Genetic optimisation of BCI systems for identifying games related cognitive states*

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ABSTRACT

This paper aims to show a glimpse of the potential benefits of using genetic algorithms (GA's) in EEG data analysis. The system attempts machine-learning based classification of a mental state reached during competitive gameplay and an idle state. EEG activity from a large number of experienced players of *League of Legends* has been recorded during both idle periods and during a competitive, ranked game. A proven, industry-tested GA is used in order to optimize aspects of the brain-computer interface (BCI) system, by evolving both electrode and feature sets. Alongside a rather high cross validation base classification accuracy, statistically significant improvements have been obtained by applying the GA in selecting both electrode subset and features. The run time improvements are evident as well, although even further improvements are possible. This not only allows major improvements in both processing power and data acquisition requirements, but it is a step further in the attempt of bringing both BCI technology closer to consumer products, and cognitive state identification as a means of improving gaming experience, as well as other aspects of everyday life.

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1 INTRODUCTION

BCI systems are devices that use electrodes that record brain signals at the surface of the scalp. Many correlations have been found between EEG and responses to video and audio stimuli, different cognitive tasks and even affective states. This paper will attempt to analyse one such state, related to computer games.

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Figure 1: Enobio EEG cap used in this experiment. Source: neuroelectrics.com

This study uses a system named Enobio (TM), produced by the company Neuroelectrics as a clinical EEG device (image in Figure 1). The variant used has 20 electrodes (19 EEG + EXT for EoG artefact detection). The maximum frequency specified in the technical specification is 125Hz. The signal resolution is 24bits per channel, and the sample rate is 500Hz.

The cognitive state explored in this study is best described as the state experienced by players during intense moments of competitive gameplay. While there are a wide range of different terms used in literature meant to describe states related to this, such as immersion [1], [4], presence, even cognitive flow [3], it is not within the scope or purpose of this paper to discuss the definition and exact nature of this state. Hence it shall not be referred to by any name other than "the studied cognitive state". For a basic understanding of the described state, an interesting read is an article written by A. Orlando [7], discussing how, in *League of Legends*, such states may be engaged even before the beginning of the game itself. Another short, rather informal article, written by Jamie Madigan [5], briefly and somewhat accurately describes the state in question, by linking and explaining some of the terms associated with it.

Applying genetic algorithms for feature selection in EEG analysis of known cognitive tasks is a tried and tested technique in the field. For example, Corralejo *et al* [2] and I. Rejer [8] present two such applications for feature selection in motor imagery based BCI systems. Applications of this technique to systems with less defined target classes (i.e. analysis of affective / cognitive states) or in more complex scenarios (such as games) are far less common.

2 METHODOLOGY

The experiment consisted in a number of questionnaires before and after the data recording session, idle state EEG recordings and a ranked game of *League of Legends* (with a short questionnaire during the game). During the recording of the gameplay, the participants are presented audio distractors, in the form of short beeps (at the same volume as the in-game sounds). They are also asked to report each death using a keystroke.

Multiple classification algorithms have been tested before settling on one classification method. All the implementations of the tested classifier are contained in the Accord.Net framework for C#. All classifiers were evaluated using 10-fold cross validation accuracy. Statistical significance was determined using a Wilcoxon Ranked Sum test. Results are described in Table 1. Based on empirical results as well as time constraints, the chosen classifier is a single layer, 30 neuron, parallel resilient neural network [9].

Table 1: Accuracies of tested classifiers

Classifier	Accuracy
Naive Bayes	32%
LDA	72%
X - 30 - 1 Neural Network	84.5%
X - 30 - 30 - 1 Neural Network	85.5%
X - 50 - 50 - 1 Neural Network	87.7%

The genetic algorithm approach and tools that were used are the same as those applied by Morosan and Poli for game balancing [6].

Each individual was represented by a vector of values representing the electrode numbers used for classification. Each value could be between 0 and the number of available electrodes. The individual could not contain any duplicate values.

The fitness function for the genetic algorithm was simply the cross validation average accuracy of the system under each scenario. For each individual of a population, 10-fold cross validation was applied and the average accuracy across the folds used as feedback.

3 RESULTS

The genetic algorithm provided improvements in both accuracy and running times (results in visual form in Figure 2 and Figure 3). By evolving only an electrode subset, the GA showed statistically significant improvements (p ¡ 0.05) using selected subsets (a Wilcoxon Ranked Sum test was used to compare the resulting accuracies to the baseline, for each of the best individuals with different number of electrodes). Furthermore, the running times using selected subsets show major improvements, from 31.6 seconds using 2 electrodes only, compared to 67 seconds with the full set (results in visual form in Figure 2). Running time is even further reduced, while maintaining classification accuracy improvements, when selecting one frequency band to evaluate together with the electrode set, down to 28.6 seconds for 2 electrodes. Of course, using one frequency band only provides good improvements to running times with a full set of electrodes (down to 34.8 seconds on average), but sacrificing some of the classification accuracy on the way. The scale of the running time improvements show potential for introducing BCI technology into the games industry, in a real-time environment - which is the main goal and contribution of the authors. It also shows that GA's also work with less defined mental states, and may even help localize complex mental processes.

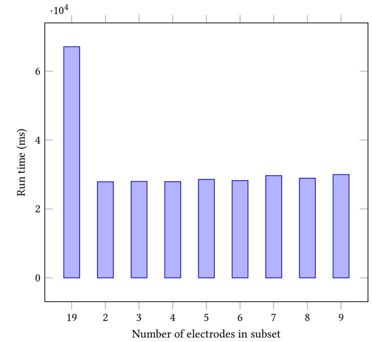

Figure 2: Graph displaying the difference in running times per size of electrode subset

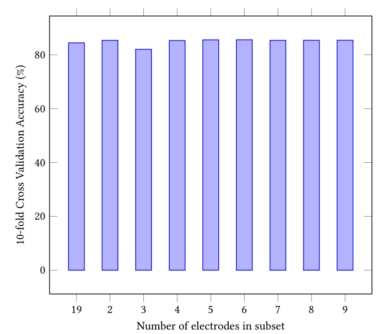

Figure 3: Graph displaying the differences in accuracy between different sized electrode subsets

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