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Application of Neural Network for Different Learning Parameter in Classification of Local Feature Image

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***Abstract*— Artificial Neural Network particularly called as Neural Networks, are recently having significant impact in many field of areas. This paper presents a local feature classification using RBF neural network. The images are taken from the Taiwanese Facial Expression Images Database (TFEID). Radial Basis Function (RBF) neural network is used in this project as it provides advantages in pattern recognition. Networks are simulated for a few configurations and different learning parameters are compared to observe the performance of RBF neural network for human face expression based on the local feature.**

***Index Terms*— Neural network, Radial Basis Function, Mouth-shape classification**

I. INTRODUCTION

Recently, the development and the application of Artificial Neural Network (ANN) are very important in the human life since it is applicable not only to biological processes, but also to technology application and mathematical arithmetic calculation. The applications can range from computer science or engineering field [1]-[3] until marketing field and it is believed that it will increase in the future. Researchers continue to develop a new type of ANNS and implement the neural network in varieties of application [4],[5], some of the neural network applications are more user-friendly human and computer interaction application such as robot that can feel, think and act like human, organization sales forecasting, fully automated smart home and many more. Therefore, in this study, Radial Basis Function neural network [6] is implemented to classify the human mouth shape and some comparison of the network learning parameter had been done to investigate the performance of RBF neural network in the mouth shape classification.

II. NEURAL NETWORK

In the past, the term neural network [7] had been used to describe the network of biological neurons, which performs the nervous system of living organism, such as human and animal. However in modern usage, it is more often to be referred to Artificial Neural Networks (ANNS) [8],[9], a programmable system created using computer instruction set that perform tasks and properties similar to biological neurons. The concept of ANNS is developed using the hypotheses obtained from biological neural networks and it is first implemented into the Turing's B-type machines and the Perceptron [10]-[12]. Perceptron is the mathematical model representation for the biological neuron. In the Perceptron model, numerical values have represented the electrical signals in the biological nervous system. The weighted sum of the inputs represented the total strength of the input signals of the biological nervous system, and an activation function represented the threshold value is applied on the sum to determine its output [10]. There are many types of ANN have been developed since decades ago. The types of the ANN [13] which have been developed consist of different types of neural architecture, different types of neural learning and also different types of neural activation functions and the learning in ANN can be categorized into supervised learning, unsupervised learning and reinforcement learning. In this study, Radial Basis neural network has been chosen due to the some advantages of using RBF neural network.

A. Radial Basis Function Neural Network

RBF neural network [6] is a type of feed-forward ANNS that uses Gaussian function as its activation function. RBF network consists of one input layer, one hidden layer and one output layer. However, the hidden layer consists of two stages, where the first stage is supervised learning and second stage is unsupervised learning. It is usually known as hybrid supervised-unsupervised topology [14]. RBF network can be trained faster and this make RBF network more preferable in pattern recognition for large scale ANNS systems. In [15], the researchers used RBF neural network for the facial expression classification and found that they have shown a simpler and greater reliability of their system in facial expression classification.

III. METHODOLOGY

The system is designed aiming to classify local feature of human face based on the two types of mouth shape, namely smile and sad. There are four parts in this section which is data collection, obtaining the images vector, training and testing using Radial Basis Neural Network and lastly the overall flow of project development.

A. Data collection

In this study, two types of mouth shape which is smile and sad are obtained from Taiwanese Facial Expression Images Database (TFEID) provided online [16]. There are 10, 20 and 30 sets of images collected from the database as a training set

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and the system is tested using another 9 sets of image available.

B. Obtaining the Images Vector

The mouth shape which is smile and sad are directly cropped from TFEID [16]. Examples of mouth shape cropped out from the images are shown in Fig. 1 and 2. However, the cropped images are in different size, thus it is very important to resize the cropped images into common size which is 180 × 180 in matrices size as shown in Fi.3. The mouth shapes are still remaining unchanged even though the images are resized. The resized images are still in true color, meaning that they are all in the three dimensional Red, Green Blue (RGB) format. Images are then change into gray scale format since it is easier to process the images in gray scale color. Fig. 4 shows the example of the images in gray scale format.

