An Interactive Control Strategy is More Robust to Non-Optimal Classification Boundaries

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ABSTRACT

We consider a new paradigm for EEG-based brain computer interface (BCI) cursor control involving signaling *satisfaction* or *dissatisfaction* with the current motion direction instead of the usual direct control of signaling *rightward* or *leftward* desired motion. We start by assuming that the same underlying EEG signals are used to either signal directly the intent for *right* and *left* motion or to signal *satisfaction* and *dissatisfaction* with the current motion. We model the paradigm as an absorbing Markov chain and show that while both the standard system and the new *interactive* system have equal information transfer rate (ITR) when the Bayes optimal classification boundary (between the underlying EEG feature distributions used for the two classes) is exactly known and non-changing, the *interactive* system is much more robust to using a suboptimal classification boundary. Due to non-stationarity of EEG recordings, in real systems the classification boundary will often be suboptimal for the current EEG signals. We note that a variable step size gives a higher ITR for both systems (but the same robustness improvement of the interactive system remains). Finally, we present a way to probabilistically combine classifiers of natural signals of *satisfaction* and *dissatisfaction* with classifiers using standard *left/right* controls.

Categories and Subject Descriptors

G.3 [**Probability and Statistics**]: Markov processes; F.1.2 [**Computation by Abstract Devices**]: Modes of Computation —*Interactive and reactive computation*

Keywords

brain-computer interface, BCI, Markov chain, non-stationarity, interactive, EEG, information transfer rate, ITR

1. INTRODUCTION

Brain-computer interface (BCI) systems typically require user training to generate reproducible and distinct brain waves. One popular class of EEG-driven BCI systems is based on imagined movement. In these systems the user interacts with a computer through performing motor imagery such as imagination of hand versus foot movement. The signal is then band-passed to the mu (8-13Hz) and beta (12-30Hz) frequency ranges which are known to show decreased power prior to and during real and imagined movement. Spatial filtering is also used to increase the discriminability between the two classes [2]. The ability of users to control such a BCI is very variable and all the factors involved are not fully understood.

One of the most critical issues in practical BCI use is non-stationarity of the EEG signals [19]. A paper by Shenoy et. al. [19] shows drifts of the optimal classification boundary during online feedback runs on the order of one standard deviation of the individual class densities (see Figure 6 in [19]). Changes between offline training and online use can be much larger due to changes in the user state evoked by the feedback. Online changes are thought to be due to state changes in the user, sweating, movement, and other factors. Drift in EEG can lead to loss of control of the BCI which leads to frustration and a vicious cycle of further drift of EEG signals from their training baselines [10].

Classification boundaries may be sub-optimal due to non-stationarity changing the optimal boundary over time but they may also be non-optimal due to having a small amount of training data with which to train the classifier (and estimate the optimal classification boundary). Thus even if the EEG was stationary, due to finite training set sizes, it is unlikely that the optimal classification boundary is found.

In a standard online BCI, the user receives sensory feedback. For example, if the user is trying to control a 1-Dimensional cursor movement, he would see the progress of the cursor. The feedback is important to inform him of his progress but does not usually or strongly influence his next command (if the cursor is moving left or right, the user will try to give a left signal if he desires a leftward movement regardless of the current feedback until the trial end).

We propose and analyse a more *interactive* way of controlling the BCI where the user changes their intended brain signal depending on the feedback received from the computer. For simplicity we consider the case of binary cursor control, though the ideas could be extended to more complex systems. Rather than imagining "right hand movement" to move the cursor *right* and "foot movement" to move the cursor *left*, we consider these same two signal classes to mean instead *'I approve of the current direction, CONTINUE in the same direction'* and *'I don't like the current direction,*

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CHANGE direction'. We will call such a system a D/S (*dissatisfaction/satisfaction*) system and call the first system a R/L (*right/left*) system. Note that while it may seem strange to use hand and foot movement to mean *continue* and *change direction*, R/L motor imagery systems often will pick the most discriminable signals for each user from between "imagine moving your right hand", "imagine moving your left hand", "imagine moving your foot", and "imagine moving your tongue". Once the two most discriminable signals are found, one is mapped to *right* cursor movements and the other to *left* cursor movements. There is no reason that these signals could not be mapped to the intentions *continue moving the cursor in the same direction* and *change cursor direction*. So initially we will assume that the pdfs of the two classes of signals is the same for each system but that they can be used, either in the standard direct (R/L) way, or in a new *interactive* (D/S) way.

