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Classification of epileptic motor manifestations using attitude sensors

Guillaume Becq, *Member, IEEE*, Stéphane Bonnet*, Lorella Minotti, Régis Guillemaud and Philippe Kahane

Abstract—Several kinds of epileptic seizures generally result in motor disorders. In an order to quantify movements observed during these seizures, attitude sensors (AS) (trixaxis accelerometer coupled with triaxis magnetometer) were placed on epileptic patients. Video recordings synchronized with AS during seizures were analyzed by an expert and divided for each limb into events corresponding to different classes of motor manifestations. For each classified event an extraction of dynamic, spectral and angular features was realized. A feature subset selection was realized using artificial neural networks and decision trees. The best artificial neural network obtained with 20% of errors was simulated on whole recordings of the patients using 4 s epochs of signal. This classification process provides a stereotypic evolution of motor manifestations that can point out movements and emphasize epileptic patterns observed during seizures.

Index Terms—epilepsy, movement, seizures, attitude sensors, classification, supervised learning, feature subset selection, monitoring, accelerometer, magnetometer.

I. INTRODUCTION

EPILEPTIC seizures are manifestations of brain dysfunction, starting from one or several areas and propagating to different ones. The prevalence of epilepsy is important since 0.5 to 1% of the average population is concerned [1], with an incidence of 0.05% and higher rates during childhood and old age [2]. Epilepsy is associated with a $\times 2$ to 2.5 rate mortality [3] and the cost of hospitalization are high with a rate of approximately 100 euros per day in France.

There are several kinds of epileptic seizures and lot of efforts are made to classify them into similar pathologies [4]. An important number of these seizures are associated with movements disorders. This is the result of the propagation of the electrical seizure on a path into the brain through the motor area. A classification of the observed motor manifestation has recently been proposed by Lüders [5]. Actually, the observation of the movement generated during a seizure is used as a diagnostic tool by doctors.

In all epilepsy units, an electroencephalographic (EEG) recording system is often coupled with a video recording system in order to monitor the evolution of the epileptic seizure and track epileptic focus(es). Although EEG recording is the gold standard to analyze epileptic seizure and understand it,

the video gives clues to precise and focalize doctor's attention. However, video presents qualitative information often hard and long to analyze. Several solutions have been proposed to quantify movement and help doctor for its analysis.

Some use specialized video processing technics [6]–[8], with or without markers set on patient's limbs. The major benefit of such approaches is that it uses a device already available at the patients' bedside. One drawback is the poor resolution of the quantification of movement and the difficulty to reconstruct the movement from 2D images. Another drawback when using markers is when some disappear from the field of view, leading to indetermination.

Another equipment used in medicine for the quantification of movement is the accelerometer [9]. In neurology, this sensor has been studied principally for Parkinson's disease [10]–[13] or to detect hand tremors [14].

3D types of this sensors have been used for epilepsy [15] where visual analysis of signals has revealed stereotypical patterns of motor seizures and has given some clues for automatic analyses. The advantage of accelerometer sensors is their low cost and their low consumption of energy enabling an ambulatory monitoring. The drawback is an indetermination of a class of movement in the horizontal plane, like undesired rotation of the head on the right or left, usually observed during seizures.

In order to obtain a full characterization of 3D movements, it is possible to coupled magnetic sensors with accelerometers. This coupled sensor is often referred as attitude sensor (AS) and it has been used, for example, in a biomedical context for the evaluation of vertical inclination and horizontal azimuth [17]. This solution is cheap and needs low energy as compared to gyroscope sensors measuring angular rates and enabling 3D movements characterization.

The aim of our study was to investigate the use of attitude sensors in the context of epilepsy units, to quantify movements observed during seizures and to propose a tool for its analysis in 3D. For that we have positioned three attitude sensors on the limbs of epileptic patients and collected data into an epileptic unit. With analyzed signals of recorded seizures, an automated classification into motor manifestations have been realized based on a medical expertise. The different procedures retained for data acquisition, feature extraction and supervised learning are presented and empirical performances of the system are evaluated.

First of all we will present the materials used to monitor epileptic patients and collect data. Then we will present the methods used: to split motor manifestation observed during

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seizures into classified events; to create a database from feature extraction of signals corresponding to these classified events; to learn classifiers using supervised learning based on artificial neural networks or decision trees. Results will be separated into the description of signals by class, the analysis of events duration, the model obtained by supervised learning and the simulation on whole recordings. A discussion will precede a conclusion by pointing out the benefits and drawbacks of attitude sensors and our methods to classify attitude sensors data into motor manifestations for monitoring epileptic movements.

II. MATERIALS

A. Monitoring of epileptic patients

Data acquisition has been realized from November 2005 to June 2006 in the epilepsy unit of the Grenoble hospital in preparation of a clinical study accepted in July 2006. The epilepsy unit hosts severe epileptic patients, generally pharmacoresistant to antiepileptic drugs, for precise investigation of the epileptic pathway associated to individual illness. This investigation is realized in order to prepare surgical intervention such as excision, isolation or coagulation of the affected pathologic areas. The exploration for the diagnosis of epileptic focus is principally realized either with scalp or stereotaxic (EEG), coupled with audio video recordings at patient's bedside. The exploration can last from one to four weeks.

1) *Video EEG*: The epilepsy unit is composed of two bedrooms, each equipped with Brain Quick video-EEG monitoring from the Micromed company [19]. The system is composed of an SD 128 amplifier accepting up to 128 leads with a 16 bits resolution and selectable sampling rate from 256 to 1024 Hz. The system is connected to a computer for data centralization with an optical link. Videos recordings are realized using a resolution of 720×576 pixels, at a rate of 25 fps, using an MS-MPEG 4 v 2 encoding and audios using a monochannel at 44.1 kHz using a GSM 6.10 encoding. Audios-videos and EEG recordings are synchronized with Micromed System Plus patient data management system software.

2) *Attitude sensors*: Triaxis accelerometers (Acc) and magnetometers (Mag) are collected on a chip encapsulated in a silicon rectangular parallelepiped measuring $50 \times 30 \times 15$ mm as described in [20]. This constitutes one attitude sensor (AS). Three AS are linked to a data logger (Trident system developed at CEA\Leti) positioned at the bedside of the patient with 3 m wires enabling the mobility of the patient. Sensors are inserted into a flexible fabric sew over a belt specifically designed for the study. The belt is adjustable to the circumference of the selected limb by self gripping fasteners. The fabric is washable and easily supported by the patient. An example of the placement of the sensors at the bedside is presented Figure 1. Accelerometer sensors are ranging from $\pm 1.7 G$ with a precision of $1e^{-3} G$. Magnetometers sensors are ranging $\pm nT$ with a precision of $1e^{-3} nT$. Magnetometers were calibrated at the center of each bed using a method based on a least square normalization proposed by Merayo [21]. Three sensors were positioned on people according to three locations selected from Table I.



