FINGER VEIN RECOGNITION BASED ON ANATOMICAL FEATURES OF VEIN PATTERNS

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ABSTRACT

Finger vein recognition is a promising biometric authentication technique that depends on the unique features of vein patterns in the finger for recognition. The existing finger vein recognition methods are based on minutiae features or binary features such as LBP, LLBP, PBBM etc. or from the entire vein pattern. However, the minutiae-based features cannot accurately represent the structural or anatomical aspects of the vein pattern. These issues with the minutia feature led to increased false matches. Recognition based on binary features have limitations such as increased false matches, sensitivity to the translation and rotation, security and privacy issues etc. A feature representation based on the anatomy of vein patterns can be an alternative solution to improve the recognition performance. In the IJCB 2020 conference, we showed that every finger vein image contains one or more of a kind of 4 special vein patterns which we refereed as Fork, Eye, Bridge, and Arch (FEBA). In this paper, we further enlarge this set to 6 vein patterns (F1F2EB1B2A) by identifying two variations in the Fork and Bridge vein patterns. Based on 6 anatomical features of the possible 6 vein patterns in a vein image, we define a 6 × 6 feature matrix representation for finger vein images. Since this feature representation is based on the anatomical properties of the local vein patterns, it provides template security. Further we show that, the proposed feature representation is invariant to scaling, translation, and rotation changes. The experimental results using two open datasets and an in-house dataset show that the proposed method has a better recognition performance when compared to the existing approaches with an EER around 0.02% and an average recognition accuracy of 98%.

Keywords:*Finger Vein Recognition, Biometric Authentication, Anatomical Features, FEBA Patterns, Feature Matrix, Template Security, Invariant Features, Fork-Eye-Bridge-Arch, Minutiae Limitation, EER, Recognition Accuracy.*

I.INTRODUCTION

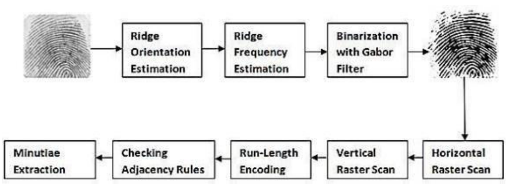
In the rapidly evolving landscape of biometric identification, finger vein pattern recognition has emerged as a highly reliable and secure method for authenticating individual identity. Unlike traditional biometric approaches such as fingerprints, facial recognition, or iris scans, finger vein recognition leverages the unique vascular patterns beneath the skin's surface, captured through near-infrared imaging. These vein patterns are inherently difficult to forge or replicate, providing a significant advantage in security-critical applications such as automated banking, criminal identification, and access control systems.

The increasing demand for robust and efficient authentication mechanisms has propelled research into advanced machine learning techniques, particularly deep learning, for feature extraction and classification of biometric data. This research work proposes a hybrid deep learning framework based on dimensionality reduction integrated with Convolutional Neural Networks (DR-CNN) to enhance the accuracy and speed of finger vein pattern recognition. The proposed system demonstrates superior performance with an accuracy rate of 97.16%, outperforming traditional models like CNN, Deep Neural Networks (DNN), and Recurrent Neural Networks (RNN).

Traditional authentication methods such as passwords, ID cards, and magnetic strips are vulnerable to theft and unauthorized use, underscoring the need for biometric systems that are both secure and user-friendly. Finger vein biometrics offers unique benefits — the vein patterns reside inside the body, are difficult to replicate, and require the presence of a living person, thereby reducing the risk of spoofing attacks. Additionally, this technology provides a contactless, quick, and cost-effective recognition process, making it suitable for modern applications ranging from mobile device security to high-security institutional environments.

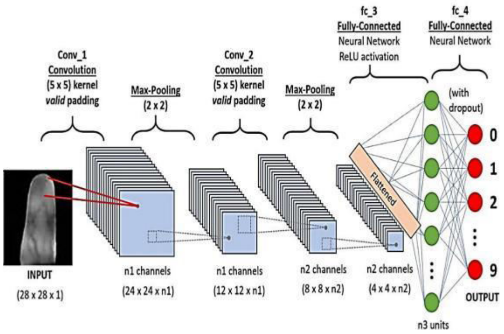
Given the limitations of other biometric modalities — such as fingerprint sensitivity to dirt, facial recognition's dependency on lighting and expressions, and the high cost and discomfort associated with iris scanning — finger vein recognition stands out as a promising solution. This research addresses the challenges of accurate and efficient biometric identification by applying a deep learning-based approach that minimizes computational complexity while maximizing recognition precision.

With the proliferation of e-commerce, mobile banking, and digital transactions, the need for secure, fast, and reliable biometric authentication is more critical than ever. The proposed DR-CNN framework not only advances the state-of-the-art in finger vein recognition but also provides a scalable solution capable of meeting the stringent security demands of contemporary digital systems.



