Asian Journal of Information Technology 15 (14): 2542-2548, 2016
ISSN: 1682-3915

Enhanced Biometric Authentication Using Multi Feature Signature Resemblance and Multi View Edge Sectional Similarity

[1]S. Kannan and [2]V. Seenivasagam
[1]National Engineering College, Anna University, Chennai, Tamil Nadu, India
[2]Research Scholar, National Engineering College, Tamil Nadu, India

Abstract: The application of biometric authentication has no limit and the dimension of biometric feature can be extended to any level. Based on the biometric features, there are many authentication mechanisms discussed earlier but suffer with the problem of authentication efficiency where there will be micro differences between one to many people. The biometric authentication system uses the micro difference and unique feature of any person to perform authentication and the efficiency of the system is depending on how accurate the system is most methods suffer with false authentication and poor verification accuracy and to solve those issues a multi view edge model has been discussed in this study. This study presents a multi view edge model which computes sectional similarity on each edge model where there will be unique noticeable difference between any two persons. The method converts the sectional features of the multi view edge model into the sectional similarity matrix and the method extracts the features of nose, eye and mouth into a signature matrix. Using multi feature signature resemblance technique, the method computes the similarity between different features of the data set. The proposed method improves the performance of biometric authentication and reduces the false positive ratio in biometric authentication.

Key words: Multi view edge model, sectional similarity, multi feature signature matrix, biometric authentication, positive

INTRODUCTION

Security enforcement is the major issue in any organization or application where it is necessary to maintain the information in a secure manner or to maintain the resources to be accessed in a secure manner. To provide such security enforcement, there are many approaches used in earlier days like password-based approaches. The password-based approaches suffer with higher rate of guessing attack which can be easily guessed by some malicious user and someone's account may be hacked. To safeguard from such attacks or malicious access, the security systems have shifted their focus to biometric authentication. The biometric authentication mechanism is about using bio features of humans to perform authentication and verification. The bio features like face, fingers, palm prints have been used now a day. Even in facial features, there are systems which use only iris features to perform biometric authentication. Whatever the feature being used, how efficient the security system is about how efficient it verifies the features. Also, the biometric authentication system has to enforce efficient measures and has to produce efficient authentication with less false positive ratio.

In this study, we discuss a multi view edge model to perform biometric authentication. The model considers the facial features in different views or sides. We consider three dimensions of face images like front, right and left. The method takes the edge features of each view model and from the edges obtained, the method extracts the sectional features. When we consider the right or left edge model, the angle and length of chin will be varying between people. These features will be more useful which represent the skeleton of the human and can be used to perform biometric authentication.

Figure 1a shows the front view image of the person whereas Fig. 1b shows the left view image of the same person. Similarly, the three view images can be obtained and used to perform biometric authentication. Figure 2a, b shows the left and the front views of a single person

Fig. 1: a) front view image and b) right view image

Fig. 2: a) the left view image and b) the font view image

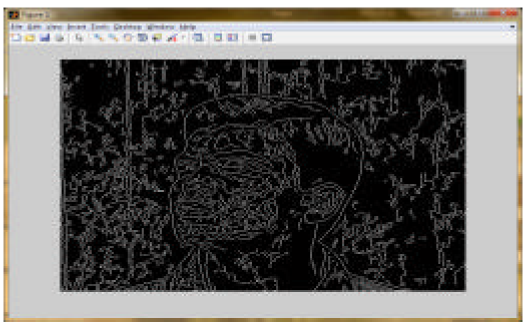

Fig. 3: Edge view of right view image

available on the IIT Kanpur data set which will be used to perform biometric authentication. Figure 3 shows the edge view of right view image and it shows the result obtained from the canny edge detection.

From the above edge model, we can identify the sectional measures by splitting the edge detected image into a number of sections and for each section we can compute the number of points with more gray values. The pixels with more gray values represent the skeleton edge and the shrinks in the skin also. By computing the values of each section or regional image, the feature can be used to compute the sectional similarity between different users. Multi feature signature matrix is one which represents the features of different facial components in matrix form.

The method extracts the features of the different facial component of the extracted features are stored in the form of a matrix which could be used to compute the similarity between different users of the system. By computing the similarity between different users based on multi feature similarity, the efficiency of biometric authentication can be improved.

Literature review: There are a number of methods used to perform biometric authentication and we discuss a few of them here in this study.

