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# Multi-View Facial Expression Recognition Based on Group Sparse Reduced-Rank Regression

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## ABSTRACT

*A Group Sparse Reduced Rank Regression (GSRRR) to describe the relationship between multi-view facial feature and expression of class label vectors. GSRRR Automatically select the optimal sub region of a face and to contribute the expression recognition. Here an efficient algorithm using Augmented Lagrangian Multiplier(ALM) to solve the optimization problem. Group Sparse Reduced-Rank Regression model to describe the relationship between multi-view facial feature and expression of class label vectors. GSRRR automatically select the optimal sub regions of a face and to contribute the expression recognition.*

**Key terms: Multi-view facial expression recognition, group sparse reduced-rank regression (GSRRR), sparse reduced-rank regression model (SRRR), reduced-rank regression model (RRR).**

## 1. INTRODUCTION

The recognition of human's emotion from facial expression images has become one of the most popular research topics in computer vision and pattern recognition. A commonly used facial expression recognition approach is to classify each given facial image into the basic expression types, e.g., happy, sad, disgust, surprise, fear and angry, defined by Ekman and Friesen [1]. Overall, the facial expression recognition methods can be roughly partitioned into two types, namely, the classifier based approaches versus the regression based approaches. The former ones usually choose a set of facial feature vectors to train a classifier, e.g., linear classifier, support vector machine (SVM) [2], or adaboost classifier [3], and then carry out the expression classification of the test facial images based on it.

Different from the classifier based approaches, the regression based ones do not directly train a classifier. The first attempt to handle the non-frontal facial expression recognition was conducted by Hu et al. [7]. The authors used the 2D displacements of 38 facial landmark points around the eyes, eye-brow and mouth as the facial features. Then, here used various classifiers to evaluate the facial expression recognition accuracies of the extracted features.

Their experiments on the BU-3DFE facial expression database [10] showed, when the facial view is fixed at 45 degree, the lowest average error rate was achieved. In [8], the authors used three kinds of features, i.e., the scale invariant feature transform (SIFT) feature [9], the local binary patterns (LBP) feature [8], and the histogram of Gaussian (HOG) feature [4], to respectively investigate the multi-view different angle facial expression recognition problem.

The experimental results showed that the lowest average error rate corresponds to the 30 head pose when the locality preserving projections (LPP) method [2] with SIFT feature (SIFT+LPP) is utilized. Zheng et al. [9] also used the SIFT feature to investigate the non-frontal view facial expression recognition.

Similar to [8], the 2D facial images

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corresponding to the five yaw facial views are generated and a set of SIFT features are extracted from 83 landmark points to represent each facial image. Their experiments showed that the lowest average error rate is achieved when the head pose is 45. Rudovic et al. [4], [10] presented a pose-invariant method to deal with the non-frontal facial expression recognition problem.

In this method, 39 landmark points are located from each non-frontal head pose and then normalized to the frontal one through coupled scaled Gaussian process regression (CSGPR) model. Experiments of the facial expression recognition are finally carried out based on the normalized 39 landmark points.

For a query face image, to propose the so-called intra-class variation image which is generated by using the training face expression images. The intra-class variation image is similar to the query face image in terms of identity and illumination.

To extract expression features, to subtract the intra-class variation image from the query face image. The expression difference is emphasized while intra-class variation due to identity and illumination is reduced. It demonstrate that the use of the intra-class variation images can improve facial expression sparsity, which leads to high FER performance. A facial expression is generally defined by begin and end with a neutral state [15]. For this reason, in some FER methods, the difference between neutral face and query face was used as expression feature [7], [16], [17].

However, face image of neutral state is not always available in reality [15]. To cope with this issue, to investigate that expressive (or non-neutral) state can be used for extracting facial expression. Expressive state could also be useful for reducing identity information and emphasizing the expression of a query face image.

Experimental results show that difference between query face image and intra-class variation image of a non-neutral expression can yield similar discriminating power to difference using intra-class variation image of neutral expression. Further, differences made by all expression states in training images are able to significantly improve FER performance.

## 2. EXISTING METHODOLOGY

In existing method using a Sparse Reduced Rank Regression (SRRR) is used. According to the facial action coding system (FACS) developed by Ekman et al., the facial regions around the eyes and mouth contain much more action units than other regions of a face.

