

**CASE STUDY AND REPORT**

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**FRONTAL FACE DETECTION METHODS –NEURAL NETWORKS AND AGGRESSIVE LEARNING ALGORITHM**

Sushma Jaiswal<sup>\*1</sup>, Dr. Sarita Singh Bhadauria<sup>2</sup>, Dr. Rakesh Singh Jadon<sup>3</sup>

<sup>1</sup>Lecturer, S.O.S. in Computer Science, Pt. Ravishankar Shukla University, Raipur (C.G.)

Jaiswal1302@gmail.com

<sup>2</sup>Professor & Head, Department of Electronics Engineering, Madhav Institute of Technology & Science, Gwalior (M.P.)

<sup>3</sup>Professor & Head, Department of Computer Applications, Madhav Institute of Technology & Science, Gwalior (M.P.)

**Abstract:** In this Case Study & report, a face detection method is presented. Face detection is the first step of face Recognition methods. Face detection is a difficult task in Pattern. There are different methods of face detection namely-Knowledge Based Face Detection Methods, Feature Based Face Detection Methods, Template Based Face Detection Methods and Appearance Based Face Detection Methods. But here we divided basically in two methods for face detection (i) image based methods (ii) feature based methods. We have developed an intermediate system, using a boosting algorithm to train a classifier which is capable of processing images rapidly while having high detection rates. AdaBoost is a kind of large margin classifiers and is efficient for on-line learning. In order to adapt the AdaBoost algorithm to fast face recognition, the original Adaboost which uses all given features is compared with the boosting along feature dimensions. The comparable results assure the use of the latter, which is faster for classification. The main idea in the building of the detector is a learning algorithm based on boosting: AdaBoost. AdaBoost is an aggressive learning algorithm which produces a strong classifier by choosing visual features in a family of simple classifiers and combining them linearly. The family of simple classifiers contains simple rectangular wavelets which are reminiscent of the Haar basis. Their simplicity and a new image representation called Integral Image allow a very quick computing of these Haarlike features. Then a structure in cascade is introduced in order to reject quickly the easy to classify background regions and focus on the harder to classify windows. For this, classifiers with an increasingly complexity are combined sequentially. This improves both, the detection speed and the detection efficiency. The detection of faces in input images is proceeded using a scanning window at different scales which permits to detect faces of every size without resampling the original image. On the other hand, the structure of the final classifier allows a realtime implementation of the detector. Due to some limitation of neural network based methods we adopt the Adaboost algorithm for face detection. Here we present some results on real world examples are presented. Our detector found good detection rates with frontal faces and the method can be easily adapted to other object detection tasks by changing the contents of the training dataset.

**Keywords:** AdaBoost algorithm, Knowledge Based Face Detection Methods, Feature Based Face Detection Methods, Template Based Face Detection Methods and Appearance Based Face Detection Methods.

**INTRODUCTION**

**In this Section,** a face detection approach is presented. Face detection is an essential application of pattern detection and it is one of the main components of face modeling, analysis and understanding with face localization and face recognition. It becomes a used in a large number of applications, among which we find security, new communication interfaces, biometrics and many others. The goal of face detection is to detect human faces in still images or videos, in different situations. In the past 30 years, large numbers of methods have been developed with different goals and for different contexts. We will make a overview of the main of them and then focus on a detector which processes images very fast while achieving high detection rates. This detection is based on a boosting algorithm called AdaBoost and the response of simple Haarbased features used by Viola and Jones [1].The motivation for using Viola's face detection method is to achieve experience with boosting and to explore issues and obstacles concerning the application of image analysis to object detection.

Automatic face detection is a complex problem which consists in detecting one or many faces in an image or video sequence. The difficulty in the fact that faces are non rigid objects. Face appearance may vary between two different

persons but also between two photographs of the same person, depending on the lightning conditions, the emotional state of the subject and pose avriations. That is why so many methods have been developed during last years. Each method is developed in a particular context and we can cluster. these numerous methods into two main approaches: image based methods and feature based methods. The first one use classifiers trained statically with a given example set. Then the classifier is scanned through the whole image. The other approach consists in detecting particular face features as eyes, nose.

The goal of this project is to detect very fast low resolution faces in cluttered background. This situation can be found in many applications as surveillance of public places. The method used is both image based and feature based. It is image based in the sense that it uses a learning algorithm to train the classifier with some well chosen train positive and negative examples. It is also feature based because the features chosen by the learning algorithm are for lots of them directly related to the particular features of faces (eyes positions, contrast of the nose bridge). The boosting techniques improve the performances of base classifiers by re-weighting the training examples. The learning using Boosting is the main contribution of this face detection. On the other hand, the simple classifiers used for the boosting are simples Haarlike features which permits a fast computation while good detection rates.

## CHALLENGES IN FACE DETECTION

Face detection is the problem of determining whether a sub-window of an image contains a face. Looking from the point of view of learning, any variations which increase the complexity of decision boundary between face and non-face classes, will also increase the difficulty of the problem. For example, adding tilted faces into the training set increases the variability of the set, and may increase the complexity of the decision boundary. Such complexity may cause the classification to be harder. There are many sources introducing variability when dealing with the face. They can be summarized as follows:

### *Image Plane Variations*

Is the first simple variation type one may encounter? Image transformations, such as rotation, translation, scaling and mirroring may introduce such kind of variations. Utilization of image pyramids with a sliding detector window is one common way to deal with such transformations for the input image. Variations in the global brightness, contrast level can also be expressed in the same category.

### *Pose Variations*

Can also be listed under image plane variations aspects. However, changes in the orientation of the face itself on the image can have larger impacts on its appearance. Rotation in depth and perspective transformation may also cause distortion. The common way to deal pose variation is to isolate pose types (i.e. frontal, profile, rotated). Some *Lighting variations* may dramatically change face appearance in the image. Such variations are the most difficult type to cope with due to fact that pixel intensities are directly affected in a nonlinear way by changing illumination intensity or direction. For example, when using skin color as a feature for face detection, varying color temperature of the light source may cause skin color filtering to fail. Some examples for lighting variations.

### *Background Variations*

Is another challenging factor for face detection in cluttered scenes. Discriminating windows including a face from non-face is more difficult when no constraints exist on background.

### *Size*

A face detector should be able to detect faces in different sizes. This we can achieve by scaling the input image. And small faces are more difficult to detect than the large face.

### *Expressions*

The appearance of a face changes considerably for different facial expressions and, thus, makes the face detection more difficult. The simplest type of variability of images of a face can be expressed independently of the face itself, by rotating, translating, scaling and mirroring its image. Also changes in the overall brightness and contrast of the image and occlusion by other objects.

### *Lighting and Texture Variation*

Now we will describe how the variation caused by the object and its environment, specifically the object's surface

properties and the light sources. Changes in the light source in particular can change a face's appearance.

- ***Presence or absence of structural components:***

Facial features such as beards, moustaches and glasses may or may not be present. And also there may be variability among these components including shape, color and size.

### *Shape Variation*

Shape variation includes facial expressions, either the mouth and eyes are open or closed, and the shape of the individual's face. The appearances of faces are directly affected by person's facial expression.

### *Occlusion*

Faces may be partially occluded by other objects. In an image with a group of people some faces may partially occlude other faces. Partial occlusions of faces can be caused by objects within the environment (e.g. poles and people), objects worn by the person (glasses, scarf, mask), other body parts of person (hands) and shadows. Image orientation: Faces can appear in different orientation the image plane depending on the angle of the camera and the face. Images directly vary for different rotations about the camera's optical axis.

### *Imaging conditions*

When the image is formed, factors such as lighting (spectra, source distribution and intensity) and camera characteristics (sensor response, lenses) affect the appearance of a face.

## BASIC TERMS

### *Detection rate*

It is defined as the ratio between the number of faces correctly detected and the number of faces determined by a human.

### *False negative*

In which faces are missed resulting in low detection rates.

### *False positive*

In which an image region is declared to be face but it is not.

## OVERVIEW

Next section, an overview of the main existing approaches is given. We first define precisely what the face detection task is and then detail the image based and feature based methods. Face Detection Section explains the developed algorithm. The main theory of Boosting is given as well as the use of the haarlike masks, a new image representation and an implementation in cascade.

Finally the last Section will focus on the experiments and results of our face detector.

## OVERVIEW OF FACE DETECTION

### INTRODUCTION

Face Detection is the first step of face Recognition, S.Jaiswal et.al.[56] given a comprehensive literature on Image Based human and machine recognition of faces during 1987 to 2010. Machine recognition of faces has several applications. As one of the most successful

applications of image analysis and understanding, face recognition has recently received significant attention, especially during the past several years. In addition, relevant topics such as Brief studies, system evaluation, and issues of illumination and pose variation are covered. In this paper numerous method which related to image based 3D face recognition are discussed.

S.Jaiswal *et.al.* [57] described an efficient method and algorithm to make individual faces for animation from possible inputs. Proposed algorithm reconstruct 3D facial model for animation from two projected pictures taken from front and side views or from range data obtained from any available resources. It is based on extracting features on a face in automatic way and modifying a generic model with detected feature points with conic section and pixalization. Then the fine modifications follow if range data is available. The reconstructed 3Dface can be animated immediately with given parameters. Several faces by one methodology applied to different input data to get a final Animatable face are illustrated.

S.Jaiswal *et.al.*[58] the proposed study, 2D photographs image divided into two parts; one part is front view (x, y) and side view (y, z). Necessary condition of this method is that position or coordinate of both images should be equal. We combine both images according to the coordinate then we will get 3D Models (x, y, z) but this 3D model is not accurate in size or shape. In defining other words, we will get 3D animatable face, refinement of 3D animatable face through pixellization and smoothing process. Smoothing is performed to get the more realistic 3D face model for the person.

In the following we will present different aspects of the face processing domain while reviewing the main existing methods. First of all, we need to define what face detection is, why it is an interesting objective and how it can be approached with various methods. We can define the face detection problem as a computer vision task which consists in detecting one or several human faces in an image. It is one of the first and the most important steps of Face analysis. Usually, the methods for face recognition or expression recognition assume that the human faces have been extracted from the images, but while the human visual system permit us to find instantaneously faces in our purview indifferently of the external conditions, doing the same automatically with a computer is a quite difficult task.

### ***A Brief History***

Along face detection, many other parts of Face analysis present useful applications and the number of these applications is increasing considerably nowadays with the evolution of the automatic systems in the life of every one of us. Face Recognition, Face localization, Face Tracking, Facial expression, alignment, registration, recognition are the main of these research domains.

### ***Face Recognition***

Consists in identifying the people present in images, in other words, we want to assign one name to one detected face. It is used in security systems for example.

### ***Face Localization***

Is the problem of finding precisely the position of one face, whose presence is already known in a single image.

### ***Face Tracking***

Has for goal to follow a detected face in a sequence of images in a real world context in most of the cases.

### ***Facial Expression***

Recognition will try to estimate the affective state of detected people (happiness sadness etc...).

### ***Face Registration***

Is the task of aligning the faces such that different faces are transformed to a common coordinate system? This task is a crucial preparation step for face recognition. Since most recognition algorithms are quite sensitive to even small changes in orientation or position correct registration is very important. If registration fails recognition cannot be performed successfully.

### ***Alignment***

After face and eye positions have been established alignment is straight forward. The image is rotated and then cropped according to the distance between the eyes. The output of the aligner is a cropped and rotated face image of given pixel size.

It is clear that the first step for all these problems is to find faces in images. For that various approaches have been developed and that is what will be detailed in this section. The first face detection systems have been developed during the 1970's but the computation limitations restricted the approaches to anthropometric techniques which could be efficient in only few applications as passport photograph identification for instance. It is only since the beginning of the 1990's that more elaborated techniques have been built with the progress in video coding and the necessity of face recognition. In the past years, lots of different techniques have been developed, in such a proportion that today we can count not less than 150 different methods.

2.1.2 Face detection difficulties If automatic face detection has not been developed before, it is because it is particularly hard to build robust classifiers which are able to detect faces in different image situations and face conditions even if it seems really easy to do this with our human visual system.

In fact, the object "face" is hard to define because of its large variability, depending on the identity of the person, the lightning conditions, the psychological context of the person etc. The main challenge for detecting faces is to find a classifier which can discriminate faces from all other possible images. The first problem is to find a model which can englobe all the possible states of faces. Let's define the main variable points of the faces:

### ***The face global attributes:***

We can extract some common attributes from every face. A face is globally an object which can be estimated by a kind of ellipse but there are thin faces, rounder faces... The skin color can also be really different from one person to one another.

### ***The pose of the face:***

The position of the person in front of the camera which has been used to acquire the image can totally change the view of the face: the frontal view, the profile view and all the intermediate positions, upside down..

### ***The facial expression:***

Face appearance depends highly on the affective state of the people. The face features of a smiling face can be far from those of an indifferent temperament or a sad one. Faces are nonrigid objects and that will limit considerably the number of detection methods.

#### **Presence of added objects:**

Face detection included objects that we can usually find on a face: glasses which change one of the main characteristics of the faces: the darkness of the eyes. Natural facial features such as mustache beards or hair which can occult one part of the face.

#### **Image Condition:**

The face appearance vary a lot in function of the lightning conditions, the type of illumination and intensity and the characteristics of the acquisition system need to be taken in account. The next figure shows some typical face examples extracted from the CMU test dataset [23].



Figure 1: Typical faces extracted from the CMU Database [23]. We can notice the great variability of the nonrigid object "Face".

The background composition is one of the main factors for explaining the difficulties of face detection. even if it is quite easy to build systems which can detect faces on uniform backgrounds, most of the applications need to detect faces in any background condition, meaning that the background can be textured and with a great variability. So our two class classification task is to assign an image to the face class or the Non faces class. Given a set of we can extract some properties of faces for representing the face but it is impossible to find properties which can represent all the non class.

## **FACE DETECTION**

Face detection is the first stage of an automatic face recognition system, since a face has to be located in the input image before it is recognized. A definition of face detection could be: given an image, detect all faces in it (if any) and locate their exact positions and size. Usually, face detection is a two-step procedure: first the whole image is examined to find regions that are identified as "face". After the rough position and size of a face are estimated, a localization procedure follows which provides a more accurate estimation of the exact position and scale of the face. So while face detection is most concerned with roughly finding all the faces in large, complex images, which include many faces and much clutter, localization emphasizes spatial accuracy, usually achieved by accurate detection of facial features.

Face detection algorithms can be divided into four categories according to:

#### **Knowledge-Based Methods**

It is based on human knowledge of the typical human face geometry and facial features arrangement. Taking advantage of natural face symmetry and the natural top-to-bottom and left-to-right order in which features appear in the human face, these methods find rules to describe the shape, size, texture and other characteristics of facial features (such as eyes, nose, chin, eyebrows) and relationships between them (relative positions and distances). A hierarchical approach may be used, which examines the face at different resolution levels. At higher levels, possible face candidates are found using a rough description of face geometry. At lower levels, facial features are extracted and an image region is identified as face or non-face based on predefined rules about facial characteristics and their arrangement. The main issue in such techniques is to find a successful way to translate human knowledge about face geometry into meaningful and well-defined rules. Another problem of such techniques is that they do not work very well under varying pose or head orientations.

#### **Feature Invariant Approaches**

Aim to find structural features that exist even when the viewpoint or lighting conditions vary and then use these to locate faces. Different structural features are being used: facial local features, texture, and shape and skin color. Local features such as eyes, eyebrows, nose, and mouth are extracted using multi-resolution or derivative filters, edge detectors, morphological operations or thresholding. Statistical models are then built to describe their relationships and verify the existence of a face. Neural networks, graph matching, and decision trees were also proposed to verify face candidates. Skin color is another powerful cue for detection, because color scene segmentation is computationally fast, while being robust to changes in viewpoint, scale, shading, to partial occlusion and complex backgrounds. The color-based approach labels each pixel according to its similarity to skin color, and subsequently labels each sub-region as a face if it contains a large blob of skin color pixels. It is sensitive to illumination, existence of skin color regions, occlusion, and adjacent faces. There are also techniques that combine several features to improve the detection accuracy. Usually, they use features such as texture, shape and skin color to find face candidates and then use local facial features such as eyes, nose and mouth to verify the existence of a face. Feature invariant approaches can be problematic if image features are severely corrupted or deformed due to illumination, noise, and occlusion.

#### **Template-Based Methods**

To detect a face in a new image, first the head outline, which is fairly consistently roughly elliptical, is detected using filters, edge detectors, or silhouettes. Then the contours of local facial features are extracted in the same way, exploiting knowledge of face and feature geometry. Finally, the correlation between features extracted from the input image and predefined stored templates of face and facial features is computed to determine whether there is face present in the image. Template matching methods based on predefined templates are sensitive to scale, shape

and pose variations. To cope with such variations, deformable template methods have been proposed, which model face geometry using elastic models that are allowed to translate, scale and rotate. Model parameters may include not only shape, but intensity information of facial features as well.