A novel feature selection algorithm which we call Joint Boosting is developed to take out discriminative facial appearance using this massive file. Unfortunately, these small sets of sample cannot capture all the promising emergence variation of each human being's face. This problem greatly limits the simplification ability of most face detection methods. The categorization process can be completed faster with no degrading of the generalization performance through this discriminative feature collection method. In the multi-view face folder, our experiment shows that this discriminative feature selection method can speed up the multi-view face detection process without corrupting the correct rate and break the long-established kernel subspace methods (Rong and Wujun, 1988). However, these essential part methods still cannot solve the small sample size problems very well. Their categorization process is very slow due to the vast conniving time in kernel machines.

Possible regions in the face image are defined as a certain kind of features and then both the universal and home features can be regarded as features chosen from all possible candidates in the face image. From this position of view, face identification can be realized by steps to select one or more facial appearance from all possible characteristic candidates; another step is to train a classifier for face acknowledgment based on the chosen features. One problem lying in most existing face acknowledgment techniques, no matter global-feature-based or local-feature-based ones is that the feature selection procedure is empirically performed by the operators consciously or automatically (Geng and Zhou, 2006). To remove such an unstable factor, an automatic image region assortment algorithm for face acknowledgment is proposed in this paper. Using multiple features in face recognition it can be re-explained from another point of view.

Principle Component Analysis (PCA) is an eigenvector method intended to model the linear variation in high-dimensional data. PCA performs dimensionality lessening by analyzing the original n-dimensional data onto the dimensional linear subspace spanned by the primary eigenvectors of the data's covariance matrix. Its target is to find a set of equally orthogonal basis functions that capture the information of most difference in the records and for which the coefficients are a pair of wise decor-related (He *et al*., 2005). For linearly fixed manifolds, PCA is assured to discover the dimensionality of the various features and produce a compact demonstration (He *et al*., 2005; Hazar *et al*., 2008). In mutual Information technique for facial feature extraction, it applies local binary pattern technique to predetermine facial expression micro-patterns. The experiment shows that using expressive regions, enhanced facial expression categorization accuracy as well as reduced feature vector size. Indeed, we attested the independency of the selected regions of the dataset and the descriptors.

Scaling up biologically-inspired computer vision: a case study in unconstrained face recognition on Facebook (Pinto *et al*., 2011), explores the effectiveness of these algorithms on a large-scale unconstrained real-world face recognition problem based on images taken from the Facebook social networking website. In particular, we use a family of biologically-inspired models derived from a high throughput feature search paradigm to tackle a face identification task with up to one hundred individuals.

Meta-Analysis of the first facial expression recognition challenge, presents a meta-analysis of the first such challenge in automatic recognition of facial expressions, held during the IEEE conference on face and gesture recognition. It details the challenge data, evaluation protocol and the results attained in two sub-challenges: AU-(Action Unit) detection and classification of facial expression imagery in terms of a number of discrete emotion categories.

Semi supervised learning for facial expression recognition, discusses training probabilistic classifiers with labeled and unlabeled data. It provides an analysis which shows under what conditions unlabeled data can be used in learning to improve classification performance. It discusses the implications of this analysis to a specific type of probabilistic classifiers, Bayesian networks and proposes a structure learning algorithm that can utilize unlabeled data to improve classification. Finally, it shows how the resulting algorithms are successfully employed in a facial expression recognition application.

In analysis and detection of human faces by using minimum distance classifier for surveillance, an algorithm has been proposed to detect human behaviors for visual surveillance. This method gives an efficient face recognition technique in a dynamic scenario using principal component analysis and minimum distance classifier.

Face recognition system to enhance e-health, utilizes the symmetry of the face for face recognition and selects average half-face for research. The consequence of this discovery may result in substantial savings in storage and computation time. The average-half-face is applied to facial feature extraction methods using wavelets and PCA.

A two-dimensional neighborhood preserving projection for appearance-based face recognition (Bhaumik *et al*., 2010) presents a two-dimensional Neighborhood Preserving Projection (2DNPP) for appearance-based face representation and recognition. 2DNPP enables one to directly use a feature input of 2D image matrices rather than 1D vectors. The same neighborhood weighting procedure that is involved in NPP to form the nearest neighbor affinity graph is used. Theoretical analysis of the connection between 2DNPP and other 2D methods is presented as well.

Survey on LBP-based texture descriptors for image classification (Sumathi and Malini, 2010) performs a depth survey to find the best way for describing a given texture using a Local Binary Pattern (LBP) based approach. First several different approaches are compared and then the best fusion approach is tested on different datasets and compared with several approaches proposed in the literature (for fair comparisons, when possible code shared by the original authors has been used).