II.WORKING METHODOLOGY

The proposed methodology in this research involves a hybrid deep learning approach for effective finger vein biometric recognition, centered on a dimensionality-reduced convolutional neural network (DR-CNN). The system begins with the acquisition of finger vein images under varying conditions, followed by preprocessing steps that include noise removal and image resizing to a standard 256x256 pixel grid, ensuring consistency and scalability. Feature extraction is performed using Gray Level Co-occurrence Matrices (GLCM) combined with Scale-Invariant Feature Transform (SIFT) to capture robust and scale-invariant vein patterns. The core of the methodology lies in the DR-CNN model, which incorporates multiple convolutional layers, pooling layers, and fully connected layers to learn and classify finger vein patterns accurately. To address issues such as vanishing gradients and overfitting common in deep networks, ReLU activation functions and a dimensionality reduction strategy within the CNN are utilized. The network architecture is composed of an encoder-decoder framework that leverages max-pooling indices for efficient upsampling during decoding, preserving essential boundary information for precise segmentation. During training, a finetuned pre-trained ImageNet model is used along with augmented datasets generated by creating difference images from matched and unmatched finger vein pairs, increasing data diversity and improving generalization. The classifier ultimately distinguishes between authentic and impostor vein patterns, achieving robust recognition performance. The entire model is implemented using the Caffe deep learning framework, ensuring efficient processing and validation on real-time and publicly available finger vein datasets.



Digital Image Processing involves extensive experimental work to validate proposed solutions for given problems, highlighting the importance of quickly formulating and prototyping approaches to reduce development time and cost. An image can be defined as a two-dimensional function, $f(x, y)$, where x and y are spatial coordinates, and the amplitude at each coordinate pair represents the intensity or gray level. When these coordinates and amplitude values are discrete and finite, the image is considered a digital image, which is processed by digital computers. Vision is the most advanced human sensor, but unlike humans who see only in the visible spectrum, imaging machines cover almost the entire electromagnetic spectrum, from gamma rays to radio waves. Digital image processing (DIP) is often distinguished from related fields like image analysis and computer vision based on whether the inputs and outputs are images or extracted attributes. Mid-level processing tasks include segmentation, object description, and classification, where images are transformed into features suitable for further computer processing. Higher-level processing involves interpreting these features to perform tasks such as image analysis and cognitive functions akin to human vision.

Images can be grayscale or color. A grayscale image is represented as a function of two spatial coordinates, where the intensity is a non-negative value within a bounded rectangle. Color images are more complex, containing information in three color channels (red, green, and blue). Digitizing a color image involves sampling spatial coordinates and quantizing intensity values, resulting in a grid of numerical values. Coordinates are usually represented as integers, with the origin at (0,0). Digital images can be represented as matrices, where each element corresponds to a pixel or picture element (pel). For example, in MATLAB, digital images are naturally stored as matrices, with pixel values indexed by row and column.

Reading images into MATLAB is accomplished using the imread function, which supports various formats such as TIFF, JPEG, GIF, BMP, and PNG. Pixel values in MATLAB are stored using different data classes, including unsigned integers of varying bit depths, floating-point numbers, characters, and logical values. These data classes determine how pixel intensities are represented and manipulated.

Image types supported include intensity images, binary images, indexed images, and RGB images. Intensity images contain pixel values representing brightness, often scaled to fit within certain numerical ranges depending on their data class (e.g., 0–255 for 8-bit unsigned integers). Binary images are logical arrays containing only 0s and 1s, representing black-and-white images. Indexed images consist of two components: a matrix of integers indicating pixel values, and a colormap matrix that assigns specific colors to those values. RGB images are represented as three-dimensional arrays, with each pixel containing three values corresponding to the red, green, and blue color components. The number of colors in an RGB image is determined by the bit depth of each channel; for example, an 8-bit per channel RGB image can represent over 16 million colors.

III.CONCLUSION

This research work provides a novel solution of efficient finger vein recognition. DR-CNN is a vein pattern categorization system that allows for reliable individual authentication. To enable supervised learning can enhance the patterns on classification, the suggested method used optimal labels. The extraction of ideal features was made possible by this clever CNN method, which included further dimensionality reduction of features. The matching and unmatching vein patterns were eventually classified by the DR-CNN. The simulation outcomes showed that proposed technique outperforms existing classifiers in terms of F1-score, specificity, sensitivity, recall, accuracy, and MAE. Additionally, DR-CNN finger vein detection method is compared with the existing approaches. However, compared to conventional finger vein recognition methods, the proposed method shown a significant improvement in accuracy and other measures. Furthermore, numerous training data are needed in order to successfully train the suggested deep CNN model. However, it is frequently the case that gathering this much data is challenging in many experimental settings. In order to reflect the properties of the original training data, the increment of training data through correct data augmentation is required. To solve this issue, dimensionality reduction-based method termed as DR-CNN method is proposed and achieved quantitative results. CNN method is trained on various standard finger vein datasets. The accuracy of proposed CNN method achieved 95.39% with execution time of 2.43 ms. Simulations and analysis were carried out using MATLAB 2019b or above which achieved quantitative results.

IV.REFERENCES

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