**Appearance-Based Methods**

While template-matching methods rely on a predefined template or model, appearance-based methods use large numbers of examples (images of faces and \ or facial features) depicting different variations (face shape, skin color, eye color, open\closed mouth, etc). Face detection can be viewed as a pattern classification problem with two classes: "face" and "non-face". The "non-face" class contains images that may depict anything that is not a face, while the "face" class contains all face images. Statistical analysis and machine learning techniques are employed to discover the statistical properties or probability distribution function of the pixel brightness patterns of images belonging in the two classes. To detect a face in an input image, the whole image is scanned and image regions are identified as "face" or "non face" based on these probability functions. Well-known appearance-based methods used for face detection are eigenfaces, LDA, neural networks, support vector machines and hidden Markov models.

Hjelmås and Low conducted a survey on face detection techniques, and identified two broad categories that separate the various approaches, namely Feature-based and Image-based approaches. Each category will be explained, providing a brief yet thorough overview of the various face detection techniques. Figure 2 illustrates the different approaches for face detection.

Figure 2 Different approaches for face detection.

**FEATURE-BASED APPROACH**

Hjelmås and Low divided the group of feature-based system into three sub-categories: *Low-level Analysis*, *Feature Analysis* and *Active Shape Models*.

**Low-level Analysis**

Low-level analysis deals with the segmentation of visual features using various properties of pixels, predominantly gray-scale or color.

Edge representation (detecting changes in pixel properties) was first implemented by Sakai et al for detecting facial features in line drawings. Craw et al developed this further to trace a human head outline, allowing feature analysis to be constrained to within the head outline. Various operators are used to detect the presence of an edge, including the Sobel operator, the Marr-Hildreth operator, and a variety of first and second derivatives of Gaussians. All edge-based techniques rely on labeled edges which are matched to a face model for verification. Labeled edges as left side, hairline, and right side, developing a system capable of detecting 76% of faces in a set of 60 images with complex backgrounds, with an average of two false alarms per image. Gray information can be used to identify various facial features. Generally eyebrows, pupils and lips appear darker than surrounding regions, and this extraction algorithm can search for local minima. In contrast, local maxima can be used to indicate the bright facial sports such as nose tips. Detection is then performed using low-level gray-scale thresholding.

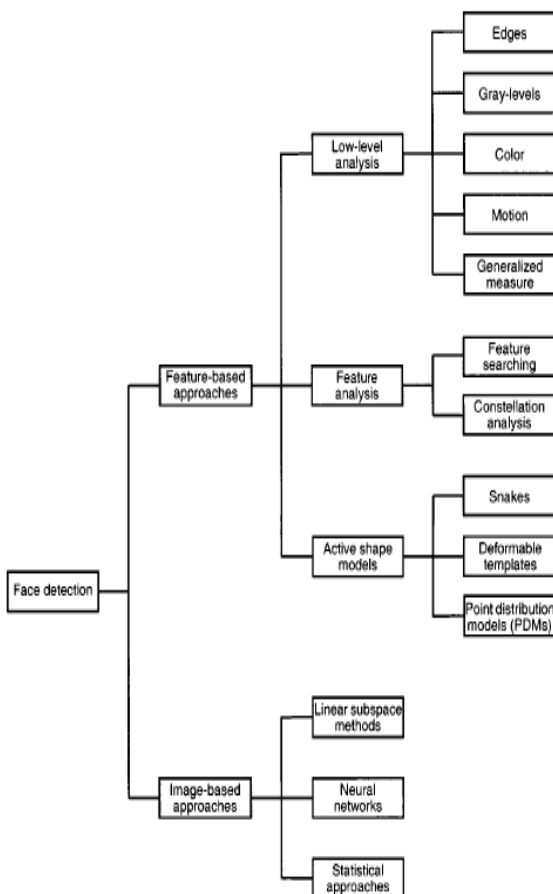
Color contains extra dimensions which can help differentiate two regions which may contain similar gray information but appear very different in color space. It was found that different skin color gives rise to a tight cluster in color space, thus color composition of human skin differs little across individuals, regardless of race. The most widely used color model is RGB, although there are many others that exist and have been used.

Motion information (where available) can be used to assist in the detection of human faces, using the principle that, if using a fixed-camera, the "background clutter" will remain somewhat static, relative any "moving object". A straightforward way to achieve motion segmentation is by frame difference analysis. Thresholding accumulated frame differences is used to detect faces or facial features. Another way to measure motion is thought the estimation of moving image contours, a technique that has proven to be more reliable, particularly when motion is insignificant.

**Feature Analysis**

Low-level analysis introduces ambiguity which can be solved by high-level feature analysis, often through the use of some additional knowledge about the face. There are two approaches for the application of this additional knowledge (commonly face geometry).

The first involves sequential feature searching strategies based on the relative positioning of individual facial features. Initially prominent facial features are determined which allow less prominent features to be hypothesized (for example a pair of dark regions found in the face area increases the confidence of facial existence). The facial



feature extraction algorithm is a good example of feature searching, achieving 82% accuracy with invariance to gray and color information, failing to detect faces with glasses and hair covering the forehead.

The second technique, constellation analysis, is less rigid and is more capable of locating faces of various poses in complex backgrounds. It groups facial features in face-like constellations, using robust modeling methods such as statistical analysis. Burl *et al* used statistical shape theory on features detected from a multi-scale Gaussian derivative filter, capable of detecting 84% of faces, with some invariance to missing features, translation, rotation and scale.

### **Active Shape Model**

Active shape model represents the actual physical and hence higher-level appearance of features. These models are released near to a feature, such that they interact with the local image, deforming to take the shape of the feature. There are three types of active shape models that have been used through the literature: snakes, deformable templates and smart snakes.

Snakes or active contours are commonly used to create a head boundary. Created nearby, they lock on to nearby edges, eventually assuming the shape of the head. The evolution of a snake is achieved by minimizing an energy function, which consists of the sum of an internal energy function, defining its natural evolution (typically shrinking or expanding), and an external energy function, which counteracts the internal energy enabling the contours to deviate from the natural evolution. Energy minimization can be obtained by optimization techniques such as the steepest gradient descent although the additional computational demands have encourages others to use faster iteration methods.

Deformable temples can be used as an extension to the snake models. Smart snakes or Point Distributed Models (PDMs) are compact parameterized descriptions of a shape based upon statistics. They use Principle Component Analysis (PCA) to construct a linear flexible model from variations of the features in a training set. Face PDM was first developed by Lantis *et al* as a flexible model with promising results (95% detection rate). Multiple faces can be detected tests have shown that partial occlusion is not a problem as other features are still available to contribute to a global optimal solution.

### **Image-based Approach**

Face detection by explicit modeling of facial features is a very rigid approach which has been shown to be troubled by the unpredictability of faces and environmental conditions. There is a need for more robust techniques, capable of performing in hostile environments, such as detecting multiple faces with clutter-intensive backgrounds. This has inspired a new research area in which face detection is treated as a general pattern recognition problem. Whereas face recognition deals with recognizing the face, face detectors must recognize an object as a face, from examples. This eliminates the problem of potentially inaccurate models based on the erroneous or incomplete face knowledge and instead places the emphasis on the training examples from which the system learns to distinguish a face. Most image-based approaches apply a window scanning technique for

detecting faces, which due to its exhaustive nature, increases computational demand.

Hjelmås and Low divided the group of image-based system into three sub-categories:

### **Linear Subspace Methods, Neural Networks and Statistical Approaches.**

#### **Linear Subspace Methods**

Images of human faces lie in a subspace of overall image space which can be represented by methods closely related to standard multivariate statistical analysis, including Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Factory Analysis (FA).

#### **Neural Networks**

Early approaches based on the simple Multiple Layer Perceptrons (MLP) gave encouraging results on fairly simple datasets. The first advanced neural approach which reported performance statistics on a large, visually complex dataset was by Rowley *et al*. Their system incorporates face knowledge in the retinally connected neural network architecture, with specialized window sizes designed to best capture facial information (e.g. horizontal strips to identify the mouth).

#### **Statistical Approaches**

Systems based on information theory, support vector machines and Bayes' decision rule are examples of image-based approaches that do not fit into either of the other categories.

In this context, various approaches have been taken to detect faces in images. But as the face detection task is quite complex, each method is build in a precise context and we will now review the main existing methods. The next sections detail the two main face detection approaches:

**Image Based Methods:** Which are built given a set of examples and uses a sliding window to perform the detection?

**Geometrical Based Methods:** Which take in account geometric particularity of face structures?

### **Definition of Some General Notions Needed to Understand Face Detection Problem**

First of all, we have to define some basic criteria that will determine the performances of the detectors. The first notion that we need to introduce is the detection rate. The detection rate  $d$  is the percentage of faces in the image that have been correctly detected by the detector. In lots of applications, it is the rate that we want to maximize. On the other hand, we have to define the false rates. The false negative  $fn$  rate is the opposite of the detection rate in the sense that it is the rate of faces that have been forgotten by the detector:  $fn = 1 - d$ . The false positive rate is the second essential rate considered in face detection: let  $fp$  be the rate of non faces windows that are classified as faces by the detector. Due to the large number of windows evaluated in a usual image, this false positive rate is usually  $10^{-5}$  or  $10^{-6}$  but this low value is not really significant.

Once these definitions are given, it is easy to understand that the objective of the face detection is to maximize the detection rate while minimizing the false positive rate  $fp$ . However, as in lots of applications in the real life, it is hard



to have both low false positive rate and high detection rate, and that is why we have to look for a trade off between the two parameters. All the methods described in the following sections will try with different approaches to find the better compromise between false positive rate and detection rate. Finally, we will see that it is hard to compare the methods because of the problem of detection evaluations and of the different contexts. How can we measure the goodness of a detector?

## IMAGE BASED DETECTION

### INTRODUCTION

Face is the collection of pixels. Each pixels gives the identical information about the images. We qualify them of "Image Based" because they are built using example images in opposition to some "template methods" which need an *a priori* knowledge about faces. In order to extract the features from some training examples, we will need to follow a statistical learning approach or other machine learning algorithms. The principle is to learn a face and a non-face distribution, given a set of positive and negative examples. For this, we will naturally be placed in a probabilistic context : An image or any input data is considered as a random variable  $x$  and the two classes *face* and *Non face* are characterized by their conditional density functions:  $p(x / \text{face})$  and  $p(x / \text{non ace})$  (see [22]). It is obvious that these density functions are unknown and one of the main goals is to approximate them in order to discriminate faces and non faces. Then there are several methods to find discriminant functions with permit to classify a given example in the face class or the non face class. In this probabilistic approach, many different methods exist, among which Eigenfaces, Fisher's Linear Discriminant and Neural network or support vector machines etc...

The main difficulty in this approach is that the example dimension, i.e. the dimension of  $x$  is often high so an important step will be to reduce this example space in order to find a discriminant function which separates positive and negative examples.

### Eigenfaces

#### Definition

The first ImageBased method that we will describe in this section is called Eigenfaces. The principle of face detection using Eigenfaces is to extract these features from a set of images by Principal Components Analysis (PCA) and estimate if the extracted Eigenfaces correspond to typical face pattern. In fact all input images can be represented by a weighted vector of Eigenfaces in the eigen space and the challenge is to determine if this linear combination is closer to one class or to the other. A global overview of face recognition using Eigenfaces can be found in [25] .

#### Principal Components Analysis

The first step for this Eigenfaces classification is to extract the Eigenfaces from the original images. For this, the Principal Components Analysis (PCA) is used. PCA which is also known as the KarhunenLoeve method reduces the input space dimensionality by applying a linear projection that maximizes the scatter of all projected samples. This subsection presents the main steps of such an analysis.

Let  $\{x_1, x_2, \dots, x_n\}$  be a set of  $N$  images which are values from a  $n$ -dimensional feature space. The orthonormal matrix  $W$  define a linear transformation from the  $n$ -dimensional space to a  $m$ -dimensional feature space where  $m < n$  (dimensionality reduction). Noticing that

$W \in \mathbb{R}^{n \times m}$  the new feature vectors  $y_k \in \mathbb{R}^m$  are defined by the linear transformation:

$$y_k = W^T x_k, \quad k = 1, 2, \dots, N \quad (2.1)$$

Then the total scatter matrix  $ST$  is defined as

$$S_T = \sum_{k=1}^N (x_k - \mu)(x_k - \mu)^T \quad (2.2)$$

where  $\mu$  is the mean of all the examples :  $\mu = \frac{\sum_{k=1}^N x_k}{N}$ ,

By applying the linear transformation, the new scatter matrix in the  $m$ -dimensional subspace is given by  $W^T S_T W$ : The PCA theory shows that the optimal linear projection  $W_{opt}$  is the one which minimizes the determinant of the projected scatter matrix (for the samples  $\{y_1, y_2, \dots, y_N\}$  i.e.

$$W_{opt}^T = \arg \max_w |W^T S_T W| = [\omega_1, \omega_2, \dots, \omega_m]. \quad (2.3)$$

The set  $\{\omega_i \mid i = 1, \dots, m\}$  are the  $n$ -dimensional eigenvectors of  $ST$ , corresponding

to the  $\{y_i \mid i = 1, \dots, m\}$  eigenvalues ordered decreasingly.

This projection in the feature space using  $W_{opt}^T$  permits to decompose the distance between an example and the face space into two components: the distance in feature space  $DIFS$  (projection on the  $m$  dimensional space) and the distance from feature space  $DFFS$ . For more details about PCA, see [26], [27] and [28].

One serious point is that the main variance cause in an object class is the lightning variations as shown in [29] . The optimal linear transformation  $W_{opt}$  given by PCA has the drawback to focus on components representing the illumination changes. One of the correction methods is to let out the first principal Eigenfaces considering that they contain almost all the variations due to lightning.

Here we present some advantages and disadvantages:

#### Advantages

Robust against noise and occlusion, Robust against illumination, scaling, orientation and translation when face is correctly normalized, Robust against facial expressions, glasses, facial hair, makeup etc., Can handle high resolution images efficiently, Can handle small training sets, Can handle very low resolution images, Fast recognition/Low computational cost.

#### Disadvantages

Removes neighborhood relationships between pixels, Sensitive to faulty normalization, Sensitive to perspective, viewing angle and head rotation (can be improved using eigen light-fields or other view-based methods), Sensitive to large variation in illumination and strong facial expression,

Slow training/High computational cost (with large databases).

**Fisher’s Linear Discriminant**

Even if the Eigenfaces method seems to be quite efficient on non noisy images, one of the drawbacks is that it does not minimize the intraclass variance. A good classifier is a classifier in which the model of each class has a small variance while a large variance between different classes. Fisher’s Linear Discriminant (FLD) is one method to find the optimal projection. The projection determined by  $Z = W_{FLD}^T x$  minimize the quantity  $\frac{S_{BC}}{S_{WC}}$  which is the

ratio between the between class variance  $S_{BC}$  and the within class  $S_{WC}$ , see [24]. If we consider the general case of a class problem, then we can define the between class covariance matrix by:

$$S_{BC} = \sum_{i=1}^c N_i (\mu_i - \mu)(\mu_i - \mu)^T \quad (2.4)$$

and the within class covariance matrix by :

$$S_{WC} = \sum_{i=1}^c \sum_{x_k \in X_i} N_i (x_k - \mu_i)(x_k - \mu_i)^T \quad (2.5)$$

Where  $\mu$  is the mean of all the samples,  $\mu_i$  is the mean of the class  $X_i$  and  $N_i$  the number of samples in the class  $X_i$ . The optimal projection is obtained if we choose the projection matrix  $W_{FLD}^T$  as follow:

$$W_{FLD}^T = \arg \max_w \frac{|W^T S_{BC} W|}{|W^T S_{WC} W|} = [\omega_1, \omega_2, \dots, \omega_m], \quad (2.6)$$

Where  $\{\omega_i \mid i = 1, \dots, m\}$  is the set of generalized eigenvectors of  $S_{BC}$  and  $S_{WC}$ , which are associated to the eigenvalues  $\{y_i \mid i = 1, \dots, m\}$ . In [24] it is shown that the upper bound for the projection space dimension is  $c-1$  where  $c$  is the number of classes. In our binary class case, the projected space is a line. An example in the next figure shows the comparison between the two methods: PCA and FLD.

