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A Novel Artificial Neural Network and 2dPCA-Based Hybrid Approach for Face Recognition

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Abstract: In this paper, we proposed a novel hybrid approach for face recognition by which the facial images are classified and clustered accurately. In this hybrid face recognition approach, the statistical measure correlation, statistical appearance based face recognition approach two-dimensional principal component analysis (2DPCA), and back propagation neural network (BPN) for classification and recognition are combined together. In our combined approach, first, a detailed correlation study was made on the standard databases such as Yale face database and Facial Recognition Technology face database. On the basis of the correlation test, train set and test set were selected. Then the distance-based feature vectors were extracted using 2DPCA method. By using these distance-based feature vectors, the faces were classified and clustered using well-trained BPN. From the experimental results, our combined approach—correlation-based automatic rearrangement and 2DPCABPN classifier—outperformed our previous approach of Duplicating Facial Images Based on Correlation Study and other statistically based face recognition methods such as Eigenface, kernel principal component analysis, Fischer discriminant analysis, independent component analysis, and 2DPCA, which used kNN, cosine similarity measure, and SVM classifiers.

Keywords: Appearance based; back propagation; classifier; clustering; correlation study; distance matrix; duplicating facial images; Eigenface; Euclidean distance; face recognition; FDA; feature vectors; ICA; kernel PCA; neural network; subjects; 2DPCA

I. Introduction

1.1. Nature of the problem

The traditional method of face recognition involves a new face recognition method or an existing face recognition method tested with standard or newly developed face databases. The databases are used as it is without any shuffle or rearrangement of subjects. The faces of a subject may have a very high or a very low correlation with the faces in the same subject depending on the pose, illumination, and orientation of faces of individuals. During the arrangement of the train set and test set from a face database, if the less correlated images are present only in the test set and if it is not present in the train set, then it result in poorer recognition accuracy.

1.2. Previous work

In the two-dimensional principal component analysis (2DPCA) algorithm (Senthilkumar & Gnanamurthy, 2016a; Yang, Zhang, Frangi, & Yang, 2004), two strategies were mainly used. In the first strategy, first five faces of subjects were selected in the train set and the remaining five in the test set. The second strategy was leave one out strategy. The 2DPCA with kNN classifier did not recognize the low correlated face images. The following standard small face databases such as Yale ("Yale Face Database," 1994), AT&T ("Our Databases of Faces," 2002), and AR (Martinez & Benavente, 1998) were tested.

Further, the face database like Facial Recognition Technology (FERET) ("Color and Gray FERET Database, 1997") consisted of more occluded and outlier face images. In this case, the Duplicating Facial Images Based on Correlation Study (DFBCS) (Senthilkumar & Gnanamurthy, 2016b) produced only 60% to 65% of recognition accuracy. For face databases that contained only frontal face images such as Our Databases of Faces Research Lab (ORL) and Yale, the DFBCS algorithm produced good results, that is, 90% to 95% of recognition accuracy. In this work, kNN or cosine similarity classifiers were used.

Pallabi and Bhavani (2006) tested multiple classifiers and they achieved 96% accuracy rate for ORL database. They combined PCA with Linear Discriminant Analysis (LDA) and used different distant measuring techniques. Oliveira, Koerich, Mansano, and Britto (2011) adopted genetic algorithm for feature selection and they succeeded in that approach. They showed significant improvement in

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dimensionality reduction and achieved 95.2% recognition rate for FERET face database. Le and Bui (2011) replaced kNN classifier with SVM classifier for 2DPCA feature classification. They showed 93% accuracy rate for FERET face database.

Besides kNN and SVM classifiers, in the recent works (Abuzenid & Mahmood, 2016; Kasar, Bhattacharya, & Takim, 2016; Sharma & Kaur, 2016) most of the pattern recognition researchers replaced kNN and SVM classifiers with BPN classifier. They showed a maximum of 97% classification accuracy rate for ORL, Yale, and FERET face databases.

1.3. Purpose

Our aim was to achieve more than the rate obtained by the earlier research works. The software used to test the proposed and existing algorithms were open source software Scilab ("Face Recognition Toolbox Using Scilab Software," 2016; "Scilab Software," 1994; "Scilab Software and Related Materials," 2009; Senthilkumar & Gnanamurthy, 2012, 2016c) and MATLAB. To improve the classification and recognition accuracy, a novel hybrid approach was proposed in this paper.

