Palmprint features matching based on KAZE feature detection

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Abstract. Palmprint is very popular biometric recognition system that is able to guarantee high accuracy. It has attracted increasing amount of attention because palmprints are abundant of many characteristics, such as the principle lines, ridges, minute points and textures for the use of images with low resolution. In this paper we propose palmprint feature detection based on KAZE technique. Palmprint texture has many important points for discrimination process. Selecting the best number of point using KAZE is very important for classification process in order to avoid overlapping features in different class. The experimental work has been done using polyU palmprint database in order to evaluate the best number of features.

Keywords: Palmprint, Biometric, KAZE, PolyU database

1. Introduction

Biometrics plays a significant role these days, in human identification and authentication. Palm print and palm vein based mostly human recognition is a matter which a lot of effort is devoted lately[1]. Automatic identification of humans terribly essential for enforcement, public places like airports and government departments etc. Common documents used for human recognition are passports, ration cards, driving licenses, however these are terribly prone for forgery. Biometric systems are probably the most effective choice for human recognition [2]. Palmprint feature has a wealth of information that is useful to identify and verify. From high and low-resolution images, various features can be extracted. High-resolution image features include the feature Minutiae, the features Ridges and the Singular Point feature[3].

Many computer vision algorithms are built upon their local characteristics and descriptors as compact vector image of a local neighborhood. They are used to record images and to detect and classify objects to track them and estimate motion. Local features help to manage changes in scale, rotation and occlusion better through these algorithms. The FAST, Harris, ORB and Shi & Tomasi processes in the detection of angles, as well as the SURF, KAZE and MSER methods to detect blob features provided in Computer Vision tools. The toolbox contains the following descriptors: SURF, KAZE, FREAK, BRISK, ORB and HOG. Detector and descriptor can be mixed and matched according to the different application requirements [4].

There are many methods for local features detection and the most common are Speeded-Up Robust Features (SURF) [5], Scale-invariant feature transform (SIFT) [6] They detect and define features at various levels by constructing or approximating the Gaussian scale of the image. Moreover, the Gaussian blurring, violates the natural limits of pictures and smoothest all info with noise to identical point, reducing localization accuracy and distinctive[7]. Alcantarilla et al proposed KAZE feature With nonlinear broadcasting filtering [8] the KAZE function recognizes and describes 2D features in a nonlinear scale. The KAZE can thus adjust the images to blur locally, reduce noise but keep object
boundaries, obtain superior accuracy and distinction in the position. KAZE feature was recently proposed to identify a central orientation in the key point by using effective additive operator splitting techniques and variable behavioral diffusion to obtain a scale and rotation invariant descriptor in nonlinear scale spaces. Based on the derivation, to approximate the first and second-order derivatives of the diffusion function, Scharr filters are applied. Compared with this method introduces nonlinear diffusion filtering for multiscale image spaces to preserve the natural image boundaries, previous Gaussian space based approaches such as SIFT and SURF [9].

![Figure 1. Features extraction flow.](image)

2. **Palmprint Database**
The PolyU palmprint database II, with 7752 images from 386 different palm trees, this database has been used during the present experiment. The palm images were taken in two sessions between the two sessions, with an average duration of two months, figure 2 shown samples of poly u database. The prepressing for ROI cropping and extraction has been done by using method in [10].

![Figure 2. Palmprint database](image)

3. **KAZE on Palmprint**
KAZE’s basic work as follows constructs an AOS and a variable conductance diffusion image nonlinear scale space and then calculates the standardized Hessian matrix for non-linear scales. Then detect 2D characteristic points in the Hessian specific matrix, by calculating the local maximum of
3 x 3 neighborhood. At the end calculate the main orientation of the function points and achieve an invariant descriptor scale and rotation on the basis of the first order image derivatives [8].

$$\frac{\partial L}{\partial t} = \text{div}(c(x,y,t) \nabla L)$$  \hspace{1cm} (1)

Where the $\nabla$ and div are respectively the divergence and gradient operators and (c) is conductivity function of the diffusion equation, the time t is the scale parameter, and larger values lead to simpler image representations.