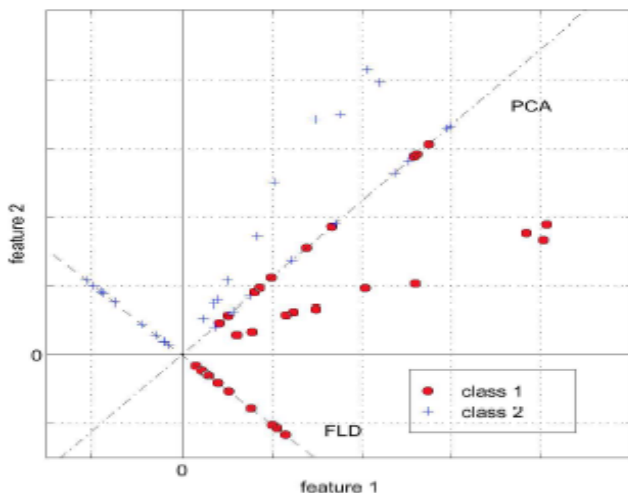


Figure 3: A comparison of principal component analysis (PCA) and Fisher’s linear discriminant (FDL) for a two class problem where data for each class lies a linear subspace. (taken from [24]).

Here we present some advantages and disadvantages:

**Advantages**

Robust against noise and occlusion, Robust against illumination, scaling, orientation and translation when face is correctly normalized, Robust against facial expressions, glasses, facial hair, makeup etc., Can handle high resolution images efficiently, Can handle very low resolution images, Fast recognition/Low computational cost.

**Disadvantages**

Removes neighbourhood relationships between pixels, Sensitive to faulty normalization, Sensitive to perspective, viewing angle and head rotation (can be improved using fisher light-fields), Does not handle small training sets well, Slow training/High computational cost (with large databases).

**Other methods in Eigenspace**

Others methods which use dimensionality reduction in the image space have been developed. One of the most efficient is the distribution based model developed by Sung and Poggio (see [4]). The method consists in modeling both the distribution of face patterns and non face patterns. The face distribution is modeled using 6 face pattern prototypes clustered by a modified version of the *kmeans* clustering algorithm. This algorithm computes the 6 centroids and covariance matrix of the 6 multidimensional Gaussian. In order to decrease the number of misclassified examples, 6 other Gaussian clusters representing the non face class are built using some critical non face pattern which are facelike patterns in the sense that their prototypes are close to the face models. These facelike non faces are chosen using a Bootstrap method which mean collecting the false positive patterns detected on a large set of images. Given these 12 clusters, a candidate window pattern has to be classified as face or non face. For this, each the distance between the tested pattern and the 12 clusters centroids are computed using 2 metrics.

The first component is normalized Mahalanobis distance between the tested pattern’s projection and the cluster centroid in a subspace spanned by the cluster’s 75 largest eigenvectors. The second is the Euclidean distance between the test pattern and its projection in the subspace. So the entire set of 12 distance measurements is a vector of 24 values. Then a multilayer perceptron (MLP) is used to separate the positive and negative examples. This approach is quite powerful but the limit is that the choice of all the parameters is not clear: what is the optimal number of clusters, how many examples do we have to use to train the classifier?

One other interesting method is a Bayesian based model.

**Neural Network, SVM, HMM, Winnow**

Other machine learning tools can be used to train good classifiers. Among these learning approaches, we can find neural network oriented systems and support vector ones. These are the more popular tools in machine learning and the most common used nowadays. The next two subsections expose them and make an overview of the different existing systems using them.



## NEURAL NETWORK

One of the best face detection system in term of false positive rate and detection rate is a Neural NetworkBased face detection developed by Rowley [11]. It uses a retinally connected neural network which decides if a scanned

window is a face or not. The face detection system can be divided in two main steps:

### *A neural networkbased filter*

The input of this first stage is a preprocessed square image (20x20 pixels in [11]) and the output of the neural network is an real value between 1 and +1. The preprocessing and neural network steps are presented in the next figure.

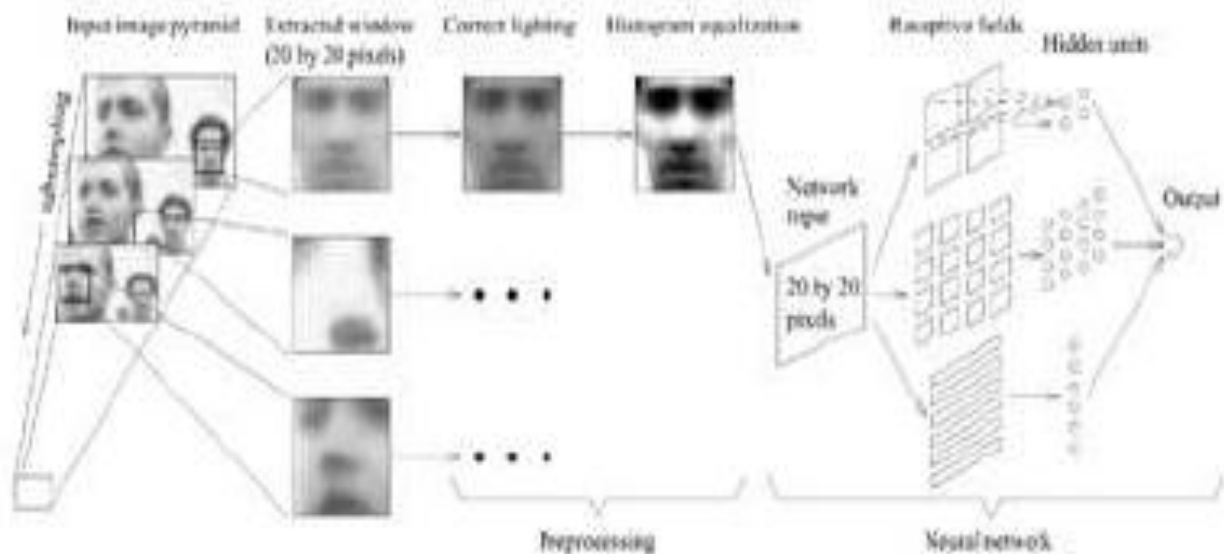


Figure 4: Neural Networkbased face detection proposed by [11]

The original image is decomposed in a pyramid of images (by simple subsampling) in order to detect faces larger than the basic detector size. The Receptive fields and Hidden units are shown in figure. There are three types of hidden units to represent local features that represent well faces. This first stage yields good detection rates (if the training set is particularly well chosen) but it remains still an insufficient false positive rate.

Arbitration and merging overlapping detections. In order to improve this high false positive rate, two neural networks are trained with various initializations ( in term of non face training set, weight initialization and order presentation). These two networks are built by the methods of the first step. Even if the two networks have individually bad false positive rates, the false alarms may differ from one network to the other. Hence, an integration of the result using a simple arbitration strategy improves significantly the detection results. The most common of this strategy is called ANDing. A window is definitively classified as face only if the two neural networks have detected it. This method using neural networks have good results in term of false positive rate and detection rate, but one limitation is that the quality of the detection depends highly on the coherence of the training sets and on the tuning of the neural networks which has lots of parameters.

### *Neural Network-Based Face Detection*

As discussed in the Literature Survey, there are many different approaches to face detection, each with their own relative merits and limitations. One such approach is that of Neural Networks. This section gives a brief introduction to the theory of neural networks and presents a neural network-based face detector developed by Sanner (REF), with the

aim of implementing and analysing the Rowley et al [11] detector with enhancements proposed by Sung and Poggio [52]. An explanation of Sanner's detector is given, and details of the experimental work carried out are also included.

### *Neural Network Theory*

Neural Nets are essentially networks of simple neural processors, arranged and interconnected in parallel. Neural Networks are based on our current level of knowledge of the human brain, and attract interest from both engineers, who can use Neural Nets to solve a wide range of problems, and scientists who can use them to help further our understanding of the human brain. Since the early stages of development in the 1970's, interest in neural networks has spread through many fields, due to the speed of processing and ability to solve complex problems. As with all techniques though, there are limitations. They can be slow for complex problems, are often susceptible to noise, and can be too dependent on the training set used, but these effects can be minimised through careful design. Neural Nets can be used to construct systems that are able to classify data into a given set or class, in the case of face detection, a set of images containing one or more face, and a set of images that contains no faces. Neural Networks consist of parallel interconnections of simple neural processors, or neuron. Neurons have many weighted inputs, that is to say each input ( $p_1, p_2, p_3 \dots p_m$ ) has a related weighting ( $w_1, w_2, w_3 \dots w_m$ ) according to its importance. Each of these inputs is a scalar, representing the data. In the case of face detection, the shade of GRAY of each pixel could be presented to the neuron in parallel (thus for a 10x10 pixel image, there would be 100 input lines  $p_1$  to

p100, with respective weightings w1 to w100, corresponding to the 100 pixels in the input image).

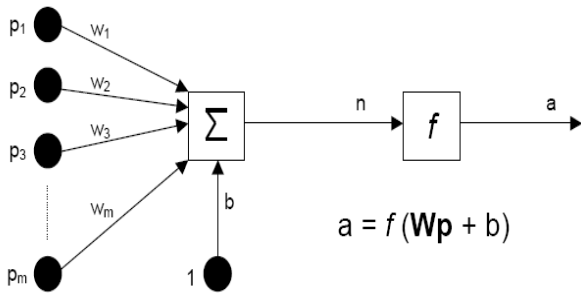


Figure 5 – a single neuron example neural network

The weighted inputs are combined together, and if present, a bias (b) is added. This is then passed as the argument to a transfer function (typically a pure linear, hardlimit, or log-sigmoid function), which outputs a value (a) representing the chosen classification.

Problems that are more complex can be realised by adding more neurons, forming multiple layers of several neurons, interconnected via a weighted matrix (as shown in figure 2.4.2). Additional layers of neurons not connected directly to the inputs or the outputs are called hidden layers (layers 1 and 2 in figure 3).

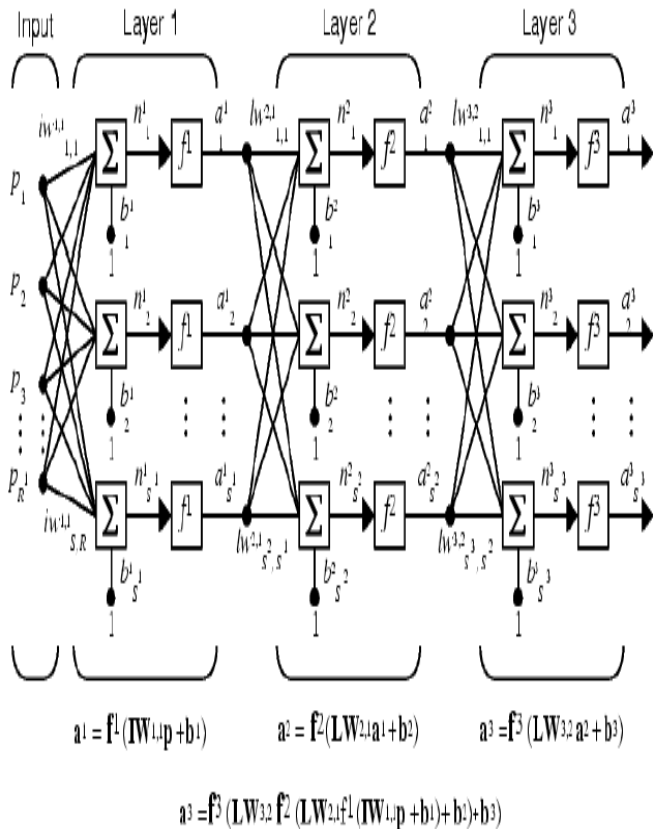


Figure 6– An example of a three layer network with multiple neurons per layer taken from Matlab documentation

Once the architecture is established, the network must be trained. A labeled representative set of examples from each class is presented to the network, which attempts to classify each example. The weights and biases are initialised with small random values and updated incrementally, such that the performance of the detector improves producing a more accurate decision boundary for the problem. Once trained,

the network can be used to classify previously unseen images, indicating whether they contain faces or not, based on the ‘location’ of the input relative to the decision boundary formed during training.

**SYSTEM OVERVIEW**

The operation of the face detection system can be broken down into three main areas:

1. Initialisation (design and creation of a neural network)
2. Training (choice of training data, parameters, and training)
3. Classification (scanning images to locate faces)

A feedforward neural network is created which is trained using back propagation. The training set used contains examples of both face and non-face images, and the classifier is trained to output a value between 0.9 and -0.9 (0.9 firmly indicating the presence of a face, -0.9 firmly indicating the absence of a face). When a new image is presented to the network, the image is rescaled and divided into windows which are individually presented to the network for classification. Windows thought to contain a face are outlined with a black bounding box and on completion a copy of the image is displayed, indicating the locations of any faces detected. In the next section a more thorough description of the system is included detailing the operation of the detector.

**SYSTEM DESCRIPTION**

There are two main functions: ‘facetrain’ to create and train a neural network and ‘facescan’ to scan new images for faces. A

**Facetrain**

A set of 25x20 images from a training set is loaded and stored as an image vector. There are two vectors, one which contains numerous face examples, the other for non-face examples. Each image vector is then augmented, adding mirror-images of the original training examples, to create a larger training set. A mask is applied to the face examples, removing pixels outside of the oval mask to focus the attention of the classifier on the true face region. Pixels in the unmasked area are then normalised: a rough approximation of the shading plane is subtracted from the image to correct for single light source effects and the histogram is rescaled to ensure all images have the same gray level range (0-1). Once the training data has been pre-processed, the neural network is created. The network has ‘NI’ inputs, 23 hidden nodes, and just one output which indicates the presence, or absence of face. Each node’s transfer function is of type ‘tansig’ – hyperbolic tangent sigmoid transfer function.

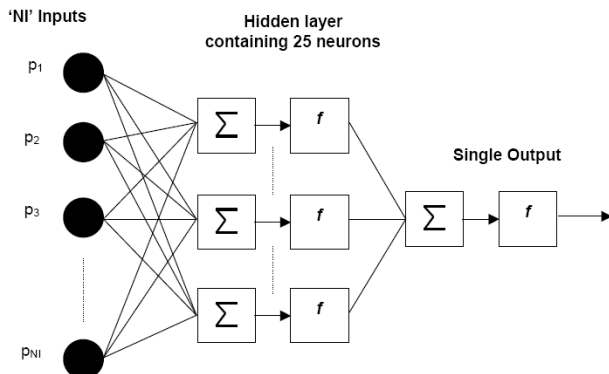


Figure 7 – A representation of the network architecture

Matlab's training algorithm 'traindm' is used which implements gradient decent back propagation with momentum. The network's weights and biases are updated according to gradient descent in order to improve the networks performance function. The Neural network is trained with all of the training data until convergence is achieved, or a decrease in performance is registered on the arbitrarily chosen validation set. Once the system has been created and trained, it is possible to classify new unseen images. The second function, "facescan", conducts the final task, scanning previously unseen images for faces. Images are processed prior to classification, which involves the construction of an image resolution pyramid, and scanning 25x20 window regions, normalising each window before passing it to the network for classification. The image resolution pyramid is used to allow faces of differing scales (sizes) to be detected. When calling the 'facescan' function, a number of parameters can be specified which control the number of levels in the pyramid and the scale factor for resizing between levels, as well as other parameters specifying the network and mask to be used, and a threshold value, above which images are classified as faces.

This focuses on Sanner's reported findings, predominantly performance statistics and the limitations of the detector. Sanner completed several tests to investigate the choice of parameters, although a comprehensive analysis of true performance was not provided in the documentation, just a few examples of images classified by the system. Several strengths and limitations were identified. The image normalisation routine was identified as a strength, as it eases the collecting of examples and the submitting of faces for scanning, due to the degree of invariance to lighting conditions that it provides. It can also lead to improvements in computational efficiency, given the small size of the matrices used during normalisation. The detector was also able to correctly process a fairly wide range of poses, emotions, and lighting conditions, despite a relatively small and limited example training set. However, the detector was unable to detect rotated faces as there were no rotated face examples in the training set and the number of false positives (areas of background or scenery that the detector incorrectly identifies as faces), was unacceptable in some images. The implementation of a retinally connected network [11], was suggested to help reduce the effect of noise. The addition of a more comprehensive set of non-face examples in the training set was also suggested as a potential improvement, a task which is extremely difficult, although improved greatly through using a bootstrapping technique to construct the non-face example set (*see section 6 for more details*). The remainder of this report will analyse

the Sanner [51] detector, evaluate its performance, and look at some possible improvements.

## EXPERIMENTS

This section details work carried out to measure the performance of the discussed Sanner face detector, and to analyse the improvements made.

### Performance Analysis - Original Detector

The performance of the original face detector developed by Sanner will be discussed, and a set of optimal values for the various tuning parameters will be investigated. All the experimental work is to be carried out in Matlab using the existing code written by Scott Sanner. Some additional scripts will be written to implement any improvements, and to automate some of the performance testing experiments which would otherwise be a tedious repetitive procedure.

