

Adaptive Facial Recognition Algorithm For Partially Occlude Images

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Abstract

In the present study we present an innovative approach towards countering the problem of partial occlusion in face recognition scenario. The partial occlusion can be caused by various objects such as scarfs, sunglasses etc., and its effects are confounding in the performances of the recognition rates. The framework tends to mathematically model the curvature and other essential features of the face such as micro-expression and the curves of the facial regions. This, significantly enhances the probability of matching the parent image to that of the occlude image. The proposed algorithm is tested over Extended Yale B and CMU PIE standardized datasets.

Keywords: Facial recognition, face detection, algorithm design and analysis

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INTRODUCTION

The past decades have witnessed the emergence of the semi-automated facial recognition system which is widely used in surveillance scenarios such as criminal identification or in other international security agencies. But the problem with the method is that it requires a fair amount of manual intervention for the localization of the facial features and thereupon the algorithms are required to find the match based on its closeness in appearance with the other images in the database which is primarily based on feature extraction and information discrimination. Based on the type of classifiers used the face recognition systems for occlude images are classified as:

1. Geometric feature based method
2. Template based method
3. Correlation based method
4. Matching pursuit based method
5. Singular value decomposition based method
6. Dynamic link matching method
7. Other learning based recognition methods.

Since, such methods have their own pros and cons and are often drop in recognition rates for occlude images have been reported [1, 2]. Among the best known approaches for face recognition, Principal Component Analysis

(PCA) is considered one of the techniques with better results and has been object of much interest in the research domain of face recognition [3, 4]. PCA involves the recognition framework based on the representation of the facial images by using eigenfaces [4–16]. The principal logic behind PCA method is to derive sets of orthogonal vectors (also called eigenfaces) which optimally represent the data distribution in form of the root mean square (rms) sense [17–25]. Therefore, in the study we presented a learning based approach independent of the variations like that of varying light illumination, pose estimation and the occlusion problem. The technique proposed in this paper is morphologically modeled extension of the PCA approach where several subsets of images are created through logical networks. In each subset, the images used in the training and recognition stages are masked in those regions where significant modifications are expected to occur as a consequence of occlusion or expression change.

METHODOLOGY

Experimental Setup

The proposed algorithm is prototyped over MATLAB R2012a under Windows platform, with hardware specifications of Intel's third

generation 8-core microprocessor, 2 GB RAM giving the clocking speed of 2.7 GHz. The standardized databases used in the study CMU PIE facial image database (Table 1) as test

images [26, 27]. The images in the study consist of two types namely the one occluded by glasses or sunglasses and the one occluded by hats or disguise.

Table 1: List of Database Used in the Recognition Test.

Database	Subjects	Images Per Person	Occlusion Type	Total
Extended Yale B	40	4	Hats/Disguise	160
CMU PIE	70	7	Glass/Sunglass	490

Methodology: Algorithm for Encoding Facial Features from Occluded Images

The idea relies over the idea to map the topological features from the given facial image and thereby coding it in logical sequence with the help of cascaded neural network; since in previous study such attempt has already been quite successful in decoding the face recognition patterns involved with human brain and then training the neural nets to mimic such process [28]. Therefore, the underlying pre-processing steps to reduce the effects posed any poor or uncontrolled lighting environment. The proposed pre-processing

steps begin with the color transformation of the given facial image in order to normalize the light illumination field. The latter steps dynamically adjust the contrast of the image by breaking down the wavelets in logical association with spatial colorized pixel field. This ensures the optimization of the reflectance field derivative from the pixel values, hence, making it easy to perform computational operations over optimized values. Such that, the given RGB standard image is to be normalized into *rg* scheme by using the following pre-processing algorithm:

Algorithm: Pre-Processing Algorithm

Input: $m \times n$ RGB standard Image

Where, m and n are the row and column of the given image.

