REPRESENTATION OF SOMATOSENSORY EVOKED POTENTIALS USING DISCRETE WAVELET TRANSFORM

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ABSTRACT. Objective. Somatosensory evoked potentials (SEP) have been shown to be a useful tool in monitoring of the central nervous system (CNS) during anaesthesia. SEP analysis is usually performed by an experienced human operator. For automatic analysis, appropriate parameter extraction and signal representation methods are required. The aim of this work is to evaluate the discrete wavelet transform (DWT) as such a method for an SEP representation. **Methods.** Median nerve SEP were derived in 52 female patients, scheduled for elective surgery with SEP monitoring, under clinically proven conditions in the awake state. The discrete wavelet transform implemented as the multiresolution analysis was adopted for evaluating SEP. The suitability of the wavelet coefficients was investigated by calculating the error between the averaged response and the corresponding wavelet reconstructions. **Results.** SEP can be represented by a very small number of wavelet coefficients. Although the individual SEP waveform has an influence on the number and selection of wavelet coefficients, in all subjects more than 84% of the SEP waveform energy can be represented by a set 16 wavelet coefficients. **Conclusions.** The discrete wavelet transformation provides an efficient tool for SEP representation and parameterisation. Depending on the specific problem the DWT, can be adjusted to the desired accuracy, which is important for the subsequent development of automatic SEP analysers.

KEY WORDS. Somatosensory evoked potentials, discrete wavelet transform, multiresolution analysis.

INTRODUCTION

Somatosensory evoked potentials

Somatosensory evoked potentials (SEP) are electrophysiological responses in reaction to the stimulation of an afferent pathway measured over the somatosensory cortex. SEP are usually derived by stimulating the median or tibial nerve with a short electrical stimulus. Depending on the stimulation and measurement modalities, short-latency, mid-latency, and long-latency SEP waveforms can be recorded from the scalp and become visible after averaging 200–2000 sweeps. While the short-latency components reflect subcortical activity, the mid-latency components indicate the arrival of the afferent volley at the primary somatosensory cortex and long-latency SEP components reflect associated cortex areas. However, the generators of the different components are still debated [1, 2].

There is a broad application of SEP monitoring in the clinical routine, for either diagnosis or guiding

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therapy. During neurosurgical, vascular or orthopaedic surgery SEPs serve as a standard technique to monitor neural tracts at risk in order to provide early indication of neural impairment [3, 4]. Moreover, SEPs are useful to measure the functional state of the central nervous system (CNS) for scientific reasons [5].

Recently SEPs have been proposed to assess the level of anaesthesia [6, 7]. Supervision of anaesthesia itself is important in order to control the adequate level of anaesthesia. A low level of anaesthesia runs the risk of intraoperative awareness, movement and neuroendocrine stress response during surgery. Is the anaesthesia too deep, a prolonged recovery or to cardiovascular problems are more likely to occur. Therefore, anaesthetists are interested in research on evoked response in order to measure the depth of anaesthesia and to guide application of anaesthetics via a close-loop feedback system [8]. Finally, SEP recording is helpful in critically ill patients, in whom the clinical investigation of the neurological status is impaired due to sedation and relaxation [9].

Median nerve somatosensory evoked responses are frequently used for the questions addressed above. They are derived by the electrical stimulation of the median nerve at the wrist. SEP, which are recorded at the contralateral primary somatosensory projection area at the scalp, usually extend over a time range of 20–70 ms after somatosensory stimulation. They contain subsequent peaks (N20, P25, N35, P45 and N50) labelled to their polarity and time in milliseconds after stimulation, which are used as markers in SEP interpretation [1]. Figure 1 shows a typical (sweep averaged) SEP of a female subject in the awake state, where all peaks are well identifiable.

The most widely used analysis of somatosensory evoked potentials is based on the classification by a human expert who has to identify the SEP markers from N20 to N50. Both latencies and amplitudes are usually used for analysis. However, this subjective evaluation has several disadvantages. First, for correct classification, usually the expert requires a long period of training. Second, even after excessive training the experts' decisions can be prone to errors and depend on subjective experience. Hence, a fully automatic analysis of SEP by digital signal processing techniques is desirable as it enhances both reproducibility and objectiveness of the SEP analysis.

