Using feedback information theory and statistical signal processing for designing high-performance brain machine interface

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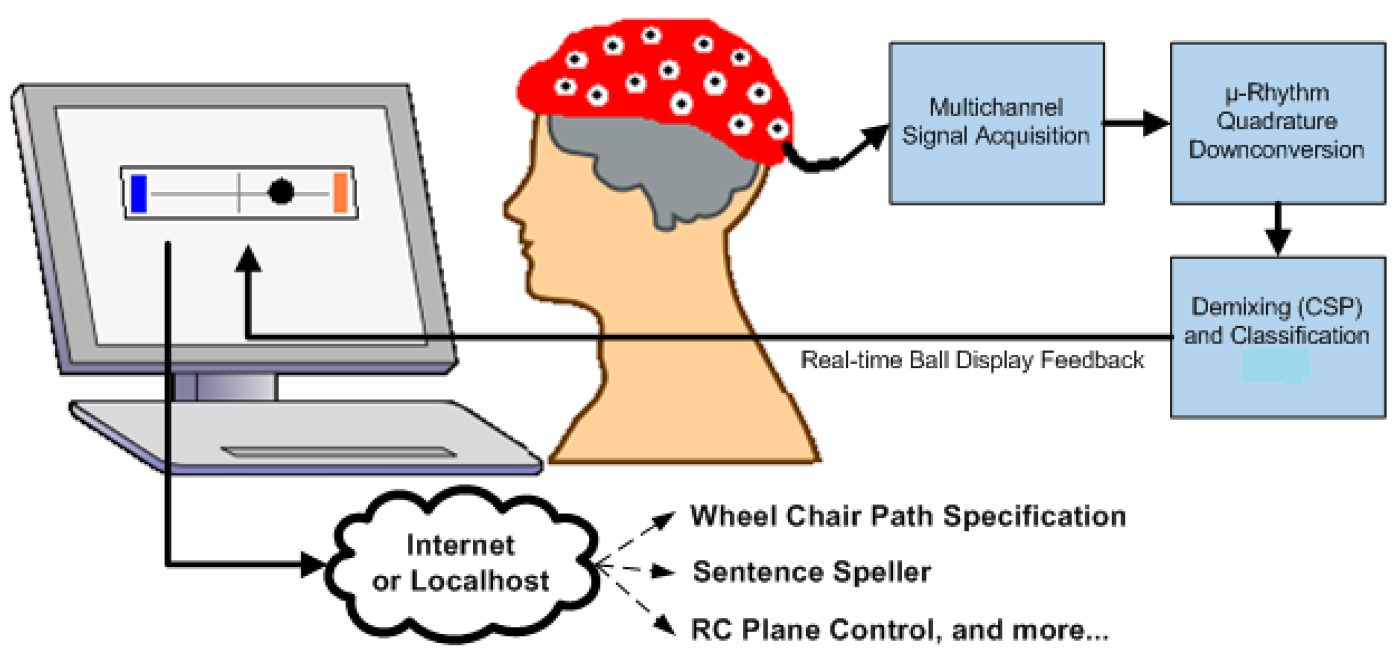
Background

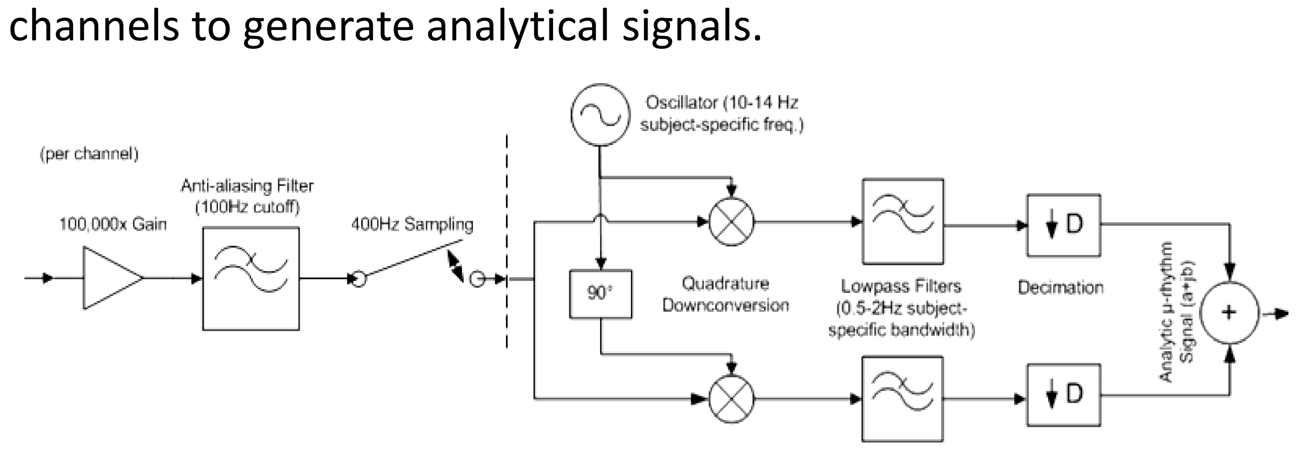
Brain machine interfaces (BMI) enable humans to control external devices with thoughts instead of physical movements. The impacts of noninvasive BCI are not limited in just disabled patient community, but hold promises for innovating human computer interactions.

