Classification of the Car Seats by Detecting the Muscular Fatigue in the EMG Signal

Mirna Atieh, Rafic Younès, Mohamad Khalil and Herman Akdag

***Abstract*— The objective of this paper is to evaluate and detect muscular tiredness in natural activities, in particular, to select the most comfortable car seat. This work consists to identifying and to classify the EMG signal of the techniques from data mining and from the statistical techniques. We thus tried hybridization between some to lead to a better separation between the classes. The methods of clustering will be applied to some signals resulting from the experiments of discomfort of long duration on seats of different vehicles. These methods consist in separating segments EMG in two classes corresponding to the frequential variation from EMG signal.** *Copyright © 2005 Yang's Scientific Research Institute, LLC. All rights reserved.*

***Index Terms*— EMG signal, data mining, clustering, muscular tiredness.**

I. Introduction

THE MYO-ELECTRIC signals, also called electro-myo-gram (EMG), are electric signals being stored at the level of muscles. These biological signals have been studied for many decades. Easier to estimate than other signals given by the nerves or the brain, they can provide various information's on an individual.

The objective of our study is to detect muscular fatigue made by the analysis of EMG electro-myo-gram signal. The applications derived from this type of study are various. Among these, we can mention: the study of the functionality of the muscles and the neuromuscular junction, the estimation of the muscular fatigue in ergonomic applications, the rehabilitation of the medicine, the valuation of moments and spinals forces, the study of muscular activity responsible for the lifting, the analysis of work's physiological . . . We are interested more in the assessment of the muscular fatigue in ergonomics applications. Tests of EMG acquisition have been led on a person, having to drive during 2h30mn, and installed on two different car seats.

Studies are made in order to interpret the EMG signals as computer control command which one the aim is not to use the computer's keyboard. Thus, an experience [5] has been led in the scope of piloting. It consists in landing a simulated 757 in the San Francisco International Airport. The pilot, instead of using a joystick, closed his hand in front of him and made some movements, captured with the help of electrodes, and analyzed. This experience has been conclusive because it has even been possible to land the plane during a scratch's script. In the same area, Sony studies the possibility to use EMG to monitor electronics' equipments such as walkmans. Thus, EMG would authorize the control of a music player with the help of predefined waves of the hand [2]. A domain of application particularly important the use of the EMG is the rehabilitation of the handicapped people. The EMG can be used thus to order the armchairs or the prostheses of hand or arm, named myo-electric prostheses [4, 12].

After a first introduction of the article, a second chapter describes EMG signal and its various parameters. The third paragraph represents a description of the different methods used for the classification of the signals following techniques of Data mining and the statistical techniques. This chapter is followed by the introduction of applications made at this stage and the results obtained. Before finishing by the conclusion and the perspectives of this domain of application, one did a comparison between the different methods following criteria's of assessment presented in the paragraph.

II. Methodology

A. Definition of the EMG Signal

The electro-myo-gram signal (EMG) is an addition of potential functioning trains on power unit, which are detected by a system of electrodes close to the fibers. When the electrodes are placed on the surface of skin, the detected signal is designated under the name of surface electro-myo-gram (SEMG). The amplitude of EMG signal is stochastic (unpredictable) with a Gaussian distribution extending from 0 to 6 m V (crest to crest). The signal's using energy is limited (from 0 to 500 hertz of frequency's range, with the dominating energy being in the range of 50-150 hertz) [3].

Every signal acquired is composed of 70.000 points. He/it will be divided in segments of which each is considered in static state. We must calculate, for every segment, the set of the below stated parameters. The methods of classification will serve to find, in every matrix of parameters, two distinct classes,: tired or non tired muscle.

B. Parameters of the Signal

We studied the two classic types of statistical and spectral parameters [6].

1) Spectral Parameters: See Table I.

2) Statistical Parameters: See Table II.

Manuscript received February 2, 2005; revised September 10, 2005.

Mirna Atieh, Rafic Younès, Mohamad Khalil and Herman Akdag, address ????. Emails: myounes@irisa.fr(M. Atieh), ryounes@ul.edu.lb(R. Younès), mkhalil@ieee.org(M. Khalil), and Herman.Akdad@lip6.fr(H. Akdag)

Publisher Item Identifier S 1542-5908(05)10405-9/$20.00

TABLE I
STUDIED SPECTRAL PARAMETERS.

