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Linear and non-linear parameterization of EEG during monitoring of carotid endarterectomy

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ABSTRACT

In this paper, new quantitative linear (HLF ratio: high frequency/low frequency spectral power ratio) and non-linear parameters (ZC: zero crossing and FD: fractal dimension) which can assist the physician in real-time decision whether a shunt is required or not during intra-operative EEG monitoring of carotid endarterectomy are presented. The results obtained with the new parameters are compared with those achieved by other indexes proposed in the literature. The HLF ratio and ZC parameters yielded the best results with a 100% of correct identification of both shunt and no-shunt situations. The ZC can be also easily implemented in the real-time monitoring of EEG.

1. Introduction

Carotid endarterectomy (CEA) is a well-known surgical procedure for the prevention of stroke in patient with high-grade carotid stenosis and is generally performed with selective shunting [1]. Intraoperative ischemia during carotid cross-clamping in patients undergoing CEA is a major complication and prompt recognition of insufficient collateral blood supply is crucial (occlusion of the controlateral internal carotid artery is considered to have a significant impact on the outcome of CEA). Several methods are used to limit perioperative stroke: the measurement of the carotid back pressure [2], the evaluation of the awake patient under regional anaesthesia [3], the transcranial Doppler measurement [4], the monitoring of somatosensory evoked potentials [5], and the continuous EEG monitoring [6–10]. The latter is still the most used form of monitoring cerebrovascular insufficiency during CEA. As EEG visual analysis is subject to human error and makes quantification of signal's alterations difficult, it is evident that a quantitative measure should identify more reliably those patients that need a shunt during artery clamping. To this aim, a series of parameters based on EEG spectral analysis, producing reasonable results, have been recently proposed [11–13]. They are supported by the fact that a decrease in relative alpha and beta band powers as well as possible hemispheric asymmetry represents clear signs that the brain is at risk during CEA [14,15].

On the other hand, in addition to the conventional linear methods of analysis based on the power spectral density (PSD) function, also non-linear measures have been proposed for EEG examination [16–20]. These parameters permit to distinguish among different comportamental states [16], sleep [19,20] and resting states [21] as well as to predict epileptic seizures [18] and to classify EEG signal [17].

In order to support the physician in a prompt decision whether or not shunting is needed, the possibility of real-time evaluation, and the reliability and ease of interpretation represent specific characteristics that quantitative EEG parameters should have. Following these requirements, in this paper some linear and non-linear EEG parameters that could be used to monitor the cerebral reaction to significant blood flow reduction are investigated and compared with those proposed in the literature [11–13]. The new linear parameter is based on the observation that in presence of brain suffering the spectral power decrease in the 8–15 Hz band is very often associated to a power increase in the low frequency band. In order to take into account both behaviours, the ratio between the signal power in the 8–15 Hz and in the 0.5–5 Hz will be considered. The non-linear parameters that will be examined are the zero crossing (ZC) and the fractal dimension (FD), that have shown to be able to distinguish various EEG situations bringing complementary information with respect to the one carried out by linear analysis.

2. Materials and methods

2.1. Patients

A group of 140 patients who underwent consecutively an EEG monitoring during CEA procedure in 2003–2006 at the University Hospital of Trieste were retrospectively examined. We underline that artifacts, well recognized by the human observer, are not trivially eliminated or compensated for by computer programs, so that after

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an off-line EEG re-analysis we simply decided to reject from the study the cases (5) in which the artifacts were so strong to make hard and unreliable also the expert decision. The remaining 46 female and 89 male patients (age of 70 ± 8 years) were considered in the study.

All CEAs were performed under general anaesthesia and decision to shunt was based on intraoperative EEG monitoring. Selective shunt was advised (21 patients) if the visual inspection of EEG, as interpreted by an experienced electroencephalographer during clamping procedure, showed significant mono- or bi-lateral EEG alterations. These modifications included a decrease in fast activity and/or an increase in slow activity (slowing down in running EEG), or an attenuation of all EEG activities (voltage reduction).

The accurate EEG off-line re-analysis finally permitted to reclassify two patients who belonged to the not shunted group as to be shunted. Hence, on the whole, 112 not shunted and 23 shunted patients were considered for the classification.