Most previous works on BMI design focused on processing neural signals. Instead, our approach is to live with the extremely limited information capacity of EEG signals, and develop intelligent algorithms to handle complex tasks.

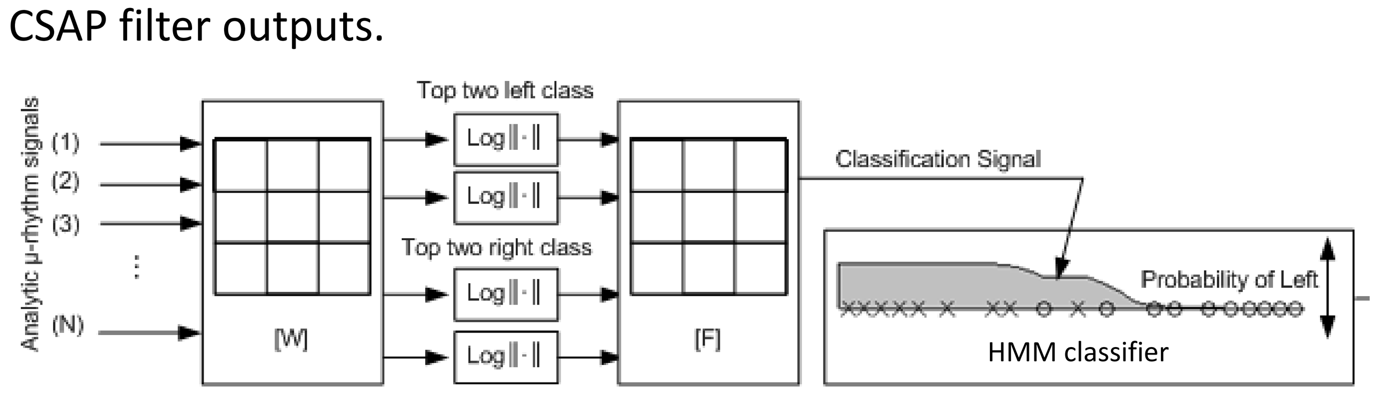


EEG Signal Processing

EEG signals are collected at 400 Hz. Multiple channels are recorded simultaneously. Quadrature down conversion is applied to all the channels to generate analytical signals.



Analytical signals were then used to compute Common Spatial Pattern (CSAP) filter. The HMM classifier estimates the user intent based on CSAP filter outputs.



