Université de Poitiers,

Master 1 Réseaux de Télécommunications, Multimédia et Automatique

Rapport de projet de fin d'année
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Outils algorithmiques pour la reconnaissance

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Introduction

At the University of Poitiers, students in Master of Information and Communication Systems, Emphasis (professional and research career) in NetworkTechnologies field have to carry out a project during their first year in order to complete the training.This is the mean reason we have being written this report of project.

In fact, several topics were proposed to us and we choose the facial recognition for its multiplicity and variety in term of application fields, such as high security applications, remote monitoring and control of access etc. Indeed, this field is closely linked with human vision reproduction researche and the interaction between a machine and a human, which is a fascinating and booming subject.

Facial recognition consist in identifying a person with a picture of his face. It appears to be a quite active field in Vision from computer and Biomety. Recognition with an individual face is a skill of Biometry which is still to improve. Indeed, the acquired (captured) picture represents variation much higher than other characteristics (makeup, presence or absence of glasses, aging and expression of emotion). The method of face recognition is sensitive to the variation of the light and change the position of the face in the image acquisition. But still the system obtained is not yet able to adapt itself to certain kinds of variations on a face.

In fact, achieve the two prototypes necessary for our analysis we adopted the following outline anouncing this report. First, we define the project environment and aims at first, then we develop the state of the art methods to be programmed, as it were the theoretical concept. Then we establish a technical report is to explain the use of our prototypes made and finally we leave the analysis of the use of these prototypes to the comparison of our results.

Chapter 1

Presentation of the project

1.1 Context and needs

1.2 Goals or objectives :

Several methods have been developed in the literature for face recognition. In our work, we chose two extraction techniques characteristics of the face image: The first method is Eigenface which is based on principal component analysis. The CPA is a mathematical method which can be used to simplify a dataset, reducing its size.

The second method is Fisherface which is based on a linear discriminant analysis. LDA is improved PCR method.

These two methods should therefore allow us to achieve two prototypes we compare the results. This step is to assess which method provides a more satisfactory result in terms of facial recognition.

1.3 Deadline

Chapter 2

State of the art

2.1 Facial Recognition

The challenge of face recognition can be formulated as followed : with one or several images of a face, the goal would be to find or check the identity of a person by comparing his face to all the face images stored in a database. By the way this skill remains the most acceptable because it more suits with what human beings use in visual interaction; and compared to other methods, the face recognition seems more advantageous, in fact it is a non-intrusive method, in other words it does not require the cooperation of the subject, and a moreover the sensors used are cheaper.

2.1.1 Facial recognition process

Any facial recognition process must take into consideration several factors that contribute to the complexity of its task, because a face is a dynamic entity which constantly changes under the influence of several factors. A facial recognition system is generally divided into the following steps (see the figure):

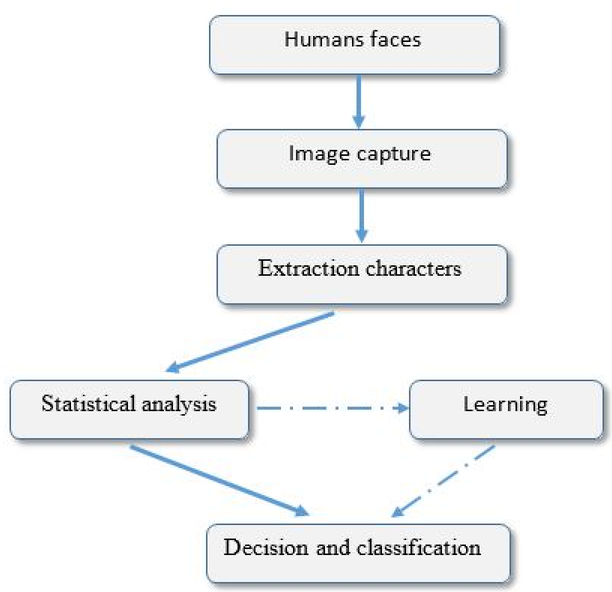

Figure 2.1: **Facial recognition system process**

Facial recognition is facing the following problems:

- Change of pose ;
- Light Variations ;
- Variations of expression, age ;
- Partial occultation of the face (concealing).

