Brain-Computer Interface Enabled Shared Control Systems For Robotic Grasping

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DER FORSCHUNG | DER LEHRE | DER BILDUNG

Content

1. Motivation
2. Background
3. Method
4. Results
5. Discussion
6. Conclusion

Motivation

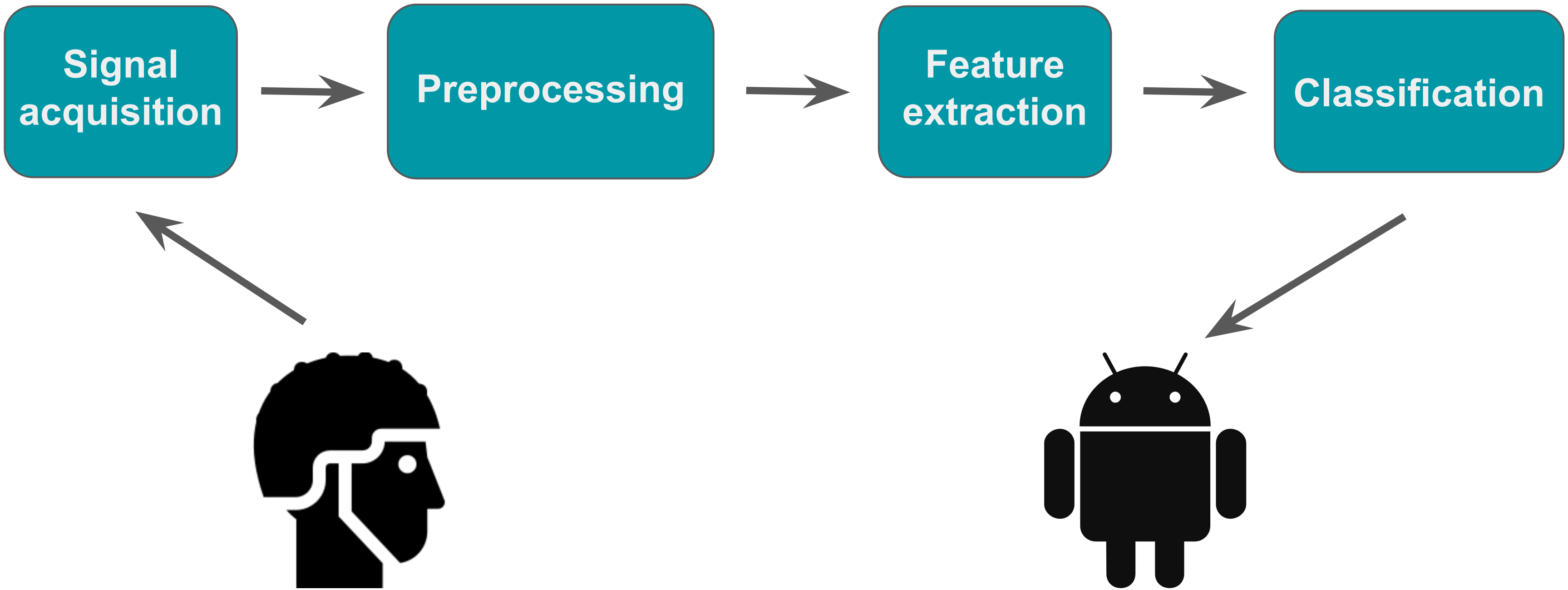
- Fascinating research topic: controlling machines with “thoughts”
- Medical uses [**Abdulkader15**]
  - Epileptic seizure detection and forecasting
  - Physically challenged or locked-in persons
    ⇒ restore movement and communication capabilities using external devices
- … but sustaining attention for BCI-only control is tiring ⇒ shared control

Background — Brain-Computer Interfaces (BCI)

- Link between human brain and computer system
- Brain signals can be used to control external devices (e.g. cursor, drone, robotic arm)
- Two broad categories [**Gandhi15**]:
  - synchronous: computer generates cues
    ⇒ user produces brain signals
  - asynchronous: user intent from brain signals

