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A NEURAL NETWORK BASED FACE DETECTION USING GABOR FILTER RESPONSE

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Abstract- Neural network based Face detection has achieved enormous success in face recognition. A hybrid neural network solution for face recognition was addressed by this research in which neural network is trained with Gabor features. Identifying a reliable feature is extremely important for all pattern recognition systems. A filter which is capable of simultaneously capturing spatial and frequency information plays a major role in numerous systems as a feature extractor. Here it is the Gabor filter. Magnitude, phase and orientation are the three basic features produced by Gabor filter Most face recognition methods based on Gabor filters use either the magnitude feature alone or a combination of the phase and magnitude features; purely based on the phase feature, in which orientation feature is ignored are very few. This system is commenced with convolving a face image with a series of Gabor filter coefficients at different scales and orientations. Gabor features are fed to feed forward neural network which is based on BAM for dimensional reduction and multi-layer perception with back propagation algorithm for training the Gabor features. Face database with images captured at different illumination conditions are collected and the effectiveness of the algorithm has been justified over that database.

Keywords- Gabor filter, RMS contrast, neural network, BAM.

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Introduction

Face recognition is one of the most relevant applications of image analysis. An automated system which equals human ability to recognize faces is a challenging module to build. Although humans are good enough in identifying known faces, but sometimes we may not that much skilled enough when we must deal with a large amount of unknown faces. Human's limitations are overcome by the computers, which has large amount of memory and computational speed.

The Gabor filter, which is derived from the uncertainty relation for information, can simultaneously capture spatial and frequency information to overcome the traditional signal representation in which a signal is represented either in the time domain or the frequency domain. Originally, it was designed for one-dimensional signal decomposition. However, since the 1980s, it has been extensively used as a spatial and convolution filter motivated by research results in biological vision systems. Although the Gabor filter has been involved in a wide range of components for pattern recognition systems, its major application is feature extraction. Gabor filters can exploit salient visual properties such as spatial localization, orientation selectivity and spatial frequency characteristics [1-2]. Considering these overwhelming capacities and its great success in face recognition, in this paper Gabor features are used to represent the face image and produces recognition task in tandem with neural network.

However, in reality, we do not get images with only faces. A system capable of detecting, locating and segregating faces in cluttered images is needed, after segregating faces they can be given as input to face recognition systems. Given an input scene, ultimate goal of a face detection algorithm is to identify the location and scale of all the faces in the image. Face detection task is so trivial for the human brain, yet it still remains a challenging task to enable a computer for face detection, since the human face changes with internal factors like beard, facial expression and glasses etc. and it is also affected by external environmental factors like lightning conditions, scale, contrast between face and background and orientation of the face. For any face processing system first step is detecting the locations in images where the face is present. However, detecting the face from a single image is a challenging task because of variability in scale, location, orientation (up-right, rotated) and pose (frontal, profile).

Facial expression, occlusion and lighting conditions also change the overall appearance of faces.

Numerous methods have been proposed to detect faces in an image. Image detection methods can be classified into four categories.

A. Knowledge-Based Methods

These rule-based methods encode human knowledge of what constitutes a face. Usually, the rules that capture the relationships between facial features are used. These methods mainly used for face localization. Yang and Huang [9] used a hierarchical knowledge-based method to detect faces.

B. Feature Invariant Approaches

These algorithms aim to find structural features that exist even when the pose, viewpoint, or lighting properties vary and then use these to locate faces. These methods are developed mainly for face localization. In early face detection system by Sakai et al. [7] Edge representation was applied.

C. Template Matching Methods

Several standard patterns of a face are stored to describe the face as a whole or the facial features separately. Input image and the stored patterns are collected and the correlations between them are computed for detection. For both face localization and detection these methods have been used for. An early attempt to detect frontal faces in photographs is reported by Sakai et al. [8]. They used several sub templates for the eyes, nose, mouth and face contour to model a face.

D. Appearance-Based Methods

In contrast to template matching, the models or templates are known from a set of training images, which should capture the representative variability of facial appearance. These learned models are then used for detection. Among all the face detection methods that used neural networks, the most challenging work is done by Henry A. Rowley, Shumeet Baluja and Takeo Kanade [4-6].

System Architecture

The system proposed in this research is designed for recognition of face images. The system consists of five modules: a) Face extraction b) Face preprocessing c) Facial feature extraction using Gabor filter d) Binarization using patterning e) Face recognition using BAM and back propagation algorithm (BPNN). The overall system architecture is shown in [Fig-1].

