

# FEATURE COMPARISON FOR REAL-TIME DETECTION OF NOCTURNAL SEIZURES USING ACCELEROMETRY

Constantin Ungureanu<sup>1,3</sup> PhD, Martien van Bussel<sup>3</sup> MSc MBA, Francis Tan<sup>2,3</sup> MD, Prof. Johan Arends<sup>1,2,3</sup> PhD, Prof. Ronald Aarts<sup>1</sup> PhD

<sup>1</sup>Eindhoven University of Technology, Signal Processing Systems Group, Eindhoven, the Netherlands

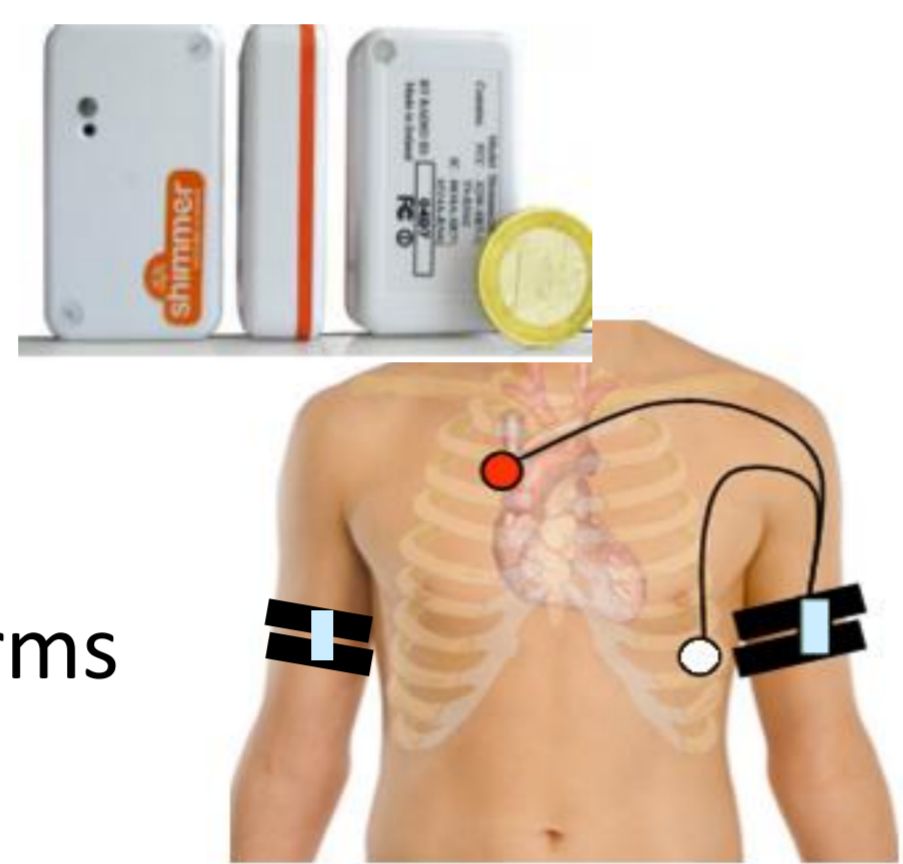
<sup>2</sup>Kempenhaeghe, Heeze, the Netherlands, <sup>3</sup>HOB0 Heeze B.V., Heeze, the Netherlands

**GOAL** To develop and validate a simple, self-learning algorithm for the detection of major nocturnal seizures using accelerometry data from various sensor systems and configurations

## PATIENT DATA AND SENSORS

### Group 1

- 5 patients (12 nights)
- 14 tonic-clonic seizures; 4 hypermotor
- 2 wired 3D accelerometers placed on both wrists
- 100 Hz sampling rate