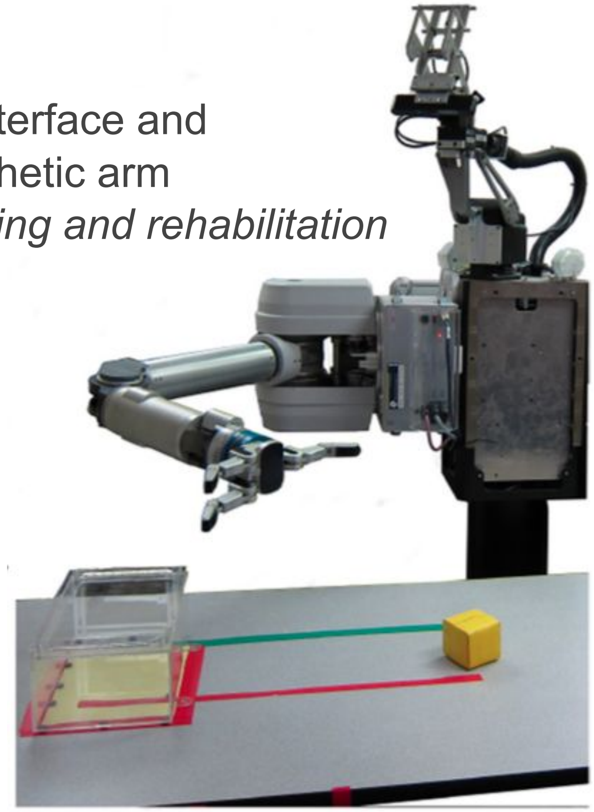
Background — Brain-Computer Interfaces (BCI)

BCI systems have 4 main components [**Abdulkader15**]



Paper overview

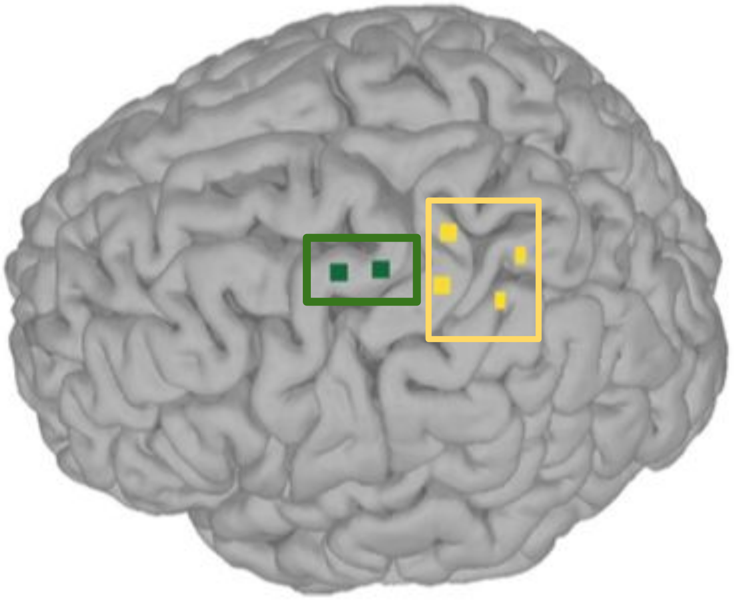
- Downey, John E., et al. "Blending of brain-machine interface and vision-guided autonomous robotics improves neuroprosthetic arm performance during grasping." *Journal of neuroengineering and rehabilitation* 13.1 (2016): 28.
- Blend human and system control for good grasp performance
  - human ⇒ BCI-enabled arm translation & object selection (high level tasks)
  - robot ⇒ infer user intent & align grasp position (low level tasks)
- Objective: Comparison of performance & ease of use of “BCI-only” to shared control



[Downey16]

