Active Observer Visual Problem-Solving Methods are Dynamically Hypothesized, Deployed and Tested

Markus D. Solbach

John K. Tsotsos

Department of Electrical Engineering and Computer Science

York University, Canada

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Tsotsos Lab
Active and Attentive Vision

ADVANCES in COGNITIVE SYSTEMS 2021
Ninth Annual Conference

YORK UNIVERSITÉ UNIVERSITY
Centre for Vision Research

Overview

- Background
- Experimental Set Up
- Some Results
- Conclusion

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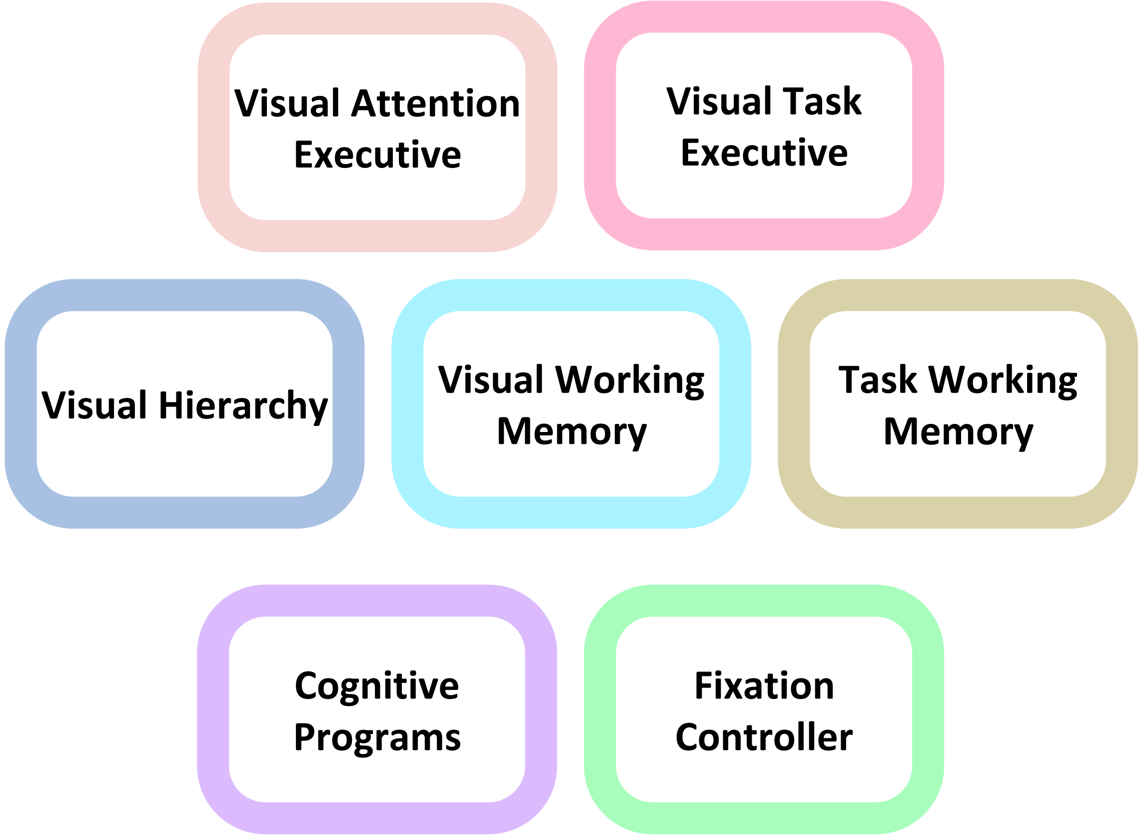
STAR

Selective
Tuning
Attentive
Reference



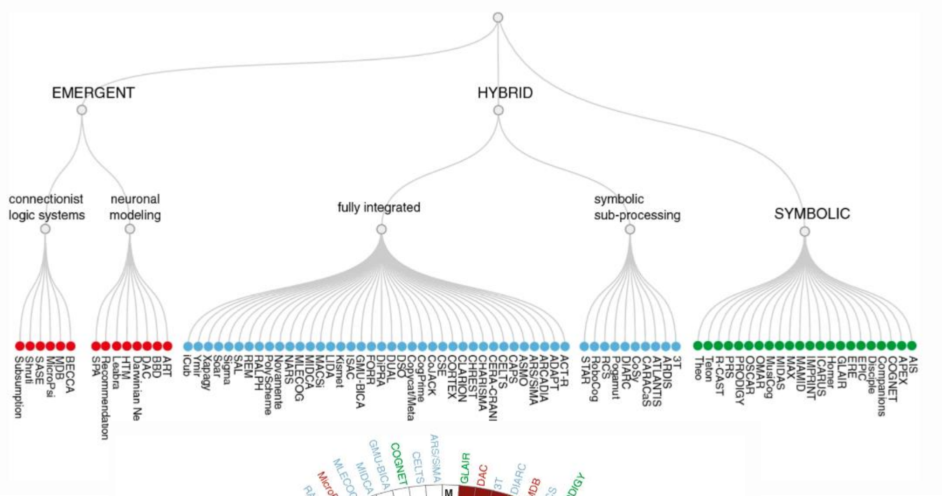
What roles does attention play in a behaving visual agent?

Tsotsos, J. K., & Kruijne, W. (2014). Cognitive programs: software for attention's executive. *Frontiers in Psychology*, 5.

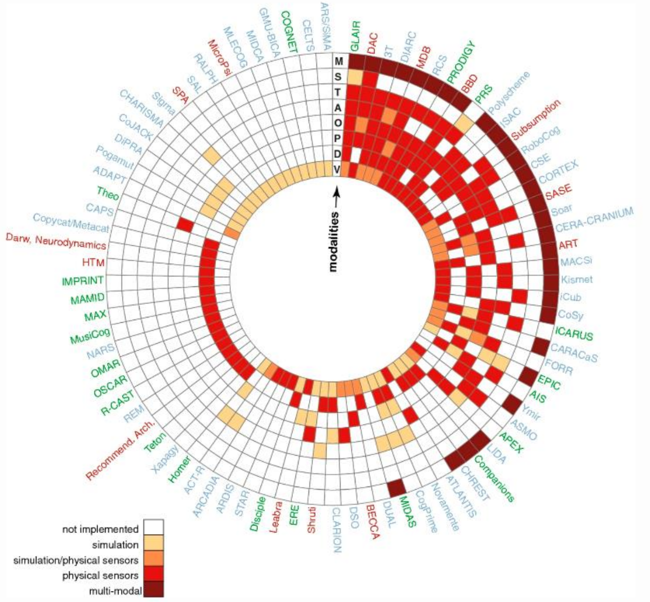
Kotseruba, I., & Tsotsos, J. K. (2020). 40 years of cognitive architectures: core cognitive abilities and practical applications. *Artificial Intelligence Review*, *53*(1), 17-94.

