Non-Invasive Brain-Actuated Control of a Mobile Robot

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BCI Introduction (paper perspective)

BCIs

- BCI = Brain Computer Interface
- BCIs for both able-bodied and physically-disabled people => realtime brainwave analysis.
- Using a virtual keyboard
- Moving a robotic or prosthetic device
- Brain state + no physical action = BCI

A Non-Invasive BCI: EEG

- EEG = electroencephalogram
- Brain activity recorded from electrodes on scalp
- According to paper: main source of the EEG signal is the "synchronous activity of thousands of cortical neurons."
- Reading EEG signals is simple and non-invasive but does not allow the single or cluster neuron resolution other techniques can provide.

EEG: Evoked Potentials

- “Automatic responses of the brain to external stimuli.”
- Relatively simple to measure, but force subject to respond rather than initiate.

EEG Rhythms

- Most used are related to the imagination of body movements => recorded from the sensorimotor cortex.
- Analysis involves looking for pre-defined patterns.
- Other possibilities:
  - Imagining movements
  - Mental math
  - Imagining language
- Analysis could then involve looking for embedded patterns as opposed to an overall "look."

Paper Purpose and Motivation

- Robotic and prosthetic control has been shown with monkeys and implantable electrodes.
- Never been accomplished with humans.
- Goal is to show that, with only a short amount of training time and utilizing non-invasive means, a human subject can control a brain-actuated robot.
- Additionally, would like to show that mental control is only slightly worse than manual control.

Interface Protocol

EEG Techniques

- Synchronous protocols often limited to low bit rates below 0.5 bits/s => “time-locked to externally paced cues.”
- New approach uses an asynchronous protocol.
- “Analyzes the ongoing EEG to determine the subject's mental state, which they can voluntarily change at any moment.”
- Theoretical bandwidth between 1 and 1.5 bits/s.

Interface Setup

- Two patients, “A” and “B”.
- Commercial EEG cap.
- Measured 8 standard fronto-centro-parietal locations: F3, F4, C3, Cz, C4, P3, Pz, and P4.
- Sampling rate: 128 Hz.

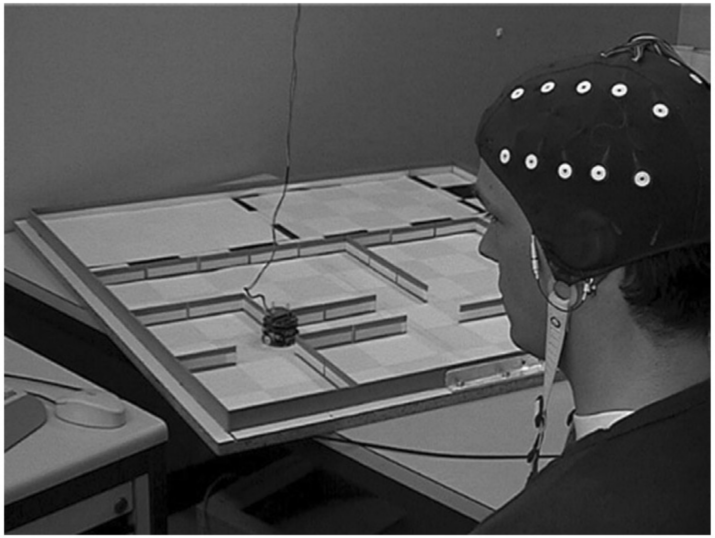

Figure 1. One of the experimental subjects while driving mentally the robot through the different rooms of the environment during the first experiment.

Interface Setup

- Raw EEG potentials => suface Laplacian transform => order 2 spherical spline.
- “This spatial filtering yields new potentials that should represent better the cortical activity due only to local sources below the electrodes.”
- Welch periodogram algorithm to estimate power spectrum over previous second.

Interface Setup

- Averaged 3 0.5 second segments with 50% overlap => resolution of 2 Hz.
- Values in 8-30 Hz normalized by the total energy in that band.
- => EEG sample: 96 features
  - 8 channels * 12 components/ch
- 16 samples computed per second (62.5 ms delay)

Training Methods

- Subjects learned to control 3 mental tasks of their choice out of:
  - Relax
  - Imagine repetitive left hand/arm movements
  - Imagine repetitive right hand/arm movements
  - Imagine a spinning cube
  - Successive subtraction by a fixed number
    - Eg. 64-3=61, 61-3=58, etc
  - Word association
- A: relax, left movement, cube rotation
- B: relax, left movement, right movement
- No previous BCI experience or training.