Method — Signal Acquisition

- Electrocorticography (ECoG): Microelectrode recording arrays implanted on cortex surface
- Green: Subject 1
  - 2 x 96-channel
- Yellow: Subject 2
  - 2 x 88-channel (squares)
  - 2 x 32-channel (rectangles)



Adapted from [Downey16]

Method — BCI Decoding

- Map firing rates ⇒ 4D vector
  - translation velocity (3D ⇒ x,y and z)
  - grasp velocity (1D ⇒ g)
- Optimal linear estimation (OLE) decoder trained:

$$f = b_0 + b_x v_x + b_y v_y + b_z v_z + b_g v_g$$

sqrt(unit's firing rate)

kinematic velocity

coefficients

Method — Two-Step Calibration

Computer-controlled movements
⇒ subjects observe & try to control

↓

First OLE decoder

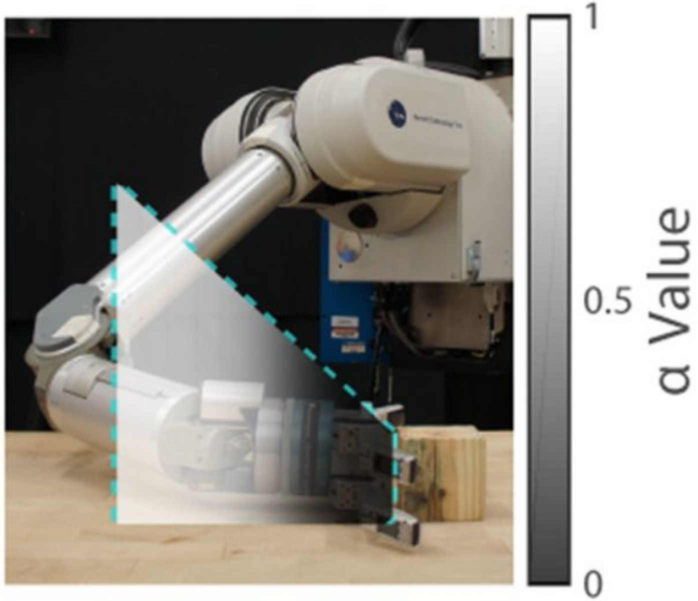
User-controlled movements based on decoder from step 1

↓

Final OLE decoder

Method — Vision-Based Shared Control

- Model library including
  - Depth-image templates for object identification
  - Hand positions and grasp envelopes
- Grasp envelope
  - truncated cone (length: 25 cm)
  - oriented along stable grasp path



[Downey16]

Method — Vision-Based Shared Control

Outside grasp envelope	● full user control

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Inside grasp envelope	● shared control ○ blending of system and user commands

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Method — Vision-Based Shared Control

Outside grasp envelope	● full user control
Inside grasp envelope	● shared control ○ blending of system and user commands ● system assistance ○ control of hand position ○ system infers user intent ● hand close to object ○ high certainty of user intention ○ higher weight of system commands ○ user issues hand-closing command to grasp

