

Image Based Periocular Biometric Authentication Using Python

Mrs.V.Sivasakthi M.E¹ , Dr.S.Sujatha²

¹Assistant Professor, Anjalai Ammal Mahalingam Engineering College, Kovilvenni, Tamilnadu.

²Professor, Anna University (BIT Campus), Tiruchirappalli, Tamilnadu.

Date of Submission: 25-11-2022

Date of Acceptance: 06-12-2022

ABSTRACT

The term "biometrics" describes the use of human physiological and behavioural traits for personal identification. A number of physical traits, including fingerprints, faces, ocular region components, and voice, can be used as biometrics. Ocular biometric features have drawn the most attention recently among the aforementioned modalities since the ocular region is a crucial and interconnected human trait made up of various elements, including the cornea, lens, optic nerve, retina, pupil, and periocular region. It is possible to get and use as a biometric the entire periocular region, also known as the area around the eye. One of the most pressing issues on peoples' minds is security. A person can be identified automatically using biometrics if their physiological or behavioural characteristics are unique. Periocular biometric describes the area of the face right around the eye. In contrast to previous ocular biometrics, periocular biometric acquisition does not necessitate tight capture distance and strong user cooperation. ICP (Iterative Closest Point algorithm), Curvelet transform, and Deep Neural Network techniques are used on photographs of a person's eyes in the automated biometric identification process known as image based periocular recognition. To cut costs, use camera-based implementation as opposed to scanner-based implementation. Neural network parallel classification provides modal security. Due to the lack of expensive equipment needed, periocular-based approaches are employed as an alternative to biometric authentication. These traits (sclera, eye lash, eye shape, and eyelids) can be leveraged for identification as opposed to the intricate iris pattern because they don't need a high resolution image and are unique to each person.

Keywords: Periocular ,ICP, Deep Neural Network

I. INTRODUCTION

In a wide range of applications, digital data are quickly evolving into a crucial platform for several authentication procedures. However, if a

computer or smartphone is protected with techniques that offer an inadequate level of security, sensitive data is at risk.

PIN and password authentication utilising a combination of alpha numeric and symbols have been the most widely used access control techniques since the invention of desktop and mobile phones. One can use long passwords with a variety of special characters at the expense of avoiding the risk associated with short passwords. Biometrics are distinguished from the broader field of human identification science by the word "automated."

The entire process of biometric authentication is carried out by a machine, typically (but not always) a digital computer.

This field does not include forensic laboratory procedures like latent fingerprint, DNA, hair, and fibre analysis.

The subjects of biometric authentication are living humans, even though automated identification techniques can be employed on animals, fruits and vegetables, manufactured items, and the deceased.

The iris texture has a mostly prototypical genesis that is distinctive for each person and allows for very high recognition accuracy, which justifies the efforts being made in iris biometric research and its swift rise to become one of the most well-liked biometric qualities. While the majority of commercially available iris recognition systems use limited near-infrared (NIR) data to enhance pattern perception while minimizing related noise components, literature on expanding the applicability of this biometric to "relaxed" visible wavelength (VW) setups has grown. However, in less-than-ideal circumstances, iris performance as a biometric trait is severely compromised. In addition, due to its relatively small size and changing profile, iris imaging from a distance and without human assistance is challenging.

Compared to standard systems, standoff biometric systems require a less regulated environment, therefore the images they take are likely to be less than optimal, including off-angle.

We offer deep learning frameworks based on convolutional neural networks (CNNs) to enhance periocular biometric modality recognition performance for off-angle photos.

