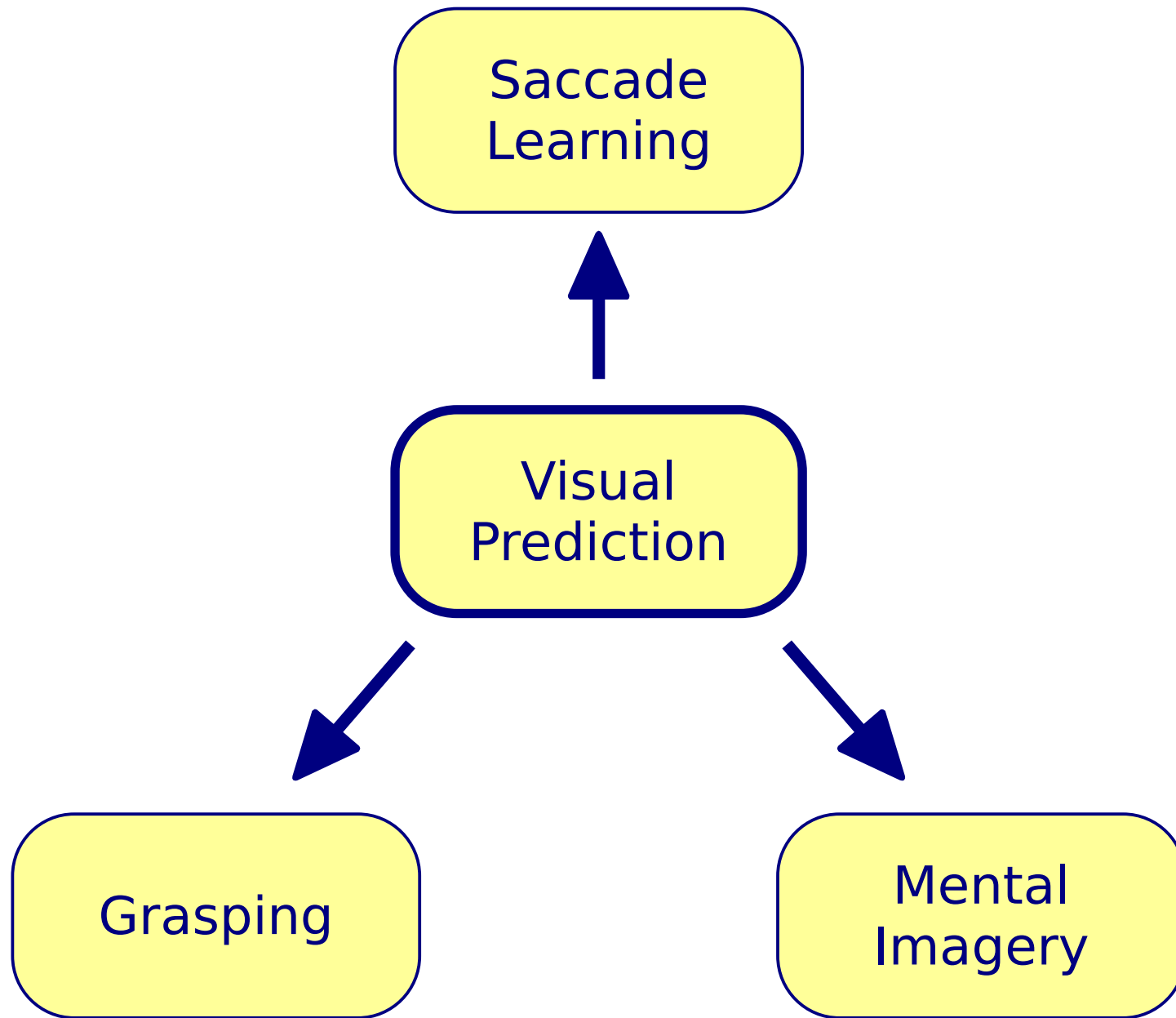


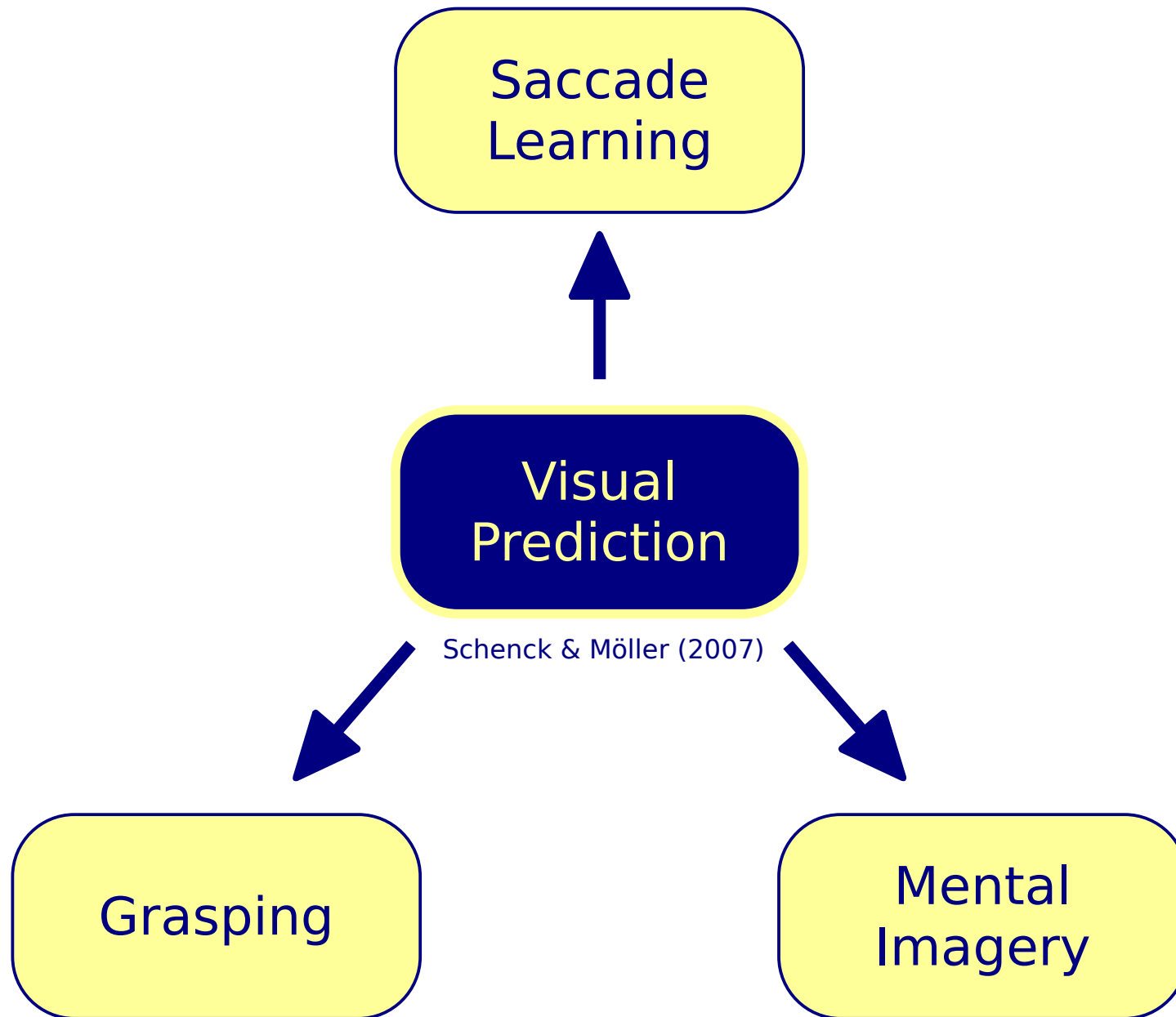
# Application Scenarios for Visual Prediction

Wolfram Schenck, Ralf Möller

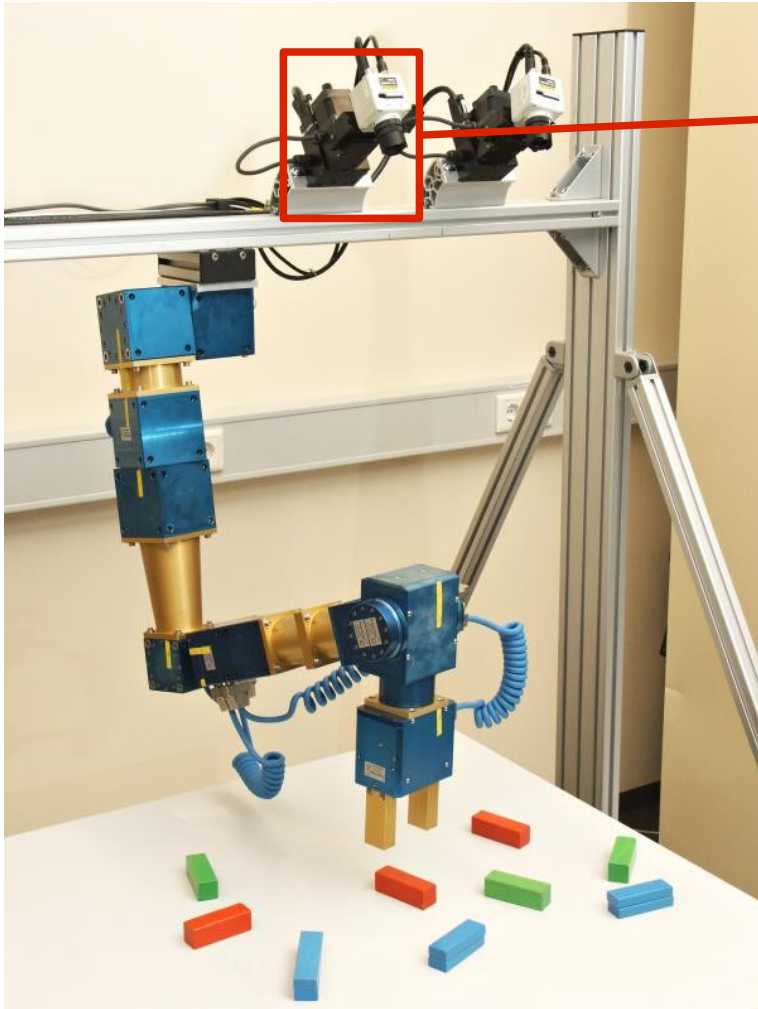
Computer Engineering Group  