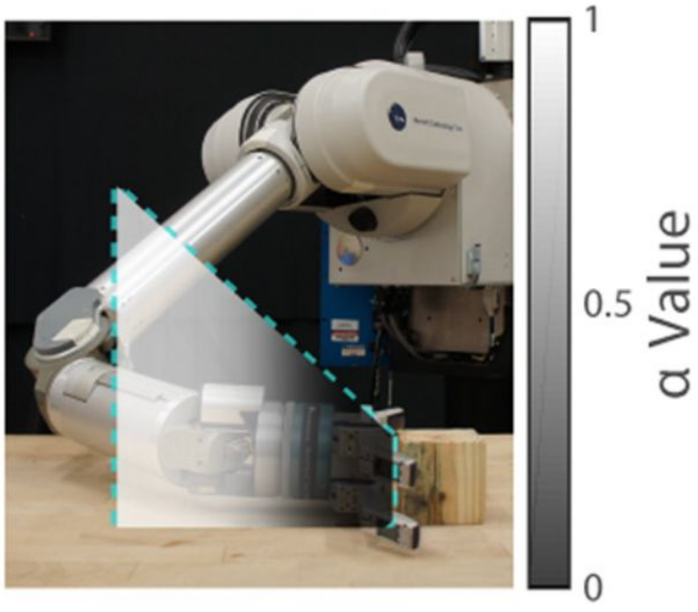
Method — Vision-Based Shared Control

- Blending of user and system commands

$$C = (1 - \alpha)R + \alpha B$$

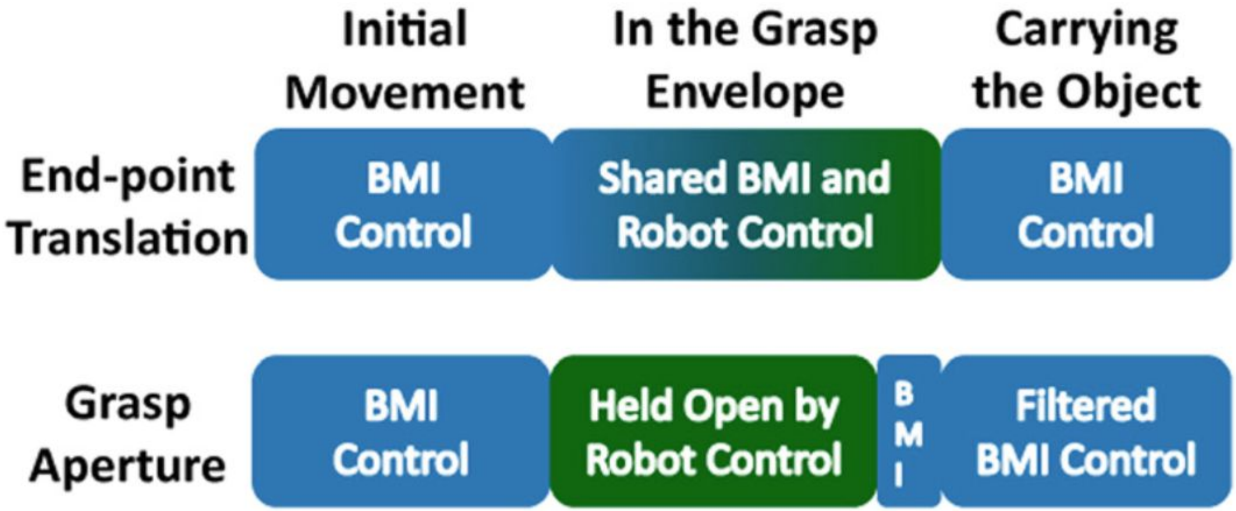
C: resulting velocity
R: system's velocity
B: user's (BCI-decoded) velocity
α: arbitration factor, $\alpha \in [0.001, 1]$

- Outside grasp envelope
  - $\alpha = 1 \Rightarrow$ full user control
- At stable grasp position
  - $\alpha = 0.001 \Rightarrow$ nearly complete system control



[Downey16]

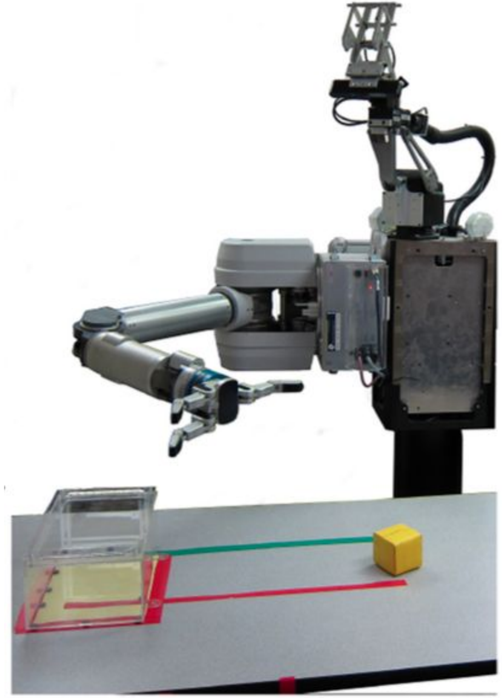
Method — Vision-Based Shared Control



[Downey16]

