

Facial Expression Recognition using Local Binary Patterns

with classification based on Support Vector Machines



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Abstract:

Since the last decade, a lot of researches have been carried out about emotion recognition. The number of projects conducted in this field demonstrates the interest and the importance of systems which can recognize human mood.

In this project, an emotion recognition system is developed, using a Microsoft Kinect. This recognition is achieved in 3 steps: Face detection, extraction and classification of facial features, this structure being the usual modus operandi in emotion recognition research.

Face detection is performed using Viola-Jones' algorithm, then Local Binary Patterns (LBP) are used to extract facial features. Finally, Support Vector Machines (SVM) classify these features into six predefined emotions.

The system is implemented to run on a computer using a Kinect and works for one person in front of it. The classifier is trained with the Cohn-Kanade database, which includes enough different faces to obtain a satisfying result.

Preface

This report documents the semester project entitled *Facial expression recognition using Local Binary Patterns*. The project was carried out during the 9th semester of specialization *Vision, Graphics, and Interactive Systems* under the Department of Electronic Systems at Aalborg University in Autumn 2012.

The report is divided into four parts plus appendices: *Introduction*, *Feature Detection*, *Feature Classification*, *Implementation* and *Evaluation*. The first part review the general structure of a facial expression recognition system and its main issues, and concludes with a state of the art of existing systems. Analysis of possible solutions and design of our system are contained in the following two parts, and the fourth part describes our implementation. The last part evaluates the performance and accuracy of our system and concludes on the project as a whole.

References to secondary literature sources are made using the syntax [number]. The number refers to the alphabetically sorted bibliography found at the end of the report, just before the appendices.

We would like to thank our supervisor at Aalborg University Zheng-Hua Tan for supporting us in this challenging project.

A CD is attached to this report which includes:

- Source code of the developed program.
- PDF file of this report.

Aalborg University, November 25, 2012

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Part I

Introduction

Contents

The main motive of this project is to understand real-time facial expression recognition systems and their applications. A review of the architecture of such systems will be done, along with a state of the art of already existing algorithms. After this study, issues coming along with this kind of recognition system will be studied. In the last part, the requirements of this project will be formulated.

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Chapter 1

Motivations

A facial expression is a "visible manifestation of the effective state, cognitive activity, intent, personality, and psychopathology of a person" [7]; facial expressions represent a huge part in dialogue and interaction with other humans. Indeed, facial expressions carry more informations than speech, informations on which humans can relay for interaction. Facial expressions have a considerable effect on a listening interlocutor; the facial expressions of a speaker represent 55 percent of the information that the listener get, 38 percent of information is conveyed by voice intonation and 7 percent by the spoken words [17].

Since Antiquity, researchers have been interested in emotion and more particularly in emotion recognition. But one of the important studies on facial expression analysis impacting on the modern day science of automatic facial expression recognition was the work carried out by Charles Darwin [3]. In 1872, Darwin wrote a book that established general expression principles, expression means and expression description for both humans and animals [5]. He also classified various kinds of expressions. This can be considered as the beginning of facial expression recognition.

Now, with the emergence of new technologies and computers, research is now focused on computer-based automatic facial expression recognition. Because facial expressions are major factors in human interaction, this research field will improve the domain of Human-Machine Interaction. Indeed, emotion recognition will enable computers to be more responsive to users' emotions, and allow interactions to become more and more realistic.

Another domain where facial expression recognition is an important issue is robotics. With the advances made in robotics, robots nowadays tend to mimic human emotion and react as as human-like as possible, especially for humanoid robots. However, since robots are being more and more present in our daily lives, they need to understand and recognize human emotions.

A lot of real time applications in the robotics field have already been created. For example, Bartlett et al. have successfully used their face expression recognition system to develop an character that is animated and that mirrors the expressions of the user (called CU Animate) [2]. They have also been successful in deploying the recognition system on Sony's Aibo Robot and ATR's RoboVie [2]. Another interesting

application has been demonstrated by Anderson and McOwen, called "EmotiChat" [1]. It is a regular chatroom, except the fact that their facial expression recognition system is connected to the chat and convert the users' facial expressions into emoticons. Because facial expression recognition systems' robustness and reliability are constantly increasing, lots of innovative applications will appear.

There are also various other domains where emotion recognition can be used: Telecommunications, behavioural science, video games, animations, psychiatry, automobile safety, affect-sensitive music jukeboxes and televisions, educational software, etc [3].

This project focuses on real-time facial expression recognition from a video stream. Indeed, facial expression recognition can be performed *statically* on input images, or *dynamically* on video sequences. Systems can also be *obtrusive*, or *non-obtrusive*, the former based on a device mounted on the user's head or body, therefore following each of his movements and perform facial expression recognition without much losses, while the latter can encounter difficulties if the user is not properly situated. However, non-obtrusive systems allow more natural user interactions. We chose our system to be non-obtrusive, and will detail further its setup in the next section.

1.1 Environment Setup

Our system will use the camera embedded into a Microsoft Kinect to record the user's video input, and we will consider a casual use of the camera, with the user sitting in front of the computer, the camera being next to it, as seen in **Insert picture of the setting & ref to figure**. This camera provides a 640×480 pixels frame resolution, while recording at 30 FPS.

For development and training purposes we will use some pre-existing emotion datasets, in order to validate the efficiency of the system before testing it in real conditions.

1.2 Emotion Datasets

Databases are very important for facial expression recognition system.

Using the same databases for studies that aims to improve existing systems is very useful. It allows to compare the results and to see if the new system is indeed better than the existing one. A lot of research studies work is based on the same databases than previous studies in order to compare the efficiency of their algorithm.

But databases are hard to construct. It has to fill all the requirements and that is why most of the work on facial expression recognition is based on existing databases. The hardest requirement to fill is to have a standardized database. Most of the actual databases use posed expressions and not spontaneous expression, and both are very different. New versions of the databases are coming out with spontaneous expressions in order to be more complete. Even with this transition from posed expressions to spontaneous expressions, there are other requirements that should be respected to have a database standardized for training and testing. It should contain images and video sequences and both should be of different resolutions. It should also contain people displaying expressions under different conditions: it could be change in the lighting, occlusions or rotations of the head [3].

Following are the databases that will be used to test this facial expression recognition system. These are part of the databases that are popular, freely available and mostly used in the past few years.

1.2.1 Japanese Female Facial Expression Database (JAFPE)

The database contains 213 images of 7 facial expressions (6 basic facial expressions: happy, angry, afraid, disgusted, sad, surprised and 1 neutral facial expression). All the images are of 10 Japanese female models. Each expression has been photographed three or four times. Each image has been rated on 6 emotion adjectives by 60 Japanese subjects. The database was planned and assembled by Miyuki Kamachi, Michael Lyons, and Jiro Gyoba [14].

This database contains only posed expressions. The photos have been taken under strict and controlled conditions: similar lighting and hair tied so that the face is not covered [3].

An example of images contained in the database is given by the figure 1.1. Here the subject is a woman and she displays 7 different emotional expressions (neutral, happy, angry, afraid, disgusted, sad, surprised):

1.2.2 Karolinska Directed Emotional Faces Database (KDEF)

The Karolinska Directed Emotional Faces (KDEF) contains 4900 pictures of human facial expressions. The material was developed in 1998 by Daniel Lundqvist, Anders Flykt and Professor Arne Ohman at Karolinska Institutet, Department of Clinical Neuroscience, Section of Psychology, Stockholm, Sweden [12].



