A Parallel and Distributed Genetic-Based Learning Classifier System with Application in Human Electroencephalographic Signal Classification

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Certificate of Authorship / Originality

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of the requirements for a degree except as acknowledged within the text.

I also certify that the thesis has been written by me. Any assistance that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Signature of Candidate

Abstract

Genetic-based Learning Classifier Systems have been proposed as a competent technology for the classification of medical data sets. What is not known about this class of system is two-fold. Firstly, how does a Learning Classifier System (LCS) perform when applied to the single-step classification of multiple-channel, noisy, artefact-inclusive human EEG signals acquired from many participants? Secondly and more importantly, is how the learning classifier system performs when incorporated with migration strategies, inspired by multi-deme, coarse-grained Parallel Genetic Algorithms (PGA) to provide parallel and distributed classifier migration? This research investigates these open questions and concludes, subject to the considerations herein, that these technological approaches can provide competitive classification performance for such applications.

We performed a preliminary examination and implementation of a parallel genetic algorithm and hybrid local search PGA using experimental methods. The parallelisation and incorporation of classical local search methods into a genetic algorithm are well known methods for increasing performance and we examine this. Furthermore, inspired by the significant improvements in convergence velocity and solution quality provided by the multi-deme, coarse-grained Parallel Genetic Algorithm, we incorporate the method into a learning classifier system with the aim of providing parallel and distributed classifier migration. As a result, a unique learning classifier system (pXCS) is proposed that improves classification accuracy, achieves increased learning rates and significantly reduces the classifier population during learning. It is compared to the eXtended learning Classifier System (XCS) and several state of the art non-evolutionary classifiers in the single-step classification of noisy, artefact-inclusive human EEG signals, derived from mental task experiments conducted using ten human participants.

We also conclude that establishing an appropriate migration strategy is an important cause of pXCS learning and classification performance. However, an inappropriate migration rate, frequency or selection:replacement scheme can reduce performance and we document the factors associated with this. Furthermore, we conclude that both EEG segment size and representation both have a significant influence on classification performance. In effect, determining an appropriate representation of the raw EEG signal is tantamount to the classification method itself.

This research allows us to further explore and incorporate pXCS evolved classifiers derived from multi-channel human EEG signals as an interface in the control of a device such as a powered wheelchair or brain-computer interface (BCI) applications.

Statement of Contribution

Contributions to Knowledge

We have proposed and tested three research hypotheses (H3, H4, H5) related to the Genetic-Based Machine Learning (GBML) Classifier System for the single-step classification of multi-channel, artefact-inclusive human electroencephalographic (EEG) signals, derived from mental task experiments. In addition we have tested two research hypotheses (H1 and H2) related to the convergence property and solution quality of a Parallel Genetic Algorithm and Hybrid Algorithm:

- Hypothesis H1 which claims "The convergence velocity and solution quality achieved by a parallel genetic algorithm, with adaptive mutation is superior to that achieved by the serial genetic algorithm on a common set of optimisation problems."

- Hypothesis H2 which claims "The convergence velocity, solution quality and computation time achieved by a hybrid search algorithm is superior to that achieved by the parallel genetic algorithm on a common set of optimisation problems."

- Hypothesis H3 which claims "A parametric representation provides superior performance compared to the frequency-band representation for the single-step classification of multiple-channel, artefact-inclusive human EEG data using evolutionary and non-evolutionary classifiers."

- Hypothesis H4 which claims "The eXtended learning Classifier System (XCS) provides superior performance when compared to the current state of the art in non-evolutionary classifiers for the single-step classification of multiple-channel, artefact-inclusive human EEG data"

- Hypothesis H5 which claims "The incorporation of a parallel and distributed classifier migration policy into the eXtended learning Classifier System (XCS) increases classification performance for the single-step classification of multiple-channel, artefact-inclusive human EEG data"

The implications of these findings provide, in some measure, new knowledge about the classification of human EEG signals using parallel and distributed Genetic-Based Machine Learning (GBML) Classifier System. In the course of examining these hypotheses, the following contributions were also made:

- We have determined, documented and implemented a simple mechanism for the parallel and distributed migration of classifiers in the discovery component of a genetic-based learning classifier system, which we called pXCS. This parallel and distributed algorithm extends Wilson's XCS learning classifier system by introducing a *migratory pressure*, with improved learning rate, improved classification accuracy and smaller classifier population size.

