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Vol. 4, Issue 11, November 2016

Emotion Recognition Using Neural Network Approaches

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ABSTRACT: Emotion Recognition is proposed, which uses the WHT transform over the entire face image as feature detector and a constructive one hidden layer feed forward neural network as a facial expression classifier proposed technique is applied to a database consisting of images of 37 having eight facial expression images(neutral, smile, anger, sad, cry, disgusted, fear, surprise). Images of 24 are used for network training, and the remaining images of 13 are used for cross validation. It is demonstrated that the best recognition rates are 100% for the training as well as cross validation. Furthermore, The Average Classification Accuracy of GFF Neural Network comprising of one hidden layers with 3 PE's organized in a typical topology is found to be superior (100 %) for Training . Finally, optimal algorithm has been developed on the basis of the best classifier performance. The algorithm will provide an effective alternative to traditional method of facial captured image analysis for deciding the Human emotion.

KEYWORDS: Neural solution, MatLab, Excel, CT scan images.

I. INTRODUCTION

Facial expression plays the major role in non-verbal communication, and also an active research area in human-computer interaction (HCI). Facial expression recognition (FER) is the technology for HCI, which is applied on images (or sequences of images). Facial expression are the consequences of the certain movements of facial features like eyes & mouth (having the essential role in formation of facial expression) and caused by various factors, that affect the human feelings such that mental status, non-verbal communications, physiological activities (pain, tiredness), verbal communication etc. The six basic emotions (Happy, Sad, Angry, Surprise, Fear, Disgust, Cry, Neutral,) also known as eight universal emotions are used by most researchers. In this work, we have taken these basic emotions in consideration

For each facial image, region of interest (ROI) is identified, which is used to extract features from the image. Thus, each facial image is represented by a unique feature vector, which corresponds to a typical emotion. Image-wise all input features along with the expressed emotion are recorded in Excel sheet, which is also known as a knowledgebase. This knowledgebase or facial image database is applied to Neural Network based classifiers with a view to recognize the emotion from facial image as correctly as possible. Different classifiers are compared on the basis of classification accuracy. Though much progress has been made, recognizing facial expressions with high accuracy remains difficult due to the complexity and variability of facial expressions. Ekman and his colleagues, in their studies of human facial expressions, identified Eight states as universal facial expressions. These states represent Smile, sadness, anger, fear, surprise and disgust or Cry, Neutral,. Facial expression recognition involves three steps face detection, feature extraction and classification of expression.





(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 11, November 2016

The pre-processing step for recognizing facial expressions is face detection. The steps involved in converting a image to a normalized pure facial image for feature extraction is detecting feature points, rotating to line up, locating and cropping the face region using a rectangle, according to the face model. The face detection involves methods for detecting faces in a single image.

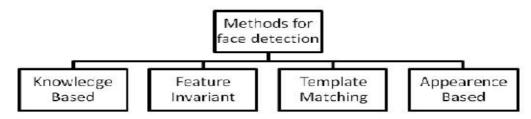


Fig. 1.1 Methods for Face Detection

The human visual system efficiently recognizes those emotions within difficult scenes having variations in illumination and perspective.

The features that are to be extracted include image statistics, 2-D image transform domain features, entropy, energy, texture, etc. Optimal feature vector is determined on the basis of relative significance of each feature. In another approach, 2-D principal component analysis is applied on the ROI of each image in order to reduce the dimensions of the input features and a suitable number of principal components are included in the feature vector in addition to some image statistics.

II. PROPOSED ALGORITHM

A. **RESEARCH METHODOLOGY** :

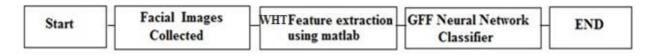


Figure 2.1 Methodology of work

It is proposed to study Emotion Recognition Using Neural Network Approaches.. Data acquisition for the proposed classifier designed for the Recognition of Human Emotion shall be in the form of facial images. Image data will be Collected from the different- different Faces .The most important un correlated features as well as coefficient from the images will be extracted .In order to extract features, statistical techniques, image processing techniques, transformed domain will be used.

B. IMAGE PRE-PROCESSING

A practical facial expression recognition system is shown in Fig. 2 below. The Recognition process begins by first acquiring the image using an image acquisition device like a camera. The image acquired then needs to be preprocessed such that environmental and other variations in different images are minimized. Usually, the image preprocessing step comprises of operations like image scaling, image brightness and contrast adjustment and other image enhancement operations. In our project work, an existing image database of human facial expressions is used to train and test the performance of the classifier. The images in the database have already been pre-processed and thus there is no need to apply any image pre-processing operation in this study.