Figure 1.1: example of images from JAFFE database

The database was at the beginning developed to be used for psychological and medical research purposes. The database was created in particular so that it can be used in perception, attention, emotion, memory and backward masking experiments. The researchers paid attention to the lighting. They tried to create a soft and similar light. They tried also to shoot expressions in multiple angles. They used T-shirt on subject that have the same colors and a grid to center the participants faces while they were shot. This grid was also used to place eyes and mouths at the same position in fixed image coordinates during scanning [12].

The database contains 70 individuals (35 males and 35 females), from 20 to 30 years, and each displaying 7 different emotional expressions (neutral, happy, angry, afraid, disgusted, sad, surprised). Each expression has been photographed (twice) from 5 different angles (-90, -45, 0, +45, +90 degrees: i.e. full left profile, half left profile, straight, half right profile, full right profile) [12].

An example of images contained in the database is given by the figure 1.2. Here the subject is a woman photographed from a straight angle and she displays 7 different emotional expressions (neutral, happy, angry, afraid, disgusted, sad, surprised):

1.2.3 Montreal Set of Facial Displays of Emotion Database (MSFDE)

The database contains facial expressions of men and women from European, Asian, and African type. Each expression was created by asking directly the subject to ex-

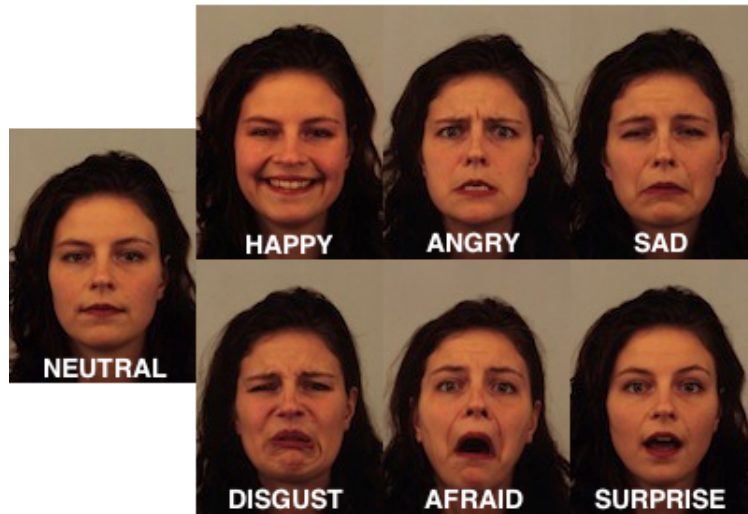


Figure 1.2: example of images from KDEF database

press this emotion and all expressions were FCAS coded in order to assure identical expressions among the subjects [23].

The database contains expressions of happiness, sadness, anger, fear, disgust, and embarrassment and 1 neutral facial expression. All expressions have been made into 5 different levels of intensity [23].

An example of images contained in the database is given in the figure 1.3. Here the subject is an african woman and she displays 7 different emotional expressions (neutral, happy, angry, afraid, disgusted, sad, ashamed):



Figure 1.3: example of images from MSDFE database

Chapter 2

Facial expression recognition

After having stated the conditions and motivations of this project, we will now describe an overview of the system we will implement. A facial recognition system can roughly be summed up as classification applied to a pre-processed image. The image processing steps, especially the feature extraction part, along with commonly used classification algorithms, will be detailed further in this chapter. Next sections will be about issues raised facial expression recognition systems, and key requirements these systems have to meet in order to be considered acceptable.

2.1 General structure

Facial expression recognition is a system enabling an automatic recognition of emotions displayed by a human face. Facial expression recognition can be image or video-based; it can also be computed real-time. Most of the time, researchers try to recognize emotions out of images of human faces. This can also be achieved real-time on video streams : While the person displays his/her emotions, the facial expression recognition system analyses the video, and detect in real-time the displayed emotion.

In both cases, facial expression recognition process is structured as in the figure 2.1

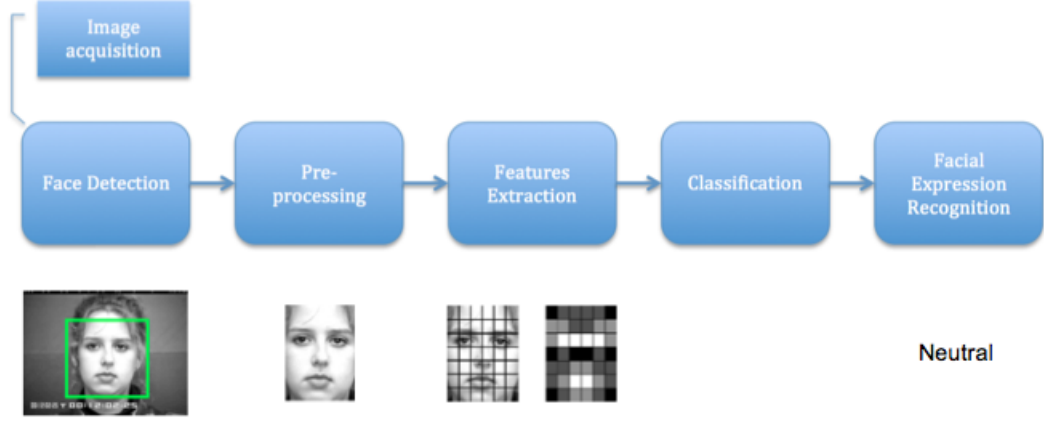


Figure 2.1: Facial Expression Recognition process

2.1.1 Image Acquisition

First step of the process is "Image Acquisition". Images used for facial expression recognition can be static images or image sequences. Image sequences give more informations about the facial expression, as the steps in muscles movement. About static images, facial expression recognition systems usually need 2D greyscale images as inputs. We can however expect future systems to use color images; first because of the increasing affordability of technologies and devices capable of capturing images or image sequences; then because colors can give more information on emotions, for example blushing [4].

2.1.2 Face Detection

Second step is "Face Detection". Indeed, in a static image and even more in an images sequence, this is an obvious need. Once the face has been detected, all other non-relevant information can be deleted, since only the face is needed. It could hence be included in the next step, which is "Pre-processing", but because of its importance it represents a step in itself. In a real-time facial expression recognition system working with image sequences, the face has to be detected, but also tracked. One of the most used and famous detection and tracking algorithm is the Viola-Jones

Algorithm, which we will explain in detail later in this report. This algorithm can be trained to detect all kind of objects, but is mostly used for face detection.

2.1.3 Pre-processing

Third step is "Pre-processing", which is about applying image processing algorithms to the image, in order to prepare it for the next step. Pre-processing is usually about noise removal, normalization against the variation of pixel position or brightness, segmentation, location, or tracking of parts of the face. Transformation, scaling and rotation of the head in the image or image sequence have an effect on emotion recognition. In order to solve this problem, the image can be geometrically standardized. References used for this standardization are usually the eyes [4].

2.1.4 Features Extraction

Once the image has gone through the "Pre-processing" step, the next one is "Features Extraction". In this step, data is converted "into a higher representation of shape, motion, color, texture, and spatial configuration of the face or its components". One of the main goals of this step is to reduce the dimensionality of the input data. The reduction procedure should retain "essential information possessing high discrimination power and high stability" [4]. There are a lot of features extraction methods. The most famous are : Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Problem Based Learning (PBL), Hidden Markov Models (HMM), Eigenfaces, Gabor Wavelets. The extracted data is then used in the "Classification" step.

