Multimodal Biometric Identification System

Subjects: Engineering, Electrical & Electronic | Computer Science, Artificial Intelligence
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In the past two decades, many physical and behavioral biometric modalities have been under extensive research, such as fingerprints, palm prints, palms/Finger Textures, faces, irises, voice, gait and signature. All these modalities are vulnerable to presentation spoof attacks; hence, the level of provided security is compromised. Fingerprint- and palm-print-based biometric systems may be deceived by using gelatin or clay-made artificial fingerprint surfaces or images. Biometric systems using faces as a biometric modality may be attacked by using photographs, 3-D face models and recorded short clips. Iris-based biometric systems may encounter spoof attacks by employing iris images taken from enrolled users. Voice- and gait-based biometric systems may be attacked by feeding prerecorded audio and video to the recognition system, respectively.

biometric modalities | convolutional neural network | Finger Texture biometric | Finger Vein biometric

1. Introduction

Automated biometric identification based on anatomical human characteristics is widely available in commercial products today. These include banking, immigration, consumer electronics, e-governance and e-commerce applications.

The human characteristic may be declared as a biometric modality if it has certain qualities. The main qualities are universality, distinctiveness, permanence, collectability, performance, acceptability and circumvention [1]. All these qualities must be present to some extent in a biometric human characteristic.

- Universality means that all humans must have that characteristic in them.
- Distinctiveness means, for each individual, the characteristic must be present in some different form.
- Permanence shows that the biometric characteristic must remain invariable over a sufficient period.
- Collectability means the biometric characteristic must be quantifiable, such that it may be collected from human subjects.
- Performance shows the ability to identify human subjects on the basis of that characteristic.

- The degree of ease and obstructiveness defines the degree of the acceptability of the biometric modality.

- Circumvention describes the degree of difficulty required to launch a spoof attack to deceive the biometric-modality-based system.

Human characteristics are divided into two main types: physiological and behavioral. Physiological characteristics are related to the human body, whereas behavioral characteristics belong to human routine actions. Physiological characteristics mostly remain constant, whereas behavioral characteristics are more vulnerable to change over time [1]. Physiological characteristics are further divided into extrinsic and intrinsic modalities. Extrinsic physiological characteristics are found outside the human body, whereas intrinsic modalities are present inside. Extrinsic modalities are open and comparatively easier to deceive using planned imposter attacks. Finger Veins are categorized under the intrinsic type of physiological human characteristic. There are some obvious reasons for working with Finger Vein biometrics.

First, the use of the vein structure of the hand or finger as a biometric trait is preferred because of the high degree of privacy. Vein patterns are hidden underneath the skin and are almost impossible to capture under visible lighting conditions. Hence, this characteristic enormously increases the reliability of a biometric system against spoof attacks. The second advantage of using the vein structure of the hand or finger is that it improves the integrity and lifetime of the biometric system. The reason behind this is the high difficulty level of altering the vein pattern within the human body through some surgical procedures [2]. The third reason for the widespread use of Finger Veins as a biometric trait is their acceptability. Finger Vein images may be captured under noncontact or weak-contact conditions. Therefore, the biometric data acquisition setup becomes more user-friendly. The lower vulnerability of Finger Vein data collection to scars, sweat or the presence of some unwanted material on the finger surface makes it more interference-resistant. Because of this quality, Finger Vein biometrics are preferably used in biometric systems.

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2. Multimodal Biometric System

According to the latest research, Finger-Vein-biometric-based systems may also have spoof attacks [1][2][3]. For real applications, a biometric system's excellent capability against spoof attacks is required. Many researchers have proposed presentation attack detection (PAD) techniques for different biometric modalities. Researchers have proposed PAD techniques for Finger Vein biometrics in [3][4][5][6][7][8]. The lack of standardization, compromising the user comfort factor and not following ethical implications are shortcomings of these research works.

Over time, many techniques have been deployed to process Finger Vein images for the generation of recognition results. The researchers of [9][10][11][12][13][14][15] have presented various techniques to improve the quality of captured Finger Vein images.

S. A. Haider et al. [3] proposed a multimodal biometric system based on intrinsic biometric modalities. They employed Finger Veins, Hand Geometry and Pulse Response as the modalities of focus. Pulse Response biometrics were employed to filter illegitimate candidates by filtering out spoof attacks launched using artificially made non-living human hands. The Near-Infra-Red Hand Images database was maintained and processed for Hand Geometry and Finger Vein biometrics separately. Matching scores were then fused at the score level using a Fuzzy Inference System to produce a final decision regarding the identification of the candidate subject.

R. Das et al. [16] proposed a convolutional-neural-network-based Finger Vein identification system. They evaluated the performance of their proposed system using four publicly available databases. They claimed to achieve accuracy beyond 95% for all four employed databases. The claimed accuracy needs to be improved further. Comparisons for no other performance metrics were reported other than accuracy. The authors of [17] proposed a multimodal biometric system using Finger Vein and fingerprint biometrics. They used feature-level fusion and reported using a new NIR imaging device to capture images. The overall recognition rate for the proposed system was claimed as 96.93% with a 0% False Acceptance Rate. The recognition rate had a margin for improvement, and the False Rejection Rate was not discussed in the conclusions.

