A&QT-R 2002 (THETA 13)
2002 IEEE-TTTC International Conference on Automation, Quality and Testing, Robotics
May 23-25, 2002, Cluj-Napoca, Romania

QUALITY ASSESSMENT OF GLOBAL OVER CLASSICAL DESCRIPTION FEATURES IN MEDICAL SIGNAL ANALYSIS

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Abstract: The EEG signal analysis has passed during last decades through and increasing variety of methods having as result a better quality of clinical usefulness and results. All used methods rely on recorded data and as the data size of multichannel EEG is high in long term monitoring, most of the methods are using relevant features extracted from the signal samples. Most recent investigations are using single global parameters in order to describe EEG signal or to track and detect clinical relevant changes. Those features as complexity, dynamical embedding, and mixture of such parameters are tested here to investigate the feasibility of using them instead of classical ones (e.g. amplitude, instantaneous frequency) for clinical related signal processing.

Key words: EEG, analysis, features, frequency, complexity

1. INTRODUCTION

Human brain activity investigations appears to be a not easy to handle task even by well trained experts. The EEG recorded data is considered to be a representative approximation of the brain neurones activity via theirs electric transmitted potentials.

EEG recording gives a way of understanding the normal or pathological problems involved. Identifying an EEG with a specific event and his nature can help support a diagnosis, and may also be used to classify the type of specific event (normal, artefact, spike, seizure, K-complexes, sleep spindles, etc.).

However, the clinicians analysis of such a huge resulting database is not only exhausting but quite impossible to be done to the same constantly level of accuracy. No matter the sophisticated tools that the clinician is using for reducing the data size without loosing useful information, the final classification step should be done by using such criteria that cannot be handled via classical automatic techniques.

The EEG research investigations are trying to improve the techniques of extracting the useful signal from the high level of external or internal noise. Next step is the data pre-processing in order to enhance the features for further extraction. Once extracted, the features (such as amplitude, frequency, time-frequency representations as wavelets, etc.), that consist of values or statistical measures of values series, are considered to completely represent the whole signal for the research purpose point of view (e.i. feature or the set of features contains all the required information for investigated event detection). This is why the feature choice is a very important step in medical signal processing investigations.

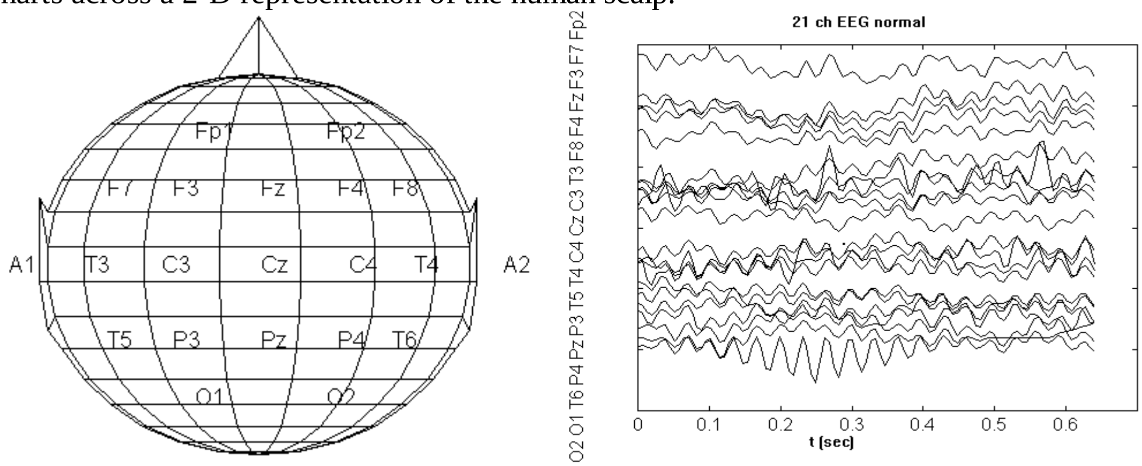
2. THE EEG RECORDING OF BRAIN NEURAL ACTIVITY

The EEG signal, emanating from the brain, can be measured by placing electrodes at various points on the subject's scalp. Principal rhythm components for EEG analysis could be described as follows by means of their frequency and amplitudes:

δ 0,5 ... 3 Hz, 50...150μVpp,
θ 4...7 Hz, 30... 70 μVpp,
α 8...13 Hz, 30... 100μVpp,
β 14...32 Hz, 30μVpp,
γ 33..55 .. 70 Hz.