Signal processing of evoked potentials

The discrete Fourier transform (DFT) is an established tool to extract frequency information. For representation of time-dependent signals such as SEPs the usefulness of the DFT is rather limited since the temporal information is not represented adequately by the DFT coefficients [10]. The discrete wavelet transform (DWT), resolving with respect to both time and frequency domain, was originally developed for evaluation of seismographic data, and formed a focus of research applied to many signal analysis problems over the last decade [11]. Consequently, many studies dealt with the applicability of the DWT to the representation of auditory evoked potentials. The aim of this work is to investigate the applicability of the DWT to somatosensory evoked potentials. Both the accuracy of the SEP representation and the amount of required data will be investigated. This is important as the results of this work forms the basis for further research into e.g. the automatic recognition of the status of awakening by means of SEP analysis.

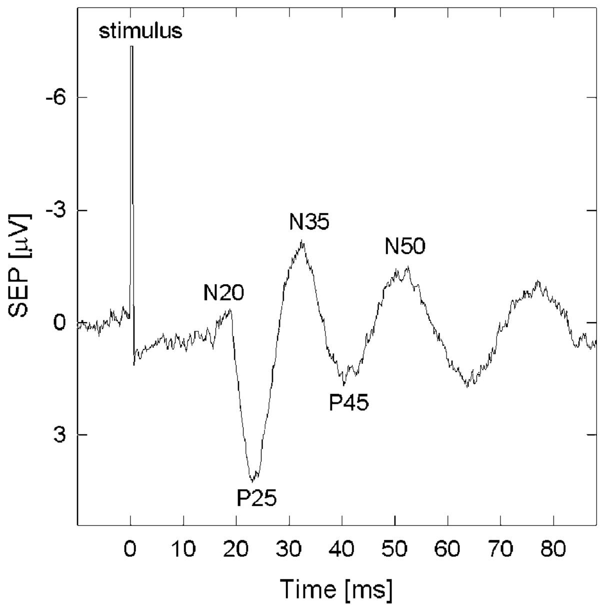

Fig. 1. Typical SEP as a response of median nerve stimulation at t=0 in an adult subject (awake) with pre-stimulus interval (10 ms), stimulus artefact and SEP components (N20, P25, N35, P45, N50). According to the midlatency standard negative scalp deflections are shown in upward direction.

MATERIALS AND METHODS

Patients

After obtaining approval from the local Ethics committee and written informed consent 52 female patients (41 ± 12 years, 1.67 ± 0.08 m, 67.9 ± 14 kg, ASA

[American Society of Anaesthesiology] classification: I–II), who were scheduled for elective surgery with SEP monitoring intra-operatively, were included in this prospective study. Patients with neurological diseases were excluded. The patients had not taken any drugs acting on the CNS.

SEP measurements

The day before surgery the patients got accustomed to the procedure of SEP recording in order to obtain baseline values in the awake state. SEP recording was performed in a standardised matter with an Evomatic 4000® system (Dantec, Copenhagen, Denmark). Generally, the right median nerve was stimulated, and in only few cases in which the planned operation interfered with this side the whole procedure was performed on the left median nerve. The stimulus intensity was increased to the individual level of tolerance. This intensity was kept throughout the whole study, and two replicate baseline recordings were performed. The stimulus frequency was 3 Hz with a 0.2 ms duration of the monophasic rectangular pulse. The SEP waveforms were recorded simultaneously on three amplifier channels using sterile platinum needle electrodes placed over the ipsilateral brachial plexus (Erb's point), the spinous process of the 6th cervical vertebra and the contralateral cortical hand area at the scalp (C3′ or C4′). For reference, a frontal electrode was applied on Fpz. Electrode impedances were kept below 10 kΩ. The analogue waveforms were digitised with a sampling rate of 10.24 kHz by the measurement equipment, which always recorded a post-stimulus interval of 90 ms ("sweep"). For later analysis, 200 consecutive sweeps were averaged and stored using a software package (EvoPC®, Müller, Hamburg, Germany). The latencies were manually evaluated. The following peak latencies were registered: N10 appeared at Erb N10, N13 at C6, and at the scalp three negative markers (N20, N35, N50) and two positive peaks in between (P25, P45) could be observed. Signal analysis of the digitised SEP signals was performed off-line using the software Matlab.

