Face Detection: Comparing Haar-like combined with Cascade Classifiers and Edge Orientation Matching

Souhail Guennouni
Sidi Mohammed Ben Abdellah University
Faculty of Science and Technology
Renewable Energy and Smart Systems Laboratory
B.P. 2202, 30000 Fez, Morocco
mrsouhail@gmail.com

Ali Ahaitouf
Sidi Mohammed Ben Abdellah University
Faculty of Science and Technology
Renewable Energy and Smart Systems Laboratory
B.P. 2202, 30000 Fez, Morocco

Anass Mansouri
Sidi Mohammed Ben Abdellah University,
National School of Applied Sciences,
Renewable Energy and Smart Systems Laboratory
BP 72 Fez, Morocco

***Abstract*— One of the major research areas attracting much interest is face recognition. This is due to the growing need of detection and recognition in the modern days' industrial applications. However, this need is conditioned with the high performance standards that these applications require in terms of speed and accuracy. In this work we present a comparison between two main techniques of face recognition in unconstraint scenes. The first one is Edge-Orientation Matching and the second technique is Haar-like feature selection combined cascade classifiers.**

Keywords—component; image processing; Edge-Orientation Matching; Face Detection;

I. INTRODUCTION (*HEADING 1*)

For real time applications detection speed is very important. Viola et al [7] proposed a rapid object detection algorithm using a basic and over-complete set of Haar-like features and a cascade of classifiers. These classifiers were combined to produce a more powerful one. The multi-stage classification procedure reduces the processing time substantially and yet achieves almost the same accuracy as the single stage classifier. Rainard and Jochen [1] implemented an optimization on the boost classifier in order to enhance the performance. Then Adaboost was singnificantly enhanced by a regularization in order to select the most productive classifiers.

A different approach is to detect face patterns in the edge orientation image. In [3] edge orientation map was extracted from the face model and was matched against the edge orientation map from an input image. Bai and Shen [4] have proposed orientation map matching based on face detection algorithm using skin color information. In [3] orientation map is extracted from the skin probability image which was converted from a color image using Gaussian skin color model. This lead to reducing false detections on high frequency areas because the skin color information was used to disregard the background.

A. Applications of Face detection

Automatic Identification:

With the increased usage of online transactions there is an emerging emphasis on security and privacy of information distributed in many databases. Fast and accurate automatic identification is becoming essential in a wide range of applications like mobile phones, ATM and large scale security identification devices.

Traditional knowledge-based means of identification are no longer fulfilling the need in modern applications and are becoming more and more obsolete and need to be replaced with a more dynamic and trustful mechanism.

Security Surveillance

The need of accurate face detection in video surveillance cameras is growing as the cameras are more accessible and distributed in many public areas. Such application will help follow and identify suspects in public places.
This kind of application require real time detection with a highly accurate results.

Social Networks

As social media is gaining ground, the amount of information shared is getting more important. One of the most shared information throughout social networks are personal photos. Therefore, face detection can be a base of many applications. One example is facial detections and suggestions in images. It

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also can be extended to changing or enhancing the face portion of the image based on user criteria.

Hence, there is a growing need to an accurate and reliable face detection technique to be a base for many social networks or photo sharing applications.

This article presents and compares two of the most widely used face detection techniques which are Haar-like and edge orientation matching.

II. Haar Like Feature Selection Combined with Weak Classifiers

A. Haar-like Feature Selection

Haar-like feature's principle is based on detection of features encoding of some information about the class to be detected. They are adjacent rectangles in a particular position of an image. Figure 1 shows the types of Haar- like features depending on the number of adjacent rectangles. According to [7] there are three types of Haar- like features. The first type is the edge feature, which is represented in figure 1 by the two upper squares. The second type is the line feature, (figure 1 lower left square). The last type of features is the center-surround feature, (figure 1 lower right square).

The Haar-like principle is simple; it lies on computing the difference between the sum of white pixels and the sum of black pixels. The main advantage of this method is the fast sum computation using the integral image. It's called Haar-like because it's based on the same principle of Haar wavelets [7].

B. Integral Image

Rectangle features can be computer rapidly using an intermediate representation of the image called the integral image [7]. The integral image consists of having small units' representation of a given image. For example (see figure 2 and 3), the value of this integral image at location 1 is the sum of pixels in rectangular A. The value at location 2 is A + B and so on. So the sum of pixels in rectangular D is:

$$sum(D) = ii(4) - ii(3) - ii(2) + ii(1) \quad (1)$$

Where sum(D) is the sum of pixels in the rectangular D only; which is the sum of pixels in the rectangle A + B + C + D, represented by ii(4), minus ii(3), which is the integral image of rectangle A+C, minus ii(2), which is the integral image of A+B, and finally we had the ii(1), which is the integral image of the rectangle A (the addition is performed because the region A is subtracted twice in ii(3)and ii(2)).

The integral image is defined as follows:

$$ii(x,y)= i(x',y') \quad (2)$$

where ii(x,y) is the integral image, and i(x',y') is the original image

Therefore, the integral value of a specific pixel is the sum of pixels on the top of it towards the left [7], [9]. Then the image can be integrated in fewer pixel operations, since the traversing starts on the top left towards the bottom right.

C. AdaBoost Learning Algorithm:

Viola and Jones [7] used AdaBoost learning algorithm to select a specific Haar-like feature as a threshold. AdaBoost is used to create strong classifier from combining a collection of weak classification functions [10].

The strongest classifier uses the strongest feature, which is the best Haar-like feature, that is, the feature that best separates the positive and negative samples.

