Motivation:

- Non-invasive BCIs, such as electroencephalographic (EEG) signals, suffer from low-signal-to-noise ratio which limits the bandwidth of control.
- Traditional BCIs for robotic control have a trade-off between cognitive load and scalability. More robotic autonomy [1] implies coarse-grained control and less flexibility, while fine-grained control [2] provides greater flexibility but higher cognitive load.
- Hierarchical architecture for brain computer interfacing allows a user to teach the BCI new skills on-the-fly; these learned skills are later invoked directly as high-level commands, relieving the user of tedious low-level control.

Methods:

- Three main components in hierarchical BCI
  1. EEG-based BCI, e.g. steady state visual evoked potential (SSVEP).
  2. Hierarchical menu and learning system that allows the user to teach the BCI new skills.
  3. The application, e.g. a simulation of a humanoid robot, wheeled robot, or real PR2 semi-humanoid robot.

Hierarchical Menu

Figure 1: A Hierarchical BCI System. A. Experimental setup, B. Application, C. Menu and SSVEP stimulation, D. Frequency domain of a subject’s EEG signal.

Results:

- Study 1: Testing the Hierarchical Architecture.
  
<table>
<thead>
<tr>
<th></th>
<th>Low-level BCI</th>
<th>Hierarchical BCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Num Selections</td>
<td>20 (7)</td>
<td>5 (2)</td>
</tr>
<tr>
<td>Task Time</td>
<td>220 (67)</td>
<td>112 (25)</td>
</tr>
<tr>
<td>Nav Time</td>
<td>124 (37)</td>
<td>73 (19)</td>
</tr>
</tbody>
</table>

Mean of three trials from best subject (std)

<table>
<thead>
<tr>
<th></th>
<th>Low-level BCI</th>
<th>Hierarchical BCI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Num Selections</td>
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<td>4</td>
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<tr>
<td>Task Time</td>
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<td>75</td>
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<tr>
<td>Nav Time</td>
<td>59</td>
<td>59</td>
</tr>
</tbody>
</table>

Figure 2: Overview of control flow in the hierarchical menu system.

Figure 3 & Table 1. Example Robot Trajectories from User-Demonstrated Low-Level Control and Hierarchical Control and Performance Comparison

- Study 2: Uncertainty-Guided Interaction [4].

- Study 3: Scaling up to Real Robot and Complex Task Learning [5].

Learned sequence 1:

Arm trajectory 1 ➔ Rotate wrist left ➔ Rotate wrist right

Learned arm trajectories:

- Low-level primitive commands: Move arm, Rotate wrist, Move head, Toggle gripper

Conclusion:

- Combining Scalability and Efficiency
- Interaction Based on Probabilistic Model
- Hierarchical Architecture, Learning with both low and high level skills
- Multi-tasking for Increasing Bandwidth
- Long-term usability

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