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TEXTURE BASED ANALYSIS OF BIOMETRICS DATA USING MACHINE LEARNING ALGORITHMS

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Abstract— **In the ever-changing world of computer security and user authentication, the username/password method is becoming increasingly antiquated. Using the same username and password for multiple accounts and websites puts a user at risk, but in the digital age, remembering multiple usernames and passwords seems unnecessary. Future authentication solutions must be dependable and fast while also allowing for secure access. Traditional username password standards should be complemented with facial biometrics, according to the literature, to improve user authentication. However, a thorough review is required to evaluate how reliable and effective this technique will be in diverse settings. In prior research, we looked explored using the vascular pattern of the sclera, episclera, and conjunctiva as a biometric indicator. These blood vessels, which can be seen on the white portion of the human eye in visible light, have rich and seemingly distinct properties that may be caught simply with commercially accessible digital cameras. In this paper, we use wavelet-derived features and neural network classifiers to provide a new method for expressing and matching the textural intricacies of this vascular system. Our findings, based on 50 subjects' data, reveal that the proposed method may quantify the distinctness of ocular surface vascular patterns, confirming our hypothesis that these patterns are indeed unique among people.**

Keywords: **WebID, authentication, biometrics, face biometrics, facial recognition, classification methods, local binary pattern.**

I. INTRODUCTION

The study of determining an individual's identity based on their distinctive physical or behavioral features is known as biometrics [1-2]. Because biological signatures cannot be easily lost, forgotten, or stolen, biometric recognition is thought to be more convenient and secure than traditional identification methods such as ID cards (token-based) and passwords (knowledge-based). The human iris's textural structure has been discovered to be the most resilient and trustworthy of all biometric traits [2-4]. On the other hand, the quality of the photographs obtained has a detrimental impact on the performance of iris recognition systems. The system's display of non-frontal iris images, in particular, can lead to unsatisfactory biometric matching results. This has piqued researchers' interest in creating algorithms for analyzing non-ideal, or off-angle, iris images. Human eyes, on the other hand, have a variety of different patterns in addition to the iris. One such pattern is created by the layers of vasculature seen on the white portion of the eyeball. When the camera obtains a non-frontal image of the iris, the vascular information of the sclera, episclera, and conjunctiva is visible, offering a complementary source of biometric information in addition to the iris in this normally challenging stance. Incorporating this modality into existing iris systems could also lessen the risk of spoof attacks, as a third party's reproduction of such exact microcirculation can result in spoof attacks. In an earlier publication [5-6], we presented the use of this ocular surface vasculature as a biometric and provided some preliminary results. In this study, we offer a new feature extraction and matching strategy that treats the vasculature as a textural entity rather than a landmark-rich structure with bifurcating points. The proposed feature extraction and matching method is evaluated on a larger dataset with more subjects, some of whom provided data over a longer period of time. Biometrics is measurements of an individual's characteristics that can be used to confirm their identification. Biometrics is a great candidate for user authentication because they are nearly impossible to spoof, copy, or duplicate. Facial biometrics has shown considerable potential for authentication applications [7, 14] due to significant variations in user looks that can be detected by systems. While WebIDs with single sign-on were the initial step toward providing such services [15], their security as a stand-alone package is inadequate [16, 17,18,19]. An attacker who gains access to a user's computer or has the user's unique certificate can quickly compromise a single sign-on WebID system with no additional protection [20, 21,22 ,23,24]. WebIDs with biometric authentication are more After that we select the ordered coefficient from 1 to N to get N coefficient. The formulae of watermark embedding are as follows.
secure, but they may consume more processing resources [25,26, 27,28]. Different schemas, such as Eigen faces [29, 30,31] and Fisher faces [32, 33,34,35,36], are good at

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identifying photographs, but they lack the speed needed for real-time biometric authentication [37,38,39], which can be a problem for some authentication systems. The Local Binary Pattern (LBP) is a discrete yet powerful texture classification scheme that can categorize and compare grayscale images [40,41,42,43,44,45,46]. While LBP has been extensively studied, a comprehensive evaluation of LBP for facial recognition, particularly specific recognition, has remained largely unexplored to our knowledge[47]. The problem at hand is complex and difficult to resolve. The issues, as well as the obstacles that must be overcome to address them, are listed below.

