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MODIFIED METHOD OF EIGENFILTERS FOR FACE RECOGNITION

Romanyuk Olexander
Doctor of Technical Sciences, Full Professor,
Head of the Department of Software
Vinnytsia National Technical University,
_,

Vyatkin Sergey
Candidate of Technical Sciences, Senior Researcher,
Laboratory of Computer Visualization Systems,
Institute of Automation and Electrometry SB RAS, Novosibirsk

Ozerchuk Dmytro A
University student,
Vinnytsia National Technical University,
_,

Annotation

A method for extracting informative features of face images is presented, which analyzes integral features, analyzes local features, and analyzes structural features of face images. An effective modification of the approach based on the principal component method is proposed. Face recognition experiments were performed on a normalized image database, and the results of these experiments revealed the advantages and disadvantages of the method.

Introduction

One of the most well-known and well-developed methods is the principal component analysis (PCA) [1]. In the face recognition problem, it is mainly used to represent the face image as a small-dimensional vector (principal components), which is then compared with the reference vectors stored in the database. The main goal of the principal component method is to significantly reduce the dimension of the feature space so that it describes "typical" images belonging to a set of faces as well as possible. Using this method, you can identify various variations in the training sample of face images and describe this variability in the basis of several orthogonal vectors, which are called eigenface. Obtained once on a training sample of face images, the set of eigenvectors is used to encode all other face images, which are represented by a weighted combination of these eigenvectors. Using a limited number of eigenvectors, you can get a compressed approximation of the input face image, which can then be stored in the database as a coefficient vector that simultaneously serves as a search key in the face database. The essence of the principal component method is as follows. First, the entire training set of faces is transformed into a single General data matrix, where each row is a single instance of the face image decomposed into a row. All faces of the training set should be reduced to the same size and with normalized histograms [2].

In this paper, we propose a modified method of eigenfilters.

Method description

To determine the integral features in the image, the principal component method was used in the following modification. On the face image, 16x16 blocks were randomly selected. Statistics of image blocks were collected - 20000 blocks. Based on these statistics, we built our own filters. Later, the resulting filters were used for recognition to extract features in the image.

Let $\vec{v}$ be a vector of dimension $nx1$, corresponding, for example, to an image $n = 16x16$ and given statistics of vectors $\vec{v}$, for example, 100 images of dimension 16x16=256x1.

$\vec{e}$ is a vector of the same dimension (256x1) as $\vec{v}$, we will project the input vectors $\vec{v}$ on it.

Let $\overline{v} = E[\{v\}]$, $p = (v - \overline{v})^T \vec{e} = \vec{e}^T (v - \overline{v})$ - is the projection of $\vec{v}$ on $\vec{e}$.

The $d^2 = E\left[p^2\right] = E\left[\vec{e}^T (v - \overline{v})(v - \overline{v})^T \vec{e}\right]$ is a variance for this image statistic is a function of $\vec{e}$:

$\varphi(\vec{e}) = d^2 = \vec{e}^T M \vec{e}$

where $M = E\left[(v - \overline{v})(v - \overline{v})^T\right]$ is the covariance matrix of dimension nxn.

The problem of principal component analysis is to choose the basis of the space $\vec{e} = (\vec{e}_1, \vec{e}_2, ... \vec{e}_k)$, so that the variance of the projection is minimal. The minimum of this function is achieved by solving the eigenvalue problem $M\vec{e} = \delta\vec{e}$. The Jacobi method is used for this purpose [3].

For this method, the number of eigenfilters ranged from 4-20 is the best results were obtained for eight eigenfilters. Accordingly, eight neural networks of the two-layer perceptron architecture were used to classify images, with the number of neurons 16x20 is the input layer, 30 is the hidden layer, and 50 is the output layer. The input layer was selected for the dimension of the principal components. The number of neurons in the hidden layer depended on the recorded statistics. The output layer corresponded to the number of target classes – recognized faces.

Conclusion

The results of the recognition method experiments show that the modified method based on principal components and neural networks allows face recognition even in the presence of significant noise and external objects (glasses). However, it is less accurate than the method based on local features and Markov models. This is because the main components carry the main information about the features of a generalized person, rather than allowing you to determine the unique features of a particular person's face.

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