Face Image Super-Resolution Algorithms using Sparse Representation

R. Jayasri[1], [2]Dr. S. Ravi[2*], [3]R. Shreya[3*]
[1]P.G. Student, [2]Assiatant Professor,[3]P.G. Student
[1, 2,3]Department of Computer Science, School of Engineering and Technology,
Pondicherry University, Puducherry - 605 014, INDIA.

Abstract: Face detection and recognition is a challenging problem in the area of image processing, computer vision, signal processing and pattern recognition. In the field of face recognition, the sparse representation is the best approach to solve the problem because it is more robustness to deviation in directions, lighting and human expressions in face recognition super resolution. Sparse representation is also called as sparse approximation approach which performs with sparse solutions for systems of linear equations. In this paper, the various methods and techniques involved in sparse representation approach are emphasized with respect to super resolution by providing the detailed analysis on the advantages and disadvantages of face recognition using sparse representation approaches used for super resolution images.

***IndexTerms* - sparse representation, face recognition, super resolution**

I. INTRODUCTION

For identifying or verifying a person from a digital image or a video frame from a video source can be performed by facial recognition system technology. A facial recognition system has multiple methods to work. But in common, it works by comparing chosen facial featuresfrom given image with faces within a database.

Classified Dictionary Learning method classifies the reasonable cluster by features of the samples and trained for each cluster using dictionary pair. The advantage of the method is that more acceptable results are achieved without the increase in time cost and computational complexity. The image resolution is improved, and detailed information recovers of targets. But the problem is that it will not optimize the dictionary training process and it has less reconstruction efficiency [1]. AMSRR and ASSS model is based on mixed samples of input low resolution image generated by the ASSS method and the complementary information effectively learns included in the mixed samples by AMSRR model. The method is based on input LR image, mixed samples will be generated adaptively. The complementary information of the mixed samples is learned effectively. But it will not examine the external and internal sample priors of a deep neural network framework [2]. Adaptive sparse representation and RPCA defines the low-rank structure from a matrix discovered by the low-rank optimization operation and thus refine the sparse representation coefficients. The method achieves better performance. But the convergence of AMDD has to be improved and computational efficiency is less [3]. Single image super-resolution using sparse representation and neighbour embedding has two learning-based methods for converting the LR patches into HR image patches. The accurate recovery is achieved by recovering the HR patch in a more compact space and the performance is improved. But it's not updating the transformation parameter faster and stable [4]. Sparse domain selection (SDS) based single image super-resolution method to obtain an effective and compact HR dictionary. It optimizes jointly between the feature spaces and the mapping has established. It improves the flexibility and LR–HR dictionary can learn accurately and obtains a better reconstruction quality and more accurate relationship. It obtains a more accurate stable SR recovery from the average sense. But it introduces some zigzagging effects [5].

A novel SR-based face image super resolution approach enforces the parallel training patches by incorporating the smooth priors having related sparse coding coefficients. The input LR face image yields superior reconstruction results when it is contaminated by strong noise. But the smoothness and sparsity of the image is not processed [6]. Robust and discriminative low rank representation (RDLRR) characterizes the representation of low-rank assumption and solves error term concurrently. The error images holistic structure and the global structure of data can be captured. The discriminative representation is simple, powerful and robust. But in training or testing registered face images are not available [7]. Sparse Gaussian process regression uses sparse GPR-based SR method that trains a GP model of the original training dataset obtained by active sample of an informative subset. The prediction efficiency is accelerated significantly while reconstruction quality becomes high. It is basically coarse-to-fine and it shows better generality than others. But the local structures are failed to consider within neighbor pixels. In order to maintain consistent structures, some rooms are needed [8].

The paper is further organized into section II, section III and section IV. Section II classifies the various related sparse representation methods. Section III reviews various sparse representation methods advantage, disadvantage and Section IV conclude the paper.

