Analyzing accelerometer data for epilepsy episode recognition

José R. Villar, Manuel Menéndez, Javier Sedano, Enrique de la Cal, and Víctor M. González

[1] University of Oviedo, Computer Science Dpt., Oviedo, SPAIN, villarjose@uniovi.es,
[2] University of Oviedo, Morphology and Cellular Biology Dpt., Oviedo, SPAIN, menendezgmanuel@uniovi.es,
[3] Instituto Tec. de Castilla y León, Burgos, SPAIN, javier.sedano@itcl.es,
[4] University of Oviedo, Computer Science Dpt., Oviedo, SPAIN, delacal@uniovi.es,
[5] University of Oviedo, Electrical Engineering Dpt., Oviedo, SPAIN, vmsuarez@uniovi.es,

Abstract. Epilepsy is one of the main neurological disorders with high impact in the patient's everyday life. An incorrect treatment or a lack in monitoring might produce cognitive damage and depression. Therefore, developing a wearable device for epilepsy monitoring would eventually complete the anamnesis, enhancing the medical staff diagnosing and treatment setting.
This study shows the preliminary results in epilepsy onset recognition based on wearable tri-axial accelerometers and simple fuzzy set learnt using genetic algorithms. A complete experimentation for learning the fuzzy set is detailed. According to the obtained results, some generalized feasible solutions are discussed. Results show a very interesting researching area that might be easily transferred to embedded devices and online health care systems.

1 Introduction

Epilepsy is one of the most common neurological disorders in the society with a high impact in the life quality, professional career and social behaviour. One of the consequences of suffering epilepsy is a lack in motorization, which is direct linked with some comorbidities, like cognitive damage and depression [1]. Epilepsy has a dramatic impact in the health care system's annual budgets [2]. Besides, an epilepsy crisis is a clinical manifestation that has its origin in an abnormal activity -either excessive or hypersyncronic- from a variable size group of brain neurons. This abnormal activity -or epileptic discharge- uses to occur suddenly, during a short and transitory period of time, that is, paroxysmal. Therefore, the symptoms and signs that characterize an epilepsy crisis also typically show paroxysmally.

The term epileptic syndromes must be used instead of epilepsy, thus it includes a wide range of epileptic symptoms, conditions, etiology, manifestations, treatments and trends. The percentage of wrong epilepsy diagnosis might be up to 20% of the patients before attending an epilepsy unit for evaluation; consequently, the delay in the diagnose might be as long as 10 years [3]. The epilepsy diagnose is basically done using a clinical procedure: the anamnesis is the starting point for the initial epilepsy diagnose, although there are several tests to support the diagnose.

Basically, there are two main epileptic types of crisis: the generalized and the focal crisis [4]. In both of them there are subtypes with or without motor activity: those with motor activity are the most common cases. The motor activity can vary from the generalized tonic-clonic crisis -losing the consciousness, a short tonic stage followed by a prolonged generalized and repeated clonic movements of the whole body- to the focal mio-clonic crisis -repeated bursting movements of one limb, the upper and lower limbs of one body side or a combination of movements of the limbs and face. After the diagnose, the patient should keep a log of the suffered seizures, so the medical staff can evaluate the evolution of the patient and the efficiency of his/her treatment.

This research aims to design a model together with a wearable device for supporting patients in maintaining the log of seizures. This preliminary study analyzes the motor activity registered in the data gathered from tri-axial accelerometer (3DACC) placed on the dominant wrist. The idea is to determine if it is possible to identify an epilepsy seizure from realistic simulated data. This realistic data is based on a protocol defined by the medical staff, describing how a patient behaves during a certain type of epilepsy crisis. To identify the seizure, a simple fuzzy partition is learnt for the subject from the data using a genetic algorithm. In this stage, no generalized method is searched, but only the possibility of using Genetic Fuzzy Systems (GFS) to deal with this time series classification task. The aim of this study is to evaluate if GFS can cope with this problem or not, in order to design a feasible solution before dealing with data from real patients. The organization of this study is as follows. First of all, a revision of the literature is presented in the next section, while in Sect. 3 the preliminary approach is detailed. The experiments are described in Sect. 4. This study ends with the discussion on the results and the conclusion remarks.

