Performance Improvement of Face Recognition Method and Application for the COVID-19 Pandemic

Suparna Biswas

Faculty of Electronics and Communication Engineering department at Gurunanak Institute of Technology, 157/F, Nilgunj Rd, Sahid Colony, Panihati, Sodepur, Kolkata, West Bengal, 700114, India, suparna.biswas@gnit.ac.in

Abstract: In this paper, a novel framework is introduced by combining compressive sensing(CS) theory, digital curvelet transform, and Principal Component Analysis to improve the performance of face recognition method. CS is a highly attractive approach in the field of signal processing, which provides an efficient way of data sampling at a lower rate than the Nyquist sampling rate. CS offers numerous advantages, like less memory storage, less power consumption and higher data transmission rate etc. Here, CS is used on the face images, which offers reduction in storage space and computational time. The use of curvelet transform provides dual benefits: (i) sparse representation (ii) improvement on detailed content. To extract the feature vector, the Principal Component Analysis is then applied. The Performance of the proposed face recognition method is computed by applying cross-validation technique, compressive sensing based classifier, neural network, Naive Bayes and Support Vector Machine classifier. The proposed technique can efficiently perform the face recognition, at a low computational cost. Extensive experiments, on ORL and AR face databases, are conducted to validate our claim. The proposed technique also recognizes face images more efficiently than the traditional PCA, with a 1.5% higher recognition rate, if a person wears a face mask, as protection from COVID-19

Keywords: Face Recognition; Compressive Sensing; COVID-19; Curvelet Transform

1 Introduction

Face recognition (FR) [1] is a widely used biometric based technique for identification of individuals in various places for security issues. FR offers various advantages over the other biometric based techniques (iris, retina, fingerprint, etc.) like face images can be captured with a low cost camera and no need for direct contact of the acquisition device. But it has some disadvantages too. One of the notable disadvantages of the FR system is that it is less reliable than other biometric based systems. Actually, different factors like quality of image or video, expression variation, Occlusion, illumination differences affect the recognition performance.

Identification through FR [2] [3] [4], is basically a matching problem, in which, test image is compared with the stored database. But sometimes automatic FR is very much challenging or hard task due to the variations of different factors like pose variations, expression variations, illumination differences, presence of noise, occlusion and blurring etc. Some form of pre-processing steps become required to reduce the noise, effect of variations in pose and illumination, which have impact on the choice of the recognition scheme. Automatic FR methods involve two important steps:

i) Extraction of features from face images

ii) Classifier design

However, classification result mostly depends on the feature extraction techniques. In traditional method of FR, pixels intensity is used as input features. However, the techniques are time consuming due to high dimensionality of input feature vector.

Various methods have been developed for extracting features in low dimensional space, such as Principal Component Analysis (PCA) [5], Linear Discriminant Analysis (LDA) [6] and Independent Component Analysis (ICA) [7]. PCA is most widely used method for feature selection and dimensionality reduction. However, PCA can't handle variation in illumination and facial expression. LDA is another powerful tool for dimensionality reduction, widely used in FR. In case of traditional LDA, classification accuracy may degrade with the sample size. PCA can give outstanding performance than LDA, if the training dataset is small. Recently lots of FR methods have been developed applying the unsupervised statistical techniques. In unsupervised statistical technique, a set of basis images are used to represent faces as a linear combination of the basis images. Higher order statistics among the pixel values provide better basis images, which contain more important information for FR. ICA is one such method depicted as generalization of PCA and superior than PCA in case of illumination and expression variations of face images.

Wavelets [8] and the various variants, namely contourlet [9] curvelet [10] etc. are found to be efficient to analyze the high dimensional signals. Wavelets offer the benefits of multiscale analysis and time frequency localization of 2D image matrix. However, wavelets are ineffective while dealing with smooth contours in different directions unlike contourlet which can handle this issue due to additional properties of directionality and anisotropy. Moreover, wavelet transform can detect only point singularities but fails to detect curved singularities. To overcome the limitations of wavelet and contourlet, Candes and Donoho [10] presented curvelet transform (CVT) which has better capability to represent edges and other singularities along curves. CVT represents the line, the edges and the curvature precisely through compact representation using less number of coefficients.

During the recent years, CS theory has received remarkable attention in the research area of FR [1]. CS theory reinvents FR technique applying sparse representation theory. Usually, in the case of FR technique using CS theory, the query image is presented as a sparse linear combination of training images. This method showed robustness in presence of noise. In CS, sparsification is an important step and degree of sparsity has a significant role in reconstruction process. So investigation of suitable sparse representation is the most vital task for FR technique, based on CS.

The global problem at present is COVID-19 caused by corona-virus which led to the worldwide lockdown. The common people are the worst sufferer having no work. Though intensive research and development of vaccines is currently underway in Russia, UK, USA and other countries giving the common people a ray of hope, yet they have decided to return to their work to earn their livelihood. Considering the present scenario wearing mask and protective gear has become mandatory for all but it may create some security issues as it is hiding the face of individuals.

The objective of the present work is to improve feature information of face images in order to recognize the individuals efficiently. In this paper features of CS, CVT and PCA are exploited to develop a new FR technique. Here, CVT has been used to perform dual role, first one is sparse representation and another is enhancement of CS reconstructed face images. To extract the features in low dimensional feature space PCA has been used on the enhanced image. Comprehensive simulations are conducted on two online accessible datasets, applying different classification technique to demonstrate the supremacy of our proposed scheme. Our proposed technique also tested on face with mask to combat with corona virus as a protective measure.