### Classification Performance

At the very heart of the system lies the classifier, the object that actually makes the decision as to whether an image receives contains a face or not. Initially tests were carried out to investigate how well the classifier could classify the data set on which it was trained. Although this is not indicative of true performance, it serves as a guide to how well the network is learning from the training data. The classify function written by Sanner, classifies 25x20 pixel images as either face or non-face images, producing a numerical value between -0.9 and 0.9 (0.9 strongly indicating the presence of a face, -0.9 indicating the absence of a face). The addition of a threshold value allows the classifier to be tuned somewhat, such that an image is marked as when the numerical output value exceeds the threshold. A script entitled "massclassify" makes use of the classify function by repeatedly classifying each example from the training data. For these experiments a virtual threshold of '0' is assumed such that anything classified positive is defined as a face image, and negative values are defined as scenery images. This additional code is included in the appendices for reference. Face and non-face examples are classified separately. Whilst processing the face examples, correct classification values (exceeding the virtual threshold) are used to increment a 'face counter'. Likewise a 'non-face counter' tallies the number of times non-face examples that are below the threshold value (again correct classification). Upon completion the classification rate and number of incorrect classifications for both the face and non-face examples are displayed. Figure 6 shows the results of 'massclassify' when used to classify the original training data set using Sanner's original detector.

Number of Faces	30
Correcr Classification on Rates	93.3%
Number of Incorrect Classification	2
Number of Scenery Examples	40
Correct Classification Rate	97%
Number of Incorrect Classifications	1

Figure 8– Original Face Detector Learning Performance Statistics

Several parameters in the system can be set to adjust various properties of the detector and tune its performance. Each of the parameters will be taken in turn, and experiments carried

out to determine an optimal value for each one. The mask is used to remove pixels towards the edge of the 25x20 images, thus focussing the attention of the network on the unmasked oval region, most likely to contain a face. The chosen mask is shown in the appendices and closely mirrors masks chosen by many others in the Literature survey. The unanimous acceptance of this mask throughout various approaches infers that the mask is somewhat optimal already, and thus no experiments will be done with other alternatives masks for the purposes of this project.

Various characteristics of the network can be changed or varied including the network type, number of hidden nodes, training algorithm used and the training duration. Each parameter will be taken in turn and analysed.

Changing the type of network used could potentially improve the performance of the detector, although the chosen feed-forward type is an excellent choice for this type of application, a choice which is mirrored by other neural network based face detection systems including Rowley *et al* [11]. Therefore due to the widespread acceptance of this network type, making changes at this stage is deemed unnecessary.

### Number of Hidden Neurons

It is thought that any complexity of problem can be solved with just a single layer of hidden neurons. With a greater number of hidden neurons, there are more weights to tune during training, and thus a more complex a decision boundary can be formed (although too many neurons can lead to over fitting of the boundary to the training set, thus poor generalisation). The number of hidden neurons will be varied from 1 through to 1000 (25 being the default number in the original design), and the 'massclassify' function will be used to see how well the system learns the training set. Figure 2.4.5 shows the results of these experiments:

No. hidden neurons	Face detection rate %	Non-Face detection rate %	Total detection rate
1	99.1	97	98.5
10	100.0	98.0	99.3
20	98.3	100.0	99.4
25	99.4	99.6	99.4
30	99.4	98.6	98.9
40	100.0	100.0	100.0
50	100.0	100.0	100.0
100	100.0	100.0	100.0
1000	100.0	100.0	100.0

Figure 9 – The effect on performance of varying the number of hidden neurons

### LIMITATIONS

Sanner [51] identified some limitations with his face detector, mainly the number of false positives (windows the classifier incorrectly believes are faces). This infers a weakness in the training set. The detector was also stated to provide translational invariance, although rotation in faces was not catered for, with the failure to detect several rotated faces in the test sets.

The system developed by Sanner [51] is a good example of a neural network based system, indicative of some of the more complex detectors in the field. It mirrors the strengths of the technology providing impressive classification results from a relatively small image training set, and also reflects the major limitations, mainly computational expense, and

reliance on the training data. It illustrates well some of the key problems that developers of intelligent artificial face detection systems are faced with, not only in the field of neural networks but across the board.

Here we present some advantages and disadvantages of these methods:

### Advantages

Stores neighbourhood relationships, Robust against noise and occlusion, Robust against scaling, orientation and translation when face is correctly normalized, Fast recognition/Low computational cost (depending only on the network and not the number of images).

### Disadvantages

Sensitive to faulty normalization, Sensitive to illumination and face expressions, Sensitive to perspective, viewing angle and head rotation (can be improved using ensembles of networks), Can be slow and difficult to train (especially for large databases).

### Support Vector Machine

Modeling of imperial data is essential in many disciplines, to build a representation of an object or a task that can deduce the results for an unseen input only by observing a set of training samples or by using predefined rules, to assign units from a target space into classes by using a representative model obtained only by using a subspace of the entire space, the choice of this subspace is essential and should contain enough information to represent the entire space or the approximation error will be high due the poor choice of the representative data, after using a representative subspace an optimal model should be selected to minimize the estimated error, both these errors (approximation error results from poor subspace and estimation resulting from poor model) are called the generalization error, which is the error resulting from the attempt of modeling a space using  $s$  subspace, most classification techniques tried to minimize this error to obtain a better model Vapnik(1998)[53].

SVM were founded by Vapnik (1995) [54] and gained popularity due their promising results in classification of complex problems and their performance, it has the ability to generalize only by using a finite set of training samples, SVMs have been applied successfully in the field of pattern recognition, as in Cortes and Vapnik(1995)[53] for handwriting recognition and in[55] for face detection.

In the case of face detection the classification problem is narrowed down to a two-class case, a face and none-face, the goal of using SVM in this case is to deduce a function which can separate the two classes by using a training set to deduce a classifier that can classify unseen examples as well, one that generalizes properly, in most classification problems there exists many functions that can separate the data but there exist only one that maximizes the margin between the function and the nearest data sample of each class, this classifier can be called as the: optima hyperplane, this hyperplane could be linear in some cases and in many other cases it is not, presenting an addition supporting function could be necessary to be associated with the misclassified set, how even another alternative is the introduction of a non-linear function that can do the same thing and separate the classes appropriately. Support Vector Machine is a learning technique introduced by Vapnik [19].

It seems to be efficient when the data sets become larger than few thousands. It the case of face detection if we want to describe precisely all the faces (because of the variability of faces.) The principle is to find the decision surfaces by solving a linearly constrained quadratic programming problem. The hyperplan decision is the one that maximize the margin between the face and the non faces classes. One of the simple margins that can be used is the distance between the closest points of the two classes. The points that are kept in the hyperplan are not numerous.

They are called supper vectors but they are the most important because they define the boundary between the two classes. Osuna and al. have developed such a face detection system using Support Vector Machine in.

### Hidden Markov Model

These Hidden Markov Models have been used by Samaria and Young (see [41] and [42]) for face localization and recognition. The principle is to divide a face pattern into several regions such as forehead, eyes, nose, mouth and chin. A face pattern is then recognize if these features are recognize in an appropriate order. In other words, a face pattern is a sequence of observation vectors where eachvector is a strip of pixels.A image is scanned in a precise order and an observation is taken by block of pixels. The boundaries between strips of pixels are represented by probabilistic transitions between states and the image data within a region is modeled by a multivariate Gaussian distribution.

The output states correspond to the class to which the observation belong. Other methods using HMM have been developed by Rajagopalan [44], and Sung [43].

Here we present some advantages and disadvantages of these methods:

### Advantages

Robust against scaling, orientation and translation when face is correctly normalized, Robust against illumination if training data has different lighting conditions, Robust against facial expressions, glasses, facial hair, makeup etc. and Easy to update.

### Disadvantages

Sensitive to faulty normalization, Sensitive to occlusion, Sensitive to perspective, viewing angle and head rotation (can be improved training models for different views), Slow training and recognition/High computational cost (can be improved using DCT or KLT feature vectors).

### Sparse Network of Winnows (SNoW)

SNoW is a sparse network of linear functions that uses the Winnow update rule defined in [45]. We define two linear units called target nodes: one as representation for the face pattern and another one for the nonface

pattern. Given a set of relations that may be of interest in the input image, each input image is mapped into a set of features which are present in it. This representation is given to the SNoW procedure and propagates to the target nodes.

Let  $A_t = \{i_1, \dots, i_m\}$  be the set of features that are present in an

example and are linked to the target node t. Then the linear unit is active *t*if and only if  $\sum_{i \in A_t} \omega_i^t > \theta_t$ , where

$\omega_i^t$  is the weight on the edge connecting the *i*-*th* feature to the target node t and  $\theta_t$  is its threshold. The Winnow update consists in a threshold  $\theta_t$  at the target t, two update parameters: a promotion parameter  $\alpha > 1$  and a demotion parameter  $0 < \beta < 1$ .

### Geometrical Based Detection

#### Introduction

The previous statistical methods are based on a learning to obtain a face model from one positive and one negative data set. They are not directly correlated to the particular geometrical features of a typical face. Some other methods are in such a point of view. They are called Geometricalbased or Featurebased.

Many approaches have been taken in this large area of featurebased detection and we can distinguish:

- The top-down approach: One model is computed for one scale. This was used by Yang and Huang [30], and Lanitis [31].
- The bottom-up approach: The faces are searched in an image by the presence of facial features. See Leung [32] and Sumi [33]. The main advantage of this geometric approach is that the face detection is not restricted to frontal faces. In fact the main face features (eyes nose, skin color etc...) are present independently of the pose and the lighting conditions.

#### Top-down Methods

This category includes all the methods that used a multi scale approach. The great majority of them use the skin color to find faces in images. The existing system use several segmentation algorithms to extract faces from the images. The more classical ones are region growing, Gibbs Random Field Filtering and more... The skin color is maybe one of the features the first noticed by the human visual system. Many methods use different color spaces. The main advantage of this approach is that the face detection is very fast. However, there is one important issue: lots of problems appears if the background contains faces of the skin color. Yang and Ahuja [36] have build their system in this sense.

Although the human skin color seems to change from one example to one other, the effective variation is more luminance than the color itself. The distribution is modeled by a Gaussian distribution. All the pixel are tested and we attribute them the skin color if their corresponding probability is greater than a given threshold. Finally, a region is declared as face if more than 70 percents of its pixels have the skin color. Another method proposed by Saber and Tekalp [47] uses Gibbs Random Field filtering as segmentation algorithm. After the segmentation, each region is approximated by an ellipse. the distance between the ellipse and the region shape is computed using the Hausdorff distance measure. If this last measure is greater than a predefined threshold, the region is rejected. Then a procedure of finding the facial features is applied. Wei and Sethi uses a quite different approach in [?, ?]. They use a partitioning of the human skin region to detect faces. The binary image of the segmented skin is obtained by performing skin color classification at each pixel location. The a morphological closing is performed followed by an

opening to remove small regions. Then the remaining regions are another time approximated by ellipses

### **Bottom-up Methods**

The principle is to find invariant features of faces. By invariant, we mean invariant by scaling, poses, lighting conditions and other variations. The common and natural features that are usually extracted are the eyes, the nose the mouth and the hair line. Any edge detector might be used to extract them. A bottom up method try to find this features in an original image and then they are grouped according to their geometrical relationships.

The difference between the methods in this bottomup approach resides in the way to choose the features and how to establish the links between them.

One of the early methods was proposed by Govindara ju in [46]. In this method, the facial features are characterized by curves and structural relationships which link them. Two successive stages are applied: First, curves of the faces are extracted from an input image to find the face candidates. The features detected are then grouped using a matching process (a cost function and one threshold).

Leung [32] uses a random graph matching by apply a set of Gaussian filters which is compared to a template graph representing a face. (The comparison between the computed graph and the template is usually a simple threshold).

In another method used by Yow and Cipolla [34], a set of derivative filter is apply in order to select edge features like the corner of the eyes for example. Then only the points that have particular properties are kept: those which have parallel edges for example. The remaining points are then linked together and they are used to build a face model. Cai and Goshtasby [35] used the color information but in a different approach than [36]. A face is recognized by the presence of particular feature.

### **Evaluation Difficulties**

As the definition of detecting faces in images is really simple: determine whether or not there are any faces in images and, if present, return the image location and extend for each face, we can think that it is easy to evaluate the performances of a face detector. However many parameters have to be taken in account to do this. How can we measure the goodness of a detection? How do we have to integrate the false alarms (how do we have to consider the false positive rate?) What about the detection speed? Several such questions make hard the face detection evaluation.

It would be interesting to compare the existing methods in face detection but the major problem is that every method is made in a particular context and today there are still no standards for face detection evaluation that will make easier the future research work about face detection.

The first step in detection evaluation is to use a common testing set which contains a large variety of situations. The most common used set is probably the CMU testing set which contains many faces manually labeled. Then we usually use the detection rate over false positive rate ratio to characterize the performances even if the number of false alarms is directly related to the way how the images are scanned (more precisely the number of subwindows scanned). A summary of the main results and method comparison can be found in [22] and [37]. Nevertheless, we can give general observations about the different approaches. The image based techniques are quite efficient

regarding the frontal face detection. The detection rate reaches more than 90% with at most several tens of false alarms in a typical sized image but the main limitation of the image based methods is that the faces detected will slightly match with the training examples. Thus it is difficult for example to include in the training set faces at many different poses, with both rotations in and out of plane. The geometrical approaches are more robust in term of face pose, i.e. the face orientation in front of the acquisition system but they generally give worse detection results. Both the segmentation part and the feature extraction are critical points. The use of the color information needs is not really representative of faces because lots of objects in the background may have the human skin color. The speed of the detector is without any doubt the parameter the most difficult to take into account.

Each method has its own speed and it is difficult to determine the speed performances: it depends on the scanning method and on the way it is implemented. So it has been shown that a lot of different approaches are available but face detection is still an open task. Many solutions are possible taking into account the results of the existing methods. The main promising approach seems to be combined approaches of image based and feature based methods. We will see one of them which uses a Boosting learning algorithm in the next chapters.

## **FACE DETECTION: AGGRESSIVE LEARNING ALGORITHM**

### **Introduction**

#### **Choice of the Method**

Due to some limitations of the neural network based system, indicative of some of the more complex detectors in the field. It mirrors the strengths of the technology providing impressive classification results from a relatively small image training set, and also reflects the major limitations, mainly computational expense, and reliance on the training data. It illustrates well some of the key problems that developers of intelligent artificial face detection systems are faced with, not only in the field of neural networks but across the board.

here, we discuss about a face detection based on a boosting algorithm which yields good detection rates.

Boosting is a general strategy for learning classifiers by combining simpler ones. The idea of boosting is to take a “weak classifier” — that is, any classifier that will do at least slightly better than chance—and use it to build a much better classifier, thereby boosting the performance of the weak classification algorithm. This boosting is done by averaging the outputs of a collection of weak classifiers. The most popular boosting algorithm is AdaBoost, so-called because it is “adaptive.” AdaBoost is extremely simple to use and implement (far simpler than SVMs), and often gives very effective results. There is tremendous flexibility in the choice of weak classifier as well. Boosting is a specific example of a general class of learning algorithms called ensemble methods, which attempt to build better learning algorithms by combining multiple simpler algorithms.

This detector is highly inspired by the Robust Real-time Object Detection of Viola and Jones [1]. We have chosen to build a model using a statistical learning given some positive and negative examples. A learning algorithm trains



a classifier by selecting visual features, so we will discuss why this chosen algorithm is appropriate for face detection and explain how it works. We will also emphasize on some other essential key contributions like a new image representation, the choice of these visual features and finally the introduction of detection in cascade.

### **Context of the Frontal face Detection**

Before going into details, we just remark that every face detection method is designed in a particular context that is why it is not always easy to compare the results between them. Some detectors have for only goal to have a detection rate as near as possible from 100% but our project is a little bit in a different context: even if we naturally want reach good detection rates, we want to build a realtime oriented detector. So the goal is to detect all the faces (or almost all of them) even if this means we have to accept a higher false positive rate (nonface images labeled as face by the detector). This choice is only in order to respect most of applications which need for example to detect all the people in front of a video camera. (Video surveillance for instance). On the other hand, if for example, a camera is placed in a airport hall, the faces are often low resolution faces, at different scales and the background seems to be quite textured and complicated. In this way, we have to build a robust detector with respect to illumination, face variation and face size. On the other side, if we keep in mind that we want to detect faces for a further face recognition or comprehension, it would be good to select only faces which can be considered as frontal faces, this will explain the choice of the training set used to learn the final classifier (see 4.1). To summarize, even if we could choose other face detection contexts, this one seems to be the most used in the realworld applications. We will particularly pay attention to the fact that it will be interesting to build a simple and unbiased representation that can represent faces. (And objects by generalization).