II. Face Image Super-Resolution Algorithms using Sparse Representation for Face Recognition

Xian Weia et al proposed for sparsifying linear transformation method by representing SparT means by coupling sparse structure image pairs by sparse transformation image for both high resolution and low-resolution spaces [9] with more robustness in finding the set of training images for occlusion and in recognizing the variations. The advantage of the method is that it links the discrepancy between input and output images and a good way has been provided by sparse representation techniques. It is robust to change in poses, expression and illumination. But the problem is that for recognition tasks and large-scale image synthesis SparT is not adaptable. The machine learning algorithms are not optimized to speed up the learning convergence [9]. In Re-identified K-nearest neighbor (RIKNN), the low-resolution space searches K-NN of LR patch and in the high-resolution space by re-identifying it's searching results. The advantage of the method is that when it encounters a huge training then the image reconstruction accuracy is significantly improved, and computational complexity is reduced. But the performance degradation will happen by the distant [10]. A novel face SR method based on Tikhonov regularized neighbour representation (TRNR) regularizes representation of the input LR patches by Tikhonov regularization term leading to consistent and distinctive solution for least squares problem. The advantage of the method is that to rebuild the high-resolution image from experimental low-resolution images the relevant patch samples can be selected by TRNR, thus will generate the detailed features discriminant HR face image. The method achieved the best generality, effectiveness, and robustness. But it can't be able to perform for LR observation face is in the wild [6]. A new approach for single image super-resolution based on sparse representation performs the basic unit can be used as a group and external database training the dictionary and the source low-resolution image is to ensure the dictionary which is proper for the group of patches. The fine details and sharp edges can be restored and by noise suppressing good result can be achieved. But in the same category between two patches there is no evaluation procedure for measuring the probability [11].

Super resolve the image using sparse representation with the specific dictionary can give the solution for the face recognition challenges in surveillance videos. SVD and HMM methods provide super resolution for face recognition. It has more recognition rate for facial images after applying the super resolution. But on natural images dictionary in, SR it didn't provide significant advantage Rasti, P.et al,.SR face reconstruction method defines image with dissimilar resolution by multi-scale linear combination and nonlocal similarity is to be constant. The robustness and computational effectiveness is more in SR method on face Hallucination. The RSIF have higher recognition accuracy. But as compare to the original VLR face images blurring operator and down sampling created images are different [12]. Local difference images using sparse-representation based face-classification method enriches the representation capacity of original dictionary by utilizing the different face images as an auxiliary dictionary. It can classify face accurately and uses auxiliary dictionary from a local difference face images in this representation power can be improved in actual dictionary. But in dictionary optimization original training samples are discarded [13].

Versatile sparse representation based post-processing defined as down-sampling high-resolution image which can be ensured certainly which leads to the equivalent low-resolution version. The internal image statistics has made the outputs comfortable and accurate. But it has less performance in most test images [14]. Position constraint-based face image super-resolution approximately maps the low resolution and high-resolution facial images to discover local linear projection matrices by adopting sparsity preserving projection method. The method is computationally fast in online reconstruction stage and the face images quality is achieved more. But in the case of preprocessing method, it can provide high recognition rate [15]. Novel framework on 2D tensor regression learning model can capably preserve the 2D pixel spatial information among the high resolution and low-resolution images for single image SR reconstruction. The method has achieved more competitiveness or even superior for HR images than other similar SR methods. The 2D pixel spatial information can be preserved efficiently between high resolution and low-resolution images. But the recognition rate is less when compared with other methods [16].

Face super resolution based on the weighted fusion of discrete and stationary wavelet in which weighting scheme is based on calculating the energy and correlation to capture rich information from both discrete and stationary wavelet features. The method has a superior performance of the ABC system with super resolved face images when compared with normal images. But it has not used any proprietary software for recording, Optimization, feature extraction and comparison [17]. Compressed-sensing theory framework represents images and signals as sets of linear combinations and combine the compression and data acquisition into a distinct process. The advantage of the algorithm is that for multi temporal and a multisource image, the image reconstruction performance is increased by using compressed sensing. When compared with other algorithm it has sharper edges and less noisy. But when it encounters a large sample rates, it won't work and its superiority will be reduced [18]. Tao Lu et al demonstrated a novel face SR method by decomposing the image patch by robust face hallucination process as information and principle component sparse regularization performs on noise [19]. The advantage of the method is that it is smooth and clear which validate robustness. It has the finest performance and effectiveness than other methods. But it will select only the small parts of patch [19]. Anchored Neighbor Regression is example-based method for SR which was proposed by Radu Timofte et al., 2015. It is retaining the qualitative performance by focusing on quick execution of recent state-of-the-art methods with better performance and speed. The algorithm gives a better speed-performance trade-off. It reduces the super-resolution mapping and is having more speed for pre-computed projective matrix. But for the video sequences it didn't consider extra dimension of time and with real-time streaming super-resolved video [20].