2.1.5 Classification

The classification step marks the end of image processing steps (face detection, normalization, feature extraction). There are many kinds of classification algorithms, some of them can even be used in the feature extraction part, as stated in Section 2.2. This step takes into input a model previously trained with pre-processed data, and test data made of feature vectors extracted from the image we want to label. Feature vectors from pre-processed data and test data have to be obtained using the same feature extraction algorithm. The chosen classifier then outputs a value corresponding to the label of the class the picture belongs to.

2.2 Feature extraction algorithms

Before developing a facial expression recognition project, it is important to know what already exists; the state of the art of facial expression recognition system. In this chapter, an overview will be given of the existing systems before to decide on a system for the project.

2 main categories of feature extraction algorithms can be distinguished : *appearance-based* or *geometry-based*. The first ones are algorithms that try to find basic vectors characterizing the whole picture, usually by a dimensionality reduction method. These algorithms lead to a simplification of the dataset, while retaining the main characteristics of the picture. However, these methods have to be carefully parametrized, so they do not encounter the "curse of dimensionality", which is about processing high-dimensional data.

Examples of appearance-based methods : Principal Component Analysis, Linear Discriminant Analysis, Hidden Markov Models, Eigenfaces

The second type of feature extraction algorithms is geometry-based algorithms. These methods tend to locate important features, and build the feature vectors depending on those regions of interest. The key point of these methods is that the face is not a global structure anymore. Indeed, it has been summarized in a set of features regions, which are themselves translated into feature vectors.

Examples of geometry-based methods : Gabor Wavelets, Local Binary Patterns

2.2.1 Principal Component Analysis (PCA)

This is a statistical method; one of the most used in linear algebra. PCA is mainly used to reduce high dimensionality of data and to obtain the most important information from this data. Because Facial Expression Recognition needs to reduce the dimensionality of data during features extraction, PCA is commonly used. A new coordinate system with lower dimensions is obtained from transformed high dimensionality of data and with preserving the most important information. PCA computes a covariance matrix and a set of values called the eigenvalues and eigenvectors from the original data [8]. Since it is a statistical method, it can also be used in the classification step.

2.2.2 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis is also a statistical method, used to classify a set of objects into groups. It is done by looking at a specific set of features that describe the objects. LDA as PCA are used to establish a linear relationship between the dimensions of the data. LDA uses this relationship to model the differences into classes and that is where PCA and LDA are different. Because PCA does not take any differences into account in the linear relationship. The idea is to perform a linear transformation on the data to obtain a lower dimensional set of features [8]. Like PCA, LDA is also a classification algorithm.

2.2.3 Local Binary Patterns (LBP)

This is an appearance-based method. It can be used to describe texture and shape. LBP extracts some informations from the neighbourhood of a central pixel. These informations extracted are from a comparison of the intensity values of the neighbourhood pixels with the intensity value of the central pixel [8]. This method is the one that will be used for this Facial Expression Recognition system.

2.2.4 Hidden Markov Models (HMM)

These models are a set of statistical models used to characterize the statistical properties of a signal [19]. It can be used as a classification algorithm, and can also be developed to recognize expressions based on the "maximum likelihood decision criterion" [13].

2.2.5 Eigenfaces

Eigenfaces are a set of eigenvectors. These eigenvectors are derived from the covariance matrix of a set of face images; and this in a high-dimensional vector space. The eigenvectors are ordered and each one represents the different amount of the variation among the face images. All of this allows to characterize the variation between face images [22].

2.2.6 Gabor Filters

Gabor filters are applied in order to extract a set of Gabor wavelet coefficients. Filter responses are obtained when Gabor filters are convolved with face image. These representations of face image display desirable locality and orientation performance [11]. However, the main limitation of the Gabor feature extraction is the processing time. It is very long and the dimension of this Gabor feature extraction is prohibitively large [18].

2.3 Issues

2.3.1 Database

Databases can be a source of issues. As said previously, databases should fulfill a number of requirements in order to be the most efficient as possible.

If the Facial Expression Recognition system wants to be close to reality, it should be able to recognize spontaneous expressions rather than posed expressions. Indeed, spontaneous expressions are closer to reality than posed expressions. Posed expressions are exaggerated. While creating a database of spontaneous expressions, Sebe and colleagues [20] made some observations of the major problems they encountered [3]:

- The same emotions can be expressed at different intensities by different subjects
- As soon as the subject is aware of being photographed and studied, the authenticity of the emotion is lost
- Because of the laboratory conditions, even if the subject is not aware of being photographed or recorded, the subject is not encouraged to display spontaneous expressions.

In order to get round of these problems, they came up with a method. The method was to record facial expressions with a camera hidden in a video kiosk. The video kiosk was displaying emotion inducing videos. Subjects were notified of the recording after the recording was done. Their permission to use the captured sequences for research studies has been asked. Then the subjects explained which emotions they felt and expressed and their replies were documented even if it was not corresponding to the recordings of the facial expressions [20].

They found that a wide range of expressions are hard to induce and particularly fear and sadness. They also found that spontaneous expressions could be misleading: some subjects express one emotion while feeling another one (for example, one subject was showing sadness while being happy) [20].

At the end, databases bring some issues that can affect the authenticity of the recognition system. It depends of the type of the expressions : spontaneous or posed expressions. If the system aims to recognize facial expressions of people unaware of it, spontaneous expressions databases will be used but it leads to authenticity issues as seen previously. If the system aims to recognize facial expressions of people asked to express certain emotion, posed expressions databases will be used but the result will not be close to the reality.

2.3.2 Real-time

The goal of the Facial Expression Recognition system of this paper is to recognize facial expression in real time. For a real-time application, the processing should not be too heavy otherwise the time of processing will be too long and the application will not be in real time anymore.

This is one of the challenges of this kind of system. Because most of the time the processing is really heavy whatever the algorithm is and it is really difficult to make it work in real-time. Most of the applications in need of Facial Expression Recognition are in need of real-time recognition. For example in robotics, or in surveillance. The solution could be to find new algorithms for Facial Expression Recognition or to improve and lighten already existing algorithms.

2.3.3 Conditions

Another one of the challenges of this kind of system is to be independent to the conditions of the recording. It means that the recognition should not be disturbed by occlusions for example, or difference in the lighting, or even by the angle that the face makes with the camera lens. This examples cover almost all the conditions that can change during the recording and have an influence on the recognition system.