2. BCI SYSTEMS AS MARKOV CHAINS

While EEG signals are high dimensional, they are often represented by just a few features before classification. Classification is then usually performed with a linear classifier (often linear discriminant analysis (LDA) or linear support vector machine (SVM)). The relevant dimension for a linear classifier is then the normal distance to the classification boundary. For the numerical computation, we assume that the EEG signals are generated from 1-Dimensional Gaussian probability density functions (pdfs) with different means (μ_1, μ_2) and the same projected variance (σ^2) along this normal dimension. In this formulation, we can represent different discriminabilities thru a single parameter

$$d' = \frac{|\mu_1 - \mu_2|}{\sigma}. \tag{1}$$

The exact form of the probability distributions, however, does not affect the main qualitative findings in the paper.

Single-trial EEG signals are very noisy and it is rare to be able to unambiguously classify a brain state (even from only two options) with a single classification. A common option to increase classification accuracy for online BCIs is to accumulate evidence over several classifications performed on overlapping or adjacent windows of the data. In this work we will consider adjacent windows (of length 500ms). We will assume that these windows are conditionally independent (given the intended class), though this is unlikely to be strictly true. The end result however will show that the D/S system is more robust to non-stationarities that underlie these dependencies and so this independence assumption should only decrease the full effect of the possible improvement with a D/S system.

One common and effective way of combining information between windows is to start with the cursor in the middle of the screen and take a step (left or right) according to the classification of each window of data. When the cursor reaches either of two targets equidistant (left and right) from the starting point, the trial ends. Accuracy can be greatly improved by chaining trials together in this way, though the time to determine an output increases.

The graphical model for state evolution in such a system is shown in Figure 1. As the next position of the cursor depends only on the current position and the classification of the window (which depends probabilistically on the subject's desired goal, the discriminability of their EEG signals, and the classification boundary), the performance of the subject can be considered as a discrete-time Markov process or a Markov chain [8] that takes each step according to a single window classification. As the process will eventually reach one of the endpoints, it is considered an absorbing Markov chain [12]. Once the walk reaches either endpoint the trial terminates and the absorbing (terminating) state determines the classifier output.

When viewed as an absorbing Markov chain, the analysis of the performance of the system is easily obtained [8, 12]. Consider the transition matrix P where p_{ij} is the probability of transitioning from state i to state j (and can be read off from the graphical model). With the transition matrix arranged so that the absorbing states are all at the top, P has the following form

$$P = \left[\begin{array}{c|c} I & 0 \\ \hline R & Q \end{array}\right].$$

If there are r absorbing states from which there are no external transitions (the two end-states in Figure 1) and t transient (non-absorbing) states (5 in Figure 1) then I is an r-by-r identity matrix and 0 is an r-by-t zero matrix. An entry $p_{ij}^{(n)}$ of P^n gives the probability of being in state j after n steps after starting in step i.

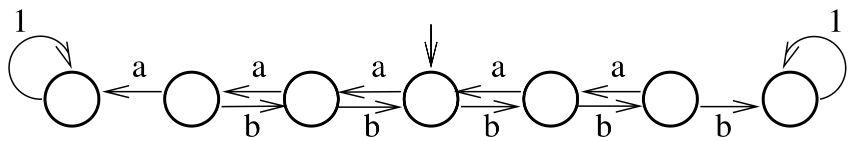
$$P^n = \left[\begin{array}{c|c} I & 0 \\ \hline \sum_{i=0}^{n-1} Q^i R & Q^n \end{array}\right].$$

In an absorbing Markov chain we are guaranteed that activity will eventually settle in one of the absorbing states which means that $Q^n \to 0$ as $n \to \infty$. Let $N = \sum_{i=0}^{\infty} Q^i$, then n_{ij} gives the expected number of times that the process is in transient state j when started in transient state i. Also note that N can be easily computed using $N = (I - Q)^{-1}$. This allows for easy analysis of expected accuracy rates for chains with different numbers of cursor positions and for different transition probabilities (which are a function of the discriminability of the signals and the current classification boundary). Nk where k is a column of t ones gives the expected number of steps before the chain is absorbed for each starting state. The entries v_{ij} from the equation $V = NR$ give the probability that the chain will be absorbed in absorbing state j when started in transient state i.

