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Electroencephalographic events prior to epileptic major motor seizures*

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***Abstract*— *Rationale.* The goal of this study is to evaluate the electroencephalographic (EEG) events, prior to clonic phases of epileptic motor seizures. Analyzing video sequences we were able to detect these special phases of motor seizures, by image features. This can be used for an early detection and alerting for these events. In the study we analyzed 42 seizures. Based on collected data we compare the quantitative results from video detection of seizures with the features computed from EEG scalp recordings from about 3 minutes prior to the seizure. We analyze the non-stationary frequency spectrum of the EEG recordings and match it against our automated video detection output in order to investigate possible precursory EEG events. *Methods.* Video recordings are analyzed by applying optical flow theory, reconstruction of geometrical flow invariants, low and high pass filtering, and suitable normalizations. EEG recordings are processed with use of a Gabor wavelet technique. Comparison is achieved by means of analysis of the cross-correlation function between the derivatives of the Gabor amplitudes and the measure of "seizureness" produced by our video detection algorithm. *Results.* In the present study certain ranges of EEG frequencies were found, where electro-graphical events precede clonic phases of clinical motor seizures from 2-8 up to 30-40 seconds. These results could be used for construction of new generation of methods for automated motor seizure detection.**

I. Introduction

Epilepsy is a clinical condition of the central nervous system that can be described as "dynamic" [1, 2] in the sense that patients are most of the time without any apparent abnormal symptoms but suddenly may get attacks or seizures impairing partially or entirely their normal functions. From the different types of seizures the motor ones are those that display the most dramatic behavior and may pose a hazard to the patient's safety. For example "clonic" and "hyperkinetic" motor seizures [3] can last for long periods and cause severe physical injuries if the patient is not attended and helped soon after the seizure onset. The idea of the present study is to find specific electro-graphical markers that may help to identify the major motor seizure's (MMS) phase. Therefore knowing the exact position in time of the seizure's "clonic" phase, may be used to process EEG recordings, backwards in time, and to find certain signal characteristics, predicting the motor phase. We applied a detection algorithm on video data, based on optical flow vector field, which reconstructs velocities of recorded objects from the image intensity changes. Further reconstructed vector fields were decomposed into a group of linear transformations of the plane velocities, and band-pass temporal filtering was applied. The algorithms are constructed in feed-forward processing mode what allows their implementation in real-time systems. In this way the "clonic" or "hyperkinetic" seizure phase could be detected successfully. Furthermore we analyzed the EEG recordings using similar decomposition methods, 200 seconds backwards from the point of major motor seizure detection (MMS), and we found statistically significant changes of certain EEG frequency components, prior to the video clonic phase detection. To validate the results we considered as a "golden standard" the detections of events involving MMS provided by two coauthors experienced clinicians (Demetrios Velis (DV) and Ben Vledder (BV)). In this work we do not attempt to validate or quantify the performance of the EEG based features as an early seizure detector. Our objective here is to identify the EEG frequency components, which may be potential candidates for "predicting" early MMS detection using EEG signals. A more dedicated analysis requires different validation tests in view of a potential practical application and will appear in a forthcoming publication.

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II. Patient Data and Signal Processing Steps

A. Patient and data acquisition

We used scalp records from routine diagnostic EEG and video observation facility[4]. EEG data were recorded using Stellate Harmonie® acquisition systems with LanNotta® ambulatory EEG recorders. The EEG recordings were always sampled at 200Hz and only 21 channels common to all recordings were analyzed. The data from 30 patients with known motor seizures contained segments of synchronized EEG and video sequences ranging from 12 to 56 minutes. One or more seizures per patient were identified in the sequences by certified clinicians (DV and BV) and the beginning and end of each "clonic"/"hyperkinetic" phase was determined from the video and EEG records. A total of 42 seizure periods were identified with a total duration of 45 minutes. The total length of the analyzed records was 746 minutes.