2.2. EEG recording and analysis

EEGs were recorded according to the international 10–20 system using Ag/AgCl electrodes. The acquisition was performed using Galileo System (EBNeuro, Florence, Italy) with a 128 or 512 Hz sampling frequency. Ten bipolar derivations were utilized for the analysis (F4–C4, C4–P4, P4–O2, F8–T6, T6–O2, F3–C3, C3–P3, P3–O1, F7–T5, T5–O1). Although some EEG derivations may be more sensitive to anomalies during carotid surgery than others [22], in this work we decided to equally weight all EEG derivations in order to simplify the procedure. The off-line investigation was carried out during the 3 min before and 3 min after the artery clamping, separately for right and left side derivations. The signal coming from each derivation was resampled (if necessary) at 128 Hz, digitally filtered with a Butterworth high pass filter with a 0.4 Hz cutoff frequency and a low pass filter at 40 Hz and divided into 50% overlapping sections having a 20 s duration (2560 points), each of which was detrended and windowed (Hamming). All parameters were calculated in these epochs and averaged among all the derivations of the same hemispheric side, obtaining one value per parameter and side every 10 s. The baseline for all parameters was evaluated from the first 3 min preceding the clamping procedure (reference period), using the median value in this period.

Finally, we quantified possible variations of the parameters after clamping with respect to the baseline value by calculating for each parameter and side, at each step t, two different functions: the % relative variation, $R(t)$, and the Z-score, $Z(t)$, defined as

$$R(t) = \frac{P(t) - \bar{P}}{\bar{P}} * 100, \quad Z(t) = \frac{P(t) - \bar{P}}{\sigma}$$

where $P(t)$ represents the generic parameter value at step t; $\bar{P}$ and σ correspond to the median and the standard deviation values, respectively, of the parameter P calculated in the reference period. The $R(t)$ function determines the percent parameter change during clamping compared to the reference period, while the $Z(t)$ function measures the significance of the difference between post-clamping and reference period values.

Linear analysis considered some spectral parameters calculated from the PSD estimated by periodogram method:

$$PSD = \frac{1}{N}|DFT|^2$$

DFT being the Discrete Fourier Transform of the EEG.

From PSD, the power in the traditional EEG-ranges (delta 0.5–4 Hz, theta 4–8 Hz, alpha 8–13 Hz, beta 13–18 Hz) and the power in a low frequency band (LF: 0.5–5 Hz) and in a high frequency band (HF: 8–15 Hz) were computed. In addition also the ratio HF/LF (HLF ratio) was calculated. The latter and the HF index were used in the following. We underline that the HF parameter is basically identical to the desynchronization index described by [12].

Beside these linear parameters, some other non-linear factors were evaluated. In particular ZC and FD of each EEG interval were estimated.

The ZC counts is a non-linear parameter used in the analysis of random signals [23]. It can be computed by counting the number of baseline crossings in a fixed time interval. Let $x(1), x(2), \ldots, x(N)$ be a zero-mean stationary Gaussian time series. Consider the associated clipped binary series $y_1(n)$ defined by

$$y_1(n) = \begin{cases} 1, & x(n) > 0, \\ 0, & x(n) \leqslant 0, \end{cases} \quad n = 1, \ldots, N$$

and let $y_2(n)$ be the associated series defined as

$$y_2(n) = y_1(n+1), \quad n = 1, \ldots, N-1$$

where $y_2(N) = y_2(N-1)$

We define three new binary series by

$$z_1(n) = y_1(n) \quad \text{OR} \quad y_2(n)$$
$$z_2(n) = y_1(n) \quad \text{NAND} \quad y_2(n)$$
$$z_3(n) = z_1(n) \quad \text{AND} \quad z_2(n)$$

Then the ZC count is computed by the sum

$$ZC = \sum_n z_3(n)$$

Fruitful connections exist between ZC counts and dominant frequency. When a certain frequency band becomes dominant, it attracts the normalized expected zero crossings and $ZC/2/N-1$ admits values in this band. Likewise, when a certain frequency f_0 becomes significantly dominant then $ZC/2/N - 1 \cong f_0$. Thus, it is possible to use the ZC parameter in order to identify possible changes in dominant spectral components during carotid clamping. The calculation of this parameter is faster than the one of the spectral power and it can be correctly estimated also on short epochs (down to 2 s).

The FD represents a measure of the complexity of the EEG signal able to distinguish specific behavioural states (sleep stages, epileptic seizure, etc.). Among the various algorithms available for FD estimation, in this study FD was computed by Higuchi's algorithm [24] which is based on the measure of the mean length of the curve $L(k)$ by using a segment of k samples as a unit of measure.

