BIOMETRICS: Human Identification based on GAIT
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Ouddane Wafaa   Benyettou Mohamed

LAMOSI : LAboratoire de **M**odélisation et d'**O**ptimisation des **S**ystems **I**ndustriels
Department of Computer Sciences
University of Sciences and the Technology of Oran Mohamed Boudiaf (USTO-MB), ALGERIA.

Abstract- Gait human identification, considered as new biometric number, became a very active research field in the last few years. Realized works, until now, was based on classical techniques. In our work, we tried to extract the best characteristics that verify the uniqueness of the silhouette of the individual and the classification was done by two methods: multi-class Separator Vast Marge (SVM) and neural networks radial basis (RBF). The recognition rates obtained are satisfactory regarding the two methods (Highest 92.12% for SVM and 90.77% for RBF). By comparing the two methods we note that the main difference remains in the time that is expensive in SVM (one against one) compared to the RBF, which are known for their speed, it allows us to say that the RBF are more appropriate for real-time applications.

I. INTRODUCTION

Know how to identify both effective and correct identity of an individual has become a critical issue for today secured access and monitoring are a subject of great importance. We live in a world full of access codes and passwords, whether to start our computer, a mobile, get cash, access to private areas on the Net (purchase and consultations bank) or even to go home. These codes are obstacles to overcome very easily by hackers. The only evidence today unfalsifiable are not physical keys (cards) or logical keys (codes) but rather so that each person is totally unique: the biological. Each individual possesses characteristics that are unique: his voice, fingerprints, facial features, shape of his hand, his signature until its DNA. These data tell "Biometric" can thus be used to identify it. Biometric systems are a very effective control against theft, terrorism, they provide a degree of security very high. In this paper, we present a new technique used in the field of biometrics, it is a system of individual recognition by gait, or the originality of our approach lies on the characteristics used to ensure uniformity of the individual or we used a hybridization between two algorithms: static and dynamic measures and for classification, we used two types of classifiers, which are support vector machines (SVM) and neural networks Radial Basis (RBF).

II. THE SYSTEM FOR GAIT RECOGNITION

The invisibility of a fingerprint or the high cost of devices capture images of the iris or retina are the main reasons that led researchers to think of another

Thanks to this broad area, it is anticipated that the approach is unique.

Compared to other characteristics, the identification approach has several advantages: **[1]**
1 - Treatment of low-resolution images
2 - No risk of intrusion
3 - The characteristics are stable
4 - High level of user acceptance
5 - Made from a distance without knowledge of the individual

Fields of application of the gait recognition
-The remote monitoring
-Access control
Recently, Chinese researchers have used the approach as a means of identification but they have combined with the face. Such as THE OLYMPIC GAMES IN BEIJING(2008) **[1,2]**.
1) Acquisition of the image:
This operation allows to extract the real world for a two- dimensional representation of 3D objects, this can be static (Camera, Scanner etc ....) Or dynamic (camera, webcam, digital camera, etc..), in which case we will have a clip. At this level we will have a raw image.

**Fig1 : Example of gait sensor**

2)Pretreatments

The raw image can be affected by various factors causing its deterioration, it can be noisy, or contain hash because of optical or electronic devices. To overcome these problems, there are several methods of processing and image enhancement, such as: standardization, histogram equalization, mathematical morphology, without forgetting the binarization of the image and other methods.

Fig2: Example of image Preprocessing of gait

2) Detection and localization:

The recognition systems are complex approach. The difficulty resides especially in the automatic detection of the silhouette is mostly scenery complexity, changes in pose, lighting conditions generally unknown, etc.. There are several methods that can be applied to automatic detection of the silhouette. It should detect the presence of the individual in the image, then locate it to extract the features to characterize and differentiate from others. The result of this step is to obtain the image portion to be treated. Thresholding algorithms are employed. **[3, 4].**
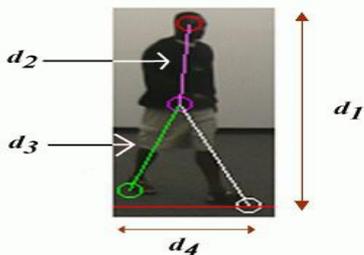
4) Extraction of parameters:

The choice of useful information back to establish a model for the process, they must be non-discriminatory and redundant. This information will then be classified, in other words, assigned to the closest class, individuals with similarities are grouped in the same class. These classes vary depending on the type of decision. **[1,4,5,6].**

4.1) The extraction algorithms

4.1.1) Silhouette-based Human Identification from Body Shape and Gait

This approach derives the human figure in between the moving object from the bottom. The subject may be identified by measures that reflect the shape and / or movement. These algorithms are based on the deployment of hidden Markov models (HMM) **[7]** and taking into

consideration two images of figure: the outline of the silhouette in binary form and the entire binary silhouette itself. **[1, 4, 5, 6, 7].**
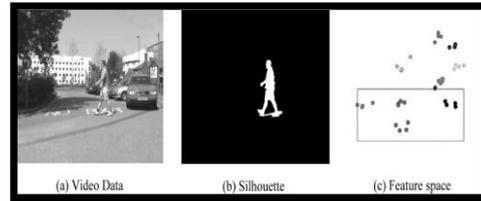
Fig 3: **Extraction of features for the model silhouette based identification**

4.1.2) Model-based approaches

Model based approaches aim to derive the motion of the torso and / or legs. In contrast to figure this one focuses on the dynamics, failing body shape. **[1,4,5,6].**

$d1$ = length of the individual

$d2$ = distance between the head and pelvis

$d3$ = leg length

$d4$ = the length of a big step

2 characteristic vectors: w = [d1, d2, d3, d4] or s = [d1, d3]

Fig 4: The characteristics of a recognition by the model based approaches

III. SEPARATOR VAST MARGE (SVM)

Separator Vast Marge or Support Vector Machines (SVM) is a method for binary classification by supervised learning, these are new techniques inspired by discriminating statistical theory of learning by Vladimir Vapnik. They were proposed in 1995 by V. Vapnik in his book "The nature of statistical learning theory". They allow to address several issues as diverse and varied regression, classification, fusion etc.. **[8].** This method relies on the existence of a linear classifier in an appropriate space. Since it is a classification problem, this method uses a set of training data to learn the model parameters. It is based on the use of so-called kernel function (kernel) which allows optimal separation of data.

1) General Principle of operation:

Basics: hyperplane, margin and support vector
Purpose: For two classes of data examples, the goal

of SVM is to find a classifier that will separate the data and maximize the distance between these two classes. With SVM, the linear classifier is called "hyperplane" [9].
The nearest points which are only used for the determination of the hyperplane are called support vectors, which are in the margin.
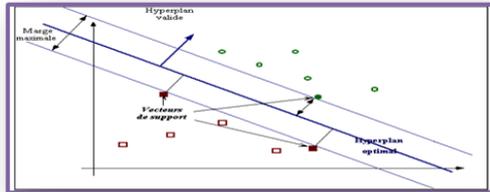

Fig 5: optimal hyperplane, margin and support vectors

It is obvious that there is a multitude of hyperplane valid but the remarkable property of SVM is the hyperplane must be optimal. We will therefore look more valid among hyperplanes, the one that goes "the middle" points of two classes of examples. That is to find a **hyperplane** whose minimum distance to the examples of learning is maximum. We call this distance "**margin**" between the hyperplane and the examples. [10].
The optimal separating hyperplane is the one that maximizes the margin. As we seek to maximize the margin, we speak of **separators vast margin**.

2) Linearity and non linearity:
In the SVM, we found two cases of separability:

 1-The **linearly** separable case: simple, easily find the linear classifier.
 2-If **not linearly** separable: more complex. In most real problems there is no separation possible between linear data, the maximum margin classifier cannot be used because it works only if the classes of training data are linearly separable. [Steve R. Gunn, 1998]. The principle therefore is to project the data from the input space (belonging to two different classes) non-linearly separable in a space of greater dimension called "feature space or space re-description" so that data becomes linearly separable. We therefore transforming a problem of separation in a non-linear representation space into a linear separation problem in an area of re-description of greater dimension. This transformation is achieved via a kernel function. **[11].**
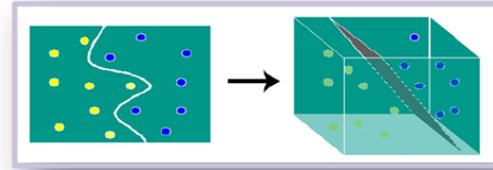

Fig6: Transformation of space representation and the separating hyperplane in the case not linearly separable.

