Biometric identification through tongue texture measurements

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Abstract: This paper proposes a method of personal identification based on tongue image. Tongue image have many advantage for personal identification and verification. In this paper a texture tongue features are extracted based on steerable filters and *WLD* (Weber Law Descriptors) transform. These features can be used in forensic applications and with other robust biometrics features can combined multi modal biometric system.

Key-Words: Tongue image, Steerable filters, Weber Law Descriptors.

1 Introduction

Automatic human recognition has become a very active topic in computer vision and biometrics. Tongue image analysis have received much attention in image analysis and computer vision. Tongue features can be used in biometrics applications and with other robust biometrics features can combined multi model biometric system. The tongue presents texture information which are potentially useful in person identity verification. Tongue images are unique to every person, except twins. The identification of a people can be based on the texture features appearing on the tongue. Tongue recognition system is presented on Figure 1 involves three major modules: tongue image acquisition and preprocessing, feature extraction, pattern recognition and classification.

In this paper, a tongue image feature extraction method is proposed, which utilizes steerable filters and local features such as *WLD*, because these features are robust against some types of geometric modifications. Weber local descriptors (*WLD*) is a simple but powerful local descriptor, which simulates the human visual perception.

Images which are considered in this paper are displayed in Figure 2.

The remainder of this paper is organized as fol-

lows. Section 2 briefly describes the preprocessing operations. In Section 3, we describe steerable filters, propose a local descriptor called *WLD* and briefly describes the definition of Weber magnitude and orientation.

2 Preprocessing

Before performing feature extraction, the original tongue images are subjected to some image processing operations, such as:

1. Image stretching. The contrast level is stretching according to

$$f_{out}(x,y) = 255 \times \left(\frac{f_{in}(x,y) - min}{max - min}\right)^{\gamma} \quad (1)$$

 $f_{out}(x,y)$ is the color level for the output pixel (x,y) after the contrast stretching process. $f_{in}(x,y)$ is the color level input for data the pixel $(x,y).\ max$ - is the maximum value for color level in the input image. min - is the minimum value for color level in the input image, γ - constant that defines the shape of the stretching curve.

2. Extraction of region of interest (*ROI*) from original tongue images. The *ROI*'s tongue blocks are selected on the central part of original tongue



Figure 1: Tongue recognition system



Figure 2: Tongue images

images manually. The size of whole *ROI* is 128×128 pixels. Next, the *ROI* image is divided into the four sub-blocks. The size of sub-block is 64×64 pixels (Figure 4).

3 Tongue feature extraction

Tongue features using in reliable identity of person can be obtained by apply the steerable filters to extract the global *ROI*'s features and Weber Local Descriptor (*WLD*) for local feature extraction.



Figure 3: Tongue ROI

3.1 Steerable filters

To find the characteristic lines in tongue ROI, different edge filters can be defined. Steerable filters are a



Figure 4: Four ROI's sub-blocks

class oriented filters in which any filter is represented by a linear combination of set of basis filters. The concept of steerable filters was proposed by Freeman and Aldeson [1].

The idea of steerable filters is brief overview below.

Let a 2D Gaussian function is defined as

$$g(x,y) = e^{-\frac{(x^2+y^2)}{\sigma^2}}$$
 (2)

The second derivative of a Gaussian function is used as a filter kernel and for built a steerable filters.

$$g_{xx}(x,y) = \frac{\partial^2}{\partial x^2} e^{-\frac{(x^2+y^2)}{\sigma^2}} = -(\frac{2x}{\sigma^2} - 1)\frac{2}{\sigma^2} e^{-\frac{(x^2+y^2)}{\sigma^2}}$$
$$g_{xy}(x,y) = \frac{\partial^2}{\partial x \partial y} e^{-\frac{(x^2+y^2)}{\sigma^2}} = \frac{4xy}{\sigma^4} e^{-\frac{(x^2+y^2)}{\sigma^2}}$$
(3)
$$g_{yy}(x,y) = \frac{\partial^2}{\partial y^2} e^{-\frac{(x^2+y^2)}{\sigma^2}} = -(\frac{2y}{\sigma^2} - 1)\frac{2}{\sigma^2} e^{-\frac{(x^2+y^2)}{\sigma^2}}$$

Use the three second derivations we obtain steerable filters along of any orientation $\boldsymbol{\theta}$

$$g_2^{\theta}(x,y) = g_{xx}(x,y)\cos^2(\theta) - 2\sin(\theta)\cos(\theta)g_{xy}(x,y) + g_{yy}(x,y)\sin^2(\theta)$$
(4)

$$g^{\theta}(x,y) = \sum_{i=1}^{M} k_i(\theta) g^{\theta_i}(x,y)$$
(5)

where M is the number of basis functions to steer a function $g^{\theta}(x, y)$ and interpolation function are following [1]

$$k_i(\theta) = (-1)^i \begin{pmatrix} M \\ i \end{pmatrix} \cos^{M-i}(\theta) \sin^i(\theta)$$
 (6)

The steerable filter template is show in Figure 5.



Figure 5: Steerable filter template

The algorithm for detecting tongue features have the following steps:

- Using eq.(5) the filter at arbitrary orientation θ is computed. In our case θ_i has to be chosen as t × π/4; t = 1,...,4;
- 2. Convolution of *ROI* original image and filter is performed. A convolution of an *ROI* tongue image with a steerable filter of arbitrary orientation is equal to :

$$f_{ROIsteer}(x,y) = f_{ROI}(x,y) * g^{\theta}(x,y) \quad (7)$$

3. The steerable representations of *ROI* image to 4 directions is obtain (Figure 6).

The features of the *ROI* tongue image responses are represented by energy, entropy and other texture parameters (Table 1).

