A Kernel Based Locality-Sensible Group Sparsity Representation of Efficient Face Detection

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Abstract- *In this paper, we consider the problem of automatically recognizing human faces from frontal views with varying expression and illumination, as well as occlusion and disguise. We cast the recognition problem as one of classifying among multiple linear regression models and argue that new theory from sparse signal representation offers the key to addressing this problem. Based on a sparse representation computed by ‘1-minimization, it propose a general classification algorithm for (image-based) object recognition. This new framework provides new insights into two crucial issues in face recognition: feature extraction and robustness to occlusion. For feature extraction, we show that if sparsity in the recognition problem is properly harnessed, the choice of features is no longer critical. This framework can handle errors due to occlusion and corruption uniformly by exploiting the fact that these errors are often sparse with respect to the standard (pixel) basis. The theory of sparse representation helps predict how much occlusion the detection algorithm can handle and how to choose the training images to maximize robustness to occlusion.*

Keywords- Face Recognition, sparse representation, occlusion, robustness.

I. INTRODUCTION

Nowadays face detection is attracting much attention in the social networks and multimedia information access. Face detection has been an active research topic in the field of pattern recognition and image recognition over the past decades. Many numerous approaches have been proposed, recognition methods that are robust to challenges such as illumination changes, occlusion, noise, facial expressions, aging, and resolution variations are still highly desirable. Human faces are arguably the most extensively studied object in image-based recognition. This is partly due to the remarkable face detection capability of the human visual system and partly due to numerous important applications for face detection technology. In addition, technical issues associated with face detection are representative of object identification and even data classification. Here, Group sparsity is used to utilize the grouped structure information in the training data. Sparse representation to represent the test sample as a sparse linear combination of the training samples, and then assign the test sample to the class which leads to the minimum reconstruction error. Main purpose of kernal method[6] is to map the original data into a high-dimensional feature space. Sparse representation is obtained in kernel space. Locality-Sensitivity is to take advantage of both data locality and group sparsity, and presented in the form of locality-constrained group sparse representation (LGSR) method for efficient face detection[1].

II. RELATED WORKS

In the existing method they have an algorithmic problem of computing sparse linear representations with respect to an overcomplete dictionary of base elements or signal atoms has seen a recent surge of interest. Much of this excitement centers on the discovery that whenever the optimal representation is sufficiently sparse, it can be efficiently computed by convex optimization, even though this problem can be extremely difficult in the general case. The resulting optimization problem, similar to the Lasso in statistics penalizes the ‘1-norm of the coefficients in the linear combination, rather than the directly penalizing the number of nonzero coefficients. Disadvantages of existing methods are difficulty in directly harnessing the redundancy in corrupted raw images. Local features computed from only a small fraction of the image pixels are clearly less likely to be corrupted by occlusion than holistic features. Errors on the original pixels become errors in the transformed domain and may even become less local.

In Hierarchical Ensemble of Global and Local Classifiers for Face Recognition, Y. Su, S. Shan [7] paper proposed the Global and Local features for face representation and recognition. In this method, global features are extracted from the whole face images by keeping the low-frequency coefficients of Fourier transform, which they believe encodes the holistic facial information, such as facial contour. For local feature extraction, Gabor wavelets are exploited considering their biological relevance.

After that, Fisher’s linear discriminant (FLD) is separately applied to the global Fourier features and each local patch of Gabor features. Thus, multiple FLD classifiers are obtained, each embodying different facial evidences for face recognition. Finally, all these classifiers are combined to form a hierarchical ensemble classifier [7]. They evaluate the proposed method using two large-scale face databases: FERET and FRGC version 2.0[7].

