COMPARISON OF FACE DETECTION ALGORITHMS

Face detection:

The current evolution of computer technologies has envisaged an advanced machinery world, where human life is enhanced by artificial intelligence. Computer vision, for example aims to duplicate human vision. In the past, the researches in the computer vision were mostly on the assembly line inspection .Currently, the researches in the computer vision are more focused on face detection and recognition and video coding techniques because these techniques find more applications in the real world.

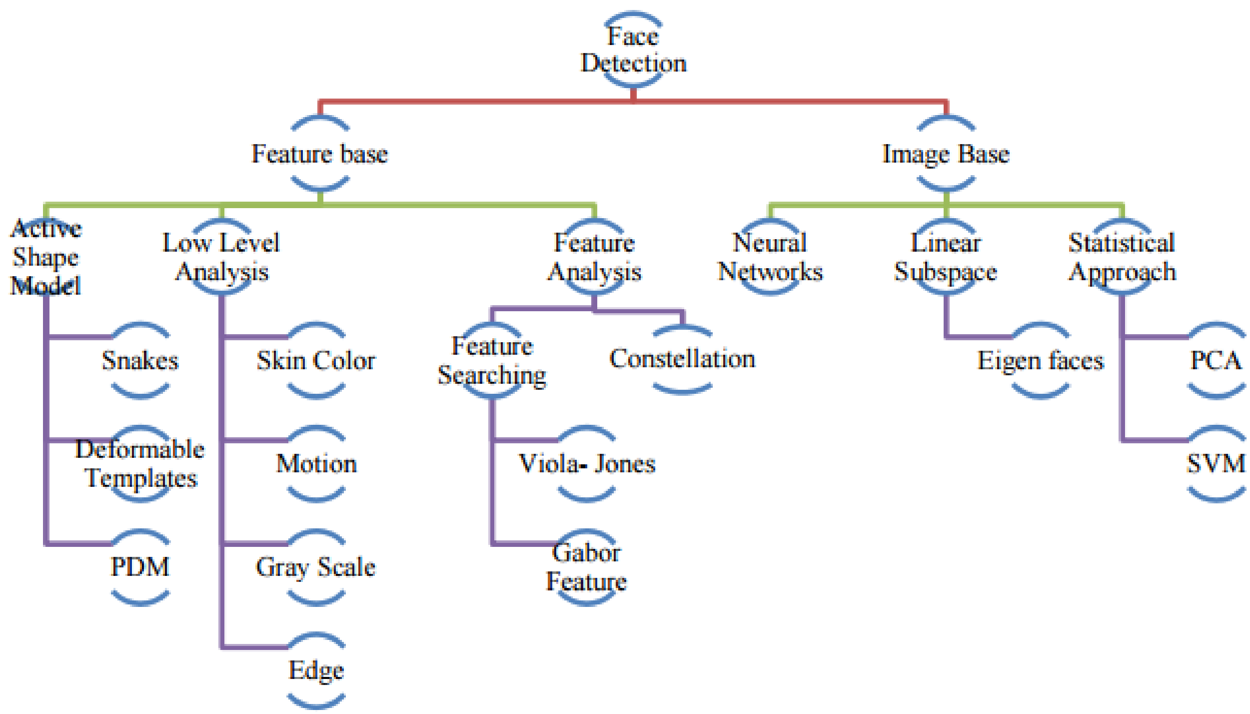
Humans can do the face detection effortlessly but this is not easy in the case of computer vision because it involves various complexities such as lighting in the image, orientation of face, background of image,etc. The task can be defined as ,given an image/video, the goal of face detection is to detect if any faces are present in the image/video and if present, it must return the location of it. Face detection is the first step in all face analysis algorithms including face alignment, face modelling, face relighting, face recognition, face verification/authentication, head pose tracking ,facial expression tracking/recognition, gender/age recognition and many more.

