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Detection system of motor epileptic seizures through motion analysis with 3D accelerometers

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***Abstract*— A system of epilepsy seizure detection in real life conditions and based on inertial sensors is presented in this paper with a focus on the signal processing to recognize seizure moves. This system is based on several models of signals, one corresponding to general movements, and two others describing seizures moves. The detection algorithm evaluates for a given time window which model fits the best with the observed signals and trigger an alarm if this model is a seizure model. The signal processing algorithm is based on hidden Markov models.**

I. INTRODUCTION

Epileptic seizures are due to brain dysfunction, which can take many manifestation forms [1]. The prevalence of this disease is close to 0.5% to 1% of the average population. 70% of the seizures can be controlled using antiepileptic drugs. For the remaining 30%, surgery can be discussed to remove the *epileptogenic zone* (the brain areas from where seizures arise) to render the patient *seizure free*.

Many of epileptic seizure symptoms are motor ones. These symptoms can be captured and analysed with several technologies such as video and motion sensors either to characterize a patient seizure or to perform seizure detection for security purposes:

[2], [3] uses some video processing methods to quantify the motor activities of a patient during a seizure. Some markers are therefore placed on the patients. The main advantage of this kind of methods is that in many hospital rooms, a camera is already used. The problems are that the movement is difficult to automatically analyse from a 2D image, and that if the marker disappear from the field of view, some uncertainties appear. Further, this kind of methods can only be used in a room where a camera is available.

Another approach for the motor characterization of epileptic seizures is to use inertial/magnetic sensors [4]. These sensors have made possible to extract relevant information about human moves through the processing of multidimensional signals. Many applications have then been developed, based on these non invasive and low cost sensors. Among which gait and posture analysis are probably the most famous ones: for example [5] proposed a processing scheme based on a 3D magnetometer to evaluate in real time a body inclination to detect movements such as a *sit-to-stand* move. Characterization of movement due to neurological causes has also been studied: Accelerometer exploitation has for example been use for Parkinson's disease [6] and the detection of hand tremor [7]. About epilepsy, [8] focus on the distinction between seizure moves and nocturnal moves. Sensors are therefore attached on a patient and the authors propose to detect period with motor activities.

In this paper, a system that detects epileptic seizure with 3D accelerometers sensors is described. This system will be detailed in section II but its objective is to detect the epileptic moves of a patient lying down on its bed for alarm purposes in real life conditions. As the patient may not be sleeping (but reading for example), the approach proposed in [8] does not fit with this system needs. An alternative approach is hence described in this paper, based on models of signal: a model for nocturnal movements and several models each describing one kind of epileptic move. Given a time window of accelerometers signals, the most compliant model is determined. If this model is an epileptic move model, an alarm is triggered. These results are described in section III.

The evaluation of algorithm capabilities to detect epileptic moves from *normal* nocturnal moves will be discussed in section IV. Conclusion are given in section V.

II. SEIZURE DETECTION SYSTEM

The developed seizure detection system has been designed to monitor a lied down person in real life conditions. This person can be sleeping, but also reading or playing as long as he/she remains lied down. The system objective is to recognize epileptic moves from nocturnal and *in bed* moves and to trigger an alarm when a seizure occurs. The system is illustrated on figure 1 and is composed of:

- 2 3D accelerometers. These sensors are wireless, to minimise the disturbance on the lied down person. One accelerometer is attached to a wrist. The second one is either attached to the other wrist or to the chest. MOVEA Motion POD have been used.
- A computer which collects and records the data, performs the seizure detection and trigger an alarm if a seizure is detected.

The design of the detection system has been done in two phases:

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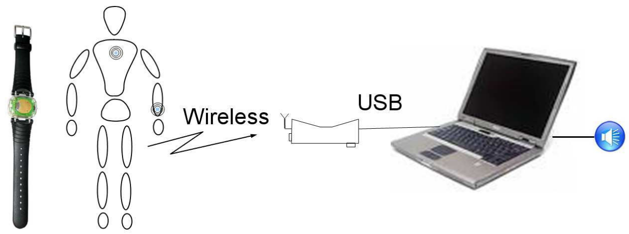

Fig. 1. Principle of the seizure detection system

1) A database acquisition phase: a database of nocturnal, *in bed* and seizure movements observed with inertial sensors has been recorded. The objective of this phase is to collect enough examples of moves to build the detection algorithm.
2) A test phase: The detection algorithm has been tested in real life conditions.