Training Methods

- 4 consecutive training sessions per day.
- ~5 mins/session, with 5-10min break between
- Subjects switched randomly between their 3 tasks every 10-15 seconds.
- Online feedback through colored buttons on a computer screen => each button corresponds to a specific task.
- Statistical classifier optimized offline.

Training Methods

- After task training, subjects trained to the robot for 2 days.
- Results presented are after the second day.
- The BCI and subjects both adapted to eachother: training was not simply for the subject.

Statistical Methods

Gaussian Classifier

- State #1, #2, #3, or unknown.
- Input: EEG samples
- Output: Probability distribution for states

Equations that Do Something

$$y_k(x) = \frac{\sum_{i=1}^{N_k} a_k^i(x)}{\sum_{j=1}^{N_c} \sum_{i=1}^{N_j} a_j^i(x)} \qquad (1)$$

$$a_k^i(x) = \left|\Sigma_k\right|^{-1/2} \exp\left(-1/2(x-\mu_k^i)^{\mathrm{T}} \Sigma_k^{-1} (x-\mu_k^i)\right) \qquad (2)$$

$$\Sigma_k = \frac{1}{S_k} \sum_{n=1}^{S_k} (x^n - \mu_k^n)(x^n - \mu_k^n)^T \qquad (3)$$

$$\Delta\mu_k^i(x) = \alpha\left(t_k(x) - y_k(x)\right) \Sigma_k^{-1}(x-\mu_k^i) \frac{a_k^i(x)}{A(x)} \qquad (4)$$

Interface Mode I

- BCI responds every 0.5 seconds.
- Mode I:
  - Computes probability for each class.
  - Averages over 8 consecutive samples.
  - Estimates probability using Bayes' formula.
  - Compares final probability with a threshold of 0.85.
  - Errors <5%, “unknown” <30%.
  - Theoretical bandwidth: 1 bit/s.

Interface Mode II

- Similar to Mode I.
- Requires two consecutive 0.5 s periods w/the same classification.
- Errors <2%, “unknown” <40%.
- Theoretical bandwidth: 1bit/s.

Robot and World Setup

The Task

- "Drive the robot through different rooms in a house-like environment."
- The robot is similar to a miniature wheelchair.
- As only 3 commands are available to the users, it is necessary to interpret them as high-level instructions rather than low-level motor commands.

The Robot

- Two wheeled vehicle: modelling a wheel chair.
- 8 infrared sensors spread out around 360 degrees.
  - Multilayer perceptron to map sensors into state.
- 3 feedback lights on robot (same as training):
  - Green => mental command #1
  - Blue => mental command #2
  - Red => mental command #3

The Commands

- High level instructions, dependent on the robot state.
- The robot transitions between states based on both BCI and sensor input => behavior based controller.
- Generalized input commands:
  - #1: Move forward.
  - #2: Turn left / follow left wall.
  - #3: Turn right / follow right wall.

BCI Interface

- High level commands can be received at any time.
- Robot continues executing command until another is received.
- Infrared sensors and built-in logic take care of low-level issues such as speed, turning radius, etc.
- BCI strictly used for communicating what, not how.

Finite State Automaton

- State changes based on sensor and BCI input.
- Commands relative to current state:
  - In an open space, left and right mean turn left and right.
  - In a confined space, left and right mean follow left/right wall until opening, and turn into room.
  - Forward signifies moving forward and not turning when an opening appears.
- Stop for obstacles.
- Visual colored light feedback allows users to correct state before action if misinterpreted.