Wavelet analysis

The discrete wavelet transform (DWT) was developed to represent time signals by appropriate time-frequency windows. Similar to the Fourier transform, the wavelet transform performs a least squares fit of an analysis function to the time domain data. However, rather than a sinusoid extending over an infinite interval, here wavelet functions with limited support are employed as basis, which is advantageous when analysing transient signals [12]. For the discrete wavelet transform (DWT) considered here, a set of orthogonal basis functions is obtained by scaling and translation of a mother wavelet.

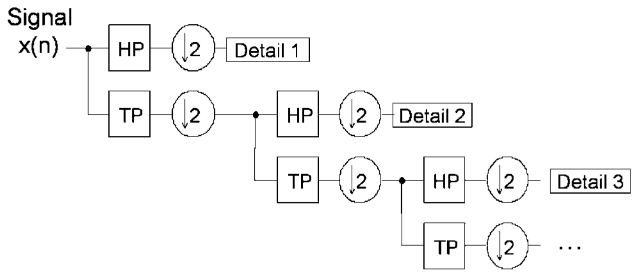

Fig. 2. Discrete wavelet transform (DWT) implemented as an octave filter bank: The signal x(n) is decomposed by subsequent lowpass and highpass filtering combined with subsampling (↓2). The Details form the DWT coefficients.

An efficient calculation of the DWT coefficients in the case of discrete-time data can be performed using the multiresolution analysis (MRA) [13]. For a dyadic DWT, this MRA is performed by filtering the signal to be analysed with an octave filter bank as shown in Figure 2. The highpass filter HP(n) forms a quadrature mirror filter (QMF) pair [14] with the lowpass TP(n) of the filter bank, where n indicates the discrete time index. The input sequence to the octave filter bank is the signal x(n) to be analysed. Through successive low- and highpass filtering of the samples in the lower frequency band, $\alpha_m(n)$ and decimation of the resulting signals by a factor of 2 (denoted as ↓2), subband samples $\beta_m(n)$ ("details") are obtained, which, except of the lowest frequency band, represent the DWT coefficients. The coefficients $\alpha_m(n)$ are intermediate values and correspond to a dual basis function of the wavelet, a so called scaling function [13]. The filters TP(n) and HP(n) are sampled versions of the underlying scaling function and wavelet, and therefore determine which DWT – amongst a large variety of possible wavelet functions [12, 14] – is being implemented.

Since the signal to be analysed, x(n), is only defined on a finite interval $n \in [0;N-1]$, suitable signal extensions [10] or boundary filters have to be selected. As both yield identical results [15], for ease of implementation the first possibility will be pursued. Zero padding is not viable for decomposition with a deep octave filter bank with many consecutive filtering operations, as information will be blurred over large intervals by the transient behaviour. Periodisation of the original data and of all intermediate filtering results $\alpha_m(n)$ however permits to filter in steady-state and thus retain all required information within a preserved period of the signal. With the possibilities of odd or even periodisations [10], the MRA yields N DWT coefficients that completely describe the original time series x(n) comprised of N samples. Recently, it was shown that odd extension is more suitable for application on evoked potentials [16]. However, restrictions to symmetric wavelets apply, if an odd periodic extension is selected [13]. An inverse discrete wavelet transform (IDWT) can be easily implemented by passing through the filter bank in backward direction. This IDWT allows either an exact reconstruction of the original signal from the DWT coefficients, or a partial reconstruction from a selected subset of coefficients.

RESULTS

Both the wavelet function and periodic extensions have to be chosen appropriately in order to achieve a good wavelet representation of the SEP. It is important to choose a wavelet function which offers good time domain localization properties and provides, at the same time, good frequency resolution. A realisation of such a function including the calculation of corresponding filter coefficients was proposed by Mallat [13], which was applied in our study.