The remaining part of the paper is structured as follows: Section 2 provides a literature review on FR method. In Section 3 the proposed FR method is described clearly and Section 4 provides the experimental results and discussion. In Section 5 the modified proposed method is discussed to combat with COVID-19. Finally, the paper is concluded in Section 6.

2 Scientific Literature Review

A brief review of FR and its superiority followed by the benefaction of the proposed method has been discussed in this section.

2.1 Related Work

Recognition of human faces utilizing PCA was first proposed by Sirovich and Kirby [11] in 1987. Some recent advancement on PCA based algorithms includes symmetrical PCA [12], two-dimensional PCA (2D-PCA) [13-14], weighted modular PCA [15], Kernel PCA [16] and diagonal PCA [17]. The method 2D-PCA is dependent on 2D image matrix. Hence, it does not need to transform the 2D image matrix into a vector, prior to feature extraction. Here image covariance matrix directly constructed from the 2D matrix and this technique is computationally more adequate than traditional PCA. In [17], fit has been reported that diagonal PCA (DiaPCA) is more accurate than both PCA and 2D-PCA. Improved FR performance was observed by combining the DiaPCA and 2D-PCA. Recently published other performance improvement techniques are [18-19]. In [18] a Local Binary Pattern (LBP) Histogram based technique and in [19] LBP and Support Vector Machine (SVM) has been used to improve the recognition rate.

Sparse representation based classification (SRC) technique for FR was introduced by Wright et al. [1]. In [1] query image is represented as sparse linear combination of the training images and applying l1 - minimization technique [20], the sparsest coding vector has been achieved. Then the classification of test image was based on minimum representation error. Wright et al. [1] declared that for large dimension of feature vector SRC is independent of feature types. To overcome the difficulty of occlusion and corruption Wright et al. [1] introduced an occlusion dictionary and showed that this technique is robust for small variations of pose and displacement.

Yang et al. [20] proposed a FR technique utilizing l1 norm minimization SRC algorithm. In this paper Gabor features are extricated from the local regions of face images, which are slightly sensitive to variations of pose, illumination and expression than the holistic features. This FR method [20] based on Gabor feature has improved the classification rate over the conventional SRC based technique and increased the computational speed in presence of occlusion.

Yang et al. [21] implemented a robust sparse coding (RSC) method to recognize the face images robustly. A suitable weight function is designed for RSC, to obtain better performance than the existing SRC [20] based method, with the intricate variations of faces. Assuming that the noise term has a sparse representation, a correntropy based sparse representation (CESR) technique was proposed in [22]. CESR technique can efficiently handle the non-Gaussian noise and yields better results for the scarf occlusion problem in FR.

Huang et al. [23] introduced a FR method which is transformation-invariant SRC technique. Zhou et al. [24] integrated Markov random model with SRC technique to recognize the face images under contiguous occlusion. Wagner et al. [25] handled pose and illumination variation FR problem by introducing SRC framework. In [26] a discriminative dictionary learning technique was proposed to increase the efficiency of FR. Yi-Haur et al. [27] developed a FR technique named as maximum probability of partial ranking on the framework of SRC. In [27] 2D-PCA and 2D-LDA feature extraction techniques has been applied on two face databases ORL and Yale B. This technique [27] showed significant improvement in recognition accuracy greater than the traditional PCA, LDA, two dimensional PCA and LDA based techniques. Considering the correlation and sparsity Wang et al. [28] presented a FR technique which is based on adaptive sparse linear model. It has been noticed that this sparse linear model behaves like SRC if the training samples are almost uncorrelated. But if the training samples are highly correlated then [28] this technique behaves as collaborative representation based classification (CRC). This technique has showed better performance over the Neural Network (NN), SRC and CRC techniques.

Some of the recent works on FR are [29] [30] [31] [32] [33]. In [29], the author presented a random sampling patch-based FR technique to cope up with the problem of occlusion. In the same year Wang et al. [30] presented another sparse representation based FR technique to overcome the same problem. Recently deep learning is widely used in different pattern recognition problems, due to its high recognition accuracy. Following this trend, Feng et al. [31] proposed a deep learning based Robust LSTM autoencoder to handle the occlusion. To address the issues of pose variation, Kishor et al. [32], presented a FR method by combining Dual Cross Pattern (DCP), local binary pattern (LBP) and SVM. Bah SM and Ming F introduced a new FR method [33] by combining LBP and different advanced preprocessing techniques, which is robust under the variation of scale, pose and different lighting conditions.

From different studies, we know that during COVID-19 pandemic, wearing masks helps to prevent the spreading of coronavirus. But masks obscure the important face region and as a result reduce the recognition rate of FR. To increase the FR rate of masked faces in [34] authors presented a Multi-Task Cascaded Convolutional Neural Network (MTCNN) based technique. By combining the convolutional neural network (CNN) and LBP, Vu HN et al. presented a masked FR technique in [35]. In [36], F. Ding et al. presented latent part detection (LPD) model to improve the recognition accuracy of masked faces. Here, the author first generates masked faces and then original and masked faces are fed into two branches CNN. Their technique [36] provides better accuracy compared to others with a large margin. In [37], at first the author cropped the masked face region and then applied CNN, namely VGG-16, AlexNet, and ResNet-50 to extract the features from face regions and then applied Multilayer Perceptron (MLP) for classification.

