# AN EFFICIENT REAL FACE VERIFICATION BY USING INTELLIGENT METRIC LEARNING

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**ABSTRACT:-**

**A Face descriptor, Local Directional Number Pattern, for robust face recognition that encodes the structural information and the intensity variations of the face's texture. LDN encodes the structure of a local neighborhood by analyzing its directional information. A compute the edge responses in the neighborhood, in eight different directions with a compass mask. The blurred face as a convex combination of geometrically transformed instances of the focused gallery face, and show that the set of all images obtained by non-uniformly blurring a given image forms a convex set. A non uniform blur-robust algorithm by making use of the assumption of a sparse camera trajectory in the camera motion space to build an energy function. A reconstruction-based metric learning method to learn a discriminative distance metric for unconstrained face verification. Unlike conventional metric learning methods, which only consider the label information of training samples and ignore the reconstruction residual information in the learning procedure, a reconstruction criterion to learn a discriminative distance metric. For each training example, the distance metric is learned by enforcing a margin between the interclass sparse reconstruction residual and interclass sparse reconstruction residual, so that the reconstruction residual of training samples can be effectively exploited to compute the between-class and within-class variations.**

## I. INTRODUCTION

Extract robust features for real-world face recognition tasks. One major challenge is that in these scenarios the face images are only roughly aligned, and spatial misalignment exists in the cropped face images. To address this issue, in this work, for each image or one video key frame into a set of blocks and only compare the features extracted from corresponding blocks. On the other hand, represent each block by a set of position-free patches without enforcing spatial constraints for the patches within the block. This simple strategy in combination with the framework leads to an effective feature, which is robust to face misalignment. Specifically, first adopt the nonnegative sparse coding to quantize each patch according to a set of visual words in a pre-constructed visual vocabulary from k-means clustering. Then we extract Token-Frequency features from each image by sum-pooling the reconstruction coefficients over the patches within each block (each spatial-temporal volume consisting of a set of blocks along the temporal dimension).

Spatial Face Region Descriptor (Spatial-Temporal Face Region Descriptor, STFRD) for images by applying Whitened Principal Component analysis to reduce the dimension of TF features and suppress the noise in the leading eigenvectors. also develop a new distance metric learning method called Pair wise-constrained Multiple Metric Learning for face verification by integrating the SFRDs from all the blocks of an image. In contrast to the existing approaches which can only learn one distance metric for one type of feature, our method simultaneously learns multiple metrics for different descriptors, which better utilizes the correlations of these descriptors.

## II. PROPOSED SYSTEM

Using Local Directional Number Pattern and these features to give efficiency of the image. Showed that the set of all images obtained from a given image by non-uniform blurring and changes in illumination forms a bi-convex set, and used this result to develop our non-uniform motion blur compute the edge responses in the neighborhood, in eight different directions with a compass mask.Divide the face into several regions and extract the distribution of the LDN features from them with the help of three different evaluation, (1) Gray-scale evaluation, (2) distance–factor evaluation and (3) Pre-pixel evaluation. To avoid these problems, we investigate a new coding scheme that implicitly uses the sign of the directional numbers to increase the encoded structural information, with two different masks: a derivative-Gaussian and a Kirsch compass mask. Implement security in this, by comparing the query image with the images in the database and let us to continue when sees fit for the query image.

A novel dictionary learning approach that tackles the pair matching and classification problem in a unified framework. A discriminative term called „pair wise sparse code error" based on pair wise constraints and combined it with the classification error term to form the objective function of dictionary learning for better discriminating power. The objective function can be optimized by employing the efficient feature-sign search algorithm. The effectiveness of our approach was evaluated on both face verification and face Recognition tasks. Experimental results on face verification demonstrated that our approach is competitive with existing techniques without using facial feature point detectors or other additional information. Also compared our approach with several recently proposed dictionary learning methods on two well-known face databases. Our approach can obtain comparable face recognition performance to state-of-art on both databases.

