A Novel 3D Palmprint Acquisition System
Wei Li, David Zhang, Guangming Lu, Nan Luo

ABSTRACT  
Palmprints have been widely studied for personal authentication because they are highly accurate and incur low costs. Most of the previous work has focused on two-dimensional (2D) palmprint identification. However, the inner surfaces of palms do not contain only texture information, but also shape information. Unfortunately, 2D palmprint systems lose the shape information when capturing palmprint images. Hence, three-dimensional (3D) information is important for palmprint systems. In this paper, we have designed and developed a novel 3D palmprint acquisition system based on structured-light imaging technology. The acquisition system can obtain 3D palmprint information and at the same time, the corresponding 2D texture, which are used for personal authentication. A 3D palmprint database that contains 8,000 samples has been established by using the developed acquisition system, and the test results illustrate the effectiveness of our system.

KEYWORDS  
3D Palmprint Measurement; Biometrics; Structured-Light Imaging; Palmprint Depth

1 Introduction

Nowadays, information security has become an important issue, and receives extensive attention. In conventional personal authentication methods, such as identity cards, integrated circuit (IC) cards, passwords, etc., there exist various defects. In addition, identity cards may be lost, forged, or misplaced, and passwords may be forgotten or compromised. Attention has therefore turned towards biometrics, and more robust and reliable information security systems are in demand. At present, commonly used biometrics include the fingerprint, hand geometry, iris, face, palmprint, signature, voice, gait, etc. [1]. As a physiological biometric characteristic, the palmprint was proposed for personal recognition more than ten years ago [2], and has been widely studied due to its merits, such as distinctiveness, cost-effectiveness, user friendliness, high accuracy, and so on.

Most of the previous work has focused on two-dimensional (2D) palmprint identification. Kong et al. proposed a competitive coding scheme for palmprint verification [3]. Sun et al. proposed an ordinal palmprint representation for personal identification [4]. Jia et al. suggested a robust line orientation code for palmprint verification [5]. There are mainly three ways to obtain 2D palmprint images with the following advantages and disadvantages:

1) ink-based images [2, 6]. Advantages: high resolution and discriminability. Disadvantages: low user acceptability and obtaining speed,
2) scanner-based images [7]. Advantage: low cost. Disadvantage: low obtaining speed, and
3) charge-coupled device (CCD) camera-based images [8, 9]. Advantages: high obtaining speed and image quality. Disadvantage: high cost for high resolution image and affected by highlights which occur when hands are sweaty.

Fig. 1 shows a CCD camera-based 2D palmprint acquisition device (left) developed by the Hong Kong Polytechnic University and a palmprint image (right) collected by this device [8]. An online palmprint identification system was then developed based on this CCD camera-based 2D palmprint acquisition device [9].

Fig. 1. CCD camera-based 2D palmprint acquisition device (left) and a palmprint image (right) that is collected by the device.
Although 2D palmprint recognition has proven to be efficient in terms of verification rate, it has some inherent drawbacks. First, the palm is not a pure plane and 3D depth information cannot be captured by using a single CCD camera. Secondly, the illumination variations in the system will substantially affect the 2D palmprint image and may lead to false recognition. Then, although the area of the palm is large, too much contamination on the palm can still render the recognition invalid. Lastly, the 2D palmprint image can be easily copied and counterfeited; hence, the anti-forgery abilities of 2D palmprint devices need to be improved. 3D palmprints show a much better performance that will more effectively deal with these problems in comparison to 2D palmprints. As the depth information of a palm is dependent on a phase of mapped stripes, it is hardly affected by illumination variation and contamination. Furthermore, it is obvious that copying 3D palmprint is much complex than copying 2D palmprint. From inked palmprint samples, we can see that the inner surface of the palm contains consistent and detailed shape information. Fig. 2 shows some inked palmprint samples, in which the prints in the first row are collected from the same palm at different times, and the prints in the second and third rows are collected from different palms. From these samples, we find that there are some blank areas in the palm centers which are consistent in the samples collected from the same palm, and vary for the samples collected from different palms. This implies that the depth of the inner surface of the palm provides useful information for personal authentication.

Fig. 2. Inked palmprint samples, the first row shows prints that are collected from the same palm at different times, and the second and third rows show prints that are collected from different palms.

