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Facial Expression Recognition at Different Dimensional Subspace Feature Dataset

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ABSTRACT: In this paper, performance of subspace methods for achieving expression recognition and classification has been evaluated. Enhancement of Gabor magnitude and phase parts have been carried out by fusing Gabor filter with geometrical feature vectors. LDA based algorithms have been developed to recognize seven different facial expressions such as happy, neutral, angry, disgust, sad, fear and surprise using JAFFE database. Performance of subspace methods have been measured for different dimensions by proposing kernel local and global feature preserving symmetrical weighted discriminant analysis methods against dimensional reduction of fused dataset. Proposed algorithm yields better performance compared to state of art approaches.

KEYWORDS: Feature extraction, Gabor filter, subspace, class discrimination, expression recognition.

I. INTRODUCTION

Facial expressions deliver rich information about human emotion and play an essential role in human communications. There are many approaches have been proposed for facial expression analysis from both static images and dynamic images in the literature. Facial expression provides an important behavioral measure for studies of emotion, cognitive processes, and social interaction. Intuitive facial expression recognition constitutes the main theoretical contribution to the video processing application [1]. In the beginning of this work, face detection and pre-processing has been carried out by removing unwanted information from the static raw input face images. Geometrical and holistic features have been extracted from image dataset and feature level fusion has been carried on these extracted features. Several discriminative based face recognition methods are not able to solve the singularity matrix problems during dimensional reduction or projection of subspace in non linear region and also not able to preserve both global and local face features during class discrimination.

This research work optimizes the problem of singularity matrix of within scatter matrix by introducing symmetrical weights on principal components in intermediate dimensional reduction stage by equally distributing eigen vectors before projecting the subspace of Fisher discriminative feature space. Along with this goal this work also supports preservation of local and global discriminative features of the image dataset while projecting the face space into subspace for dimensional reduction under nonlinear region. Inially face detection has been carried out using static image face detection method. Section II presents related work, Section III describes proposed frame work. Section IV presents experimental results showing results of images tested. Finally, Section V presents conclusion.

II. RELATED WORK

Wang and Sun [3] proposed multiple kernel local Fisher discriminant analysis (MKLFDA) which produces dimensional reduction of nonlinear discriminant features of face image dataset. Ming et al. [4] introduced spectral regression kernel discriminate analysis (SRKDA) which is based on regression and spectral graph analysis. Wang et al. [5] proposed semi supervised kernel marginal Fisher analysis (SKMFA) in which author suggested that singularity problem can be avoided by non linear structure captured by the data dependent kernel based on labelled and unlabeled data. Rahulamathavan et al. [6] developed facial expression recognition system with encrypted domain using Local Fisher discriminant analysis (LFDA). Authors are suggested there was a challenge to work with encrypted domain even



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if there is a not enough or good recognition rate for unencrypted domain. This method was applied to JAFFE and MUG database and achieved 94.37% and 95.24% recognition rates. Shih et al. [7] worked on 2DLDA and support vector machine and tested with JAFFE database and they were found 95.71% recognition accuracy using leave one out classification strategy and 94.13% using cross validation strategy. Yu and Yang [8] have developed a direct LDA algorithm (DLDA) for high dimensional data with application to face recognition that diagonalises simultaneously the two symmetric matrices. The key idea of their method is to discard the null space from scatter matrices. But DLDA is more scalable and more expensive for computation. As pointed out by Yu and Yang [8] the traditional LDA procedure takes the reverse order and consequently discards the null space of within scatter matrix which contains discriminative information. Ye and Li [9] proposed a two-stage LDA method, namely LDA/QR, which aims to overcome the singularity problems of classical LDA, while achieving efficiency and scalability simultaneously.