Recently, for a more accurate analysis alpha and beta rhythms are split each in two regions of clinical interest α1, α2 and β1, β2.

Actual stage of charts of components representations are made using either FFT of the signal or PSD from cross-correlation function of the signal or just filtering the signal according to each band and integrating the power. Analysis systems are showing frequency charts across a 2-D representation of the human scalp.



a) b)

Fig. 1. Electrodes recording position (a) and recorded EEG (b) non-pathological

3. CLASSICAL FEATURES IN EEG SIGNAL DESCRIPTION

3.1. *FFT Features*

These features use power or coherence spectra to determine their values.

CSFeature: The power spectra density (μV/Hz) from a two dimensional spectrogram. The Frequency Band Min/Max, the channels, and the channel combination method (avg, max, min, stddev) could be arguments.

PowerFeature: The average power spectra (μV) over the selected frequency range. The Frequency Band Min/Max, the channels, and the channel combination method (avg, max, min, stddev) could be arguments.

EdgeFeature: The edge frequency (Hz) over the selected frequency range. The Frequency Band Min/Max, the frequency edge percentage (e.g., 90%), the channels, and the channel combination method (avg, max, min, stddev) could be arguments.
If the feature "Edge 90 1-14" has a value of 4 Hz, then 90 percent of the total power (in μV^2) in the 1-14 Hz range appears in the range 1-4 Hz.

CoherenceCSFeature: The coherence spectra (0 to 1) from a two dimensional spectrogram. The Frequency Band Min/Max and the two channels could be arguments.

CoherenceFeature: The average coherence spectra (0 to 1) over the selected frequency range. The Frequency Band Min/Max and the two channels could be arguments.

PeaksCSFeature: The discrete peaks of the power spectra from a two dimensional spectrogram. The Frequency Band Min/Max, the number of peaks, the attribute (rhythmicity or amplitude), the channels, and the channel combination method (avg, max, min, stddev) could be arguments.
The discrete peaks are found by identifying the largest N local maximums of the power spectrum. The peak half-width is also determined and used to calculate the rhythmicity parameter (μV/Hz) as the peak's amplitude divided by its half-width. (Each peak is described by its frequency, amplitude, and half-width.)

PeaksFeature: One of the discrete peaks of the power spectra. (This is a one dimensional portrayal of a portion of the information from PeaksCSFeature.) The Frequency Band Min/Max, the peak of interest (peak 1 is the largest peak), the attribute (frequency, rhythmicity or amplitude), the channels, and the channel combination method (avg, max, min, stddev) could be arguments.

FFTMiscellaneousFeature: The FFT parameter of interest, which is calculated over the selected frequency range. The Frequency Band Min/Max, the FFT parameter, the channels, and the channel combination method (avg, max, min, stddev) could be arguments.

The parameters that can be displayed are FreqAvg, FreqStdDev, FreqStdDevOverAvg, Mobility, and Complexity.

<u>FreqAvg and FreqStdDev</u> (Hz) are computed by using the power spectrum (μV^2) as the weighting factor.

<u>FreqStdDevOverAvg</u> = FreqStdDev / FreqAvg and may be thought of as a measure of rhythmicity (small peak width).

3.2. *Multi-Epoch Features*

These features utilise the values of previous epochs in the calculation of the current value.