1.4. Contribution of the paper

According to this method, the existing DFBCS approach was combined with 2DPCABPN (two-dimensional principal component analysis back propagation neural network) classifier. It is called DFBCS–2DPCABPN classifier. In this approach, first, the train set was automatically rearranged using DFBCS algorithm and the distance-based 2DPCA feature vectors were extracted for both train and test set. The BPN was trained using train set feature vectors, and the weight matrices corresponding to the hidden layer and output layer were stored. Using these weight matrices in recognition phase, the BPN (Chakraborty, 2010; Cilimkovic, 2010; Nielsen, 2016;"Tutorial http://cortex.snowcron.com/neural_networks.htm)") classified the faces in the test set. The results obtained confirmed that the proposed hybrid approach performed well for simple, small face databases and also for large complicated face databases.

Our entire work is discussed in detail in the following sections: Section 2 describes our hybrid approach in step-by-step manner. Section 3 explains in detail the DFBCS approach, the steps involved in appearance-based 2DPCA face recognition method and the BPN training and classification. Experimental results obtained for a traditional approach and our approach for standard face recognition algorithms such as Eigenface (one-dimensional PCA) (Turk & Pentland, 1991), Fischer discriminant analysis (FDA) (Belhumeur & Hespanha, 1996; Swets & Weng, 1996), kernel principle component analysis (KPCA) (Yang, 2002), independent component analysis (ICA) (Bartlett, Movellan, & Sejnowski, 2002), and 2DPCA are discussed in Section 4. Section 5 draws conclusions and related future work.

II. Proposed Approach

The first step in this approach is the rearrangement of train set of face database. The rearrangement is based on the correlation study performed on the complete database. If the correlation coefficient of a particular face image is less than the critical value or threshold, then it will be clustered in the train set. Suppose, if the initial train set does not have less correlated face images and they are present only in the test set, it must be duplicated in the train set also. The DFBCS algorithm is discussed briefly in Section 3. Initially, this algorithm is tested for the Yale face database. Then it is extended to test FERET face database.

As a second step, the features are extracted from the train set and test set of FERET face database using 2DPCA. Actually, the projection vectors will not be used for training and testing back propagation artificial neural network (BPANN). Instead, first feature vectors are extracted from the train set. Then the facial images of the train set are projected on feature vectors. The Euclidean distance between the projected feature vectors of the train set is calculated. This is stored in a matrix format and is used to train the BPN. Then the test set facial images are projected on the feature vectors extracted from the train set. Now the Euclidean distance between the projected train set and projected test set feature vectors is calculated. This is stored in a matrix format and is used to test the BPN during the recognition phase.

In the third step, a two-layer BPN is used to classify and to cluster the facial images to their respective classes. As the FERET faces are of size 96 × 64, the 2DPCA feature vector size is 96 × *K*, where "*K*" varies from 1 to 96. The BPN consists of one input layer, one hidden layer, and one output layer. The input layer size depends on the number of face images in the train set. If the number of face images in the train set is 297, then 297 input nodes are present in the input layer. However, the hidden layer size is chosen based on the rules given in the research by Chakraborty (2010), Cilimkovic (2010), Nielsen (2016), and"Tutorial"(http://cortex.snowcron.com/neural_networks. htm). In our application, 100 hidden nodes were used. The

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number of nodes in the output layer depended on the number of clusters or the number of subjects. Here, first 100 subjects were selected from the FERET face database for testing and training. Of the 100 subjects, the facial images of the 11th subject could not be read out. Hence, we used 99 subjects for testing our approach. For 99 subjects, 99 output nodes and 99 target vectors were used.

First phase is the training phase. BPN is trained for the required number of epochs or iterations using the train set feature distance matrix. After the completion of BPN training, the weights of hidden layer and output layer are updated and stored. The detailed steps involved in BPN training and testing are given in Section 3. Later, in the recognition phase, the test set feature distance matrix is applied for only one iteration using the weight matrices obtained in the training phase. The BPN classification is done based on the minimum error (difference between output node NET value and target value) produced by a particular output node for a particular test face image distance matrix.

The block diagram representation of the proposed combined approach is illustrated in Figure 1.

