In search of Human TLE rhythms

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Abstract— **Temporal Lobe Epilepsy is the most common type of adult focal epilepsy. The brain activity that characterizes the patients having this disorder is the main window for diagnosis and is studied relying electroencephalogram recordings. Another characteristic of this disorder is the typical motor manifestations in different parts of the human body, such as manual or oral automatisms. These seizure induced movements can now be quantified using sophisticated video processing technology. We aim to explore this technical possibility and shed light on its relation with intracranial electrical activity. We tackle the problem by exploring the similarity and synchrony of electrical activity and movement signals, as well as their rhythms. We use a modified version of the chi-squared statistical association test applied to time series – the Cramér V measure.**

I. Introduction

Temporal lobe epilepsy (TLE) is the most common type of adult focal epilepsy [1]. This type of epilepsy is drug resistant and many times associated to brain hippocampus sclerosis. The brain electrical activity of these patients is the main window for diagnosis and is studied relying on surface electroencephalograms (EEG) and intracranial recordings. It presents typical spiking patterns that have been studied for many years to provide clear information on the disease [2].

Another characteristic of this neurological disorder are its typical seizure motor manifestations in different parts of the human body [2]. During seizures patients "lose contact" with the world, presenting uncoordinated and erratic body movements. For example, it is known that abdominal auras, which evolve into seizures characterized by oral and manual automatisms (automotor seizures) clearly point to a TLE [3]. Epileptologists empirically use these movement patterns to aid their diagnosis. It is now possible to quantify this seizure induced movements using sophisticated video processing technology [4, 5].

Video processing technology or 3D motion systems have been used extensively to quantify human movement in a variety of application areas. In motion pictures and games they have been used to help understand and replicate human motion in computer created characters; in sports they have been used to perfect certain actions that may be significantly improve the performance of the athlete; in military, to train personnel; in virtual reality, for live tele-presence and realistic avatars; in medicine, for orthopaedists and prosthetists, it is useful to obtain quantitative gait analysis and an objective documentation of walking ability; and in education, for photo-realistic 3D virtual teachers and students [6]. It is obvious that quantifying movement in epileptic seizures can help to objectively document and analyse movement patterns that would otherwise be affected by the specialist inherent subjectivity.

We aim to explore this technical possibility and investigate relations of its characteristics with intracranial electrical activity. We use information captured synchronously before and during seizures, both from seizure 3D movement quantification and EEG readings. To be able to find a relation between seizure movement and EEG would yield significative impact in the clinical community, and in understanding epilepsy in general. Our goals are twofold: to investigate quantitative characteristics of seizure movements such as similarity and synchrony to TLE electrical activity, and to analyse the rhythms of seizure movements.

This document is organized as follows. In section II we present the system that allows the recording of both electrical activity and movement, and its configuration. In section III we describe our approach to achieve the goals we set. We follow in section IV with the experimental analysis and present some results. Finally, in V we present some further research, and we draw some conclusions in section VI.

II. System setup and configuration

The movement and EEG data is obtained from the Epilepsy Monitoring Unit of the University of Munich. This unit contains the infrastructure that allows capturing the data of epileptic activity. This includes rooms, 3D and vision, 64 channels Video-EEG, and computing systems that allow the synchronization and capture of the signals before and during seizures. The vision system is composed by 4 cameras, having high resolution (1280 x 1024 pixels), and high frame rate (200 Hz). The cameras are sensible to infra-red light, so that they are immune to noise and work also at night. In order to capture the patients' movements, 10 sets of infra-red reflecting blobs are distributed along their body. Software developed in the project allows the synchronization and recording of both movement and electrical activity signals.

III. Method

We explore the relation between seizure movement and electrical activity by means of its similarity and synchrony. Similarity is measured in terms of statistical association of the two signals. Synchrony is measured in terms of variation of similarity as measured across a certain delay range. We tackle the investigation of the movement rhythms by analysing the movement signal's power spectral density.

A. *Similarity and Synchrony*

We will now formalize the concepts of similarity and synchronize upon which we base our work.

