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Face and Vein Identification Using LBP, LDiP and LDNP as Local-Feature Descriptors

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Abstract: Visual pattern recognition using face and vein images as input to identify someone is not a new issue in the filed of pattern recognition. However, to acquire a face image is totally different with a vein image. In addition, factors that affect the recognition rate among them are also different. This study describes simulations that were conducted on three kinds local descriptors, i.e., LBP, LDiP and LDNP to represent face and vein images for identification. The classification is using Chi-square histogram matching as a dissimilarity measure. From the simulations conducted it was shown that the local-feature descriptor was not properly applied directly for vein images.

Key words: LBP, LDiP, LDNP, face, vein, recognition rate

INTRODUCTION

The ultimate goal of a supervised pattern recognition system is to determine a novel pattern as one of the predefined classes correctly. One has to design a better representation for each class pattern that makes it more discriminative than others that leads to achieve a better recognition rate. Better representation means that when extracting features, one has to minimize the intra-class variations but at once maximize the inter-class variations. If it fails, even the most sophisticated classifier will fail to accomplish the recognition task (Jain and Li, 2011).

Generally, there are two kinds feature extraction techniques, namely global-feature descriptor and local-feature descriptor. Global-feature descriptor works on the whole image directly to get the prominent information from an image. In contrast, local-feature descriptor first extracts features from each component/block/region of an image and then gather all features together to represent the image. In addition, the role of both descriptors in recognition/classification is totally different. Global-feature descriptor has a global discriminant feature such as the face shape for a face image that leads to a coarse representation meanwhile local-feature descriptor gives a finer representation such as an eye for a face image (Su *et al*., 2009).

The last decade witnesses that researchers are more interested in developing local-feature descriptors because their recognition rates are better than global-feature descriptors (Heisele *et al*., 2007) especially for face detection and face recognition. Among them, there are Local Binary Pattern (LBP) (Ahonen *et al*., 2006), Local Derivative Pattern (LdeP) (Zhang *et al*., 2010), Local Ternary Pattern (LTP) (Tan and Triggs, 2010), Local Directional Pattern (LdiP) (Jabid *et al*., 2010) and Local Directional Number Pattern (LDNP) (Rivera *et al*., 2013). LBP that originally was designed for texture description then successfully applied as a local-feature descriptor for face analysis (face exepression and face recognition). LBP was not the first face local-feature descriptor (Pentland *et al*., 1994; Penev and Atick, 1996; Wiskott *et al*., 1997) but its simplicity to extract the local-feature from a face image resulted in a famous local-feature descriptor as a comparative algorithm.

LDeP developed a high-order local-feature descriptor to get a more discriminative feature because it considered LBP as a first order local-feature descriptor. Instead of using a two-valued coding, LTP extended by using a three-valued coding to improve resistance against noise. In the other hand, LDiP and LDNP then tried to extract the edge information by first convolving a face image with a mask (Kirsch mask and Gaussian derivative mask) rather than just directly thresholding the intensity of a pixel with its neighbours for LBP. LDiP uses 8 bits as its code just as LBP but LDNP only needs 6 bits as its code.

These local-feature descriptors, that were originally applied to extract local features in a face image, then were used for a vein image (Mirmohamadsadeghi and Drygajlo, 2011, 2014). They worked effectively in terms of that the authors already customized the local-feature descriptor such as using multi-block LBPs or tuning the parameters to fit the problem in vein recognition. This study tries to

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compare three local-feature descriptors directly for face and vein recognition. They are LBP, LDiP and LDNP. The motivation is to evaluate whether they may work effectively without customizing each of them. We chose LBP due to its famous as a local-feature descriptor, LDiP for its simple technique like LBP but more discriminative and LDNP because of its code more succinct than LBP and LDiP.

This study is an extension of our work where we used only one local-feature descriptor, i.e., LDNP. The data used were only one image for face and vein images to create the database and also only left vein images were used.

LBP, LDiP and LDNP: As stated earlier, LBP is a kind of local-feature descriptor that extracts features from an image by first dividing the image as several components/blocks/regions. As a grey-level comparison technique every pixel of each region from an image was labeled by first thresholding the 3×3-neighborhood of each pixel with the center pixel value. The resulting binary number can be considered as its decimal one as expressed in Eq. 1:

$$LBP_{P,R}(I_c) = \sum_{k=1}^{P} x(I_k - I_c)2^{k-1} \quad (1)$$

$$\text{where } x(u) = 1 \text{ if } u\,0 \text{ and } 0 \text{ otherwise}$$

Where:

P and R = The number of neighbouring pixels considered and radius of the neigbourhood, respectively

I_c = The center pixel value

We chose P = 8 and R = 1 in this study. In this study, we also separate the resulting code for every pixel as uniform or nonuniform pattern (Ahonen *et al*., 2006). Figure 1 shows the LBP to extract the local-feature.