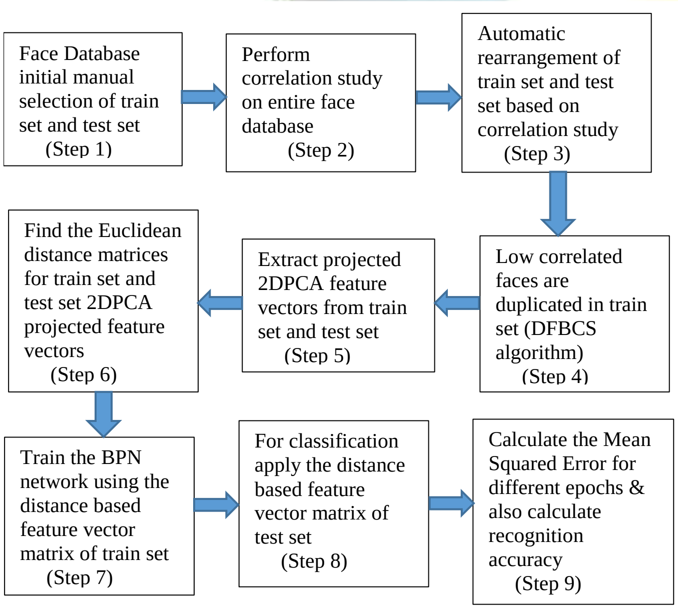

Figure 1. Block Diagram Representation of Duplicating Facial Images Based on Correlation Study (DFBCS)–Two-Dimensional Principal Component Back Propagation Neural Network (2DPCABPN) Classifier.

frontal images. Then it is tested with large face database like FERET, which contains occluded and outlier face images.

The simple Yale face database contains 165 gray scale images of 15 individuals. There are 11 images per subject, one per different facial expression or configuration: center-light, with glasses, happy, left-light, without glasses, normal, right-light, sad and sleepy, surprised, and winking as shown in Figure 2. The FERET face database contains around 11,000 face images for 994 subjects. Of the 994 subjects, 591 are male subjects and 403 are female subjects. For testing the proposed approaches, only first 100 subjects are considered from the database. A sample of the five faces of subject01 is shown in Figure 3.

First, the faces of individuals in Yale database are tested for correlation with mean face of each class. Then the faces are tested for correlation with mean face of complete database. The face image with the lowest correlation with mean face of its cluster is shown in Figure 4 and the face image with the lowest correlation with mean face of whole database is shown in Figure 5. Both these faces belong to subject 6.

The ... cognition algorith... Scilab. A Scilab-based face recognition toolbox ("Face Recognition Toolbox Using Scilab Software," 2016) has been developed for the following face recognition algorithms such as Eigenface, Fischerface, ICA, KPCA, and 2DPCA. Scilab function for automatic rearrangement of faces in a train set from the complete set of face database based on the correlation study is shown in Figure 6.

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(a) (b) (c) (d) (e)

Figure 3. Sample Face Images of Subject01 in FERET Face Database.

Figure 4. Face Image 06 of Subject 06 has Lowest Correlation with Its Cluster Mean.

Figure 5. Face Image 02 of Subject 06 has Lowest Correlation with Mean Face of all

```
function [ ]= trainset(X, threshold, corr_coeff1, corr_coeff2,
                  numimgs)
  //X is the face image to be placed in train set or test set
  //threshold = 0.5 for Yale face database
  //corr_coeff1- is the correlation coefficient obtained for the given face/image with
mean image its own cluster
 //corr_coeff2- is the correlation coefficient obtained for the given face
  //image with mean image of entire database
  //numimgs- number of images in database

for i =1:numimgs
  imgname = getstring(i);
 if((corr_coeff1(i)<threshold)&(corr_coeff2(i)<threshold))
       imwrite(X(i,:,:),'trainset\imgname');
  end if
end
endfunction
```

Figure 6. Scilab Software Function for Automatic Rearrangement of Faces in Train Set Based on Correlation Statistics in Yale Face Database.

2DPCA feature extraction

The 2DPCA is based on 2D Eigen vectors. In this method, the image covariance matrix is a 2D matrix and it is directly calculated from the 2D original image matrices. Therefore, this method has the advantage of easier evaluation of the covariance matrix and requires less time to find out Eigen vectors and Eigen values.

Back propagation neural network classifier

The BPANN is a multilayer network suitable for training with back propagation and can be applied to networks with any number of layers. The BPN is shown in Figure 7, and it uses supervised learning technique, that is, the target is known. In this network, an input vector is applied, and the output of the vector is calculated and compared to the corresponding target vector. The difference is fed back through the network and the weights are changed according to an algorithm that tends to minimize error. For pattern recognition and pattern classification, BPANN is the best and it produces better results.

