POWER SPECTRUM ESTIMATION IN THE CALCULATION OF SPECTRAL ENTROPY TO ASSESS DEPTH OF SEDATION

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Abstract: The problem of the dependence of spectral entropy on data length is addressed. The EEG data recorded from 12 ICU patients is analyzed using four different schemes of power spectrum estimation for obtaining spectral entropy. Two of the schemes comprise the Welch periodogram averaging method, one scheme is based on the estimation of the autocorrelation function and one on the autoregressive modelling. The results show that spectral entropy values depend highly on the smoothness of the power spectrum estimate. Spectral entropy correlates significantly with data length only if FFT is used for power spectrum estimation and the FFT size varies together with the data length.

Introduction

Developing an objective measure for anesthetic depth has been a subject of great interest during the past decade. Although EEG-based devices for anesthesia monitoring were available already in 1970s [1], a breakthrough took place in 1997 when Aspect Medical Systems Inc., USA, introduced the Bispectral Index Score (BIS). This scalar index is a combination of three parameters calculated from the EEG signal: 1) the Beta Ratio, based on the power spectrum, 2) the SynchFastSlow measure, calculated in the bispectral domain, and 3) the burst-suppression ratio [2]. BIS gained much popularity and is currently widely used by anesthesiologists. It is often referred as the 'golden standard' in anesthesia monitoring.

Since the introduction of BIS, many companies have developed their own algorithms for the assessment of depth of anesthesia. The following commercially available methods can be mentioned as examples: the Patient State Index (PSI) by Physiometrix Inc., USA [3], the Narcotrend index by MonitorTechnik, Germany [4], the Entropy index by Datex-Ohmeda, Finland [5], the cAAI Index by Danmeter, Denmark (the algorithm is partly described in [6]). The performance of these indices has been discussed in numerous papers. However, comparison of the methods is difficult as the studies differ in various aspects like the anesthetic drug used, medication, patient condition etc.

Besides the various commercially available systems several new measures have recently been proposed for the assessment of anesthetic depth. This has mainly been motivated by the complexity of the problem – the available methods are far from being exhaustively studied while at the same time the field of application of depth-of-anesthesia/sedation measures is getting wider comprising the Intensive Care Unit (ICU) as well as Emergency. Main interest has been in measures quantifying the entropy and/or complexity of the EEG signal like approximate entropy [7], Shannon entropy [8], Lempel-Ziv complexity [9], Higuchi fractal dimension [10], spectral entropy [5].

Our interest has recently been to compare the behavior of the various entropy/complexity measures at different levels of sedation in the ICU. We have found that the various ways of quantifying signal entropy/complexity depend on different signal properties causing sometimes their contradictory behavior. For example, while all the other entropy measures decrease with deepening sedation, Shannon entropy tends to increase. Shannon entropy depends purely on the amplitude distribution of the signal regardless of the information about the time order of the samples. Another important observation is the sensitivity of the results on the EEG frequency band incorporated into the analysis. For example, cutting off the high frequencies and incorporating the delta frequency band tends to reverse the relation between sedation depth and EEG entropy at light levels of sedation.

This paper addresses a problem we met in comparing the entropy/complexity measures of the EEG signal – the dependence of spectral entropy on the length of the signal window. Our aim was to test if this dependence was due to added information when incorporating more data or if it was due to the algorithm.

Material

The results presented in this paper are based on EEG recordings from 12 ICU patients (age from 29 to 83 with the mean 63 years). Patients with known neurological disorders and patients admitted to the ICU after drug overdose were excluded from the study. The study was approved by the Ethics Committee of the South Karelia Central Hospital. The EEG electrodes were placed bilaterally to the forehead, below the hairline, approximately 5 cm above the eyebrows. The

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distance of the electrodes from the midline was about 4 cm to either direction. The EEG signal was sampled with 400 Hz frequency.

Ramsay score assessments were performed by the ICU nurse during the course of the recordings according to predefined protocol. The Ramsay score uses 6 stages to evaluate the level of consciousness with score 1 indicating the subject being fully awake and score 6 indicating full unconsciousness, i.e., the lack of response to slightly painful stimulus [11]. The time instants of Ramsay score assessment were determined according to the following protocol (if the status of the patient allowed scoring):

1) during steady state periods:
   - 30 minutes after previous scoring
   - the patient had been in a steady state for at least 10 minutes
2) during interventions
   - immediately after the bolus dose of the anesthetic drug given before the intervention
   - if bolus dose was not given, just before the intervention
   - in addition, 1-2 minutes after the intervention
3) when sedation was stopped:
   - immediately after the sedation was stopped
   - in addition, 10-15 minutes after the sedation was stopped

All the recordings were carefully annotated.

Spectral entropy was calculated of manually selected signal segments. The segments were extracted according to the following rules:

- the segments had to precede the Ramsay score assessment
- the segments had to be as close to the Ramsay score assessment as possible
- if burst-suppression pattern was seen in the EEG or if the signal was too noisy the corresponding Ramsay score assessment was discarded.