From a given time series $x(1), x(2), \ldots, x(N)$, the algorithm constructs k new time series x_m^k defined as

$$x_m^k = \left\{ x(m), x(m+k), x(m+2k), \ldots, x\left(m + \left\lfloor \frac{N-m}{k} \right\rfloor \cdot k\right)\right\}$$

for $m = 1, 2, \ldots, k$, where m and k are integers indicating the initial time value and the discrete time interval between points, respectively, and $\lfloor a \rfloor$ means integer part of a. For each of the k curves x_m^k the length $L_m(k)$ is calculated as

$$L_m(k) = \frac{\sum_{i=1}^{\lfloor N-m/k \rfloor} |x(m+ik) - x(m+(i-1)\cdot k)| \cdot (N-1)}{\left\lfloor \dfrac{N-m}{k} \right\rfloor k} \frac{1}{k}$$

where N is the total number of samples and the term $(N-1)/(\lfloor N-m/k \rfloor \cdot k)$ is a normalization factor. The length of the curve, for the k-th time interval, $L(k)$, is computed by averaging the k values $L_m(k)$ for $m = 1, 2, \ldots, k$. The procedure is repeated for each k ranging from 1 to $k_{\max}$. If $L(k)$ is proportional to k^{-FD}, the curve is fractal-like with dimension FD. Then if $L(k)$ is plotted against $1/k$, for k ranging from 1 to $k_{\max}$, on a double logarithmic scale, the data should fall on a straight line with a slope equal to $-$FD. Thus, by means of a least-squares linear fitting procedure applied to the series of pairs ($L(k)$, k), the FD value is estimated.

Table 1
Threshold values for the parameters used in the subject classification.

	$R(t)$ threshold
FD	−5%
ZC	−15%
HLF ratio	−40%
HF/desync index	−35%
ΔsSBI	0.05
ΔtBSI	0.02

The values are expressed in terms of % relative variation, $R(t)$, during clamping compared to the pre-clamp reference period. For the sBSI and tBSI parameters the thresholds described in [13] were used.

Like in the case of ZC, the estimation of FD is faster than spectral analysis and it can be reliably performed on short epochs (down to 2 s).

The behaviour of the three new indexes (HLF ratio, ZC and FD) was compared to that of the HF (or desynchronization index) and of the sBSI and tBSI parameters suggested by van Putten [11,13]. The sBSI index is a normalized measure for interhemispheric spectral symmetry defined as

$$sBSI = \frac{1}{N}\sum_{i=1}^{N}\left\| \frac{1}{M}\sum_{j=1}^{M}\frac{R_{ij}-L_{ij}}{R_{ij}+L_{ij}} \right\|$$

where R_{ij} (L_{ij}) are the Fourier coefficients belonging to frequency $i = 1, \ldots, N$ of the right (left) hemispheric bipolar derivations $j = 1, \ldots, M = 5$. In our case $N = 50$ (frequency range 1–25 Hz, with spectral bandwidth of 0.5 Hz). Before calculating the FFT transform, the EEG data were resampled at 256 Hz in order to replicate the work of van Putten [13].

On the other hand the tBSI index is sensitive to diffuse EEG changes. With the aim of eliminating the contribution of a possible spatial asymmetry the tBSI is calculated [13] as

$$tBSI = \frac{2 * tBSI' - sBSI}{2} \tag{1}$$

with tBSI′, a measure of temporal EEG changes, defined as

$$tBSI' = \frac{1}{N}\sum_{i=1}^{N}\left\| \frac{1}{K}\sum_{j=1}^{K}\frac{S_{ij}-Sref_{ij}}{S_{ij}+Sref_{ij}} \right\| \tag{2}$$

where S_{ij} are the Fourier coefficients belonging to frequency $i = 1, \ldots, N$ of the right and left hemispheric bipolar derivations $j = 1, \ldots, K = 2{*}M$, and $N = 50$ as before. All van Putten's parameters were calculated on 10 s intervals.

2.3. Patients classification

To decide if a subject should be identified as to be shunted or not, the values for each side of the four parameters (HF, HLF ratio, ZC and FD) during the post-clamp period were compared with suitable thresholds. Different thresholds for $R(t)$ functions were manually tested starting from values that visually could discriminate the pre-post clamp changes when present (see for example Subject3 in Fig. 2). The thresholds that produced the best classification (in terms of accuracy) are reported in Table 1. For $Z(t)$ functions a threshold of −1.2, very poor for the significance level ($P > 0.23$) but representing a good compromise to achieve the best accuracy, was set for the parameters. We determined that shunting has to be advised if the parameter exceeds, at least in one of the two sides, the threshold value for no less than 30 s. A procedure was then implemented in order to automatically recognize each CEA as belonging to "shunted group" or to "non-shunted group". For the tSBI and sBSI indexes the classification criterion followed the thresholds on ΔtBSI and ΔsBSI reported in van Putten [13].

Table 2
Scheme of the truth table used in the classification process.

		Automatic classification based on the thresholds of Table 1	
		Shunted	Not shunted
EEGrapher expert classification	Shunted	A	B
	Not shunted	C	D

A and D represent the number of true positive and true negative cases, respectively. B is the number of false negative and C is the number of false positive cases.

To estimate the effectiveness of a correct patient classification (shunted or not), for each parameter a truth table (scheme in Table 2) was calculated by comparing the parameter classification with that of the electroencephalographer experts (this corresponds to the real-time clinical choice followed by off-line re-analysis).

