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# Faster and Accurate Matching Technique for Palmprint Identification

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*Abstract:* **This paper presents the palmprint identification based on 2D and 3D palmprint matching methods. The methods are more efficetive, less extraction time, less matching time and accurate for palmprint matching. Firstly, we remove noises from palmprint images using hybrid median filter methods. Secondly,In 3D palmprint matching follow two arguments and proposed a new method for palmprint features. The proposed method has better perfomance and also significantly reduce the templete size. This method of 3D shape palmprint to either convex or concave. The experimental results shows that the better palmprint matching, more accurate and less extract time features compare to existing methods.**

*Index Terms*— **Palmprint; Palmprint Matching and Shape Index;**

## I. INTRODUCTION

The rapid growth in the use of *e*-commerce applications requires reliable and automatic personal identification for effective security control. The biometric computing based approach is concerned with identifying a person by his/her physiological characteristics, such as iris pattern, retina, palmprint, fingerprint and face, or using some aspect of his/her behavior, such as voice, signature and gesture [1-2]. Fingerprint-based personal identification has drawn considerable attention over the last 25 years [8]. However, workers and elderly may not provide clear fingerprint because of their problematic skins and physical work. There are many unique features in a palmprint image that can be used for personal identification. Principal lines, wrinkles, ridges, minutiae points, singular points and texture are regarded as useful features for palmprint representation [6]. Various features can be extracted at different image resolutions. For features such as minutiae points, ridges and singular points, a high-resolution image, with at least 400 dpi (dots per inch), is required for feature extraction [7]. However, features like principal lines and wrinkles can be obtained from a low-resolution palmprint image with less than 100 dpi [3,6]. In general, high-resolution images are essential for some applications such as law enforcement, where ridges, singular points and minutiae points are extracted and matched in latent prints for identification and verification. Some companies, including NEC and PRINTRAK, have developed automatic palmprint identification and verification systems for law enforcement applications.

Automatic palmprint identification systems can be classified into two categories: *on-line* and *off-line*. An on-line system captures palmprint images using a palmprint capture sensor that is directly connected to a computer for real-time processing. An off-line palmprint identification system usually processes previously captured palmprint images, which are often obtained from inked palmprints that were digitized by a digital scanner. In the past few years, some researchers have worked on off-line palmprint images and have obtained useful results.

## II. 2D PALMPRINT MATCHING

We propose a palmprint identification system utilizing both 2D and 3D features of human palm. Our aim is to improve the performance of existing 2D image based system. Block diagram of the 2d palmprint matching system is shown in Figure 1.

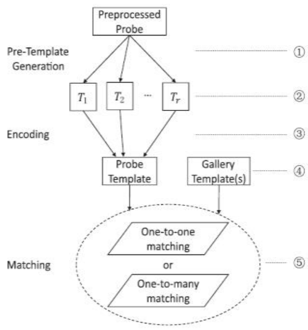



***Fig.1. block diagram of palmprint matching***

There are two types of prominent template/feature matching strategy are used, *i.e.* (a) *one-to-one* and (b) *one-to-many* matching strategy. For one-to-one palmprint matching strategy, the Hamming distance between the codes with same location is returned as the final distance. For one-to-many matching strategy, the code in one template matrix is matched to the another of the corresponding code in another matrix, and the minimum Hamming distance is returned as the final distance.

**a) Feature extraction**

During the feature extraction stage, we take the gabor filter and CompCode and RLOC use six spatial filters to extract dominant texture templet and generate one feature template. In the matching feature stage, they use one-to-one matching strategy and one-to-many matching strategy respectively. The feature extraction stage of two spatial filters in Ordinal Code and remain four spatial filters to extract feature and for each probe, the processing is repeated three times and therefore three filters feature templates are generated. In the matching stage, it employs one-to-one matching strategy and the sum of three distances is the final matching distance. A family of 2D Gabor wavelets, satisfying wavelet theory and the neurophysiological constraints can be derived from general complex 2D Gabor function as

$$p = \arg\ \min_j (I(x, y) * \psi_R(x, y, \omega, \theta_j))$$

where $I$ is a 2D subimage, $R$ □ represents the real part of the Gabor filter, and '*' denotes discrete convolution. Orientations of the filters are chosen to be ϴ=Π / 6, {0, 1...,5}

## III. 3D PALPRINT MATCHING

3D palprint matching to define a coordinate system that is used to take different palmprint images for matching. To extract the central part of a palmprint, for reliable feature measurements, we take the gaps between the fingers as reference points to determine a coordinate system. They are some steps to follow 3D palmprint matching.

**Step 1**. Apply a binary feature, such as binary, to the original image b(x,y). A threshold, Tp, is used to convert the gray image to a binary image.

**Step 2.** Obtain the labelling of the gaps, L(x,y), between the objects using a boundary labelling algorithm. The boundary of the gap between the ring and middle objects is not extracted since it is not useful for the following processing.