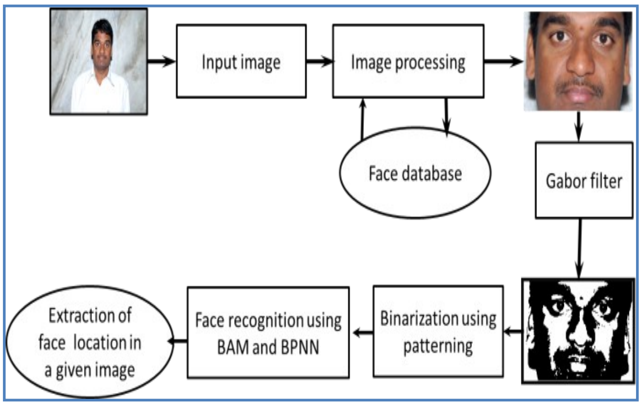

Fig. 1- Overall system architecture

Image Pre-Processing

The original images are first converted into gray-scale images. The centers of two eyes on each face image are made as central point and all images are properly scaled, rotated, translated and cropped into 100×100 pixels. Images are then subjected to some image pre -processing operations. The image preprocessing phase includes histogram equalization, contrast and illumination equalization and fuzzy filtering.

Contrast and Illumination Equalization- Contrast is a measure of the human visual system sensitivity. To achieve an efficient and psychologically-meaningful representation, all images are converted to the images with same illumination and rms contrast. The standard deviation of luminance is nothing but rms contrast metric.

Images of different human faces have the same contrast if their rms contrast is equal. The rms contrast does not depend on spatial frequency contrast of the image or the spatial distribution of contrast in the image. All images are maintained with the same illumination and same rms contrast using the following equation:

$$g = \alpha f + \beta$$

Where α is the contrast and β is the brightness to be increased or decreased from the original image f to the new image g. α and β values are chosen empirically. The rms contrast equalization process is illustrated in [Fig-2].

Fig. 2- Illumination and rms contrast equalization

Histogram Equalization- The face images may be of poor Contrast because of the limitations of the lighting conditions. To compensate for the lighting conditions and to improve the contrast of the image by Peli [3] histogram equalization is used.

Implementation of Methodology Used

Introduction to Gabor Filters

The functionality of the Gabor filters are very near to the neurons of the visual system and also it serves as a solution for mutual information maximization problem. Maximum information from local image regions can be extracted using Gabor receptive field. For face recognition applications, the number of Gabor filters used to convolve face images varies with applications, but usually 40 filters (5 scales and 8 orientations) are used.

Introduction to Neural Networks

Neural network is a parallel distributed process which is made up of simple processing units for storing experiential knowledge and making it available for use in future. In the present system neural networks are used to classify the set of images with faces and set of images without faces.

Implementation Details

Implementation of system in neural networks divided into four main ares as shown in [Fig-3]. Present system operations is as follows:

a. Creation of database (Detection of facial features by Gabor filters)

b. Initialization of network (Design and creation of a Neural Network)

c. Training (Choice of training data, parameters and training)

d. Classification (Scanning images to locate faces)

Creation of Database

A set of two classes namely “non-face” and “face” images of size 27X18 are provided to the system with pre-processing techniques applied on them. And including original faces, their mirror images and their left-right mirror images enlarges face database. Similarly including non-faces images, their mirror images and up-down mirror images enlarges non-face database. Facial features of the given images are extracted using Gabor filter, with this features face images and non-face images databases are created.

Initialization of Neural Network

A custom network is created and its properties are set as desired.net = network // Creates a custom neural net-work. The various properties of the network are set. These properties [Fig-4] determine the number of network sub objects (which include inputs, layers, outputs, targets, biases and weights) and how they are connected.

Training the Neural Network

The two classes both “non-faces” and “faces” are ready to train the neural network on them. But random images are taken from training set and fed into the system. Training [Fig-4] occurs according to the trainscg's training parameters shown here with their default values:

net.trainParam.epochs // Maximum number of epochs to train

net.trainParam.show // Epochs between showing progress

net.trainParam.goal // Performance goal

“trainscg” that is Scaled conjugate gradient back propagation, is a network training function that updates weight and bias values according to the scaled conjugate gradient method. Training stops when any of these conditions occur:

i. Maximum number of epochs (repetitions) is reached.

ii. Maximum amount of time has been exceeded.

iii. Performance has been minimized to the goal.

Classification

Here the trained network that has been trained is used to test a particular image to find out whether it contains any face or not. Any image to be tested is first converted into gray scale. When a new image is presented to the network, the image divided into windows that are individually presented to the network for classification. Windows thought to contain a face are outlined with a red bounding box of size 127X127 and on completion a copy of the image is displayed.