3) SVM multi-classes:

Originally, the SVM has been designed primarily for 2-class problems, however, several approaches for extending this algorithm to the case N classes have been proposed **[12]**
3.1. One against all
The most natural approach is to use this method of discrimination and learn binary N decision functions (fm)   m = 1 ... N to make the discrimination between each class every other (each class is opposed to all others). We must therefore ask N binary problems. The kth classifier separates data from the class k from the rest of the training data. Each classifier returns 1 if the shape to recognize belongs to class -1 otherwise. So to recognize a form must submit to all other classifiers, to make a classification decision, we keep the class that had the maximum value of all decision functions. So assigning a new point x to a class Ci is given by the formula: **[8,13].**

$$\{i = \arg\max fm\,(x)\} \qquad (1)$$

$$m = 1 \dots N$$

3.2. A one against one
Instead of learning N decision functions, by each class is discriminated from another. Thus, N (N-1) / 2 decision functions (classifiers) are learned and each of them makes a vote for the appointment of a new point x. The class of this point x to the largest number of votes becomes then the majority class. **[8,13].**

IV. NEURAL NETWORKS BASED RADIAL

Neural networks RBFs are mainly used to solve problems of approximation of functions in spaces of large dimensions.

1) The learning phase:

Several learning methods have been developed for these types of networks, it is often said that learning of RBF network is a hybrid name for supervised the construction phase of the network and monitored to determine the weight of output layer. During the

construction phase of the network, there are four main parameters to set:

   - The number of RBF neurons.

   - The position of the centers of Gaussians of each neuron.

   - The width of these Gaussians.

   - The weights of the connections between neurons and the RBF (s) neuron (s) output. **[14].**

The great advantage characterized in neural networks with radial basis is that they have only one hidden layer, making them the easiest to use and faster.
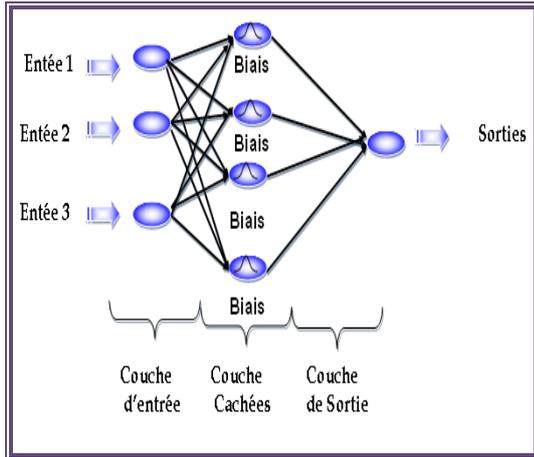

Fig7: The radial function networks

They read suitable because of local learning. This type of learning can make the process of training much faster than in the case of an MLP, who teaches in a comprehensive manner.

But this advantage is paid for performance that may not be as good on the data in spaces of large dimension (many input variables) or on very noisy data **[14,15].**

