Evaluation of Haar Cascade Classifiers for Face Detection

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Evaluation of Haar Cascade Classifiers Designed for Face Detection

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***Abstract*—**In the past years a lot of effort has been made in the field of face detection. The human face contains important features that can be used by vision-based automated systems in order to identify and recognize individuals. Face location, the primary step of the vision-based automated systems, finds the face area in the input image. An accurate location of the face is still a challenging task. Viola-Jones framework has been widely used by researchers in order to detect the location of faces and objects in a given image. Face detection classifiers are shared by public communities, such as OpenCV. An evaluation of these classifiers will help researchers to choose the best classifier for their particular need. This work focuses of the evaluation of face detection classifiers minding facial landmarks.

***Keywords*—**Face datasets, face detection, facial landmarking, haar wavelets, Viola-Jones detectors.

I. Introduction

ALTHOUGH recognizing an individual by the face is an easy task for humans, it is a challenge for vision-based automated systems. It has been an active research area involving several disciplines such as image processing, neural networks, statistics, pattern recognition, anthropometry and computer vision. Vision-based automated systems can apply facial recognition and facial identification in numerous commercial applications, such as biometric authentication, human-computer interaction, surveillance, games and multimedia entertainment.

Unlike other biometrics, face recognition is non-invasive, and does not need physical contact of the individual with the system, making it a very acceptable biometric. Vision-based automated systems applied to face recognition can be divided into 4 steps: face detection, image pre-processing, feature extraction and matching [1]. Face detection is a hard task, once faces form a similar class of objects and their features, such as eyes, mouth, nose and chin, have, in general, the same geometrical configuration. The captured image of the face may be pre-processed to overcome illumination variations [2]. Feature extraction is the process where a geometrical or vectorial model is obtained gathering important characteristics presented on the face. Feature extraction can be divided into 3 approaches: holistic, feature-based and hybrid. Principal component analysis [3] [4], fisher discriminant analysis [5] [6] and support vector machine [7] are examples of holistic approach. Feature-based approach is based on geometrical relation of the facial features. [8] applied active shape model, gathering important information presented in some of the facial features. Statistical classifiers such as Euclidian distance [9], Bayes classifier [10], Mahalanobis distance [11] and neural classifiers [12] can be used to compare the characteristic vector with other classes (individuals) in the matching step.

Face detection has been improved in terms of speed with the application of haar-features with the contribution of the Viola-Jones object detection framework. Implementations of this framework, such as OpenCV, provide different face classifiers created by authors that used different datasets into their training. The performance and reliability of these classifiers vary a lot. [13] evaluated the performance of some classifiers and also tested their accuracy.

This paper focuses on evaluating facial classifiers regarding facial features contained in the found face. We propose a method using different scores given to each facial feature contained in the located face. Two different face databases (FEI database and yale face database) were used to evaluate 10 face classifiers.

II. Materials

A. Yale face database

The yale face database [14] contains facial images of 15 individuals, with 11 pictures per person, taken with different illumination conditions. The subjects have different facial expressions (with glasses, sad, sleepy, surprised, wink). The size of each image is 320x243 pixels.

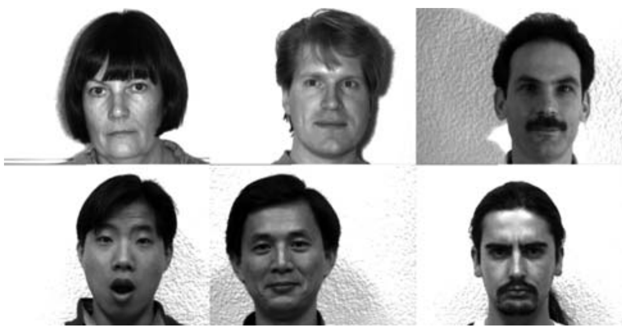

Fig. 1 Yale face database images

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B. FEI face database

The FEI face database [15] is a Brazilian database containing 14 images for each of 200 individuals, with a total of 2800 images. The images are colorful in different rotations with neutral, smiling and non-smiling expressions. We used 2 frontal images per individual, considering the smiling and non-smiling expression, in a total of 400 images. The original size of each image is 640x480 pixels.

Fig. 2 FEI face database images

C. Viola-Jones face detectors

Motivated by the challenge of face detection, [16] proposed an object detector framework using Haar-like features, which has been widely used by other works not only for face detection, but also for object locations.

