Face Detection and Recognition

[1]**Mohaned Zakaria Salem* , **[2]**Ali Hussein Khalaf AL-Sammarraie****

[1,2] *Ministry of Education, Directorate General of Education Salah al-Din ,Samarra, Iraq
** Ministry of Education , Directorate General of Education Diyala, Baquba, Iraq
Email : * mohanad.201339@gmail.com **,** ** sahk383@yahoo.com

Abstract Facial identification in photos or videos is a common theme in biometrics research. Many public places usually have video capture surveillance cameras and these cameras are very important for protection. Facial recognition has traditionally been recognized as a significant factor in the monitoring framework, as it does not require the cooperation with the object. The real advantages of facial authentication over other biometrics are their singularity and identification. Since the human face is a highly diverse dynamic object, computer vision makes face recognition a challenging question Accuracy and speed of identification are the main challenges in this field. This paper aims at testing various facial detection and recognition methods as an initial video monitoring phase for image-orientated face detection, and provides an entire solution with greater accuracy, greater response time. The method is recommended for subjects, posture, emotions, race and light, based on studies carried out on various face-rich databases.

Keywords: Face Detection, Face Recognition, Biometrics, Face Identification.

1.   Introduction

Face detection can be defined as a new way of scanning and taking the resulting datasets to the image of an object. An algorithm involves the use of an algorithm that makes it possible to identify moving images from a running video stream and to monitor the various positions in the image processing dataset. In general face recognition systems are designed for the identity behind the video images to be recorded and labelled with an identity to complete this process. It's a major focus of image processing research. The faces are recognized on a couple of facets with the help of patterns matching images of the same individual or recognition of a face where the mark is seen on an unfamiliar face in relation to a certain training sequence. In daily college or schools there is a clear need for technology-based monitoring. It provides an image-processed medium for weaving out unwanted and unsolicited persons by on-screen tagines by providing warning messages to the user, which shows aliens and other unknowns 'Unknown' and helps check that unauthorized persons gain access to private information. Auto face identification and recognition has made tremendous success in the military and other top-secret organizations in recent decades. If the training samples are few and the circumstances are difficult to capture as images for the dataset, it can be a very challenging problem. There are different levels of tracking the behavior of student pupils in a school setting. In an educational campus setting, our work towards face recognition takes student and instructor practices to one hemisphere of vision and the surveillance activities that rule the campus as another hemisphere. The algorithms that are used are of superior strength and can perform the detection and tagging of names in a single video capture for a group of 5 students. We see a case of face photographs that differ greatly in orientation, speech, and lighting, where only frontal images are captured as part of the dataset. In our work, we concentrate on the challenging issue of understanding student photographs taken from a visual stream that flows. [1],We teach them to provide caught faces with name tags and other personal details relating to the student in question. In this analysis, we provide three modules. Firstly, creation of the data object (detection). The teaching module and, eventually, the visual recognition module that finishes the device [4].

2.   Related works

Specific characteristics on the faces, such as organs, i.e. eyes, mouth or nose area, were used for identification in the earliest evolved facial recognition algorithms. These were strictly feature-oriented classifiers and had a significant effect on the use of data sets based on the face and classifier. [4].However, because of the uncertainty and the low amount of knowledge used, these approaches did not contribute to successful outcomes. The Viola-Jones[5] Object detection architecture, proposed in 2001 by Paul Viola and Michael Jones is the first object detection device to have a strategic advantage. While a number of groups of objects can be identified, it was primarily driven by the problem of face detection. In OpenCV, the cvHaarDetectObjects algorithm is implemented. Since the 1990s, new techniques have been created that apply global facial features. Turkish and Pent land suggested Eigen Faces [5] A main feature analysis is used (PCA). Other techniques as Fisher faces or

[1]Mohaned Zakaria Salem* , [2]Ali Hussein Khalaf AL-Sammarraie**

Laplacianfaces derive characteristics from face images and are used to carry out nearest neighbor identification using Euclidean distance scales .Babacket al. uses a Bayesian[6] approach where classification is done using a probabilistic similarity measure. The Sparse Reporting Classification (SRC) scheme was suggested by Wright et al. for facial recognition, which was a dictionary-based learning approach to facial identification. This strategy is much more robust and can take occlusions and corruption of facial pictures into consideration as improvement towards previous ones. A visual descriptor used for classification in computer vision is LBP, introduced and defined in early 1994[8]. The basic case of the Texture Continuum model, suggested in 1990, is LBP. Since it has been found to be a strong texture classification feature, it has also been determined that when LBP is combined with (HOG) Histogram of directed descriptor gradients, certain datasets dramatically enhance the output of detection. Centered on the Eigen faces method, the PCA algorithm[4] extracts relevant information in a face image, and encodes it in an effective data structure. It was first implemented at the beginning of the 1900s, and is currently the oldest algorithm. Pearson(1901) first introduced it and Hoteling developed it independently. The basic principle of PCA is to decrease the dimensionality of the dataset in which vast quantities of interrelated variables occur, while preserving all of the potential variance in the dataset. These were the templates for removing differences in posture and voice. In recent years, the issue of facial recognition has been resolved through profound learning approaches. Such strategies achieve very good identification rates and obviously surpass "standard" algorithms. In practice, though, a large number of data and advanced hardware are generally needed for training and deployment. This makes them harder to train and less suitable for embedded and low strength systems.

