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Feature-Based Comparative Evaluation of Amphibian Iris Patterns

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Abstract. The use of animal biometrics has gained importance for reliable individual identification, with iris patterns offering a stable and distinctive characteristic for each organism. This study focuses on analyzing iris patterns in frogs by examining both geometric and color-based features. The objective is to identify key attributes that can support ecological research, biodiversity monitoring, and species conservation, while also enabling unique identification of individual frogs. The methodology involves capturing images of amphibian eyes, followed by iris localization and segmentation. Subsequently, feature extraction is performed using a combination of geometric descriptors and color characteristics to evaluate variations across different samples.

Keywords. Authentication; amphibian; iris; pattern recognition.

1 Introduction

Amphibians are distributed across diverse ecological regions, with some species commonly encountered while others have become increasingly rare or are now classified as endangered. The decline in amphibian populations has raised serious concerns among conservationists and wildlife management organizations, which are actively involved in monitoring, counting, and protecting these species. In recent years, several amphibian species have faced a significant risk of extinction due to environmental changes, habitat loss, and other ecological pressures. As a result, there is a growing need for reliable methods to study, identify, and track these organisms. Amphibians are biologically unique, as they typically 2.begin their life cycle in aquatic environments and later transition to terrestrial habitats.

In this paper, an approach is presented for analyzing and classifying iris patterns of different amphibian species. The method begins with image enhancement using the Laplacian of Gaussian operator to improve the visibility of structural details in the iris region. Subsequently, color-based features are extracted to capture distinctive patterns. Feature selection is carried out using histogram-oriented descriptors derived from color information. For classification, a minimum distance classifier is employed, and Euclidean distance is used as the similarity measure for matching. Experimental observations indicate that the proposed approach achieves performance levels comparable to those reported in human iris recognition studies. A considerable amount of research has been conducted in the field of iris recognition, primarily focused on human biometrics and database development. Some studies have also explored iris-based identification in animals such as birds and mammals. For example, earlier work has examined iris

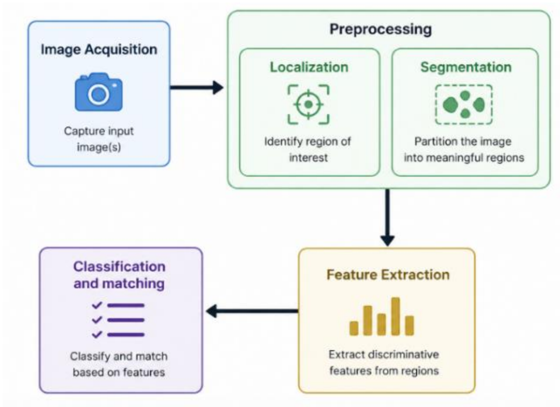

Fig. 1. Flow diagram of iris recognition for amphibians

recognition in species like kingfishers, monkeys, and owls. In addition, research efforts in animal identification have extended to livestock monitoring, plant classification using machine learning techniques, and non-biometric as well as biometric approaches for tracking cattle and other animals. Investigations have also been carried out on iris-based identification in goats, cows, and horses, including the use of advanced techniques such as deep learning for periocular recognition. Despite these developments, there is a noticeable lack of research focusing on iris recognition in amphibian species. To the best of our knowledge, no comprehensive study addressing amphibian iris-based identification has been reported so far. This gap highlights the significance of the present work, which aims to contribute to the field of wildlife biometrics by introducing a novel approach for amphibian species identification based on iris pattern analysis.

2 Proposed Methodology

In the present study, we have implemented an iris recognition system for various endangered amphibian species, aiming to support their identification and conservation. The overall framework of the proposed system is illustrated in Fig. 1. The process begins with Image Acquisition, where high-quality images of amphibian eyes are captured under controlled or natural conditions. This is followed by Preprocessing, which enhances the image quality by reducing noise, normalizing illumination, and isolating the region of interest through localization and segmentation techniques.

Next, Feature Extraction is performed to obtain distinctive patterns from the iris region. These features represent unique textural and structural characteristics that can differentiate one individual or species from another. Advanced algorithms are used to ensure robustness against variations in lighting, orientation, and occlusion. Finally, the system performs Classification and Matching, where the extracted features are compared with a stored database to identify or verify the amphibian. This step utilizes efficient matching techniques to achieve high accuracy and reliability. Overall, the proposed iris recognition pipeline provides a non-invasive and effective method for monitoring and conserving endangered amphibian species.