- The *degree-of-connectivity* implicit in the fully-connected, bi-directional and uni-directional ring topologies have a significant influence upon the learning and classification performance of pXCS. This finding extends the number of topologies found in the literature.

- The *rate* and *frequency* of distributed classifier migrations in pXCS does have a significant impact on the learning and classification performance. This finding is at variance with the literature which portrays classifications performance for idealised problems.

- A *selection* and *replacement* scheme based upon ranking of classifier *fitness*, *numerosity* and *random* in pXCS can have significant impact on the learning and classification performance. This finding extends the number of such schemes found in the literature for idealised problems. Furthermore, we have shown that fitness bias selection can inhibit classification performance.

- We have provided extensive benchmarking for the classification performance of XCS and pXCS in an observable and repeatable manner in the single-step classification of multiple-channel, artefact-inclusive human EEG signals. This approach allowed for the comparison of evolutionary and current state-of-the-art non-evolutionary classifier systems, in terms of average classification accuracy and its variance.

- In terms of learning and classification performance of XCS and pXCS, in conjunction with typical real-time constraints of similar applications we have determined:
  (a) an optimal EEG segment size of 2.0-seconds,
  (b) an optimal autoregressive model order of p=6 for the Burg, Covariance, and Modified Covariance parametric methods.

- We have achieved significant improvements in classification accuracy by increasing the ability of XCS to form generalisations in the single-step classification of multiple-channel, artefact-inclusive human EEG signals. More specifically, establishing a generalisation or 'don't care' probability of $P_{\#}$=0.86 tended to provide significant improvements in classification accuracy compared to $P_{\#}$=0.76.

- We have discovered that an XCS classifier population of N=8000 did not provide significant improvement or degradation in classification accuracy when compared with N=2000 and N=4000 for parametric representations and $P_{\#}$=0.86.

- We have developed, documented and implemented a simple hybrid search algorithm employing an iterative global search heuristic and cascaded architecture. Our method loosely couples our parallel genetic algorithm with a non-evolutionary search algorithm, which based on the Reduced Feasible Sequential Quadratic Algorithm. The hybrid algorithm achieved significant improvements in convergence velocity, solution quality and computation time for a suite of idealised objective functions.

- We have developed, documented and implemented a multi-deme parallel genetic algorithm (PGA) employing an adaptive mutation function. In general, adaptive mutation can increase convergence velocity and solution quality of a multi-deme PGA for a suite of idealised objective functions. This finding supports the current literature.

Related Publications

- *Performance Study of a Multi-Deme Parallel Genetic Algorithm with Adaptive Mutation*, B.T. Skinner, H.T. Nguyen, D.K. Liu, International Conference on Autonomous Robots and Agents (ICARA), pp. 88-94, New Zealand, December 2004.

- *Hybrid Optimisation Method Using PGA and SQP Algorithm*, B.T. Skinner, H.T. Nguyen, D.K. Liu, IEEE Symposium on Foundations of Computational Intelligence (FOCI), pp. 73-80, Honolulu, Hawaii, USA, April 2007.

- *Classification of EEG Signals Using a Genetic-Based Machine Learning Classifier*, B.T. Skinner, H.T. Nguyen, D.K. Liu, 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 3120-3123, Lyon, France, 2007.

- *Distributed Classifier Migration in XCS for the Classification of Electroencephalographic Signals*, B.T. Skinner, H.T. Nguyen, D.K. Liu, IEEE Congress on Evolutionary Computation (CEC), pp. 2829-2836, Singapore, 2007.

Other Publications during PhD Candidature

- *Distributed Simultaneous Task Allocation and Motion Coordination of Autonomous Vehicles Using a Parallel Computing Cluster*, A.K. Kulantunga, B.T. Skinner, D.K. Liu, H.T. Nguyen, in Robotic Welding, Intelligence and Automation, Lecture Notes in Control and Information Sciences (Vol. 362), Springer-Verlag, 2007, pp. 409-420.

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