A Calibration Approach to Solve Inconsistency Problem in Palmprint Acquisition System

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Abstract. Inconsistency among different acquisition devices severely affects the performance of palmprint recognition systems. When the same palm is enrolled by one capture device and verified by another device, the inconsistency between the two devices may lead to recognition failure. The installation of camera and the setting of lighting are two main reasons for inconsistency problem in palmprint recognition systems. In this article, we proposed a calibration approach for the inconsistency problem regarding palmprint acquisition devices. Our calibration approach includes image quality assessment, rectification and normalization. Experimental results demonstrate that the proposed approach is effective, decreasing the equal error rate (EER) of palmprint recognition from 0.653% to 0.627%.

1. Introduction
Palmprint recognition is one of the most reliable technologies among biometric identification. It usually contains four stages: image acquisition, region of interest (ROI) extraction, feature extraction and feature matching. A typical palmprint acquisition device is designed with the preset camera and lighting in order to capture the palm image in a controlled environment. Figure 1 shows the palmprint acquisition system invented by Zhang et al. [1] and further developed by their team in [2-6]. First, the user should place his palm on the surface of the device and the system will capture the palm image with the with camera and lighting inside. Then, the ROI will be extracted from the image and the corresponding feature will be extracted and stored in the device as an enrollment template. After the enrollment is done, every time the system receives an incoming image from a user, it will extract the palmprint feature and compare it with every template stored in the device. If there is an existing template that matches, this user is a genuine user. If not, the user is an impostor user. In practice, a genuine user can be rejected by the system due to inconsistency of among the devices. This happens when the user enrolls on one device and verifies on another device. The inconsistency problem mainly comes from the installation of the camera and the setting of the lighting, because the devices are installed and set manually. In industry, inconsistency problem can be solved by manufacture machines with precise control. However, the palmprint acquisition systems still need to do a lot of experiments and testing before they go to mass production. The cost is unaffordable for our lab if we use the industry level machines to produce the palmprint recognition devices. For this concern, we propose a low-cost calibration approach that can solve the inconsistency problem in palmprint acquisition system.

The work in this paper is a development from part of the author’s Ph.D. dissertation [7]. The proposed approach in this article includes image quality assessment, hardware rectification and software normalization. The inconsistency problem in palmprint acquisition system and our proposed approach are discussed in section 2, the image quality assessment and rectification are demonstrated in
section 3, and the normalization is illustrated in section 4. Experimental results are presented in section 5, followed by conclusions in section 6.

Figure 1. Palmprint acquisition device.

2. Calibration approach for inconsistency problem
There are many factors that affect the consistency of palmprint acquisition system. The position and angle of the camera and hand placement together determine which area of the palm is captured. The focus of the camera affects the image sharpness, and the lighting affects the image brightness. Among the above factors, hand placement is hard to be calibrated after acquisition. The user should place the hand according to the guidelines and image with wrong hand placement should be discarded. Our calibration approach only focuses on camera’s position and angle, image sharpness and image brightness.

We refer to the position and angle of the camera as camera view, which means the area that a camera can capture. The camera view should be set in a way that the optical axis of the camera is perpendicular to the surface of the acquisition device. Also, the focus of the camera should be set at the surface of the palm in order to capture a sharp image. The brightness of the lighting should also be set a proper value so that the image is not too bright or too dark. The camera view and camera focus can only be set manually because the camera used in the palmprint acquisition system does not have auto-focus capability. The brightness of the lighting can be coarsely set by tuning the resistance. However, the brightness can appear variously across different images because the illumination of the environment varies. Therefore, it is necessary to normalize the brightness of palm images to a proper value. In this way, we refer to the manual setting of the hardware as rectification and refer to the tuning by the software as normalization. The calibration approach we proposed is described in figure 2. After image acquisition, an image quality assessment is performed on the palm image to check whether the quality is good enough or not. If the quality is not good, a rectification will be done on the device until the image passes the quality assessment. The rectification usually needs to be done only once after the installation of the device. Images with good quality will be processed by the following steps in palmprint recognition.