Vitomir Struc and Nikola Pavesi (2010) [12] defined about oriented Gabor phase congruency model by separating magnitude and phase parts of Gabor filter. These filters can serve as excellent band-pass filters for onedimensional signals. Fasel et al. [13] presented a systematic analysis of Gabor filters banks for detection of facial landmarks. Dongcheng and Fang (2013) [14] worked on Gabor wavelets and extracted magnitude and phase parts features separately. In their approach both feature datasets were fused together. Principal Component Analysis (PCA) and 2DPCA methods were implemented for feature dimension reduction and they achieved 91% and 94% respectively for JAFFE dataset. Fazli et al. [15] presented a person independent facial expression recognition method based on Gabor wavelets and dimensional reduction was carried out by combining PCA and Linear Discriminant Analysis (LDA) methods. They got 89% accuracy for Cohn-Kanade database.

Abdulrahman et al. [16] introduced an approach which is implemented using Gabor wavelet transform with PCA and LBP. This hybrid approach resulted 90% average recognition rate for JAFFE database. Goyani et al. [17] proposed a PCA for face recognition and facial expression recognition. They found recognition rate is 81.36% for CSU dataset and 85.5% for ATT dataset. Jin and Ruan (2009) [18] did the work on combination of Gabor wavelets and supervised locality preserving projections (SLPP) for face recognition. They designed first Gabor filter to extract the features from the whole face images, and supervised locality preserving projections was used to train the labels and dimension reduction, which is improved by two-directional 2DPCA to eliminate redundancy among Gabor features and achieved 82% to 87.50% of recognition accuracy. Samad et al. [19] developed and focused on the algorithm to recognize the expressions using parameters used for Gabor filter design. They used Gabor filter for face recognition and down sampled the Gabor feature vectors. The dimensions of feature vector were reduced using principal component analysis. Classification using SVM claims 81.7% recognition rate for FEEDTUM database. Wang et al. [20] proposed an effective recognition technique using Principle Component Analysis and Support Vector Machine classifier. Liu and Wechsler [23] concluded that ICA outperforms PCA for face recognition, and Moghaddam [24] claims that there is no statistical difference in performance between the PCA and ICA. In a recent study with visible light and infra-red images, Socolinsky and Salinger [25] reported that ICA outperforms PCA on visible light images. Uddin et al. [26] have shown ICA and enhanced ICA recognizes the expression with 60.4% and 65.8% accuracy.He and Niyogi [27] introduced the Locality Preserving Projections (LPP) as when the high dimensional data lies on a low dimensional manifold embedded in the ambient space. Zheng et al. [28] proposed supervised locality preserving projection (SLPP), using class labels of data points to enhance its discriminant power in their mapping into a low dimensional space. Weiwe et al. [29] proposed two dimensional discriminate locality preserving projections (2D-DLPP), which benefits from three techniques, i.e., locality preserving projections (LPP), image based projection and discriminant analysis. All these subspace approaches not able to provide efficient class discrimination of images. Figure 1 shows the proposed framework.

III. PROPOSED FRAME WORK

1. In the beginning required face regions were detected from raw input images. Then all the images from JAFFE database have been resized and cropped. Image database have been created.

2. Texture features and geometrical feature have been extracted from train database images and fused together. Feature level fused dataset have been created. (Dimensions of both features are added.)

3. From each expression group one image has been selected and test database have been created. Second step is repeated for test dataset also.



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4. Subspace methods has been implemented on both trained and test database image sets.

5. SVM classifier has been used to classify the expressions.

6. During testing one test image was inputted from each expression and every time highest recognition rate have been noted. This procedure is repeated for each one expression image from each group of expression. Finally average value of overall recognition rate, classification time and correct and wrong recognition rates have been noted. Dimensional reduction value was chosen for higher overall recognition rate.

7. Steps 2 to 6 have been repeated for different values of Gabor filter parameters (m and n) for different dimensions of feature datasets.

8. MATLAB 8.1 (R2013a) version has been used to code the entire system of facial expression recognition.



Figure 1. Flow diagram of proposed frame work

IV. RESULTS AND DISCUSSIONS

In this work, Japanese Female Facial Expression (JAFFE) database was used for experiment. Figure 2 shows cropped samples of JAFFE database. Total 210 images were cropped into 111x126 size. Only required areas like mouth nose, eyes and chin areas has been considered during face detection for extraction of texture features and rest of the part was removed. Features of small portion of forehead portion was also considered.