**Step 3.** Compute the tangent of the two gaps. Let x,y1 and x2; y2 be any points on object pixel. If the line (y ¼ mx þ c) passing though these two points satisfies the inequality, then the line (y ¼ mx þ c) is considered to be the tangent of the two gaps.

**Step 4.** Line up x1; y1 and x2; y2 to get the Y-axis of the palmprint coordinate system, and use a line passing through the midpoint of these two points, which is perpendicular to the Y-axis, to determine the origin of the coordinate system.

**Step 5**. Extract a subimage of a fixed size based on the coordinate system. The subimage is located at a certain area of the palmprint image for feature extraction

**b) feature extraction**

During the feature extraction stage, Maximum/Minimum encoding method is applied on the two intermediate results to generate the feature. More specifically, the binary feature matrix *F* is computed as follows

$$F_{i,j} = \tau([f(n) * I - f(m) * I]_{i,j}),$$

where *Fi, j* is the feature value at position *(i, j)*, *I* is the preprocessed image, ∗ is convolution operation, *n* and *m* are given parameters, [*O*]*i, j* is the value of matrix *O* at position *(i, j ), τ(·)* is defined as

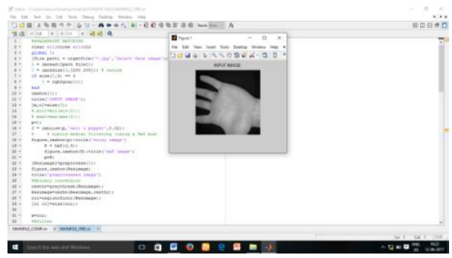
$$\tau(\alpha) = \begin{cases} 0, & \alpha < 0 \\ 1, & \alpha \geq 0. \end{cases}$$

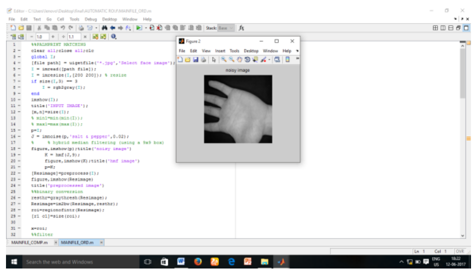
Two matrixes, *f (n)* ∗ *I* and *f (m)* ∗ *I*, are two intermediate pre-templates. The substraction operation is equivalent to max, min operation as step 3 in the framework. The parameters of the proposed feature in our framework. We can efficiently use one filter *g(n,m)* instead of *f (n), f (m)* and the feature extraction equation can be rewritten as

$$F_{i,j} = \tau([g(n, m) * I]_{i,j}).$$

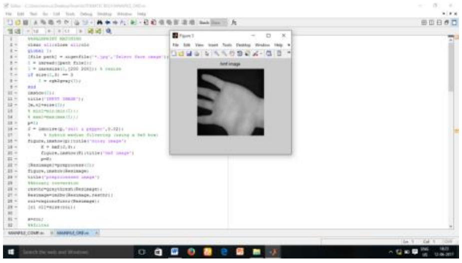
The shape of *g(n,m)* is similar to a hat. Each code resulting from spatial filtering operation describes the shape of corresponding point on the 3D palmprint images, which is either convex or concave.

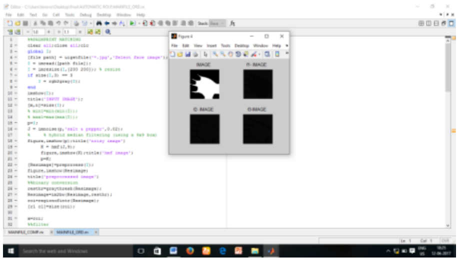
## IV. EXPERIMENTAL RESULTS

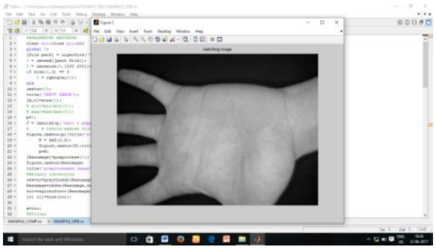


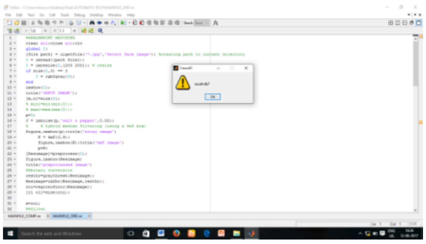










## V. CONCLUSION

In this work, the palmprint identification using 2D and 3D palmprint identification methods. It has less extracting time for features and more accurate results. A preprocessing algorithm to remove the noise from a palmprint image for feature extraction. To represent a low-resolution palmprint image and match various palmprint images, we extend the use of 2D Gabor feature to represent a palmprint image using its texture feature, and apply a normalized hamming distance for the matching measurement.

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