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Face Recognition Based Hostel Student Security System Using Artificial Intelligence

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ABSTRACT: Artificial Neural Networks are biologically inspired, that is they perform in a manner that is analogous to the most elementary functions of a biological neuron. A set of input values are applied to the artificial neuron. Each input is multiplied by a corresponding weight and all of the weighted inputs are then summed to determine the activation level of the neuron. The Net Signal is further processed by activation functions like **Hard Limiter, Sigmoidal Logistic Function, And Hyperbolic Tangent Function**. The general learning rule adopted in Neural Networks is that, the weight vector increases in proportion to the product of input and learning signal. The various rules for the generation of the learning signal are **Hebbian rule 2) perception rule 3) delta rule 4) window-hoff rule 5) correlation rule 6) winner-take all rule 7) outstar rule**. Various applications can be extracted from these networks and are successfully implemented.

I. INTRODUCTION

The power of neural computation comes from connecting neurons into networks. A network has several layers of neurons which offer computational capabilities. The layers whose output becomes the network output are called output layers. The other layers are hidden layers. The output of each layer acts as input to the subsequent layer. Then the network is systematically trained.

Training is a procedure that assigns weights to connections between neurons given a set of initial states and final states. The error in the output is minimized by feedback mechanism (with the help of the written algorithm). Supervised training requires the pairing of each input vector with a target vector. Together, these are called *training pairs*. Usually a network is trained over a number of such training pairs. An input vector is applied, the output of the network is calculated and compared to the corresponding target vector and the difference is fed back through the network and weights are changed according to an algorithm that tends to minimize the error. The vectors of the training set are applied sequentially and errors are calculated and weights are adjusted for each vector, until the error for the entire training set is at an acceptably low level. The different techniques have been used to identify faces using the Neural Networks approach. The two main methods used are

- 1) Extracting features from the front view of the human face and
- 2) Extracting features from the side view of the human face.

Of these several applications, machine recognition of faces has been found useful in applications ranging from static matching of controlled photographs and credit card verification to surveillance video images.

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- 3) Extracting features from the front view of the human face and
- 4) Extracting features from the side view of the human face.

As compared to the side view, the extraction of features from the front view is not very economical as the feature set obtained in front view is very large and thus takes greater training time. Thus to overcome this, features can be

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II. COMMERCIAL APPLICATIONS OF FACE RECOGNITION:

Face recognition systems can be widely used in commercial transactions such as bank cards, credit cards and ATM cards. Encoding each card with facial features can provide an identification method which would be very effective in bank card fraud statistics. The advantages of facial identification over alternative methods such as finger print identifications are primarily based on the convenience and cost. Facial recognition can be corrected in uncertain cases by humans without extensive training.

APPLICATIONS IN LAW ENFORCEMENT:

The basic approach to the mug shots problem in criminal identification is for the system to compare features from the target with those stored in the database. The nature of the target image relative to the images in the database is crucial and determines the difficulty of the overall procedure. The target may be a mug shot or from another photographic source and may need to be rotated before the features can be extracted and compared to the mug file images.

FEATURE EXTRACTION:

Face is a unique feature of human beings. Even the faces of identical twins differ in some aspects. Identification and distinction of faces is done with a very casual inspection. Thus facial feature extraction has become an important issue in automated visual interpretation and recognition of human faces. Feature extraction plays a vital role in designing a good recognition system and the success of the system is usually determined by whether a good feature with high discriminating power is extracted or not.

EXTRACTION OF FACIAL FEATURES:

The outline of the side view of human face patterns yield a set of good discriminant features for the identification of the human face. Eleven such points have been identified which may help in extracting certain characteristic feature for that particular face. It is seen that these points do not generally change with age. Hence these points have been selected for the extraction of various feature measures for identification purposes. These points are

- Point 1 Nose Point
- Point 2 Chin Point
- Point 3 Forehead Point
- Point 4 Bridge Point
- Point 5 Nose Bottom Point
- Point 6 Throat Point
- Point 7 Upper Lip Point
- Point 8 Centre Lip Point
- Point 9 Lower Lip Point
- Point 10 Chin Curve or Lip Bottom Point
- Point 11 Brow Point

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MARKING OF FIDUCIAL POINTS ON THE PROFILE:

After having selected fiducial points on the profile, the next step is to mark them on the profile. Algorithms have been developed for marking of these points on the side profile of the face. It is important that these points are found out without any ambiguity. A side profile marked with 11 fiducial points is shown in fig.

NOSE POINT (Point 1):

Nose Point is the left most point on the profile as the protrusion of the nose is maximum in any normal face. Outline profile of the face is scanned from left to right and top to bottom. As the coordinates of all the points lying on the profile are already calculated, the point which has the minimum (alternatively maximum) value is selected as the nose point. In case there are more than one such point, then the bottom most point is selected as the nose point. It has been observed that with small rotation of the photograph (+10 or -10 degree), the nose point remains the same.