These variations are the most difficult because the variations in the appearance of a person face according to different pose or light conditions are often far more important than the variation between face images of two different individuals acquired under the same conditions. This explains why pictures should be taken in specific conditions so that facial recognition can be efficient.

2.1.2 The methods used for face recognition

Facial recognition methods can be classified into two broad categories: local and global methods. Amongst those methods, main ones will be presented thereafter.

2.1.2.1 Global methods

Global methods are based on well known techniques of statistical analysis. In these methods, face images (which can be shown as matrices of pixel values) are used as input of the recognition algorithm and are generally transformed into vectors, which are easier to handle. The main advantage of global methods is that they are relatively quick to set up in. However, they are very sensitive to variations of illumination, pose and facial expression.

The main existing methods are:

- The Principal Component Analysis (PCA) : EigenFaces
- The LDA (Linear Discriminant Analysis) Algorithm : FisherFaces

2.1.2.2 Local methods (Geometric)

The local methods include transformations applying to specific areas of the image, usually around characteristic points (corners of the eyes, mouth, nose, ...). Therefore, they require a priori knowledge on images. These methods are more difficult to implement but are more robust to the problems due to variations of illumination, pose and facial expression. The main existing methods are:

- EBGM (Elastic Bunch Graph Matching);
- Modular Eigenface;
- Hidden Markov Method.

But in fact, our aim on this project will be obviously to use both main global methods.

Both methods that we will present are using a common training algorithm steps that are :

- Preprocessing of training image set
- Normalization and estimation of mean image
- Use of PCA/ LDA

PCA/ LDA are statistical tools used to implement facial recognition method. For instance the use of PCA is divided into two steps :

- The determination of the input image weight from projecting input image into the face space and by multiplying the resulted vector to eigenfaces of the database.
- A Comparison of results with metrics such as euclidian distance.

2.2 Eigenfaces

2.2.1 Presentation of Eigenfaces

The Eigenface approach began with a search for a low-dimensional representation of face images by Sirovich and Kirby in 1987. It is the first method considered as a successful technique of face recognition. The Eigenface method uses Principal Component Analysis (PCA) to linearly project the image space to a low dimensional feature space and it is the name given to a set of eigenvectors when they are used in the computer vision problem of human face recognition

2.2.2 Procedure

A set of eigenfaces can be generated by performing a mathematical process called Principal Component Analysis (PCA) on a large set of images.

To create a set of eigenfaces, one must:

- Load a training set of face images. The pictures of the training set should have been taken under the same lighting conditions, and must be normalized to line up the eyes ,mouths and other features.
- Compute the average image : add each columns of the matrix T and dividing the previous obtained vector by the number of input images.
- Subtract the mean from matrix T to obtain matrix S
- Calculate the covariance matrix S.
- Calculate the eigenvectors and eigenvalues of the covariance matrix S. Each eigenvector has the same dimensionality as the original images. The eigenvectors of the matrix S are called eigenfaces.
- Choose the principal components. The number of principal components k is determined arbitrarily by setting a threshold ϵ on the total variance.
- Determinate the input image weight determination from projecting each image
- Each image is represented by a vector which is used to reconstruct the images. We then save the average image, eigenfaces and the projection (weight) of images.

This ends the training part of the implementation of eigenfaces and shows the skills used.

2.2.3 EigenFaces logigram

The flowchart we have to use is divided into two basic parts: the learning phase and the identification phase where the Euclidean distance is used to calculate the difference between the weight of the image to be identified and the database images, then the program displays the nearest.

But retain before these two major steps,we have pretreatments and it's the phase which is carried out :

- The selection of the learning base ;
- Reading images ;
- The conversion of grayscale images ;
- Resizing images ;
- And finally the application of histogram equalization.