B. Data processing steps

Using markers for the identification of the beginning and the end of the seizure "clonic" phase, we marked these events on video recordings. This yield a series of video segments, each one of which contained one seizure "clonic" phase. We

applied the video detection algorithm to these segments. In general this algorithm is based on averaging optical flow over the whole image, i.e. on the reconstruction of motion vector fields from the changes of intensity of light. Next we reconstruct the group of six motion invariant parameters that include: two translations, one rotation, one dilatation, and two shear transformations velocities. To these "resulting" six parameter signals we apply low and high pass filters, and appropriate normalization in order to extract only the frequencies between 2 and 6 Hz, since the latter likely result from seizure driven movements. Using simply the average value of these six parameters, or some special combination of these values, one can define a function, by means of which the degree of "seizureness" of the observed scene may be quantified. In the present study we used the average value of all six parameters. Once we detect the maximum of the "seizureness" function, or the CPM ("clonic phase maximum"), we look at the EEG recordings backwards in time, in order to see "what are the electro-graphical precursors of the maximum of the seizure "clonic" phase. We consider segments of EEG recordings each of which ends at the selected CPM, and starts 200 seconds before that point. We selected the range 2-6 Hz as characteristic for the "clonic" and/or "hyperkinetic" seizures on the basis of semi-quantitative observations of Gabor power spectra of the video time series compared with the power spectra of the synchronously recorded EEG signal. We applied a Gabor set of scale transformed filters with bandwidths of 10% of the corresponding central frequencies and subsequently we averaged the amplitudes calculated from all the EEG channels.

III. METHODS

A. Optical flow

Optical flow is a well established technique for approximate reconstruction of spatial movements as recorded in sequences of optical images [5, 6]. In our case the method aims to reconstruct the vector field of velocities from the luminance changes that are generated by moving objects when recorded by video camera.

$$L(x,y,t) \to \{V_x(x,y,t), V_y(x,y,t)\} \tag{1}$$

Where $L(x,y,t)$ is the intensity field contained in the video recording as function of the 2D spatial coordinates (x,y) and the time t. To compute optical flow we used a standard implemented method provided by the Computer Vision System Toolbox version 4.1 from Matlab®, Mathworks Inc. Natic, USA, release 7.13 (2011b).

B. Reconstruction of group motion parameters

Once we reconstructed the velocity fields, we reduced the data by extracting only rates of global motion parameters. To simplify the notation in (1) we first introduce complex coordinates and velocities:

$$W(z,t) = V_x(z,t) + iV_y(z,t) \tag{2}$$

Where $z = x + iy$, and $i = \sqrt{-1}$. The group of non-homogeneous linear transformations is then defined by the linear decomposition of (2):

$$W(z,t) = T(t) + R(t)z + S(t)\bar{z}\ ; \tag{3}$$

Here $T(t), R(t)$ and $S(t)$ are complex scalars representing: T - the translational rates (velocities) along the two image axes (the real and imaginary parts); R - the rotational and dilatational rates, and S - the shear rates.

The estimation of T, R and S is done directly from the optical flow output W (3) as follows:

$$\begin{aligned} T(t) &\cong \langle W(z,t) \rangle_z \\ R(t) &\cong \langle \bar{z} W(z,t) \rangle_z \\ S(t) &\cong \langle z W(z,t) \rangle_z \end{aligned} \tag{4}$$

In (4) we used a normalized parameterization of the image coordinates such that:

$\langle z \rangle_z = 0$; $\langle z^2 \rangle_z = \langle z\bar{z} \rangle_z = 1$; or in real notation $\langle x \rangle_{x,y} = \langle y \rangle_{x,y} = \langle xy \rangle_{x,y} = 0; \langle x^2 \rangle_{x,y} = \langle y^2 \rangle_{x,y} = 1$

In summary, from the original video image sequence, we derive three complex, or equivalently six real, time series representing the rates of linear spatial transformations.