Output: *rg* normalized color scheme

Loop: **for** i to m

Loop: **for** $j:n$ //RGB normalization to *rg* scheme

$$r_{i,j} = \frac{R}{(R + G + B)}$$

$$g_{i,j} = \frac{G}{(R + G + B)}$$

end

end

Check and Segment

if $(\gamma_M \leq \sum_M P(r_{i,j}, g_{i,j}))$ //To adjust contrast
{

$P_{skin} = P(skin|rg, N)$ //for sampling skin texture

else

$P_{background} = (background|rg, \gamma_M)$ //for sampling background light
 //illumination field

}

Where, the value M represents the model of skin color, which is embarked as low intensity pixels after the pre-processing. γ_M & $\sum_M$

are the mean and covariance of the pixel distribution based on intensities in *rg* color scheme after pre-processing.

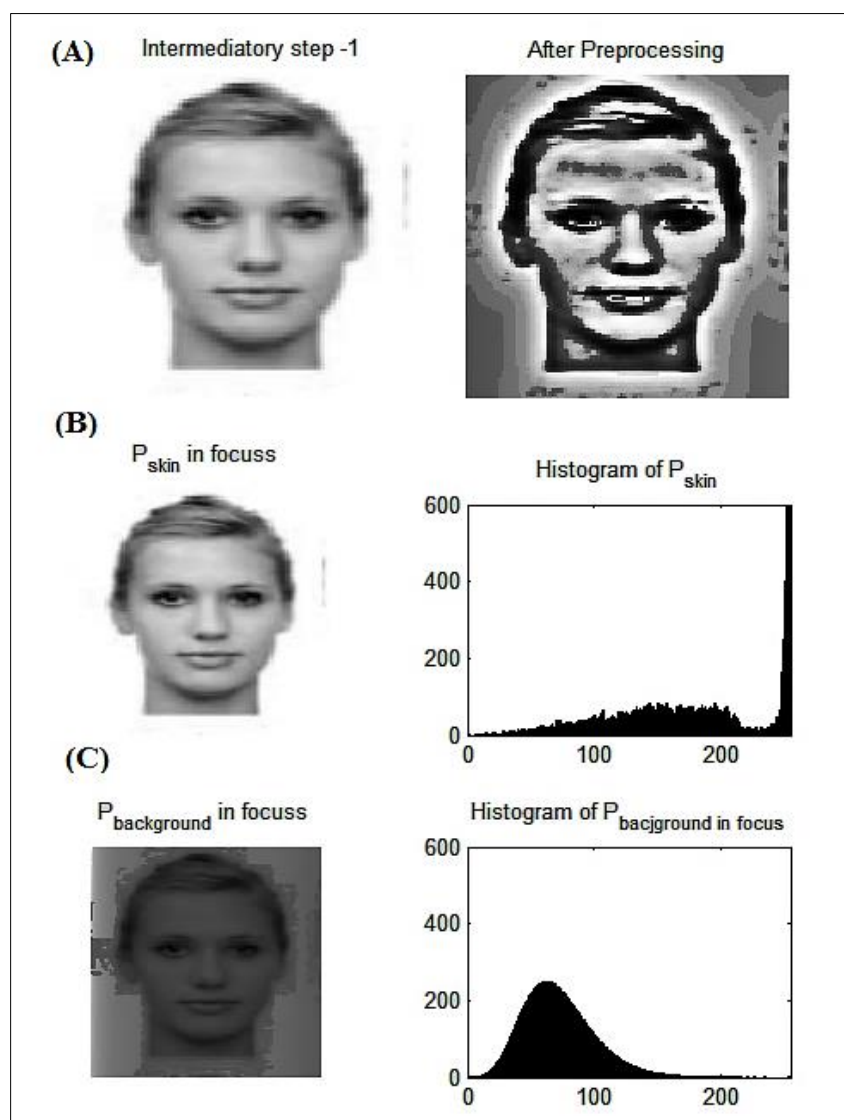


Fig. 1: The Sample results of each pre-processing steps and histogram plot of various sections of the image after pre-processing. (a) Intermediary steps of pre-processing and final output of pre-processing. (b) Shows that of the distribution of sampled skin pixels P_{skin} for the normalized rg-color scheme. (c) Shows that of the distribution of sampled non-skin pixels or other background extracted pixels in pixel set $P_{background}$.