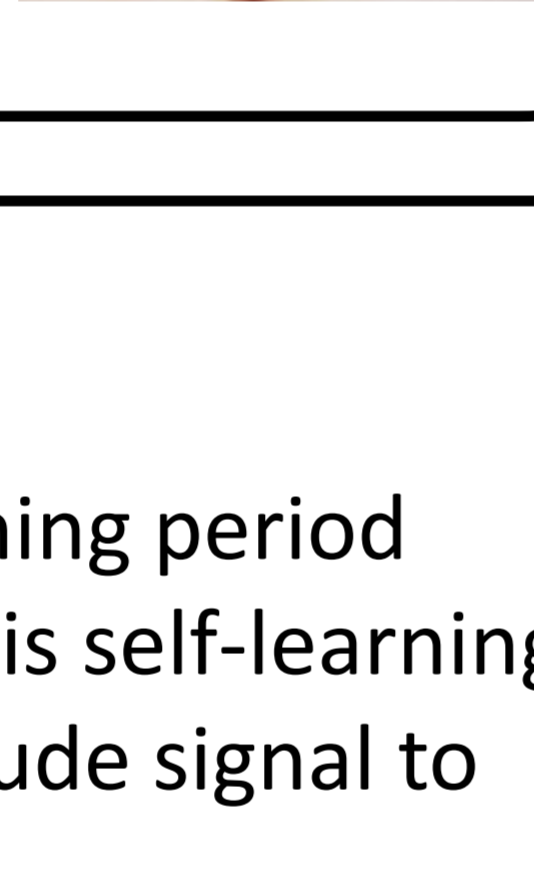
### Group 2

- 4 patients (4 nights)
- 9 tonic-clonic seizures
- 2 Shimmer™ accelerometer sensors placed on both upper arms
- Wireless transmission
- 100 Hz sampling rate



### Group 3

- 5 patients (7 nights)
- 8 tonic-clonic seizures
- 1 accelerometer Holst™ sensor placed on upper left arm
- Wireless transmission
- 40 Hz sampling rate



## FEATURES AND THEIR DISCRIMINANT POWER

- 8 features computed per hand on 1 second non-overlapping windows ( $w$ )
- Feature ( $f_j$ ) used for comparison: sum of the features for left and right hand ( $h$ ) signals
- Features used: mean of RMS ( $f1$ ), standard deviation ( $f2$ ), median of RMS ( $f3$ ), energy of signal ( $f5$ ), jerk ( $f6$ ), signal magnitude area ( $f7$ ) and waveform length ( $f8$ )

$$RMS_x(w) = \sqrt{\frac{\sum_{i=1}^n acc(i)_x^2}{n}}$$

$$\Delta RMS_h = |RMS_h(i) - RMS_h(i-1)|;$$

$$RMS_h(i) = \sqrt{acc(i)_x^2 + acc(i)_y^2 + acc(i)_z^2};$$

$$f(j) = f_j(\text{righthand}) + f_j(\text{lefthand}); j = \overline{1:8};$$

$$f1 = \left(\sum_{i=1}^n RMS_h(i)\right)/n;$$

$$f2 = std(RMS_h(w));$$

$$f3 = median(RMS_h(i)); i = \overline{1:n};$$

$$f4 = (RMS_x(w) + RMS_y(w) + RMS_z(w))/3$$

$$f5 = \sum_{i=1}^n acc(i)_x^2 + \sum_{i=1}^n acc(i)_y^2 + \sum_{i=1}^n acc(i)_z^2$$