C. Temporal filtering and normalization

To segment the epochs containing repetitive motor movements resembling seizures, we applied a filtering procedure extracting the seizure movements' frequencies, i.e. variations between 2Hz and 6Hz of the transformation rates (4). We used a custom method that appeared to give fast performance and results not differing from standard filtering procedures. The method was also suited for potential real time application as a seizure alarm system. The filtering steps are described in short below. Let $X^c(t)$ denote any of the six real quantities estimated by (4). Here the letter c denotes the channel number, 1…6.

a) Low-pass filtering: High frequencies are removed by smoothing the signals using neighbor point averaging. Given the frame rate of 25Hz and an upper limit for "clonic" events of 6Hz we averaged over every two sequential time points. $X^c(t) \to (X^c(t) + X^c(t-1))/2.$

b) High-pass filtering: We build a temporal embedding vector: $\{E^c(t,\tau)\}_{\tau=0}^{n-1} \equiv (X^c(t), X^c(t-1) \ldots X^c(t-n+1))$ - a redundant representation of the original signal. We then linearly de-trend E^c around every point t along the time shift dimension τ. In this way slow oscillations extending beyond n-points are removed. We assumed $n = 12$; for a frame rate of 25Hz this would provide high-pass filtering of around 2Hz as required.

c) Signal Variation: As a measure of signal strength we take $P^c(t) = std_\tau(E^c(t,\tau))$

d) Feature smoothing: To obtain a smoother identifier of "clonic" events, we consider the sequences: $\{P^c(t-k)\}_{k=0}^{N-1}$, removing the largest and the smallest element, and perform harmonic averaging $P^c(t) \to \exp(\langle \log(P^c(t-\tau)) \rangle_\tau)$. We choose N=100 which corresponds to 4 seconds, the assumed minimal length of a detectable "clonic" seizure.

e) Normalization factor: The same procedure as described above is performed with respect to the original signal $X^c(t)$ but without Low- and High pass filtering (no de-trending in step ***b)*** and performing in step ***d)*** simple averaging. In this way we obtain the signal variation $P_0^c(t)$ containing all motion frequencies.

We define now the likelihood of a MMS event contained in each of the six channels (4) as $Q^c(t) \equiv P^c(t)/P_0^c(t)$. At the end of this step, six output motor seizure likelihoods ranging between 0 (no –seizure) and (1 –certain seizure) are produced $Q(t) = \langle Q^c(t) \rangle$.

D. Selection of filtering parameters using Gabor spectral technique.

For the analysis of the non-stationary spectrum of the EEG signals [7, 8] we have constructed a set of Gabor wavelets with 65 members and central frequencies ranging exponentially between 4 and 100 Hz.

The Gabor aperture functions are given as

$$g(t-t',\nu) = \frac{1}{N_\nu} e^{-\pi^2\alpha^2\nu^2(t-t')^2 - i2\pi\nu(t-t')} - O_\nu \qquad (5)$$

Where ν is the central frequency and the product $\alpha\nu$ is the bandwidth of the filter. The normalization factor N and the offset factor O_ν are chosen so that the functions have zero mean and unit 1-norm, or $\sum_{t=-\infty}^{\infty} |g(t,\nu)| = 1$. We have also selected for the factor α a constant value of 0.1. The result of our choice for the Gabor set (5) is therefore a sequence of scale transformed filters with bandwidths of 10% of the corresponding central frequencies.

In other words the sequence $\{\nu_i\}_{i=1}^{65}$ was chosen so, that $\frac{(\nu_k - \nu_{k-1})}{(\nu_k + \nu_{k-1})} = \alpha, k = 2,\ldots,65$. For each electrophysiological trace (channel) $F_{ch}(t)$ where $ch = 1,2,\ldots,21$, we define its Gabor time-frequency dependent amplitude as

$$G_{ch}(t,\nu) \equiv \left| \int_{t'} dt'\, g(t-t',\nu) F_{ch}(t') \right|$$

To reduce the data, we averaged the spectral amplitudes first in the time domain, considering windows of 4 seconds with 50% overlap. Next we averaged the Gabor amplitudes over the set of EEG traces $G(t,\nu) = \langle G_{ch}(t,\nu) \rangle$

E. Cross-covariance.

The cross-covariance measures similarity between two signals or time series as a function of the time-lag. In this study we use the normalized cross-covariance between discrete functions (vectors):

