Topics in Brain Signal Processing

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***Abstract*—This brief paper provides an introduction to the area of brain signal processing, and also serves as an introductory presentation for the special session entitled *Advanced Signal Processing of Brain Signals: Methods and Applications* at APSIPA 2010. Several topics related to the processing of brain signals are discussed: preprocessing, inverse modeling (a.k.a. source modeling), and signal decoding. The papers in the special session are centered around those three topics. Obviously, this paper does not aim to give an exhaustive overview of all emerging topics in brain signal processing.**

I. Introduction

The human brain is arguably one of the most complex systems in the universe. Nowadays various technologies exist to record brain waves, e.g., electroencephalograms (EEG) [1], [2], magnetoencephalograms (MEG) [3], and functional MRI (fMRI) [4]. Those brain imaging tools allow researchers to gain understanding of the complex inner mechanisms of the brain. On the other hand, abnormal brain waves have shown to be associated with particular brain disorders (e.g., Alzheimer's disease and epilepsy). Therefore, the analysis of brain waves plays an important role in clinical diagnosis as well.

Despite the impressive advancements in brain imaging, interpreting brain waves remains remains difficult: brain imaging data are often complex and vast; it is often impossible to visually inspect all data. Therefore, techniques from signal processing may play an increasingly important role in the area of brain imaging.

In this introductory section, we will outline for what purposes neurologists, neuroscientists, and neural engineers record and analyze brain signals. In the next sections, we will briefly address three central topics in brain signal processing: preprocessing (Section II), inverse modeling (a.k.a. source modeling; Section III), and decoding (Section IV). At the end of the paper, we will briefly touch upon various other challenges in the analysis of brain signals.

A. Neurology

Neurologists try to diagnose and treat brain disorders. They investigate whether a patient suffers from a brain disorder; they try to identify brain disorders, and decide which treatments are the most appropriate. As a first step in this multi-stage decision process (see Fig. 1), neurologists acquire data about patients: they conduct interviews with the patients and family members; they use brain imaging technologies to measure the brain activity, such as electroencephalograms (EEG), magnetoencephalograms (MEG), and magnetic resonance imaging (MRI). This typically results in a wealth of data, that needs to be stored, managed, and analyzed. The latter may involve various medical experts besides neurologists, e.g., radiologists and neurosurgeons. The opinions from various experts are then eventually combined and a decision is made, in terms of diagnosis and/or treatment.

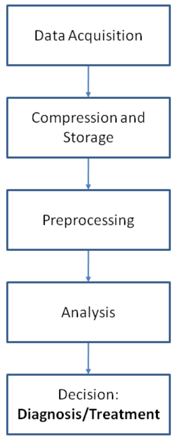

Fig. 1. Decision making in neurology; from data acquisition to diagnosis/treatment.

Making the right diagnosis and choosing an appropriate treatment for brain disorders remains a challenging task. First of all, the brain is an immensely complex organ, and we have limited understanding of its inner workings. Second, we can only measure certain properties of the brain (e.g., electrical) at a limited number of locations, e.g., by electrical recordings from an array of electrodes. In other words, we have limited information about the electrical/biochemical state of a patient's brain. At the same time, even though we record only from a limited number of brain areas, the resulting data sets are often huge, and need to be suitably stored and managed. The data is often noisy. Moreover, data from different sources (e.g., EEG and MRI) might be contradictory. Summarizing, the problem at hand might be viewed as decision making from multiple sources of noisy, ambiguous and potentially contradictory data. This generic problem, known as *data fusion*, is one of the key topics in signal processing. As a consequence, state-of-the-art tools from signal processing may prove to be quite useful for analyzing and interpreting brain imaging data, especially for clinical purposes.

B. *Neuroscience and Neural Engineering*

Neuroscientists try to gain insight in how the brain works. One of the main research problems is to unravel how the brain encodes, processes, stores, and retrieves information. To address that problem, neuroscientists often record brain signals while subjects are stimulated in a controlled fashion (e.g., visual stimulation), or perform certain well-defined tasks (e.g., memory task).