2 Epilepsy episode recognition

The current trend in bio-engineering is introducing wearable sensors as the mechanism of gathering data from real or even controlled scenarios. Due to the fact that the majority of epilepsy episodes have a clear impact in the motor system, the main part of the literature focuses on reported studies that make use of 3DACC for their solutions.

As stated in [5], it is possible to observe epilepsy episodes using 3DACC when experts visualize the data gathered from experiments. However, the author have asserted that the problem is by any means solved [6]: there is not any feasible solution able to recognize epilepsy episodes out of controlled environments. As stated in [7], the characteristic movements vary according to the type of epilepsy crisis.

In [8], 3DACC bracelets were placed on the wrists of patients suffering from epilepsy. The wearable device were programmed for detecting the rhythmical movements in topic-clonic episodes: 7 out of 8 of the considered types were detected, but up to 204 false alarms were also arose. Although the approach is very interesting, its current status is not valid enough for deployment.

Not only the acceleration values have been considered, but also several different transformations. For instance, the amount of movement was used for generating alarms for epileptic episodes occurring during the sleeping periods of the patients has also been publish [9]. In this study, thresholds were defined as the limits of the amount of movement an individual can perform when sleeping: values higher than these limits were considered alarms of epilepsy crisis. Due to the use of thresholds, the study was limited to reduced movements activities.

The use of several sensors -3DACC among others- for epileptic episodes discovering is proposed in [10]. As in previous studies, the focus of the study is kept on discovering epileptic episodes while the subject is sleeping. Actually, very impressive results were reported as up to 95% of the cases were discovered. Nevertheless, the cost of this approach as well as the restrictions in the type of activities considered represent the most relevant drawback of this approach. Interestingly, Schulc and colleagues studied different transformations for the data gathered from the sensors in order to recognize the epileptic episodes [11]. These transformations represent a valid starting point for discovering patterns on the data.

3 A study for epilepsy identification

From now on, the terms raw acceleration (AC), body acceleration (BA) and gravity (G) refer to the acceleration data gathered from the 3DACC, the acceleration of the part of the body where the sensor is placed and the gravity acceleration, correspondingly. When a single subindex is included, it refers to the axis -e.g., AC_x or G_z-. A second subindex might be included for referencing the time stamp -e.g., $AC_{x,i}$-. To extract the BA and G from the ACC, a high pass filter or a low pass filter must be used [12].

One of the first steps when focusing the identification of a pattern is the visualization of the time series. Fig. 3 shows the evolution of the acceleration components during a simulated tonic-clonic epilepsy episode. The duration of the episode is about 30 seconds long; then the subject remains still in the post-episode recovery. It was simulated by the medical staff following the behavior that is well documented in the literature. All the scales are the same for the sake of readability. The simulation started from a seated position, the data goes from a very steady signal to a high deviation signal in all the cases.

From the figure it might be concluded that using statistical data could be enough for identifying an epilepsy episode. However, if we consider the different

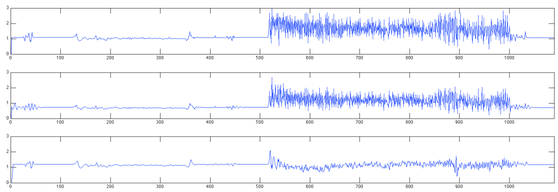

Fig. 1. Acceleration signals from a 2G 3DACC sampled at 16 Hz placed on the dominant wrist. Upper, central and lower parts depict the AC, BA and G, respectively.

activities a subject may carry during his/her everyday life, the problem becomes more complex. For instance, walking may have a similar variability of the signals but with smaller the mean values, while running have higher mean values. Furthermore, a feasible solution must consider the variability among the episodes and the differences performed by the different subjects.