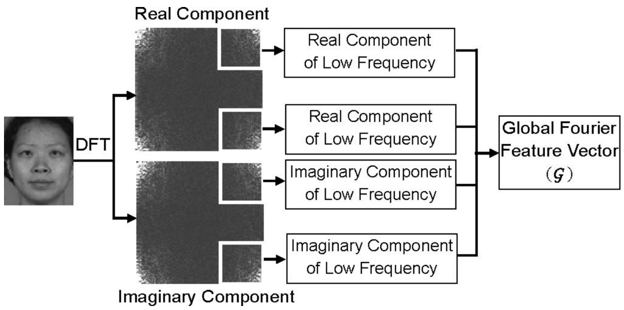

Fig 1.Global and Local Classifiers for Face Recognition by Hierarchical Ensemble

Pushing the Frontiers of Unconstrained Face Detection and Recognition: IARPA Janus Benchmark A, Brendan F. Klare, Ben Klein [3] is a method to rectify the a chief limitation in most benchmark datasets is the use of a commodity face detector to select face imagery. The implication of this strategy is restricted variations in face pose and other confounding factors. This paper introduces the IARPA Janus Benchmark A (IJB-A), a publicly available media in the wild dataset containing 500 subjects with manually localized face images.

The term “unconstrained” implies a system can perform successful identifications regardless of face image capture presentation or subject condition [3]. Face identification in certain scenarios may forever be elusive, such as when a face is heavily occluded or captured at very low resolutions, there still remains a large gap between automated systems and human performance on familiar faces. In order to close this gap, large annotated sets of imagery are needed that are representative of the end goals of unconstrained face recognition [3].

Graph-Preserving Sparse Nonnegative Matrix Factorization With Application to Facial Expression Recognition, Ruicong Zhi, Markus Flierl [10] proposed about commonly accepted that the intrinsic dimensionality of the space of possible face images is much lower than that of the original image space. Thus, it is necessary to look for efficient dimensionality reduction methods for facial feature extraction. Nonnegative matrix factorization [10] (NMF) algorithm is a recent method for finding a nonnegative decomposition of the original data matrix. NMF is based on the idea that negative numbers are physically meaningless in many data-processing tasks.

NMF represents a facial image as a linear combination of basis images. The GSNMF algorithm is derived from the original NMF algorithm by exploiting both sparse and graph-preserving properties[10]. Therefore, GSNMF can be conducted as an unsupervised or a supervised dimension reduction method. A sparse representation of the facial images is obtained by minimizing the $l1$-norm [2] of the basis image. As a parts-based representation can naturally deal with partial occlusion and some illumination problems, it is considered to perform superior for facial image processing. For NMF, the columns of matrix W denote basis images, and the elements of coefficient matrix H are nonnegative.

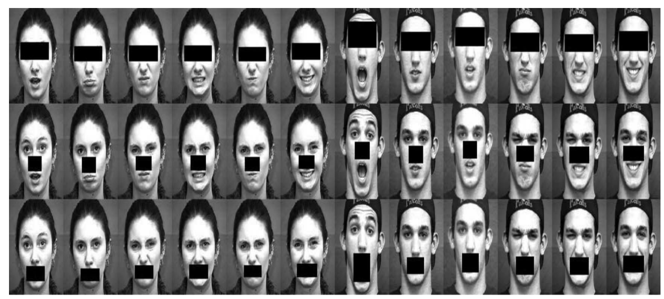

Fig 2.Some facial expression samples taken for Non-Negative matrix factorization

Particle Filter Re-detection for Visual Tracking via Correlation Filters, Di Yuan, Donghao [4] **,** is basically ,a visual object tracking method which was proposed based on adaptive background modelling to improve the robustness of the particle filter framework. A particle resampling strategy to provide more target candidates and use the correlation filter to choose the best one as the target object to improve the computational efficiency has been proposed. An efficient method for accurately locating the tracking object by particle filter redetection[4]. This method allows us to redetect the location of target object if the result of the correlation filter tracking is ambiguous or unreliable.

A novel scale-evaluation strategy is given by comparing the relationship of the maximum response values in consecutive frames. This scale evaluation mechanism can effectively reduce the impact of variations in the scale of the target on the performance and increase the robustness of the algorithm[4]. The proposed approach consists of the CF-tracking part, which is used to track the target object directly, and the redetection part, which is used to re-detect the object target. During the tracking process, the feature is extracted according to the known target position in the first frame, and the correlation filter is trained directly. The correlation filter based tracker (CFT) is strongly dependent on the maximum response value of the response map.