$f(t) = dQ(t)/dt$, $g(t,\nu) = \partial G(t,\nu)/\partial t, t = 1,2,..., N$, where $N = 200$ in our case, and we choose as time-lag interval $[-N_\tau,\ldots,N_\tau]$ as $\tau = -99,\ldots,-1,0,1,\ldots 99$

The cross-covariance is then defined as:

$$C_{gf}(\tau \geq 0,\nu) = \frac{1}{N-\tau} \sum_{t=1}^{N-\tau} (g(t+\tau,\nu) - \bar{g})(f(t) - \bar{f}),$$

$$C_{gf}(\tau < 0,\nu) = C_{fg}(-\tau,\nu), \bar{g} \equiv \frac{1}{N}\sum_{t=1}^{N} g(t,\nu), \bar{f} \equiv \frac{1}{N}\sum_{t=1}^{N} f(t).$$

After normalization with the product of two auto-covariance functions at zero lag (equivalent to the signal variations) we obtain the normalized cross-covariance function with $2N_\tau + 1$ elements:

$$C_{gf}(\tau,\nu) \Rightarrow C_{gf}(\tau,\nu) / \sqrt{C_{gg}(0,\nu) C_{ff}(0)}$$

This last function is depicted on Figure 3.

IV. Results

We consider separately each case from the available set of 42 seizures. The time course of the spectral amplitudes obtained from all the EEG traces showed high level of EEG activities starting between 10 and 15 seconds before the CPM, or on occasions even earlier. To establish the spectral dependence of this activity, the average over the EEG channels was examined and matched against the video detection. Each particular frequency has been normalized to its value at the CPM point - the result is presented on Figure 1. Note that a) because of the recording method (scalp recording), muscular artifacts are always present during MMS that are characterized by high frequencies typically in the gamma range, and b) during the recording some artifacts around the frequency of 50Hz may be present due to signal contamination induced by the mains AC frequency.

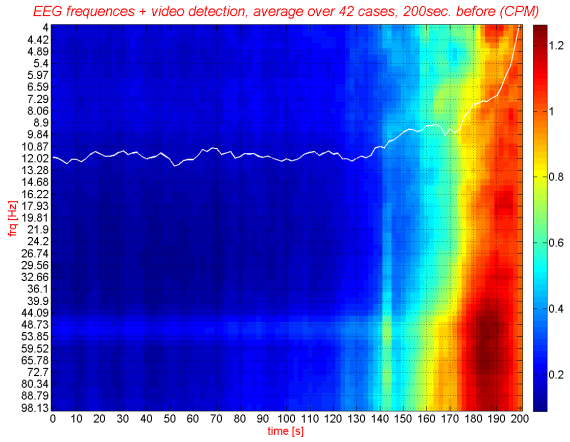

Figure 1. –The horizontal axes shows the time before CPM- total 200 seconds; on the right side (right time limit) is the CPM, as detected by our algorithm.; the vertical axes shows frequency from 4 to 100 Hz logarithmically scaled; the embedded white line illustrates the video detection quantification, and has been rescaled to fit the main image plot.

During the last 20 seconds before CPM, features related to the activities during the "clonic" phase, most likely muscle scalp activities, are visible in the frequency range of 40-100Hz. Approximately 40 to 60 seconds before CPM one can find EEG activities at the low frequency range 4-8Hz, which gradually disappear (within 10-15 seconds interval) by decreasing as frequency drops further towards 4Hz.

In Figure 2 the distribution of the video detection quantity, the "seizureness", as function of the time preceding a seizure is shown.

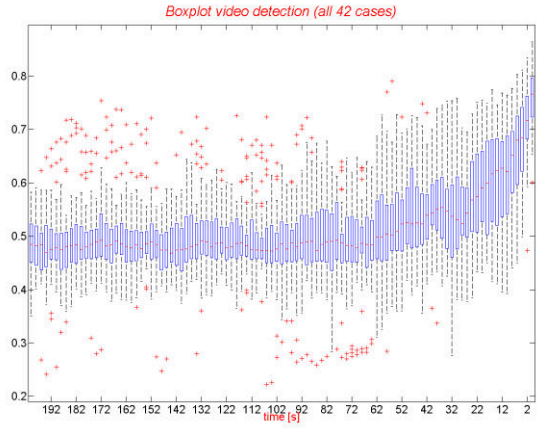

Figure 2. Illustration of the time course of the distribution of video detection feature from all the 42 cases; The horizontal axes shows the time before CPM- total 200 seconds; Each box represents statistical distribution of video detection function values for all 42 cases corresponding to each time mark. On each box, the central mark is the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data points not considered outliers, and outliers are plotted individually with red stars.

