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Human Face Recognition Using Neural Networks

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Abstract: In this study, we present an artificial neural network-based face detection system. Unlike similar systems which are limited to detecting upright, frontal faces, this system detects faces at any degree of rotation in the image plane. The system employs multiple networks; the first is an orientation network which processes each input window to determine its orientation and then uses this information to prepare the window for identifier network. We present the training methods for both types of networks. We also perform performance analysis on the networks and present empirical results on a large test set. Finally, we recognize the face using Principal Component Analysis approach.

Key words: Face detection, pattern recognition, computer vision, artificial neural networks, machine learning

INTRODUCTION

In this study, we present a neural network-based algorithm to detect rotation invariant, frontal views of faces in gray-scale images. The algorithm works by applying one or more neural networks directly to portions of the input image and arbitrating their results. Each network is trained to output the presence or absence of a face. The algorithms and training methods are designed to be general, with little customization for faces. Many face detection researchers have used the idea that facial images can be characterized directly in terms of pixel intensities. These images can be characterized by probabilistic models of the set of face images (Henry *et al*., 1998), or implicitly by neural networks or other mechanisms (Ming and Fulcher, 1996). The parameters for these models are adjusted either automatically from example images (as in our work) or by hand. A few authors have taken the approach of extracting features and applying either manually or automatically generated rules for evaluating these features (Lin *et al*., 1997). In our observations of face detector demonstrations, we have found that users expect faces to be detected at any angle. Training a neural network for the face detection task is challenging because of the difficulty in characterizing prototypical "nonface" images. Unlike face recognition, in which the classes to be discriminated are different faces, the two classes to be discriminated in face detection are "images containing faces" and "images not containing faces". It is easy to get a representative sample of images which contain faces, but much harder to get a representative sample of those which do not. We avoid the problem of using a huge training set for nonfaces by selectively adding images to the training set as training progresses (Ming and Fulcher, 1996).

Unlike similar previous systems (Osuna *et al*., 1997; Turk and Pentland, 1991; Xiaoguang and Nixon, 1995) which could only detect upright, frontal faces, this system efficiently detects frontal faces which can be arbitrarily rotated within the image plane. Our system directly analyzes image intensities using neural networks, whose parameters are learned automatically from training examples. There are many ways to use neural networks for rotated-face detection. The simplest would be to employ one of the existing frontal, upright, face detection systems.

ALGORITHM

The overall algorithm for the proposed approach is given in Fig. 1. Initially, a pyramid of images is generated from the original image. Each 140×140 pixel window of each level of the pyramid then goes through several processing steps. First, the window is preprocessed using histogram equalization and given to the orientation network. The rotation angle returned by the network is then used to rotate the window with the potential face to an upright position. Finally, the derotated window is preprocessed and passed to Identifier network, which

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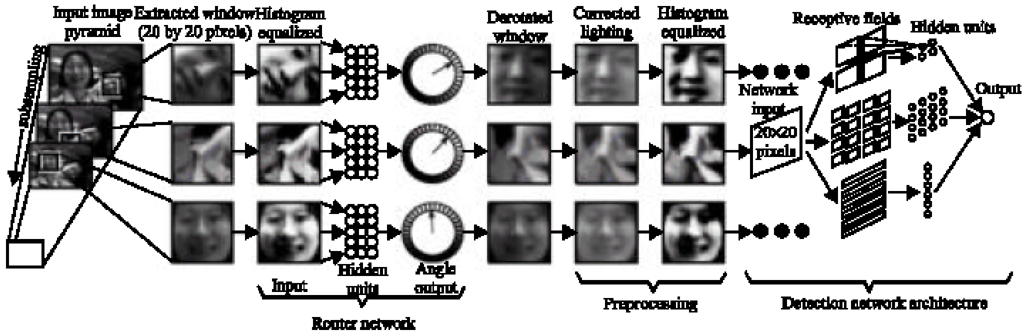

Fig. 1: Overview of the algorithm

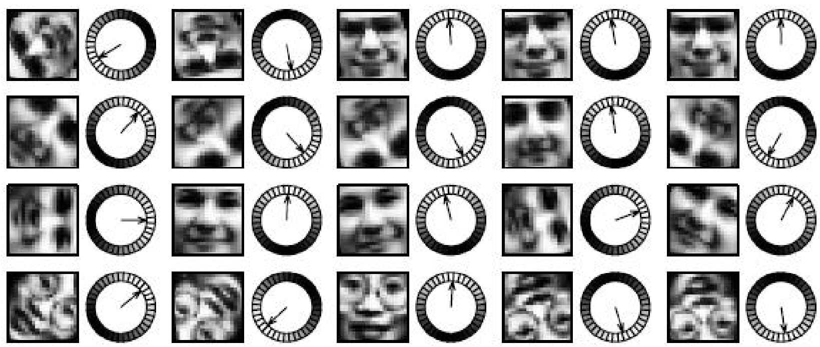

Fig. 2: Training pattern for the orientation network

decide whether or not the window contains a face. The system as presented so far could easily signal that there are two faces of very different orientations located at adjacent pixel locations in the image. To counter such anomalies and to reinforce correct detections, some arbitration heuristics are employed. The design of the orientation and identifier networks and the arbitration scheme are presented in the following subsections.

The orientation network: The first step in processing a window of the input image is to apply the orientation network. This network assumes that its input window contains a face and is trained to estimate its orientation. The inputs to the network are the intensity values in a 140×140 pixel window of the image. The output angle of rotation is represented by an array and affine transformation is used to rotate the image (Vaillant *et al.*, 1994). Examples of the training data are given in Fig. 2. The training examples are generated from a set of manually labeled example images containing 75 faces.

