A HYBRID GENETIC ALGORITHM APPROACH FOR IMPROVING THE PERFORMANCE OF THE LF-ASD BRAIN COMPUTER INTERFACE

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ABSTRACT

An asynchronous Brain Computer Interface (BCI) continuously monitors the brain signals and is activated only when a user intends control. Initial results from an asynchronous system, the LF-ASD, designed by our group have shown promise, but the reported error rates are still high for most practical applications. To improve its performance, we propose user customization. Since energy normalization of all channels' signals is shown to significantly improve the performance of the system, we choose to customize the parameters related to this normalization. We apply a hybrid Genetic Algorithm (a Genetic Algorithm followed by a Local Search) to customize the size of the energy normalization windows. This is shown to significantly improve the results. For a fixed false positive rate of 2%, the improvement in the true positive rate was raised from 65.7% to 76.9 % in one subject and from 53.1% to 63.3% for another subject.

1. INTRODUCTION

Brain-Computer Interface (BCI) aims at providing an alternative communication channel between a user's brain and a computer. A successful BCI design enables people to control their environment (such as light switches in their room or a wheelchair), a neural prosthesis or a computer by thinking of it only. This is done by measuring specific features of a person's brain signal that relate to his/her intent as to whether or not to affect control. These features are then translated into signals that are used to control/actuate devices.

The Low Frequency-Asynchronous Switch Design (the LF-ASD) was first introduced as a BCI for asynchronous control applications [1, 2]. The LF-ASD recognizes scalp potentials related to Movement Related Potentials (MRPs) in the EEG signal. Unlike the synchronous BCI systems that monitor the brain signals in specific periods of time, the LF-ASD continuously monitors the brain signals. Being an asynchronous BCI, it is activated only when a user intends control (Intentional Control or IC state) and maintains an inactive state output when a user is *not meaning to control* the device (i.e., they may be idle, thinking about a problem, or performing some action other than control). This is called No Control (NC) state. Results from the LF-ASD evaluations have shown promise, although the reported error rates are still high for most practical applications. To improve its performance, in [3] we proposed customization of the system for a specific user. Since each person has different biological features, user customization would improve the performance of the system. User customization is very important and a method for automating customization process is clearly needed [1]. Since in the previous studies, energy normalization of the signals of all the different channels have been shown to improve the performance of the system to a great extent [1, 3], we choose to customize the parameters related to this normalization.

Genetic Algorithms (GAs) have been shown to be useful tools for automatic customization of many practical systems [4, 5]. In [3], encouraging results about GAs' ability to improve the system performance were shown. However, the statistical significance of these findings was not explored. In this paper, we study the statistical significance of the results found by using GAs. On the other hand, although GAs are known to be good at exploring the search space to find promising regions where the optima lie, but they are weak at fine-grained search resulting in slow convergence. However, local search methods are adept to this kind of fine-grained search [6]. Once close to the sought optimum, they converge quickly. Hence, intuitively, a combination of a GA with a local search method (a hybrid GA) should yield performance improvements. Past work has indicated that hybrid GAs often outperform a pure GA in real-world applications (for review, see [6]).

In this paper, a Hybrid Genetic Algorithm (HGA) will be applied for user customization of the energy normalization parameters and it will be shown that the performance obtained here is better compared to the performance of the previous asynchronous BCI systems. Section 2 presents the structure of this system and the energy normalization process. In Section 3, data collection is discussed and the Hybrid Genetic Algorithm is presented. In Section 4, offline analysis of previously recorded data for two subjects is presented. It is shown that the proposed method yields statistically significant improvements in the performance of the asynchronous BCI system. Conclusions are discussed in Section 5.

2. THE ASYNCHRONOUS BCI SYSTEM AND ENERGY NORMALIZATION

2.1. Description of the LF-ASD

The block diagram of the most recent version of the Low Frequency Asynchronous Switch Design (the LF-ASD) [1] is shown in Figure 1. This design uses features extracted from the 0-4Hz band in six bipolar EEG channels. After amplification, all the six EEG channels are normalized with an Energy Normalization Transform (ENT). Then a low-pass-filter is used to decrease the interference with the features in the high-frequency band. A wavelet-like function is applied as feature generator. The Karhunen-Loève Transform (KLT) component is used to reduce the 6-dimensional feature space produced by the Feature Generator to a 2-dimensional space. A 1-NN classifier is used as the feature classifier. The codebook generation mechanism that was used to generate a codebook for the classifier from training data is based on the method employed in [2]. In this method, the k-means algorithm with 3 vectors per class is used to generate initial clustering of each class. This is followed by Learning Vector Quantization (LVQ3) to generate the final codebook. Finally, a moving average and a debounce block are used in order to further improve the classification accuracy of the system by reducing the number of false switch activations (for details, see [1, 2]). After training, the system classifies the input patterns to one of No Control (NC) or Intentional Control (IC) classes.

