IJCTA, 9(25), 2016, pp. 193-209 ISSN: 0974-5572

Facial Image Reconstruction and Recognition from a Corrupted Image by Mahalanobis Kernel-based Support Vector Data Description (MKSVDD)

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ABSTRACT

Facial recognition system is a computer application for automatically identifying or verifying a person from a digital image or a video frame from a video source. Although the available approaches provide good results under particular conditions, the illumination alterations, occlusions and recognition time are still main issues in face recognition authentication systems (FRAS). The main reason for the overall performance degradation is due to the transformations in appearance of the user based on the aspects like ageing, beard growth, sun-tan etc. In this paper, damaged face is considered for facial recognition. However, the variations introduced by damaged face remain difficult to be modelled by existing face recognition systems and degrade the performances of face recognition algorithm. Therefore damaged face changes facial features to large extend and thus creating a major problem to face recognition system. In this paper, a non-iterative approach is proposed that can match multiple feature points in order to obtain the correspondences between the input image and the reference face. Furthermore, shape and texture of the whole face are reconstructed by Mahalanobis Kernel-Based Support Vector Data Description (MKSVDD) from the partial correspondences obtained by matching.

1. INTRODUCTION

The application of facial identification and recognition technology has increased in entrance/exit security, immigration control using electronic passports, criminal search etc. This technology has become more robust to various changes in illumination, expression, viewing angle and so on. On the other hand, in addition to its robustness, it can realize significantly enhanced performance if it can efficiently reconstruct facial images that have been corrupted by camera sensor noise, glasses, hand, occlusion or by tampering or by contamination from external substances.

Recently, an object-based reconstruction method, which models the object in the image and applies it to the reconstruction, has been studied. This method can be used even when the image has been corrupted by object occlusions as well as camera noise and thermal degradation. The most representative of this reconstruction method is the one that uses the morphable face model [2, 3, 8, 9, 11]. This morphable reconstruction method consists of the input image-to-reference face correspondences extraction and data reconstruction that reconstructs the complete shape and texture from partial shape and texture based on the extracted correspondences.

In the previous studies related to the facial image reconstruction the process of reconstruction itself is too much complex. In previous studies [1][2], they followed very complex data completion algorithms, and digital image processing operations for the process of reconstruction. In various recent studies they

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have taken entirely different approach for reconstruction [3][7]. In their work Deng, Dong, Xudong, Kin and Qionghai proposes a spectral graph based algorithm for face Image repairing [3]they first cluster the images which have a similar sparse representation to the query image. Then find the best-matched patch for guiding the synthesis of the missing parts. The patch obtained is used to guide the in-painting work of the damaged part of the occluded face. But here the key is to find the ideal patch, which is not always easy. In their work Tang, Zhuang, Wang, Shih and Tsai [7] aims to remove only part of a face region (e.g., part of mouth or nose), whereas in most papers, the complete components can be removed. Their approach uses the source information in the same face, instead of using deduced sample face regions from the face database.

In this paper a facial database has been used [9], the input to the system is a damaged frontal facial image. The database contains facial images with constant illumination and frontal view of the face, from the database the average of all the faces is derived, and is called as REFERENCE FACE. Then separate the shape and texture of the input image [4]. The shape is the displacement of the pixel in the input image to the corresponding pixel in the reference image, and the texture is the gray value of the pixel when the input image is mapped on to the reference face (warped image). Data completion algorithm has been applied for reconstructing incomplete facial data (Shape and Texture) [5][6] with the help of reference image. After that we will combine the reconstructed shape with the reconstructed texture to obtain the reconstructed facial image [1][2][4].

The proposed method helps to reconstruct images distorted due to noise or if any object (like eyeglasses or scarf etc) covered any part of the face. And the reconstructed images are classified using Improved Classification approaches.

2. RELATED WORKS

A probabilistic approach using part-based matching has been proposed in for expression invariant and occlusion tolerant recognition of frontal faces. The global approaches and a component-based approach to face recognition and evaluate their robustness against pose changes have presented. The global method consists of a straight forward face detector which extracts the face from an input image and propagates it to a set of SVM classifiers that perform the face recognition [6].

B. Heisele, P. Ho, J. Wu and T. Poggio describes a semi-automatic alignment step in combination with support vector machine (SVM) classification was examined. Due to self-occlusion, automatic alignment procedures will eventually fail to compute the correct correspondences for large pose deviations between input and reference faces. Combining view-specific classifiers has also been applied to face detection. A probabilistic approach using part-based matching has been used for expression invariant and occlusion tolerant recognition of frontal faces. There are two global approaches and a component-based approach to face recognition and evaluate their robustness against pose changes. The ûrst global method consists of a straightforward face detector which extracts the face from an input image and propagates it to a set of SVM classifiers that perform the face recognition. By using a face detector achieves translation and scale invariance [7].

Yin Zhang and Zhi-Hua Zhou says that preliminary research which simply pursuing a low error rate in face recognition is not as reasonable as it might have been expected before, because different kinds of mistakes lead to different amount of losses. Formulate face recognition as a multi- class cost-sensitive learning task and under such formulation, try to minimize the total cost rather than the total error rate. To the best of knowledge, this is the first study on cost-sensitive face recognition [8].

Fan et al. [9] presented Nomalized Linear Discriminant Analysis for use in self-updating systems. Based on the simulation results in various data bases, it is observed that Normalized cross-correlation is better than semi-supervised linear discriminant examination. But, this technique does not acknowledge the corruption of training data due to misclassified examples.

Unlike previous work we combine shading information along with prior knowledge of a single reference model to recover the three-dimensional shape of a novel face from a single image. Our method does not use symmetry in the reconstruction process, and it does not require correspondence between many models in a database since it uses a mere single model as a reference. At its core our method solves a shape from shading problem, but it does not assume knowledge of part of the sought 3D model. Our algorithm works with general unknown lighting by representing reflectance using spherical harmonics. We let the gradient in the direction of the normal vanish on the boundaries, and we exploit the reference model to linearize the problem (which leads to increased robustness) and to fill in the missing information – an initial estimate of the albedo and for recovery of the illumination and pose. Finally we regularize the difference between the reference model and the sought 3D shape, instead of smoothing directly the sought shape, which increases the accuracy of the reconstruction.

Most face reconstruction methods assume that faces can accurately be modeled as Lambertian. It was shown in [22] that in many common situations the human skin indeed exhibits nearly Lambertian reflectance properties. Specifically, a face surface was photographed from a sequence of positions and with different lighting directions. Then, by assuming that the face shape and the light source position are known, the photographs were analyzed to determine the bidirectional reflectance function (BRDF). The analysis showed that at incident lighting angles around 30° the BRDF was close to Lambertian. Deviations from the Lambertian reflectance occurred at larger incident angles (above 60°). Specular effects, however, may exist, e.g., when the skin is oily.

3. PROPOSED METHODOLOGY

The Face Recognition Authentication System (FRAS) used in this research work is shown in Figure 1 and it has six main building blocks namely face detection, segmentation, normalization, classification and selection block for automatic learning. In the following sub-sections, the algorithms used in each block are described.