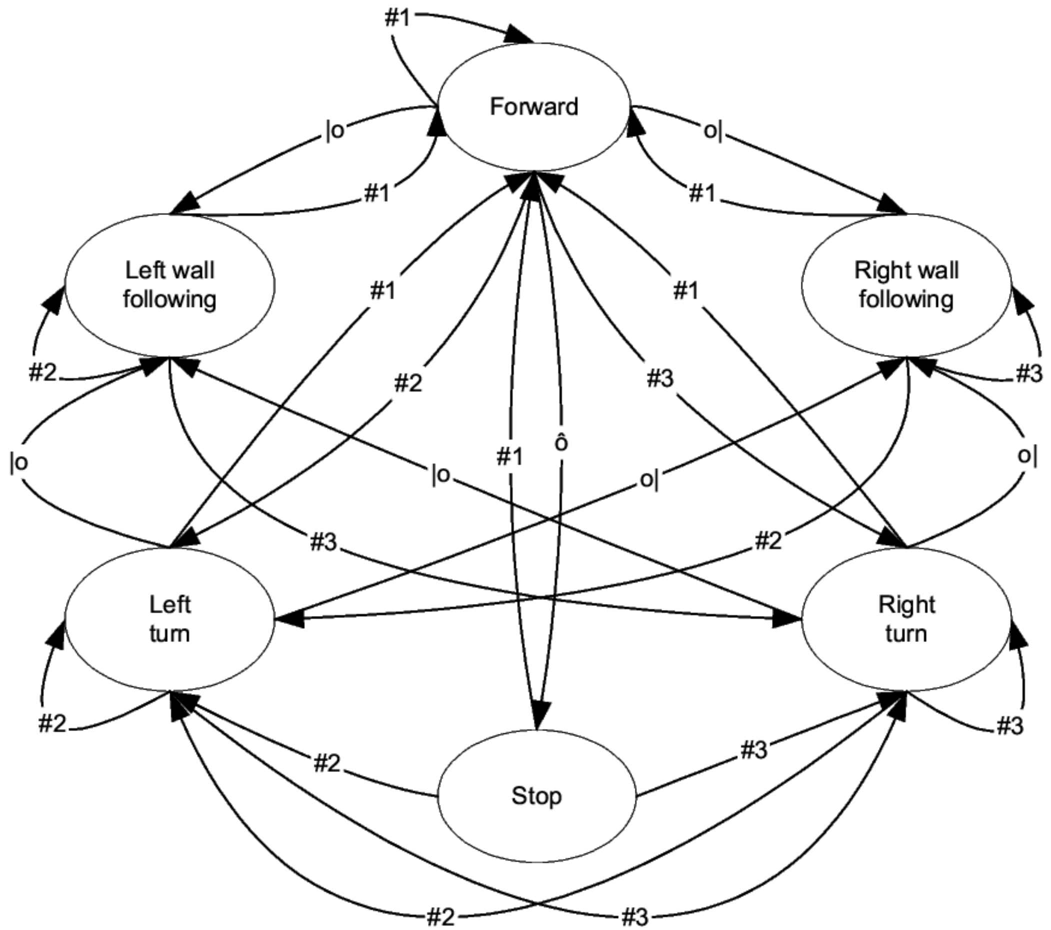

Figure 2. Finite state automaton used for the control of the robot. Transitions between the 6 behaviors were determined by 3 mental states (#1, #2, #3), 6 perceptual states (|o: left wall, o|: right wall, ô: wall or obstacle in front), and some memory variables. The memory variables and some of the perceptual states are not shown for the sake of simplicity.

Results

Mode I Training Results

- Subject A – 5 days of initial training
- Subject B – 3 days of initial training
- Satisfactory performance: >60% correct, <5% errors

Mode II

- Task: Visit 3 different randomly chosen rooms.
- ~10 minutes continuous usage
- 100% success, in order
  - Failure when BCI was too slow (missed a door etc)
  - Correctable by user