2.2. Description of the ENT

The Energy Normalization Transform (ENT), applied as in Figure 1, demonstrated that normalizing input energy results in a better class separation between IC and NC periods [7]. The output of the ENT is calculated using

$$y(n) = \frac{x(n)}{\sqrt{\sum_{s=-(W_N-1)/2}^{s=(W_N+1)/2} x(n-s)^2}} \tag{1}$$

Where *x(n)* is the input signal and W_N is the length of the input data window used to normalize *x(n)*. The idea behind using energy normalization is based primarily on an observation that high frequency power of EEG signals decreases significantly when the subject moves or intends to move [8]. Thus energy normalization that increases the low frequency power level strengthens the 0-4 Hz features used in the LF-ASD and hence reduces errors. In addition, as a side benefit, energy normalization can automatically adjust the mean scale of the input signal and desensitize the system to changes in the EEG power. Such changes are known to vary over time and from individual to individual.

Since primary results show that the ENT improves the performance of the LF-ASD to a great extent [1, 3, 7], we expect that tuning the length of the normalization window for each EEG channel (6 channels in total) and for each subject may further improve the results. In the original ENT design, the length of the normalization window was determined by data from one subject and the same parameter value was used for all other subjects as well. Also, the length of the normalization window used for all the EEG channels was the same. As the characteristics of different channels and different subjects are different, choosing a fixed window size for energy normalization of all the EEG channels and for all subjects would not necessarily yield the optimal results. Thus we expect the automation of the customization process of the BCI system for each subject improves the performance. This will also save time and energy significantly.

Based on these remarks, in the next section, we show how Hybrid Genetic Algorithms (HGAs) are used to automatically adjust the parameters of the energy normalization process for each subject.

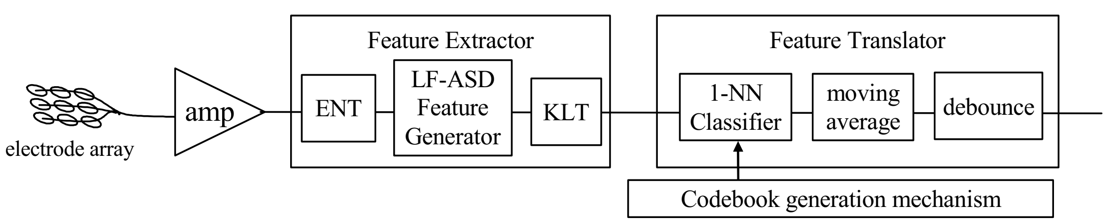

Figure 1. Components of the LF-ASD transducers (from [1])

3. METHODS

3.1. Data Collection

Data used in this offline evaluation was collected in a previous study (see [1] for details). EEG signals were recorded from six bipolar electrode pairs positioned over the supplementary motor area and the primary motor cortex (based on the International 10-20 System at F_1-FC_1, F_z-FC_z, F_2-FC_2, FC_1-C_1, FC_z-C_z, and FC_2-C_2). All signals were sampled at 128 Hz.

The data of two subjects, one with a high-level Spinal Cord Injury (SCI) and one able-bodied subject, recorded over six sessions, was considered for this study (see Table 1 for subject information in this study). The SCI subject had no residual sensation or motor function in the hands and no other compounding physical or emotional conditions that may have interfered with the study and was not ventilator dependent.

Table1. Subject information for this study

Subject	Gender	Age	SCI/Able-bodied
BK	Male	56	SCI
ID	Male	43	Able-bodied

3.2. The Hybrid Genetic Algorithm (HGA)

In this paper, a hybrid binary genetic algorithm (HGA) is used for tuning the size of the normalization windows of the ENT for each EEG channel. We ran the algorithm 10 times for each subject starting from different initial populations. The data of the first session was used for training and the rest of the data was used for testing. The results of each run were stored on a hard disk for further statistical analysis.

The specifications of the HGA used here are as follows:

Chromosomes: Each chromosome consists of a concatenated binary version of seven parameters. Six of these parameters are the energy normalization windows related to six bipolar channels. The last parameter is a scaling factor, which determines the operating point on the receiver operating characteristic curve (ROCC). The ROCC shows the relationship between TP and FP for each parameter configuration (for details, see [1]).

Fitness Function: In defining fitness function for an asynchronous BCI, two evaluation criteria should be considered: True Positives (TPs) and False Positives (FPs). A TP rate is the percentage of correct system responses during those periods when the user intends control and a FP rate is the percentage of incorrect system responses during the No Control periods. These criteria are positively correlated [1] and our aim is to maximize the TP for a reasonably low fixed FP rate. We explored various configurations for the fitness function, which are not reported because of space limitation. Based on previous results, a FP rate above 2% causes excess frustration and distraction in subjects using an asynchronous system [1]. Thus it is very important to keep the FP rates below 2%.

