10-168.

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Detection of nocturnal frontal lobe seizures in pediatric patients by means of accelerometers: a first study

Kris Cuppens, Lieven Lagae, Berten Ceulemans, Sabine Van Huffel, and Bart Vanrumste

Abstract— **The monitoring of epileptic seizures is mainly done by means of video/EEG-monitoring. Although this method is considered as the golden standard, it is not comfortable for the patient as the EEG-electrodes have to be attached to the scalp which hampers the patient's movement. This makes long term home monitoring not feasible. A detection system with accelerometers attached to the wrists and ankles can solve this problem. Nocturnal frontal lobe seizures often include bicycle pedaling movements or uncontrolled movements with the arms which are clearly visible in the accelerometer signals. Data from three patients suffering from nocturnal frontal lobe seizures is used in this paper for the development of an automatic detection algorithm for this type of seizure. First movement epochs are detected as a preprocessing step by calculating the standard deviation of a sliding window. Afterwards a moving average filter is applied to the data and thresholds are set to the signals of the arms and legs to detect the seizures. This resulted in an algorithm with a sensitivity of 91.67% and a specificity of 83.92%.**

I. Introduction

EPILEPSY is a generic term for a brain disorder which is characterized by epileptic seizures. During seizures abnormal sensations, emotions and (motor) behavior is seen. Some patients may also show repetitive convulsions, muscle spasms and loss of consciousness. Almost one percent of the world population suffers from the effects of epilepsy. Epilepsy is the most common serious neurological disorder during childhood [1],[3],[5].

The golden standard for the detection of epileptic seizures is video/EEG-monitoring. The video and EEG-data are analyzed by an expert who labels (i.e. determining the time when the seizures occur) the data. The video shows the abnormal movement of the patient's body, whereas the EEG shows the brain activity. A combination of those two elements has a very high specificity and sensitivity to identify seizures.

Although this detection method can robustly determine epileptic seizures, it is not feasible for a long term (multiple weeks or months) home monitoring as the EEG-electrodes have to be attached to the patient's scalp which is labor intensive for the technical staff. Furthermore the electrodes are uncomfortable to wear for the patient.

Long term home monitoring can provide the neurologist an objective measure of the number of seizures a patient has during the night. It permits a better follow-up of the disease which may lead to a better adjustment of the medication and a more optimal treatment of the disease which ultimately results in a better quality of life for the patient.

Another problem is that the parents of pediatric patients are afraid to miss a seizure of their child during the night, because in some of the heavy epileptic attacks the patient needs care after or during the seizure. That is why the child often sleeps in bed with his parents so that the parents do not miss a seizure. This leads to an uncomfortable situation for parents and child. An automatic epilepsy detection system which is comfortable to wear for the patient would be a solution for these problems, as it can alert the parents when a heavy seizure occurs and log the seizures in a database so that the neurologist has a better view on the frequency of the occurrence of nocturnal seizures.

A solution to this problem could be the detection of seizures based on video data [3]. A downside of this method is that movements which occur under blankets may be difficult to detect. To counter this problem a detection based on accelerometers is used.

The use of accelerometers for the detection of human movement and epileptic seizure is already studied in [4]. Five 3D accelerometers were attached to the four limbs (ankles and wrists) and one was attached to the chest. Stereotypical patterns for myoclonic, clonic and tonic seizures were found in the accelerometer data which made it possible for a human observer to distinguish them from normal movement. It was found that it was possible to detect epileptic seizures by means of accelerometers, and in some cases the human labeler even detected seizures which were not clearly visible in the EEG-signal.

The goal in this paper is to develop an automatic detection algorithm based on 3D accelerometers to detect nocturnal frontal lobe seizures, which eases the task of labeling epileptic seizures.

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K. Cuppens is with MOBILAB of the K.H.Kempen University College, Geel, Belgium (phone: 0032 14 56 23 10; e-mail: kris.cuppens@khk.be).

L. Lagae is with the department of pediatrics of the University Hospital of Leuven, Belgium (e-mail: lieven.lagae@uz.kuleuven.ac.be).

B. Ceulemans is with the department of child neurology of the University Hospital of Antwerp, Belgium (e-mail: berten.ceulemans@uza.be).