Experiments

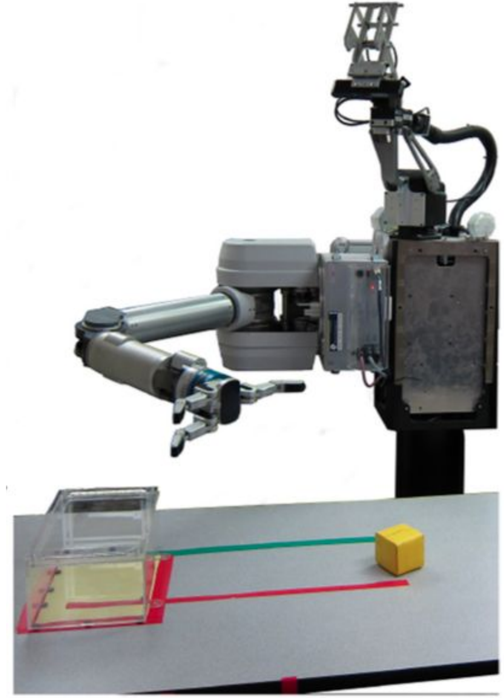
	Action Research Arm Test (ARAT)	Multiple Object Task
Task		
Target object		
Conditions		
Subjects		



[Downey16]

Experiments

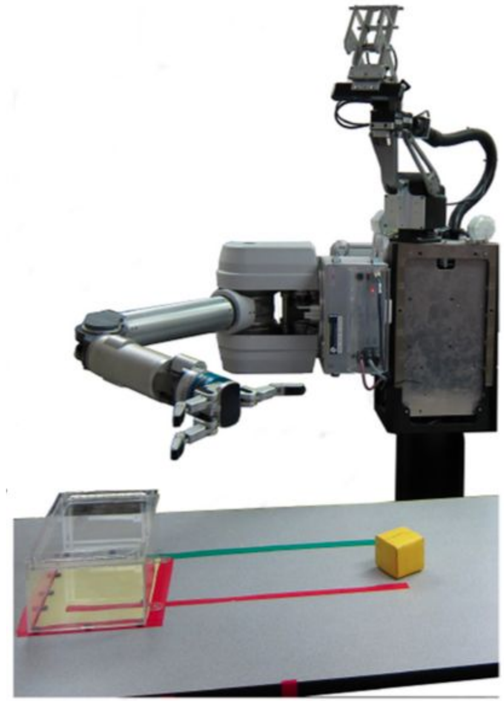
	Action Research Arm Test (ARAT)	**Multiple Object Task**
Task	Grasp the target object and move it to release area	
Target object	Single cube (2.5, 5, 7.5 and 10 cm)	
Conditions	With and without shared control	
Subjects	1 and 2	



[Downey16]