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Figure 2: Sample pre-processed JAFFE images

To analyze the performance of subspace approaches JAFFE, database have been tested. Approaches like CEGKPCA, CEGLPP, CEGFLDA, CEGKLFDA, CEGKLFDA, CEGKLSWFDA and CEGKGLSWFDA has been compared. Baseline feature vector dimensional parameters used to evaluate the performance of subspace approaches are given in Table 1.

Table 1 Baseline feature vector dimensional parameters used to evaluate the performance of subspace approaches for IAFFE database

JATTE database								
No. of	No. of	Gabor	Image size	Gabor filter	Geometrical	Combinational Gabor		
scales	orientations (n)	filter size	(a×b)	feature vector	feature vector	feature vector		
(m)		(GF _{mn})		dimension	dimension	dimension (CEG _{FVD})		
				(GF _{FVD})	(G _{FVD})			
5	4	20	111×126	279720	16	279736		
3	8	24	111×126	335664	16	335680		
3	4	12	111×126	167832	16	167848		
5	8	40	111×126	559440	16	559456		

For CEGLPP, CEGKPCA CEGLFDA, CEGKLFDA, CEGKLSWFDA and CEGKGLSWFDA algorithms nearest neighbor number k has been set to 7. Where the value of α was set to be 0.5. The overall expression recognition rates for JAFFE database is shown in Table 2.

Subspace approaches	Overall facial expression	Classification time in	Dimension reduction feature
	recognition rate in	(sec)	vector (DR _{FV})
	(%)(OFERR)	(CT)	
CEGPCA	82.35	1.012	147
CEGICA	85.03	1.245	147
CEGKPCA	87.52	1.045	147
CEGFLDA	90.45	0.994	126
CEGLPP	88.08	1.010	147
CEGLFDA	93.45	0.997	147
CEGKLFDA	95.83	0.982	126
CEGKLSWFDA	97.14	0.929	105
CEGKGLSWFDA	99.05	0.847	105

Table 2 Performance of subspace approaches at m=5, n=8 for JAFFE database

Overall expression recognition rate for JAFFE database is found to be 97.14% with dimensional reduction 105 for CEGKLSWFDA approach. It has been also noted that for JAFFE database the recognition accuracy is 99.05% with dimensional reduction 105 with less classification time for CEGKGLSWFDA approach.

Figure 3, shows the comparison of overall recognition rate for expression recognition with respect to dimensional reduction values of proposed fused feature vector dataset of different subspace approaches for JAFFE database.



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Figure 3: Comparison of Overall facial expression recognition rate Vs Dimensional reduction of different linear and nonlinear subspace approaches at m=5 and n=8.

Table 3, Table 4 presents confusion matrix of JAFFE, databases for using CEGKLSWFDA and CEGKGLSWFDA subspace approach using SVM, "Leave One Out Technique" in (%) at m=5 and n=8 Gabor parameters. From Table 3, it is noted that anger, happy and fear expression recognition rate is 93.33% for CEGKLSWFDA approach. Probably it is due to confusion with sad and disgust expressions. For CEGKGLSWFDA subspace approach using SVM, "Leave One Out Technique" in (%) at m=5 and n=8 Gabor parameters, it has been also noted that from Table 4 for JAFFE database happy expressions recognition rate is 93.33%. But remaining expression recognition rate is 100%. Probably it is due to confusion with sad and disgust expressions.

Table 3 Confusion matrix of JAFFE database using CEGKLSWFDA subspace approach using SVM, "Leave One Out technique".