As there is a tradeoff between accuracy and number of steps (time) to completion, it is important to deal with a measure that incorporates both, such as the information transfer rate (ITR). ITR measures the number of bits of information learned about the user's desired class per unit time. For the case of equal accuracy for each class, and equal proportions of each class, the information transfer rate, can be computed using [20]:

$$ITR = (\log_2(C) + p\log_2(p) + (1-p)\log_2((1-p)/(C-1)))/T$$

where p is the classification rate of each class and C is the number of classes to be distinguished and T is the length of time for the computation. We wish to investigate how the ITR varies as the class pdfs drift due to nonstationarity of the EEG. In this work we simulate this with static pdfs but a moving classification boundary. This also simulates the problem of a non-optimal classification boundary due to a noisy estimate of the classification boundary. When the



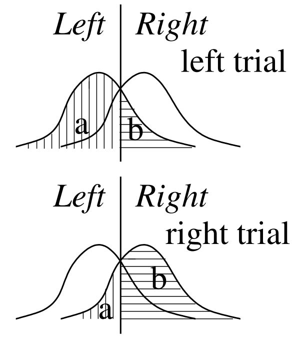


Figure 1: LEFT: The graphical model for system evolution for the standard R/L system. The spatial layout of the states corresponds to spatial cursor location. The rightmost/leftmost state represents hitting the rightmost/leftmost target. The numbers and variables on the arrows represent the transition probabilities between states. For best performance the chain is started in the center state (pointed to by the vertical arrow). This particular model shows a chain with 7 possible cursor positions (NCP=7). RIGHT: Sample 1-D probability density functions (pdfs) show how the transition probabilities a and b relate to the pdfs for the different classes and the classification boundary (shown by the vertical lines separating the hatched areas a and b). When the user intends to give a *left* signal, with probability a he will succeed and the chain will move left, and with probability b he will fail and the chain will move right. The bottom set of pdfs show how a and b are computed in a trial where the user desires to move the cursor right. Note that the classification boundary is shown in the Bayes optimal position. Our analysis investigates how the system performs as the classification boundary moves slightly to the left or right (changing the probabilities a and b).

classification boundary (or the class pdfs) shift the classification rates will differ for the right and left classes with the standard R/L system. In this case, a more general equation for the ITR is used [6]:

$$ITR = \left(\sum_{j=1}^{C} -p(y_j) log_2(p(y_j)) + \sum_{i=1}^{C} \sum_{j=1}^{C} p(x_i)p(y_j|x_i) log_2(p(y_j|x_i)) \right) / T$$

where $p(y_j) = \sum_{i=1}^{C} p(x_i)p(y_j|x_i)$ and x_i represents intended class i and y_j represents decoded class j. (For our example $C = 2$). In order to compare information transfer rates for our systems with different numbers of steps, it is important to also consider the overhead time in setting up the trial (including preparation time and interstimulus interval) thus the time component (T) consists of the sum of the times for each step plus the overhead time in setting up the trial. For this paper we use an overhead time of 5 steps (2.5 seconds). Other reasonable overhead times lead to similar results.

Accuracy, number of steps, and ITR were computed for Markov chains with different numbers of cursor positions (NCP). The results are shown in Figure 3. The black dashed curves represent the performance of R/L systems as the classification boundary is varied over the range shown. Each curve shows the result for a system with a different NCP. Several things can be immediately noticed with the regular R/L system. Accuracy increases with the number of cursor positions between the two absorbing states. Expected time to completion also increases. The best option for maximal information transfer rate, depends on the overhead time. For a d' of 1 and an overhead time of 5 computation steps, the maximal information transfer rate, is achieved for NCP=9. Changing d' for the simulated signals, changes the numeric values and may change the optimal NCP but does not change the general pattern of results. The optimal chain NCP for the best ITR, depends on d' and the overhead.

An analogous D/S system can also be created. In this case the user tries to control the cursor movement with control signals that are not *right* and *left* but *continue (satisfaction)* and *change (dissatisfaction)*. In this case we find that the next cursor position (state) depends not only on the previous cursor position (state) but also the direction the cursor was moving (which can be determined from the state before that). This means that when states represent only cursor positions a D/S system can be considered as a second-order Markov chain since the next state (cursor position) depends on the two previous states. If, however, we duplicate the interior transient states and let a state represent both cursor position and incoming direction, then we once again have a first-order Markov chain where the next state (cursor position and direction) depends on the current state (cursor position and direction) as well as the subject's desired goal, the classification boundary, and the discriminability of their signals. That is, for the the D/S system, the Markov chain is a second order system if only cursor position is considered, but can be considered a first order chain if the state includes the movement direction. The graphical model for this first-order D/S system is shown in Figure 2. The states at the top of the figure represent previous motion from the right and the bottom states represent states that had previous motion from the left. The transitions between the top and bottom rows correspond to cursor direction changes and are triggered by an interpreted *dissatisfaction (change)* signal. Interpreted *satisfaction (continue)* signals result in continuing movement along the current track. For this *interactive* system, if the subject intends to move the cursor to the right then the subject should give a *satisfaction* signal for rightward movements and a *dissatisfaction* signal for leftward movements. The probabilities for the different transitions

