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Finger vein recognition based on spares representation classifier

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Abstract

Nowadays, identification systems have assisted being to avoid, Bank robbery, financial losses, etc. Biometric systems are one of the best technologies that connect identity of individual behavior or their physical characteristics in order to prepare security and safety. Finger vein recognition is one of the recent methods of biometric systems that regarded as matchless and successful way to identify humans based on the physical characteristic of the human finger vein patterns. This paper presents a new novel finger vein recognition method which is combination of principal component analysis (PCA) as a feature extraction and an effective classifier named spares representation classifier (SRC). Further, the significant of the proposed method is proven by comparing SRC result with traditionally classifier named KNN. Finally, experimental results demonstrate that the proposed method has achieved better performance over the same finger vein database. The obtained accuracy of SRC for 1 training and 9 testing finger vein images is 91.14% while for KNN in same condition is 70.86%.

Keywords

Biometrics, Finger Vein Recognition, K-Nearest Neighbor (KNN), Spares Representation classifier (SRC)

1. Introduction

Biometric technology is an efficient and popular personal identification technique. In the modern society, the demands of identity management system have increased as the level of security breaches and transaction fraud are increasing (Mobarakeh et al., 2013, Liu et al., 2010). Today, finger vein has become a new biometric technology which is unique for each individual, unaffected by aging and no significant changed in adults except in size (Rosdi et al., 2011, Damavandinejadmonfared et al., Yang et al., 2010). In this research, a new approach for finger vein recognition is proposed that uses principal component analysis (PCA) (Wold et al., 1987) as a feature extraction and the spares representation classifier (SRC) (WRIGHT, 2009) as an effective classifier method. In order to evaluate the merit of the proposed method, the obtained recognition rate results compared with traditional method PCA using K-Nearest Neighbor classifier (KNN) (T. M. Cover, 1967, Samsudin and Bradley, 2010).

Paper organized as follows: section two, describes the finger vein recognition algorithm that has used in this research. Next section presents the identification process. Performance of the system has been analyzed in Section 4. Conclusions presented in the last Section.

2. Finger Vein Recognition Algorithm

Finger vein recognition is a new physiological biometric technology that is able to distinguish an individual (Lee et al., 2010, Lee et al., 2011, Mobarakeh et al., 2013, Mahri et al., , Damavandinejadmonfared et al., 2012). A finger vein is a network of vessels that located under the finger skin that it is not possible to recognize by the human eyes. Based on the recent researches, the vein patterns (Figure 1) are unique for each person and it can be used in security applications where high level of privacy and security is a vital issue, as an instant medical, financial, industrials and still other applications. In addition, the general model of Finger vein recognition has shown in the Figure 2, including three general stages: image acquisition, image pre-processing (cropping, resizing and enhancement) and identification process. Image acquisition and image pre-processing have done on finger vein database (Rosdi et al., 2011, Mahri et al., 2010).