Starting from each truth table the results were statistically described in terms of sensitivity (true positive/[true positive+false negative]), specificity (true negative/[true negative+false positive]), and accuracy ([true positive+true negative]/total number of maps) that are classical statistical measures of the performance of a binary classification test related to the concepts of type I and type II errors.

All the EEG analyses were performed using our software developed in the MatLab (The Mathworks, Inc) environment.

3. Results

The analysis of the EEGs showed that hypoperfusion was generally accompanied by a decrease (monolateral or diffuse) of the power in the alpha, beta and HF bands and frequently also by an increment in the delta band, confirming previous results [9,14]. The HLF ratio also decreased during suffering while FD showed different behaviour during clamping: for more than 50% of shunted cases it increased rather than decreasing even if it was able to point out asymmetries (as shown, for example, in the Subject2 of Fig. 2).

Examples of EEG traces and corresponding parameters time courses in typical patients who underwent a CEA are shown in Figs. 1 and 2, respectively. Fig. 1 presents 5 s during the pre-clamping and 5 s during the post-clamping periods of EEG traces of a patient who did not need the shunt (Subject1) and of two patients presenting, after clamping, monolateral changes (Subject2) or mainly diffuse suffering (Subject3). While the EEG changes are evident in Subject3, for all the EEG channels, these are visible only on left derivations in Subject2; in Subject1 the EEG remains substantially unchanged.

In Fig. 2 the $R(t)$ function trends of FD, ZC, HLF ratio, HF, sBSI and tBSI parameters during 3 min before and after the clamp, in the three typical patients of Fig. 1, are shown. The vertical dashed line corresponds to the clamp start time while the horizontal dashed lines correspond to the threshold values reported in Table 1. Points below (for FD, ZC, HLF ratio and HF parameters) or above the threshold (for sBSI and tBSI parameters) are considered as mark of suffering. For FD, ZC, HLF ratio and HF parameters, the selected thresholds (Table 1) correspond to those that produced the best subject classification (in terms of accuracy); the thresholds for sBSI and tBSI parameters were selected following the criteria reported in van Putten [16]. These refer to a difference between the actual value during clamp and the mean value during pre-clamp period.

Left column of Fig. 2 shows that in five of the six monitored parameters, changes due to clamping are not able to pass the threshold, confirming that no changes occurred in the EEGs analysis (Subject1 in Fig. 1). Only the tBSI parameter fluctuates around the threshold, which proves to be too low. In a second example shown in Fig. 1 (Subject2), visual EEG analysis recognizes severe changes in the left