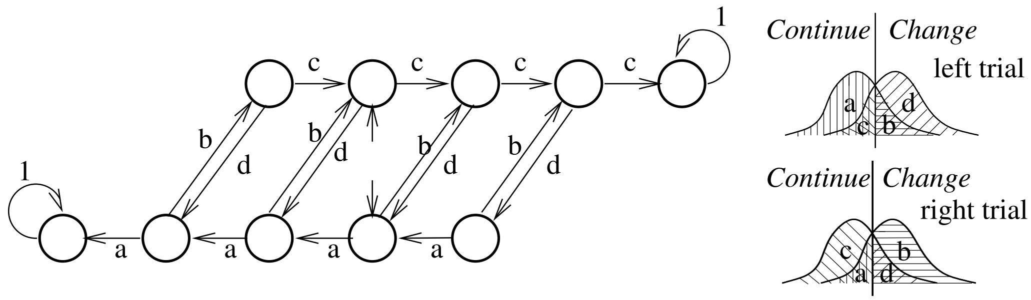


Figure 2: LEFT: The graphical model for system evolution for the proposed D/S system. The horizontal layout of the states corresponds to spatial cursor location. The rightmost/leftmost state represents hitting the rightmost/leftmost target. The numbers and variables on the arrows represent the transition probabilities between states. The vertical layout of the states corresponds to cursor motion direction. The top row of states correspond to states that have cursor movements to the right. The bottom row are the analogous states for cursor movement to the left. The initial cursor direction is randomly selected from between rightward and leftward (with end of first step ending at the center). These two starting states are indicated with the vertical arrows. This particular model shows a chain with 7 possible cursor positions (NCP=7). RIGHT: Sample 1-D pdfs show how the transition probabilities a, b, c, and d relate to the pdfs for the different classes and the classification boundary (shown by the vertical lines separating the hatched areas a and c from b and d). In a trial where the subject desires leftward motion, she generates a signal from the *continue (satisfied)* distribution when the cursor is already moving left (bottom states). This will be correctly detected with probability a and fail to be correctly classified with probability b (resulting in a *change* in cursor direction). When the cursor is going right and the subject desires leftward movement, the user generates a signal from the *change* distribution. This will be correctly classified with probablity d and incorrectly classified with probability c. When a subject desires rightward cursor movement, she should generate a signal from the *continue* distribution when the cursor is already moving right (top-states) and from the *change* distribution when the cursor is already moving left (bottom states). Note that the classification boundary is shown in the Bayes optimal position. Our analysis investigates how the system performs as the classification boundary moves slightly (changing the probabilities a,b,c and d).

are again derived from the assumed pdfs and are shown on the right of Figure 2 for both trials with desired leftward and desired rightward cursor movements.

Performance results for the D/S system are also shown in Figures 3 and 4. The range of high performance is much larger (as a function of classification boundary shift) for the D/S system than the R/L system. The curves show far less sensitivity to the exact boundary in the D/S method. Peak information transfer rates can also be better and are not always at the Bayes optimal classification boundary for distinguishing individual signals for the *continue* and *change* classes. It is interesting to analyze this difference. The R/L system depends crucially on the location of the classification boundary. If the boundary is too far towards the *right* distribution (so that too many windows are classified as *left*), then more left trials are classified correctly but fewer right trials are. The cost to the right trials is larger and the overall accuracy of the classifier goes down. In the D/S method, the classification boundary does not reflect the boundary between *right* and *left* classifications, but between *continue* and *change* classifications. When the classification boundary is moved so that *continue (satisfaction)* is more likely to be interpreted, we decrease the accuracy but also the expected completion time (there are less changes of cursor direction). Note that when the boundary is moved so that *dissatisfaction/change* is made more prevalent, the accuracy actually increases as more decisions are needed to be combined before the cursor reaches a target endpoint. By moving the classification boundary so that *change* is more likely we increase both the convergence time and accuracy. This is very similar to increasing the chain's NCP. Similarly moving the boundary to make *continue* more likely is similar to making the chain shorter. For chains with smaller than optimal NCP for a given d', ITR can be increased by moving the classification boundary so that *change* is more likely to be output. For chains that have a larger than optimal NCP for a given d', ITR can be increased by moving the classification boundary so that *continue* is more likely to be output. This can be seen in the right panel of Figure 3 and the right panel of Figure 4. Note that this means that improvements in the system ITR (for reaching left and right targets) are possible for classification boundaries removed from the Bayes optimal boundary for separating individual signals from the *continue* and *change* classes. Figure 4 also clearly shows that the D/S curves are more parallel to the ITR contours and the R/L curves are more perpendicular which is another way of seeing that the D/S system is much more robust to classification boundary drift. (ITR does not change drastically as the classification boundary drifts). Also note from the state diagram that areas a and d are pushing the cursor right and areas b and c are pushing the cursor left. As the *continue/change* classification boundary is moved, a and d trade off to some extent, as do b and c.