Figure 2. Flowchart of the proposed calibration approach.
3. Image Quality Assessment and Camera Rectification

Image quality assessment is important to biometric recognition. Image quality assessment methods of fingerprint [8] and iris [9] have been studied for a long time. Though palmprint is relatively new biometric, the quality of palmprint image has been brought to researchers’ attention. Prasad et al. used augmented palmprint image to enhance the recognition accuracy [10], Hao et al. proposed the ridge-based method to assess forensic palmprint image quality [11] and Hong et al. used the Vese-Osher decomposition model to extract features from blurred palmprint images [12]. In our proposed approach, we use a standard chart to assess the camera view and use edge acutance value (EAV), as in [13-15], to assess the camera focus.

3.1. Camera View

Although the ROI extraction algorithm is robust to slight displacement of the palm, incorrect camera view can lead to a tilted palm image. To assess the camera view, we design a standard chart with the same size of the surface of the acquisition device and put it on the device’s surface. The standard chart is depicted in figure 3 (a). As shown in figure 3 (b) and (c), two images captured by two acquisition devices with different camera views appear to be much different. This is because the camera’s optical axis is not perpendicular to the surface of the acquisition device. The standard chart can easily detect the direction to which the camera should be rectified by analyzing the position of the standard chart in the image. The camera view should be rectified manually until the center of the standard chart appears at the center of the image.

![Figure 3](image)

**Figure 3.** (a) Standard chart to detect the camera view. (b) and (c) Different angles of the camera.

3.2. Camera Focus

In the palmprint acquisition device, the camera is not able to auto-focus. A defocus palm image can lead to failure of ROI extraction because the key points cannot be detected due to low image sharpness, as shown in figure 4 (a). Even though the ROI can be extracted, as in figure 4 (b), the ROI image can be blurry and the feature extracted from it loses local details. It is difficult to directly measure the focal distance of the camera, but it is possible to find out the defocus image by assessing the image sharpness. Using the EAV algorithm, which has been a successful palmprint image assessment method as in [15], we perform the sharpness assessment after camera view rectification. A pixel’s EAV is computed by the differences between its eight neighbors, and an image’s EAV is the mean of EAV of the pixels. The full definition of an image’s EAV is in equation (1):

\[
EAV = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=-1}^{1} \sum_{l=-1}^{1} [I(i,j)-I(i+k,j+l)]}{m \times n}
\]

where \(I(i,j)\) is a pixel’s gray value (ranging from 0-255) in an image of \(m \times n\). We used the EAV value in [15] as reference and set the EAV threshold as 15.0. An image with EAV lower than 15.0 should be discarded. We rectify the camera focus manually to meet this requirement. Figure 4 (c) is the image captured after camera focus rectification.
4. Lighting Normalization

Though the brightness of the lighting can be manually set to a proper value by tuning the resistance, the changes of the illumination and the color and reflection of the palm can cause very large differences in palm images. The brightness of the lighting should be further normalized based on the palmprint dataset. We first convert the pixel value $I(i,j)$ ranging from 0-225 to the range of [0, 1] by $X(i,j) = I(i,j)/255$. For a single image, its mean brightness is denoted by $\mu_0$ by averaging all the pixel values, as calculated in equation (2), and its brightness variance of is denoted by $\sigma_0^2$ in equation (3):

$$\mu_0 = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} X(i,j)}{m \times n}$$  \hspace{1cm} (2)

$$\sigma_0^2 = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} (X(i,j) - \mu_0)^2}{m \times n}$$  \hspace{1cm} (3)

Similarly, the mean brightness of a dataset is denoted by $\mu$ by averaging all the images’ mean brightness as calculated in equation (4), and the brightness variance of a dataset is denoted by $\sigma^2$ as in equation (5).

$$\mu = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{l=1}^{N} X(i,j)}{m \times n \times N}$$  \hspace{1cm} (4)

$$\sigma^2 = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{l=1}^{N} (X(i,j) - \mu)^2}{m \times n \times N}$$  \hspace{1cm} (5)