Now, that we have the segmented pixels sets; it is required to pass the segmented pixels from an adaptive algorithm to encode facial features and its orientation for both high and low resolution images. Therefore, we use the cascaded neural networks for the same. To form an associative pattern between the neighboring sets of pixel blocks the cascaded coding of training sets, this requires three types of vectors:

- The displacement vector field with the bit rate of 48.75.
- Bit rate corresponding to the sequencing connectomes of information tree.

(c) The error rate in learning $E(i, j)$.

Given the segmented data sets derivable from the above algorithm P_{skin} in form of each rg-color scheme is given as: $(x_1, y_1), (x_2, y_2), \dots, (x_l, y_l) \in P_{skin} \times [1, 0]$. Let $v_i \in V$ be the set of displacement vectors for each of the neighboring nodes n_i . Such nodes represent the positioning of the feature sets. Therefore, in order to sequence the features of the facial image from the reconstructed rg-color scheme we use the following Pyramidal Section Algorithm (PSA) algorithm; for which its face recognition process is depicted in Figure 2.

Algorithm: Pyramidal Section Algorithm (PSA)**Input:** $(x_1, y_1), (x_2, y_2), \dots, (x_i, y_j) \in P_{skin}$ **Output:** $P_{face}(i, j)$ **Step 1:** while $l \leq \min(\sum_{i=1}^N D(v_i, n_i))$ //D is the displacement vector**Step 2:** Evaluate the feasible value of target nodes T_{target} :

$$T_{target} = \sum_{i=1}^N D(v_i, n_i)$$

Step 3: Create target vectors for feasible neighboring nodes:Loop: for 1 to n_i

$$\sum_{i=1}^N T(v_i, n_i) \leq T_{target}$$

Step 4: Using Lagrange multiplier λ for the activation function of the cascaded neural network [15]:
for 1 to m

for 1 to n

$$CC(i, j) = \sum_{i=1}^m \sum_{j=1}^n \text{sgn}(D(v_i, n_i) + \lambda T(v_i, n_i)) + \sum_{i,j}^{m,n} E(i, j)$$

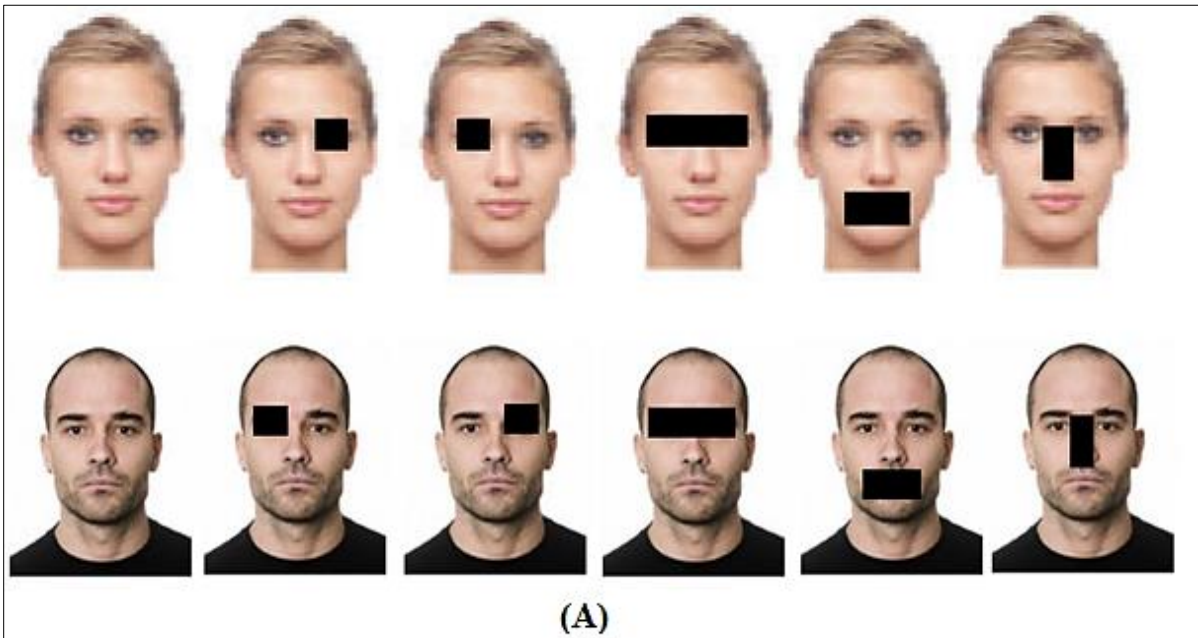
$$E(i, j) = \frac{\|T(v_i, n_i) - T_{target}\|}{|D(v_i, n_i)|} // \text{Normalized error}$$