## 3. IMPLEMENTATION METHODOLOGY

In GSRRR model, the responses are the expression class label vectors, whereas the model predictors correspond to multi-view facial feature vectors.

### 3.1 GSRRR has two major factors.

The first one may attribute to the use of multi-view facial feature fusion strategy in this system.The second factor may attribute to the optimal region selection ability of GSRRR. The second is a expression recognition method.



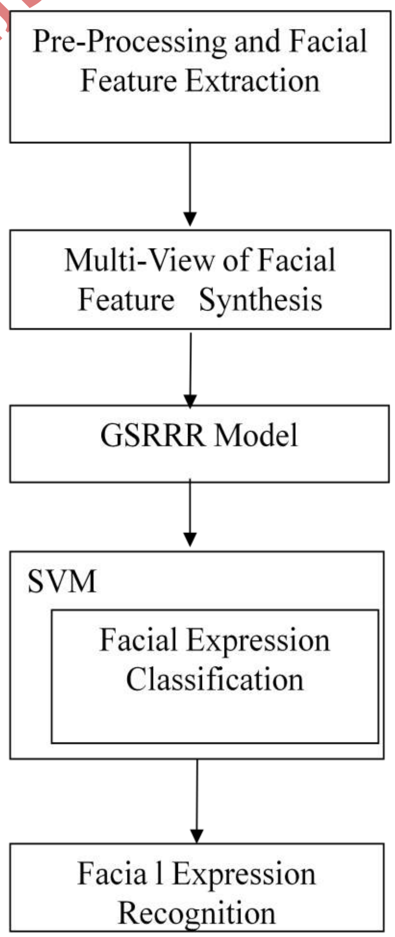


**Fig 1: Block diagram for GSRRR method**

## 4. METHODOLOGIES USED

The multi-view face recognition method consider the following process are: preprocessing, feature extraction, multi-view vector of facial feature, group sparse reduced-rank regression (GSRRR) model, SVM, facial expression recognition.

### 4.1 Preprocessing

In this part image going to done as per which calculation size. And crop the image by skin detection algorithm. Create the Eigen vector in to the cropped image.

### 4.2 Feature extraction

This part mainly focuses on extracting facial features from multi-view facial images. Two kinds of facial features (sparse SIFT feature and LBP feature) will be investigated in this part. Next to the feature extraction procedure is the use of Linear Discriminant Analysis (LDA) method. All the transformed feature vectors belonging to the same facial image are then concatenated into a vector to represent the facial image.

### 4.3 Multi-view vector of facial feature

The basic idea is to use the Kernel Reduced-Rank Regression (KRRR) model for describing the relationship between the facial feature vectors of different facial views. In the KRRR model, the responses are the feature vectors corresponding to another facial view. The predictors are the feature vectors from the given facial view. By utilizing the KRRR model, a feature vector from any one of the given facial views can be used to estimate the feature vectors of all other facial views.

### 4.4 Group Sparse Reduced-Rank Regression (GSRRR) model

In this stage, the GSRRR model is used to describe the relationship between the expression class label vectors and the corresponding synthesized multi-view facial feature vectors. To solve the regression coefficient matrices of GSRRR.

### 4.5 Support Vector Machine (SVM)

The Linear SVM classifier is a separating hyper-plane. Most "important" training points are support vectors; to define the hyper-plane. Quadratic optimization algorithms can identify which training points $x_i$ are support vectors with non-zero Lagrangian multipliers. Both in the dual formulation of the problem and in the solution training points appear only inside dot products.

### 4.6 Facial expression recognition

This part focuses on the expression recognition for testing facial images. First extract the facial features and then perform the head pose estimation, where LDA and linear classifier are used for this purpose. Then synthesize multi-view facial feature vectors based on testing facial feature vector and use them as the model predictors of the GSRRR model. Finally the model response corresponding to the expression class label vector is calculated and the expression category of the testing facial image can be obtained.