Valid signal segments obtained from the data were distributed according to the Ramsay score values as follows:

Ramsay score	1	2	3	4	5	6
Number of segments	7	20	69	82	36	107

Methods

Spectral entropy is defined as:

$$S[f_1, f_2] = \sum_{f_i = f_1}^{f_2} P_n(f_i) \log \frac{1}{P_n(f_i)},$$

where $P_n(f)$ is the normalized power spectrum (normalization here means that $\sum_i P(f_i) = 1$) and spectral entropy is estimated in the frequency range $f_1 \dots f_2$. Usually the result is also normalized to give entropy values between 0 and 1:

$$S_N[f_1, f_2] = \frac{S[f_1, f_2]}{\log(N[f_1, f_2])},$$

with $N[f_1, f_2]$ being the number of frequency values in the considered frequency range. Thus, spectral entropy is a measure of 'flatness' of the power spectrum with pure sine wave and white noise giving the entropy values 0 and 1, respectively.

In the calculation of spectral entropy usually periodogram is used to estimate the power spectrum. However, it is well known that periodogram is an unconsistent estimate of power spectrum - in other words, the estimate does not converge to the true power spectrum as more data becomes available.

In order to study the cause of the dependence of spectral entropy on data length, the selected 20 second segments of the EEG signal were processed using four different schemes of the estimation of power spectrum:

1) Welch periodogram averaging method I; the signal segment was divided into subsegments with 50% overlap. The subsegments were windowed using the hamming window and the FFT was taken. The estimate of the power spectrum was obtained as the average of the FFTs of the subsegments. We used four subsegment lengths: 1.25 sec., 2.5 sec., 5 sec. and 10 sec. - the shorter the subsegment the more subsegments were incorporated into the average. The FFT size was increased together with the subsegment length.
2) Welch periodogram averaging method II; this scheme was similar to the previous one except that the FFT size was kept constant - 4096 data points. The signal subsegments were zero-padded before taking the FFT.
3) Autocorrelation method; the autocorrelation function was estimated and power spectrum was obtained as the FFT of the hamming-windowed middle part of the autocorrelation function. Four different window lengths were used for cutting the middle part of the autocorrelation function: 5 sec., 10 sec., 20 sec. and 40 sec. The FFT size was equal to the window length.
4) Autoregressive modeling; power spectrum was estimated based on the coefficients of the autoregressive model. Model orders of 16, 32, 48 and 64 were used.

Results

The results are shown in figures 1…4 for the different schemes of power spectrum estimation. Figure 1 shows that if the FFT size is varied, the obtained spectral entropy is highly dependent on the signal subsegment length over which the FFT is calculated. Figure 2 shows that this dependence is actually reversed if the segmentation scheme remains the same but the FFT length is kept constant – in our case 4096 data points. The dependence is not as severe as in the case of scheme 1. Figure 3 shows that using the autocorrelation function for power spectrum estimation did not eliminate the dependence of the results on the window length as far as the FFT size changes together with the window length.

In the case of AR modelling, the behaviour of the power spectrum depends on the model order rather than the length of the signal window. Therefore, the coefficients were estimated over the whole 20 sec. signal segment. Figure 4 shows that if sufficient AR-model order is used, the obtained spectral entropy is fairly stable, not depending on the choice of the model order.

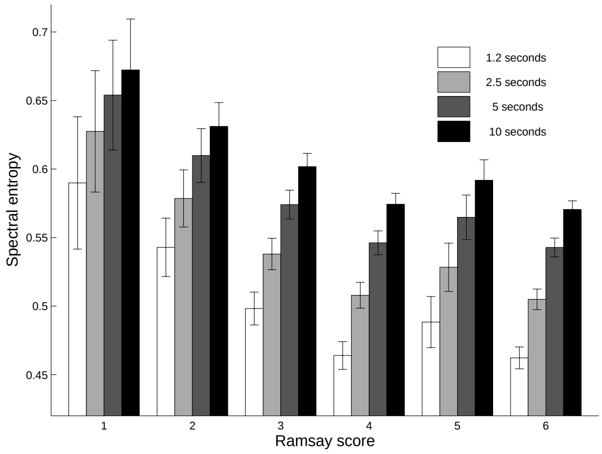

Figure 1: Correlation of spectral entropy with the Ramsay score. Power spectrum is estimated using the Welch periodogram averaging method I. The window lengths of 1.2 sec., 2.5 sec., 5 sec. and 10 sec. are used; the length of the FFT is increased together with the window length.