3.1. Step 1: Face Detection

The face detection block identifies whether there are face(s) in an image. If there are face(s) in the image then the detector outputs their position and size. The main necessities of the face detection block are that it

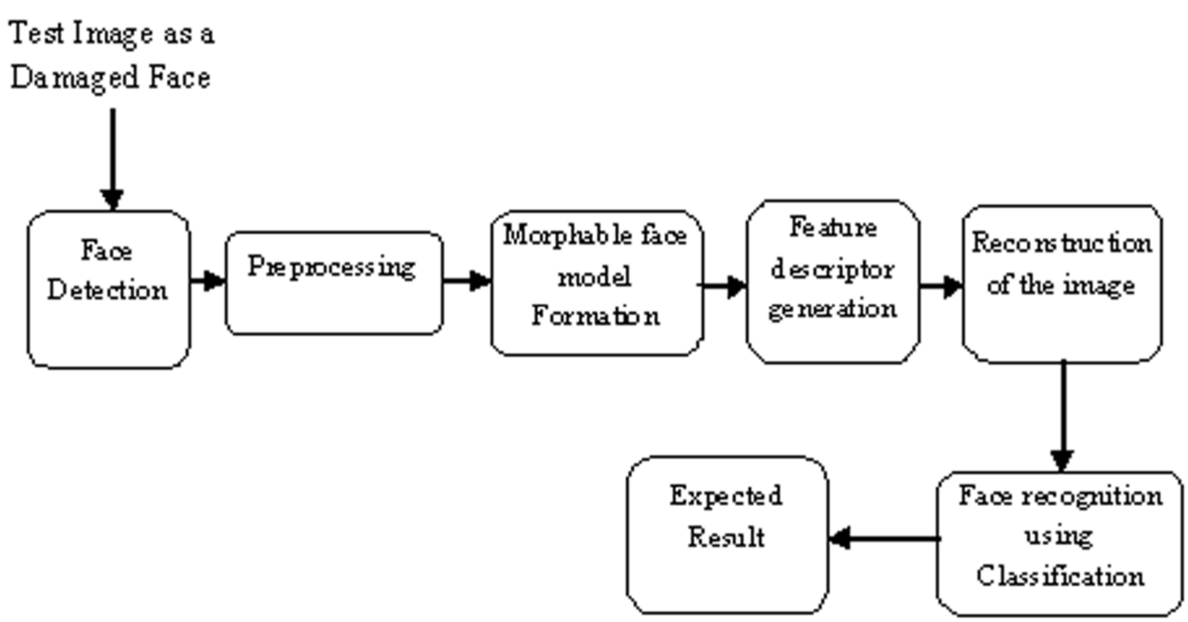

Figure 1: Flowchart of Proposed FRAS

functions at real-time while being highly accurate [10]. The real-time speed is essential in order to minimize the waiting time of the user to be determined. High accuracy is required to minimize the problem caused to a user if the user's face is not located by the system. In this approach, the detector presented in [12] is utilized, which uses weak classifiers based on Haar-like features [13] with optimally weighted rectangles.

3.2. Step 2: Preprocessing using filtering approaches

Preprocessing the input image is a vital step. Every image that is fetched from the database undergoes preprocessing step. After the image is given as a input to the system, the face is detected using (Viola and Jones, 2001) haar-cascades. The unwanted noises presented in the images are pre-processed using Gaussian approach. .

3.3. Step 3: Face Segmentation Using Active Appearance Model

The main aim of segmentation is to partition an image into regions and objects, in such a way that the segmented regions can be examined individually. Thus, a complex image is minimized into less complex segments that are much easier to interpret. Segmenting an object out of an image is determining and defining the boundary that encapsulates that object. In several scenarios, the shape of the boundary can give a lot of data about the object itself. Based on this, it is easy to observe that segmentation is valuable for isolating objects and shape.

Separation of a face from the background and accurate localization of facial features is essential as it is easy to extract facial features according to either shape or image intensities, considering region correspondences.

For the segmentation of the well-known facial features, this approach system utilizes Active Shape Models with Invariant Optimal Features (IOF-AAM) [11]. This approach integrates local image search with global shape constraints depending on a Point Distribution Model (IPDM [15, 16].

An Active Appearance Model (AAM) is a computer vision approach for matching a statistical model of object shape and appearance to a new image. They are constructed during a training phase. A group of images, along with coordinates of landmarks that appear in all of the images, is given to the training supervisor.

It is based on the Active Shape Model (ASM). But, the main drawback of ASM is that it only uses shape constraints and does not take benefit of all the available data – the texture across the target object. This can be modeled using an AAM.

3.4. Step 4 Morphable Face Model

The facial data in this paper are defined in the morphable facial model. A facial image is divided into shape and texture based on the pixel correspondences between the input facial image and the reference face [20]. The multivariate normal distributions of shape S and texture T from a data set of faces are obtained.

The multivariate normal distributions are expressed by the average shape $\vec{S}$ and average texture $\vec{T}$ and the covariant matrix $\sum_S$ of the differences between the shape and the average shape in Equation (1), X^s, and covariant matrix $\sum_T$ of the differences between the texture and the average texture, X^T.

$$X^S = S - \overline{S},\ X^T = T - \overline{T}$$

By Singular value decomposition (SVD), basis transformation is performed to an orthogonal coordinate system formed by eigenvectors S_i and T_i of the covariance matrices $\sum_S$ and $\sum_T$ on our data set of N faces (Equation (2)).

$$S = \overline{S} + \sum_{i=1}^{N-1} \lambda_i^S S_i, T = \overline{T} + \sum_{i=1}^{N-1} \lambda_i^T T_i$$

where $c = \{c_1, c_2, ..., c_m\} \in R^{N-1}$ and λ_i^S and λ_i^T are the standard deviations of the shape and texture. **The** dimension of the space spanned by S_i and T_i is at most N1.

3.5. Feature descriptor generation using LDP Variance (LDPv) Descriptor

In this section, first review the LDP code, and then, the descriptor based on LDPv is explained.

Generally, texture can be well represented when characterized by a spatial structure along with its contrast [21]. The LDP feature only contains the distribution of local structures. A low contrast structure contributes equally with a high contrast one in the LDP histogram. However, texture with significant contrast should impact more since human eyes are more sensitive to high contrast regions. Hence, we account for the contrast information within the feature descriptor. The variance of a structure is related to the texture. Generally, high frequency texture regions have higher variances and contribute more to the discrimination of texture images [19]. Therefore, the variance is introduced as an adaptive weight to adjust the contribution of the LDP code in the histogram generation. The proposed LDP_v descriptor is computed as:

$$LDP_v(\tau) = \sum_{r=1}^{M} \sum_{c=1}^{N} w\left(LDP_k(r,c)\tau\right)$$

$$w\left(LDP_k(r,c)\tau\right) = \begin{cases} \sigma\left(LDP_k(r,c)\right). & LDP_k(r,c) = \tau \\ 0 & Otherwise \end{cases}$$

$$\sigma\left(LDP_k(r,c)\right) = \frac{1}{8}\sum_{i=0}^{7}\left(m_i - \overline{m}\right)^2$$

Where, $\overline{m}$ is the average of all directional responses $\{m_i\}$ calculated for a position (r, c). When LDP and variance σ are treated as the two orthogonal axes in a coordinate system, the LDPv can be regarded as the integral projection [6] along the σ axis. LDPv generated from the whole image loses some location information, but for face images, some degree of location and spatial relationship well represent the image content [1, 2, 12]. Hence, the basic histogram is modified to an extended histogram, where the image is divided into g number of regions R0, R1, …, Rg-1 shown in Figure 5, and the LDPvi histogram is built for each region Ri using equation 8. Finally, concatenating all of the basic LDPvi distributions with equation 9 yields the descriptor vector of size p(= g × n), where n is the size of each basic LDPv histogram.

$$LDP_v^i(\tau) = \sum_{r=1} \sum_{c=1} w\left(LDP_k(r,c),\ \tau\right) \ \ where (r,\ c) \in R_i$$

$$LDPv = \left[LDPv^0,\ LDPv^1,\ ...,\ LDPv^{g-1}\right]$$

This extended feature vector represents both texture and contrast information with some extent of spatial relationship. Two parameters can be adjusted for better feature extraction: 1. The prominent directions to encode in the LDP pattern. 2. The number of regions. The optimal parameters are selected from a good trade-off between recognition performance with feature representation and feature- vector length.