$$f6 = \left(\sum_{i=1}^n \Delta RMS_h(i)\right)/n$$

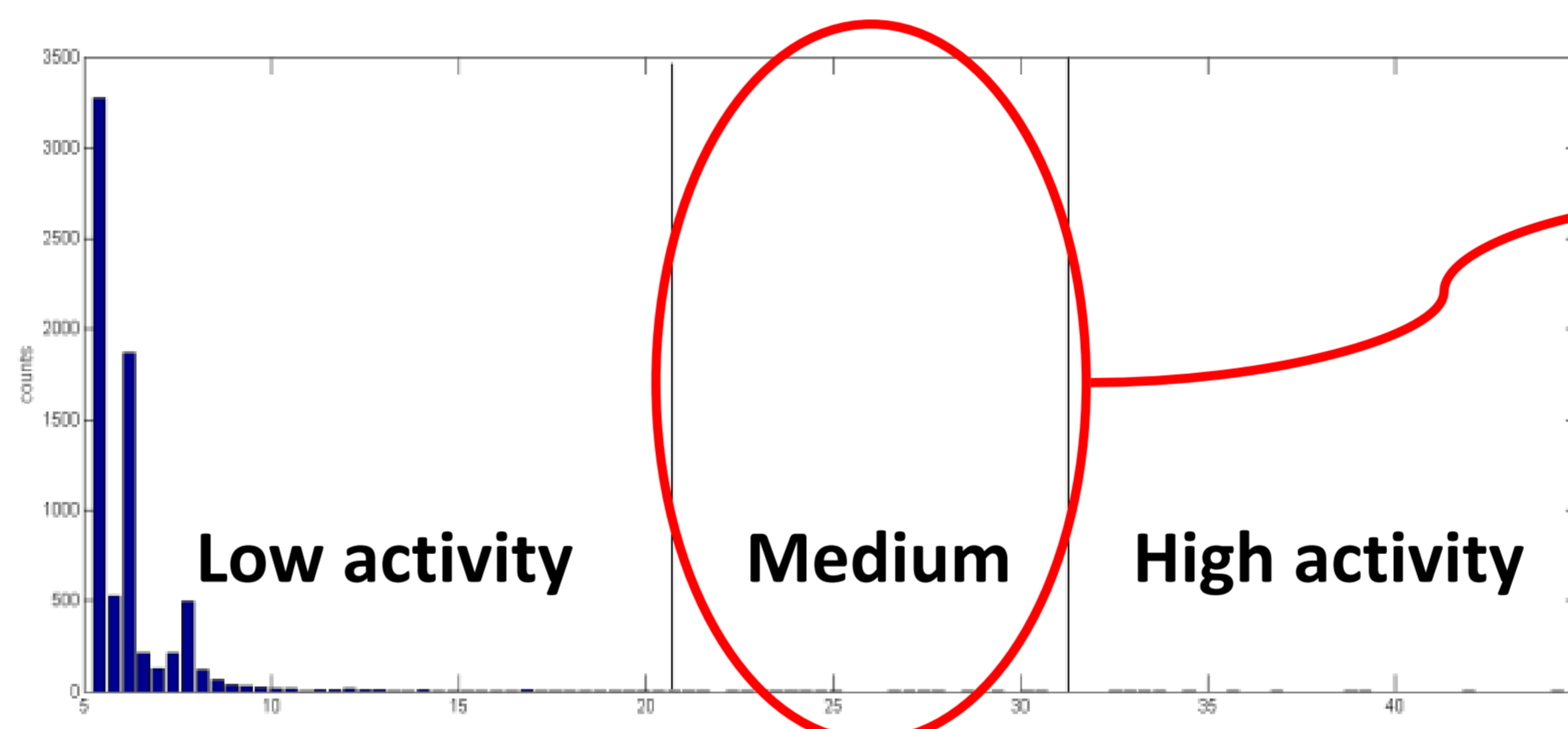
$$f7 = SMA_h = \sum_{i=1}^n (|acc(i)_x| + |acc(i)_y| + |acc(i)_z|);$$

$$f8 = wl_{x,h}(w) = \sum_{i=2}^{100} |acc(i)_x - acc(i-1)_x|$$

- For comparison, features were normalized to their respective mean
- Feature discriminative power (DP): the ratio between the maximum amplitude of the feature during a seizure and the baseline

