Face Recognition using Fourier Descriptor and FFNN

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Abstract-We present in this paper, Fourier descriptor and feedforward neural network for face recognition. Analysis is done for various numbers of iterations. Comparison shows that faces are recognized with FFNN more accurately with 50000 iterations. For experiment, FERET database is used.

Keywords: Fourier Descriptor, FFNN.

I. INTRODUCTION

Face recognition involves computer recognition of personal identity based on geometric or statistical features derived from face images. Even though humans can detect and identify faces with little or no effort, building an automated system that accomplishes such objective is, however very challenging. The challenges are even more profound when one considers the large variations in the visual stimulus due to illumination conditions, viewing directions or poses, facial expression, aging, and disguises such as facial hair, glasses or cosmetics.

Face recognition research provides the cutting edge technologies in commercial, law enforcement, and military applications. An automated vision system that performs the functions of face detection, verification and recognition will find countless unobtrusive applications, such as airport security, and access control, building surveillance and monitoring, human-computer intelligent interaction and perceptual interfaces[1].

II. FOURIER DESCRIPTOR[2]

Location and description of substantial variations in the first derivative of object boundaries often yield suitable information. A typical mathematical technique is shape description based on the Fourier transform[4].

We are dealing with two-dimensional images, but our world is three-dimensional and the same objects, if seen from different angles, may form very different 2D projections.

If \(x(k)=x_k\) and \(y(k)=y_k\) are the coordinates expressed notation for the boundary of an image can be represented as the sequence of coordinates \(s(k)=[x(k),y(k)]\) for \(k=0,1,2,...,k-1\). Each coordinates pair can be treated as a complex number so that \(s(k)=x(k)+jy(k)\).

The discrete fourier transform (DFT) of \(s(k)\) is \(a(u)=\sum s(k)e^{-j2\pi uk/K}\) for \(k=0\) to \(k-1\) and \(u=0,1,2,...,k-1\).

The complex coefficients \(a(u)\) are called the Fourier descriptors of the boundary.

The inverse fourier transform of these coefficients restores \(s(k)=\sum a(u)e^{j2\pi uk/k}\) for \(k=0,1,2,...,k-1\) and \(u=0,1,2,...,k-1\).

Although only \(P\) terms are used to obtain each component of \(s(k)\), \(k\) still ranges for \(0\) to \(k-1\).

III. FEEDFORWARD NEURAL NETWORK

A feedforward artificial neural network consists of layers of processing units, each layer feeding input to the next layer in a Feed forward manner through a set of connection weights or strengths. The weights are adjusted using the back propagation learning law. The patterns have to be applied for several training cycles to obtain the output error to an acceptable low value. Once the network is trained, it can be used to recall the appropriate pattern for a new input pattern. The computation for recall is straightforward, in the sense that the weights and the output functions of the units in different layers are used to compute the activation values and the output signals. The signals from the output layer correspond to the output.

Back propagation learning emerged as the most significant result in the field of neural networks. The back propagation learning involves propagation of the error backwards from the input training pattern, is determined by computing the outputs of units for each hidden layer in the forward pass of the input data. The error in the output is propagated backwards only to determine the weight updates [3].
IV. ANALYSIS OF IMAGE RECOGNITION WITH FD

In Fourier descriptor method, images are first converted to binary images. Using labeling, all regions in the image are found and take boundaries of each region in the image. These boundary values are used to find fourier descriptors, which are imaginary values in the form of (x + iy). Inverse Fourier descriptors using different values of Fourier descriptors such as 100%, 50%, 30% and 20% are obtained and analyzed the recognition results with different values. Instead of using FD images, mean values of each row of the image are used for classification.

\[ \text{p}_{\text{mean}} = \text{mean}(v_i) \]

where, vi is the ith vector in the image.

V. RESULT ANALYSIS

1. FFNN is trained for front face images with 100%, 50%, 30%, 20%, 10% FD (350 images of 70 persons, 70*5=350) and following network architecture is used:
   i) Number of layers=3
   ii) Neurons in first layer=48
   iii) Neurons in second layer=192
   iv) Neurons in third layer=350
   v) Transfer function for all layers is ‘tansig’

Test results for different face images and different percentages of reconstructed images with Epochs=50000 are shown in Table1 and Graph1.

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<thead>
<tr>
<th>% of FD used for testing</th>
<th>No. of images for Front faces</th>
<th>Alternate expression</th>
<th>Quarter left</th>
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Graph1: Recognition rate by 3-layer (48-192-350) FFNN (50000 epochs) with all (100%, 50%, 30%, 20%, 10%) FD values.

2. FFNN is trained front face images with 100%, 50%, 30%, 20%, 10% FD (350 images of 70 persons, 70*5=350) and following network architecture is used:
   i) Number of layers=3
   ii) Neurons in first layer=48
   iii) Neurons in second layer=240
   iv) Neurons in third layer=350
   v) Transfer function for all layers is ‘tansig’

Test results for different face images and different percentages of reconstructed images with Epochs=60000 are shown in Graph2 and Table2.

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<th>% of FD used for testing</th>
<th>No. of images for Front faces</th>
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Graph2: Recognition rate by 3-layer (48-240-350) FFNN (60000 epochs) with all (100%, 50%, 30%, 20%, 10%) FD values.

3) Comparison between recognition rate with two architectures given below of FFNN and using all (100%, 50%, 30%, 20%, 10%) FDs are shown in Table3 and Graph3:
   i) 3-layer (48-192-350) FFNN, epochs=50000
   ii) 3-layer (48-240-350) FFNN, epochs=60000

Graph3 shows the difference between recognition rate of two network architectures. When number of neurons in the hidden layer are increased above some limit, the result is inverse. Generally, up
to some limit, increasing number of neurons in hidden layers and/or number of iterations improves recognition rate.

**VI. CONCLUSIONS**

FFNN is a multilayer Neural Network, which uses back propagation for learning. From the obtained results, it can be said that, three layers are sufficient for classification. As number of layers increased more than three, it does not improve the recognition rate, but instead of that, if number of epochs and neurons in hidden layers are increased upto some limit, it improves the recognition rate.

Reconstructed images are obtained which reduces dimensions of database. Instead of training network for one image of each person with some reduced dimensions, images with different dimensionality reduction (i.e. more than one feature vectors of each person) gives recognition rate more than others. Here, 5 feature vectors for each person with different dimensions i.e.100%, 50%, 30%, 20%, 10% dimensions, (70*5=350 feature vectors for 70 persons) are used.

**REFERENCES**

[14] Website: www.icgnt.com

![Graph 3: Recognition rate by two FFNNs](image-url)