Fig. 1. Attitude sensors set on an epileptic patient. A specific design for the positioning of the sensor has been realized into flexible fabric with self gripping fasteners to be easily adjustable to the anatomy of the limb and well supported by the patient.

TABLE I
ABBREVIATIONS FOR SENSORS LOCATION

Abbreviation	Location	Sensor position
O	Other parts	–
LLL	Left lower limb	Left ankle
LUL	Left upper limb	Left wrist
H	Head	Frontal
A	Axis	–
RUL	Right upper limb	Right wrist
RLL	Right lower limb	Right ankle

3) *Data logger*: Data from sensors are parsed into a data logger (Trident) developed by our laboratories. The energy of the data logger can be supplied by two 1.5 V LR4-AA energy cells for an autonomy of about 24 h or can be supplied with a transformer certified for medical applications for infinite recordings. Data can be stored to a multimedia card (MMC) enabling the system to be portable or directly to a PC computer through an RS232 connection. In this case, an opto-coupling unit has been introduced to isolate the patient from the computer electrical source coming from the hospital network. The Trident system enables a recording of data at 46 Hz with a resolution of 16 bits. Data corresponds to the 18 signals coming from the 3 AS each sensing 3 Acc and 3 Mag, plus a marker coming from an external source for systems synchronization.

4) *Synchronization unit*: In order to synchronize the video-EEG system and the data logger, a synchronization unit has been introduced into the process. The synchronization unit collects a signal from an output of the Micromed system originally introduced to drive intermittent photic stimulation (IPS), detects the intermittent patterns and translates it to a

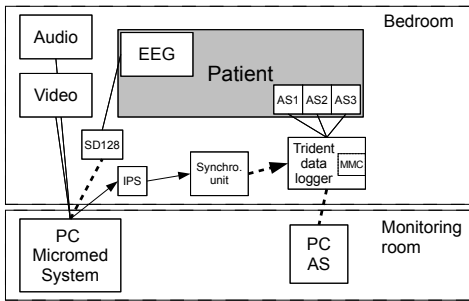


Fig. 2. Diagram of the data acquisition process at the bedside of the patient. Micromed system enabling Video-EEG recordings and Trident system connected to attitude sensors are synchronized through a Synchronization unit. Video-EEG data are recorded following the usual protocol. AS data and marker data are recorded directly to the Trident system on a multimedia card (MMC) or to a PC through an RS232 connection. The synchronization is made with an intermittent photic stimulation (IPS) signal driven by the medical staff thanks to Micromed software. Dotted lines represents isolated links to ensure patient safety.

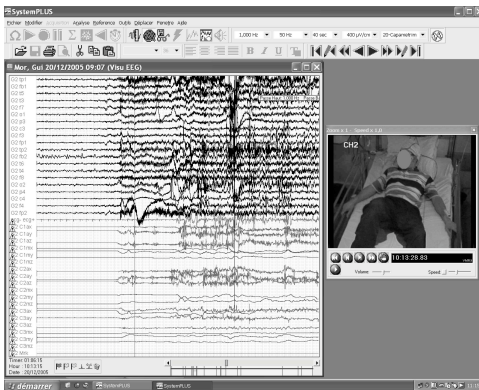


Fig. 3. Visualization of the synchronized recordings after merging data from the two systems. Video (right) EEG (top) and AS (bottom) data can be observed together.

marking signal (binary signal) then transfers it to the Trident unit for data recordings. The synchronization unit is linked to the Trident system through an electrical relay to ensure electrical isolation.

A diagram of the data recording process is proposed in Figure 2.

Data recorded on both systems are merged offline with a software developed by our laboratories running under Matlab (The MathWorks, Inc.) [18]. Synchronization is made after eliminating the temporal delay between the two systems computable according to the marker signs on both recordings. An example of a visualization of the resulting file with the viewer of the Micromed system is proposed Figure 3.

B. Data collection, population and data processing

A protocol has been elaborated to collect the data with the medical staff in order to be applied on a daily routine. A checklist has been proposed to respect the synchronization of data presented previously. Data analyzed in this article comes from the setting of this protocol (submitted to a committee for the protection of patient that has received an agreement in June 2006 for further studies).

TABLE II
MOTOR MANIFESTATIONS CLASSES

Abbreviations	Name	Class #	Color		
			R	G	B
NOMVT	no movements	ω_1	255	255	255
AUTO	automatisms	ω_2	128	0	0
CLONIC	clonic manifestations	ω_3	0	255	255
TONIC	tonic manifestations	ω_4	0	0	255
TC	tonico-clonic manifestations	ω_5	0	255	0
HYPER	hypermotor manifestations	ω_6	255	0	0
VERSIVE	versive manifestations	ω_7	128	0	128
OTHERS	others manifestations	—	—	—	—

Data has been recorded on 17 patients, 12 women, 5 men, aged from 8 to 45 years $24, 2 \pm 11, 2 y$ during 211 half days of 3 h recordings. On these patients, only 9 have generated motor seizures. Only 29 seizures were obtained corresponding to a ratio of approximately 1.4 episodes per week of working days.

Data have been processed offline on an x86 Intel PC at 1,5 GHz with 512 Mo of memory. Matlab has been used to process the data using signal processing, wavelet, identification and statistical toolboxes.

III. METHODS

A. Medical expert classification

Each seizure has been analyzed and segmented into events corresponding to different motor manifestations for each part of the body. This has been done to attribute to signals contained in each event, a class of manifestation given by an expert. This classification task, corresponding to a visual scoring of motor manifestation thanks to video, has been the base for the supervised learning realized on features extracted from these signals.

1) *Definition of manifestations*: Seven types of motor manifestations have been retained which corresponds in part to the classification proposed by Lüders et al. [5]. Abbreviations of the different classes are listed in Table II.

- **No movements**: No movements are observed.
- **Automatisms**: Gestures mimicking a task more or less repetitive but being unusual in the context when it appears. Observations are made at the distal part of members, principally from hands, feet or mouth.
- **Clonic manifestations**: successive contractions of agonist and antagonist muscles, more or less repetitive. This class includes myoclonies and clonies.
- **Tonic manifestations**: alteration of the tonus of a muscle resulting or not in a change of position more or less quickly of the affected part of the body. This class includes dystonies, atonies, hypotonies, hypertonies.
- **Hypermotor manifestations**: succession of movements, more or less rapid, violent and repetitive, principally generated at the level of the trunk or at the proximal part of the limb.
- **Tonico-clonic manifestations**: movements combining both clonic and tonic manifestations.