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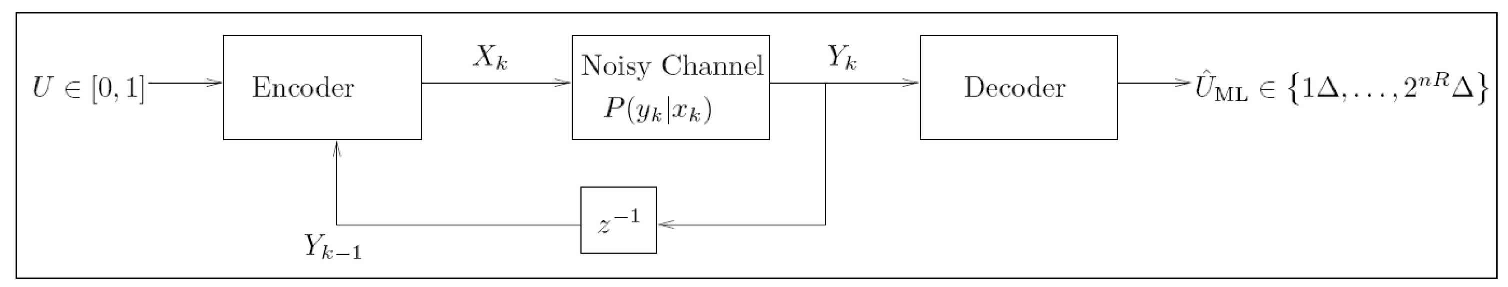
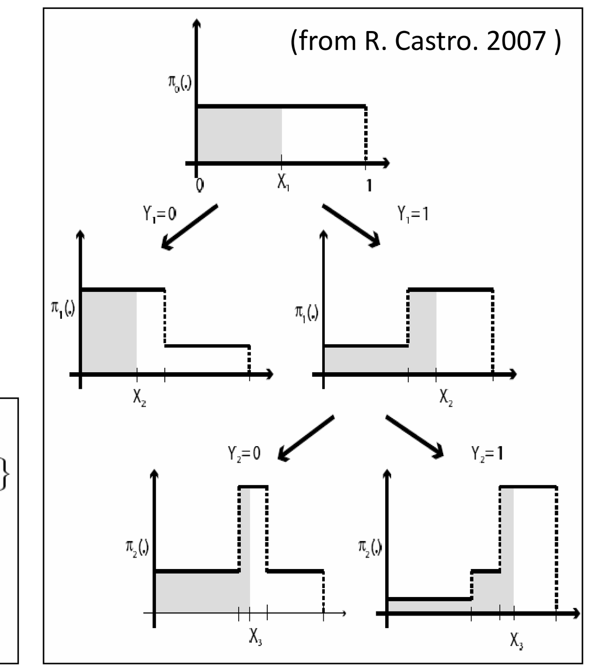
Feedback Information Theory: Posterior Matching

We formulated BMI design as a feedback information problem, and, as natural consequence, employed posterior matching scheme that provides a probabilistic bisection method to efficiently search for the message encoded as a real number on the [0,1] interval. The advantage is it only requires 1 bit/channel-use input signals, which significantly simplifies the coding scheme while achieving high accuracy.





$$
\begin{aligned}
W_{n+1} &= F_{W|Y^n}(W|Y^n) \\
X_{n+1} &= F_X^{-1}(W_{n+1}) \\
&\quad \text{for the BSC:} \\
X_{n+1} &= 1, \text{if } W < median(f_{W|Y^{n+1}}(\cdot|Y^{n+1})) \\
&= 0, \text{otherwise}
\end{aligned}
$$

$W = U$
X_n is the user intent at nth step.
$X^n = \{X_1 \ldots X_n\}$
Y_n is the HMM classifier's estimate about X_n.
$Y^n = \{Y_1 \ldots Y_n\}$

Posterior matching is an iterative scheme which ensures that the input X_{n+1} to the channel is statistically independent from $\{X_1 \ldots X_n\}$ and $\{Y_1 \ldots Y_n\}$. A piece of message U is communicated by a sequence of user intents X. The observed sequence of Y depends on X according to a statistical model. The upper-right figure demonstrates how the posterior is updated in Binary Symmetric Channel case.

Hidden Markov Model & Sum Product Algorithm

HMM

For each channel, at the i^{th} step,

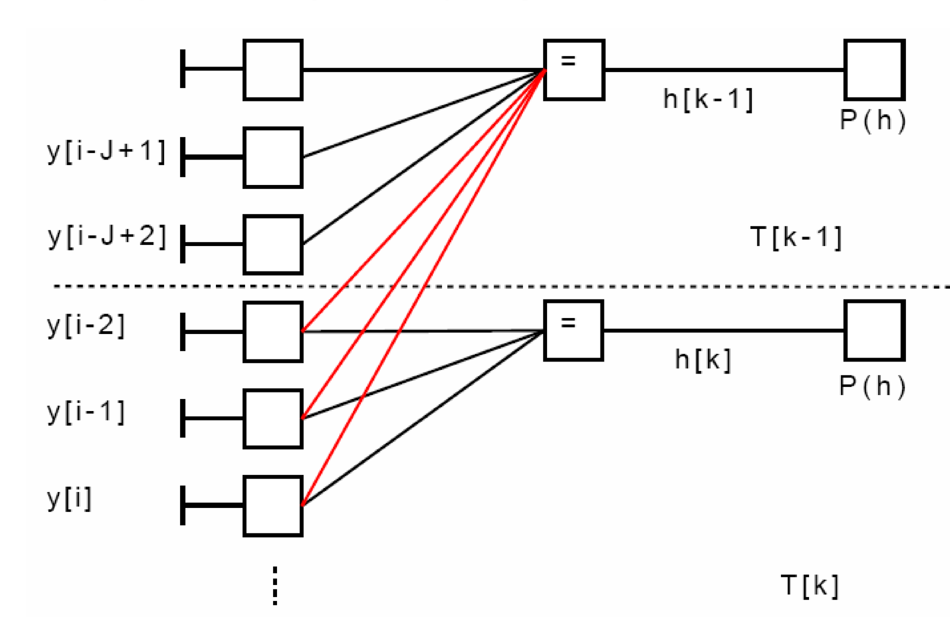
$$Y_i = \sum_{j=0}^{J-1} \alpha_j X_{i-j} + W_i$$