In computing the principal local binary patterns for face recognition using data mining tools (Zhang *et al*., 2012), local binary patterns are considered as one of the texture descriptors with better results; they employ a statistical feature extraction by means of the binarization of the neighborhood of every image pixel with a local threshold determined by the central pixel. The idea of using local binary patterns for face description is motivated by the fact that faces can be seen as a composition of micro-patterns which are properly described by this operator and consequently, it has become a very popular technique in recent years.

DBC-based face recognition using DWT (Nanni *et al*., 2012), proposes DBC based face recognition using DWT (DBC-FR) Model. The Poly-U Near Infra Red (NIR) database images are scanned and cropped to get only the face part in pre-processing. The face part is resized to 100×100 and DWT is applied to derive LL, LH, HL and HH sub bands. The LL sub band of size 50×50 is converted into 100 cells with 5×5 dimension of each cell. The Directional Binary Code (DBC) is applied on each 5×5 cell to derive 100 features. The Euclidian distance measure is used to compare the features of test images and database images. The algorithm renders better percentage recognition rate compared to the existing algorithms.

The PCA-based method discussed in Francisco conducts survey on face recognition as it has received significant attention in recent years. After a few decades of research it is able to provide promising solutions for the applications such as commercial and law enforcement. The availability of protocols, viz. FERET, XM2VTS and

MPEG-7 has made researchers improve algorithms with constraints. Face recognition system for enhanced e-health (Karim *et al*., 2010) implemented a reliable PCA-based face recognition system and evaluated the performance using standard face databases such as Indian database and the face recognition data, University of Essex, UK. The different techniques such as sum of absolute difference, sum of squared difference and normalized cross correlation are used for matching unknown images with known images.

Minimum distance classifier (Jagadeesh *et al*., 2012) proposed an efficient algorithm to detect human behaviors for visual surveillance. The face recognition technique is for dynamic scenario using PCA and minimum distance classifier. The mathematical analysis is made on the video of human face captured to understand or interpret the behavior.

LBP-based texture for face classification (Bhaumik *et al*., 2010) conducted survey on local binary patterns. First several different approaches are compared and then the best fusion approach is tested on different datasets and compared with several approaches. The experiments show that a fusion approach based on uniform Local Quinary Pattern (LQP) and a rotation invariant LQP where a bin selection based on variance is performed and Neighborhood Preserving Embedding (NPE) features transform is applied to obtain better results on six different data sets with a support vector machine classifier.

All the above-mentioned methods have the problem of mismatching and false positive results. We propose a new face recognition algorithm which uses multi attribute-based facial features with eccentric measures to recognize the faces.

Multi view edge model: The proposed multi view edge model maintains the facial feature of each person in different edge views. For each view considered straight, left and right, the method maintains the features. First it computes the sectional features and maintains them in the sectional matrix and extracts the features of mouth, nose and eye. These entire feature is used by the multi feature resemblance technique which computes the similarity of features considered between different persons to perform authentication. The proposed method has different stages, namely multi view edge feature generation, sectional feature extraction, facial feature grabber and multi feature resemblance technique. We discuss each of the functional stages in detail in this study. Figure 4 shows the architecture of the proposed multi view edge model-based biometric authentication mechanism.

Multi view edge feature generations: The multi view edge features represent the different edge models in different shots of facial image. The person may be turning to his right, left or he may be facing straight. At each shot, the method generates the edge view of the input image and the method maintains the edge view of the person in 3 directions. The method applies the canny edge detection technique which preserves the edges in the image in an efficient manner. The generated edge features will be used in the next stage of biometric authentication:

Algorithm A; Pseudo code of multi view edge feature generation:

```
Input: Facial image set Fs
Output: Tri shot edge set Es
Start
    Read input image set Fs
    For each edge image I from Fs
        Apply canny edge detector
        l = Canny-Edge-Detector (l)
        Add to Es =∑(Img ∈ Es) U l
    End
Stop
```

Sectional feature extraction: At this stage, the method reads the input edge view set and from each edge view, the method generates sectional image set. The sectional image is a tiny image which represents the part of the image. The whole input image is converted into a number of small sized partial images. The numbers of tiny images produced are depending on the size of the window being used. From the generated sectional image, the method extracts the histogram value of grayscale values. The computed histogram values will be used in the authentication phase to compute the multi feature resemblance value.

