Detecting and Recognising Faces in Images

Huanjie Guo
10655496

1 Summary

With the development of computer vision, face detection and recognition has become an important field. These technologies can be applied to face payment, criminal tracking, etc., which facilitates people's daily life and makes our society more efficient and safer. However, many algorithms cannot be used in face detection and recognition due to the complicated calculation. At the same time, changes in illumination, viewpoint, etc., will also affect the accuracy of detection and recognition. This article will start with the most basic PCA-based EigenFaces and introduce various face detection and recognition algorithms optimized for different situations.

2 Overview

2.1 Eigenfaces for Recognition

The eigenfaces algorithm uses principal component analysis for face recognition. Eigenfaces is an unsupervised learning algorithm that reduces the dimensions of high-dimensional pixels into principal components through PCA and only selects the first few essential principal components as features, which significantly saves the calculation for face recognition.

The eigenfaces steps are listed as follows:

1. Use all facial images to generate a two-dimensional matrix. Each column of the matrix represents all the pixels of a face.
2. Calculate the average of each row of the matrix to generate a column vector. This column vector is the average face.
3. Each column in the matrix is subtracted from the average face vector to get the difference from the average face.
4. Calculate the covariance matrix and decompose it to get the eigenvalues and eigenvectors. Eigenvectors is called eigenfaces.
5. Sort the eigenvectors according to the eigenvalues and take the first N eigenvectors to construct new coordinates.
6. After the face image comes in, it is projected to the newly constructed coordinates to obtain low-dimensional features.

In the experiment, the size or scale of the head seriously affects the recognition performance, and we need to find a method of scale transformation (Matthew, Turk; Alex 1991).

2.2 Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection

Fisherfaces method uses linear discriminant analysis, which is a kind of supervised learning. This algorithm is similar to PCA. Its core idea is to maximize the distance between classes and minimize the distance within classes when constructing new projection coordinates (Belhumeur et al. 1996). In the experiment, FisherFaces performed best under light conditions. At the same time, in the case of lighting changes, the PCA algorithm significantly reduces the error rate after removing the first three principal components. In addition, Fisherfaces requires less calculation than Eigenfaces.

2.3 Probabilistic Visual Learning for Object Representation

This article introduces an unsupervised learning method for searching and positioning an object in an image, which is still based on PCA. The high-dimensional image is decoupled from the feature space and transformed into the low-dimensional space for easy calculation. Features need to conform to a single Gaussian distribution or a mixed Gaussian distribution (Moghaddam et al. 1997). A sliding window is used to calculate the scanned matching image to find the area with the maximum likelihood of matching. Experiments show that the performance of the target detection algorithm based on density estimation and maximum likelihood detector is better than the existing detection algorithm.

2.4 Nonlinear Component Analysis as a Kernel Eigenvalue Problem

Kernel principal component analysis achieves nonlinear dimensionality reduction of data and deals with the inseparable linear problem. Kernel PCA maps data from a low-dimensional space to a high-dimensional space until a high-dimensional space is found to make the data linearly separable, and PCA is used to reduce the dimensionality in this space. Through the "kernel trick", calculation in high-dimensional space can be reduced. However, how to choose parameters for Kernel PCA is still a question (Schölkopf et al. 1998).

2.5 Rapid Object Detection Using a Boosted Cascade of Simple Features

This paper proposes a method to improve detection efficiency while ensuring a high detection rate and low false-negative rate. The main rule of target detection is to train a classifier with the training set and then scan the images with windows of different sizes. For each scan, the classifier needs to determine whether this image is the target object. The article mainly mentions three points. The first one is that the system uses harr-like to convert the original pixels into features, which speeds up the calculation. The second one is to use AdaBoost to combine multiple efficient but straightforward classifiers, each of which uses only one feature to consider. The final one is to use the cascaded structure to connect multiple classifiers from simple to complex. The first few classifiers have high detection rates and low false-negative rates, which can filter out most areas that do not contain human faces, but the latter classifiers will make more strict judgments on areas that are suspected of human faces (Viola and Jones 2001). The cascade model dramatically improves the efficiency of face detection.

2.6 Multilinear Analysis of Image Ensembles: TensorFaces

TensorFaces uses multilinear analysis to solve the image ensemble problem. It projects the image from the pixel space to N different mode spaces. This method uses multiple coefficient vectors to describe a face image, and each vector represents a specific factor, such as a person, perspective, illumination, or expression (Vasilescu and Terzopoulos 2002). This method uses N-mode SVD to decompose coefficient vectors and obtain low-dimensional features. Experimental results show that the multilinear approach uses the tensor's mathematical model to better adapt to any factors.