Graph Discriminant Analysis on Multi-Manifold (GDAMM) is used to resolve the LR probe image into HR version. The matching will be performed with the resolution of the HR gallery. The SR process of GDAMM method has faster running time.It can be used to preserves geometric structure of high-resolution face images and the high-resolution face images can be used as discriminatory power. But reconstruction error is high and performance loss will happen when regularization parameters are increased [21]. Face super resolution method based on sparse coding can gather the missing information in LR test images to HR sample image while the entire sample image and test image are separated as atoms by sliding windows sampling. The advantage of the method is that the facial image resolution is improved by reserves most facial characteristics and recognition rate is also increased and making it recognizable for practical use. But the problem is that the method can work only for the same pose, position, and illumination conditions [22] .Image super-resolution algorithm based on sparse signal representation between the LR and HR images can correlate patches by compromising the elastic net between ridge regression and Lasso regression. The advantage of the method is that with a lessnumber of significant coefficients, it can find a representation. The facial recognition rate is more accurate than the other methods. But the problem is that for generating high-resolution image different value of α is needed [23].General classification algorithm for (image-based) object recognitionprovides a framework for robustness to occlusion and feature extraction in face recognition. It helps to forecast how much barrier the recognition algorithm can manage, and it also helps to maximize the robustness to occlusion by guiding to choose training images. But it's not robust in object detection and recognition. It can't tolerate only misalignment and pose variation [24].It can also be described as a Biometric Artificial Intelligence based application that can distinctively recognize a person by analyzing patterns based on the person's facial textures and shape. Sparse representation is paying concentration in recent years and this is surely valuable and helpful in different fields. Image classification is one among them, classifying the test image into many predefined groups is the fundamental goal. It is proven that from the viewpoint belongs to visual neurons the natural images can be represented sparsely [25].In neural network system, Sparse Representation Classification (SRC) method is used to reduce the storage requirements and improve the performance of a neural network system. The fundamental idea of SRC is to extract the minimum features on a face for face recognition. Thus, it helps for the performance improvement and in reducing the database for storing the captured faces [26].

Sparse representation face recognition (SRC) which is modeled based on the image subspace assumption, to span a face subspace it uses training sample images. By using training images, it tries to construct test images [27]. In sparse representation, faces to be tested are roughly expressed for all types of training faces as a linear sparse combination, and testing samples for the minimum reconstruction remains of various types of training samples are determined by calculating the sparse combination coefficient. This approach improves the recognition performance and reduces the effect of occlusion [27].Several variations to the basic sparse approximation problem are there such as Structured sparsity, Collaborative (joint) sparse coding and other sparse approximations. In the original version of the problem, any of the atoms in the dictionary can be picked. In the structured (block) sparsity model, instead of picking atoms individually, groups of them are to be picked. These groups can be overlapping and of varying size. The objective is to represent x such that it is sparse while forcing this block-structure [28].