Essentially, LDiP is a 8 bits binary string that codes each pixel from an image (Jabid *et al*., 2010). These binary code patterns were acquired by calculating the relative edge response for several different orientations of each pixel from an image. LDiP uses eight edge response from an image by using a mask (Kirsch mask) for eight different orientations, namely M_0-M_7. The eight Kirsch masks are depicted in Fig. 2.

The first step to get the LdiP for each pixel is by applying eight masks to obtain eight response value $m_0, m_1, ..., m_7$. For the response values are not equally important in all directions due to the presence of corner or edge that show high response values in particular directions then we may choose the k prominent directions in order to generate the LdiP code. Then therefore, we may get the k top values $|m_j|$ and set

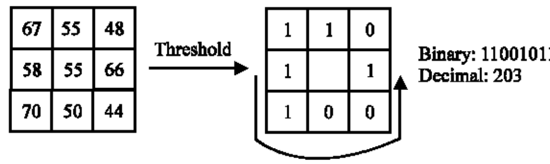


Fig. 1: The basic LBP operator

$$\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & 5 \\ -3 & 5 & -3 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

East (M_0) **North East (M_1)** **North (M_2)** **North West (M_3)**

$$\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

West (M_4) **South West (M_5)** **South (M_6)** **South East (M_7)**

Fig. 2: Kirsch edge response masks in eight directions (Jabid *et al*., 2010)

them to 1. The other (8-k) bits of 8 bits LdiP are set to 0 (Jabid *et al*., 2010). The following equation details the process:

$$C[f(x,y)] := (c_j = 1) \text{if } 0 \le i \le 7 \text{ and } m_i \ge \varphi \quad (2)$$

Where ϕ = k^{th}(M) and M = $\{m_0, m_1, ..., m_7\}$ (Jabid *et al*., 2010). LDNP code is generated by analyzing edge response for each mask $\{M^0, M^1, ..., M^7\}$ that represent significant edge in its own orientation and combining the numbers that have dominant orientations (Rivera *et al*., 2013). Not all edge response are equally important; the most negative and positive number show the dark and bright, respectively. Therefore, to encode the prominent area we use three most significant bits to represent the maximum positive number and three least significant bits to represent the minimum negative number to get the LDNP code. Formally, the LDNP code expressed as following Eq. 3:

$$LDNP(x,y) = 8i_{x,y} + j_{x,y} \quad (3)$$

Where:

(x, y) = The central pixel of the neighbourhood being coded

$i_{x,y}$ = The directional number of the maximum positive response

$j_{x,y}$ = The directional number of the minimum negative response

It defined by:

$$i_{x,y} = \arg\max_i \{ \mathcal{I}^i(x,y) \mid 0 \le i \le 7 \} \quad (4)$$

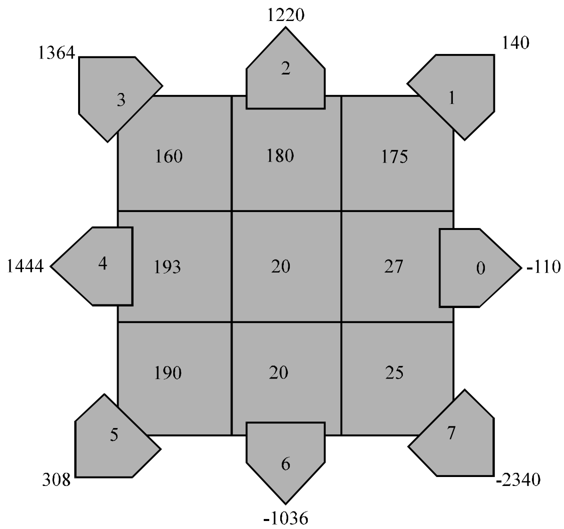


Fig. 3: The illustration for extracting LDNP code

$$j_{x,y} = \arg\min_{j} \left\{ \mathcal{I}^{j}(x,y) \mid 0 \leq j \leq 7 \right\} \tag{5}$$

Where $\mathcal{I}^{i}$ is the convolution between the original image I and the ith mask, M^i, defined by:

$$\mathcal{I}^{i} = I * M^{i} \tag{6}$$

Figure 3 depicts the LDNP to extract the local-feature. The directional number of the maximum positive response is 4 or in binary is 100 whereas the directional number of the minimum negative response is 7 or in binary is 111 ultimately, the LDNP code is 100111.