CHIN POINT (Point 2):

After the coordinates of the nose point have been calculated, the Chin Point is calculated. With Nose Point as the reference point, imaginary lines are drawn recursively with the other points lying on the profile below the nose point and angle of these lines with the vertical or horizontal is calculated. The point on the lower profile with which the nose point as the second point makes a line, which forms minimum angle with the vertical or maximum angle with the horizontal, gives the chin point. In figure, the Point2 makes maximum angle with the horizontal.

The tangents between the two points is given by

$$\tan \theta = (y_2 - y_1) / (x_2 - x_1)$$

$$\theta = \arctan (\tan \theta)$$

where (x_1, y_1) are the coordinate of nose point (fixed) and (x_2, y_2) are coordinates of points lying on the profile below nose point (variable). Whichever (x_2, y_2) point subtends maximum angle will be selected as the chin point.

FOREHEAD POINT (Point 3):

The Forehead point is just a reflection of the chin point on the forehead through the nose point. Therefore initially the distance between the nose point and chin point is calculated and with the nose point as the centre and the distance between the nose point and the chin point as the radius a circle is drawn. The point where the arc of the circle cuts the upper portion of the profile is taken as the forehead point. In actual practice the distance of all points can be computed lying above the nose point from the nose point and the point which has the distance closest to nose-chin distance is marked as the forehead point.

BRIDGE POINT (Point 4):

Bridge point lies on the profile between nose point and forehead point. It lies on the depression where nose and forehead join together. For finding the bridge point, the equation of the line joining forehead and nose point is found out. From this line, the perpendicular distance of all the points lying on profile between nose and forehead point is calculated. The point having maximum distance from this line is marked as the bridge point, as in figure. The equation of a straight line through two points $A_1(x_1, y_1)$ and point $A_2(x_2, y_2)$ is given by

$$(x - x_1) / (x_2 - x_1) = (y - y_1) / (y_2 - y_1)$$

Or

$$(y_2 - y_1)(x - x_1) = (x_2 - x_1)(y - y_1)$$

NOSE BOTTOM POINT (Point 5):

The nose bottom point is the point where the nose ends and lip portion starts. As was the case of chin, the tangent of the angles between nose point and the points lying between nose point and chin point is calculated. The point having minimum angle with the horizontal yields the nose bottom point as shown in the figure.

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THROAT POINT (Point 6):

This point is also calculated in a similar manner as the nose bottom point. In this case the angle is found out between chin point and the points lying on the profile after chin point. The point subtending the minimum angle with chin point is marked as the throat point as in figure.

LIP BOTTOM POINT or CHIN CURVE POINT (Point 10):

In this case we move upward from chin point and the point having maximum value in x - coordinate is chosen as the chin curve point. If there are more than one such point in succession the central point out of these is marked as chin point.

BROW POINT (Point 11):

The brow point is the most raised point between the forehead point and the bridge point. Therefore, the point having the minimum value in x-coordinate in between forehead and bridge points is marked as the brow point.

UPPER LIP, CENTRE LIP AND LOWER LIP POINTS:

To find out the three lip points, nose bottom and chin curve points are joined by an imaginary line. The distance of all points lying between nose bottom point and chin curve point is calculated and stored in an array. First point from top having the maximum distance from this imaginary line is marked as upper lip point. After that the point which has the minimum distance from this imaginary line is marked as the centre lip point. The point having the maximum distance to the imaginary line after the centre lip point is termed as the lower lip point in the figure.

COMPUTATIONAL OF FEATURE MEASURES FROM THE FIDUCIAL POINTS:

Eleven fiducial points on the face profile are used to generate three kinds of feature characteristics.

1. Area
2. Angles between the fiducials
3. Distance between the fiducials

AREA:

Only one area measure is used. The area defined by the chin-forehead line and the profile curve is the area required. Area on the left side of the chin-forehead line is only considered as shown in the figure.

ANGLE BETWEEN FIDUCIALS:

Three angles are computed from the fiducial points. The angles that are calculated are angle<123>, angle<134>, and angle <415> as shown in the figure.

Here angle<123> is the angle between the lines joining points<1,2> and points<2,3> , angle<134> is the angle between the lines joining points<1,3> and points<3,4> and angle<415> is the angle between the lines joining points<4,1> and <1,5>.

Calculation of angle between two straight lines: The angle is obtained by finding the slopes m_1 and m_2 of the two straight lines. The angle is then computed using the formula

$$\tan \square = \frac{m_2 - m_1}{1 + m_1 m_2}$$

This yields the angle \square .