Fig.1. Example of the smile image [16]

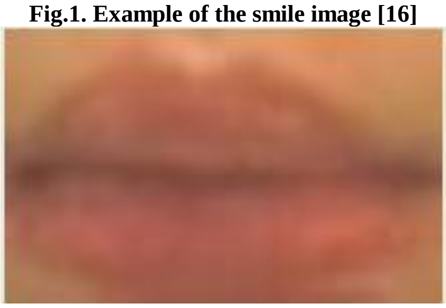

Fig.2. Example of the sad image [16]

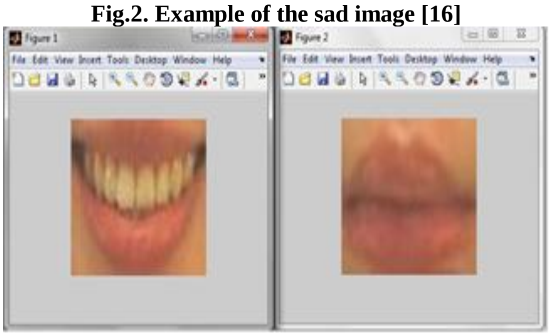

Fig.3. Example of the mouth's shape after standardization resizing processing [16].

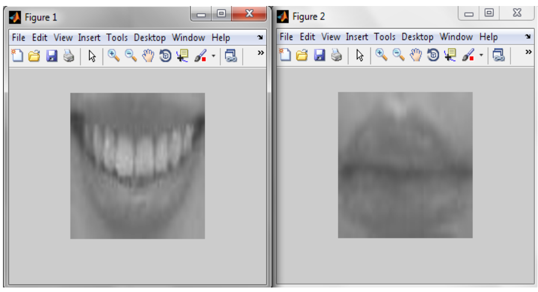

Fig.4. Example of the mouth shape after RGB format to gray scale format conversion processing [16].

Furthermore, contrast enhancement operations are done on the gray scale images so that these images are specified to a common range. The purpose of contrast enhancement operations is because the gray color of each mouth might lie in different range due to deepness of different color for different person's lip, skin color and also the brightness of the surrounding. Fig.5 shows the images after the operation of contrast enhancement. The images after contrast enhancement in matrices array form are then easily converted into the column vector using the reshape command in MATLAB. Reshaping of the images is done by combining the numbers of column into one single column vector. The column vectors were the data that BFF neural network can process and train the network.

C. Implementation of Radial Basis Neural Network

In this study, Radial basis Neural Network is used to simulate the required network that can classify the mouth shapes whether it is smile or sad. In the RBF simulation, MATLAB has provided the function newrb or newrbe for the simulation. The input class vectors, target class vectors, mean squared error goal for RBF can be set. The network architecture consists of two layers of network, which are Radial Basis layer and linear layer. Two activation functions were involved in the RBF architecture, that are RADBAS which stands for linear transfer function, and is located at the output layer of the RBF network and PURELIN which stands for linear transfer function, located at the output layer of the RBF network. Both layers have biases [17]. The Radial Basis layer has the RADBAS neurons and it shows that the || dist || box accepts the input vector p and the input weight matrices IW1,1, and produces a vector having S1 elements. The elements are the distances between the input vector and vectors iIW1,1 formed from the rows of the input weight matrices. The bias vector b1 and the output of || dist || are combined with the MATLAB's multiplication operation, which does element-by-element multiplication [17]. If an input vector is input to the network, each neuron in the radial basis layer will output a value according to how close the input vector is to each neuron's weight vector. If a neuron has an output of 1, its output weights in the second layer pass their values to the linear neurons in the linear layer [17].

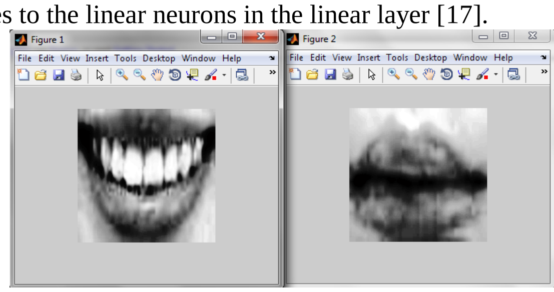

Fig.5. Example of the mouth's images after contrast enhancement processing [16].

In fact, if only one radial basis neuron had an output of 1, and all others had outputs of 0's (or very close to 0), the output of the linear layer would be the active neuron's output weights [17]. The Liner layer has PURELIN neurons and the weights LW2,1 and biases b2 are found by simulating the first-layer

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outputs a1, and then solving the linear expression as in Equation (1) [17].

$$[LW2,1\ b2] * [a1\ ;\ ones] = T. \qquad (1)$$

The first-layer outputs a1, the target T and the second layer is linear. The weights and biases of the second layer with Q input vectors to minimize the sum-squared error can be calculated using Equation (2) [17].

$$Wb = T / [P;\ ones(1,Q)] \qquad (2)$$

Where Wb contains both weights and biases, with the biases in the last column. initially the RADBAS layer has no neurons as in the functionality of RBF in MATLAB. The following steps are repeated until the network's mean squared error falls below GOAL or the maximum number of neurons are reached [18]:

1. The network is simulated
2. The input vector with the greatest error is found
3. A RADBAS neuron is added with weights equal to that vector.
4. The PURELIN layer weights are redesigned to minimize error

IV. RESULTS AND DISCUSSIONS

Networks for different number of training set are simulated to observe the accuracy and performance of the RBF neural network to classify untrained images. Networks are trained with 10 set, 20 set and 30 set of training set images with the 10 times training and tested with another 9 set of untrained set images. The RBF neural network is first tested with the trained images and result show that it can recognize all the trained facial expression. The RBF neural network then is tested with the untrained images and the results of simulated values are shown in Table 1, 2 and 3. The successfulness of correct mouth shape classification is based on assumption of matching percentage more than 50%.