- Wanted to be certain our question had novelty – confirmed
- 86 architectures and 700 application systems using those architectures included

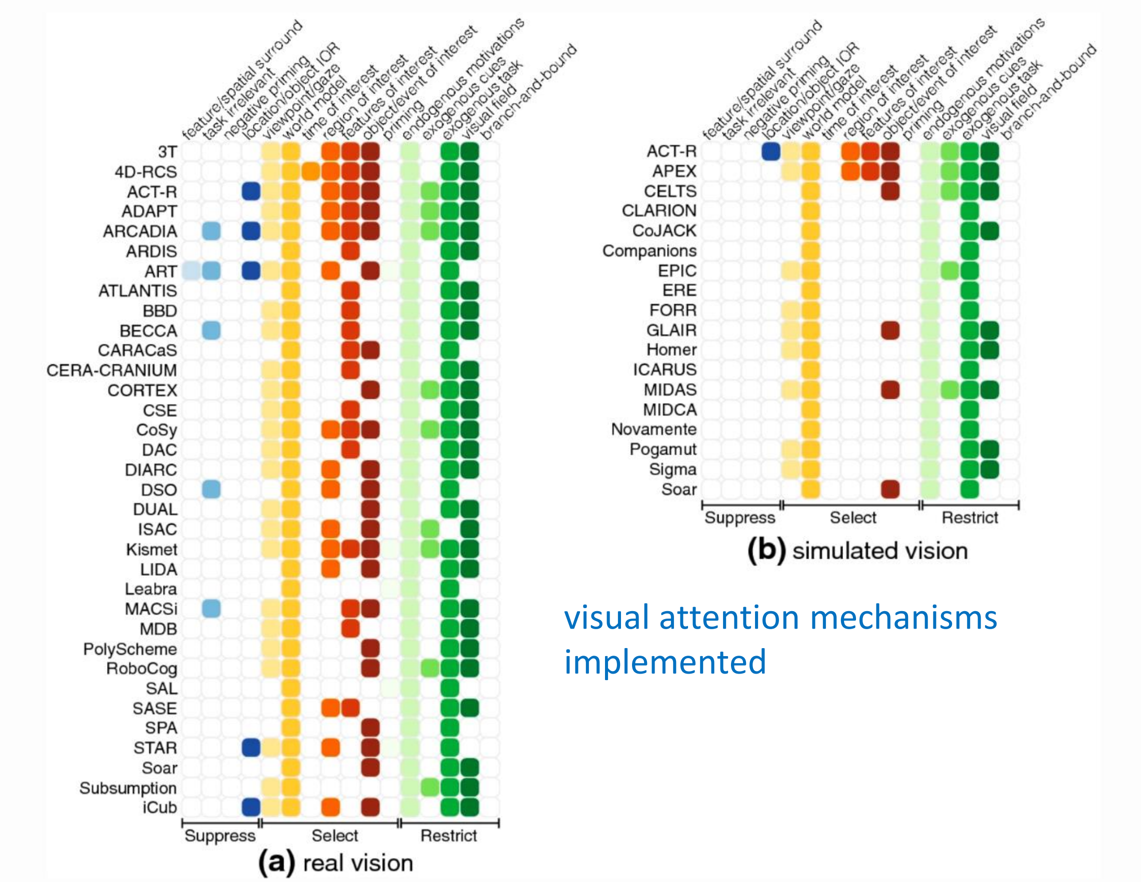
taxonomy of architectures



modalities represented across architectures



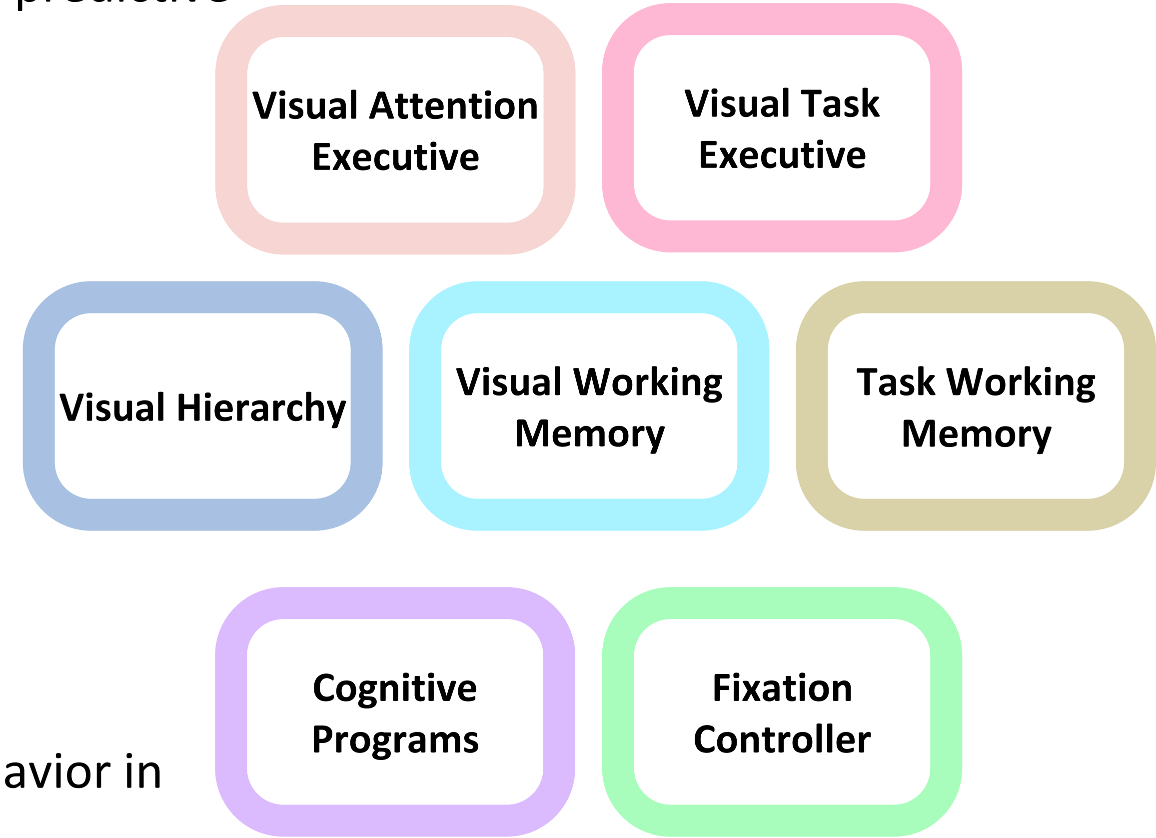
M – multi-modal
S – smell
T – touch
A – audition
O – other
P – proprioception
D – symbolic inout
V – vision



visual attention mechanisms implemented

Elements of STAR

- Elements of STAR in place included:
- Selective Tuning model of visual attention with strong predictive evidence
    - Tsotsos (2011) MIT Presss
- Attentive visual hierarchy prototypes
    - Biparva & Tsotsos (2019) ICCV-W
    - Rosenfeld et al. (2018) CVPR-W
- Human-equivalent fixation control
    - Tsotsos et al. (2016) *J. Eye Movement Research*
    - Wloka et al. (2018) CVPR
- Representation plan : Cognitive Programs
    - Tsotsos & Kruijne (2014) *Frontiers in Psychology*
- Needed a task that requires complex active visual behavior in order to understand the scope and nature of attentional/executive control – past explorations into such human behavior seem minimal



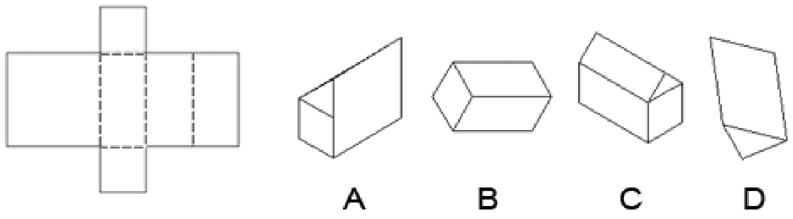
Our Broad Span of Visuospatial Abilities