3.6. SIFT descriptors

In the multiple example images generation steps of the preparation process, example images of various textures and shapes are generated in order to extract sufficient feature points needed for input image matching in reconstruction. Firstly, we generate morphable face models which be composed of shape and texture basis based on morphable model from face database with shape and texture information, and then we can generate sufficient number of shapes and textures applying multivariate normal coefficients to shape and texture basis. In this paper, forward warping is performed to different combinations of shapes and textures information to generate example facial images.

In the step of feature point descriptor generation in the reconstruction process, the feature points that are robust to noise and illumination variations are extracted and feature descriptors that express the inherent texture around the feature points are obtained. The correspondence between point on the reference and a feature point on the example face is computed by using the known shape for the example face and triangle mesh interpolation algorithm. In this case, the feature descriptor information of the feature points of each example facial image and the position information of the features points on the reference face can be saved in the feature information reference table. Using this table, the correspondences of the input image can be rapidly obtained in the reconstruction process. In this paper, feature points were extracted and their feature descriptors were generated by using the SIFT method and SIFT descriptor of Lowe [15].

If an input face is given for the reconstruction, the SIFT descriptors at feature points are obtained and matched with those of multiple example faces by one by one. Then, the ratio of the similarity level of the most similar feature descriptor information M_{first} and the similarity of the second most similar feature descriptor information M_{second}, R_M $(= M_{second} = M_{first})$ is obtained in each example image. If the similarity ratio RM is greater than the threshold value, then the feature points of the input image are assumed not to match those of the example facial images [18].

Once the feature descriptors for the specific example image that correspond to those of the input facial image are determined, correspondence of feature points between input face and reference face can be easily obtained by referring to the feature information. Although the number of corresponding feature points between the input image and each example facial image is small, through multiple example facial image matching sufficient number of corresponding feature points can be obtained indirectly for shape reconstruction (Step 2). In this paper, since the input image and reference face are assumed to have normalized size and position, if any corresponding feature points are at a distance greater than the defined threshold value, these points will be eliminated from the set of corresponding feature points.

Generally, the feature points extracted from the input facial image do not all correspond to the reference face, but the results of our experiment showed that at least 30 feature points from the input facial image corrupted by either Gaussian noise (with standard deviation of 30 in 256 gray level image) or object occlusion (20% of facial area) ultimately correspond to the reference face. These corresponding feature points are sufficient for image reconstruction, as shown in Figures 2 and 3.

3.7. Step 6 Reconstructing Shape and Texture Based On Mahalanobis Kernel-Based Support Vector Data Description (MKSVDD)

In this paper, a method for reconstructing the shape and texture by Mahalanobis Kernel-based Support Vector Data Description (SVDD) is presented. Unlike the linear projection method, in which the area of study was projected onto a linear space, MKSVDD directly estimates the existing space of the training data by a hyperball. MKSVDD aims to find the smallest hyperball that will include the maximum number of the training data from a specified domain. Generally, the existing SVDD would be more effective if the input space can be converted to feature space, where the input image can be better expressed. The Gaussian kernel is applied in traditional SVDD. Consequently, SVDD with Gaussian kernel has no problem detecting shifts in the mean vector, but is not so sensitive to shifts in covariance [reference]. This research paper explores another choice for kernel, which is based on the Mahalanobis distance rather than the traditional Euclidean distance as seen above:

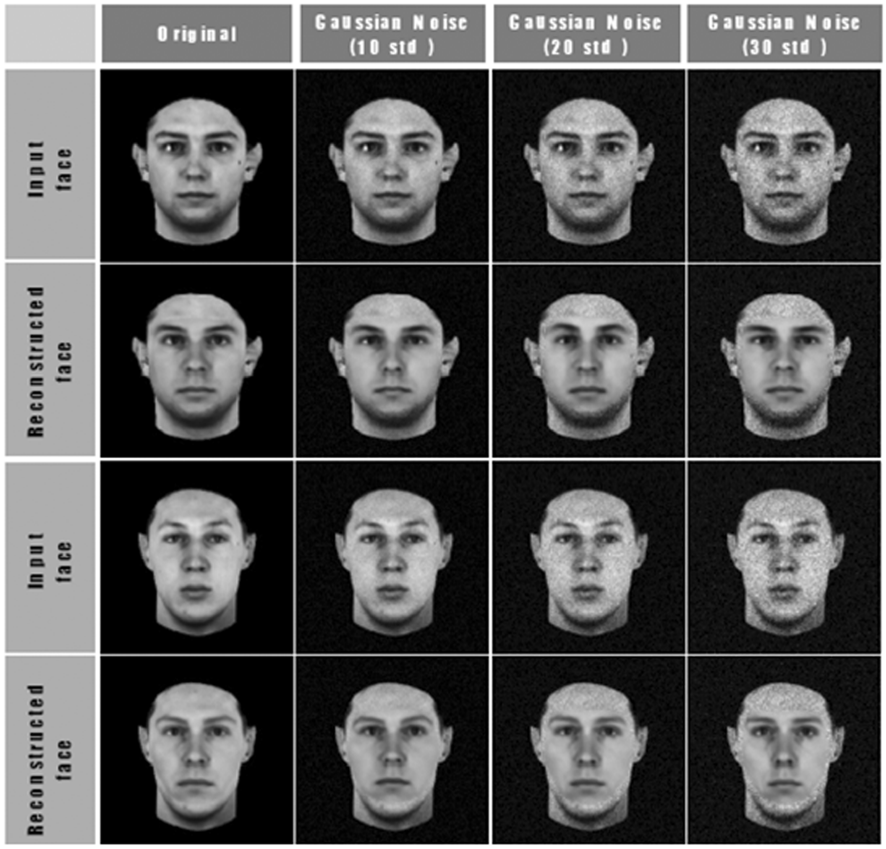

Figure 2: Examples of input faces

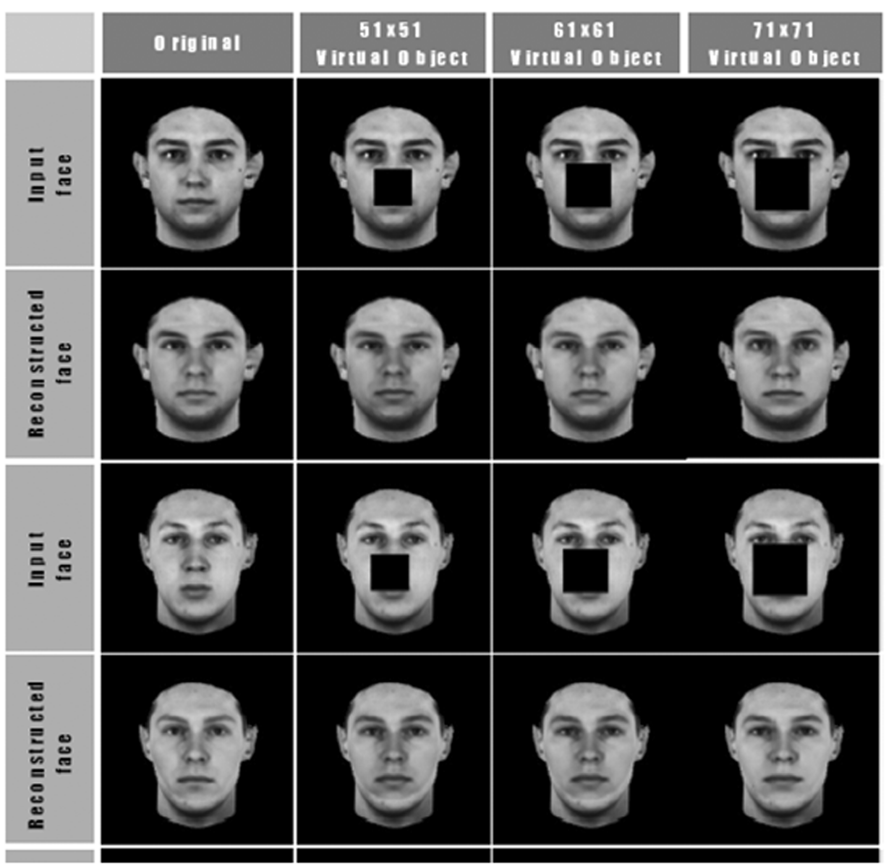

Figure 3: Examples of reconstructed faces

$$d_M(x,y) = \sqrt{(x-y)^T S^{-1}(x-y)}$$

It is called Mahalanobis-distance based kernel (hereinafter referred to as Mahalanobis kernel), whose function is defined as:

$$K_M(x,y) = \exp\left[-\frac{(x-y)^T S^{-1}(x-y)}{\sigma^2}\right]$$

$K_M(x, y)$ satisfies the Mercer condition (2. 13) mentioned above, so (2. 26) is a valid kernel function. The Mahalanobis kernel and distance functions are mostly similar to their Gaussian counterparts, with the only difference being the incorporation of a covariance matrix S in the calculation. Hence, K chart powered by SVDD with Mahalanobis kernel-distance ought to be more sensitive to changes in the covariance matrix than with Gaussian kernel.

We consider each corrupted test pattern x. When the decision function yields a nonnegative value for x, the test input is accepted normal as it is, and the reconstruction process is bypassed. Otherwise, the test input is considered to be abnormal and corrupted or corrupted. To reconstruct the corrupted area, an SVDD based projection approach that we recently proposed [12] is used, in which we move the feature vector toward the center up to the point where it touches the hyperball. Obviously, this movement is a kind of the projection, and can be interpreted as performing reconstruction of the corrupted area in the feature space. Note that as a result of the projection we have the obvious result. Here, we try to find the pre-image of the refined feature. If the inverse map is well-defined and available, this final step attempting to get the reconstructed image. However, exact pre-image typically does not exist. Thus, we need to seek an approximate solution instead. For this, we follow the strategy of [19], which uses a simple relationship between feature-space distance and input space distance together with the multi-dimensional scaling. The overall proposed step is introduced in [1]. After obtaining the reconstructed vectors from the above MKSVDD method, synthesize a facial image by forward warping the texture onto the input face by using the shape. This synthesis step 7 is well explained in [20].

4. EXPERIMENTAL RESULTS

The experimental results are drawn to evaluate the performance of the proposed approach. The experiment was implemented in MATLAB. Initially four images are considered from our facial database [9] to verify the proposed method. Then the real time phases are used for experimentation.

Figure 4: Input Images

Now the process of reconstruction performed on them, as per the algorithm. The average of these four images are calculated and named it as reference image as shown below.

Now input the damaged image to be reconstructed. One image has been taken from the database and some part of it is damaged as (10% to 20% of the face). In present case the left eye of an image has been damaged or removed as shown below.

Now warped the input image on to the reference image, i.e. taken the texture of the input damaged face and placed it in to the reference face i.e. on to the shape of the reference face, as shown below.

In the continuation the texture at corresponding points on warped image and the reference image are collected. A GUI (Graphical User Interface) may be used for collecting the co-ordinates of major parts of the face like Tip of Nose, Lip's area, Ear's corners, Forehead, etc. With the help of these points we take the Gray value at those points on both the Warped as well as the input image. As the shape of both the images are same, so it's not required to collect co-ordinates from both the images, so only the co-ordinates on reference image are collected and used it for getting texture on both the images.

After that the difference between them is calculated, and then the average of all differences (i.e. the average texture difference). Then the reference and damaged input image has been taken and on the similar ways got the co-ordinates of few major parts of them, for the undamaged part. The only difference to the previous calculation is this time opened both the images on the GUI for taking the corresponding points on both the images. As the shape of the images are not same. Then calculate the average difference between them (the average shape difference). Finally the co-ordinates of damaged region on input as well as corresponding points on reference face has been stored, and replaced the pixels adding shape and texture difference to them, and got the reconstructed image of the input damaged image, as shown below.

Figure 5: Face detection Results

Figure 6: Preprocessing Results

Figure 7: Reference Image

Figure 8: Damaged Image

Figure 9: Warped Image

Figure 10: Reconstructed Facial Image

Similarly the real time faces are considered for experimentation. The input images taken for

The face detected result from the input dataset is shown in the figure 10. The given input image is checked, where it consists of a face or not a face is shown in the figure 10.It can be helps to identify the given input images are real face images.