2.2 Scope and Contribution

The principal contributions of this paper are presented as follows:

1) A CS based novel framework of FR is presented, where CVT performs a dual role:
   (a) Sparses representation using transform domain
   (b) Preprocessing of the face images
2) Proposed method utilizes a new preprocessing technique based on CS, to extract detail edge information from the face images by using CVT which has better ability of providing directional and edge representation.
3) For CS reconstruction Smoothed Projected Land weber (SPL) [38] method has been used for faster implementation.
4) Proposed CS based FR framework improve the recognition rate.
5) Extensive simulations are performed on two data sets AR and ORL. The performance of the proposed method has been evaluated using different classifier such as K-fold cross validation technique, CRC with regularized least square (CRC RLS), NN, Naive Bayes (NB) and SVM classifier.
6) The proposed technique is also a suitable method during the COVID-19 Pandemic.

3 Proposed Method

This section provides the description of proposed CS based FR technique. The structural outline of the proposed FR technique is depicted in Figure 1. It consists of mainly four modules: CVT, CS based preprocessing, PCA for feature selection and classification.

At first CVT [39] has been applied on each input image to capture the detail and directional edge information. Actually CVT is an appropriate basis function for the sparse representation, because maximum numbers of coefficients values are negligible after the application of this transform. So CVT is used in this FR technique due to its high degree of sparsity property compared to other transform. For the reconstruction of image with enhanced information, different percentage of samples (PS) are chosen randomly from the detail sub-bands and then sub-bands are reconstructed back applying SPL [38] reconstruction algorithm. Inverse CVT (ICVT) has been applied on the coarse sub-band and the reconstructed detail sub band. After that we get the resulting image as Image1 (Figure 1).

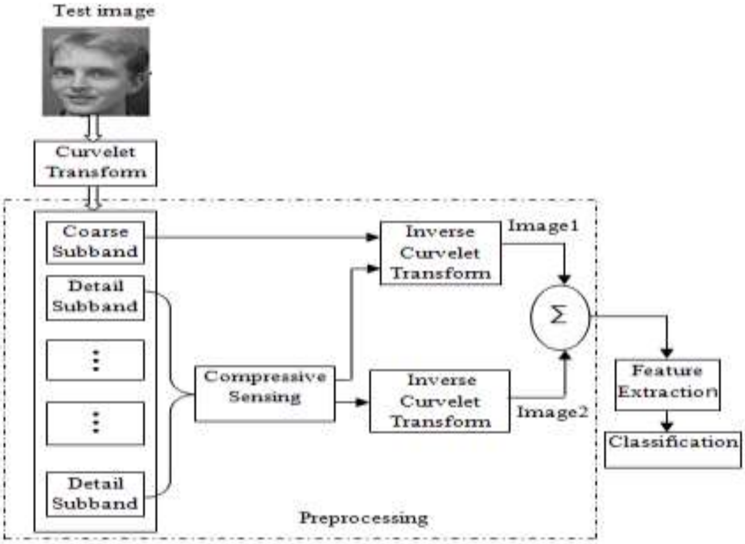

Figure 1
Structural outline of the proposed FR technique

ICVT is also applied on the reconstructed detailed sub-bands only considering all the coefficients of coarse sub-band to zero and then we obtain Image2 (Figure 1). Two images Image1 and Image2 are superimposed to enrich the reconstructed face images in which detail edges are more informative. So the technique enhances the features in this preprocessing.

Both reconstructed images (Image2 and Image1) for different PS are shown in Figure 2. Figure 2 (a) is the input original image, while Figure 2 (b) is the reconstructed Image1 for different percentages of detailed sub-bands, Figure 2 (c) is the reconstructed Image2 from different percentages of detailed sub-bands coefficient only and Figure 2.(d) is the superimposed image. From Figure 2 it is noticed that with the increase in the PS of the detail sub-band coefficients, improvement on reconstruction quality is observed. It is expected that this improvement in reconstruction quality has a subsequent effect on classification rate. PCA has been applied to extract the features from the superimposed images. Then different classifiers are applied on the extracted features to recognize the face images. Algorithm 1 describes the total process of the proposed technique.

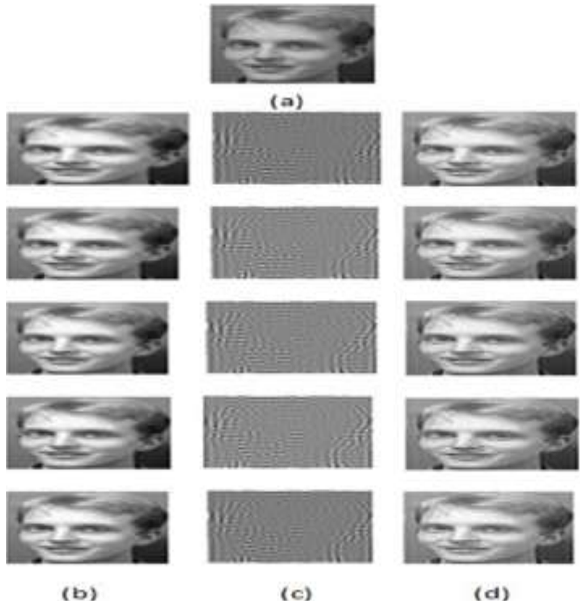

Figure 2

(a)input image, (b)CS based reconstructed images(Image1), by varying the value of PS (c)CS reconstructed images(Image2) for different PS value (d)Superimposed images. (1st row for 50% PS, 2nd row for 60% PS, 3rd row for 70% PS, 4th row for 80% PS, 5th row for 90% PS).

