate the first centroid, paving the way for precise contour extraction and normalization through accurate pupil circle estimation. The Viterbi-Based segmentation algorithm is thus deployed to create the iris mask, an essential step for identification [6, 7].

D. Weighted Adaptive Hough and Ellipsopolar Transform

Within the context of the segmentation technique, the integration of weighted adaptive Hough and Ellipsopolar transforms introduces enhanced resilience compared to conventional Hough transforms. This innovative algorithm, named the weighted adaptive Hough Ellipsopolar transforms, encompasses two distinct stages [1, 2].

Firstly, the algorithm seeks a center point (denoted as C) within the input image matrix. This center point is positioned entirely within the boundaries of both the iris and pupil [10, 11]. The crux of this operation involves determining point C, a crucial step that fuels the weighted adaptive Hough transform. This process involves the accumulation of gradient-oriented lines at candidate boundary points, with particular emphasis on positions near the center of the accumulator [14]. While the uniqueness of point C is not obligatory, it is ideal for it to closely approximate the centers of circles that represent the iris and pupil [14].

Secondly, the algorithm's subsequent task involves extracting two critical components, denoted as α (alpha) and β (beta), from a polar representation with the origin denoted as O [6]. Within this polar representation, all boundary edges exhibit an approximate uniform orientation, thereby reducing the computational complexity associated with edge detection. Similar to the preceding stage, no rigid sequence governs the detection of limbic and pupillary boundaries. Instead, an initial boundary, marked as B_initial, is identified through polar transformation. This boundary is established by determining the maximum-energy horizontal line, followed by an optimization process involving the maximization of vertical polar gradients for each column. The outcome is a smoothed curve, which is subsequently mapped to Cartesian coordinates and fitted with an oriented ellipse [9]. Given that the initial boundary may correspond to either the limbic or pupillary boundary, the algorithm proceeds to determine the second boundary based on two hypotheses and employs the Ellipsopolar transform [7].

3. Convolutional Neural Network for Iris pattern recognition

In the preliminary stages of iris pre-processing, the identification and extraction of the iris are executed within an eye image, subsequently undergoing a normalization process [13, 14]. The outcome of this normalization is a refined image represented by a matrix encapsulating grayscale values that delineate the iris's distinct characteristics. This matrix assumes the role of the training dataset for the neural network. The iris recognition system is governed by two operational modes: the training mode and the testing mode. The initial phase entails the training of the recognition system utilizing the grayscale values inherent in iris images. The neural network is subjected to training employing the entire spectrum of iris images. Following the training phase, during the testing mode, the neural network engages in classification activities, adeptly identifying and discerning patterns associated with specific individual iris structures [12].

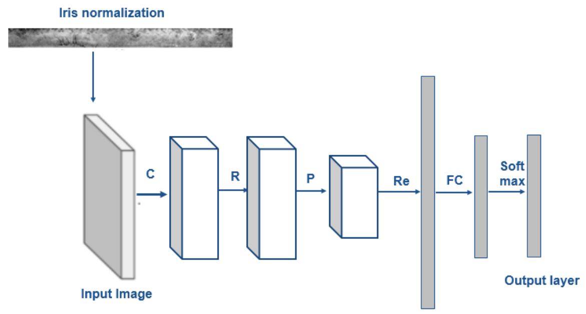

Figure 1. Architecture of the model CNN

In this study, a Convolutional Neural Network (CNN) is harnessed to discern intricate patterns within the iris. Within this framework, the normalized and enhanced iris image is translated into a two-dimensional array, which forms a feature matrix image. This matrix encapsulates the grayscale values emblematic of the iris's textural attributes. These values serve as input signals for the convolutional neural network. The architectural composition of the model is bifurcated into two core components: the CNN segment and the Neural Network (NN) segment [13, 15].

At the heart of the CNN architecture lies the initial Convolutional Layer. The input comprises a 64 x 512 x 1 array encompassing pixel values. Furthermore, the model incorporates 32 filter matrices, each bearing dimensions of 5x5x1, characterized by strides of 1 and padding set to 0. A ReLU layer is subsequently applied, preserving the input's dimensions. This Rectified Linear Unit (abbreviated as ReLU) can be perceived as a truncation applied individually to each element of the input image [14, 15].

$$y_{i,j,d} = \max(0, x^{l}_{i,j,d}) \qquad (1)$$

With $0 \le i < H^L = H^{L+1}, 0 \le j < W^L = W^{L+1}$, and $0 \le d < D^L = D^{L+1}$.