V. PROPOSED APPROACH

Beginning with our system of recognition offered by its various stages:
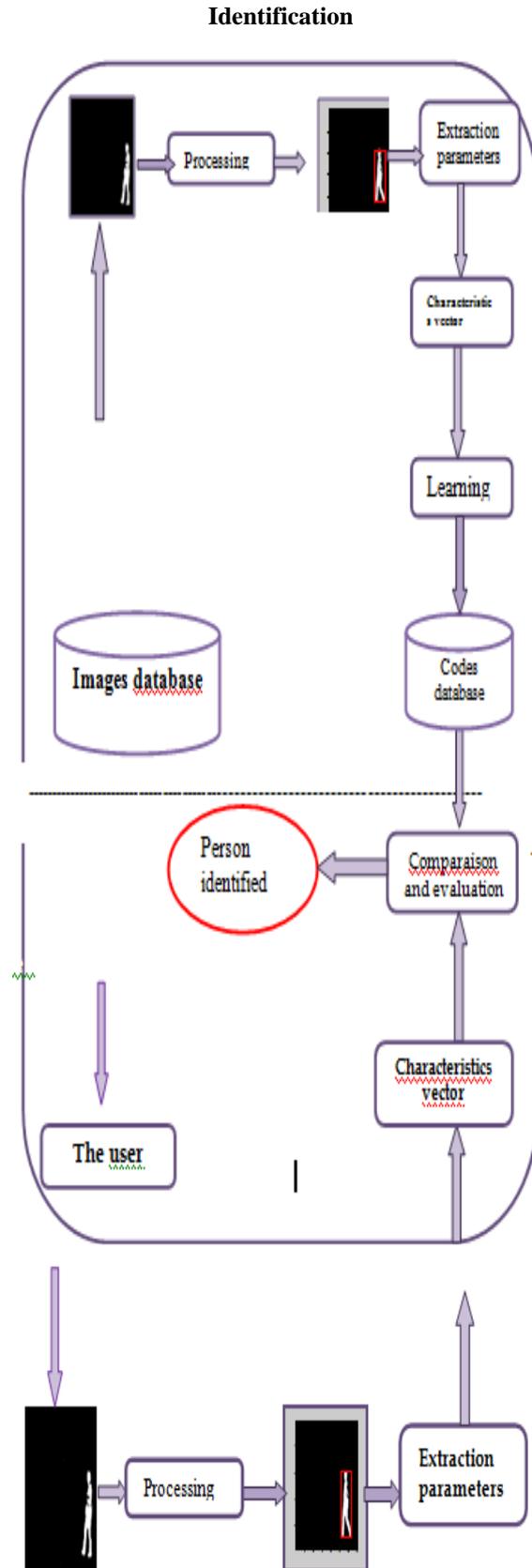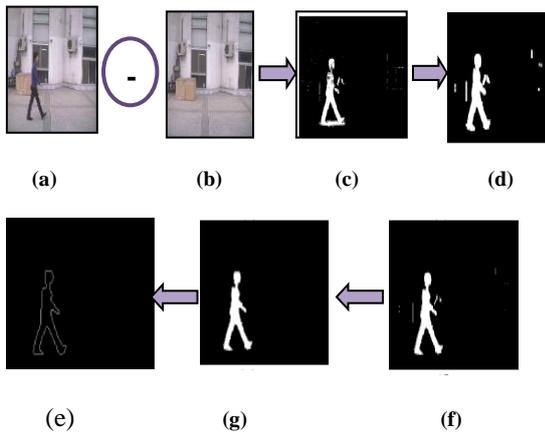
Identification

Fig8: Architecture of proposed system

1) The gait database

The images we used in our experiments are from a database that was created on December 10, 2001, by CASIA "Chinese Academy of Sciences, Institute of Automation", it contains essays by 20 people. [2]

2) Preprocessing Images

For our system, the preprocessing phase consists of:

| (a) | (b) | (c) | (d) |

| (e) | (g) | (f) |

(A) ORIGINAL IMAGE. (B) SUBTRACTION OF THE BACKGROUND. (C) RESULTING IMAGE. (D) (E) EROSION AND DILATION. (F) RESULT IMAGE OF EROSION AND DILATION. (G) MORPHOLOGICAL GRADIENT (EDGE DETECTION).

FIG9: THE MAIN STEPS OF IMAGE PREPROCESSING OF THE SILHOUETTE

3) Feature extraction and coding

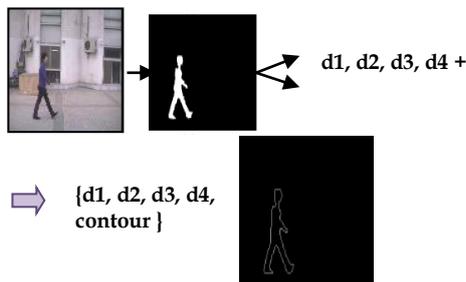d1, d2, d3, d4 +

{d1, d2, d3, d4, contour }

Fig10: Extraction of the vector of image features

As a result, we obtain a vector of characteristics of dimension equal to four distances and in addition of the contour of the silhouette we will outline a vector of five elements. This vector will be as input, subsequently, for learning and classification of individuals.