S. Van Huffel is with the department of Electrical Engineering (ESAT) of the K.U.Leuven University, Leuven, Belgium (e-mail: sabine.vanhuffel@esat.kuleuven.be).

B. Vanrumste is with MOBILAB of the K.H.Kempen University College, Geel, Belgium and with the department of Electrical Engineering (ESAT) of the K.U.Leuven University, Leuven, Belgium (e-mail: bart.vanrumste@esat.kuleuven.be).

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II. METHOD

A. Acquisition of datasets

The datasets of the epileptic patients are acquired in Pulderbos revalidation and epilepsy centre for children and youth (Belgium).

The datasets with the accelerometers are recorded during video/EEG-monitoring of the patients. Three axis accelerometers are attached to the wrists and ankles to monitor the movements of the limbs. This led to datasets with synchronized video, EEG (electroencephalogram), ECG (electrocardiogram), EOG (electro-oculogram) and accelerometer data. The accelerometer signals are sampled at 250 Hz.

TABLE I
OVERVIEW OF PATIENT DATA

Patient	Duration of dataset	Number of movement events	Number of seizures
A	11h 6m 32s	263	8
B	12h 34m 39s	470	1
C	12h 20m 0s	379	15
Total	36h 1m 11s	1112	24

Overview of the patient's data used in this paper.

The datasets are acquired during the night as there is a reduced supervision of the patient by the caregivers. Furthermore the acquired data is not much influenced by noise sources such as voluntary movement.

Three datasets of three different patients between the age of 5 years and 11 years are used. All of the patients suffer from frontal lobe seizures which results in marked motor manifestations. Table I gives an overview of the used datasets. A total of 1112 movement events are detected in the datasets, including 24 epileptic seizures. Notice that the movement events are not labeled by an expert but detected by the movement detection step, discussed in the next section. Here it is of importance that all the movement epochs are detected so that all the important data is preserved. Some small movements due to e.g. breathing of the patient are also preserved.

An expert labels the epileptic events with the information from the video/EEG-data, the starting point and the duration are marked. This information is considered as the ground truth.

B. Preprocessing

A preprocessing step is executed on the raw data. This step has two goals: first it reduces the amount of data significantly, second it divides the data into separate movement epochs which are further used to classify as a seizure or a normal nocturnal movement.

The first preprocessing step consists of the accelerometer data being filtered with a low pass 36th order type 2 Chebyshev filter with a cut-off frequency of 47 Hz. To avoid the phase distortion introduced by the filter, we processed the input data in both the forward and reverse directions, which results in a zero-phase filtering. The cut-off frequency is chosen such that the filter cancels out the aliasing effect when the data is downsampled. Moreover, a possible influence of the net frequency (50 Hz, and the first harmonic at 100 Hz) is also eliminated. We noticed that the frequency contents of the accelerometer signals were always smaller than 40 Hz hence a downsampling by a factor of two to 125 Hz is still acceptable.

After the downsampling the influence of the static earth gravity field (represented by a DC component) is eliminated by a high pass filter with a cut-off frequency of 0.2 Hz. Here, a fourth order type 2 Chebyshev filter is used. As with the previous filtering, here also a zero-phase filtering is used.

Next, the resultant of each accelerometer signal is calculated. As a result it gives the size of the dynamic acceleration of the sensor, with a reduction from twelve to four channels. The total data reduction in these first steps is a factor of six (from 12*250 samples per second to 4*125 samples per second).

After this data reduction step, the epochs without movement are discarded. To discriminate between movement and non-movement, the standard deviation of a sliding window of two seconds is calculated. If the standard deviation crosses a certain threshold, the epoch is considered as a movement, otherwise the epoch is discarded. The threshold is determined by a simulation where a simulator lies in bed during five minutes, after which he makes small movements of the fingers and toes which should be detected by the algorithm. This resulted in a threshold of 10 mg. After this step, the data is clustered. Epochs within 30 seconds are clustered together and are considered as a single movement epoch.

Ten to twenty percent of the datasets are considered as movement events. Considering all the preprocessing steps, this means that only about 1.5% to 3% of the original has to be processed, which is a considerable reduction.