BackgroundChangesFeature: Look for differences between recent and previous epochs. On the basic feature to operate on, the operation must be applied, and the foreground, lag and background durations might be arguments. The operations include:

$$\text{AvgRatio} = x_f / x_b \tag{1}$$

$$\text{AvgDelta} = x_f - x_b \tag{2}$$

$$\text{StdDevRatio} = s_f / s_b \tag{3}$$

$$\text{StdDevDelta} = s_f - s_b \tag{4}$$

$$\text{DeltaAvgOverStdDev} = (x_f - x_b)/ s_b \tag{5}$$

$$\text{TStat (student's T-test statistic)} = (x_f - x_b)/\text{sqrt}(s_f^2 / N_f + s_b^2 / N_b) \tag{6}$$

where x is the average, s the standard deviation and N the number of epochs (determined from the duration) of the foreground and background.

StatisticalControlFeature: This feature is similar to the **BackgroundChangesFeature**, but it allows to compare the foreground to a (statistical) population of choice (including a fixed background). The feature to operate on, the operation, the foreground duration, and the control population's count, average and standard deviation might be arguments.

EventDensityFeature: The event density for a particular type of event. The type of the event, the summation method (Count or Perception), and the normalisation method (per epoch, second, minute or hour) could be arguments. If the event include a perception flag (number as e.g. 0.5) then the weighted Perception summation method may be used.

TimeFunctionsFeature: Result of apply a multi-epoch function to a feature. For the feature to operate on, the function is the operation (average, standard deviation, min or max), and the duration of the foreground (active operation epochs) and possibly a lag duration might be other arguments.

3.3. *Functional Features*

ConstantFeature: The feature takes on a constant value for all epochs. The constant value is a unique reference.

FunctionFeature: Result of applying a function to a feature. The feature and the function to apply (LOG10, SQRT, SQUARE, ABS, POS, or NEG).

FuzzyFeature: Result of applying a soft threshold to one or more features. The features, the threshold center and width, the comparison type (greater than, equal or less than), and threshold function (linear or logistic).

If the standardised variable x is given by
$x = (v-c) /w$, where v is the feature value, c is the center and w is the width.
The linear equations are given by:

$$GT = \max (0, \min(1,1/2+x) \tag{7}$$

$$EQ = \max (0, \min(1,1+2x) \text{ for } x<0 \text{ and } \max (0, \min(1,1-2x) \text{ for } x\geq 0 \tag{8}$$

$$LT = \max (0, \min(1,1/2-x) \tag{9}$$

Functionally, the logistic equations can be described in terms of a base function f(x) given by

$$f(x) = 1 / (1 + e^{-8x}) \quad (10)$$

The logistic feature value is then calculated from the base function and the comparison type and given by:

$$GT = f(x) \quad (11)$$
$$EQ = 4 f(x)(1-f(x)) \quad (12)$$
$$LT = 1 - f(x) \quad (13)$$

The chart in figure 2 plots these functions.

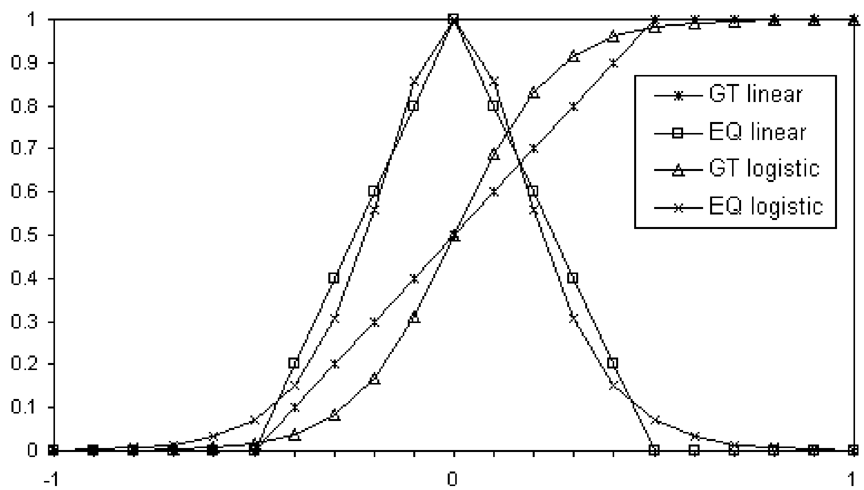


Fig. 2. Base functions for fuzzy feature

4. GLOBAL FEATURES IN EEG CHARACTERISATION

4. 1. *Underlying System Features*

Mobility (Hz) and **Complexity** (unitless, greater than or equal to 1.0) are Hjorth parameters [6].