Different alternatives were applied to the accelerations but no relevant patterns were extracted from the data: using the acceleration data was not enough. In a previous study concerned with human activity recognition [12], several transformations of the different accelerations were analyzed. Additionally, some of these features were analyzed regarding epilepsy identification [11]. After a study of the most promising features, the *Signal Magnitude Area* -computed as **SMA**$= \frac{1}{w}\sum_{i=1}^{w}(|b_{x,i}| + |b_{y,i}| + |b_{z,i}|)$-, was found the most representative. Still, the problem of obtaining a generalized solution can not be considered solved as different activities might have similar SMA values and because of the differences between subjects and episode intensities and behavior.

In order to make the problem easier to tackle, only one of the possible epilepsy episodes is considered in this study: the myoclonic type. This epilepsy episode is characterized by repeated contracting-elongating movements of the forearm, with a angle variation about 30 degrees, with a frequency about 1 swing every 3 seconds [7]. An episode uses to last about 30 seconds with a pos-critic period of 30 seconds, in which the movements of the subject are somewhat erratic, without a clear pattern nor intention. The subject neither falls nor loses consciousness.

3.1 The proposal for identifying tonic-clonic epilepsy episodes

In order to tackle the above mentioned problem, a fuzzy set based solution has been developed. The idea underneath is to take advantage of the generalization capabilities that fuzzy sets provide in order to determine if a sequence of SMA values belong or not to the Epilepsy class. A single fuzzy set with trapezoidal membership function is proposed for determining the membership degree of current window's SMA value to the analyzed epilepsy episode. However, the fuzzy generalized solution can not be obtained from scratch but from a learning stage: a genetic algorithm (GA) is proposed to evolve the fuzzy membership function parameters.

The GA will evolve the parameters of the trapezoidal fuzzy membership function. The individual representation of the fuzzy function parameters is a vector of 4 double values $\hat{x} = [x(1), x(2), x(3), x(4)]$ with the corresponding restrictions. Furthermore, the following default options hold: random individual generation provided they accomplish with the restrictions, an elite subpopulation, rank fitness scaling, stochastic uniform selection, a fraction of the new population is generated by means of crossover, adaptive feasible mutation operator -generating random directions that are adapted to the last successful or unsuccessful generation according to the bounds and restrictions- and the scattered crossover operator. The stopping criteria includes the generation limit of 50 generations or whenever 20 generations are performed without fitness improvement is smaller than $1 \cdot 10^{-6}$.

To evaluate each individual a set of segmented files are given, reducing the problem to a two-class classification. The classification error, calculated as the number of misclassified examples, is used as the fitness function. A penalty factor is included for favoring those individuals with smaller width. This measurement has been chosen to avoid as much as possible the imbalanced problems that use to happen with time series classification. A sample is considered of the class if its membership value is better than 0.5.

In this study, a cross validation scheme based on 5x2 is introduced. Firstly, each data set file is tagged as {TRAIN, TEST or TRAIN-AND-TEST}. A file marked with TRAIN will be used for training exclusively; similarly, a file marked with TEST will be used in the validation of the approach only. A file marked with TRAIN-AND-TEST will be included in both the training and the validation stages. Using this 5x2 cross validation scheme has two main purposes. Firstly, it might keep the proportion the samples belonging or not to the analyzed class. Secondly, the generalization capabilities are strongly tested as the number of unseen files is increased. The mean value of the error measurement among the different files used for training or validating is used for aggregating the results for each fold.

4 Experiments and results

4.1 Data set generation

The medical staff designed a protocol for the simulation of the tonic-clonic trials of myoclonic epilepsy episodes. These episodes are as briefly outlined in Sect. 3.

In this way, several simulations were carried out for a subject and, afterwards, realistic data from 10 believable fiction subjects were generated. Special care was taken to mimic the time series in the onset of the epilepsy. Half of the files generated for normal activities were considered to be tagged as TRAIN with probability 0.8; the remaining were tagged as TEST. Additionally, half of the epilepsy files were tagged as TRAIN, while the remaining were tagged as TRAIN-AND-TEST.

