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A Model-based Dynamic Stopping Method for c-VEP BCI

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Introduction: Brain-computer interfaces (BCIs) are becoming a reality and passes the borders of being only used for assistive technology. To increase the speed of BCIs, dynamic stopping methods [1] at any timepoint make a decision to eject a symbol or wait for more information, based on the decoder reaching a certain confidence. Thus, a speedup can be achieved by exploiting variance between trials, (good trials are detected earlier) while overall adequate accuracy is obtained without a drastic extension of the selection time. However, optimizing measures such as symbol per minute (SPM) and information transfer rate (ITR), do not necessarily reflect the performance of the system for a certain application or certain type of user. For example, for a brain-controlled alarm signal, while high accuracy is essential, it may be vital to have a low miss rate. This shows the need for dynamic stopping methods that can assign different costs to each type of error (false alarms and misses) and minimize cost instead of error rate.

Material, Methods and Results: We propose a model-based approach that takes advantage of the analytical knowledge that we have about the underlying classifier model. We can analytically show that the similarity score between the observed and predicted response, for both target and non-target classes, follows Gaussian distributions. We have formulated the dynamic stopping paradigm as a binary hypothesis decision problem with the following hypotheses:

H_1: observed score F_y is drawn from the distribution of the target class $N(\alpha b_1, \Sigma_1)$
H_0: observed score F_y is drawn from the distribution of the non-target class $N(\alpha b_0, \Sigma_0)$

We can assign different costs to different courses of action, namely: C_{00}: the cost of choosing 0 while 0 is true (Correct Rejection), C_{01}: the cost of choosing 0 while 1 is true (Miss), C_{10}: the cost of choosing 1 while 0 is true (False Alarm), C_{11}: the cost of choosing 1 while 1 is true (Hit). We define the cost ratio as $CR= C_{10}/C_{01}$ and calculate the risk (R) as the sum of costs weighted by the likelihood of each course of action. We then use a likelihood ratio test based on Bayes criterion to find the decision region in which on average R is as small as possible [2]. Using this formulation, we can tune the dynamic stopping algorithm to aim for minimizing the total risk. Additionally, we can set target values for the probability of False Alarm (p_f) and the probability of a Miss (p_m). We have tested the proposed dynamic stopping method on the c-VEP data set provided by [3]. Our preliminary results show that by only using a small cost ratio, the system tends to be very fast (average time $\bar{t}$=318*ms* for CR=1) and inaccurate (error rate Err=81.9% for a 36-class problem). Increasing the cost ratio to $CR=10^6$, resulted in $\bar{t}$=2.32 seconds and Err=22.9%. By adding constraints on the probability of false alarm (p_f=0.05) and determining a minimum probability of detection ($p_d=1-p_m$=0.8), the system withholds making decision, resulting in $\bar{t}$=1s and Err=45.8% for CR=1 and $\bar{t}$=3.4s and Err=15.9% for $CR=10^6$.

Discussion: Using the model-based dynamic stopping approach based on signal detection theory, a BCI system can be tuned to achieve desired performance in terms of False Alarm and Miss rates. Our results show that minimizing risk can result in a very fast detection rate that can be useful in applications where the relatively low accuracy can later be compensated by post-processing, for example, employing a language model. Imposing a target probability of false alarm and a minimum detection rate makes it possible to tune the system for more error-sensitive applications.

Significance: Our proposed model-based dynamic stopping algorithm allows for tuning the BCI systems according to the requirements of each application.

References:

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