### **Why We Choose Boosting and Haar Features?**

Previous Section presented the main approaches available to build a face detection system. Now the context of our face detection is given, we can explain why we choose this approach using a boosting learning algorithm and simple Haar features. As we want to detect faces in various background and principally low resolution faces, it would be improper to use purely geometrical methods. In fact the main advantage to these geometrical methods is the geometric invariant properties. We are not interested by them because we have chosen to stay in a frontal face detection context. So it is quite naturally that we have oriented our choice towards learning algorithms. Boosting is a powerful iterative procedure that builds efficient classifiers by selecting and combining very simple classifiers. Good theoretical results have been demonstrated, so we have some theoretical guarantees for achieving good detection rates. This idea is interesting in the sense that a combination of simple classifiers may intuitively give a rapid detection without deteriorating the detection rates. So it seems to be one of the best compromises between efficiency in term of detection and speed.

### **Overview of the Detection**

This new method given by Viola [1] is a combined method of more traditional ones like geometrical and image based detection. It is a geometrical in the sense that it uses general features of human faces: position of particular features among which the eyes the nose and the mouth. We will not try to extract particular face features: It is only an *a posteriori* observation in the sense that the selected Haarlike masks are effectively representing particular facial features but it is not our decision. See section 4.2 for details about the selected features. On the other hand, it is also image based because we use a statistical learning with the use of a consequent data set needed to build the face model. Viola has developed this face detector in July 2001 and he was inspired by the work of Papageorgiou[2]. It seemed to be the fastest and the most robust and it is still today. The speed of the detection is notably given by the simplicity of the features chosen and the good detection rates are obtained by the use of the fundamental boosting algorithm AdaBoost which selects the most representative feature in a large set.

To have a concrete idea of the performances of the detection, imagine that Viola's detector can process 15 frames of 350x260 pixel images per second on a conventional 700 MHz Intel Pentium. Let us look at the main steps of the fast face detector that will be explored in the next sections. The detector consists in scanning an image by a shifting window at different scales. Each subwindow is tested by a classifier made of several stages (notion of cascade). If the subwindow is clearly not a face, it will be rejected by one of the first steps in the cascade while more specific classifier (later in the cascade) will classify it if it is more difficult to discriminate. The first contribution is the choice of the features that describe the faces. The principle of the detection is to apply successively simple classifiers to combine them in a final strong classifier. The choice of these features is fundamental for the performances of the detection. The difficulty is to find masks simple enough to permit a fast classification but characteristic enough to discriminate faces and non faces.

A good compromise for that is obtained by the use of reminiscent of Haar Basis functions. In fact the feature response is nothing more than the difference of two, three or four rectangular regions at different scales and shapes. To improve the computation time of these features, we introduce a new image representation called Integral Image which permits to compute a rectangle area with only 4 elementary operations, i.e additions and subtractions. Then, as we have a large set of features at disposition, AdaBoost is used to select a small set of them to construct a strong final classifier. We want to keep only the feature which separates the best positive and negative examples. At each selection step, a weak classifier (one feature) is selected so AdaBoost provides an effective learning algorithm and strong bounds on generalization performance. Finally, the third important contribution is the cascade implementation which focuses the detection on critical regions of interest. Thus, it first eliminates quickly regions where there are no positive examples and then, the more we go down in the cascade process, the more specific the classifiers are and so almost only faces are detected.

For example, the first stage of Viola's detector is a combination of only two features which rejects 60% of negative examples and it provides a false negative rate of

1% with only 20 simple operations. Sections 2 will describe the particularity of the features and the computation with the integral image. Then, section 3 will focus on the learning algorithm and the method in which the weak classifiers are combined to ensure a strong final classifier. Finally, section 4 will expose the cascade structure.

**Features and Integral Image**

This section presents the features used in our statistical face detection. Human faces are objects particularly hard to model because of their significant variety in color and texture and there are no constraints on the background. In fact, if we want to build a model which is able to take in account this face variability without identifying cluttered backgrounds, it will not work to use such as maximum likelihood methods for example. The next few subsections expose different methods used to model the faces. 3.2.1 Overview of the existing face models. Due to the context of our face detection, methods like maximum likelihood are particularly not efficient. We will thus focus on example based face models to train a significant classifier. Many descriptive features could be used to train a classifier by Boosting. The next subsections explain some of them that have been used recently. We can distinguish to main methods that seems to be the more efficient:

- Pixel based models
- Haar Like features models

**A Pixelbased Method**

A possible way of modeling faces is to use a pixel representation as presented in Pavlovic’s detection [5]. In order to train a boosted classifier as we will discuss later, Pavlovic uses a combination of weak classifiers based on the pixel values to boost the model. Let

$$h_k \in \{t(X | \theta, l) = \text{sign}(X^{(l)} - \theta)\} \quad (3.1)$$

A weak classifier where  $X$  denotes a vectorized image of grayscale pixel values and  $X^{(l)}$  is its  $l$ th pixel. The weak classifier has an image as input and a decision face or non face as output, in comparison with a threshold  $\theta$ . The used learning algorithm is AdaBoost which selects from the training dataset the pixels which represent the best a face structure. As you can see on the following figure, the geometrical basic features of faces are recognized: the eye region, the nose and the mouth.

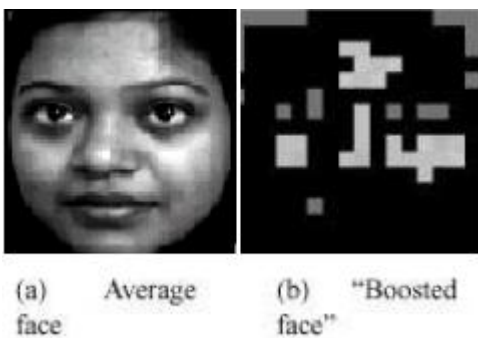


Figure 9 (a) shows an example of an average face obtained from the training dataset. Figure 3.1(b) shows a typical “face” image sampled from a function learned using boosting. Each non white location corresponds to a pixel selected by the boosting algorithms.

This method seems to be quite efficient because the boosting learning theoretically gives good training results but imagine

that in a 19 x19 pixel image, there are some 361 pixels, we have to apply at each scanning window 361 weak classifications and combine them to obtain a final strong classifier. We will try to improve the computation time by using other face models.

**Haarlike Features**

Comparing these face modeling methods and taking into account the specific needs of our application, we arrived to conclusion that a feature based method would be more appropriate rather than pixel based. There are many motivations for using features (some reminiscent of Haar Basis functions) than pixels directly as Pavlovic [5]. The most common reason is that features can act to encode adhoc domain knowledge that is difficult to learn using a finite quantity of training data. And as we will see, these features can operate much faster than pixel based system. These features are the same as those used by Papageorgiou[2]. The Haar wavelets are a natural set basis functions which computes the difference of intensity in neighbor regions. The next subsection recalls basic theory about wavelet representation.

**Rectangular Haar Features**

In our face detection system, very simple features are used. We use some reminiscent of Haar Basis. Recall that the wavelet function corresponding to Haar wavelet is:

$$\begin{aligned} \psi(x) &= 1, \text{ if } 0 \leq x < 1/2 \\ \psi(x) &= -1, \text{ if } 1/2 \leq x < 1 \\ \psi(x) &= 0, \text{ otherwise} \end{aligned} \quad (3.2)$$

Are three kinds of Haarlike features. The value of a two rectangle feature is the difference between the sum of the pixels within two rectangular regions. The regions have the same size and shape and are horizontally or vertically adjacent. (see figure 10). A three rectangle feature computes the sum within two outside rectangles subtracted from the sum in a center rectangle. Finally, a four rectangle feature computes the difference between diagonal pairs of rectangles.

Given that the basic resolution of the detector is 15x20, the exhaustive set of rectangle features is quite large: 37525. Note that unlike the Haar basis, the set of rectangle features is overcomplete.

Figure 3.3 shows the different two three and four rectangle prototypes used by our detector.

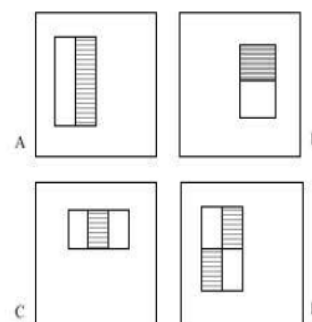


Figure 10: Example rectangle features shown relative to the enclosing detection window. The sum of the pixels which lie within the white rectangles are subtracted from the sum of pixels in the grey rectangles. Two rectangle features are shown in (A) and (B). Figure (C) shows a three rectangle feature, and (D) a four rectangle feature.

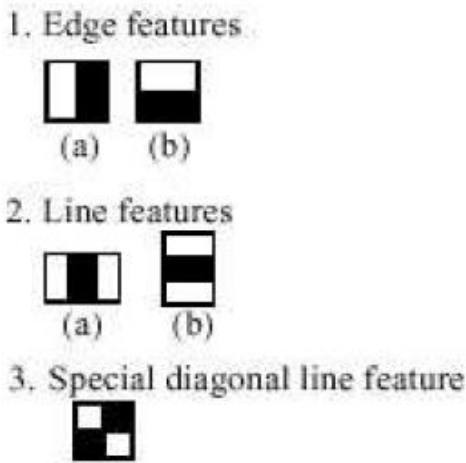
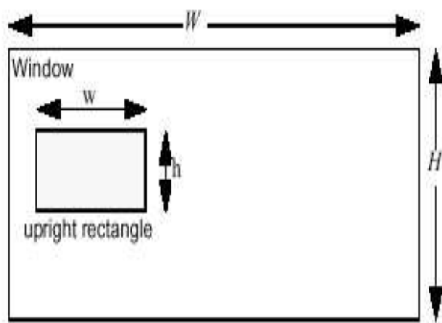


Figure 11: Feature prototypes of simple Haarlike . Black areas have negative and white areas positive weights.

**Number of Features:**

The number of features derived from each prototype is quite large and differs from prototype to prototype and can be calculated as follows. Let  $H$  and  $W$  be the size of a  $H \times W$  pixels window and let  $w$  and  $h$  be the size of one prototype inside the window as shown on figure 3.4.



Let  $X = \lfloor \frac{W}{w} \rfloor$  and  $Y = \lfloor \frac{H}{h} \rfloor$  be the maximum scaling factors in  $x$  and  $y$  direction. An upright feature of size  $w \times h$  then generates features for an image of size  $W \times H$ .

$$X.Y \left( W + 1 - w \frac{X + 1}{2} \right) \left( H + 1 - h \frac{Y + 1}{2} \right) \quad (3.3)$$

Results with the notations of Figure 3.3:

Table 3.2: Number of features in a  $15 \times 20$  window for each prototype

Feature Type	$w / h$	$X / Y$	Count
(1a) (1b)	2/1;1/2	7/20	23592
(2a) (2b)	3/1;1/3	5/20	8402
(3)	2/2	7/10	5603
Total			37524

As detailed in Table 3.2 and given that the base resolution of the detector is 15 20, the exhaustive set of rectangle features is quite large: 37520. Note that unlike the Haar basis, the set of rectangle features is over complete.

Even if our detector only uses these four types of features, we could use other types: for instance we could introduce the same rectangular features but rotated by 45 degrees as made by [7] as shown in Figure 12.

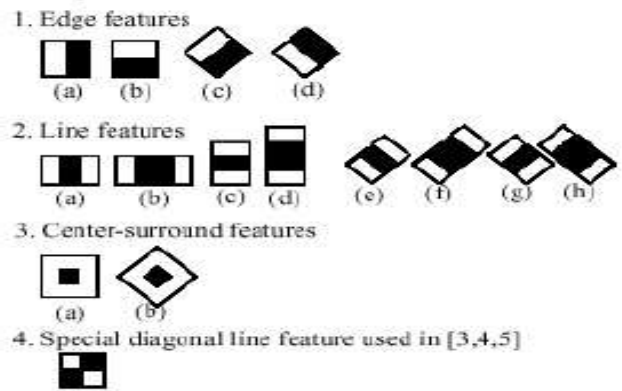


Figure 12: Feature prototypes of simple Haarlike and centersurround features, in line and rotated by 45 degrees. Black areas have negative and white areas positive weights.

With these other rotated features and centersurround features, the new set of features has 117,941 components in a 20x24 window.

On another side, Papageorgiou [2] introduce another kind of Haarfeature called *quadruple density transform* . This one permits to achieve the spatial resolution necessary for detection and to increase the expressive power of the model. It is nothing more than an extension of the 2D Haar wavelet as shown in Figure 3.6.

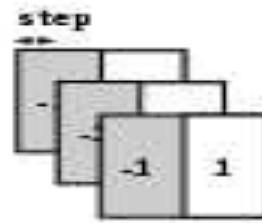


Figure 13: Quadruple density 2D Haar basis.

We have decided to limit our set to the simple Haarlike wavelets because it seems to be complete enough to obtain good detection results. The choice of the feature is important but not crucial in order to train the classifiers because as explained in the next section, the training is a combination of weak classifiers. It does not really matter if the features are not optimal, and it seems that the horizontally and vertically oriented features represent better faces that rotated ones which would represent nonsymmetries of faces. It is not a lack or a great loss to limit our set to basics features. We leave other types of features for a future work. rectangular features seem to be primitive if we compare them to other alternatives such as steerable filters [10]. Steerable filters are really well adapted to boundaries detection, image compression and texture analysis whereas the rectangle features are more sensitive to bars, the presence of edges and quite simple image structures. All the dilemma of choosing the representation resides in the compromise between the simplicity which provides fast computing and more representative filters but slower computation. In the next subsection a new image representation will be introduced in order to improve the computing speed of these Haarlike masks responses.

**Integral Image**

We now know that we need Haarlike features to train the classifiers. The goal of this part is to introduce a new image

representation called *Integral Image* which yields a fast feature computation. This representation is in close relation with “sum area tables” as used in graphics [8]. The value of the *Integral Image* at the coordinates (x, y) is the sum of all the pixels above and to the left of (x, y), including this last point as shown in Figure 3.7.

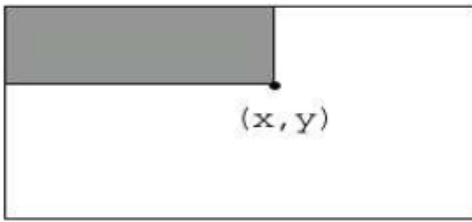


Figure 14: The Integral Image representation. The Integral image value at the point (x,y) is the sum of all the pixels above and to the left of (x,y).

Let *ii* be the integral image of the initial image *i* and *ii*(x, y) the value of the integral image at the point (x, y). We can define the integral image *ii* by:

$$ii(x, y) = \sum_{\substack{x' \leq x, \\ y' \leq y}} i(x', y'). \tag{3.4}$$

As we use this new representation to improve the computation time, let us explain its advantages. First it can be computed in a efficient way using the following pair of recurrences:

$$\begin{cases} s(x, y) = s(x, y - 1) + i(x, y) \\ ii(x, y) = ii(x - 1, y) + s(x, y) \end{cases}$$

*s*(x, y) is the cumulative row sum,  $\forall x, s(x, -1) = 0$ , and  $\forall y, ii(-1, y) = 0$ . The integral image can thus be computed in one pass at the beginning of the detection over the original image *i*. The main advantage using such a representation is that any rectangular sum in the original image can be computed in four array references (see Figure 15) in the integral image. The difference between two rectangular sums can be computed in eight references. Therefore computing a feature is only a difference of two, three or four rectangular sums.

The two rectangle features are computed with six references because the two rectangles are adjacent. The three rectangle features need eight references and the four rectangle array only nine.

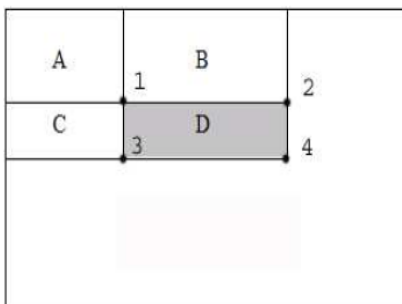


Figure 15: The sum of the pixels within rectangle D can be computed with four array references.

The value of the integral image at location 1 is the of the pixels in rectangle A. The value at location 2 is A+B, at location 3 is A+C, and at location A+B+C+D. The sum within D can be computed as 4+1(2+3).

There are some other reasons which made us choose the integral image representation. One of them is given by the box let work of Simard, et al. [ 9]. It is based on a fundamental property of linear operations (e.g.  $f \cdot g$  or  $f * g$ ). Any invertible linear operation can be applied to or if its inverse is applied to the result. For instance, assuming that and have finite support and that  $f^n$  denotes the *n*th integral of (or the *n*th derivative if *n* is negative), we can write the following convolution identity:

$$(f * g)^n = f^n * g = f * g^n \tag{3.5}$$

where denotes the convolution operator. They also show that the convolution can be significantly accelerated if the derivatives of and are sparse. From this property we can extract that for example:

$$(f^n) * (\int \int g) = f * g. \tag{3.6}$$

We can apply this last formula to the rectangle sum computation: let *r* be the rectangle ( with value 1 inside and 0 outside) and *i* the image, the sum in the rectangle is *ir* and it can be computed as follow:

$$i.r = (\int \int i).r^n. \tag{3.7}$$

The integral image is in fact the double integral of the image (that is why it is called integral image) and the second derivative of the rectangle yields four delta functions at the corners of a rectangle. The evaluation of the second dot product is accomplished with four array accesses.