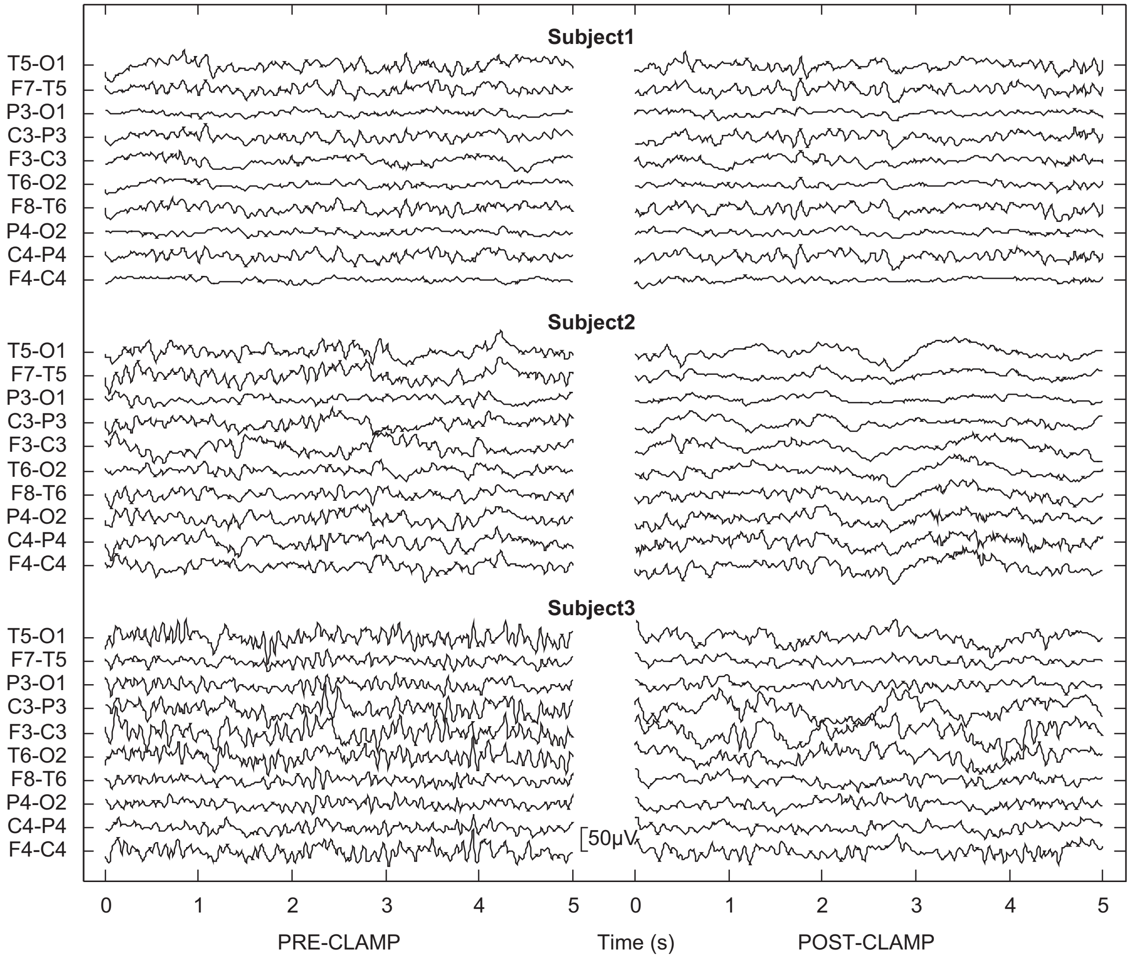

Fig. 1. Five seconds of EEG traces during pre- (left columns) and post-clamp (right columns) periods in three typical patients presenting no changes (Subject1), monolateral differences (Subject2), and mainly diffuse suffering (Subject3). Subject1 was not shunted while the remaining two were shunted.

hemisphere, correctly reflected in a more or less asymmetric reduction in four of the examined parameters (central column of Fig. 2). In this case both the tBSI and sBSI parameters correctly point out the monolateral suffering. In the third case, a decision to shunt was based on the appearance of alterations in the activity of both hemispheres, detectable in the curves shown in Fig. 1 (Subject3) as well as in the behaviour of the three new proposed parameters and of the HF index (right column of Fig. 2). In this case the sBSI parameter alone is not able to identify the suffering, showing its intrinsic limitation due to the demand of an altered EEG symmetry in order to operate in a correct way. Instead, the tBSI parameter well highlights the situation. We underline that even if the FD parameter shows the presence of asymmetry (Fig. 2, central column) or of evident gap (Fig. 2, right column), it does not exceed beyond doubt the preset threshold.

Behaviours similar to those of the $R(t)$ functions are presented by the four parameters expressed in terms of Z-score functions. In the latter case a fixed threshold of -1.2 was used for all the considered parameters.

Table 2 shows the truth table scheme used in the classification process. In order to analyze the classification outcomes, the results obtained from each examined parameter by using both the $R(t)$ and the $Z(t)$ functions are shown in Table 3. The classification is expressed in terms of number of subjects correctly classified in the two classes (shunted: true positive and no shunted: true negative) to which they were assigned by the visual EEG analysis. In the same table, the sensitivity, the accuracy and the specificity of each parameter are also displayed.

The classification obtained from the $R(t)$ functions is slightly better than that gained from the $Z(t)$ ones, and in the following we considered only the $R(t)$ functions.

The ZC and HLF ratio parameters presented the best result, correctly classifying all the considered subjects, demonstrating a complete correlation with hypo-perfusion complications. Also the HF parameter showed a very good discrimination capability producing only four false positives. The FD parameter as well as the sBSI index, even though they showed a very good specificity (100% of no shunted cases correctly classified), unfortunately were not able to suitably identify the cases to be shunted (60–70% of wrong cases). On the contrary, the tBSI index permitted to recognize all the shunted cases but produced a large quantity (25%) of false positives.

4. Discussion

Although the visual analysis of the EEG represents the standard method to decide when the shunt is needed during CEA, it is current opinion that this procedure is subject to human error and requires great experience in interpreting the graphs' alterations. Thus, quantitative real-time EEG analysis becomes any day more and more required, representing a useful additional information assisting in the decision for selective shunting. In the literature some parameters, like for example BSI [11], sBSI and tBSI [13], have been proposed