Thanks to the Open Computer Vision Library implementation [17], the general object detector framework has become popular and motivated the community to generate their own object classifiers. These classifiers use haar-like features that are applied over the image. Only those image regions, called sub-windows, that pass through all the stages of the detector are considered to contain the target object. Fig. 3 shows the detection cascade schematic with N stages. The detection cascade is designed to eliminate a large number of negative examples with a little processing.

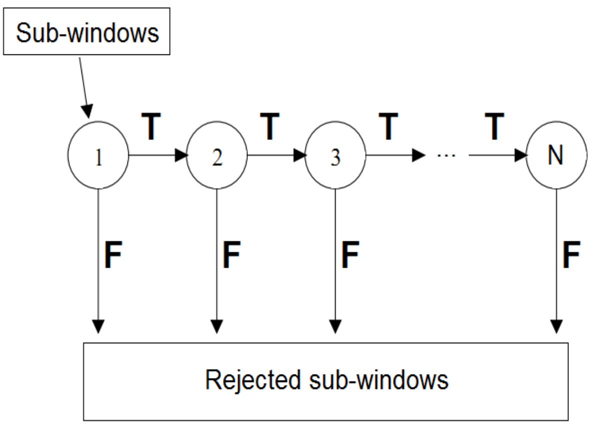

Fig. 3 Detection cascade

Some face location classifiers are distributed in the OpenCV implementation [17]. In this work, we used 10 classifiers that are presented in Table I. We kept the same description used by [13] to ease the comparisons.

TABLE I
CLASSIFIERS

Classifier	Size	Stages	References	Target faces
FD	24x24	25	[18,19]	Frontal
FA1	20x20	22	[18, 19]	Frontal
FAT	20x20	46	[18, 19]	Frontal
FA2	20x20	20	[18, 19]	Frontal
FW	30x30	19	[20]	Frontal
FWQ	30x30	20	[20]	Quarter turned
FWH	25x30	20	[20]	Half turned
PR	20x20	26	[21]	Profile
HS1	22x18	30	[22]	Upper Body
HS2	22x20	19	[22]	Head and Shoulders

III. LANDMARKS

Landmark detection is important not only to generate a geometric face model, but also can be used for face detection [23]. [24] compared different algorithms for facial landmark localization and proposed a set of tools that ease the integration of other face databases. [25] proposed a technique for face segmentation using Active Shape Model based on border landmarks of the face. [26] used a facial geometrical model based on the distance of the eyes to estipulate the position of other landmarks for face segmentation, shown in Fig. 4.

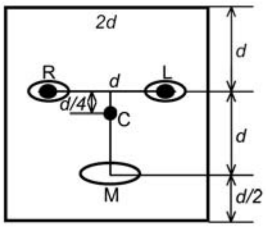

Fig. 4 Geometrical model of the face (Liu, Z et al – 2008)

FGnet project has published the location of 22 facial features of each face of the AR face database [27]. We also marked manually the same 22 facial feature points of the yale and FEI face database images used in this work. Fig. 5 shows an image with the marked facial points. In the total, 565 images were used and for each one of the 22 landmarks, a score was given (see Table II). The scores were either 1 or 2. The landmarks located in the contour of the face were given the highest score. The application of the scores will be explained in the next section.

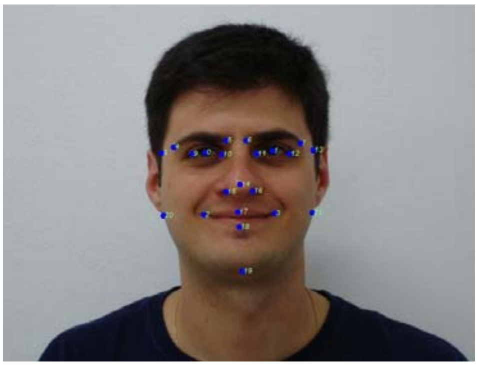

Fig. 5 Example of landmarks marked manually

TABLE II
LANDMARKS AND SCORES

Landmark	Description	Score
0	Center of the right eye	1
1	Center of the left eye	1
2	Right corner of the mouth	1
3	Left corner of the mouth	1
4	Right eyebrow right corner	2
5	Right eyebrow left corner	2
6	Left eyebrow right corner	2
7	Left eyebrow left corner	2
8	Right upper facial limit	2
9	Right eye right corner	1
10	Right eye left corner	1
11	Left eye right corner	1
12	Left eye left corner	1
13	Left upper face limit	2
14	Nose tip	1
15	Right nostril	1
16	Left nostril	1
17	Upper lip limit	1
18	Bottom lip limit	1
19	Chin	2
20	Right facial limit	2
21	Left facial limit	2