### 4.7 Testing Stage

Similar to the training stage, the testing stage also includes the operation of facial feature extraction, dimension reduction of feature vectors and multi-view feature vector synthesis. Moreover, there are two additional operations in the testing stage. One is the head pose estimation and the other is the class label vector prediction. The result of the head pose estimation will be used to select appropriate KRRR model parameters for synthesizing multi-view facial feature vectors. Suppose that It is a testing facial image. Then after dividing the facial image into J facial regions, here apply the LBPu2 operator to each facial region and obtain J facial feature vectors f j t (j ¼ 1; . . . ; J). These feature vectors will be used for the head pose estimation.

### 4.8 Head Pose Estimation

To estimate the head pose of the testing facial image, here propose to use the combination of principal component analysis (PCA) and linear classifier to this goal. Let eir ¼ For all of the feature vectors eir (i ¼ 1; . . . ; V ; r ¼ 1; . . .;N), to train a PCA projection matrix Wpca: Then, both training and testing feature vectors are transformed to lower-dimensional feature space via the PCA matrix Wpca.

Finally, the head pose classification is carried out by using linear classifier on the transformed feature vectors. In this case, it can obtain the head pose classification result of the testing facial image.

### 4.9 Multi-View Feature Vectors Synthesis

After estimating the head pose of the testing facial image, here select the corresponding optimal LDA transformation
matrix obtained in the training stage to reduce the dimensionality of the LBPu2 feature vectors f j t . Without loss of generality, to assume that the estimated head pose of the testing facial image is i. Then, the optimal LDA transformation
matrix corresponding to the j-th facial region is Wij.

### 4.10 Facial feature extraction

Feature extraction plays a crucial role for a facial expression recognition system. Generally, the facial expression feature can be roughly divided into geometric feature and appearance feature. One of the most popular methods of obtaining geometric feature is to use the coordinates of facial landmark facial points or the displacements among them as the facial feature. The appearance feature aiming to capture the expression information from the skin textures can be extracted from
either the whole face image or some specific face regions.

In this method is used to the sparse SIFT feature extracted from 83 landmark facial points of a facial image as facial feature, which can be seen as the mixture of geometric feature and appearance feature. The experiments on BU-3DFE database confirmed the high recognition accuracy of sparse SIFT feature in contrast to most of other features reported in the literatures. Nevertheless, it should be noted that the extraction of the sparse SIFT features requires the accurate landmark facial points location, which is still a challenging work for non-frontal facial images.

The region-based feature extraction approach in multi-view facial expression recognition. It is divided the whole face image into a set of grids, and then extracted the facial features, e.g., LBP, from each grid region. All the facial features are finally concatenated into a high-dimensional feature vector to represent the facial image. The avoidance of the feature points location makes this approach very appropriate for the multi-view feature extraction problem.

## 5. EXPERIMENTAL RESULTS

GSRRR with the ones achieved , where the average recognition accuracy of GSRRR is obtained by averaging the recognition results over the 10 trials of experiments.



FIG 2(a) FIG 2(b)





FIG 2(c) FIG 2(d)


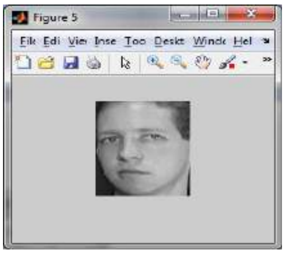


FIG 2(e)

FIG 2(f)

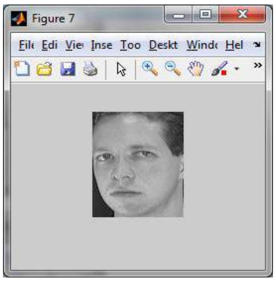


**FIG 2(g)**


**FIG 2(h)**


**FIG 2(i)**

FIG 2 (a,b,c,d,e,f,g,h,i) represents the different view expressions. The accuracy results is analyzed by the performance metrics

## 6. CONCLUSION

In GSRRR model, the responses are the expression class label vectors, whereas the model predictors correspond to multi-view facial feature vectors. Experiments on both Multi-PIE and BU-3DFE facial expression databases are carried out to evaluate the recognition performance of this method. For the Multi-PIE database, the LBPu2 features are extracted and used as the facial features. For the BU- 3DFE database, to use LBPu2, sparse SIFT and landmark points as facial features to carry out the experiments. The experimental results on both databases showed that the method achieves competitive recognition performance compared with the state of the art methods under same experimental settings and same facial feature.

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