Automatic Extraction of Command Hierarchies for Adaptive Brain-Robot Interfacing

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Brain-Computer Interfaces (BCIs) for severely paralyzed or "locked-in" persons.

- Artificial neural pathway
- Can we provide more independence via a BCI and a robotic proxy?



Non-invasive EEG

- Practical, but suffers from low throughput (< 60 bits/min)
- Fine-grained control impractical in long term
- But need flexibility to deal with a wide variety of situations



Hierarchical skill learning example:

- Learn individual pen strokes
- Learn to put pen strokes together to form letters
- Learn to put letters together to form words
- Etc.



Hierarchical BCI (HBCI):

- User performs tasks with lower-level skills
- HBCI observes user to learn higher-level skills
- User can execute higher-level skills directly
- Raises effective throughput of the interface
- Can work independently of the choice of BCI paradigm

System Overview



System Overview



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System Overview

HBCI Control Agent:

- Extracts patterns from history of user actions
- Prunes patterns which are:
 - shorter than 3 commands
 - appear less than twice
 - other pruning
- Presents patterns as higher-level skills
- Decodes stored patterns to send to robot



Algorithm 1 – Sequitur (Nevill-Manning) Algorithm

Sequitur Algorithm [Nevill-Manning and Witten 1997]

- Extracts context-free grammar from sequence of discrete symbols
- Applied to J.S. Bach:





Algorithm 1 – Sequitur (Nevill-Manning) Algorithm

Sequitur Algorithm [Nevill-Manning and Witten 1997]

• User input:

abcdefab0defabcdef

• Sequitur returns:

R0 -> R1 c R2 0 R2 c R3



R3 -> d e f

After pruning user would see only R2, R3

Maximum-length chaining:

- Stochastic model helps deal with input noise
- Prefers long chains for maximum throughput increase
- Intuition: iteratively concatenate to observed sequences while next input can be reliably* predicted
 - Example: if 'c' always appears after 'a b', then discard 'a b' and begin again with 'a b c'
 - *'Reliable' determined by a probability threshold

Algorithm 2 – Maximum-length Chaining

Maximum-length chaining:

• User input:

abc<mark>defab</mark>0<mark>defab</mark>cdef

• Max-chaining returns:



 Recognizes intended control sequence a b c d e f

The Experiment



Ingredient mixing task w/simulated PR2



Example GUI screen; user sees robot's view, stimuli on perimeter of screen

The Experiment

Multi-phase experiment:

- Each user given two recipes to mix
- In each phase, the user mixes both recipes
- Order they are mixed varies
- Four phases per experiment
- User runs experiment twice
 once with each algorithm
- Abstracted commands make
 later phases easier



Example Results

Recipes: Green, Blue, Yellow | Red, Blue, Yellow

Phase 1:



Results – User Study

Actions Sent to Robot by Experiment



Simulated user experiment:

- 1000 simulated users run the same set of experiments
 - 500 average noise, 500 high noise
- High noise = each command 2.5 times higher probability of mistake



Results – Simulated Users

Simulated Users With Noise - Actions Sent to Robot



Improvements / Challenges

- Scalability:
 - Simple demonstration showed short, simple skills
 - HCl issue: how do we present longer, more complicated skills?
 - How do we make use of the state space?
- Dealing with contingency:
 - What if something goes wrong during execution?