Fig. 3. A depiction of a 3D palmprint surface.

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The rest of the paper is organized as follows. Section 2 describes the details of the system design. Section 3 gives the experimental results. Section 4 discusses the performance evaluation and analysis, and Section 5 concludes the paper.

2 3D Palmprint Acquisition System Design

A. Feasibility Analysis

Non-contact vision-based 3D imaging technology primarily incorporates multi-view imaging and structured-light imaging. Multi-view imaging is based on human visuals. It is high in speed and low in cost. However, it is hard to obtain high accuracy because it is difficult to find and match corresponding point pairs in two or more images. Some 3D face databases have images that are collected by multi-view imaging devices. Structured-light imaging is widely used as a 3D imaging method for its high accuracy, speed and stability. A projector casts a certain pattern of structured light onto a surface, the structured light is modulated by the surface shape, and the modulated stripes are captured by a CCD camera at a constant distance from the projector. The distance from the measured surface to the reference plane can be calculated according to the modulated stripe images and the geometric correlation between the measured surface, projector and CCD camera.

There are four kinds of 3D imaging models according to structured light patterns: point structured light, line structured light, multiple line structured light and grid structured light, as shown in Fig. 4. Point structured light is the simplest model. It is very easy to calculate the point depth.
position according to the triangulation. However, it has low efficiency as it only measures one point each time. Line structured light is the extension of point structured light. We must let the line light scan the measured surface and record the images by a high speed CCD camera to obtain the 3D information of objects. So, it is still not very efficient. Multi-line structured light can obtain all of the 3D information by one or several images, which is very efficient and accurate. Although grid structured light is also efficient, it is much too complex for application. So, we choose multi-line structured light to establish the system.

Fig. 5 illustrates the imaging principle of the multi-line structured-light technique \cite{12}. Interested readers can refer to \cite{12} for more details. In Fig. 5, there is a reference plane in which the height is 0. By projecting light through the grating to the object surface, the relative height of point D at spatial positions \((x, y)\) to the reference plane can be calculated as follows \cite{12}:

\[
 h(x, y) = \overline{BD} = \frac{P_0 \cdot \tan \theta_0 \cdot \phi_{CD}}{2\pi (1 + \tan \theta_0 / \tan \theta_a)} \tag{1}
\]

where \(P_0\) is the wavelength of the projected light on the reference plane, \(\theta_0\) is the projecting angle, \(\theta_a\) is the angle between the reference plane and the line which passes through the current point and the CCD center, and \(\phi_{CD}\) is the phase difference between points \(C\) and \(D\).

From (1), we can see that the key to this method is to solve the phase information. There are mainly three methods to solve the phase information of the grating image: Fourier transform, time domain convolution filtering and phase shifting \cite{15}. The phase shifting method is widely recognized as the most effective and reliable method \cite{14, 15}. It has low computational complexity and capacity to reduce noise. Hence, we adopted the phase shifting method to calculate the phase information \cite{16}. With a four-step interferometer \cite{16}, four intensity images: \(I_1, I_2, I_3, I_4\), were obtained by projecting four sinusoidal grating patterns onto the object, separated by the phase steps of \(\pi / 2\):

\[
 I_n(x, y) = I_0 + I_r + 2A_r A_o \cos(\phi(x, y) + \delta_n),
\]

\[
 \delta_n = (n-1)\pi / 2, \quad n = 1, 2, 3, 4 \tag{2}
\]

where \(A_r\) and \(A_o\) are the reference and object beam amplitudes with corresponding intensities \(I_r\) and \(I_o\). \(I_1, I_2, I_3, I_4\) and \(\phi\) are all functions of \(x\) and \(y\). According to (2), the phase mapping can be calculated as:

\[
 \phi(x, y) = \tan^{-1}\left(\frac{I_3(x, y) - I_1(x, y)}{I_4(x, y) - I_2(x, y)}\right) \tag{3}
\]

From (3), we can see that all of the phase values fall into the interval of \([-\pi / 2, \pi / 2]\). In order to obtain a continuous distribution of phase values, the phase values first need to be extended to \([-\pi, \pi]\). This can be done according to the signs of the sine and cosine values of the phase values. Then, we use the phase unwrapping method \cite{17} to retrieve the continuous phase map. The main steps are as follows.