Mobility, giving a measure of the standard deviation of the slope with reference to the standard deviation of the amplitude … may be conceived as a mean frequency as in [6]. Mobility is similar to FreqAvg, but the square of the frequency is used.

Complexity, giving a measure of excessive details with reference to the "softest" possible curve shape, the since wave, this corresponding to unity. Complexity is another measure of rhythmicity with a perfectly rhythmic (single component) spectrum having a value of 1.0.

4.2. *Dynamical Embedding Features*

EMFeature: Embedding matrix feature can be used to quantify system complexity, uncovering as much information as possible about the generators based only on the measured (EEG) data as in [7]. Further possible processing for changes detection of this EMFeature includes: entropy, Fisher's information measure, or even Independent Component Analysis that can lead to a set of ICA Features.

4.3. *Combinations of Features*

It is possible to implement neural network or fuzzy system rules through various combinations of features. (The logistic GT FuzzyFeature applied to the output of a WeightedSumFeature is a NN node.)
Generally the development of event or state detectors require the use of specific development tools for experimentation or learning.

The complex analyses systems generally use combination of feature as the best choice for parameter input of the detection or recognition step. Very related to results in using combinations seems systems as [5] concerned with three primary features, amplitude, asymmetry and front/back differentiation.

5. CONCLUSIONS

As an estimate result of the feasibility of using global parameters instead of classical local ones, the investigation of all candidate features described in section 3 and 4, showed the advantage of mixed features choice in EEG brain signal investigations. For specific event as the epileptic seizure or either low waves in EEG recordings the global parameter resulted as a weighted sum of EMFeature and a 1/3 percentage of Frequency features are showing the best results of over 92% over 52 test sets available each of 20 min EEG pathological (19 sets) and non-pathological (33 sets) recordings from the test set. Advantage and best possible application of global feature is to the long term automatic monitoring of EEG signals leading to an increased percentage in detection of the event. The limitations of the features combinations that include global features is due to the low detection of short time events as spikes that better fit to features described in 3.1.

6. REFERENCES

[1] Bigan C. and Woolfson M. (2000), Time-frequency analysis of short segments of biomedical data, *IEE Proceedings Science, Measurement and Technology* , 147 pp.368,
[2] C. J. James, R. D. Jones, P. J. Bones, G. J. Carroll, (1998), Spatial analysis of multi-channel EEG recordings through a fuzzy-rule based system in the detection of epileptiform events, *Proc. of the 20 th Annual Int. Conf of IEEE EMBS*, Hong Kong, pp198.
[3] S. Hibino, T. Hanai, E. Nagata, M. Matsubara, K. Fukagawa, T. Shirataki, H. Honda, T. Kobayashi, (2001) Fuzzy neural network model for assessment of Alzheimer-type dementia, *Journal of Chemical Eng. of Japan*, Vol.34 No. 7 pp.936-942.
[4] P. Hilfiker, M. Egli,(1992) Detection and evolution of rhythmic components in ictal EEG using short segment spectra and discriminant analysis, *Electroenceph. Clin. Neurophysiol.*, 82, pp255-265.
[5]. Y. Si, J. Gotman, A. Pasupathy, D. Flanagan, B. Rosenblatt, R. Gottesman (1998) An Expert System for EEG Monitoring in the Pediatric Intensive Care Unit, *Electroencephalography and Clinical Neurophysiology*, 106, pp. 488-500.
[6] B. Hjorth, (1970) EEG analysis based on time domain properties, *Electroenceph. Clin. Neurophysiol*., 29, pp. 306-310.
[7] C.J. James, D. Lowe, (2001), Information dynamics view of brain processing function, *Proc. of IEEE 23-rd Annual International conference of the IEEE EMBS*, pp.120.