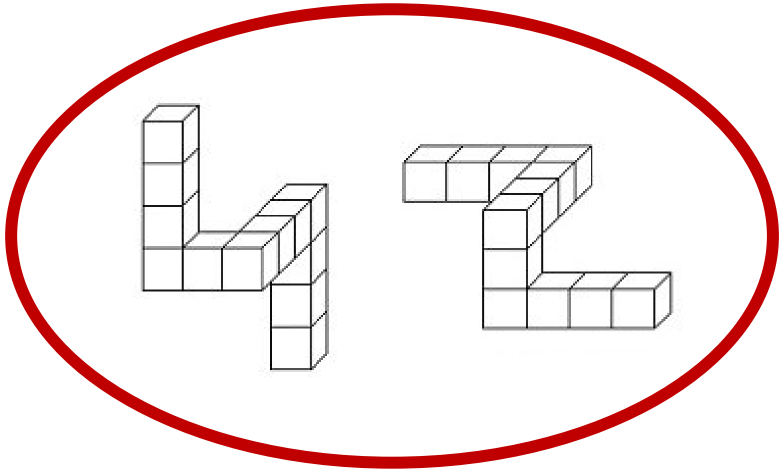
From Carroll 1993:

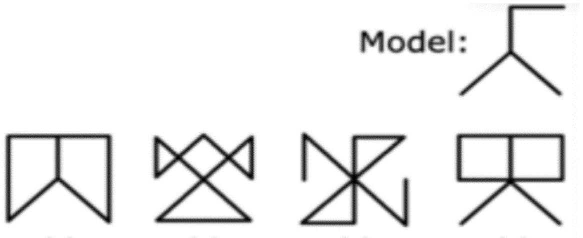
- **Spatial Visualization:** processes of apprehending, encoding, and mentally manipulating spatial forms (paper folding or spatial relations).

- **Speeded Rotation:** requires mental transformations but also involves manipulations (usually planar rotations) of two-dimensional objects and speed is emphasized (card rotation and the flag test, requiring a same-different judgment for each rotated pattern).

- **Visuospatial Perceptual Speed:** speed or efficiency of perceptual judgments (Identical Pictures Test - quickly identify which of five alternative patterns is identical to a model pattern; Hidden Patterns Test: quickly decide whether a simple target pattern is present in a more complex pattern).







Are Two Objects the Same or Different?

- This is an everyday task:
  - Often, we design objects to be easily discriminable, say by colour or size or pattern, but this is not always the case.
  - Consider a task where you are given a part during an assembly task and need to go to a bin of parts in order to find another one of the same (e.g. assembly of IKEA furniture).
  - LEGO requires one to perform such tasks many times while constructing a block configuration, either copying from a plan, mimicking an existing one or building from one's imagination

- We push this to the extreme in order to discover its characteristics and limitations

- The Problem: What is the sequence of actions to correctly determine if two objects are the same?

➢Equal interest for Human Behaviour as well as Robot Behaviour

954 I. van Rooij/Cognitive Science 32 (2008)

Table 2
A sample of computational-level theories whose combinatorial search spaces are potentially super-polynomial in $|i|$

Cognitive Domain	Computational-Level Theory (ψ_T)	References
Categorization	*Input:* A set of objects, P, and a (dis)similarity value for each $(p, q) \in P \times P$. *Output:* A partition of P into categories such that within-category similarity and between-category dissimilarity is maximum.	Pothos and Chater (2001, 2002); Rosch (1973); Rosch and Mervis (1975)
Similarity	*Input:* Two objects x and y and a set of transformation rules T. *Output:* The length of the shortest sequence of transformation rules from T that, when applied to x, yields y.	Chater and Vitányi (2003a, 2003b); Hahn, Chater, and Richardson, (2003)
Coherence	*Input:* A set of propositions, P, positive and negative constraints, $C \subseteq P \times P$. *Output:* A truth assignment $T(P)$ satisfying a maximum number of constraints.	Millgram (2000); Thagard (2000); Thagard and Verbeurgt (1998); van Rooij (2003)
Gestalt perception	*Input:* A string s and a decoding function $f : C \to S$ mapping codes to strings. *Output:* A code $c \in C$ such that $f(c) = s$ and the length of c is minimum.	van der Helm (2004); van der Helm and Leeuwenberg (1986, 1996)
Visual search	*Input:* A target T, a visual display D, and two numbers x and y. *Output:* A subset $S \subseteq D$ such that the number of (mis)matching elements in S and T is at least x (at most y).	Kube (1991); Tsotsos (1990); van Rooij (2003).
Defeasible reasoning	*Input:* A knowledge base K and a set of default rules R. *Output:* All propositions $p_1, p_2, \ldots, p_k$ derivable from K using R, such that $p_1, p_2, \ldots, p_k$ and K are consistent.	Oaksford and Chater (1993, 1998); Reiter (1980).
Bayesian inference	*Input:* A knowledge base K and a set of competing hypotheses H. *Output:* A hypothesis $h \in H$ that maximizes the conditional probability $P(h\|K)$.	Chater, Tenenbaum, and Yuille (2006); Cooper (1990); Roth (1996)
Decision making	*Input:* A set of choice alternatives P and a value function $u : S \to N$ (where $S \subseteq P$ and N is a set of numbers). *Output:* A subset $S \subseteq P$ such that $u(S)$ is maximum.	Fishburn and LaValle (1993, 1996); van Rooij, Stege, and Kadlec (2005)
Language processing	*Input:* Surface form s, lexicon D, lexical-surface form relation mechanism M. *Output:* Set of lexical forms U generated by D from which M can create s.	Barton, Berwick, and Ristad (1987); Ristad (1990, 1993); Wareham (1996, 1999, 2001)
Planning	*Input:* An initial state s, a goal state g, and a collection of operators O. *Output:* A sequence of operators that when applied to s produces g.	Bylander (1994); Joseph and Plantinga (1985); Newell and Simon (1988a, 1988b)
Network harmony	*Input:* A harmonic (e.g., Hopfield) neural network. *Output:* An activation pattern that maximizes harmony.	Jagota (1997); Rumelhart et al. (1986); Smolensky and Legendre (2006)
Network learning	*Input:* A neural network N and function f. *Output:* A weight assignment to the connections in N such that N computes f.	Judd (1990); Parberry (1994, 1997)