A. Performance of RBF Neural Network with 10 Training Sets

Table 1 shows the results of the RBF neural Network with the 10 training sets trained 10 times and testing with another nine untrained images for each mouth-shape. It is observed that the RBF neural network trained with ten images resulting with two failure images classification while all other images been classified successfully. The network is based on the setting of 2 neurons. Most of the matching percentages are above 80% while there are six images with the matching percentage are lower than 80%.

B. Performance of RBF Neural Network with 20 Training Sets

Table 2 shows the result of RBF neural network trained with 20 images for each mouth shape for the training of 10 times with nine testing images where all these images can be successfully classify. However, the setting of network is based on 3 neurons. It is observed that the matching percentage with 20 sets of training images yield the better results when compared to the network trained with 10 images which is about eight images more than 90% matching percentage and the highest matching percentage is about 99 %.

C. Matching Percentage with 30 Training Images trained 10 Times (2 neurons)

Table 3 shows the result of network training based on 2 neurons with 30 images for each mouth shape trained 10 times and tested with nine sets of untrained images (9 images of smile and 9 images of sad) with all images classifications were successful with the highest matching percentage 99.9%. From the results shown in Tables 1, 2, and 3, it is shown that the successfulness of classifying the untrained images increased as the amount of the training set increased. There is failure in classifying the untrained images with the network that is trained with only 10 training set images, but there are no failures for the network that is trained using 20 or 30 training set images. The reason of the increased successfulness in classifying the untrained expression's images is that as more training set is provided, more variation for the same target are provided to the RBF neural network to be more easily recognize. The overall matching percentage for the untrained images also increased as the amount of training set is increased from the highest matching in 10 images (91.2%) to the highest matching percentage in 30 images (99.9%).

Table 1. Matching Percentage with 10 training images [16] trained 10 times (2 neurons)

Testing Images	Recognition Accuracy (%)
Smile01	82.3
Smile02	85.0
Smile03	83.6
Smile04	88.6
Smile05	90.2
Smile06	74.9
Smile07	73.3
Smile08	84.2
Smile09	90.8
Sad01	88.4
Sad02	79.7
Sad03	91.2
Sad04	76.8
Sad05	71.6
Sad06	89.5
Sad07	-
Sad08	78.5
Sad09	-

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Table 2. Matching Percentage with 20 Training images [16] trained 10 times (3 neurons)

Testing Images	Recognition Accuracy (%)
Smile01	92.3
Smile02	71.9
Smile03	94.9
Smile04	96.1
Smile05	91.2
Smile06	65.2
Smile07	87.6
Smile08	86.1
Smile09	87.2
Sad01	89.5
Sad02	86.7
Sad03	84.8
Sad04	93.9
Sad05	96.1
Sad06	97.3
Sad07	69.7
Sad08	99.0
Sad09	76.7

Although the percentage of matching for most individual untrained images also increased, but the percentage of matching for some particular untrained images decreased as the amount of training set increased. The reason for the degradation in p matching percentage is due to the large difference in variation which occurred in the particular images compared to the other images, such as the thickness of the lips or the mimicking of the lips are greatly different compared to others.

Table 3. Matching Percentage with 30 Training images [16] trained 10 times (2 neurons)

Testing Images	Recognition Accuracy (%)
Smile01	88.5
Smile02	61.4
Smile03	99.9
Smile04	85.7
Smile05	88.4
Smile06	62.5
Smile07	79.1
Smile08	89.0
Smile09	90.9
Sad01	89.0
Sad02	92.7
Sad03	91.1
Sad04	74.6
Sad05	98.6
Sad06	92.0
Sad07	80.7
Sad08	93.4
Sad09	91.1

V. CONCLUSION

In conclusion, RBF neural network is used for mouth shape classification. Different sets of training images are compared in order to investigate the performance of RBF neural network. The network is trained with 10, 20 and 30 training sets. The results show successful finding but there are some improvements that can be done to improve the performance and recognition accuracy. This can be done by using more effective feature extraction preprocessing and 3-dimensional modeling. The effectiveness of the neural system can be increased by training the network of the system using matrices array input method.

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