DISTANCE MEASURES:

The following nine distance measurements are carried out between the various fiducial points

- 1) d12 : The distance between the nose and chin point.
- 2) d14 : The distance between the nose point and bridge point
- 3) d15 : The distance between the nose point and the nose bottom point
- 4) d16 : The distance between the nose point and the throat point
- 5) d11 : The distance between the nose point and the brow point
- 6) d34 : The distance between the forehead point and the brow point
- 7) d42 : The distance between the forehead point and the chin point

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- 8) d_{51} : The distance between the bottom point and the chin curve
9) d_2 perpendicular to 45: The distance of point 2 from line joining the bridge point and the nose bottom point. This point can be left or right of point 2. Accordingly if the line is to the left, the distance is taken as negative, otherwise it is positive.

FORMING THE FEATURE VECTOR:

The above mentioned measures namely area, three angles and nine distances together form the thirteen dimensional feature vector arrays. Each facial photographed image is reduced to this feature vector array. This feature vector array is expected to be unique for each face and is used for the given face. To remove the effect of scaling, distance and area values have to be normalized.

BACKPROPAGATION NETWORK:

Back propagation is a systematic method for training multilayer artificial neural networks. Backpropagation training algorithm for training feed – forward networks was developed by Paul Werbos, and later by Parker and Rummelhart and McClelland. This type of network configuration is the most common in use, due to its ease of training.

In Backpropagation, there are two phases in its learning cycle, one to propagate the input pattern through the network and the other to adapt the output, by changing the weights in the network. It is the error signals that are back propagated in the network operation to the hidden layers. The portion of the error signal that a hidden - layer neuron receives in this process is an estimate of the contribution of a particular neuron to the output error.

TRAINING:

The feed forward backpropagation undergoes supervised training, with a finite number of pattern pairs consisting of an input pattern and desired or target output pattern. As input pattern is presented at the input layer, the neurons here pass the pattern activation to the next layer neurons, which are in a hidden layer. The outputs of the hidden layer neurons are obtained by using a bias and also a threshold function with the activation determined by the weights and the inputs. These hidden layer outputs become inputs to the output neurons, which process the inputs using an optional bias, and a threshold function. The final output of the network is determined by the activations from the output layer.

The computed pattern and the input pattern are compared, a function of this error for each component of the pattern is determined and adjustment to weights of connections between the hidden layer and the output layer is computed. A similar computation, still based on the error in the output is made for the connection weights between the input and hidden layers.

BACKPROPAGATION TRAINING ALGORITHM:

The backpropagation training algorithm is an *iterative gradient* algorithm designed to minimize the mean square error between the actual output of a multilayer feed forward perception and the desire output. It requires continuous differential non-linear ties. The following algorithm assumes a sigmoid logistic nonlinearity where the function $F(\text{NET})$ is DEFINED as,

$$F(\text{NET}) = 1 / (1 + \text{EXP}(-\text{NET})) \quad \text{NET} = X * W = X_1W_1 + X_2W_2 + \dots + X_nW_n$$

1. INITIALIZE WEIGHTS

Set all weights to small random values.

2. PRESENT INPUT AND DESIRED OUTPUT

Present a continuous valued input vector $S_0, S_1, S_2, \dots, S_{n-1}$ and specify the desire outputs $d_0, d_1, d_2, \dots, d_{m-1}$

3. CALCULATED ACTUAL OUTPUTS

Use sigmoidal nonlinearity from above and formulate from the figure.

Calculate outputs $u_0, u_1, u_2, \dots, u_{m-1}$

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Vol. 9, Issue 3, March 2020

4. ADAPT WEIGHTS

Use a recursive algorithm starting at the output nodes and working back to first hidden layer. Adjust weights by

$$W_{kj}(t+1) = W_{kj}(t) + \eta \delta_j x_k$$

Where,

W_{kj} - weight from hidden neuron k to node j at time t

η - gain term

δ_j - Error term for node j

if node j is an output node then,

$$\delta_j = u_j * (1 - u_j) * (d_j - u_j)$$

Where,

d_j - desired output of node j and

u_j - actual output

if node j is an internal hidden node then,

$$\delta_k = h_k * (1 - h_k) * \delta_j \cdot W_{kj}$$

Adjust weights by,

$$V_{jk}(t+1) = V_{jk}(t) + \eta \delta_k^* x S_i$$

Where,

S_i - input at i^{th} neuron

Convergence is sometimes faster if a momentum term is added and weight changes are smoothed by,

$$V_{jk}(t+1) = V_{jk}(t) + \eta \delta_k^* x S_i + \alpha (V_{jk}(t) - V_{jk}(t-1))$$

5. Repeat by going to step 2 till the error is reduced below a pre established limit.

TESTING

In testing phase of back propagation the user provides the feature vector of a person as test data and the network classified input in one of the photographs stored in the database. The network goes through one cycle of operation in testing mode, covering all the patterns.

III. CONCLUSION

In our paper, the computer has been trained to recognize human faces and this has been achieved by training the neural network with three facial photographs taken along the side view by using back propagation algorithm. Such a system capable of recognizing human faces find extensive applications in law enforcement agencies with their large mug shot databases. Further improvements in the system can make it useful for commercial transactions.

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