The test phase will be described in section IV. We focus in this section on the first phase about the constitution of the database signals.

As mentioned above, the objective is to develop a system able to detect epilepsy seizures in real life conditions when the person is lying down in its bed. The database constitution has hence been done with epileptic volunteers who have used the detection system and have worn the sensors at home (these volunteers have been found, selected and informed by EPI, an association that helps epileptic persons to integrate into society). In this learning phase, the wireless sensors are connected to a computer which only records the sensors data. No detection algorithm runs and no alarm is triggered. If a seizure occurs and is detected by a relative to the volunteer, this relative press a keyboard key to mark the file. Thanks to this method, a database of records has been recorded with the following information for each entry:

- General information such as a code to identify the volunteer and the acquisition period.
- Instants of crisis detected by the relative of the volunteer (the markers).
- 3-D data from inertial sensors:

In this system, each sensor is composed of a 3-D accelerometer working at $1/T_e = 200$ Hz. The accelerometer measures the sensor acceleration (a 3D vector) at each sampling time:

$$\gamma(pT_e) = \begin{bmatrix} \gamma_x(pT_e) \\ \gamma_y(pT_e) \\ \gamma_z(pT_e) \end{bmatrix} = \gamma_g(pT_e) + \gamma_p(pT_e)$$

where $\gamma_g(t)$ is the projection of the gravitational acceleration on the 3-D accelerometer axis at time t, and $\gamma_p(t)$ the projection of the inner acceleration of the sensor on these 3 axis at time t.

Thanks to the help of the association EPI, a database of sleeping, *in bed* and seizure movements of 2 different epileptic volunteers has been constituted. 63 nights have been recorded and 47 epileptic seizures have been marked.

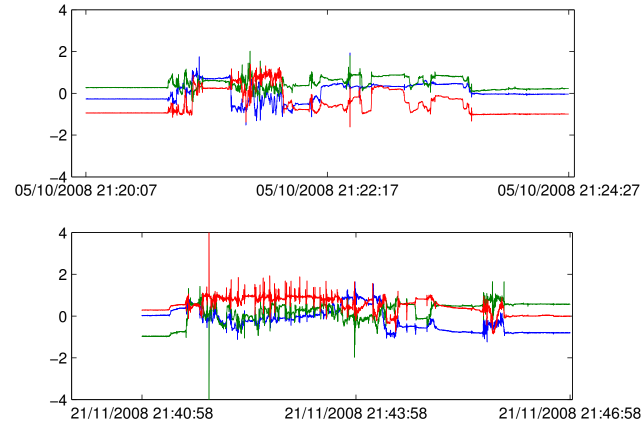

Fig. 2. Two examples of seizures movement observed with a 3D wrist accelerometer for person #1

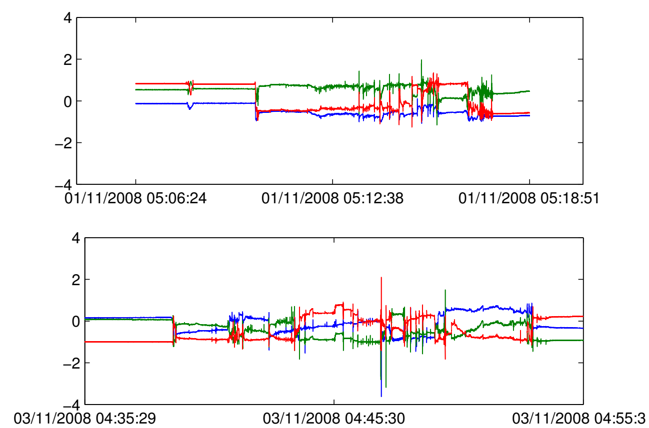

Fig. 3. Two examples of seizures movement observed with a 3D wrist accelerometer for person #2

III. Seizure detection algorithm

The seizure detection algorithm has to be able to distinguish seizure moves and *in-bed* or nocturnal moves. A seizure move can take many forms in general, but for a given person, its seizure motor symptoms are usually similar from an observer point of view. This similarity also appears on the accelerometer signals. For example, consider the figure 2 which illustrates two seizure motor symptoms seen by an accelerometer of a same volunteer. There are some similarities between the two signals despite it does not seem that one can be derived from the other. Another example is given on the figure 3 which also illustrates two seizure motor symptoms seen by an accelerometer of another volunteer. Again, some similitude appears between the two 3D signals despite no direct relation can easily be derived.