III. RESULTS AND DISCUSSION

The table I shows the comparative analysis on face image super-resolution algorithms using sparse representation for face recognition. The sparse GPR-based super resolution method proposed by [8] trains a GP model of the original training dataset obtained by active sample of an informative subset[8] and ASSS and AMSRR models proposed by [2] based on mixed samples of input low resolution image generated by the ASSS method and the complementary information are effectively learnt included in the mixed samples by AMSRR modelhave achieved more efficiency though getting the higher reconstruction quality than the Classified Dictionary Learning method which is presented by Fei Liu et al classifies the reasonable cluster by features of the samples and trained for each cluster using dictionary pair[1] and RPCA and adaptive sparse representation method proposed by Xuesong Li et al in which the low-rank structure from a matrix will be discovered by the low-rank optimization operation and thus refine the sparse representation coefficients [3]. The RIKNN method proposed by QU Shenming et al in which the low-resolution space which searches K-NN of LR patch and in the high-resolutionspace by re-identifyingits searching results [10]. Jun Yang et al proposed a method called versatile sparse representation which is based on post-processingdefines as down-sampling high-resolution image can be ensuredcertainlywhich leads to the equivalent low-resolution version[14]. Graph Discriminant Analysis on Multi-Manifold (GDAMM) method presented by Junjun Jiang et al is used to resolve the LR probe image into HR version. Then matching will be performed with the resolution of the HR galleryhas have lesser in performance because of distance neighbours[10], test images [14] and regularization parameters can’t be set to high [21].
The methods proposed by R. Raghavendra Christoph Busch et al forface super resolution is based on the weighted fusion of discrete and stationary wavelet in which weighting scheme is based on calculating the energy and correlation to capture a rich information from both discrete and stationary wavelet features [17]. Lizhe Wang et al[18]presented acompressed-sensing theory framework which represents images and signals as a sets of linear combinations and combine the compression and data acquisition into a distinct process [18] and Tao Lu et al demonstrated a novel face SR method by decomposing the image patch by robust face hallucination process as information and principle component sparse regularization performs on noise [19]and has higher performance in image reconstruction than the method presented in [10] ,[14] ,[21] .Classified Dictionary Learning method presented by Fei Liu et al [1] classifies the reasonable cluster by features of the samples and trained for each cluster using dictionary pair[1] , V. Abdu Rahiman et al proposed a neighbour embedding and the sparse representation method whichis having two learning based methods for converting the LR patches into HR image patches [4] and sparse domain selection based single image super-resolution methodproposed by Wen Lu et al obtains aneffective and compact HR dictionary by optimizing jointly and between the feature spaces. The mapping has achieved a more accurate recovery of images than the other state-of-art methods [5].
Ningbo Hao et al proposed a novelsuper resolution face reconstruction methodby defining the image with dissimilar resolution by multi-scale linear combination and nonlocal similarity is to be constant [12]. Changbin Shao et al proposed sparse-representation based face-classification method, which enriches the representation capacity of original dictionary by utilizing the different face images as an auxiliary dictionary[13] and Seno Purnomo et al proposed a new image super-resolution algorithm based on sparse signal representationbetween the LR and HR images. The correlated patch has been found out by compromising the elastic Net between Ridge regression and Lasso regression [23] has achieved more accuracy in classification [13] and recognition [12], [23] of facial images. Junjun Jiang et al proposed a novel face super resolution method based on TRNR regularization representation of the input LR patches by Tikhonov regularization term which leads to consistent anddistinctive solution for least squares problem[6]. John Wright et al proposed a general classification algorithm for (image-based) object recognition which provides a framework for robustness to occlusion and feature extraction in face recognition[24]. GuangweiGaoet al proposed a robust and discriminative low rank representation method for characterizing the representation of low-rank assumption and solves error term concurrently. The error images holistic structure and the global structure of data can be captured [7]. Xian Weia et al proposed for sparsifying linear transformation method by representing SparT means by coupling sparse structure image pairs bysparse transformation image for both high resolution and low-resolution spaces [9]with more robustness in finding the set of training images for occlusion and in recognizing the variations. Hasan Demireet al proposed a sparse representation with the specific dictionary for giving the solution for theface recognition challenges in surveillance videos. SVD and HMM methods provide super resolution for face recognition (Rasti, P.et al., 2016) with a high recognition rate than the position constraint-based face image SR method proposed by YuhuaLi et al approximately maps the low resolution and high-resolution facial images to discover local linear projection matrices by adopting sparsity preserving projection method [15].

