Lecture 7: Attention and Intention

Part 4

Intention: Predicting and Controlling

Relevance

Duarte, N.F., Rakovic, M., Tasevski, J., Coco, M.I., Billard, A. and Santos-Victor, J., 2018. Action anticipation: Reading the intentions of humans and robots. IEEE Robotics and Automation Letters, 3(4), pp.4132-4139.

Sburlea, A.I. and Müller-Putz, G.R., 2018. Exploring representations of human grasping in neural, muscle and kinematic signals. Scientific reports, 8(1), pp.1-14.

Hu, Z., Zhang, C., Li, S., Wang, G. and Manocha, D., 2019. Sgaze: A data-driven eye-head coordination model for realtime gaze prediction. IEEE transactions on visualization and computer graphics, 25(5), pp.2002-2010.

Jeong, J.H., Shim, K.H., Kim, D.J. and Lee, S.W., 2019, July. Trajectory decoding of arm reaching movement imageries for brain-controlled robot arm system. In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 5544-5547). IEEE.

Learning Objectives

To provide some examples of how experiments can be designed to measure people's intentions.

To provide examples of how human intention can be measured.

To provide examples of how intention research has been applied to interface design.

Learning Outcomes

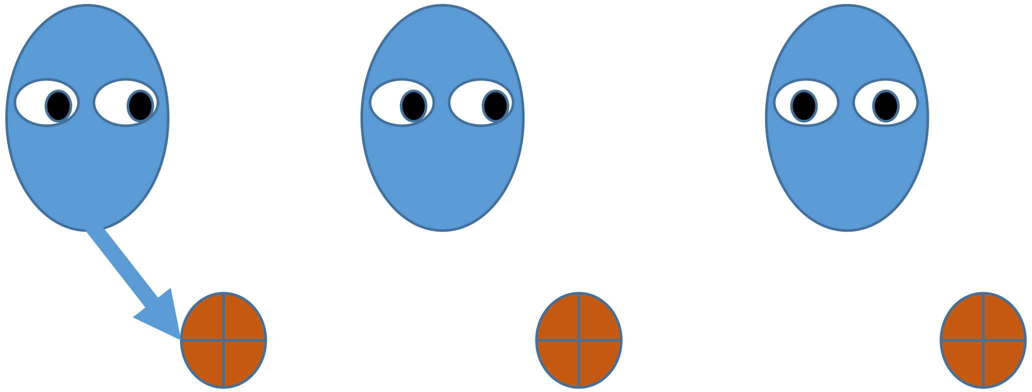
To develop an understanding of how experiments can be designed to measure people's intentions.

To develop an appreciate of some of the considerations underlying work to measure intention.

To be able to provide examples of how human intention can be measured

To be able to provide examples of how intention research can be applied to interface design.

Predicting peoples' intentions



Grasp Gaze Control

Pierno et al (2006): predictive power of watching where someone is looking by having participants view 3 short videos:

1: Grasping- person reaches and looks at a grasped target

2: Gaze- a person looks at target object

3: Control- person does not look at the object or grasp it.

Recorded participants' brain activity.

Predicting peoples' intentions

Found brain activation in 2 areas of the brain (Premotor and Frontal), was the same when participants were watching a person grasp the ball (grasp condition), and watching the person look at the ball (gaze condition).

Concluded: Watching someone else look at the ball activates the participant's observation system, and indicates the person's intention to grasp the ball.

Neurons in brain areas that contain mirror neurons may be useful in helping us predict what another person is thinking of doing, and so may help us predict what the person may do next.

Controlling a cursor with the mind

First step: What is involved in moving a computer mouse?

Cursor creates activity in visual areas of the brain and is perceived

Signals from visual areas are sent to specific brain regions involved in planning of movement of the individual’s hand so as to move the mouse in such a way as to achieve cursor movement from position A to position B. (motor plan)

Signals from this brain are are sent to the relevant muscles (e.g., arm and hand)

Hand moves mouse in such a way at to achieve intended cursor movement from A to B.

Constant updating: movement creates new activity in visual areas, motor plan is recalculated if requires adjustment to cursor path..

Controlling a cursor with the mind

Case 1: Spinal cord injury. Use brain activity to control cursor (bypassing mouse)

Person thinks about moving the mouse.
A neural prosthesis picks up signals from the relevant part of the brain.
This information is then used to generate the signal(s) used by the computer to control cursor on screen

Hochberg et al (2006) Nature, 442, 164-171.

Precision- Often not as precise or quick as manual cursor manipulation.

Correct selection of brain signals is crucial.

Reading the Intentions of Humans and Robots

Duarte, N.F., Rakovic, M., Tasevski, J., Coco, M.I., Billard, A. and Santos-Victor, J., 2018. Action anticipation: Reading the intentions of humans and robots. IEEE Robotics and Automation Letters, 3(4), pp.4132-4139.