To find a common description tools for the different kind of epileptic move, and then distinguish them from a *in-bed* or a nocturnal move, models of signals have been designed to describe the different kinds of movements. This algorithm is based on Hidden Markov Model [9]:

A. Hidden Markov model and nocturnal, in bed and seizure moves description

A hidden Markov model is composed of two random processes. The first one is the process X_k which is unobserved and which follows a Markov rule:

$$p\left(X_k|X_{k-1},\cdots,X_0\right)=p\left(X_k|X_{k-1}\right)$$

For the presented algorithm of epilepsy seizure detection, the hidden process X_k takes its value within a finite set $\mathcal{X}=\{1,\cdots,5\}$. Each value of this set represents a state of the person wearing the sensors:

1 No activity
2 Shaking with low amplitude
3 Shaking with large amplitude
4 Moving with low amplitude
5 Moving with large amplitude

The transition probabilities, i.e. the probability to pass from a state i to a state j is given by

$$a_{i,j}=p\left(X_k=j|X_{k-1}=i\right)$$

and is fully described by the set of values $\{a_{i,j}\}_{i,j\in\{1,\cdots,5\}^2}$.

The second random process of the hidden Markov process is the observation process which is linked to the unobserved process through the probability density $p\left(O_k|X_k\right)$. In other words, the density probability of the observation O_k depends on the unobserved process X_k and for example, is not the same if $X_k=1$ or $X_k=5$. These probabilities are modelled as, for each state i:

$$f_i(O_k)=p\left(O_k|X_k=i\right)$$

For the epilepsy detection problem, and for each sensor, O_k is a $3-D$ vector defined as:

$$O_k=\left[\gamma(kT_e)^T\right]^T$$

where $.^T$ stands for the transpose operator.

The set $\{a_{i,j}\}$ and the functions $\{f_i(O_k)\}_{i\in\{1,\cdots,5\}}$ are free to be chosen such as to model specific signals. For example, if the following choice is made: $\forall i, a_{i,1}=1$, and $\forall i,j>1$, $a_{i,j}=0$, the hidden state is always equal to 1 which describe a *no activity* state. If the person wearing the sensor indeed does not move, this choice of values perfectly describes the observed signal. If the person is moving, the signal is badly described by the hidden Markov model.

A model of signal is hence described by the sets $\{a_{i,j}\}$ and $\{f_i(O_k)\}$. Another set is required to completely describe the model: the set of initial conditions, i.e. the probabilities $\pi_i=p\left(X_0=i\right)$. We will assume in the following that $\forall i$, $\pi_i=1/5$. Further, the choice of the function $\{f_i(O_k)\}$ is not described in this paper because of the lack of space. Nevertheless, the set $\{f_i(O_k)\}$ is common to every model used for the seizure detection algorithm.

A model of signal is then fully defined by the set of values $\{a_{i,j}\}$. The idea behind the algorithm is to define several models of signal, one corresponding to general moves, and two others modelling seizures moves:

1) The first model that describes very general moves is defined as:

$$\forall i\ ,\ a_{i,i}^{(1)}=0.9 \text{ and } \forall i,j\neq i\ ,\ a_{i,j}^{(1)}=0.1/4$$

2) A model that describes shaking moves. The transition probabilities are denoted by $\{a_{i,j}^{(2)}\}$ and described on figure 4.
3) A model that describes hustle. The transition probabilities are denoted by $\{a_{i,j}^{(3)}\}$ and described on figure 5.

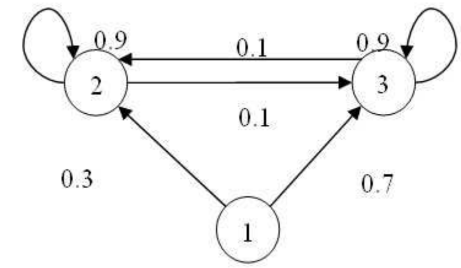

Fig. 4. Movement model #2 : a first crisis model

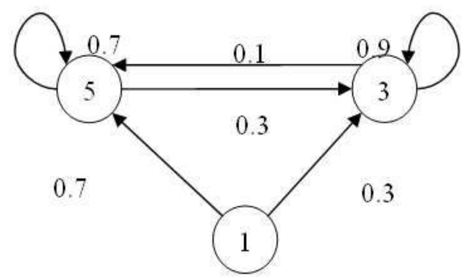

Fig. 5. Movement model #3 : a second crisis model

Note that in models 2 and 3, the hidden variable can not stay in state 1 which stands for *no activity*. With this choice, if the person that wears the sensors is lying without moving on its bed, models 2 and 3 are always misadapted to the observed signal.