Algorithm B; Pseudo code of sectional feature extraction:

```
Input: Edge view Set Es
Output: Sectional Feature Matrix
Start
    Read edge view set Es
    For each image Ei from Es
        Initialize window size Ws = Rand (M)
        M is the width of the image
        Generate sectional image SIS = ∫_{i = ws}^{size(Ei)} Crop(Ei)×Ws
        For each sectional image Si from SIS
            Generate Histogram Hist = Histogram(Si)
            Add Hist into Sectional Feature Matrix
            SFM =∑(Hist∈SFM) U Hist
        End
    End
Stop
```

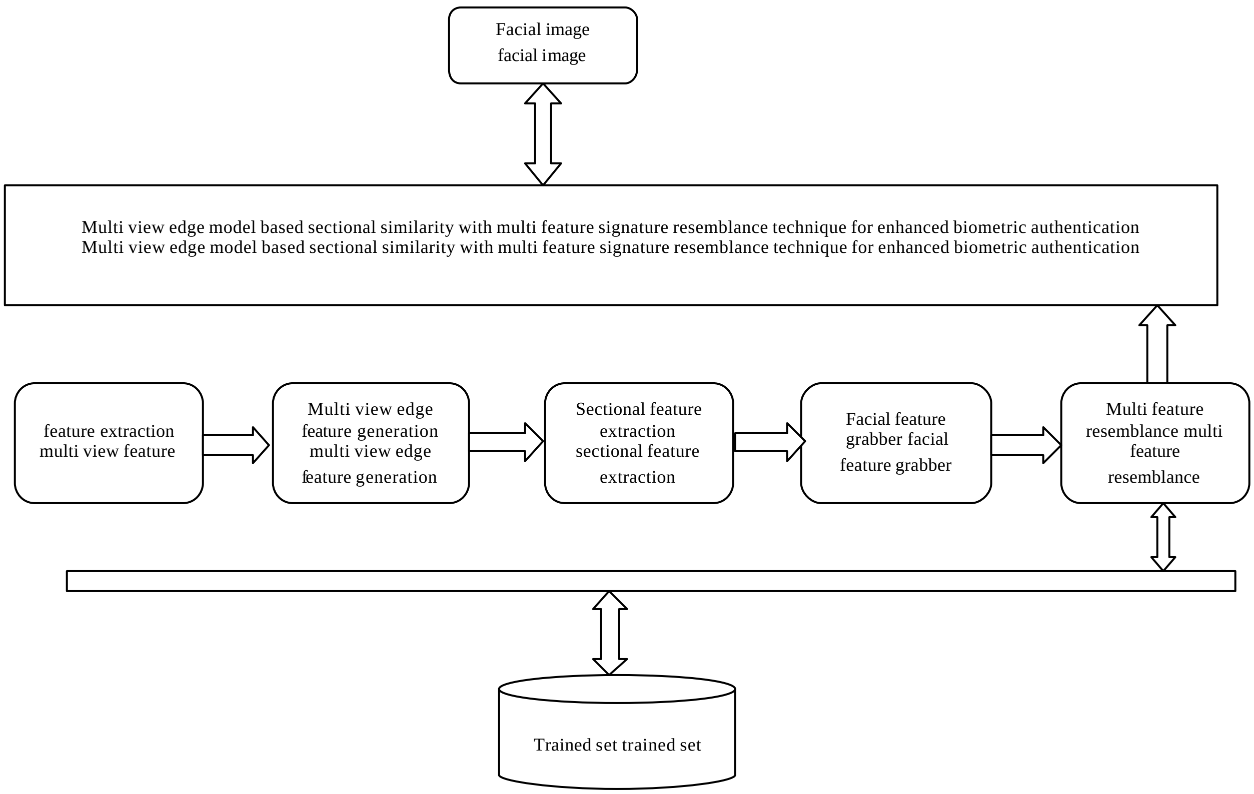

Fig. 4: Architecture of multi view edge model

The algorithm discussed above computes the sectional features present in each sub sampling image. The extracted feature is stored in the sectional feature matrix to be used in biometric authentication mechanism.

