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THÈME

FINGERPRINT RECOGNITION BY INVARIANT MOMENTS

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Introduction

Introduction general

Biometrics is the technique that makes it possible to identify people through Physical and behavioral characteristics. Use body parts that man recognizes people is an old process. There are different physical or behavioral means that allow Recognition of the individual. Footprint, iris, face and hand shape are Physical means are called "biometric method". We can also cite the example. From the vein of the hand, from the retina and from the ear. As for conditions Behavioral, we can cite signature (dynamic or constant), approach, etc. Biometric characteristics are permanent in principle (per individual) He keeps for the duration of his existence), unique (special to each individual) and Universal (found in all individuals). They represent a very good alternative. Strong passwords or PINs (PINs)easily forgotten or exposed to fraudulent use or keys or The magnetic cards that an individual must carry and facilitate their theft, copy it or lose it. Several research projects in the field of fingerprint recognition are based on the extraction and comparison of minutiae. Minutiae are biological characteristics of the finger that distinguish a person’s fingerprint from the footprint of another. Methods based on minutiae are the most answered and more mature. However, they have limitations that can influence their effectiveness and performance. Minute-based methods are sensitive to noise in the image of the fingerprint view that noise points are generally treated as minute points and true minutiaes can be ignored. In addition, the number of different from one fingerprint to another, which can reduce the reliability of minute-based systems.

These limitations of the minutiae-based methods have encouraged researchers to direct their efforts towards exploiting other characteristics of the footprint digital. Methods based on textures, that is to say the information of the peaks(ridges) and singular global points (delta and core) gradually take their place in the fingerprint recognition domain. The new trend towards the use of the full texture of the footprint requires the use of a powerful description tool to properly describe the texture in order to use it in comparison in a more efficient way. On our part, we will try to test the effectiveness of a mathematical tool that has demonstrated its effectiveness as a descriptor in several domains, these are the moments of Tchebichef and The seven moments of Hu are invariants to translations and changes rotations.

Thus, these moments have the ability to describe the foot print independently of its position, size and rotation. Theoretically these moments can bring one more to the fingerprint recognition domain. Thus, these moments have the ability to describe the footprint independently of its position, size and rotation.

Their invariance to translation and rotation avoids the alignment step and all calculations it requires (calculation of reference points). The invariance to scale change allows comparison without the need to unify the size of the fingerprint images which implies the preservation of all information about the impression and its shape (without the distortion of the image footprint that may be caused by the scale change). In this regard, the question that arises is: Is what the moments of Tchebichef are really powerful features for fingerprint discrimination digital? To answer this question, we used two fingerprint databases, one acquired and the other by an optical sensor. The prints are taken with different rotations (between 0° and 180°), another fingerprint base is extracted at starting from these two bases by changing the scale. For the sake of clarity, our submission is organized as follows:

- In the first chapter we wish to briefly present the characteristics of the fingerprint and then the general architecture of a fingerprint recognition system as well as the various Recent fingerprint recognition methods.
- In the second chapter, we will first introduce the moments of Tchebichef & HU followed by their characteristics,
- In the third chapter we will describe our recognition system of fingerprints by presenting the different methods and algorithms used for the implementation of its modules.

Chapter I

Biometrics & Recognition of Digital Fingerprint

I.1 Introduction

Biometrics are all biometric technologies that exploit physical or behavioral characteristics to identify individuals. These technologies exploit the characteristics that are unique to each individual and cannot be lost neither stolen nor reconstituted as with traditional means based or magnetic cards. For this reason, biometrics appears to be one of the best parades against identity fraud.

I.2 Biometrics

I.2.1 Definition

Biometrics is composed of two terms: bio/ metric is the «measurement of the living».

It is a global technique aimed at establishing a person's identity by measuring one of his physiological or behavioral characteristics. There may be several types of characteristics, some more reliable than others, but all must be tamper-proof and unique in order to be representative of one and only one individual. [2]

I.2.2Why biometrics?

The arguments for biometrics can be summarized in 2 categories:

-Convenience: Passwords such as credit cards, debit cards, ID cards or keys can be forgotten, lost, stolen and copied. In addition, today everyone must remember a multitude of passwords and have in their possession a large number of cards. Biometrics, on the other hand, would be immune to this kind of disease, in addition to being simple and practical, because there are no cards or passwords to remember.

-Biometrics would be able to reduce, but not eliminate, crime and terrorism because, at the very least, it complicates the lives of criminals and terrorists.[1]

Biometrics is based on the analysis of data related to the individual and can be classified into three main categories:

- ✓ Morphological analysis: fingerprints, iris, shape of the hand, facial features, venous network of the retina.
- ✓ Biological analysis: DNA, blood, saliva, urine, smell, thermographs.
- ✓ Behavioral analysis: speech recognition, keyboarding dynamics, signature dynamics, walking.

I.2.3 Biometric System Architecture

There are always at least two modules in a biometric system:

The Learning and Recognition Modules The third module (optional) is the adaptation module. During learning, the system will acquire one or more biometric measures that will be used to build a model of the individual.

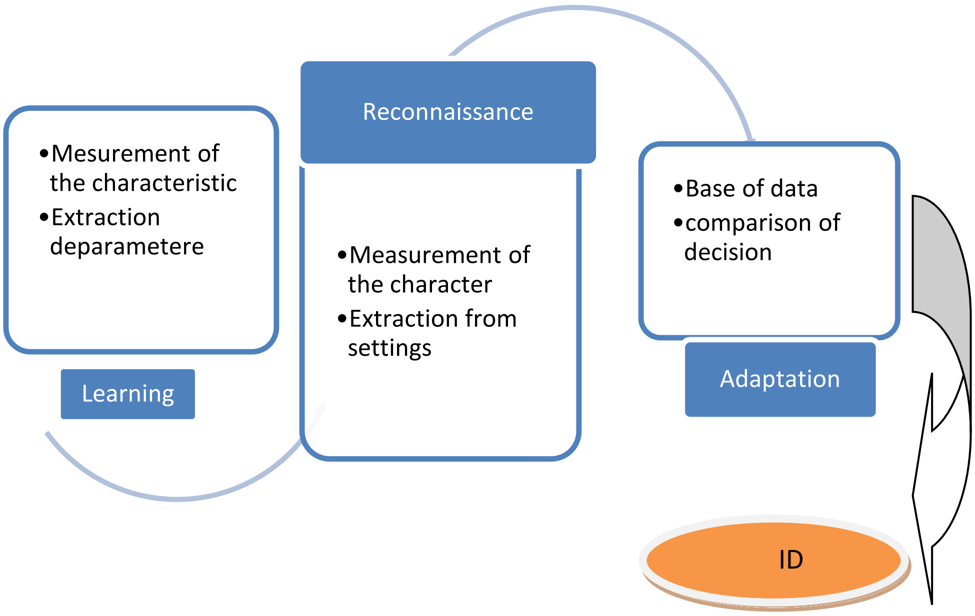

Figure I.1: Biometrics System Architecture

I.2.3.1 Learning Module:

During learning, the biometric characteristic is first measured using a sensor; In general, this capture is not directly stored and transformations are applied to it. Indeed, the signal contains useless information to the recognition and only the relevant parameters are extracted.

I.2.3.2 Recognition Module

During recognition, the biometric characteristic is measured and a set of parameters is extracted as during learning. The sensor used must have properties as close as possible to the sensor used during the learning phase. If the two sensors have too different properties, it will usually be necessary to apply a series of additional preprocessing to limit the degradation of performance. The sequence of recognition will be different according to the procedure of the identification or verification system. In identification mode, the system must guess the identity of the person. So he answers a question like, "Who am I?" In general, when we talk about identification, we assume that the problem is closed, that is to say that anyone who uses the system has a model in the database. [1]

I.2.3.3Module Adaptation :

During the learning phase, the biometric system often captures only a few instances of the same attribute in order to limit the inconvenience for the user. It is therefore difficult to construct a general model capable of describing all possible variations of this attribute. In addition, the characteristics of this biometrics and its acquisition conditions may vary. Adaptation is therefore necessary to maintain or even improve the performance of a system after use.

I.2.4 Application of biometrics

Three sectors are particularly affected by the use of biometrics [WEB 01].

- Judicial Application:

This is certainly the first area where biometric identification has been applied: Identification of criminals, terrorists, corpses, missing children, etc...

- Government Application:

Biometrics can prevent fraudulent use of documents (e.g. passport, driver's license, etc.).

- Physical and logical access control:

- Logical access control (computer access control, network login, remote access VPN connections, etc.). - Control of physical access to premises (computer room, research department, sensitive site, etc.), electronic locks, etc.

I.3 Digital Fingerprint

I.3.1 Fingerprints as Biometric

Fingerprint method of identification is the oldest and widely used method of authentication in biometrics authentication. The trait of friction ridge skin means that no two finger prints are ever exactly alike (never identical in every detail), even two impressions recorded immediately after each other, this is the main basis for usage of fingerprints in biometric authentication. [3]

I.3.2 Characteristics of prints

A fingerprint consists of a set of locally parallel lines forming a unique pattern for each individual (Figure 1.1.2), distinguishing between streaks (or ridges, these are lines in contact with a surface to the touch) and grooves (these are the hollows between two streaks). The streaks contain a set of 7evenly spaced pores in the center.

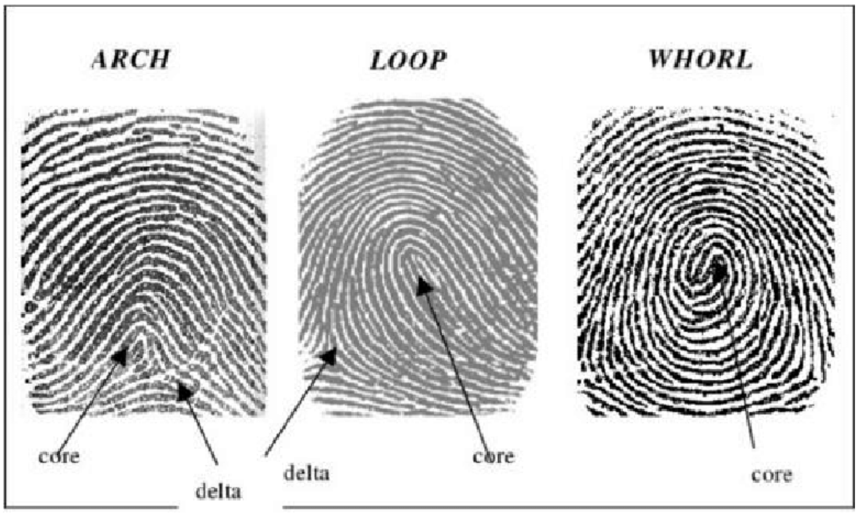

Figure I.2: Fingerprint characteristics

Each imprint has a set of singular global points (centers and deltas) and local points ( ). The centers correspond to places of convergence of striations, while the deltas correspond to places of divergence [1] . Several studies have shown the existence of sixteen different types of minutiae (Figure I.2) but in general algorithms are only interested in bifurcations and terminations that allow to obtain the other types by combination.

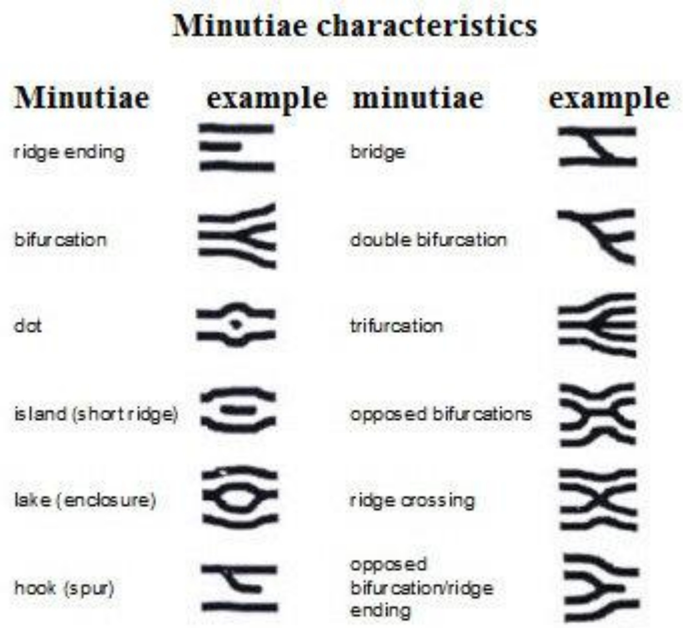

Figure I.3: The different types of minutiae.[6]

The position and number of centers and deltas allow to classify the imprints in category according to their general pattern, we distinguish mainly trios large females (see Figure I.4):

(loop) represent 65% of the fingerprints encountered.

