

# Context Aware Recursive Bayesian Estimation in BCI for Graph Navigation

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**Introduction:** Noninvasive BCIs, specifically the ones that utilize EEG for intent detection need to compensate for the low signal to noise ratio of EEG signals. In many applications, the information from temporal dependency of consecutive decisions and the contextual data can be used to provide a prior probability for the upcoming decision [1]. In this study we proposed two probabilistic graphical models (PGMs), which use context information and previously observed EEG evidences to estimate a probability distribution over the decision space in graph based decision-making mechanism. In this approach, user navigates a pointer to the desired vertex in the graph in which each vertex represents an action. To select a desired vertex, either user utilizes a “Select” command, or a proposed probabilistic selection criterion (PSC) can be used to automatically detect the user intended vertex. We compare the performance of different PGM and decision criteria combinations, over a keyboard as a graph layout.

**Material and Methods:** In a hierarchical/pointer-based decision-making mechanism the user navigates the pointer in the connected graph with  $n$  vertices (number of actions) of degree  $m$  (number of EEG classes or the cardinality of decision space) to choose from several actions. Each navigation sequence to a desired vertex is finalized by a selection, based on a selection criterion. Here a sequence of navigations which lead to an action selection is called an epoch. Fig. 1, (a) represents a PGM used for the action/direction joint maximum a posteriori (MAP) inference and (b) shows the PGM utilizing the grid structure to estimate the direction of interest while marginalizing out the actions. In both models, the prior probabilities over the vertices are recursively updated as the user is navigating throughout the graph. The goal, is to estimate the next pointer location,  $s_{e_t}$ , at epoch  $e$  and iteration  $t$ . Here the context information,  $\omega_e$ , defines a prior distribution over the actions. Moreover,  $X_{e_t}$  is the EEG evidence corresponding to  $s_{e_t}$ , and  $L$  represents graph structure. In graphical model (a),  $T_e$  represents the true state of the system in epoch  $e$ . Finally, in (b)  $y_{e_t}$  is the desired pointer location at iteration  $t$  of epoch  $e$ ; and  $A_{e_t}$  represents a particular action assignment on the graph. Two decision criteria for epoch conclusion was utilized; first the user need to choose a “Select” command, second, if the ratio of the current pointer location probability, to the next most probable action exceeds a predefined threshold the system selects highlighted vertex. In this manuscript we refer to this condition as PSC.

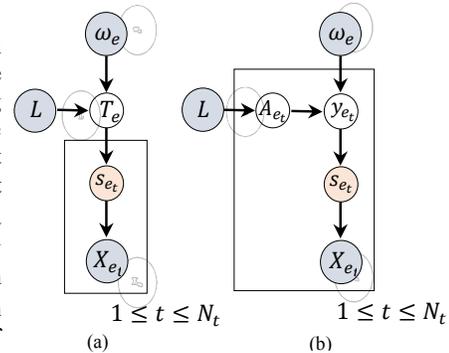


Figure 1. Two proposed probabilistic graphical models.(a) joint inference. (b) marginalizing the estimated action probabilities.

**Results:** In this study, a code visually evoked potential (c-VEP) based BCI gridded keyboard with  $28^1$  characters utilized to assess the effectiveness of PGMs and stopping criteria pairs. Here each character in keyboard represent one vertex of four degree in graph;  $n = 28, m = 4$ . 6-gram language model provide context information for each character. Twenty Monte Carlo simulations were used to mimic the system operation while typing ten different words. Seven pre-recorded calibration data sets with high, average, and low accuracies were utilized to run these simulations. Fig. 2 indicates using PGMs enhance the typing speed. This effect is clear on the performance of the users with low EEG classification performance. Overall, the PGM in figure1 (b) along with PSC provided the highest performance improvement. However, when the context information is more reliable, the PGM in Fig. 1 (a) along with PSC gave the best performance.

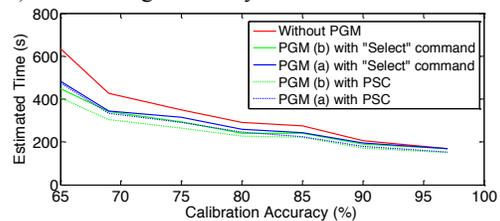


Figure 2. Average estimated time based on 20 Monte Carlo simulations, to type ten words, employing different PGMs.

**Discussion and Significance:** In this study, we proposed two PGMs which use context information and previously observed EEGs in addition to the EEG recorded during the current iteration. Our simulation results show PGMs along with PSC can enhance the typing speed especially for users with poor EEG classification performance.

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**References**

[1] Volosyak, Ivan. "SSVEP-based Bremen-BCI interface—boosting information transfer rates." *Journal of neural engineering* 8.3 (2011): 036020.

<sup>1</sup> 26 English alphabet letters, space and backspace symbols