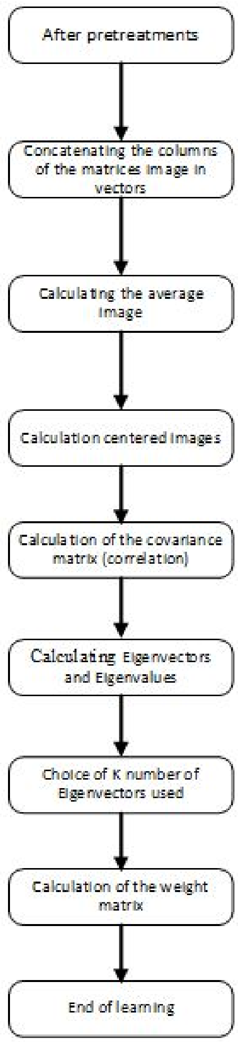

Figure 2.2: **EigenFaces logigram learning phase**

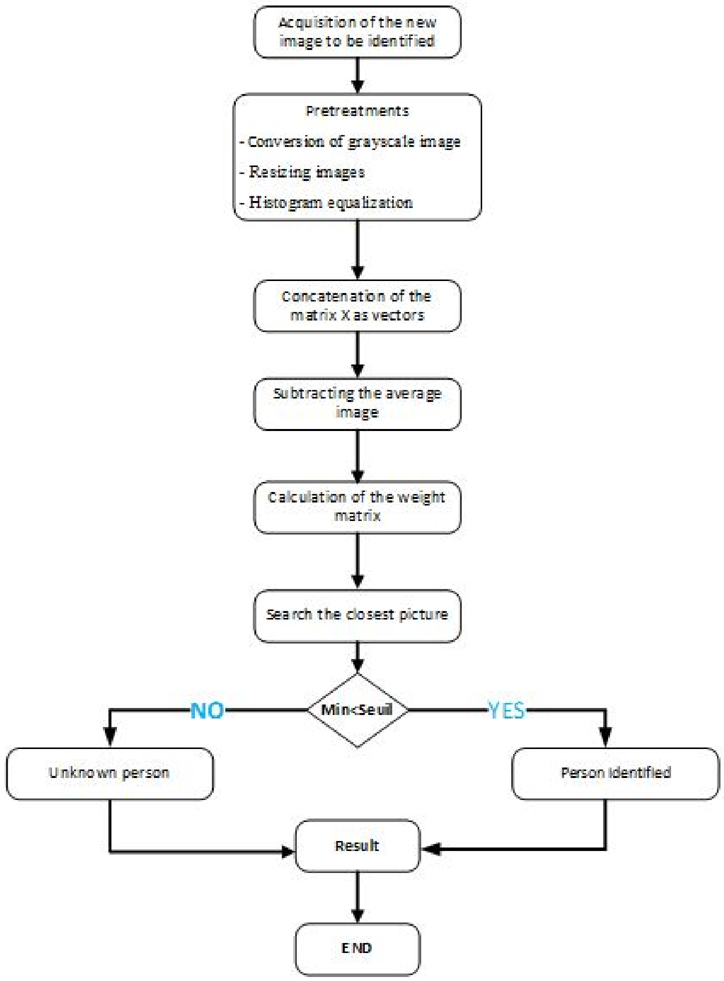

Figure 2.3: **EigenFaces logigram identification phase**

2.2.4 Benefits and deficiencies

2.2.4.1 Benefits

Eigenface provides an easy and cheap way to realize face recognition in that:

- Its training process is completely automatic and easy to code.
- Eigenface reduces statistical complexity in face image representation.
- Eigenface can used large databases.

2.2.4.2 Deficiencies

The deficiencies of the eigenface method are:

- Very sensitive to lighting, scale and translation;
- Eigenface has difficulty capturing expression changes.

The most significant eigenfaces are mainly about illumination encoding and don't provide useful information regarding the actual face.

2.3 Fisherfaces

Eigenface method uses PCA for dimensionality reduction, which yields projection directions that maximize the total scatter across all classes of images. This projection is best for reconstruction of images from a low dimensional basis. However, this method doesn't make use of between-class scatter. The projection may not be optimal from discrimination for different classes.

While this is clearly a powerful way to represent data, it does not consider any classes and so a lot of discriminative information may be lost when throwing components away.

The Fisherface method is an enhancement of the Eigenface method that it uses Fisher's Linear Discriminant Analysis (FLDA or LDA) for the dimensionality reduction. The LDA maximizes the ratio of between-class scatter to that of within-class scatter, therefore, it works better than PCA for purpose of discrimination. The Fisherface is especially useful when facial images have large variations in illumination and facial expression.

This projection maximizes the ratio of between-class scatter to that of within-class scatter. The idea is that it tries to "shape" the scatter in order to make it more reliable for classification.