4.2 Tuning the GA parameters

Basically, the number of generations and the stop conditions are kept constant, while the the performance of the rest of parameter sets are studied. During the experimentation, once a parameter set is found better it is kept for the remaining experimentation. More specifically, the following comparisons have been evaluated: i) the use of subpopulations versus a single big population, ii) the migration factor if subpopulation outperforms the single population results, iii) the elite population size, iv) the selection operator, v) the fraction of individuals created using the crossover genetic operator and vi) the crossover operator. Besides, the mutation operator does not change for the sake of the defined bounds and constraints.

For the sake of space, only a remark of the experimentation findings. Single population definitely performs better, with enhanced diversity. There were no variations in the results with the elite size. The uniform selection performs with a slightly better diversity and the default crossover fraction -0.75- seemed to be the best choice. In the remaining text the experimentation with the crossover operator is shown.

Four different crossover operators were compared: the scattered operator -randomly picking a gene from each parent-, the classic two points crossover, the heuristic crossover -generating an offspring from a linear combination of the parents- and the arithmetic crossover -a weighted combination of the parents is used-. Not only the fitness evaluation of the final population will be used for comparing the methods, but also the diversity at this stage. The results are depicted in Figures 2 and 3, and in Table 1 as well. Small variations again are found in the phenotype, the main advantage is found in the diversity. According to this value, the most interesting operator is the heuristic operator.

Op.	Dataset	Mean	Median	Std	Op.	Dataset	Mean	Median	Std
scat	Trn	98.5570	97.4742	4.0126	heu	Trn	96.8538	96.8036	1.8787
	Tst Mi	125.8407	122.4060	12.9749		Tst Mi	125.8407	122.4060	12.9749
	Tst Mn	173.4868	171.2261	16.9209		Tst Mn	173.4868	171.2261	16.9209
	Diversity	1.2314	1.1836	0.6073		Diversity	3.9885	4.1978	1.7753
arth	Trn	103.1752	99.5921	12.8982	2pnt	Trn	99.1747	98.4409	4.7719
	Tst Mi	125.8407	122.4060	12.9749		Tst Mi	125.8407	122.4060	12.9749
	Tst Mn	173.4868	171.2261	16.9209		Tst Mn	173.4868	171.2261	16.9209
	Diversity	3.1480	3.2235	2.1385		Diversity	1.5561	1.4894	0.6469

Table 1. Results for the crossover operators comparison. scat, heu, arth and 2pnt stand for the scattered, the heuristic, the arithmetic and the two points crossover operators, respectively.

The results shown in Fig. 3 are really interesting as that is what might be happening when deploying this model. The On/Off output depicted the figure is calculated as 1 when the value of membership of belonging to the class

EPILEPSY is higher than 0.5. Clearly, the output of the model is not what is desired, as plenty of the EPILEPSY samples were wrongly classified. Therefore, a more complex system is needed as simple linguistic variables or even thresholds are not valid.

The question is what kind of models can be valid for solving this type of problems. This question is partially solved by that Fig. 3 : learning rules from the data will lead to obtaining rules that might have an output like the On/Off depicted. It is possible to learn several rules and use ensembles in order to obtain a more continuous output.

Nevertheless, this behavior suggests that it may be interesting to learn models that keep track of the current state, and the rules acting as transitions between states. In other words, this may lead to Finite State Machines. There are several approaches that can be suitable, as the Genetic Fuzzy State Machines [13] or the Hidden Markov Models [14]. The idea, then, can include developing a suitable model for each type of epilepsy episode and make use of an ensemble scheme for the fusion of the different outputs. These techniques represent the most promising research lines in order to learn classifiers for the different types of epilepsy episodes.

In apart, the evaluation of the models needs further study. How to evaluate the fitness of a model according to the goodness of its output is the main concern. Typically, classification error based measurements have been used in the literature. After the experimentation stage, it seems that using distance measurements between the class and the output of the model instead of the classification error measurements can enhance the learning process. All of these issues need further study.