III. Experimental Results and Discussion

Figure 8(a) shows the MSE obtained after the reconstruction of test images using 2DPCA features. The MSE is evaluated between the original and reconstructed test images. The MSE decreases with an increase in feature size, whereas the time elapsed for reconstruction increases. Figure 8(b) is the plot between feature size versus recognition accuracy and MSE. The MSE decreases with an increase in feature size. However, the recognition accuracy is different. It can be predicted. It is maximum for feature size 96 × 2 and minimum for 96 × 5 as listed in Table 2.

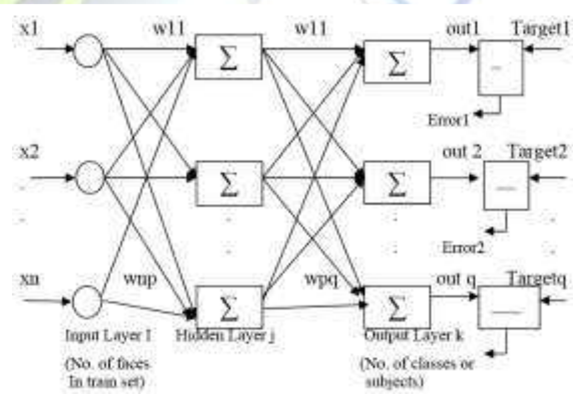

Figure 7. BPN Network Classifier Block Schematic.

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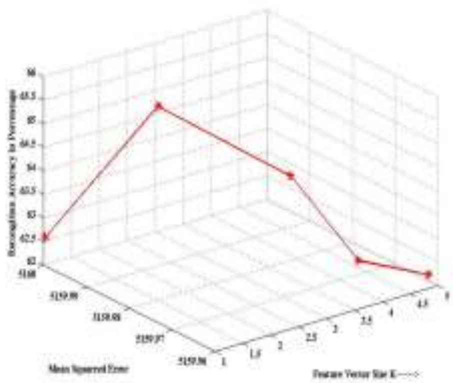

Figure 8. (b) Feature Vector Size vs. Mean Square Error and Recognition Accuracy.

Table 1. Recognition Rate, Mean Square Error, and Elapsed Time Obtained for Different Feature Vector Sizes of Two-Dimensional Principal Component Analysis.

Feature size	Recognition accuracy	Mean square error	Elapsed time in seconds
96 × 1	62.62	5159.999574	28.0910
96 × 2	65.65	5159.986270	29.2460
96 × 3	64.64	5159.968349	36.1150
96 × 4	62.62	5159.965662	41.8140
96 × 5	62.12	5159.962222	43.0230

The 2DPCABPN classifier network is trained for different feature vector size varying from one to five. However, the number of training faces is fixed to 396 and the number of test faces is fixed to 198 for all these five tests. The network is trained for 200 epochs. In Figure 9(a) only seven epochs (from third to tenth epoch) are shown to differentiate the MSE for different epochs. The MSE decreases as the number of epochs is increased. As the feature size increases, the MSE decreases gradually. However, for feature size $K = 4$, it is different. The maximum MSEs are obtained for $K = 1$ and minimum MSEs are obtained for $K = 5$. Figure 9(a) shows the MSEs obtained in the training phase and Figure 9(b) shows the MSEs obtained in the recognition phase. Similar to training phase, $K = 5$ also gives minimum MSEs.

The FERET face database is used to test three standard face recognition algorithms such as Eigenface, KPCA, and 2DPCA using our approach (DFBCS) and traditional approach as shown in Figure 10(a). The results in Table 2 show that the DFBCS-based approach gives better recognition rates for all three different face recognition methods. Figure 10(b) shows that the DFBCS approach gives better recognition accuracy compared with traditional approach. The new combined approach with 2DPCABPN classifier gives almost 100% recognition rate for all the feature dimensions as listed in Table 3.

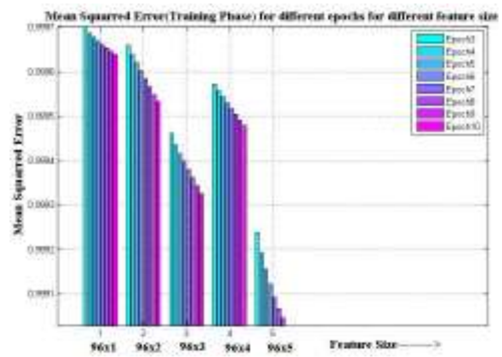

Figure 9. (a) Mean Squared Error Obtained in ... k.