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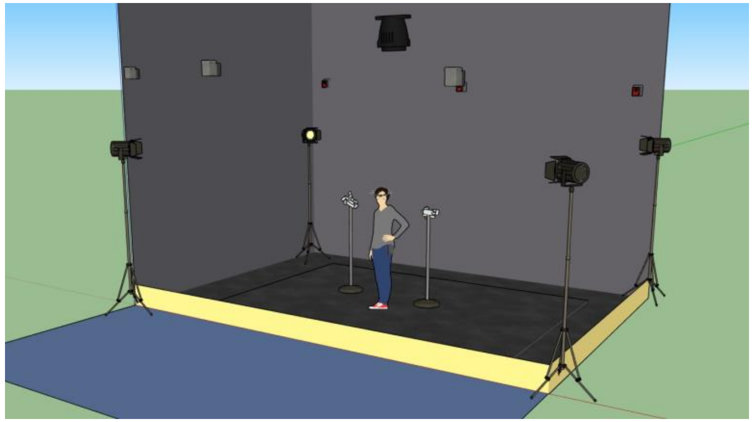
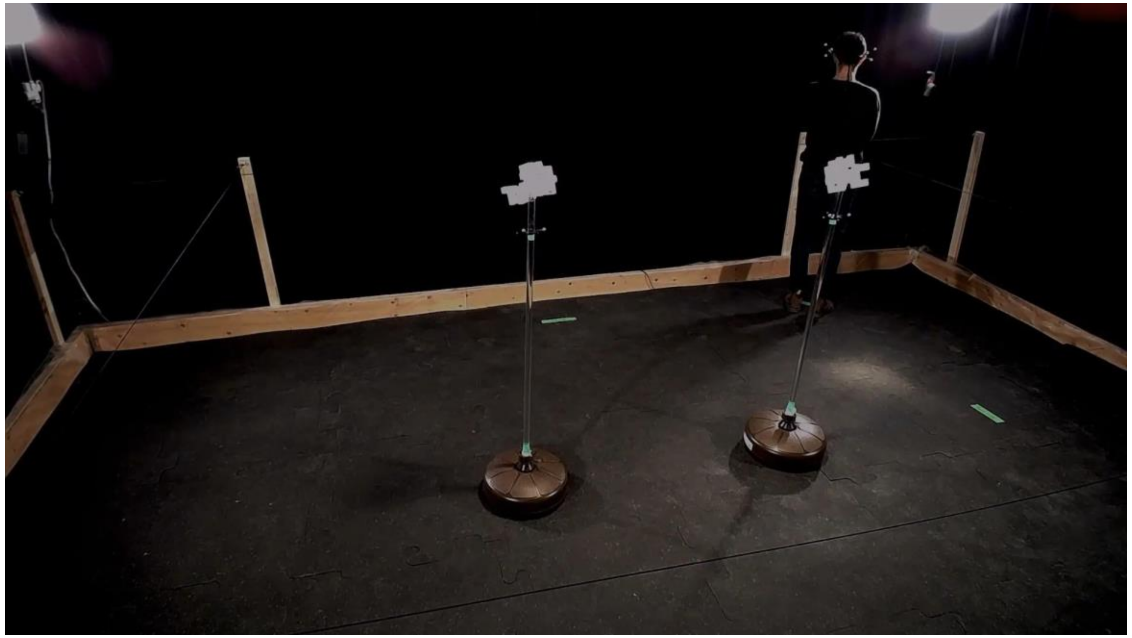
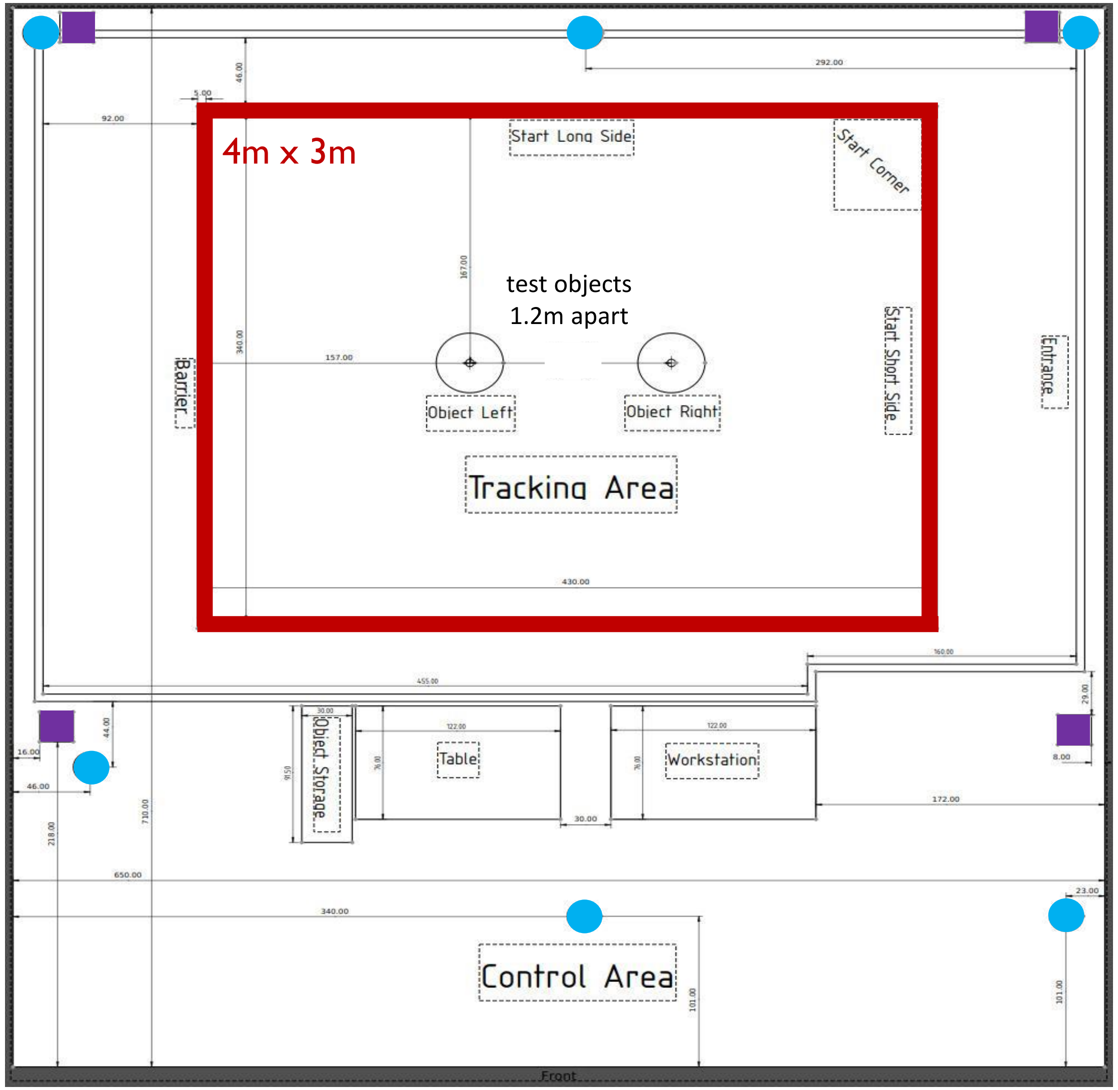
PESAO:Psychophysical Experimental Setup for Active Observers

Solbach, M.D. & Tsotsos, J.K. (2021). Tracking Active Observers in 3D Visuo-Cognitive Tasks, Proc. ACM Symposium on Eye Tracking Research and Applications, (1-3)



motion tracking camera
light source

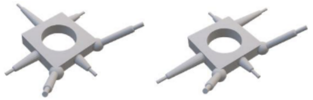




PESAO

Motion Tracking OptiTrack Robotics Package with six Flex 13 cameras on 10ft camera stands,

Gaze Tracking Tobii Pro Glasses 2 with TobiiPro Lab software and prescription lens package

Object Tracking Custom 

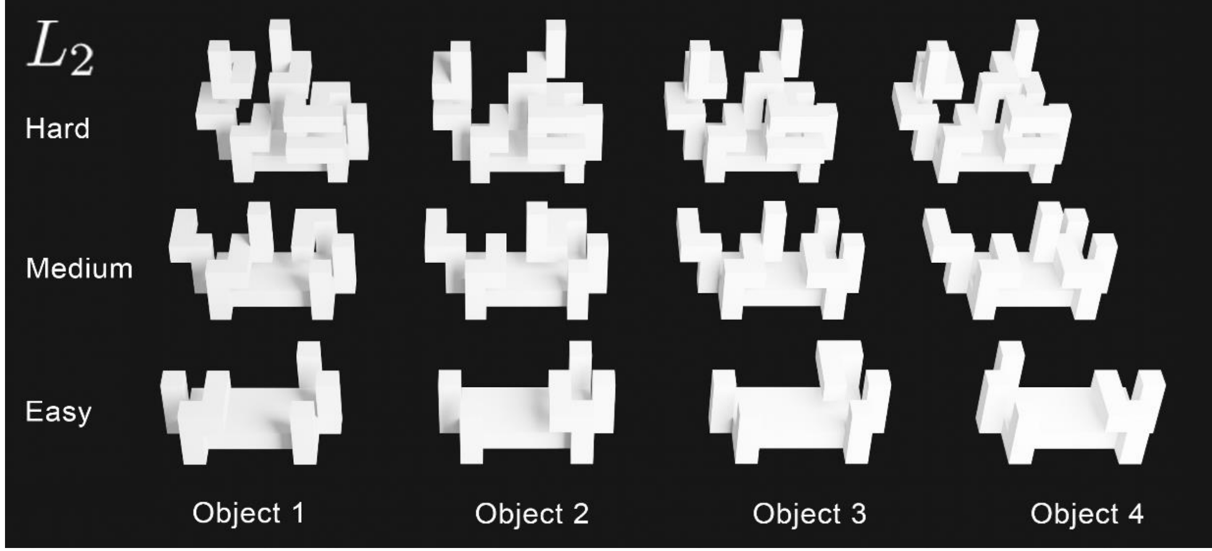
Custom Gear OptiTrack M4 markers on custom frame