Evolution of face detection algorithms:

Early efforts in face detection have dated back as early as the beginning of the 1970s, where simple heuristic and anthropometric techniques were used. These techniques are largely rigid due to various assumptions such as plain background, frontal face—a typical passport photograph scenario. To these systems, any change of image conditions would mean fine-tuning, if not a complete redesign. Despite these problems the growth of research interest remained stagnant until the 1990s , when practical face recognition and video coding systems started to become a reality. Over the past decade there has been a great deal of research interest spanning several important aspects of face detection. More robust segmentation schemes have been presented, particularly those using motion, color, and generalized information. The use of statistics and neural networks has also enabled faces to be detected from cluttered scenes at different distances from the camera. Additionally, there are numerous advances in the design of feature extractors such as the deformable templates and the active contours which can locate and track facial features accurately. Because face detection techniques requires a priori information of the face, they can be effectively organized into two broad categories distinguished by their different approach to utilizing face knowledge.

The techniques in the first category make explicit use of face knowledge and follow the classical detection methodology in which low level features are derived prior to knowledge-based analysis. The apparent properties of the face such as skin color and face geometry are exploited at different system levels. Typically, in these techniques face detection tasks are accomplished by manipulating distance, angles, and area measurements of the visual features derived from the scene. Since features are the main ingredients, these techniques are termed the feature-based approach. These approaches have embodied the majority of interest in face detection research starting as early as the 1970s and therefore account for most of the literature reviewed in this paper. Taking advantage of the current advances in pattern recognition theory, the techniques in the second group address face detection as a general recognition problem. Image-based representations of faces, for example in 2D intensity arrays, are directly classified into a face group using training algorithms without feature derivation and analysis. Unlike the feature-based approach, these relatively new techniques incorporate face knowledge implicitly into the system through mapping and training scheme.

Face detection techniques:



TABULAR COMPARISON:

S.NO	ALGORITHM	WORKING	ADVANTAGE	DISADVANTAGE
ACTIVE SHAPE MODEL				
1.	SNAKE	Initialized around a head boundary and from there it interlocks nearby edges minimizing the energy and assuming the shape of head. Esnake=Einternal+Eexternal	They employ fast iteration using greedy algorithms.	They have some demerits like contour often becomes trapped onto false image features and another one is that snakes are not

				suitable in extracting non convex features.
2.	DEFORMABLE TEMPLATES	They took the concept of snakes , a step further by incorporationg global information of the eye to improve the reliability of the extraction process. Deformation is based on local valley, edge, peak, and brightness E = Ev + Ee + Ep + Ei + Einternal.	They were better performing than the previous approach .	The low brightness contrast around some of the features makes the detection process problematic.
3.	POINT DISTRIBUTION MODEL	The idea is that once you represent shapes as vectors, you can apply standard statistical methods to them just like any other multivariate object. These models learn allowable constellations of shape points from training examples and use principal components to build what is called a Point Distribution Model	This approach was able to detect faces with beards or chin covered.	
LOW LEVEL ANALYSIS				
4.	SKIN COLOR BASE	In the implementation of the algorithms there are three main steps viz. (1) Classify the skin region in the color space, (2) Apply threshold to mask the skin region and (3) Draw bounding box to extract the face image.	Color processing is much faster than processing other facial features. Under certain lighting conditions, color is orientation invariant	1.Tracking human faces using color as a feature has several problems like the color representation of a face obtained by a camera is influenced by many factors (ambient light, object movement, etc.). 2.This algorithm fails when there are some more skin region like legs, arms, etc.