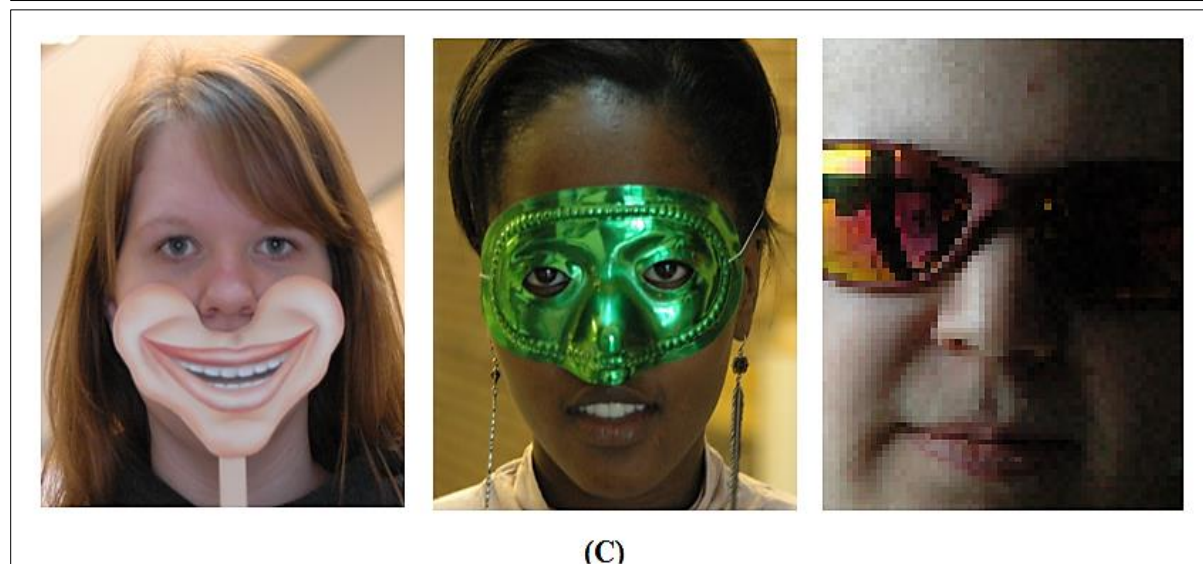
