VeinNet: CNN Palm Vein Identification System

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Abstract

VeinNet is a Convolutional Neural Network (CNN)–based system for palm vein identification. The approach begins by extracting the palm region of interest (ROI) from a dataset of multispectral hand images, focusing on the vein patterns within this ROI as input to the CNN. Trained on these hand images, VeinNet demonstrates the ability to effectively recognize unique vein patterns in the human palm. The system is evaluated using three distinct types of evaluations: identification with a closed set, identification with an open set, and verification. The dataset is split differently for each evaluation setup, ensuring that the system is tested under various conditions. The results demonstrate the effectiveness of VeinNet in identifying individuals based on their palm vein patterns, with promising performance metrics across all evaluation setups.

1 Introduction

In recent years, hand biometrics has become an increasingly popular modality in biometric recognition systems due to its accessibility and rich discriminatory features. Traditionally, hand-based systems have relied on contact-based devices equipped with pegs or plates for image acquisition. While effective, these systems often raise hygiene concerns and reduce user acceptance. In response, there has been a shift toward contact-free systems that eliminate the need for physical contact during data capture [Xiong et al., 2005b, Jiang et al., 2007, Xiong et al., 2005a]. However, increased freedom of hand movement in contact-free setups often leads to reduced recognition accuracy.

The integration of multispectral imaging techniques has been successfully applied to improve recognition performance in other biometric domains, such as face recognition [Kong et al., 2007, Singh et al., 2008]. Similarly, for hand biometrics, [Wang and Leedham, 2006] demonstrated that passive infrared imaging is inadequate for extracting vein patterns from the palm. This limitation has led to the exploration of active multispectral imaging across visible to near-infrared wavelengths. Previous studies, such as [Wang et al., 2007], have illustrated the potential of combining palmprint and palm vein images using fusion techniques applied at the image level. However, these approaches often rely on semi-touchless acquisition systems or frequency-division hardware, which may limit scalability and increase costs.

This report proposes a method for palm vein pattern recognition using a convolutional neural network (CNN) architecture. Unlike traditional approaches relying on pixel-level fusion and feature-level registration techniques, the proposed method uses the power of CNNs to automatically learn and extract distinctive features from palm vein patterns. By focusing on the rich discriminatory information inherent in vein structures, the method improves recognition accuracy while maintaining a fully contact-free acquisition environment. This approach represents a significant step forward in developing efficient, hygienic, and user-friendly biometric systems.

2 Dataset

This section provides an overview of the CASIA Multi-Spectral Palmprint Image Database, including data acquisition details and a description of the dataset.

2.1 Data Aquisition

The self-designed imaging device for acquiring hand images [Hao et al., 2008, Hao et al., 2007] is shown in Figure 1. The device operates in a contact-free environment, The imaging process involves the following steps:

1. Illumination Setup:

- The device uses six groups of LEDs (violet to near-infrared) activated sequentially, employing a time-division strategy to acquire multispectral images under varying illumination, capturing different skin layers through light absorption and scattering.

2. Reflective Imaging:

   - Images are captured reflectively in a sheltered environment with consistent illumination, while circularly arranged LED groups, diffused with ground glass, ensure even lighting across the hand.

3. Contact-Free Operation:

   - Subjects are instructed to naturally stretch their hands, palms facing the camera, without any physical contact with a tangible surface or plate.

4. Sequential Image Capture:

   - A single camera is used to sequentially capture images under each spectral light. This time-division strategy improves scalability and offers a better performance-to-cost ratio compared to frequency-division methods requiring multiple cameras.

The design allows for a detailed capture of both superficial and subsurface skin structures, revealing features like principal lines and blood vessels, which are critical for biometric analysis.

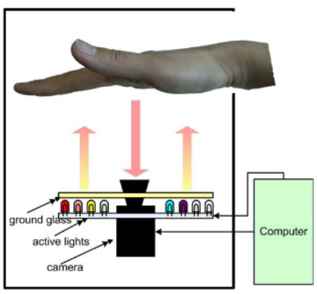

Figure 1: Imaging Device Architecture for Hand Image Acquisition.