(whorl) represent 30% of the impressions encountered.

(arch) represent 5% of the impressions encountered.

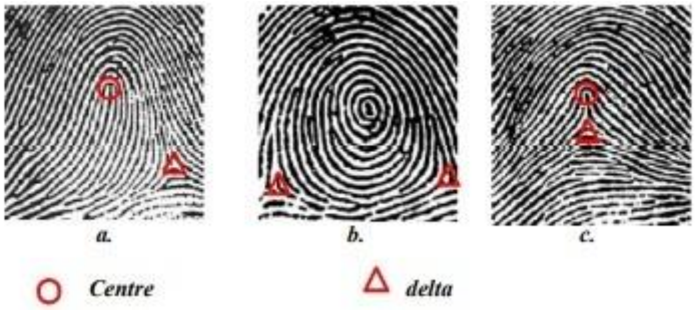

Figure I.4: The three main classes of imprints, loop (a), spire (b), arch (c) .

I.4 Stages of Fingerprint Authentication

Most approaches to recognizing a fingerprint involve five basic stages: (i) acquisition, where the image is obtained from hardware or a file; (ii) pre-processing, which may include thinning, noise reduction, image enhancements and error correction; (iii) structural extraction, where global and local structures may be found; (iv) post-processing, where the structures are converted into a more useful format; (v) and then matching, where fingerprints are compared against a database [8] .These stages are shown in this steps:

- ✓ Acquisition

  Image is obtained from input device or file.
- ✓ Pre-Processing

  Image Enhancements

  Finding reference point, interest region

  Conversion to black and white

  Thinning and minutiae extraction
- ✓ Structural Extraction

  Local and/or global structures are extracted from the image

  While some authors propose minutiae extraction methods that need previous binarization, others use approaches that work directly with gray-scale images, as binarization is time consuming and some information may be lost during its process
- ✓ Matching

  Fingerprints are compared against a database, A fingerprint matching algorithm compares two given fingerprints and returns either a degree of similarity or a binary decision.

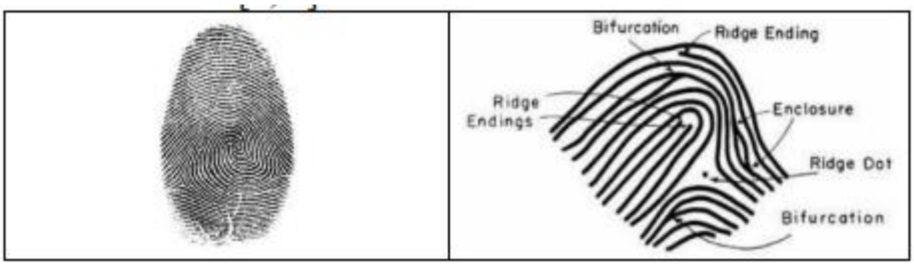

Figure I.5 : Fingerprint Sample

The method chosen for acquisition of a fingerprint image depends on many different factors, including the cost and reliability of an input device[4][5] The general system architecture of Fingerprint Authentication is depicted in Figure I.5.

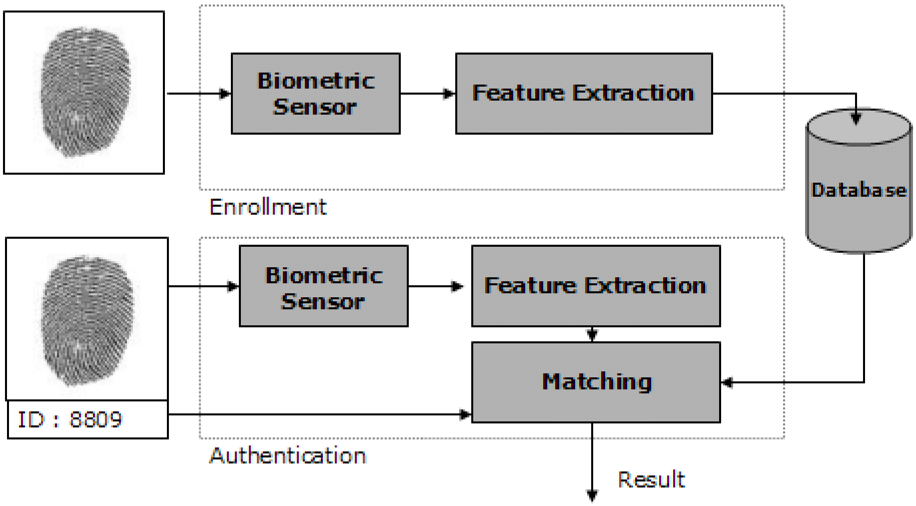

Figure I.6: General architecture of fingerprint authentication[7]

I.5 Conclusion

Fingerprint recognition is a modern imaging technology. The reliability of any automatic fingerprint recognition system strongly relies on the precision obtained in the features extraction process.

Chapter II

INVARIANT MOMENTS

II.1 Introduction

Moments and moment functions have been extensively used for feature extraction in pattern recognition and object classification. One important property of the moments is their invariance under affine transformation. The pioneering work on this subject was by Tchebichef. Since then, many applications have been developed, which made use of geometric, complex, rotational and orthogonal moments. Considerable attention has been paid on the theoretic study and application of the orthogonal moments since they can be easily used to reconstruct the image, and have the minimum information redundancy to represent the image. Recently, discrete orthogonal moments such as Tchebichef, Krawtchouk, dual Hahn, Racal and Hahn moments have been introduced in image analysis community. It was show one main difficulty concerning the use of moments as feature descriptors is their high computational complexity. To solve this problem, a number of fast algorithms have been reported in the literature. Most of them concentrated on the fast computation of geometric moments and continuous orthogonal moments. Less attention has been paid on the fast computation of discrete orthogonal moments. Wang and Wang proposed a recursive algorithm based on Glenshaw's recurrence formula to compute the Tchebichef moments.

Discrete orthogonal moment gives better representation of image even with less order, effective under translation, rotation and tilt and less sensitive to noise. [9]

II.2 Moments :

The feature representation capability of different types of image moment functions defined in the rectangular regions, such as the Geometric moments, Central moments, Legendre moments, and Gegenbauer moments has been widely studied and applied in several areas of computer vision, including image analysis and recognition. The moment-based image features can capture global properties of an image and represent it in the moment space uniquely. [10]

We will present five class of geometrical and orthogonal moment:

II.2.1 HU moment:

Using nonlinear combinations of geometric moments, Hu derived a set of invariant moments, which has the desirable property of being invariant under image translation, scaling and rotation. [11] the central moments, which are invariant under any translation, are defined as:

$$M_{pq} = \iint_{\propto}^{\propto} (x-\bar{x})^p \,(y-\bar{y})^q f(x,y)dxdy \quad (1)$$

Where:

$$\overline{x} = \frac{\bar{M}_{10}}{\bar{M}_{00}}\,, \overline{y} = \frac{\bar{M}_{10}}{\bar{M}_{00}}\ , \qquad \bar{M}_{pq} = \int_{-\propto}^{\propto}\int_{-\propto}^{\propto} x^p\, y^q f(x,y)dxdy \quad (2)$$

However, for images, the continuous image intensity function f(x,y) is replaced by a matrix, where x and y are the discrete locations of the image pixels. The integrals in equations (3) and (4) are approximated by the summations:

$$M_{pq} = \sum_{x=0}^{m}\sum_{y=0}^{n}(x-\bar{x})^p \,(y-\bar{y})^q f(x,y)dxdy \quad (3)$$

$$\bar{M}_{\mathrm{pq}} = \sum_{\mathrm{x=0}}^{\mathrm{n}}\sum_{\mathrm{y=0}}^{\mathrm{m}} \mathrm{x^p\, y^q}\, f(x,y)dxdy \quad (14)$$

Where m and n are the dimensions of the image. The set of moment invariants that has been used by Hu are given by:

$$\Phi_1 = M_{20} + M_{02} \quad (5)$$

$$\Phi_2 = (M_{20} - M_{02}) + 4M_{11}^2 \quad (6)$$

$$\Phi_3 = (M_{30} - 3M_{12})^2 + (3M_{21} - M_{03})^2 \quad (7)$$

$$\Phi_4 = (M_{30}+M_{12})^2 + (M_{21} + M_{03})^2 \quad (8)$$

$$\Phi_5 = (M_{30} - 3M_{12})(M_{30} + M_{12})[(M_{30} + M_{12})^2 - 3(M_{21}+M_{03})^2] +$$

$$(3M_{12} - M_{02})(M_{21} + M_{03})[3(M_{30} + M_{12})^2 - (M_{21} + M_{03})^2] \quad (9)$$

$$\Phi_6 = (M_{30} + M_{02})[(M_{30} + M_{12})^2 - (M_{21} + M_{03})^2]$$

$$+4M_{11}(M_{30} + M_{12})(M_{21} + M_{03}) \quad (10)$$

$$\Phi_7 = (M_{21} - M_{03})(M_{30} + M_{12})[(M_{30}+M_{12})^2 - 3(M_{21}+M_{03})^2] + 3(M_{21}-M_{03})$$

$$(M_{21}+M_{03})[3(M_{30}+M_{12})^2-(M_{21}+M_{03})^2] \quad (11)$$

These functions can be normalized to make them invariant under a scale change by using the normalized central moments instead of the central moments. The normalized central moments are defined by:

$$M_{pq} = \frac{M_{pq}}{M_{00}^{a}} \text{ where } a = \frac{(p+q)}{2}+1 \quad (12)$$

II.2.2 Zernike moment:

Zernike defined a complete orthogonal set$\{Vnm|(x, y)\}$ of complex polynomials over the polar [12]coordinate space inside a unit circle$(x^2 + y^2 = 1)$ as follows :

$$V_{nm}(x, y) = V_{nm}(\rho, \theta) = R_{nm}(\rho)e^{jm\theta} \quad (13)$$

Where j=$\sqrt{-1}$, n≥ 0,m is a positive or negative integer, |m| ≤ n, n − |m| is even, ρ is the shortest distance from the origin to (x, y) pixel, θ is the angle between vector ρ and x-axis, is the orthogonalρin counter clockwise direction, and$R_{nm}(\rho)$ radial polynomial given by:

$$R_{nm}(\rho) = \sum_{s=0}^{n-|m|!2}(-1)^s \frac{(n-s)!}{s!\left(\frac{n+|m|}{2}-s\right)!\left(\frac{n-|m|}{2}-s\right)!}\rho^{n-2s} \quad (14)$$

Note that $R_{n-m}(\rho) = R_{nm}(\rho)$ .these polynomials are orthogonal and satisfy the following condition:

$$\int\int_{x^2+y^2\leq 1}^{1}[V_{nm}(x, y)] * V_{pq}(x, y) \qquad dxdy = \frac{\pi}{n+1}\delta_{np}\delta_{mq} \quad (15)$$

Where:

$$\boldsymbol{\delta_{ab}} = \begin{cases} \mathbf{1}; \boldsymbol{if} \quad \boldsymbol{a = b} \\ \mathbf{0}; \quad \boldsymbol{othewise} \end{cases} \tag{16}$$