ALGORITHM

Algorithm 1: Algorithm of Face recognition

Input: Face image and PS

1: Compute CT

2: Extract coarse sub-band $Image_{coarse}$ and detail sub-band $Image_{detail}$

3: Set PS from $Image_{detail}$

4: Reconstruct $Image_{detail}$ applying SPL method

5: Construct $Image1=ICT\ (Image_{coarse}, Image_{detail})$

6: Set $Image_{coarse} = \mathbf{0}$

7: Construct $Image2=ICT\ (Image_{coarse}, Image_{detail})$

8: Image = $superimpose(Image1, Image2)$

9: Apply PCA

10: Apply classifier

Output: class label

4 Result and Discussions

Every input face image is decomposed using CVT considering scale value of 2 and angle 8. To generate the feature vectors PCA is applied on the enhanced training face images. The feature vectors of the test image are compared with that of the training images to find the best match training image and recognized as the face of the test image. System performance has been evaluated by applying CRC_ RLS [40] and K-fold cross validation technique considering K=10. For K-fold cross validation technique, results are obtained by averaging the recognition rates of 1000 different rounds in MATLAB. Performance of the proposed method is computed on two publicly available facial image databases: ORL and AR. Additionally we have also studied the recognition rate using NN, NB and SVM classifiers. Proposed method is executed on MATLAB 2012b and Weka 3.7.9, in Intel Core i3-380M CPU, 2GB RAM, Windows 7 platform.

4.1 ORL Database

ORL dataset contains grayscale images of 40 individuals with varying illumination, contrast, pose and expressions (open or closed eyes, smiling or no smiling). Some sample images are shown in Figure 3. This database consists of 400 images with frontal and near frontal view faces (rotation of the face up to 20 degrees with and without spectacles).

Recognition rate for different dimensions of feature vector, using cross validation technique is presented in Table 1. Table 2 shows the classification rate for CRC_RLS classifier by varying the PS. It is noticed that recognition rate gradually increases with increase of PS and PC and finally, achieved maximum recognition rate when PC= 50 and PS=90. All the results presented in all tables and graphs are obtained by taking average from 1000 runs.

Figure 3
Few sample images from ORL dataset

Table 1
Recognition rate of ORL dataset for cross validation technique

PS	PC=10	PC=20	PC=30	PC=40	PC=50
90%	87.89%	95.21%	96.43%	96.83%	97.36%
80%	87.75%	95.34%	96.29%	96.74%	97.35%
70%	87.85%	95.33%	96.25%	96.75%	97.28%
60%	87.60%	95.24%	96.28%	96.83%	97.27%
50%	87.77%	95.08%	96.27%	96.69%	97.09%
40%	87.74%	95.14%	96.22%	96.74%	97.19%
30%	87.36%	94.96%	96.35%	96.72%	97.24%
20%	87.38%	94.91%	96.39%	96.73%	97.17%
10%	87.22%	94.88%	96.32%	96.63%	97.25%

Table 2
Recognition rate of ORL database for CRC_RLS

PS	PC=10	PC=20	PC=30	PC=40	PC=50
90%	64%	83 %	87.0%	90.0%	91.5%
80%	64%	82.5%	86.5%	90.0%	91.0%
70%	64%	82%	86.5%	90.0%	91.0%
60%	63.5%	82%	86.0%	90.0%	91.0%
50%	62%	82%	86.0%	89.5%	90.5%
40%	62.5%	81%	85.5%	90.0%	90.5%
30%	62%	80.5%	86.5%	90.0%	90.5%
20%	61%	81%	86.5%	89.0%	90.0%
10%	61%	81%	86.5%	89.0%	90.0%

In this case, in order to observe the dependence of recognition rate on two parameters (feature dimension or PC value and PS value) in the right way, we should trade-off two parameters and the graphical representation will become a three dimensional plot, as shown in Figure 4 and Figure 5. Figure 4 and Figure 5 show how the recognition rate changes according to the changes of the feature dimension and PS value for CRC RLS and cross validation technique. Figure 4 shows that the best recognition rate 91.5% is obtained when the feature dimension is set to 50 and PS= 90%.

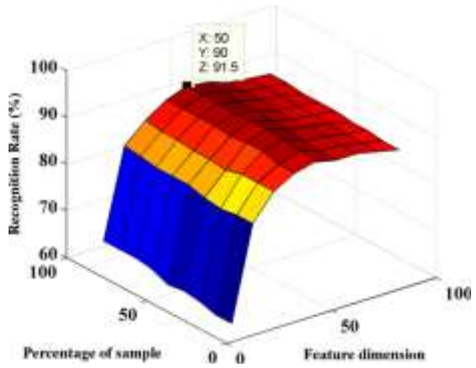

Figure 4
Recognition rate vs. Feature Dimension vs. PS (on ORL dataset considering CRC_RLS)