$$c(x,y,t) = g(\nabla L \sigma(x,y,t))$$  \hspace{1cm} (2)

Where the $\nabla L \sigma$ is the gradient of a Gaussian smoothed version of the original image $L$, for Perona and Malik described two different formulations for the conductivity function g:

$$g_1 = \exp\left(-\frac{\|\nabla L\|}{k}\right) \quad g_2 = 1 + \frac{\|\nabla L\|}{k}$$  \hspace{1cm} (3)

Where $k$ is the contrast factor regulating the diffusion level, the $g_1$ feature encourages edges of high contrast, when $g_2$ encourages large and smaller regions Additive Operator Splitting (AOS) formulation:

$$\frac{L^{i+1} - L^i}{\tau} = \sum_{l=1}^{m} A_l(L^i) L^{i+1}$$  \hspace{1cm} (4)

Where $A_l$ is a matrix encoding each dimension’s image conductivity. The solution $L^{i+1}$ can be obtained as:

$$L^{i+1} = (I - \tau \sum_{l=1}^{m} A_l(L^i))^{-1} L^i$$  \hspace{1cm} (5)

For detecting points of interest:

$$L_{\text{Hessian}} = \partial^2 (L_{xx} L_{yy} - L_{xy}^2)$$  \hspace{1cm} (6)

Where $(L_{xx}, L_{yy})$ is the horizontal and vertical derivative of the second order, and where $L_{xy}$ is the cross derivative of the second order. Due to the set of filtered images from $L^i$ nonlinear space. The key-points location is determined using the proposed in [11] sub-pixel accuracy.

4. Result and Discussion

We use the state-of-the-art methods on PolyU palmprint database from Hong Kong Polytechnic University in order to evaluate our proposed method and system to measure how well our method is performed. In this experience two individuals has been used and each one have two images.

![Figure 3](image_url)

**Figure 3.** (a) 297 point default parameters of KAZE with palm image for the first person and first image (b) 276 point default parameters of KAZE with palm image for the first person and second image.
Figure 4. 256 point default parameters of KAZE with palm image for the second person and first image

Figure 5. 259 point default parameters of KAZE with palm image for the second person and second image

The number of points for KAZE features are changing from one to another person according to different palm hand, each person have different number of features, as shown in figure 3 the number of features are 297 and in figure 4 the number of features are 256. When compare the person one with different palm image will notice the number of features not that much different as the different between different person.

|     | KAZE points image 1 | KAZE points image 2 |
|-----|---------------------|---------------------|
| P1  | 297                 | 276                 |
| P2  | 256                 | 259                 |

Thereby, apply SURF feature on palm image it can notice that as shown in figure 6 and figure 7, the number of features very low comparing to KAZE

Figure 6. (a) 3 point of SURF features for first images of first person (b) 2 point of SURF features for second image of first person
Figure 7. (a) Zero point of SURF features for first images of second person, (b) 1 point of SURF features for second image of second person

Table 2. SURF point between person 1 and person 2

|       | SURF points image 1 | SURF points image 2 |
|-------|---------------------|---------------------|
| P1    | 3                   | 2                   |
| P2    | 0                   | 1                   |

5. Feature matching
In matching stage, the features matching has been done by using the nearest neighbors, between image 1 and image 2 are two feature vectors match when the distance between them is less than the threshold set by the Match Threshold parameter of the algorithm in [12]. Around 124 features matched in figure 8 by using KAZE which is show a good impact in this experience comparing to SURF, as shown in figure 9 the total number of feature matching is zeros and close to.

Figure 8. 124 Features matched using KAZE

Figure 9. 2 features matched using SURF
Figure 10. Graph for features value according to feature numbers between features for two different images belongs to same person using kaze

6. Conclusion
This paper discussed in detail feature detection and extraction using KAZE to extract important data point or features exist in palmprint texture. The experimental work demonstrates KAZE is able to produce high number of important features that can be used in the classification process. The high discrimination features is very important in the biometric recognition system in order to differentiate different person.

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