Facial feature grabber: The facial components like nose, eye and mouth features are grabbed for extraction of facial features. In this stage, the method extracts the shape features of the facial components and computes the average white and gray mass values in the iris. First, the method computes the width and height of the eyes and computes the gap between the two eyes. Second the method extracts the iris region and computes the average white and gray mass values. Third the method computes the height and width of the nose to the angle. Finally, the size of the mouth is computed and all these features are converted into a feature vector or a matrix:

Algorithm C; Pseudo code of facial feature grabber:

Input: Front view image fimg
Output: Facial feature matrix Fm
Start
Locate the region of eyes
Compute width of eyes Ew
Compute height of eyes Eh
Extract iris features IF
Compute average white mass $Awm = \frac{\sum P_i(IF) > 50}{size(IF)}$
Compute average gray mass $Agm = \frac{\sum Pi(IF) < 50}{size(IF)}$
Compute the size of the nose
Compute nose height Nh
Compute nose width Nw
Compute nose angle $Na = \frac{Hh}{Nw} \times \frac{1}{2}$
Compute mouth width Mw
Compute Mouth height Mh
Generate feature vector Fv = {Ew, Eh, Awm, Agm, Nh, Nw, Na, Mw, mh}
Add to facial feature matrix Fm
$Fm = \sum(Fv \in Fm) \cup Fm$
Stop

The algorithm discussed above computes the facial feature matrix from the facial components considered.

Multi feature resemblance techniques: The multi feature resemblance technique computes the multi feature similarity between the features maintained in the facial feature matrix and the sectional feature matrix. For the given input image, the method extracts the sectional features and the facial features. Then, the method computes the similarity towards each feature matrix with the generated feature value. Based on both the similarity values, a cumulative legitimate weight is computed using which the authentication is performed.

Algorithm D; Pseudo Code of Multi Feature Resemblance Technique:

Input: Sectional Feature Matrix SFM, Facial Feature matrix FM, Input Image Set Is
Output: Boolean Start
Es = Multi-View-Edge-Feature-Generation (Es)
Compute sectional feature Sf = Sectional-Feature-Extraction(Es)
Compute Facial Feature FF = Facial-Feature-Generation(Es)
Read SFM, FM
For each SF_i from SFM
Compute sectional feature similarity SFS

$$SFS = \int_{i=1}^{size\,(SFS)} \frac{\sum SFS(i) <> SF - Theshold}{size\,(SFS)}$$

End
For each FF_i from FF
Compute facial feature similarity SFS

$$FFS = \int_{i=1}^{size(FM)} \frac{\sum FM(i) <> FF - Theshold}{size(FM)}$$

End
Compute cumulative legitimate weight Lw =SFS×FFS
If LW>BA threshold then
Return true
Else
Return false
End
Stop

The algorithm discussed above computes the legitimate weight towards each class of feature being maintained and based on computed legitimate weight the authentication is performed.

MATERIALS AND METHODS

The proposed biometric authentication system has been implemented using MATLAB and the method has been evaluated for its efficiency in biometric authentication using different data sets. The details of the data set used to evaluate the performance of the proposed approach have been listed below.

Table 1 shows the details of the data set being used to evaluate the performance of the proposed algorithm. The IIT Kanpur database contains a set of face images taken in February, 2002 in the IIT Kanpur campus. There are eleven different images of 40 distinct subjects. For some subjects, some additional photographs are included. All the images were taken against a bright homogeneous background with the subjects in an upright, frontal position. The files are in JPEG format.

Table 1: Details of the data set being used

Data set name	No. of samples	No. of views	Total samples
Feret	1199	11	14126
Multi-PIE	337	15	750,000
IIT Kanpur	23	3	69

The FERET database was collected in 15 sessions between August 1993 and July 1996. The database contains 1564 sets of images for a total of 14,126 images that includes 1199 individuals and 365 duplicate sets of images. A duplicate set is a second set of images of a person already in the database and was usually taken on a different day.

The Multi-PIE database contains 337 subjects, captured under 15 view points and 19 illumination conditions in four recording sessions for a total of >750,000 images.

RESULTS AND DISCUSSION

The proposed method has produced efficient results in all the data sets and has produced efficient biometric authentication efficiency. The method has been evaluated for its efficiency by splitting the data set into 70/30 and 80/20. In each case, the efficiency of the proposed method has been evaluated, and the analysis shows that the proposed method has produced efficient results. The results obtained are compared with the results of the other methods.

Figure 1 shows the comparative result of biometric authentication efficiency produced by different methods at different number of samples per class and the bio metric authentication efficiency of joint faces is 80% for 5 images, 83% for 10 images and 84% for 15 images of LBP for 5 images is 85% for 10 images is 87% and for 15 images is 88%; of DBP for 5 images is 87% for 10 images is 88% and for 15 images is 88%. The biometric authentication efficiency of the proposed method for 5 images is 97% for 10 images is 98% and for 15 images is 99%.