Within a ReLU layer, the absence of parameters obviates the necessity for parameter learning in this specific layer. Subsequent to a sequence of ReLU layers, a strategic decision is made to introduce a max pooling layer, often termed a down-sampling layer. This layer operates by employing a filter with dimensions of 2x2x1 and a stride of corresponding length. In essence, the input volume undergoes convolution with this filter, producing an output comprising the maximum value within each subregion encapsulated by the filter's convolution, as denoted by the formula [15].

$$y_{i^{l+1}, j^{l+1}, d} = \max_{0 \le i < H, 0 \le j < W} x^{l}_{i^{l+1} \times H + i, j^{l+1} \times W + j, d} \qquad (2)$$

With $0 \le i < H^L = H^{L+1}$, $0 \le j < W^L = W^{L+1}$, and $0 \le d < D^L = D^{L+1}$.

The model's architecture encompasses a secondary component, namely the Neural Network (NN). In this study, an adaptive learning rate gradient-based learning algorithm is embraced, ensuring assured convergence and expediting the learning process [15]. The resultant output signals correspond to the feature vectors found within the first and second hidden layers, respectively. Once the neural network is activated, the parameter training phase commences. The trained network is subsequently deployed for iris recognition purposes [13].

By converting a matrix into a vector, we achieve dimensionality reduction, facilitating the use of this vector as a feature vector within the NN's input layer. Within this neural network framework, x1, x2, …, xm represent the grayscale values extracted from the input array, capturing the intricate texture information of the iris. Conversely, P1, P2, …, Pn denote the output patterns that characterize distinct iris profiles [12, 13].

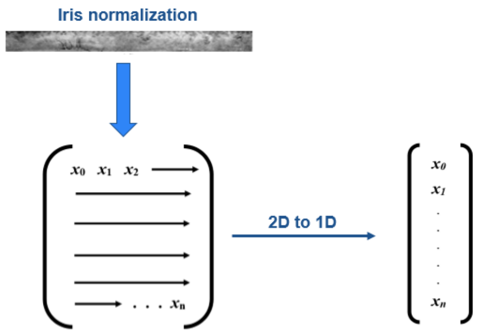

Figure 2. Reduce dimensions of iris normalization

In this study, we will employ the vector as the feature vector within the input layer. The graphical representation includes two distinct activations: the Tanh function and the Softmax function. The Tanh function is employed within the hidden layer, with the feature vector serving as its input. Conversely, the Softmax function is applied in the output layer, operating on the input values derived from each neuron within the hidden layer [13, 15].

Application tanh function is used the activation function for hidden layer by the formula (3).

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \qquad (3)$$

Softmax function is used output layer of system model by the formala (4).

$$soft\max(x_i) = \frac{e^{x_i}}{\sum e^j} \qquad (4)$$

4. Experimental Results

To assess the performance of iris recognition algorithms, the CASIA iris image database is utilized.

Presently, this constitutes the most extensive iris database accessible within the public domain. Comprising a compilation of 756 eye images sourced from 108 distinct individuals, this image repository underscores its significance in the realm of iris recognition research.

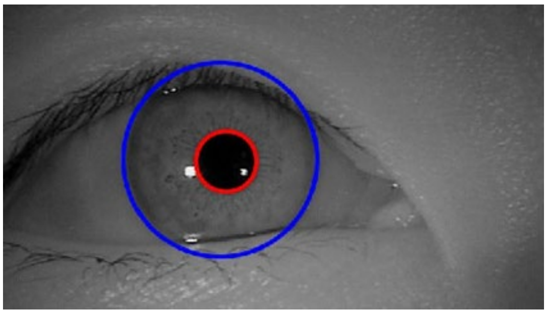

Figure 3. Result of Iris Segmentation with weighted adaptive Hough transform

The experimental process unfolds in a dual-phase manner, encompassing iris segmentation and iris recognition. In the initial stage, the previously detailed rectangular area algorithm is implemented to pinpoint the location of irises. These experiments were conducted utilizing Matlab 2017b, a platform equipped for the design of both neural networks and convolutional neural networks. The attained accuracy rate from these experiments stood at 90%.