SEP waveforms as provided by the measurement system consist of 1024 samples representing a time interval of 100 ms. As shown in Figure 1, a pre-stimulus interval of 10 ms and a post-stimulus interval of 90 ms was recorded. Prior to analysis, the signals were baseline corrected by subtracting the mean value of the first 90 samples contained in the pre-stimulus interval. The stimulus itself is clearly identifiable as a large peak at $t = 0$ ms. Additionally, the stimulus influences the first 10–20 ms of the SEP recording due to saturation effects of the EEG amplifiers.

The first SEP component which is detectable is the N20 with a latency of about 20 ms after the stimulus. Therefore, the first 256 samples (representing the prestimulus interval and 15 ms poststimulus interval) were discarded form further analysis and subsequent processing was only applied to the remaining 768 samples.

The representation of SEP in the awake state was analysed by means of DWT. For this, the SEPs of all 52 patients were decomposed using the DWT with a wavelet function as proposed by Mallat.

For this decomposition, the time domain signal x(n) was identified with the digitised SEP, with the discrete time index $n = 1, \ldots 768$ covering the SEP time interval 15 and 90 ms . Further, let y(n) be the reconstruction obtained from a certain set of DWT coefficients calculated from x(n). We are interested in the reconstruction error $\mathrm{REK}_{\mathrm{error}}$, here defined as

$$\mathrm{REK}_{\mathrm{error}} = \sum (\mathrm{x(n)} - \mathrm{y(n)})^2 / \sum (\mathrm{x(n)})^2$$

The maximally possible reconstruction error is a zero-line signal reconstructed with all DWT coefficients set to zero, yielding $\mathrm{REK}_{\mathrm{error}} = 1$. The minimum of $\mathrm{REK}_{\mathrm{error}} = 0$ is reached for a perfect reconstruction y(n) = x(n) based on all 768 DTW coefficients. For any other number of DWT coefficients used in the reconstruction, the error $\mathrm{REK}_{\mathrm{error}}$ varies between the values 0 and 1, therefore indicating the quality of the reconstruction and providing a measure how good the information within the SEP can be parameterised within only few DWT coefficients.

For evaluation of the most SEP significant DWT coefficients, the SEP of all 52 subjects were decomposed with the DWT. For each of the 768 coefficients a reconstruction y(n) was computed via an IDWT and a $\mathrm{REK}_{\mathrm{error}}$ was calculated. First, the wavelet coefficient giving the best reconstruction, i.e. with the lowest $\mathrm{REK}_{\mathrm{error}}$ was identified. Next, a second DWT coefficient was identified, which minimizes the error in combination with the previously determined one in the same way. This procedure was repeated until a set of sixteen DWT coefficients were determined.

The mean values of $\mathrm{REK}_{\mathrm{error}}$ (averaged over the 52 patients) are given in Figure 3 using the cumulated

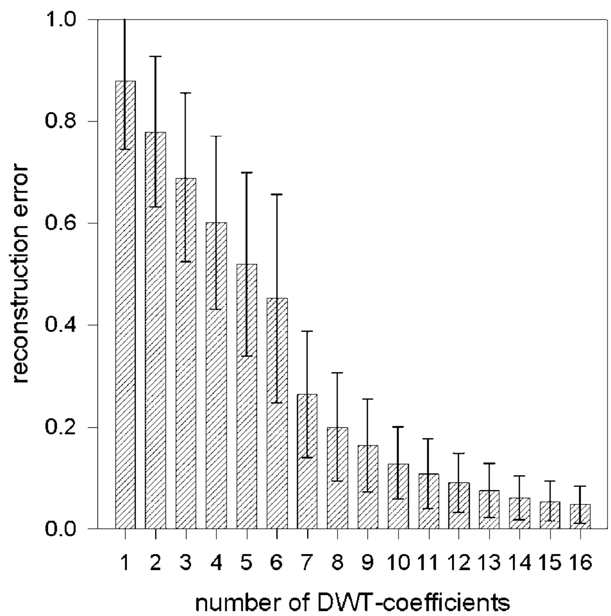

Fig. 3. Mean SEP reconstruction error using just 1, 2, 3…DWT coefficients for all subjects in awake. Additionally, standard deviations are plotted.