Zernike moments are the projection of the image intensity function f (x, y) onthe complex conjugate of the previously defined Zernike polynomial V_{nm}(ρ, θ), which is defined only over the unit circle***:***

$$\boldsymbol{A_{nm}} = \frac{\boldsymbol{n+1}}{\boldsymbol{\pi}} \int \int_{\boldsymbol{x^2+y^2 \leq 1}}^{\mathbf{1}} \boldsymbol{f(x, y) V_{nm}^{*}(\rho, \theta) dxdy} \tag{17}$$

For a digital image ,Zernike moments are given by:

$$\boldsymbol{A_{nm}} = \frac{\boldsymbol{n+1}}{\boldsymbol{\pi}} \sum_{\boldsymbol{x}} \sum_{\boldsymbol{y}} \boldsymbol{f(x, y) V_{nm}^{*}(\rho, \theta)} \qquad \boldsymbol{where\ \ x^2 + y^2 \leq 1} \tag{18}$$

II.2.3 Pseudo-Zernike moments:

Pseudo-Zernike moments are derived from Zernike moments; therefore, both these moments have analogous properties [13]. The difference lies in the definition of the radial polynomial, which is given by:

$$\boldsymbol{R_{nm}(\rho)} = \sum_{\boldsymbol{i=0}}^{\boldsymbol{n-|m|}} (\mathbf{-1})^{\boldsymbol{s}} \frac{(\boldsymbol{2n+1-s})!}{\boldsymbol{s}!(\boldsymbol{n-|m|-s})!(\boldsymbol{n+|m|+1-s})!} \boldsymbol{\rho^{n-1}} \tag{19}$$

II.2.4 Legendre moments :

The well-known Legendre polynomials [14] form the basis function in the Legendre moments. Recall that the pth order Legendre polynomial is defined as:

$$P_p(x) = \frac{1}{2^p p!} \frac{d^p}{dx^p} (x^2 - 1)^p x \in]-1,1] \tag{20}$$

$$L_{pq} = \frac{(2_p+1)(2_q+1)}{4} \int_{-1}^{1} \int_{-1}^{1} p_p(x) p_q(y) f(x, y) dxdy \tag{21}$$

Where p,q are integer between $(0, \propto)$, and x and y are the x-and y-coordinate of the image

Similarly , the Legendre moment for a(N*N)digital image is given by :

$$L_{pq} = \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} p_p(m_n) p_q(n_N) f(n, m) \tag{22}$$

Where:

$$m_n = \frac{2n-N+1}{N-1} \tag{23}$$

To compute the Legendre moments, a given image is mapped into the limit domain [−1,1] as the Legendre polynomial is only defined over this range.

II.2.5 Tchebichef moments:

Chebyshev (sometimes referred to as Tchebichef) moments, introduced by Mukundan et al., belong to a class of discrete orthogonal moments. [13]The two-dimensional (2-D) Tchebichef moment of order (n+m) of an image intensity function f(x, y) with size N × N is defined as [21] :

$$t_n(x) = \frac{(2n-1)t_1(x)t_{n-1}(x)-(n-1)\left(1-\frac{(n-1)^2}{N^2}\right)t_{n-2}(x)}{n} \quad (24)$$

With the initial condition:

$$\begin{cases} t_0(x) = 1 \\ t_1(x) = \frac{2x+1-N}{N} \end{cases} \quad (25)$$

Where $n = 0,1 \dots \dots \dots \dots.., N-1.$ The Tchebichef moment of order$(p+q)$of an image intensity function is defined as:

$$T_{nm} = \frac{1}{\rho(m,M)\rho(n,N)} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} t_m(x) t_n(y) f(x,y) \quad (26)$$

Where $n, m = 0,1, \dots \dots \dots \dots \dots \dots \dots, N-1$. The Tchebichef polynomial satisfies the property of orthogonally with:

$$\rho(n,N) = \frac{N(1-\frac{1}{N^2})(1-\frac{2^2}{N^2})(1-\frac{n^2}{N^2})}{2n+1} \quad (25)$$

Note: that with Tchebichef moments, the problems related to continuous orthogonal moments are purged by using a discrete orthogonal basis function (i.e., Tchebichef polynomial) [13]. In addition, no mapping is required to compute Tchebichef moments as the Tchebichef polynomials are orthogonal in the image coordinate space.

II.3 Conclusion

Moments was often the first choice to many authors in the field of pattern recognition and vision by the computer. Their consistency in translation, rotation and resizing gives them the potential for use in new image processing fields and even combined with Other times to get a better result by taking advantage of each other's strengths Moment.

CHAPTER III

Application and experimental results

III.1 Introduction

We introduce in this chapter an integrated system for recognition of a digital fingerprint by the Hu and Tchebichef moments. We started with explaining the system architecture from the collecting of the dataset to the preprocessing techniques done on the data, to the final step of prediction.

The datasets are collected from "bias.csr.unibo" [15] and "kaggle" [16],the first dataset contains 80elements the second one contains around 6k fingerprint sample of different persons. After that, we did some basic image resizing to our data so the finale model is much more efficient.

In the second part, we exposed the results we got with some discussion to evaluate the performance of this model based on the K Nearest Neighbor (kNN) classifier which has widely been used in the applications of data mining and machine learning due to its simple implementation and distinguished performance.[19]

III.2 System Architecture

The Figure down present the architecture of our system which recognize the fingerprints.

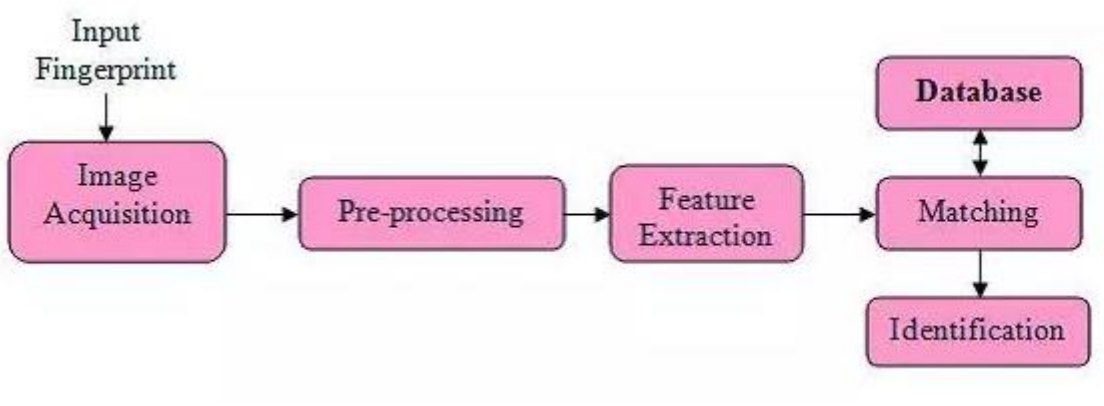

Figure III.1: System architecture.

III.3 Dataset Description

We have used two different datasets from different sources. The first dataset from bias.csr.unibo contain 80 sample which is divided for ten person each person has 8 samples for the same finger are 150*150 pixels.

Therefore the second dataset (Sokoto Coventry Fingerprint Dataset -SOCOFing-) from Kaggle Has 6000 element of 600 person each person with his ten fingers are 90*90 pixels the table down below show more details :

Table III.1: Dataset Description

Dataset	Number of elements	Training	Testing
Dataset1	80	75%	25%
Dataset2	6000	90%	10%

III.4 Resizing

When working with raster images (pixel-based) it is important to understand that scaling an image in programs, does not actually resize the image, but rather stretches images larger or scales them smaller. When scaling, the resolution is not adjusted to best suit the new size, rather the pixels are stretched and can appear pixilated. The most common side effect of scaling an image larger than its original dimensions is that the image may appear to be very fuzzy or pixilated. Scaling images smaller than the original dimensions does not affect quality as much, but can have other side effects.[17]

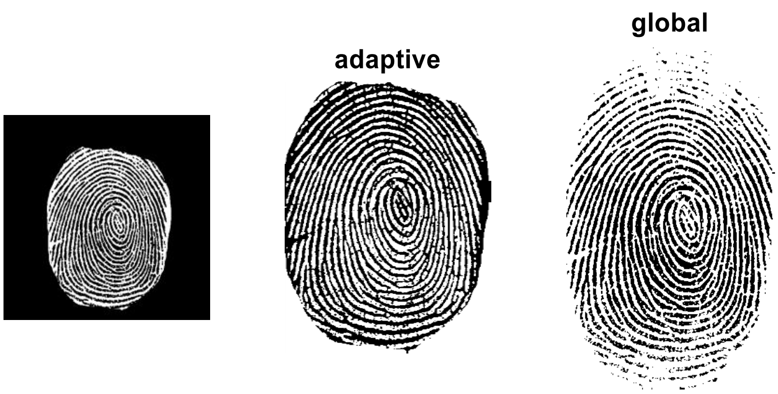

Figure III.2: Possible samples resizing.

III.5 Binarization :

The simplest binarization approach uses a global threshold and works by setting the pixels whose gray-level is lower than the threshold to 0 and the remaining pixels to 1. However, different portions of an image may have different contrast and intensity and thus a single threshold for the entire image may not be sufficient .[18]

Figure III.3: Binarization.

III.6 Hu and Tchebichev moment values

Table III.2 present Tchebychev and Hu moment value for 8 fingerprint of the same person, the results show their invariance to the geometric transformations

Table III.2: Hu Moment Invariant Values For 8 fingerprint

								
Φ_1	0.2438	0.2476	0.2586	0.2608	0.2512	0.2486	0.2411	0.2532
Φ_2	4.2960	1.1990	2.0776	2.8453	1.9434	1.7598	1.3439	2.4580
Φ_3	2.9088	1.6540	9.0304	1.4008	5.0930	1.4216	6.2760	2.6603
Φ_4	0.0150	0.0138	0.0141	0.0154	0.0144	0.0147	0.0125	0.0140
Φ_5	-3.1411	-1.6110	-3.1643	5.0400	-4.7636	-1.9699	-5.1350	-5.3912
Φ_6	-8.7878	-5.3113	1.4914	7.0335	-4.8491	-5.7765	-3.2586	-1.4686
Φ_7	7.7620	-8.7189	-2.8450	-8.9999	-5.6841	3.9475	-2.0580	-1.8078

Table III.3: Tchebychev Moment Invariant Values For 8 fingerprint

								
t_1	0.7887	0.7764	0.7519	0.7464	0.7594	0.7629	0.7756	0.0619
t_2	-0.0163	0.0209	0.0512	0.0118	0.0119	0.0063	0.0513	0.0361
t_3	-0.0335	0.0099	0.08620	0.0162	0.0238	0.0481	0.0481	0.0620
t_4	0.0320	-0.0432	-0.0342	-0.0253	0.0254	-0.0034	-0.1057	-0.1018
t_5	-0.5056	0.2690	-0.3922	-0.3507	-0.4768	-0.4707	-0.4370	-0.3804
t_6	-0.0125	-0.0350	0.0038	0.0265	0.0137	0.0350	-0.0166	0.0156
t_7	-0.2071	-0.2071	-0.1486	-0.1794	-0.1086	-0.0486	-0.0776	-0.1104
t_8	-0.1104	-0.0776	-0.0486	-0.1086	-0.1794	-0.1486	-0.2071	-0.0376
t_9	0.0894	0.1490	-8.4296	-0.0354	0.0528	0.1067	0.1234	0.1905
t_{10}	0.0159	0.0530	0.1330	-0.0025	0.0098	0.0040	0.0253	-0.1139
t_{11}	-0.0375	0.0472	0.0456	0.0412	-0.0412	-0.067	-0.054	-0.0461
t_{12}	-0.0481	0.0487	0.0471	0.0462	0.0399	0.0452	0.048	0.0421

III.7 Performance of the system using different KNN distances

We used different distances: see Annexe A. This tables reports the results obtained.

Table III.4: Performance of the system by KNN classifier with HU moments.

