A Novel Approach to Brain Computer Interfaces

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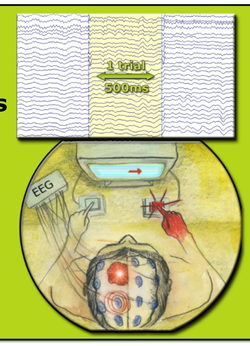
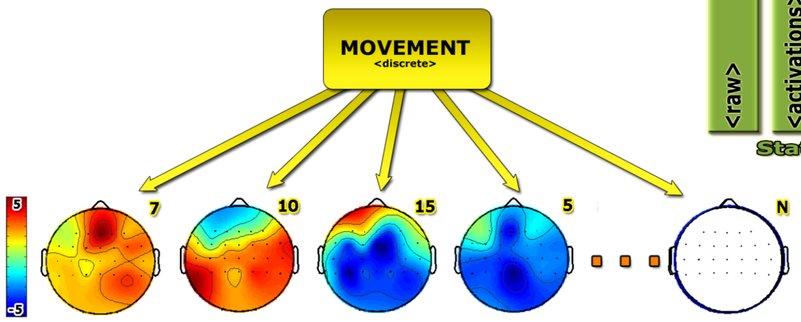
Introduction:

Brain signal classification has become a primary focus of the Brain Computer Interface field. Many approaches have been proposed to solve this problem. Most of these attempts have relied on signal artifacts specific to the motor domain. In our current work we propose a noval approach which combines Independent Component Analysis with Bayesian Networks to decompose brain Electroencephalography signals into statistically Independent Components (ICs) and then learn the correlation between the ICs and subject finger movement using a Bayesian Network. This should provide us with a more general approach that is not explicitly tied to the motor domain.

Methods and Background:

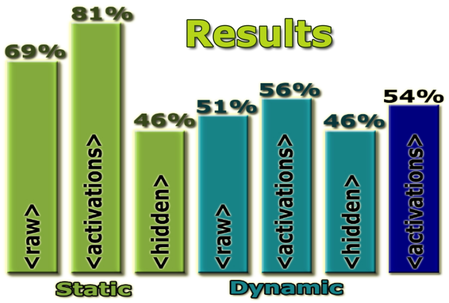
* Dataset 1: right vs left finger movement, 316 trials, 28 electrodes
* Dataset 2: 1 finger tap, 4 finger tap, 4 finger sequence, 648 trials, 64 electrodes
* Selected 500 ms ending 130 ms before key press for further analysis.
* Decompose each data set with ICA (Infomax)
* Model Independent Components with Bayesian Network
* Apply variety of static and dynamic network structures (naive and hidden).
* Hill climb on successful networks to find best subset of components
* Compare Component Activations with raw EEG channels



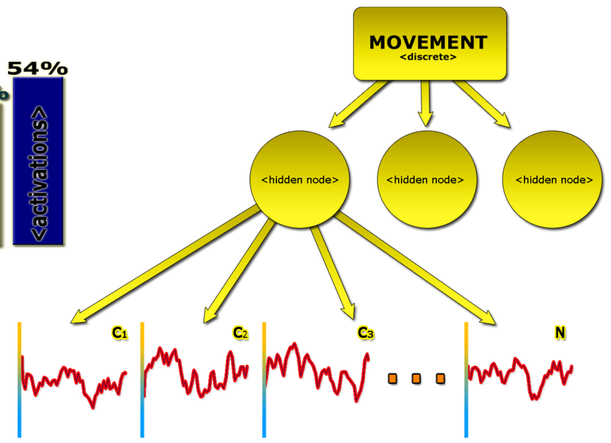


Above is a static naive Bayesian Network structure. The square node represents the movement type, it is modeled as a discrete distribution with 2 values for right vs. left finger movement in data set 1or 3 values for 1 finger tap, 4 finger tap, and 4 finger sequence in the data set 2. The circular nodes are modeled as continuous distributions taking on the mean value across time of each IC Activation or each raw EEG channel.

