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Synopsis

Biomedical Signal Processing

Introduction

In biomedical signal processing, major progress has been made due to a better understanding of the underlying physiological processes, due to the further development of high-quality measurement techniques, and due to novel mathematical algorithms, which have recently evolved. Significant improvements were achieved with regard to the measurement of biomedical signals. For example, high-quality biopotential amplifier and recording systems have been developed for a signal-to-noise ratio up to 40 Decibel. Also, today, we have a better understanding of the “source-field-relationship”, in particular for the human brain and heart. Such an understanding is very important in order to apply the proper mathematical tools and to understand the limitations of the applied approaches. Beside statistical approaches, model-based signal processing techniques have been developed. In general, these approaches are based on a biophysical model of the underlying physiological process. Formulating a linear or a nonlinear input-output relationship is the basis for these model-based approaches, which are powerful techniques also in the case of very complex and noisy signals, like the magneto- (MEG) and electroencephalogram (EEG).

Today, biomedical signal processing is further developed at an organ level and, in particular, on a cellular and subcellular level. Traditional signal processing techniques, like time-frequency domain or wavelet analysis, are these days also applied to biomolecular data. For instance in microarray analysis or in the analysis of mass spectrometric data, statistical and model-based approaches are just on the way to be introduced for a better and more specific analysis. Here, classification and pattern recognition algorithms play a fundamental role.

Selected papers of excellence

Five outstanding papers were selected for this section [1-5]. The papers are dedicated to the analysis of transcranial Doppler ultrasound data for embolus identification, to the segmentation of the EEG signal waves, to the analysis of spinal somatosensory evoked potentials, to the determination of the complexity of EEG signals for measuring the depth of anesthesia, and to the reconstruction of neural activity from MEG data. All five papers deal with biomedical signal processing at an organ level.

In the following, these five papers of excellence are summarized and shortly discussed:

Blood flow in the middle cerebral artery can be monitored by transcranial Doppler ultrasound. It may be used to detect cerebral emboli in patients with an increased stroke risk and during invasive cardiovascular examinations and operations. The paper by Fan et al. [1] describes an interesting approach for a quantitative interpretation and analysis of transcranial Doppler ultrasound data for automated embolus identification. An automatic system was developed that replaces the so-called “Human Expert” (HE). Doppler signal patterns were analyzed in both the time domain and frequency domain. The system was trained and tested on Doppler signals recorded during the dissection and recovery phases of carotid endarterectomy. The results were compared with the results obtained by HEs. The automatic system displayed a high sensitivity and specificity.

From a technical point of view, the applied frequency and time domain evaluation has several advantages. It makes pattern recognition much more stable than a pure time domain approach. Also, this approach can handle noisy ultrasound data, which often is the case in a clinical environment. From a clinical perspective, transcranial Doppler ultrasound has several significant benefits. The technique is noninasive, painless and safe. The procedure is quick and with training, 30-40 minutes is sufficient for acquisition and analysis. The instrumentation is inexpensive and portable. The most crucial aspect in applying transcranial Doppler ultrasound is achieving good operator technique. With training and experience, however, reproducibility between operators is good.

The work by Gharieb et al. [2] involves segmentation of EEG data for tracking the delta, theta, alpha, sigma, beta and the gamma wave. An adaptive recursive bandpass filter is employed for estimating and tracking the center frequency associated with each of these waves. The main advantage is that the employed adaptive filter has only one unknown coefficient to be updated. This coefficient represents an efficient distinct feature for each EEG specific wave. The proposed approach is simple and accurate in comparison with existing multivariate adaptive approaches. It can be applied to on-line EEG data and was used for the detection of sleep spindles.

Evoked potentials have been used to detect the integrity of spinal cord function during spinal surgery to minimize the possibility of spinal cord injury. Traditional methods for evoked potential monitoring use only amplitude and latency measurements to indicate potential injury to the spinal cord. However, spectral changes in evoked potentials also occur during neurological injury. Hu et al. [3] conducted an investigation of various time-frequency analysis techniques to detect both temporal and spectral changes in spinal somatosensory evoked potentials waveforms. The time-frequency distributions (TFDs) computed using these methods were assessed and compared. As shown, short-term Fourier transform with a 20-point length Hanning window provides the best result for spinal somatosensory evoked signals. The authors demonstrated the applicability and validity of time frequency analysis of evoked potentials to detect spinal cord function.

The monitoring of depth of anesthesia is an important aspect for patients during interventions and operations. Several methods for automatic segmentation, classification and compact presentation of suppression patterns in the EEG have been developed. A new approach for quantifying the relationship between brain activity patterns and depth of anesthesia is presented by Zhang et al. [4]. The authors analyzed the spatio-temporal patterns in the EEG using Lempel-Ziv complexity analysis. Twenty-seven patients undergoing vascular surgery were studied under general anesthesia. The EEG was recorded and patients' anesthesia states were assessed according to the responsiveness component of the observer's assessment of alertness/sedation score. Complexity of the EEG was quantitatively estimated by the Lempel-Ziv complexity measure C(n). The study shows that C(n) is a very useful and promising EEG-derived parameter for characterizing the depth of anesthesia under clinical situations.

The analysis of the MEG for purpose of reconstructing neural electrical activity and for pattern recognition in the temporal or frequency domain has been a subject of research in the last years. The work by Sekihara et al. [5] involves the analysis of MEG data and is an important contribution to enhance contrast in the reconstructed images. The basic idea of applying the beamformer technique to this approach is very promising and might give a significant improvement for source localization. A method for reconstructing spatio-temporal activities of neural sources by using MEG data is presented. The method extends the adaptive beamformer technique to incorporate the vector beamformer formulation in which a set of three weight vectors is used to detect the source activity in three orthogonal directions. Both spatial resolution and output signal-to-noise ratio of the proposed beamformer are significantly higher than those of the minimum-variance-based vector beamformer. The authors also applied the proposed beamformer to two sets of auditory-evoked MEG data. The results clearly demonstrated the method's capability of reconstructing spatio-temporal activities of neural sources. In reconstructing neural electrical activity, one of the key problems is that we still not have a proper and physically based source model available. The beamformer technique may overcome this limitation, in particular for the imaging of independent electrical sources.

On an organ level there are various research areas in which novel methodology is developed [1-7]. Examples are the imaging of electrical function within the human brain and heart from observations on the body surface (from electric potential (e.g., EEG) or magnetic field mapping (e.g., MEG) data), the non-invasive and real-time beat-to-beat monitoring of stroke volume, blood pressure, total peripheral resistance and for assessment of autonomic function by measuring ECG, blood pressure and thorax impedance, and the classification of biosignals like EEG or MEG.

Future perspectives

Today, signal processing methods developed at an organ level are further developed also for the application to biomolecular data [7-10]. Recently, in the signal processing community, terms like genomic signal processing came up [8-10]. Under genomic signal processing we understand solving problems in making use of the well established theory, tools, and methodologies from the field of biomedical signal processing. Fields of research are clustering, detection, prediction, and classification of gene expression data, signal transforms and statistical models for the interpretation of biological sequences and statistical and dynamical modeling of gene networks. Sequence analysis techniques including Hidden Markov models, wavelet analysis, and artificial neural networks are on the way being introduced.

From a biomedical signal processing point of view it is very challenging to see that mathematical approaches developed for "traditional" signals like the EEG are now further developed for the application to data on a molecular level [7-10]. In a couple of years it will be fascinating to see the wide spectrum of biomedical signal processing from an organ to a sub-cellular level and the similarities of the signal processing approaches used for these different scaling dimensions.

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