C. Detection algorithm

The movements linked to nocturnal frontal lobe seizures differ from normal nocturnal movements in duration and intensity of the movement. Movements as turning in bed only take a couple of seconds whereas the epileptic seizures discussed in this paper most of the time last for ten seconds or more.

To emphasize the strong long movements and suppress short, but nevertheless sometimes strong, movements as turning in bed, a moving average filter is used. The mean energy of a sliding window is calculated by the following expression

$$y[i] = \frac{1}{n+1} \sum_{j=i-n}^{i} (x[j])^2 \qquad (1)$$

where *x[j]* is the accelerometer input signal of one limb, *y[i]* is the output of the filter and *n+1* is the length of the sliding window expressed in the number of samples.

Thanks to this filter not only the size of a single acceleration is of importance but also the number of accelerations per window. The length of the window should be more or less in the order of the length of the seizures to make a good distinction. The ideal value for the window is determined in the next section and it is dependant of the properties of the seizures.

To indeed discriminate between seizures and normal movements, a threshold is set to the signals of the arms and legs after applying the moving average filter. Because the intensity of the movement of the arms and legs can differ substantially, two different thresholds for the arms and legs are set. If two of the four signals cross the threshold, the epoch is considered as a seizure. Not all four signals have to cross the threshold. If for example the arms of the patient lie under the pillow, the intensity of the arm movement is significantly lower. The determination of the threshold values is also discussed in the next section.

D. Determine optimal parameters

To find the optimal parameters for the detection algorithm, we make use of ROC-curves. The different parameters which have to be optimized are:

- The length of the moving average filter
- The threshold for the arms
- The threshold for the legs

ROC-curves give an indication of optimal parameters by means of the sensitivity and the specificity, where the sensitivity is defined as the number of true detected seizures divided by the total number of seizures labeled, and the specificity is defined as the number of detected normal nocturnal movements divided by the total number of normal nocturnal movements. Both the sensitivity and specificity should be as high as possible with a maximum of 1 (100%).

III. Results

When we apply the ROC-curve to the datasets of the three patients we get the result shown in figure 1.

11968 combinations of the three parameters are tested with a value between 0.5 and 20 seconds for the length of the filter, a value between 10,000 and 810,000 mg^2 for the threshold for the arms and a value between 20,000 and 2,000,000 mg^2 for the threshold for the legs.

As visible in the figure, the point of 100% sensitivity and specificity is not reached. The optimal point has a specificity of 84.19% and a sensitivity of 91.67%. This matches with a value for the moving average filter of 10 seconds, a threshold for the arms of 20,000 mg^2 and multiple thresholds for the legs are possible between 200,000 and 2,000,000 mg^2.

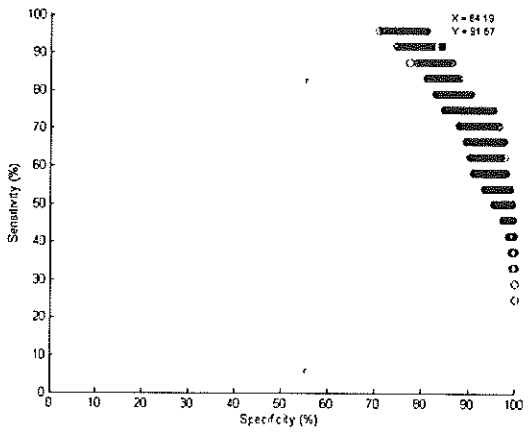

Fig. 1. ROC-curve with sensitivity and specificity for different values of the length of the moving average filter, the threshold for the arms, and the threshold for the legs.

IV. Discussion

The optimal values for the three different parameters are different for each dataset individually. If we only use the datasets of patients A en B, we can find a point on the ROC-curve where both a sensitivity and a specificity of 1 is reached. The values of the parameters where this optimal points are found is shown in figure 2. Notice that if the filter length increases, the threshold decreases because the signal is averaged over more samples. For the datasets of patient C such an optimal point with a sensitivity and specificity of 1 is not found. Mainly due to a slightly different manifestation

