ENGG7803: Engineering PG Project B

Annotated Bibliography

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[1] C. Papadimitiou and K. Steiglitz, Combinartorial Optimization: Algoithms and Complexity, New York: Dover Publications, Inc., 1998.

Papadimitriou and Steiglitz cover a broad range of topics including: linear programming algorithms, complexity analysis, np-completeness and intractable problems. This second edition book includes corrections and updated results while maintaining the basic theorems and style present in the first edition, published 15 years prior. The book assumes little prior knowledge of the subject and is designed as a useful text for computer science and/or operations research students. The content begins by both defining and providing solutions for simple optimization problems, and then continues to do so for more complex problems as the chapters progress. While there may have been further advances in the field over the past 20 years since the books republishing, it still serves as useful reference material for fundamental concepts.

[2] C. Blum and A. Roli, “Metaheuristics in Combinatorial Optimisation: Overview and Conceptual Comparison,” *ACM Computing Surveys (CSUR),* vol. 35, no. 3, pp. 268-308, 2003.

This article clearly defines Combinatorial Optimisation problems and a number of popular Metaheuristic approaches and provides examples. The authors explores the concepts of intensification and diversification as attributes of Metaheuristic search methods, and the classification of elements of algorithms as intensifying or diversifying. Blum and Roli conclude that the presence of both intensification and diversification are key to finding suitable solutions efficiently and they speculates that as most algorithms are biased in either one or the other, hybrid solutions may improve overall performance. This may provide an interesting motivation for combining optimization methods in my thesis.

[3] R. Poli, J. Kennedy and T. Blackwell, “Particle Swarm Optimization,” *Swarm Intelligence,* vol. 1, no. 1, pp. 33-57, 2007.

This article summarises some of the advances in particle swarm optimization (PSO) from its introduction in 1995 to 2007 in response to an increase in interest from global researchers. The validity of the source is supported by Kennedy being an authoritative figure on the subject, having been directly involved with the algorithms invention. The article revisits the original algorithm and then explores improvements, variations, applications and open problems at the time. Poli et al. conclude that PSO is a paradigm in its youth, full of potential and, at the time, experiencing exponential growth in interest. PSO has been used in the context of my thesis topic previously as is shown later by Satti et al. [8].

[4] M. Tolic and F. Jovic, “Classification of Wavelet Transformed EEG Signals with Neural Network For Imagined Mental and Motor Tasks,” *Kinesiology,* vol. 45, no. 1, pp. 130-139, 2013.

Tolić and Jović examine the performance of a single hidden layer neural network for classification of events from EEG samples. Two datasets are used to evaluate the type of events which are classifiable: data from a 1988 study which sampled EEG during subjects performing various mental tasks such as math problems and visualisation, and the Physionet motor/imagery dataset from 2004 where subjects opened and closed their fists in response to visual cues. The article reports mixed results, including particularly poor classification for the motor/imagery task. The datasets used could provide useful data for my thesis project, and the article itself may provide direction as Tolić and Jović suggest that further exploration of feature extraction methods could lead to better performance.

[5] D. McFarland, L. Minor, T. Vaughan and J. Wolpaw, “Mu and Beta Rhythm Topographies During Motor Imagery and Actual Movements,” *Brain Topography,* vol. 12, no. 3, pp. 177-186, 2000.

This article aims to address mixed results from prior studies concerning the EEG activity in the beta and mu frequency bands during imagery and actual motor function. The study examines 33 adults between 18 and 60 years old and concludes that clear variations in the signals can be distinguished consistently from both each other, and data collected from rest. This supports the notion that not only can motor/sensory information be detected in EEG, but that frequency bands may provide a valid set of features.

[6] Y. Kim, J. Ryu, K. K. Kim, C. C. Took, D. P. Mandic and C. Park, “Motor Imagery Classification Using Mu and Beta Rhythms of EEG with Strong Uncorrelating Transform Based Complex Common Spatial Patterns,” *Computational Intelligence and Neuroscience,* vol. Online, 2016.