Definition 1. Similarity: Let *X* be the signal of the seizure movement quantified as displacement of a specific blob in the vertical axis, and *Y* be the electrical activity of a specific electrode in the scalp. The similarity of signals *X* and *Y* is the statistical association between the two signals, as measured by the *V* measure [8].

V is a measure of the degree of association, or strength of dependence of two or more variables, and it was introduced by Cramér [9] in 1946. It can be interpreted as the squared departure from independence in a scale between zero and one [8]. Although it is not a metric, it displays the symmetry property. It is fast to calculate and is mostly used with categorical variables. Nevertheless, we use the method in [8] to quantify the dependence of two numerical time series.

Algorithm:

1) First, each signal is discretized according to slope and polarity. Slope is the set of successive variations (increasing, decreasing) of the signal, and polarity is the set of the signal states (positive, negative). Each of the four different slope-polarity combinations is attributed a different symbol, as depicted in Table I.

Table I – Slope and polarity combinations

Slope	Polarity	Symbol
↑	+	a
↑	-	b
↓	+	c
↓	-	d

The discretized sequence has the length of the original signal minus one.

2) Using the previously converted symbols as classes, we can build a contingency table. We fill the contingency table by counting the co-occurrences of each symbol in each position of the sequences.

3) We then employ the chi-squared statistical test over the just built contingency table, as follows:

$$\chi^2 = \sum_{i=1}^{I}\sum_{j=1}^{J}\frac{O_{ij} - E_{ij}}{E_{ij}} \quad (1)$$

where O_{ij} and Eij are respectively the actual and expected number of co-occurrences of symbols *i* and *j*.

4) Finally, we apply the Cramér's coefficient method to T in order to normalize it in the [0, 1] interval. This coefficient can be obtained by:

$$V = \sqrt{\frac{\chi^2}{N \cdot (I-1)}} \quad (2)$$

where N is the total count of the contingency table, and assuming I=J. This coefficient provides a meaningful interpretation for the strength of the association between the two sequences.

In order to properly define synchrony we need to first introduce the definition of time series subsequence.

Definition 2. Subsequence: Given a signal *T* of length *m*, a subsequence *C* of *T* is a sampling of length $n \leq m$ of contiguous positions from *T*, that is, $C = t_p, ..., t_{p+n-1}$ for $1 \leq p \leq m-n+1$ [10].

Definition 3. Synchrony: Let *X* of length *m* be the signal of the seizure movement quantified as displacement of a specific blob in the vertical axis, *Y* of length *n* be the electrical activity of a specific electrode in the scalp, and $m<n$. Given X, Y, the index *s* of Y_s ($s>1$) captured in the same instant of X_1, the index *e* of Y_e captured in the same instant of X_n, and a maximum delay *d*. The synchrony of X and Y is the vector *Vs*, calculated as follows:

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FOR EACH POINT i in [-d, +d ]:
    Eeg_i = Subsequence(length=xl, start=Y_s+i, end=Y_e+i)
    Vs_i  = Similarity(X, Eeg_i)
END
RETURN Vs
```

The synchrony of two signals intends to capture the intuition that some subsequences of the electrical activity signal that precede the seizure by a certain number of milliseconds might most strongly be associated with the movement. It contains the variations of similarity as searched along a delay interval.

B. Rhythms

We analyse the movement rhythms by measuring the synchrony between the movement and electrical activity. As in the previous case, we measure synchrony in terms of association in function of a delay. However, in this case we use the power spectral density (PSD) of the signals.

IV. Results

Following the method described in the previous section, we hereby describe our experimental analysis. First we describe the material, then the experimental methodology and the obtained results.

A. Material

To perform our experiments we have data from one patient. These data include the period during and before a seizure, being both movement and electrical activity data recorded synchronously.

We take as an instance of movement data the left (OSL) and right (OSR) thigh displacement in the vertical axis, and the instantaneous velocity for these data, respectively OSL' and OSR'. Similarly, we take as electrical activity instances the central (C3, C4), temporal (T7, T8), parietal (P3, P4), and frontal (F3, F4) electrodes. We also list as material our MATLAB implementations of similarity and synchrony.

B. Results

We will now outline our experimental methodology for the similarity and synchrony relation of the movement and electrical activity, and then for the rhythms.

1) Similarity and Synchrony

For each electrical activity instance, we calculate the

synchrony in the interval [-2500ms, 2500ms] with the opposite hemisphere's movement velocity. The velocity is used instead of the original displacement, because we believe that what is of interest is not the actual displacement *per se*, but the velocity at which it occurs. With the velocity concept, we can more faithfully represent the energy concept, than with the displacement itself. It is likely that a movement of one centimetre for the left or right, for example, is not very important. Instead, the velocity at which that displacement occurs is a carrier of more information for our endeavour. We intend to discover if there is some specific delay that presents a higher degree of association with the velocity the patient performs the movement. We use the maximum delay of 2500 milliseconds because it is believed that this relation, if existent, is likely not to precede the seizure by a large amount of time. This value is apparently a good starting point. We use the opposite hemisphere's electrodes and blobs (even-number electrodes indicate the right hemisphere), because it is now proved scientifically that brain hemispheres control the opposite part of the body.

In Figure 1 we show the graphical representation of the synchrony vector between movement velocity OSL' and electrode C4.

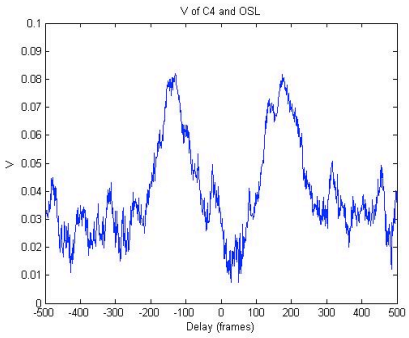

Figure 1 – Synchrony between OSL' and C4

It can be observed that the absolute association results as measured by the V measure are overall very low. However, interesting behaviour can be observed if we regard the relative results, as the delay changes. There is a clear peak of association in the -150 frames delay, which is about 0.75 seconds before the seizure occurs. Notice that no prior knowledge was incorporated in this first experiment: this means no pre-processing, no artefact removal; we are just working with the raw data.

In the next experiment, we incorporate the knowledge that EEG is typically described in terms of rhythmic activity which is divided into frequency bands. These bands are believed to have a certain biological significance most likely related to the activities being performed by the individual. Up to 3 Hz in frequency we have Delta waves, in the 4-7 Hz range the Theta waves, 8-12 Hz correspond to Alpha waves, Beta waves range from 12-30 Hz, and finally in the 26-100 band the Gamma waves. We take this knowledge into consideration, and intent to quantify which relation exists between each particular band and the original movement. We apply the following methodology: for each instance of the electrical activity, we apply band-pass filters according to the bands described above. Then, we calculate the synchrony between the original movement velocity signal and the electrical activity for each band.