To summarize, in all the simulations, if the classification boundary is optimal (at the crossing point between the class pdfs), the expected number of steps, accuracy, and ITR are the same for both the R/L and D/S system. For the R/L system as the boundary drifts relative to the class pdfs the system will end up over classifying *right* or *left* and the average classification error falls off. In the D/S system differ-

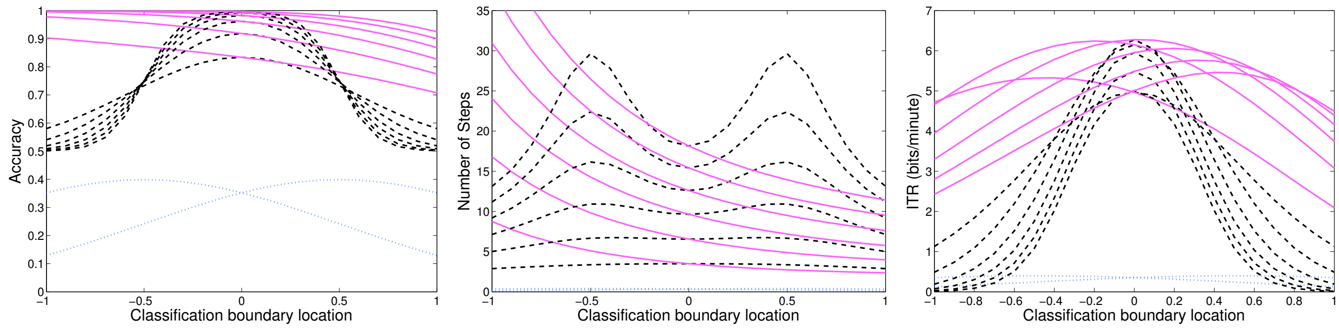


Figure 3: The blue dotted curves at the bottom of each panel show the simulated probability density functions (pdfs) for *left* and *right* for the R/L simulation. They do not have the same units as the other curves but are plotted on the same plot (with the same numeric scaling) so that the classification boundary placement can be seen with respect to the class pdfs. These same pdfs are also used for *continue* and *change* for the D/S simulation (with *change* on the right.) In the left panel, the black dashed curves show the accuracy for the R/L system as a function of classification boundary placement. (Note that optimal placement for a single window classification is at the crossing point of the class pdfs). Positive values for boundary placement mean that the classifier is more likely to output *left*. The magenta curves show the accuracy for the D/S system as a function of the classification boundary placement (between the *continue* and *change* pdfs). Positive values for boundary placement in these curves means that the classifier is more likely to output *continue*. The different curves in each color are for chains with different NCP (5, 7, 9, 11, 13, 15) with the higher accuracies resulting from chains with larger NCP. Note that in the D/S case, system accuracy actually increases as the system is more likely to classify *change* for the observed cursor movement. The middle panel show the number of steps for the same simulations (black dashed R/L, magenta D/S). The curves with more steps are for larger NCP. The final panel shows ITR for the same simulations. In the D/S simulations, for NCP larger than optimal, better ITR is associated with the classifier being more likely to output *continue*; for smaller NCP, better ITR is achieved with the classifier being more likely to output *change*.