VII.   THE CLASSIFICATION

1) Classification method of SVM multi-classes

To test the robustness of SVM multi-classes in the case of identification of individuals through the gait, two approaches were analyzed:
One *against one and the one against all approaches*

TABLE 1: *One* against one results

Tests	LT (secondes)	TT (secondes)	RT
D, c=100	1965.2	82	60,75%
D, c=500	2003.5	90.9	73,54%
D, c=1000	2887	110.2	84,1%
CS, c=100	2056	198.3	53,66%
CS, c=500	2557.3	242.9	65,89%
CS, c=1000	3089.1	287.5	72,3%
D, CS, c=100	2355	136.9	69,83%
D, CS, c=500	2650.83	165	87,63%
D, CS, c=1000	3000.6	200	92,12%

TABLE 2: *One* against all results

Tests	LT (secondes)	TT (secondes)	RT
D, c=100	1220	65	62,3%
D, c=500	1413.3	71	68,98%
D, c=1000	1789.7	80	80,19%
CS, c=100	1530	92	55,22%
CS, c=500	1766	101	60,75%
CS, c=1000	2050.6	115	75,11%
D,CS, c=100	1629.7	99	68,75%
D,CS, c=500	1800.4	104	79,31%
D,CS, c=1000	1999.3	113	89,65%

LT: Learning Time (seconds)
TT: Test Time (seconds)
RT: Recognition rate
D = 4distances calculated (d1, d2, d3, d4)
CS: Contour of the Silhouette
c = margin used

2) Classification using RBF Networks

The network architecture is as follows:
The network used is a RBF network with one hidden layer, its architecture is as follows:
   - Inputs: the neural network receives 5 entries, this corresponds to the number of calculated distances and contour of the figure (4 +1).
   - The hidden layer: This layer in the number of neurons increases until reaching the optimal solution. This number was chosen after several tests to result in better generalization for a given problem, we cannot know beforehand that appropriate network architecture to solve this problem.
   - The output layer: the number of neuron is the number of classes of the database (20 individuals).

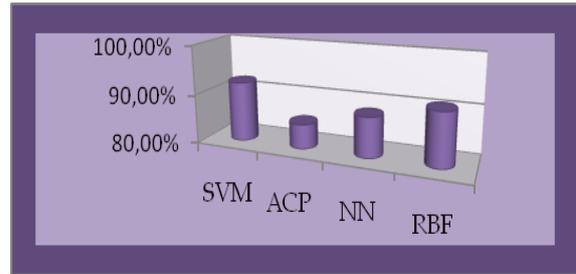### 3) Comparison of results obtained with other approaches

Fig11: Comparison of results obtained with other approaches (PCA, NN: Neural Network).

VIII. DISCUSSION AND ANALYSIS OF RESULTS

In summarizing the results obtained in both approaches, we say that the analysis differs in two compromises: the time of the test and the recognition rate. If we are interested in a real time application, where the time factor of recognition is very important, the one against one approach, who got the best recognition rate cannot be used in this case (quadratic programming). It would be interesting to use the neural network with radial basis since the recognition rate by this method is not unlike the one against one.

IX.   CONCLUSIONS

We mention that our results are very encouraging with a recognition rate of 92.12%, exceeding the results obtained by earlier works (which did not exceed 88.1%).

The study conducted throughout this article we have a pretty clear idea about the performance obtained from our implementation methods multi-class SVM and RBF.
First, note that the preprocessing phase is very important in the recognition process. The database we used was designed specifically for research, why it contains noisy images with nonuniform illumination, hence it is necessary to properly process these images to get a good classification.
The experiments showed a recognition rate slightly higher in the classification by the SVM multi-classes (especially the one against one approach) compared to the classification by RBF. However, the method SVM multi-classes is not as effective as regards the recognition time.
Indeed, the recognition by the SVM approach one against one, for example, consumes more time than the RBF approach, making it (RBF) more suitable for real-time applications.

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