Percentiles f_k : $\int_{P-1}^{f_P} S_x(f)df = k\int_0^{f_{\max}} S_x(f)df$, $0<k\le 1$	Spectral moments : $M_r = 2\int_0^{+\infty} f^r S_x(f)df$
Relative energy per frequency : $W_n = \frac{\int_{f_n-1}^{f_n} S_x(f)df}{M_0}$ with $f_n = \frac{n}{N} f_{\max}$ And $1<n<N$	Median frequency : $\int_0^{Fmed} S_x(f)df = \int_{Fmed}^{F\max} S_x(f)df$
Ratio H/L (High/Low) : $\frac{H}{L} = \frac{\int_{f_{H1}}^{f_{H2}} S_x(f)df}{\int_{f_{L1}}^{f_{L2}} S_x(f)df}$; $H=[H_1,H_2]$ and $L=[L_1,L_2]$	Mean frequency: MPF = M_1/M_0

TABLE II
STUDIED STATISTICAL PARAMETERS.

Mean Value : $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$	Standard deviation : $\sigma = \left(\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2\right)^{1/2}$
Dissymmetry : $y = \frac{E(x-\bar{x})^3}{\sigma^3}$	Flatness : $k = \frac{E(x-\bar{x})^4}{\sigma^4}$

III. CLASSIFICATION METHODS

Different methods are programmed and tested. Statistical methods are tried like: the k-means method, LBG and PCA. Mata mining based methods are also programmed: Fuzzy c means, competitive neural network, the ants algorithm.

A. Statistical Methods

1) C-means Algorithm: Its principle is the next one: "we have points in the space of the observations that we wish to clustering, without having knowledge a priori of property(s) particular(s) on these classes; only their p number is fixed a priori."

The basic k-means algorithm consists of the following steps [1]:

1) Define randomly the centers,
2) For each vector, assign that pixel to a class such that the distance from this pixel to the center of that class is minimized,
3) For each class, recalculate the means of the class based on the pixels that belong to that class,
4) As long as pixels are involving, go to 2.

2) LBG Algorithm: The K-mean algorithm is not locally optimal. The choice of the initial centers is important. Another method proposed by Linde, Buzo and Gray [8], consists of classifying hierarchically and making an iterative initialization: we choose only one centre of gravity (of all elements), divided it into two elements and then every one will converge to a set of points.

3) Principal Component Analysis (PCA): Principal component analysis (PCA) involves a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called *principal components*. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. Let us suppose that $S_1,\ S_2,\ \ldots,\ S_n$ are the signal parameters to be classified; each signal has N_p points. To make the principal component analysis, we make the approximation that these N_p points can form an ellipsoid in the space and the aim of this analysis is to compute the axes of this ellipsoid and their direction.

For that, we need to make the projection of these points on the new axis formed by the axis of the ellipsoid, using a transformation matrix: ($P_1,\ P_2,\ \ldots,\ P_n$); this matrix can be obtained by digitalization of the covariance matrix of the original samples.

So we compute the diagonal matrix D and its eigenvalues. The matrix ($S_1,\ S_2,\ \ldots,\ S_n$) in the new base ($P_1,\ P_2,\ \ldots,$ P_n) can be written as (after classifying the eigenvalues in ascending way):

$$\left[\mathrm{S}_1^{\mathrm{PCA}},\ \mathrm{S}_2^{\mathrm{PCA}},\ \ldots,\ \mathrm{S}_n^{\mathrm{PCA}}\right] = \mathrm{P}^{-1}\,[S_1 \quad S_2 \ldots \quad S_n]^T$$

$\mathrm{S}_1^{\mathrm{PCA}}$corresponds to the biggest eigenvalues [11].