Multiple Kernel Learning for Sparse Representation-Based Classification, A.Shrivastava, V. M. Patel [6] proposed a multiple kernel learning (MKL) algorithm that is based on the sparse representation based classification (SRC) method. Taking advantage of the nonlinear kernel SRC in efficiently representing the nonlinearities in the high-dimensional feature space, it propose an MKL method based on the kernel alignment criteria[6]. This method uses a two step training method to learn the kernel weights and sparse codes. the sparse codes are updated first while fixing the kernel mixing coefficients, and then the kernel mixing coefficients are updated while fixing the sparse codes.

These two steps are repeated until a stopping criteria is met. The effectiveness of the proposed method is demonstrated using several publicly available image classification databases and it is shown that this method can perform significantly better than many competitive image classification algorithms[6]. The SRC method is based on finding a linear representation of the data. However, linear representations are almost always inadequate for representing non-linear structures of the data which arise in many practical applications. Kernel SRC [1] methods require the use of a predetermined kernel function such as the polynomial kernel or the Gaussian kernel. Selection of the kernel function and its parameters is an important issue in training when kernel SRC methods are used for classification. Multiple Kernel Learning [6] (MKL) methods that allow one to use multiple kernels instead of using a specific kernel function.

III. THE PROPOSED METHOD

Our project comes under image processing it is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them. Steps involved in image processing is Importing the image with optical scanner or by digital photography. Analyzing and manipulating the image which includes data compression and image enhancement an spotting patterns that are not to human eyes like satellite photographs. Output is the last stage in which result can be altered image or report that is based on image analysis.

Biometric verification is any means by which a person can be uniquely identified by evaluating one or more distinguishing biological traits. The oldest form of biometric verification is fingerprinting. Facial structure is also a physiological modality that can be used for personal identification and authentication. Human facial structure is an individual characteristic. Facial recognition biometrics makes use of this fact to identify and authenticate individuals. Human brains have natural ability to remember and distinguish different faces. We identify and authenticate people just by recognizing their face on a daily basis.

In this paper, we exploit the varying nature of sparse representation to perform classification. Instead of using the generic dictionaries, represent the test sample in an overcomplete dictionary whose base elements are the training samples themselves. If sufficient training samples are available from each class, it will be possible to represent the test samples as a linear combination of just those training samples from the same class. This representation is naturally sparse, involving only a small fraction of the overall training database. Argue that in many problems of interest, it is actually the sparsest linear representation of the test sample in terms of this dictionary and can be recovered efficiently via 1-minimization [2]. 1-minimization refers to finding the minimum 1-norm solution to an underdetermined linear system, a norm is a function that assigns a strictly positive length or size to each vector in a vector space save for the zero vector, which is assigned a length of zero[2].

Seeking the sparsest representation therefore automatically discriminates between the various classes present in the training set. It illustrates this simple idea using face recognition as an example. Sparse representation also provides a simple and surprisingly effective means of rejecting invalid test samples not arising from any class in the training database: these samples' sparsest representations tend to involve many dictionary elements, spanning multiple classes. Advantages of this proposed method is corrupted pixels are randomly chosen for each test image. The performances of various features in conjunction with 1-minimization converge, with conventional and unconventional features.

Fig 3.General methodology for face recognition

IV. WORKING METHODOLOGY

Human faces are arguably the most extensively studied object in image-based recognition. This is partly due to the remarkable face detection capability of the human visual system and partly due to many important applications for face detection technology. In addition, technical issues associated with face recognition are representative of object recognition and even data classification. A physical or behavioral sample is captured by the system during enrollment ie. capture the image of the person who wants to access the system.