- **Versive manifestations:** external rotation of the head associated with eyes deviation into one direction.
- **Others manifestations:** unclassified manifestations with light movements such as grinning, paining ...

2) *Visual scoring:* Each video sequences corresponding to a recorded seizures has been analyzed and segmented into events corresponding to movement manifestations. This work was realized for each part of the body according to the different classes previously described. The different time of the seizure were identified on the EEG signals and noted t_0 start of the electrical seizure, t_1 start of the clinically observable seizure (visually observable by behavior changes) and t_2 end of the seizure for temporal definition of the seizure. Visual example is given in Figure 4.

3) *Data entry and visualization:* Results from the visual scoring has been entered into a computer by applying the formalism introduced by Table I and Table II in a text format and saved into files in order to be used for data mining. For each entry, time stamp for the beginning and end of the event has been noted according to the date format YYYYMMDDTHHMMSS (iso 8601) with a precision rounded to the near second. An example of such text file following this format is given Appendix I.

A direct application of such an entry is visualization of the seizure that can be obtained directly by processing files to generate graphics. For these graphics, we have decided to represented each manifestation with a colored box with color associated to a manifestation class as defined in Table II horizontal. The different part of the body can be represented in vertical. We have decided to starting from the left part at the top of the graph to the right part of the body at the bottom of the body with head and axis in the middle in correspondence to the visualization of EEG montage proposed in monitoring. Examples of such a representation are given in Fig. 9(a), 9(b) et 9(c) for three patients.

4) *Artifacts collection:* All video sequences of seizures have been analyzed to collect all the different artifacts occurring during motor manifestations. These artifacts results from three principal causes : the test by the medical staff of a limb to determine its state (for example to evaluate the tonic of the limb standing in a position); the unnatural movement created by the reflex handling of the patient body by the medical staff to protect him or replace him in a good position; others unexpected artifacts caused to sensors due to the patient himself or the staff for example the displacement of the sensor out of its original position.

In the same way as motor manifestation collection, the different artifacts have been entered to a computer in order to be used for data mining. This was done in order to remove corrupted signals by artifacts that can not be used for data processing and supervised learning.

B. Database creation for supervised learning

Thanks to the scoring realized by the expert, AS signals from each manifestation and for each location has been collected for features extraction. In this study, location has not been taken into account for the learning of classifiers and data

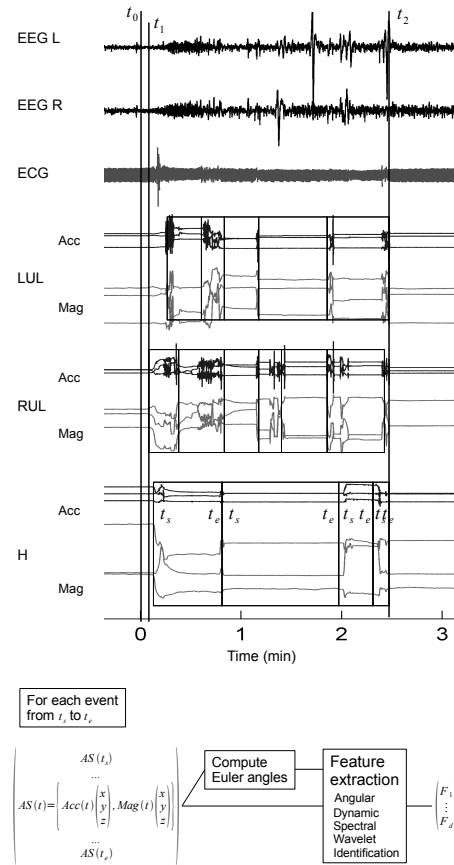


Fig. 4. Feature extraction process. Accelerometric data are passed through a filter and grouped with magnetometric data to obtain attitude sensor (AS) data. AS data are used to compute rotation components between two samples. Rotation and AS data are used to obtain features supposed to be relevant of motor manifestations events.

from different location have been mixed together and grouped only by manifestation class.

1) *General concept:* AS signals from the different events have been processed following the block diagram given Fig. 4 that produces features grouped into the following components: angular, temporal, dynamic, spectral, wavelet and identification. The different features extracted from the AS sensors are summarized in Table III.

Some features have been used for the supervised learning, some others have been used for the determination of parameters for windowing. t_s is used to defined the beginning of the event, t_e is used for the end of the event.

2) Angular features:

a) *Angular computation from AS:* The interest of AS is to enable for any measure, to compute the rotation of the sensor to its actual position, from a referential.

Given a vector associated to a body $AS_b(t)$, of measures combining 3D $Acc(t)$ and $Mag(t)$, and a referential AS_{ref} , it is known that both the rotation matrix of Euler's angles or the Euler's principal angles (θ) and axis can be computed in condition that sensors accelerations are not important [20].

In this study, we have focused on instantaneous rotation by computing the angular rotations from samples to samples. We only retained Euler's principal angle as a variable of interest

TABLE III
LIST OF FEATURES ASSOCIATED TO MANIFESTATION EVENTS

Feature	Notation	Description
1	k	index of event
2	i_{file}	index of file
3	i_{pat}	index of patient
4	i_{bed}	index of bedroom
5	dT	duration
6	τ_{step}	Time constant for step input
7	τ_{ramp}	Time constant for ramp input
8	$Med_{\ \vec{Acc}\ }$	median of $\ \vec{Acc}\ $
9	$Mean_{\ \vec{Acc}\ }$	mean of $\ \vec{Acc}\ $
10	$En_{\ \vec{Acc}\ }$	entropy of $\ \vec{Acc}\ $
11	$Mobility$	Mobility
12	$Range$	Range of rotation
13	Med_{Θ}	Median of rotation
14	$SEF_{10, Acc_{ml}}$	Spectral edge frequency at 10 % for Acc_{ml}
15	$SEF_{95, Acc_{ml}}$	" 95 % " Acc_{ml}
16	$SEF_{10, Mag_{ml}}$	" 10 % " Mag_{ml}
17	$SEF_{95, Mag_{ml}}$	" 95 % " Mag_{ml}
18	$SEF_{10, \Theta}$	" 10 % " Θ
19	$SEF_{95, \Theta}$	" 95 % " Θ
20	$W_{\Theta}(\delta_1)$	Wavelet coefficients ratio in δ_1 band for Θ
21	$W_{\Theta}(\delta_2)$	" δ_2 " Θ
22	$W_{\Theta}(\delta_3)$	" δ_3 " Θ
23	$W_{Acc_{ml}}(\delta_1)$	" δ_1 " Acc_{ml}
24	$W_{Acc_{ml}}(\delta_2)$	" δ_2 " Acc_{ml}
25	$W_{Acc_{ml}}(\delta_3)$	" δ_3 " Acc_{ml}
26	i_{Ttype}	Motor manifestation class
27	i_{Loc}	Location

and extracted features from it.

b) Angular features extraction: We have based our feature extraction and adapted our methods from the work by Salarian [10] with gyroscopes with a measure of rotation rate.

