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Biometrics Based on Multi-View Features of Teeth Using Principal Component Analysis

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We present a new biometric identification system based on multi-view features of teeth using principal components analysis(PCA). The multi-view features of teeth consist of the frontal view, the left side view and the right side view. In this paper, we try to start the foundations of a dental biometrics for secure access in real life environment. We took the pictures of the three views teeth in the experimental environment designed specially and 42 principal components as the features for individual identification were developed. The classification for individual identification based on the nearest neighbor(NN) algorithm is created with the distance between the multi-view teeth and the multi-view teeth rotated. The identification performance after rotating two degree of test data is 95.2% on the left side view teeth and 91.3% on the right side view teeth as the average values.

Keywords : Multi-view teeth, Principal Component Analysis, Biometric identification, Nearest neighbor method

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Introduction

The most generalized biometric techniques include the recognition of fingerprints, faces, iris, retina, hand geometry, voice and signature [1, 2, 3, 4, 5, 6]. Biometric identification systems based on biometric features are expected to provide secure access in the near future to physical and virtual resources or spaces. Any physiological feature could be used for individual identification.

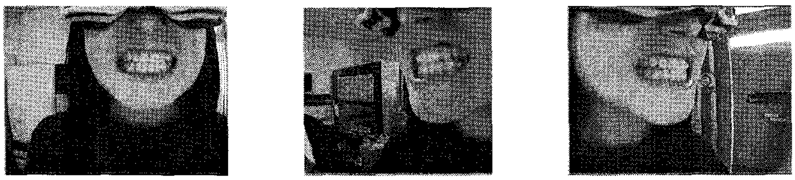
Biometric technologies need some requirements in order to be used in real applications. They are reliability, ease of use, ease of implementation and cost etc. Iris identification requires a complexity of the data collection. Face can be deformed by expressions of a user. Fingerprint can be contaminated with materials such as sweat or dust. Teeth of human do not generally deformed at the moment of image acquisition because of rigid objects. This can remove a complexity of the data collection. In addition to, teeth identification does not require high resolution images. Thus data collection can use the cameras with low cost.

Most studies on teeth identification had been used in postmortem identification and locating missing and unidentified persons [7, 8, 9, 10, 11, 12, 13]. Jain and Chen [7, 8] utilized dental radiographs to identify victims. Ammar and Nassar [9] analyzed radiographs to utilize underlying image structure that are often difficult to be assessed merely by visual examination. Zhou and Abdel-Mottaleb [11], Mahoor and Abdel-Mottaleb [12] extract the teeth contours and use shape representation based on dental X-ray images. The dental radiographs have a challenging problem of the shape extraction since poor quality images. Fahmy et al. present a web based environment for the dental identification [13]. In this paper, we present a new dental biometrics system using digital cameras to provide secure access in real life environment.

Our algorithm utilizes a information of features of the three views teeth acquired with low cost camera. The three views teeth consists of the frontal view, the left side view and the right side view. We developed a representation of dental images based on PCA included the 42 principal components as the features for individual identification. The nearest neighbor algorithm for the classification of individual identification was applied with the distance between the three side view teeth and the three side view teeth rotated.

Dental Database

Dental data was acquired with images of the three views teeth in an experimental environment designed specially with three digital cameras. The experimental environment was designed to fix a position of subjects' the eyes and mouse and to support a regular distance between a subject and camera. To make an exact mouse shape we use a definite onomatopoeia. The database consists of images of 48 individuals of males and females. Each individual includes three images on a frontal view teeth, the left side view teeth and the right side view teeth. The data set used for research contained a total 126 gray level images of 42 individuals with a single set as the three views images, each image using 320 by 240 pixels. Examples of the original images are shown in figure 1.



(a) (b) (c)

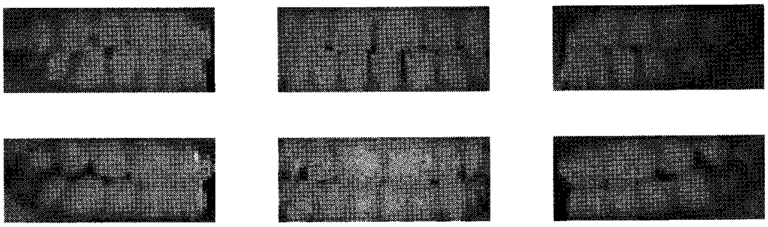
Fig. 1. Examples from the dental database of the three views teeth: (a) left-side view teeth (b) frontal view teeth (c) right-side view teeth