	AN	DI	HA	FE	SA	SU	NE
AN	93.33%	6.67%	0	0	0	0	0
DI	0	100%	0	0	0	0	0
HA	0	0	93.33%	0	6.67%	0	0
FE	0	0	6.67%	93.33%	0	0	0
SA	0	0	0	0	100%	0	0
SU	0	0	0	0	0	100%	0
NE	0	0	0	0	0	0	100%

Table 4 Confusion matrix of JAFFE database using CEGKGLSWFDA subspace approach using SVM, "Leave One Out technique".

	AN	DI	HA	FE	SA	SU	NE
AN	100%	6.67%	0	0	0	0	0
DI	0	100%	0	0	0	0	0
HA	0	0	93.33%	0	6.67%	0	0
FE	0	0	6.67%	100%	0	0	0
SA	0	0	0	0	100%	0	0
SU	0	0	0	0	0	100%	0
NE	0	0	0	0	0	0	100%



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From the results it has been noted that proposed feature level fusion improves the recognition rate using CEGKLSWFDA and CEGKGLSWFDA approaches by consistently outperforming the CEGKPCA, CEGLPP, CEGFLDA, CEGLFDA and CEGKLFDA expression recognition approaches. This work clearly analyzes that CEGFLDA algorithm performs comparatively better than CEGLPP algorithm. It demonstrates that discriminative features make an efficient recognition using class label information. Although the CEGLFDA algorithm outperforms CEGKPCA, CEGLPP algorithms by using both local subspace structure and class label information, it is still a linear algorithm and is in adequate to describe the nonlinear face image space due to high variability of the image content and style. Therefore it performs worse and weak than the kernel based KLFDA algorithm. Confusion matrix was derived from SVM_RBF kernel based using "Leave One Out "strategy. It demonstrates the correct and misclassification of expressions.

V. CONCLUSIONS

The performance of all the subspace approaches are found to be better at m=5 and n=8, Gabor filter parameters. For other values of m and n overall recognition rate, correct recognition rate of expressions and classification time measures are found to be not good enough to improve the performance of recognition.

CEGKLSWFDA approach is tested with JAFFE dataset, the reduced dimensionality of feature vector is found to be 105 for 213 images, For JAFFE database over all accuracy rate of recognition is 97.14%. Another approach CEGKGLSWFDA finds improvement in performance of both recognition of expressions and dimensional reduction compare to other related approaches. Due to preservation of global and local structure of images, loss of information has been reduced. It would cause the improvement in global and local feature preservation for scatter matrices while discriminating the classes of different expressions. Dimensional reduction is found to be better compare to earlier approaches. For JAFFE database overall expression recognition rate using CEGKGLSWFDA approach is found to be 99.05%.

Individual correct expression recognition rates are also has been improved in both CEGKLSWFDA and CEGKGLSWFDA approaches as mentioned in our earlier work [32][33]. Preservation of global and local image content preservation has been carried out during dimensional reduction or projection of high dimensional space as well as discriminating the image features. Baseline approaches like CEGPCA and CEGICA preserves the global structure of the image space but not able to provide the discrimination of classes of different expressions. CEGFLDA baseline approach is not able store global information. CEGLPP approach is able to preserve the local structures of image space but not suitable for class discrimination of expressions. Compare to these approaches CEGLFDA and CEGKLFDA approaches finds significant role for preservation of local structures and but still not able to provide complete solution for efficient class discrimination due to problem of singularity in scatter matrices. Proposed approach improves the performance of CEGKLFDA approach regarding overall and correct recognition rate of expressions. Proposed approach also finds more effective for dimensional reduction and classification of expressions. Elimination of zero valued principal components by solving the problem of singularity scatter matrix proposed algorithms consistently outperforms the CEGLFDA and CEGKLFDA approaches. Although the CEGLFDA algorithm outperforms CEGKPCA, CEGFLDA, CEGLPP algorithms by using both local subspace structure and class label information, it is still a linear algorithm and is in adequate to describe the nonlinear face image space due to high variability of the image content and style. Therefore CEGLFDA performs worse and weak than the kernel based KLSWFDA algorithm.

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