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Incremental Learning Models for Identifying Imagined Words in Continuous EEG Signals

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Abstract. In the task of building a fully asynchronous Brain Computer Interface that takes imagined words in continuous EEG signals as input, it is needed to be able to detect when an imagined word starts and finishes. In this work, two algorithms are studied. The first one to detect the onset and ending of imagined words in continuous EEG signals. The results showed an average True Positive Rate of 0.55, 0.63 and 0.69 for detecting the onset of imagined words using a Time Error Tolerance Region of 2,2.5 and 3 seconds respectively. For the ending of imagined words, the results showed an average True Positive Rate of 0.58, 0.64 and 0.71 using a Time Error Tolerance Region of 2,2.5 and 3 seconds respectively. In the second algorithm, an incremental learning approach is proposed to detect idle states versus imagined words, the results showed that in more than 75% of subjects, the incremental learning model performed better than the batch learning model.

Keywords: Imagined speech, incremental learning.

1 Motivation

In recent decades, intensive scientific research has been done in the area of Brain Computer Interfaces (BCI) [1] to develop devices that can improve the living conditions of people with disabilities.

Among the ways a BCI can be implemented [2] are the ones based on imagined words in electroencephalogram (EEG) signals [10]. However, in order to build a fully asynchronous BCI based on imagined words, many problems need to be solved, among them is the problem of detecting the onset and ending of the words and the problem of implementing incremental learning models in order to face the changes in EEG signals due to the natural neuro-plasticity of human brain.

2 Previous Works in the Area

To the best of our knowledge, there is not any work that solves the problem of detecting the onset and ending of imagined words using incremental learning models. However, there exist some works that can lead the way.

Some works face the problem of identifying imagined sound production vs. idle states. In [5] they investigated a method for classification of siren sound covert production and the idle state in an off-line system. Wavelet packet decomposition was employed for feature extraction and a Support Vector Machine (SVM) was used for classification. they reported an average True Positive Rate (TPR) of 79.2% for five subjects. In [6], they use sound imagery in a self-paced BCI. They implemented an online interface where the subject tried, by imagining a high pitched tone, to open a message that randomly appeared on a screen. Before the message randomly appeared, the screen was either playing a movie or the subject was reading a text, this was to simulate common tasks in daily life. Autoregressive coefficients, band power, common spatial patterns and discrete wavelet transform were used for feature extraction to cover all time, frequency, and spatial domains. Linear Discriminant Analysis was used for classification. The averaged TPR with six subjects was 88.9% in the watching video scenario and 78.9% in the reading text case. The average False Positive Rates (FPR) were 4.2% and 3.9%, respectively.

There are also works that deal with the problem of identifying imagined words vs. idle states. In [7], they attempted to classify imagined words states against two non linguistic states: relaxed and visual attention. They used features from spatial domain and time domain. In [8], they studied classification between idles states and imagined words. They use two corpus and two feature extraction methods: Wavelet energies and statistical values. They used three classifiers: Random Forest (RF), SVM and Naive Bayes. The higher accuracies they reported for the first corpus was 83% with the statistical features and the RF classifiers. For the second dataset, the higher accuracy they reported was 91% with the RF classifier and the statistical features also.

On the problem of detecting the onset of imagined words, there are some approaches that deal with the Onset detection of movement imagery [9]. And with the problem of Onset detection of high pitch sound imagery [10] using a Timing Error Tolerance Region (TETR).

3 Hypothesis and Research Objectives

The hypothesis driving this research is:

An incremental learning approach can lead to a better adaptive performance of personalized classification models in the task of detecting from continuous EEG signals, the onset and ending of imagined words.

The main objective of this research is:

To design and develop an incremental learning model capable of identifying from continuous EEG signals, when a subject starts and finishes to imagine a word.

The specific goals of the research are:

1. Find the features in which the information needed to discriminate when a subject's mind is in a state non relevant to the BCI, and when the subjects imagines a word is encoded.
2. Design a model capable to identify when a subject starts and finishes to imagine a word in continuous EEG signals.
3. Design a model capable of detect imagined words in the incremental learning approach in a way that is able to learn from new samples given by the user.

4 Methodology

1. **Classification of imagined words vs. non relevant states:** Experiment several feature extraction methods (time and frequency domain). Test several models (RF, SVM, ANFIS).
2. **To identify the onsets and endings of imagined words:** Design algorithm to evaluate the signal sequentially. Use of metrics for onset and ending detection (TFPR, TF, ROC, etc).
3. **To design models in an incremental learning approach:** Make use of already available algorithms (SVM, MLP). Design new algorithms in incremental learning way (RF, ANFIS).

5 State of the Research

The research is in its second year. Two algorithms are studied and performed using a dataset of 27 subjects that imagine 5 different words.

The first algorithm is focused on identifying the onset and ending of imagined words in a continuous EEG signal. The feature extraction consists of calculating The Generalized Hurst Exponent (GHE) [11] and a RF classifier is trained in order to classify the signal sequentially in windows of 1 second and determine when the imagined words start and finish.

The second algorithm is focused on studying the performance of incremental learning models in the task of identifying segments as imagined words vs. idle states. Instant Wavelet Energy and GHE are calcualted as features and a SVM is trained in both approaches (Batch learning and Incremental learning).

In order to finish the research, it is still needed to implement an algorithm that solves the problems of the two algorithms currently being studied. It is needed to have a better resolution in order to reduce the TETR and being able to have a better detection of the onset and ending of imagined words. Though the incremental learning algorithms currently studied outperform the batch learning approach, they still achieve poor accuracy in some subjects which suggest to try another incremental learning models or other feature extraction methods. Finally the resulting model must be tested with other data sets.

6 Results

In the task of detecting the onset of imagined words. The results reported an average TPR of 0.55, 0.63 and 0.69 with a TETR of 2, 2.5 and 3 seconds respectively.

In the task of detecting the ending of imagined words the same feature set was calculated. The results showed an average TPR of 0.58, 0.64 and 0.71 with a TETR of 2, 2.5 and 3 seconds respectively.

In the test of performance of incremental learning models in the task of classifying segments as imagined words or idle states, the incremental learning approach showed after 80 samples, a higher accuracy vs the batch learning approach.

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