A new simultaneous feature and dictionary learning method for image set based face recognition. By jointly learning the feature projection matrix and the structured dictionary, our approach extracts more discriminative information for image set based face representation. Experimental results on four widely used face datasets have shown the superiority of our approach over the state-of-the-art image set based face recognition methods in terms of accuracy and robustness. How to design more efficient optimization methods to improve the speed of our SFDL method appears to be an interesting future work improvement of the proposed method and did not consider other covariates, in a way to investigated a kind of upper bound accuracy as a fundamental study. therefore plan to evaluate the method against more realistic outdoor gait databases such as the USF gait database in our future work. The method is capable of mining out the discriminative parts, from among a large set of randomly sampled candidate parts, at the appropriate locations and scales. While the traditional metric learning algorithms use axed grid based image representation and are strongly misguided by occlusions, the proposed method has the edibility to be able to ignore the occluded parts and work with the next best matching visible parts and hence has better robustness to occlusions. The electiveness of the proposed method worst. The traditional metric Learning methods were verified by experiments on the challenging Labeled Faces in the Wild (LFW) dataset with a single feature channel. In the future we would like to use the method with multiple channels of features and perhaps use similar principle to do feature selection as well.

A reconstruction-based metric learning method to learn a discriminative distance metric for unconstrained face verification. Unlike conventional metric learning methods, which only consider the label information of training samples and ignore the reconstruction residual information in the learning procedure, we apply a reconstruction criterion to learn a discriminative distance metric. For each training example, the distance metric is learned by enforcing margin between the interclass sparse reconstruction residual and interclass sparse reconstruction residual, so that the reconstruction residual of training samples can be effectively exploited to compute the between-class and within-class variations. To better use multiple features for distance metric learning, A reconstruction-based multi metric learning method to collaboratively learn multiple distance metrics, one for each feature descriptor, to remove uncorrelated information for recognition. The evaluate methods on the Labeled Faces in the Wild (LFW) and YouTube face data sets and our experimental results clearly show the superiority of our methods over both previous metric learning methods and several state-of the-art unconstrained face verification methods.

The category labels of training images are provided. A unified discriminative dictionary learning approach for both pair matching and multiclass classification tasks. More specifically, we introduce a new discriminative term called „pair wise sparse code error" for the discriminativeness in sparse representation of pairs of signals and then combine it with the classification error for discriminativeness in classifier construction to form a unified objective function. The solution to the new objective function is achieved by employing the efficient feature-sign search algorithm. The learned dictionary encourages feature points from a similar pair (or the same class) to have similar sparse codes. We validate the effectiveness of our approach through a series of experiments on face verification and recognition problems

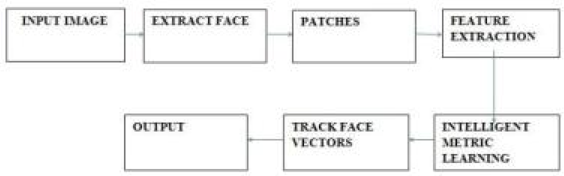


**Fig 1** Block Diagram

## III. METHODS

The following modules constitute the major methodologies for MRI image system.

- Extract face module.
- Patches module.
- Feature Extraction module.
- Intelligent metric learning module.
- Track face vectors module.

### A. Extract Face Module

Face recognition systems have demonstrated promising results under well-controlled conditions with cooperative users. However, face recognition in the wild is still a challenging problem due to dramatic intra-class variations caused by pose, lighting and expression. Moreover, the faces in surveillance or internet videos are commonly with low-resolution and may be even blurred, which brings additional challenges for face recognition systems.

### B. Patches Module

Adopt the nonnegative sparse coding to quantize each patch according to a set of visual words in a pre-constructed visual vocabulary from clustering. Then we extract Token-Frequency (TF) features from each image by sum-pooling the reconstruction coefficients over the patches within each block. Spatial-temporal volume consisting of a set of blocks along the temporal dimension.