Occlusion

"Occlusion" represents all the elements that can cover the face or a part of it. For example, a beard, a scarf masking the bottom of the face, glasses or bangs. By hiding a part of the face, these occlusions can affect the recognition. Indeed, these Facial Expression Recognition systems are based on comparison of features and if all the features cannot be compared because something is covering a part of the face, the recognition is affected. In order to compensate for this problem, some databases includes data with already occlusions in it as beard, glasses or scarf for example. This is the case for the AR Face database and some examples of the images contained in this database are given by figure 2.2 and figure 2.3 [15]:



Figure 2.2: example of occlusion by sunglasses in the AR Face database



Figure 2.3: example of occlusion by scarf and glasses in the AR Face database

Lightning

As for occlusion, lightning is an element that can affect Facial Expression Recognition system. With a lightning different from the one used in the database, the recognition will be less efficient. All the conditions that change from the one of the database on which is based the recognition process will disturb the recognition in

itself. If the images are brighter or darker than the one of the database, some details can disappear or some features cannot be recognized as well as if the conditions were the same. In order to compensate for this problem, some databases includes data with already changes in the lightning. This is the case for the AR Face database and an example of the images contained in this database is given by the figure 2.4 [15]:



Figure 2.4: example of different lightnings (from left to right: dark to bright) in the AR Face database

Angle

The angle of the head from the camera lens is one of the conditions that can affect the most the recognition process. Indeed if the head is too much turned from straight angle, some features will disappear. For example, with a profile angle, one eyes and half of the nose and of the mouth disappear. And if the database does not contain sample with profile face, the recognition will not succeed. This constraint is based on the database; if the database contains images from straight angle as well as from profile angle and other, the recognition will be possible even if the head is not with a straight angle. But if the database contains images only from straight angle, the recognition will be almost impossible if the head is turned. An example of the different images taken from different angles for one emotion, "Fear", from the KDEF database is given in figure 2.5:

2.4 Requirements

Based on everything that was said previously, the Facial Expression Recognition system of this paper can be defined by some requirements. Additional requirements may be defined further in this paper. Here are the requirements already defined :

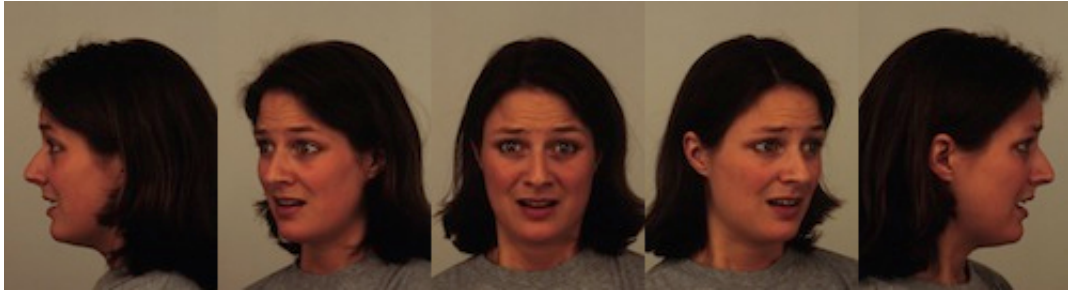


Figure 2.5: example of different angles of the "Fear" emotion (from left to right: full left profile, half left profile, straight, half right profile, full right profile) in the KDEF database

- Able to recognize basic emotions : As explained before, Facial Expression Recognition systems are able to recognize 6 basic emotions and the neutral state. This system would be able to do the same: recognize the 6 basic emotion that are "Happiness", "Fear", "Surprise", "Disgust", "Sadness", "Anger" and the neutral state.
- Able to work in real-time : This system would be able to recognize emotion in real-time. It means that it could recognize expressions based on a video sequences . It also means that the algorithm for the feature extraction could not have heavy processing or to use one that would be lightened.
- Recognition from straight angle of the face : This system would be able to recognize facial expression from a straight angle of the face. It means that the system would be able to detect faces that are in front of the camera lens and to recognize expressions in these faces. It would not be able to recognize emotions on a face that is from profile or half-profile.
- Recognition with no occlusion on the face : This system would be able to recognize emotions with no occlusion on the subject's face. It means that the face would not be cover in any way: no glasses, no beard or no scarf. The face would be complete and not masked.
- Recognition with no change in lightning : This system would be able to recognize emotions on faces under the same lightning conditions. It means that the light would not vary during the recognition part. The light would stay the same and the level of intensity of the light would be as close as possible that the one of the database. This way the lightning would not have any influence

on the recognition.

Part II

Feature detection

Contents

Before getting to the main part of this project that is Feature extraction, there is a mandatory step that is Feature detection. In order to avoid the more computation and processing as possible, only the parts that contains the regions of interest for a Facial Expression Recognition system have to be processed. It means by consequence that there has to be beforehand the detection of the interesting features. This detection can be summarized into face detection. This part will explain how face detection works in general. Then the most famous and efficient algorithm for face detection will be introduced and studied. This algorithm is the Viola-Jones algorithm.

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Chapter 3

Face detection

Face detection is the first step after image acquisition. It represents a requirement for a Facial Expression Recognition system. All the background is not taken into account. It allows to focus only on what is interesting in the input image: the face, which helps reducing the processing during the next step that is feature extraction.

3.1 Detection

Finding out if the input image or video sequence represents or contains a particular object is what is called Detection. Usually after the detection step comes the recognition step. For this system, the recognition step consists in facial expression recognition. But depending on the recognition, there can be another step that is the tracking step. Tracking consists in following a moving target on the images of a video sequence [6].

To represent an object detector, the term "black box" can be used. The box gets an image as its input and at a high level the output can be considered as an image with annotations saying where the object of interest appears, if it appears [6]. For example, the output can look like in figure 3.1 [6].

But at a low level, the output is not anymore an annotated image. The object detector has a basic component that is something required to say if an instance of the object of interest is contained in a certain region or sub-region of the original image or not. This is what a binary classifier does [6]. For example, what a binary classifier does can look like in figure 3.2 [6].

3.2 Classifiers

Classification aim to solve the problem of identifying in a set of categories or sub-populations to which a new observation belongs. It is based on a training set of data that contains instances whose category affiliations are known. A classifier is an al-



Figure 3.1: Example of an output of face detection

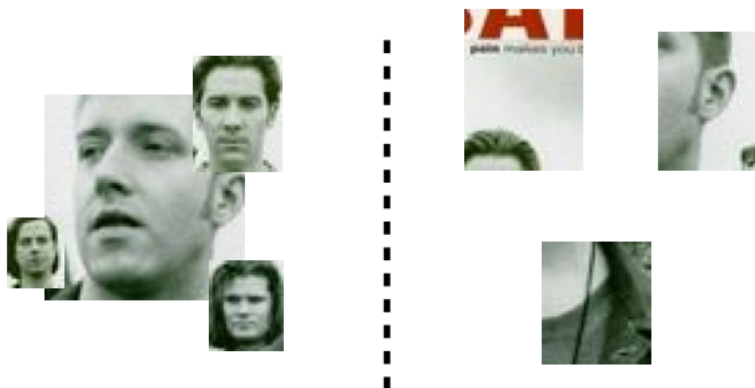


Figure 3.2: Example of what does a binary classifier for face detection

gorithm that implements classification. Classifiers groups data into categories. This can be done based on some measures of inherent similarity; for example, vectors represent the distance between instances, and this in a multidimensional vector space [25].

Chapter 4

Viola-Jones

Viola-Jones algorithm is "a visual object detection framework that is capable of processing images extremely rapidly while achieving high detection rates". 3 main points characterize this algorithm. The first one is the use of what is called an "Integral image". It is a new representation of the image and it allows the features used to be computed very quickly. The second one is the use of a learning algorithm based on AdaBoost. It results in giving extremely efficient classifiers. The third and last one is the use of a method to combine classifiers. This method combine classifiers in "cascade". It allows to focus on the promising object-like regions by discarding the background in a very quick way [24].

4.1 Overview

The Viola-Jones algorithm works as following [6]:

- The Viola-Jones detector is a strong, binary classifier build of several weak detectors
- Each weak detector is an extremely simple binary classifier
- During the learning stage, a cascade of weak detectors is trained so as to gain the desired hit rate / miss rate (or precision / recall) using AdaBoost
- To detect objects, the original image is partitioned in several rectangular sub-regions, each of which is submitted to the cascade
- if a rectangular image sub-region passes through all of the cascade stages, then it is classified as "positive"
- The process is repeated at different scales

4.2 Haar features

The features used by Viola and Jones are called Haar features and are based on Haar wavelets. Haar wavelets are single wavelength square waves. It is composed of one

high interval and one low interval. In two dimensions, a square wave is represented by a pair of adjacent rectangles: one rectangle that is light and one rectangle that is dark. The true Haar wavelets are not the one used for this rectangle combinations that is used for visual object detection. They use instead rectangle combinations that are better suited to recognition tasks. That is because of this difference that these features are called Haar features rather than Haar wavelets (they can also be called Haarlike features) [10].