We have first computed the root mean square of the signal, referred as the mobility by Salarian, by applying Eq. 1, taking into account that we were working with instantaneous rotations $\theta(t)$ (rotation between $AS(t)$ and $AS(t-1)$) with $t_i = t_s + i/F_s$ and $t_e = t_s + (N-1)/F_s$:

$$Mobility = \sqrt{\frac{1}{(N-1)} \sum_{i=1}^{N-1} \theta^2(t_i)} \quad (1)$$

We have also selected instantaneous rotations θ_s with angular velocities $\theta(t) * F_s$ higher than $10^\circ/s$ and removed the others considering them to be no movement as in Salarian, to compute the cumulated rotation Θ according to:

$$\Theta(t_j) = \sum_{i=1}^j \theta_s(t_i) \quad (2)$$

From this cumulated angular rotation, we have extracted two statistical features as in Salarian: the median value med_{Θ} and the range of values $Range$.

3) *Dynamical features:* The extraction of dynamical features has been principally based on the norm of acceleration, supposed to be an aggregated information of both tri-axis dynamics. It has been retained for its potential to discriminate no movement, normal movement, and hypermotor movements with high acceleration. $\|\vec{Acc}\|$ has been calculated using Eq. 3.

$$\|\vec{Acc}\|(t) = \sqrt{Acc_x(t)^2 + Acc_y(t)^2 + Acc_z(t)^2} \quad (3)$$

We have also retained the entropy of the norm of acceleration in order to have a feature weighting the complexity of the signal in the sense of a deterministic signal with few states versus a stochastic signal with several states. We used the Shannon's entropy given in Eq. 4 where p_i denotes the probability to be in the state i . We used a quantification of 16 bits between 0 and 3G and computed $h_i = n_i/N = \mathbb{1}(\|\vec{Acc}\|(t) = q_i)/N$, with n_i the number of samples at level q_i and N the number of samples in the event. $h_i \log(h_i)$ has been considered to be null for $h_i = 0$ to obtain Eq. 5.

$$En = - \int_{i \in \mathbb{R}} p_i \log(p_i) di \quad (4)$$

$$En_{\|\vec{Acc}\|} = - \sum_i h_i \log(h_i) \quad (5)$$

4) *Spectral features:* Spectral edge frequency (SEF) can be seen as a robust summary of the spectral behavior of a signal, indicating the frequency value for which $\alpha\%$ of the spectral power is obtained.

We have computed SEF at 10 and 95 % (respectively SEF_{10} and SEF_{95}) in order to quantify the frequencies during visual interpretation of clonic manifestations (0.2 – 5 Hz), with energy in high frequencies expecting an important SEF_{95} , or slow tonic postural manifestation, with energy in low frequencies expecting an important SEF_{10} .

Let $S_{xx}(f_i)$ be the power spectral density computed at frequency f_i for signal x . We can define $P_{xx,rel}(0, f)$ the relative power in the frequency band $[0, f]$ by Eq. 6 mapping to $[0, 1]$.

$$P_{xx,rel}(0, f) = \frac{\sum_{f_i=0}^f S_{xx}(f_i)}{P_{xx,tot}(f)} \quad (6)$$

With $P_{xx,tot}(f)$ the total power defined by Eq. 7 with F_s sampling frequency of the signal x :

$$P_{xx,tot}(f) = \sum_{f_i=0}^{F_s/2} S_{xx}(f_i) \quad (7)$$

Then the spectral edge frequency at level $\alpha\%$ can be defined as:

$$SEF_{\alpha} = \max_f \{f | P_{xx,rel}(f) \leq \alpha/100\} \quad (8)$$

We have computed SEF_{α} for Acc_{ml} , Mag_{ml} and Θ .

5) *Wavelet features:* The wavelet analysis was used in order to work accurately in the frequency domain of the signals without making assumption of the length of the window or of the stationarity of them. For the time-frequency analysis we have computed the coefficients of the continuous wavelet transform using a Morlet atom wavelet $\psi(t) \sim \exp(-x^2/2) \cos(5x)$,

with the Matlab wavelet toolbox based upon Eq. 9, where a denotes a scale parameter and b a lag parameter:

$$C_x(a, b) = \int_{-\infty}^{\infty} x(t)\psi(a, b, t)dt \quad (9)$$

The different scales retained were chosen to correspond to the pseudofrequencies grouped into three different bands $\delta_3 = \{23, 20, 17, 14, 12, 10, 9\} Hz$, $\delta_2 = \{8, 7, 6, 5, 4, 3, 2\} Hz$, $\delta_1 = \{1.25, 1, 0.75, 0.5, 0.25, 0.1, 0.05\} Hz$. Results of such a decomposition for different prototypic manifestations is given Fig. 6 (bottom) and represents the evolution of the different wavelet coefficients at different scales over time.

For feature wavelet based extraction, we have retained the ratio of coefficients in a given band to the sum of all coefficients $W_x(\delta_i)$ with scales a associated to the pseudofrequency band δ_i defined previously:

$$W_x(\delta_i) = \sum_{a \in \delta_i} \sum_b C_x(a, b) / \sum_a \sum_b C_x(a, b) \quad (10)$$

At the end of this process, we have obtained three features for each event respectively for Acc_{ml} , Mag_{ml} and Θ .

6) *Identification features*: The observation of tonic and versive manifestations have led us to consider two specific kinds of model-based movements: the first is like an answer to a positioning command and the manifestation stops when the limb reaches a given position, this is particularly observed during tonic manifestation; the second is like the answer of a pursuit command as if the limb was following an offsetting position, this is particularly observed during versive manifestation. We have made the assumption that these movements could be modeled by first order models represented by their answer time τ_{ramp} or τ_{step} .

The cumulated rotation $\Theta(t)$ computed on the principal Euler's angle has been selected to identify these parameters. An example of such signal and their associated models are given Fig. 5.