B. Data Mining Methods

1) Fuzzy C-Means Algorithm: Fuzzy C-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This method is used in pattern recognition. It is based on minimization of the following objective function:

$$J_m(U,c) = \sum_i \sum_k (u_{ik})^m \,.\, \|x_i - c_k\|^2$$

where m is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the ith of d-dimensional measured data, c_j is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{ij} and the cluster centers c_j by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}}, \quad c_j = \frac{\sum_{i=1}^{N} u_{ij}^m x_i}{\sum_{i=1}^{N} u_{ij}^m}.$$

This iteration will stop when

$$\max_{ij}\left\{\left|u_{ij}^{(k+1)} - u_{ij}^{(k)}\right|\right\} < \varepsilon$$

where ε is a termination criterion between 0 and 1, whereas k are the iteration steps. This procedure converges to a local minimum or a saddle point of J_m. The algorithm is composed of the following steps:

2) Competitive Neural Networks(CNN): With the competitive learning paradigm, a single-layer of neurons competes among themselves to represent the current input vector. The winning neuron will adjust its own weight to be closer to the input pattern. As such, competitive learning can be regarded as a sequential clustering algorithm.

If the input is very close to the weights of a neuron, that neuron will give an output 1, signifying it is the winner to represent the current input feature vector. The remaining losing neurons will have their output remain at 0.

Therefore, the self-organizing map is a neural network whose behavior is governed by competitive learning. In the ideal situation, each neuron will represent a cluster of input feature vectors (points) that may share some common semantic meaning. Consequently, the array of neurons can be regarded as a mapping from points in the input feature space to a coarsely partitioned label space through the process of clustering. The initial labeling of individual neurons allows features of similar semantic meaning to be grouped into closer clusters. In this sense, the self-organizing map provides an efficient method to visualize high-dimensional data samples in low-dimensional display. [1].

The adjustment of the weights will be done by:

$$\Delta_{w_{kj}} = \begin{cases} \eta(x_j - w_{kj}), & \text{if the neuron k is winner;} \\ 0, & \text{if the neuron k is not winner.} \end{cases}$$

3) The Ants Algorithm (LF: Lumer & Faieta): The main idea is to use repeated and often recurrent simulations of *artificial ants* (mobile agents inspired by real ant behavior) to generate new solutions to the problem at hand. The ants use information collected during past simulations to direct their search and this information is available and modified through the environment. Many different artificial ant algorithms have been implemented and no universal definition of an artificial ant fits them all.

In the theory, we use the probability of taking an object is (P_p) and the probability of putting object is (P_d) [10]: When an ant having no element, its probability to take an element founding on its pass is: $P_p = \left(\frac{k_1}{k_1+f}\right)^2$, where k_1 is a positive constant and f is the set of elements regarded by the ant. When a few elements is regarded, $f \ll k_1$ so P_p near to 1 and the probability to take an element is big. Is the medium is very dense, so $f \gg k_1$ and P_p near to 0.

When the ant have element, its probability to put it is:

$$P_d = \left(\frac{f}{k_2 + f}\right)^2$$

where k_2 is a positive constant. f is the set of elements regarded by the ant. Lumer and Faieta propose an algorithm using the measure of dissimilarity between objects. (Euclidien distance) [9]. The local density function is computed as:

$$f(o_i) = \begin{cases} 1 - \frac{1}{a^2} \sum\limits_{o_j \in R_a(r(o_i))} \frac{d(o_i - o_j)}{a}, & \text{if } f \succ 0; \\ 0, & \text{otherwise.} \end{cases}$$

It depends on the considered object o_i and its position on the grid r. $f(o_i)$ is the measure of the mean similarity of the object o_i *with the object* o_j presented on its neighbor. a is a scale factor.

IV. Application of these methods

These methods are applied on two real signals. We are interested to classify events of real EMG signals "EMGX" (Figure 1) and "EMGY" (Figure 2) which are two real signals issued from the same person seated on two car seats, X and Y. The global aim of this study is to choose the more comfortable seat.

A. Choice of Relevant Parameters

The signal, as it has been acquired, can only be read from its parameters. There is the necessity to calculate the different parameters of the signal. Nevertheless, the choice of these parameters must take into account the following criteria:

- *A maximum separation of classes:* this criteria permit to ensure that the resulting classification's rate of errors is the lowest.
- *The sturdiness:* the choice of the selected characteristics must be functioning even when changing the signal.
- *The complexity:* the complexity of the calculation of the parameters must be limited in such a way that the identification's procedure of EMG can be implemented with a reasonable material system.