5	GRAY SCALE BASE	This algorithm uses hierarchial face location analysis	This algorithm gives fine response in complex background where size of the face is unknown.	When the colour of the image is dark ,the algorithm fails.
6.	EDGE BASE	It involves three steps. 1. The images are enhanced by applying median filter for noise removal and histogram equalization for contrast adjustment. 2. The edge image is constructed from the enhanced image by applying sobel operator. 3. Then ,they used Back propagation Neural Network (BPN) algorithm to classify the sub-window as either face or non-face	The performance of the system was found to be fast.	
FEATURE ANALYSIS				
7.	VIOLA JONES METHOD	It uses the concept of Integral Image, it generates a large set of features using haar cascade classifier and uses the boosting algorithm Ada Boost to reduce the over complete set and the introduction of a degenerative tree of the boosted classifiers provides for robust and fast interferences.	It works with 95% accuracy at 17fps which is remarkable and it's available open source.	Though the accutracy is higher, it fails when part of a face is hided or only portion of face is visible.
8.	GABOR FEATURE METHOD	The proposed system applies 40 different Gabor filters on an image. As a result of which 40 images with different angles and orientation are received. Then maximum intensity is calculated and distance between various point is reduced using distance formula.	The face detection accuracy is high.	The gabor feature is too high dimensional and computational cost is high.

9.	CONSTELLATION METHOD	This algorithm uses the statistical shape theory on the features detected from a multiscale Gaussian derivative filter.	This algorithm is able to locate faces of various poses in a complex background.	This algorithm is difficult to design and implement.
IMAGE BASE APPROACH				
10.	NEUTRAL NETWORK METHOD	In the early days hierarchical neural networks were used but now back propagation and auto associative neural networks are used. They can perform better when the training set contains huge database of images with respective features.	The advantage of using neural networks for face detection is the feasibility of training a system to capture the complex class conditional density of face patterns	The network architecture has to be extensively tuned (number of layers, number of nodes, learning rates, etc.) to get exceptional performance.
11	PRINCIPLE COMPONENT ANALYSIS	1.PCA on a training set of face images is performed to generate the Eigenfaces in face space. 2.Images of faces are projected onto the subspace and clustered. 3.Nonface training images are projected onto the same subspace and clustered. 4.To detect the presence of a face in a scene, the distance between an image region and the face space is computed for all locations in the image	This algorithm has an accuracy of more than 90 percent when tested over various datasets.	They are normally used for face recognition rather than face detection.

COMPARITIVE EVALUATION:

Test 1:

This test was done on a dataset which has both CMU and Stanley datasets. The datasets were divided into four types. They are CMU 130,CMU 125, MIT 23 and MIT 20.

Results Reported in Terms of Percentage Correct Detection (CD) and Number of False Positives (FP), CD/FP, on the CMU and MIT Datasets

Face detection system	CMU-130	CMU-125	MIT-23	MIT-20
Schneiderman & Kanade—E[a] [170]		94.4%/65		
Schneiderman & Kanade—W[b] [170]		90.2%/110		
Yang *et al.*—FA [217]		92.3%/82		89.4%/3
Yang *et al.*—LDA [217]		93.6%/74		91.5%/1
Roth *et al.* [157]		94.8%/78		94.1%/3
Rowley *et al.* [158]	86.2%/23		84.5%/8	
Feraud *et al.* [42]	86%/8			
Colmenarez & Huang [22]	93.9%/8122			
Sung & Poggio [182]			79.9%/5	
Lew & Huijsmans [107]			94.1%/64	
Osuna *et al.* [140]			74.2%/20	
Lin *et al.* [113]			72.3%/6	
Gu and Li [54]			87.1%/0	

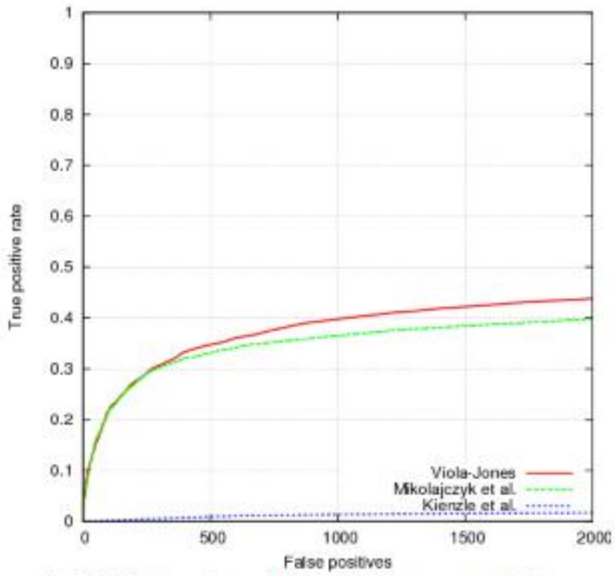
[a] Eigenvector coefficients.
[b] Wavelet coefficients.