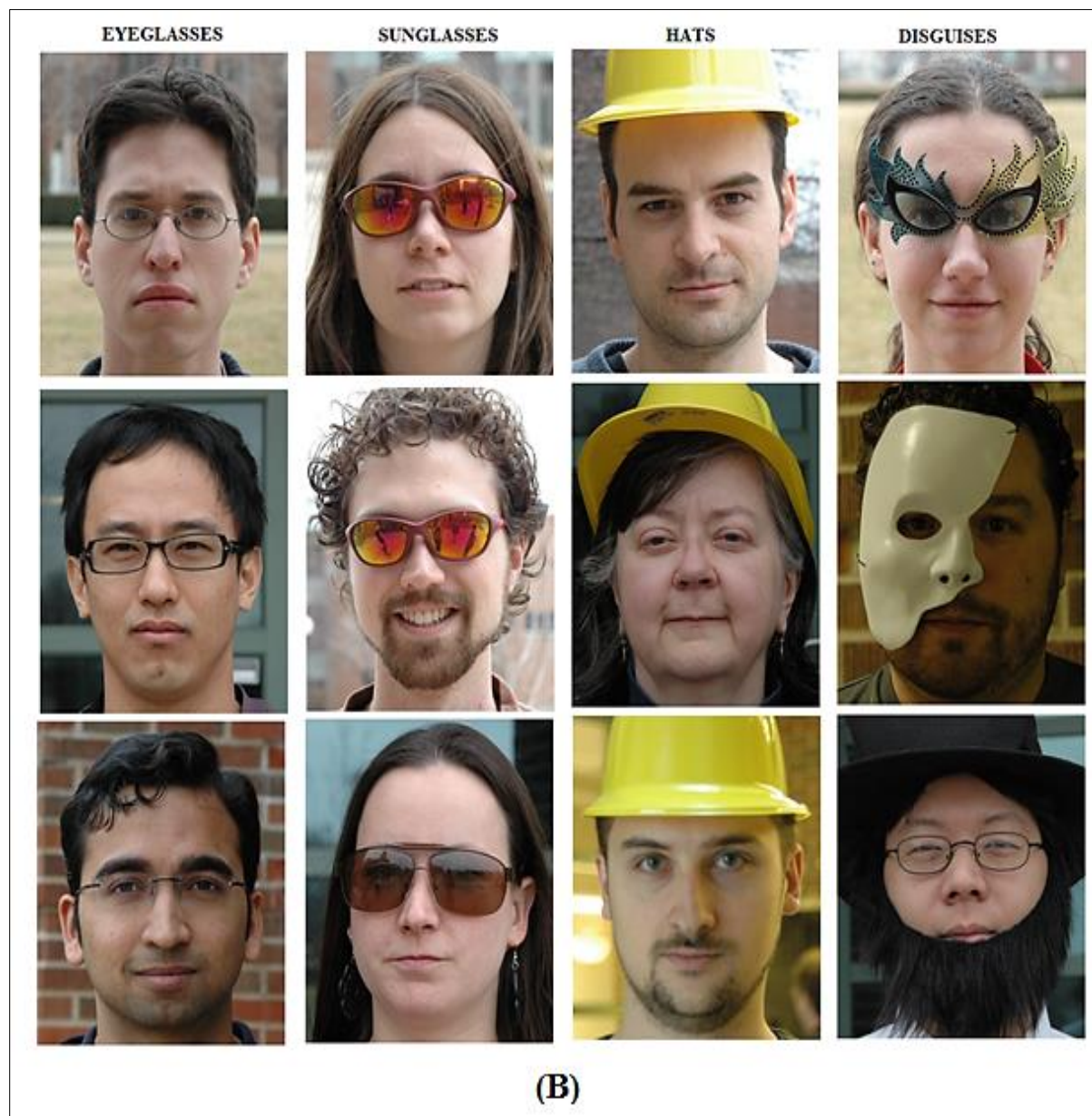
end