For example, the figure 4.1 shows the first two Haar features in the original Viola-Jones cascade [10]. These are all features from the original set of features. In figure 4.2, there is an example of features from the extended set of features [6]. In the figure 4.3 , it is an example of a early stage in the Haar cascade. Each black and white rectangle represents a feature. And that is what the algorithm hunts for in the image [9].



Figure 4.1: Example of the first two Haar features

To detect if a Haar feature is present or not, basic subtraction is used. The subtraction consists in subtracting the average pixel value of the dark-region from the average pixel value of the light-region. Then it is a simple comparison. The result of the subtraction is compared with a threshold. If the result is above the threshold, then the feature is considered as present and it can go to the next stage [10]. There is about 20 to 30 different stages to detect the presence of Haar features. The first stage is a very coarse scan of the image. The second stage is more detailed, the third stage is once again more detailed and harder to pass, the fourth stage is even harder and it goes on and on till the end. The more it moves forward into the cascade, the more it becomes harder. The features become increasingly complex and larger. All this processing takes indeed more time to compute [9].

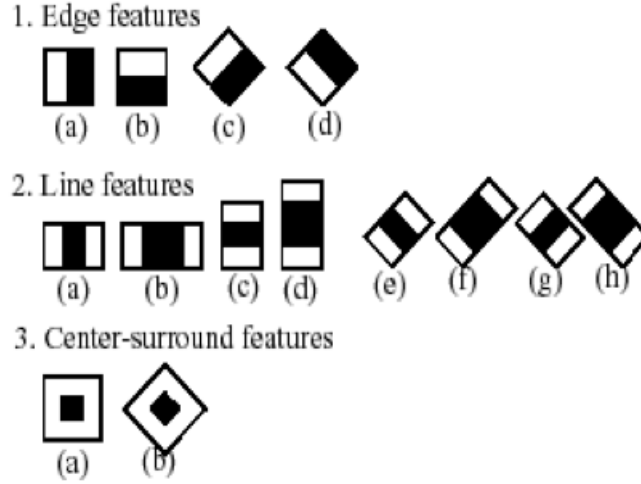


Figure 4.2: Extended set of features

For example, the figure 4.4 shows the later stage in the Haar cascade. There are many more patterns of black and white rectangles that need to match the input image [9].

It exists three kinds of feature that Viola and Jones use: a two-rectangle feature, a three-rectangle feature and a four-rectangle feature. To find the value of the two-rectangle feature, it consists in the difference between the sum of the pixels that are in the two rectangular regions. The regions (or rectangles) are the same: they have the same size and the same shape. And they are horizontally or vertically adjacent. The three-rectangle feature are calculated by the sum of the pixels of the two outside rectangles subtracted from the sum of the pixels in the center rectangle. The last kind of feature is the four-rectangle feature consists in the difference between the diagonal pairs of rectangles [24].

For example, the figure 4.5 shows the different kinds of rectangle features used by the Viola-Jones algorithm. The images (A) and (B) show the two-rectangle features. The image (C) shows the three-rectangle feature, and the image (D) shows the four-rectangle feature [24].

Viola and Jones admit that rectangle features can be considered as primitive features. In contrast with other features, rectangle features are quite coarse (even though they are sensitive to the presence of edges, bars and other simple image structure). It appears that however, a rich image representation is provided by this set of rectangle features and furthermore this representation supports effective learning. In compar-



Figure 4.3: Example of an early stage in the Haar cascade

ison with the extreme computational efficiency provided by rectangle features, their limited flexibility is not much of a problem [24].

4.3 Integral image

Viola and Jones used an intermediate representation of an image that they called "integral image". This integral image allows to compute very quickly the rectangle features [24]. This technique allows to determine the presence or absence of hundreds of Haar features. It can be determined for every image location and for several scales efficiently. In general, adding small units together is what is called "integrating"; here, the small units are pixel values. The sum of all the pixels above and to the left of each pixel is the the integral value. And this value can be found for each pixel.