3 Stages of Iris Recognition Process

3.1 Image Acquisition of Iris

The capturing of high quality iris image is called acquisition. The quality of the eye image should be very high. Good resolution and clarity of eye image will lead to a better recognition rate. Noises such as illumination should be removed in case of image capturing which may lead to occlusion and blurring of the image.

3.2 Preprocessing

Preprocessing of the iris is performed to obtain a noise-free image, ensuring that the unique features of each individual's iris are clearly distinguishable. This stage consists of two main components: localization and segmentation. First of all the eye image captured and the image is sharpened by reducing various noises like reflection, occlusions etc. After then, localization is followed by segmentation.

Localization – In localization process, only the inner and outer circle boundary are taken into account. This is done by circular half transform to identify the boundary between pupil/iris and iris/sclera.

Segmentation – The Image acquisition step only captures the image of the Iris portion of the eye which is the area of interest in this paper. So

Fig.2. Iris patterns of various amphibians

iris segmentation must be carried out to discard the noises that are present in the image such as eyelash, eyebrows and cornea. So for feature extraction of process, it is of utmost important to localize the portion of the image that consists of only the iris.

3.3 Laplacian of Gaussian (LoG)

The Laplacian operator is a two-dimensional method that looks at how quickly intensity changes across an image at a deeper level. It is widely used in image processing because it helps identify areas where the brightness shifts suddenly, making it especially useful for detecting edges and fine details. These rapid intensity variations usually correspond to edges, boundaries, or fine structural details within the image. Because of this property, the Laplacian operator is widely used for edge detection and feature enhancement tasks.

However, one limitation of the Laplacian operator is its sensitivity to noise, as noise also produces sharp intensity variations. To address this issue, the input image is commonly smoothed before applying the Laplacian. This smoothing is typically performed using a Gaussian filter, which reduces noise while preserving the overall structure of the image.

The combination of Gaussian smoothing followed by the Laplacian operation is known as the Laplacian of Gaussian (LoG). This approach improves the accuracy of edge detection by minimizing false responses caused by noise [13-14].

In most practical implementations, the input to the process is a single grayscale image, as intensity variations are easier to analyze in one channel. After applying the Laplacian or LoG operation, the output is also a grayscale image, where the edges and significant transitions in intensity are clearly highlighted. This processed image can then be used for further analysis, such as segmentation, feature extraction, or object recognition.

The Laplacian L(x,y) with pixel intensity values I(p,q) of an image is given by:

$$L(p,q) = \frac{(\delta^2 I)}{(\delta p^2)} + \frac{(\delta^2 I)}{(\delta q^2)}. \quad (1)$$

The above formula can be calculated using a convolution filter. The LoG (Laplacian of Gaussian) kernel can be pre-calculated in advance so only one convolution needs to be performed at run-time on the image.

The 2-D LoG function centered on zero and with Gaussian standard deviation has the form:

$$LoG(p,q) = \frac{-1}{(\pi\sigma^4)}\left[1 - \frac{(p^2+q^2)}{(2\sigma^2)}\right] e^{\frac{-(p^2+q^2)}{(2\sigma^2)}}. \quad (2)$$

3.4 Feature Extraction of Iris

3.4.1 Various Geometrical Features

- The area of the elliptical iris = πab,
- The length of the major axis of the amphibian iris = 2a.
- The length of the minor axis = 2b.
- The aspect ratio of the iris is given by b/a.

3.4.2 Color Features

To determine the color of objects, specific features are analyzed. The key color features are listed below

Color histogram — Consider two histograms corresponding to images A and B:

$$A = \{h_1^A, h_2^A \ldots h_K^A\},$$
$$B = \{h_1^B, h_2^B \ldots h_1^B\}. \quad (3)$$

The similarity between two images is given by the color distance. Color distance is given by the measure:

$$d = \sum_{j=1}^{k} | h_j^A - h_j^B |. \quad (4)$$

The histogram intersection, that is, pixels that are common in two images, is given by:

$$I(H^A, H^B) = \sum_{j=1}^{k} min\left(h_j^A - h_j^B\right). \quad (5)$$

To compute the color coherence vector, the image is separated into two regions. One region

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contains pixels that belong to large, uniform areas, while the other includes pixels from smaller, scattered regions. The vector is represented as a pair (P,Q)(P, Q)(P,Q), where PPP denotes coherent pixels and QQQ represents incoherent pixels.

Similar to grayscale images, statistical measures such as mean, variance, skewness, kurtosis, and higher-order moments can be calculated for color images. Detailed histogram-based features are extracted, which play a significant role in distinguishing color images. These features are widely applied in content-based image retrieval systems, where color information is a key factor.