Figure 11: Input Images of real time dataset

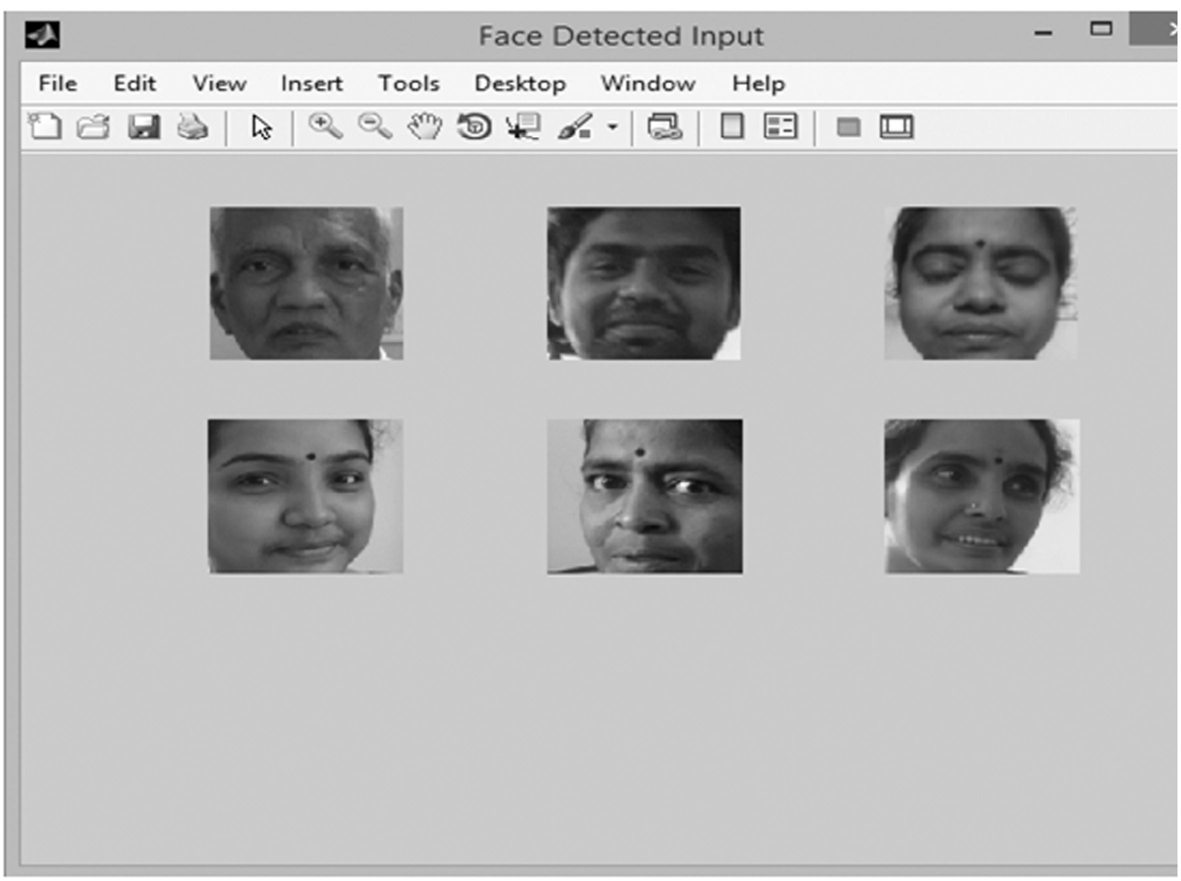

Figure 12: Face detected Input

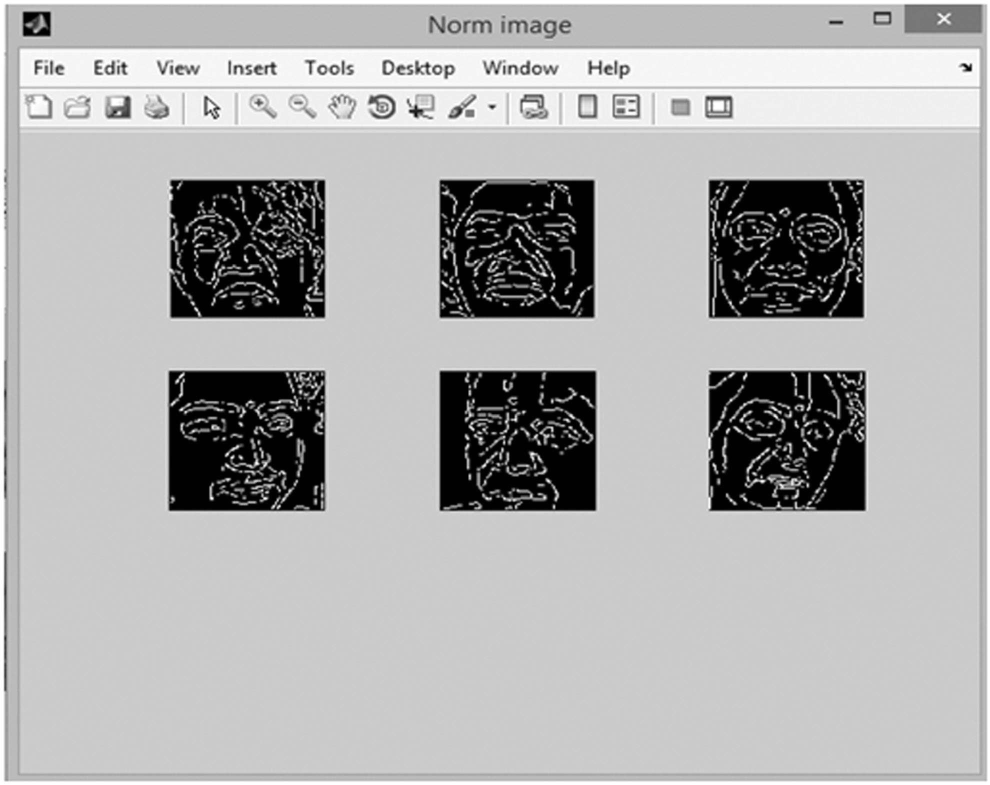

Figure 13: Preprocessing Normalization image

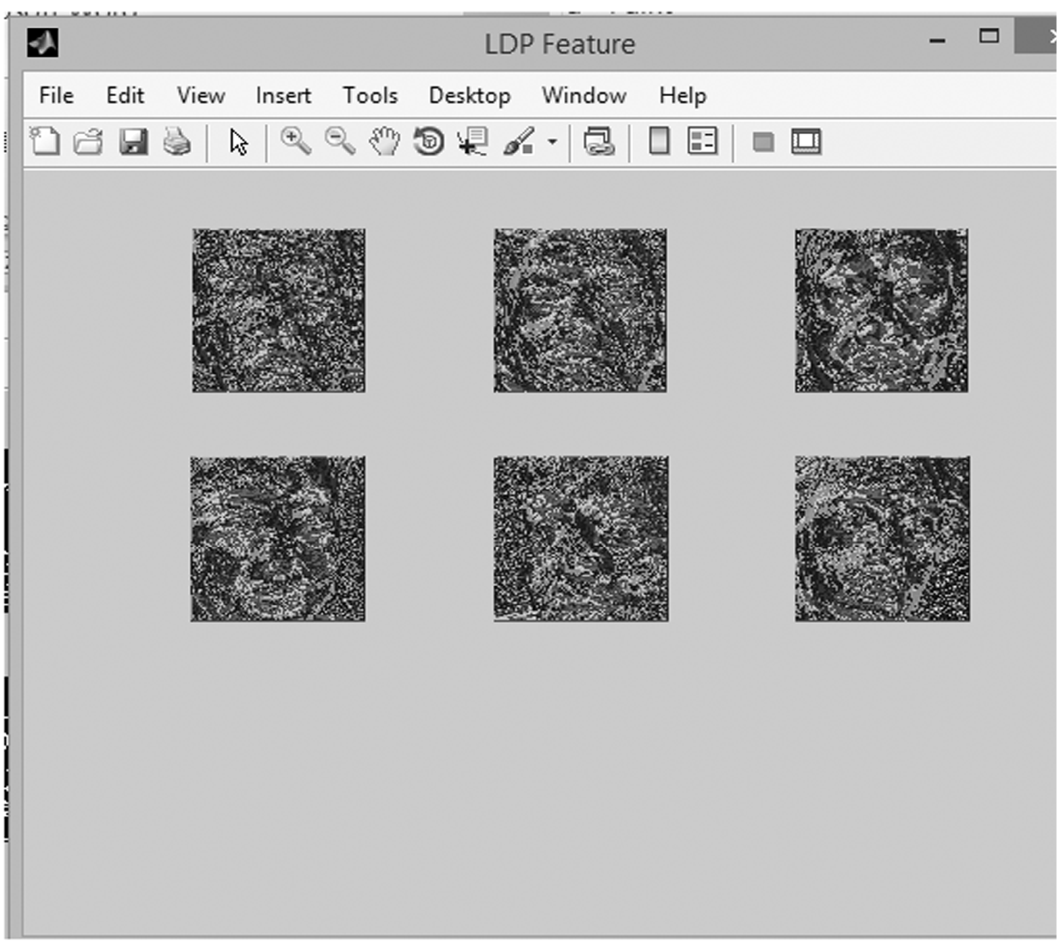

Figure 14: LDP feature image

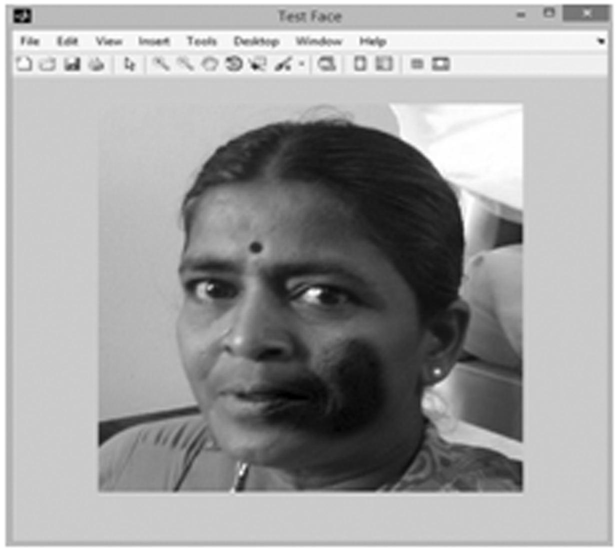

Figure 15: Damaged Image

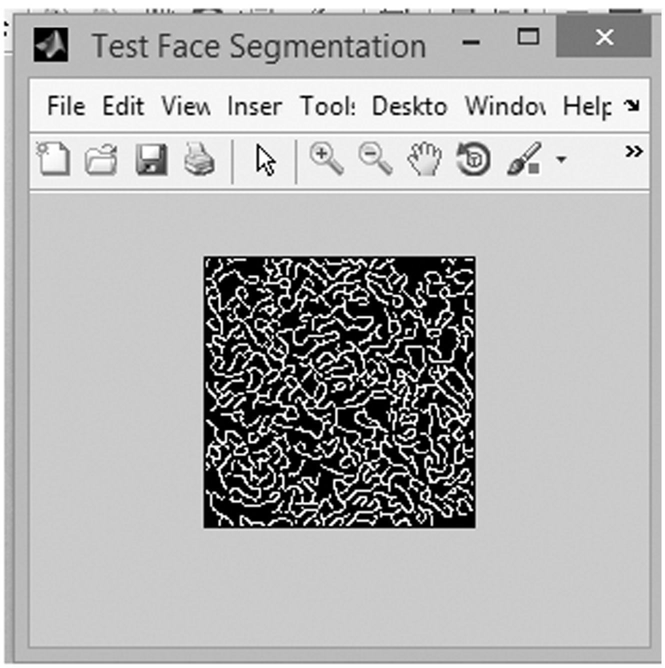

Figure 16: Segmented Image

Figure 17: Gabor Feature Image

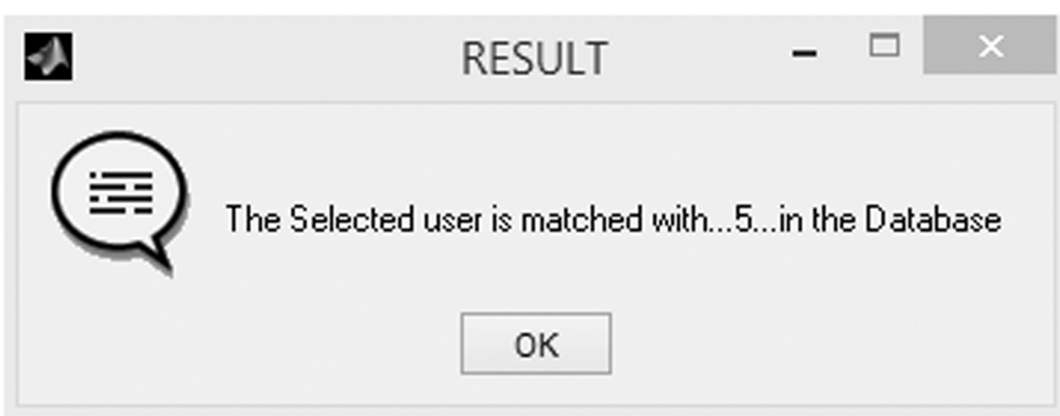

Figure 18: Matching Result

Figure 14 show the result of segmentation of the test image. From this the segmented features are used by Active Shape Models with Invariant Optimal Features for matching a statistical model of object shape and appearance to a new image.

Figure 15 show the global feature extraction of the test image for identification and verification.

The input image is selected and it is matched with the database images.

Figure 16: Reconstructed Image

The other performance metrics used for analyzing the proposed method are Mean square error (MSE), Peak signal to noise ratio (PSNR).

4.1. Peak Signal to Noise Ratio

