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# A Sensorimotor Rhythm based Goal Selection Brain-Computer Interface

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*Abstract*— **Different control strategies exist for use in a brain-computer interface (BCI). Although process control is the prevailing control strategy for most sensorimotor rhythm based BCIs, the goal selection strategy more closely resembles normal motor control and may be more accurate, faster to use, and easier to learn. We describe here a sensorimotor rhythm based goal selection BCI and a pilot study to compare it with process control strategy in terms of accuracy and speed of use. In both trained and naïve subjects studied, goal selection outperformed process control.**

## I. Introduction

A brain-computer interface (BCI) attempts to create an output pathway from the brain that does not rely on motor control so that paralyzed individuals can interact with the world around them [1], [2]. One class of BCIs uses non-invasive EEG to record signals generated from imagination of motor tasks. These sensorimotor rhythms (SMRs) fall in the mu and beta bands of 8 to 12 Hz and 13 to 26 Hz, respectively [1], [2]. Understanding normal motor control can lend insight into SMR BCI design. Normal motion is produced by carefully trained interactions of many parts of the brain and spinal cord. An EEG based BCI obtains its signal primarily from the cortex of the brain and bypasses the other communication so intrinsic to normal motion. Not surprisingly, even the best BCIs produce motion that would be considered ataxic by neuromuscular control specialists [3].

One possible explanation for this ataxia is that the majority of BCIs use a control strategy known as process control. In process control the user controls the fine details such as velocity, acceleration, and/or position. In normal motion these details are controlled by parts of the brain other than the cortex. In an alternative strategy known as goal selection the user communicates their goal, or final intent, to the BCI. The BCI then handles the fine details to achieve the user's goal. The goal selection control strategy more closely resembles natural motor control [3]. The minority of BCIs that use goal selection include the P300-based BCIs (e.g. [4]) as well as a few SMR-based BCIs [5], [6].

Since goal selection more closely resembles natural motor control, we hypothesize that it is more accurate, faster in use, and easier to learn. A comparison study was conducted in a group of human subjects to directly assess these two control strategies.

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## II. Materials and Methods

### A. Experimental Setup and Data Acquisition

Eight young healthy human subjects participated in the study according to a protocol approved by the IRB of the University of Minnesota. Five of the subjects were naïve and had never used a BCI before this study. Three subjects were trained in BCI usage approximately once per week for 6 to 8 sessions. EEG data were acquired via a 64 electrode cap configured in the international 10-20 system. The cap led to Neuroscan amplifiers connected to a computer running BCI2000 [7]. The subjects were instructed to make a cursor hit the left/right target by imagining left/right actions of the hand, arm, or shoulder. The cursor control signal was the auto-regressive spectral amplitudes from 7.5 to 13.5Hz of electrodes C4 and C3.

The naïve group completed 2 sessions on different days. The trained subjects completed either one or two sessions. Each session, subjects completed 15 runs. Runs were four minutes long and consisted of as many trials as the subject could complete in 4 min. Subjects had three seconds of rest between trials and a self-determined amount of rest between runs.

### B. Experimental Paradigms

During each session, subjects completed 3 runs of five different paradigms [9]: goal selection (GS), goal selection with feedback limited by time (GSFT), goal selection with feedback limited by distance (GSFD), process control with no aborts (PCNA), and process control (PC). The paradigms were similar in their underlying signal processing and used the same control signal. However, the paradigms differed in their underlying control strategy. Three paradigms were based on goal selection (GS, GSFT, and GSFD), and two were based on process control (PCNA and PC). Multiple paradigms of goal selection and process control existed to facilitate the comparison to previous studies.

The details of each paradigm are shown in the timeline in fig. 1. At time 0s, all paradigms began by presenting the two targets with the desired target indicated in yellow. One

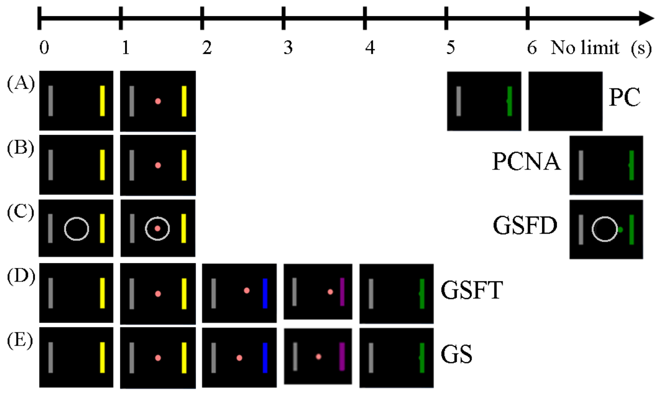


Fig. 1. Experimental paradigm timing illustrated for a hit. The right target (yellow) is the intended target. Once the cursor appears, it moves under cortical control. Trial timing for PC (A), PCNA (B), and GSFD (C) is more flexible than for GSFT (D) or GS (E), where targets are selected or reconfirmed each second. Trials end when a target is hit or, for PC, after 6s.

second later, the cursor appeared and started moving under cortical control. For all paradigms, a correctly hit target turned green, and an incorrectly hit target turned red to indicate a miss. In the PC paradigm (fig. 1A), subjects had 6s to hit a target before the trial timed out and aborted. In PCNA (fig. 1B), the subjects had to hit a target in order for the trial to end. GSFD (fig. 1C) was very similar to PCNA. The difference was that GSFD had a circle in the middle with a radius of 20% of the screen. Once the user moved the cursor outside this circle, the cursor automatically went to the closest target.