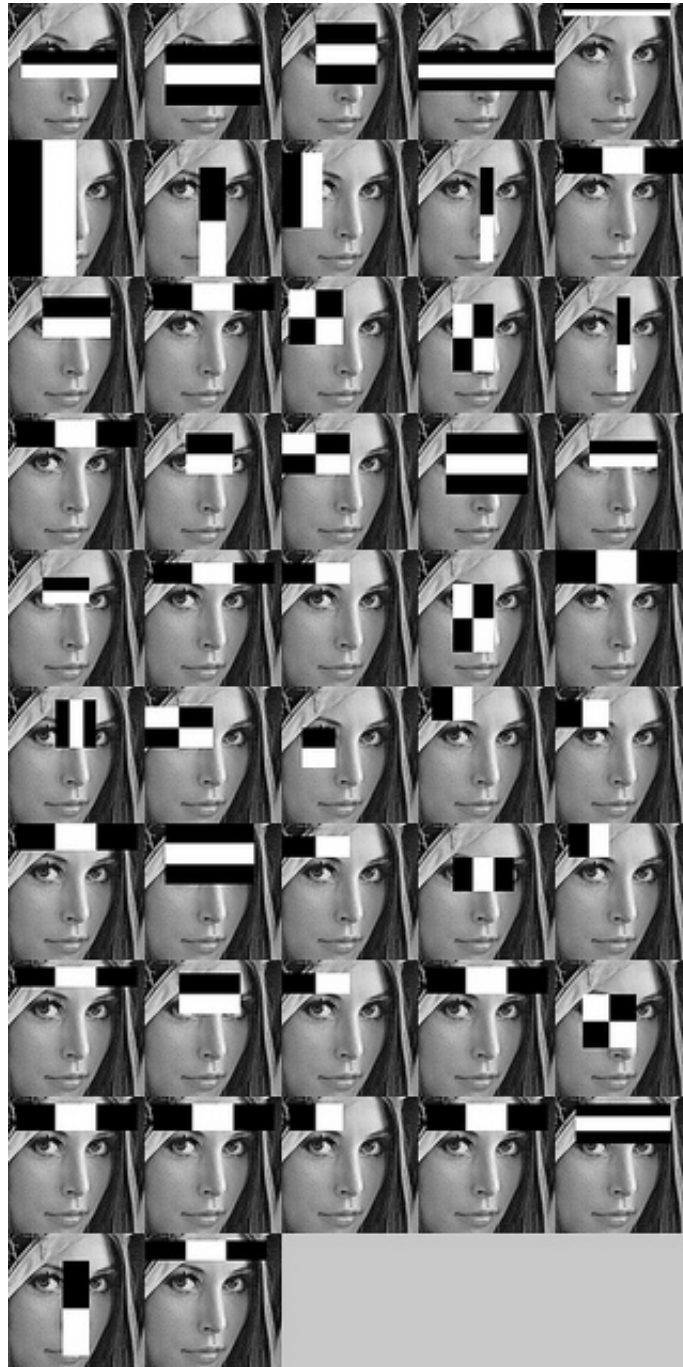


Figure 4.4: Example of the later stage in the Haar cascade

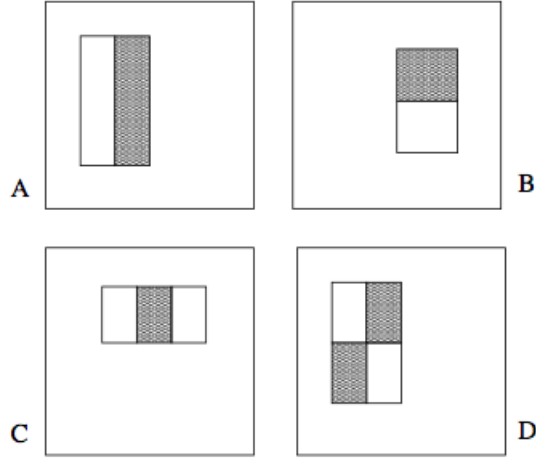


Figure 4.5: Example of the different kinds of rectangle features

That is why this technique is efficient: the entire image can be integrated only with a few calculations per pixel. This integration starts at the top left corner and go through all the image to the right and down [10].

It means that the integral image, at location x, y contains the sum of the pixels above and on the left of x, y , x, y included:

$$ii(x, y) = \sum_{x' \leq x, y' \leq y} i(x', y')$$

where $ii(x, y)$ is the integral image and $i(x, y)$ is the regional image. In the figure 4.6, the value of the integral image at point (x, y) is the sum of all the pixels above and on the left [24].

Using the following pair of recurrences:

$$s(x, y) = s(x, y - 1) + i(x, y) \quad (4.1)$$

$$ii(x, y) = ii(x - 1, y) + s(x, y) \quad (4.2)$$

(where $s(x, y)$ is the cumulative row sum, $s(x, -1) = 0$, and $ii(-1, y) = 0$) the integral image can be computed in one pass over the original image.

Thanks to the integral image, any rectangular sum can be calculated in four array references. In the figure 4.7, the sum of the pixels in rectangle D can be calculated with four array references. The value of the integral image at the point 1 is the sum

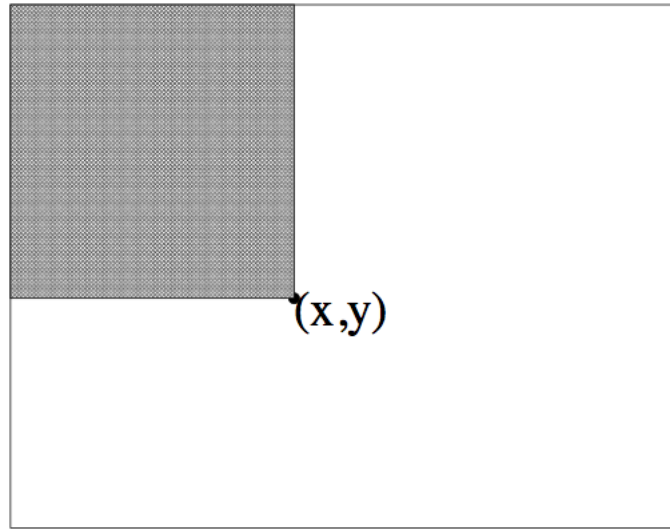


Figure 4.6: Integral image

of the pixels in rectangle A . The value at the point 2 is $A + B$, at the point 3 is $A + C$, and at the point 4 is $A + B + C + D$. The sum in D can then be computed as $4 + 1 - (2 + 3)$ [24].

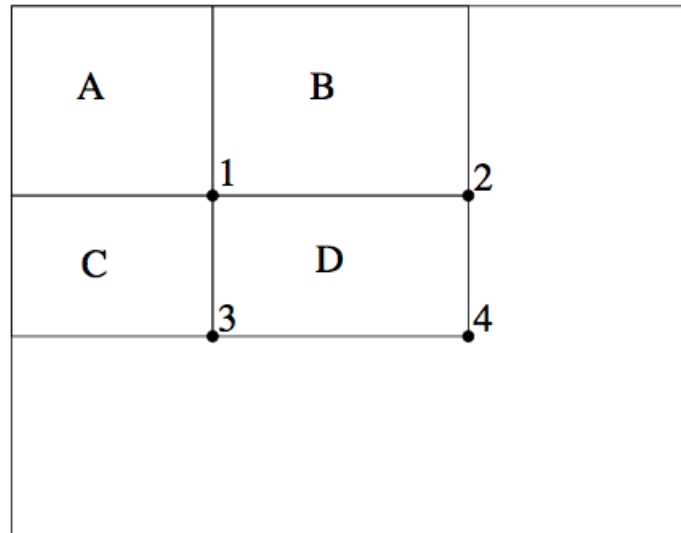


Figure 4.7: Integral image with four array references

4.4 Weak classifiers and AdaBoost

Features are extracted from a sub windows of a sample image. The base size for this sub window is 24 by 24 pixels. Each of all the features types are scaled and shifted across all possible combinations (In a 24 pixel by 24 pixel sub window, there are about 160,000 possible features to be calculated) [21].

To select the specific Haar features to use, and to set threshold levels, Viola and Jones use a machine-learning method called AdaBoost. AdaBoost combines many "weak" classifiers to create one "strong" classifier. "Weak" here means that the classifier only gets the right answer a little more often than random guessing would. That is not very good. That is why a lot of weak classifiers are used. If a whole lot of these weak classifiers are used, and each one "pushed" the final answer a little bit in the right direction, this represents a strong, combined for to arrive at the correct solution.

AdaBoost selects a set of weak classifiers to combine and assigns a weight to each (see figure 4.8). This weighted combination is the strong classifier [10]. The challenge is to associate a large weight with each good classification function and a smaller weight with poor functions. AdaBoost is an aggressive mechanism for selecting a small set of good classification functions which nevertheless have significant variety [24].

Initial experiments demonstrated that a classifier constructed from 200 features using AdaBoost would yields reasonable results. Given a detection rate of 95%, the classifier yielded a false positive rate of 1 in 14084 on a testing dataset (see figure 4.9)[24].

The 200-feature classifier provides initial evidence that a boosted classifier constructed from rectangle features is an effective technique for object detection. In terms of detection, these results are compelling but not sufficient for many real-world tasks. In terms of computation, this classifier is probably faster than any other published system, requiring 0.7 seconds to scan an 384 by 288 pixel image. Unfortunately, the most straightforward technique for improving detection performance, adding features to the classifier, directly increases computation time [24].