Faculty of Technology  
Bielefeld University

**ABiALS 2011, Bielefeld, 22.02.2011**



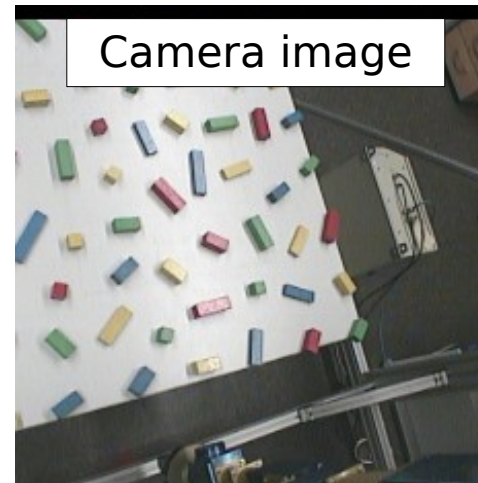


# Setup

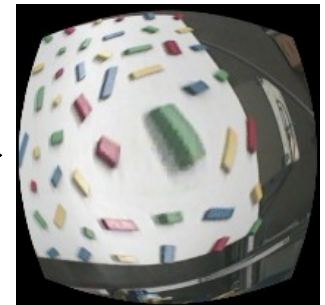


Two degrees of freedom:

- $\Delta\text{pan}$
- $\Delta\text{tilt}$



Retinal image



- ▶ Power function:  $r_C = \lambda r_R^\gamma + (1-\lambda)r_R$ 
  - $r_C$ : Normalized radius in camera image
  - $r_R$ : Normalized radius in retinal image
  - $\lambda = 0.8, \gamma = 2.5$

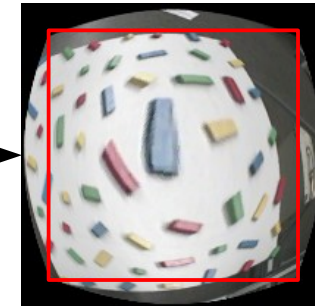
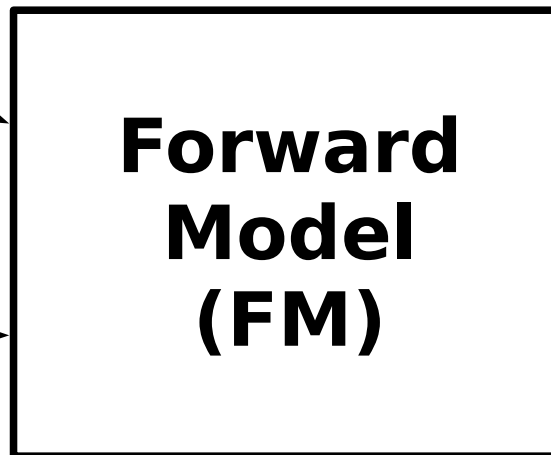
# Visual Forward Model for Saccades

Input image: 207x207 pixels

Output image: 159x159 pixels

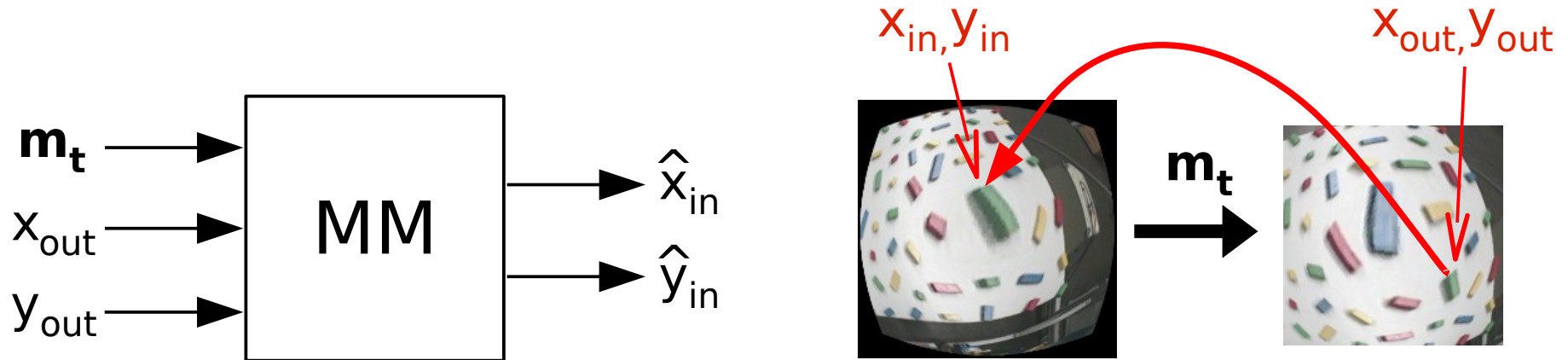


$\mathbf{m}_t$



$$\mathbf{m}_t = (\Delta\text{pan}_t, \Delta\text{tilt}_t)$$

# Mapping and Validator Model



**Predictive remapping:** Visual prediction in the brain by shifting receptive fields (e.g., Duhamel et al., 1992; Umeno & Goldberg, 1997)