In GSFT and GS, a target first had to be selected, and then reconfirmed, before the cursor would automatically move to the target. In GSFT (fig. 1D), after 1s of cursor movement, the closest target was selected and turned blue. After an additional second of cursor movement, one of two things could happen based on the position of the cursor. If the cursor was still closest to the selected/blue target, that target was reconfirmed, the target turned purple, and the cursor automatically moved to that target (fig. 1D). If the cursor was closest to the other target, that target became selected and turned blue. The user then had an additional second to control the cursor in order to reconfirm one of the two targets. The GS paradigm (fig. 1E) was identical in behavior to GSFT except that the user saw a fixation point, and the movement of the cursor was invisible. The only feedback the user received was the changing colors of the targets to blue and then purple. Once a target was purple, the cursor became visible in the center of the screen and moved automatically to the purple target.

The naïve subjects started their first session with PC followed by PCNA, GSFD, GSFT, and GS. The order was reversed for their second session. The trained subjects used the same order as the naïve subjects and reversed the order each session. For data analysis, we compared the number of hits in an average run, speed, accuracy, and information transfer rate [2] of the five different paradigms in the pooled data from each group.

## III. Results

For both the trained and naïve subjects, the goal selection paradigms had significantly more hits in an average run than the process control paradigms. The trained and naïve subjects had similar time distributions for when the cursor was under cortical control leading to a hit. All three goal selection paradigms were faster than the process control paradigms. For both groups of subjects, GSFD had the highest accuracy and PC had the lowest accuracy. GSFT and GSFD were significantly more accurate than PC for the trained subjects. For the naïve subjects, PC was significantly less accurate than all other paradigms.

Speed and accuracy of a system can be combined into the single metric of information transfer rate. This makes information transfer rate a good summary statistic for this study. Fig. 2 shows the information transfer rate in bits per minute for both the trained and naive subjects. GSFT and GSFD transferred the most information, whereas PC transferred the least. In the trained data, GSFT and GSFD had a significantly higher bit rate than both GS and PC. In fact, GSFT and GSFD had more than twice the bit rate than PC, and were 47-60% higher than PCNA. In the naive data, both GSFT and GSFD transferred significantly more information than PC; they had more than double the information transfer rate. Additionally, GSFT and GSFD had a higher bit rate than PCNA by 47% and 58%, respectively.

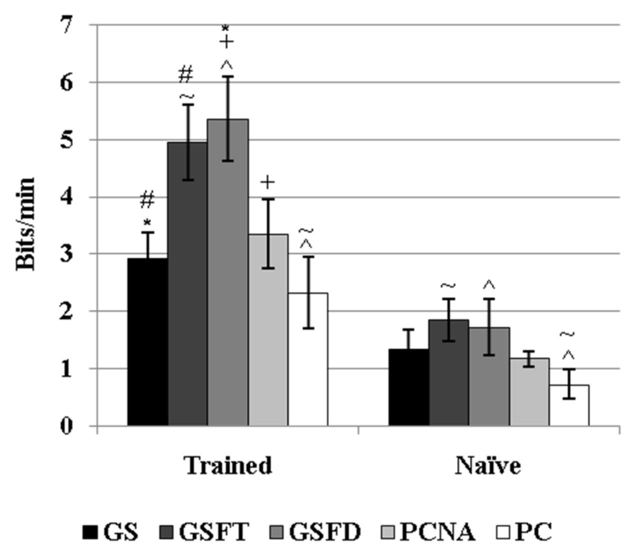


Fig. 2. Information transfer rate in bits per minute for both trained and naïve subjects across the five paradigms. Symbols indicate pair-wise significance within group of trained or naive. For the trained subjects, # and + indicate $p < 0.05$, ^, * and ~ indicate $p < 0.01$. For the naïve subjects, all symbols indicate $p < 0.05$. Error bars indicate standard error. GSFT and GSFD had the highest bit rate and PC had the lowest.

## IV. Discussion

We directly compare process control and goal selection as control strategies for a brain-computer interface. Since goal selection more closely resembles normal motor control, we hypothesized that a goal selection based system would be more accurate, faster in use, and easier to learn. The design of this study did not address learning since each subject experienced both goal selection and process control paradigms. Instead, we focused on comparing accuracy and speed of the different control strategies. We found that, for both trained and naive subjects, goal selection had more hits in an average run, was faster in use, more accurate, and had a higher information transfer rate than process control. In short, goal selection outperformed process control in every measure studied here in the group of subjects studied.

Although goal selection outperformed process control, the goal selection paradigms were not optimized. The one second selection and reconfirm times, as well as the radius of the circle, were set somewhat arbitrarily. Extremely high information transfer rates on the order of 6.5 bits per second have been achieved by optimizing the selection and reconfirm times of goal selection in an invasive system [8]. The present study was able to more than double the information transfer rate of process control by using goal selection. On an individual level, this study produced a 50 % to 1600% improvement from a process control-based paradigm to an un-optimized goal selection-based paradigm [9]. That improvement suggests what is possible by incorporating goal selection into BCI design.

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