B. Detection algorithm

For a given time window of observation, the detection algorithm compares the adequation of the different models to the observed signal. This test is done every second on a time window of length K in samples. From a formal point a view, the following probability is computed for each model i:

$$p_i(n)=p\left(O_n,\cdots,O_{n-K+1}|\{a_{i,j}^{(i)}\}\right)$$

where K stands for the observation time and n is the current time. $p_i(n)$ is often called the evidence of the model i and is computed with a forward-backward algorithm as described

		#1	#2	#3
Database	# Nights	33	30	X
	# Marked seizure	31	16	
	# Detected seizure	25	11	
	# False alarms	8	26	
Real time Hospital	# Nights	3	X	X
	# Marked seizure	6		
	# Detected seizure	6		
	# False alarms	0		
Real time home	# Nights	21	13	8
	# Marked seizure	10	4	0
	# Detected seizure	8	3	0
	# False alarms	17	4	0

TABLE I

DETECTION SYSTEM PERFORMANCE

in [9]. Two cost functions are then defined:

$$J_1(n) = \frac{p_1(n)}{p_2(n)} \text{ and } J_2(n) = \frac{p_1(n)}{p_3(n)}$$

It is obvious that if the person wearing the sensors is having a seizure, J_1 and J_2 take small values. And if the person has no activity, J_1 and J_2 take high values. The same algorithm is applied on both sensors signals, and an alarm is then triggered if on one of the sensor:

$$J_1(n) < \lambda_1 \text{ or } J_2(n) < \lambda_2$$

where λ_1 and λ_2 are thresholds.

IV. PERFORMANCE EVALUATION

The seizure detection system has been evaluated one three persons and in three different contexts. In these different configurations, the two cost functions have been used with the following parameters: $K = 45T_e$ (the detection algorithms runs on a 45 seconds time window), $\lambda_1 = 1e^{-1}$ and $\lambda_2 = 1e^{-4}$.

The first context is the one used to record the database. As mentioned in the section II, a collection of 63 nights and 47 marked seizures based on two volunteers has been constituted to build the detection algorithm. The detection algorithm has hence been tested on these data.

In the second context and the third context, the detection algorithm runs in real time on the incoming data. When an alarm is triggered, some information about the motor activities of the person is hence gathered. In the second context, the system runs at the hospital. The detection system has been connected to a camera with a buffer able to store 20 minutes of video signal around the alarm trigger time. This video camera has made possible to observe the patient motor activities when a seizure is detected by the system.

In the third context, the system runs at home. No video camera is used and a relative to the volunteer is supposed to validate or not the algorithm detection when an alarm is triggered and also to indicate if a seizure is missed by the system. In this context, a third person who is not an epileptic person has also worn the sensor.

The results are shown on the table I. The system has been able to detect 53 seizures over 67 (sensibility). Most of the non detected seizures are explained by the fact that the seizure is too short. Either because the seizure stopped by itself or because a relative to the epileptic has provided some cares. It can be highlighted that no seizure which has lasted has been missed by the system.

About the specificity of the system, results show that the system does not trig any false alarms on non epileptic person (real time home) or when the first person spent its night at the hospital. But at home, (either with real time analysis or with the database), the number of false alarms is quite important. This difference can be explained by the fact that epileptic volunteers set up the detection system while remaining active in their beds, whereas in the hospital or with non epileptic person, the system is set up when the persons are willing to rest. The algorithm is hence able to distinguish nocturnal moves from epileptic moves, but can misevaluate *in-bed* moves.

The perspectives of this work are hence to reduce the detection time, and to introduce new models to identify *in-bed* moves.

V. CONCLUSION

A system of epilepsy seizure detection in real life conditions has been presented with a focus on the signal processing to recognize seizure moves and trigger an alarm. This system is based on several models of signals, one corresponding to general moves, and two others describing seizures moves. The actual models leads to a good sensibility and to a good distinction between seizure signals and nocturnal signals but do false alarms on *in-bed* moves. The false alarms number could be reduced with the introduction of new models to describe this kind of activities.

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