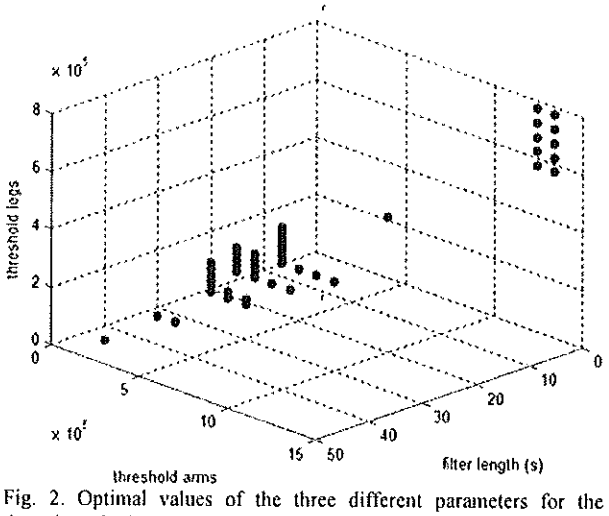

Fig. 2. Optimal values of the three different parameters for the detection of seizures for patients A and B.

of the epileptic seizures.

Notice also that in most cases a higher sensitivity for the detection of seizures is wanted. A false negative is worse than a false positive. A sensitivity of 1 can be reached as shown in figure 1. The specificity in this case would be 73.99%.

A possible better way to find an optimal point is to work with the Positive Predictive Value (PPV) instead of the specificity. This measure is calculated by dividing the number of true positives by the total number of detections

(true positives and false positives). The PPV is more sensitive for false positives as the number of true positives is smaller than the number of true negatives.

V. Conclusion

A detection algorithm for nocturnal frontal lobe seizures is developed and tested on a first group of patients. A sensitivity of 91.67% and a specificity of 84.19% is reached. This research shows that epileptic seizure detection by means of accelerometers is possible for this type of seizure.

Our future work will include the optimization of the algorithm and the development of detection algorithms for other types of seizures with a motor component.

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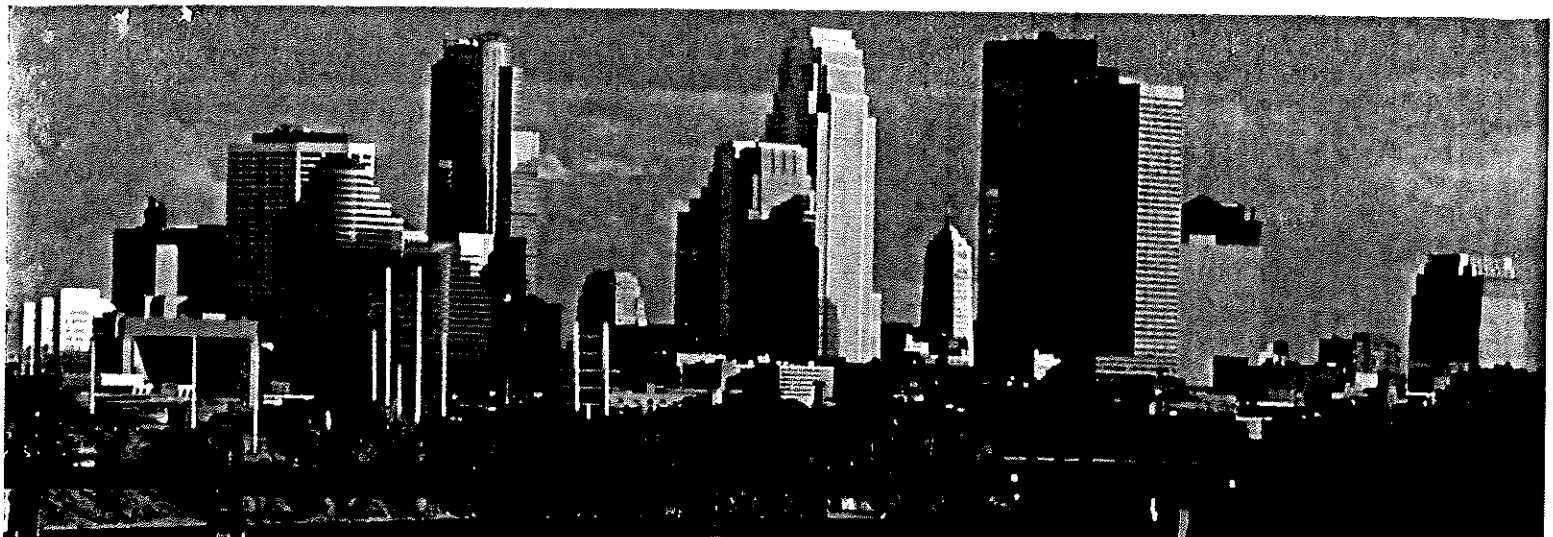