In order to quantify the dependences between the time courses of the EEG spectral amplitudes and the video detection feature, we used cross-correlation analysis between the time derivatives of the corresponding sequences. The normalized correlation functions for all the 42 seizures are averaged and the result is presented in Figure 3.

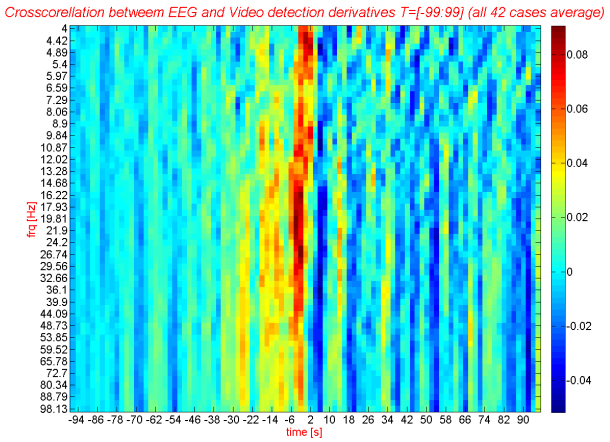

Figure 3. The result of cross-covariance between the time derivatives of the EEG spectra and video detection; Plot shows normalized cross-covariance function averaged for all the 42 seizures; Frequencies are presented on the vertical axis; Horizontal axis presents time lags indicated in seconds; Where EEG preceded the video signal appears in the negative part (negative time scale) of the plot; where video preceded the EEG appears in the positive part (positive time scale) of the plot. The pseudo-color scale indicates level of normalized covariance coefficient from -1 (fully anti-correlated) to 1 (fully correlated); Note that the video detection applies to the clonic phase of the motor seizure. This may be preceded by a tonic phase of variable duration. The latter, however, is not taken into account in the analysis presented here.

At most frequencies the EEG spectral amplitudes precede the video detection by about 2-8 seconds. Note the precursory high values of the amplitudes at around 5Hz preceding the video detection by 20 seconds and those in the interval between 20Hz and 80Hz preceding with 30 seconds. The detailed information about the maximal amount of correlation between the spectral amplitudes and the video detection feature is shown on Figure 4.

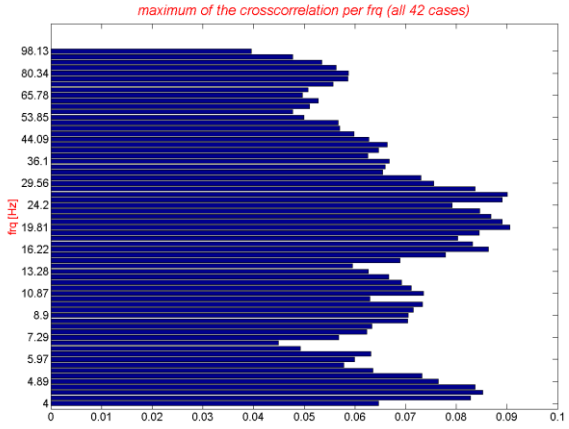

Figure 4. Distribution of frequency ranges, preceding the video detection

V. Conclusions and Discussion

The robust quantification and the early detection of epileptic motor events are major challenges in the field of epilepsy research. This study shows that there are identifiable electro-graphical events which occur prior to the seizure "clonic" seizure phase as detected by video analysis. This suggests some possibilities for earlier detection. Fully automated detection algorithms could be developed on the basis of the present study. Automated systems for such seizure detection may contribute to the quality of life of patients suffering from those conditions and also may provide a faster and more efficient tool for diagnostic screening of large data sets [9].

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