THE USE OF ADVANCED INFORMATION PROCESSING METHODS IN EEG ANALYSIS

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Introduction – The Problematic EEG

Most 'real-world' classification and processing problems start with a data set about which we may have incomplete information. This is especially the case in the field of medical signal and image processing, where the usual uncertainties in our knowledge are often compounded by a poor understanding of the physical mechanisms by which the data is generated and a subjective evaluation of the data by a human observer. In the case of the EEG, the effects of scalp, fluid and bone on the tiny electrical currents generated in the cortex may be modelled only poorly and the large size of scalp electrodes and the effects of muscle and instrument noise all contribute to the difficulty of EEG analysis. The belief that the EEG contains some *objective* information regarding brain 'state' is tantalising. To some extent, though, such optimism is unfounded as many of the inherent problems may never be solved for EEG alone. We will not discuss in detail in this paper the problems of noise and artifact removal, nor the problems of modelling the passage of the EEG from cortex to scalp, but instead will concentrate on the EEG *as is* and suggest that, even if such problems are not solved, the EEG contains significant objective information regarding cortical functioning. We focus upon two main areas of information processing, namely information extraction from an EEG record (feature extraction and representation) and pattern recognition and inference.

Why 'advanced' methods?

Traditional EEG analysis is based upon signal power in a series of frequency bands, 0.5-4Hz the delta band, 8-12Hz the alpha band etc. Whilst such a paradigm is well-suited to analysis by eye it is not necessarily the 'best' way to perform an automated analysis. In the case of multiple channels of information, for example, it is not immediately clear how information about the spectral content of one channel relates to that in other channels. Over the last decade advances in computing have enabled more sophisticated methodologies to tackle the large data processing tasks involved in EEG analysis. We focus on two techniques; firstly feature encoding using measures of stochastic complexity and secondly the use of flexible models (in particular 'neural' networks) for pattern recognition.

Stochastic complexity

Whilst frequency-based changes clearly do occur in EEG recordings, we have argued that they are manifestations of changes in synchronisation in populations of neurons. We observe, for example, that determination of brain state is complicated by the fact that the effect on the EEG's frequency spectrum by changes in state differs from individual to individual. Frequency-based methods, therefore, cannot be guaranteed to be robust. We argue that methods which measure the complexity, or synchronisation, of EEG activity are hence more meaningful as these parameters are not defined via notions of *absolute* frequency. In much of our current work, therefore, we have chosen to investigate measures of signal complexity. The parameters we are investigating are based upon the information entropy of both the dynamic evolution of the signals and signal inter-relationships. Full details of these methods may be found in [4, 6].

Why 'neural' networks?

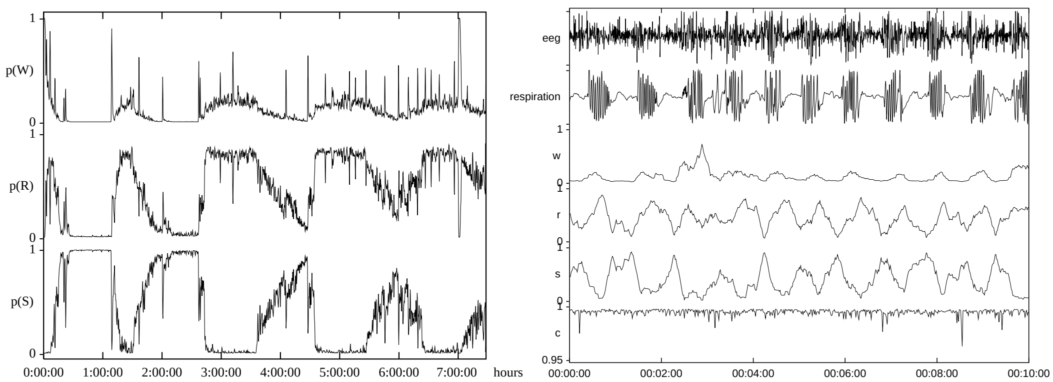
It is well known, however, that the *minimum risk* classifier ascribes an unknown input to the class with the highest Bayes' *a posteriori* probability. 'Traditional' classification techniques rely upon a variety of methods for estimating the class-conditional likelihood functions and class priors from which the posteriors may be estimated. The determination of the likelihood functions, however, is a difficult task, and becomes exponentially difficult for finite data sets as the dimensionality of the data increases. Feedforward 'neural' network classifiers have, it may be argued, become so popular because they can estimate posterior probabilities *directly* by forming a mapping function from the data space to a probability space.[1]

[1] We must, however, be careful in the choice of error function and learning algorithm to make sure that posteriors are indeed estimated as the network outputs.

One of the key requirements of any statistical system is to assess its own confidence in a decision. In the field of medical diagnostics this requirement is paramount. The notion of uncertainty in decision making processes is strictly defined via the set of posterior probabilities, with the quantity $1 - \max\{P(\mathcal{C}_k \mid \mathbf{x})\}$ defining this uncertainty. Under a Bayesian learning scheme (see, for example, [1, Chap. 10]) uncertainty due to small data sets, over-complex models, etc. has the effect of *moderating* the set of posterior probabilities such that they lie closer to the class priors. This naturally increases the measure of decision uncertainty. This has no effect if we are to hard classify all data but if a reject option is used (whereby decisions are rejected on data which have high uncertainty) it can alter the performance of the system.