Test 2:

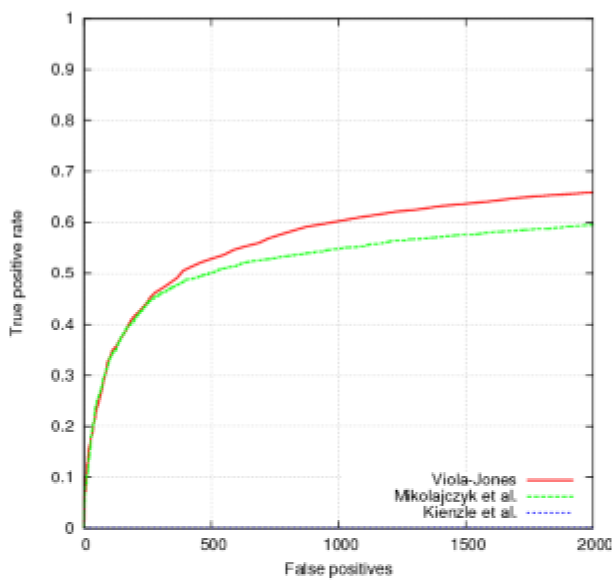
This test was done on dataset of images which is a combination of GENKI ,KODAK,UCD,VT-AAST.Totally there were 2845 images with a total of 5171 faces. The specification of face regions were elliptical and had both grayscale as well as colour images.

The evaluation were based mainly on ROC curves . Although comparing the area under the ROC curve is equivalent to a non-parametric statistical hypothesis test (Wilcoxon signed-rank test), it is plausible that the cumulative performances of none of the compared approaches is better than the rest with statistical significance. Furthermore, it is likely that for some range of performance, one approach could outperform another,whereas the relative comparison is reversed for a different range. For instance, one detection algorithm might be able to maintain a high level of precision for low recall values, but the precision drops sharply after a point. This trend may suggest that this detector would be useful for application domains such as biometrics-based access controls, which may require high precision values, but can tolerate low recall levels. The same detector may not be useful in a setting (e.g., surveillance) that would requires the retrieval of all the faces in an image or scene. Hence, the analysis of the entire range of ROC curves should be done for determining the strengths of different approaches.

The benchmark test was done for three algorithms namely Viola Jones detector, Mikolajczyk's detector and Kienzle et al.'s face detection library.



(b) ROC curves based on continuous score (CS)



(a) ROC curves based on discrete score (DS)

The number of false positives obtained from all of these face detection systems increases rapidly as the true positive rate increases. Note that the performances of all of these systems on the new benchmark are much worse than those on the previous benchmarks, where they obtain less than 100 false positives at a true positive rate of 0.9. Also note that although our data set includes images of frontal and non-frontal faces, the above experiments.

Test 3:

The aim of this work is to propose parameters of FD algorithms quality evaluation and methodology of their objective comparison, and to show the current state of the art in face detection. Also it's should be stressed that a correct experiment should consists of two parts: algorithms learning on the training set and comparative testing. Unfortunately, we are not able to train all algorithms on the same data for several reasons. However, we believe that this does not diminish the correctness of this research, because our goal is to evaluate face detection systems rather than the learning methods. The following algorithms were tested in this work:

1. Intel OpenCV
2. Luxand FaceSDK
3. Face Detection Library
4. SiFinder
5. UniS
6. FaceOnIt
7. VeriLook

The image dataset is a collection of dataset including Face Place,IMM Face Database, Achermann face collection, BioID , UMIST Face database , PIE data subset ,Indian Face database, The ORL Database of faces, Laboratory of Data Analysis. Total test dataset contains 59888 images of which 11677 faces and 48211 non faces.