	Dataset 1		Dataset 2	
	Train	test	Train	Test
Euclidean	**90%**	**40%**	**100%**	**20%**
Mahalanobis	**90%**	**40%**	**100%**	**25%**
Cosine	**90%**	**35%**	**100%**	**20%**
Correlation	**90%**	**25%**	**100%**	**15%**
Spearman	**90%**	**15%**	**100%**	**10%**
Hamming	**90%**	**10%**	**100%**	**10%**
Jaccard	**90%**	**10%**	**100%**	**15%**
Minkowski	**90%**	**40%**	**100%**	**25%**
Cityblock	**90%**	**40%**	**100%**	**20%**
Chebychev	**90%**	**35%**	**100%**	**15%**

Table III.5: Performance of the system by KNN classifier with Tchebichef moments.

	Dataset 1		Dataset 2	
	train	**Test**	**Train**	**Test**
Euclidean	**90%**	**40%**	**100%**	**20%**

III.8 Discussion

In order to give an idea of the performance of the system to recognition a fingerprint, we used two types of moments (Hu and Tchebichev) with two datasets. In stat of art [20] we find they are used a moments HU with two classifier SVM & KPPV, with another different dataset witch contain 50 sample which is divided for ten persons each person has 5 samples for the same finger, their results with the SVM classifier are as 56.66% On training dataset and 43.33% on testing dataset, and results with the KNN classifier are as 30% On training dataset and 20% on testing dataset. I note that the result we got is perfect compared the results before and with more improvements such as to used multiple classifiers.

III.9 Conclusion

In this work we find the results obtained are good and we may get much better results by using other classifiers.

Conclusion

Conclusion general

In this work, we tried to evaluate the effectiveness of moments as fingerprint descriptors. Several methods and algorithms have been tested to finally realize the fingerprint recognition system. To evaluate the performance of Tchebichef moment & Hu moments objectively, we tried improve image quality as much as possible by applying several steps to preprocessing: resizing, binarization. Several prints with rotations have been recognized, which shows that Hu moments can be used as descriptors but they are not sufficient. In combination with other descriptors the moments of Hu can produce better results. To conclude, we tried to evaluate the performance of Tchebichef and Hu moments as fingerprint descriptors using KNN classifiers with different types of distances (Euclidean, mahalanobis, cosinecorrelation, spearman, hamming, jaccard, minkowski, cityblock, chebychev).

Other preprocessing methods and classifiers may be used, and even, by the combination of different classifiers, In future work. Two factors are emphasized to take advantage of the attractive features of Tchebichef moments, the first is the need for a step very effective pre-treatment as Tchebichef is moments are sensitive to noise and the second is the need to combine Tchebichef moments with other types of descriptors for best results.

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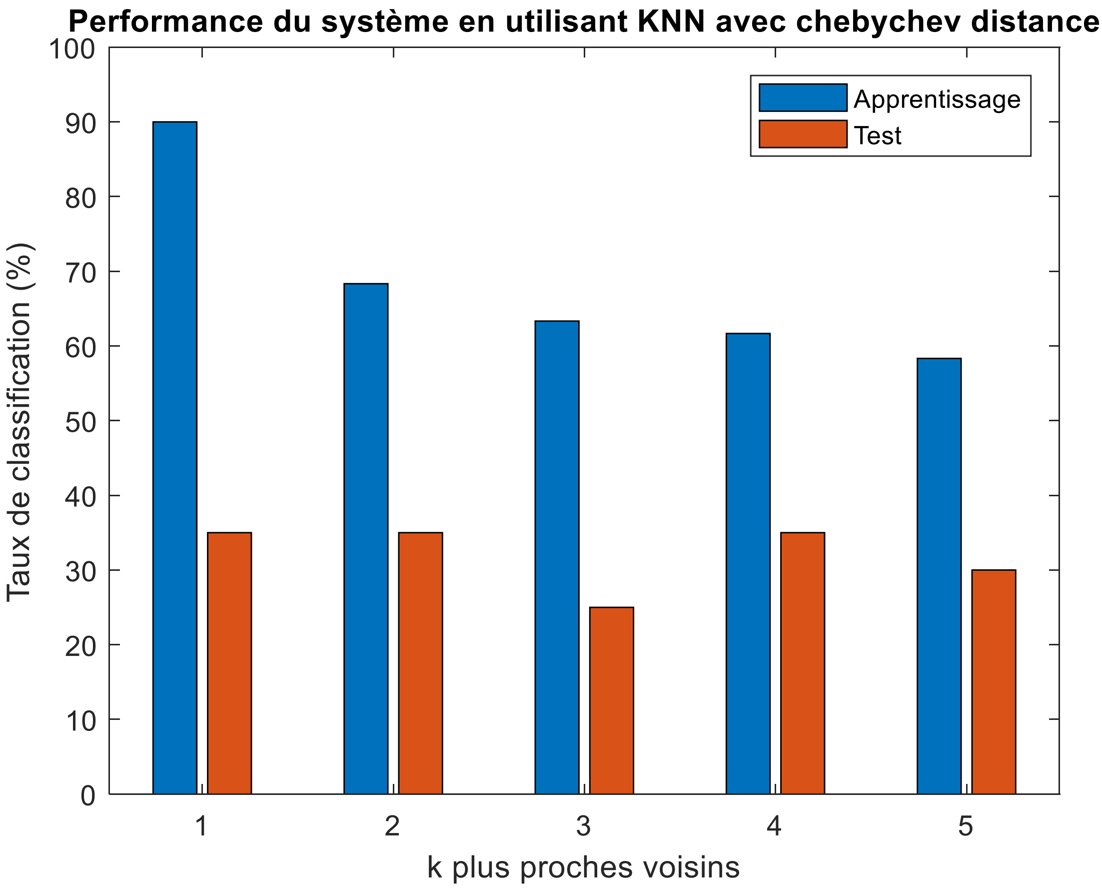
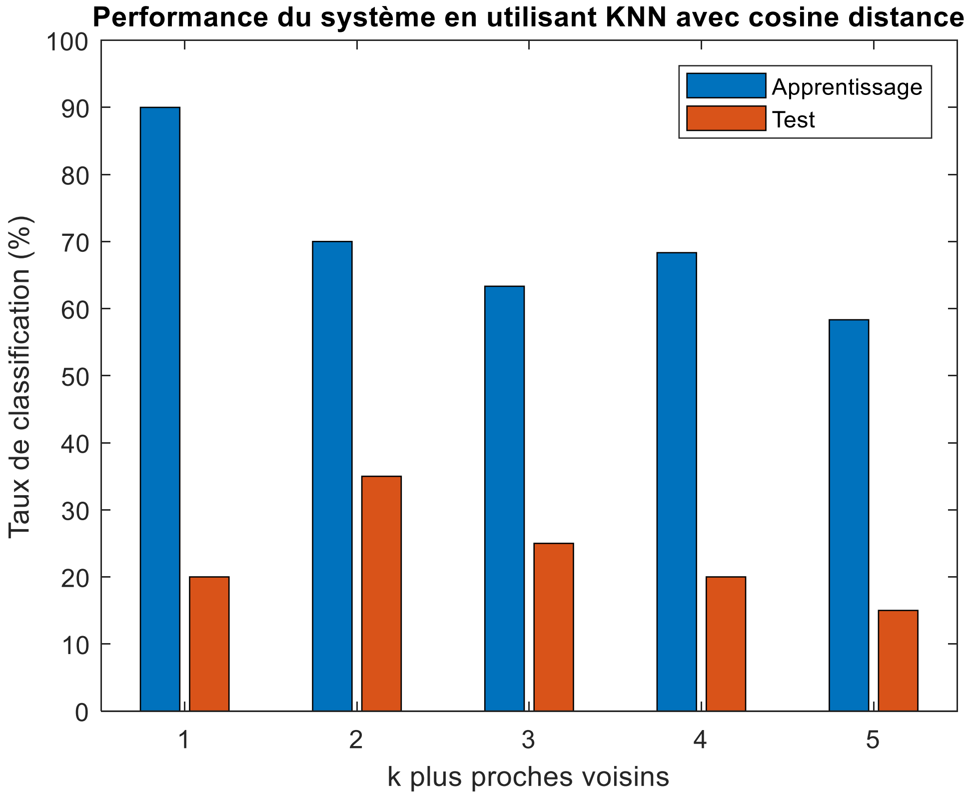
Annexes