OCULAR SURFACE VASCULATURE

The use of vascular patterns for personal identification has been studied on the fingers [4], palm [5], and retina [6]. In the case of retinal biometrics, which is closely related to the novel modality stated here, a one-of-a-kind optical device for imaging the back of the eyeball is required. Because of its perceived invasiveness and the required level of subject cooperation, the use of retinal biometrics may not be acceptable to some people. The conjunctiva is a thin, transparent, and moist membrane that covers the sclera (white of the eye) and the inner lining of the eyelid. Palpebral conjunctiva is the component of the conjunctiva that covers the inner lining of the eyelids, while ocular (or bulbar) conjunctiva is the part that covers the outer surface of the eye. The vasculature (including those of the episclera and sclera) can be seen through the ocular conjunctiva because it is thin and translucent. From the layers of visible surface microcirculation develops a complex network of fine veins (Fig. 1).From now on, conjunctival vasculature refers to all visible vascular structures on the white of the eye. Because of their apparent complexity and uniqueness, we looked into the possibility of using these vascular patterns as personal IDs [7]. Humans are the only species having a significant area of transparent sclera, allowing imaging of the surrounding conjunctival vasculature [8].

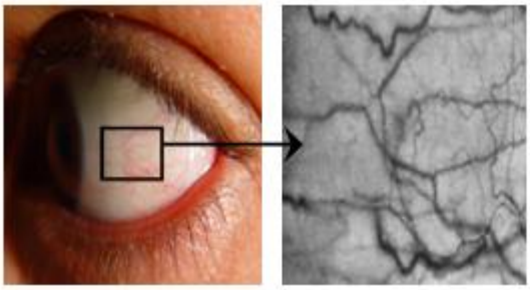

Fig.1.Enhanced closeup of ocular surface vasculature.

Based on our pilot investigation with 50 individuals and relevant literature disputes, we established that conjunctival vasculature is a good candidate for biometric identification [9]:

(a) The white portion of the eye, as well as the transparent skin, has conjunctival vasculature (universality criterion).
(a) Vasculature occurs during embryonic vasculogenesis. Its uniqueness arises from the fact that the final structure is fundamentally stochastic in nature. Even among identical twins, research on specialized areas such as the eye fundus have proven the distinctiveness of their circulation systems [10].We believe that adding conjunctival biometrics to current iris-based systems will improve their usability and precision, notably in the following scenarios: I the subject is uncooperative (for example, the subject will not hold still for iris registration or is looking away from the camera); (ii) the patient's iris cannot be successfully enrolled due to trauma.

II. PROCESSING METHODS

A. Image Capture

The conjunctival vasculature can be photographed whether a person is "looking straight into the camera," "looking to the left," "looking to the right," or "looking up." Such captures are not ideal for the "looking-down" attitude due to the natural dip of the upper eyelid. These positions can be utilized to authenticate conjunctival biometrics individually or collectively. We photographed the volunteer's eyes digitally at three different distances: 30 cm (or 1 foot with a macro lens), 152 cm, and 274 cm (or 5 and 9 ft, with telephoto lens). With a 20-minute pause between each series of shots, this technique was repeated twice for each volunteer, giving two sets of images. The "looking to the left" and "looking to the right" attitudes from the initial batch of pictures were utilized to record the individuals' conjunctival vasculature biometrics (and later used for classifier training).A similar second batch of photographs was used to create the biometric authentication findings (i.e. for classifier testing). The eye grabs were carefully split from the facial pictures. We used a simple intensity-based process to further segment the image into scleral regions of interest, which included rectangular sections of the eye's white as well as the left and right iris. For all computations, we used the MATLAB®7 software on x86-based desktop PCs

B. Image Preprocessing and Feature Extraction

Following the extraction of target conjunctival areas, the green layer of the original RGB captures was removed to create a gray-level image, which is recognized to produce the best "red-free" vascular image [13],[14]. We then employed a contrast-limited adaptive histogram equalisation to emphasize segmented images of the conjunctival vasculature even more (Fig. 2). We divided target segments of conjunctival images on the left and right of the iris into 808 tiles each for more targeted augmentation. We used 256-bin histograms for little contrast enhancement on each tile (uniform intensity distribution adjustment). Image compression techniques such as the Discrete Cosine Transform (DCT) and Wavelet-based algorithms have also been effectively used as feature extractors for neural network-based image classifiers in other cases [15],[16].Based on our research with our current dataset in terms of separate DCT and Wavelet-based features, we noticed that some types of Wavelet-based features performed somewhat better using a feed-forward neural-network for this application.