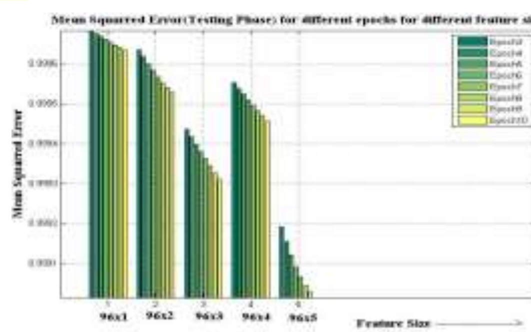

Figure 9. (b) Mean Squared Error Obtained in Recognition Phase in Back Propagation Neural Network.

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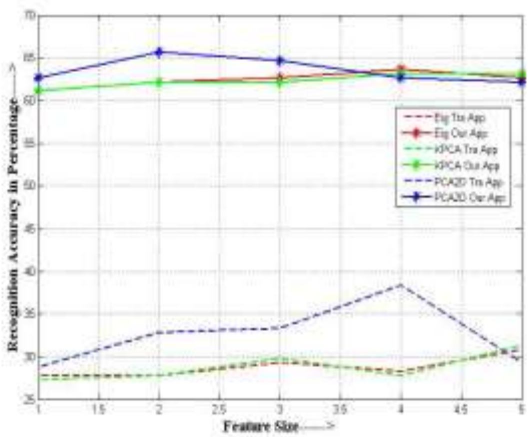

Figure 10. (a) Performance Comparison of Eigenface, Kernel Principal Component Analysis (KPCA), Two-Dimensional Principal Component Analysis (2DPCA) for Traditional Approach, and Duplicating Facial Images Based on Correlation Study (DFBCS) Approach.

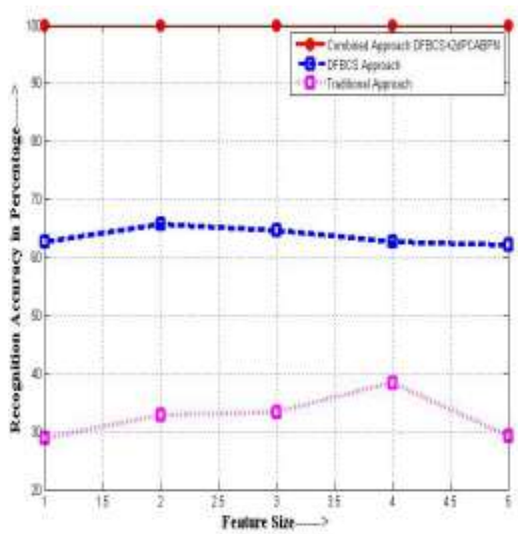

Figure 10. (b) Performance Comparison of Two-Dimensional Principal Component Analysis (2DPCA) for Traditional Approach, Duplicating Facial Images Based on Correlation Study (DFBCS) Approach, and Combined Hybrid Approach.

Table 2. Comparison of Recognition Rate for Different Face Recognition Algorithms for Traditional Approach and DFBCS Approach.

Recognition methods	Recognition accuracy				
	Test 1	Test 2	Test 3	Test 4	Test 5
Eigenface traditional approach	27.77	27.77	29.29	28.28	30.8
Eigenface DFBCS approach	61.11	62.12	62.62	63.63	62.62
Kernel PCA traditional approach	27.27	27.77	29.79	27.77	31.31
Kernel PCA DFBCS approach	61.11	62.12	62.12	63.13	63.13
2DPCA traditional approach	28.78	32.82	33.33	38.38	29.29
2DPCA DFBCS approach	62.62	65.65	64.64	62.62	62.12

DFBCS, duplicating facial images based on correlation study; 2DPCA, two-dimensional principal component analysis; PCA, principal component analysis.

Table 3. Comparison of Traditional Approach with the Proposed Approaches.

Recognition approaches	Recognition accuracy				
	$K = 1$	$K = 2$	$K = 3$	$K = 4$	$K = 5$
2DPCA traditional approach	28.78	32.82	33.33	38.38	29.29
DFBCS + 2DPCA	62.62	65.65	64.64	62.62	62.12
DFBCS + 2DPCA + BPN classifier	100	100	100	100	100

BPN, back propagation neural network; DFBCS, duplicating facial images based on correlation study; 2DPCA, two-dimensional principal component analysis.