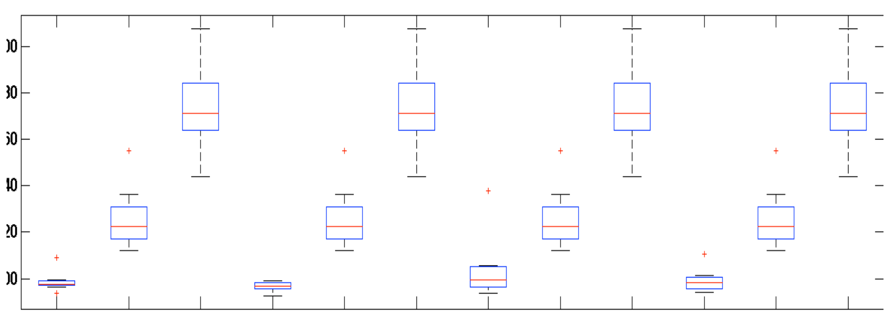

Fig. 2. The boxplot of the fitness results: each crossover operators has 3 box plots -best individual in training, best individual in test and mean individual in test-. From left to right: the scattered, the heuristic, the arithmetic and the two points crossover operators, respectively.

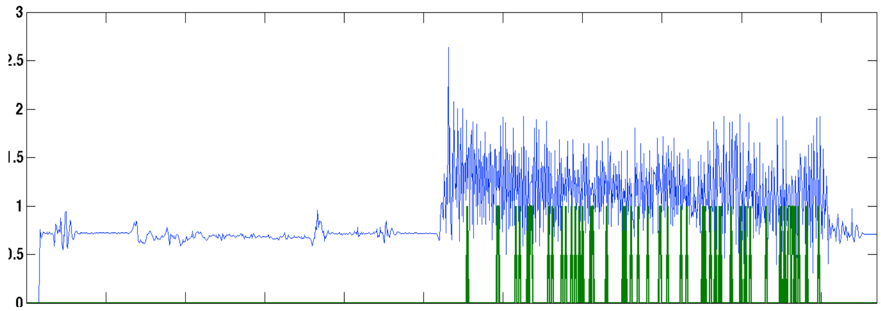

Fig. 3. Evaluation of the Fuzzy set with a simulation of an epilepsy episode The lower On/Off signal the discretized output when the membership function for the value of SMA is higher or equal to 0.5.

5 Discussion and Conclusions

After all this experimentation, the best set of genetic parameters subset for the genetic algorithm evolving the fuzzy membership function characteristic points has been found. With this simple tool we have been able to correctly classify the time series with a test classification error that has been kept lower than 200 wrong classified samples when using the realistic data. However, this approach did not seems to be a generalized solution as far as the performance of the fuzzy set degrades when using the data from one subject to other. It was found that such a simple approach can not deal with the problem of identifying an epilepsy episode, as seen in Fig. 2. The analysis of the results suggests that considering the current state of the subject and learning Finite State Machines can lead to valid solutions. Nonetheless, generalized solutions should be considered because it would be practically impossible -and undesirable- to gather data from epilepsy episodes for a subject in order to learnt the solution model for him/her. These models should consider the variability of the behavior and the uncertainty in the data as well. Thus, it may be interesting to include Fuzzy Finite State Machines. Additionally, the use of Markov Hidden models and Fuzzy Finite State Machines represent an alternative to the previous mentioned approaches. Instead of transforming the time series into a, let's say, static data sets, these approaches aim to learn from the dynamic and to learn the causes of change of state.

Furthermore, it is expected that using some transformations apart from the SMA -like the amount of movement and the intensity of the movement- would eventually allow us to cluster the time series from an epilepsy crisis. The feature selection needs further study. Besides, a very related to the approach to that of the clusters is the learning of Fuzzy Association Rules. The data that can be gathered from patients will include quite a few time series; the higher the number of time series and the larger they are, the worse the clustering might perform. However, the learning of Fuzzy Association Rules have been successfully tested in large data sets and big data problems; the challenge will be to choose a suitable representation of the time series.

Acknowledgment

This research has been funded by the Spanish Ministry of Science and Innovation, under projects TIN2011-24302 and TIN2014-56967-R, Fundación Universidad de Oviedo project FUO-EM-340-13, Junta de Castilla y León projects BIO/BU09/14 and SACYL 2013 GRS/822/A/13.