end

end for loop

end while loop

Step 5: END PROCESS



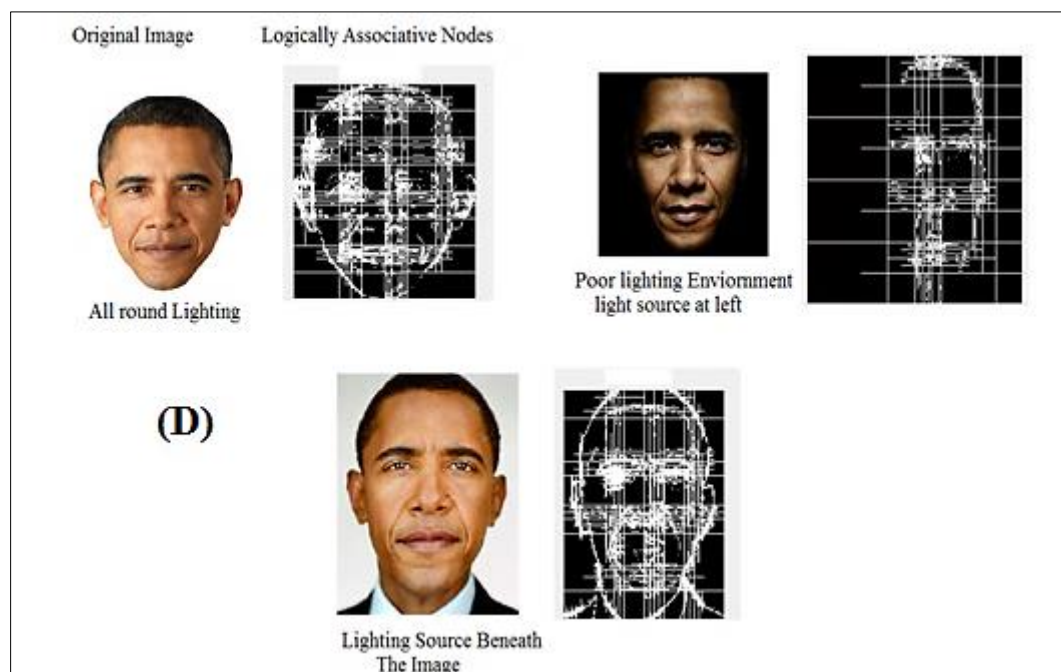


Fig. 2: (A) The Sample Results of the PSA Algorithm Showing the Recognized IDs of the Test Images with Occluded Sub Spaces During the Training Period of the Cascaded Neural Network. (B) Sample Images from the Four Test Categories. (C) Images from the Category of Disguise and Sunglasses which Fails in the PSA Cascading Network in Aligning with the Trained Datasets Resulted in Inappropriate Classification. (D) Results of the Formation of Associatively Cascaded Logical Blocks with the Curvature of the Face in the Given Facial Images with Different Positioning of Light Source.