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Figure 11(a) shows the MSE obtained for different learning epochs. MSE is evaluated for the traditional approach and proposed approach. In the traditional approach, the train set and test set are not disturbed and they are used without any shuffling and rearrangement in FERET database. In the DFBCS approach, the train sets are altered on the basis of the correlation study performed on the entire dataset. In both these approaches, features (Euclidean distance between projected feature matrices) are extracted using 2DPCA algorithm and trained and classified using BPN classifier. The results show that the MSE obtained for the proposed approach is minimum compared with the MSE obtained in the traditional approach for the same iteration.

The proposed approach based on the classification gives minimum MSE not only in training phase but also in testing phase (recognition phase) as shown in Figure 11(b). The plot of change in weight gradient between hidden layer weights and output layer weights is shown in Figure 11(c). In the proposed approach based on 2DPCABPN classifier, the change in weight gradient is significant even after 250 iterations, whereas in the traditional approach based on 2DPCABPN classifier, the weight gradient gets saturated after 170 epochs.

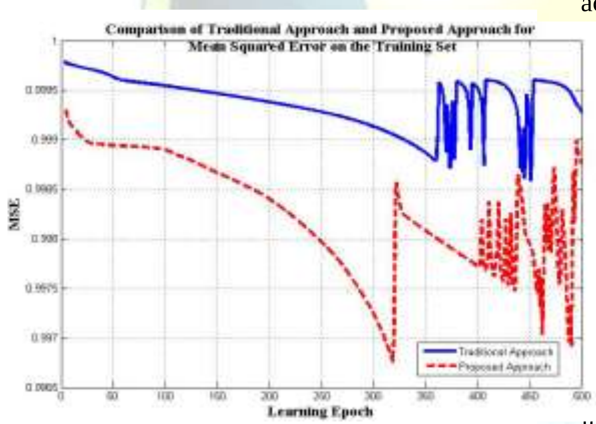

Figure 11. (a) Comparison of Mean Squared Error Obtained for Different Epochs in

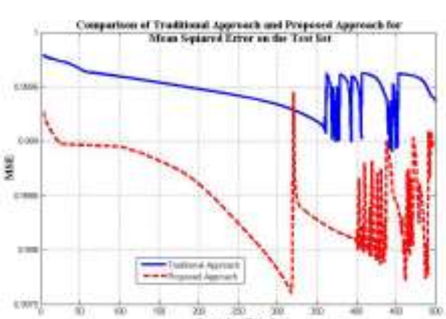

Figure 11. (b) Comparison of Mean Squared Error Obtained in Recognition Phase.

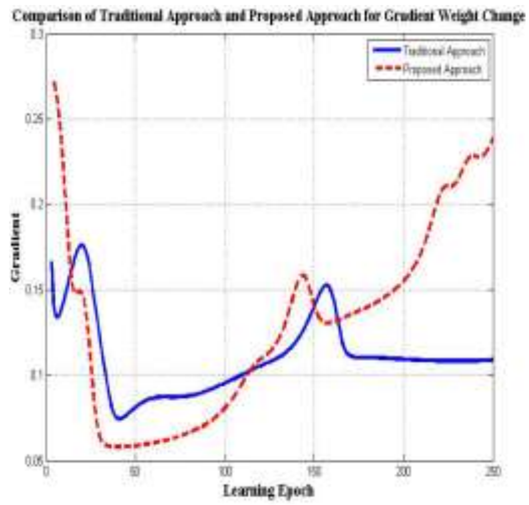

Figure 11. (c) Comparison of Weight Gradient Change for Traditional and Proposed Approaches.

From the results, it is justified that our DFBCS approach was better than the traditional approach of database arrangement. Our approach showed better recognition accuracy.

The DFBCS approach showed better performance for mple face databases like Yale, which contained only frontal ice images. For large databases like FERET, which ontained more outlier faces, it showed moderate erformance. The combined approach, DFBCS + 2DPCA + PN classifier, discussed in this paper showed better erformance for both Yale and FERET face databases with lmost 100% classification accuracy. Further, we had eveloped an algorithm and program code using Scilab oftware for automatic rearrangement of train and test set ice images based on the correlation study.

Our future work involves reducing the dimensionality of ace image using wavelet transform. This technique automatically reduces 2DPCA feature vector size. As BPANN structure depends on the 2DPCA feature vector size, small feature vector size will reduce the ANN network complexity and thereby computational complexity.

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