Fig. 1. Human-Human Interaction: an experiment involving one actor (top-right) *giving* and *placing* objects and three subjects reading the intentions of the actor (left); Human-Robot Interaction: a robot performing the human-like action and subjects try to anticipate the robots' intention (bottom-right).

Study to analyse the importance of different nonverbal cues for action perception.

Used motion/gaze recordings to build a computational model describing the interaction between two people.

Used this model in the controller of an humanoid robot.

Then used the robot as an actor, to validate the model's "intention reading" capability.

Results: Possible to model (nonverbal) signals exchanged by humans during interaction, and incorporate this information in a robotic system, so that the robot can "read" human intentions of action.

Representations of human grasping

Sburlea, A.I. and Müller-Putz, G.R., 2018. Exploring representations of human grasping in neural, muscle and kinematic signals. Scientific reports, 8(1), pp.1-14.

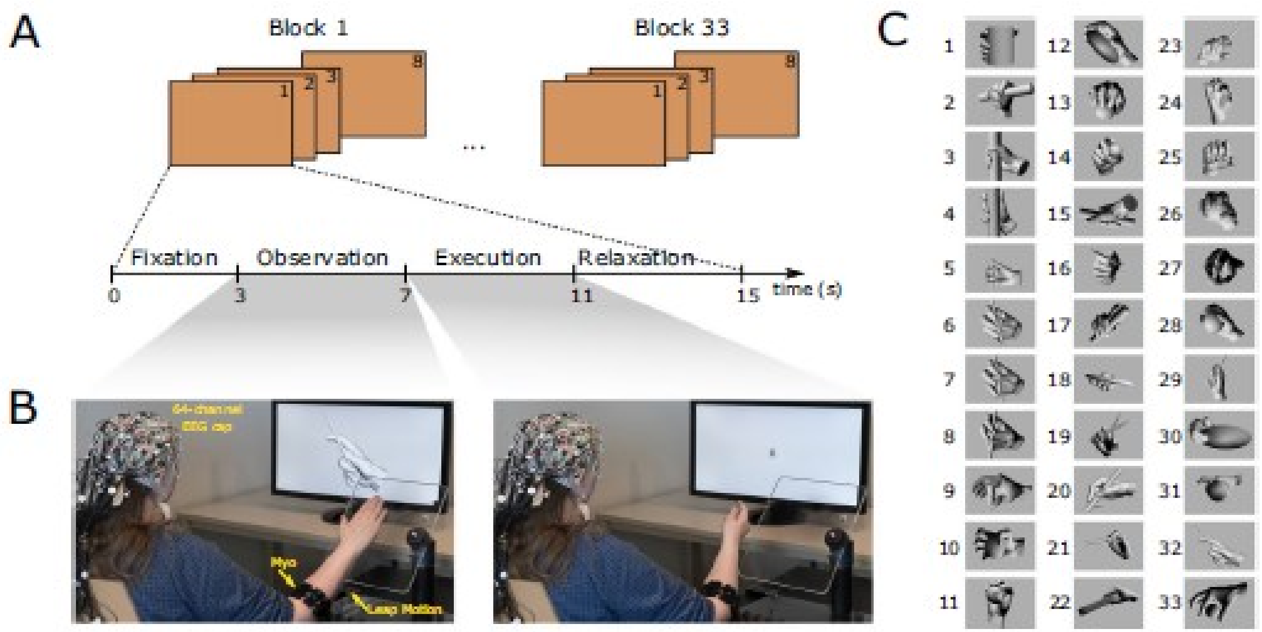


Figure 1. (**A**) Experimental protocol. Each of the 33 blocks contained eight consecutive repetitions (trials) of the same grasp. Each trial had four phases: fixation (three seconds long), observation (four seconds long), execution (four seconds long) and relaxation (four seconds long). (**B**) Experimental setup. Photos of one participant during the observation and execution phases, and the materials used during recording. (**C**) Pictograms of the grasping movements.

Study to measure electrical signals from the brain measured via special sensors (EEG) in response to individuals' grasping movements.

The EEG measured from the brain showed that different areas of the brain were activated at different stages of the grasping motion.

Results useful for design of more natural control of robotic devices or neuroprostheses.

Real-time gaze prediction

Hu, Z., Zhang, C., Li, S., Wang, G. and Manocha, D., 2019. Sgaze: A data-driven eye-head coordination model for realtime gaze prediction. IEEE transactions on visualization and computer graphics, 25(5), pp.2002-2010.

