© April 2018 | IJIRT | Volume 4 Issue 11 | ISSN: 2349-6002

Face Detection and Recognition & Investigation

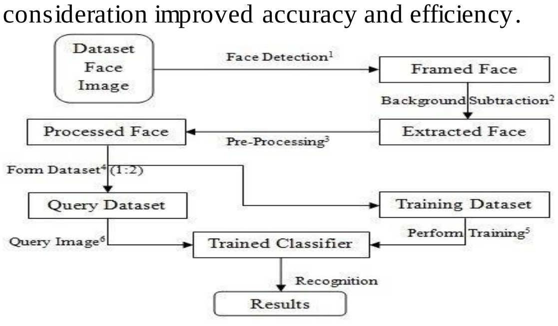
Rahul Bajaj[1], Ronet Swaminathan[2], Tanay Srivastava[3] Graceline Jasmine[4]
[1,2,3,4] *Vellore Institute of Technology, Chennai*

***Abstract-* The detection and recognition of human faces in images, be it in a motive or static environment is one of the most popular topics in international research. In order create a face recognition system, this paper uses the Convolutional Neural Network to identify prominent parts of the human face, and then uses the AdaBoost algorithm to detect human face in the region. The processed image is then converted into a 128 bit encoding, which keeps only the most specific details of the extracted human face. For an image to be recognized, we then find the normalized difference of the Eucledian distance between the known image in the database and the input unknown image. The output of the system is the known name saved in the database.**

I. INTRODUCTION

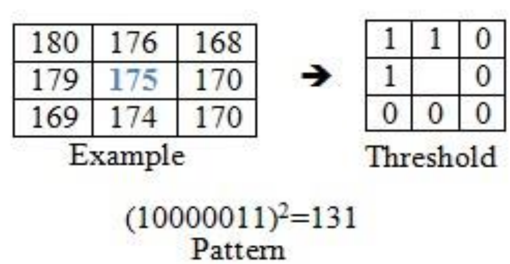
Over the past few year, lots of work has been done in face detection and recognition. It has been considered as one of the best ways for person identification because of the lack human cooperation. Lots of methods have been introduced for detection and recognition, and have been considered as a milestone. Although these methods are used several times for the same purpose, each have their own uniqueness. Popular recognition algorithms include principal component analysis using eigenfaces, linear discriminant analysis, elastic bunch graph matching using the Fisherface algorithm, the hidden Markov model, the multilinear subspace learning using tensor representation, and the neuronal motivated dynamic link matching.

This paper also aims to device a new, improvised algorithm to achieve the same feat, taking into consideration improved accuracy and efficiency.



II. FACE DETECTION

The AdaBoost classifier has been used in junction with the Haar and Local Binary Pattern (LBP) features whereas Support Vector Machine (SVM) classifier is used with Histogram of Oriented Gradients (HOG) features for face detection evaluation. Haar-like features are judged through the use of a new image representation that generates a large dataset of features and uses the boosting algorithm AdaBoost for efficient and fast interferences. Only simple rectangular Haar like features have been used that provides a number of additional benefits , one of which is sort of ad-hoc domain knowledge, which is implied as well. A speed increment over the regular pixel based systems, associated to Haar basis functions, equivalent to intensity difference readings are quite easy to compute. Implementing such a system that uses such features would provide a feature set that will be huge, hence



the feature set must be only restricted to a small number of critical and specific features which has been achieved by the boosting algorithm, Adaboost.

The original LBP operator fixes the pixels of an image by thresholding the 3-by-3 neighborhood of each pixel with the center pixel value and then, has taken the result as a binary number. Each face image can be considered as a composition of micro-patterns, which can be detected by the LBP operator. To extract the shape information of faces, we divide the face images into N small non-overlapping regions T0, T1, ..., TN. The LBP histograms extracted from each sub-region are then clubbed into a single, spatially enhanced feature histogram defined as: $Hi,j = \Sigma_{x,y} I(fl(x,y) = i) I((x,y)Tj)$ where i = 0, ... , L-1; j = 0, ..., N-1. The extracted feature histogram describes the local texture and global shape of face images.

Gradients have to be computed at the available scale in the current pyramid layer and strong local contrast normalization is a necessity for better results. SVM are formulated to solve a two class problem which returns a binary value, the class of the object. To train the SVM algorithm, we construct the problem in a difference space, that specifically captures the dissimilarities between two facial images. The resultant summary of the above are given below:

Table 1: Face detection results summery

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%

III. FACE RECOGNITION

Eigenfaces are considered as a 2-D face recognition issue, faces will be mostly vertical and posterior. It converts the face images into a set of basis methods, which are the leading components of the face images that seeks directions in which it is more efficient to represent the data. This is primarily applicable for the reduction of computational effort. Linear discriminant analysis is used to decrement the number of features to a more handy number; before recognition to make things simpler. Each of the new dimensions made is a linear combination of pixel values. LBP is an order set of binary comparisons of pixel intensities between the center pixel and its eight surrounding pixels.

LBP (xa,ya) $= 7\ \Sigma_{n=0} s(im - ia)2n$

Where ia corresponds to the value of the center pixel (xa,ya), im to the value of eight surrounding pixels, function f(x) is defined as: $f(x) = 10 if x < if x >= 00$

Gabor filters can exploit salient visual properties such as spatial localization, orientation selectivity, and spatial frequency characteristics.

Dataset	Recognition			
	PCA	LDA	LBP	Gabor
[1]	72.10%	79.39%	85.93%	93.49%
[2]	69.87%	76.61%	80.47%	89.76%
[3]	70.95%	78.34%	84.14%	92.68%
[4]	74.79%	81.93%	86.45%	96.91%
[5]	68.04%	73.21%	77.69%	88.93%
Mean	71.15%	77.90%	82.94%	92.35%

IV. DATASET

Seven datasets been used in the above investigations. Face collection database is used to train the model. Convolutional Neural Networks are trained on dataset.

V. CONCLUSION

With the experimental investigations, we are able to create a new algorithm which enhances the precision to detect and recognize faces in an image. The normalization of the encoding generated from the face in an image, can be used on different experiments ahead.

VI. FUTURE SCOPE

Expanding our investigation to recognize side face, partial face and eyes.

ACKNOWLEDGMENT

We are grateful for the guidance provided by our teacher and mentor, Professor Graceline Jasmine.

REFERENCES

[1] Face Recognition Data, University of Essex,http://cswww.essex.ac.uk/mv/all faces/faces94.html UK, Face 94,

[2] Face Recognition Data, University of Essex, http://cswww.essex.ac.uk/mv/all faces/faces95.html UK, Face 95,

[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
[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.