References

1. Marinas, A., Elices, E., Gil-Nagel, A., Salas-Puig, J., Sánchez, J., M.JC, C., Villanueva, V., Rosendo, J., Porcel, J., Serratosa, J.: Socio-occupational and employment profile of patients with epilepsy. Epilepsy Behaviour **21**(3) (2011) 223–227
2. Villanueva, V., Girón, J., Martín, J., Hernández-Pastor, L., Lahuerta, J., Doz, M., Lévy-Bachelot, M.C.L.: Quality of life and economic impact of refractory epilepsy in spain: the espera study. Neurologia **28**(4) (2013) 195–204
3. Smith, D., Defalla, B., Chadwick, D.: The misdiagnosis of epilepsy and the management of refractory epilepsy in a specialist clinic. QJM **92**(1) (1999) 15–23
4. Jr, J.E.: International league against epilepsy (ilae). a proposed diagnostic scheme for people with epileptic seizures and with epilepsy: report of the ilae task force on classification and terminology. Epilepsia **42**(6) (2001) 796–803
5. Nijsen, T., Arends, J., Griep, P., Cluitmans, P.: The potential value of three-dimensional accelerometry for detection of motor seizures in severe epilepsy. Epilepsy and Behavior **7**(1) (2005) 74–84
6. Nijsen, T., Cluitmans, P., Arends, J., Griep, P.: Detection of subtle nocturnal motor activity from 3-d accelerometry recordings in epilepsy patients. IEEE Transactions on Biomedical Engineering **54**(11) (2007) 2073–2081
7. Silva, C.J.P., Rémi, J., Vollmar, C., Fernandes, J., Gonzalez-Victores, J., Noachtar, S.: Upper limb automatisms differ quantitatively in temporal and frontal lobe epilepsies. Epilepsy and Behavior **27**(2) (2013) 404–408
8. Lockman, J., Fisher, R., Olson, D.: Detection of seizure-like movements using a wrist accelerometer. Epilepsy and Behavior **20**(4) (2011) 638–641
9. Bonnet, S., Jallon, P., Bourgerette, A., Antonakios, M., Guillemaud, R., Caritu, Y., Becq, G., Kahane, P., Chapat, P., Thomas-Vialettes, Thomas-Vialettes, F., Gerbi, D., Ejnes, D.: An ethernet motion-sensor based alarm system for epilepsy monitoring. IRBM **32**(2) (2011) 155–157
10. de Vel, A.V., Cuppens, K., Bonroy, B., Milosevic, M., Huffel, S.V., Vanrumste, B., Lagae, L., Ceulemans, B.: Long-term home monitoring of hypermotor seizures by patient-worn accelerometers. Epilepsy and Behavior **26**(1) (2013) 118–125
11. Schulc, E., Unterberger, I., Saboor, S., Hilbe, J., Ertl, M., Ammenwerth, E., Trinka, E., Them, C.: Measurement and quantification of generalized tonic–clonic seizures in epilepsy patients by means of accelerometry- an explorative study. Epilepsy Research **95**(1-2) (2011) 920–1211
12. Villar, J.R., González, S., Sedano, J., Chira, C., Trejo, J.M.: Human activity recognition and feature selection for stroke early diagnosis. In Pan, J.S., Polycarpou, M.M., Wozniak, M., de Carvalho, A., Quintián, H., Corchado, E., eds.: Hybrid

Artificial Intelligent Systems. Volume 8073 of Lecture Notes in Computer Science. Springer Berlin Heidelberg (2013)
13. Alvarez-Alvarez, A., Triviño, G., Cordón, O.: Human gait modeling using a genetic fuzzy finite state machine. IEEE Transactions on Fuzzy Systems **20**(2) (2012) 205–223
14. Cilla, R., Patricio, M.A., García, J., Berlanga, A., Molina, J.M.: Recognizing human activities from sensors using hidden markov models constructed by feature selection techniques. Algorithms **2** 282–300