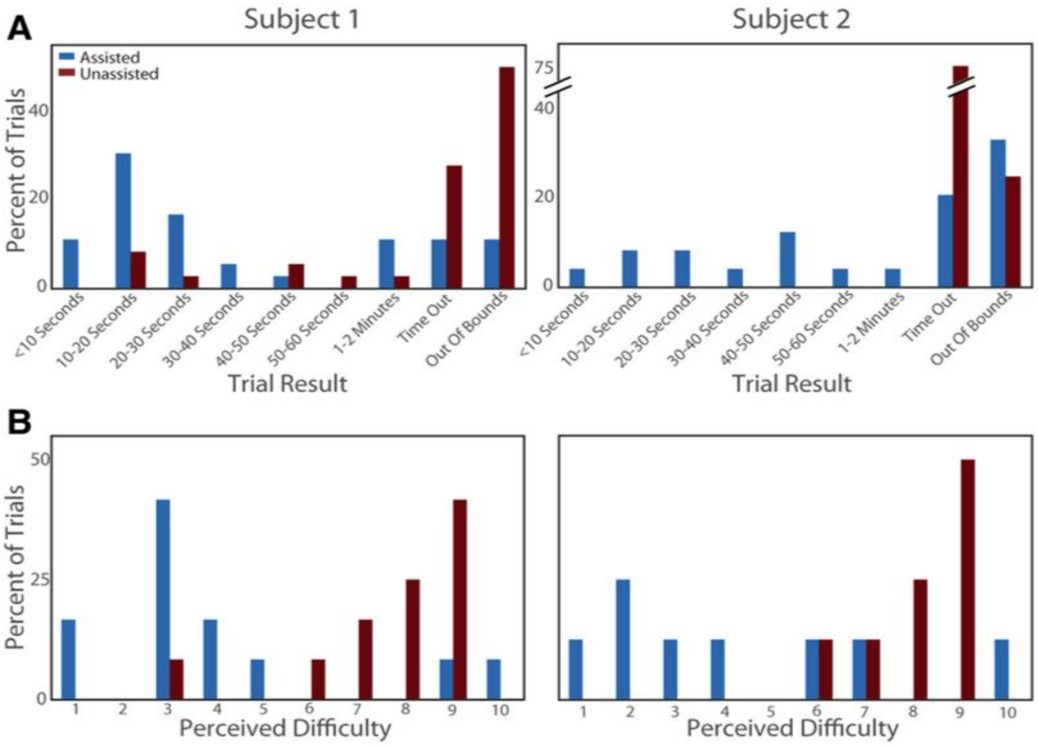
Experiments

	Action Research Arm Test (ARAT)	**Multiple Object Task**
Task	Grasp the target object and move it to release area	Grasp the target out of two objects and lift it
Target object	Single cube (2.5, 5, 7.5 and 10 cm)	One of two cubes (7.5 cm)
Conditions	With and without shared control	With and without shared control
Subjects	1 and 2	2



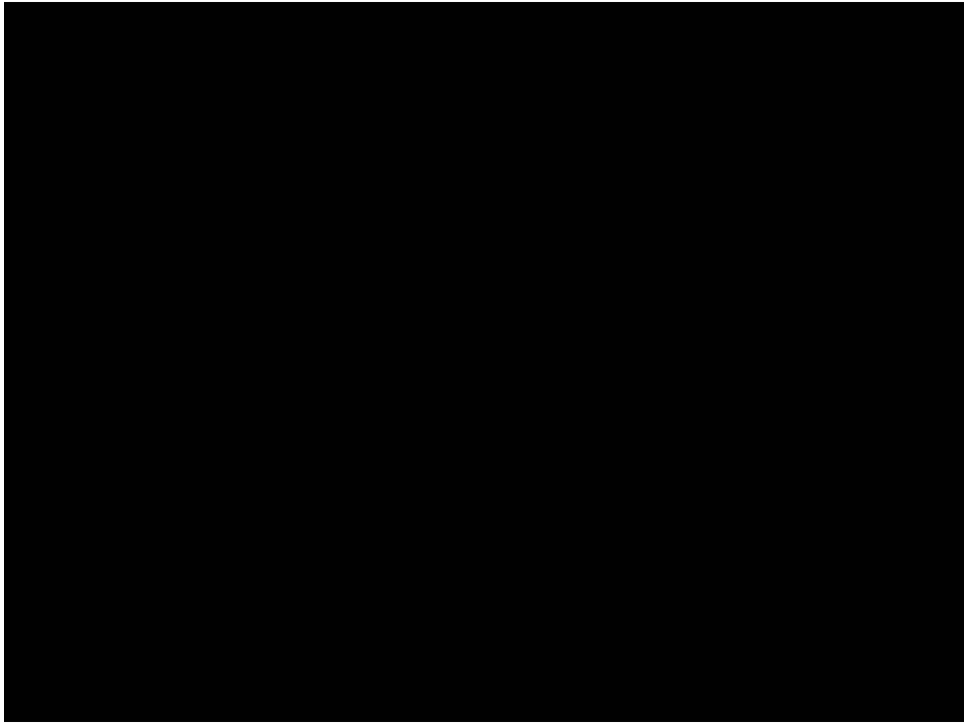
[Downey16]