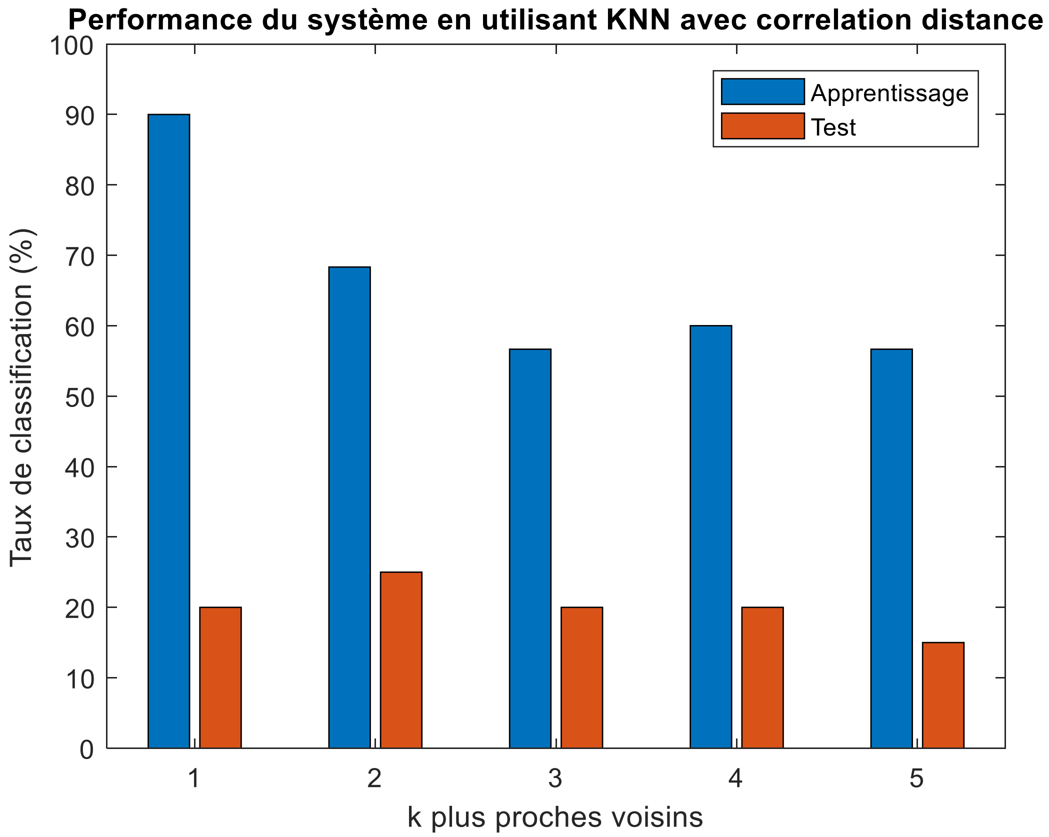
ANNEXE A

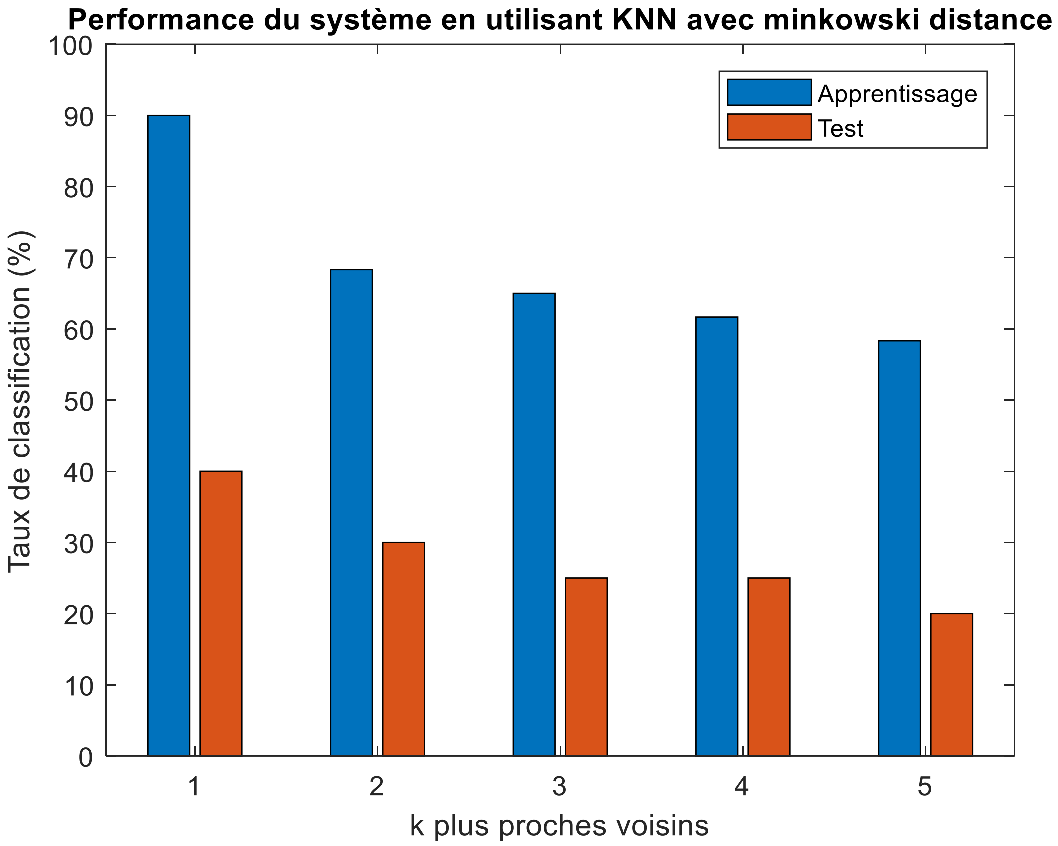
The following graphs present The Performance of the system using different KNN distances with two moments and two dataset

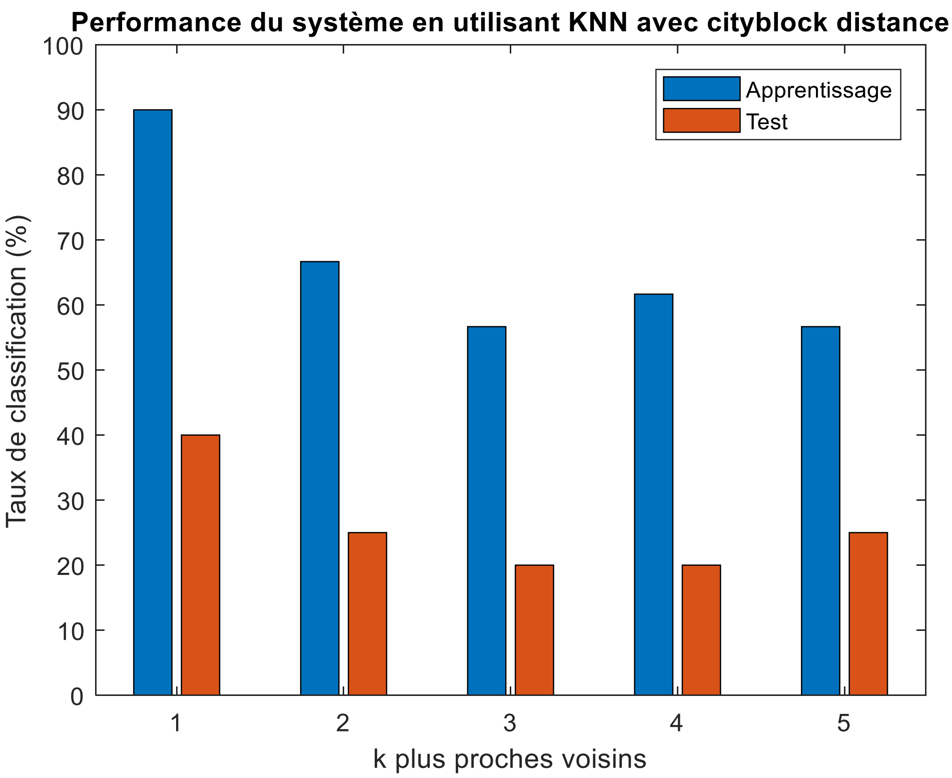
First dataset result with HU Moments :

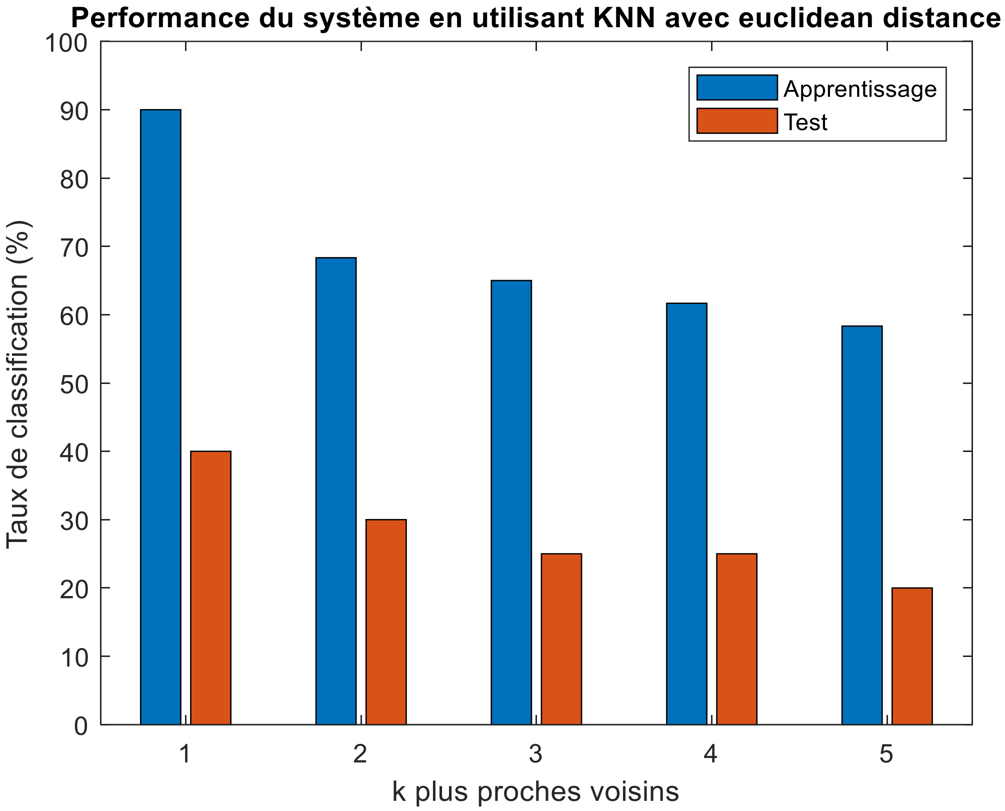



Performance du système en utilisant KNN avec cosine distance
Apprentissage
Test
Taux de classification (%)
k plus proches voisins
0
10
20
30
40
50
60
70
80
90
100
1
2
3
4
5

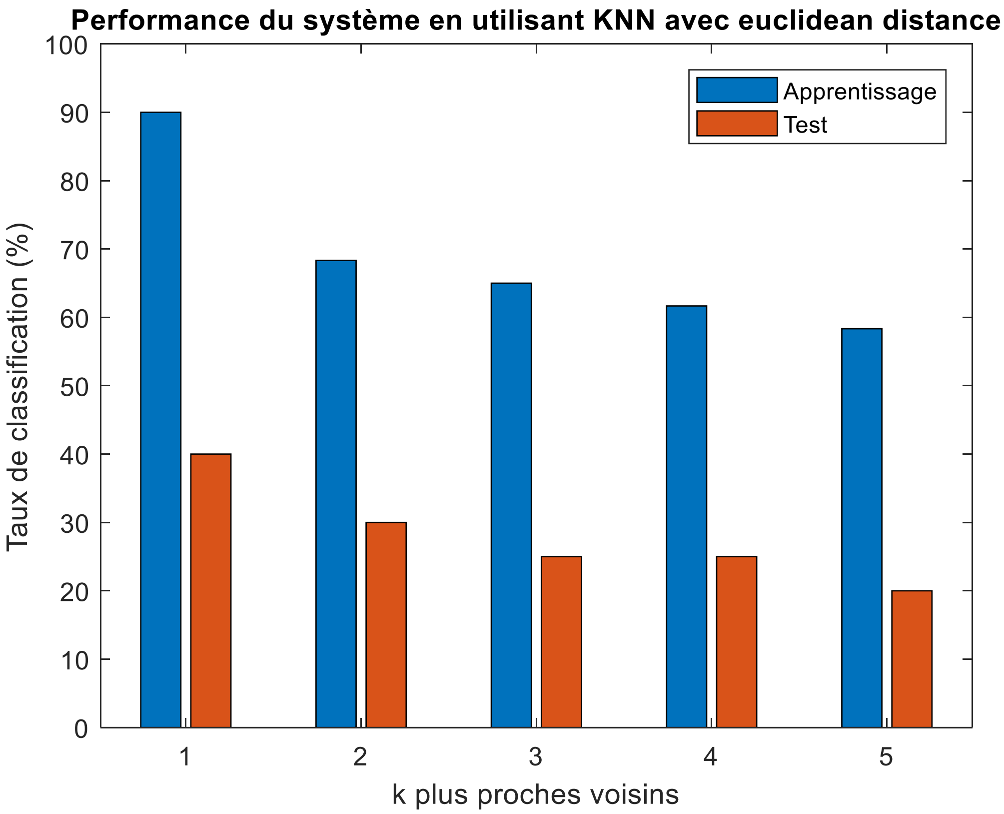

Performance du système en utilisant KNN avec correlation distance
Apprentissage
Test
Taux de classification (%)
k plus proches voisins
0
10
20
30
40
50
60
70
80
90
100
1
2
3
4
5


Performance du système en utilisant KNN avec minkowski distance
Apprentissage
Test
Taux de classification (%)
100
90
80
70
60
50
40
30
20
10
0
1
2
3
4
5
k plus proches voisins

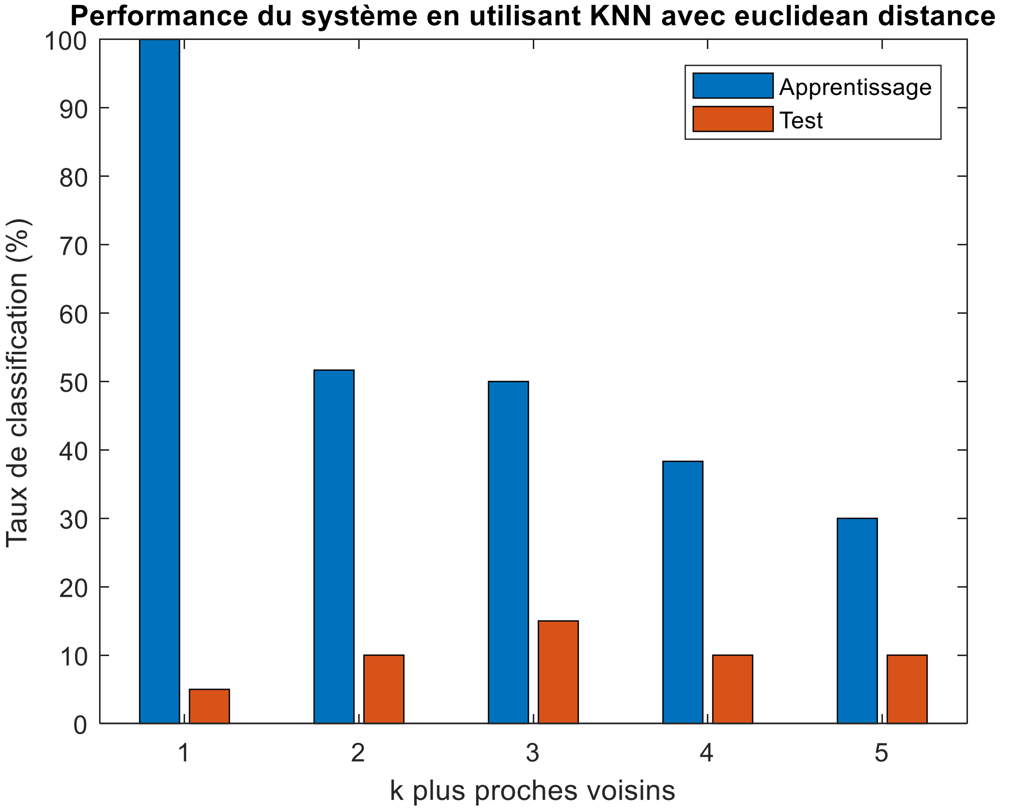

Performance du système en utilisant KNN avec cityblock distance
Apprentissage
Test
Taux de classification (%)
100
90
80
70
60
50
40
30
20
10
0
1
2
3
4
5
k plus proches voisins