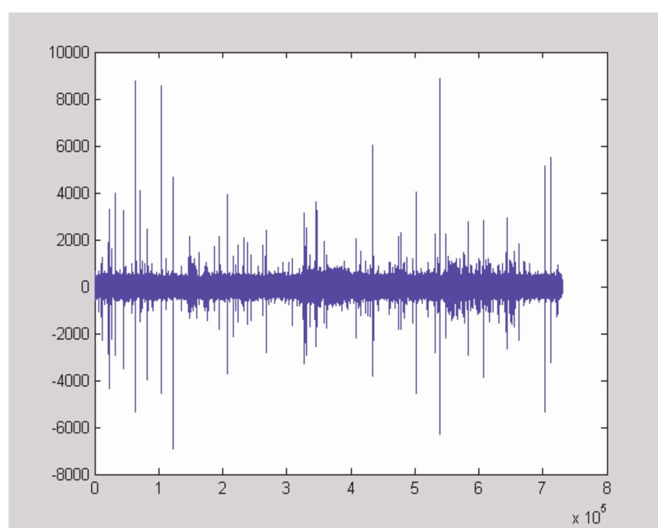

Fig. 1. Real signal EMGX.

Table III represents, in detail, the rate of errors given by each type of parameters, tested on the "EMGY" signal:

The statistical parameters don't have any influence on the detection of fatigue; among the spectral parameters, one

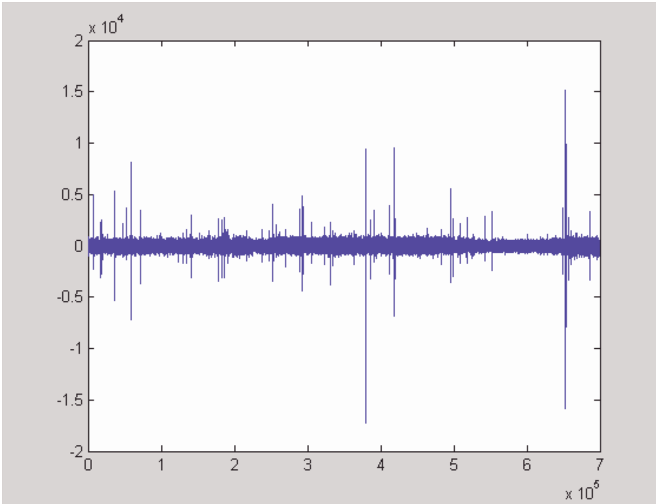

Fig. 2. Real signal EMGY.

TABLE III

ERROR RATE BY TYPE OF PARAMETERS.

Class C1	**Class C2**	**Error rate**
Statistical parameters	No classification	
M_1 & M_2	No classification	
W_n	16 %	8.3 %
f_k	20 %	28 %
Fmed, MPF, H/L	18 %	7 %
Spectral parameters	No classification	
All except M_1 & M_2	12 %	27 %

noticed that the energies of frequency gave the best results of classification answering the above stated criteria.

B. Results of C-Mean, LBG, FCM and CNN

After the application of these methods the first signal EMGX has a low variation in terms of frequency. We note the apparition of the muscular fatigue from the segment 81, indicating the comfort better of the "X" seat. The second signal EMGY shows more variation in frequency by comparing it to EMGX. We note the apparition of the muscular fatigue from the segment 51.

TABLE IV

RESULTS OF CLASSIFICATION.

		Class C1	Class C2	**Error rate**
EMGX	C-MEAN	Segments 1-81 => 55%	Segments 82-146 => 45%	37.7 %
	LBG			36.3 %
	FCM			35 %
	CNN			34.9 %
EMGY	C-MEAN	Segments 1-50, 112-139 =>56%	Segments 51-111 => 44%	12.3 %
	LBG			12.3 %
	FCM			12.3 %
	CNN			12.3 %

C. Results of PCA

The number of axis is defined according to criterion of Kaiser [11]. It consists on:

1) Calculate the first differences of the eigenvalues: $\lambda_1 - \lambda_2 = \varepsilon_1$ and $\lambda_2 - \lambda_3 = \varepsilon_2, \ldots$;
2) Calculate the second difference: $\varepsilon_1 - \varepsilon_2 = \delta_1$ and $\varepsilon_2 - \varepsilon_3 = \delta_2, \ldots$;
3) Only the eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_k, \lambda_{k+1}$, which have positive δ_1, δ_2, and δ_k are retained.

The application of this criterion on the signal " EMGY " and " EMGX " give the results in Table V.

TABLE V

APPLICATION OF CATTELL CRITERIA.