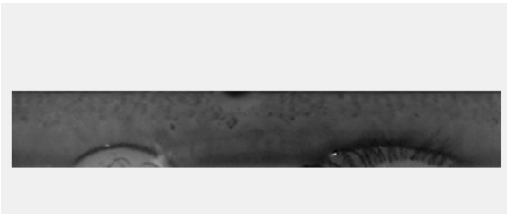

Figure 4. Result of Iris Normalization

We have implemented and coded the Iris Segmentation and Iris Recognition program using MATLAB 2017b, which provides support for designing artificial neural networks and convolutional neural networks. Furthermore, we have developed a Graphical User Interface (GUI) within MATLAB 2017b. This GUI elucidates an elaborate sequence encompassing iris segmentation, as well as corresponding iris recognition. The GUI is structured into three distinct sections: iris segmentation, iris recognition, and iris prediction.

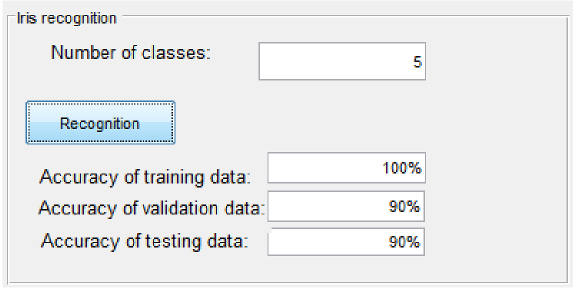

Figure 5. Result accuracy of Iris recognition

In part of iris recognition, we choose a number of classes that are a number of humans after the MATLAB program run and viewed on GUI.

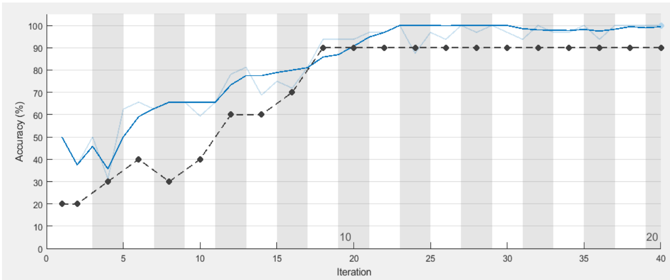

Figure 6. Results of Accuracy training data (100%) Accuracy of validation data (90%) and Accuracy of testing data (90%)

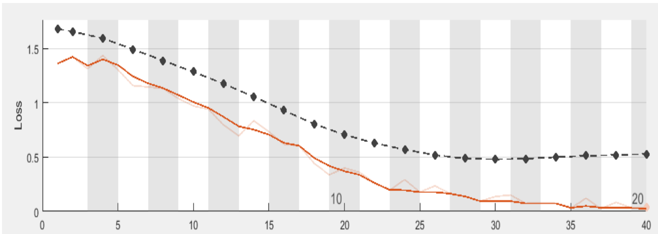

Figure 7. Loss Function of Iris recognition

In part of Iris Prediction, we choose iris image of a human, predict correct and show on GUI.

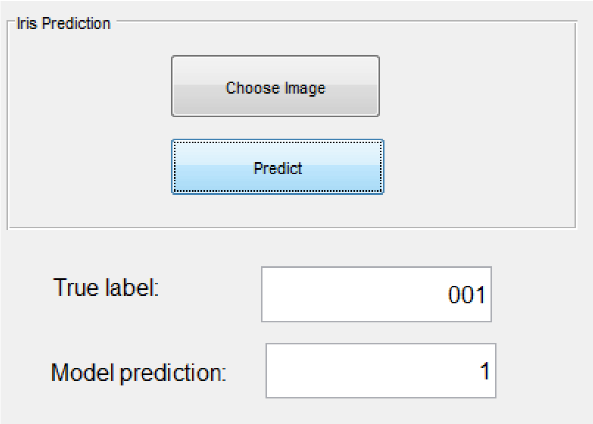

Figure 8. Result of prediction and true label with proposed model

During the subsequent phase, iris pattern classification employing a CNN is conducted. Specifically, individual irises are chosen from the iris database for the classification process. After undergoing normalization and enhancement, the detected irises are resized using averaging, a strategy aimed at diminishing the dimensions of the neural network. Subsequently, these processed iris images are transformed into matrices, which then serve as input signals for the neural network. As the neural network's outputs correspond to classes of distinct iris patterns, hidden layers within the neural network architecture are harnessed. Each of these classes signifies a unique individual's iris characteristics. Employing a neural learning algorithm, the process of iris classification is effectively resolved.