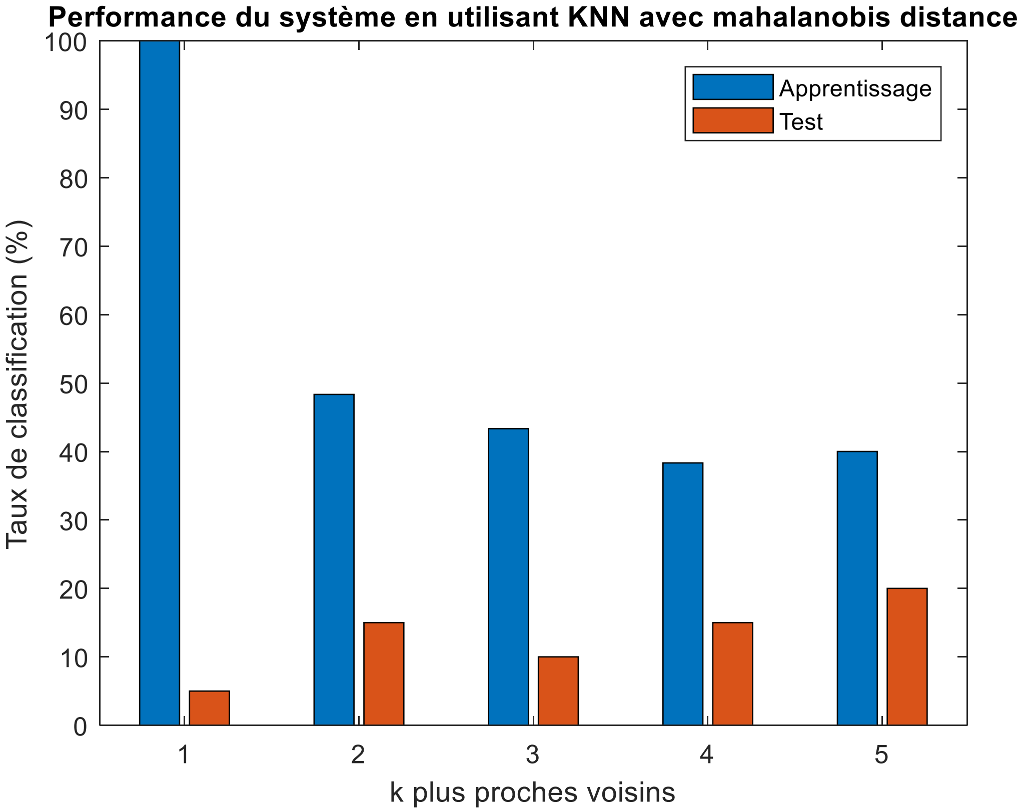


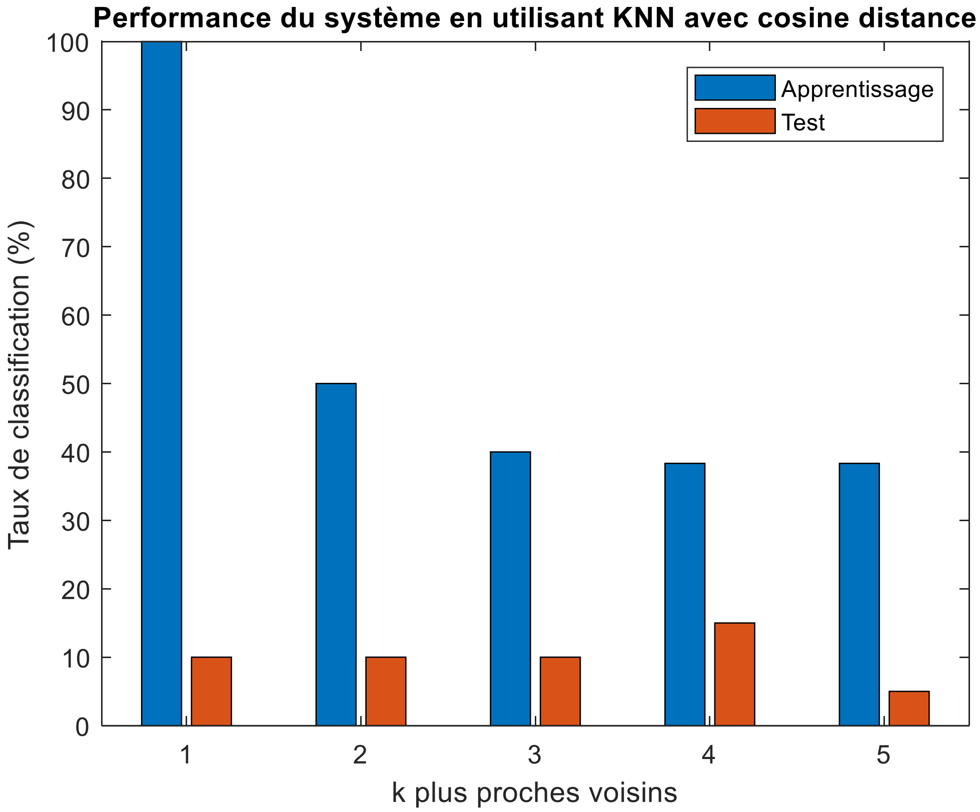
First dataset result with Tchebichef Moments :

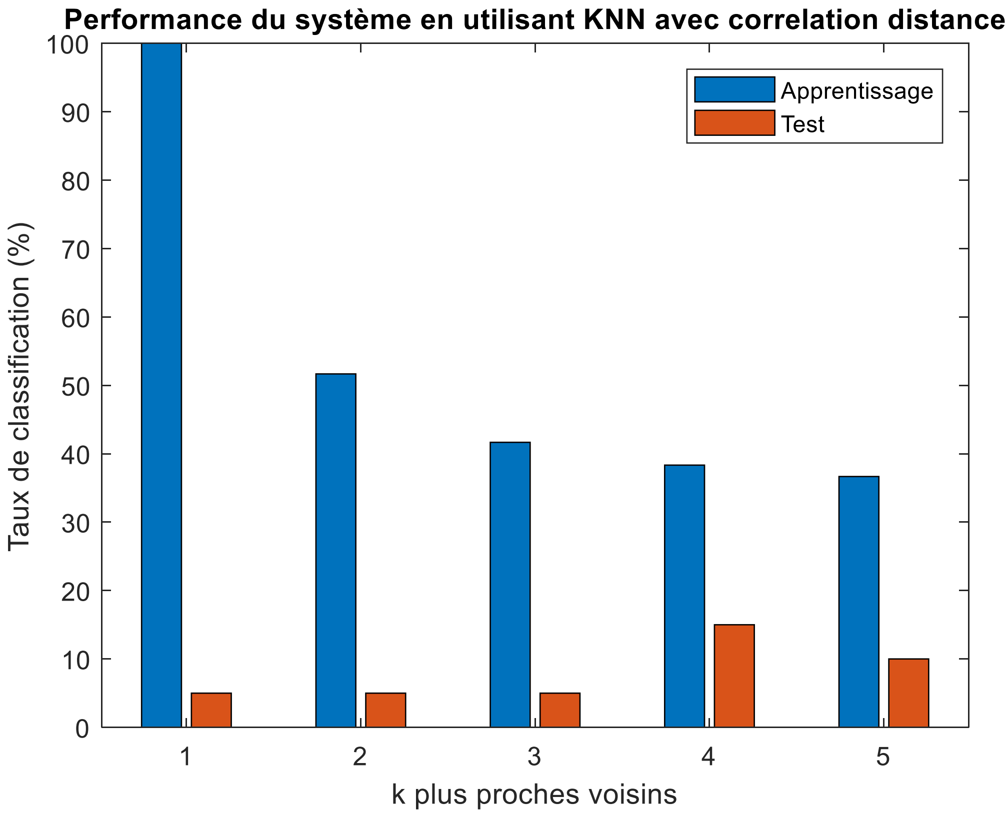


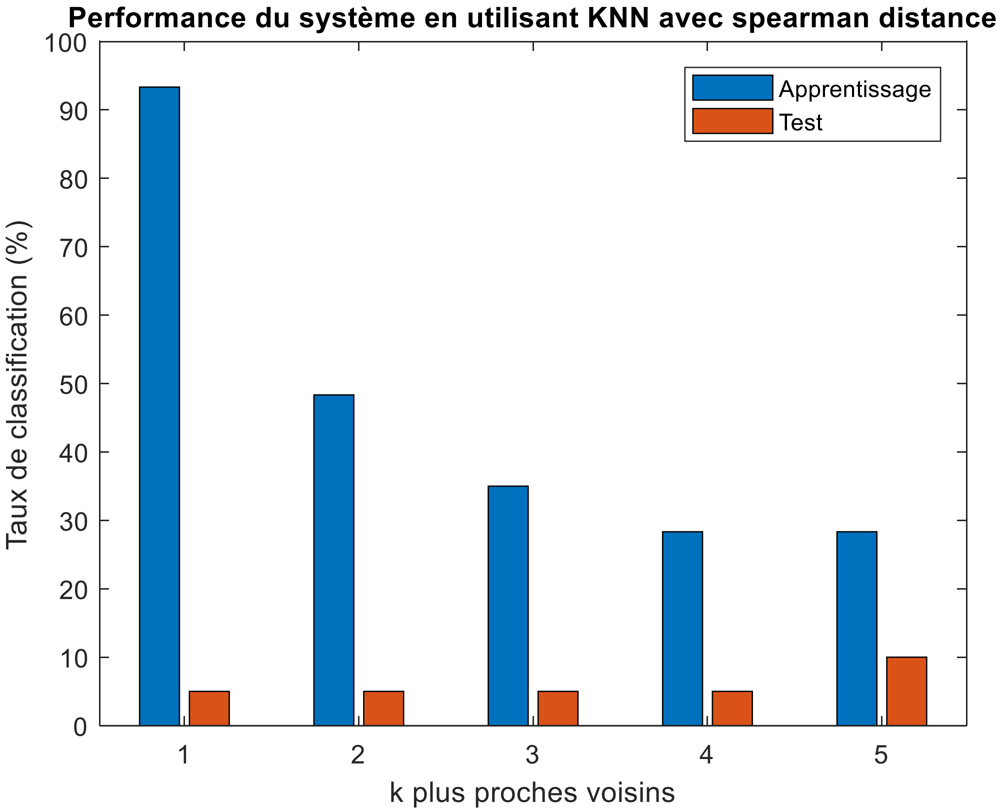
Second data set results with HU Moments:






Performance du système en utilisant KNN avec cosine distance
Apprentissage
Test
Taux de classification (%)
100
90
80
70
60
50
40
30
20
10
0
1
2
3
4
5
k plus proches voisins