Results — Action Research Arm Test (ARAT)



[Downey16]

Results — ARAT Best Trials



[Downey16]

Results — Multiple Object Task

	Success rate		Median completion time (sec)	
Target	w/Assist	w/o Assist	w/Assist	w/o Assist
1	100 %	50 %	8.7	19.3
2	100 %	50 %	8.4	17.8
3	75 %	67 %	7.7	30.5
4	100 %	80 %	8.1	20.7
5	100 %	25 %	8.3	28.7
6	75 %	0 %	9.6	–
Total	92 %	46 %	8.3	26.3

[Downey16]

Discussion

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- Shared control at all times
- Allows for error correction
  - wrong object ⇒ abort grasp
  - relocate dropped objects
- Decreased perceived difficulty of usage with shared control
- Selection between multiple objects

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- Cubes are simple objects ⇒ generalizability?
- Only 2 subjects
- Electrocorticography (ECoG) requires invasive operation

Conclusion

- Real-time shared control of BCI and system improves grasp performance
- Users have control of robotic arm most of the time, but were assisted in difficult parts of task
- Future directions
  - Extend object library ⇒ more complex geometries
  - Allow users to switch shared control on / off
  - Enable object selection by BCI commands instead of proximity

References

- **[Downey16]:** Downey, John E., et al. "Blending of brain-machine interface and vision-guided autonomous robotics improves neuroprosthetic arm performance during grasping." *Journal of neuroengineering and rehabilitation* 13.1 (2016): 28. DOI: 10.1186/s12984-016-0134-9

- **[Gandhi15]:** Gandhi, V. "Chapter 2-interfacing brain and machine." *Brain-Computer Interfacing for Assistive Robotics* (2015): 7-63. DOI: 10.1016/C2013-0-23408-5

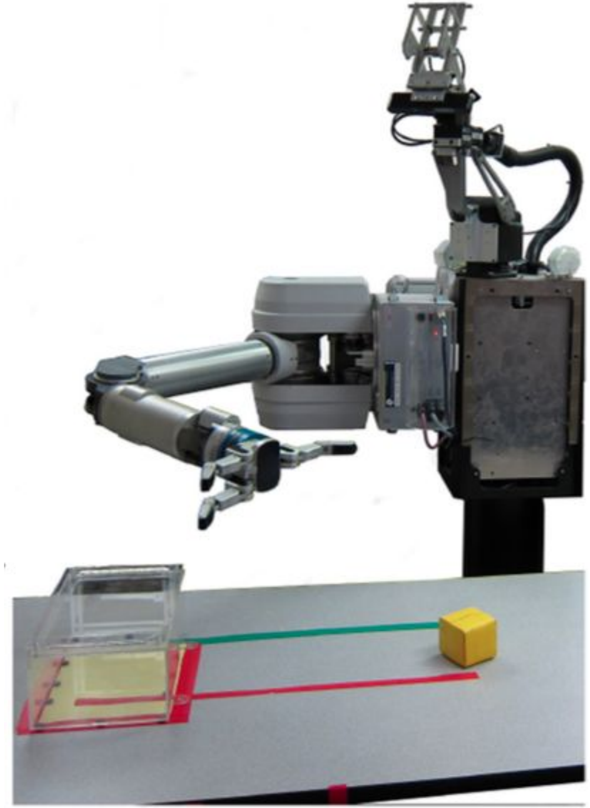
- **[Abdulkader15]:** Abdulkader, Sarah N., Ayman Atia, and Mostafa-Sami M. Mostafa. "Brain computer interfacing: Applications and challenges." *Egyptian Informatics Journal* 16.2 (2015): 213-230. DOI: 10.1016/j.eij.2015.06.002

Thank you for your kind attention!