Custom Software PESAOlib: control and execute experiments,
record data with accurate to microsecond-level timestamps, synchronize, analyze, display

Lighting Five 660 LED Video light-panels from Neewer one in each corner and one above
Colour temperatures from 3200 – 5600K and lumen of up to 7300 Lux/m.
Light level sensor: Yocto-Light-V2 by Yoctopuce up to 65,000 lux.

Basic Workstation Windows 10 (Motive motion capture software)
Intel i7-7700k, Ryzen 7 2700x or comparable
> 8GB RAM ; > 128GB SSD storage ; NVIDIA Quadro, > 2GB VRAM

Objects



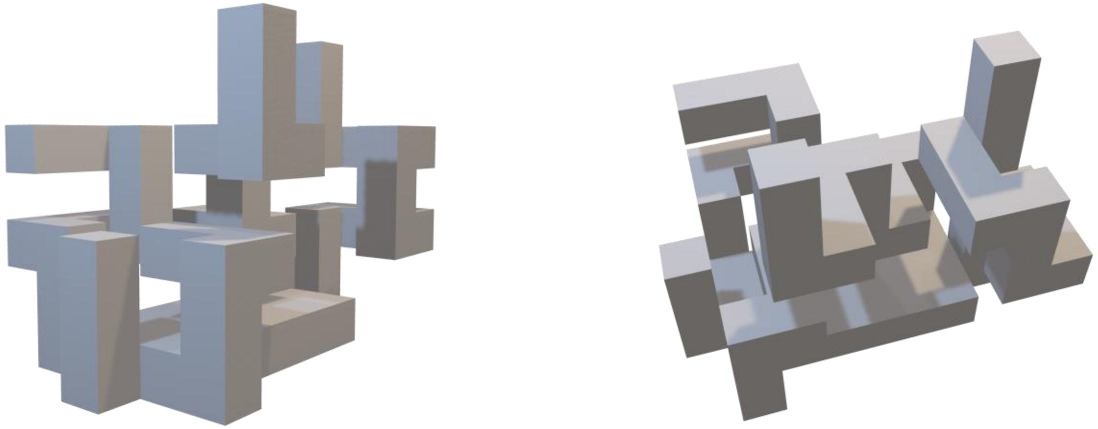
- Shepard and Metzler objects are used as an inspiration
  - Made from geometrical blocks
  - Assembled flush

- TEOS
  - All objects are made up by a base and a number of cuboids
  - Always starting with a base
  - Five connection points
  - Known complexity ($compl = n + 1$)
  - Common coordinate system

  - Also:
    - No intersection of elements
    - No continuation of direction

  - L_2 TEOS data set

The same or different?



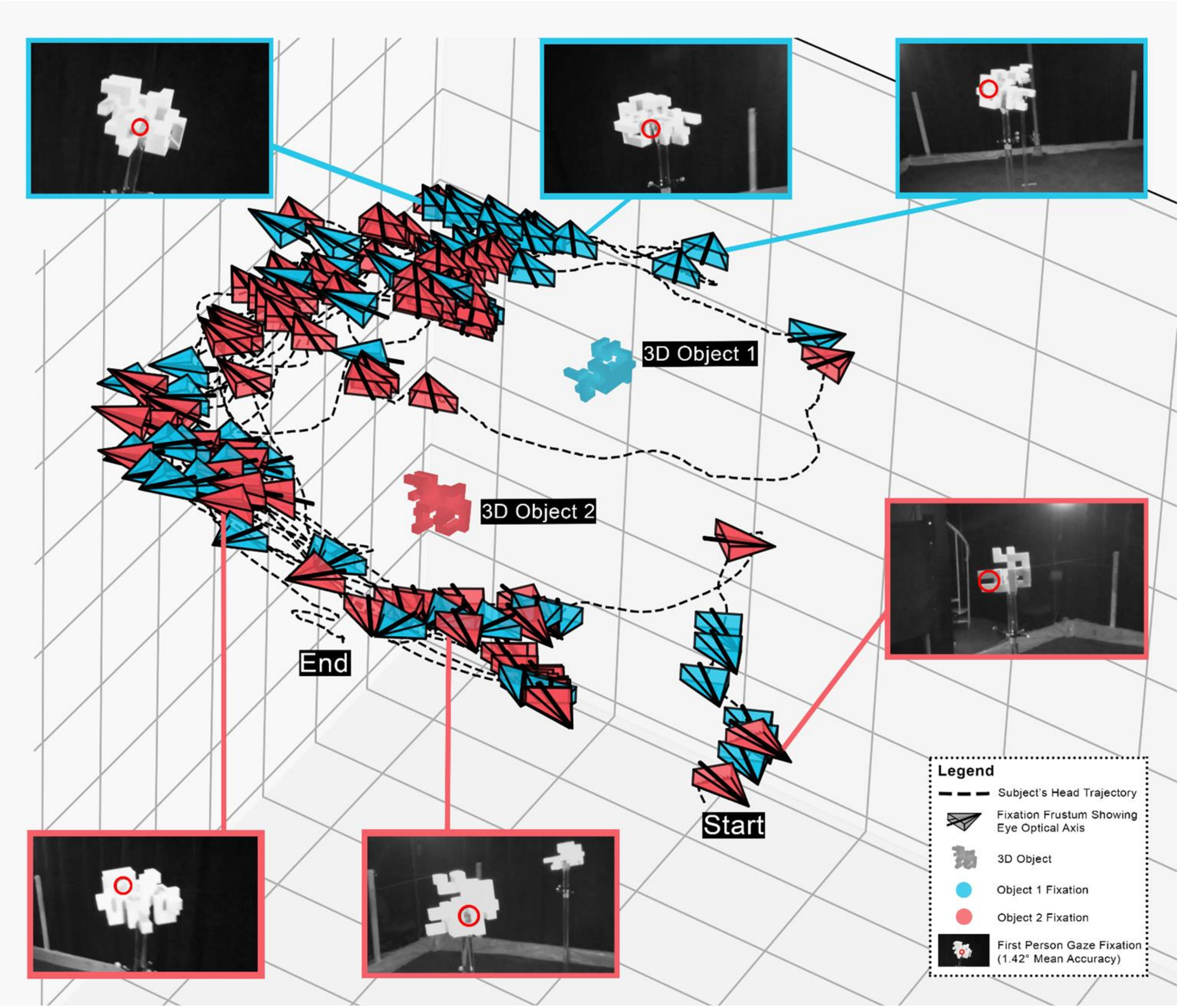
They are different!

Solbach, Markus D., Tsotsos, John K. "Blocks World Revisited: The Effect of Self-Occlusion on Classification by Convolutional Neural Networks" Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops. 2021.