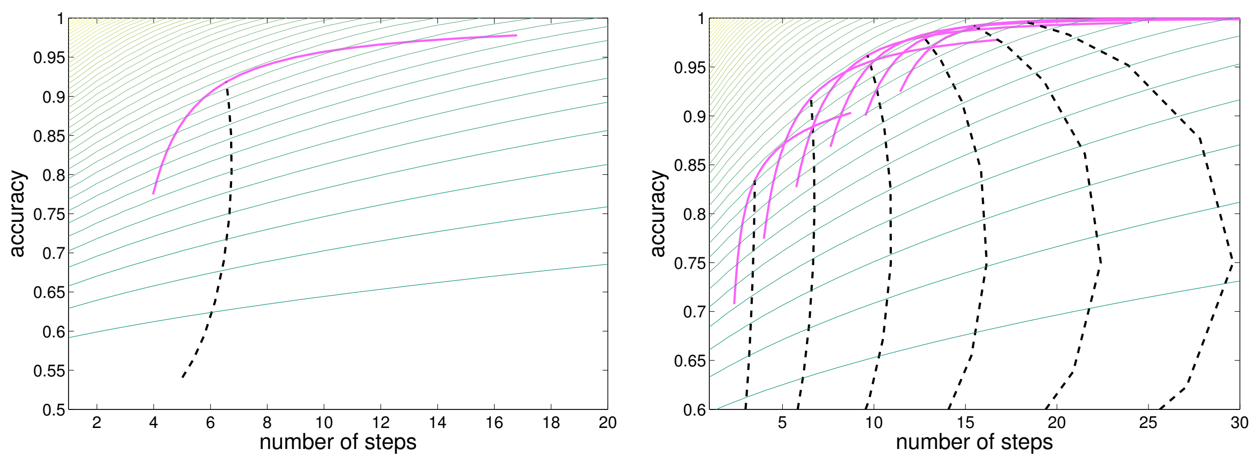


Figure 4: The left plot shows accuracy vs steps for the chains with NCP=7. The black dashed curve shows the values for the standard R/L algorithm as the classification boundary is moved by $\pm 0.5\sigma$ from the optimal boundary with a d' of 1. The magenta curve shows how the D/S values change for the same boundary movement (this time when considered as the boundary between *continue* and *change*). The place where the curves meet represents the values at the optimal classification boundary for distinguishing the single window class pdfs (for *left/right* or *change/continue*). The R/L algorithm performs symmetrically with respect to movements in either direction from this boundary so the curve falls down in the same way as the boundary is moved to the right and left. The thin curves in green show the contours of information transfer rate for an overhead of 5 steps (with higher ITRs in lighter colors and towards the top left corner) and equal classification rates for both classes. The right panel shows the same plots for chains with different NCP (5, 7, 9, 11, 13, and 15) with chains with larger NCP showing more steps and greater peak accuracy. This plot shows the same data presented in Figure 3. For all NCP as the boundary moves away from the single-window optimal boundary, the D/S system does not suffer as much in ITR (and sometimes improves - this is possible because the boundary is only optimal for the single window classification).

ent behavior is experienced if the boundary drifts. If the boundary drifts so that *continue/satisfaction* is more likely, accuracy decreases a little and the expected number of steps also decreases. Note that accuracy falls off much slower than for the R/L system. If the boundary drifts so that *change (dissatisfaction)* is more likely, accuracy will improve and the expected number of steps increases.

2.1 Variable step size is better

A variable step size may be used, so that if the classifier is more confident, the cursor takes a bigger step. This can still be modeled with an absorbing Markov chain where the number of cursor positions is made very large (even the number of pixels between targets) and the probabilities are more finely computed. See for example in Figure 5 a four part option in the R/L system (with NCP=7). Note that analogous modifications can easily be made to the D/S system (Figure omitted because of its visual complexity). Information transfer rate improves with the variable step size for both the standard R/L and *interactive* D/S system. The equality of the solutions at the Bayes optimal classification boundary and the superior robustness of the D/S system are also maintained.

Good performance is obtained with an update rule that performs

$$\mathrm{x} = \mathrm{x} + k\left(\frac{1}{1+\exp(-\frac{(\mathrm{s}-\theta)d'}{\sigma})} \times 2 - 1\right)$$

where x is the cursor position, (s -θ) is the signed normal distance of the sample EEG feature vector from the classification boundary. k is a scale variable that can be set optimally for the given chain NCP. $\frac{1}{1+\exp(-\frac{(\mathrm{s}-\theta)d'}{\sigma})}$ computes the probability that the observed sample belongs to the class with larger mean (between μ_1 and μ_2) (assuming Gaussian pdfs with means μ_1, and μ_2, equal class variances of σ^2 and disciminability d' given by Equation (1)). The multiplication by 2 and subtraction of 1 converts the probability into a scaled value from -1 to 1 which can then be multiplied by k to obtain a step size (and direction given by the sign).