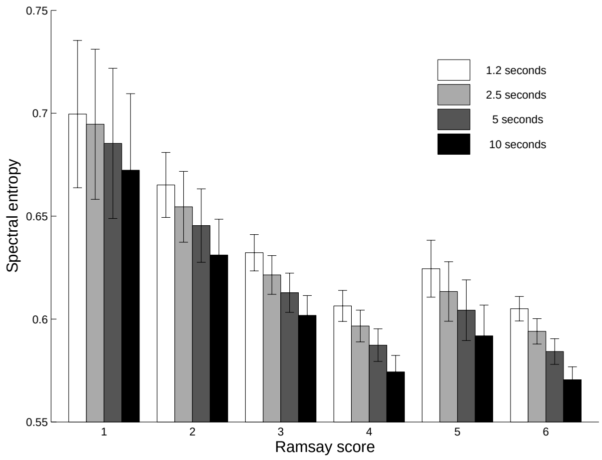

Figure 2: Correlation of spectral entropy with the Ramsay score. Power spectrum is estimated using the Welch periodogram averaging method II. The window lengths of 1.2 sec., 2.5 sec., 5 sec. and 10 sec. are used; the signal subsegment is zero-padded to give the FFT length of 4096 samples for all window lengths.

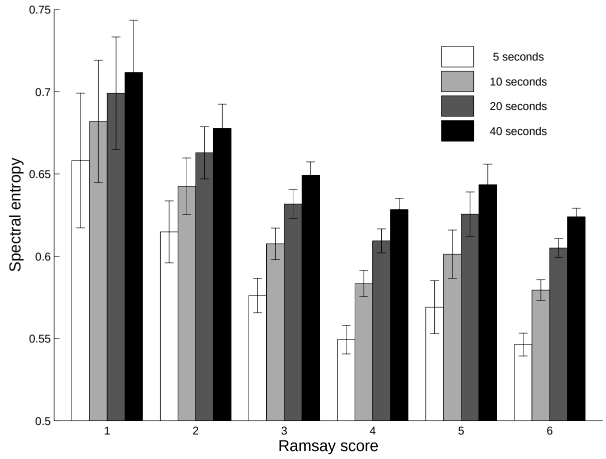

Figure 3: Correlation of spectral entropy with the Ramsay score. Power spectrum is estimated using the autocorrelation method. FFT is taken over the middle 5 sec., 10 sec., 20 sec. and 40 sec. part of the autocorrelation function.

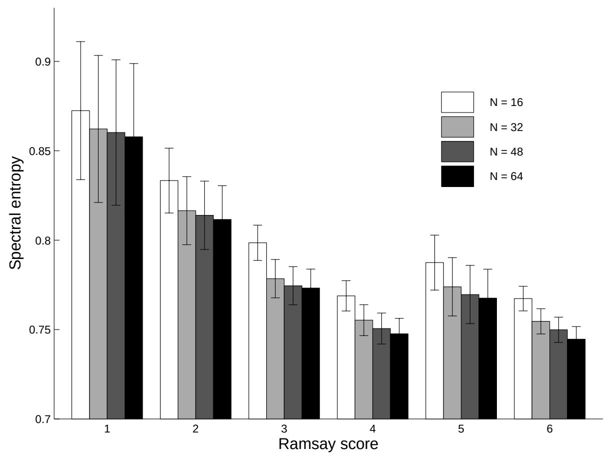

Figure 4: Correlation of spectral entropy with the Ramsay score. Power spectrum is estimated using autoregressive model coefficients. The order of the AR model of 16, 32, 48 and 64 is used.

An important result based on the figures is the correlation between the smoothness of the power spectrum and the value of spectral entropy. AR-model gives generally smoother power spectrum compared to the Welch periodogram averaging method. The figures show that the entropy values obtained using AR-model coefficients are in the range of 0.75…0.87 while the other schemes give values in the range approximately 0.5…0.7. Also, if constant FFT size is used (fig. 2), the entropy value is higher for shorter subsegment length, corresponding to smoother power spectrum (shorter subsegments mean averaging over larger number of subsegment spectra). In figure 1 this does not hold due to the effect of varying FFT size.

Discussion

The results presented in this paper show that the dependence of spectral entropy values on the length of the signal window is not caused by the variable amount of information available but rather the properties of the periodogram as the estimate of the power spectrum. The amount of data available was equal – 8000 samples – for all the calculation schemes. Both schemes using varying FFT size (schemes 1 and 3) caused severe correlation between the FFT size and the spectral entropy value.

Based on the results we suggest that the AR-model based calculation scheme for spectral entropy is the most stable with respect to data size. Model order 16 seems to be too low to capture the behaviour of the true power spectrum. Model of order 32…48 can be suggested.

It is important to note that although the different schemes for power spectrum estimation gave different values of spectral entropy, the correlation of the entropy with depth of sedation was not affected. This implies that as far as equal window lengths are used, the choice of the power spectrum estimation method is not critical.

Conclusions

The following conclusions can be drawn from the analysis presented in this paper:

- the ability of the estimate of EEG spectral entropy to differentiate between various levels of sedation does not depend on the method used for power spectrum estimation in general. However, spectral entropy values achieved using different methods for power spectrum estimation are not comparable with each other
- in the case of periodogram averaging, higher spectral entropy estimates for longer data windows are not due to the additional information contained in the data but rather comes from high variance of the power spectrum estimate typical to this method
- in general, smoother power spectrum estimates (using AR-model coefficients, for example) give higher values of spectral entropy.

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