Some early work - sleep analysis system

In previous publications [5] we have detailed a 'neural' network based sleep analysis system. This system, in its basic form, does not attempt to reproduce the Rechtschaffen & Kales (R & K) sleep scoring format of 6 or 7 discrete stages [3]. Through investigation of the dynamics of stable patterns in the EEG we proposed that the sleep EEG, as observed, is governed by only three basic processes. Process S, corresponding to a drive to slow-wave sleep (SWS or deep sleep), process R (REM or dreaming sleep) and process W (wakefulness). We found that an excellent representation of *any* sleep EEG state may be regarded as some mixture of these three basic processes or states. Our classification problem is now significantly reduced in complexity, from the seven discrete stages of R & K to only three. Furthermore, as we regard all intermediate stages transitions between these three basis states, we estimate the 'mixing' fractions of each. These 'mixing' fractions are the posterior beliefs in each process given a section of EEG, and these may be estimated using an appropriately trained feedforward network. Due to the small time resolution (1s) we may observe subtle changes in these probabilities during, for example, sleep apnoea. Figure 1(a) shows the outputs of the network for an 8-hour EEG record of a normal subject. Note the clear REM/non-REM sleep cycle and the abrupt arousals. Figure 1(b) shows the outputs of the network during a 10-minute period from a patient with Cheyne-Stokes respiration (CSR). Note how the probabilities wax and wane with the changes in the respiratory cycle. The bottom trace is a (heuristic) network 'confidence' estimate.



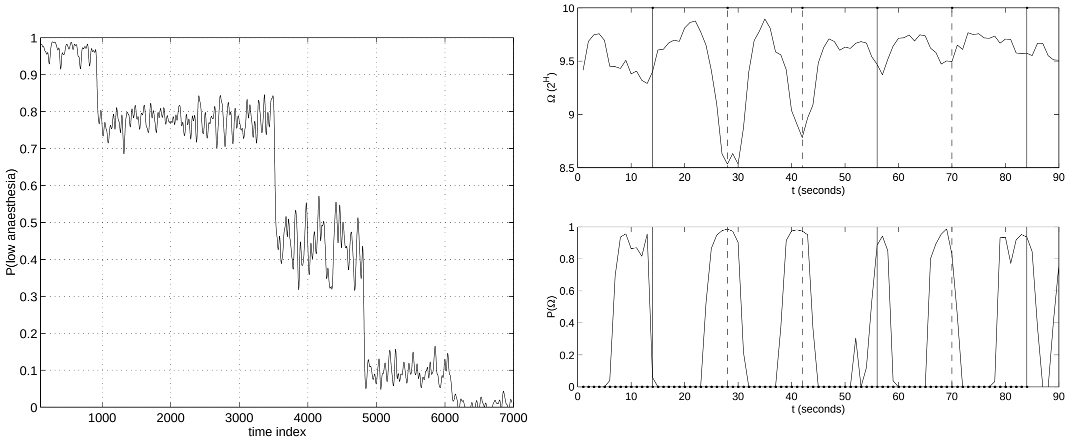
(a) Figure 1: (b)

Some current work

As well as active work in the sleep analysis field, we are currently researching several other EEG-related analysis problems, namely assessment of depth of anaesthesia, determination of an EEG-based 'state of vigilance' and classification of motor-cortex potentials during planning of *imagined* limb movements to form a rudimentary brain-computer interface (BCI). Figure 2(a) shows a probabilistic anaesthetic depth measure over five graded levels of anaesthetic agent (1 represents low dose, and 0 high dose) [2]. Complexity measures were used to train a feedforward network *on the lowest and highest dose levels only.*[2] We see that all five levels are clearly shown by the network. We note that the first, second and fifth levels consist of equal amounts of data from *two* different anaesthetic agents (desflurane & propofol), and there is no significant difference in network response between them.[3] As a final example we show the spatio-temporal complexity

[2] If all five levels are used for training, the overlap and mis-labelling present in the intermediate levels makes the network's performance considerably poorer.

[3] The third and fourth levels are taken using propofol only.



(a) Figure 2: (b)

measure between EEG channels C4 and C3 during imagined limb movements in a BCI experiment. Plot (b) of Figure 2 shows the time course of this measure over 90 seconds with a 0.2 second resolution (upper trace). Clear changes in complexity are associated with imagined movement cues[4] (solid lines - right movements, dashed lines - left movements). The lower trace of the same plot shows the probability of significance of drops in complexity. Once more the changes are well correlated to event cues. Further details may be found in [6].

Conclusions

There is little doubt that, if appropriately used, non-traditional methods of analysis offer robust means of estimation, prediction and classification. Their application to EEG analysis is well-founded. Although their use does not offer a solution to some of the problems encountered in EEG analysis, we would argue that used as methods for providing a *continuous* measure of a system's state, in a probabilistic framework, they provide information which is lost in more traditional analysis methods.

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[4] These are due to movement planning, rather than any evoked response due to the cues. On separate control blocks in which cues were presented but no imagined movements were performed there are no significant event-related changes.