We used the identification toolbox from Matlab to identify the parameters, after matching the best delayed step or ramp signal according to a maximization of the correlation between signals.

C. Supervised learning

1) *General concept*: From here, for each manifestation event, we have on one hand a classification given by an expert, on the other hand the extracted features. The aim of supervised learning is to estimate the parameters of a model that can classify each event represented by its extracted features into its given class given by the expert.

In a mathematical framework, the problem of classification is to find a function \mathcal{C} mapping features vectors in a space of d dimensions into a class represented by an integer number:

$$\begin{aligned} \mathcal{C} : \mathbb{R}^n &\rightarrow \mathbb{N} & (11) \\ (F_1, \dots, F_n)^t &\mapsto \omega_i, \quad \omega_i \in \{\omega_1, \dots, \omega_K\} & (12) \end{aligned}$$

For more general details about supervised learning and more generally machine learning, the reader is referred to [22], [23].

For the classification, we have used neural networks and decision trees. In order to select the best informative features and reduced the dimension of the input space, we have used features subset selection heuristic: we have used a sequential forward selection [23] for neural networks and pruning for decision trees.

2) *Data cleaning, preprocessing and performance evaluation*: Cleaning of the database has been realized using multiple criterion. Data coming from events with a duration $< 2 s$ or $> 150 s$ have been discarded because they have been considered as irrelevant. Data coming from events with several artifacts have been manually removed. Data have been normalized using a z transformation $z_j = (x_j - \mu_j)/\sigma_j$ with μ_j and σ_j estimated mean and variance from feature j .

For regularization, artificial growing of the database has been realized by duplicating 30 times each sample of class k , adding uniform noise [25] with a variance σ_{jk} , variance of feature j estimated from samples in class k .

Classifiers learnings have been realized over stratified subsets of examples, i. e. by selecting the same number of samples for each class set to 100. The empirical error, error between the classification given by the classifier from the learning set and the classification given by the expert, has been used as the performance criterion.

3) *Neural network classifiers*: Artificial neural networks (ANN) selected for this study have been multilayer perceptrons (MLP) with one hidden layer for their ability in discriminant analysis. We have used J neurons in the input layer, 10 in the hidden layer and K in the outputs. The dimension in the hidden layer has been used after a test on the dimension from 1 to 20 and selected where no performances has been obtained. J corresponds to the dimension of the input space being the dimension of the features subset. K corresponds to the dimension of the output space being the number of desired classes. Tangent sigmoid ($y = \frac{2}{1+e^{2x}} - 1$), linear ($y = x$) and log-sigmoid ($y = \frac{1}{1+e^x}$) transfer functions have been used respectively for input layer, hidden layer and output layer.

MLP weights have been randomly initialized using the Nguyen-Widrow layer initialization function and their optimization have been obtained using a Levenberg-Marquardt method [24]. Due to random initialization, for each set, 15 MLP have been evaluated and the best one has been retained.

4) *Decision trees*: A decision tree has been generated using the statistical toolbox from Matlab.

5) *Features subset selection*: In order to reduce the input space dimension for neural networks, we used a sequential forward selection (SFS) algorithm. It is a greedy algorithm which starts with an empty set of retained features, tests samples according to the set of features retained, and selects features one after another by minimizing a given criterion. For example, at step one, if d features are enabled, SFS starts by learning model with one feature. It tests the performances obtained with the d models and selects the model with feature (i_{r-1}) that maximizes the performance. At step two, SFS tests $d - 1$ models constructed with the retained feature (i_{r-1}) and one of the $d - 1$ remaining features. At the end of the process, d subsets are presented with their associated performances, respectively with dimension 1 to d . The analysis

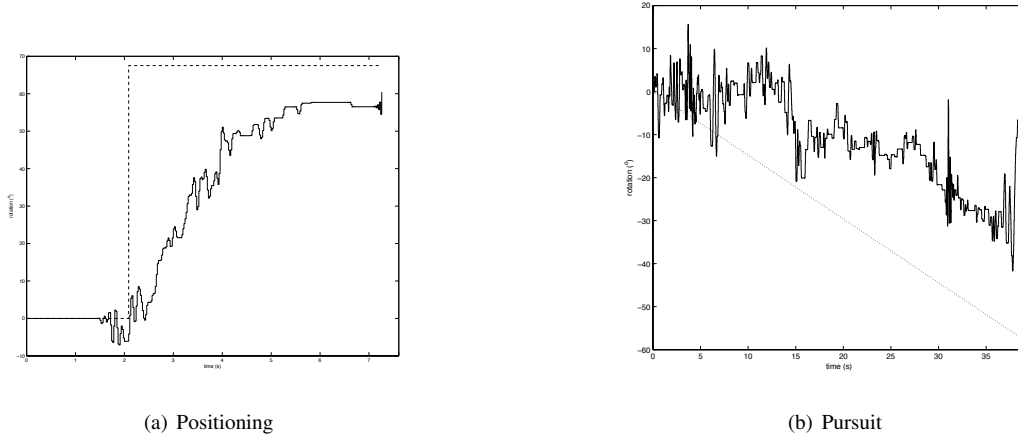


Fig. 5. Identification of the parameter of a first order model from tonic or versive movements appearing as : a) positioning command, b) pursuit command. Before identification, delays between step or ramp inputs and outputs are found according to a maximum of correlation.

of the progression of the selection enables to select a subset satisfying the Occam's razor principle that is to take the model with the minimal dimension since no or few performances are gained when complexifying the system. The selection is done following the algorithm proposed in Appendix II.

For the decision tree, we have pruned the original decision tree at the minimal level where all the classes were represented.

IV. RESULTS

226 manifestations events have been scored, representing in each class: 42 NOMVT, 25 AUTO, 17 CLONIC, 70 TONIC, 21 TC, 20 HYPER, 11 VERSIVE, 20 OTHERS.

For this study, versive manifestations have been considered as tonic manifestations ($\omega_4 = \{\omega_4, \omega_7\}$), tonico-clonic manifestations have been considered as clonic seizures ($\omega_3 = \{\omega_3, \omega_7\}$) and others manifestations have not been taken into account. 51 events have been removed during cleaning. The addition of noisy examples into the database for regularization have lead to a database with 5425 examples: 1178 NOMVT, 620 AUTO, 1147 CLONIC, 2015 TONIC, 465 HYPER.