According to a literature review, ocular and facial biometrics are the most popular types of biometrics, followed by fingerprint, ear, sclera, retina, and face biometrics. Face biometrics frequently fails if the collected face photographs (those of human volunteers) have A-PIE (Aging, Pose, Illumination, and Expression) problems because ocular biometrics (using the iris of the eyes) demands a great deal of user participation, a high-quality camera, and a good camera stand-off distance for taking the images. The periocular region, the area around the eye, was suggested by researchers as a potential solution to these issues. Eyelashes, tear ducts, eye shape, eye lids, eyebrow, outer corner, and skin were ranked from most useful to least helpful in the first study to look at the viability of a biometric trait's periocular region by Park et al. For visible spectrum photos, the brow's contour stands out the most, while the shape of the eyelids is most distinctive for NIR spectrum images. Regarding biometrics, the periocular region is also essential for soft biometric classification and matching the characteristics of medically altered facial images. (Recognition of surgically altered faces; human subjects' photos taken before and after cataract surgery; and photos taken both during and before the process of gender reassignment.) The primary benefit of this biometric characteristic is that it requires very little user participation and low-quality images, which makes the periocular region appealing for security and surveillance applications as well as situations when faces are partially obscured. This work presents a state-of-the-art review of the periocular biometrics literature in order to address the shortcomings of the current system.

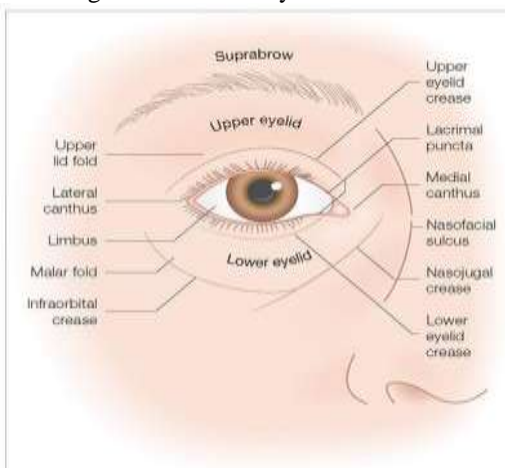


Figure 1: Periocular region

II. LITERATURE SURVEY

1. SOFT-BIOMETRIC CLASSIFICATION USING PERIOCCULAR REGION FEATURES, Jamie R.

Lyle Philip E. Miller Shrinivas J. Pundlik Damon L. Woodard and 2010. Utilizing grayscale pixel intensities and periocular texture calculated by local binary patterns as our features and an SVM classifier, we can extract gender and ethnicity information from the periocular region images. The preferred classifiers include Adaboost (along with many boosting variations), SVM, neural networks, and LDA, among others. The resulting soft biometric data can be successfully applied to enhance the functionality of current periocular-based recognition techniques. This can be because the left side of the face appears darker than the right because of the uneven lighting on the face. Additionally, women are more likely than men to apply makeup, which may have an impact on how accurately these genders are classified.

2. PERIOCCULAR RECOGNITION: ANALYSIS OF PERFORMANCE DEGRADATION

FACTORS, Chandrashekha r N. Padole and Hugo Proenca, 2012. There are various biometric features, such as face, iris, fingerprint, and gait, that provide for the freedom to select one or combine multiple modalities for recognition, depending on the availability and viability related to the application objectives. In contrast to the conventional method of initialising the ROI based on the location of the iris centre, a novel approach to initialising the periocular ROI based on the geometric mean of the eye corners can consistently increase performance, as our trials revealed. Although the creation of non-cooperative systems has driven many research efforts, biometric recognition systems typically work in limited lighting settings and under strict data collection standards. The key challenges are the declining data quality and its nonuniformity in comparison to conventional methods.

3. PERIOCCULAR BIOMETRIC RECOGNITION USING IMAGE SETS Muhammad Uzair, Arif Mahmood, Ajmal Mian, Chris McDonald and 2013.

For iris biometric human identification, a cooperative subject must provide high-resolution iris photographs. Applications that don't require intrusion, like surveillance, cannot produce such images. The entire periocular region, as it is known, can, however, be obtained nonintrusively and used as a biometric. In this work, we examine the use of the periocular region for the identification of individuals. Six cutting-edge image-set classification techniques are used to examine the effectiveness of the periocular biometrics. Affine and convex hull-based