We show results for the synchrony between velocity OSL' and the following electrode-band pairs: C4-Delta, C4-Theta, C4-Alpha, C4-Beta, and C4-Gamma in Figure 2.

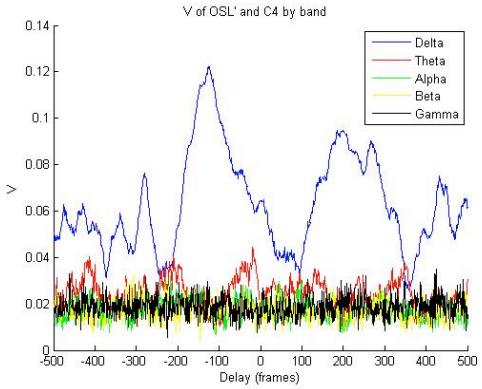

Figure 2 – Synchrony between OSL' and C4 by band

It can be observed that although the absolute results continue to be overall low, we can see a peak in specific delays, which may indicate a relation of movement and electrical activity that may precede the seizure. Also, we noticed an increase in the absolute V result at 0.75 milliseconds before the seizure, reaching the value of 0.12. Another observation that can be noticed is the clear distinction if we compare the synchrony for each band. We represent this idea graphically in Figure 3.

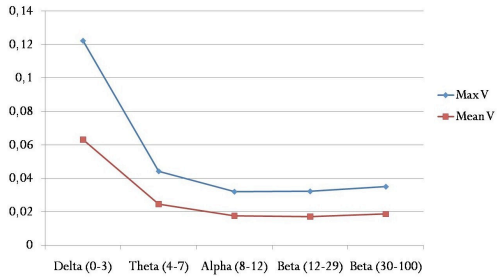

Figure 3 – Variation of maximum and mean V for the different bands

As it can be observed, both the maximum and mean V decrease as we move from lower frequency bands to higher frequency bands. This might show that lower frequency bands are indeed more strongly associated with seizure movements. However it also may be a consequence of the fact that lower frequency band filters act as a low-pass filter which smooth the signal, improving the V result. These hypotheses need further experimentation.

C. Rhythms

We calculate the power spectral density of each electrical activity signal. Then, we calculate the PSD of the opposite

hemisphere's movement velocity. Finally, we obtain the synchrony of the two PSD in the interval [-2500ms, +2500ms]. In Figure 1 we plot the results for the T7 electrode and OSR' PSD.

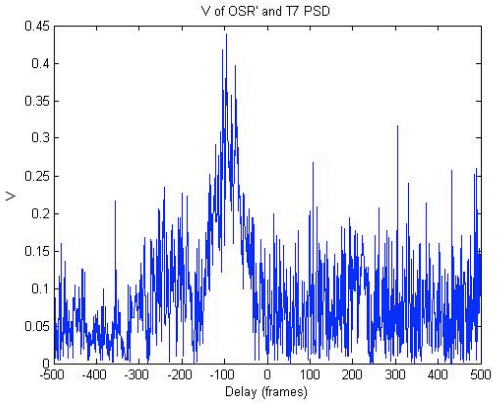

Figure 4 – Synchrony of OSR' and T7 PSD

As one can observe, there is one clear peak in the similarity between the brain's electrical activity about half second before the seizure. This, when proved empirically with more patients data, might be an indicator that the frequency of the rhythms of the electrical activity and movement's velocity are indeed similar before the seizure actual occurs.

V. Future work

We first outline some directions to overcome some limitations of our work, and then present some new directions which we believe are promising.

Regarding the limitations of our work, the first one is to use a Laplacian montage of the EEG electrodes. Using this type of montage, each channel represents the difference between an electrode and a weighted average of the surrounding electrodes [12]. This seems to be more accurate than our approach in which we use the actual channel readings. Also, in the rhythms analysis, it would be interesting to use more sophisticated approaches to calculate the PSD, such as the Welch method.

We now present two possible new approaches for further work. The first one is to use approaches from the time series data mining community to build contingency tables in the V calculation. One of those is SAX [11]. SAX is a clever way to discretize signals: it first divides the signal in a number of frames, then it averages the signal points that lie in each frame, then it divides the signal amplitude in a set of equiprobable intervals, and finally it attributes a different symbol to each frame according to the interval the average of that frame lies into.

Other one is to apply pattern recognition algorithms in time windows that contain information that can help predict seizures. One way to obtain such information rich windows is to identify the regions that immediately precede the seizures. With these regions identified these could be used to train pattern recognition algorithms. One pattern that is found to be frequent in these regions is likely to be useful in the prediction of new seizures.

VI. Conclusion

In this work we investigate the relation of epilepsy seizure movements with brain electrical activity in terms of similarity and synchrony, as well as rhythms of such movements.

Our results are overall low in terms of association. However, indicators observed in terms of relative value of association are both interesting and promising.

We need to perform further research, perhaps a more comprehensive experimental analysis, with more patients' data, better exploring pre-processing (smoothing and filtering), and with the intuition that the overall signal state is more important than immediate variations (that may be cause by noise or artefacts). We also think is necessary to empirically demonstrate the thesis that as band frequency increases, association decreases.

Finally, we need to be aware that association, or correlation, doesn't imply causality. This fact is important if we are going to derive prediction algorithms using the measure used in this work.

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