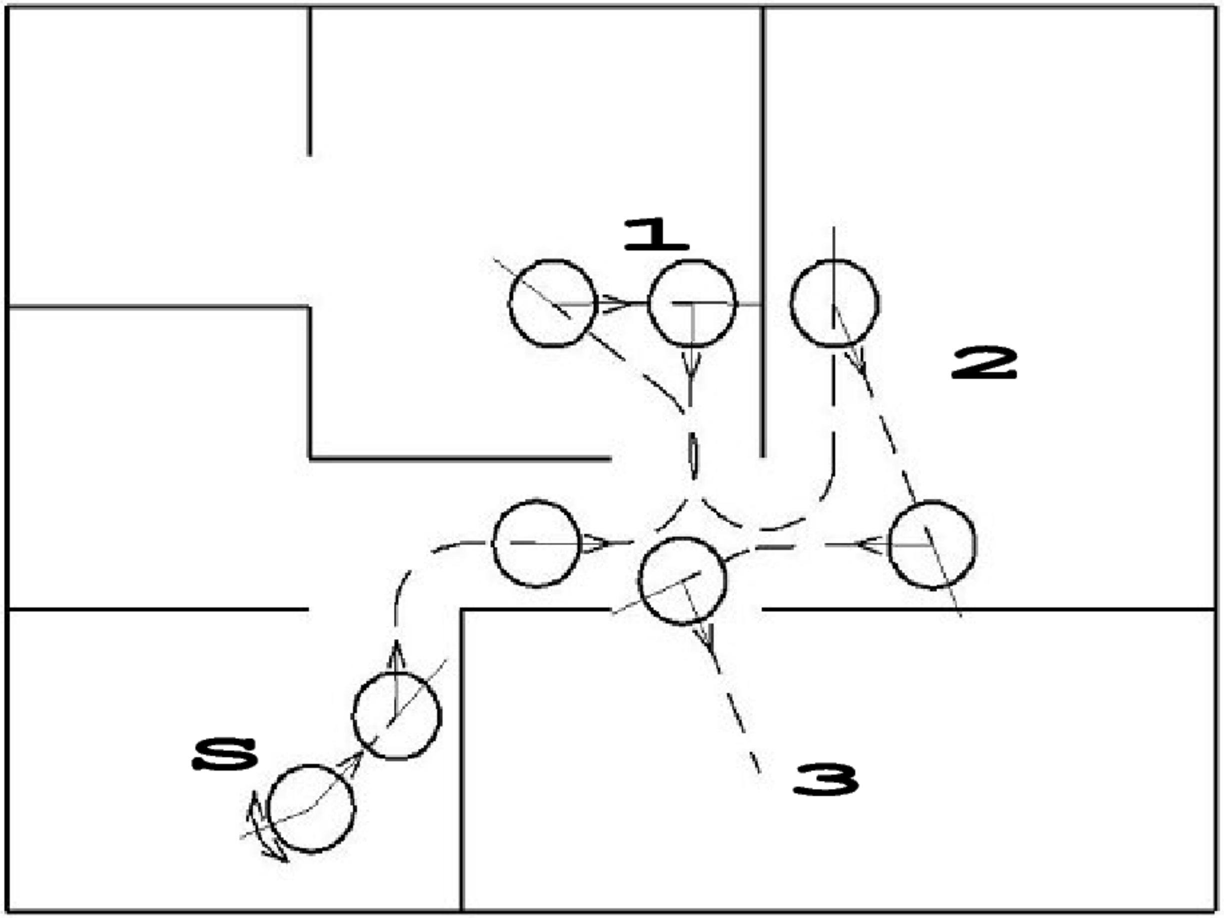

Figure 3. Trajectory followed by the robot under the mental control of subject "A" during one of the trials of the first experiment. The robot started in the bottom left room and then visited 3 other rooms, top center, top right and bottom right, sequentially. The figure does not show the details of the trajectory inside the rooms.

Quantitative Results

- New experiment used a different room layout.
- Subjects first drove under mental control, and then manual control.
- Results compared: average only 35% longer for brain control.

Table 1. Time in seconds for three different trials where subjects “A” and “B” controlled the robot first mentally and then manually.

Subject	Trial	Mental	Manual
“A”	1	149	124
	2	183	135
	3	191	129
	Average	*174*	*129*
“B”	1	219	156
	2	189	155
	3	175	117
	Average	*194*	*143*