Where X_i = -1 if h[k] = Left, X_i = 1 if h[k] = Right. Y_i (4x1) is redefined as the output of the Common Spatial Filter at time i, a noisy observation of neural activity. W_i (4x1) is the additive Gaussian noise.

We used MLE to estimate the HMM coefficients α's(4xJ). Under Gaussian assumption, this can be done by simple Least-square estimation.

[notice that the Y_i here is different from the Y_n in posterior matching scheme.]

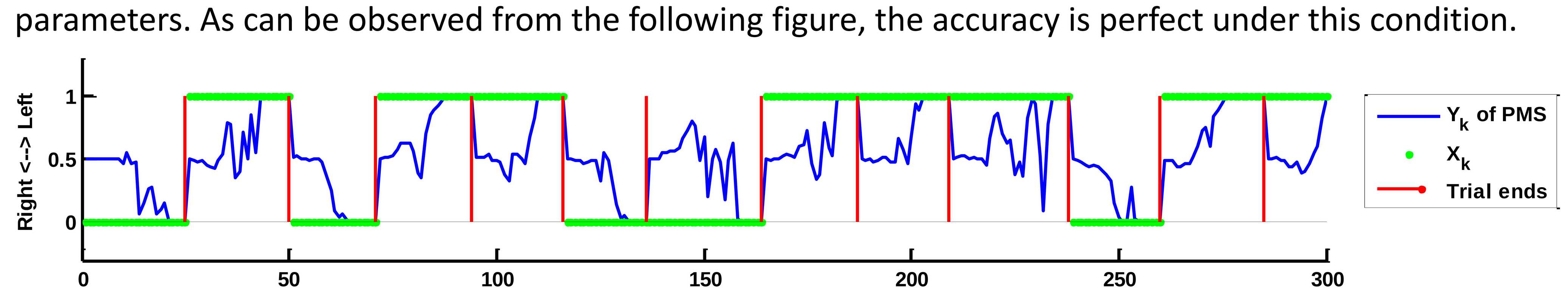
Loopy Belief Propagation



Once the parameters of the HMM are estimated by MLE procedures, they are passed on to the Belief Propagation algorithm to estimate the user intent.

Result from simulation

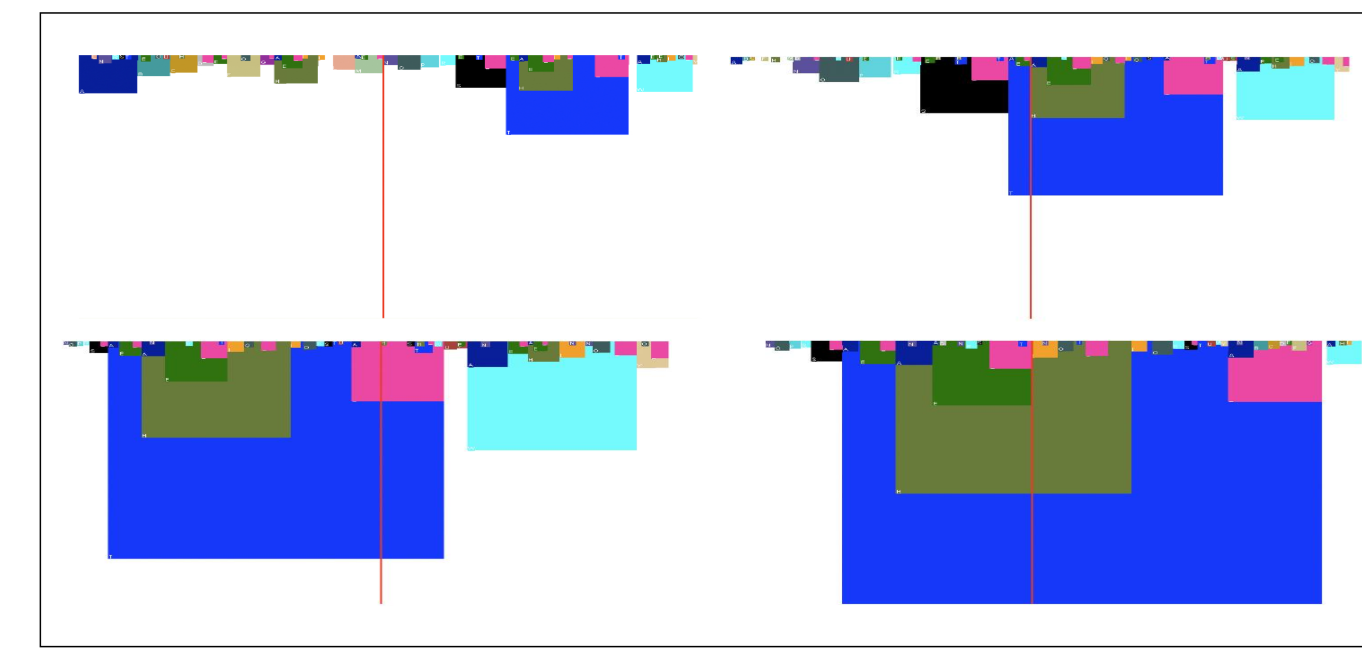
The inputs to the classifier are artificial noise generated based on the HMM fitted with the data from real human subject. The classifier has full knowledge of the HMM parameters. As can be observed from the following figure, the accuracy is perfect under this condition.