The peak signal to noise ratio is represented by the ratio between the maximum possible powers to the power of corrupting noise. It is also referred as the logarithmic function of peak value of image and mean square error and hence represented as:

$$PSNR = 10\log_{10}\left(MAX_i^2 / MSE\right)$$

4.2. Mean Square error

Mean square error (MSE) of an estimator is to quantify the difference between an estimator and the true value of the quantity being estimated.

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left[(i,j) - K(i,j)\right]^2$$

The specificity results of the Proposed LDP Variance Descriptor are higher than the existing methods such as PCA and PCA-LBP. Fig.8 shows the graphical representation of comparison of specificity results with other methods such as PCA, PCA-LBP and Fast ICA-LGXP.

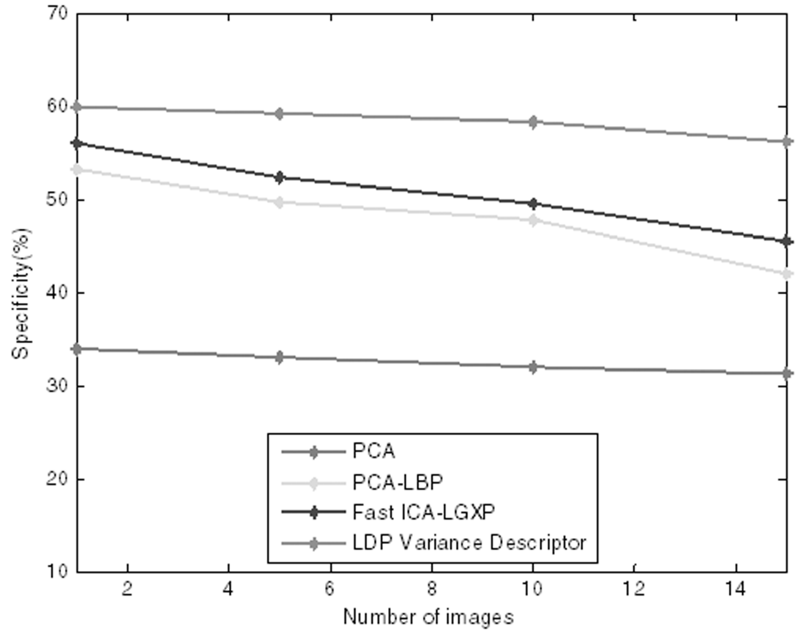

Figure 17: Specificity Comparison

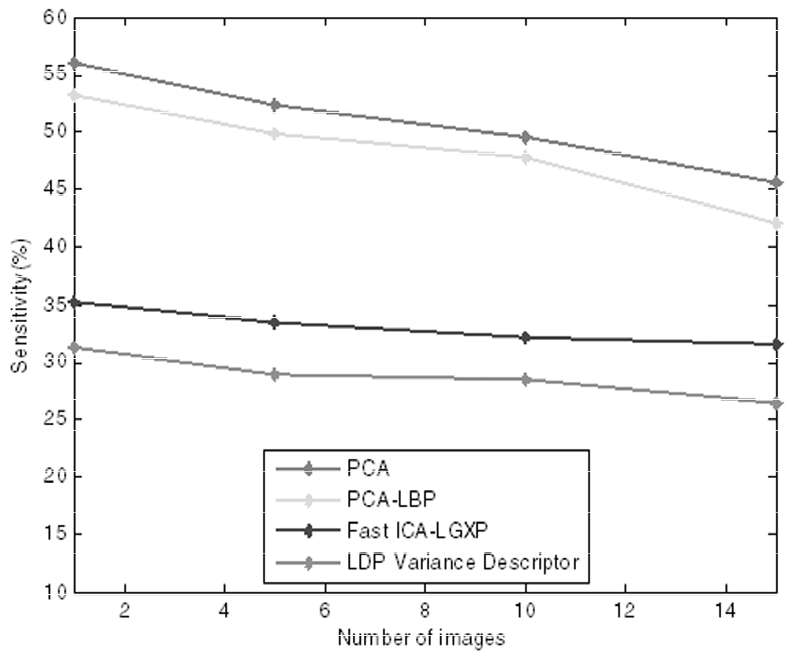

Figure 18: Sensitivity Comparison

The sensitivity results of the proposed LDP Variance descriptor have also been compared with the other methods such as PCA, PCA-LBP, Fast ICA-LGXP. The graphical representation of comparison of sensitivity results is shown in Fig.7.The results showed that the proposed LDP Variance descriptor is less sensitive than the existing edge detection methods such as PCA and PCA-LBP.