	Signal EMGX	Signal EMGY
the second difference	0.0056	0.0061
	0.0024	0.0003
	0.0014	-0.0001
	0.0002	0.0001
	0.0000	0.0004
	0.0001	0.0000
	0.0000	0.0000
	0.0000	0.0000

We notice well that two axes are sufficient for EMGY and four for "EMGX". However, this criteria is not absolute; it gives sufficient results but not inevitably necessary. It can happen that the number of useful axes for the separation in two classes is lower to the number given by the criteria of Cattell, as in the case of EMGY where, of after figures 3 and 4, only one axe is sufficient and therefore the classification will be detected visually, what is not the case of "EMGX".

This method can be followed by another method to minimize the error rate. This can be done by applying the FCM algorithm.

V. RESULTS GIVEN BY LF ALGORITHM

As showing by the Figures 4 and 5, LF algorithm gives the first step for the classification. It can collect all vectors according to the degree of likelihood to a finite number of groups. To increase the precision, we can apply another algorithm, FCM for example, just after LF algorithm. The results given on EMGX and EMGY are:

- EMGX (total error between 30 and 45%)
- EMGY (total error between 5 and 20%)

VI. COMPARISON OF METHODS

A. Evaluation of Different Techniques

The following criteria are used to compare our methods of classification: The possibility of interpretation of the results, the time of learning and the number of iterations, the response time, the error rate, the possibility of fixing with other methods.

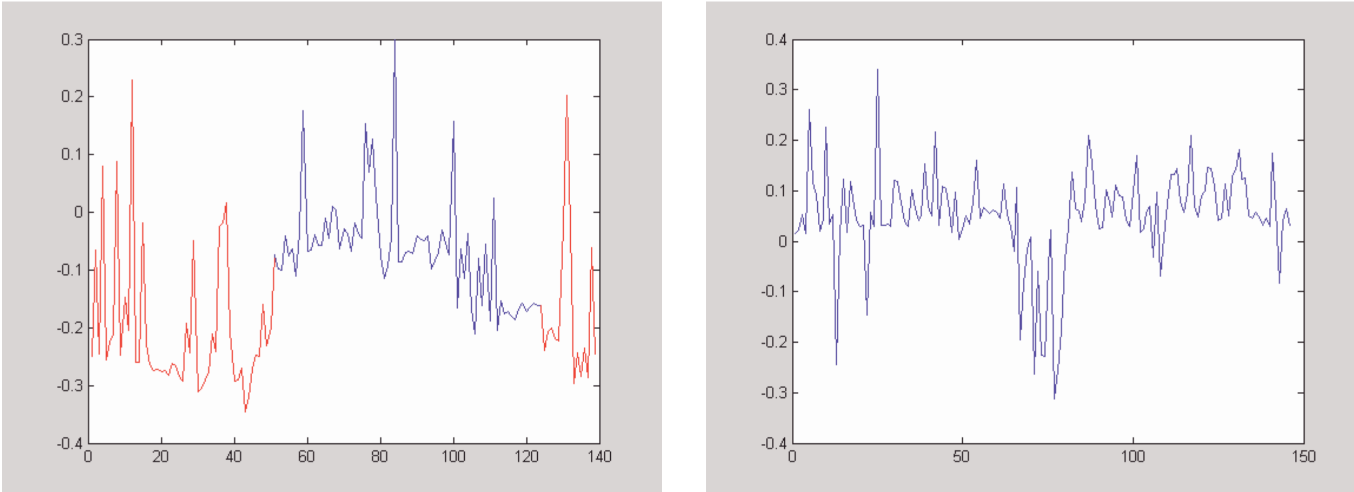

Fig. 3. Principal axe PCA of EMGY and EMGX.

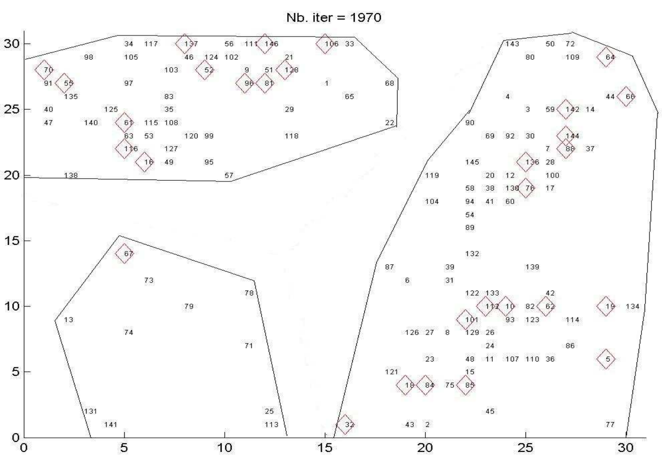

Fig. 4. Results on “EMGX ” given by LF.