Researchers of NIR [18] explored remote photo-plethysmography to identify and prevent illegitimate user attacks using artificially generated Finger Vein data. An overall accuracy of 96.46% was reported which may be improved further. Although more comparisons may be included in terms of performance metrics. The algorithm proposed in another research article [19] claimed to present a novel and effective technique regarding region of interest localization for the Finger Vein biometric system. They discussed only the Equal Error Rate and showed a comparison, but an overall accuracy discussion was missing. In [20], an efficient multimodal biometric system was proposed using an image-capturing setup based on Finger Vein and finger shape biometric modalities. They recovered the shapes of fingers by employing their proposed method. The finger shape part of their research work may easily be broken into using a fake finger imposter attack. In [21], the researchers discussed iris-, face- and Finger-Vein-biometric-based multimodal biometric systems employing deep learning techniques. This method is less user-friendly, as three different parts of the body are involved in biometric data capturing. The claimed accuracy values are unrealistically high, i.e., 100% and 99.39% for score-level and feature-level fusion, respectively. The researchers of [22] proposed an efficient method for the enhancement of NIR Finger Vein images.

The proposed method is only for enhancing NIR images, but a discussion regarding the overall recognition system was not included in the research article.

In [23], supervised discrete hashing and convolutional neural networks were employed for a Finger-Vein-based biometric authentication system. The researchers reported unmatched performance after comparison with a publicly available two-session Finger Vein database. The researchers of [24] presented a technique of employing fuzzy inference system to propose Multi-criteria decision-making method. This proposed method is used for prioritizing the health and safety risks that may occur during an experiment.

The authors of [25] also employed a convolutional neural network for Finger Vein biometric identification. They reported performing a comparative analysis of different databases and also considered environmental changes. They maintained new image databases and reported that, after testing, performance was improved in comparison with existing systems. In [26], an accurate and reliable multimodal biometric system was proposed using fingerprint, Finger Vein and face biometrics. The publicly available SDUMLA-HMT database was used for testing and evaluation purposes. They generated matching scores for the three modalities of focus and implemented score-level fusion. The recognized subject was declared after comparing the overall score with a predefined threshold.

The researchers of [27] proposed an efficient noise removal algorithm without affecting the texture features present in the Finger Vein images. They claimed to preserve texture features using the proposed denoising algorithm, which was tested on the training database. Different types of noises like Poisson, salt-and-pepper, Gaussian and Speckle noise were introduced into the training database for a performance evaluation of the proposed algorithm in comparison with traditional and famous denoising algorithms. They reported improved performance for the proposed algorithm.

In another article [28], the researchers discussed a multimodal biometric identification system considering Finger Veins and palm veins as biometric traits. They performed preprocessing of the captured vein images, employing a revised 2-D Gabor filter and a gradient-based technique, before the extraction of features for the modalities of focus. The extracted features were matched using the Euclidean Distance metric. The matching scores were then fused at the score level using a Fuzzy Inference System. They reported performing experiments on standard databases for Finger Vein and palm vein images. They claimed improved performance parameters for the biometric system.

The authors of [29] proposed a multimodal biometric system consisting of three biometric modalities: irises, palm veins and Finger Veins. They reported employing a hybrid fusion model comprising an enhanced feature fusion algorithm and a novel weighted voting strategy. They tested the proposed system on databases from CASIA, PolyU and SDU and reported improved recognition accuracy and reliability in comparison with existing multimodal systems. They claimed to achieve an average recognition accuracy of 99.33%. The level of acceptability and the degree of ease of use were low for this research, as two body parts were involved in biometric raw data collection. The researchers of [30] proposed new architecture for a CNN. They named it Xception. They tested it on two different databases, i.e., the SDUMLA and THU-FVFDT2 datasets. They reported improved performance metrics. **Table 1** summarizes the cited multimodal biometric systems.

Table 1. Summary of cited state-of-the-art multimodal biometric systems.

Cited Articles	Modalities Employed	Methodology and Shortcomings	Reported Evaluation Metrics and ROC Curves
[3]	1. Finger Vein 2. Hand Geometry 3. Pulse Response	CNN model training and testing for Finger Veins, Handcrafted technique for Hand Geometry, Fuzzy Fusion for the final result, EER was not reported.	Accuracy, Precision, Recall, FAR vs. GAR, Threshold vs. FAR/FRR
[17]	1. Finger Vein 2. Fingerprints	Feature-level fusion, LBP for feature extraction and SVM as the classifier, Accuracy, FRR, Precision and Recall were not reported. May only handle small datasets.	FAR, Recognition Rate
[20]	1. Finger Vein 2. Fingerprint	CNN models, score-level fusion for identification results, Accuracy, Precision and Recall were not reported.	FAR vs. GAR, EER
[21]	1. Iris 2. Face 3. Finger Vein	CNN models, feature- and score-level fusion, FAR, FRR, EER, training and testing times were not reported.	Accuracy, Rank vs. Recognition Rate
[26]	1. Finger Vein 2. Fingerprint 3. Face	Random forest classifier, softmax function and CNN were used for Finger Veins, faces and fingerprints, score-level fusion was implemented. No other metric was reported except Accuracy.	Accuracy
[28]	1. Finger Vein 2. Palm Vein	2D Gabor Filter, Gradient Filter was used for feature extraction, Fuzzy score-level fusion was used. Precision, Recall, etc., were not reported.	Accuracy, Threshold vs. FRR, FRR vs. FAR, EER
[29]	1. Iris 2. Palm Vein 3. Finger Vein	The best from the Gabor Filter, LBP, LDA, PCA was used for feature extraction, feature-level, decision-level and hybrid fusion were proposed. Precision, Recall, etc., were not reported.	Accuracy, Recognition Rate graphs were reported

The research findings for the discussed research articles [23][25][26][27][28][29] are lacking in terms of ease of the methodology followed. There is still space for better overall accuracy and other evaluation metrics like False Acceptance Rate, False Rejection Rate, etc. Further, the overall training and testing times for the proposed methods may be improved. Resistance capabilities against any imposter attack are lesser wherever extrinsic modalities are employed in the proposed biometric systems.

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