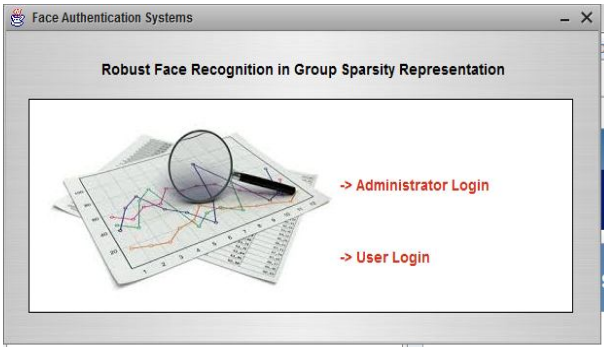

Fig 4.Administrator and user login page

The user details are filled by admin and stored in database. On clicking add button a message will be shown indicating the candidate ID. Candidate details tab will show you the details of the candidates entered by admin. If you want to remove some candidate, we can also be able to remove it from the list.

Fig 5.Administrator authority page

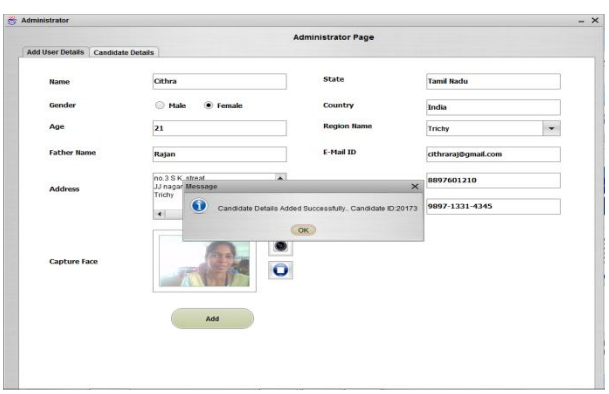

Fig 6. Adding user details

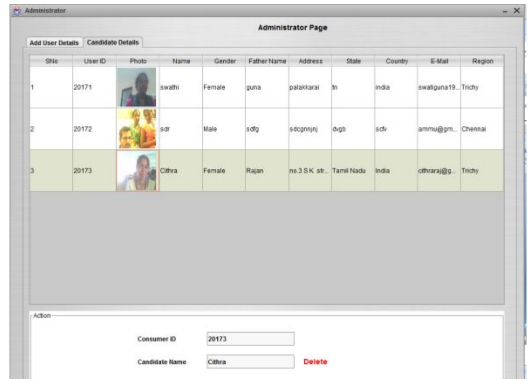

Fig 7. Candidate details in database

Next step is extracting features, the role of feature extraction starts from an initial set of measured data and builds derived values. The question of which low dimensional features of an object image are the most relevant or informative for classification is a central issue. The feature transformations for projecting the high-dimensional test image into lower dimensional feature spaces: examples include Eigen faces[8], Fisherfaces, Laplacian faces [9], and a host of variants. With so many proposed features and so little consensus about which are better or worse, practitioners lack guidelines to decide which features to use. Within our proposed framework, the compressed sensing implies that the precise choice of feature space is no longer critical: Even random features contain enough information to recover the sparse representation and hence correctly classify any test image.

Then occlusion [5] poses a significant obstacle to robust real-world face recognition. This difficulty is mainly due to the unpredictable nature of the error incurred by occlusion: it may affect any part of the image and may be arbitrarily large in magnitude. This error typically corrupts only a fraction of the image pixels and is therefore sparse in the standard basis given by individual pixels. When the error has such a sparse representation, it can be handled uniformly within our framework : the basis in which the error is sparse can be treated as a special class of training samples. The subsequent sparse representation of an occluded test image with respect to this expanded dictionary (training images plus error basis) naturally separates the component of the test image arising due to occlusion from the component arising from the identity of the test subject. In this context, the theory of sparse representation and compressed sensing characterizes when such source-and error separation can take place and therefore how much occlusion the resulting recognition algorithm can tolerate.

Data locality, group sparsity and the kernel trick is further explored, and a joint sparse representation method, named kernelized locality-sensitive group sparsity representation (KLS-GSRC) [1] is proposed in this algorithm. It is shown that, by integrating data locality, group sparsity and the kernel trick, the structure and nonlinear information embedded in the training and test data can be better exploited, and consequently a more discriminative representation can be obtain. To utilize the label information and further enforce the data locality in the kernel feature space, group sparsity and the kernel trick is used to propose a joint-sparsity representation method, named kernelized locality-sensitive group sparsity representation classification (KLS-GSRC). In KLS-GSRC, the data similarity is measured in the kernel feature space, thus the non-linear relationship of data can be better explored.