The parameters for result evaluation :

1. False Rejection Rate (FRR) — Ratio of type I errors, which indicates the probability of misclassification of the images containing a face.
2. False Acceptance Rate (FAR) — Ratio of type II error, which indicates the probability of misclassification of the images not containing a face.
3. Distance to the “exemplary” algorithm--We consider a FD algorithm to be ”exemplary” (exemp), if its FAR and FRR equals 0. Thus the distance between ”exemp” algorithm and this one is dexmp which is equal to square root of sum of square FAR and and square FRR.
4. Speed parameters such as mean and median of animage processing time(ms) from the dataset. These results were obtained in following configuration: Intel Core2Duo 1.66 GHz, 2Gb RAM, Windows Vista HP.

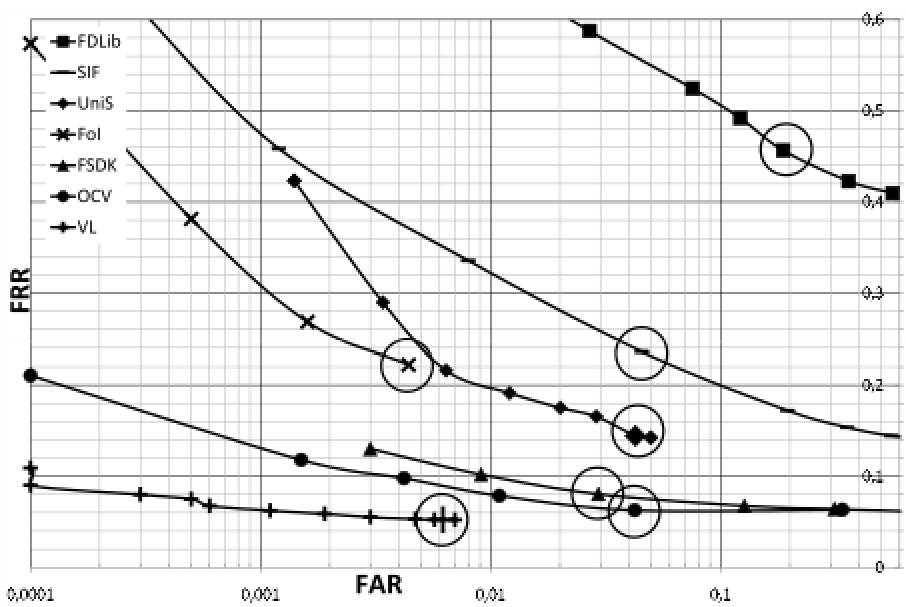
RESULTS:

Table 1. Coefficients of the model of supposed coordinates of eyes estimation

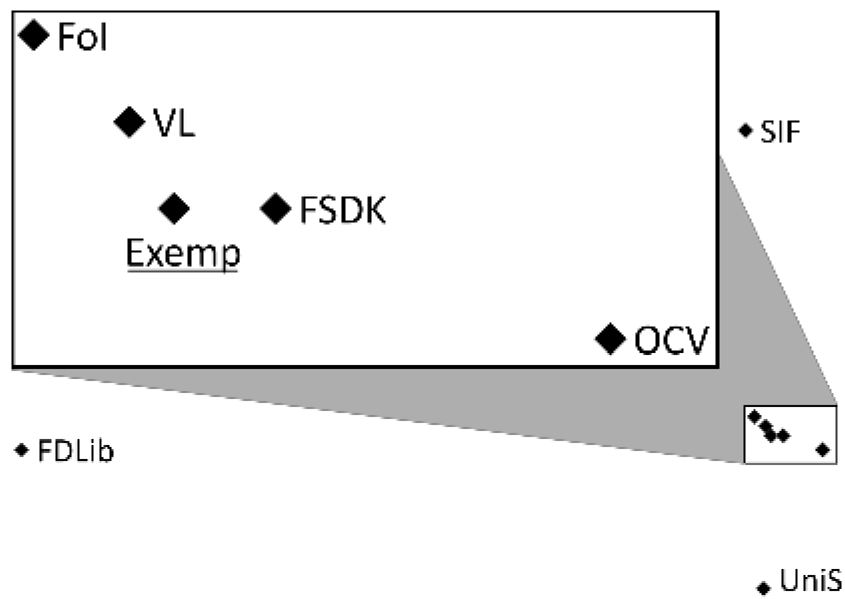
Algorithm	FDLib	OCV	FoI
coefficient A	0.3332	0.3858	0.2646
coefficient B	0.3830	0.3666	0.5124