Table 1: Texture parameters

Tongue ROI	
Energy	0.009
Contrast	26.345
Entropy	5.675
Homogeneity	0.725
Variance	181.897



Figure 6: The steerable representations of *ROI* image to 4 directions

To code ROI tongue image with steerable filters, responses of a bank of steerable filters of multiorientation are concatenated to feature vector which represent the ROI pattern. We represent the pattern by a set of K invariant-features - as a point in K dimensional feature space. Points corresponding to patterns of the same class are assumed to be close together, not close to those of different classes. The similarity distance between two feature vectors and for a pair of ROI images is computed as the Euclidean distance. The value of the similarity distance is zero or small for identical or similar objects and high for other objects.

3.2 Weber Law Descriptors

In 1834 Ernst Weber states that "the ratio between the smallest perceptual change in a stimulus Δf_{min} and the background level of the stimulus f is constant e.g. $\frac{\Delta f_{min}}{f} = k$ " [4]. Inspired by Weber's Law, a robust and powerful Weber Local Descriptor (*WLD*) is a recently developed for local feature extraction. For each pixel of the input image, we compute two joint descriptors: a differential excitation *DE* operator and a gradient orientation *GO* descriptor. The *DE* is a function of the ratio between two terms: one is the relative intensity differences of a current pixel against its neighbors (e.g., 3×3 square region) and the other is the intensity of the current pixel. The orientation component is the *GO* of the current pixel.

If f(x, y) is the center pixel of a 3×3 window, and f(x+i, y+j); i = -1, 0, 1 j = -1, 0, 1 are the neighbors of the center pixel, DE is calculated as

$$DE = \arctan\left[\frac{\left(\sum_{i=-1}^{1}\sum_{j=-1}^{1}f(x+i,y+j)\right) - 9f(x,y)}{f(x,y)}\right]$$
(8)

where f(x + i, y + j) i = -1, 0, 1; j = -1, 0, 1is the gray level intensity of the corresponding pixel. The positive value of DE indicates that the current pixel is darker than the neighboring pixel, while the negative value represents the opposite.

The main purpose of the DE component is to extract the local salient patterns from the image.

The GO of the center pixel f(x, y) is calculated as

$$GO = \arctan\left[\frac{f(i, j-1) - f(i, j+1)}{f(i+1, j) - f(i-1, j)}\right] = \\ = \arctan\left[\frac{A}{B}\right]$$
(9)

where the numerator is the intensity difference between the left and the right of f(x, y), while the denominator is the intensity difference between the below and the above of f(x, y).

Next, the GO are quantized into dominant orientations as follows:

$$GO' = \arctan 2 \left[\frac{A}{B} + \pi\right]$$
 (10)

$$\arctan 2 \left[\frac{A}{B} \right] =$$

$$= \begin{cases} GO & A > 0 \text{ and } B > 0 \\ \pi - GO & A > 0 \text{ and } B < 0 \\ GO - \pi & A < 0 \text{ and } B < 0 \\ -GO & A < 0 \text{ and } B > 0 \end{cases}$$
(11)

The GO is then quantized into T dominant orientations. For each dominant orientation, histogram, H, is calculated using the DE [3].

Because not all the features are equally important, the feature selection technique is used.



Figure 7: Tongue feature extraction

To compute the distance of two histograms chi-square χ^2 distance is used

$$\chi^{2}(H^{1}, H^{2}) = \sum_{i} \frac{(h_{i}^{1} - h_{i}^{2})^{2}}{h_{i}^{1} + h_{i}^{2}}$$
(12)

where H^1 and H^2 are two histograms and h^1_i , h^2_i are the $i{\rm th}$ bin of the histograms.

4 Conclusion

In the paper, are presented some approaches for tongue recognition.

To evaluate the performance of tongue recognition methods we use own tongue database that consists 30 images. The tongue recognition is realized based on a method which combines the recognition results of steerable filters and *WLD* features to tongue recognition. The *WLD* texture features are robust against rotation and noise.

The proposed system will be evaluated on other tongue databases in future study.

References:

- Feeman, W.T., Adelson, E.H.: The design and use of steerable filters, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 13(9), pp. 891 – 906, 1991.
- [2] Jacob, M., Unser, M.: Design of steerable filters for feature detection using Canny-like criteria, *IEEE*

Trans. on Pattern Analysis and Machine Intelligence, 26(8), pp. 1007 – 1019, 2004.

- [3] Chen, J., Shan, S., He, C., Zhao, G., Pietikinen, M., Chen, X., and Gao, W.: WLD: A robust local image descriptor, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 32(9), pp. 1705 – 1720, 2009.
- [4] Jain, A.K.: Fundamentals of a Digital Signal Processing, Prentice-Hall, Englewood Clifts, NJ., 1989.
- [5] Zhang, D., Liu, Z., Yan, J.,Shi, P.: Tongue-print: A novel biometrics pattern, *ICB 2007*, Springer-Verlag LNCS 4642, pp. 1174 – 1183, 2007.
- [6] Lahmiri, S.:Recognition of tongueprint textures for personal aAuthentication: A wavelet approach, *Journal of Advances in Information Technology*, vol.3 ,no.3, pp. 168 – 175, 2012.