2.3.1 Linear Discriminant Analysis (LDA)

The Linear Discriminant Analysis (LDA) is used to find the linear combination of characteristics that better separate object or event classes. The resulting combinations can be used as a linear classifier, or generally in reducing characteristics before the posterior classification.

LDA is closely related to the PCA, because both seek the linear combinations of the variables that better represents the data. This statistic skill explicitly to model the difference between data classes unlike the PCA which does not take into account the differences between classes.

2.3.2 LDA for recognition

The LDA by recognition algorithm is divided into two phases, one for the calculation of person models called system learning phase and the other which is to recognize a person thanks to registered models called test stage.

2.3.2.1 Learning phase

As in the PCA, it gathers the images of the learning database in a large image matrix T where each column represents a image listed Ti, then the average image is calculated. For each class C, the average image is calculated. Each image Ti of each class Ci is then refocused in comparison of the average. This produces a new image. Then we proceed at calculation of the different scatter (dispersion) matrixes named as followed:

- The Intra-class Distribution Matrix;
- The Inter-class Distribution Matrix;
- Total Dispersion Matrix.

After we have defined the different dispersion matrixes, we must find the best projection that maximizes the intra-class dispersion on its matrix while minimizing inter-class dispersion, also on its matrix.

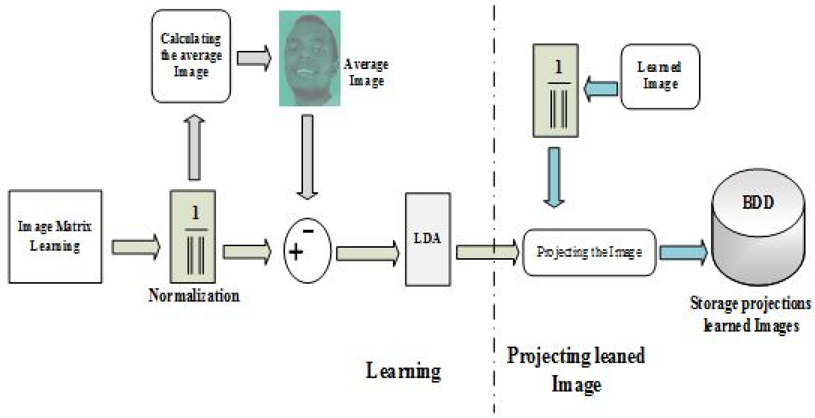

Figure 2.4: **Learning phase of a face recognition system using a global method**

2.3.2.2 Test phase or test stage

Once the optimal projection that maximizes the found intraclass dispersion, the same pattern as the PCA on the projection of learned image and the projection of a test image is applied. Then we project the test image in the Fisher space. We compare the models obtained in learning phase. The comparison is made by calculating the distances (for instance, one can use calculation of the Euclidean Distance) between models and the test vectors and a decision rule is used to classify people.