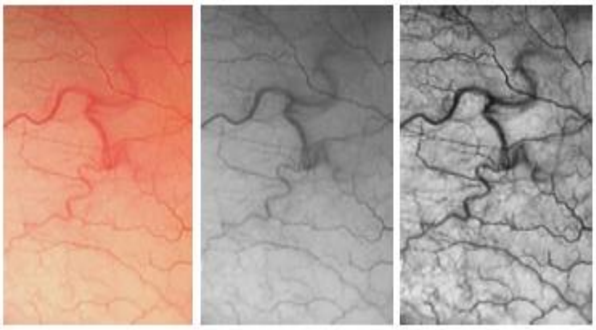

Fig. 2. Preprocessing of images. Right: the green layer picture after segmentation (RGB image under normal indoor lighting); middle: the grey scale image produced from the green layer; left: the green layer image after segmentation (RGB image under normal indoor lighting).

We selected the Discrete Cohen-Daubechies-Feauveau 9/7 Wavelet transform, CDF 9/7, which is an effective biorthogonal Wavelet employed in JPEG2000 and FBI fingerprint compressions [17], based on studies with our classifier and data.
We concatenated and down- sampled the mosaicked picture to 100X200 pixels using the conjunctival segments present to the left and right of the iris, and then performed a two-dimensional CDF 9/7 transformations on the output after the previously indicated preprocessing. This is simply a lossy compression of the target vascular segments that keeps the majority of the conjunctivae pattern textural information in a tiny feature vector (see Fig. 3).

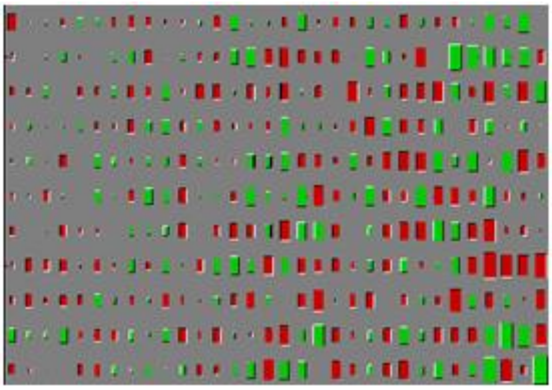

Fig. 3. Left: a mosaic of the scleral regions to the left and right of the iris as an input image. The resulting CDF 9/7 wavelet feature matrix (1632=512 features) is shown on the right.

C. Classification
For identification, the claimant's template must be compared (one-to-one matching) to his or her documented template or to the entire database of templates (one-to-many matching). Based on their nonparametric, data-driven discriminating abilities on datasets with uncertain distributions [18], as well as their claimed effective biometric identification applications (e.g., here), In our experiments, N is the total number of training samples, ei is the classification error for the ith capture, P is the total number of free parameters (i.e. network weights wk), and 0.2 is the regularisation constant. The weight decay pressure is determined by this parameter, which is the consequence of the second term's weight- shrinking.

square is proportional to the connection weight it represents, and the color denotes the corresponding sign (red/dark denotes negative, and green/light denotes positive).

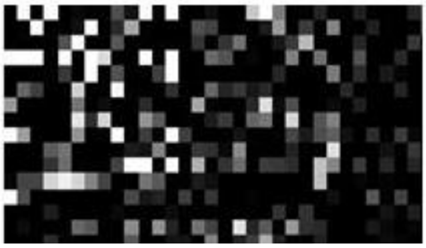

Fig. 4. A sample Hinton map showing the input receptive field of a neuron (from 16□32 Wavelet features) in the trained classifier. The areaof each square is proportional to the connection weight it represents, and the color denotes the corresponding sign (red/dark denotes negative, and green/light denotes positive).