For example, neuroscientists have investigated how the brain responds to visual stimulation at specific frequencies (see [5] for a recent review). When the retina is excited by a visual stimulus ranging from 3.5 Hz to 75 Hz (and perhaps even in a larger frequency range), the brain generates electrical activity at the same frequency of the visual stimulus and/or multiples of that frequency (see Fig. 2); those brain signals are referred to as steady-state visually evoked potentials (SSVEP). Since SSVEP signals are fairly robust to artifacts and can relatively easily be detected, they provide a powerful tool to study the human visual system [5].

Moreover, SSVEPs are quite useful for neural engineering, particularly in the context of brain-computer interfaces (BCI) [5]; the latter use brain waves to control devices such as a wheelchair, computer mouse or keyboard. BCI systems may provide a communications channel for the motion-disabled. To create such BCI communications channel, SSVEP may be utilized as follows: one may display several visual stimuli at different frequencies. As an example, let us consider a BCI-controlled wheelchair; three stimuli with distinct frequencies may encode the commands “turn left”, “turn right”, and “move forward”. If the subjects focusses on one of those three stimuli, an SSVEP with the corresponding frequency will be induced. By detecting that SSVEP, one may be able to infer which stimulus (and hence command) the subject has selected, and the wheelchair may be controlled accordingly (turn left; turn right; move forward).

The example of SSVEP demonstrates first of all that neuroscience and neural engineering often go hand in hand: insight from neuroscience may turn to be useful for neural engineering; conversely, neural engineering may trigger research questions in neuroscience.

Secondly, it also shows that neuroscientists and neural engineers deal with brain signals in a similar fashion (see Fig. 3): Brain imaging is used to acquire brain signals, which are then perhaps compressed before being stored. Subsequently, potential artifacts and/or interfering signals are removed. After this preprocessing step, the brain signals are analyzed by means of signal processing methods. For example, one may extract SSVEPs by applying a simple bandpass filter or more sophisticated adaptive filters. Information in the extracted SSVEP may help us to better understand the human visual system. Alternatively, in the context of SSVEP BCI, the frequency of the SSVEP may encode a particular command. In both cases, signal processing helps us to understand, interpret, and decode brain signals. More generally, signal processing may help us to map sensory stimuli unto brain signals and vice versa; this bidirectional mapping provides us insight into neural information processing, and it is also a key principle behind BCI systems. Interestingly, this mapping also plays a crucial role in neurology. Indeed, abnormal responses to specific sensory stimuli may be associated with certain brain disorders. Not surprisingly therefore, neurologists, neuroscientists, and neural engineers process brain signals in similar ways (as can be seen by comparing Fig. 1 and Fig. 3). In conclusion: signal processing plays a major role in neurology, neuroscience, and neural engineering; most likely, those three distinct research areas will benefit greatly from advances in signal processing.

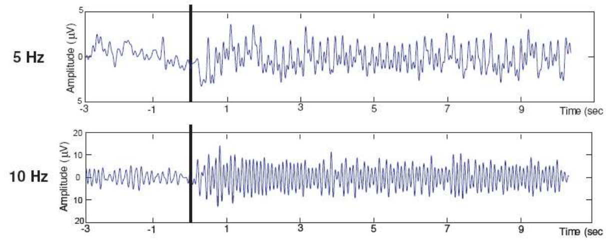

Fig. 2. SSVEP averaged over 10 trials (induced by visual stimulation at 5Hz and 10Hz) [6]. The signals clearly contain sinusoidal components at the stimulation frequency; it is much harder, however, to detect those components from single trials. Therefore, detecting SSVEPs from single trials is non-trivial, and designing BCI systems based upon SSVEP is far from straightforward.