Fig. 6 illustrates the principle of phase unwrapping where (a) shows an example of calculated phase values which are not continuous. We can see that there must be a step of \(2\pi\) for very discontinuous points, as shown in Fig. 6 (b). If we can correctly compensate the step at the discontinuous points, then we can obtain the original continuous phase values, as shown in Fig. 6 (c). The
The process of the phase unwrapping method is as follows:

Step 1. Set threshold $T$ at a little less than $2\pi$, e.g. $T=1.8\pi$;

Step 2. Start from $i=0$, complete the following Steps (3), (4) and (5) until all the phase values have been accessed;

Step 3. Calculate the phase difference of the adjacent points:

$$\Delta \phi = \phi(x_{i+1}, y) - \phi(x_i, y)$$  \hspace{1cm} (4)

Step 4. If $|\Delta \phi| < T$, then $\phi(x_{i+1}, y) = \phi(x_i, y)$, else

$$\phi(x_{i+1}, y) = \begin{cases} 
\phi(x_i, y) - 2\pi, & \text{if } \Delta \phi > 0 \\
\phi(x_i, y) + 2\pi, & \text{if } \Delta \phi < 0 
\end{cases}$$  \hspace{1cm} (5)

Step 5. $i = i + 1$, go to Step 3.

**B. Components of the system**

Fig. 7 illustrates the architecture of the developed 3D palmprint data acquisition system. The system consists of two parts, the projection and image capturing units. The projection unit contains the casting lens, liquid crystal display (LCD) panel, controller board, back convergent lens, front convergent lens and white light-emitting diode (LED) light source. The image capturing unit contains the CCD camera and camera lens. A light source projects varying structured light patterns (stripes) onto the surface of an object. The reflected light is captured by the CCD camera and then a series of images are collected. After performing calculations, the 3D surface depth information of the object can be obtained. In earlier stages, parallel lights, such as lasers or point light arrays, were used. With the development of light source techniques, parallel lights have been successfully replaced by liquid crystal light projectors as the new light source \cite{18}. In our developed system, a cost-effective grey LCD projector with an LED light source is employed, and some shift light patterns are projected onto the palm.

**Fig. 7. Architecture of the developed 3D palmprint data acquisition device:** 1) CCD camera; 2) camera lens; 3) casting lens; 4) LCD panel; 5) controller board; 6) back convergent lens; 7) front convergent lens; 8) white LED light source; 9) signal and power control box; and 10) box shell.

**Fig. 8. Main components of the controller board.**

**Fig. 9. The controller board and the LCD.**
C. System calibration and measurement

Calibration is an important step for 3D object measurement. Here, we use a comprehensive calibration method. There are three parameters, \( P_0, d \) and \( L \), which need to be calibrated as shown in Fig. 5, where \( P_0 \) is the wavelength of the projected light on the reference plane, \( d \) is the distance from the center of the CCD camera to the center of the projector, and \( L \) is the distance from the center of the CCD camera to the reference plane. According to triangular correlation, we can get the following equation:

\[
\frac{L-h}{h} = \frac{d}{2P_0} \cdot P_0
\]

That is,

\[
h = \frac{\phi_{CD} \cdot L \cdot P_0}{2\pi d + \phi_{CD} \cdot P_0}
\]

From (7), we can see that if \( h \) and \( \phi_{CD} \) are known, the unknown parameters are \( P_0, d \) and \( L \). Actually, if a regular target is measured, its height is known, and \( \phi_{CD} \) can be calculated by the collected images. So, given three different heights, \( h_1, h_2, h_3 \), as shown in Fig. 10, we can get three equations from (7), and then, the three unknown parameters, \( P_0, d \) and \( L \), can be solved. In our system, these values are \( P_0=1.700 \text{mm}, d=102.400 \text{mm} \), and \( L=126.388 \text{mm} \).

Fig. 10. Illustration of the three heights for calibration.