The architecture for the orientation network consists of three layers, an input layer of 2 units, a hidden layer of 70 units and an output layer of single unit. Each unit uses a hyperbolic tangent activation function and the network is trained using the standard error back propagation algorithm.

The identifier network: After the orientation network has been applied to a window of the input, the window is derotated to make any face that may be present upright. The remaining task is to decide whether or not the window contains an upright face. The resampled image, 140×140 pixels, is preprocessed in two steps. First, we resize the image in window of size 18×27. Second, histogram equalization is performed, which expands the range of intensities in the window. The preprocessed window is then given to the identifier network and gabor filter features are detected (Jianke *et al.*, 2004). The identifier network is trained to produce an output of +1 if a face is present and -1 otherwise.

Training a neural network for the face detection task is challenging because of the difficulty in characterizing prototypical "non-face" images. The two classes to be discriminated in face detection are "images containing faces" and "images not containing faces". It is easy to get a representative sample of images which contain faces, but much harder to get a representative sample of those which do not. The features of the image are a face vector field using Gabor filters (Jianke *et al.*, 2004). The features are also extracted for the images by flipping and also to the mirror of the image.

The steps followed for training the identifier network are outlined as follows:

- Create an initial set of non-face images by generating 1000 random images.
- Train the neural network to produce an output of +1 for the face examples and -1 for the nonface examples. In the first iteration, the network's weights are initialized random. After the first iteration, we use the weights computed by training in the previous iteration as the starting point.
- Run the system on an image of scenery which contains no faces. Collect sub images in which the network incorrectly identifies a face.

The architecture for the identifier network consists of three layers, an input layer of 2160 units, a hidden layer of 100 units and an output layer of single unit. Each unit uses a hyperbolic tangent activation function and the network is trained using the scaled conjugate gradient back propagation algorithm.

KLT FOR FACE RECOGNITION

Karhunen-Loeve Transform based dimensionality reduction for face images was first proposed by Kirby and Sirovich (1990) and Karhunen *et al.* (1997). Mathematically, the eigenface method tries to represent a face image as a linear combination of orthonormal vectors, called eigenfaces. These eigenfaces are obtained by finding the eigenvectors of the covariance matrix of the training face image set (Turk and Pentland, 1991; Xiaoguang and Nixon, 1995). Let I_1, I_2, I_3,…I_k be a set of k face images, each ordered lexicographically.

The eigenvectors of the matrix

$$C = \sum_{i=1}^{K} I_i I_i^T \tag{1}$$

that correspond to the largest eigenvalues span a linear subspace that can reconstruct the face images with minimum reconstruction error in the least squares sense. This L-dimensional subspace is called the face space. Assuming is a lexicographically ordered face image and is the matrix that contains the eigenfaces as its columns, we can write

$$x = \phi a + e_x \tag{2}$$

where, a is the feature vector that represents the face and e_x is the subspace representation error for the face image. As a larger training data set is used and the dimensionality of the face space is increased, the representation error gets smaller. Letting

$$a = [a_1, a_2, \ldots\ldots. a_L]^T \tag{3}$$

be the feature vector and

$$\phi = [\phi_1, \phi_2, \ldots\ldots\ldots.\phi_L] \tag{4}$$

be the matrix where are the eigenface vectors, is computed as follows:

$$a_i = \phi_i^T x \tag{5}$$

EXPERIMENTS

We assessed the feasibility and performance of our novel algorithm on the face recognition task, using a real data set. Specifically we used 125 frontal face images, which were acquired under variable illumination and facial expressions. The database used for evaluating face recognition algorithms displays diversity across gender, ethnicity and age. The image sets were acquired without any restrictions imposed on facial expression and with at least two frontal images shot at different times during the same photo session. First, the centers of the eyes of an image are manually detected, then rotation and scaling transformations align the centers of the eyes to predefined locations. Finally, the face image is cropped to the size of 18×27 to extract the facial region, which is further normalized to zero mean and unit variance. The corresponding dominant eigen vectors and eigen faces are estimated and using this the face is recognized using Euclidean distance classifier. Figure 3 shows an example of the recognition of a rotated face.

Upright detection accuracy: To check the capability, detecting rotated faces has not come at the expense of accuracy in detecting upright faces. In Table 1, we present the result of applying the original identifier networks only and recognition using Principal Component Analysis (PCA). As expected, this system does well on the upright test set, but has a poor detection rate on the rotated test set.

Fig. 3: Recognition example from the mixed image

Table 1: Classification results without rotation

	Upright test set (%)	Rotated test set (%)
Classification rate	91.3	17

Table 2: Classification results with rotation

	Upright test set (%)	Rotated test set (%)
Classification rate	91.8	88.5

Proposed approach detection accuracy: To check the capability, rotated and upright faces are applied with both the orientation and identifier networks. In Table 2, we present the result of applying the total image set and recognition using PCA. This system does well on the upright test set and on the rotated test set.

CONCLUSION

Face recognition has been an attractive field of research for both neuroscientists and computer vision scientists. Humans are able to identify reliably a large number of faces and neuroscientists are interested in understanding the perceptual and cognitive mechanisms at the base of the face recognition process. In this study we have designed a feature based pose estimation system and face recognition system using 2D gabor wavelets as local feature information. The system is able to detect 88.5% of faces over two large test sets, with a small number of false positives. The technique is applicable to other template-based object detection schemes.

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