4.5 Classifiers cascade

Viola and Jones combined a series of AdaBoost classifiers as a filter chain, that is especially efficient for classifying image regions. Each filter is a separate AdaBoost classifier with fairly small number of weak classifiers. As in figure 4.10, the classifier cascade is a chain of filters. Image subregions that make it through the entire cascade

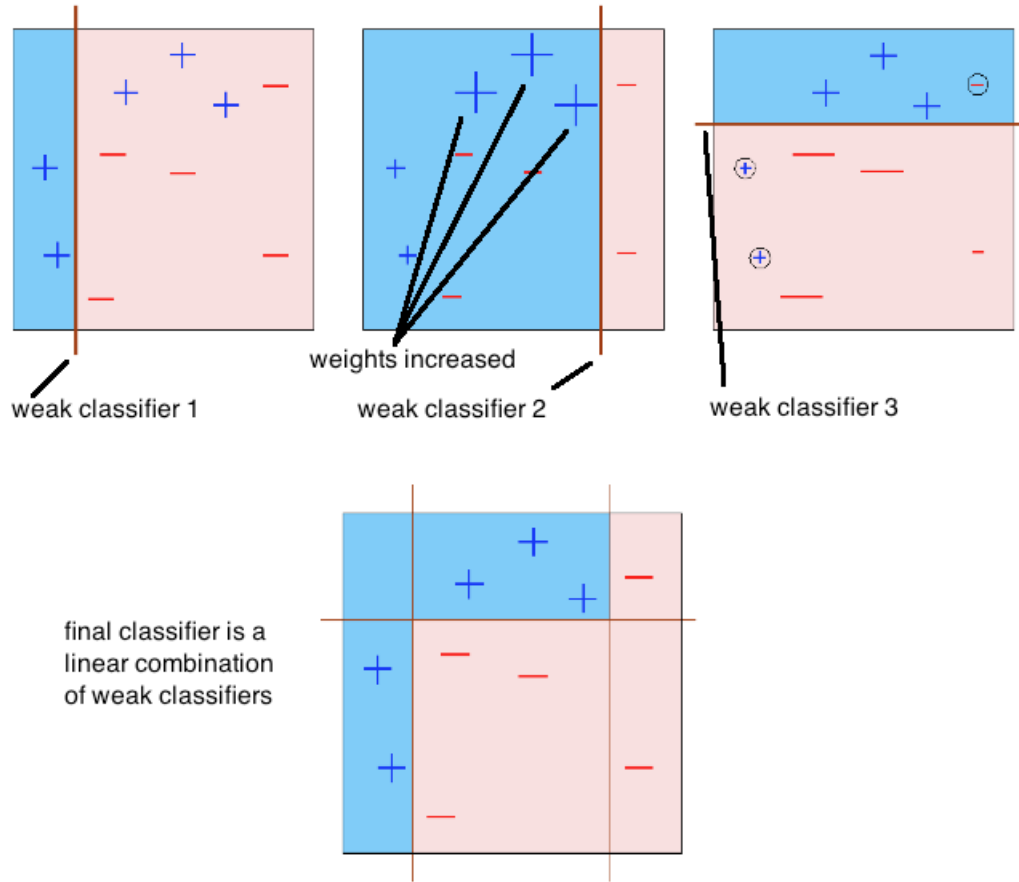


Figure 4.8: AdaBoost method

are classified as "Face". All others are classified as "Not Face" [10]. This algorithm for constructing a cascade of classifiers achieves increased detection performance while radically reducing computation time [24].

In order to explore the feasibility of the cascade approach two simple detectors were trained: a monolithic 200-feature classifier and a cascade of ten 20-feature classifiers. Figure 4.11 gives the ROC curves comparing the performance of the two classifiers. It shows that there is little difference between the two in terms of accuracy. However, there is a big difference in terms of speed. The cascaded classifier is nearly 10 times faster since its first stage throws out most non-faces so that they are never evaluated by subsequent stage [24].

The acceptance threshold at each level is set low enough to pass all, or nearly all,

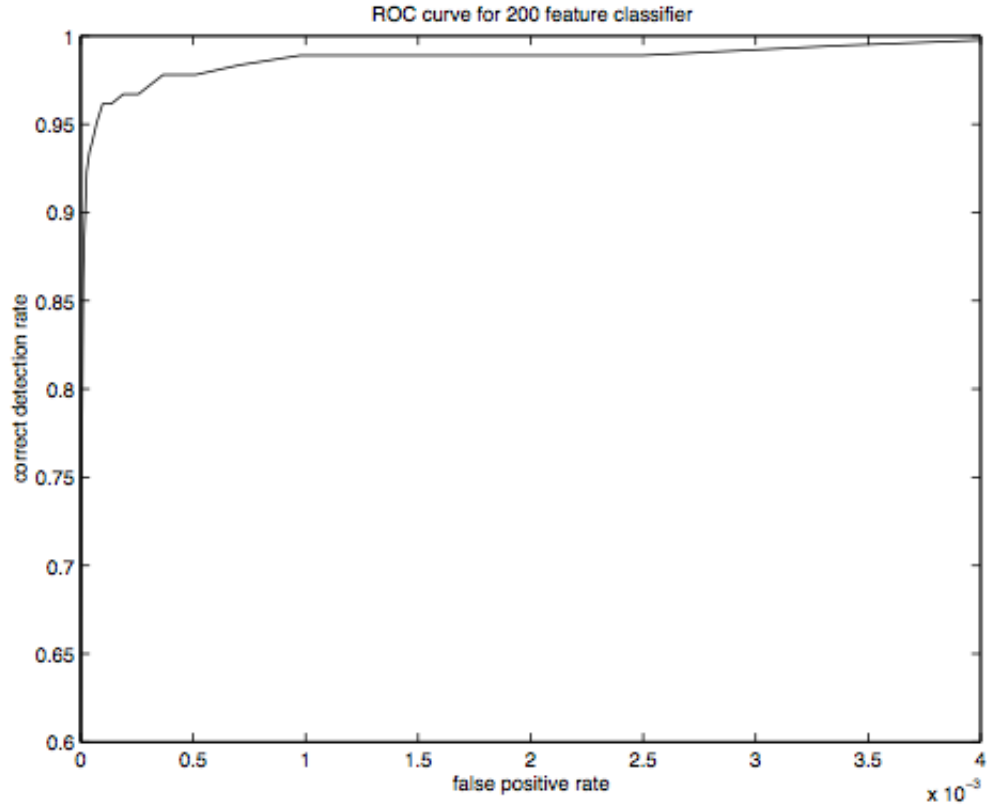


Figure 4.9: Receiver operating characteristic (ROC) curve for the 200 feature classifier

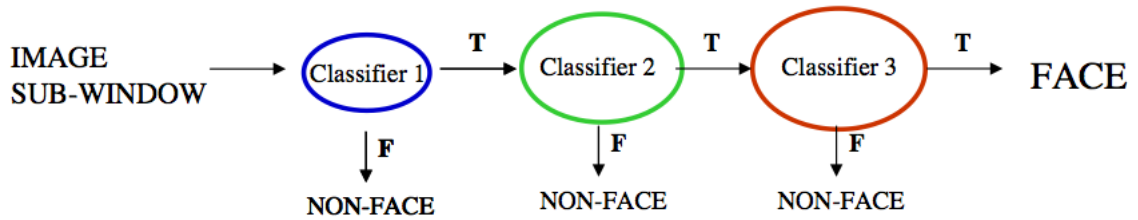


Figure 4.10: Cascade of boosted classifiers

face examples in the training set. The filters at each level are trained to classify training images that passed all previous stages. During use, if anyone of these filters fails to pass an image region, that region is immediately classified as "Not Face". When a filter passes an image region, it goes to the next filter in the chain. Image

