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# A REVIEW: SPARSE REPRESENTATION USING MULTIPLE KERNEL APPROACH FOR EFFICIENT AND ACCURATE FACE RECOGNITION

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***Abstract* - This review paper highlights accuracy of MKL-SRC(Multiple Kernel Learning Sparse Representation Classification) algorithm on different image classification databases like AR , Extended Yale B, RGBD. Different classification techniques are reviewed. The main objective of MKL-SRC is to classify images in environment having occlusion and noise. MKLSRC using non linear kernel with kernel trick where L1 minimization is used to find sparse representation.**

***Keywords*— Sparse representation-based classification, multiple kernel learning, occlusion, non linear kernel, L1 minimization, kernel trick.**

## I. INTRODUCTION

As security concern is increasing day by day, face biometric is not sufficient to meet these security requirement. For that classifiers are effective alternative in terms of accuracy, costing, hardware and software requirement. In different kind of applications like face biometric, cancelable iris biometric, automatic target recognition, denoising, deconvolution, image inpainting, pattern recognition different classifier plays a very important role to classify images. In every application, images may or may not be noise free. So for feature extraction from these images classifiers are required. Various classifiers such as KNN (K Nearest Neighbour), SVM (Support vector machine), SRC (Sparse representation classifier) are available for classification as compared to traditional classifier, Sparse representation classifier shows better result [6]. Even by using kernel with support vector machine and k nearest neighbor higher accuracy is not achieved as compared to SRC. In case of background clutter, it is difficult to recognize images containing various semantic information. Due to different features of sparse representation it is widely used in compression, acquisition and reconstruction of signal. As requirement of various application increasing, classifiers are undergoing various changes from algorithm and theory. Simple SRC method cannot properly represent nonlinear structure of data. For representation of nonlinear structure of data efficiently data mapped to higher dimension feature space. Selection of kernel function and its parameter is important issue in training when kernel sparse representation classifier method is used for classification [6] to improve sparse representation in terms of accuracy and efficiency. Dimension reduction techniques like feature selection and feature extraction are used. Feature selection methods are laplacian score, pearson correlation coefficient and feature extraction method is principle component analysis.

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The review is organized as follows: the model of different classifier representation is discussed; in Section I. Related work is presented in section II. In section III proposed methodology is presented. In section IV, conclusion and set of remarks presented at the end of the brief.

## II. RELATED WORK

Different classifiers that are used for classification purpose are as follow:

Problems occurring in face recognition is to extract feature from noisy, corrupted face images. Based on L1 minimization sparse representation algorithm presented [1] which solves issue of noisy environment. This paper concludes that number of features and proper sparse representation are more important than choice of feature. Also comparison of recognition rate on Extended Yale B database and with partial face features for different classifiers are discussed.

Challenges occurring during face and iris recognition like security, privacy etc.[2] are discussed. To reduce computational complexity and feature dimension greedy pursuit algorithm is proposed. As issues like sparse concentration index, selection performance measurement are addressed. This paper also concludes that sparse representation along with random projection recognize face and iris recognition securely.

Efficient optimization algorithm, dictionary construction, structure preserving dimension reduction techniques used in SRC to overcome the problem of complexity are discussed [3]. Hierarchical sparse coding framework proposed to reduce the expensive computational during optimization. Residuals on different category by using L1 minimization performance of different classifier with feature extraction and feature selection methods are discussed. Experimental results verifies that principle component analysis with sparse representation classifiers are effective in case of face data set.

Effect of parameters like patch size, dictionary size, sparsity level on multiple sparse representation are discussed [4]. Performance of support vector machine, sparse representation classifier , K nearest neighbor classifier on application like texture images, lumen segmentation in carotid artery magnetic resonance imaging(MRI), bifurcation point detection in carotid artery MRI are compared. Experimental result shows that the redundancy is removed by multiple sparse representation classifier, more effectively is compared to other classifier.

Performance of classifier increases with the use of kernel trick in addition with sparse representation is discussed [5]. This paper presents accuracy of classifier in application like computer vision and machine learning task. Experimental result shows that discriminative structure analysed in more detail by using kernel than simple sparse representation.

Classification accuracy on dataset like RGBD, AR, Caltech 101 with respect to multiple feature is given [6]. Graphical representation of convergence of kernel weight with respect to the iteration is presented. Compared to other classifier disadvantage is increase in cost of computation. Sparse representation classifier, kernel SRC, non linear SRC techniques are discussed. Experimental results on various databases have shown to produce MKL-SRC as effective classifier.

### A. *Classifier Performance*

Classifier accuracy is more in sparse representation classifier than other classifiers in a trade off computational complexity. To reduce computational complexity cost dimension reduction technique is used. But it did not affect the performance of system. So sparsity of system reserved along with nonlinearity handling.