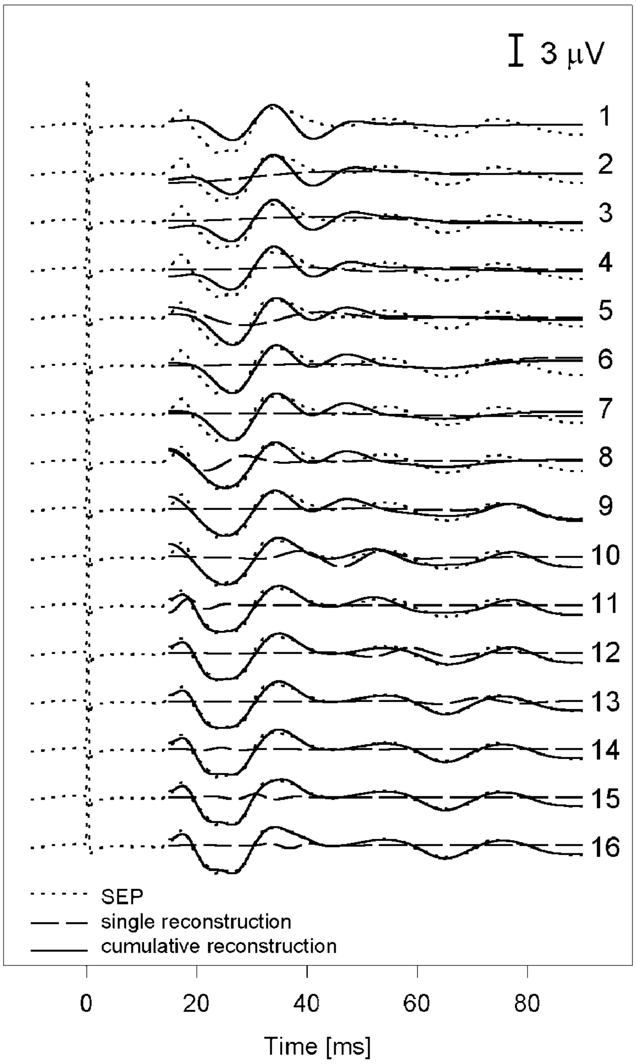

Fig. 4. SEP of a single patient (dotted line) with corresponding wavelet reconstructions (dashed and solid lines). From top to bottom the number of DWT coefficients used for reconstruction is increased. Solid line represents cumulative reconstruction with the n most relevant coefficients (n shown on the right), dashed line represents single coefficient reconstruction.

DWT coefficient sets as described above. Additionally, the standard deviations over all subjects are given. As shown in this figure, sixteen DWT coefficients give a reasonably low REK_{error} values – here less than 5% for most of the SEP – and hence provide enough information to represent most of the SEP features faithfully. The largest single error REK_{error} occurring with all sixteen DWT coefficients was 16%.

As an example for the quality of reconstruction based on the selected set of DWT coefficients, Figure 4 shows the SEP (dotted line) x(n) for a single patient in combination with its reconstruction y(n) (solid line). Starting with just the first coefficient in the selected set at the top, with each step towards the bottom, one more coefficient is added to the set until the final set of sixteen DWT coefficients is reached. The dashed line always shows the information added to the new reconstruction by the added coefficient. Obviously, from top to bottom the cumulated reconstruction resembles more and more the original SEP.

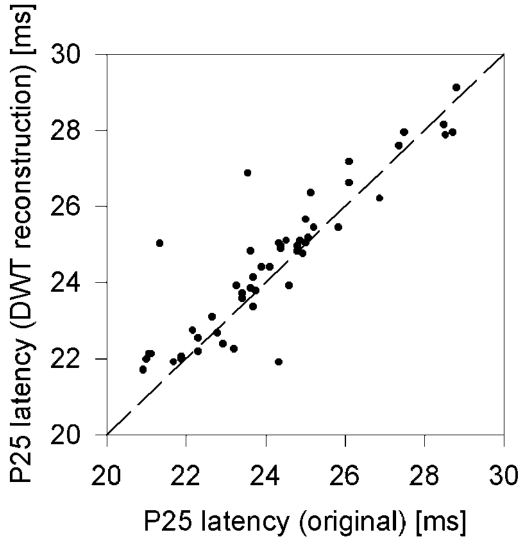

Fig. 5. P25 latency as determined by analyzing the original SEP (x-axis) and the DWT reconstruction using 16 coefficients (y-axis). The dashed line marks the identical (errorless) latency determination.