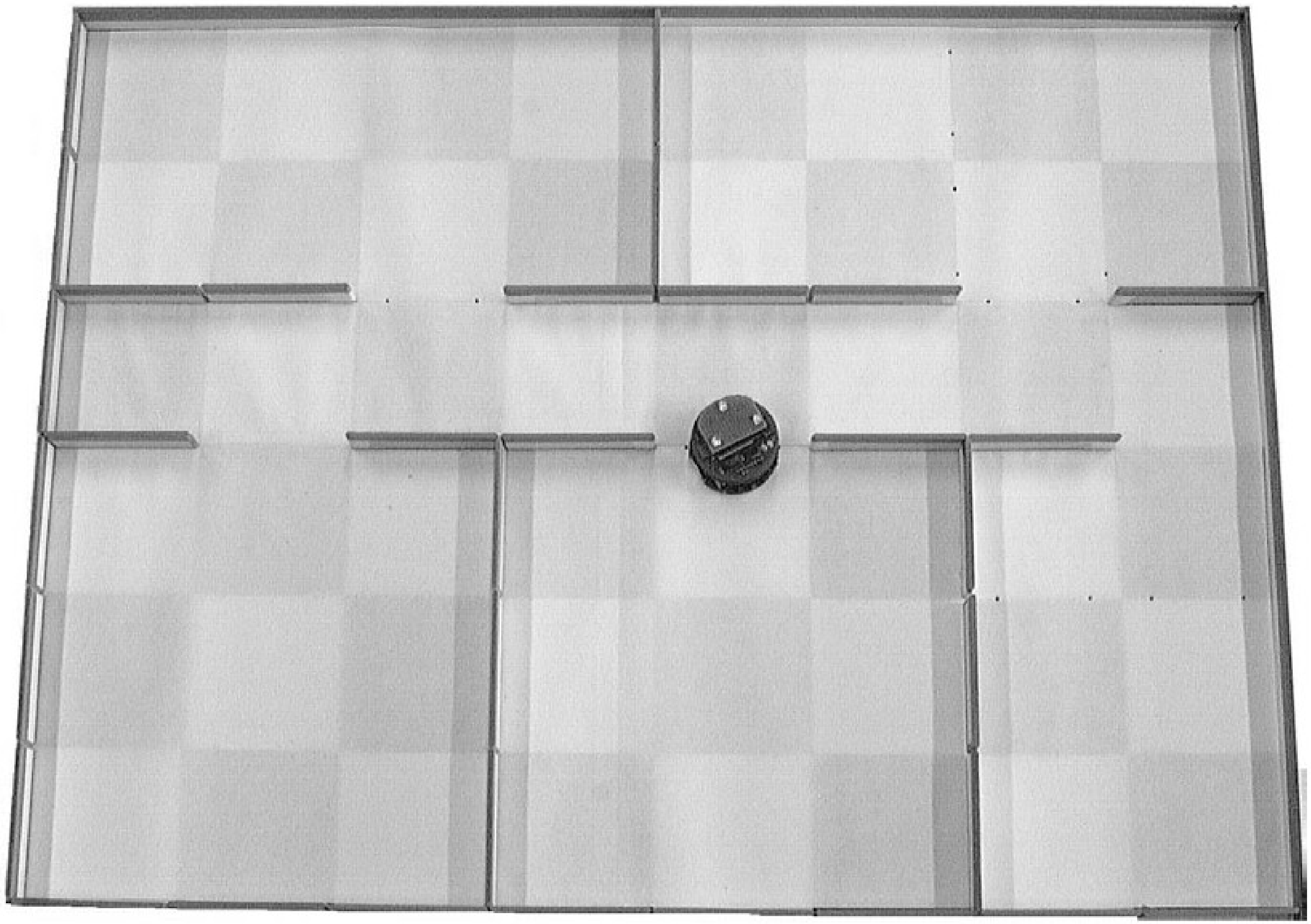

Figure 4. Environment used for the second set of experiments.

Conclusion

EEG for Robotic Control

- Much lower quality and resolution than implantable electrodes.
  - Still sufficient to operate a robot with the appropriate constraints and goals.
- “This is possible because of the combination of:
  - Advanced robotics
  - An asynchronous protocol
  - Machine learning techniques.”

Extending into the Real World

- Not quite feasible for a real-world wheel chair:
  - Movement would effect BCI readings.
  - The “real world” has many more obstacles and would require finer control.

Future Research

- [Michel et al 2001] suggests that it is possible to extract a larger number of mental states, specifically enough to more fully control robotic and prosthetic devices.
- Larger numbers of electrodes would be used.
- Scalp potentials => brain maps => activity in small areas.
- Use activity in distinct parts of the brain map as opposed to overall EEG features.