A. Description of observed signals by class

According to the classification and the computer entries of expert's analysis, prototypical examples of signals by class can be obtained easily and represented as in Fig. 6. In a signal processing view, one can notice that :

- Tonic: low frequencies for Acc et Mag associated to low rotations lasting for 3 s to 20 s [1], [5], [15]
- Versive: Same as Tonic with favorite direction.
- Clonic: Typical 0.2 – 5 Hz frequencies [5], [15] from Acc and Mag.
- TonicoClonic: Both clonic and tonic components.
- Hypermotor: melted frequencies with high accelerations.
- Automatism: melted frequencies with repetitive patterns.

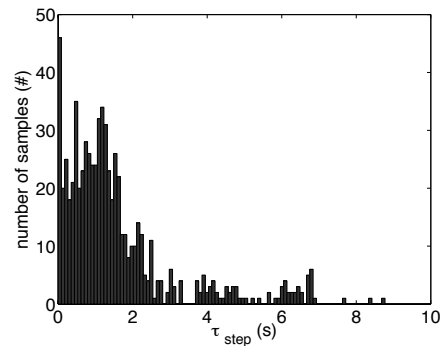


Fig. 7. Histogram of the constant time obtained from identification for tonic manifestations.

B. Manifestation event duration

Duration of events by class indicates (mean \pm std): AUTO (11,59 \pm 10,00 s), CLONIC (20,47 \pm 17,77 s), TONIC (11,00 \pm 9,56 s), HYPER (8,99 \pm 7,46 s).

The analysis of the histogram of τ_{step} as proposed in Fig. 7 gives us the repartition of time constant for TONIC manifestations. It is shown that most values are about 1 s. Considering that at 3τ , 95% of the answer to a step is realized, we can consider that with a temporal windowing of duration > 3 s, all the phenomenon can be observed.

C. Feature subset selection

1) *Sequential forward selection*: The feature subset selection by the SFS procedure is given in Figure 8(a). Features retained in order of appearance are : $\{ Mean_{\|\vec{Acc}\|}, Med_{\Theta}, Mobility, En_{\|\vec{Acc}\|}, Range, Med_{\|\vec{Acc}\|}, W_{\Theta}(\delta_2), W_{\Theta}(\delta_3), W_{Acc_{ml}}(\delta_2), SEF_{95,\Theta}, SEF_{95,Acc_{ml}}, SEF_{10,\Theta}, W_{\Theta}(\delta_1), SEF_{95,Mag_{ml}}, W_{Acc_{ml}}(\delta_1), W_{Acc_{ml}}(\delta_3) \}$. The progression is linear with the dimension of the space up to the level 6, when it decreases and saturates to a maximum performance obtained with an error rate of approximately 5%.

The selection indicates that features extracted from the norm of acceleration ($Mean_{\|\vec{Acc}\|}, En_{\|\vec{Acc}\|}, Med_{\|\vec{Acc}\|}$) and from

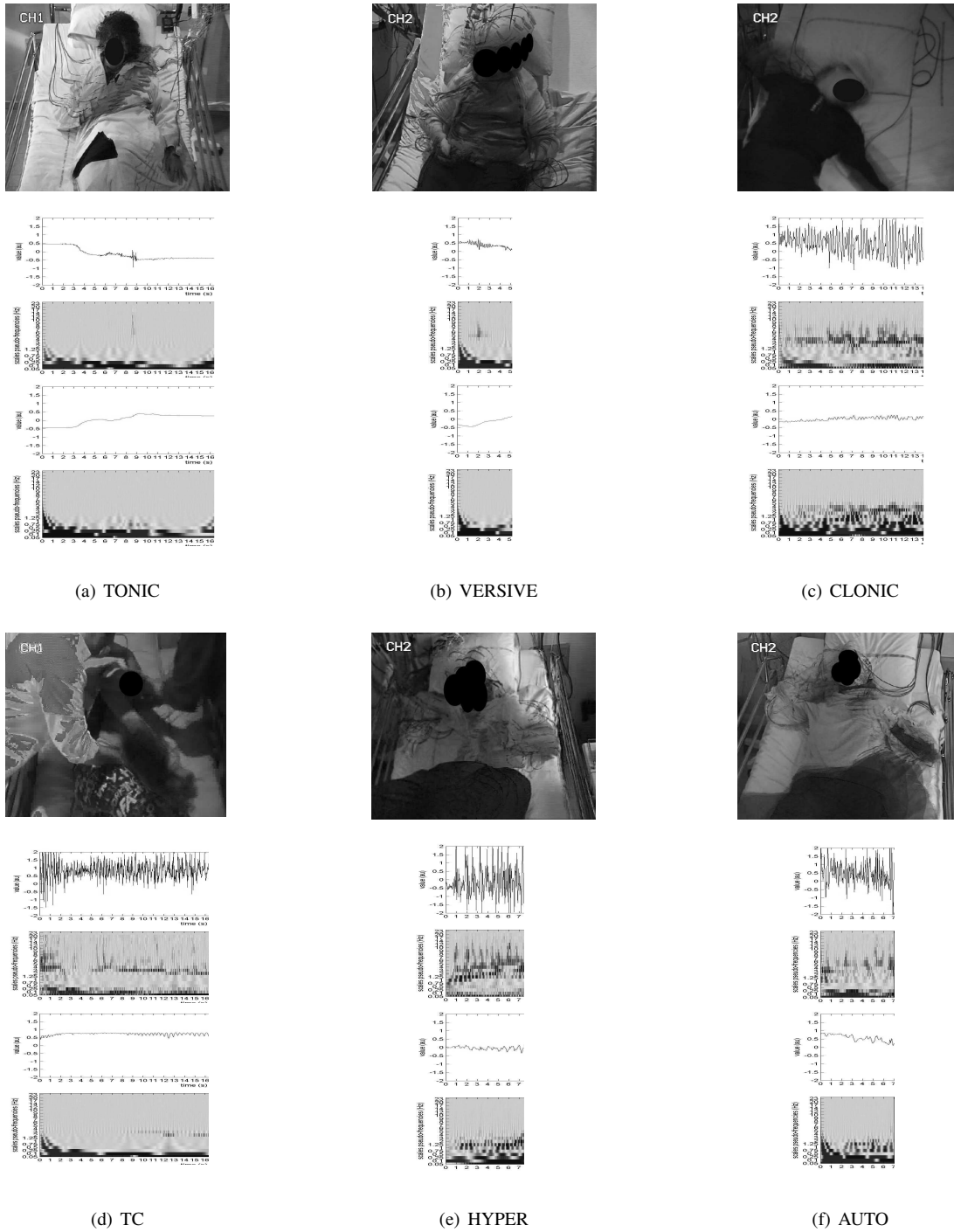


Fig. 6. Prototypical signals description by class. From top to bottom : superposition of images corresponding to the prototypical manifestation class; Acc from the y axis and its time frequency representation into 21 scale pseudo-frequencies from $0,05 Hz$ to $23 Hz$; Mag from the y axis and its time frequency representation. a) Tonic, low frequencies for Acc et Mag associated to low rotations; b) versive, same as Tonic with favorite direction to right or left around the axis; c) Clonic, typical $0.2 - 5 Hz$ frequencies; d) TonicoClonic, both clonic and tonic components; e) Hypermotor, melted frequencies with high accelerations; f)Automatisme, melted frequencies with repetitive patterns