$$\mathbf{m}_t = (\Delta\text{pan}_t, \Delta\text{tilt}_t)$$

# Prediction Examples

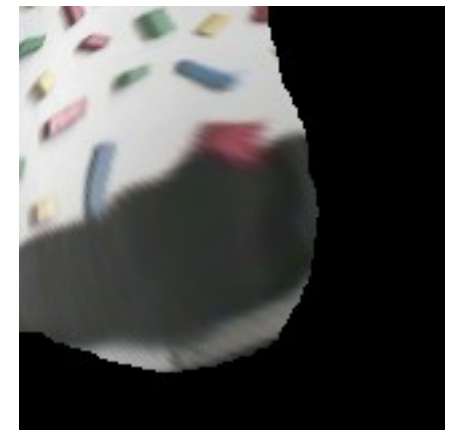
Real



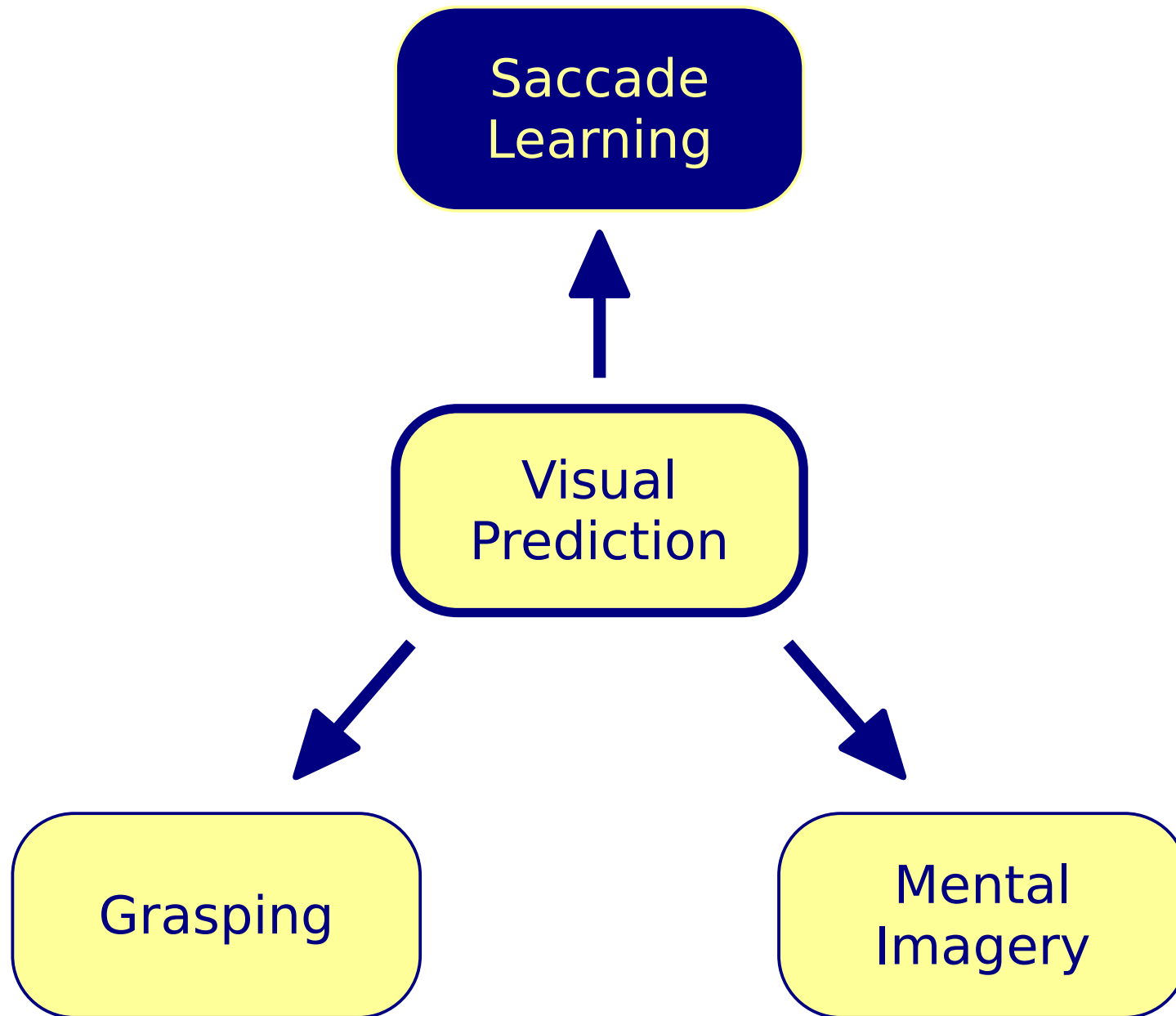
Predicted



Real



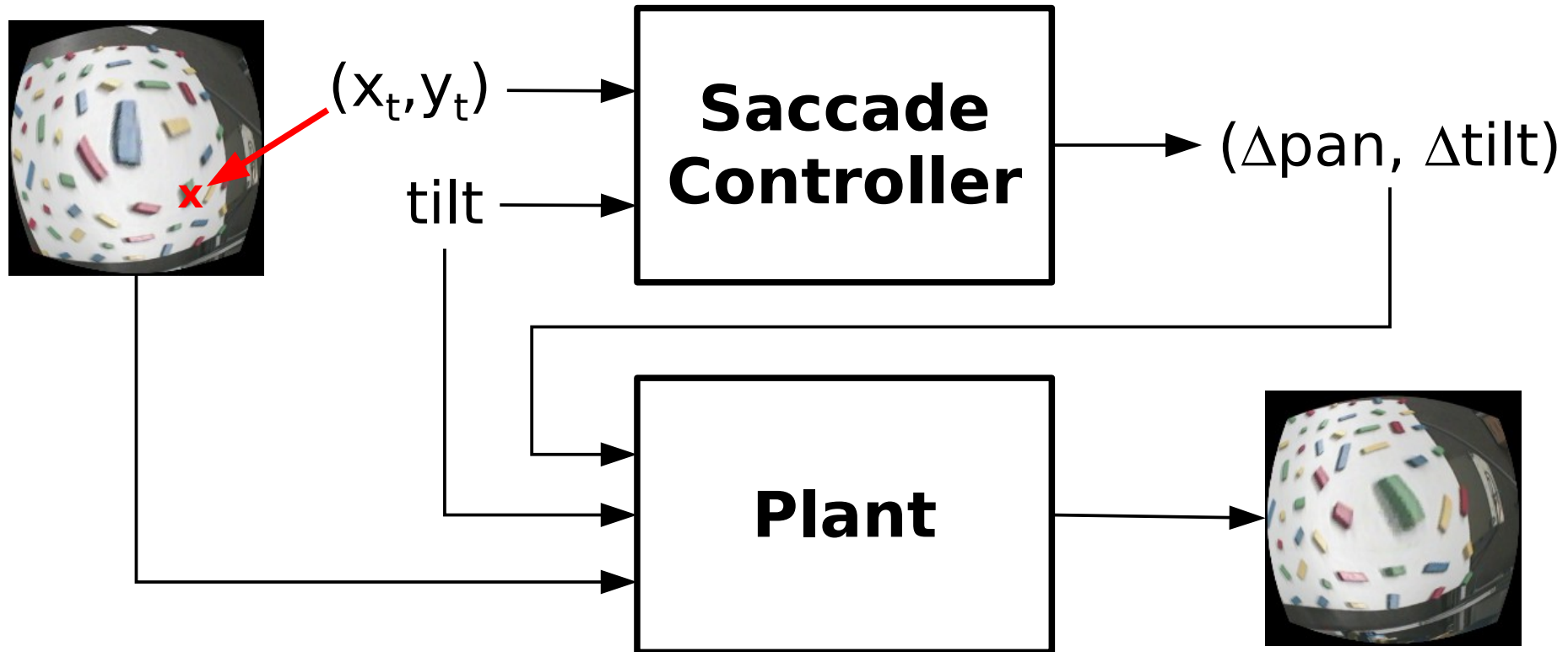
Predicted





# Saccade Control Task

- ▶ **Task:** Schedule commands  $(\Delta\text{pan}, \Delta\text{tilt})$  such that a target object is projected onto the center of the camera image



# Problem of the Missing Teacher Signal

- ▶ **Goal:** Train an adaptive saccade controller
- ▶ **Required:** Learning examples associating sensory input and the correct motor output
- ▶ **Problem:** The correct motor output (and thus the motor error  $\Delta\mathbf{m}$ ) is unknown...
- ▶ **Solution:** “Direct Inverse Modeling” (DIM) (e.g., Kuperstein, 1990)
- ▶ **But:** DIM requires  $\mathbf{s}_t$  and  $\mathbf{s}_{t+1}$

# Target Re-Identification Problem

- ▶ Sensory state for the saccade learning task: target position  $\mathbf{s}_t = (x_t, y_t)$
- ▶ To determine  $\mathbf{s}_{t+1}$  after saccade execution:
  - Target re-identification necessary
  - In past studies with plain camera images: By correlation approach
- ▶ Problem: Correlation approach not applicable to retinal images



Strongly non-linear  
image warping



# Visual Prediction for Target Re-Ident.

## ► **Solution:**

- Predict location of target object after saccade by visual FM
- Search for real target in close vicinity of the predicted location
  - Use other distinct features like color or shape for final re-identification