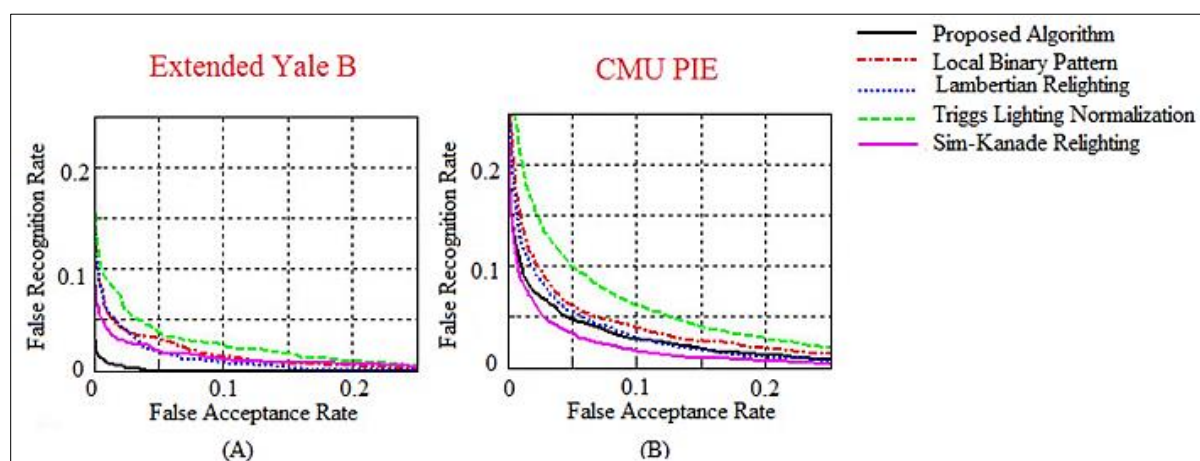


Fig. 3: The Comparison Plot of the Proposed PSA Algorithm with that of the Other Principal Cited Methods for Solving Occlusion Problem in the Literature.

CONCLUSION

As shown in the Figure 3 above the plot depicts the comparison of the several methods of face recognition relatively with the proposed PSA algorithm. The result is plotted between the two results i.e., false recognition rate and false acceptance rate. Here, the false acceptance rate represents the matching points chosen by the algorithm to be used for matching whereas false recognition rate is the

matching points which are matched with the criteria chosen with the designated algorithms. As can be concurred from the above plot the error rate has been minimal from rest of the methods as only unique match point is selected by the algorithm and latter used it to render over the other similar images which gives the higher correct match acceptance rate in nominal rate. This, detection method gives us an advantage over the present existing

methods which indulges in pointless computation and matching of the pixel sets with numerous data entries. Our method has reduced this redundancy to a higher limit and it promises to be useful in industrial applications. The issues with the other methods are that they heavily rely on the visual cues for face detection and thus are time consuming. This method proposes a scalable algorithm with cascaded neural network for

logically associative defining nodes of the facial feature sets and thus the searching of match properties is reduced to a very fine scale. Also, for lower resolution images PSA works fine from coarse to fine scales of visual cues in context of skin color and textures. Recognition of facial images from different plane shall be pursued in the near future that will add depth to the current PSA algorithm.

Table 2: Recognition Rates Performance of the Proposed Algorithm on Real Database for All Categories of the Significant Occlusion Types.

Database Type	Normal	Glasses	Sunglasses	Hats	Disguises
Extended Yale B	91.5	90.3	83.4	59.2	42.3
CMU PIE	99.2	98.5	76.8	45.5	39.5

As shown in the Table 2 above; the presented algorithm has effectively tried to cope with the problem of partially occluded faces in the four different categories and consequent variations. The results have shown that the performance of the face recognition algorithm can be increased by the effective utilization of the cascaded neural networks. The main advantage with this method is that the computational cost of processing is significantly reduced as compared to the other methods and thereby giving a minimal set of errors in false recognition rate, though the algorithm fails at places where more than 56% of the facial region is covered or obstructed. The current method will make real implementation of the face recognition system for viable.