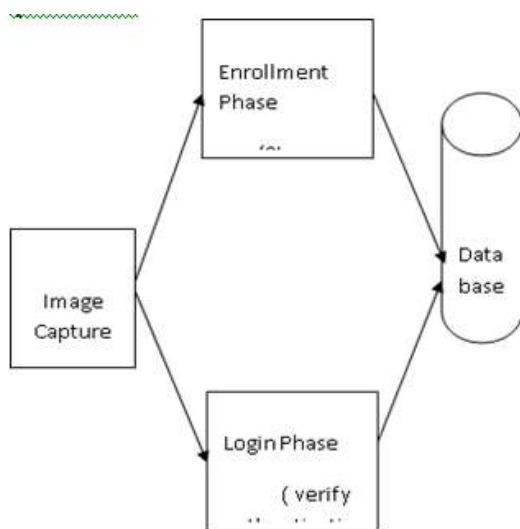
image set distance (AHISD and CHISD), sparse approximated nearest points distance (SANP), discriminative Canonical Correlation, manifold manifold distance, and manifold discriminant analysis are also examples of such methods.

III. PROPOSED FRAMEWORK

Using a web camera and a biometric recognition system, collect periocular images for identification. Curvelet transforms can be used to extract the periocular pattern. Using a neural network approach, users in a database are categorized. Due to their great accuracy, convolutional neural networks are used for image recognition and classification. The main objective is to create a biometric authentication system based on periocular images. This study addresses the drawbacks of face and iris databases, opening the path for their future use in a range of real-time applications.

A. SYSTEM ARCHITECTURE

In this method, periocular images are collected using a camera, and the corresponding periocular images are stored in a database after the periocular region has been acquired and pre-processing has begun. A continuous range of values is converted into a finite range of discrete values through the process of quantization. Quantization is required since there are only so many bits available to indicate a pixel's intensity when changing it from colour to grayscale (let's pretend this is a grayscale image for ease). A pixel uses 8 bits, and its equivalent value is between 0 and 255. (discrete values) Pure white is represented by 255, and pure black by 0. As seen in this image, grayscales use intermediate values. This is quantization in action. For 8 bit pixels, quantization level is 256.



The deep learning field of system architecture comes next. The first step in deep learning is called feature extraction. Dimensionality reduction and feature extraction are connected. Algorithms are used in image processing to identify different features in digitised images. Matching Features Establishing correspondences between two photographs of the same scene or object is the objective of many computer vision applications, like image registration, which is a part of camera calibration and object recognition. Finding a set of interest points from picture data and associating them with individual image descriptors is a frequent strategy for image matching. The next step is to create some preliminary feature matches between the images after the features have been extracted from the photos.

Iterative closest point:

A neural network can be trained using the iterative closest point (ICP) approach, which also helps to reduce error rates and account for differences between two point clouds.

The reference cloud, which is frequently used in image processing, is kept fixed while the other point clouds are transformed using coordinates to achieve the best possible alignment with the reference cloud. The reference, or target, is held constant while the other, the source, is altered to most closely resemble the reference at the iterative closest point (ICP), or in some sources, the iterative correspondence point.

The algorithm iteratively revises the transformation (combination of translation and rotation) required to minimise an error metric, typically a distance from the source to the reference point cloud, such as the sum of squared discrepancies between the matched pairs' coordinates.

ICP is one of the most often used techniques for aligning three-dimensional models, given a preliminary estimation of the rigid transformation necessary. Following segmentation, a recognition module searches the database for a match using an iterative matching method akin to the iterative closest point (ICP) algorithm.

B. MODULES

1. Enrollment phase:

Systems that can use multiple physiological or behavioural traits for enrollment, verification, and identification are known as modal biometrics. Periocular image-based human identification is a developing trend, and increasing recognition accuracy is one of the key factors in their combination. There are additional justifications for periocular biometrics, such as when security is

crucial to safeguarding sensitive data or when alternative biometric modalities may be more appropriate for particular deployment scenarios. When measuring different biometric traits, modal biometric systems use input from one biometric device. This module allows us to implement the system for authenticating people. Simple user information is entered into the system.

2. Face features extraction

The technique of extracting facial feature components from a human face photograph includes elements like the lips, nose, and eyes. For the start of processing techniques like face tracking, facial emotion recognition, or face recognition, facial feature extraction is crucial. Eye localization and detection are fundamental among all facial features since they allow for the identification of the positions of all other facial features. Basic facial feature points are extracted in this module. The ICP algorithm is used to extract these features. In the form of feature vectors, features are produced.