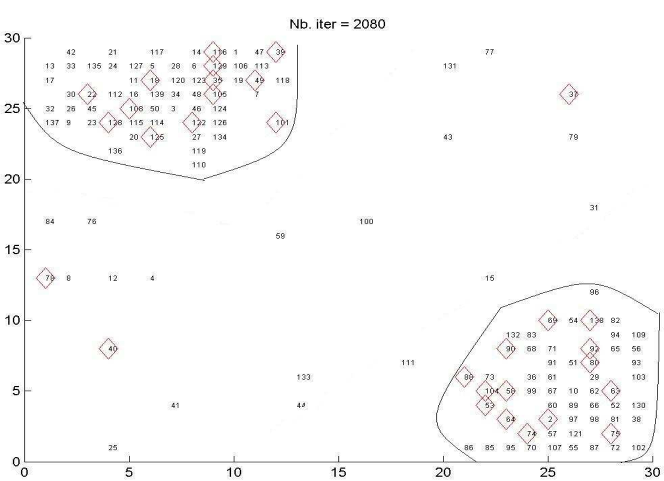

Fig. 5. Results on “EMGY” given by LF.

1) Possibility to Interpret: It is the possibility to assign significance to the constituted results. Indeed, the network of neurons works like a black box; it doesn't give a physical significance bound to the parameters of entry for the gotten results. On the other hand, the k-middle algorithms, LBG and FCM give, at a time, the classes and the centers. These parameters represent, in our case, of the energy of the signal in frequency band, what can be considered like a physical interpretation. In the LF algorithm, the behavior of the ant is based on the local similarity between the data to regroup them. The analysis in PCA permits to create a size on which the classification becomes very easy. But the interrelationship that joins the parameters between them is not interpretable.

2) Time of Learning and the Number of Iterations: It is the time that takes the algorithm to make the classification. One measures it according to the number of the iterations. The CNN uses an algorithm of training capable to converge slowly. C-Means, LBG and FCM can do a consequent number of distance calculations before getting the prototypes but yet, the number of iterations is very small (6 iterations on average) in relation to the CNN (25 iterations). An artificial ant is an intelligent agent that can make three functions; LF asks an important training time to succeed to the classification, especially in the case of the real signals. This time of training becomes negligible in PCA as soon as one arrives to a representative direction of all parameters, a simple tree of decision will be able to, thereafter, to help to make the classification.

3) Response Time: Once the algorithms of classification finished their training, the time of the classification of every test data is considered like a response time. This time is very fast in all algorithms that one tried, except in LF that asks, to every new entry, a research of the good position of this entry.

4) Reactivity: Reactivity represents the faculty of the system to react when the signals alter during the time (Insertion of new cases in the data base). In RNC, the fact to add new data imposes a new a phase of training to adapt to this evolution. It is the same way for the other methods. But, all these methods require less time because they take advantage of the already gotten ordering.

5) Error Rate: It is about the number of elements badly classified. This rate is very important in LF, least in CNN, LBG and C-Means and minimum in FCM.

6) Possibility of Fixing with Other Methods: It is the power that an algorithm has to combine with another method. This property concerns LF that one must combine it with another method to divide the different groups in two classes; and PCA that, after having found the representative axis of all parameters, use any method to make the classification, of preference the FCM algorithm. This one gives us more precise answers with a percentage of adherences to every class. Concerning the other algorithms, one could succeed to the classification without any need to other methods.

B. Comparison between Statistical Methods and Data Mining Methods

In signal processing domain, Statistical methods are widely used and give important results. K-means and LBG method are widely used to make the unsupervised classification.