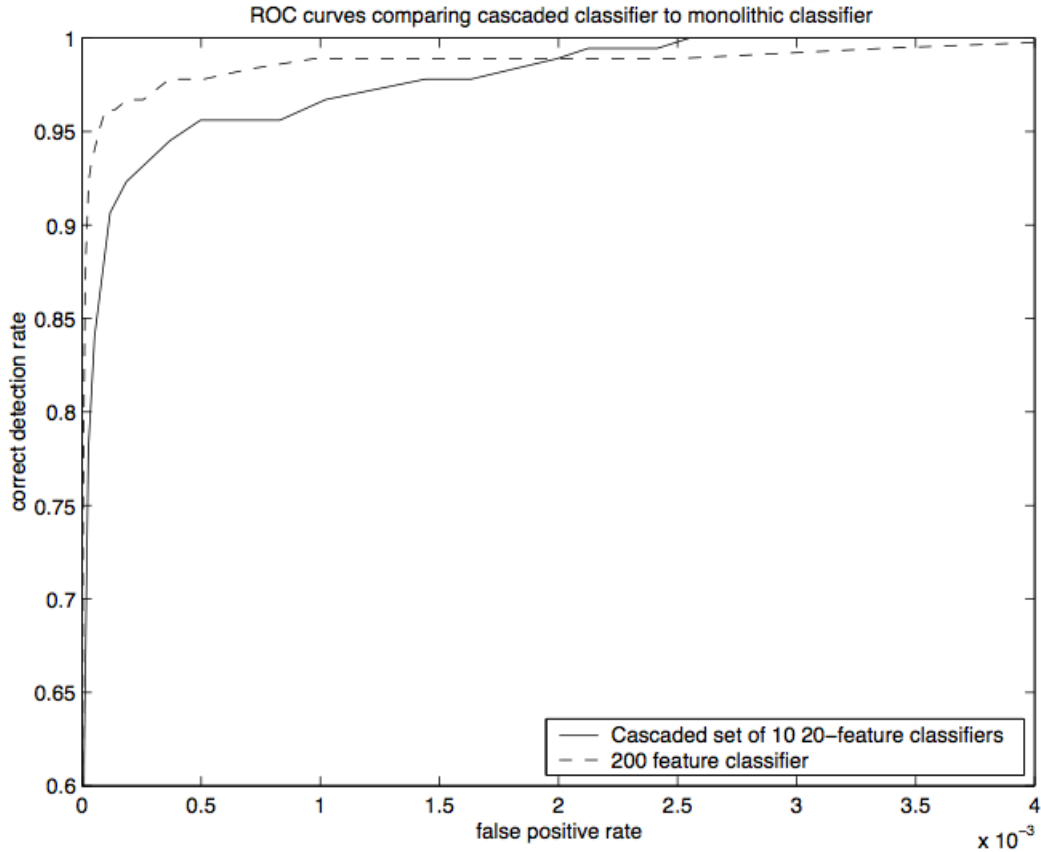


Figure 4.11: ROC curves comparing a 200-feature classifier with a cascaded classifier containing ten 20-feature classifiers

regions that pass through all filters in the chain are classified as "Face". Viola and Jones named this filtering chain a cascade [10].

The key insight is that smaller, and therefore more efficient, boosted classifiers can be constructed which reject many of the negative sub-windows while detecting almost all positive instances. Simpler classifiers are used to reject the majority of sub-windows before more complex classifiers are called upon to achieve low false positive rates [24].

The order of filters in the cascade is based on the importance weighting that AdaBoost assigns. The more heavily weighted filters come first, to eliminate non-face image regions as quickly as possible. In figure 4.12, it shows the first two features from the original Viola-Jones cascade superimposed on a face. The first one keys off the cheek area being lighter than the eye region. The second uses the fact that the

bridge of the nose is lighter than the eyes [10].



Figure 4.12: The first two Haar features in the original Viola-Jones cascade

The structure of the cascade reflects the fact that within any single image an overwhelming majority of sub-windows are negative. As such, the cascade attempts to reject as many negatives as possible at the earliest stage possible. While a positive instance will trigger the evaluation of every classifier in the cascade, this is an exceedingly rare event [24].

Following are the different numbers about cascade classifiers (see figure 4.13) [16]:

- A 1 feature classifier achieves 100% detection rate and about 50% false positive rate
- A 5 feature classifier achieves 100% detection rate and about 40% false positive rate (20% cumulative)
- A 20 feature classifier achieves 100% detection rate and about 10% false positive rate (2% cumulative)

4.6 Test set and training

The face training set consisted of 4916 hand labeled faces scaled and aligned to a base resolution of 24 by 24 pixels. The faces were extracted from images downloaded during a random crawl of the world wide web. Some typical face examples are shown

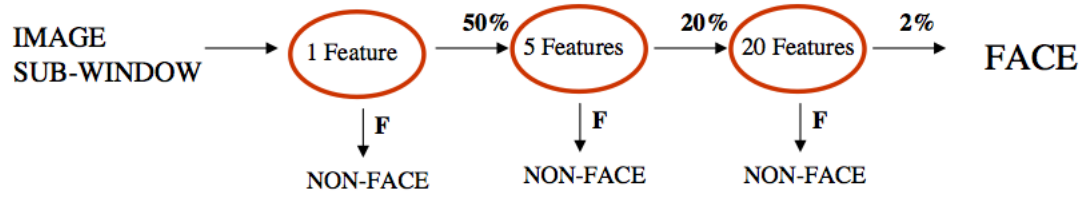


Figure 4.13: Cascade of boosted classifiers rate



Figure 4.14: Example of frontal upright face images used for training

in figure 4.14 [24].

The training set is composed of [16]:

- 5,000 faces

- All frontal
- 300 million non faces
 - 9,400 non-face images
- Face are normalized
 - Scale, translation
- Many variations
 - Across individuals
 - Lightning
 - Pose (rotation both in plane and out)

The test set is usually divided into a training set and a validation set. A typical training set may contain about 5,000 positive samples (faces) and 10,000 negative samples (non-face sub-windows randomly chosen from non-face images) [6]. Training time for an entire 32 layer detector is on the order of weeks [24].

Viola-Jones training stage proceeds with the following step [6]:

- Given the number K of possible features (about 160,000 on a 24×24 gray-level image)
- Fix the number L of desired stages in the cascade
- Iterate until L weak classifiers have been selected:
 - Given reweighed data from the previous stage
 - Train all K weak classifiers (find the best threshold to classify the training set)
 - Select the best classifier at this stage
 - Reweight the data

The weak classifiers are associated to weights that depends on their classification error. Those weights are used in a linear combination of the weak classifiers which represents a huge computational cost [6].

Part III

Feature extraction and classification

Contents

This part will focus on the steps following face detection, which are feature extraction and classification. Chapter 5 will present the main issues on feature extraction, and usual feature extraction methods, while the next chapter will focus on the Local Binary Patterns algorithm. Classification will then be introduced in Chapter 7, with a general overview of the classification problem, along with a presentation of some classification algorithms. The last chapter will describe Support Vector Machine classification.

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Chapter 5

Feature extraction

bla

5.1 Overview

5.2 Appearance-based methods

bla

5.3 Geometry-based methods

bla

Chapter 6

Local Binary Patterns

bla

6.1 Overview

bla

6.2 Histogram computing

bla

6.3 Improvements

bla

6.3.1 Circular LBP

bla

6.3.2 Uniform LBP

bla

Chapter 7

Feature classification

bla

7.1 Supervised and unsupervised learning

bla

7.1.1 Supervised learning

bla

7.1.2 Unsupervised learning

bla

Chapter 8

Support Vector Machine

bla

8.1 Overview

bla

8.1.1 Margin maximization

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8.1.2 SVM kernels

bla

8.2 Combining LBP and SVM

bla

Part IV

Implementation

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Bla bla bla

Part V

Evaluation

Contents

Bla bla bla

Conclusion

In case you have questions, comments, suggestions or have found a bug, please do not hesitate to contact me. You can find my contact details below.

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Appendix A

Appendix A name

Here is the first appendix