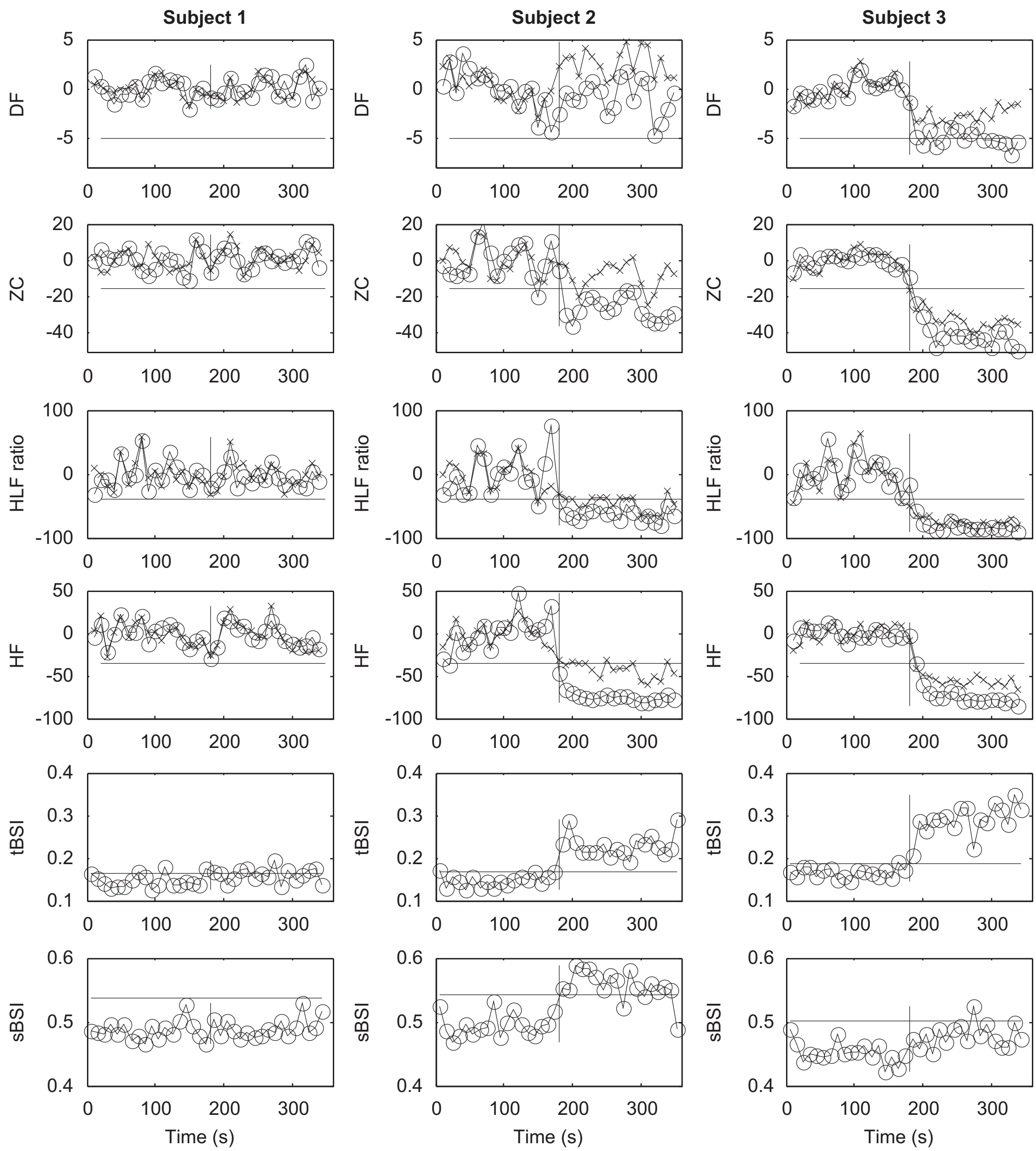

Fig. 2. Percent relative variation, $R(t)$, time courses of the considered parameters, corresponding to the three typical situations in Fig. 1. Left column: Subject1 presenting no changes; central column: Subject2 with asymmetric differences; right column; Subject3 showing mainly diffuse suffering. For the FD, ZC, HLF ratio and HF parameters "x" represents the right hemisphere and "o" the left hemisphere. Vertical lines: clamping start; horizontal lines: threshold values.

even if their validity has been evaluated only preliminarily on few cases [11–13]. In this paper we proposed and evaluated, on a large number of CEA cases, three new parameters (HLF ratio, ZC and FD) helpful in the monitoring of cerebral hypoperfusion due to artery clamping, and we compared their behaviours and reliability with those of the indexes suggested in the literature. The HLF ratio and ZC parameters yielded the best results with 100% correct identification of both shunt and no-shunt situations, while FD did not yield satisfactory results and produced many (about 70%) false negatives.