If the number of parameters is high, CNN and LF are not used because the error increases with the number of parameters. However, FCM has the advantage to mix the fuzzy logic and the statistical methods and give supplement information for classification. This avoids the interlacement of classes. In fact, the use of m with value equal to 2 (3 or 4 for example) and the increase of the belonging value (u_{ik}) to a class can decrease the error rate. In our case, we chose this parameter equal to 0.35 and this reduce the error rate to 25% for EMGX and 9% for EMGY.

Furthermore, the mix of FCM and the principal component analysis give the moist important result in our case. PCA reduce the number of parameters. The following diagram (Fig. 6) shows the synoptic scheme of the classification on EMG signal:

VII. CONCLUSIONS

This article shows the utilization of the data mining on the classification of EMG signals. The selection of the pertinent data was an essential task to achieve correctly this problem. In our case, we use the energy of the signal in some frequency band (after wavelet transform).

The application of many techniques of classification, known in data mining and in statistics, takes the big part of this article. We presented the methods of K-means, method of Linde, Buzo and Gray (LBG), the technique of fuzzy C-means (FCM), the Ants algorithm (LF), the competitive neural network (CNN) and the principal component analysis (PCA). For a good separation of classes, we tried to mix some algorithms like PCA and FCM. The results give information about the frequency content of the EMG signal which is used to detect the comfortable car seat. EMG signals are acquired during long way driving. After a discussion based on some criteria of evaluation, we choose mixed methods based on PCA and FCM to achieve our problem. The adjustment of the two parameters (u_{ik} and m) gives us good results.

REFERENCES

[1] Dreyfus G., Martinez M., Gordon M. : *Réseaux de neurones*. Eyrolles. 2002.

[2] Dubost G. et Tanaka A. "*A Wireless NetWork based Biosensor Interface for Music*". Proc. Of Intern. Computer Music Conf., sept. 2002.

[3] El-Falou W., "*Une approche de la segmentation dans des signaux de longue durée fortement bruités. Application en ergonomie*", Thèse de doctorat, UTT, 2002.

[4] Huet S., "*Classification de signaux EMG en vue de la commande automatique d'une main artificielle*". Handicap 2004, Paris, 2004.

[5] Jorgensen C., Wheeler K. & Stepniwski S. "*Bioelectric Control of a 757 Class High Fidelity Aircraft Simulation*". .Proceedings of the World Automation Congress, Hawaii, 2000.

[6] Khalil M., Duchène J. "*Uterine EMG Analyzing: A dynamic approach for change detection and classification*". IEEE Transaction on Biomedical Engineering, 2002.

[7] Knaflitz M. & Bonato P. "*Time-frequency methods applied to muscle fatigue assessment during dynamic contractions*". Journal of Electromyography and Kinesiology, vol.9, 2002, pages 337- 350.

[8] Linde Y., Buzo A., Gray R.M. "*An algorithm for vector quantization (QV) design*". IEEE transactions on communication. 1980.

[9] Lumer E., Faieta B., "*Diversity and Adaptation in Populations of Clustering Ants*", Cliff et al. (CLI 94), p. 501–508.

[10] Monmarché N., "*Algorithmes de fourmis artificielles: applications à la classification et à l'optimisation*". Thèse de doctorat, Université de Tours, 2000.

[11] Saporta G. "*Probabilités, Analyse des données et Statistiques*". Editions Technip, 1999.

[12] M. Atieh Younes & al, "*Utilisation des signaux EMG pour la commande intelligente de prothèses de main et de coude*", Congrès CITE, Rennes, 2005.

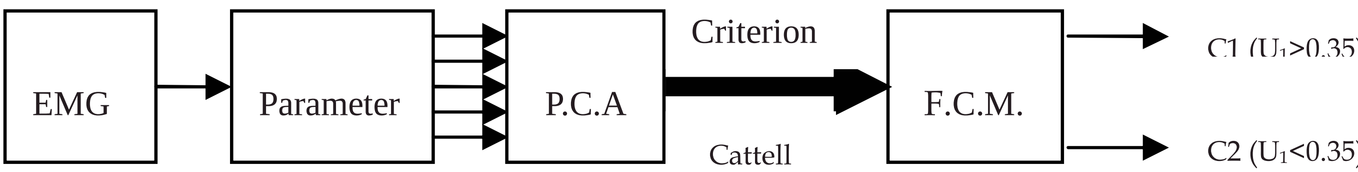

Fig. 6. Synoptic scheme for EMG clustering.