Experiment

Experiment

- 47 subjects recorded
- 846 trials
- About 80,000 fixations; 40,000sec of video
- Constant lighting; shadows minimized
- Subjects interviewed afterwards



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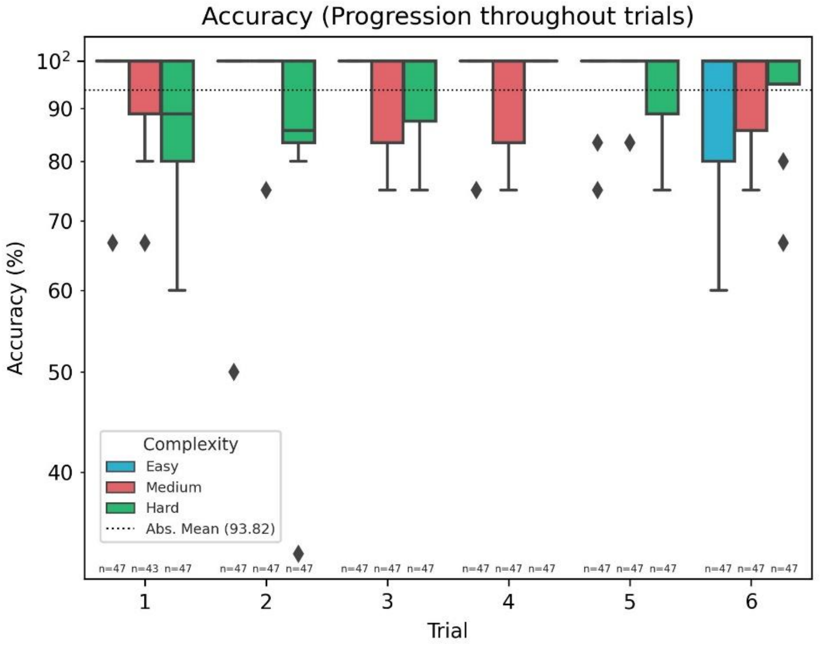
Characteristics across Trials (1)

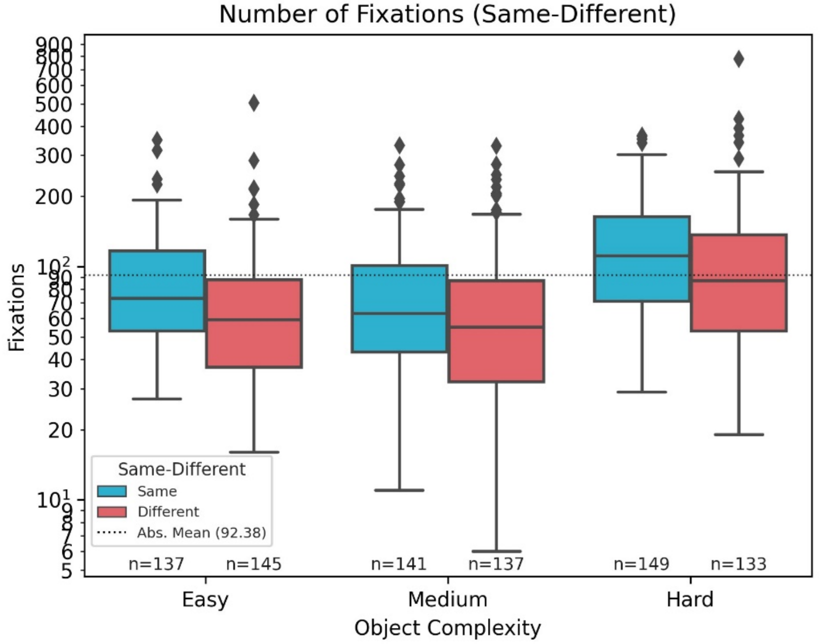


- People are very good at this task. The range of response times from simplest to most difficult cases ranged from 4 - 298 sec. and accuracy from 80% to 100%.

- There is a great deal of data acquisition occurring during all trials with the range of eye movements (and thus separate fixations and separate images processed) from 6 to 800 fixations.

- Error responses take more time and require more fixations

- Subjects did up to 18 trials each; no learning effect observed

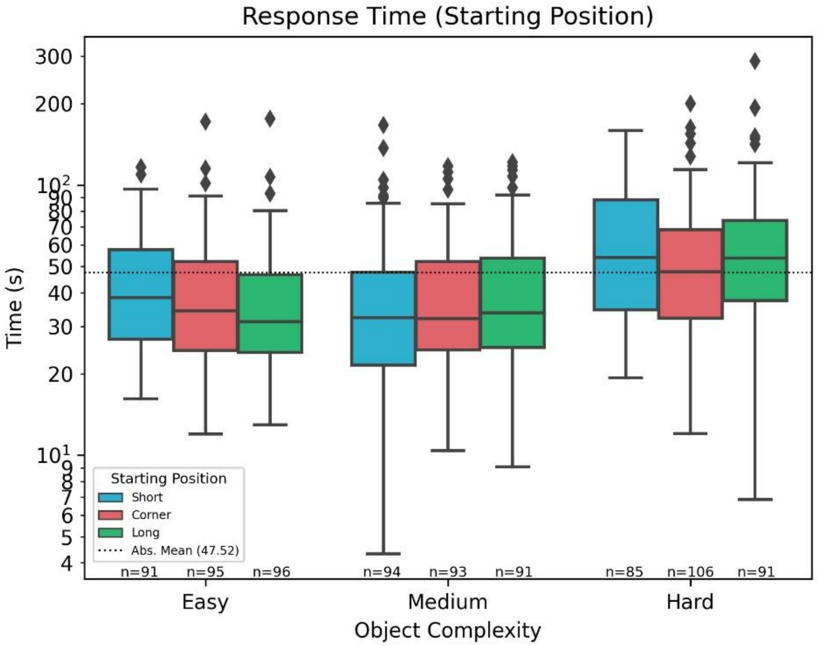


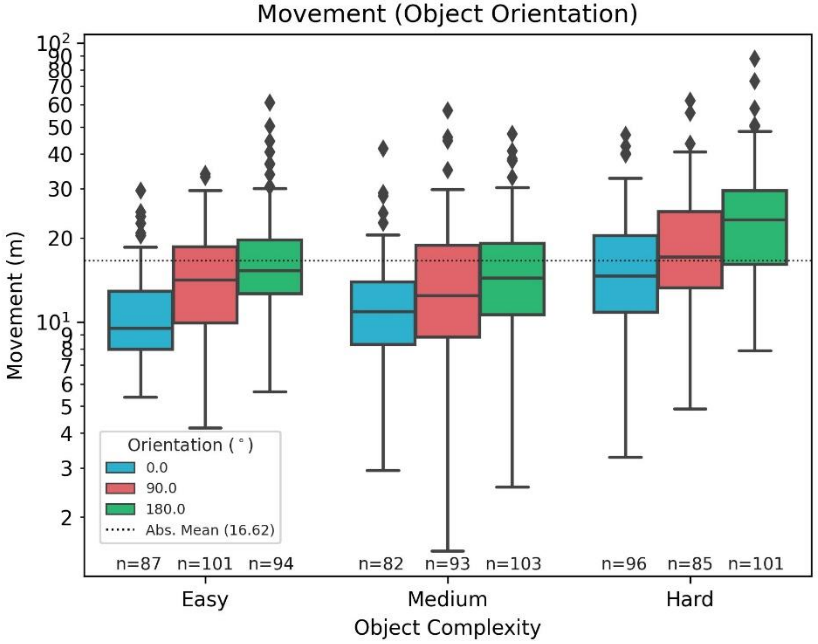
Characteristics across Trials (2)

- Overall average of 93 fixations during an average of 48 seconds; with 300ms per fixation change, this leaves over 20 seconds for 'thinking' (reasoning, planning, decision-making, working memory).