3 Comparison

3.1 Strengths and Weaknesses

Eigenfaces is unsupervised learning based on principal component analysis. It can reduce the dimensionality of face images and sort the principal components by importance and discard unimportant components. However, the difference between the same faces under different lighting conditions is more significant than the difference between different faces under the same lighting conditions. Therefore, Eigenfaces performs poorly under changing lighting conditions. The influence of illumination is mainly concentrated in the first few of the principal components. Therefore, the first three principal components can be discarded, and the fourth principal component can be selected backwards to reduce the influence of different illumination on face recognition.

Fisherfaces algorithm uses linear discriminant analysis and is a supervised learning algorithm. The primary purpose of LDA is to maximize the between-class distance and minimize the within-class distance. The PCA algorithm maximizes the between-class distance that is useful for classification but also maximizes the unwanted within-class distance. The LDA algorithm performs better than PCA when the illumination changes. The reason is that eigenfaces only pays attention to the pixels of the face image when generating the projection space, and fisherfaces also combines the labels of this image.

Kernel PCA and PCA have different application scenarios. PCA mainly deals with the linear separable problem, and KPCA is used to deal with the linear inseparable problem. KPCA maps the features to high-dimensional space until the data is linearly separable and then uses PCA to reduce the dimensionality. For Kernel PCA, it takes time to select the appropriate Kernel parameters, while PCA does not need it.

PCA dimensionality reduction of face images based on density estimation is a very innovative method, but the disadvantage is that features need to satisfy Gaussian distribution.

Compared with Eigenfaces, TensorFaces can recognize faces more accurately when the illumination, viewpoint, and characters change. Therefore, in the case of significant illumination changes, the TensorFaces method is more suitable.

3.2 Compare to Active Appearance model

The Active Appearance model needs to collect a large number of training sets, and at the same time, give a set of suggested shape points for the image manually. Methods such as Fisherfaces do not need that, but Fisherfaces also need labels since it is supervised learning. The AAM model is more sensitive to changes in illumination, but Fisherfaces and Tensorfaces perform well under changes in illumination. At the same time, the initial value of AAM is vital, and it is easy to fall into local optimization. The average model obtained by the AAM model is a contour model and a texture model, which is more reliable than Eigenfaces, Fisherfaces, etc.

3.3 Rank

TensorFaces considers factors such as illumination, viewing angle, etc., it is the best face recognition algorithm. Fisherfaces solves the impact of illumination variation to a certain extent and is the second-best algorithm. The AAM algorithm considers the face contour and texture model, but it performs poorly under changing lighting conditions and is considered the third-best algorithm. The remaining algorithms such as EigenFaces, Kernel PCA and probability-based PCA are ranked last.

4 Conclusions

This article introduces a variety of face recognition algorithms, each of which has its usage scenarios. Eigenfaces is a good choice when face images are only frontal. When it comes to illumination variations, Fisherfaces and Tensorfaces perform better, but Tensorfaces requires more data in building Tensors. Kernel PCA can be used for mapping when features are linearly inseparable. At the same time, PCA based on density estimation performs better under Gaussian distribution data. In the face detection process, the cascade model can significantly improve detection efficiency. In summary, there is no best face recognition algorithm, and the most suitable algorithm needs to be selected according to different scenarios.

References

Belhumeur, P.N., Hespanha, J.P. and Kriegman, D.J. (1996). Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 1064(7), pp.45–58.

Matthew, Turk; Alex, P. (1991). Eigenfaces for Recognition. , pp.68–70.

Moghaddam, B., Member, S. and Pentland, A. (1997). Probabilistic Visual Learning for Object Representation. , 19(7), pp.696–710.

Schölkopf, B., Smola, A. and Müller, K.R. (1998). Nonlinear Component Analysis as a Kernel Eigenvalue Problem. *Neural Computation*, 10(5), pp.1299–1319.

Vasilescu, M.A.O. and Terzopoulos, D. (2002). Multilinear analysis of image ensembles: Tensorfaces. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2350, pp.447–460.

Viola, P. and Jones, M. (2001). Rapid object detection using a boosted cascade of simple features. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 1.