Fig. 11 illustrates the 3D palmprint data collection and processing process. The computer controls the projector to cast a series of 13 structured-light stripes onto the inner surface of the palm and the CCD camera captures the palm images with the projected stripes. At the same time, the computer sends a command to the data collection board to store the images. The data collection requires about 2 seconds. From these palm images, the depth information of each point on the palm can be computed by using phase transition and phase expansion techniques [16, 17]. The processing steps, which are marked by using blue arrows in Fig. 11, will require about 0.5 second. Hence, the total time to generate a 3D palmprint is about 2.5 seconds.

Fig. 11. 3D palmprint data collection and processing process (the red solid arrows denote the sending command, green arrows, from “CCD camera” to “Computer”, denote the data transport of collecting, and blue arrows, from “Computer” to “3D palmprint”, denote data processing).

Fig. 12 shows the developed 3D palmprint authentication system. A series of 13 palmprint images with different stripes on them which are used to generate 3D palmprints are given in Fig. 13. Fig. 14 indicates some 3D palmprint samples and their corresponding 2D images.

Fig. 12. The developed 3D palmprint authentication system.

Fig. 13. A series of palmprint images with different stripes on them.
3 System Testing

The original 3D palmprint collected by the developed device contained 768×576 points. First, we removed the redundant and noisy boundary regions by using a very simple region of interest (ROI) extraction process (Fig. 15). We segmented a 400×400 point ROI square with a constant value that has 68, 108, 234 and 134 points at the top, bottom, left and right boundaries, respectively, of the 3D palmprint image as shown in Fig. 15 (a). Fig. 15 (b) shows the extracted ROI. After downsampling the 3D ROI to 200×200 points, we stored it into a 200 by 200 matrix, \(d_{ij}\), where \(d_{ij}\) is the depth value of the ith row and jth column point of the 3D ROI.

To describe the shape of the 3D palmprint, we used a group of equidistant horizontal planes to cut the 3D ROI as shown in Fig. 18. Then, Fig. 19 gives the contours that are cut by the equidistant horizontal planes which are collected at different times. The top six contours are obtained from one palm, and the bottom six contours are obtained from another palm. From Fig. 19, we can see that the contours are consistent for the former and vary for the latter.

With the obtained 3D ROI, we calculated the maximum depth (MD) value of the 3D palm from a reference plane, as shown in Fig. 16. We tested the depth of 100 palms. From each palm, 10 samples were collected. In Fig. 17, every vertical line illustrates the depth range of ten samples taken from one palm. The red mark is the maximum value, blue mark is the minimum value, and green mark is the mean value of the MD of the ten samples from one palm. From Fig. 17, we can see that the MD variation of each palm is small in comparison with the MD variation of 100 palms. So, the depth information of a 3D palmprint is consistent for the same palm, but varies for different palms.
score between $C_j$ and $C_i$ can be defined as:

$$R = \frac{\sum_{k=1}^{n} \sum_{m=1}^{m} |C_j - C_i|}{k \times n \times m}$$  \hfill (8)$$

where $k$ is the level num, and $n \times m$ is the size of the matched samples. Since this is course matching, we downsample the ROI from 200x200 to 100x100, and finally, only use the central points. Through this matching method, the equal error rate (EER) is 3.36% on a database which contains 1000 samples collected from 100 palms.

From Eq. (1), we can see that the phase value is the most important factor for calculating the depth information of a measurement object. Theoretically speaking, measurement accuracy is independent from the grating period. However, as the image obtained by the CCD camera is not continuous but discrete, the grating period needs to be taken into consideration.

As described in Section 2.1, sinusoidal grating is expected. We separately tested the grating wavelengths for 8, 16, and 32 pixels as shown in Fig. 21. Wavelengths of 2 and 4 imply square and triangular waves which greatly deviate from the sinusoidal waves. Figs. 21 (a), (b) and (c) show gratings that are cast by a projector whose wavelengths are 8, 16, and 32 pixels, respectively. Two periods of wave curves along the vertical direction are depicted in Figs. 21 (d), (e) and (f) for the three grating wavelengths, respectively. Figs. 21 (g), (h), (i), (j), (k) and (l) indicate the corresponding grating images and two periods of wave curves as captured by the CCD camera. From Fig. 21, we can see that for the grating projected by the projector, the accuracy of the sinusoidal curve is improved with the growth of the wavelength. However, due to limitations by the electrical devices, the accuracy of the captured image is not always improved.
with the growth of the wavelength, as shown in Figs. 21 (g), (h) and (i). Table 1 lists the root mean square deviation of different wavelengths for captured images by the CCD camera. From Table 1, we can see that the root mean square deviation is minimized when the grating wavelength is 16 pixels and the wavelength of the projected light on the reference plane is 1.7 mm. So, in our system, we set the grating wavelength to 16 pixels.