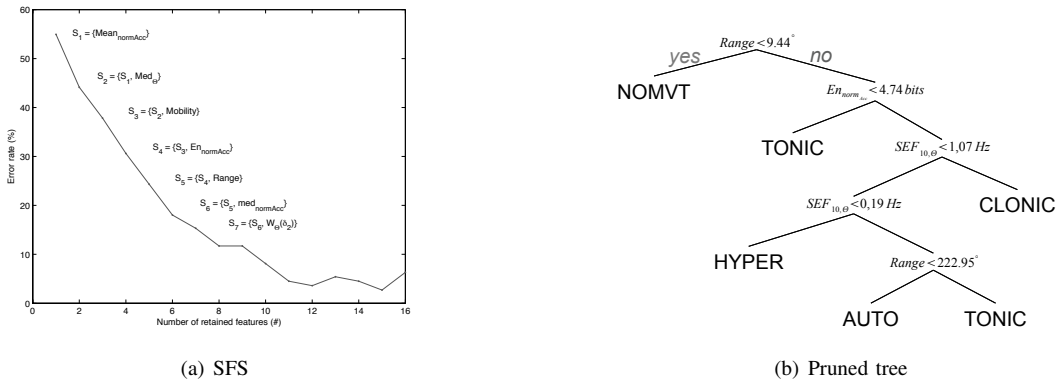


Fig. 8. Feature subset selection : a) SFS, b) pruned tree

the rotation, computed from both the acceleration and the magnetometers are chosen at first (Med_{Θ} , $Mobility$, $Range$). It shows that spectral or wavelets features are rejected to the end of the selection process, meaning that classification can be realized principally on dynamical or angular features.

2) *Pruned tree*: The selection realized using a pruned decision tree is presented in Fig. 8(b). $Range$ is selected first to discriminate no movements versus movements manifestations. Then the entropy of the norm of acceleration discriminates between tonic movements with low entropy (few states) and other movements with high entropy (more complex movements). SEF_{10} is used to discriminate clonic movements for which it is higher than $\approx 1 Hz$, indicating a poor energetic components and a concentration into a given frequency band higher than $1 Hz$. SEF_{10} is also used to discriminate hypermotor movements, which have 10 % of their energy below $0, 19 Hz$ indicating high energetic movements at low frequencies. Automatism and tonic manifestations with high energetic low movements below $1 Hz$ are discriminated according to their range of rotation with high range of rotation for this kind of tonic manifestations.

D. Simulations with MLP

The selection indicates that with a MLP with 6 features as inputs, we can obtain 20 % of errors as compared to the database. Using the MLP learned from this selection and using it on whole recordings realizing a feature extraction over 4 s non overlapping windows, leads to motor manifestations representations of AS recordings as the examples proposed in Fig. 9(g), 9(h) and 9(i). On these representations all the movements are classified into one of the manifestation classes even if movements are non pathologic, indicating the different times when the patient was active or not.

However, pathological movements occurring during seizures are also taken into account. A zoom on the seizure episodes as the one represented in Fig. 9(d), 9(e) and 9(f), gives the succession of the different motor manifestations during the seizure, according to the different limbs. This enables a comprehensive analysis of the temporal stereotypy of the seizure and points out some interesting patterns.

V. DISCUSSION

From the design of the system and with the results obtained several points can be discussed.

A. Results

We have seen that classification from AS sensors into manifestation events was possible using the system designed in this paper. More precisely, we have seen that seizures were completely analyzed and can give to the neurologist interesting components used for diagnosis such as:

- Time of the clinical start of the seizure.
- Stereotaxic localization of this start.
- Motor propagation of the seizure.
- Motor pattern and principal manifestation.

From these different points, the machine can give a precise quantification of searched components that can help to diagnose the patient pathology.

An important point in favor of the use of AS sensors is the fact that rotation extracted from Acc and Mag seems to be an important variable to compute features selected during the subset selection. This is true both for neural network and decision tree.

A confusing point is the fact that spectral or wavelet features have not been selected even if they were thought to be good candidates. One reason can be that dynamical or angular features are more discriminant than others according to the samples collected in the database. Then, they are selected at first and others competitive features are rejected at last. This doesn't tell that using a model using wavelet or spectral features would not give good results, but results with other features are better.

Besides, correlations between the different features exist and selecting one feature into the model rejects another at this end of the selection because taking it into account doesn't improve the performance. We think that adjusting the frequencies bands of our model for wavelet features will possibly improve the results by leading to more discriminant features.

We have used a non specific location of the sensor and design a model with data coming from all the location to learn the classifiers. We think that the use of stereotypical classifier, adapted to a special position, would improve the