3.5 Classification and Matching Minimum Distance Classifier

A variety of classifiers can be used for pattern recognition, such as Support Vector Machines (SVM), neural networks, and minimum distance classifiers.. Each of these approaches has its own strengths and computational requirements. SVMs and neural networks are powerful techniques capable of modeling complex decision boundaries, but they typically require a training phase, parameter tuning, and higher computational resources. In contrast, the minimum distance classifier offers a simpler and more efficient alternative, particularly suitable for problems where computational speed and ease of implementation are important.

In this work, the minimum distance classifier is adopted due to its effectiveness in pattern matching applications. One of its primary advantages is that it does not involve an explicit training process. Instead, it relies directly on the feature vectors extracted from known samples. This makes the method faster and easier to implement, especially when working with moderate-sized datasets. Additionally, it is straightforward to update the system by adding new samples without retraining a model, which is often required in more complex classifiers.

The performance of the minimum distance classifier largely depends on the quality and discriminative power of the extracted features. If the features are well-designed and can clearly separate different classes, the classifier can achieve high accuracy. However, if there is significant overlap between feature distributions of different classes, the classifier may struggle to produce reliable results. In such cases, more sophisticated methods like SVMs or neural networks may provide better classification performance.

The working principle of the minimum distance classifier is based on measuring the similarity between feature vectors. For an unknown sample, its feature vector is compared with those of all known samples (or class prototypes). The distance between these vectors is computed using a suitable distance metric, and the unknown sample is assigned to the class corresponding to the smallest distance. This approach essentially assumes that samples belonging to the same class will be closer to each other in the feature space than to samples from different classes.

Common distance measures used in this context include Euclidean distance and Mahalanobis distance. Euclidean distance is the most straightforward and widely used metric, calculating the straight-line distance between two feature vectors in multidimensional space. It works well when the features are uncorrelated and have similar scales. On the other hand, Mahalanobis distance takes into account the variance and correlation among features, making it more robust when the data exhibits different scales or correlations. As a result, Mahalanobis distance often provides better discrimination in cases where feature distributions are not uniform.

Overall, the minimum distance classifier provides a simple, fast, and effective solution for classification problems when the feature space is well-structured. Its ease of implementation and low computational cost make it a practical choice, although its success ultimately depends on the quality of the feature extraction process:

$$r^2 = (x - m_x)' c_x^{-1} (x - m_x) \,. \quad (6)$$

It is referred to as the Mahalanobis distance between a feature vector xxx and the mean vector mxm_xmx, where CxC_xCx represents the covariance matrix of the feature set.

In a minimum distance classification framework, let m1,m2,…,mcm_1, m_2, …, m_cm1,m2,…,mc denote the mean vectors (prototypes) of ccc different classes, and let C1,C2,…,CcC_1, C_2, ...,

Table 1. Comparison of data from different authors

Authors	Recognition Rate (%)	EER (%)	FAR (%)	FRR (%)
LiMa et al.	96.00	4.74	0.02	1.98
Hamed et al.	98.10	2.40	1.60	1.20
S.Roy et al.	96.00	1.70	1.80	2.10
Brock et al.	95.10	2.30	2.06	2.76
Proposed Approach	98.8	1.50	1.46	1.56

C_cC1,C2,…,Cc be their corresponding covariance matrices. An unknown feature vector XXX is assigned to a class by computing its Mahalanobis distance to each class mean and selecting the class for which this distance is the smallest.

A key benefit of using Mahalanobis distance is that it inherently accounts for differences in scale along feature dimensions and also adjusts for correlations between features. This leads to more reliable classification boundaries compared to simple distance measures. The method effectively defines optimal minimum-distance decision boundaries in the feature space.

The achieved classification accuracy is approximately 98.8%. These results are also evaluated against those reported in earlier studies, considering metrics such as recognition rate, equal error rate, false acceptance rate, and false rejection rate.

4 Conclusion

A conceptual study has been carried out for iris pattern recognition in amphibians using Circular Hough Transform and Laplacian of Gaussian techniques. Feature extraction is performed through histogram-based representation of color characteristics, and classification is achieved using a minimum distance approach with Mahalanobis distance.

Although the obtained results are compared with those reported in existing studies on iris pattern recognition, the primary focus is on evaluating the effectiveness of the proposed method through a comparative analysis.

It has been observed that the processing and execution time of the system is relatively high. This could be improved by reducing the use of computationally intensive operations, such as repeated exponential calculations, or by combining certain steps to achieve similar outcomes more efficiently. The findings of this study are expected to provide a useful foundation for future research, particularly in applications related to the identification and conservation of diverse amphibian species.

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