VeinNet: CNN Palm Vein Recognition System

Lucian Dorin Crainic
Department of Computer Science
crainic.1938430@studenti.uniroma1.it

La Sapienza University of Rome

Abstract

VeinNet is a Convolutional Neural Network (CNN)–based system for palm vein recognition. 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 achieves a 90% accuracy on the test dataset, showcasing the effectiveness of a CNN-based solution.

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

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, during the imaging process:

1. Illumination Setup:
    - The device uses six groups of LEDs with wavelengths ranging from violet to near-infrared. These LEDs are turned on sequentially, allowing a time-division strategy for acquiring multispectral images.
    - This setup ensures the acquisition of images under varying illumination conditions, covering different layers of the skin due to light absorption and scattering properties.
2. Reflective Imaging:

- Images are captured in a reflective manner under a sheltered environment, ensuring consistent illumination and reducing external noise.
- Each group of LEDs is arranged circularly and diffused using a ground glass to provide even illumination 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. This setup enhances hygiene and minimizes user resistance.

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.

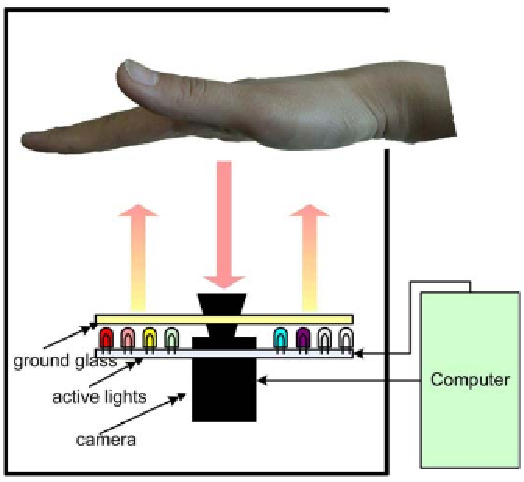

Figure 1: Imaging Device Architecture for Hand Image Acquisition.

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.

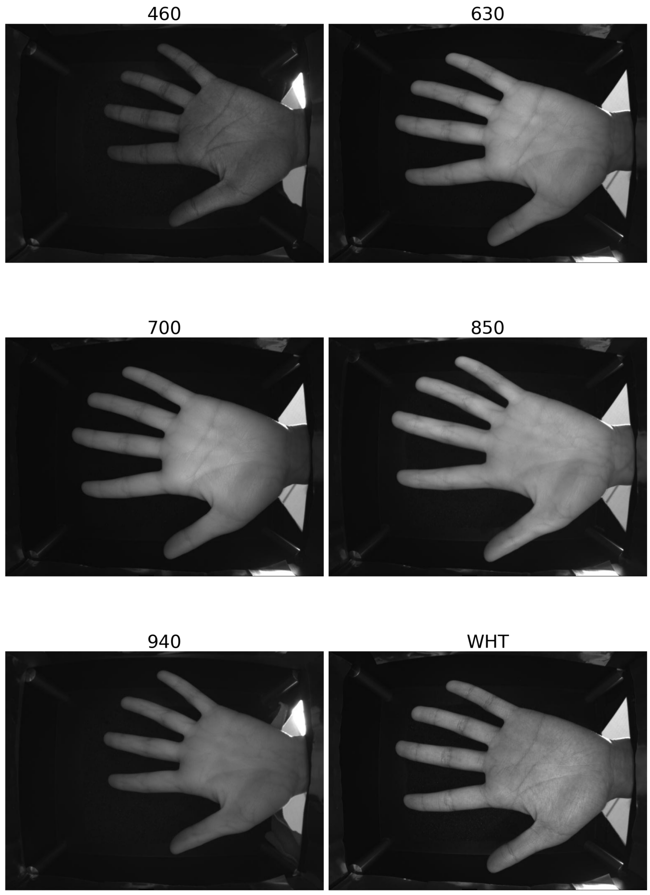

Figure 2: Palmprint images from the CASIA Multi-Spectral Palmprint Image Database with the six spectral bands. Starting from the top-left corner and moving clockwise: 460 nm, 630 nm, 700 nm, 850 nm, 940 nm, and white light.

3 Methodology

3.1 Data preprocessing

3.2 Model Architecture

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