Table I The Comparative Analysis on Face Image Super-Resolution Algorithms using Sparse Representation for Face Recognition

AUTHOR	MERITS	DEMERITS	ACCURACY
Liu, F.et al., (2018) [1]	The image resolution is improved, and detailed information recovers of targets	It has less reconstruction efficiency	---
Zhang, C.et al., (2018) [2]	Mixed samples will generate adaptively.	Will not examine the external and internal sample priors of adeep neural network framework	82.42%
Xuesong Li et al.,(2018) [3]	It achieves better performance	The convergence of AMDD has to improve and computational efficiency is less	83.77%
Abdu Rahiman, V.et al., (2017) [4]	The performance is improved	It's not updating the transformation parameter faster and stable	81.17%
Wen Lu et al.,(2017) [5]	Obtains a better reconstruction quality and more accurate relationship	It introduces some zigzagging effects	89.88%
Junjun Jiang et al.,(2016) [29]	Yields superior reconstruction results when it is contaminated by strong noise.	The smoothness and sparsity of the image not processed	---
Guangwei Gao et al ., (2017) [7]	The discriminative representation is simple, powerful and robust	In Training or testing registered face images are not available	---
Haijun Wanget al., (2017) [8]	The reconstruction quality becomes high.	The local structures are failed to consider within neighbor pixels.	93%
Wei, X.et al., (2017) [9]	Robust to change in poses, expression and illumination.	For recognition tasks and large scale image synthesis SparT is not adaptable.	---
Qu shenming et al., (2016) [10]	Image reconstruction accuracy is significantly improved and computational complexity is reduced	The performance degradation will happen by the distant	91.5%
Jiang, J.et al., (2016) [6]	Achieved the best generality, effectiveness, and robustness.	It can't able to perform for LR observation face is in the wild.	76.46%
Lu, X.et al., (2016) [11]	The fine details and sharp edges can be restored and by noise suppressing good result can be achieved	In the same category between two patches there is no evaluation procedure for measuring the probability	94.1%
Rasti, P.et al., (2016)[25]	More recognition rate for facial images after apply the super resolution	On natural images dictionary in SR it didn't provide significant advantage	98.06%
Hao, N.et al., (2016) [12]	The robustness and computational effectiveness is more in SR method on face Hallucination.	As compare to the original VLR face images blurring operator and down sampling created images are different	---
Shao, C.et al., (2017) [13]	Classify face accurately and uses auxiliary dictionary from a local difference face imagesinthis representation power can be improved inactualdictionary	In dictionary optimization original training samples are discarded	59.49%
Yang, J.et al., (2016) [14]	The internal image statistics has made the outputs comfortable and accurate	It has less performance in most test images	89.83%
Li, Y.et al., (2015) [15]	It is computationally fast in online reconstruction stage and the face images quality is achieved more	Only in the case of preprocessing method it can provide high recognition rate	92.67%
Yin, M.et al., (2015) [16]	Achieved more competitiveness or even superior for HR images than other similar SR methods.	The recognition rate is less when compared with other methods	74.4%
Raghavendra, R.et al., (2015) [17]	Superior performance of the ABC system with super resolved face images when compared with normal images	It not used any proprietary software for recording, optimization, feature extraction and comparison	72.29%
Wang, L.et al., (2015) [18]	The image reconstruction performance is increased	When it encounter a large sample rates, it won't work	---
Lu, T.et al.,(2013) [19]	Has the finest performance and effectiveness than other methods	It can select only the small parts of patch	90.76%
Timofte, R.et al., (2015) [20]	Reduce the super-resolution mapping and having more speed for pre-computed projective matrix	For the video sequences it didn't consider extra dimension of time and with real-time streaming super-resolved video	---
Jiang, J.et al., (2012) [21]	Can be used to preserves geometric structure of high-resolution face images and the high resolution face images can be used as discriminatory power	The reconstruction error is high and performance loss	72.06%

Hu, Z.et al., (2012) [22]	The facial image resolution is improved by reserves most facial characteristics	It can work only for the same pose, position, and illumination Conditions	---
Purnomo, S.et al., (2010) [23]	The facial recognition rate is more accurate than the other methods	For generating high-resolution image different value of α is needed	---
Wright, J.et al., (2009) [24]	Helps to maximize the robustness to occlusion by guiding to choose training images	Not robust in object detection and recognition. It can't tolerate only misalignment and pose variation	90.3%

IV. CONCLUSION

Face detection and recognition is a challenging problem in the area of pattern recognition, image processing, signal processing and computer vision. To solve the problem of face recognition, the sparse representation is the best approach because it is more robustness to deviation in directions, lighting and human expressions in face recognition super resolution. A sparse representation method having the capability of adopting to different level of information. A fine analysis of different sparse representation methodologies, which is also called as sparse approximation approach performs with sparse solutions for systems of linear equations are discussed andtheir advantages, disadvantages and certain comparative study reports are presented. This paper can be used as guidance for the fellow researches in the field of face recognition using sparse representation approaches in image processing.