Applications

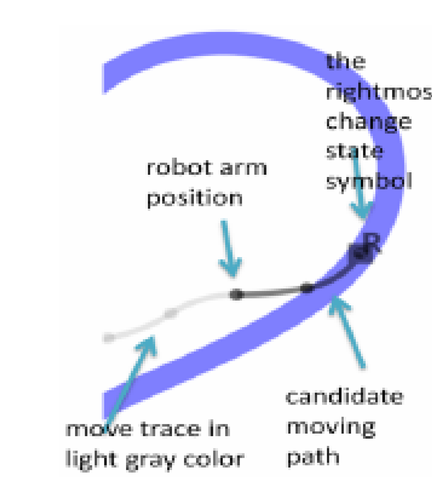
In combination, the posterior matching scheme and the HMM classifier have enabled plenty of intelligent functions, which include an English speller, wheelchair path planning, and RC flight control, all of which use binary motor imagery EEG inputs.

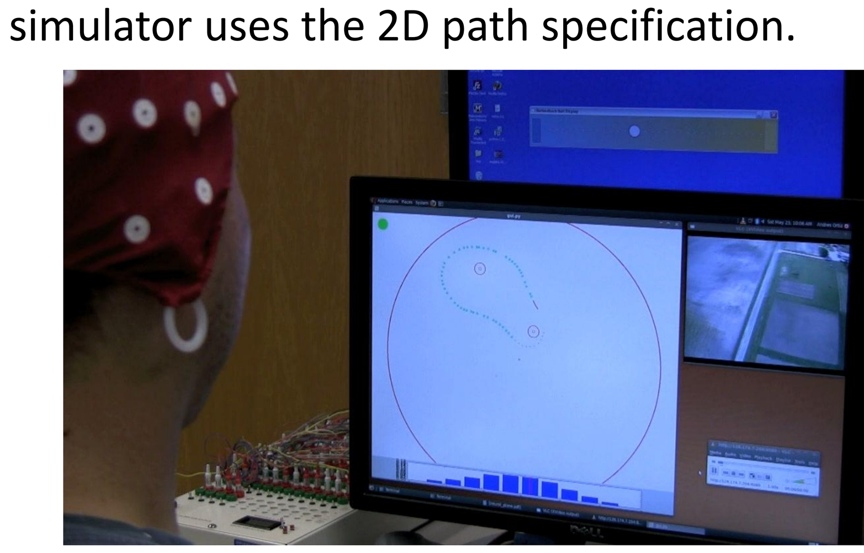
Any possible English sentences can be represented by a binary expansion on the [0, 1] interval. The a priori distribution of all sentences can be utilized to make the spelling more efficient.



2D path specification alphabetizes a finite set of possible moving directions, and updates the posterior on the next direction to go.

A radio-controlled flight simulator uses the 2D path specification.





Discussion

Our design successfully avoids dealing with the extremely weak SNR of the EEG, and instead, has enabled a lot of potential applications by utilizing the results from feedback information theory and belief propagation in estimating the user's intents on a simple, binary alphabet. We have achieved satisfactory performance with the design.

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