### C. Feature Extraction Module

Geometry can be studied by representing this set of images as a tensor and mapping the tensor to a point on a product manifold. The product manifold served as a latent domain where domain Shifts due to multifactor variations such as illumination, blur and 2D alignment were jointly modeled For cases where only a single gallery image per subject was available, geodesic distance was used to perform nearest-neighbor classification on the latent domain shifts due to other facial variations such as 3D pose and expression that were not explicitly modeled. Finally, a probabilistic method for classifying image sets on the latent domain using divergence was also introduced.

### D. Intelligent Metric Learning Module

A novel way of learning a part-based face representation with Convolution Fusion Network built on multiple CNN models. Different representations are learnt for different facial regions to adapt to the geometrically non-stationary distribution. The independence leads to a better generalization performance with the holistic fusion.

The decoder has a symmetric structure to the encoder. Also, the encoder and decoder have tied weights; the weight metric for the decoder layer is the transpose of that for the corresponding Decoder layer. The encoded feature is forward into the third layer, the mixture layer. The mixture layer is composed of multiple branches, each of which corresponds to a mixture component. The output of each component sub-net is the probability of certain patch committed to the corresponding component.

### E. Track Face Vectors Module

The Vector Boost algorithm for multiclass learning, which is well suited for multitier pose estimation. However, all these methods have to learn one cascade classifier for each specific view (or view range) of face, requiring an input face image to go through different branches of the detection structure.

## IV RESULTS

To Develop the an efficient real face verification by using intelligent metric learning for authenticating or identifying the person original image in long view projection. Also to improve the efficient real face compared to previously enhanced image using IML (Intelligent Metric Learning model).

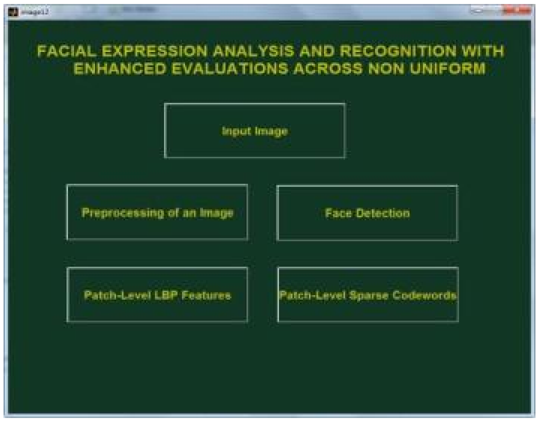


**Fig.4** Input Images

## V. CONCLUSION

We proposed an Efficient Real Face Verification by using intelligent metric Learning based person authentication method that uses to increase the accuracy deterioration due to view changes. It is face analysis and recognition with enhanced evaluation across non uniform images.it is find the specify area identify the images

## REFERENCES


1. Ahonen.T(2006)"Face Description with local binary patterns: Application to face recognition vol.28,No.12,pp.2037-2041
2. Barkan.O (2013)"Face high dimensional vector multiplication face recognition,"pp.1960-1967
3. Belkin.Mand P.Niyogi,(2001) "Laplacianeigenmaps and spectral techniques for embedding and clustering," pp.585-591
4. Bickel.S and T.Scheffer,(2004) "Multi-view clustering" in proc ICDM,2004,pp19-26.,
5. Cao.Q,Y.Ying,and P,Li,(2013) "Similarity metric learning for face recognition" in Proc.IEEE ICCV,pp.2408-2415.
6. Chen.D,Cao.X(2012)"Bayesian face revisited:A joint formulation in Proc.ECCV,2012,pp.566-579"
7. Cui.Z,(2013) "Fusing robust face region descriptors via multiple metric learning for face recognition in the whild" in Proc.IEEE CVPR,Jun 2013,pp.3554-3561.
8. Davis.J.V, and Kulis.B,Jain.P,(2007) "Informationtheoretic metric learning" in Proc.24th ICML,pp.209-216
9. Wu X.and Memon N.(1997) "Context-based,adaptive,lossless image coding"vol.45 No.4,pp437-444
10. Zobel J and Moffat A.(1995) "Adding compressiontoafull-text retrival system,"Vol.25 No.8,pp 891-903