4.3. Precision

Precision is defined as the proportion of the true positives against both true positives and false positives results for fake and real fingerprint images. It is defined as follows:

$$\Pr ecision = \frac{T_p}{T_p + F_p}$$

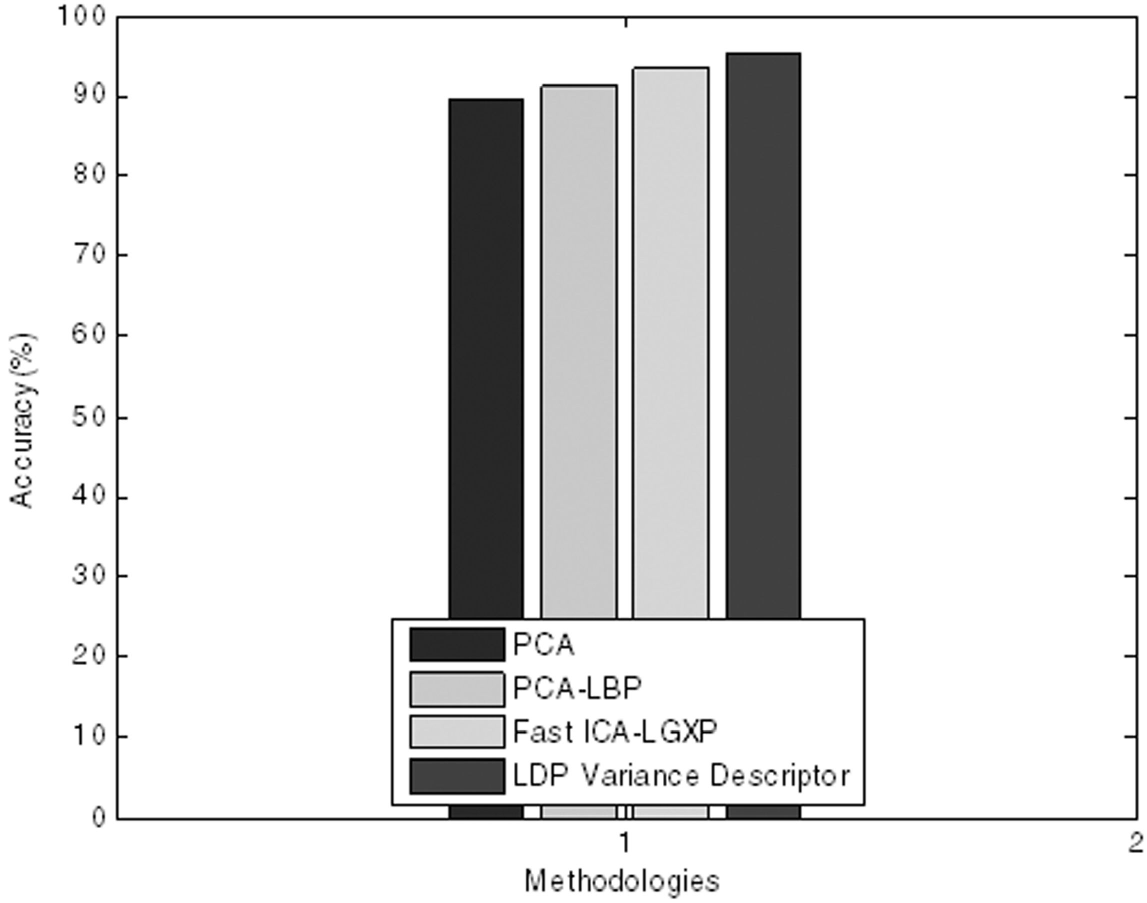

Figure 19: Accuracy Comparison

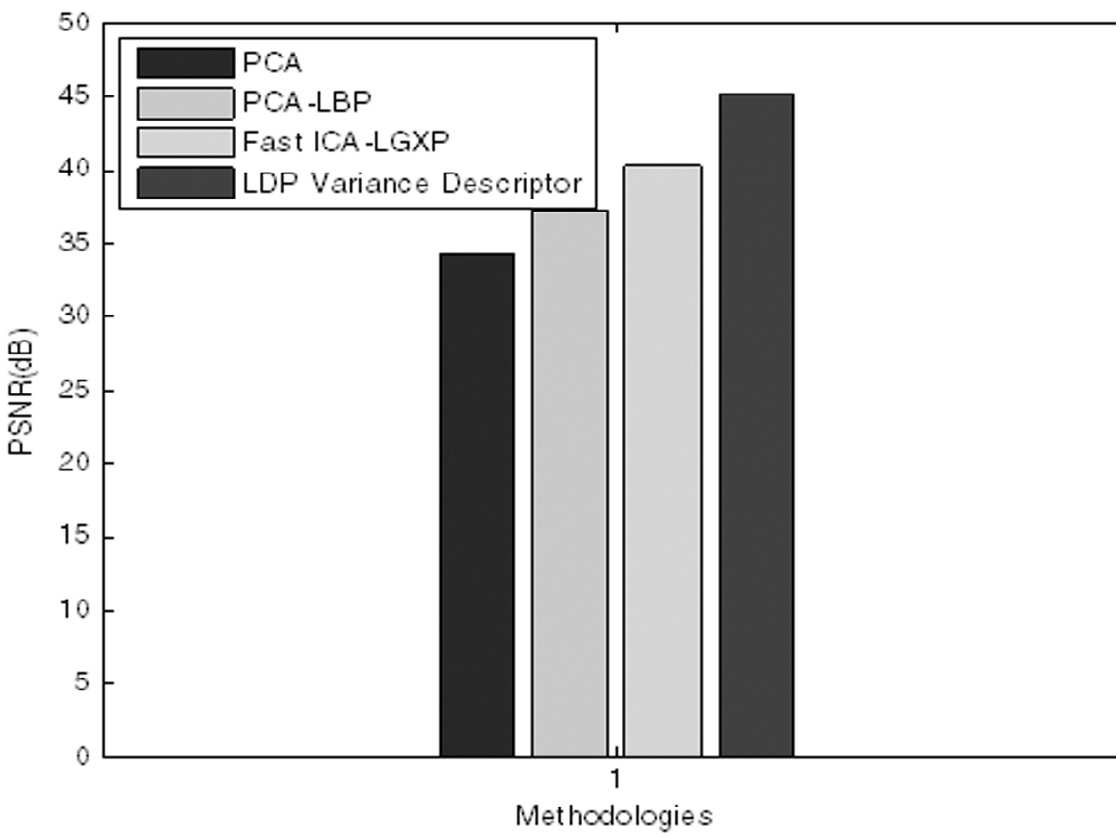

Figure 20: PSNR Comparison

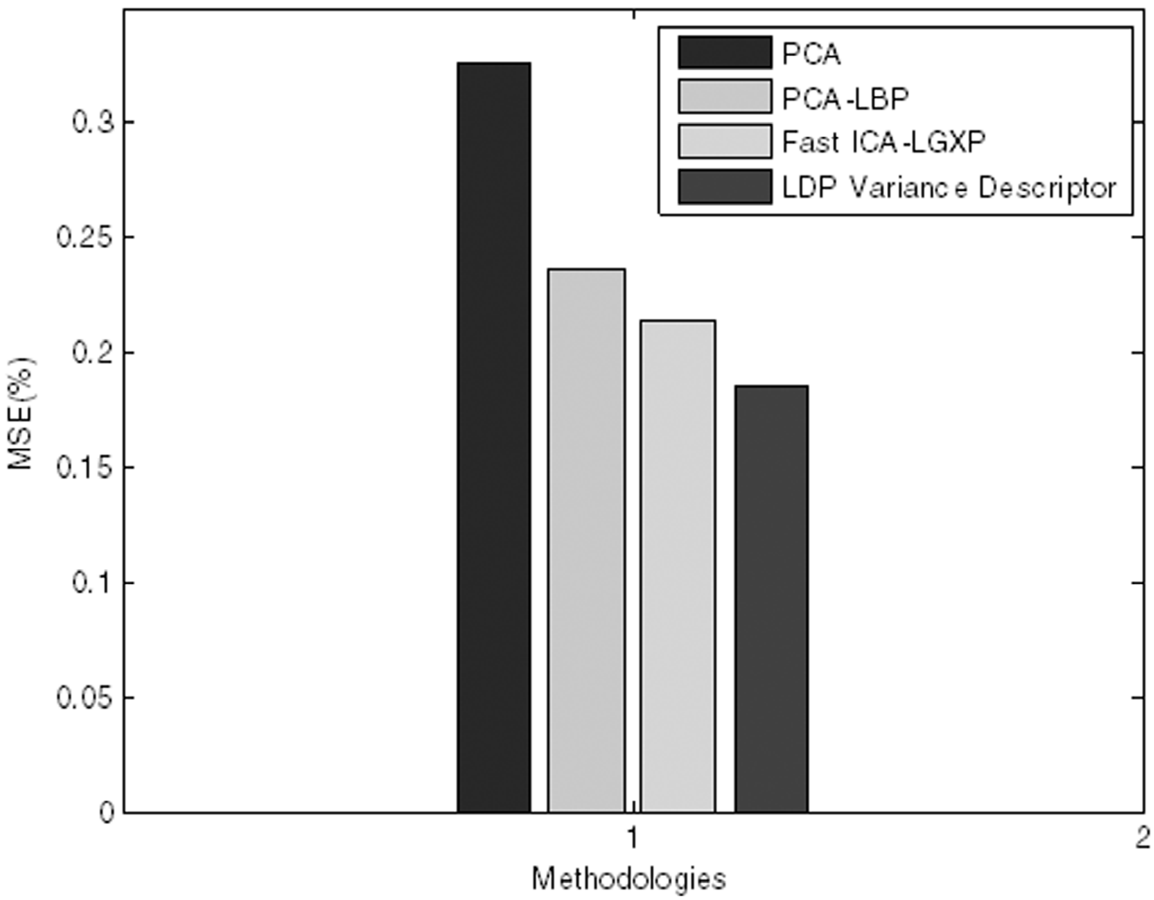

Figure 21: MSE Comparison

The graphical representation of comparison of MSE and PSNR of the proposed method with the existing methodologies such as PCA,PCA-LBP, Fast ICA- LGXP has been represented graphically in Fig.19 and Fig.20. Hence, the performance of the proposed methodology using LDP Variance Descriptor is found to be far better than the existing edge detection algorithms such as PCA and PCA-LBP.

5. CONCLUSION

The presented method can be improved by introducing various methods for calculation of better reference image and the reconstruction can also be tried with some complex mathematical operators for data completion. These improvements can produce more realistic and clear reconstructed images. The database contains images of 7 views of 200 laser-scanned (Cyberware TM) heads without hair [9][10]. The 200 head models were newly synthesized by morphing real scans to avoid close resemblances to individuals [11]. The proposed method has been implemented using the system configuration as follows:

Processor: Intel® Pentium® 4 CPU 2.80GHz

Installed Memory (RAM): 2GB

System Type: 32-bit Operating System

Operating System: Windows 7 Enterprise Service Pack 1

Programming Language Used: MATLAB 8

Further the work can be utilized to reconstruct images of historical monuments. It can be extended for skull to image construction, for use in forensic studies and for 3D Face reconstruction.

REFERENCES

[1] B. Fan, Z. Lei, and S. Z. Li, "Normalized lda for semi-supervised learning," in Proc. Int. Conf. Automatic Face Gesture Recognit., 2008, pp. 1–6.

[2] B. Fan, Z. Lei, and S. Z. Li, "Normalized lda for semi-supervised learning," in Proc. Int. Conf. Automatic Face Gesture Recognit., 2008, pp. 1–6.

[3] Edwards, G. J.; Taylor, C. J.; Cootes, T. F. (1998). "Interpreting face images using active appearance models". Proceedings Third IEEE International Conference on Automatic Face and Gesture Recognition. p. 300.