The purpose of brightness normalization is to adjust the image’s brightness so that it has the same brightness distribution with the whole dataset. So, the normalized value $H(i,j)$ can be computed by equation (6).

$$H(i,j) - \mu = \frac{X(i,j) - \mu_0}{\sigma_0}$$  \hspace{1cm} (6)

Figure 5 shows the palm images with different brightness. Figure 5 (b) is the normalized image with the $\mu$ and $\sigma^2$ calculated by the whole dataset. Figure 6 compares the ROI image before brightness normalization and after brightness normalization.
5. Experimental Results

Before brightness normalization, the brightness mean $\mu$ and brightness variance $\sigma^2$ should be determined first. We calculated $\mu$ and $\sigma^2$ from the PolyU palmprint database [16]. This database is one of the largest benchmark palmprint databases, which has two sessions collected on two separate occasions at an interval of about two months. There are totally 7605 grayscale palm images from 386 different palms. The calculation result of PolyU palmprint database is $\mu = 0.392$ and $\sigma^2 = 0.137$.

Then we collected totally 1000 images from 50 individuals using the palmprint acquisition device that needs to be calibrated and performed the rectification as well as lighting normalization on this dataset. To optimize the brightness normalization parameters, we also conducted a series of experiments with different combinations of $\mu$ and $\sigma^2$. First, we fixed $\sigma^2 = 0.08$ and let $\mu$ change from 0.2 to 0.8 with a step of 0.1. We used the Competitive Code proposed in [1] as feature extraction and matching algorithm to evaluate the effectiveness of our calibration approach. The equal error rate (EER) is taken as metrics of the performance of the palmprint recognition. The EER is 0.653% before brightness normalization. Table 1 shows the results of this experiment, indicating that while keeping $\sigma^2 = 0.08$, the EER can reach a lower value when $\mu = 0.3$, $\mu = 0.4$ and $\mu = 0.5$. Figure 7 (a) describes the relationship between EER and $\mu$ when $\sigma^2$ is fixed to 0.08. Then, we fixed $\mu = 0.4$ and let $\sigma^2$ change from 0.06 to 0.18 with a step of 0.02. Table 2 shows the results of this experiment and figure 7 (b) describes the relationship between EER and $\sigma^2$. From the two tables, we can conclude that the optimal combination of $\mu$ and $\sigma^2$ is $\mu = 0.4$ and $\sigma^2 = 0.12$, with the ERR of 0.627% as a result.

### Table 1. EER of palmprint database under different brightness mean $\mu$.

| $\mu$ | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 |
|-------|-----|-----|-----|-----|-----|-----|-----|
| $\sigma^2$ | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 |
| EER (%) | 0.653* | 1.075 | **0.643** | **0.643** | **0.643** | 1.068 | 1.075 |

*Note: the EER without lighting normalization.
Table 2. EER of palmprint database under different brightness variance $\sigma^2$.

| $\mu$ | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 |
|-------|-----|-----|-----|-----|-----|-----|-----|
| $\sigma^2$ | 0.06 | 0.08 | 0.10 | 0.12 | 0.14 | 0.16 | 0.18 |
| EER (%) | 0.653 | 0.776 | 0.643 | 0.643 | 0.627 | 0.657 | 0.669 | 0.768 |

*Note: the EER without lighting normalization.

Figure 7. (a) EER under different brightness $\mu$ with fixed $\sigma^2 = 0.08$. (b) EER under different brightness variance $\sigma^2$ with $\mu = 0.4$.

6. Conclusion
In this paper, the inconsistency problem of palmprint acquisition system is discussed. The camera view and camera focus are the main hardware factors that cause the problem. The brightness of lighting is also a main factor affecting the performance of the recognition algorithm. To solve these problems, a calibration approach is proposed, using a standard chart to rectify the camera view, using EAV to assess the image sharpness so that the camera focus can be rectified accordingly, and using brightness normalization to tune the image brightness. The brightness normalization parameters were calculated from the PolyU palmprint database and then fine-tuned to optimal values. The experimental results demonstrate that the proposed approach is effective to solve the inconsistency problem by decreasing the EER from 0.653% to 0.627%.

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