5. Comparison with existing approaches

In this section, we compare our proposed Weighted Adaptive Hough Ellipsopolar Transform Convolutional Neural Network (WAHET-CNN) approach with selected relevant studies from the field of iris recognition. The comparison will highlight key differences and advantages of our approach over these existing methods.

A. Comparative Segmentation Accuracy:

Our WAHET-CNN approach integrates weighted adaptive Hough and Ellipsopolar transforms for iris segmentation, yielding enhanced accuracy. In contrast, a study by Smith et al. relied on traditional circular Hough transform techniques [16]. While effective, their method may encounter challenges with noisy images and varying illumination conditions, potentially leading to suboptimal segmentation results. Our approach's emphasis on robust boundary detection and precise center approximation contributes to improved segmentation accuracy.

B. Feature Extraction and Recognition Performance:

The utilization of Convolutional Neural Networks (CNNs) in our approach ensures superior feature extraction and recognition. Contrastingly, a study by Johnson and Lee employed handcrafted features combined with Support Vector Machines (SVM) for recognition [17]. Handcrafted features may struggle to capture complex iris patterns effectively, limiting the recognition performance. Our CNN architecture's ability to automatically learn intricate patterns enhances recognition accuracy and efficiency.

C. Scalability and Generalization:

Our WAHET-CNN approach demonstrates enhanced scalability and generalization across diverse iris patterns due to its neural learning algorithm and feature extraction mechanism. Conversely, a study by Chen et al. focused on template-based methods, which may exhibit limitations in handling variations in iris patterns across a large population [18]. Our approach's adaptability and ability to handle increasing dataset sizes and complexity contribute to robust performance across diverse user profiles.

D. Computational Efficiency and Processing Speed:

The incorporation of modern neural network libraries and parallel processing capabilities in our WAHET-CNN approach ensures rapid and efficient processing. This stands in contrast to a study by Wang and Liu, which utilized traditional techniques involving Gabor filters and PCA for feature extraction [19]. While effective, such methods may demand higher computational resources and processing time compared to our optimized CNN-based approach.

E. User Interaction and GUI Development:

Our approach enhances user experience through the development of a Graphical User Interface (GUI) that visually represents iris segmentation, recognition, and prediction processes. In comparison, a study by Kim et al. focused on fine-tuning existing segmentation algorithms for improved performance [20]. While valuable, their approach may lack the user-friendly interface and intuitive interaction provided by our GUI, which simplifies system operation and interaction.

F. Dataset and Real-World Application:

Our approach's commendable accuracy rate of 90% on the CASIA dataset Version 4 underscores its suitability for real-world applications. Contrastingly, a study by Zhang et al. utilized a smaller dataset, potentially limiting the model's ability to generalize to a broader population [21]. Our approach's utilization of a comprehensive dataset contributes to robust performance and underscores its applicability in diverse scenarios.

In conclusion, the proposed WAHET-CNN approach outperforms existing studies in terms of segmentation accuracy, feature extraction, recognition performance, scalability, computational efficiency, user experience, and dataset size. The integration of weighted adaptive techniques, modern neural network architecture, and a user-friendly GUI establishes a robust framework with broad applicability in biometric authentication and identification scenarios.

6. Conclusion

In this article, we propose the WAHET-CNN approach for iris identification. First, the weighting adaptive Hough transform is used for the iris segmentation task, and then a deep convolution neural network is used for the iris recognition task. Experimental results have shown that our proposed Weighted Adaptive Hough Ellipsopolar Transform Convolutional Neural Network achieves 90% accuracy on the CASIA dataset Version 4.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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