[4] S.-K. Pavani, D. Delgado-Gomez, and A. F. Frangi, "Haar-like features with optimally weighted rectangles for rapid object detection," Pattern Recognit., vol. 43, no. 1, pp. 160–172, 2010.

[5] C. P. Papageorgiou, M. Oren, and T. Poggio, "A general framework for object detection," in Proc. 6th IEEE Int. Conf. Comput. Vis., Bombay, India, 1998, pp. 555–562.

[6] H. A. Rowley, S. Baluja, and T. Kanade, "Neural network-based face detection," IEEE Trans. Pattern Anal. Mach. Intell., vol. 20, no. 1, pp. 23–38, Jan. 1998.

[7] Heng LU, Sheng Liu, Wan-liang Wang, S. Y. Chen, "Generation of a Point Distribution Model Using Genetic Algorithms", 4th International Conference: Sciences of Electronic, Technologies of Information and Telecommunications March 25-29, 2007.

[8] V. N. Vapnik, Statistical Learning Theory. New York: Wiley, 1998.

[9] S. Xie, S. Shan, X. Chen, and J. Chen, "Fusing Local Patterns of Gabor Magnitude and Phase for Face ecognition," in IEEE Transactions On Image Processing, vol. 19, no. 5, May 2010.

[10] Di Huang, Caifeng Shan, Mohsen Ardabilian, Yunhong Wang, and Liming Chen, "Local Binary Patterns and Its Application to Facial Image Analysis: A Survey", IEEE Transactions On Systems, Man, And Cybernetics—Part C: Applications And Reviews, Vol. 41, No.6, 2011.

[11] N. S. Lakshmiprabha, J. Bhattacharya, and S. Majumder, "Face recognition using multimodal biometric features", International Conference on Image Information Processing IEEE, pp. 1–6, 2011.

[12] P. Fasca Gilgy Mary, P. Sunitha Kency Paul, J.Dheeba, "Human Identification Using Periocular Biometrics", International Journal of Science, Engineering and Technology Research (IJSETR) Volume 2, Issue 5, 2013.

[13] D. Woodard, S. Pundlik, J. Lyle, and P. Miller, "Periocular region appearance cues for biometric identification", CVPR Workshop on Biometrics. IEEE, pp. 162–169, 2010.

[14] Xiao benlin, Li Fangfang, Mao xingliangc, Jin Huazhong, "Study On Independent Component Analysis' Application In Classification And Change Detection Of Multispectral Images", The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B7. Beijing 2008.

[15] Lowe, D. G.: Distinctive Image Features from Scale-Invariant Keypoints. International Journal of Computer Vision, Vol. 60, 2004, No. 2, pp. 91–110.

[16] Mikolajczyk, K.—Schmid, C.: A Performance Evaluation of Local Descriptors. IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 27, 2005, No. 10, pp. 1615–1630.