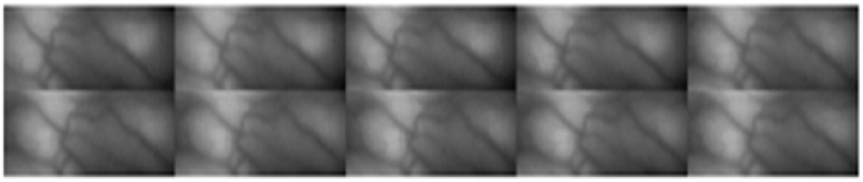

Fig. 1. *An example of captured images from one person*

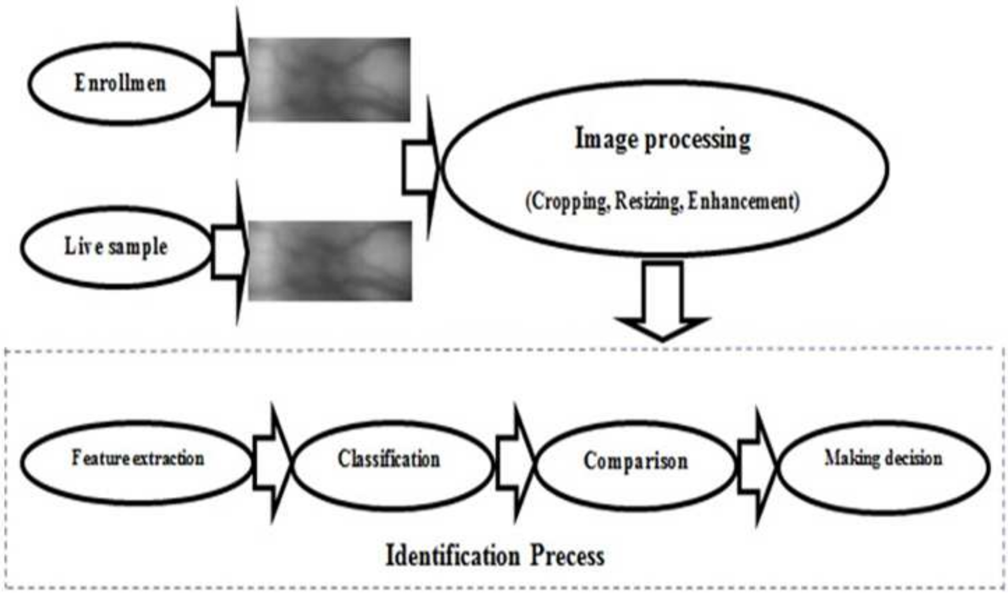

Fig. 2. *Proposed finger vein recognition algorithm*

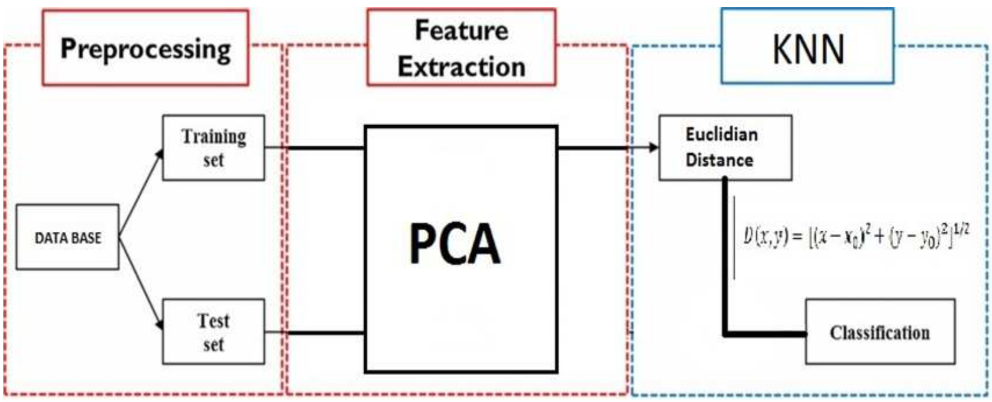

Fig. 3. *Block diagram of KNN as classifier in finger vein recognition*

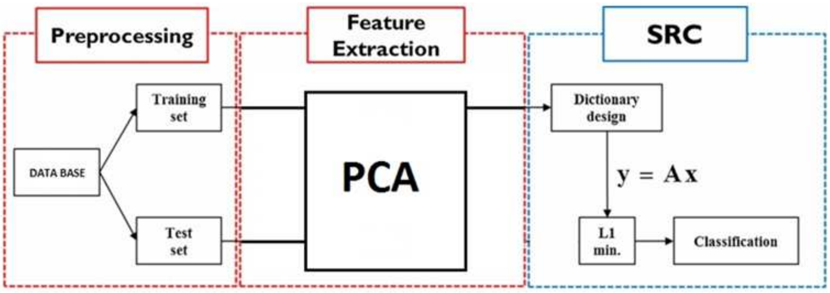

Fig. 4. Block diagram of our proposed method using SRC

3. Identification Process

3.1. Feature Extraction

PCA is one of the fundamental and effective methods in terms of dimensional reduction (Delac et al., 2005). This kind of transformation method is used to simplify data analysis. Dimension reduction and feature extraction of the images are the main targets of proposed of (L. K. SAUL, 2005). Images are the main targets of proposed of (L. K. SAUL, 2005).

3.2. Classification

The former PCA used KNN as a classifier suffers from variety of problems such as negative effect of outliers and accuracy reduction in case of small training sample size (Gou et al., 2012). Therefore, spares representation classifier (SRC) used in PCA in order to improve the finger vein recognition performance. Figure 3 shows the block diagram of the KNN classifier and Figure 4 demonstrates the block diagram of the proposed method using SRC a classifier.