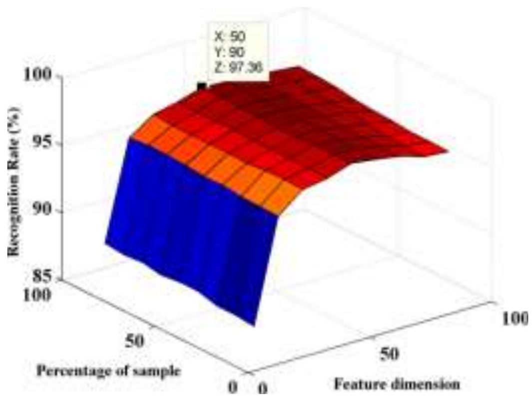

Figure 5
Recognition rate vs. Feature Dimension vs. PS (on ORL database considering cross validation technique)

In case of Figure 5 the maximum recognition rate 97.36% is obtained for feature dimension is equal to 50 and PS=90%. From both the figures it is also observed that the recognition rate decreases even after increasing the PC value after 50. But there is a trend of increase of recognition rate with increase of PS value. Recognition rate for NN, NB and SVM classifiers have been studied by varying the PC and depicted in Figure 6. Maximum recognition rate has been achieved for PC=50, beyond which no significant change in result. For ORL database, SVM and NN classifiers produce the maximum rate of recognition for PC=50. Comparing three classifiers (NN, NB and SVM) from Figure 6, it is seen that SVM provide the best result compared to others for the entire range of feature dimension variation. The ROC curve for NB, NN and SVM classifiers for PS=90% are depicted in Figure 7. Here SVM classifier gives excellent result for the proposed technique.

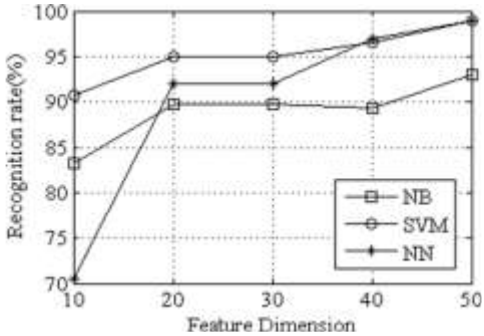

Figure 6
Recognition rate for NB, NN, SVM classifier

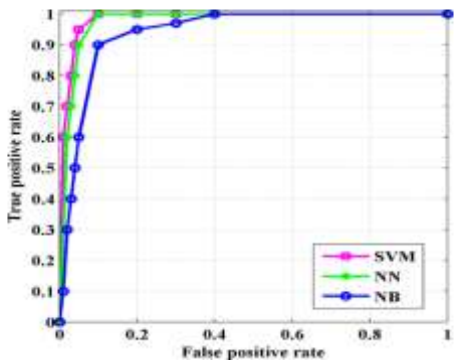

Figure 7
ROC curve for ORL database

The performance of this proposed technique is also compared with the method (CVT+ PCA), where PCA is applied directly on approximation coefficient after applying curvelet transform (CVT is used for curvelet transform). Our proposed method shows superior results than the (CVT+ PCA) as shown in Figure 8. From Figure 8 it has been observed that the proposed method is better than the PCA based methods. For the cases, the best performance has been achieved at PC=50. Results of performance comparison with the existing techniques are summarized in Table 3. The proposed FR technique shows better performance compare to the techniques as described in [27] [42] [41], for PS=90% and PC=50. Computational time required for this proposed pre-processing scheme is given in Table 4.

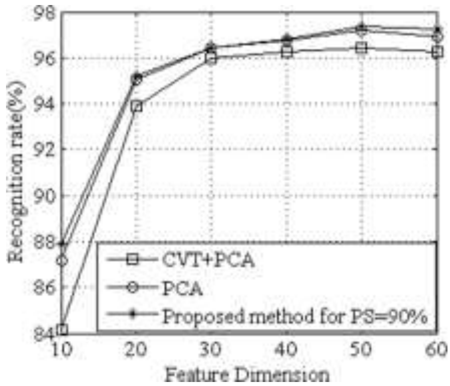

Figure 8
Comparison using cross validation technique

Table 3
Comparisons with other methods for ORL database

Method	Accuracy
PCA+SRC-MP[21]	89.00%(for dim 60)
PCA+SR[41]	93.7%(for dim 100)
Homotopy + SR [42]	97.31%
Proposed Method +SVM	99.00%(for dim 50) 96.00%(for dim 60)
Proposed Method+NN	99.00%(for dim 50) 96.00%(for dim 60)

Table 4
Time required for CS based processing

PS	50%	60%	70%	80%	90%
Time	16.533s	16.633s	16.700s	21.583s	23.894s

4.2 AR Database

The AR dataset consists of 4000 images (consisting of 126 individuals) with variation in illumination and expression. In this work, we choose 1399 images (consisting of 50 males and 50 females) with illumination and expression variation. For each person, 7 images are selected for training and rests of 7 images are used for testing. The images are cropped to (60 × 43) shown in Figure 9.

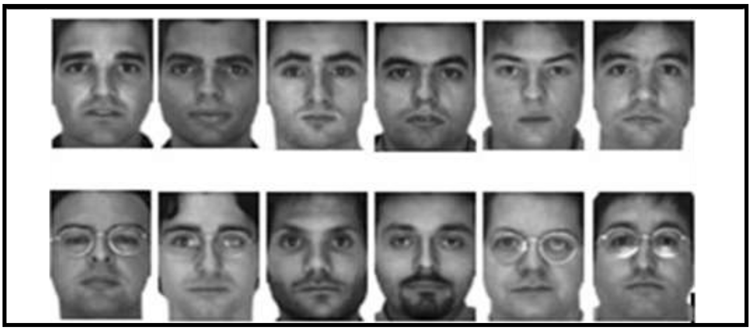

Figure 9
Sample images of AR face database

Recognition rates for different value of PCs and PS using CRC RLS classifier is given in Table 5. For this database also, we have observed the same result that the recognition rate gradually increases with increase of PS and PC. Recognition rates for NN, NB and SVM classifiers have been studied by varying the number of PC and are presented in Table 6 for PS=90%. For AR database, NN classifier produces the maximum accuracy of 98.928% for PS=90%.