PCA Representations of Dental Features

Preprocessing

The dental images were cropped with fixed coordinates locations, and then rescaled to 20x50 pixels. Figure 2 shows the images of the three views teeth rescaled. The luminance was normalized in two steps. First, a "sphering" step prior to principal component analysis is performed. The rows of the images were concatenated to produce 1 × 1000 dimensional vectors. The row means are subtracted from the dataset, X. Then X is passed through the zero-phase whitening filter, W, which is the inverse square root of the covariance matrix:

$$
\begin{aligned}
W &= E\{XX^T\}^{-\frac{1}{2}} \\
\Phi &= WX
\end{aligned}
\tag{1}
$$



(a) (b) (c)

Fig. 2. Examples of 2 individuals with multi-view teeth after rescaling: (a) left-side view teeth (b) frontal view teeth (c) right-side view teeth

This indicates that the mean is set to zero and the variances are equalized as unit variances. Secondly, we subtract the local mean gray-scale value from the sphered each patch. From this process, Φ removes much of the variability due to lightening.

Principal Component Analysis Based on Multi-View Features of Teeth

The most successful algorithms applied PCA representation are "eigen faces[14]" and "holons[15]". These methods are based on learning mechanisms that are sensitive to the correlations in the images. PCA provides a dimensionality-reduced code that separates the correlations in the input. Redundancy reduction has been discussed in relation to the visual system at several levels. A first-order redundancy is mean luminance. The variance, a second order statistic, is the luminance contrast. PCA is a way of encoding second order dependencies in the input by rotating the axes to corresponding to directions of maximum covariance.

PCA can be used to find a subspace whose basis vectors correspond to the maximum variance directions in the original space. If Z represents the linear transformation that maps the original s-dimensional space onto a t-dimensional feature space where normally $t<s$, the new feature vectors $y_i \in R^t$ are defined by $y_i = Z^T x_i, i = 1, \ldots, n$. The columns of Z are the eigenvectors Φ_i obtained by solving the eigen structure decomposition $\Sigma \Phi_i = \lambda_i \Phi_i$, where $\Sigma = XX^T$ is the covariance matrix and λ_i the eigenvalue associated with the eigenvectors Φ_i.

For individual identification based on dental features in the frontal view, the left side view and the right side view, we employed the 42 PCA coefficients, P_n. The principal component representation of the set of images in Φ in equation (1) based on P_n is defined as $U_n = \Phi * P_n$. The approximation of Φ is obtained as:

$$\overline{\Phi} = U_n * P_n^T \tag{2}$$

The columns of U_n contains the representational codes for the training images. Best performance for individual identification based on multi-view of dental features was obtained using 42 principal components. Figure 3 shows PCA based representation using the first 42 principal component vectors based on multi-view features of teeth.

(a) (b) (c)

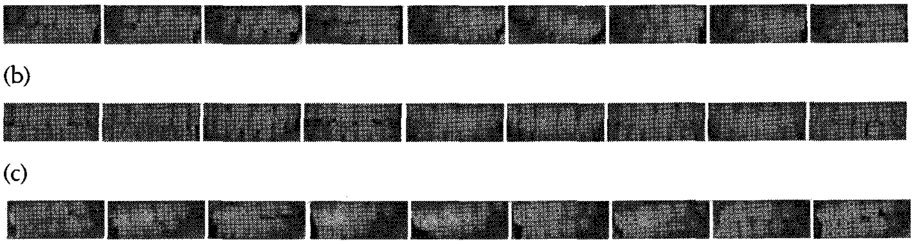


Fig. 3. PCA representation included the first 42 principal components based on multi-view: (a) left-side view (b) frontal view (c) right-side view

Results

For training, images of 42 individuals with the multi-view teeth were used. The multi-view is a frontal view, the left-side view and the right-side view. The total number of training images is 126(42x3). Teeth of human do not generally deformed at the moment of image acquisition because of rigid objects. But some times subjects can cause a little moving their jaw at the moment of image acquisition. Thus for testing, a total 252(126x2) images of 42 individuals after rotating one and two degree in each view from the training set were used. The nearest neighbor(NN) algorithm was applied to classification for person identification. The principle of the NN algorithm is that of comparing input image patterns against a number of paradigms and then classifying the input pattern according to the class of the paradigm that gives the closest match.