2.2 Dataset Description

The CASIA Multi-Spectral Palmprint Image Database consists of 7,200 palm images captured from 100 individuals using a self-designed multispectral imaging device. The images are 8-bit gray-level JPEG files. For each hand, two sessions of palm images were captured, with a time interval of more than one month between the sessions to simulate real-world conditions and introduce natural variability. Each session includes three samples, with each sample containing six palm images captured simultaneously under six different electromagnetic spectrums, corresponding to wavelengths of 460 nm, 630 nm, 700 nm, 850 nm, 940 nm, and white light. Variations in hand postures were allowed between the two sessions to increase the diversity of intra-class samples, thereby simulating practical usage scenarios and enhancing the robustness of biometric recognition systems trained on this dataset.

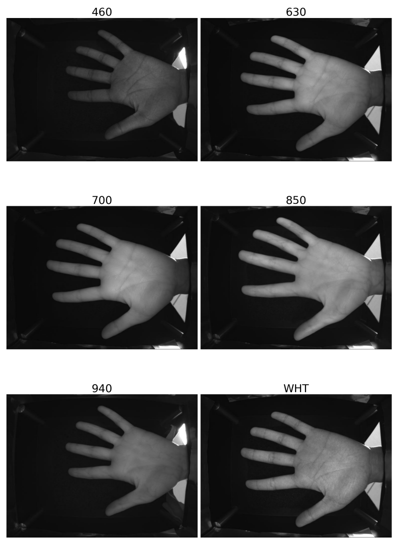

Figure 2: Palmprint images from the CASIA Multi-Spectral Palmprint Image Database with the six spectral bands. Starting from the top-left corner and moving clockwise: 460 nm, 630 nm, 700 nm, 850 nm, 940 nm, and white light.

3 Methodology

3.1 Data Preprocessing

3.2 Model Architecture

4 Experimental

This section describes the experimental setup introducing the 3 evaluation setups used to assess the performance of the proposed biometric system and the data splitting strategy used for each evaluation setup.

4.1 Evaluation Setups

The evaluation was performed using three distinct types of evaluations:

- **Identification with a Closed Set**: involves including all enrolled patients in the dataset. Each image is classified into one of the known classes (patients) based on its extracted features. The system is trained and tested with the same predefined set of enrolled patients, ensuring no unknown users are present in the dataset.

- **Identification with an Open Set**: excludes a percentage of the enrolled patients from the dataset during training. These excluded patients represent unknown users during the evaluation phase. The model is tested on both known and unknown classes, where the unknown classes are expected to be classified as unknown to simulate open-set identification.

- **Verification**: tests the system's ability to verify the identity of users. Genuine samples consist of images correctly matched to their claimed identities, while imposter samples are created by associating images with incorrect user identities to simulate attempts to mislead the system.

4.2 Data Splitting

The dataset used in this study was split differently for the three evaluation setups:

Identification with a Closed Set includes all patients in the dataset, and their images are divided into training and test sets. The first four images per patient are used for training and the remaining images are used for testing. This setup ensures that all enrolled patients contribute images to the training and testing phases, facilitating evaluation in a controlled, closed-set scenario.

Identification with an Open Set For open-set identification, 70% of patients are randomly selected as known, with their images split into training (first four images) and testing (remaining images). The remaining 30% serve as unknown patients, with their images used solely for testing to assess the system's ability to handle unenrolled users, simulating open-set scenarios.

Verification includes genuine and imposter samples for evaluation. For each patient, the first four images are used for training, and the remaining images are used for testing. Genuine samples consist of matching the correct image to the claimed identity, while imposter samples are created by pairing images from different patients, simulating attempts to impersonate other users.

To ensure consistency and reproducibility across all splits, a fixed random seed was used during shuffling. This guarantees that the data partitioning remains consistent across different runs and experimentsss

5 Evaluation Metrics

6 Results

6.1 Identification with a Closed Set

6.2 Identification with an Open Set

6.3 Verification

7 Conclusion and Future Work

7.1 Conclusion

In this work, a straightforward yet highly effective CNN-based recognition system was developed for the purpose of hand vein recognition. Despite the architecture's simplicity, it demonostrated remarkable efficiency by achieving rapid training convergence and maintaining low computational requirements. The results indicate that the model achieves an accuracy of **xx.x%** on the training set, traslating to a robust perfomance when deployed on the test set, where it obtained an accuracy of **xx.x%**. Such a perfomance level is significant for a recognition task, as it ensures reliable identification while keeping resource consumption and development complexity to a minimum. Overall, this implementation highlights that even a relatively uncomplicated CNN framework can deliver strong accuracy and efficiency, making it an appealing solution for practical vein-based recognition systems.

