Chapter 14
Assessment and Confidence Estimates of Newborn Brain Maturity from Sleep EEG

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ABSTRACT

Electroencephalograms (EEGs) recorded from sleeping newborns contain information about their brain maturity. Although these EEGs are very weak and distorted by artifacts, and widely vary during sleep hours as well as between patients, the main maturity-related patterns are recognizable by experts. However, experts are typically incapable of quantitatively providing accurate estimates of confidence in assessments. The most accurate estimates are, in theory, provided with the Bayesian methodology of probabilistic inference which has been practically implemented with Markov Chain Monte Carlo (MCMC) integration over a model parameter space. Typically this technique aims to approximate the integral by sampling areas of interests with high likelihood of the true model. In practice, the likelihood distributions are typically multimodal, and for this reason, the existing MCMC techniques have been shown incapable of providing the proportional sampling of multiple areas of interest. Besides, the lack of prior information increases this problem especially for a large model parameter space, making its detailed exploration impossible within a reasonable time. Specifically, the absence of information about EEG features has been shown affecting the results of the Bayesian assessment of EEG maturity. In this chapter, authors discuss how the posterior information can be used in order to mitigate the problem of disproportional sampling in order to improve the accuracy of assessments. Having analyzed the posterior information, they found that the MCMC integration tends to oversample the areas in which a model parameter space includes EEG features making a weak contribution to the assessment. This observation has motivated the authors to cure the results of MCMC integration, and when they tested the proposed method on the EEG recordings, they found an increase in the accuracy of assessment.

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INTRODUCTION

In clinical neonatology, the brain maturity is typically assessed by expert analysis of maturity-related patterns recognizable in electroencephalograms (EEGs) recorded from sleeping newborns. The analysis undertaken by experts has to be made confidently despite that the maturity-related patterns widely vary during sleep hours as well as between patients. The required confidence cannot be achieved in the absence of regular rules for interpretation of the EEG patterns (Tharp, 1990; Holthausen et al., 2000; Cooper et al., 2003).

Normally, post-conceptional ages (PCA) of healthy newborns match their EEG-estimated ages. However when a mismatch is more than two weeks, the newborn's brain development is likely abnormal (Scher, 1997). Thus, the mismatch between PCA and EEG-estimated ages alerts about abnormal brain development.

One of the first attempts of using sleep EEG for assessment of newborn brain development has been described in (Parmelee et al., 1968). In this work, experts have visually analyzed 47 EEG recordings made in 11 PCA groups between 39 and 43 weeks, and as a result, they found 10 maturity-related EEG patterns which then have been used for estimating the PCA of each EEG recording. For assessment, the experts calculated the distribution of the maturity-related patterns, and then they found that their estimates have exactly matched the stated PCA in 27.6% of cases, within an interval ±1 week the matches were counted in 59.5%, and within ±2 weeks – 77.5%. of cases. In this work the matches have been counted within intervals 0 week (exact match), ±1 and ±2 weeks as there has been an uncertainty in evaluation of PCA.

Other approaches have been undertaken to learn brain development models from sleep EEG recorded from newborns whose maturation was preliminary estimated by experts. Scher et al. (1996) have applied the regression models to mapping the brain maturity into EEG index. The classification models have been applied to distinguish the maturity levels of brain development as described in (Crowell et al., 1978; Schetinin & Schult, 2005). These attempts were made to learn a single model providing the maximum likelihood on given EEG data. Such a model selection methodology, however, cannot ensure finding the maximum when likelihood distribution is affected by noise and if the distribution is multimodal. Besides, within this methodology a full posterior distribution cannot be estimated, and thus the uncertainty in model outcomes cannot be accurately assessed.

In contrast, the methodology of model averaging enables the full posterior distribution to be accurately estimated within the Bayesian paradigm (Duda et al., 2000). This methodology has been made feasible by using Markov Chain Monte Carlo (MCMC) integration over areas of high densities of likelihood (Chipman et al., 1998; Denison et al. 2002; Barbieri et al., 2005). The posterior distribution is estimated with the Bayesian averaging over an ensemble of models.

The use of Decision Tree (DT) models has been shown providing the selection of features making distinguishable contribution to the assessment. Such an ability of DT models becomes critical when prior information about EEG features is absent or deficient. Besides, DTs can be represented as a set of rules experts can easily interpret. When an ensemble of DT has to be interpreted, a single DT providing a Maximum Posterior can be selected for interpretation as we described in (Schetinin et al., 2007).

In theory, results of Bayesian averaging are critically dependent on the prior information and the diversity of model parameters. When the prior information is sufficient, the integration is mostly done over areas of interest with high likelihood, and the estimates of the class posterior distribution are likely to be unbiased. However, when the prior information is insufficient or absent, the areas of interest cannot be specified and therefore cannot be explored in detail to ensure that the estimates are unbiased. In such cases, the ensemble can be

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