Performance du système en utilisant KNN avec correlation distance
Apprentissage
Test
Taux de classification (%)
100
90
80
70
60
50
40
30
20
10
0
1
2
3
4
5
k plus proches voisins


Performance du système en utilisant KNN avec spearman distance
Apprentissage
Test
Taux de classification (%)
k plus proches voisins
100
90
80
70
60
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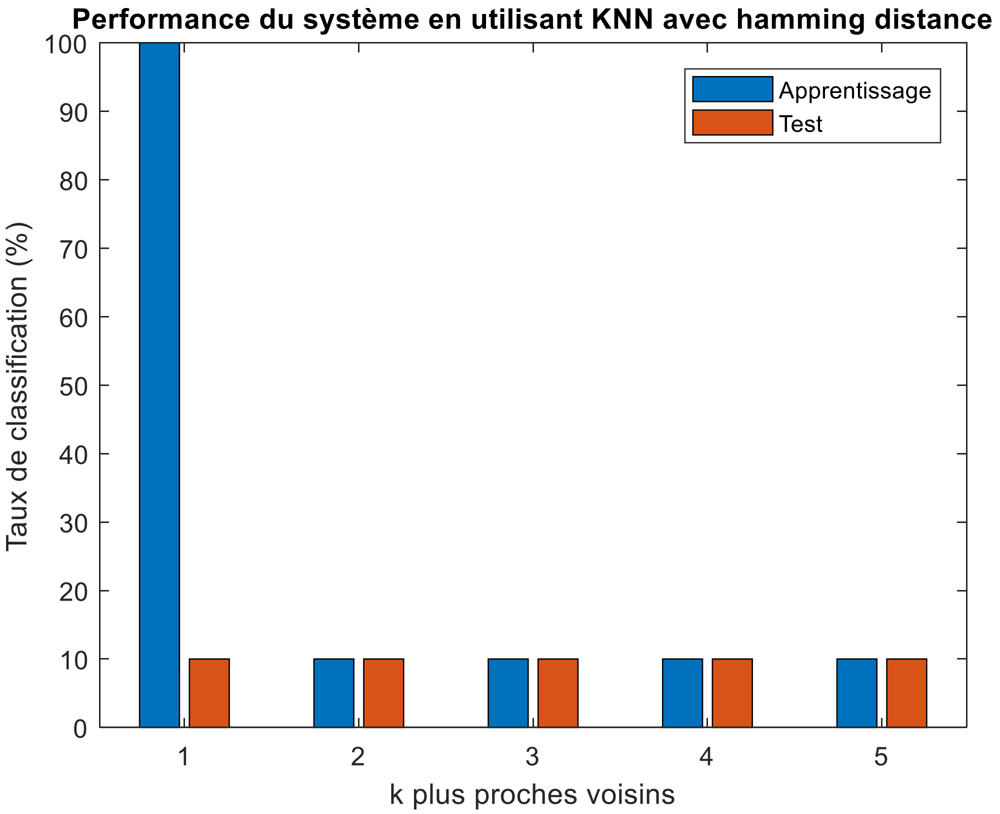
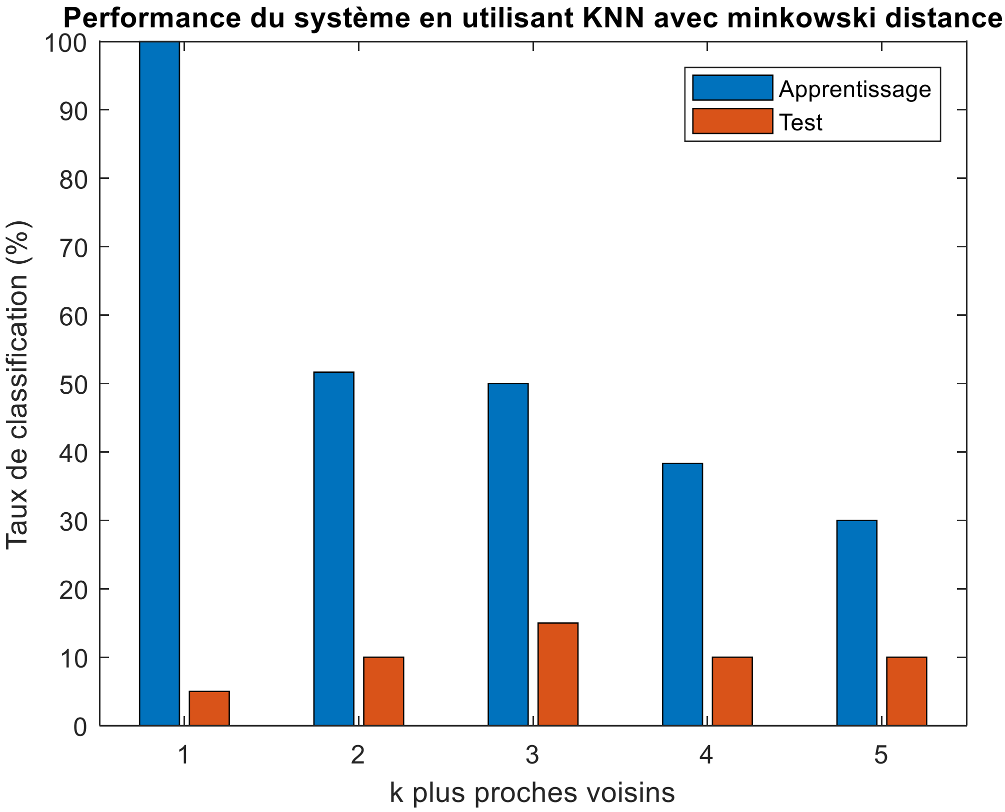
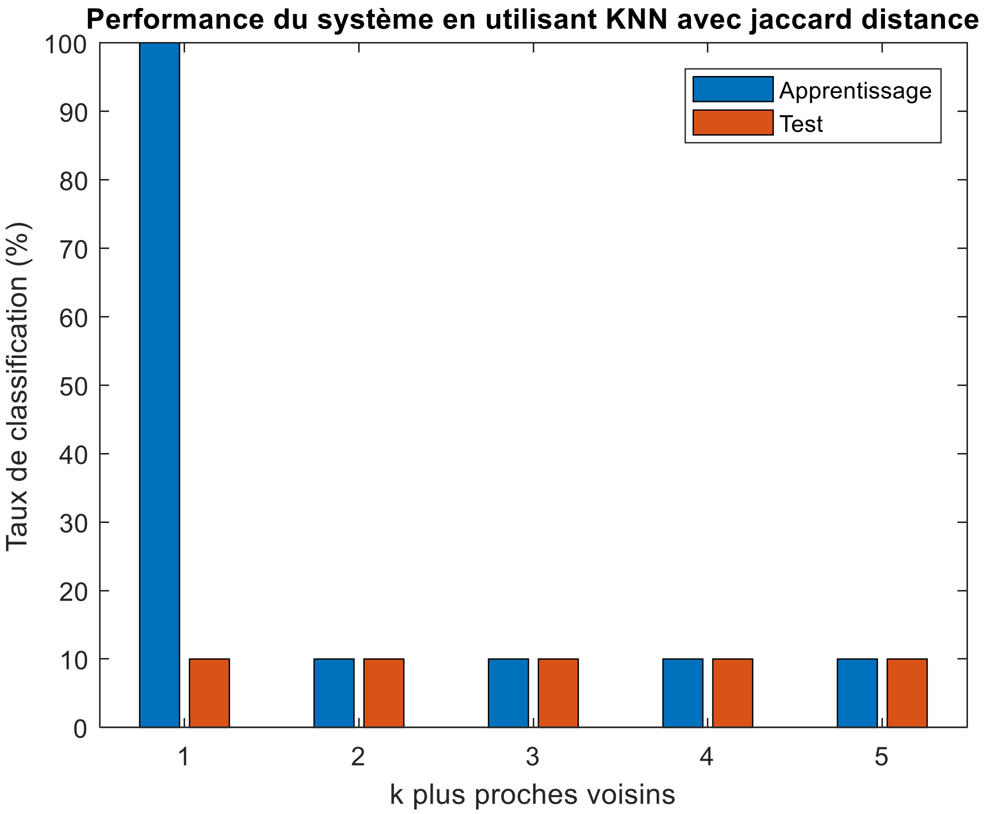
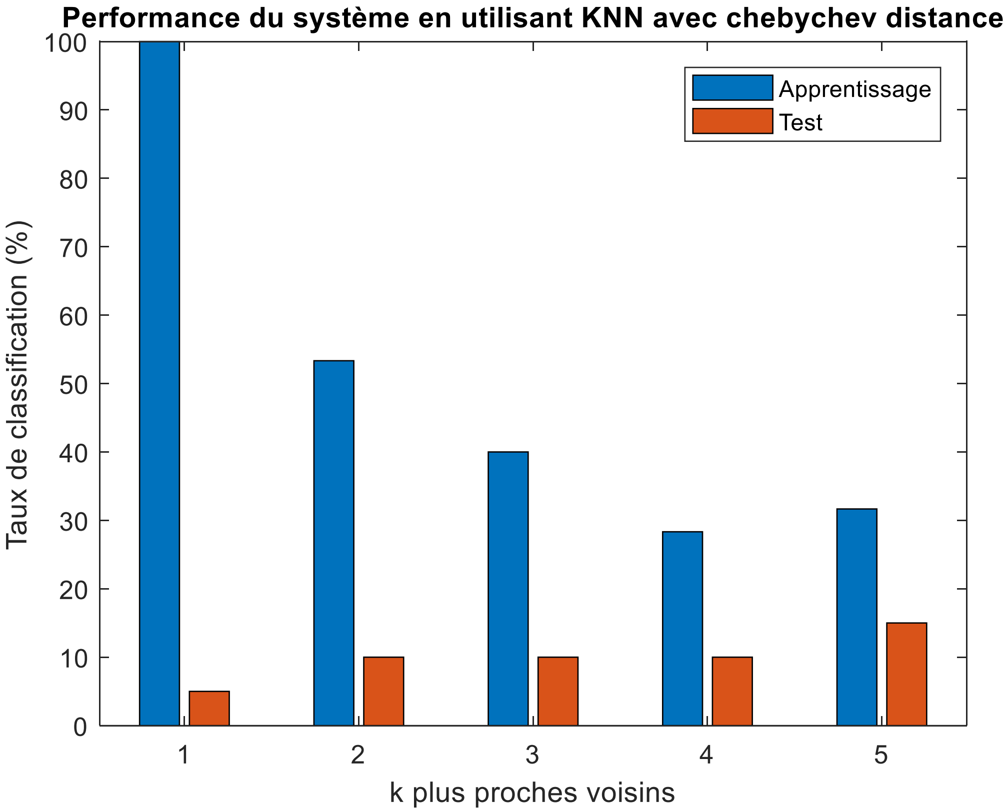
40
30
20
10
0
1
2
3
4
5