III. RESULTS AND DISCUSSIONS

The Receiver Operating Characteristics (ROC) curves for 50 participants are shown below, which were constructed by graphing the Genuine Accept Rate (GAR) versus the False Accept Rate (FAR) and altering the decision threshold applied to the continuous outputs of the neural network. Figure 5 displays the test ROC curves for our 50-subject unseen test data using conjunctival vasculature data from both eyes. The Equal Error Rate (EER) of these curves is also included for comparison purposes. When GAR=FAR, EER is simply the error rate. The EERs for short distance images (1 ft), medium distance images (5 ft), and long distance images (9.2 ft) are 4.3 percent, 8.8 percent, and 9.2 percent, respectively, when conjunctival images from both eyes are used (9 ft). It was a fantastic performance.
Poor illumination (glare), photography (equipment and human operator error), and image segmentation were all found to be sources of mistake in this research. A closer look at our current dataset reveals a significant amount of changing glare, which was produced by the restriction that no special lighting arrangements be utilized in the first place. As a result, we believe that poor illumination is our primary source of

mistake, which has an impact on the segmentation and feature extraction operations that follow.

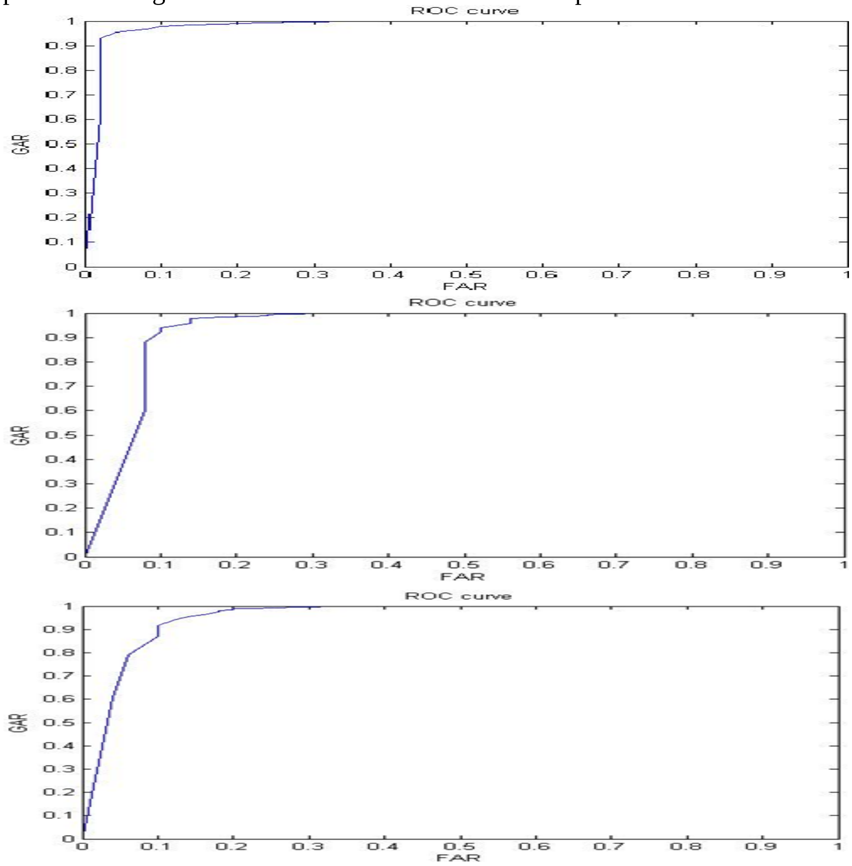

Fig 5. ROC curve

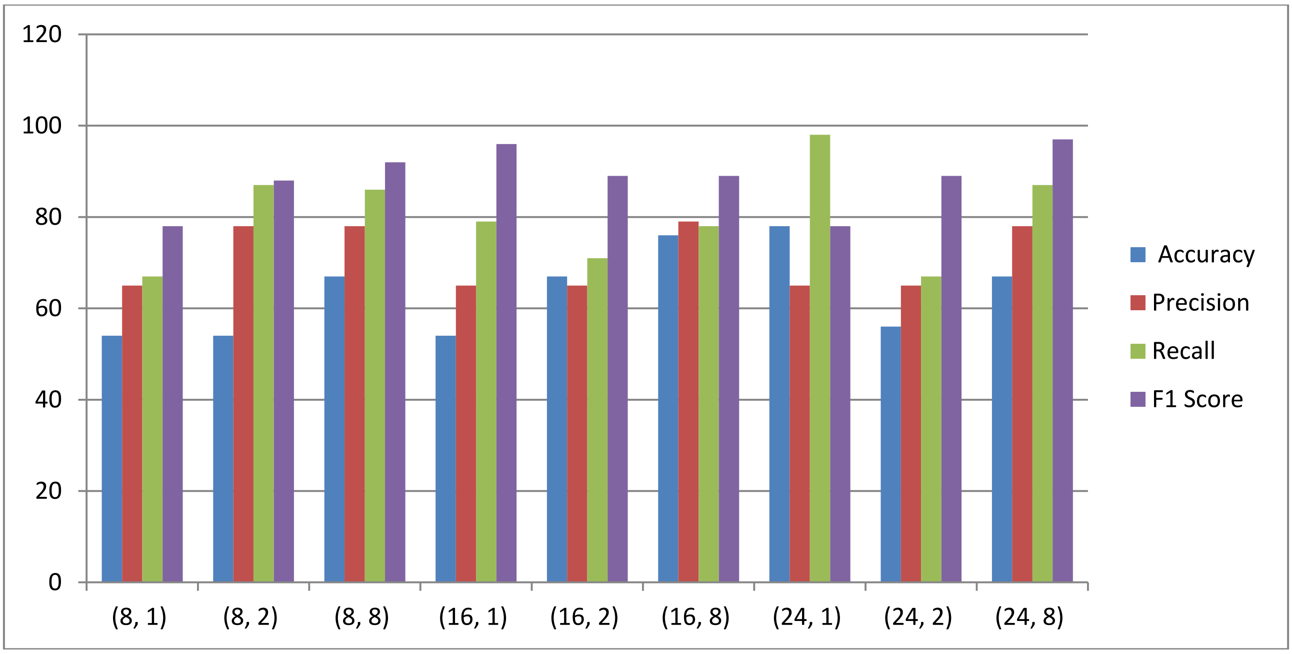

Fig 6. Comparative Analysis

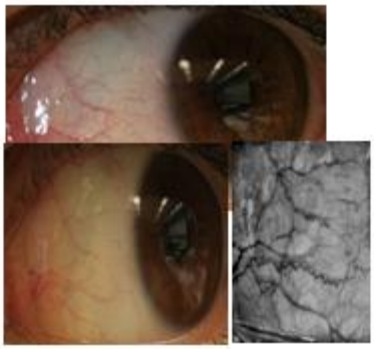

Fig.7. Neighborhood and Radius Size Configurations and for multi-distance conjunctival vasculature matching, using both eyes. Top: 1 ft distance,4.3%EER;middle:5ftdistance,8.8%EER; and bottom:9ftdistance9.2%EER.

IV. CONCLUSIONS AND FUTURE WORK