At first we examined the differences in the classification (Table 3) obtained by using $R(t)$ and $Z(t)$ functions: for all the parameters, $R(t)$ functions allowed the correct classification of one or two more cases than by using $Z(t)$ functions. This very small difference may be due to the use, for the $Z(t)$ functions, of a single threshold value (i.e. -1.2) for all the parameters while, for the $R(t)$ ones, the thresholds were optimized for each parameter (see Table 1). This fixed value represented only a compromise to achieve the best accuracy; in fact a threshold of 1.96, corresponding to a significant ($P < 0.05$) difference between pre- and post-clamp mean values, is more correct from a statistical point of view but is inappropriate for a good classification. However, the $Z(t)$ functions are also influenced by the signal variability and consequently by the noise present on the EEG: more noise produces larger variance and smaller $Z(t)$ changes, making harder to exceed the threshold.

Another remark concerns the EEG derivations used in the parameter calculations: even if some authors [22] suggest to use selected derivations because of their higher sensitivity in detection of anomalies during carotid surgery than others, in this work we obtained

Table 3
Sensitivity, accuracy and specificity together with the number of shunted (true positive) and of not shunted (true negative) subjects correctly classified on 23 and 112 total cases, respectively.

Parameter	True positive	True negative	Sensitivity	Accuracy	Specificity
FD–$R(t)$	7	112	0.30	0.88	1.00
FD–$Z(t)$	8	110	0.35	0.87	0.98
ZC–$R(t)$	23	112	1.00	1.00	1.00
ZC–$Z(t)$	22	112	0.96	0.99	1.00
HLF ratio-$R(t)$	23	112	1.00	1.00	1.00
HLF ratio-$Z(t)$	21	112	0.91	0.99	1.00
HF–$R(t)$	23	108	1.00	0.97	0.96
HF–$Z(t)$	23	106	1.00	0.96	0.95
sBSI	9	112	0.39	0.90	1.00
tBSI	23	84	1.00	0.79	0.75

The values refer to each considered parameter and to both the % relative variation, $R(t)$, and the Z-score, $Z(t)$, functions.

good results also using equally weighted bipolar EEG channels; consequently, a channel selection was not considered necessary.

A main result of this work is to show that the $R(t)$ functions of two of the new examined parameters, namely the ZC and the HLF ratio, were able to correctly identify all cases presenting either mono- (asymmetric) or bi-lateral (diffuse) hemispherical suffering (as suggested by visual EEG analysis). In these cases the left and right $R(t)$ time courses presented, for a 30 s segment at least, a significant decrease below a threshold of −15%, for ZC, and of −40%, for the HLF ratio, of the pre-clamp mean values, thus providing precise indications of possible cerebral ischemia. In addition, the two parameters were also able to precisely discriminate all the cases in which the shunt was not necessary, corresponding to no significant EEG changes, showing they could capture EEG variations due to any kind of intra- or inter-hemispheric suffering. Furthermore, the simultaneous use of two $R(t)$ curves, one for each EEG side, permits to immediately identify possible asymmetries present in the EEG changes during CEA.

The HLF ratio was based on the hypothesis, described in the literature [8,14,25], that alpha and beta EEG spectral powers decrease in presence of brain hypoperfusion followed by an increase of delta power, the latter being frequently not significant. Basing on a similar idea, but limited only to the alpha and beta bands, Cursi et al. [12] suggested the desynchronization index (corresponding in this paper to the $R(t)$ function of the HF parameter). As reported in the results, the HF was really able to correctly identify all the subjects to be shunted and only four cases of no shunted patients were wrongly classified. Moreover, we underline that the threshold value we found for the HF index is the same suggested in [12].

Adding the information coming from lower frequencies (0.5–5 Hz band), used as the denominator in the HLF ratio parameter, improves the HF performance: exact subject classification is achieved. This work confirms that the 8–15 Hz frequency range is the band which is most sensitive to possible cerebral suffering during CEA [12,14]. Moreover, the results support the hypothesis that the utilization of the information included into the 0.5–5 Hz band may slightly improve the specificity, producing a more accurate identification of the cases that do not require shunting.

The ZC parameter, recently proposed for detecting dementia, sleep-stage characteristics as well as background activity [19,26,27] from EEG series, showed to be capable of sensing reduction of fast activity as well as possible slow activity changes, thus producing an indicator that can assist in the decision whether to proceed with shunting during CEA. The ZC parameter, measuring possible dominant frequency (or band) modifications, proved to be strongly correlated with the visual assessment of the EEG changes due to brain suffering.

We underline that the ZC parameter is very easily calculated directly from temporal signals and it does not require power spectrum evaluation of the EEG (as the HLF ratio or the HF do). Hence it is suitable for a real time implementation and its time course, added as a further signal in the visualization of the EEG derivations, may permit the successful outcome of the surgical procedure.