3. Periocular regions extraction

Periocular-based biometrics describes the automatic identification or categorization of a person using characteristics taken from the region of the face that surrounds the eye. The typical facial area used comprises the region from the midline of the nose to the cheekbone. It also includes the top of the brow. By means of the curvelet transform technique, these features are retrieved.

4. Registered faces

In deep learning, feature vectors are used to express an object's numerical or symbolic qualities, or features, in a mathematically sound and straightforward manner. They are crucial for a variety of deep learning and pattern processing applications. This module stores user information in a database along with face vector and peri-ocular area attributes. These details allow for user verification.

5. Classification

Implement the back propagation neural network method in this module. The backpropagation algorithm employs a method known as the delta rule or gradient descent to find the least value of the error function in weight space. The learning problem is then thought to have an answer in the weights that minimise the error function. A username and password are required for login. Take note of the peri-ocular and facial details. Finally, matched extracted feature available in the database.

6. Alert system

If a match is found, the person is immediately recognised as an authorised person. If a match cannot be found, notify the administrator about an unknown person.

C.EXPERIMENTAL RESULT:

This experiment uses the iterative nearest point technique and image-based periocular biometric characteristics to recognise subjects (ICP). The experiment made extensive use of the textural data that is present surrounding the eye. Standard biometric measurements are used to evaluate the system's performance. The database's main goal is to create a new tool to assess the viability of recognition in less than optimal imaging circumstances. With the fusion of three separate matchers, the results of this study demonstrate a rank-one identification accuracy of 87.32% using 10 probes and 200 gallery periocular images collected from the periocular Recognition Grand Challenge (version 2.0) database. The coloured face photos that make up the experimental set of periocular area images were taken in controlled lighting.



IV. CONCLUSION

The major goal of this study is to provide an explanation of the periocular biometrics literature, including a list of the features, feature extraction techniques, matching algorithms, and matching schemes that have been studied so far, along with any unresolved questions in the subject. Periocular biometrics is a great way to solve this issue because it allows for less user interaction in the rapidly expanding technological world. Periocular biometrics is used to identify and verify people in systems that are used to identify and verify people. The periocular region is a very promising characteristic that can be used as a modality as well as a support for iris and face biometrics. The periocular region has achieved better results in many cases where face biometrics are constrained by different factors such as pose, lighting variation, occlusion, and ageing effect.

In comparison to the iris as a stand-alone modality, fusion of the periocular region and iris also produced better outcomes. Additionally, iris biometrics demands photos taken in the NIR spectrum and significant user cooperation. Periocular biometrics, in contrast to the current system, don't need a lot of user participation and are compatible with color-saturated and natural-light photography.

The periocular region has been shown to be one of the most promising qualities for biometric identification systems through soft biometric categorization (classification of gender, race, and ethnicity) and recognition of medically altered faces (transgender, cataract surgery).

D.FUTURE SCOPE

Even after a few years, periocular biometrics offers a variety of possibilities, as seen below:

1. Improving latency and image recognition accuracy
2. Deep neural networks can be employed with periocular biometrics to identify key periocular traits and improve accuracy in the presence of occlusion and low-resolution photos.
3. For recognition during the pandemic, we now focus on the periocular environment.

REFERENCES:

- [1]. A.Abdelwhab and S.Viriri,"A Survey on soft biometrics for human identification,"in *Machine Learning and Biometrics*,2018.
- [2]. Ahuja, K., Islam, R., Barbhuiya, F.A., Dey, K., 2017. Convolutional neural networks for ocular smartphone-based biometrics. *Pattern Recogn. Lett.* 91,17–26.<https://doi.org/10.1016/j.patrec.2017.04.002>.
- [3]. Ahuja, K., Bose, A., Nagar, S., Dey, K., Barbhuiya, F., 2016. User authentication in mobile devices using ocular biometrics in visible spectrum. In: *IEEE International Conference on Image Processing (ICIP)*. IEEE, pp. 335–339. <https://doi.org/10.1109/ICIP.2016.753237>
- [4]. Alonso-Fernandez, F., Bigun, J., 2016. A survey on periocular biometrics research. *Pattern Recogn. Lett.*82, 92–105.<https://doi.org/10.1016/j.patrec.2015.08>.