- The absolute mean of head movement was 16.62m and no trial was less than 1m.

- A clear trend between amount of head movement and orientation; 0° least amount, 90° increase of 2-5m, and 180° additional increase of 1-5m.

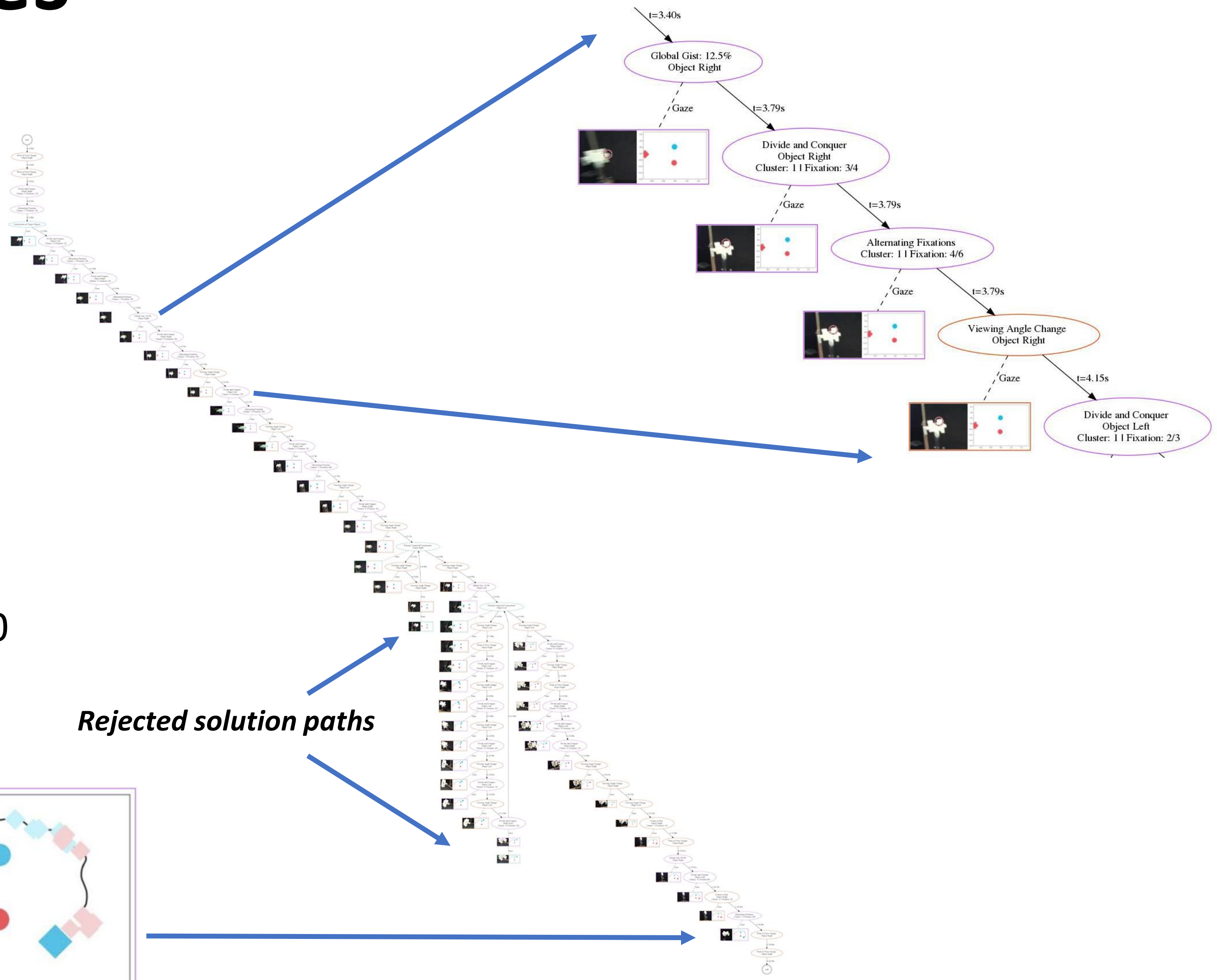


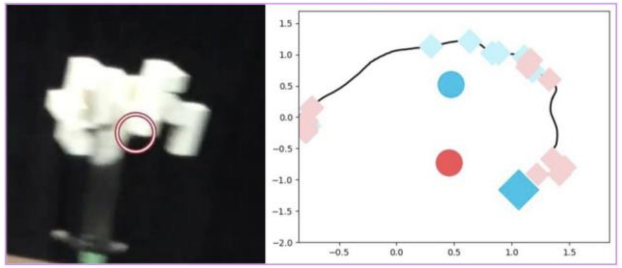


Action Sequences

- An example sequence of actions
  - Complexity: Easy
  - Orientation: 90°
  - Sameness: Same
  - Start: Long

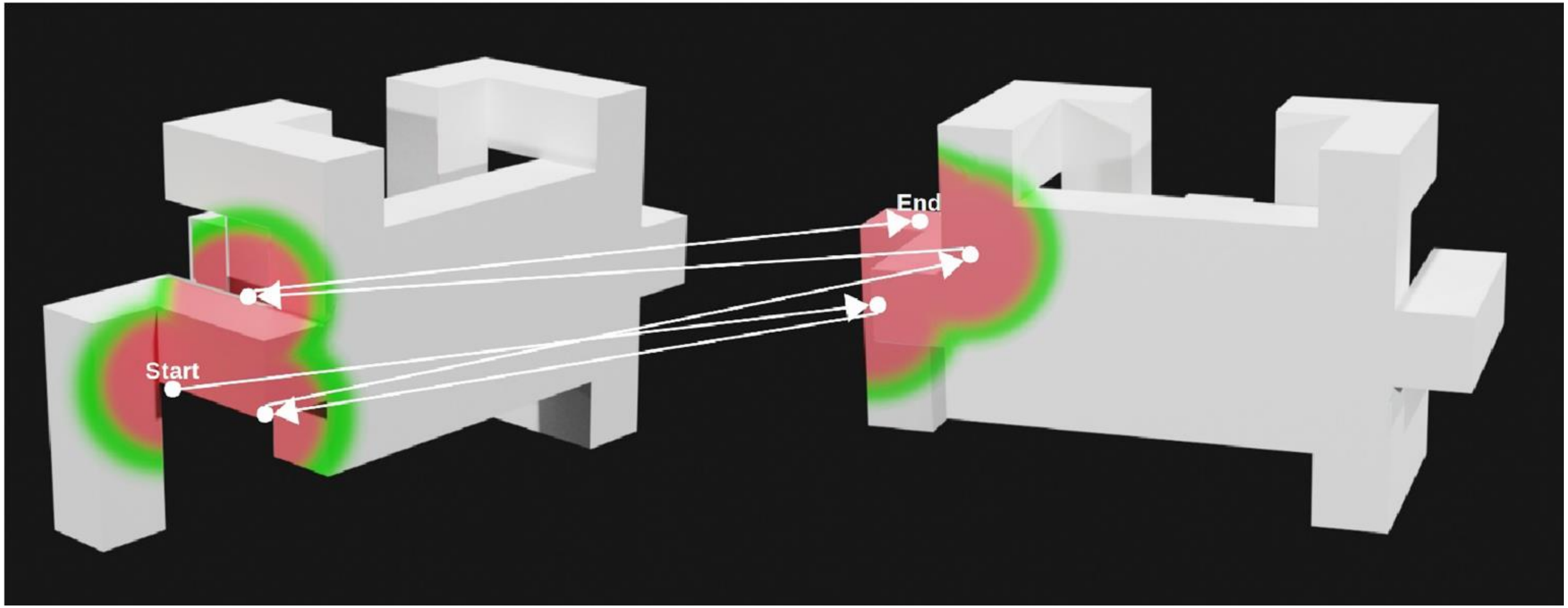
- No direct path to a solution
- Almost always several trials and error components
- Generally, complex graphs, with up to 800 nodes