Final Program and Abstract Book

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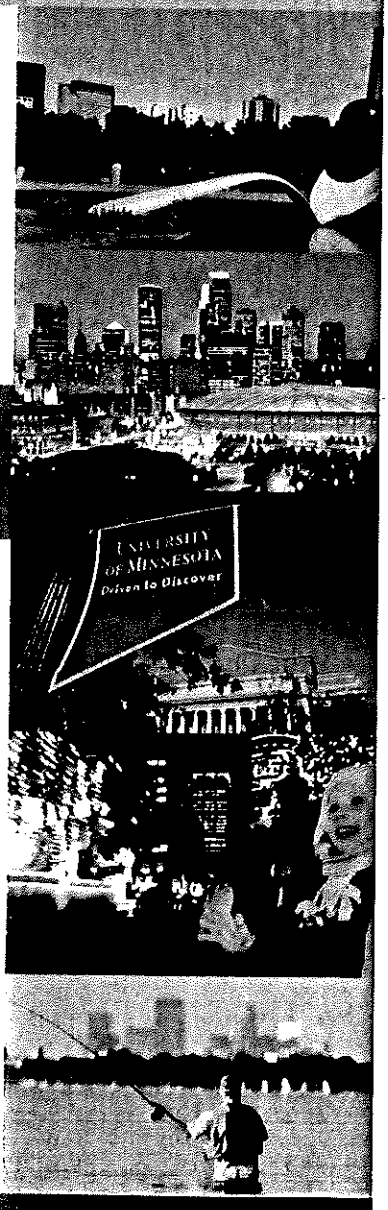

2 - 6 September, 2009

Minneapolis, Minnesota, USA

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E14: 16:40-18:10 Marquette III
.3 Diagnostic Devices and Instrumentation (Oral Session)
air: Mike McShane, *Texas A&M Univ.*
-Chair: Steven Johnson, *EMBS Buenaventura Chapter*

40-16:55 SaE14.1
velopment of Effective Photoplethysmographic
asurement Techniques: From Contact to Non-Contact
l from Point to Imaging T249
lu, Sijung (Loughborough University); Azorin Peris, Vicente (Loughborough University); Echiadis, Angelos (Loughborough University); Zheng, Jia (Loughborough University); Shi, Ping (Loughborough University)*

55-17:10 SaE14.2
ntitative Spectral Reflectance Imaging Device for
aoperative Breast Tumor Margin Assessment T249
amanujam, Nimmi (Duke University)*

0-17:25 SaE14.3
tial Mapping of Real-Time Quantitative Shear Stress
Vascular Oxidative Stress T250
, Lisong (Univ.of Southern California); Hsiai, John T. K. (USC)*

5-17:40 SaE14.4
tal Microfluidic Chips for Chemical and
ogical Applications T250
ir, Richard (Duke University)*

-17:5 SaE14.5
lopme... of a Multispectral Tissue Characterization
em for Optimization of an Implantable Perfusion Status
tor for Transplanted Liver T250
ba, Justin S. (Oak Ridge National Laboratory); Letzen, Brian (Oak Ridge National Laboratory); Ericson, Nance (Oak Ridge National Laboratory); Coté, Gerard L. (Texas A&M); Xu, Weijian (VA Pittsburgh Healthcare System); Wilson, Mark A. (VA Pittsburgh Healthcare System)*

5: 16:40-18:10 Marquette IX
Wireless Biomedical and Health Technologies (Oral Session)
Emil Jovanov, *Univ. of Alabama in Huntsville*
hair: Kwang S. Park, *Seoul National Univ.*

16:55 SaE15.1
tial and Challenges of Body Area Networks for
al Health T271
ders, Julien (Stichting IMEC Nederland); van de Molengraft, (Holst Centre); Brown, Lindsay (Stichting IMEC Nederland); ndlehner, Bernard (Holst Centre); Gyselinckx, Bert (Stichting C-NL); Van Hoof, Chris (IMEC)*