7.2 Future Work

An interesting extension to this project for future exploration involves expanding the focus beyond the current palm-based Region of Interest (ROI). Instead of restricting the system solely to the palm vein pattern, it would be beneficial to consider additional hand characteristics such as overall hand geometry, finger length and spacing, and other distinctive biometric features of the hand. Using these complementary features would allow us to develop multiple specialized models, one dedicated to palm veins (as implemented in this project), another concentrating on hand geometry, another on finger structure, and so on. By utilizing an ensemble learning strategy (see Figure 3), where each specialized model contributes its prediction, we could combine these outputs into a final, more robust decision. This multi-model, ensemble-based approach has the potential to significantly improve the overall accuracy and reliability of the system.

References

[Hao et al., 2007] Hao, Y., Sun, Z., and Tan, T. (2007). Comparative studies on multispectral palm image fusion for biometrics. In *Asian conference on computer vision*, pages 12–21. Springer.

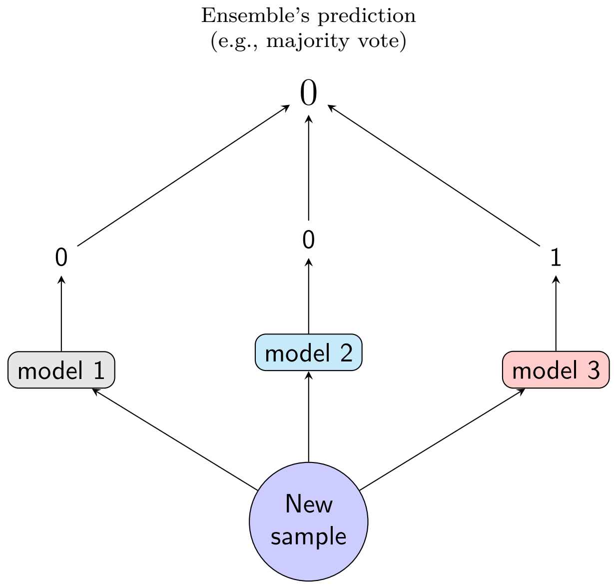

Figure 3: Illustration of an ensemble learning strategy. Each model processes the same input and produces a prediction. These predictions are combined (e.g., through majority voting) to create the ensemble's final output.

[Hao et al., 2008] Hao, Y., Sun, Z., Tan, T., and Ren, C. (2008). Multispectral palm image fusion for accurate contact-free palmprint recognition. In *2008 15th IEEE International Conference on Image Processing*, pages 281–284. IEEE.

[Jiang et al., 2007] Jiang, X., Xu, W., Sweeney, L., Li, Y., Gross, R., and Yurovsky, D. (2007). New directions in contact free hand recognition. In *2007 IEEE International Conference on Image Processing*, volume 2, pages II–389. IEEE.

[Kong et al., 2007] Kong, S. G., Heo, J., Boughorbel, F., Zheng, Y., Abidi, B. R., Koschan, A., Yi, M., and Abidi, M. A. (2007). Multiscale fusion of visible and thermal ir images for illumination-invariant face recognition. *International Journal of Computer Vision*, 71:215–233.

[Singh et al., 2008] Singh, R., Vatsa, M., and Noore, A. (2008). Integrated multilevel image fusion and match score fusion of visible and infrared face images for robust face recognition. *Pattern Recognition*, 41(3):880–893.

[Wang et al., 2007] Wang, J.-G., Yau, W.-Y., Suwandy, A., and Sung, E. (2007). Fusion of palmprint and palm vein images for person recognition based on" laplacianpalm" feature. In *2007 IEEE Conference on Computer Vision and Pattern Recognition*, pages 1–8. IEEE.

[Wang and Leedham, 2006] Wang, L. and Leedham, G. (2006). Near-and far-infrared imaging for vein pattern biometrics. In *2006 IEEE International Conference on Video and Signal Based Surveillance*, pages 52–52. IEEE.

[Xiong et al., 2005a] Xiong, W., Toh, K.-A., Yau, W.-Y., and Jiang, X. (2005a). Model-guided deformable hand shape recognition without positioning aids. *Pattern recognition*, 38(10):1651–1664.

[Xiong et al., 2005b] Xiong, W., Xu, C., and Ong, S. H. (2005b). Peg-free human hand shape analysis and recognition. In *Proceedings.(ICASSP'05). IEEE International Conference on Acoustics, Speech, and Signal Processing, 2005.*, volume 2, pages ii–77. IEEE.