Table 5
Recognition rate of AR database using CRC_RLS

PS	PC=60	PC=120	PC=300
90	86.69%	91.99 %	93.99%
80	86.69%	91.41%	93.42%
70	85.69%	91.13%	93.84%
60	85.27%	91.27%	94.28%
50	84.97%	90.55%	93.99%
40	82.97%	90.27%	92.41%
30	83.11%	90.41%	91.56%
20	83.26%	90.41%	91.56%
10	82.69%	90.12%	91.55%

Figure 10 shows how the recognition rate changes according to the changes of the feature dimension and PS value for CRC RLS for AR database. From Figure 10, it is noticed that the best recognition rate 94.91% is obtained when the feature dimension is set to 270 and PS= 90%. From this figure it is also observed that there is a trend of increase of recognition rate with the increase of PS value. The ROC curve for NN and SVM classifiers, using cross validation technique is depicted in Figure 11, showing excellent result. Performance is also compared with PCA (on original image) based methods considering PS=50% and 90% taken from detail sub-band.

Table 6

Recognition rate of AR database for different classifier and PS=90

PC	Accuracy for NB	Accuracy for NN	Accuracy for SVM
60	91.065%	97.856%	97.069%
120	90.278%	98.928%	98.071%
300	83.774%	98.570%	98.000%

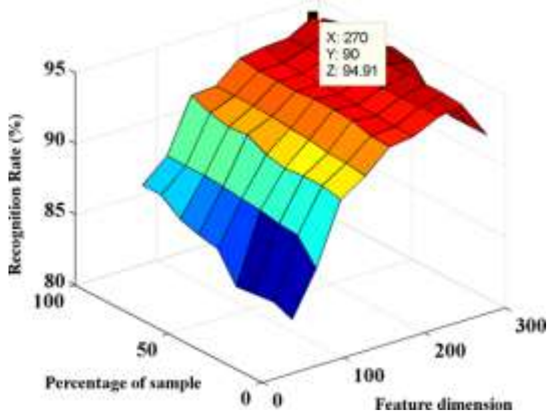

Figure 10

Recognition rate vs. Feature Dimension vs. PS (for AR, considering CRC_RLS)

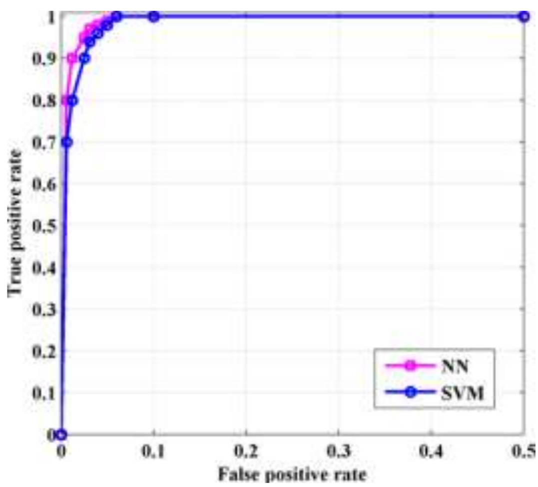

Figure 11

ROC curve for NN and SVM classifier

Comparisons with the existing methods are summarized in Table 7, showing that performance of our technique is better compare to

Table 7
Comparisons with other methods for AR database

Method	Accuracy
PCA+CRC_RLS(31)	90.00% (for dim 120)
SRC(21)	90.100% (for dim 120)
Proposed Method+NB	90.278%(for dim 120)
Proposed Method+NN	98.928%(for dim 120)
Proposed method+SVM	98.071%(for dim 120)

5 Modified Proposed Method to Combat COVID19

The modified flow diagram to recognize the face images is depicted in Figure 12.