(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 11, November 2016



Fig2.2Facial expression recognition system overview

1) Neural Networks

Following Neural Networks are tested:

a) Feed-Forward Neural Networks

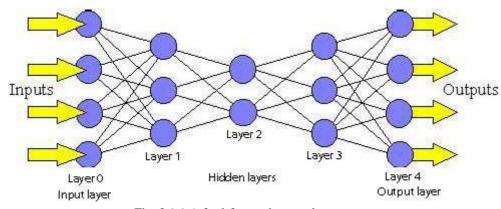


Fig. 2.1.1 A feed-forward network.

Feed-forward networks have the following characteristics:

- 1. Perceptrons are arranged in layers, with the first layer taking in inputs and the last layer producing outputs. The middle layers have no connection with the external world, and hence are called hidden layers.
- 2. Each perceptron in one layer is connected to every perceptron on the next layer. Hence information is constantly "fed forward" from one layer to the next., and this explains why these networks are called feed-forward networks.
- 3. There is no connection among perceptrons in the same layer.

A single perceptron can classify points into two regions that are linearly separable. Now let us extend the discussion into the separation of points into two regions that are not linearly separable. Consider the following network: [10]



(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 11, November 2016

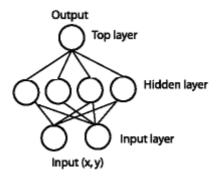


Fig. 2.1.2 A feed-forward network with one hidden layer.

Learning Rules used:

▹ Momentum

Momentum simply adds a fraction m of the previous weight update to the current one. The momentum parameter is used to prevent the system from converging to a local minimum or saddle point. A high momentum parameter can also help to increase the speed of convergence of the system. However, setting the momentum parameter too high can create a risk of overshooting the minimum, which can cause the system to become unstable. A momentum coefficient that is too low cannot reliably avoid local minima, and can also slow down the training of the system.

Conjugate Gradient

CG is the most popular iterative method for solving large systems of linear equations. CG is effective for systems of the form A=xb-A (1) where x _is an unknown vector, b is a known vector, and A _is a known, square, symmetric, positive-definite (or positive-indefinite) matrix. (Don't worry if you've forgotten what "positive-definite" means; we shall review it.) These systems arise in many important settings, such as finite difference and finite element methods for solving partial differential equations, structural analysis, circuit analysis, and math homework.

Developed by Widrow and Hoff, the delta rule, also called the Least Mean Square (LMS) method, is one of the most commonly used learning rules. For a given input vector, the output vector is compared to the correct answer. If the difference is zero, no learning takes place; otherwise, the weights are adjusted to reduce this difference. The change in weight from ui to uj is given by: $dwij = r^* ai^* ej$, where r is the learning rate, ai represents the activation of ui and ej is the difference between the expected output and the actual output of uj. If the set of input patterns form a linearly independent set then arbitrary associations can be learned using the delta rule.

It has been shown that for networks with linear activation functions and with no hidden units (hidden units are found in networks with more than two layers), the error squared vs. the weight graph is a paraboloid in n-space. Since the proportionality constant is negative, the graph of such a function is concave upward and has a minimum value. The vertex of this paraboloid represents the point where the error is minimized. The weight vector corresponding to this point is then the ideal weight vector.

> Quick propagation

Quick propagation (Quickprop) [1] is one of the most effective and widely used adaptive learning rules. There is only one global parameter making a significant contribution to the result, the e-parameter. Quick-propagation uses a set of heuristics to optimise Back-propagation, the condition where e is used is when the sign for the current slope and previous slope for the weight is the same.



(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 11, November 2016

> Delta by Delta

Developed by Widrow and Hoff, the delta rule, also called the Least Mean Square (LMS) method, is one of the most commonly used learning rules. For a given input vector, the output vector is compared to the correct answer. If the difference is zero, no learning takes place; otherwise, the weights are adjusted to reduce this difference. The change in weight from ui to uj is given by: $dwij = r^* ai^* ej$, where r is the learning rate, ai represents the activation of ui and ej is the difference between the expected output and the actual output of uj. If the set of input patterns form a linearly independent set then arbitrary associations can be learned using the delta rule.