REFERENCES

- Martinez AM. Recognizing Imprecisely Localized, Partially Occluded and Expression Variant Faces from a Single Sample per Class. *In IEEE Trans. on PAMI*. 2002; 24: 748–763p.
- Quintiliano P, Santa-Rosa AN, Guadagnin R. Face Recognition based on Eigenfeatures. *Proc. SPIE. Image Extraction, Segmentation, and Recognition*. 2001; 4550: 140–145p.
- Turk MA, Pentland AP. Face Recognition using Eigenfaces. *Proc. IEEE Computer Society Conf. on Computer Vision and Pattern Recognition*. Hawaii 1991; 586–591p.
- Zhang J, Yan Y, Lades M. Face Recognition: Eigenface, Elastic Matching, and Neural Nets. *Proc. IEEE*. Sep 1997; 85(9): 1423–1435p.
- Zhao W, Chellappa R, Phillips PJ, et al. Face Recognition: A Literature Survey. *ACM Computing Surveys (CSUR)*. 2003; 35: 399–458p.
- Rurainsky J, Eisert P. Eye Center Localization using Adaptive Templates. *In Proc. of the 1st IEEE CVPR Workshop on Face Processing in Video*. Washington DC, USA. Jun 2004.
- Candes E, Wakin M, Boyd S. Enhancing Sparsity by Reweighted ℓ_1 -Minimization. *J Fourier Anal. Appl.* 2008; 14(5): 877–905p.
- Cevher V, Duarte MF, Hegde C, et al. Sparse Signal Recovery using Markov Random Fields. *In NIPS*. 2008.
- Georghiades A, Belhumeur P, Kriegman D. From Few to Many: Illumination Cone Models for Face Recognition under Variable Lighting and Pose. *PAMI*. 2001; 23(6): 643–660p.
- Jia H, Martinez A. Face Recognition with Occlusions in the Training and Testing Sets. *In FGR*. 2008.
- Jia H, Martinez A. Support Vector Machines in Face Recognition with Occlusions. *In CVPR*. 2009.
- Kim J, Choi J, Yi J, et al. Effective Representation Using ICA for Face Recognition Robust to Local Distortion and Partial Occlusion. *PAMI*. 2005; 27(12): 1977–1981p.

13. Kolmogorov V, Zabih R. What Energy Functions can be Minimized via Graph Cuts? *PAMI*. 2004; 26(2): 147–159p.
14. Lee K, Ho J, Kriegman D. Acquiring Linear Subspaces for Face Recognition under Variable Lighting. *PAMI*. 2005; 27(5): 684–698p.
15. Leonardis A, Bischof H. Robust Recognition Using Eigenimages. *CVIU*. 2000; 78(1): 99–118p.
16. Li S, Hou X, Zhang H, et al. Learning Spatially Localized, Parts-Based Representation. *In CVPR*. 2001.
17. Maragos P, Schafer R. Morphological Filters. Part I: Their Set-Theoretic Analysis and Relations to Linear Shift in Variant Filters. *IEEE TASSP*. 1987; 35: 1153–1169p.
18. Martinez A. Recognizing Imprecisely Localized, Partially Occluded, and Expression Variant Faces from a Single Sample Per Class. *PAMI*. 2002; 24(6): 748–763p.
19. Martinez A, Benavente R. The AR Face Database. *CVC Tech. Report No. 24*. 1998.
20. Pentland A, Moghaddam B, Starner T. View-Based and Modular Eigenspaces for Face Recognition. *In CVPR*. 1994.
21. Sanja F, Skocaj D, Leonardis A. Combining Reconstructive and Discriminative Subspace Methods for Robust Classification and Regression by Subsampling. *PAMI*. 2006; 28(3)p.
22. Turk M, Pentland A. Eigenfaces for Recognition. *In CVPR*. 1991.
23. Wagner A, Wright J, Ganesh A, et al. Toward a Practical Face Recognition System: Robust Pose and Illumination via Sparse Representation. *In CVPR*. 2009.
24. Wright J, Ma Y. Dense Error Correction via l^1 -Minimization. *IEEE Trans. on Inform. Theory*. 2009 (preprint, 2008).
25. Wright J, Yang A, Ganesh A, et al. Robust Face Recognition via Sparse Representation. *PAMI*. 2009; 31(2): 210–227p.
26. Sim T, Baker S, Bsat M. The CMU Pose, Illumination, and Expression database. *IEEE PAMI*. 2003; 25(12): 1615–1618p.
27. Gross R, Matthews I, Cohn J, et al. The CMU Multi-Pose, Illumination, and Expression (Multi-PIE) Face Database. *Tech Rep TR-07-08, CMU*. 2007.
28. Rai A. Characterizing Face Encoding Mechanism by Selective Object Pattern in Brains Using Synthetic Intelligence and Its Simultaneous Replication of Visual System That Encode Faces. *Research & Reviews: J. Comput. Biol*. 2014; 3(2).

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