Table 2. Matrix of dissimilarity of algorithms with fixed parameters (see value of parameters in the parentheses)

	OCV	SIF	FDLib	FSDK	UniS	FoI	VL	Exemp
OCV(2)	0	0.099	0.227	0.052	0.076	0.053	0.047	0.043
SIF(-3)		0	0.226	0.089	0.097	0.070	0.075	0.073
FDLib(1)			0	0.222	0.223	0.213	0.215	0.216
FSDK(5)				0	0.069	0.043	0.035	0.030
UniS(20)					0	0.051	0.053	0.047
FoI(5)						0	0.026	0.019
VL(2)							0	0.011
Exemp								0



The ROC plots. FAR (in log scale) against FRR. Perfect performance would be the bottom left corner: $FRR = FAR = 0$.



Two dimensional FastMap diagram obtained on the data represented in Table 2 (the closest five algorithms are also represented on an expended scale in the frame).

Table 3. Results of algorithms' testing with fixed parameters (see value of parameters in the parentheses); Estimations of time (Mean and Median) are given in ms.

Algorithm	**FRR**	**FAR**	d_{exemp}	**Mean, ms.**	**Median, ms.**
OCV(2)	0.0628	0.0423	0.0757	90	88
SIF(-3)	0.2362	0.0454	0.2405	260	254
FDLib(1)	0.4565	0.1868	0.4932	64	62
FSDK(5)	0.0805	0.0294	0.0857	1305	1041
UniS(20)	0.1444	0.0426	0.1505	176	149
FoI(5)	0.2222	0.0044	0.2222	84	85
VL(2)	0.0523	0.0062	0.0527	47	43

Table 4. Peculiar images distribution on the datasets (Dataset ID corresponds to the index in the image datasets' list (Section 5))

	Dataset ID									
	1	2	3	4	5	6	7	8	9	NonFaces
Number of images	1247	240	300	1520	416	68	513	400	6973	48211
Peculiar Cases										
"easy" images	315	31	121	713	28	44	4	248	2881	34093
"challenging" imag.	9	3		5	6		7		51	
only OCV	2				5		1		6	
only SIF									5	
only FDLib					1				2	
only FSDK		1			2		2		8	
only UniS	1	2					3		18	
only FoI	3						1		21	1
only VL	12			2	23		2		21	

In this work the seven FD algorithms were tested and the statistical model of eyes' position estimation for algorithms describing faces by rectangle was proposed .

According the result of our study VeriLook has the best performance under various parameters and has the first place in the speed test (18-20 images per second). FDLib shows good speed characteristics (second place), but it demonstrates the worst performance. OpenCV – the most popular and free available FD algorithm – took the second place in the performance test and has sufficient speed. SIF developed in Tula State University has demonstrated the average performance. It's worth noting that VeriLook has the biggest number of uniquely classified images, i.e. images that were misclassified by other algorithms. It should be noted that about 64% of images were correctly processed by all algorithms. Such images are called "easy" in this work.

CONCLUSION:

Based on the study of above algorithms ,we have chosen the OpenCV algorithm for implementation of face detection in ROS because it is open source and the performance is also better when compared with other algorithms and it has easy implementation.

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