Results and Discussions

In this experiment 68 faces and 55 non-face images are used for the trying of the feed forward neural network. All the images are resized to have a dimension of 127X127 for minimizing the learning rate. Different sizes of the images are used for testing the system. The main menu of face detection is shown in below. An insight into the true performance of the system can only be achieved through the use of an independent test set of “unseen” images. The appropriate choice of an image database for training is extremely important in order to fulfill the goals set for training. With these considerations in mind, the human face database chosen for training was the Yale face database that contains 10 frontal images per person, each with different facial expressions, with and without glasses and under different lighting conditions. The strengths include the large number of different subjects; the dataset has good diversity across age, race and gender. The training dataset was restricted only to frontal view images and it contains 148 training examples, 93 face and 55 non-face images. The images in the dataset are of 27x18 pixels; each image is a Gray scale image in TIFF format. Some samples of images of faces and non-faces from database are shown in Samples of Faces from Database used in the Face Detection System Samples of Non-Faces from Database used in the Face Detection System This face detection system was run on a 3.00 GHz Intel Pentium (R) D processor system with 2 GB of memory running Windows 7. It took 2 minutes to create the database of 1120 images.

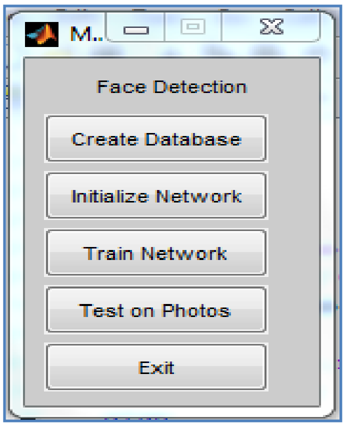

Fig. 3- GUI tool box illustrating various options

The feature points are typically located at positions with high information content (such as facial features) and at each of these positions we extract a feature vector consisting of Gabor coefficients Testing of Images and Results The Hybrid face detection system was tested on 35 images having different number of faces.

In order to evaluate the effectiveness of the proposed method, experiments were carried out for real images at different illumination conditions. We used CMU Pose, Illumination and Expression

(PIE) database and selected 200 images of 40 individual subjects with two different poses and five different illumination conditions.

Half of the images in the database were used as a training dataset and the remaining images were used as probe images in the recognition test. All images were subjected to Gabor filters and were convolved with 15 Gabor filters. To each face image, the outputs were 15 images which record the magnitudes of the Gabor filter responses [Fig-5]. The output of the Gabor filters was used to train the neural network. In order to evaluate the method for contrast equalization, we made a comparison among our proposed system (rms scaling Gabor), the Elastic Bunch Graph Matching (EBGM) and the log-polar Gabor methods.

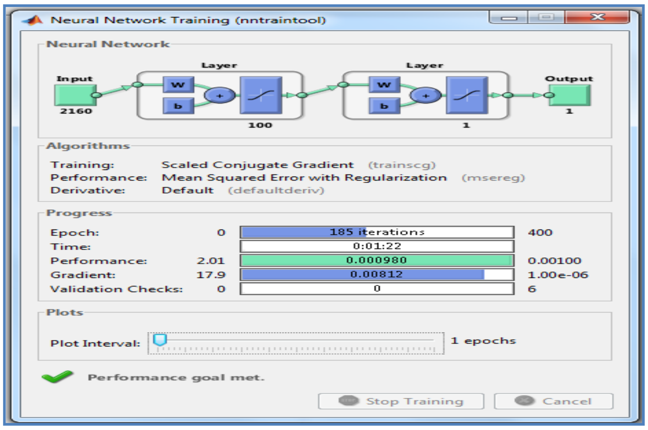

Fig. 4- Neural Network training tool box

Fig. 5- Gabor filter response of a typical face image.

Conclusion

This paper presents a neural network based face recognition system using Gabor filter coefficients that can cope with illumination changes. The performance of recognition has been improved substantially due to implication of contrast equalization using the rms value of the image pixels. Application of a hybrid network (BAM and BPNN) rather than BPNN takes less iteration to train and less time to recognize faces. Since each pixel of the magnitude response of Gabor filter corresponds to a Gabor feature, the number of Gabor features for each sample is 100×100×15=150,000. Therefore, our next step will be to improve the algorithm which would be able to employ more complex classifiers and distance measures to represent Gabor faces with spatial and frequency features.

Future work

The main limitation of the implemented system is that it only detects upright frontal faces and the variation like rotated faces and side views are restricted. The goal of any future improvement should be to improve the detection rate and to minimize the number of false positives and to improve the speed of the detection process.

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