SRC discriminates between subsets of base vectors in a way that those express input signals more compactly have chosen while those with less compactly have rejected. Therefore, automatically various classes present in the training set are discriminated by the sparsest representation. This classifier has an excellent performance in a case of small training samples size (SSS). Following are the mathematics of SRC(Wagner et al., 2009):

First some definitions: A = training sample $\in IR^{m\times n}$,Y=test sample $\in IR^{m}$, δ_i =residual, X =coefficient, Ɛ =error tolerant:

Step 1 (input): new (test) sample y $\in IR^{m}$ from the same class will approximately stand linearly in a span of the training samples associated with object i:

$$y = \alpha_{i,1} v_{i,1} + \alpha_{i,2} v_{i,2} + + \ldots + \alpha_{i,ni} v_{i,ni} \tag{1}$$

Step 2 Normalization: a new matrix A for the entire training set is defined as the concatenation of the n training samples of all k object classes:

$$A = [A_1, A_2 \ldots, A_K] = [v_{1,1}, v_{1,2} \ldots, v_{k,nk}] \tag{2}$$

Step 3: compute coefficient:
$y = x_0$, $y \in IR^{m}$ Where

$$x_0 = [0, \ldots, 0, \alpha_{i,1}, \alpha_{i,2} \ldots, \alpha_{i,n}, 0, \ldots, 0]^t \quad x_0 \in IRm \tag{3}$$

Step4: Solve the l^1- minimization problem and Compute the residual:

$$x1 = argmin\ x1 \text{ subject to } Ax - y2 \le \varepsilon \tag{4}$$

$$\min r_i(y) = \|y - A\delta_i(\hat{x}_1)\|_2 \text{For } i = 0, \ldots, k \tag{5}$$

Step 5: output

$$\text{Identity (y)} = \arg\min_i r_i(y) \tag{6}$$

4. Experimental Results

The Finger Vein dataset (Rosdi et al., 2011) that is used in this research is collected by Intelligent Biometric Group of the School of Electrical and Electronic Engineering in University Sains Malaysia USM Engineering Campus. It contains 2040 finger images taken from 204 different people, each of which has 10 different images from each subject (each subject is one finger). According to the Table 1, in order to demonstrate the efficiency of SRC, the comparison between SRC and KNN is done in 9 different numbers of testing and training images from 1 to 9. Experimental results which are shown in Figure 5 clearly indicate that SRC algorithm performance is much better than KNN classifier in all different number of implementations. As explanation of this outstanding performance should refer to the concept of SRC that uses the sparse representation of each individual test sample directly in classification and adaptive selection of the training samples that preserves the most compact representation.

Table 1. Comparison of the results for KNN and SRC

No train/test	KNN	SRC
9train,1test	98.53	98.82
8train,2test	97.55	98.66
7train,3test	97.71	98.36
6train,4test	96.45	97.89
5train,5test	95.59	97.39
4train,6test	94.12	96.49
3train,7test	91.67	95.35
2train,8test	84.68	93.47
1train,9test	70.86	91.14

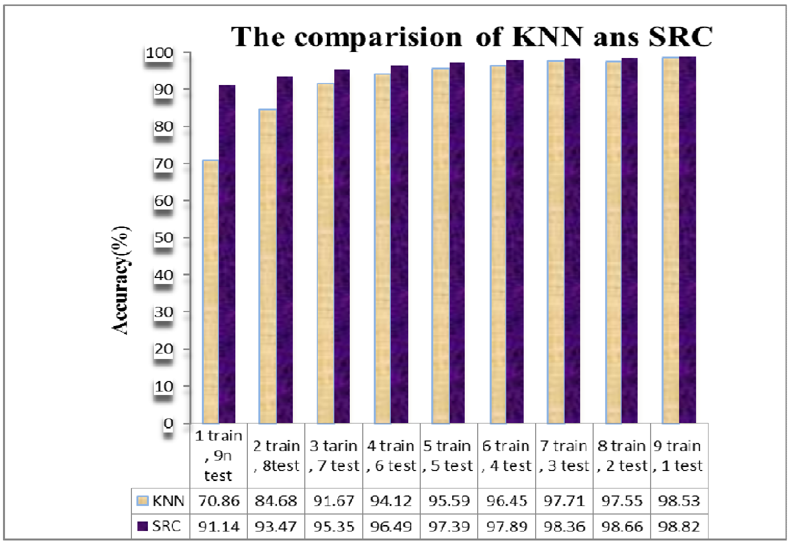

Fig. 5. *Comparison between the percentage of having highest accuracy between SRC and KNN*

5. Conclusion

In this research a new idea of finger vein recognition was investigated. Principle Component Analysis (PCA) used to extract the feature from the finger vein dataset. K-nearest neighbor (KNN) classifier and spares representation classifier (SRC) employed to classify the data. Finally, the experimental results demonstrate that the proposed method using SRC classifier results much better than traditional classifier method PCA using KNN in all different number of testing and training images, especially in the case of small training samples size.

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