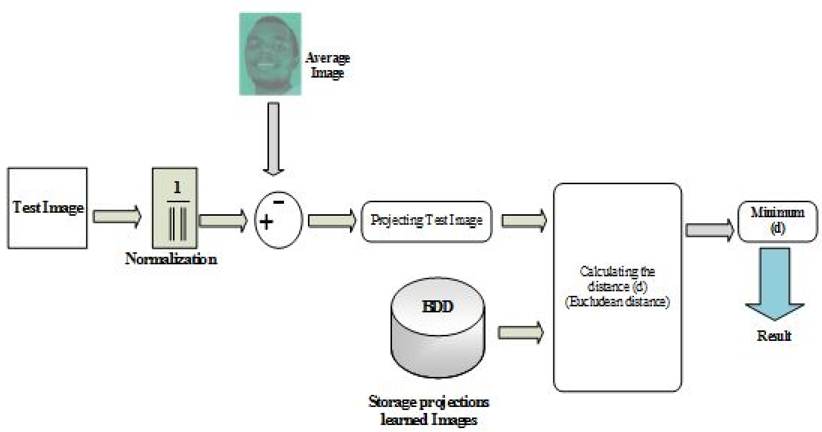

Figure 2.5: **Test phase of a face recognition system using a global method**

2.3.2.3 Fisherfaces logigram

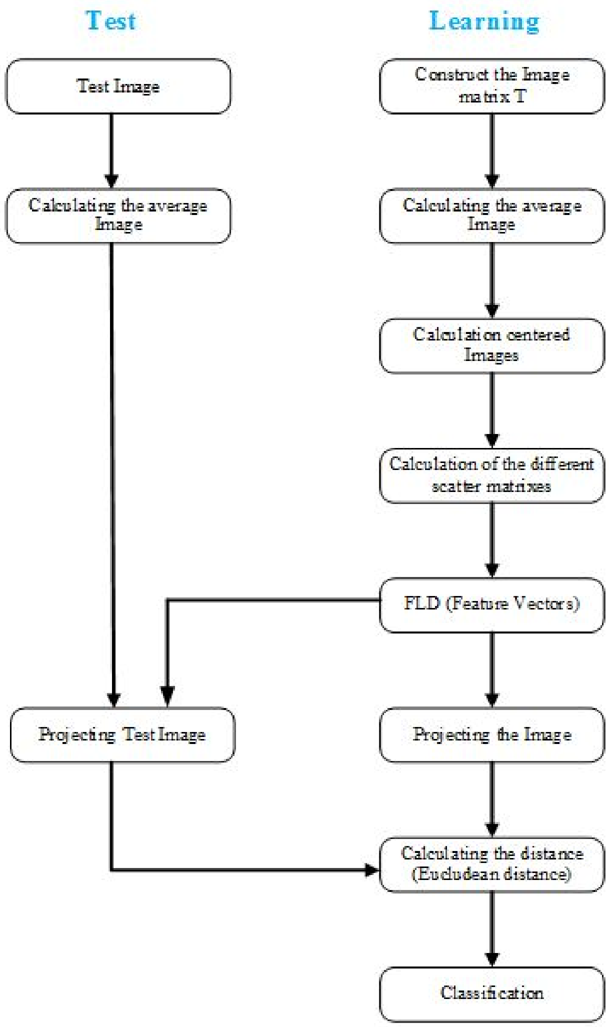

Figure 2.6: **FisherFaces logigram**

2.3.2.4 Benefits and deficiencies

The use of the LDA method for face recognition afford the following advantages:

- Maximizing inter-class scatter ;
- Reduction of intra-class scatter ;
- The method of Fisherfaces solves the problem of robustness to changes in pose, and facial expressions.

Despite these advantages, in the literature a serie of negative spikes still exists as:

- Costly (heavy) in computation time ;
- Costly (heavy) in memory space ;
- Makes poor results when the number of training images is great.

Chapter 3

Organization

In order to achieve our project on schedule we had to define steps to optimize the management of our time and to avoid delay on deadline.

Step 1 During early months at the launch of project, we started by writing the user requirements, which is a document etablished according to the need of the product owner. The user requirements allowing all users to orient the project progress and to keep in view the expected objectives. So this is a writing task. This user requirements was presented to the product owner and before an academic jury. This was about getting validation on user requirements of the product owner so that we make sure that his needs are clearly understood by us.

Then we had, thanks to Mister Chatelier's training a project manangement system called scrum. This system was about detailling all the tasks there was to complete and specifically the sprints.

Step 2 Thanks to the training given by Mister Christian Chatellier, we achieved the implementation of the project management system. This system includes the backlog writing which listseach individual task there is to complete during the project and affords us to define every sprints (knowing that a sprint represents a week of work). Obvisoulsy, a Trello account was created from that document to allow us to hold a daily project meeting whiwh lasts fifteen minute and is called Scrum. Scrum is useful for daily monitoring of the current sprint.

The main purpose of this organization was for us to complete a second important task which is the writing of the state of art. A document reporting the theoretical aspect to be developped in the project but also the explanation of the methods used and the algorithms to be programmed. This task was carried out throughout the sprint 1. And at the sprint 2, we did a literature search to deepen the appearance of algorithmic methods and presented the results of our research so that we all stand on the same point of view.

Step 3 Once, an organization detailling progressively every single task there is to complete and the different actor on it we could more easily work on the programming part of our project to program the prototypes.