D. Cascade Classifier:

Cascade classifier [7] is a chain of weak classifiers for efficient classification of image regions. Its goal is to increase the performance of object detection and to reduce the computational time. As shown in figure 3, each node in the chain is a weak classifier and filter for one Haar feature. AdaBoost gives weights to the nodes, and the highest weighted node comes first.

When a filter fails to pass image regions, that specific sub-window of the image is eliminated for further processing. It is then considered as a non-object. Meaning that the image regions processed, do not contain the object to be detected. This is very crucial to the performance of the classifier, since all or nearly all negative image sub-windows will be eliminated in the first stage. On the other hand, when image regions successfully passed the filter, they go to the following stage, which contains a more complex filter. Only regions that successfully pass all filters are considered to contain a match of the object. This means that regions of the image contain the object subject to detection.

The reason behind the multi-stage classifier is to reject efficiently and rapidly the non-object sub-windows. The next nodes in the chain in Figure 7 represent complex classifiers, in the case of face detection. The classifier is used to reject more false positives (non-face regions) of the sub-windows [7]. The number of false positives is radically reduced after several steps of processing.

III. Orientation Matching

A. Sobel Operator:

Sobel operator consist of a pair of convolution kernels 3x3, each kernel is the same representation of the other rotated 90° as it's shown in figure 1 and figure 2.

+1	+2	+1
+0	+0	+0
-1	-2	-1

Figure 1: Horizontal matrix

-1	+0	+1
-2	+0	+2
-1	+0	+1

Figure 2: Vertical matrix

On a pixel grid, these kernel are optimized to respond to edges that run horizontally and vertically.
The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation. [11]
The gradient magnitude is given by:

$$|G|=\sqrt{Gx^2+\ Gy^2} \qquad (3)$$

An approximate magnitude is computed using:

$$|G| = |Gx| + |Gy| \qquad (4)$$

Which is much faster to compute.

The angle of orientation of the edge (relative to the pixel grid) giving rise to the spatial gradient is given by:

$$\theta = \arctan(Gy/Gx) \qquad (5)$$

B. Edge Orientation Extraction

The basic feature of our detection framework relies on the extraction of edge information from a grey-scale image. In this work we used Sobel method.
For face detection, the orientation model Vm(x, y) is calculated and normalized as follows:

$$S_O(i,j) = \frac{\sum_{u=i-\frac{w}{2}}^{u=i+\frac{w}{2}} \sum_{v=j-\frac{h}{2}}^{v=j+\frac{h}{2}} sim(V_m(u,v), V_I(i+u, j+v))}{M} \qquad (6)$$

where VI (x, y) is the orientation map of the input image, w is the width of the model orientation map, h is the height of the model orientation map, M is the number of orientation vectors with strength > 0 in the model orientation map and where

$$sim(\mathbf{V}_1, \mathbf{V}_2) = \begin{cases} \cos(|\arg(\mathbf{V}_1) - \arg(\mathbf{V}_2)|) & if \quad |\mathbf{V}_1|, |\mathbf{V}_2| > 0 \\ 0 & else \end{cases} \qquad (7)$$

C. Matching

Orientation maps were extracted from twenty arbitrary faces that we used, these faces were aligned and cropped then scaled. Therefore, twenty orientation maps were extracted then a model orientation map was computed by averaging our orientation maps.

We also used histogram intersection in our algorithm to match two histograms. The similarity score is computed as bellow:

$$S_H = \frac{\sum_{j=1}^{N} \min(q_j, v_j)}{\sum_{j=1}^{N} v_j}$$

Where N is the number of bins, qj, vj are values that corresponds to bin j in histograms q and v.

IV. Results

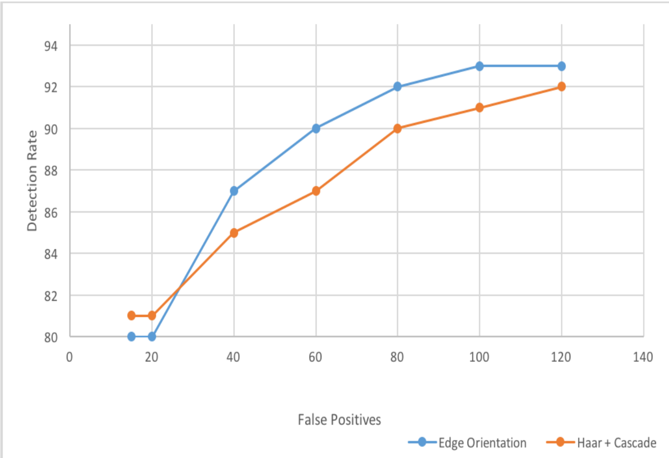

Figure 3: ROC Curves

These experimental results were conducted using MIT library dataset. In the graph above, the red dots represent the Haar based algorithm false positives and the blue dots represent the Edge-orientation matching based algorithm.
The results extracted from both algorithms shows that Orientation based matching performs better than Haar-like and cascade classifier in terms of accuracy. It means that it generates less false positives for a specific detection rate.
However, it has been observed that Haar-like based detection algorithm's detection speed is better than Edge-orientation matching based algorithm.

V. Conclusion

This article presents the results of our edge orientation matching algorithm and it compares it to Haar-like combined with weak classifiers. Although these are two different techniques of detection, the comparison shows that edge matching is more accurate than Haar-like with weak classifiers.

In a future work, we will extend this comparison to other detection algorithms, both terms of accuracy or in terms of speed of detection.

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