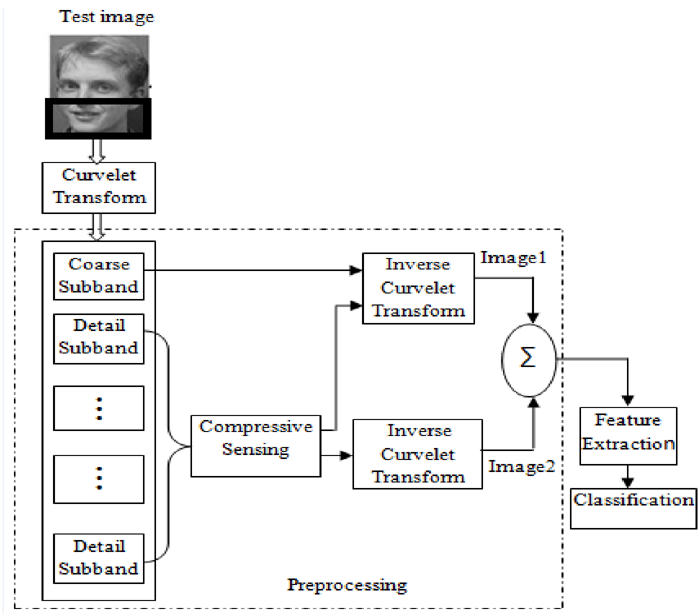

Figure 12
Modified flow diagram of proposed technique to combat with COVID 19

In this technique we cut the 1/3 portion of the face image (as indicated by black box) from the lower region and excluding this lower portion we performed the same technique as discussed in Figure 1. At present, no database is available with a mask and that is why we have used the ORL database. Actually mask covers the lower portion of our face images and as a result we are unable to extract the features of face images, which are covered by mask. So we can extract the features only from the upper uncovered portion. Through this preprocessing technique, as discussed in Figure 1, we have tried to improve the face recognition rate in this pandemic situation to combat with corona virus. Some of sample images of ORL database after excluding the lower portion (which is considered as covered region by mask) are shown in Figure 13. The recognition rate for the ORL database is given in Table 8 for CRC RLS classifier. From the results of Table 8, we can say that the proposed technique performs better than a conventional PCA.

Figure 13

Some of face images of ORL database after excluding the lower portion

Table 8

Recognition rate for ORL database covered with mask

PC	Recognition rate (Conventional PCA)	Recognition rate (Proposed technique)
10	47.00%	51.00%
20	76.50%	79.00%
30	80.00%	82.00%
40	82.00%	86.50%
50	87.50%	89.00%

Conclusions and Future Work

In this paper, a preprocessing technique, based on CS for the performance improvement of FR method, is proposed. This presented integrated FR technique performs preprocessing, compact presentation and dimensionality diminution. The method shows assuring results while the recognition rate is evaluated using CRC RLS, NN, NB and SVM classifiers. Experimental results of this proposed technique show the superiority compared to other methods. Our method shows excellent performances, such as maximum recognition rate of 99% (for SVM classifier) for ORL database and 98.92% (for NN and SVM classifier) for AR database. The proposed CS based FR method, improves rate of recognition and shows robustness against the effect of Gaussian noise. The proposed technique provide maximum of 89% recognition accuracy for the ORL database in case of masked faces, which is greater than conventional PCA. The proposed technique may be extended for future work, as follows:

i) The importance of other feature extraction technique such as LDA and ICA may be studied to improve the rate of face recognition.

ii) A deep learning model can be developed to improve the recognition.

References

[1] J. Wright, A. Y. Yang, A. Ganesh, S. S. Sastry, and Y. Ma: Robust Face Recognition via Sparse Representation, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 31, No. 2, 2009, pp. 210-227

[2] R. Chellappa, C. L. Wilson, and S. Sirohey: Human and machine recognition of faces: A survey, Proceedings of the IEEE, Vol. 83, No. 5, 1995, pp. 705-741

[3] W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld, Face recognition: A literature survey, ACM Computing Surveys, Vol. 35, No. 4, 2003, pp. 399-458

[4] A. K. Jain, A. Ross, and S. Prabhakar: An introduction to biometric recognition, IEEE Transactions on Circuits and Systems for Video Technology, Vol. 14, No. 1, 2004, pp. 4-20

[5] M. Turk, A. P. Pentland, Face Recognition Using Eigen- faces, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 1991, pp. 586-591

[6] J. W. Lu, K. N. Plataniotis and A. N. Venetsanopoulos, Face Recognition Using LDA-based Algorithms, IEEE Transactions on Neural Networks, Vol. 14, 2003, pp. 195-200

[7] C. Liu and H. Wechsler: Comparative assessment of independent component analysis (ICA) for face recognition, Proceedings of the Second International Conference on Audio- and Video-based Biometric Person Authentication, 1999

[8] C. C. Liu, D. Q. Dai: Face Recognition Using Dual-Tree Complex Wavelet Features, IEEE Transactions on Image Processing, Vol. 18, No. 11, 2009, pp. 2593-2599

[9] M. N. Do, M. Vetterli: The Contourlet transform: an efficient directional multi resolution image representation, IEEE Transactions on Image Processing, Vol. 14, No. 12, 2005, pp. 2091- 2106

[10] J. L. Starack, E. J. Candes, D. Donoho: Curvelet transform for image denoising, IEEE Transactions on Image Processing, Vol. 11, No. 6, 2002, pp. 670-684

[11] L. Sirovich, M. Kirby: Low-dimensional Procedure for the Characterization of Human Faces, Journal of the Optical Society of America A - Optics, Image Science and Vision, Vol. 4, No. 3, 1987, pp. 519-524

[12] Q. Yang, X. Q. Ding: Symmetrical Principal Component Analysis and its Application in Face Recognition, Chinese Journal of Computers, Vol. 26, 2003, pp. 1146-1151

[13] J. Yang, D. Zhang: Two-Dimensional PCA: A New Approach to Appearance-Based Face Representation and Recognition, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 28, No. 1, 2004, pp. 131-137

[14] J. Meng, W. Zhang: Volume measure in 2DPCA- based face recognition, Pattern Recognition Letters, Vol. 28, 2007, pp. 1203-1208

[15] A. P. Kumar, S. Das, and V. Kamakoti: Face recognition using weighted modular principle component analysis, Neural Information Processing, Lecture Notes In Computer Science: Springer Berlin / Heidelberg, Vol. 3316, 2004, pp. 362-367

[16] V. D. M. Nhat, S. Lee: An Improvement on PCA Algorithm for Face Recognition, Advances in Neural Networks, Lecture Notes in Computer Science. Chongqing: Springer, Vol. 3498, 2005, pp. 1016-1021