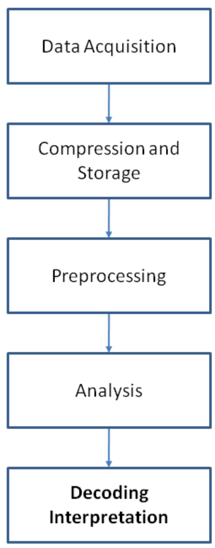

Fig. 3. Analysis of brain signals in neuroscience and neural engineering; from data acquisition to decoding and interpretation.

II. Preprocessing of Brain Signals

Before brain signals can be analyzed, they need to be appropriately processed, for example, to remove artifacts; this section is devoted to such preprocessing methods. We first explain why preprocessing is necessary, and then we outline the state-of-the-art in preprocessing of brain signals. For the sake of brevity, we will limit ourselves to electroencephalograms (EEG); many of the methods carry over to other brain signals. In this section, we will closely follow [7].

A. Need for Preprocessing

EEG recordings typically not only contain electrical signals from the brain, but also several unwanted signals [8], [9], [10], [11]:

- interference from electronic equipment, as for example the 50 or 60Hz power supply signals,
- electromyographic (EMG) signals evoked by muscular activity,
- ocular artifacts, due to eye movement or blinking.

Those unwanted components may bias the analysis of the EEG, and may lead to wrong conclusions [11], [12].

B. Preprocessing Methods

We describe here several preprocessing techniques to remove unwanted signals from EEG; this list is by no means exhaustive.

1) Basic Filtering: The spurious 50 or 60Hz power supply signals are typically removed by a band-stop filter, which is a filter that passes most frequencies unaltered, but attenuates those in a specific range (e.g., at 50 or 60Hz) to very low levels. However, other artifacts such as electromyogram (EMG) signals and ocular artifacts typically affect a large frequency band and their spectrum may vary over time. Therefore, band-stop filters are usually not effective to eliminate such artifacts.

One is often interested in specific frequency bands in the EEG, such as 4–8Hz (theta), 8–10Hz (alpha 1), 10–12Hz (alpha 2), 12–30Hz (beta), and 30–100Hz (gamma) [1]. Such frequency bands are usually extracted by a bandpass filter, which is a filter that passes frequencies within a certain range and rejects (attenuates) frequencies outside that range.

2) Adaptive Filtering: The spectrum of artifacts is often a priori unknown. Therefore, applying a fixed filter to EEG data would not be effective to remove artifacts. The filter needs to adapt to the spectrum of the recorded EEG: it should attenuate the recorded EEG in frequency ranges that mostly contain artifacts [13], [14], [15]. For instance, instead of using an online notch filter centered at a fixed frequency, one may apply an offline notch filter whose characteristics are determined by the spectrum of the recorded EEG. One may additionally use EOG (electro-oculographic) or EMG (electromyographic) measurements to design the adaptive filter, since those measurements are usually strongly correlated with artifacts.

3) Blind Source Separation: An alternative approach, known as "blind source separation" (BSS; see, e.g., [16]), starts from the assumption that EEG signals can be described, to a good approximation, by a finite set of sources, located within the brain; each of those sources generate certain components of the EEG. Besides EEG, one sometimes also incorporates EOG and EMG signals into the analysis. In the context of artifact rejection, one makes the additional assumption that artifacts are generated by a subset of the extracted sources; one removes those sources, and next reconstructs the EEG from the remaining "clean" sources [9], [10], [12], [17], [18], [19], [20].

C. Preprocessing: Discussion

Brain signals often contain unwanted signals which may bias the analysis of the signals, and may lead to wrong conclusions. We have reviewed several modern approaches to reduce such artifacts; each of those approaches has its own pros and cons. On a more fundamental level, however, it is clear that in order to reliably extract artifacts, one needs to know how brain signals generally look like, and what information content they encode. Therefore, as our understanding of brain signals improves, it should become less difficult to detect and remove artifacts.