One of the consequences of the use of such a representation is the way to scan the images.

The conventional system computes a pyramid of images to process the detection at several scales. By using the integral image, we only need to rescale the 20x15 pixels detector and apply it on the first integral image. No resampling and no image rescaling are needed that is why it provides a significant gain of time and it becomes easier to implement than using the pyramid approach.

This approach permits to compute a single feature at every location and at every scale in few operations. The power of all these independent feature is still quite weak, so the challenge of the next section is to find how the best features are selected and how we can combine them to produce a strong final classifier.

**Learning with Ada Boost**

Considering a mono stage classifier and given a set of features, we can build a face detector by applying all the masks at each image location (each shift and each scale).For this many different learning methods could be used. Moreover, we have a complete set of 37520 features which is far larger than the number of pixels, so even if the features responses are very simple to compute ( notably with the integral image representation), applying the all set of features would be two expensive in time. The next stage in the building of the face detector is thus to use a learning function which selects a small set of these features: the ones which separates the best positive and negative examples. The resulting final classifier would be a simple linear combination of these few Haarlike features. For this, we will discuss in this section about an algorithm called Ada Boost (Adaptive Boosting) (see Figure 16) which has two main goals:

- Selecting a few set of features which represents as well as possible faces. Train a strong final classifier with a linear combination of these best features.

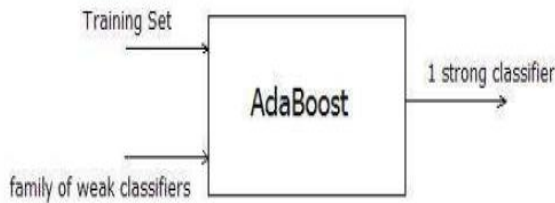


Figure 16: Basic scheme of AdaBoost.

In the following subsections, it is explained why we have chosen this algorithm instead of more classical ones and then we some theory is explained to show why AdaBoost is efficient and how it can be adapted to face detection.

#### Possible Algorithms:

Given a set a features and a training set of positive and negative examples (see section 4.1 on page 65 for details about the training dataset), any machine learning approach could be used to learn a classification function. AdaBoost is efficient boosting algorithms which combine simple statistical learners while reducing significantly not only the training error but also the more elusive generalization error. As all the learning functions, it presents advantages and drawbacks which are exposed here:

#### ADVANTAGES:

- No a prior knowledge. As shown in Figure 3.9, AdaBoost is an algorithm which only needs two inputs: a training dataset and a set of features (classification functions). There is no need to have any *a priori* knowledge about face structure. The most representative features will automatically be selected during the learning.
- Adaptive algorithm. At each stage of the learning, the positive and negative examples are tested by the current classifier. If an example  $x_i$  is misclassified, that means that it is hard to classify i.e it cannot clearly be assign in the good class. In order to increase the discriminant power of the classifier these misclassified examples are upweighted for the next algorithm iterations. So the easily classified examples are detected in the first iterations and will have less weight in the learning of the next stages to focus on the harder examples.
- The training errors theoretically converge exponentially towards 0. As proved by Freund and Schapire in [12], given a finite set of positive and negative examples, the training error reaches 0 in a finite number of iterations.

#### DISADVANTAGES:

The result depends on the data and weak classifiers. The quality of the final detection depends highly on the consistence of the training set. Both the size of the sets and the interclass variability are important factors to take in account. Other way, the types of basic classifiers which are combined have some influence on the result. The only need for all the basic functions is to be better than random selection but if we want to achieve good detection rates in a cogent number of iterations, they have to be as well chosen as possible.

- Quite slow training. At each iteration step, the algorithm tests all the features on all the examples which requires a computation time directly proportional to the size of the features and examples sets. Imagine that the training set has many thousands of positive and negative examples and a complete set of 37520 features. However, the computation time is increased linearly with the size of the both sets.

#### The Weak Classifiers

This subsection shows how the Haarlike features can be used to build simple classifiers which need AdaBoost. The principle of the Boosting is to combine simple classifiers which are called weak learners. These weak learners are called weak because we do not expect even the best classification function to classify the data well, they only need to classify correctly the examples in more of 50% of the cases. One easy way to link the weak learner and the Haar features is to assign one weak learner to one feature. So the AdaBoost algorithm will select at each round the feature that provides the best separation between positive and negative examples.

#### From Features to Weak Classifiers

This subsection shows how to build the weak classifiers with the rectangle features. A feature response is a difference of the sum of pixels in neighbor regions. We hope that these responses then permit to distinguish positive and negative examples. For each feature and at each iteration of AdaBoost (because all the examples are re-weighted at each iteration, so the response to one feature of one example will not necessary be the same at each stage). In other terms, one weak classifier is a feature evaluation followed by an optimal thresholding. This threshold is optimal in the sense that the minimum numbers of examples are misclassified. We can summary this by the following formula: Aweak classifier  $h_j(x)$  consists of a feature  $f_j$ , a threshold  $\theta_j$  and a parity  $p_j$  indicating the direction of the inequality sign:

$$h_j(x) = \begin{cases} 1, & \text{if } p_j f_j(x) < p_j \theta_j \\ 0, & \text{otherwise} \end{cases} \quad (3.8)$$

$w x$  is an weighted example, as well positive as negative. It is weighted in the sense that all the examples are reweighted at each stage of the algorithm.

The next subsection shows how to find the optimal threshold for each feature.

#### The Optimal Threshold

Given one feature  $f_j$  and all the examples responses  $f_j(x_i)$ , training set to this feature, we want the threshold  $\theta_j$  that separates the best positive and negative examples. One easy method would be to approximate the positive and negative distributions by two Gaussian, with only two parameters for each Gaussian. This approach would work in theory in the sense that we only want classifiers which achieve more than 50% of detection rate. But in practice the distributions have for many features a great standard deviation such that lots of examples are not characterized by the appropriate Gaussian.

#### Ada Boost

History of Boosting and AdaBoost methods The chosen learning algorithm AdaBoost is a Boosting algorithm



sobefore explaining the use of AdaBoost in the context of face detection, basic theory about boosting will be introduced.

The Boosting theory takes its roots in the PAC learning [12]. They proved that a combination of simple learners, only better than random could yield a good final hypothesis. That is the main idea of what is called Boosting. AdaBoost (Adaptive Boosting) was introduced as a practical algorithm of the Boosting theory.

Let  $h_1, h_2, \dots, h_T$  be a set of simple hypothesis and consider the composite ensemble of hypothesis

$$f(x) = \sum_{i=1}^T \alpha_i h_i(x), \quad (3.9)$$

where  $\alpha_i$  denotes the coefficient with which the ensemble member  $h_i$  is combined. Both  $\alpha_i$  and  $h_i$  have to be learned during the boosting process.

In the beginning, Boosting algorithms were appreciated for their performances with low noise data. However, the first algorithms provided too bad results with noisy patterns due to overfitting so the applications of Boosting were limited.

On the other hand, AdaBoost can be viewed as a constraint gradient descent in an error function with respect to the margin. AdaBoost asymptotically achieves a large margin classification, that means that it concentrate its resources on a few hardtolearn patterns that are interestingly very similar to support vectors. [13].

Trying to improve the robustness of Boosting, it was interesting to clarify the relations between Optimization Theory and Boosting procedures. From here, it became possible to define Boosting algorithms for regressions [14], multi class problems, unsupervised learning and to establish convergence proofs for boosting algorithms by using results from the Theory of Optimization.

For details about Boosting applications, publications, softwares and demonstrations, see [15].

Introduction to Boosting and Ensemble Methods In this whole section, we focus on the problem of binary classification to stay in the context of face detection with the face class and the nonface class.

The task of the binary classification is to find a rule, which, given a set of patterns, assigns an object to one of the two classes.

Let  $X$  be the input space which contains the objects and we denote the set of possible classes by  $Y$  (In our case,  $Y = \{-1, +1\}$ ). The task of learning can be summarized as follow: Estimate a function  $f : X \rightarrow Y$ , using input, output training data pairs generated independently at random from an unknown probability distribution  $P(x,y)$ ,

$$(x_1, y_1), \dots, (x_n, y_n) \in R^d \times \{-1, +1\} \quad (3.10)$$

such that will correctly predict unseen examples  $(x,y)$ . In the case where  $Y = \{-1, +1\}$  we have a so-called *hard classifier* and the label assigned to an input  $x$  is given by  $y = f(x)$ .

The true performance of the classifier  $f$  is assessed by

$$L(f) = \int \lambda(f(x), y) dP(x, y), \quad (3.11)$$

Where  $\lambda$  is a chosen loss function. The risk  $L(f)$  is often called the *generalization error* in the sense that it measures the loss with respect to the example not observes

in the training set. For binary classification, we usually use the loss function  $\lambda(f(x), y) = I(y, f(x) \leq 0)$  where  $I(E)=1$  if the event  $E$  occurs and 0 otherwise. In other words,

$$\lambda(f(x_i), y_i) = \begin{cases} 1, & \text{if } x_i \text{ misclassified} \\ 0, & \text{Otherwise} \end{cases}$$

Since the probability distribution  $P(x,y)$  is unknown, this risk  $L(f)$  cannot be directly minimized. So we have to estimate a function as close as possible from *foptimal* based on the available information, i.e. the training examples and the properties of the function class  $F$  from which  $f$  is chosen. One classical solution is to approximate the generalization error by the empirical risk defined as follow

$$\hat{L}(f) = \frac{1}{N} \sum_{n=1}^N \lambda(f(x_n), y_n), \quad (3.12)$$

Is the case if the examples are uniformly distributed. If the training set is large enough, we expect that:

$$\lim_{N \rightarrow \infty} \hat{L}(f) = L(f)$$

one stronger condition is required to validate the last formula: The risk error  $\hat{L}(f)$  has to converge *uniformly* over the class of functions  $F$  to  $L(f)$ .

While this condition is possible for large size training sets, for small samples size large deviations are possible and over fitting might occur. If it is the case, the generalization

cannot be obtained by minimizing the training error  $\hat{L}(f)$ .

As Boosting algorithms generate a complex hypothesis, one may think that the complexity of the resulting function class would increase dramatically when using an ensemble of many learners. It is the case under some conditions.

Now discuss about a strong and weak model called PAC for learning binary classifiers.

Let  $S$  be a sample consisting of data points

$$\{(x_n, y_n)\}_{n=1}^N, \text{ where } x_n \text{ are generated independently at}$$

random from some distribution  $P(x)$  and  $y_n = f(x_n)$ , belongs to some known class  $F$  of binary functions. A strong PAC (Probably Approximately Correct) learning algorithm has the property that for every distribution  $P$ , every  $f \in F$  and

every  $\epsilon \geq 0, \delta \leq \frac{1}{2}$  the probability larger than  $1 - \delta$ , the

algorithm outputs a hypothesis  $h$  such that  $\Pr[h(x) \neq f(x)] \leq \epsilon$ . The running time of the algorithm should be polynomial in  $1/\epsilon, 1/\delta, n, d$ , where  $d$  is the dimension (appropriately defined) of the input space. A weak PAC learning algorithm is defined without any constraints, except that it is only required to satisfy the conditions for particular  $\epsilon$  and  $\delta$  rather than all pairs.

Consider a combination of hypothesis as shown in 3.9. There are many approaches for selecting both the coefficients  $\alpha_i$  and the base hypothesis  $h_i$ . In a Bagging

approach, the hypothesis  $\{h_i\}_{i=1}^T$  are chosen based on a set of  $T$  bootstrap samples, and the coefficients  $\alpha_i$  are set to



$\alpha_t = 1/T$  (see [16] for detailed Bagging approach). The advantage of this simple method is that it tends to reduce the variance of the overall estimate  $f(x)$ . The AdaBoost algorithm is a more sophisticated algorithm for boosting the combination of the hypotheses. It is called Adaptive in the sense that examples that are misclassified get higher weights in the next iteration, for instance the examples near the decision boundary are harder to classify and therefore get high weights in the input set after the first iterations. The next figure illustrates AdaBoost learning on a 2D data set.

**ADABOOST CONCEPT**

- Adaboost starts with a uniform distribution of “weights” over training examples. The weights tell the learning algorithm the importance of the example.
- Obtain a weak classifier from the weak learning algorithm,  $h_t(x)$ .
- Increase the weights on the training examples that were misclassified.
- (Repeat)
- At the end, carefully make a linear combination of the weak classifiers obtained at all iterations.

$$f_{\text{final}}(\mathbf{x}) = \alpha_{\text{final},1} h_1(\mathbf{x}) + \dots + \alpha_{\text{final},n} h_n(\mathbf{x})$$

Ada Boost is explained here, it will be discussed after in detail

**Algorithm 1 The AdaBoost algorithm. [17]**

1. Input  $S = \{(x_1, y_1), \dots, (x_N, y_N)\}$  Number of iterations T.

2. Initialize:  $d_n^{(1)} = 1/N$  for all  $n=1, \dots, N$ .

3. Do for  $t=1, \dots, T$ .

(a) Train Classifier with respect to the weighted sample set  $\{S, d^{(t)}\}$  and obtain hypothesis

$$h_t : X \rightarrow \{-1, +1\}, \text{ i.e. } h_t = L(S, d^{(t)}).$$

(b) Calculate the weighted training error  $\epsilon_t$  of  $h_t$ .

$$\epsilon_t = \sum_{n=1}^N d_n^{(t)} I(y_n \neq h_t(x_n)),$$

(c) Set :

$$\alpha_t = 1/2 \log \frac{1 - \epsilon_t}{\epsilon_t}$$

(d) Update the weights:

$$d_n^{(t+1)} = d_n^{(t)} \exp\{-\alpha_t y_n h_t(x_n)\} / Z_t,$$

Where  $Z_t$  is normalization constant, such that

$$\sum_{n=1}^N d_n^{(t+1)} = \mathbf{1}.$$

4. Break if  $\epsilon_t = 0$  or  $\epsilon_t \geq 1/2$  and set  $T=t-1$ .

5. Output:  $f_r(x) = \sum_{t=1}^T \frac{O_t}{\sum_{t=1}^T O_t} h_t(x).$

To understand this fundamental algorithm, the main steps are detailed in the following paragraphs.

**AdaBoost Step by step AdaBoost**

Is an aggressive algorithm which selects one weak classifier at each step A weight ( $d^{(t)} = d_1^{(t)}, \dots, d_N^{(t)}$ ) is assigned to the data at step  $t$  and a weak learner  $h_t$  is constructed based on  $d^{(t)}$ . This weight is updated at each iteration. The weight is increased for the examples which have been misclassified in the last iteration.

The weights are initialized uniformly:  $d_n^{(1)} = 1/N$  for the general version of AdaBoost but how it is modified to adapt AdaBoost to our face detection problem. To estimate if an example is correctly or badly classified, the weak learner produces a weighted empirical error defined by:

$$\epsilon_t(h_t, d^{(t)}) = \sum_{n=1}^N d_n^{(t)} I(y_n \neq h_t(x_n)). \quad (3.13)$$

Once the algorithm has selected the best hypothesis  $h_t$ , its weight  $\alpha_t = 1/2 \log \frac{1 - \epsilon_t}{\epsilon_t}$  is computed such that it

minimizes a loss function. One of the possible loss function considered in AdaBoost is:

$$G^{AB}(\alpha) = \sum_{n=1}^N \exp\{-y_n(\alpha h_t(x_n) + f_{t-1}(x_n))\}, \quad (3.14)$$

where  $f_{t-1}$  is the combined hypothesis of the previous iteration given by:

$$f_{t-1}(x_n) = \sum_{r=1}^{t-1} \alpha_r h_r(x_n). \quad (3.15)$$

The iteration loop is stopped if the empirical error  $\epsilon_t$  equals 0 or  $\epsilon_t \geq 1/2$ . If  $\epsilon_t = 0$ , the classification is optimal at this stage and so it is not necessary to add other classifiers. If  $\epsilon_t \geq 1/2$  the classifiers does not respect the weak condition anymore. They are not better than random selection so AdaBoost cannot be efficient at all. (see 3.3.3.3) Finally, all the weak hypotheses selected at each stage  $h_t$  are linearly combined as follow:

$$f_T(x) = \sum_{t=1}^T \frac{\alpha_t}{\sum_{r=1}^T \alpha_r} h_t(x) \quad (3.16)$$

The final classification is a simple threshold which determines if an example  $x_i$  is classified as positive or negative. Other similar algorithms such as LogitBoost or Arcing algorithms use different loss functions.

**Leverage of the Weak Learners**

At each iteration, AdaBoost, constructs weak learners based on weighted examples. We will now discuss the performances of these weak learners based on re-weighted examples.