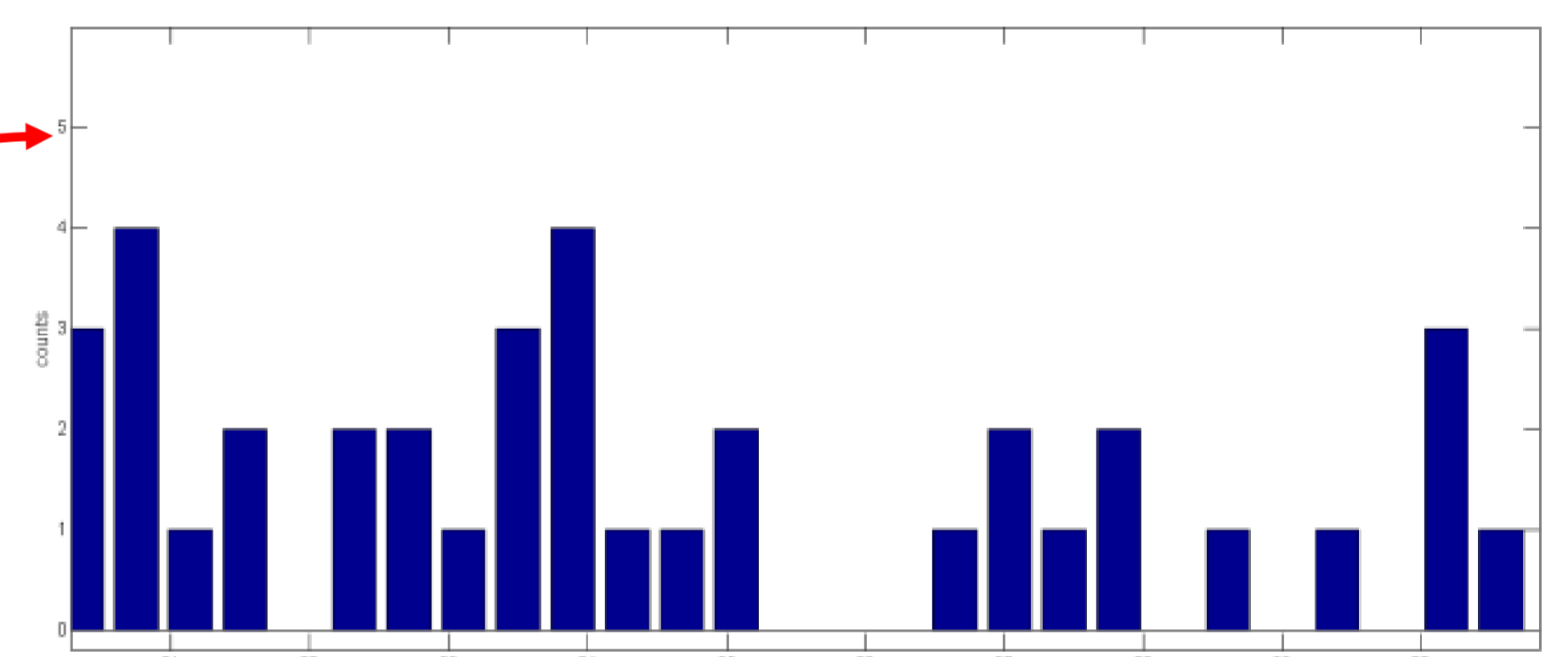
## CLASSIFICATION

1. Each individual has a 2 hour training period
2. During this period the algorithm is self-learning
3. It uses a histogram of the amplitude signal to determine a threshold ( $th$ )
4. A possible event represents an activity that last more than 3 seconds with intensity higher than  $th$



Histogram of feature in interval between 8 and 10 PM

1. Features are computed
2. Histogram is created (divided in 3 equal regions)
3. Threshold derived from the middle region of histogram



Zooming in on the middle zone of histogram  
 $th$  = mean of values from this histogram region

## RESULTS

Total SEN and PPV (per group) = mean of individual SEN and PPV.

### Group 1

Both hands: SEN = 100% PPV = 59%  
Right hand: SEN = 70% PPV = 40.4%  
Left hand: SEN = 75% PPV = 44%

### Group 2

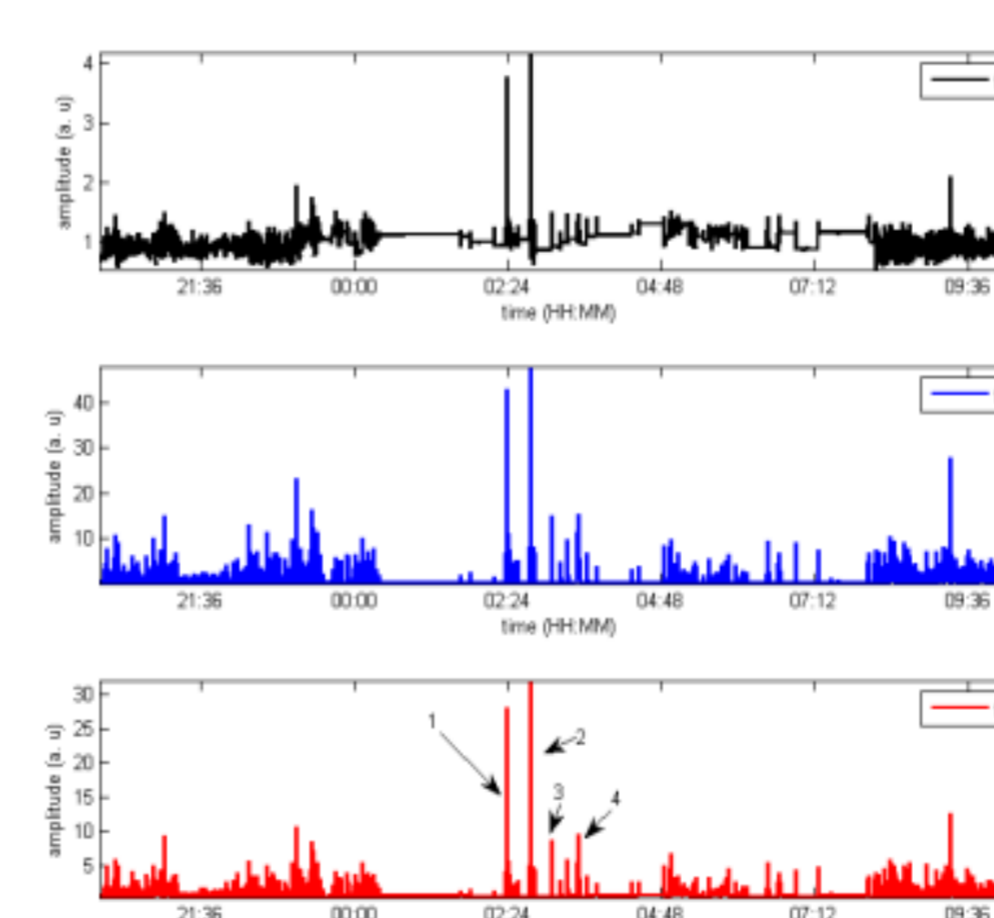
Right hand: *sensor malfunction*  
Left hand: SEN = 41.5% PPV = 50%