3. Face detection

The classificatory of Adaboost [6] use the Histogram of Directed Gradients (HOG)[13] for face-reconnaissance evaluation, and the Local Binary Pattern (LBP)[8] are used. A new image representation that uses an extensive range of features with the Adaboost[7] boosting algorithm to decrease the boosted classifier degenerative tree to generate stable, fast and rectangular hair-like interference.[7Features have a range of advantages such as ad-hoc domain knowledge and a speed increase over pixel-based systems, making it very easy for Haar[7] base functions to measure intensity differential readings comparable. Implementation of a system using these features will include a much wider set of features, so that only a few important characteristics obtained by improving the Adaboost algorithm[6] could be used. The original LBP[8] operator marks an image's pixels by thresholding the middle pixel value of the 3-by-3 neighborhood of each pixel and taking the output as a binary number. It is possible to regard each face picture as a composition of micro-patterns that the LBP[8] operator can effectively detect. They grouped face images into N small non-overlapping regions T0, T1, ..., TN to consider the shape details of faces. The histograms of LBP[8] derived from each sub-region are then concatenated into a single histogram of spatially enhanced features defined as:

$$H_{i,j} = \Sigma_{x,y} I(f_l(x,y)=i) I((x,y)\epsilon T_j)$$

If I = 0, ... , L-1; j = 0,... and N-1.In the extracted histogram function, the local texture and global form of the face image is seen. For facial recognition of HOG [13] features, the SVM classification is used[12]. HOG[13] exceeds significantly waves and smoothing before calculating damage to gradients, stress is caused so much of the feedback that it was a mistake to brittle this to minimize spatial exposure. Gradients should be measuring at the best possible level in the current pyramid sheet and an efficient normalization of local contrast is critical for good results. SVM[12] is designed to solve a conventional two-class problem that returns the binary value of an object class. We express the problem in a separate room to shape our SVM[12] algorithm, which shows explicitly the difference between two facial images. Here are the summer results of the above approaches. Table 1: Face detection results summary

Dataset	Detection		
	Adaboost		SVM
	Haar	LBP	HOG
[1]	99.31%	95.22%	92.68%
[2]	98.33%	98.96%	94.10%
[3]	98.31%	69.83%	87.89%

[4]	96.94%	94.16%	90.58%
[5]	90.65%	88.31%	89.19%
Mean	96.70%	89.30%	90.88%

In addition, the system has been evaluated on datasets [1,2,3,4,5] and the findings are illustrated below on the basis of the system demonstrated above:

Two additional activities conducted in the pre-processing stage to enhance identification outcomes are required to minimize pose variance and lighting in extracted faces:
1) The identification of eyes has been
Used in Figure 4 to eliminate head shift, tilt, slant and face location, as shown; 2) Histogram equalization is done.

4. Face recognition.

Its properties[9] will mainly be straight and frontal faces, called a 2-D facial recognition issue. Therefore it is not appropriate to provide 3-D facial information, which greatly reduces complexity. It transforms face-to-face images into a collection of main functions that can be used, in particular, to represent the data more efficiently. The main objective is to minimize the number of features before the detection to a more manageable number, since a broad range of pixel values is present on your face. Fisherfaces [10] is the linear combination of the linear discriminant of Fisher. LBP[8] is an order range of pixel intensity binary contrasts between the middle pixel and its eight adjacent pixels.

$LBP(x_a, y_a) = {}^7\Sigma_{n=0}s(i_m - i_a)2_n$

Where i_a corresponds to the value of the center pixel (x_a, y_a), i_m to the value of eight surrounding pixels, function f(x) is defined as:

$f(x) = 1$ if $x >= 0$
0 if $x < 0$

Gabor[11] filters can leverage influential visual properties such as spatial localization, selectivity of direction, and characteristics of spatial frequency. Gabor[11] characteristics are oblivious to improvements such as lighting, posture and expressions in view of these devastating capacities and its great performance in face recognition, while Gabor[11] transition is not specially built for face recognition. Instead of learning from the face training results, the transformation formula is predefined. In addition, global features are considered by PCA[9] and LDA[10] classifiers, while local features are considered by LBP[8] and Gagor classifiers, based on current experimental findings.