3. TOWARDS USING A NATURAL DISSATISFACTION/SATISFACTION SIGNAL

We have shown theoretically that if the *satisfaction* and *dissatisfaction* signals were as equally distinguishable as standardly used signals for right and left desired motion (for example if the same brain states were used to represent these controls), the D/S system would be more robust to error in estimating the optimal boundary and to shifts in this boundary. In a real online system there are other issues. It has been found that users' ITRs decrease with longer trials (possibly due to fatigue or loss of attention) [15]. This means that keeping trials shorter (smaller NCP) may be preferred. The D/S method of control is also not natural for most human users and may be a bit difficult for them at first. Real-time performance can also be strongly affected by feedback. It has been found that a run of bad performance can lead to a much longer term loss of control, possibly due to frustration and the change in signals this causes [10]. Based on these findings, it may be more useful to use a natural *dissatisfaction* signal instead of co-opting a standard motor imagery signal. This *dissatisfaction* signal may involve emotional changes as well as error signals generated in response to seeing the computer incorrectly interpreting their desired signal. It may also have a more active aspect in encoding internal thoughts of "No!" (or a stronger word or expression).

Thus a dissatisfaction signal could arise from both active signals (thinking "No!" including the emotion and the phonation of the word) and passive signals (automatic emotion, error responses). Potentially this may lead to a richer more discriminable signal than the more commonly investigated motor imagery signals (at least for some users). A D/S system using natural *dissatisfaction/satisfaction* signals (as opposed to co-opting the motor imagery of feet and hands) would have the advantage that loss of control should be less of a problem as the system is specifically trained to recognize the frustration and dissatisfaction resulting from loss of control and so natural frustration responses should help the system perform better, rather than working against the system by introducing new untrained factors.

Finally the natural *dissatisfaction* signal could be combined with other more actively generated signals to create a stronger more robust signal. In the next section we briefly discuss a possible hybrid system with a standard R/L system being actively controlled and a more passive D/S system running simultaneously to look for some subset of frustration, errors, and imagined negative words.

4. A HYBRID SYSTEM

Several studies have been performed that use various EEG error (including the error-related negativity (ERN) and other error potential brain signals [18]) to improve performance [9, 5]. Error signals have been used to improve performance on a speeded motor task where the subject physically pushes a button [17], to correct machine-induced errors [11, 21] and to modify the policy (probability of selecting actions) of an automatic agent [3]. Error related signals have also been investigated in motor-imagery based BCIs [7, 1, 13] to change the BCI response after a trial is over [1] or to cancel individual movements [7]. We are not aware, however, of a system that has explored treating error and active signals equivalently and combining the signals in a Markov-chain-like way as we suggest below.

In Section 2 we compared an *interactive* D/S system to a standard R/L system, assuming that both could be used with the same underlying motor imagery signals just used and interpreted differently (as *continue*/*change* instead of *right*/*left*). It is also possible to combine the standard active R/L control signal with a passive and reactive D/S signal. In this case the user would be actively controlling the cursor movement to the right and left with motor imagery but passively detected satisfaction or frustration and reactively generated error signals could be used as well. In this system, it is important to weight the signals according to their confidences. This can be done in an online manner using the following formula:

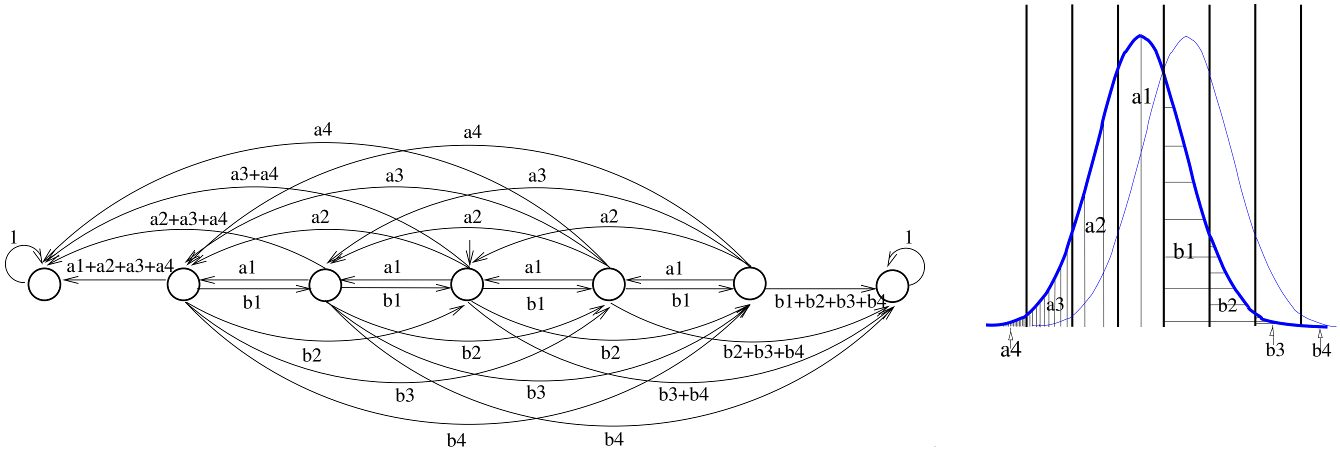


Figure 5: A more fine-scaled R/L Markov chain to allow for variable step size. Larger steps are taken when the classifier is more sure of the class decision. In this figure, the a and b probabilities from Figure 1 are each subdivided into four parts $a1$, $a2$, $a3$, $a4$ and $b1$, $b2$, $b3$, and $b4$. They are drawn at equal intervals along the projected input space but would actually be positioned at equal steps of change in estimated probability for each class. Only the probabilities for a leftward desiring trial are shown to save space. An analogous fine-scaled markov process can be used for a D/S system (not shown due to space limitations).

$$\mathrm{x} = \mathrm{x} + k\left(\frac{1}{1+\exp\left(-\frac{(\mathrm{s}-\theta)d'}{\sigma}\right)}\times 2 - 1\right) - r\left(k_{ds}\left(\frac{1}{1+\exp\left(-\frac{(s_{ds}-\theta_{ds})d'_{ds}}{\sigma_{ds}}\right)}\times 2 - 1\right)\right)$$

where x is the current cursor position on the screen, $(s-\theta)$, is the signed normal difference of the EEG R/L feature vector from the *left/right* classification boundary and $(s_{ds}-\theta_{ds})$ is the signed normal difference of the EEG D/S feature vector from the *continue/change* classification boundary. r is a binary variable (-1/+1) that represents the current direction of the cursor (r=1, for cursor moving right, r=-1 for cursor moving left). Scale factors k and k_{ds} may be set equal or optimized on a per-subject basis with cross-validation. Further work will be required to compare this method of integrating natural D/S signals with the previously used approaches.

5. DISCUSSION

The D/S idea works naturally with a two class system and in this paper we have restricted our analysis to a binary cursor control task. It has been found that information transfer rates for people in online systems tend to not improve beyond three or four classes [4, 14]. Kronegg et. al. (2007) state that "increasing the number of mental tasks from two only produces a very limited improvement in terms of information-transfer rate... This observation is in accordance with Dornhege et al. theoretical model [4]...Even if increasing the number of tasks would lead to an increase in ITR, the small gain might not justify the added complexity in terms of protocol design."

Omar and colleagues [16] have shown how to combine binary BCI control signals to generate text and curved trajectories (made from non-binary alphabets). The binary signals in their case are generated from combined evidence from right/left motor imagery. Our paper deals with how best to generate those binary signals.

Though less natural, the D/S idea could be expanded to work with a slightly larger number of classes. A 3 or 4 target D/S system could be set up where the cursor starts to move towards one of the targets at random. It would continue if it interprets a *continue* and it would start towards the clockwise next one when it interprets a *change*. It could also be used for 1-Dimensional cursor control with several targets in a line. Standard R/L systems of 1-Dimensional cursor control with more than two classes in a line have an *interactive* aspect in that to get to a middle target the command is different depending on whether the cursor is currently to the right or left of that target. However this is not the same as a full D/S system because if the classification boundary (on the right/left control signals) has moved so that *left* is overclassified, it will be very hard to hit the rightmost targets. In the D/S system, if the classification boundary has moved so that *continue* is overclassified, accuracy and convergence time will decrease as in the binary system, but ITR will not be as drastically affected. If the boundary has moved so that *change* is overclassified, error rate will decrease and convergence time will increase, and again as in the binary case, the ITR will not be as drastically affected. The D/S system is *interactive* based on both position and direction of motion. A R/L system with three or more classes in a line is just interactive based on position.

The D/S system has another possible advantage. We can recognize drift by noticing that either the average classification time has gone up or down and in each case we know the required direction of change. We also know that we should expect at most one *dissatisfaction* per trial and this may also be used in future work to keep the system tuned in an unsupervised, automatic way.

We have seen that by interacting with the signal, the BCI system can be much less harmed by non-optimal classification boundaries (and thus non-stationarities). By building a control signal that depends intimately on what has already been transmitted, interpreted, and received (and using both direction of motion and position) a much more robust system can be achieved. Future work will involve investigating natural D/S signals and testing both their use (and the use of co-opted standard signals) in online D/S and hybrid BCIs. Finally, while the finding that an *interactive* control signal should result in greater robustness to classification boundary placement was presented in the context of a motor-imagery EEG-based brain computer interface, the result is applicable for any situation where the control signals are noisy (and the optimal classification boundary is unknown or changing) and windows of classification are combined (with feedback of the current progress provided).

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