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III. SIMULATION RESULTS

1) Computer Simulation

The GFF neural network has been simulated for 37 different facial emotion images out of which 24 were used for training purpose and 13 were used for cross validation.

The simulation of best classifier along with the confusion matrix is shown below :

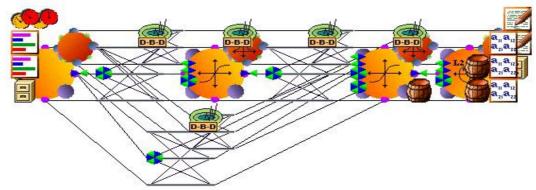


Fig.3.1 GFF neural network trained with DBD learning rule

i suns								
Output / Desired	FEAR	SURPRICE	SMILE	SADNESS	NUTRAL	DISGUSTED	CRY	ANGER
FEAR	1	0	0	0	0	0	0	0
SURPIRICE	0	1	0	0	0	0	0	0
SMILE	0	0	1	0	0	0	0	0
SADNESS	0	0	0	2	0	0	0	0
NUTRAL	0	0	0	0	2	0	0	0
DISGUSTE D	0	0	0	0	0	2	0	0
CRY	0	0	0	0	0	0	2	0
ANGER	0	0	0	0	0	0	0	2

Table I. Confusion matrix on CV data set

2) Results



(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 11, November 2016

Output / Desired	FEAR	SURPRICE	SMILE	SADNESS	NUTRAL	DISGUSTED	CRY	ANGER
FEAR	2	0	0	0	0	0	0	0
SURPIRICE	0	2	0	0	0	0	0	0
SMILE	0	0	3	0	0	0	0	0
SADNESS	0	0	0	4	0	0	0	0
NUTRAL	0	0	0	0	3	0	0	0
DISGUSTE D	0	0	0	0	0	4	0	0
CRY	0	0	0	0	0	0	3	0
ANGER	0	0	0	0	0	0	0	3

TABLE II. Confusion matrix on Training data set

Here Table I and Table II Contend the C.V as well as Training data set.

Performan									
се	FEAR	SURPIRICE	SMILE	SADNESS	NUTRAL	DISGUSTED	CRY	ANGER	
MSE	0.002	0.0898	0.001	0.0144	0.0009	0.012	0.003	0.002	
NMSE	0.038	1.265	0.022	0.110	0.006	0.0926	0.028	0.0197	
MAE	0.045	0.148	0.036	0.101	0.0242	0.0584	0.049	0.0495	
Min Abs									
Error	0.009	0.0018	0.002	0.0299	9.774	0.0010	0.0093	0.0234	
Max Abs									
Error	0.109	0.9590	0.055	0.2512	0.0579	0.3746	0.146	0.0555	
r	0.982	0.6661	0.994	0.948	0.996	0.9557	0.9882	0.9975	
Percent									
Correct	100	100	100	100	100	100	100	100	
TABLE III. Accuracy of the network on CV data set									

TABLE III. Accuracy of the network on CV data set

Performance	FEAR	SURPIRICE	SMILE	SADNESS	NUTRAL	DISGUSTED	CRY	ANGER
						0.00100768		
MSE	0.0009	0.001	0.001	0.0008	0.0005	2	0.001	0.002
NMSE	0.012	0.014	0.015	0.006	0.005	0.007	0.010	0.0232
MAE	0.024	0.027	0.037	0.025	0.018	0.026	0.028	0.048
Min Abs Error	0.001	0.001	0.002	0.0005	0.0003	0.001	0.001	0.012
Max Abs Error	0.055	0.055	0.055	0.055	0.055	0.0653	0.054	0.055
R	0.995	0.995	0.997	0.997	0.998	0.996	0.997	0.998
Percent								
Correct	100	100	100	100	100	100	100	100

TABLE IV. Accuracy of the network on training data set



(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 11, November 2016

Here Table III and Table IV Contain the C.V and Training result. Table III show the result or identify the all 8 type of Emotion 100% and also Table IV show the result or identify all 8 type of Emotion 100%.

IV. CONCLUSION AND FUTURE WORK

The GFF classifier with DBD learning rule gives best performance of 100% in Training as well as in Cross validation Also identify 100%.

VI. ACKNOWLEDGMENT

We are very grateful to our HVPM College of Engineering and Technology to support and other faculty and associates of ENTC department who are directly & indirectly helped me for these paper.

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