IV. EXPERIMENTS

A. Preparation

First, we collected face location classifiers. They differ among each other by the number of stages and the minimal size of the faces that can be detected. They were designed to detect faces in different positions (frontal and profile faces) and accuracy (head only and head and shoulders together).

Two criteria were used to determine the precision of each classifier.

B. Criterium I

The accuracy of a classifier was measured by the score obtained by the located face. The detected face region must contain as many facial features as possible. The scores of each facial feature were added if the rectangle representing the position of the face overlaps these features.

Fig. 6 shows an example of a face with a face located by a classifier. Notice that there are 2 important feature points missing, landmarks 13 and 21.

By analyzing different faces, we estimated that a face is well located if its total score is higher or equal to 27, once lower scores leave important feature points out of the face image.

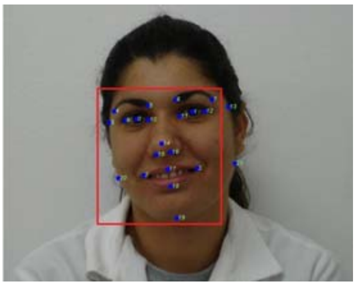

Fig. 6 Face located with a classifier, having score equals to 27

C. Criterium II

We also considered the same criterium used by [13] to evaluate the accuracy of the size of the detected face. A face is correctly detected if its height and width are not greater than four times the distance between the eyes. Differently from [13], we did not evaluate the time of processing of each classifier, our goal is to evaluate the accuracy of the classifiers regarding facial features and the size of the retrieved face.

V. RESULTS

By applying the selected classifiers in both databases and analyzing the precision of important facial features included in the detected face, described by Criterium I, it was noticed that the classifiers FA1, FAT and FA2 obtained better results. When FA1 and FA2 were used to locate faces in yale database, 100% of the faces obtained scores equal or higher than 27. FAT classifier obtained better results when used with FEI database, having 99.25% of the faces a score equal or higher than 27. Fig. 7 shows the percentage of images for both databases with score equal or higher than 27 of each classifier. Criterium II was used to determine if the region of the detected face is accurate. The best results with yale database were obtained by applying the classifiers FD, FA1 and FA2, where 100% of the images had faces detected with their height and width not greater than for times the distance of the eyes. With FEI database, the classifiers FAT, FWQ and FA1had better results with percentages equal to 99.25%, 98.75% and 98.50% respectively.

It is important to mention that the images used in this work are frontal faces images and the classifiers designed to locate mainly frontal faces are FD, FA1, FAT, FA2 and FW. It explains the poor results obtained by the other classifiers.

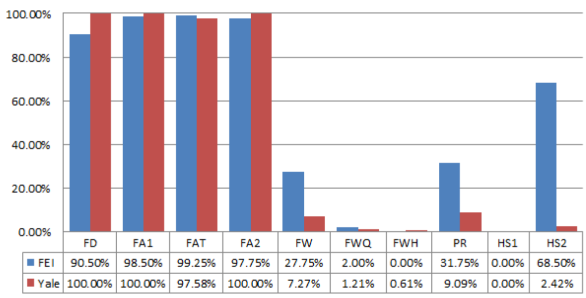

Fig. 7 Results using criterium I

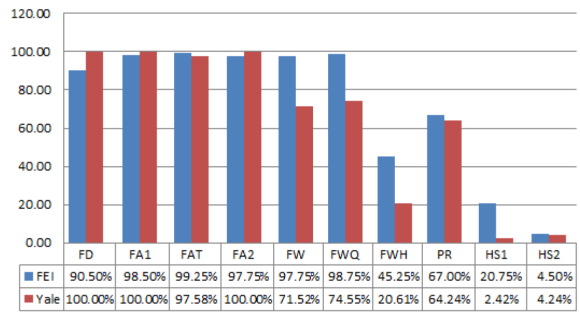

Fig. 8 Results using criterium II

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