Kim et al. extend the work of McFarland et al. [5] further by transforming features from mu and beta band EEG recordings into a reduced set of uncorrelated features with maximal interclass variance to improve classification of left or right-hand motor imagery events. The data is taken from the Physionet dataset which will likely be used for my thesis. The paper implements various pre-processing, feature extraction and classification methods, and yields meaningful results with a classification accuracy of 80%. With respect to my thesis, this paper provides further evidence that EEG frequency bands make suitable features and that feature reduction/optimization may be an avenue worth exploring to increase classification performance.

[7] S. Suily, Y. Li and Y. Zhang, EEG Signal Analysis and Classification: Techniques and Applications, Gewerbestrasse: Springer International Publishing, 2016.

This book is a considerable source of current analysis techniques for EEG data. The text focusses on EEG analysis for the purposes of epilepsy diagnoses and brain computer interfacing, however does briefly explore other applications. Concerning BCI techniques, Siuly et al. delve into the problems faced by engineers and scientists in classifying motor imagery events in EEG, and current methods of feature extraction and classification being successfully implemented. This book will likely be a primary resource for my thesis as it has amalgamated several references to relevant prior research papers and datasets.

[8] A. R. Satti, D. Coyle and G. Prasad, "Spatio-spectral & temporal parameter searching using class correlation analysis and particle swarm optimization for a brain computer interface," in *IEEE International Conference on Systems, Man and Cybernetics*, 2009.

Satti et al. focus on the performance of a BCI system which uses classification parameters that are optimised to each specific user. The EEG channels to be analysed are first selected based on their cross-channel correlation, then PSO is used to determine which frequency bands would make the most useful parameters for classification. The results depict an ~8% increase in classification performance with the use of user-specific parameter tuning over a sample of 8 subjects. This report highlights an interesting notion that a 'one size fits all' BCI solution may not be the optimal one, this concept may be explored further as an extension of my thesis. The paper is also a notable example of an optimization algorithm being used to create a BCI, which is the central theme of my project.

[9] M. H. Alomari, A. Samaha and K. Alkamha, "Automated Classification of L/R Hand Movement EEG Signals using Advanced Feature Extraction and Machine Learning," *International Journal of Advanced Computer Science and Applications,* vol. 4, no. 6, pp. 207-212, 2013.

This article attempts to classify motor imagery events using the Physionet EEG dataset. The authors investigate the behaviour of mu and beta wave (de) synchronisation about a movement event, as well as delta band behaviour during an event, and use this information to develop an informed vector of temporal features. They then extract the mean, power and energy of each feature, resulting in a 108x26 feature matrix. They evaluate the performance of the feature set using two machine learning algorithms: a neural network and a support vector machine with resulting classification accuracy of 86% and 97% respectively. This report closely resembles the themes and framework my thesis will likely take. A limitation in the system may be the large feature matrix being used in a live real-world system as high speed is a crucial factor in BCI control. Optimising feature selection to reduce the number of parameters may be a valid area of exploration for my project.

[10] S. Chandaka, A. Chatterjee and S. Munshi, "Cross-correlation aided support vector machine classifier for classification of EEG signals," *Expert Systems With Applications,* vol. 36, no. 2, pp. 1329-1336, 2009.

Chandaka et al. use features of cross correlograms to classify epilepsy events from large EEG samples. The article is motivated by current methods of epilepsy diagnoses being limited to visual inspection of EEG data by an experienced professional. The proposed method trains a support vector machine using features collection from cross correlations between EEG samples of true epileptic events and normal rhythms. This method of feature extraction may be worth considering for my project. The results appear to yield high classification accuracy and include meaningful confusion tables and calculate the sensitivity and specificity of the model. Such performance measures will likely be used to evaluate models used in my thesis.