17:10 SaE15.2
trusive Measurement of Biological Signals for
lous ...thcare T271
Kwang S. (Seoul National University)*

17:25 SaE15.3
m: An Ultra-Low-Power Wireless Body Sensor
k Platform: Design & Application Challenges T272
g, Alan Chi Wai (Toumaz Technology Ltd.); nagh, Declan (Toumaz Technology Ltd.); Omeni, Okundu (Toumaz Technology Ltd.); Nunn, Chris (Toumaz Technology Ltd.); Silveira, Miguel (Toumaz Technology Ltd.); tt, Alison (Toumaz Technology Ltd.)*

7:40 SaE15.4
Applications of Wearable Technology T272
o, Paolo (Harvard Medical School)*

17:40-17:55 SaE15.5
UK and Canadian Perspectives of the Effectiveness of
Mobile Diabetes Management Systems T272
Istepanian, Robert (Kingston University London); Cafazzo, Joseph (University Health Network); Seto, Emily (University Health Network); Logan, Alexander (Mount Sinai Hospital); Sungoor, Ala (Kingston University London)*

SaE16: 16:40-18:10 Grand Ballroom - Salon A
11.4.2 Minisymposium: People, Places and Companies Involved in the Early History of Biomedical Devices and Instrumentation
Chair: Robert P. Patterson, *Univ. of Minnesota*
Co-Chair: Ron Leder, *Univ. Nacional Autonoma de Mexico*

16:40-17:10 SaE16.1
Medical Alley: The Rise of the Medical Device Industry in
Minnesota T280
Rhees, David (Bakken Museum)*

17:10-17:40 SaE16.2
Evolution of Microcomputer-Based Medical Instrumentation T280
Tompkins, Willis J. (University of Wisconsin - Madison)*

17:40-18:10 SaE16.3
Otto Schmitt's Contributions to Basic and Applied
Biomedical Engineering and to the Profession T280
Patterson, Robert P. (University of Minnesota)*

SaE17: 16:40-18:10 Directors Row 4
SS 4. Pathways to Success in Biomedical Engineering: Early Career Development (Special Session)
Chair: Kaustubh Patil, *Medtronic, Inc.*

Sunday, 6 September 2009

SuA01: 08:30-10:00 Conrad B
1.2.6 EEG Signal Processing II (Oral Session)
Chair: Chang-Hwan Im, *Yonsei Univ.*
Co-Chair: Yingchun Zhang, *Univ. of Minnesota*

08:30-08:45 SuA01.1
A New Method for Spatiotemporal Identification of Event-
Related Potential Subcomponents T18
Mohseni, Hamid (Cardiff Univ.); Sanei, Saeid (Cardiff Univ.)*

08:45-09:00 SuA01.2
Regularized Common Spatial Patterns with Generic
Learning for EEG Signal Classification T18
Lu, Haiping (Univ. of Toronto); Plataniotis, Konstantinos (Univ. of Toronto); Venetsanopoulos, Anastasios (Ryerson Univ.)*

09:00-09:15 SuA01.3
Automated Epilepsy Diagnosis Using Interictal Scalp EEG T18
Bao, Forrest S. (Texas Tech University); Gao, Jue-Ming (Jiangsu Provincial Hospital of Chinese Medicine); Hu, Jing (Jiangsu Provincial Hospital of Chinese Medicine); Lie, Donald (Texas Tech University); Zhang, Yuanlin (Texas Tech University); Oommen, K. J. (Texas Tech University Health Sciences Center)*

09:15-09:30 SuA01.4
Detection of Nocturnal Frontal Lobe Seizures in Pediatric
Patients by Means of Accelerometers: A First Study T19
Cuppens, Kris (Katholieke Hogeschool Kempen); Lagae, Lieven (University Hospital of Leuven); Ceulemans, Berten (University Hospital of Antwerp); Van Huffel, Sabine (Katholieke Universiteit Leuven); Vanrumste, Bart (Katholieke Universiteit Leuven)*

09:30-09:45 SuA01.5
Age-Independent Seizure Detection T19
Faul, Stephen (Univ. College Cork); Temko, Andriy (Univ. College Cork); Marnane, Liam (Univ. College Cork)*