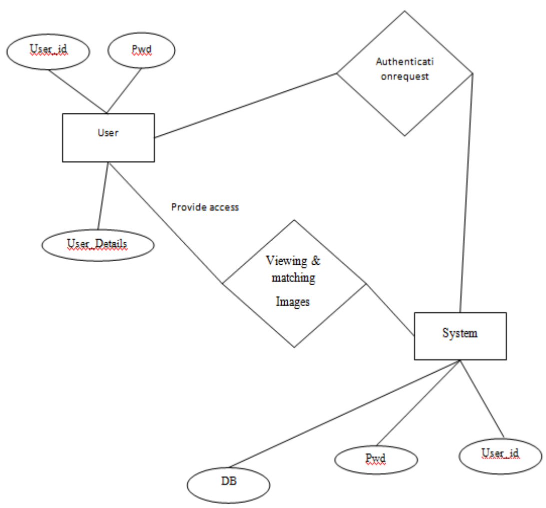

Fig 8. ER-Diagram of working methodology

V. CONCLUSION

This paper presents a kernel based locality-sensible group sparsity representation (KLS-GSRC) method for efficient face detection. KLS-GSRC considers the data locality in the kernel space. As a result, the structure and nonlinear information embedded in the training and test data can be better utilized, and more discriminative sparse representation can be obtained. This method achieves better performance than other sparse representation based methods.

REFERENCES

[1] Shoubiao Tan, Xi Sun, Wentao Chan, Lei Qu, and Ling Shao "Robust Face Recognition with Kernelized Locality-Sensitive Group Sparsity Representation'',vol. 26,no. 10,october 2017.

[2] Allen Y. Yang, Zihan Zhou ,Arvind Ganesh Balasubramanian , S. Shankar Sastry, and YiMa,,"Fast 1-Minimization Algorithms for Robust Face Recognition" vol. 22, no. 8, august 2013.

[3] Brendan F. Klare, Ben Klein, Emma Taborsky, Austin Blanton, Jordan Cheney."Pushing the Frontiers of Unconstrained Face Detection and Recognition: IARPA Janus Benchmark A !".

[4] Di Yuana, Donghao Lia, Zhenyu Hea, Xinming Zhangb "Particle Filter Re-detection for Visual Tracking via Correlation Filters'' 1711.10069v1 arXiv: [cs.CV] 28 Nov 2017.

[5] W. Ou, X. You, D. Tao, P. Zhang, Y. Tang, and Z. Zhu, "Robust face recognition via occlusion dictionary learning," Pattern Recogn., vol. 47, no. 4, pp. 1559–1572, 2014.

[6] A.Shrivastava, V. M. Patel, and R. Chellappa, "Multiple kernel learning for sparse representation-based classification," IEEE Trans. Image Process., vol. 23, no. 7, pp. 3013–3024, 2014

[7] Y. Su, S. Shan, X. Chen, and W. Gao, "Hierarchical ensemble of global and local classifiers for face recognition," IEEE Trans. Image Process., vol. 18, no. 8, pp. 1885–1896, 2009.

[8] M. Turk and A. Pentland, "Eigenfaces for Recognition" ,Journal of Cognitive Neuroscience ,vol.3, no. 1, pp. 71-86, 1991.

[9] Xiaofei He, Shuicheng Yan, Yuxiao Hu, Partha Niyogi, and Hong-Jiang Zhang "Face recognition using laplacianfaces"vol. 27, no. 3, march 2005.

[10] R. Zhi, M. Flierl, Q. Ruan, and W. B. Kleijn, "Graph-preserving sparse nonnegative matrix factorization with application to facial expression recognition," IEEE Trans. Syst., Man, Cyb. B, vol. 41, no. 1, pp. 38–52, 2011.