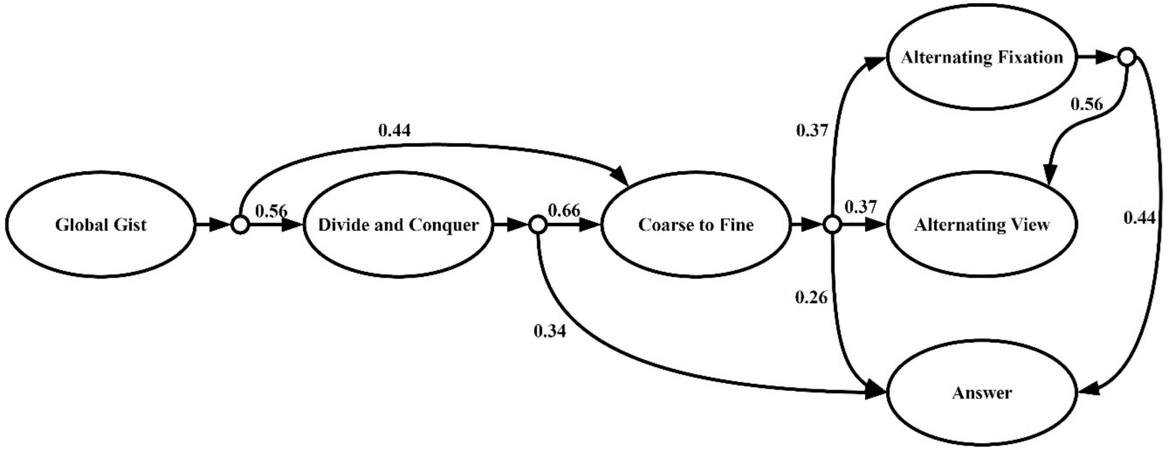
Patterns within Action Sequences (1)

- Found many patterns
  - Each has usage frequency dependent on complexity, orientation, and starting position
  - For example, subjects would move gaze back and forth between objects seemingly inspecting a single spatial region for similarity – we termed this the ***Alternating Fixation*** strategy



Patterns within Action Sequences (2)

- Over the course of a trial, subjects used several such strategies in sequence and these formed higher order patterns – they form directed graphs
- These higher order patterns were compositions of the strategies but with different frequency of occurrence depending on the experiment initial conditions – have found several to date
- They bear a remarkable similarity to the ***Cognitive Programs*** of Tsotsos & Kruijne (2014), to the Dynamic Bayes Nets of Ballard & Hayhoe (2009) and to the Visual Routines of Ullman (1984).



If target objects are the same, this Cognitive Program was used in 99.7% of trials.

Patterns within Action Sequences (3)

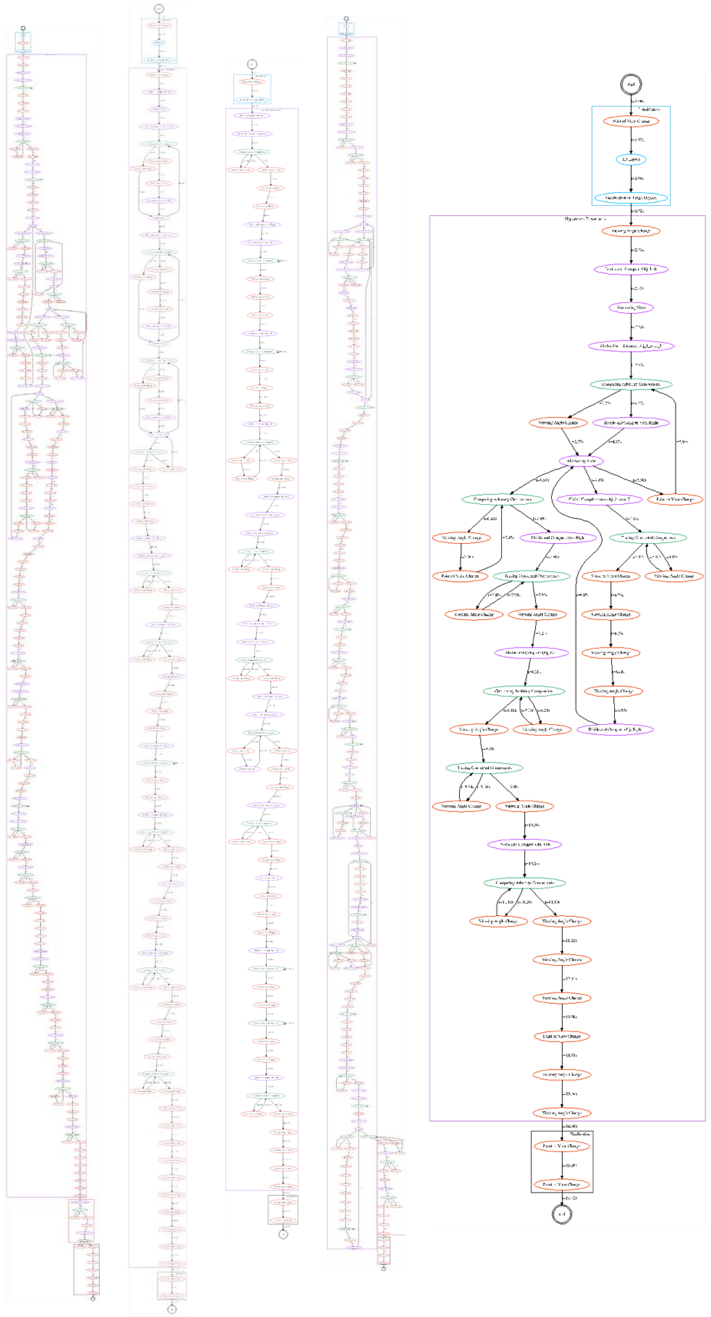
- These provide the answer to our motivating question

- Across each Cognitive Program, attention is seen to play one of several roles as specified by the attentional mechanisms of Selective Tuning:
  - Task Priming
  - Fixation change
  - Viewpoint change
  - Top-down surround suppression and localization
  - Selection

- An attentional/executive controller seems needed to choose, parameterize, sequence, initiate, monitor for success, plan remedial action, and more

Conclusions

- Motivated to understand the scope and nature of attentional/executive control for STAR for an active observer
- Lack of human experimental knowledge led us to do the experiment ourselves
- The Same-Different task for an active observer seems like an excellent testbed for systems that purport intelligent behavior
- To date, our subjects show a complex solution process that is dynamically deployed, highly accurate, composing known elements into a hypothesize and test framework until a solution achieved
- Human solutions seem to fill the criteria for Cognitive Program representations, an upgraded form of Ullman's Visual Routines
- Within these, attention has many roles and the dynamic nature of their application indicates what the nature of a controller might be, whose design is now underway
- Moving forward
    - We intend to also experiment with 3D ‘spatial relations’, 3D ‘visual search’, and to add shadowing to all the tasks, within the PESAO facility.
    - The goal is to discover the common elements of a generic visual problem-solving strategy. (Not to solve each separately.)



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