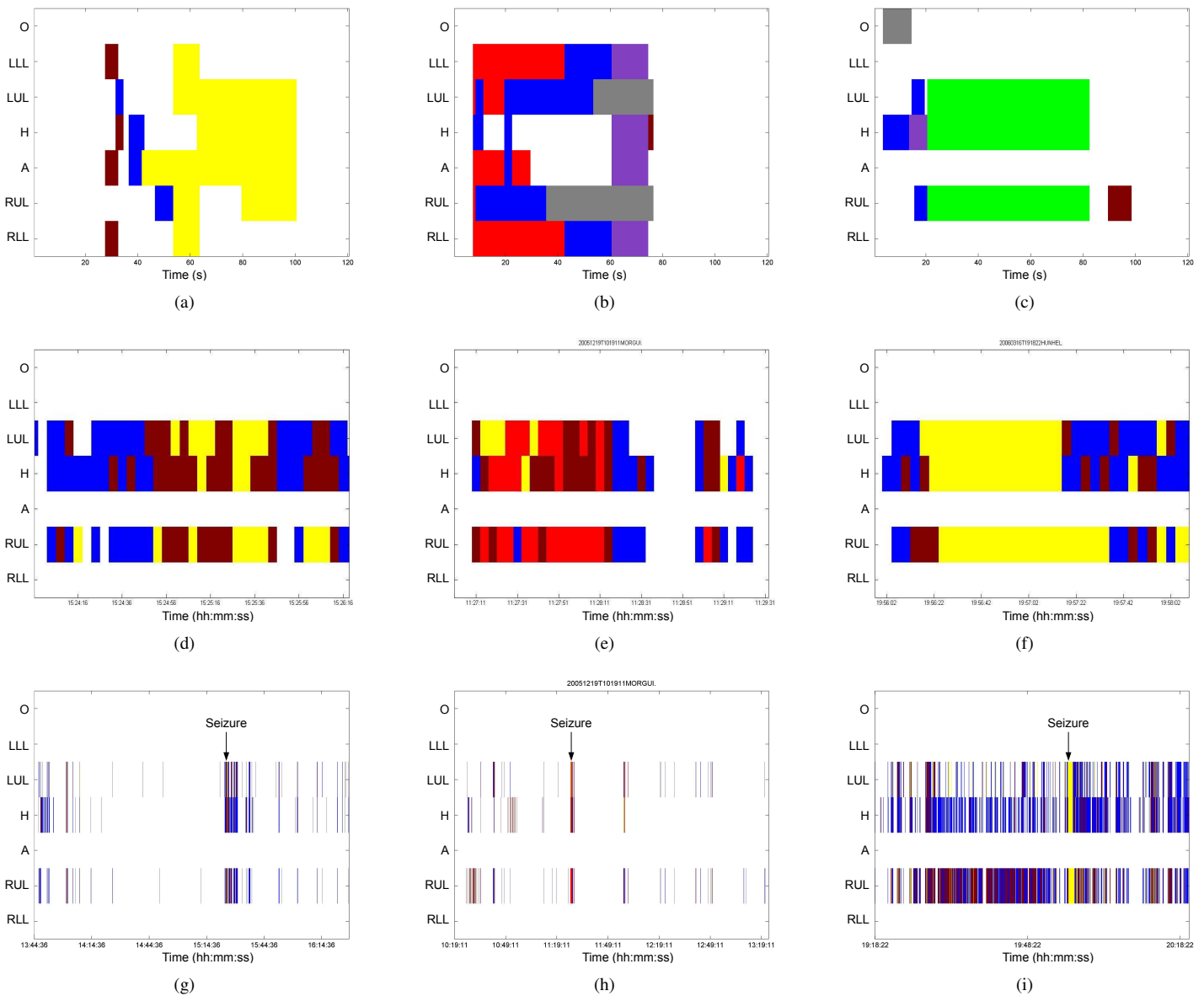


Fig. 9. Representation of the visual scoring by an expert after computer entry. The different parts of the body are represented in Y coordinates, with the left part of the body at the top and the right part of the body at the bottom with head and axis in the middle. The evolution of the manifestations through time is obtain with the temporal axis in X-coordinate. This seizure shows priority tonic manifestations.

results, for example by learning classifier adapted to the head or the hand...

B. Classification

At this stage of design, it is hard to evaluate the performance of the classifier in term of sensibility and specificity since all the movements, pathologic or not are classified by the machine. Besides we see that the classification given by the expert is not so sensitive that the one given by the machine, so it would be hard to evaluate the performance of the classifier by comparing expert versus machine classification using feature extracted over 4 s windows.

In order to evaluate the detection of seizure, another stage of processing is required to recognize temporal and stereotypical patterns associated to seizures from one patient or a group

of patient. After the completion of this stage, the use of sensitivity and specificity can be relevant. What is sure is that sensitivity and specificity will be possible only for specific epileptic seizure and not for all with this pattern recognition stage. For example a pure TONIC manifestation can not be detected by this kind of processing since lot of pure TONIC non pathologic movements are realized in daily life. For this kind of movement, an analysis of signal between pathological and non pathological signals must be adapted.

But the aim of our study was not to realized an epileptic seizure detector, but it was to give a quantification of movement disorder in order to help the decision making of the neurophysiologist.

C. Data cleaning and supervised learning

An interesting point is the data cleaning of the database since lot of data are not prototypical or artifacted by the introduction of . The data cleaning has been realized on one part by hand from visual inspection. Further studies need to be realized to perfect the database but tis is a long time work. The introduction of automated process to realized it, for example by using unsupervised learning to cluster data could be an interesting work.

VI. CONCLUSION

It has been shown that data coming from triaxial accelerometers and magnetometers could be classify into epileptic motor manifestations. The process for such a classification and its design have been presented resulting in an empirical performance of approximately 20% of errors between a classification given by an expert and the machine. We think that further studies will improved the classification given by the machine and that the feature subset selection will give better results with a larger database.

The benefits of such a classification have been presented indicating that it could be helpful for the diagnosis of epileptic seizures, especially for determining the beginning of the motor manifestation, the associated limbs or dominant patterns.

Studies are followed to find out epileptic patterns from one patient or from patients with same pathologies.

APPENDIX I

EXAMPLE OF A SEIZURE FILE

Here is an example of the text resulting from the entry of the visual scoring by an expert associated to the representation given in Fig. 9.

After the header containing t0 t1 t2 and the general class of manifestation, each line corresponds to an event defined with 7 fields separated by a space: Ts Te Loc Subloc Type Subtype Comment; Ts is the beginning of the event; Ts the end of the event; Loc the localization and Subloc a sublocalization if specified; Type is the class of manifestation and Subtype is a description if specified; Comment contains additional information or no comments (nc).

```
t0 20051115T130931 nc
t1 20051115T130938 nc
t2 20051115T131016 nc
TONIC
20051115T130938 20051115T130955 H nc TONIC flexion nc
20051115T130940 20051115T130954 RUL nc TONIC nc nc
20051115T130942 20051115T130947 LLL nc TONIC flexion nc
20051115T130955 20051115T131008 H nc VERSIVE R nc
20051115T131008 20051115T131022 RUL nc AUTO nc nc
```

APPENDIX II

ALGORITHM FOR THE SEQUENTIAL FORWARD SELECTION

```
Start
Let  $I_r := \{\emptyset\}$ , indices set of retained features
Let  $I_d := \{1, \dots, d\}$ , indices set of disposable features
While ( $I_d \neq \{\emptyset\}$ ) do
  For  $i \in I_d$  do
     $I_c(i) := I_r \cup i$ , indices set of running features to evaluate
```

```
    Create  $S_{I_c(i)}$ , set of examples with features in  $I_c(i)$ 
    Compute  $\Xi(i)$ , performance criterion for  $I_c(i)$ 
  End For
  Select  $i_r$  that minimizes  $\Xi$ 
  Update :
   $I_r := I_r \cup i_r$ 
   $I_d := I_d \setminus i_r$ 
End While
End
```

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