### Group 3

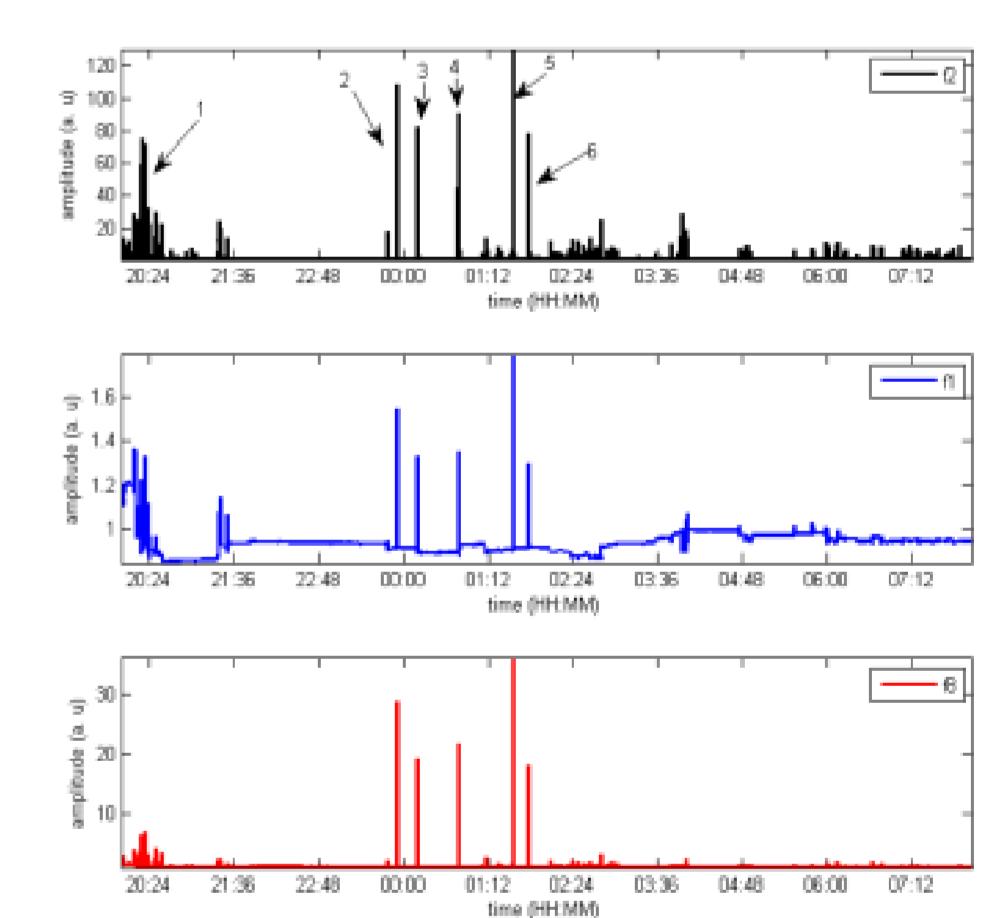
Left hand: SEN = 92% PPV = 49.3%

	BH	LH	RH
TP	4	3	3
FP	1	1	1
FN	0	1	1
SEN (%)	100	75	75
PPV (%)	100	75	75

Example classification for patient 1 from group 1



Normalized features 2 patients For patient 1 (left) arrows 1,2,3,4 indicate a seizure. For patient 2 (right) arrows 2,3,4,5,6 indicate seizures; arrow 1 indicates normal activity.



## CONCLUSIONS

- The algorithm achieves 100% SEN on data from two accelerometer sensors placed on the wrist (group 1)
- PPV is high during sleeping hours: the majority of false positives occurred in the early night and early morning when patient was awake and active
- The difference between SEN determined from group 2 data vs. data from group 3 can be attributed to differences in individual seizure dynamics
- A patient specific training algorithm that does not need a-priori seizure information was introduced
- Features based on changes in the phase of the signal - jerk, waveform length - show *higher discriminant power* than the ones based on absolute amplitude - mean of RMS, SMA (based on visual observation of results from all patients from group 1)
- Research is ongoing; further analysis is required to improve the classification algorithm