We created a texture-based categorization approach for our unique conjunctival vasculature biometrics. We used a typical photography setup and existing Wavelet-derived features and neural network classifiers to illustrate the feasibility of conjunctival biometrics as an independent authentification method for a new application domain. Existing iris biometric systems could benefit from this new biometric modality's precision and security. In the future, we intend to do related research on the merging of iris and conjunctival scans. Other and complementary methods for extracting and matching conjunctival characteristics, such as integrating our previous minutiae-based technique [3] with the present texture-based system for a robust, multi-algorithmic approach, are also being considered. We anticipate that part-uncorrelated identification score mistakes will occur as a result of the different nature of these techniques, and that a committee comprising the aforementioned classifiers will result in decreased error rates.

Our findings also suggest that long-range ocular biometrics are viable, with recent studies indicating that conjunctival identification from up to 3 meters away is possible. The performance of our technology over long distances will be the focus of future research. We detected modest visible conjunctival vascular variation over the course of four months, but we wish to extend our invariance investigation over longer periods of time to acquire greater insight into possible template ageing. We'd also like to study at larger groups of people in other situations, such as conjunctivitis (pink eye) and spoofing scenarios. In this paper, we develop a strategy for recognizing facial images from a single LBP run by combining several parameters. The accuracy of the configuration is provided once the user has run the software. We also create a program to handle several LBP runs. Once the user has set the parameters, the software is run a quantity of times equal to the settings. Each configuration is plotted on the x-axis, and the accuracy of those configurations is plotted on the y-axis. We improve the recommended technique by providing the user with a number of choices. In our studies, both the LDA and DT classification algorithms were able to correctly classify images 95% of the time.

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