Any questions?

Method — Hardware

- WAM Arm by Barrett Technology Inc.
  - 7 DoF robot
  - 4 DoF 3-fingered Barrett Hand
- RGB-D camera mounted above arm base
- Neuroport Neural Signal Processor (Blackrock Microsystems)



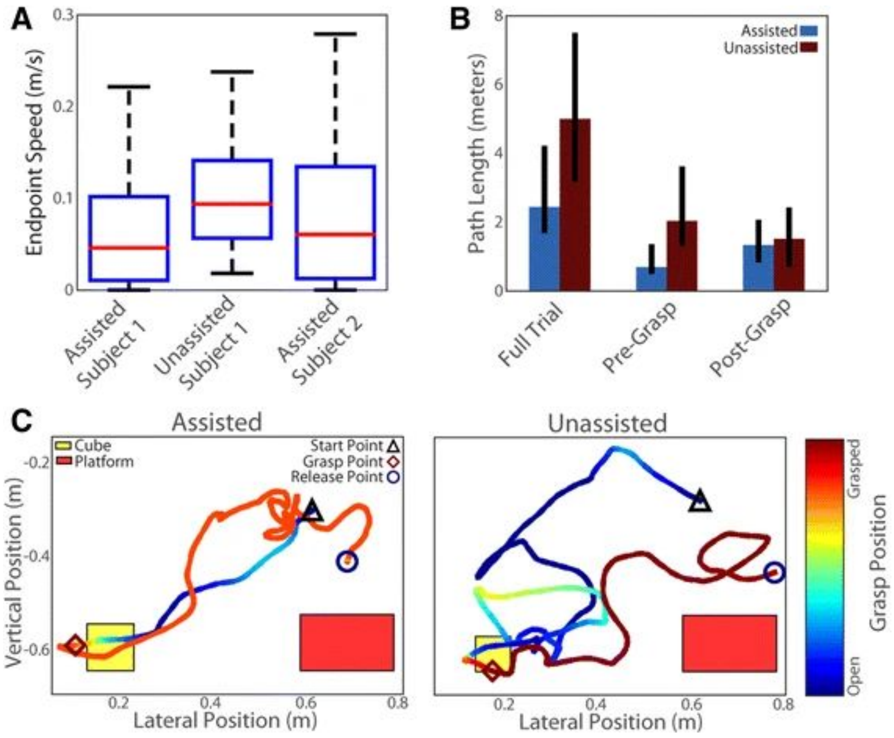
[Downey16]

Results — Action Research Arm Test (ARAT)

		Success rate		Mean completion time (sec)		Mean difficulty	
Sessions	Cube	w/Assist	w/o Assist	w/Assist	w/o Assist	w/Assist	w/o Assist
Subject 1	10 cm	67 %	0 %	25	–	3.7	8.3
	7.5 cm	100 %	44 %	22	23	3.0	6.3
	5 cm	67 %	11 %	16	14	4.7	7.7
	2.5 cm	78 %	33 %	48	64	5.0	8.3
	Total	78 %	22 %	28	37	4.1	7.7
Subject 2	10 cm	0 %	0 %	–	–	7.0	7.0
	7.5 cm	50 %	0 %	29	–	4.5	7.5
	5 cm	50 %	0 %	20	–	4.0	9.0
	2.5 cm	83 %	0 %	42	–	2.0	9.0
	Total	46 %	0 %	33	–	4.4	8.1

[Downey16]

Results — Action Research Arm Test (ARAT)



[Downey16]