**Convergence of the Training Error to Zero**

We have seen just before that under some appropriate conditions, that the weighted empirical error could be

smaller than  $\frac{1}{2} - \frac{1}{2}\gamma, (\gamma > 0)$  We will now explain how this condition can imply a strong and fundamental result for AdaBoost (it can be generalized to most of Boosting algorithms): The condition  $\epsilon_r (h_r, d) \leq \frac{1}{2} - \frac{1}{2}\gamma, (\gamma > 0)$  is sufficient to ensure that the empirical error of the strong final hypothesis approaches zero as the number of iterations increases. The proof of this important property of AdaBoost is given in this paragraph. Let  $f$  be a real-valued classification function. The classification is performed using  $sign(f)$  but we will work with the actual value of  $f$ . Let  $y \in \{-1, +1\}$  be the labels of the binary classification and  $f \in R$ , we define the margin of  $f$  at the example  $(x_n, y_n)$  as :

$$\rho_n(f) = y_n f(x_n). \tag{3.20}$$

Consider the following function defined for  $0 \leq \theta \leq \frac{1}{2}$

$$\varphi_\theta(z) = \begin{cases} 1, & \text{if } z \leq 0 \\ 1 - \frac{z}{\theta}, & \text{if } 0 < z \leq \theta \\ 0, & \text{otherwise} \end{cases} \tag{3.21}$$

Let  $f$  be a real-valued function taken values in  $[-1, +1]$ . The empirical margin error is defined as :

$$\hat{L}^\theta(f) = \frac{1}{N} \sum_{n=1}^N \varphi_\theta(f(x_n), y_n). \tag{3.22}$$

If it is obvious from the definition that the classification error, namely the fraction of misclassified examples, is given by  $\theta = 0$ .

We note that we often use the so-called 0/1-margin error defined by:

$$\hat{L}^\theta(f) = \frac{1}{N} \sum_{n=1}^N I(f(x_n), y_n) \leq \theta. \tag{3.23}$$

Noting that  $\varphi_\theta(yf(x)) \leq I(yf(x) \leq \theta)$ , (3.24)

$$\hat{L}^\theta(f) \leq \tilde{L}^\theta(f). \tag{3.25}$$

**Generalization Error Bounds**

We know that the training error produced by AdaBoost approaches exponentially zero as the number of iterations increases. However, as the examples of the training set are manually labeled, it is not really interesting to know that these examples are well classified. It will be wiser to see how efficient the final model is on other dataset which haven't been used for the training. The error committed on this new dataset (with positive and negative examples) is called the generalization error and it will be shown in this paragraph how it can be bounded. Recalling that AdaBoost, such as all learning algorithms can be viewed as a procedure for mapping any data set

$$S = \{(x_n, y_n)\}_{n=1}^N \tag{3.26}$$

to some hypothesis  $h$  belonging to a hypothesis class  $H$  consisting to functions from  $X$  to  $\{-1, +1\}$ . We want to test the performance of the hypothesis  $f$  on future data,

considering that  $\hat{f}$  and  $S$  is random variables. Let  $\lambda(y, f(x))$  be a loss function which measures the loss caused by using the hypothesis  $f$  to classify input  $x$ , the true label of which is  $y$ . The loss expected is given by

$$L(h) = \lambda(y, f(x)) \tag{3.27}$$

where the expectation is taken with respect to the unknown probability distribution generating the pairs  $(x_n, y_n)$ : We will use the following loss function:

$$\lambda(y, f(x)) = I[y \neq f(x)] \tag{3.28}$$

Vapnik [19] proved a classical result about the empirical classification of binary hypothesis  $f$ , to the probability of error.

**Adaptation to Face Detection**

The algorithm presented in the previous paragraph is not specific to face detection. This new subsection will explain how the algorithm can be adapted to our face detection context, particularly with the introduction of an asymmetric classification. AdaBoost, as described in 1, is an algorithm which minimize the classification error (or generalization error) but it does not minimize the number of false negative as explained in 3.1.2. There are several methods to modify AdaBoost in order to obtain an asymmetric algorithm, asymmetric in the sense that we want to increase the influence of the positive examples which have been misclassified earlier in the process in order to minimize the false negative rate, i.e. the rate of the faces which are missed.

One first simple mean would be to unbalance the initial distribution of the positive and negative examples as in [20]. If we want to minimize the false negatives, we can increase the weight on positive examples so that the minimum error criteria will also have very low false negatives. This idea can be introduced by changing the loss function in a non symmetric loss function.

Recall that the classical AdaBoost minimizes

$$\prod_t Z_t = \sum_i \exp(-y_i \sum_t h_t(x_i)). \tag{3.31}$$

Each term in the summation is bounded above by the loss function from

3.28:

$$\exp(-y_i \sum_t h_t(x_i)) \geq \lambda_i(y_i, f(x_i)) = I[y_i \neq f(x_i)], \tag{3.32}$$

where  $\lambda_i$  is the loss function. It follows that minimizing  $\prod_t Z_t$  minimizes an

upper bound on simple loss. So we can introduce the asymmetric loss defined

by:

$$\lambda_i = \begin{cases} \sqrt{k}, & \text{if } y_i = 1, \text{ and } f(x_i) = -1 \\ \frac{1}{\sqrt{k}}, & \text{if } y_i = 1, \text{ and } f(x_i) = 1 \\ 0, & \text{otherwise} \end{cases} \tag{3.33}$$

where false negative cost  $k$  times more than false positives. If take 3.32 and multiply both sides by  $\exp(y_i \log \sqrt{K})$  we find :

$$\exp(-y_i \sum_t h_t(x_i)) \cdot \exp(y_i \log \sqrt{K}) \geq A \lambda_i \quad (3.34)$$

In order to minimize this bound, we can use a non-uniform weight initialization:

Modify 2 in AdaBoost algorithm 1 by

$$d_n^{(1)} = \exp(y_i \log(\sqrt{k})) / N.$$

Updating the weights will become:

$$D_{i+1}(i) = \frac{\exp(-y_i \sum_t h_t(x_i)) \cdot \exp(y_i \log(\sqrt{k}))}{\prod_t z_t} \quad (3.35)$$

The modification of the pre-weighting is transmitted through the second term of the numerator. This new weighting process permits to reduce efficiently the false negative rate. However, the effects of the unbalanced weights are lost after the first iteration. In fact, the AdaBoost algorithm seems to be too greedy. The first classifier absorbs the effects of the asymmetric weights. AdaBoost selects thus a small set of features and as detailed in section 4.2, good results can be obtained with some 201 features. The first features selected in the process can be quite easily interpreted: they emphasize on particular features of faces. The eye region is often darker than the front and the nose bridge is brighter than the eyes. However, this is not enough to reach the fixed goal of our project. The computation time for a 201 features classifier is too large to satisfy us. We will introduce a way to combine classifiers in cascade in order to focus quickly on the regions of interest.

**Classification in Cascade**

We know how to select a small number of critical features and to combine them into a strong classifier. However, we need to introduce a new main contribution in our face detection system in order to reduce significantly the computation time. This contribution is an attentional cascade which furthermore achieve better detection performances. We have seen that it is possible to minimize the number of false negatives instead of classical training error that is precisely the main idea that will be used to build this cascade classifier.

**Why is it so Efficient?**

The principle is to reject quickly the majority of negative windows while keeping almost all positive examples and then focus on more sensitive sub-windows with more complete classifiers. To do that, the first stages in the cascade will contain only few features, which achieve very high detection rates (about 100 %) but will have a false positive rate of roughly 40 %. It is clear that it is not acceptable for a face detection task but combining successively many of these stages which are more and more discriminant will permit to reach the goal of fast face detection. We can just compare this cascade structure with a degenerated decision tree. If a sub-window is classified as positive at one stage, it proceeds down in the cascade and will be evaluated by the next stage. It will be like this until this sub-window is found negative by one stage or if all the stages classify it as positive. In this last case, it will finally be considered as a positive example. The Figure 3.4.1 shows this cascade process.

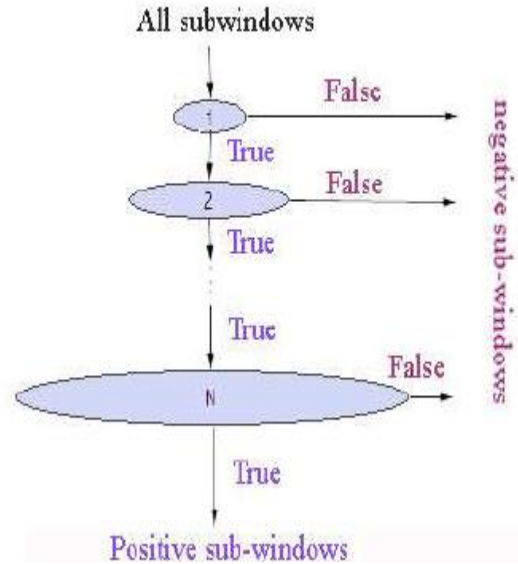


Figure 17: Schematic description of cascade detection.

the goal of the project is to detect faces in images which contain few faces. Noticing that there are about 25.000.000 windows in a 100 X100 image for only a few faces, the great majority of windows are negative ones. So it is a real gain of time to reduce quickly this number. Even if the last stages of the cascade are based on many thousand features, they will be called only for few sub-windows.

**Building More Consistent Classifiers**

We have defined the cascade as a succession of classifiers. The first ones are quite simple but as we progress in the cascade, the classifiers have to be more consistent. This paragraph describes how such more consistent classifiers can be built at each stage.

First of all, the last stages of the cascade have more features than the first ones. The AdaBoost algorithm generates a training error which decreases theoretically exponentially with the number of iteration. If there are more features (i.e. AdaBoost has been ran with more iterations) the final classifier is more discriminant between positive and negative examples, in other words, we can say that such classifier are “stronger” than classifiers with few features (i.e. few iterations). The second but not less important reason for using a cascade classification is the way chosen to select the training set. At each learning step, the classifier or the *i*th stage, so-called *i*th classifier is tested on a test set of negative examples. All the misclassified examples are kept for the (*i*+ 1)th classifier such that the (*i*+1)th classifier will focus on harder examples than ordinary ones. By this mean, we force the further classifiers to have better false positive rate.

**Training a Cascade of Classifiers**

The goal of the cascade detection is to achieve given both false positive rate and detection rate. The choice of these goals is arbitrary. Typically, past systems have achieved detection rates between 83 and 94percent and false positive rate on the order 10<sup>-4</sup>. The number of features in each stage and the total number of stages will depend of these constraints. Let F be the false positive rate of the cascaded classifiers, K the number of classifiers and *f<sub>i</sub>* the false

positive rate of the  $i$ th classifier on examples that get through to it. For a given trained cascade of classifiers,  $F$  is given by

$$F = \prod_{i=1}^K f_i, \quad (3.36)$$

Then the detection rate can be computed as:

$$D = \prod_{i=1}^K d_i, \quad (3.37)$$

Where  $d_i$  is the detection rate of the  $i$ th classifier on the examples that get through to it. To fix the ideas, an example is given here. If we want to achieve a detection rate of 90 percent, we can build a 10 stage classifier in which each stage has a detection rate of 0.99. Indeed,  $0.9 \cong 0.99^{10}$ . If each of these stages rejects 70 percent of negatives (i.e. a false positive rate of 30 percent), the total false positive rate is  $0.30^{10} \cong 6.10^{-6}$ . The number of features evaluated when scanning real images is necessarily a probabilistic process. Any window will progress down through the cascade, one classifier at a time, until it is decided that the window is negative or, in really rare cases, the window succeeds in each test and is labeled positive. The behavior of this process is determined by the distribution of the images of the test set. The main tool which can measure the performance of a given classifier is its positive rate, which is the proportion of windows which are labeled as potentially containing the object of interest. Given a number of stages in the cascade  $K$ , the positive rate  $p_i$  of the  $i$ th classifier. Let  $n_i$  be the number of features in the  $i$ th stage. The expected number of features which are evaluated is given by:

$$N = n_0 + \sum_{i=1}^K (n_i \prod_{j<i} p_j) \quad (3.38)$$

We can notice only few examples are objects, that is why the positive rate is almost equal to the false positive rate. As it was explained in section 3.3.3.7, the original AdaBoost algorithm has to be modified to ensure the minimization of the false negative rate instead of the training error. One simple way to impose that is to adjust the final threshold. Increasing this threshold will affect badly the detection rate and improve the false positive rate, while the opposite will yield lower detection rate with higher false positive rate. The main problem is that it has never been proved that modifying the AdaBoost theoretical training threshold preserves the guarantees in terms of generalization error.

The cascade structure has three main parameters that we have to determine:

The total number of classifiers:  $K$

The number of features  $n_i$  of each stage

The threshold  $\theta_i$  of each stage  $i$ .

Finding the three optimal parameters is quite complicated if we keep in mind that we want to minimize the computation time of the total classification. The principle is to increase the number of features and of stages until the given detection objective are reached.

Given the minimum acceptable rates  $f_i$  (false positive rate for the  $i$ th stage) and  $d_i$  (detection rate for the  $i$ th stage), the detection rate  $d_i$  is reached by decreasing the AdaBoost threshold  $\theta_i$  and this also directly affects  $f_i$ . We increase the

number of features  $n_i$  in the  $i$ th stage until  $f_i$  is obtained. The general principle of the cascade learning is given in the algorithm 2 :

One major factor for the efficiency of the cascade learning is the management of the sets during the training. Usual training sets are used for the first stage, and then, at each iteration, the current stage classifier is evaluated on a validation set in order to minimize coherent false positive and false negative rates. It would obviously be unskilled to evaluate  $F_i$  and  $D_i$  on the training set which was used to obtain the model because these values would be evaluated much better than with other examples. Then, at each stage we reinitialize the negative training set. Once the objectives  $F_i$  and  $D_i$  are reached for the stage  $i$ , the current model is tested on a large negative set chosen randomly and many false positive alarms are introduced into the negative training set for the stage  $i - 1$ . As the new negative training set is made with examples which have been misclassified by the stage  $i$ , the stage  $+ 1$  will be built with examples which can be considered as "hard examples". So, the more we go down into the cascade, the more critical the examples are, and the last stages in the cascade are more robust models which discriminate better positives and negatives than the first stages. Since the large majority of negative windows have been rejected by the first stages, even if the further stages need more computation time to classify the windows, only few windows have passed earlier stages and the global computation time is not too much affected by these last discriminant stages.

### Scanning

As explained with the definition of the integral image in 3.2.3, the scanning of an input image is quite simple and efficient with the integral image representation. To detect faces of different sizes and places in an image, we will apply scaled and shifted detectors all over the image. Our basic detector is a  $20 \times 15$ . All the images used to train the model, as well as faces as non faces are of this size, and accordingly, all the selected rectangular features that we have to apply in the windows are defined in this  $20 \times 15$  basic window.

Although the scanning process seems to be simple at the first sight we need to take some care while rescaling the detector if we want to preserve the efficiency of the model. See A.1 for details about the implementation issues about the scanning window.

Once all the possible windows have been scanned all over the image, we have to integrate a process which clusters the multiple detections of a single face in order to have finally one bounding box around one face. It is clear that the shifting of the window at different scales using a small shift step and a small scaling step permits to detect all the faces of any size and position. However, one face may be detected several times during the scanning process (by neighbor windows or very close scales at the same position). The chosen method to cluster these multiple detections is to cluster all the positive windows which are close enough. Then the center of the resulting bounding box is simply the gravity center of all the centers in the cluster and the size is the mean of all the sizes. Let  $\{c_1, c_2, \dots, c_n\}$  be the centers of the windows in

a cluster containing  $n$  windows and  $\{w_1, w_2, \dots, w_n\}$  their respective width (The height of the window is directly given and preserved by the constant ratio  $r = h / w$ ). The center

of the cluster is given by:  $c = \frac{1}{n} \sum_{i=1}^n c_i$  and the final

width is simply  $w = \frac{1}{n} \sum_{i=1}^n w_i$ .

### Algorithm 2 Learning in Cascade.

1. Input: Definition of the targets of the learning  
 $f$  the maximum acceptable false positive rate per stage.  
 $d$  the minimum acceptable detection rate per layer  
 $F_{target}$  the false positive rate desired at the end of the process.

$P$  the set of positive examples  
 $N$  the set of negative examples

2. Initialization:

$F_0 = D_0 = 1$

$i = 0$  the number of the current layer.

3. Main loop:

While  $F_i > F_{target}$

$i \leftarrow i + 1$

$n_i = 0$

$F_i = F_{i-1}$

While  $F_i > f \times F_{i-1}$

\*  $n_i \leftarrow n_i + 1$

Train a classifier using AdaBoost with  $P$  and  $N$  as training set.

Compute  $F_i$  and  $D_i$  for the current classifier with the validation set.

Decrease the threshold of the classifier until the detection rate for the  $i$ -th classifier is at least  $d \times D_{i-1}$ :

$D_i \geq D_{i-1} \cdot d$

– Empty the negative training set.