[17] D. Zhang, Z.-H. Zhoua, S. Chen: Diagonal principal component analysis for face recognition, Pattern Recognition, Vol. 39, 2006 pp. 140-142

[18] Deeba Farah, Memon Hira, Ali Dharejo Fayaz, Ahmed Aftab, Ghafar Abddul: LBPH based enhanced real-time face recognition, Int J Adv Comput Sci Appl.10(5), 2019

[19] Nisha Maitreyee Dutta, Improving the recognition of faces using LBP and SVM optimized by PSO technique, Int J Exp Diabetes. 5(4), 2017, pp. 297-303

[20] M. Yang, l. Zhang: Gabor Feature based Sparse Representation for Face Recognition with Gabor Occlusion Dictionary, Proceedings of the 11th European conference on Computer vision, 2010, pp. 448-461

[21] M. Yang, L. Zhang, J. Yang, D. Zhang: Robust Sparse Coding for Face Recognition, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2011, pp. 625-632

[22] R. He , W. S. Zheng, and B.G. Hu: Maximum Correntropy Criterion for Robust Face Recognition, IEEE Transactions on Biometrics Compendium, Vol. 33, No. 8, 2011, pp. 1561-1576

[23] J. Huang, X. Huang, and D. Metaxas: Simultaneous image transformation and sparse representation recovery, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2008, pp. 1-8

[24] Z. Zhou, A. Wagner, H. Mobahi, J. Wright, and Y. Ma: Face Recognition With Contiguous Occlusion Using Markov Random Fields, Proceedings of the IEEE International Conference on Computer Vision, 2009, pp. 1050-1057

[25] A. Wagner, J. Wright, A. Ganesh, Z. Zhou, Y. Ma: Towards a practical face recognition system: robust registration and illumination by sparse

representation, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2009, pp. 597-604

[26] M. Yang, L. Zhang, X. Feng, and D. Zhang: Fisher discrimination dictionary learning for sparse representation, Proceedings of the IEEE International Conference on Computer Vision, 2011, pp. 543-550

[27] Yi-Haur Shiau1 and Chaur-Chin: A Sparse Representation Method with Maximum Probability of Partial Ranking For Face Recognition, Proceedings of the IEEE International Conference on Image Processing, 2012, pp. 1445-1448

[28] J. Wang, C. Lu, M. Wang, X. Hu: Robust Face Recognition via Adaptive Sparse Representation, IEEE Transactions on Cybernetics, Vol. 44, No. 12, 2014

[29] Cheheb I, Al-Maadeed N, Al-Madeed S, Bouridane A, Jiang R: Random sampling for patch-based face recognition, 5th international workshop on biometrics and forensics (IWBF), IEEE, 2017, pp. 1-5

[30] Iliadis M, Wang H, Molina R, Katsaggelos AK: Robust and low-rank representation for fast face identification with occlusions, IEEE Trans Image Process 26(5), 2017, pp. 2203-2218

[31] Zhao F, Feng J, Zhao J, Yang W, Yan S: Robust LSTMautoencoders for face de-occlusion in the wild. IEEE Trans Image Process 27(2), 2017, pp. 778-790

[32] Bhangale Kishor B, Jadhav Kamal M, Shirke Yogesh R: Robust pose invariant face recognition using DCP and LB, International Journal of Management, Technology and Engineering September 2018;8(IX):1026–34. ISSN NO: 2249-7455

[33] Bah SM, Ming F: An improved face recognition algorithm and its application in attendance management system. 2020, Array 5:100014

[34] M. S. Ejaz and M. R. Islam: Masked Face Recognition Using Convolutional Neural Network, 2019 International Conference on Sustainable Technologies for Industry 4.0 (STI), 2019, pp. 1-6

[35] Vu HN, Nguyen MH, Pham C: Masked face recognition with convolutional neural networks and local binary patterns. Appl Intell (Dordr). 2021 Aug 14, pp. 1-16

[36] Feifei Ding, Peixi Peng, Yangru Huang, Mengyue Geng, and Yonghong Tian: Masked Face Recognition with Latent Part Detection, Proceedings of the 28th ACM International Conference on Multimedia Association for Computing Machinery, New York, NY, USA,2020, pp. 2281-2289

[37] Walid Hariri: Efficient masked face recognition method during the COVID-19 pandemic, Signal, Image and Video Processing, November, 2021

[38] S. Mun and J. E. Fowler: Block Compressed Sensing of images using Directional Transforms, Proceedings of the international conference on Image processing, 2009, pp. 3021-3024

[39] E. J. Candes, L. Demanet, D. L. Donoho, L. Ying: Fast discrete curvelet transform, SIAM Journal of Multiscale Modeling and Simulations, Vol. 5, No. 3, 2007, pp. 861-899

[40] L. Zhang, M. Yang, X. Feng: Sparse representation or collaborative representation: Which helps face recognition?, Proceedings of the IEEE International Conference on Computer Vision, 2011, pp. 471-478

[41] Y. Wang, C. Wang and L. Liang: Sparse Representation Theory and Its Application for Face Recognition, International Journal on Smart Sensing and Intelligent Systems, Vol. 8, No. 1, 2015

[42] Z. Zhang, Y. Xu, J. Yang, X. Li and D. Zhang: A Survey of Sparse Representation: Algorithms and Applications, IEEE Access, Vol. 3, 2015, pp. 490-530