The reconstruction shown on the top of Figure 4 was calculated using a single DWT coefficient only. However, the reconstruction shows that this coefficient represents the N35 component with the correct latency. The reconstruction error REK_{error} as defined above decreases monotonically with increasing number of DWT coefficients used as already evident from Figure 3. Additionally, the representation of the SEP components (i.e. the amplitudes and latencies) is improved. The P45 deflection, for example, is very small in the shown data. Hence, P45 emerges within the reconstructed waveforms with correct latency not until approximately 12 DWT coefficients are used for reconstruction. With 16 DWT-coefficients the here shown SEP can be represented with an error of 2 %. The reconstruction allows correct identification of all previously described SEP markers. Peak latencies for the original SEP and the reconstruction are identical when 16 DWT coefficient were used.

The latencies are important features of the SEP, because the inter- and intra-individual variability is lower than for amplitudes, which are more depending on stimulation modalities like intensity of the stimulus. Therefore we performed a comparison of the latencies determined by a human expert for the original SEP and for the wavelet reconstruction. The marker P25 was chosen because it is the most prominent one. Figure 5 shows the P25 latencies for the original SEP and the wavelet representation when sixteen DWT-coefficients are used. The maximum incurred error in latency is 4.3 ms. The mean deviation of the P25 latency between both representations is 0.84 ms.

DISCUSSION

The DWT implemented as the multiresolution analysis was shown to provide a useful tool for representation of somatosensory evoked potentials. For the first time, the application of the DWT to SEP was demonstrated. It was shown that the DWT representation is more appropriate than a complete time or complete frequency domain evaluation since it enables the decomposition of an SEP in positive and negative deflections with specific time extensions at characteristic times (latencies). Each SEP component (N20, P25, ...) is represented by a couple of DWT coefficients.

By defining a quantitative measure for SEP representation based upon the reconstruction error it was shown that the more coefficients are used, the higher is the accuracy for SEP representation and consequently the determination of SEP latencies. When the complete set of DWT coefficients is used, the SEP can be reconstructed without any error. The number of DWT coefficients which are required for an adequate SEP representation depends upon the specific problem.

From the clinical point of view the latencies can be regarded as an important feature during follow up of patients, e.g. in patients during coma or intraoperatively [17]. SEP latencies have been shown to be sensitive parameters to document the effects of anaesthetics [7]. Compared with SEP amplitudes the latencies can be determined with higher reliability within one subject. They have physiological relevance as they may be regarded as the runtime which is necessary for signals to reach specific anatomical regions within the brain. It was shown in this paper, that the wavelet representation does not influence the determination of latencies substantially, even when large data reduction (i.e. a very small set of DWT coefficients in the reconstruction) is applied. However, depending upon the specific task, the degree of data reduction, i.e. the number of DWT coefficients which have to be included into analysis, has to be adjusted carefully.

The wavelet decomposition of SEP may be used for a large variety of applications. First, it may serve as a data reduction algorithm in order to minimize computer storage [18]. Second, the DWT can be used to extract most prominent time frequency regions within the SEP signals [19, 20]. Third, the DWT may be used as a preprocessing step for objective signal detection. In this case, only a few coefficients are needed. Recently it was shown for auditory evoked potentials that even with a very small number of DWT coefficients objective detection of evoked potentials is possible [16].

In summary, it was shown that the wavelet representation of SEP is a useful tool for any preprocessing step towards automatic evaluation. Since rapid on-line evaluation of SEPs in anaesthetized patients means an important step to detect changes in cerebral processing with minimal time delay intraoperatively, further studies are warranted, to document the feasibility of SEP analyses by DWT in clinical settings. When DWT analyses is applied to single sweeps it may allow to monitor SEP variations during anaesthesia without time delay and unrivalled accuracy

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