In SRC classification accuracy decreases for non linear data. To solve this problem, kernel SRC is used which uses kernel trick along with SRC. But it results into over fitting. So multiple kernel learning SRC used with multiple kernel and due to that classification not affected. Classification method like SVM, SRC and KSRC does not give optimum mark accuracy. So new method proposed is multiple kernel learning sparse representation classifier. Techniques used by KNN classifier is nearest neighbor while that by SVM is hyperplane. SRC use only sparse representation. SRC and MKLSRC uses sparse representation along with kernel trick.

### B. *Limitation And Challenges Of Classifier*

Traditional classifier does not classifies upto the mark in case of image database and real images which are not in the linear form. Also as compared to sparse representation classifier they are not robust to noise and variation to illumination etc. Time required for training in multiple kernel learning sparse representation classifier required is high. Due to that computational complexity and time required for classification increases.

Table 1. shows different classifiers performance with respect to various parameters.

| Sr. No. | Parameter | SVM | SRC | SKL SRC | MKL SRC |
|---|---|---|---|---|---|
| 1 | Accuracy | Moderate | Low | Higher | Highest |
| 2 | Handling Of Nonlinearity | Medium | Lowest | High | Highest |
| 3 | Ease Of Understanding | Simpler | Simple | Moderate | Difficult |
| 4 | Computational Complexity | Lower | Lower | Moderate | Highest |
| 5 | Real Time Costing | Moderate | Moderate | Higher | Highest |
| 6 | Dimension Reduction Used | Yes | No | Yes | Yes |

Application like biomedical, face recognition, pattern analysis recognition of images i.e. accuracy required should be maximum. For that classifier should classify image more precisely.

a) Real time costing of classifier should be minimum.
b) Computational complexity should be less.
c) It should be secure.
d) It should be robust to noise, occlusion, variation to illumination.
e) Non linear data should be handled efficiently.

## III. PROPOSED METHODOLOGY

Proposed system has normalization, computation of residual, finding sparse code, kernel weight updation.

Selection of kernel depends on types of non linearity present in image. But for comparison purpose base kernel quantity is decided. Results obtained at the end and corresponding result of SRC, KNN, SVM, Single kernel SRC, Simple SRC are compared. As efficiency of linear SRC is less than non linear SRC for classification. Multiple kernel SRC is used for classification.

As shown in figure working of proposed classifier will be go follows:

1. Different databases like real, synthetic data samples have different features so sample data also changes which given to normalization process.

2. Training data normalized and to compute residual minimization technique is to be used. Generally L1 minimization technique is used. As solution L0 minimization has problem of NP-hard which cannot be solved in polynomial.

3. Residuals obtained from L1 minimization are to be used to find sparse code.

4. To avoid over fitting problem over fitting regularizer is to be used for updation of kernel weight updation.

For finding kernel which can handle non linearity of data set sparse code and kernel weight updated. This is iterative process where sparse code are kept constant and kernel weight updated. Similar process happen in next iteration until it converges.

5. As convergence criteria met finding of sparse code and updation of kernel weight stop.

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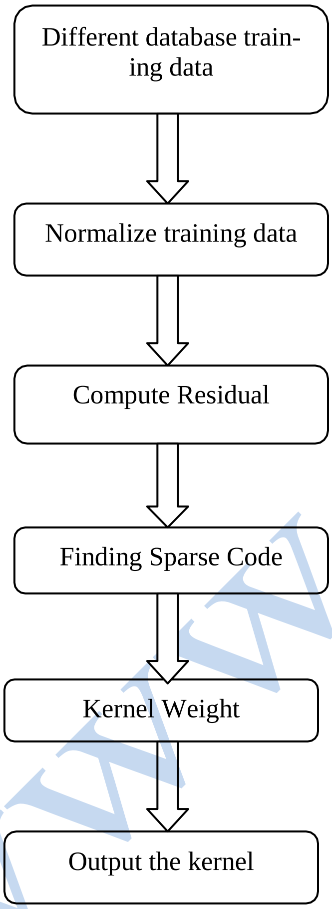


Fig. 1. Proposed system block diagram.

## IV. Conclusions

With the increase of kernel for classifier more discriminative part can be analysed. Due to that recognition performance of multiple kernel learning sparse representation classifier (MKLSRC) is more than SRC. Type of classifier can be selected depending on need of face recognition security level or image recognition accuracy level. Various classification result proves MKLSRC as efficient classifier and also handles occlusion and corrupted images environment. Future research topic will be reduction in computational complexity and cost for classification.

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