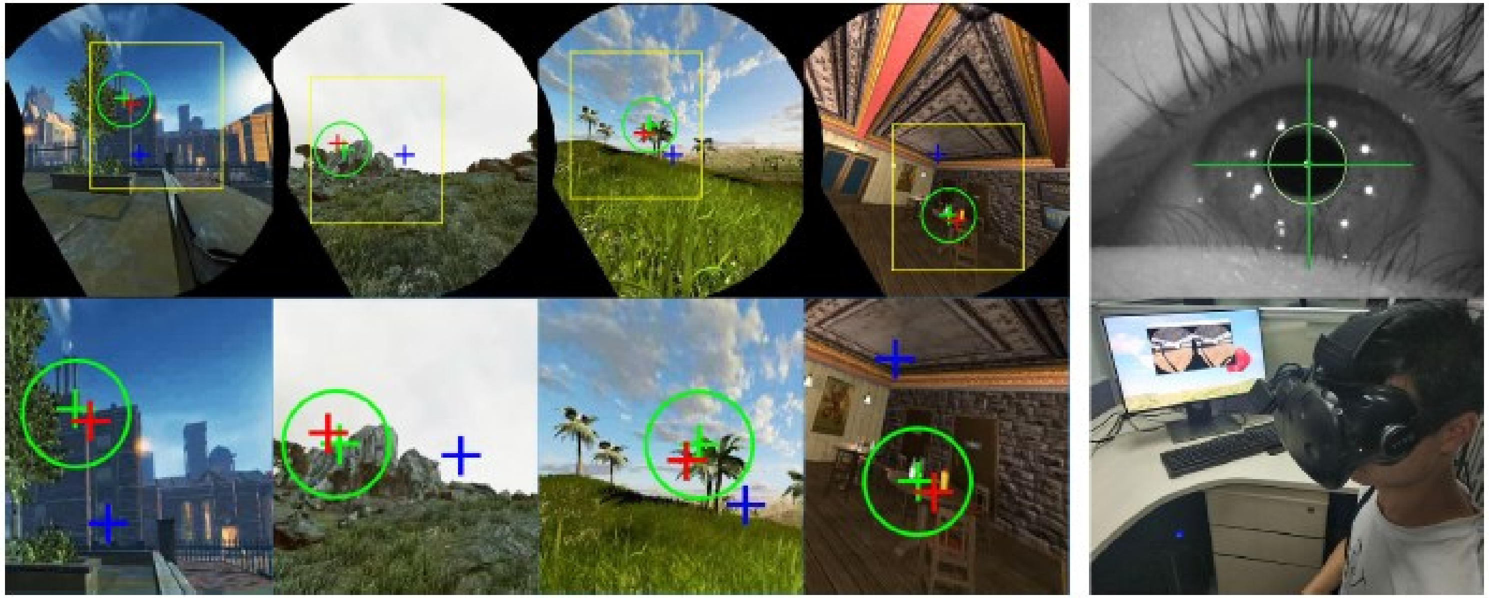


Fig. 1: Realtime gaze prediction performed using our eye-head coordination model. The quadruplet on the left demonstrates the gaze prediction results tested using different scenarios. The upper row shows the images captured from an HMD's screen, with zoomed-in view in the lower row. The ground truth of eye gaze in each scenario is marked using a green cross, the blue cross denotes the mean baseline, and the red one denotes our result. The green circle shows the foveal region with a 15 ° field of view. The figure of a user's eye gaze on the top-right illustrates that our goal is to predict realtime gaze position, and the bottom-right illustrates our experimental setup. From these results, our model has high accuracy when compared with the ground truth from the eye tracker.

Devise a data-driven eye-head coordination model (SGaze) that can be used for real-time gaze prediction for immersive HMD-based applications.

This approach does not require any special hardware (e.g. an eye tracker) and is based on dataset collection and statistical techniques.

Found that there is a range within which gaze positions have a strong linear correlation with head rotation angular velocities.

Resources

Essential:

Sensation and Perception- E. Bruce Goldstein: Chapter "Taking action". [Chapter 7 in 8th Edition]

Hochberg, L. R., Serruya, M. D., Friehs, G. M., Mukand, J. A., Saleh, M., Caplan, A. H., et al. (2006). Neuronal ensemble control of prosthetic devices by a human with tetraplegia. Nature, 442, 164-171.

Hu, Z., Zhang, C., Li, S., Wang, G. and Manocha, D., 2019. Sgaze: A data-driven eye-head coordination model for realtime gaze prediction. IEEE transactions on visualization and computer graphics, 25(5), pp.2002-2010.

Duarte, N.F., Rakovic, M., Tasevski, J., Coco, M.I., Billard, A. and Santos-Victor, J., 2018. Action anticipation: Reading the intentions of humans and robots. IEEE Robotics and Automation Letters, 3(4), pp.4132-4139.

Supplementary:

Sburlea, A.I. and Müller-Putz, G.R., 2018. Exploring representations of human grasping in neural, muscle and kinematic signals. Scientific reports, 8(1), pp.1-14.

Jeong, J.H., Shim, K.H., Kim, D.J. and Lee, S.W., 2019, July. Trajectory decoding of arm reaching movement imageries for brain-controlled robot arm system. In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 5544-5547). IEEE.