The third examined new parameter, FD, capable of distinguishing specific comportamental states as well as sleep stages, epileptic seizures, etc. [16–20] did not yield satisfactory results. In fact it produced many (about 70%) false negatives (i.e. it did not identify many subjects to be shunted), even if it correctly recognized all the subjects that did not need shunting. This situation was mainly due to an uncertain decrement of the FD values in many cases of cerebral hypoperfusion; the FD changes were too small and an increase of the threshold value produced a very large increment of false positive cases.

The FD parameter, measuring the fractal behaviour of an EEG signal, was not able to recognize generalized EEG decreases, since it does not change if the signal is merely rescaled in amplitude; thus it produced many classification errors. Furthermore, the EEG complexity changes sensed by the FD were so small they did not exceed the threshold.

The sBSI parameter produced slightly better results than the FD one. The index corresponds to the previously proposed [11] brain asymmetry index (BSI) and it should quantify hemispheric changes in spectral symmetry. Unfortunately, the sBSI index excluded about 60% of the subjects to be shunted (false negative), confirming the limits already underlined by [13] even if on a limited number of cases (4). In fact, the sBSI parameter was able to detect only the cases presenting asymmetric spatial changes in the EEG, showing on the contrary insensitivity to distributed attenuation of fast activity or to diffuse increase of delta activity.

In order to overcome this limitation and to be also sensitive to temporal changes in spectral characteristics, a further index (tBSI) was proposed by van Putten in [13]. The tBSI index yielded 28 wrongly classified cases, on a total of 112 (25% of false positive), suggesting shunt when it was not necessary. We point out that the combined use of the sBSI and tBSI indexes did not improve the results; probably both sBSI and tBSI parameters are able to identify asymmetric changes. It is evident that the equation (Eq. (1)) used by van Putten could be not sufficient to cancel the influence of spatial asymmetries on tBSI, or (alternatively but improbably) all the cases here considered showing asymmetry also included diffuse EEG changes sensed by the tBSI parameter. However, in all our examined subjects the tBSI index alone produced the same classification result as when used with the sBSI contribution.

Furthermore, since the tBSI index calculation considers the absolute value of the pre/post-clamp difference (Eq. (2)), it is modified not only by a signal decrease but also by a signal increase that generally indicates activation [9], as it could happen when the haematic flow increases or anaesthesia becomes less deep. This situation is signalled by the tBSI parameter as a need of shunt when it is actually not required; this fact could explain some of the false positives obtained with this index.

5. Conclusions

Since routine shunting may increase the risk of perioperative stroke [8], EEG monitoring by means of suitable parameters quantifying the EEG changes proved to be useful in shunt decision during CEA.

In this paper the $R(t)$ functions of some new parameters, in particular the HLF ratio and the ZC indexes, showed to be able to correctly identify cases presenting mono- or bi-lateral hemispherical changes capturing both asymmetric and diffuse suffering situations. As proved by our retrospective analysis, in those patients where the mean value of the HLF ratio or the ZC parameters go below −40% and

−15% thresholds, respectively, in the 3 min before clamping, visual EEG analysis showed significant changes, and shunting was advised. Slightly worse results (4% of false positives) had been achieved also with the HF/desynchronization index (previously proposed by [12]) while the pair of sBSI/tBSI parameters (or the tBSI alone) produced about 25% of false positives. Finally, the FD parameter and the sBSI index alone did not yield good results, and generated large classification errors.

In conclusion, we think that the $R(t)$ function of the ZC parameter represents the best choice both for a correct classification and for the possibility of a real time implementation. The contemporary utilization of the $R(t)$ left and right functions permits an immediate quantification of possible asymmetries as well as, when used as continuous display beside the EEG derivations, the identification of EEG changes due to artefacts or anaesthesia. Thus, we propose to use the ZC parameter to support the visual assessment of the EEG during CEA, offering a quantitative measure for EEG alterations due to cerebral hypo-perfusion.

6. Summary

Intra-operative EEG monitoring during carotid endarterectomy is the commonest method used to reduce the risk of brain ischemia. Beside visual assessment of the EEG, some quantitative parameters, based on spectral information, have been recently suggested as additional criteria for shunt need decision. In this paper we explore new linear (HLF ratio) and non-linear parameters (ZC and FD) which can assist the physician in real-time decision whether a shunt is required or not. The results obtained with the new parameters are compared with those achieved by means of previously proposed indexes, the desynchronization index and both the sBSI and tBSI. The HLF ratio and ZC parameters prove to be slightly better than the other ones producing 100% correct identification of both shunt and no-shunt situations offering easily detectable EEG indexes during surgery. In particular, these parameters are more effective than the previous ones for recognition of patients that do not need shunt. The FD parameter shows 100% correct identification for no-shunt situation but only 38% for shunt condition. Since the ZC parameter can be also easily implemented in a real-time analysis of EEG, we suggest to add this parameter in EEG monitoring.

Conflict of interest statement

None declared.

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