Results



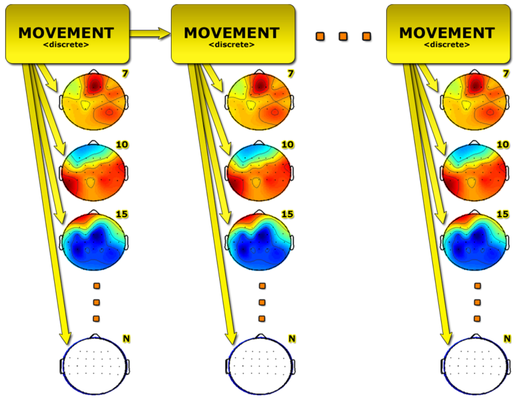
Static



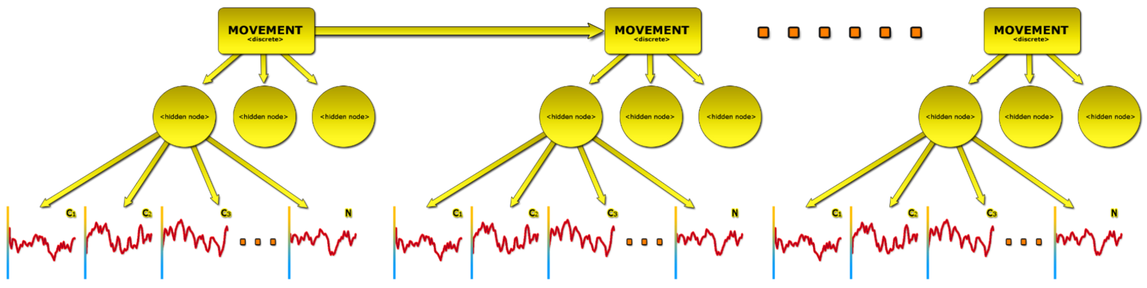
In the above static hidden network, the square node represents movement and is modeled as a discrete distribution taking on 2 values for right vs left finger movement in data set 1 and 3 values for 1 finger tap, 4 finger tap, and 4 finger sequence in data set 2. The children of the movement nodes (circular nodes) are hidden nodes modeled as continuous distributions, each representing a single IC. Each IC node has 28 children modeled as continuous distributions, which are the mean across time of each EEG channel in that IC's back projection.

Dynamic

The dynamic network below is the "unrolled" version of the static network above. Each time slice is a complete static naive Bayesian Network. The square node (movement node) was modeled with either a discrete distribution or a continuous distribution taking on 2 values for data set 1 and 3 values for data set 2 as in the other networks. Each child of the movement node is modeled with a continuous distribution and takes on the value of an IC's Activation at each time step.



The dynamic network below has a similar structure to the static network above, except it is "unrolled" across time. As in other network structures the square node models movement (we used either a continuous distribution or a discrete distribution), each of its children are hidden nodes modeling a single IC, and each of those IC nodes has 28 children that take on the value of each EEG channel in the IC's back projection at each time step.



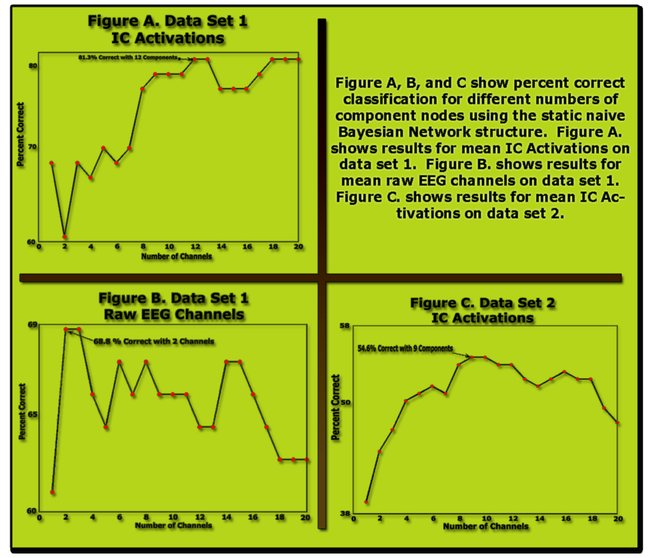


Figure A, B, and C show percent correct classification for different numbers of component nodes using the static naive Bayesian Network structure. Figure A. shows results for mean IC Activations on data set 1. Figure B. shows results for mean raw EEG channels on data set 1. Figure C. shows results for mean IC Activations on data set 2.

Discussion:

* Bayesian Networks show successful results, and warrant further study!
* Direct use of ICA significantly improved results
* Future work should focus on adding "memory" to dynamic Bayesian networks

References:

All Bayesian Networks were modeled using Kevin Murphy's FullBNT Package,
->http://bnt.sourceforge.net/usage.html.

All ICA decompositions were done using the Infomax algorithm as implemented in EEGLAB,
->http://www.sccn.ucsd.edu/eeglab/

o A Delorme & S Makeig. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics, Journal of Neuroscience Methods 134:9-21 (2004)