III. Inverse Modeling of Brain Activity

Brain signals are often recorded from the scalp, e.g., scalp EEG and MEG. From those scalp recordings, we may try to reconstruct the signals within the brain. In our earlier example of SSVEPs, source reconstruction would allow us to infer which brain areas generate SSVEPs, and how the SSVEPs propagate to other brain areas; that would provide crucial information about visual pathways.

Inferring brain activity from scalp recordings is a classic example of an *inverse problem*, which is well-studied in signal processing. The inverse problem is clearly ill-posed, since from recordings at a few locations (contacts on the scalp), one tries to determine the activity at each location inside the brain; the same scalp recordings may be generated by a large number of brain activity distributions.

To regularize the inverse problem, one often imposes constraints or makes assumptions [1], [2], [21]. For example, it is commonly assumed that the brain activity may be modeled by a small number of electric or magnetic dipoles; from the recorded scalp signals, one tries to infer the number, location and orientation of those dipoles (see, e.g., [22], [23]). Alternatively, one may assume that the brain activity is continuous in space; an other assumption is that the brain signals are only non-zero at a few locations ("sparsity"; see, e.g., [25]).

Once the assumptions and constraints are determined, one can try to infer the brain activity by minimizing the error between the actual scalp recordings and predicted scalp recordings. The latter can be determined by solving the Maxwell equations, taking the geometry and physical properties of the subject's head into account. Depending on the model, this may boil down to least-squares fitting. Alternatively, the inverse problem may be solved through Bayesian inference, where the assumptions and constraints are encoded in statistical priors [23], [24], [25], [26].

IV. Decoding of Brain Signals

Decoding brain signals means mapping of brain signals to distinct stimuli (e.g., visual stimulation at particular frequency), mental states (e.g., asleep, awake, or drowsy), emotions (e.g., anger or fear), etc. There are various approaches to decoding of brain signals.

A popular methodology is to extract a multitude of features from the brain signals (after suitable preprocessing). Those features are then used to train classifiers from labeled data; the output of the classifier (label) represents a particular stimulus, mental state, or emotion (see, e.g., [27]–[34]). When this system is applied to new (unseen) brain signals, it automatically maps those brain signals unto labels (see Fig. 4). Depending on the accuracy of the classifier, this mapping may or may not be reliable.

Common brain signal features include relative power, complexity measures (e.g., sample entropy, approximate entropy, compression ratio), and synchrony measures (e.g., correlation coefficient, phase synchrony, magnitude coherence); we refer to [7] for details on various brain signal features.

In principle, any state-of-the-art classifier can be used, e.g., support vector machines [32] and neural networks [33]; several studies have compared various classifiers in the context of brain signal decoding (see, e.g., [34]).

As an alternative to the procedure depicted in Fig. 4, one may construct *forward models* that map stimuli/mental states/emotions unto brain signals. By applying Bayesian inference, one may invert this process in a principled way, and map brain signals back unto stimuli/mental states/emotions. Obviously, the key to success are accurate forward models; such models have been developed for sensory pathways. However, such models are far more difficult to construct for specific mental states and emotions. Therefore, detection of mental states and emotions is most often carried out by the procedure of Fig. 4.

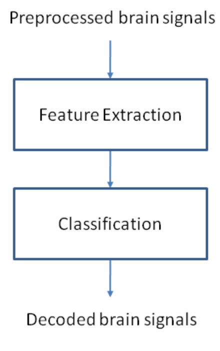

Fig. 4. Decoding of brain signals: features are extracted from the preprocessed brain signals, which are then processed by classifiers. The output of the classifier may represent different mental states (e.g., asleep, awake) or different stimuli (e.g., SSVEP at particular frequency).

V. Conclusions

In this paper, we have given a brief and potentially biased introduction into brain signal processing. This paper mainly serves as introduction to the special session entitled *Advanced Signal Processing of Brain Signals: Methods and Applications* at APSIPA 2010. We have addressed three topics: preprocessing, inverse modeling, and decoding of brain signals.