Chapter 4

Technical report

4.1 Explanations on Eigenface prototype

In this section, we will explain the implementation of eigenfaces method with the differents expressions

4.1.1 Algorithm

Using mostly PCA (principal components Analysis),eigenfaces method is based on the calculation of eigenvectors and eigenvalues. The algorithm consists of two steps: The learning phase and the identification phase

4.1.1.1 learning phase

The learning phase can be divided in several steps:

- Step 1 : It is necessary to have an image database consisting of M images. In our case we used the basis of ATT pictures composed of 400 images. The database consists of 40 subjects and each subject has 10 images. All these images are the basis for learning.Each image is a matrix.
- Step 2 :Each image matrix is converted into vector

$$\begin{pmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nm} \end{pmatrix} \Longrightarrow A = \begin{bmatrix} a_{11} \\ \vdots \\ a_{nm} \end{bmatrix}$$

- Step 3 : all M image vectors are then combined into a single matrix Γ. Note that each column of the matrix represents an image Γ_i.

$$\Gamma = \begin{pmatrix} a_{11} & \cdots & z_{11} \\ \vdots & \ddots & \vdots \\ a_{nm} & \cdots & z_{nm} \end{pmatrix}$$

Figure 4.1: **matrix of images database**

a:the subject 1 and z the subject n

- Step 4 : Calculate the average Ψ of all images

$$\Psi = \frac{1}{M}\sum_{i=1}^{M} \Gamma_i$$

- Step 5 : substract the average image from each image

$$\varphi_i = \Gamma_i - \Psi$$

- Step 6 : calculate the covariance matrix S

$$S = \sum_{i=1}^{M} \varphi_i \ . \varphi_i^T = A.A^T \text{ Avec } A = [\varphi_1, \ldots \ldots . \varphi_m]$$

- Step 7 : After the covariance matrix ,eigenvalues and eigenvectors are computed. Eigenvectors are then sorted by decreasing order.

  $S * e_i = \lambda_i * e_i$

  Formulas : $\begin{cases} e_i = A * v_i & \text{eigenvectors} \\ \lambda_i = \mu_i & \text{eigenvalues} \end{cases}$

4.1.1.2 identification phase

The identification phase consists of two steps and will help to recognize an input image in the image database.

- Step 1 : compute projection vectors

  $w_k = e_k^t * (\lambda_i - \psi)$

  The projection vectors are called "weight vectors " and form a single matrix which will help for compute Euclidean distance. It also will help to find the class for an input image.

- Step 2 : compute the Euclidian distance

4.1.2 Functions programmed

4.2 Explanations on Fisherface prototype

4.2.1 Alorithm

4.2.2 Functions programmed

Chapter 5

Implementation

5.1 Implementation results

5.2 Prospects

Facial recognition develop tools very useful for people such as our first goals which were to improve parental control and to develop serious in order to help childrens with handicap. But so far, still there are some applications like high security, and ... All those applications require less human efforts, and then the use of this method are factor of unemployement and reduce responsibility from parents. On this project, we would have expected to have much more time to implement the methods in other way and to optimize much more the programs.

5.3 Difficulties faced and summary

5.3.1 Difficulties faced

When the project began, we set several objectives. To achieve them, we have established a schedule for work organized. But throughout the project, we have encountered some difficulties: technical difficulties and organizational difficulties.

The main difficulties are :

- implementation difficulties : because for programming methods, we had to define a unique way to structure the program for consistency in all codes. We have thus established a reference document to have uniform codes.
- understanding difficulties :everyone had understood in a different way from others the concept of the methods(eigenfaces and fisherfaces) for the implementation of our algorithm.
- Programming difficulties :we have different levels in programming. But that does not prevent us to program
- Using tools difficulties : everyone had to program a part of the code, so we needed a way for share and synchronize our codes. the tool was new and we took time to control this,

- management difficulties : as we have already said, we set goals and we had established a schedule for work in an organized way, but many secondary, unanticipated and unforeseeable tasks appeared.

However we faced all these difficulties, which allowed us to learn more about the two main domain of our project: images processing and programming language . Finally, these difficulties may be helpful for future work. These can be apprehended in another project

5.3.2 Summary

This project allowed us to gain maturity in the work and help us to understand the importance of planning, organization, and discipline for the success of a project. In addition, it also gave us the satisfaction of completing the project in a group. Each member benefits from the skills of other members,

We could see that it was a very positive experience for our future because this experience has allowed us to understand the complexity to manage a project, but also the difficulty of understanding and the importance of communication in a group