On the other hand, the computation time of the TP rate at a fixed FP rate from the receiver operating characteristic curve (ROCC) was relatively high. Hence, our final configuration incorporated the FP as a constraint in the fitness function and we defined the fitness function as follows:

$$fitness(Chromosome) = \begin{cases} TP, & if \;\; FP \leq 2\% \\ TP - 20FP, & if \;\; 2\% < FP \leq 3\% \\ 0.1TP, & if \;\; 3\% < FP \end{cases} \quad (2)$$

where in (2), TP and FP are in %. In equation (2), only for FP less than 2%, the TP rates remain intact. We also kept FP rates between 2% to 3 % (with penalized fitness), in hope of finding a very high value of TP for a moderate FP. As for values of FP > 3%, we attenuated the fitness of these chromosomes dramatically in order to prevent the less fit chromosomes from becoming active members of the population. Because although these chromosomes had high TP rates, but they also had very large FP rates at the same time.

-*Selection Method:* Tournament-based selection (tournament size =2)

- *Uniform crossover* and *uniform mutation*
- *Size of the initial population:* 100 (random initialization), size of the population 50.
- *Memory:* a memory block was used to store the values of the chromosomes and the corresponding fitness function. This memory block was used in order to prevent calculation of fitness function for similar chromosomes.

-*Termination Criterion of the HGA:* Even for a relatively fast PC with 1.7 GB Pentium IV processor, each evaluation of the cost function of the LF-ASD takes several minutes (it is desired that a near optimal performance be achieved with a reasonable number of function evaluations). Hence, for this paper, the number of evaluations was set to 3000. Also if for more than 10 consecutive generations, the amount of improvement in the best solution found so far is less than 1%, the algorithm is terminated.

- *Local Search*: Upon termination, a systematic local search based on bit flipping is performed on the best solution. The solution of this stage will be chosen as the final solution of the HGA.

4. RESULTS

The results of applying the HGA to optimize the length of the Energy Normalization Transform (ENT) are shown in Table 2. The optimum points found by the HGA are very close to the constraint boundary (*FP*=2%) which is what we were seeking to achieve, because the points near the boundary have the highest value of TP (for $FP \leq 2\%$). As for the comparison with the original system, we calculated

Table 2. Results of applying GA to ENT for FP=2%

Sub	Ave. TP (%)	TP for Window Size=51(%)	Improve p<0.01	Number of Eval.
ID	63.3	53.1	10.2	1616.9
BK	76.9	65.7	11.3	1407.8

the TP rates for the same subject when all the normalization window sizes were set to 51 (the window size used in [1]). The 4th column in Table 2 shows significant improvements in terms of classification accuracy for both subjects ($p<0.01$). This shows the importance of customizing the length of the ENT for each subject automatically. Also in Figures 2 and 3, we have plotted the ROCC for each subject based on two different settings: (a) a dashed curve denoting fixed normalization window (window size=51) and (b) a gray region denoting the region between the ROCC corresponding to best and worst results obtained in 10 runs of HGA. As it can be observed in these figures, the optimal values of the normalization window yield better ROCC with respect to their fixed window size counterparts for all values of scale factors. Further analysis also showed an average improvement of 2.7% in the performance of the HGA compared to the performance of a simple GA (used in [3]) for subject BK and 1.6% for subject ID (averaged over 10 runs of algorithms). This shows the benefit of adding a local search algorithm in order to further fine-tune the results.

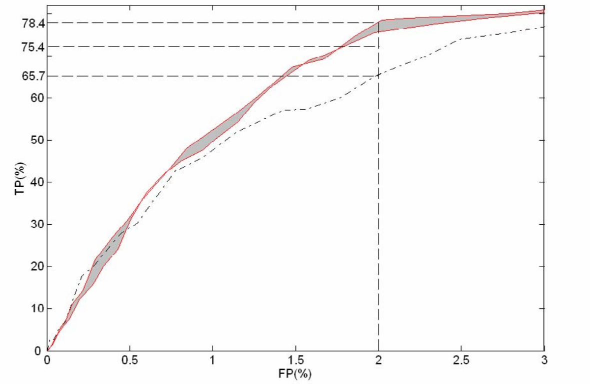

Figure 2. The ROCC for subject ID.

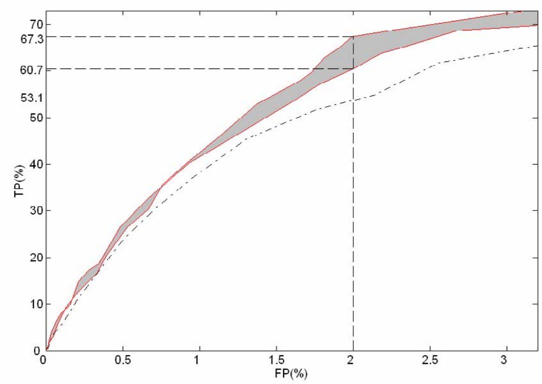

Figure 3. The ROCC for subject BK.

5. CONCLUSIONS

In this paper, we presented the results of applying a Hybrid Genetic Algorithm (HGA) to user customize the optimal window size of the energy normalization transform of an asynchronous BCI system. The importance of this new approach is two-fold:

1) We used a HGA to improve the local search capability of the genetic algorithm.

2) The statistical significance of the HGAs compared to the previous methods showed superior performance in terms of classification accuracy.

As for future work, we plan on optimizing the parameters of all components of the LF-ASD.

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