Figure 4 has shown a recognition result using the variance of dimensionality based on PCA after rotating one and two degree onto frontal view of teeth. Best performance for individual identification onto frontal view of teeth was obtained by

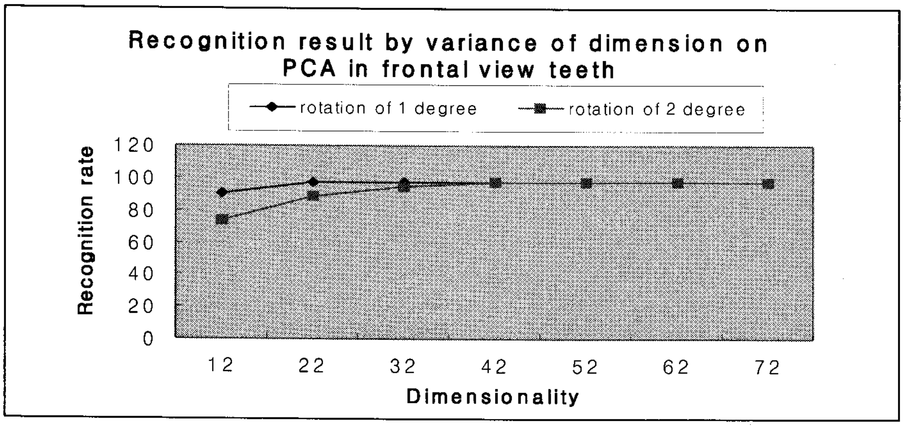


Fig. 4. Recognition result by variance of dimension onto PCA in frontal view teeth

42 principal components and individual identification onto left-side view and right-side view was also best by 42 principal components. More than 42 principal components did not outperform the recognition performance on 42 principal components. Since we used 42 sample each on the multi-view teeth and since we have 42 classes, this gives us an upper bound of 42 for the dimensionality of the PCA space. We thus decided finally recognition performance with 42 principal components.

The recognition performance onto the multi-view teeth shows in table 1. The orientation of rotation reflected the difference on the recognition performance. Specially the recognition performance on the right-view teeth was lower than the

Table 1. The result of recognition performance based on multi-view teeth

rotation degree	orientation	Recognition Performance			
		Frontal view	Left-side view	Right-side view	average
1	left	97.6%	100%	97.6%	98.4%
	right	92.9%	97.6%	100%	96.8%
2	left	97.6%	97.6%	90.5%	95.2%
	right	92.9%	90.5%	90.5%	91.3%

frontal view and left-view, we can infer a possibility that the subjects of this experiment might use mainly the right-view teeth.

Conclusions

With PCA representation based on multi-view including a frontal view, the left-side view and the right-side view, we developed a new biometric identification system for secure access in real life environment. We can support the requirements in order to be used in real applications. That is to say, our system can satisfy a reliability, ease of implementation and cost etc. This simulation demonstrates that PCA representation based on multi-view teeth can include quite important features for personal identification.

Our system extracts PCA representation included only 42 principal components from 20x50 pixels and person identification can recognize successfully through the combination of features of the three views teeth. It can reflect the fact that the holistic analysis is quite a important for person identification with dental features based on multi-view teeth like a frontal view, the left-side view and the right-side view. We suggest that in order to recognize dental features for secure access in real life environment, the combination of features of multi-view teeth may complete an error of individual identification from only one side view teeth.

In the future study we are planning to analyze individual identification difference from teeth patterns in much larger database than on present system.

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요 약

주성분분석을 이용한 치아의 다면 특징 기반 생체식별

정 찬 욱	김 명 수	신 영 숙
정보통신공학과	치과대학 치과약리학	정보통신공학과
조선대학교	조선대학교	조선대학교

본 논문은 주성분분석기법을 이용한 치아의 다면특징을 기반으로 한 새로운 생체 식별시스템을 제안한다. 치아의 다면 특징들은 정면치아와 좌측, 우측 치아들로 이루어진다. 우리는 실생활 환경에서 보안 접속을 위하여 치아를 이용한 생체식별을 목표로 한다. 다면 치아 영상들은 특별히 고안된 실험환경에서 획득되었으며, 개인 식별을 위한 특징으로 42개의 주성분이 개발되었다. 개인 식별은 학습된 다면치아와 회전된 다면치아 사이의 최소근접기법에 의해 계산되었다. 2도 회전 후의 다면치아 인식성능은 평균값으로 좌측면 치아 95.2%, 우측면 치아 91.3%을 보였다.

주제어 : 다면치아, 주성분분석, 생체식별, 최소근접기법