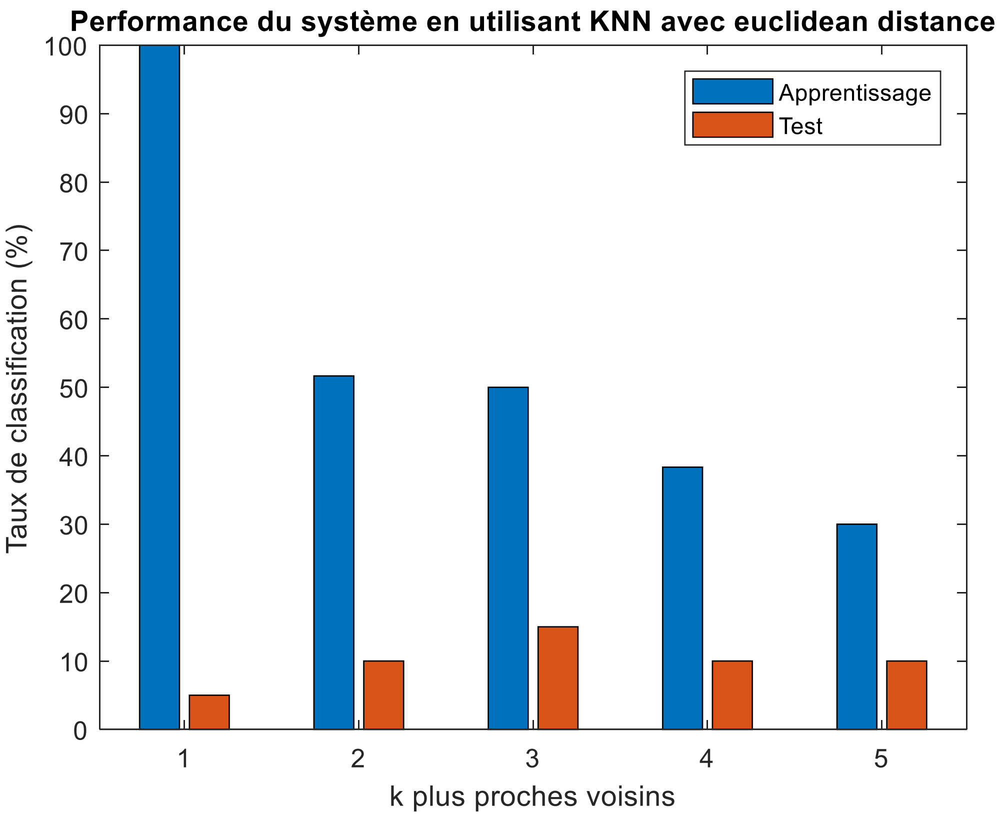

Performance du système en utilisant KNN avec hamming distance
Apprentissage
Test
Taux de classification (%)
k plus proches voisins
100
90
80
70
60
50
40
30
20
10
0
1
2
3
4
5


Performance du système en utilisant KNN avec minkowski distance
Apprentissage
Test
Taux de classification (%)
k plus proches voisins
0
10
20
30
40
50
60
70
80
90
100
1
2
3
4
5


Performance du système en utilisant KNN avec jaccard distance
Apprentissage
Test
Taux de classification (%)
k plus proches voisins
0
10
20
30
40
50
60
70
80
90
100
1
2
3
4
5



Second data set results with Tchebichef Moments:



ANNEXE B

All images used for identification tests are 504*480 pixels and are freely available for download at the following address: http://bias.csr.unibo.it/fvc2004/databases.asp or the first number indicates the finger and the second indicates the scan number sample:

101_ 1.tif

101_ 2.tif

101_ 3.tif

101_ 4.tif

101_ 5.tif

101_ 6.tif

101_ 7.tif

101_ 8.tif

102_1.tif

102_ 2.tif

102_ 3.tif

102_ 4.tif

102_ 5.tif

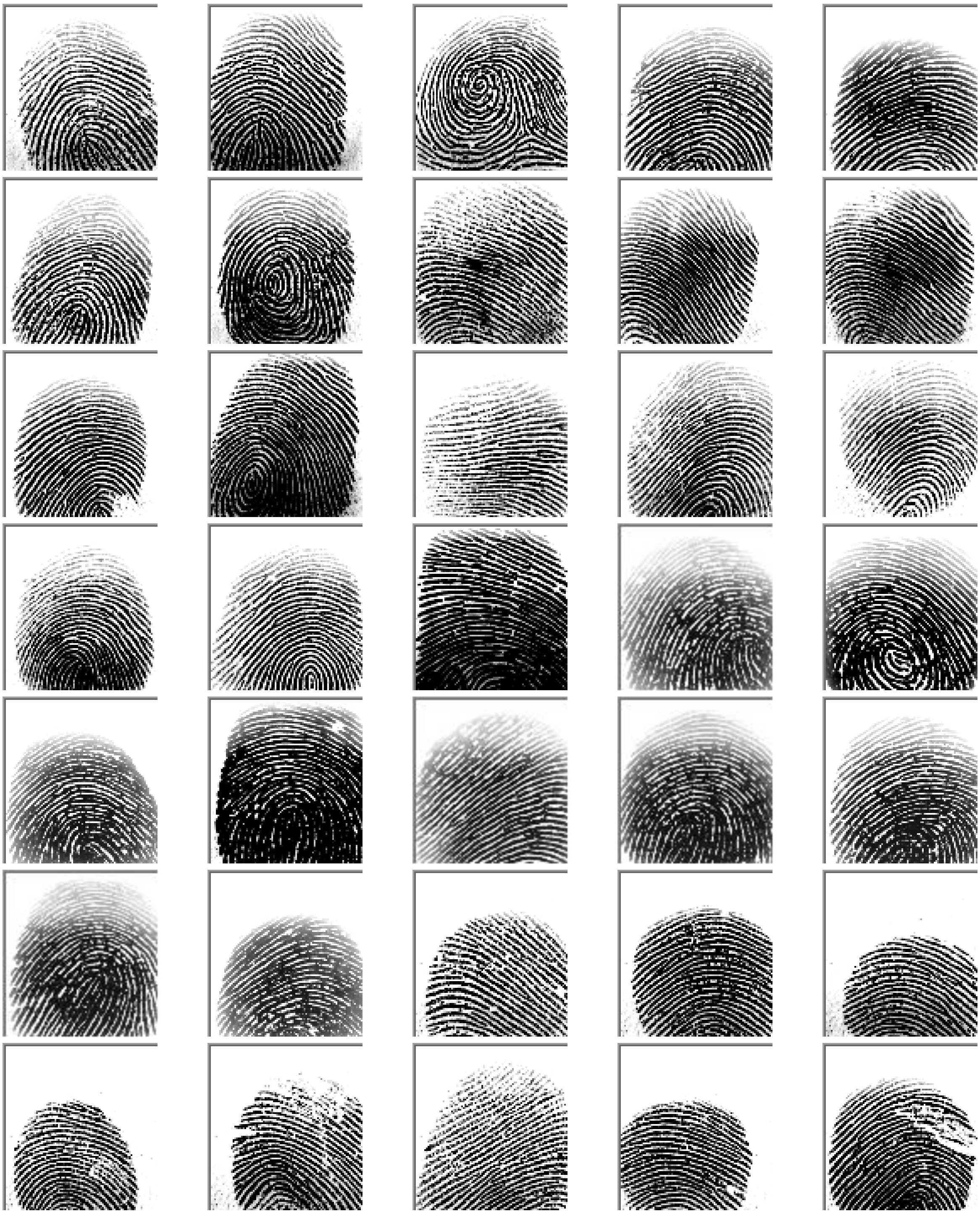
102_ 6.tif

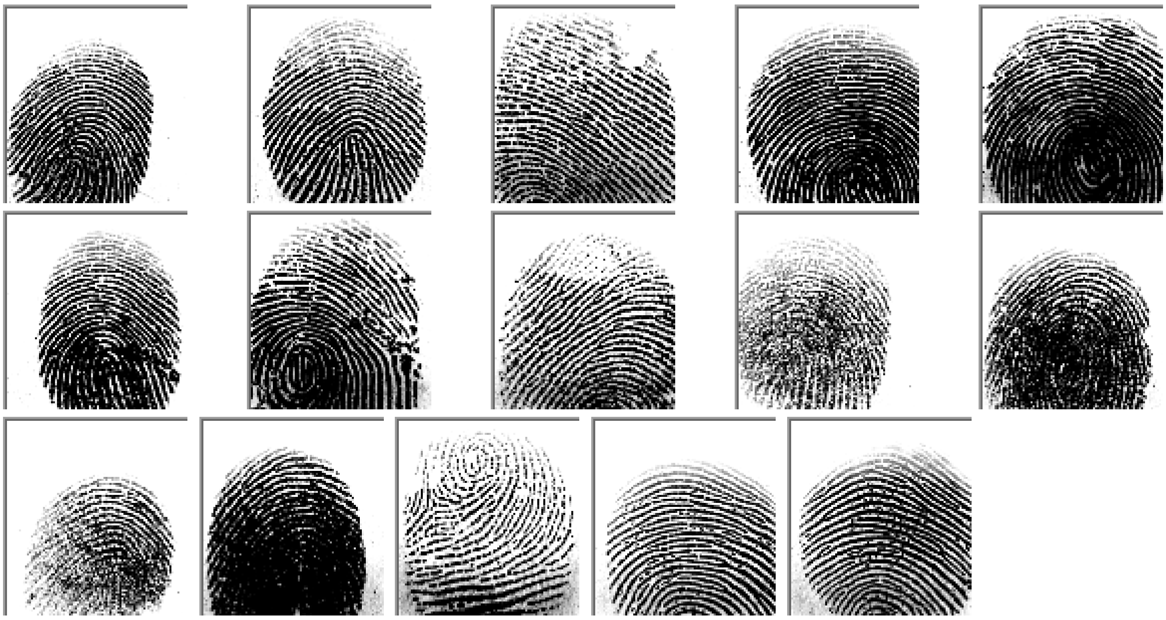
102_ 7.tif

ANNEXE C

The second dataset images used for identification tests are 100*93 pixels and are freely available for download at the following address:

https://www.kaggle.com/datasets/ruizgara/socofing





Abstract

Invariant moments are descriptors that have shown their effectiveness in several fields. In this work we have tried to take advantage of their invariance to translation, rotation and scale change in the field of fingerprint recognition digital. Our fingerprint recognition system contains three steps, preprocessing, extraction of characteristics (Tchebichef & Hu moments), classification Using KNN classifiers with different distances (Euclidean,mahalanobis,cosinecorrelation,spearman,hamming,jaccard, minkowski,cityblock,chebychev). The results obtained show that the moments of Tchebichef & Hu are not sufficient as fingerprint descriptors, they can give better results in combination with other descriptors.

Keywords: Fingerprint recognition, Moments of Hu, Tchebichef moment, KNN.

Résumé

Les moments invariants sont des descripteurs qui ont montré leur efficacité dans plusieurs domaines. Dans ce travail, nous avons essayé de tirer profit de leur invariance à la translation, rotation et changement d'échelle dans le domaine de la reconnaissance digitale. Notre système de reconnaissance des empreintes digitales contient trois étapes : prétraitement, extraction des caractéristiques (Tchebichef & Hu moments), classification En utilisant le classificateurs KNNavec differents distances (Euclidean,mahalanobis,cosinecorrelation,spearman,hamming,jaccard, minkowski,cityblock,chebychev).Les résultats obtenus montrent que les moments de Tchebichef & Hu ne sont pas suffisants comme descripteurs d'empreintes digitales, ils peuvent donner de meilleurs résultats en combinaison avec d'autres descripteurs.

Mots-clés : Reconnaissance des empreintes digitales, Moments de Hu, Moments de Tchebichef, KNN.

الملخص

العزوم الثابتة هي خصائص وصفية أظهرت فعاليتها في عدة مجالات. في هذا العمل، حاولنا الاستفادة من ثباتها بالنسبة للحركة والدوران وتغير الحجم في مجال التعرف على البصمات الرقمية. يتكون نظام التعرف على بصمات الأصابع لدينا من ثلاث وحدات : المعالجة المسبقة ، واستخراج الخصائص (عزوم TchebichefوHu)،التصنيف باستعمال المصنفKNN (مع الابعاد التالية: إقليدي، وهامين، وشبيتشيف، ومينكووسكي، و مهالنوبيس،كوزن،كوريلاسيو،سبيرملن ،جاكارد،سيتيبلوك)، تظهر النتائج التي تم الحصول عليها أن العزوم Tchebichef و Hu ليست كافية كخصائص وصفية لبصمات الأصابع، ويمكن أن تعطي نتائج أفضل باستعمال خصائص وصفية أخرى.

الكلمات الرئيسية: التعرف على بصمات الأصابع، عزوم **Hu** ، **عزوم Tchebichef**،**KNN**