Face Detection

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The Problem: The problem is to develop a trainable system for face detection which is able to handle faces rotated in depth and partially occluded faces.

Motivation: Faces form a class of fairly similar objects. Each face consists of the same components in the same geometrical configuration. This is the main reason for the success of frontal face detection systems. However, the problem of pose invariance is still unsolved. Detecting faces which are rotated in depth remains a challenging task.

Previous Work: Most of the previous work dealt with frontal faces. [1] used clustering to generate face and non-face prototypes. For each test pattern they calculate the distances between the pattern and the prototypes. These distances form the input to a multi-layer perceptron which classifies the pattern into a face and non-face class. In [2] they used a Support Vector Machine (SVM) with a 2nd degree polynomial kernel to classify normalized gray value patterns. A system able to deal with rotations in the image plane was proposed by [3]. It consists of two neural networks: the first estimates the orientation of the face, the second recognizes the derotated faces (frontal views). They extended this approach by using multiple networks of identical structure in the classification step [4]. An approach based on the probabilities of the occurrence of small intensity patterns (16x16 pixels) in the image of the whole face (64x64 pixels) is proposed in [5].

In our laboratory we recently developed a component-based technique [6] for detecting frontal and near frontal faces in gray images using SVMs. The system consists of two types of classifiers: The component classifiers independently detect facial components (eyes, nose, mouth, and cheeks). The geometrical classifier verifies if the configuration of the detected components conforms with the configuration typical for a frontal face. We compared the component-based system with a whole face detection system similar to the one proposed in [2]. Both systems were trained on the same data base of frontal faces and tested on two different test sets. The first test set consisted of gray images of frontal faces only, both classifiers performed about the same. The second test set consisted of synthetic face images generated from 3D head models. The faces were rotated in depth (-30 to 30 deg.) and in the image plane (-10 to 10 deg.). With increasing rotation the component-based classifier clearly outperformed the whole face classifier (about 50% less FP at ± 30 deg. rotation in depth and 50% less FP at ± 10 deg. rotation in the image plane).

Approach: The basic idea is to train a set of classifiers on components of a face instead of training one classifier on the whole face image. The motivation for this approach is that changes in patterns of small face components due to rotation in depth are less significant than changes in the whole face pattern. Another advantage of a component-based detector compared to a whole face detector is its robustness against partial occlusions. A fundamental problem of the component-based approach is how to determine discriminative components for a given class of objects. We developed a method that determines the components automatically from a set of 3D head models based on the discriminative power of the components and their robustness against pose changes.

Difficulty: The detection system must be robust against changes in the appearance of faces due to rotations in depth and against partial occlusions.

Impact: Face detection is the first step of an autonomous face recognition system. It also has potential application in human-computer interfaces and surveillance systems.

Future Work: The previously developed component-based system was only trained on frontal faces. Experiments have shown that it can detect faces rotated up to about 20 deg. in depth without significant loss in performance. However, to build a system which can deal with larger rotations it seems necessary to train a set of classifiers on a data base of rotated faces, with each classifier being tuned to a specific range of rotations. Further work has to be done on how to choose the number of components and how to combine the outputs of the component classifiers.

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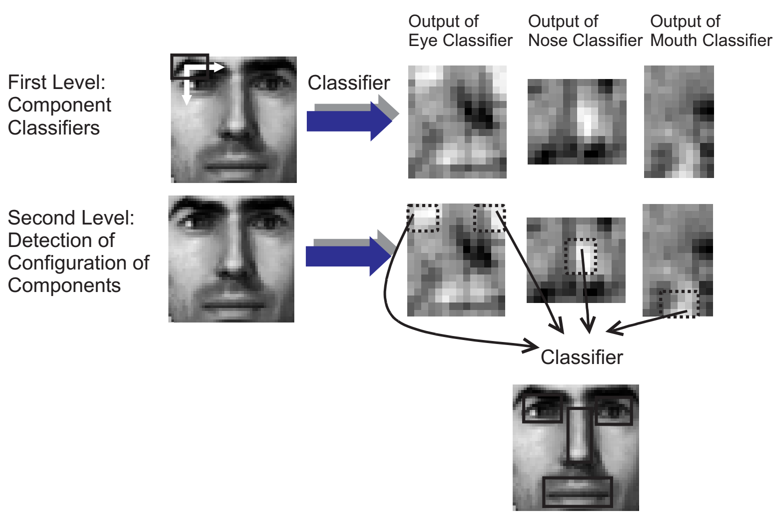

Figure 1: System overview of the component-based classifier. On the first level, windows of the size of the components (solid lined boxes) are shifted over the face image and classified by the component classifiers. On the second level, the maximum outputs of the component classifiers within predefined search regions (dotted lined boxes) are fed into the geometrical configuration classifier.

Figure 2: Results of component-based face detection for frontal and rotated faces. The components have been learned from a set of 3D head models.