REFERENCES

[1]. Liu, F., Han, P., Wang, Y., Li, X., Bai, L., & Shao, X. (2018). Super resolution reconstruction of infrared images based on classified dictionary learning. *Infrared Physics and Technology*, *90*, 146–155.

[2]. Zhang, C., Liu, W., Liu, J., Liu, C., & Shi, C. (2018). Sparse representation and adaptive mixed samples regression for single image super-resolution. *Signal Processing: Image Communication*, *67*(June), 79–89.

[3]. Li, X., Cao, G., Zhang, Y., & Wang, B. (2018).Single image super-resolution via adaptive sparse representation and low-rank constraint. *Journal of Visual Communication and Image Representation*, *55*(June), 319–330.

[4]. Abdu Rahiman, V., & N. George, S. (2017).Single image super resolution using neighbor embedding and statistical prediction model. *Computers and Electrical Engineering*, *62*, 281–292.

[5]. Lu, W., Sun, H., Wang, R., He, L., Jou, M. J., Syu, S. S., & Li, J. S. (2017). Single image super resolution based on sparse domain selection. *Neurocomputing*, *269*, 180–187.

[6]. Jiang, J., Ma, J., Chen, C., Jiang, X., & Wang, Z. (2016). Noise Robust Face Image Super-Resolution Through Smooth Sparse Representation, *47*(11), 1–12.

[7]. Gao, G., Yang, J., Jing, X. Y., Shen, F., Yang, W., &Yue, D. (2017). Learning robust and discriminative low-rank representations for face recognition with occlusion. *Pattern Recognition*, *66*(9), 129–143.

[8]. Wang, H., Gao, X., Zhang, K., & Li, J. (2017). Fast single image super-resolution using sparse Gaussian process regression. *Signal Processing*, *134*(July 2016), 52–62. https://doi.org/10.1016/j.sigpro.2016.11.006.

[9]. Wei, X., Li, Y., Shen, H., Xiang, W., & Lu Murphey, Y. (2017). Joint learning sparsifying linear transformation for low-resolution image synthesis and recognition. *Pattern Recognition*, *66*(August 2016), 412–424.

[10]. Qu, S., Hu, R., Chen, S., Jiang, J., Wang, Z., & Zhang, M. (2016). Super-resolution for face image with an improved K-NN search strategy. *China Communications*, *13*(4), 151–161.

[11]. Lu, X., Wang, D., Shi, W., & Deng, D. (2016).Group-based single image super-resolution with online dictionary learning.*Eurasip Journal on Advances in Signal Processing*, *2016*(1).

[12]. Hao, N., Liao, H., Qiu, Y., & Yang, J. (2016). Face super-resolution reconstruction and recognition using non-local similarity dictionary learning based algorithm. *IEEE/CAA Journal of AutomaticaSinica*, *3*(2), 213–224.

[13]. Shao, C., Song, X., Feng, Z. H., Wu, X. J., &Zheng, Y. (2017).Dynamic dictionary optimization for sparse-representation-based face classification using local difference images.*Information Sciences*, *393*, 1–14.

[14]. Yang, J., Guo, J., & Chao, H. (2016). A versatile sparse representation based post-processing method for improving image super-resolution. *Neurocomputing*, *205*, 287–300. https://doi.org/10.1016/j.neucom.2016.04.038

[15]. Li, Y., & Qi, C. (2015). Position constraint based face image super-resolution by learning multiple local linear projections. *Signal Processing: Image Communication*, *32*, 1–15.

