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EEG under anesthesia—Feature extraction with TESPAR

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ARTICLE INFO

Article history:
Received 4 June 2008
Received in revised form
4 March 2009
Accepted 7 March 2009

Keywords:
Depth of anesthesia
EEG
MLP
TESPAR
MLAEP

ABSTRACT

We investigated the problem of automatic depth of anesthesia (DOA) estimation from electroencephalogram (EEG) recordings. We employed Time Encoded Signal Processing And Recognition (TESPAR), a time-domain signal processing technique, in combination with multi-layer perceptrons to identify DOA levels. The presented system learns to discriminate between five DOA classes assessed by human experts whose judgements were based on EEG mid-latency auditory evoked potentials (MLAEPs) and clinical observations. We found that our system closely mimicked the behavior of the human expert, thus proving the utility of the method. Further analyses on the features extracted by our technique indicated that information related to DOA is mostly distributed across frequency bands and that the presence of high frequencies (>80 Hz), which reflect mostly muscle activity, is beneficial for DOA detection.

1. Introduction

Feature extraction techniques applied to biomedical signals have proven essential in life-science applications (automated external defibrillators, implanted pacemakers, diagnosis of epilepsia, etc.). For general anesthesia it remains a challenge to monitor the impact of anesthetics on the brain. Two recent studies showed an incidence of unwanted and primarily undetected patient awareness during general anesthesia of about 0.13% [1,2]. Since awareness and memory formation can cause severe psychological trauma [3], these studies have motivated the need for DOA monitoring devices. Substantial progress has been made in identifying signal features that relate well to anesthetics, in a dose-dependent way, for both spontaneous electroencephalogram (EEG) and mid-latency auditory evoked potentials (MLAEPs). Consequently, monitoring devices are commercially available today [2,4–7].

An important issue in automated DOA assessment is the feature extraction technique applied to the EEG signal. The most successful commercial monitors extract a combination of features based on time- and frequency-domain (BIS: Aspect Medical Systems; Narcotrend: Monitor Technik) or entropy (Narcotrend, M-Entropy: Datex-Ohmeda) from spontaneous EEG. In addition, evoked potentials (electrical responses of

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0169-2607/$ – see front matter
doi:10.1016/j.cmpb.2009.03.001

the nervous system elicited by and time-locked to external stimulation) have also kept a major role in DOA assessment [8]: certain peaks and troughs in the MLAEP decrease in amplitude and increase in latency with increasing DOA [9,10]. Other methods, extracting features in the time-domain [2,11–14] have also been developed, most based on probabilistic approaches. Such a method is the A-line ARX Index (Danmeter A/S) [15], the only commercially available monitoring device based on MLAEP.

Situations may arise in which some monitors fail to perform adequately [6,16–21]. Therefore, it has been suggested that improved DOA assessment should rely on multiple features extracted from EEG [22]. Here we propose an additional feature extraction technique, namely Time Encoded Signal Processing And Recognition (TESPAR) that is novel to the problem of EEG DOA detection. It has shown impressive performance in voice recognition and engineering applications [23–25], and being a time-domain approach, it has the possibility to capture information that is not distinguishable in the frequency-domain. We combined TESPAR with a nonlinear classification technique based on multi-layer perceptrons (MLPs), in order to validate the usefulness of TESPAR for DOA detection. The technique we introduce is not to be considered a competitor of well-established DOA monitors, but the additional features extracted by TESPAR may be useful to enhance the already established methods.

2. Materials and methods

We developed an artificial system that extracts features from the raw EEG signal using TESPAR. The features are then fed to a nonlinear MLP classifier, which is trained and tested on trials labeled by a human expert relying on a morphologically different signal (MLAEP).

2.1. *Anesthesia*

With the approval of the local ethics committee (Ludwig-Maximilians-University, Munich), 62 patients were enrolled in the study after having provided their written informed consent. After the induction of general anesthesia and administration of muscle relaxation, the anesthesia was maintained with a combination of hypnotics and opioids. The choice of these substances was left to the discretion of the attending anesthesiologist and the dosage was based on clinical routine. The administration of hypnotic agent was adjusted when signs of wakefulness were present and was preemptively increased before anticipated painful surgical stimulation. The MLAEP was not available to the responsible anesthesiologist (for detailed information see Appendix A.1).

2.2. *Data acquisition*

During the medical procedures (see also Appendix A.2) auditory stimulation was applied to the patients in the form of short clicks with a continuous repetition rate of 9.1 Hz. All the intraoperative events such as awake, induction, intubation, coughing, spontaneous breathing, response to simple or complex requests and so on were coded by keystrokes and stored along the recorded EEG. Data was recorded continuously from induction to wake-up. The EEG signal was recorded differentially between A1 and Fp2, according to the international 10/20 system [26], with a sampling rate of 4 kHz.

2.3. *Data pre-processing*

The amplified and recorded data, with a bandwidth of 0.5–600 Hz, were processed offline for further filtering, artifact removal (for detailed information see Appendix A.3), and rejection of power line frequency (50 Hz). Next we divided the data into 100 s long segments, recorded before and after intraoperative events. These events offered additional information to the human expert and were concomitant with actions performed on the patient (e.g. changes in the drugs administration, intubation, skin incision, etc.) or with feedback detected from the patient (e.g. blood pressure variation, tears, heart rate change, active breathing, etc.). The data from each segment were analyzed in two different ways. First, we divided the segment into short trials (110 ms long) aligned to the auditory stimulus. Segments that contained less than 600 artefact-free trials were discarded. The trials were used for the MLAEP-based classification performed by human experts. Second, segments validated previously were also analyzed in their full length (without dividing them into trials) using the TESPAR method. Subsequently, features extracted by TESPAR were used for the classification performed by MLP artificial neural networks. To further identify the importance of different frequency bands for classification, filtering was also applied on each segment, prior to feature extraction.

2.4. *Human expert classification*

We randomly selected 600 segments across all 62 patients that included periods with different depths of anesthesia. To manually classify the data based on the MLAEP, we computed the evoked responses by averaging 600–800 artefact-clean trials per segment. Next the MLAEPs were visually categorized into one of five classes by two human experts, each expert being unaware of the other expert's judgement. Additional information was provided by the corresponding intraoperative events (see above). The experts relied on this additional information to decide between two adjacent DOA classes. The five DOA classes were defined as follows: class 5 corresponded to an awake patient able to respond to complex verbal requests; class 4 was defined as very light anesthesia with patients able to respond to very simple requests like hand squeeze; class 3 was associated with states of sleep, in which patients do not respond to light stimuli but might react to strong ones; class 2 corresponded to the optimal anesthesia level; and class 1 was linked to too deep anesthesia, where brain activity is unnecessarily low (burst suppression).

The Observer's Assessment of Alertness/Sedation (OAA/S) [27] scale has been widely in use to develop and evaluate DOA monitoring devices with a main focus on periods when induction of anesthesia is performed or when patients return to consciousness. With the DOA scales used in this study we intended to cover the full range of clinical anesthesia. With the DOA assessment as used in our study there is a coarser resolution for the states of sedation with the DOA levels 4 and