Table I. Root Mean Square Deviation of Different Wavelengths

<table>
<thead>
<tr>
<th>Grating wavelength (pixels)</th>
<th>8</th>
<th>16</th>
<th>32</th>
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<tr>
<td>Wavelength of the projected light on the reference plane (mm)</td>
<td>0.9mm</td>
<td>1.7mm</td>
<td>3.4mm</td>
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<tr>
<td>Root mean square deviation</td>
<td>2.22</td>
<td>0.96</td>
<td>5.28</td>
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B. Signal to Noise Ratio

Another very important factor for system accuracy is the signal to noise ratio (SNR) of the CCD camera. We tested four CCD cameras which had SNRs of 54 dB, 56 dB, 58 dB and 60 dB, respectively. A smooth plane was measured by the system with the different cameras. Fig. 22 shows the curve of the standard deviation to the SNR. We can see that with the growth of the SNR, the standard deviation of the data decreases, which means that accuracy is improved. However, the cost of a high SNR CCD camera is expensive. In consideration of the performance and cost, we chose the 58 dB SNR CCD camera. The depth precision of the 3D image measured by this system is between 0.05 and 0.1 mm.

\[ \text{Fig. 22. Curve that shows standard deviation to SNR.} \]

C. Data Analysis

A 3D palmprint database has been established by using a newly developed 3D palmprint imaging device. The database contains 8000 samples from 200 volunteers, including 136 males and 64 females between 10 to 55 years old. The 3D palmprint samples were collected in two separate sessions, and in each session, 10 samples were collected from both the left and right hands of the subject. The average time interval between the two sessions was one month. Fig. 23 shows some ROIs of 3D palmprint samples, in which each row is collected from one palm at different times. In [19], we proposed a curvature-based 3D palmprint recognition method which achieved good performance. Then, we fused 2D and 3D palmprints by an alignment refinement method [20] to further improve the performance. Table 2 lists the EERs by 2D, 3D and 2D+3D palmprints, and Fig. 24 illustrates the corresponding receiver operating characteristic (ROC) curves. From Table 2 and Fig. 24, we can see that with a 3D palmprint alone, the EER is 0.294%, which is accurate enough for most of the applications, and by fusing 2D and 3D palmprints, the EER is much less than for any single pattern. These experiments demonstrate the effectiveness of the proposed 3D palmprint system.

\[ \text{Fig. 23. 3D ROI samples (each row is collected from one palm at different times).} \]

\[ \text{Fig. 24. The ROC curves from 2D, 3D and 2D+3D palmprints.} \]

Table II. The EERs from 2D, 3D and 2D+3D Palmprints

<table>
<thead>
<tr>
<th>Methods</th>
<th>EER</th>
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<tr>
<td>2D palmprint</td>
<td>0.046%</td>
</tr>
<tr>
<td>3D palmprint</td>
<td>0.294%</td>
</tr>
<tr>
<td>Fusing 2D and 3D palmprints</td>
<td>0.025%</td>
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</table>

5 Conclusions

In this paper, we have introduced a novel 3D palmprint acquisition system based on structured-light imaging...
technology. The principle and process of the generation of 3D data have been discussed. The details of the components of the 3D palmprint acquisition device have been described. The measurement accuracy of the developed system is between 0.05 and 0.1 mm which is accurate enough for capturing the depth information of palmprints. The experiments show that the developed 3D palmprint acquisition system can obtain valuable 3D information from a palmprint which is useful for palmprint identification.

References


作者简介

黎伟，2010年于上海交通大学模式识别与智能系统专业获工学博士学位，现任深圳先进技术研究院助理研究员。研究方向：生物特征识别，图像处理，虚拟化，海量数据挖掘等。已在国际期刊，如IEEE Transactions，以及国际会议，如CVPR等，发表多篇相关学术论文。