We have left many important topics untouched, e.g., compression and visualization of brain signals, fusion of different brain imaging modalities, fusion of brain imaging with other data sources (e.g., clinical behavior data, and genetic data), efficient hardware implementations of algorithms for brain signal processing. Given the wide range of topics and challenges in the analysis of brain signals, it is clear that brain signal processing will play an increasingly important role in neurology, neuroscience, and neural engineering.

References

[1] P. Nunez and R. Srinivasan, *Electric Fields of the Brain: The Neurophysics of EEG*, Oxford University Press, 2006.

[2] S. Sanei and J. Chambers, *EEG signal processing*, Wiley-Interscience, 2007.

[3] Cohen D., 1972. Magnetoencephalography: detection of the brain's electrical activity with a superconducting magnetometer. Science 175:664–66.

[4] Scott A. Huettel, Allen W. Song, Gregory McCarthy, *Functional Magnetic Resonance Imaging*, Sinauer Associates, 2004.

[5] Vialatte F.B., Maurice M., Dauwels J., Cichocki A., 2010. Steady-State Visually Evoked Potentials: Focus on Essential Paradigms and Future Perspectives. Progress in Neurobiology, 90:418–438.

[6] Vialatte F.B., Maurice M., Dauwels J., Cichocki A., 2009. Steady State Visual Evoked Potentials in the Delta Range (0.5–5 Hz). 15th International Conference on Neural Information Processing, ICONIP 2008, LNCS, Part I, 5506:399-406.

[7] Dauwels J., Vialatte F.B., Cichocki A., 2010. Early Diagnosis of Alzheimer's Disease from EEG Signals: Where Are We Standing? Current AD Research 7(6), pp. 487–505.

[8] Verleger R., 1991. The instruction to refrain from blinking affects auditory P3 and N1 amplitudes. Electroencephalogr Clin Neurophysiol. 78(3):240–51.

[9] Hoffmann S. and Falkenstein M., 2008. The correction of eye blink artefacts in the EEG: a comparison of two prominent methods. PLoS ONE 3(8):e3004.

[10] Dammers J., Schiek M., Boers F., Silex C., Zvyagintsev M., Pietrzyk U., and Mathiak K. , 2008. Integration of amplitude and phase statistics for complete artifact removal in independent components of neuromagnetic recordings. IEEE Trans Biomed Eng. 55(10):2353–62.

[11] Delorme A., Sejnowski T., and Makeig S., 2007. Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis. Neuroimage 34(4):1443–9.

[12] Romero S., Mañanas M.A., and Barbanoj M.J., 2009. Ocular reduction in EEG signals based on adaptive filtering, regression and blind source separation. Ann Biomed Eng. 37(1):176–91.

[13] Celka P., Boashash B., and Colditz P., 2001. Preprocessing and time-frequency analysis of newborn EEG seizures. IEEE Eng Med Biol Mag. 20(5):30–9.

[14] Bonmassar G., Purdon P.L., Jääskeläinen I.P., Chiappa K., Solo V., Brown E.N., and Belliveau J.W., 2002. Motion and ballistocardiogram artifact removal for interleaved recording of EEG and EPs during MRI. Neuroimage 16(4):1127–41.

[15] He P., Wilson G., and Russell C., 2004. Removal of ocular artifacts from electro-encephalogram by adaptive filtering. Med Biol Eng Comput. 42(3):407–12.

[16] Cichocki A. and Amari S.I., 2002. Adaptive Blind Signal and Image Processing: Learning Algorithms and Applications. Wiley, New York.

[17] Jung T.P., Makeig S., Humphries C., Lee T.W., McKeown M.J., Iragui V., and Sejnowski T.J., 2000. Removing electroencephalographic artifacts by blind source separation. Psychophysiology 37(2):163–78.

[18] Jung T.P., Makeig S., Westerfield M., Townsend J., Courchesne E., and Sejnowski T.J., 2000. Removal of eye activity artifacts from visual event-related potentials in normal and clinical subjects. Clin Neurophysiol. 111(10):1745–58.