5. Dataset

The following tests have been made using five datasets. A transparent green backdrop face collection in the dataset[1], no headscale and light variation but with minor head turn, tilt, inclination and facial orientation adjustments and significant facial changes. Variation is induced by shadows as the subject moves ahead in the

[1]Mohaned Zakaria Salem* , [2]Ali Hussein Khalaf AL-Sammarraie**

datasets[2], a red-curtain background facial collection, with little changes in head moving, bending, tilting; a wide range in head; a variation on the voice, translation of face position and change in illumination as the topic moves ahead. Complication in data set history[3]; broad variation in head scale; minor variations in head change, tilt, slant and expression; some conversion of facial location and considerable light variance due to the object's artificial light moment. Low variation in head size; major variation in head shift, tilt, slope and substantial changes in expression; translation of the small face direction and change in lightness. Clear dataset history[4]. Constant background face array with a slight variance in the head and light data collection;[5] major move, tilt, slant, voice, and variation in the face location.

6. Conclusion

In our present work, we have established a framework to test the methods used for the identification

Table 3: Face database summary

Data Set	Sub-Division	Images	Resolution	Individuals	Image/Individual
A	Face 94	3078	180*200	153	~20
	Face 95	1440	180*200	72	20
	Face 96	3016	196*196	152	~20
	Grimace	360	180*200	18	20
B	Pain Expressions	599	720*576	23	26

A: Face Recognition Data, University of Essex

B: Psychological Image Collection at Stirling (PICS)

and recognition of faces. Some methods have also been used over multiple datasets, whereas other approaches have been performed very randomly, however the overall results of studies have been based on five datasets. The summary outcome of the face detection and recognition process is given in Table 1 and Table 2 respectively, while summery datasets are provided in Table 3. Haar-like in the new method [7]features reported reasonably well, but it has a lot more false detection than LBP[8], which should be considered to be a potential surveillance job to minimize false detection in Haar-like[7] features and gabor[11] is reported for the recognition portion, as its characteristics overcome the difficulty of datasets.

References

1. Face Recognition Data, University of Essex, UK, Face 94, http://cswww.essex.ac.uk/mv/all faces/faces94.html.
2. Face Recognition Data, University of Essex, UK, Face 95, http://cswww.essex.ac.uk/mv/all faces/faces95.html.
3. Face Recognition Data, University of Essex, UK, Face 96, http://cswww.essex.ac.uk/mv/all faces/faces96.html.
4. Face Recognition Data, University of Essex, UK, Grimace, http://cswww.essex.ac.uk/mv/all faces/grimace.html.
5. Psychological Image Collection at Stirling (PICS), Pain Expressions, http://pics.psych.stir.ac. uk/2D_face_sets.htm.
6. K. T. Talele, S. Kadam, A. Tikare, Efficient Face Detection using Adaboost, "IJCA Proc on International Conference in Computational Intelligence", 2012.

7. T. Mita, T. Kaneko, O. Hori, Joint Haar-like Features for Face Detection, "Proceedings of the Tenth IEEE International Conference on Computer Vision", 1550-5499/05 ©2005 IEEE.

8. T. Ahonen, A. Hadid, M. Peitikainen, Face recognition with local binary patterns. "In Proc. of European Conference of Computer Vision", 2004.

9. M. A. Turk and A.P. Pentland, Face recognition using eigenfaces, "Proceedings of the IEEE", 586-591, 1991.

10. J Lu, K. N. Plataniotis, A. N. Venetsanopoulos, Face recognition using LDA-based algorithms, "IEEE Neural Networks Transaction", 2003.

11. L. Wiskott, M. Fellous, N. Krger, and C. Malsburg, Face recognition by elastic bunch graph matching, "IEEE Trans", on PAMI, 19:775–779, 1997.

12. I. Kukenys, B. McCane, Support Vector Machines for Human Face Detection, "Proceedings of the New Zealand Computer Science Research Student Conference", 2008.

13. M. M. Abdelwahab, S. A. Aly, I. Yousry, Efficient Web-Based Facial Recognition System Employing 2DHOG, arXiv:1202.2449v1 [cs.CV].

14. W. Zhao, R. chellappa, P. J. Phillips, Face recognition: A literature survey, "ACM Computing Surveys (CSUR)", December 2003.

15. G. L. Marcialis, F. Roli, Chapter: Fusion of Face Recognition Algorithms for Video-Based Surveillance Systems, Department of Electrical and Electronic Engineering- Univ- ersity of Cagliari- Italy.

16. A. Suman, Automated face recognition: Applications within law enforcement. Market and technology review, "NPIA", 2006.