[16]. Yin, M., Gao, J., &Cai, S. (2015). Image super-resolution via 2D tensor regression learning.*Computer Vision and Image Understanding*, *132*, 12–23.

[17]. Raghavendra, R., & Busch, C. (2015, july). Face Image Resolution Enhancement based on Weighted Fusion of Wavelet Decomposition. *18th International Conference on Information Fusion*, 2108–2114.

[18]. Wang, L., Lu, K., & Liu, P. (2015).Compressed Sensing of a Remote Sensing Image Based on the Priors of the Reference Image.*IEEE Geoscience and Remote Sensing Letters*, *12*(4), 736–740.

[19]. Lu, T., Hu, R., Han, Z., Jiang, J., & Xia, Y. (2013). Robust super-resolution for face images via principle component sparse representation and least squares regression. *Proceedings - IEEE International Symposium on Circuits and Systems*, 1199–1202.

[20]. Timofte, R., De Smet, V., & Van Gool, L. (2015). A+: Adjusted anchored neighborhood regression for fast super-resolution. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *9006*, 111–126. https://doi.org/10.1007/978-3-319-16817-3_8.

[21]. Jiang, J., Hu, R., Han, Z., Huang, K., & Lu, T. (2012, september). Graph discriminant analysis on multi-manifold (GDAMM): A novel super-resolution method for face recognition. *Proceedings - International Conference on Image Processing, ICIP*, 1465–1468.

[22]. Hu, Z., Li, W., Tang, Q., & Chen, Y. (2012, Aug). Face super resolution by patch-based sparse coding. *Proceedings - 2012 International Conference on Computer Science and Service System, CSSS 2012*, 1522–1525.

[23]. Purnomo, S., Aramvith, S., &Pumrin, S. (2010).Elastic net for solving sparse representation of face image super-resolution.*ISCIT 2010 - 2010 10th International Symposium on Communications and Information Technologies*, 850–855.

[24]. Wright, J., Yang, A. Y., Ganesh, A., Sastry, S. S., & Ma, Y. (2009).Robust face recognition via sparse representation.*IEEE Transactions on Pattern Analysis and Machine Intelligence*, *31*(2), 210–227.

[25]. Zhang, Z., Member, S., Xu, Y., & Member, S. (2015). A survey of sparse representation : algorithms and applications, 1–42.

[26]. Reddy, J., Gupta, R. K., &Awasthy, M. (2015). A Survey : Face Recognition by Sparse Representation, (2), 27–29.

[27]. Mane, R., &Agrawal, P. (2014). Literature Survey on Sparse Representation for Neural Network Based Face Detection and Recognition. *An International Journal (CSIJ)*, *1*(2), 23–31.

[28]. Eldar, Y.C, Kuppinger, P. and Bolcskei, H. (2009). "Block-sparse signals: Uncertainty relations and efficient recovery" (PDF). IEEE Transactions on Signal Processing. **58**: 3042–3054. doi:10.1109/TSP.2010.2044837.

[29]. Jiang, J., Chen, C., Huang, K., Cai, Z., & Hu, R. (2016). Noise robust position-patch based face super-resolution via Tikhonov regularized neighbor representation. *Information Sciences*, *367–368*, 354–372. https://doi.org/10.1016/j.ins.2016.05.032.

[30]. Peleg, T. Eldar, Y.C. and Elad, M. (2012). "Exploiting Statistical Dependencies in Sparse Representations for Signal Recovery" (PDF). IEEE Transactions on Signal Processing. **60**: 2286–2303. arXiv:1010.5734. doi:10.1109/TSP.2012.2188520.

[31]. Tonisuiboupin, pejmanrasti, gholamrezaanbarjafari, hasandemirel (2016, May).Facial Image Super Resolution Using Sparse Representation for Improving Face Recognition in Surveillance Monitoring.signalprocessingand communication applicationconference (SUI), 2016 24th, 437-440, 2016.

[32]. Tropp, J.A., Gilbert, A.C. and Strauss, M.J. (2006). "Algorithms for simultaneous sparse approximation. Part I: Greedy pursuit". Signal Processing. **86**: 572–588. doi:10.1016/j.sigpro.2005.05.030.