Table 2 shows the comparative result of biometric authentication efficiency produced by different methods at different number of samples per class. It is clear that the proposed method has produced efficient results than the others.

Figure 2 shows the false classification ratio produced by different methods and the false classification ratio is 17% for joint faces, 15% for LBP, 13% for DBC and the proposed method has only 2% false classification ratio. It is clear that the proposed method has less false classification ratio than the other methods.

Table 2: Comparison of authentication efficiency

	Authentication efficiency (%)			
No. of images	JF	LBP	DBC	Proposed
5 images	80	85	87	97
10 images	83	87	88	98
15 images	84	88	88	99

Table 3: Comparative result on time complexity

	Time complexity (time in seconds) (images)		
Methods	100	500	1000
JF	80	250	550
LBP	80	220	490
DBC	70	180	350
Proposed	30	70	220

Figure 3 shows the comparative result on time complexity produced by different methods on different number of images. The methods have been validated with different number of samples like 100, 500 and 1000 number of images. The time complexity of joint faces for 100 images is around 80, for 500 images is around 250 and for 1000 images is around 550. The time complexity of LBP for 100 images is around 80, for 500 images is around 220 and for 1000 images is around 490. The time complexity for DBC for 100 images is around 70, for 500 images is around 180 and for 1000 images is around 350. The time complexity of the proposed method for 100 images is around 30, for 500 images is around 70 and for 1000 images is around 220.

Table 3 shows the comparative result on time complexity produced by different methods on different number of images. It is clear that the proposed method has less time complexity than the other methods.

CONCLUSION

We proposed a multi view edge model to perform biometric authentication using multi feature resemblance technique. The method extracts the sectional features from the multi view image and generates the sectional feature matrix. Similarly from the facial components, the method extracts the facial features and constructs the facial feature matrix. Using both the matrices, the method computes the cumulative weight to perform biometric authentication. The method has been evaluated with different data sets and compared with the other methods. It shows that the proposed method has produced efficient results than the other methods.

REFERENCES

Bhaumik, G., T. Mallick, K.S. Chowdhury and G. Sanyal, 2010. Analysis and detection of human faces by using minimum distance classifier for surveillance. Proceeding of the 2010 International Conference on Recent Trends in Information Telecommunication and Computing, March 12-13, 2010, IEEE, Kochi, India, ISBN: 978-1-4244-5956-8, pp: 265-267.

Geng, X. and Z.H. Zhou, 2006. Image region selection and ensemble for face recognition. J. Comput. Sci. Technol., 21: 116-125.

He, X., S. Yan, Y, Hu, P. Niyogi and H.J. Zhang, 2005. Face recognition using Laplacianfaces. Pattern Anal. Mach. Intell. IEEE. Trans., 27: 328-340.

Jagadeesh, H.S.1., B.K Suresh and K.B. Raja, 2012. DBC based Face Recognition using DWT. Signal Image Process. Int. J., 3: 1-15.

Karim, T.F., M.S.H. Lipu, M.L. Rahman and F. Sultana, 2010. Face recognition using PCA-based method. Proceedings of the 2010 IEEE International Conference on Advanced Management Science (ICAMS), July 9-11, 2010, IEEE, Chengdu, China, ISBN: 978-1-4244-6931-4, pp: 158-162.

Nanni, L., A. Lumini and S. Brahnam, 2012. Survey on LBP based texture descriptors for image classification. Expert Syst. Appl., 39: 3634-3641.

Pinto, N., Z. Stone, T. Zickler and D. Cox, 2011. Scaling up biologically-inspired computer vision: A case study in unconstrained face recognition on Facebook. Proceedings of the Workshops on CVPR 2011, June 20-25, 2011, IEEE, Colorado, USA., ISBN: 978-1-4577-0529-8, pp: 35-42.

Rong, X. and L. Wujun, 1988. Joint Boosting Feature Selection for Robust Face Recognition. Microsoft Research Asia, Beijing, China,.

Sumathi, S. and R.R. Malini, 2010. Face recognition system to enhance E Health. Proceedings of the 2010 International Conference on E-Health Networking Digital Ecosystems and Technologies (EDT), April 17-18, 2010, IEEE, Shenzhen, China, ISBN: 978-1-4244-5514-0, pp: 195-198.

Zhang, H., Q.J. Wu, T.W. Chow and M. Zhao, 2012. A two-dimensional neighborhood preserving projection for appearance-based face recognition. Pattern Recognit., 45: 1866-1876.