[19] Vialatte F.B., Solé-Casals J., and Cichocki A., 2007. EEG windowed statistical wavelet deviation for estimation of muscular artifacts. Proc. IEEE 32nd Int. Conf. on Acoustics, Speech, and Signal Processing (ICASSP'07) vol. 4, 1161–4.

[20] Vialatte F.B., Solé-Casals J., and Cichocki A. EEG windowed statistical wavelet scoring for evaluation and discrimination of muscular artifacts. Physiol Meas. 29(12):1435–52.

[21] C. Phillips, M.D. Rugg, and K.J. Friston. Systematic Regularization of Linear Inverse Solutions of the EEG Source Localisation Problem. NeuroImage, 17(1):287-301, 2002.

[22] C. Phillips, M.D. Rugg, and K.J. Friston. Anatomically Informed Basis Functions for EEG Source Localisation: Combining Functional and Anatomical Constraints. NeuroImage, 16(3):678-695, 2002

[23] S.J. Kiebel, J. Daunizeau, C. Phillips, and K.J. Friston. Variational Bayesian inversion of the equivalent current dipole model in EEG/MEG. NeuroImage, 39(2):728–741, 2008.

[24] D.P. Wipf, R.R. Ramrez, J.A. Palmer, S. Makeig, and B.D. Rao, Analysis of Empirical Bayesian Methods for Neuroelectromagnetic Source Localization, B. Schlkopf, J. Platt, and T. Hoffman, editors, Advances in Neural Information Processing Systems 19, MIT Press, 2007.

[25] K.J. Friston, L. Harrison, J. Daunizeau, S.J. Kiebel, C. Phillips, N. Trujillo-Bareto, R.N.A. Henson, G. Flandin, and J. Mattout, 2008. Multiple sparse priors for the M/EEG inverse problem. NeuroImage, 39(3):1104–1120.

[26] D.P. Wipf and S. Nagarajan, "A Unified Bayesian Framework for MEG/EEG Source Imaging," NeuroImage, vol. 44, no. 3, February 2009.

[27] M. Murugappan, M. Rizon, R. Nagarajan, S. Yaacob, D. Hazry and I. Zunaidi. Time-Frequency Analysis of EEG Signals for Human Emotion Detection, Proc. 4th Kuala Lumpur International Conference on Biomedical Engineering. 2008.

[28] Charles W. Anderson, Saikumar V. Devulapalli, and E.A. Stolz. Determining Mental State from EEG Signals Using Parallel Implementations of Neural Networks. In: Scientific Programming, Special Issue on Applications Analysis, 1995.

[29] Kannathal Natarajan, Rajendra Acharya, Fadhilah Alias, Thelma Tiboleng, and Sadasivan K Puthusserypady, Nonlinear analysis of EEG signals at different mental states, Biomed Eng Online. 2004; 3:7.

[30] EEG-Based Estimation of Mental Fatigue: Convergent Evidence for a Three-State Model, Leonard J. Trejo, Kevin Knuth, Raquel Prado, Roman Rosipal, Karla Kubitz, Rebekah Kochavi, Bryan Matthews, and Yuzheng Zhang. Lecture Notes in Computer Science, Foundations of Augmented Cognition, vol. 4565/2007.

[31] EEG-based estimation of mental fatigue by using KPCA-HMM and complexity parameters, Jianping Liu, Chong Zhang and Chongxun Zheng, Biomedical Signal Processing and Control Volume 5, Issue 2, April 2010, Pages 124–130.

[32] B. Schölkopf and A. Smola, *Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond*, The MIT Press, 2001.

[33] Christopher M. Bishop, *Neural Networks for Pattern Recognition,* Oxford University Press, 1995.

[34] A review of classification algorithms for EEG-based brain-computer interfaces. F. Lotte, M. Congedo, A. Lecuyer, F. Lamarche and B. Arnaldi J. Neural Eng. 4 (2007) R1-R13.