– If  $F_i > F_{target}$ , evaluate the current cascade classifier on a set of negative examples and put any false detections into the set  $N$ .

Experiments and Results this Section exposes the different results obtained by the face detector that has been developed. We will discuss our choices, try to interpret some results such as the power of the selected features and finally estimate the global performances of the system. Of course, all these results are obtained in specific conditions and we will particularly pay attention to explain these testing conditions. The first step we will focus on is the choice of the datasets because it influences a lot the quality of the learning (and the evaluation of the results). Then, an important step is the result of the learning algorithm, how does AdaBoost perform? What kinds of features are selected? What are the different training rates which can fix the quality of the learning? Then in which way the cascade implementation improves the face detection will be explained. The final section relates about the performances of the final detector tested on a particular Testing Set.

### Datasets

The Datasets represent all the images that we use for our face detection task. It is really important to notice that the

choice of the datasets is crucial for the learning and the tests on the detectors. We can separate the Datasets as follows:

- Learning Data
- Testing Data

Learning Data: It clusters all the examples that have been used to train and test the different classifiers. There are some positive and negative examples. On one side there are positive examples which are faces extracted from different sources: Banca database (see [39]), the BioID images (can be found in [38]) and XM2VTS [40]. The faces are thus pictures from different acquisition conditions and lightning conditions. Concerning the Negative examples (non faces), they have to represent the best the backgrounds that can be found in real situations. Thus we just extract them randomly from the web in images without faces. It is hard to know a priori which images are the most representative of the non face class and the number of non faces that we need to train the classifier. However a bootstrap method will select non face images that are the hardest to classify and so to find more precisely the boundary between the face and non face classes. The images from the various Databases are of different sizes and the faces are more or less cropped while our learning set has to be homogeneous in term of size and face repartition. As most of the faces are higher than larger, we have chosen a rectangular window of 20x15 pixels. All the faces have been cropped and rescaled if necessary in order to respect this basic detector size. (We notice that the examples are effectively low resolution ones as imposed in the context of the detection.)

Training Set : It is the input of AdaBoost for the monostage classifier (to train some 500 features) and for the first stage of a learning in cascade. Recall that one of the limitations of AdaBoost is the large influence of the input data on the boosting results, the choice of the training set needs particular careful. The use of diverse databases is well adapted because images from a single database are often taken from similar conditions. For example, faces of the BANCA database have a lot of variety in the sense that people do not always look exactly at the camera but the lightning conditions are quite troublesome because the light often comes from one side of the face. Regrouping the different sources, we have 8257 faces and more than 300.000 non faces. Testing Set : Once a classifier has been trained using AdaBoost, we have to train it on another set of images (both positive and negative images). Thus we can obtain the test error of the classifier. In the case of the cascade, this set is used during the learning to test the current cascade. The misclassified examples become the train examples of the next stage. Thus each stage is directly adapted to the efficiency of the previous ones, in the sense that it is trained from the examples that have been badly classified by the previous stages. For the monostage classifier, we have 60.000 non faces built by an intermediate detector and 8257 faces. The examples used by the cascade are the same as the ones used in the training set.

Validation Set: This set is used to test the performances of the cascade:

Some images are presented to the final cascade detector and it permits to evaluate the global quality of the detector. Testing Data : Images from the CMU: They represent many real situations with several faces and unconstrained background. They are used to test the final classifier using a scanning window. They are the most used Test images

because they englobe a large radius of real situations and the exact position of the faces in these images has been manually labeled in a groundtruth file containing the position of the eyes. This set differs from the learning set because the images are not 20x15 ones. The sizes of the images vary (roughly from 80x80 to 750x750). Testing these images allows to evaluate the detection rates, the speed of the detector (and the scanning window) and the behavior of the scaling system.

### Learning Results

This section explains the performances of AdaBoost and all the learning process in general by giving the results of different classifiers trained with different parameters such as the dataset used number of features, the number of stages in the cascade, etc...

#### Weakness of the Weak Classifiers

It has been shown in theory that the weak classifiers used to train with AdaBoost need to satisfy one condition. They have to be better than random selection. That means that they have to classify correctly the examples in at least 50% of cases. Let us look how evolves the error rate of the selected features. The model used is trained with 3000 faces and some 30.000 non faces. The results are shown in Figure 4.1. We can notice that the best feature (the first selected by AdaBoost) misclassifies roughly 13% of the examples (faces and non faces are treated indifferently), while this error rate increases quickly until more than 40% for the last selected features. That shows clearly why the feature responses followed by a threshold are qualified of weak. It proves that the challenge of boosting is to organize many of these weak classifiers into a linear combination followed by another final threshold.

#### Test results

##### Monostage

Classifier Let us see what are the performances of a single stage classifier trained with about 37.520 features, 3000 faces and 30.000 non faces chosen by bootstrapping (false alarms from a previous simple classifier.) To evaluate the learning performances, i.e. the classification rates after the Boosting process, we have to recall the definition of two of the main evaluation errors:

1. The Training error noted which is the error rate made on the training set:

$$\epsilon_{tr} = \frac{1}{N_{tr}} \sum_{i=1}^{N_{tr}} |H(x_i^{(tr)}) - y^{(tr)}(x_i^{(tr)})|,$$

Where  $N_{tr}$  denotes the total number of training examples (positive + negative),  $x_i^{(tr)}$  the  $i$ -th example and  $y^{(tr)}$  the label of the  $i$ -th example. The theory about Boosting shows that this training error tends to 0 when the number of iterations increases.

2. The Testing error noted  $\epsilon_{te}$  which is the error rate made on the testing set:

$$\epsilon_{te} = \frac{1}{N_{te}} \sum_{i=1}^{N_{te}} |H(x_i^{(te)}) - y^{(te)}(x_i^{(te)})|,$$

Where  $N_{te}$  denotes the total number of training examples (positive +negative),  $x_i^{(te)}$  the  $i$ -th example and  $y^{(te)}$  the label of the  $i$ -th example.

In this first experiment, the testing set is made of 6.000 faces taken from the Banca Database and a part of the BioID database, while we use 30.000 randomly selected non faces. The Figure 4.2 shows the obtained results.

### The Multiple Detections

As it is shown in the last figures, it is difficult to see and evaluate clearly which are the regions of the images that contain faces. Indeed, many bounding boxes often frame a single face and the arbitration is made by the integration of multiple detections. Here are some pictures before and after the multidetection algorithm.

The integration of these multiple detection is quite intuitive. All the detected windows in the image are clustered. Two windows are clustered together if their recovering area is higher than a predefined threshold. Then for each cluster, the final window is computed as the mean of the windows in the cluster. Thus, the center of the final window is the gravity center of all the centers and the definitive size is the mean of the size. One problem may arise when two faces are very close. In fact, when neighbor windows containing two close faces are detected, they are clustered together and so the resulting window can be between the two faces. Thus both of the faces may be missed.

To solve this problem, we can introduce another condition to cluster two windows together. The difference of their sizes has to be larger than a predefined threshold. Another implementation which may be more appropriate would be the use of median windows instead of simple mean window. This is let to a future work.

### The Cascade Classifier

In this project, a cascade of classifiers has been developed. The final version of the cascade was built as follows. First of all, we had to choose the training examples and the cascade parameters which determine the number of stages and the number of features in each stage.

We use an initial set of about 340.000 negative examples. This set is built by bootstrapping and then, each example is symmetrized in order to ensure he invariability to face illumination orientation. We have a total of 8500 faces.

The goal of the cascade is to apply classifiers more and more specialized when we go through the process. To reject quickly the great majority of negative windows while keeping a high detection rate, during the learning process, we start with roughly 340.000 negative examples. Then, at each stage, only the examples that are considered as positive are kept for the next training set. Thus, the stages in the process are directly trained to classify the examples that have been misclassified by the previous ones. The examples that are hardest to classify are left to the last stages of the cascade. Thus we have trained a cascade of 25 stages.

### Scanning Implementation

Like the most of the Image-based methods, we use a sliding window to scan the images. The implementation of this sliding window needs some care for different reasons if we want to obtain good results in term of detection rate and speed.

Once again our basic detector is 20 X 15 pixels and that the training of the classifiers using AdaBoost has been made



with examples of the same size. We want to detect faces from different scales and positions so we have to re-scale this basic detector along the scanning process. We have seen that the Integral representation permits to re-scale the detector instead of using a traditional image pyramid, i.e. no down-sampling is needed to scan the image at different scales.

Let us see how to re-scale the basic window of  $h \times w$  where  $h$  and  $w$  are respectively the height and the width of the initial window. Suppose that we want to re-scale this window by a factor of  $\Delta = 1.25$ . It is clear that the  $h$  and  $w$  values are integers so we have to make an approximation to obtain a window at the next scale. We choose to preserve the ratio  $r = h/w$  to keep a window of the same shape as the basic detector. Thus, the size of the window rescaled by  $\Delta$  is:

$$\lfloor \Delta \cdot h \rfloor \times \left( \left\lfloor \frac{r}{\Delta} \cdot h \right\rfloor \right)$$

Where  $\lfloor \_ \rfloor$  represents the rounding operation towards the largest integer smaller than the argument. The problem is now to re-scale the Haar-like features which have been selected by AdaBoost. For example, consider a 2-rectangle feature as defined in Figure:

Denote  $x$  and  $y$  the coordinates of the up left corner of the feature,  $h_f$  and  $w_f$  the height and width of the feature. We choose another time to keep the ration between height and width such that  $r = h/w = x/y = h_f/w_f$ . So the feature is rescaled and moved proportionally in the window. The problem is that rounding the values of the coordinates of the rectangle's corners changes a few the properties of the mask. The rescaled mask is one mask which is maybe not so good than the basic one, and it would maybe not be selected by AdaBoost. However, there is no other possibility than making an approximation. The experiments made on several set of images shows that this issue has not too bad consequences on the final results. In fact choosing sufficiently small shift step and scale step ensure to detect faces in different scales so even if a face is missed because the imprecision of one scale, it is in most of the cases detected at other scales.

### Ada Boost Implementation

We have seen that AdaBoost is a powerful learning algorithm which selects the best weak classifiers given a set of training images. One of the main drawbacks is that the result depends highly on the size and consistence of the datasets. Our final choice has been to choose a training set containing some 340.000 negative examples and more than 6000 positive ones. Recalling that there are 37518 features, the computing time during the learning is quite long as well as the memory used is big.

For example, if we want to build a simple mono-stage classifier using 200 features. The first step is to write the integral images of all the positive and negative examples. Considering our 308.000 images  $15 \times 20$  (which means 300 integers per image) written into a binary format, the integral image file takes 352 Mb on the disk. Then, given these integral images, we have to compute the total set of features responses. Indeed, as the same feature responses are used at each learning step, it would be too heavy to compute them at each iteration. A feature response is an integer (sums and

differences of integers) and we have a total of 37518 features which means that a single file containing all the features responses. Assuming that this file would be created, we have then to read it completely at each iteration step (It can not be loaded into the memory in one time, of course). It would take many days to build a classifier with these data.

In order to improve that, we have chosen to work using a parallel implementation to distribute the work on several processors. For this we have used the MPI (Message Passing Interface) library. The cluster on which we have provided the training has 5 machines and we just launch 2 processes on each machine so we have a total of 10 processes that can work in parallel. The parallel method chosen in a traditional master slave implementation. The master process (Process 0) sends the respective data to each of the 10 slave's processes and then clusters all the independent results. In the practice, the repartition of the processes is made as follow: As we have to evaluate and compare the features responses for 308.000 images and 37518 features, each slave process will treat 3751 features for all the images.

The process 0 sends the image weights to each slave process, then each process finds, independently of the others, the best feature into the set of 3751 and send the results back to the process 0 (the index of the best feature and the corresponding classification error). Finally, the master processes compare the results of the 10 processes and extract the best of the 10. Then the weights are reevaluated and a new iteration begins with the new weights. Thus the total computing time is reduced by a factor of 10 (or a few less if we take into account that all the processes have access to the same hard-disk in the same time).

## RESULTS

This section gives the main results that have been obtained using a cascade of 14 classifiers. The first stage has five features while the second one has seven. The number of features increases until the last stage which has 40 features. The first stages reject a great majority of negative examples, those which are easy to distinguish from faces and then as the number of stages increases, the remaining examples are harder to reject. The last stage focuses only on few examples hard to classify which we could call face-like examples. The evaluation of the performances of the classifier can be divided into two groups: the test on the test set made of 8500 faces and about 900.000 non faces and the test on the CMU Dataset. The detector has been tested on the MIT-CMU frontal face test set [23]. We have 132 images with a total of 507 frontal faces. The performances of the detector can be placed at every functioning point. By changing the final threshold of the detection, we can modify the detection rate and the false positive rate.

Decreasing the threshold will yield a better detection rate (100% if the threshold equals 0) but the false positive rate will increase slightly. On the other hand, increasing the threshold will decrease the number of false alarms and also the detection rate. We can choose the threshold depends on the goals of the detector. In our case, we want a high detection rate so the threshold will be quite low. In these tests, we use a shifting step of 1 pixel for the scanning window and a scale factor of 1.20. The next figures show some results using this detector. The detector using these 14 stages is robust and quite efficient on the CMU Dataset. We obtain 86% of detection rate considering the 500 faces in the

test set and 52 false alarms. 86% of detector rate may appear insufficient but we have to take into account the content of the CMU set. Some of the 500 faces in the 130 images are not well adapted to be detected by our cascade. In fact some of the faces are not really frontal faces but more profile views, other faces are manually drawn or photographs of cards and these kinds of examples were not in our training set. So they were not supposed to be classified as faces.

We have also used these examples and taken them into account in our test because they already were used in testing previous detectors. Thus we can compare our work with existing methods. Our detector is quite efficient on this set even if Viola's detector is more efficient. We can notice that Viola's detector contains 30 stages with more features which yields lower false positive rate. The detector has also been tested on video sequences. We have applied our detector on 220 images successively. The situation is a classical real time application: a video camera was placed in a corridor and some people crossed the scene. The detector is quite efficient and it permits us to evaluate the power of the features. In fact, faces were quite well detected during the sequence but not in every image. A well detected face in the image number  $i$  was not necessarily detected in the image  $i + 1$  even the visual difference between the two images is very low. That shows the detection is really precise. A single pixel may have a lot of weight in the detection. We have to notice that in this test, no time integration was used.

**Conclusions and Future Work**  
 Conclusion Many methods can be used existing in a precise context for each of those methods. We have chosen an intermediate method between the image based and the feature based detection method. A face detection system has been developed using a Boosting algorithm and simple rectangular Haarlike features. The boosting characteristics are- iterative, successive classifiers depends upon its predecessors, look at errors from previous classifier step to decide how to focus on next iteration over data.

This method presents many advantages in comparison with other methods for detecting faces.

- The frontal face detector yields very good detection performances (in term of ratio over detection rate and false positive rate).
  - The performances can be highly increased in specific applications. In fact, if the face detector is placed in a fixed scene, the training set can be adapted to this scene to build a robust detector.
  - The computation of the classifier is very fast because of the use of simple rectangular features which are easily computed with the integral image.
  - The method can be easily adapted to other kind of application such as pedestrian detection for example. The principle is to change the training sets.
- AdaBoost has achieved great success, however, we have to recall that this method, as every face detection method has its own limitations:

- The training process could be unmanageable when the number of features is extremely large;
- The same weak classifier may be learned multiple times from a weak classifier pool, which does not provide additional information for updating the model;

- There is an imbalance between the amount of the positive samples and that of the negative samples for multi-class classification problems.
  - The detector has been trained with only frontal faces with uniform pose.
  - It is difficult to predict the optimal values of some parameters. It is the case, for example, of the number of training examples. The efficiency of the final detector depends directly on this dataset. The main problem remains the generalization power of the trained model. If the model is efficient on the train data set, we do not know a priori how it acts on the testing data. Particularly, if the train set is too complete, the classifier will be too specialized on the train faces and some faces may be missed on real set images.
  - This detection of low resolution images gives the position of eventual faces and an idea of their size. However we do not have a precise position of the faces.
  - We do not know precisely the position of the eyes for examples such that a further face analysis may be applied in some applications.
  - The performance of boosting on a particular problem clearly relies on the particular data and the choice of the weak learner. In some cases boosting may fail to perform well, especially for the data with noises.
- Our face detection system gives practically best results. The result is that the detector is efficient in terms of detection rate in spite of a non negligible number of false positions. We use a learning procedure to extract feature which are representative to the statistical characteristics of faces. We can distinguish three main contributions in this face detection system:
- The learning algorithm AdaBoost which selects the best set of these Haarlike threshold;
  - Rectangular Haar-features computed efficiently with a new image representation called image integral;
  - Finally an implementation in cascade which permits to decrease the detection time while increasing the detection rates;

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