We represent all pattern codes resulted in each region for the three local-feature descriptors as histogram as its feature vector. These histograms are concatenated together to represent the whole image. For classification, we compare the encoded feature vector with all other candidate's feature vector with the chi-square dissimilarity measure. This measure between two feature vectors, S and M of length N is defined as:

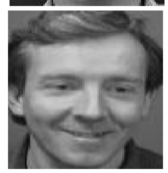
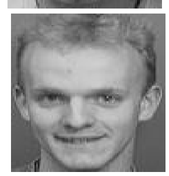
$$\chi^{2}(S,M) = \sum_{i=1}^{N} \frac{(S_i - M_i)^2}{(S_i + M_i)} \tag{7}$$

Where the corresponding image of the feature vector with the lowest measured value indicates the match found.

RESULTS AND DISCUSSION

The evaluation for the face images uses ORL databse (Olivetti Research Laboratory) (Samaria and Harter, 1994)

Table 1: Face recognition for one image for each subject in the database using LDNP

Tested images	Match with	Notes
		True
		True
		True
⋮	⋮	⋮
		True
		False

that consist of 40 subjects with 10 images each and for the vein images uses PUT Vein Pattern Database. The vein images consists of 40 subjects with 10 images each and from two hands (left and right). For each kind of images, there are two kinds of simulations were conducted. First, each image either face or vein from every subject was selected only one image to represent that subject. This representation was stored in the database and the rest nine images were tested to determine their identities. The second one we pick two images to represent each subject. The rest 8 images were tested just as the first one.

Table 1 and 2 illustrate the classification for the face and vein images using LDNP as local-feature descriptor, respectively. These tables are for the first simulation that showing the resulting simulation process. The true/false at the 4th column for Table 1 and 2 mean the correct/incorrect identity of each tested image. Table 3 and 4 show the complete recognition rate of

Table 2: Vein recognition for one image for each subject in the database (left hand) using LDNP

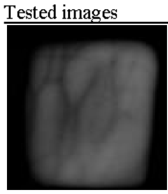
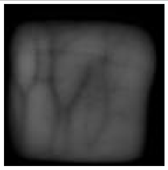
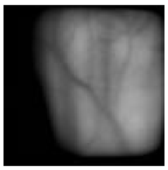
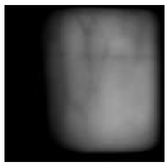
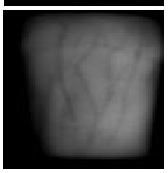
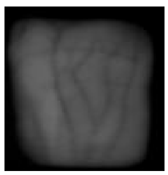
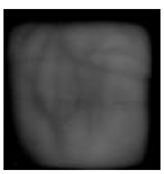
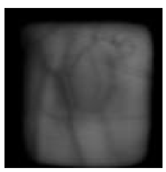
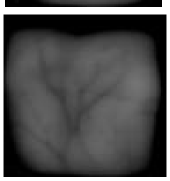
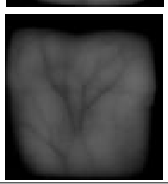
Tested images	Match with	Notes
		True
		False
		True
• • •	• • •	• • •
		False
		True

Table 3: Recognition rates (%) for one image from each subject in the database

		Vein	
Local-feature descriptor	Face	Left	Right
LBP	74.17	35.83	35.83
LDiP	71.67	33.06	32.22
LDNP	72.22	33.89	34.72

Table 4: Recognition rates (%) for two images from each subject in the database

		Vein	
Local-feature descriptor	Face	Left	Right
LBP	85.94	33.44	39.06
LDiP	83.75	34.06	34.69
LDNP	85.31	32.81	37.81

each local-feature descriptor for one and two images in the database, respectively. From Table 3 and 4 we see that the face images are better than vein images. It seems that we may not use the local-feature descriptor directly for the vein images to get the prominent information. It is also almost consistent that the addition of image for face and vein in the database will increase the recognition rate for all local-feature descriptors.

CONCLUSION

This study describes the simulation of three local-feature descriptors for face and vein images. From the simulations conducted, it is clear we may not use the local-feature descriptors directly for the vein images because it may decrease its recognition rate.

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