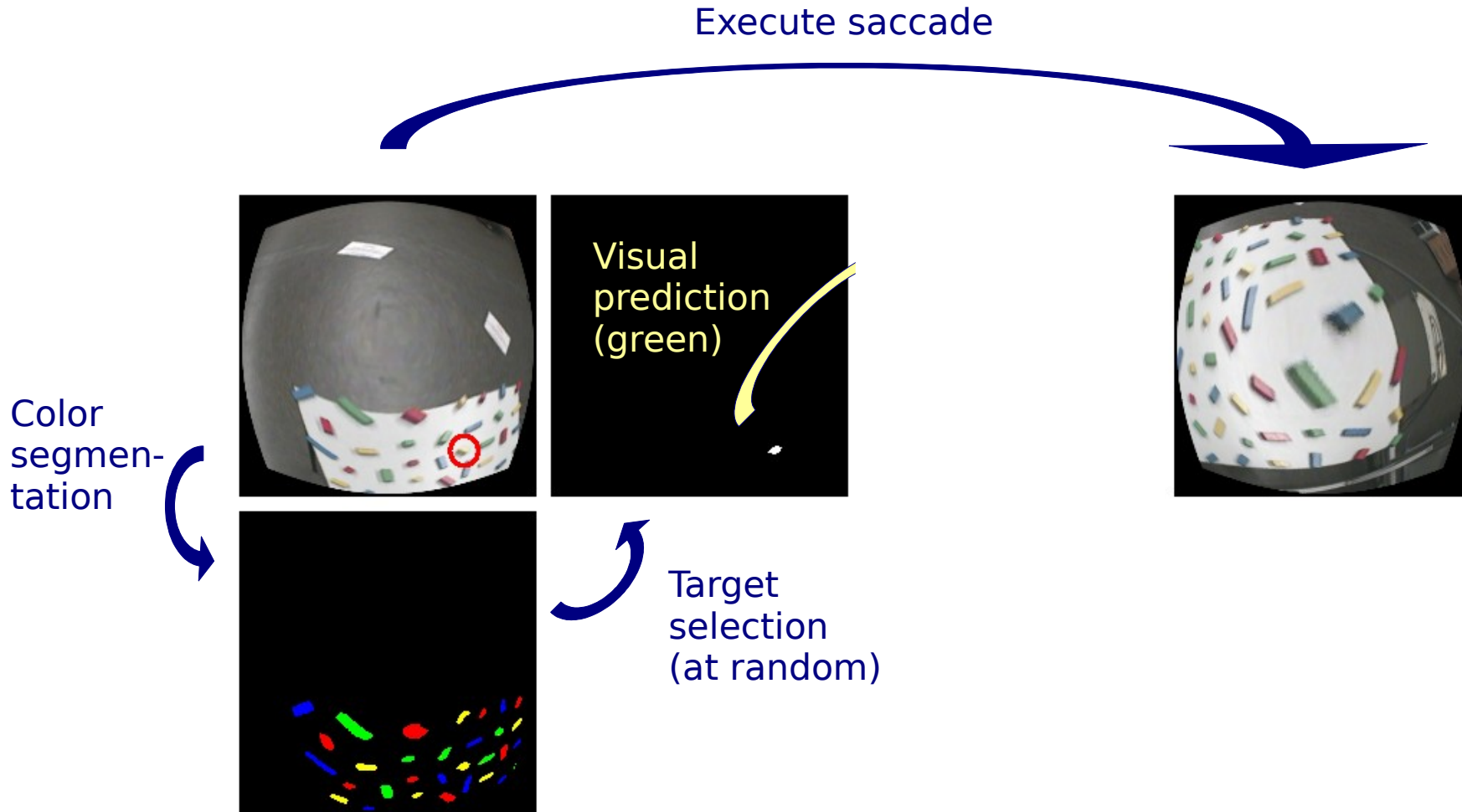
# Basic Image Processing Steps



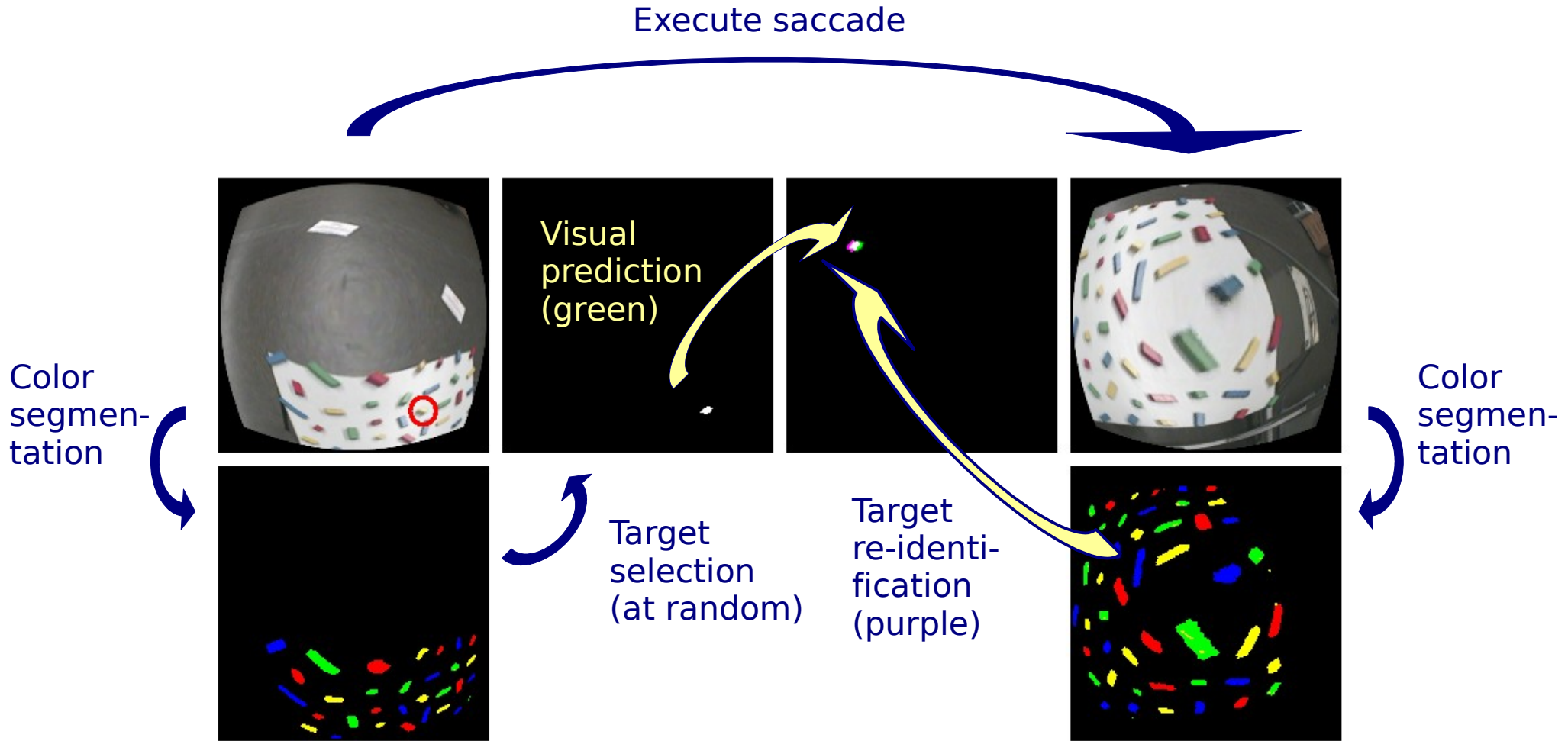
Color  
segmen-  
tation



# Basic Image Processing Steps



# Basic Image Processing Steps



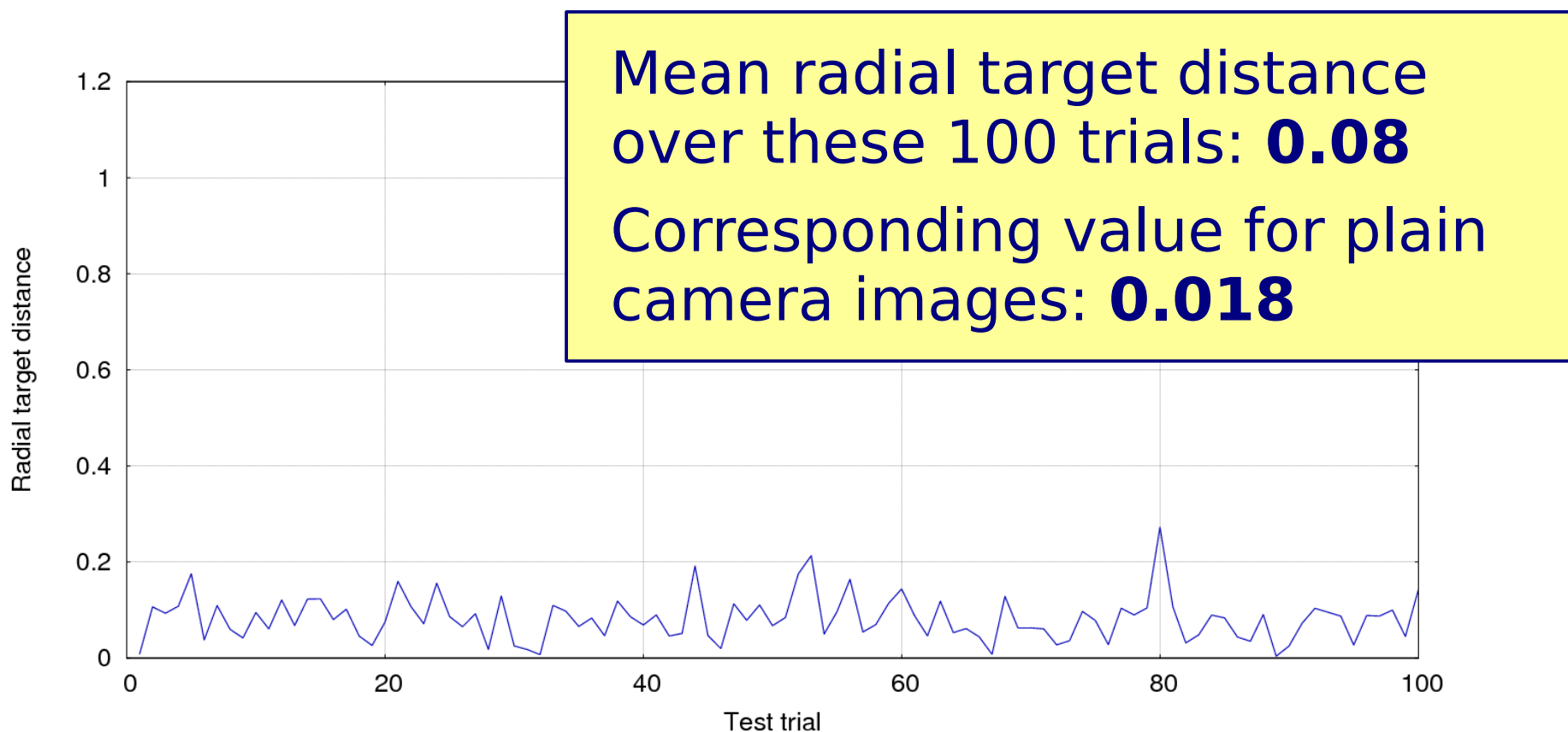
# Experiments

- ▶ Controller network:
  - Multi-Layer Perceptron (MLP)
  - Weight adaptation by online back-propagation
  - Training set: 6000 randomly collected learning examples
- ▶ Indicator for saccade precision:  
*Radial target distance*
  - Distance between center of mass of target object and image center (normalized to range [0;1] along the horizontal/vertical direction)



# Training Results

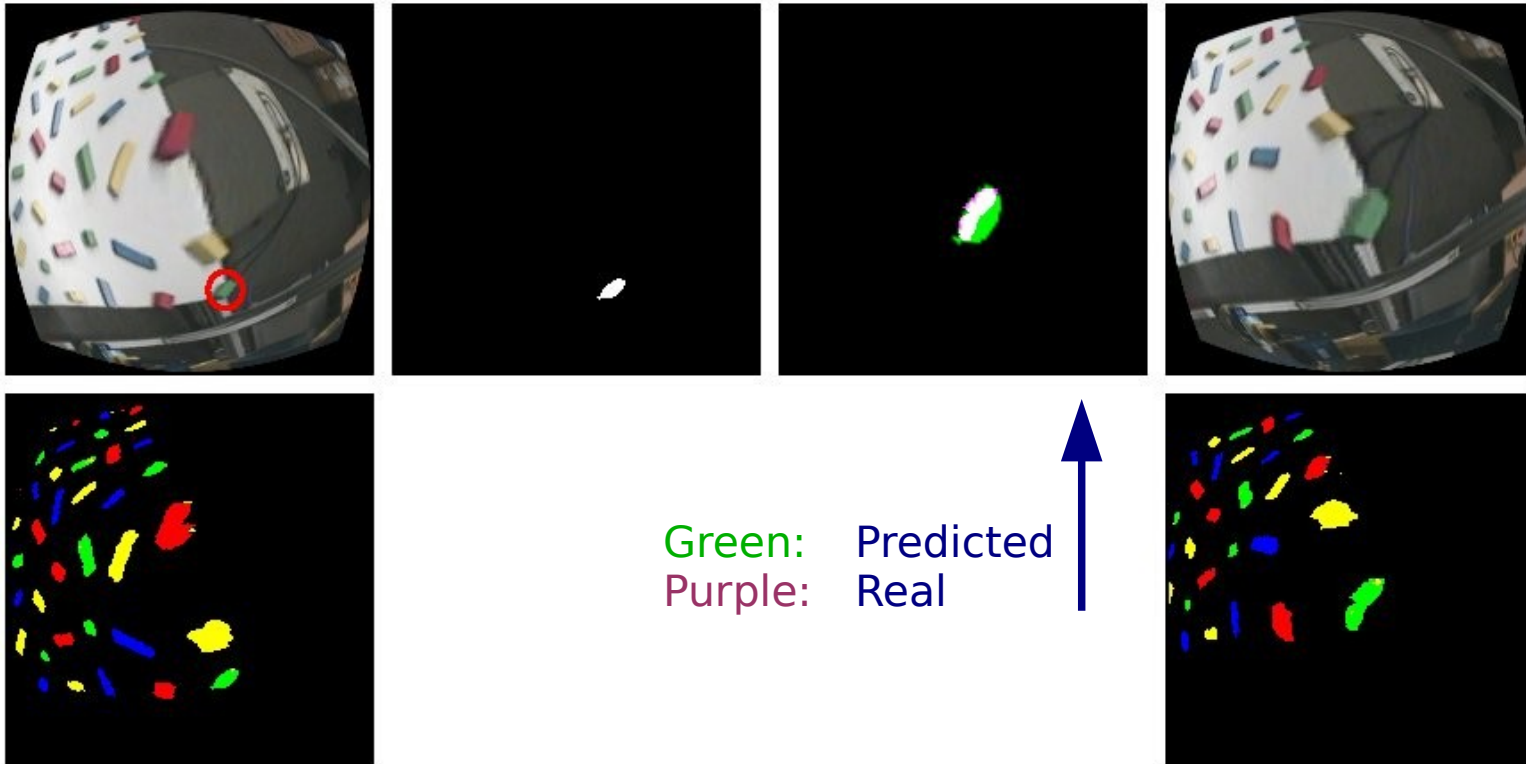
- ▶ Controller training over 3,000 epochs:  
⇒ Test error down from 0.09 to 0.0002
- ▶ Controller network performance over 100 trials:



# Results for DIM: Examples

**Pre-saccadic**

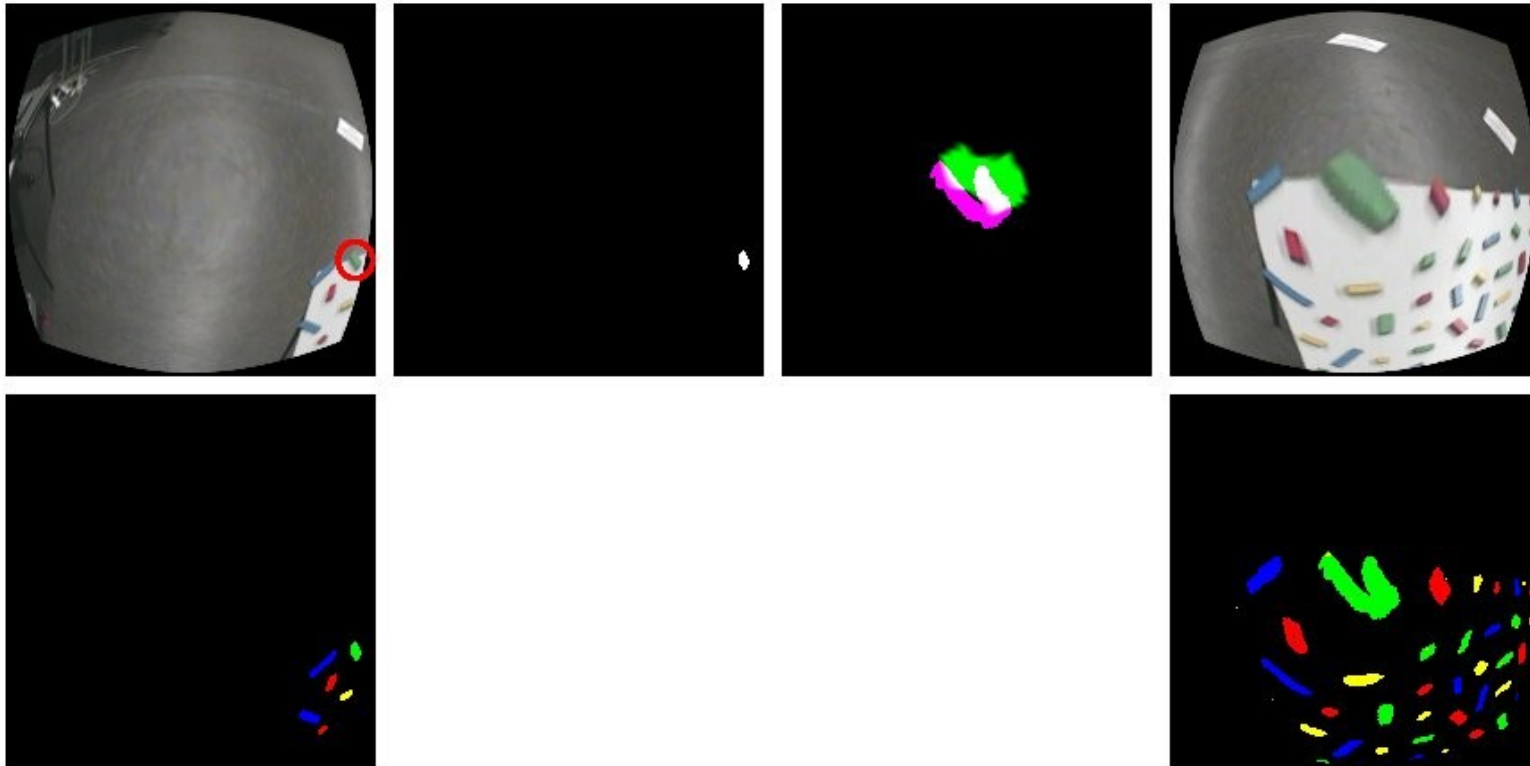
**Post-saccadic**



# Results for DIM: Examples

**Pre-saccadic**

**Post-saccadic**

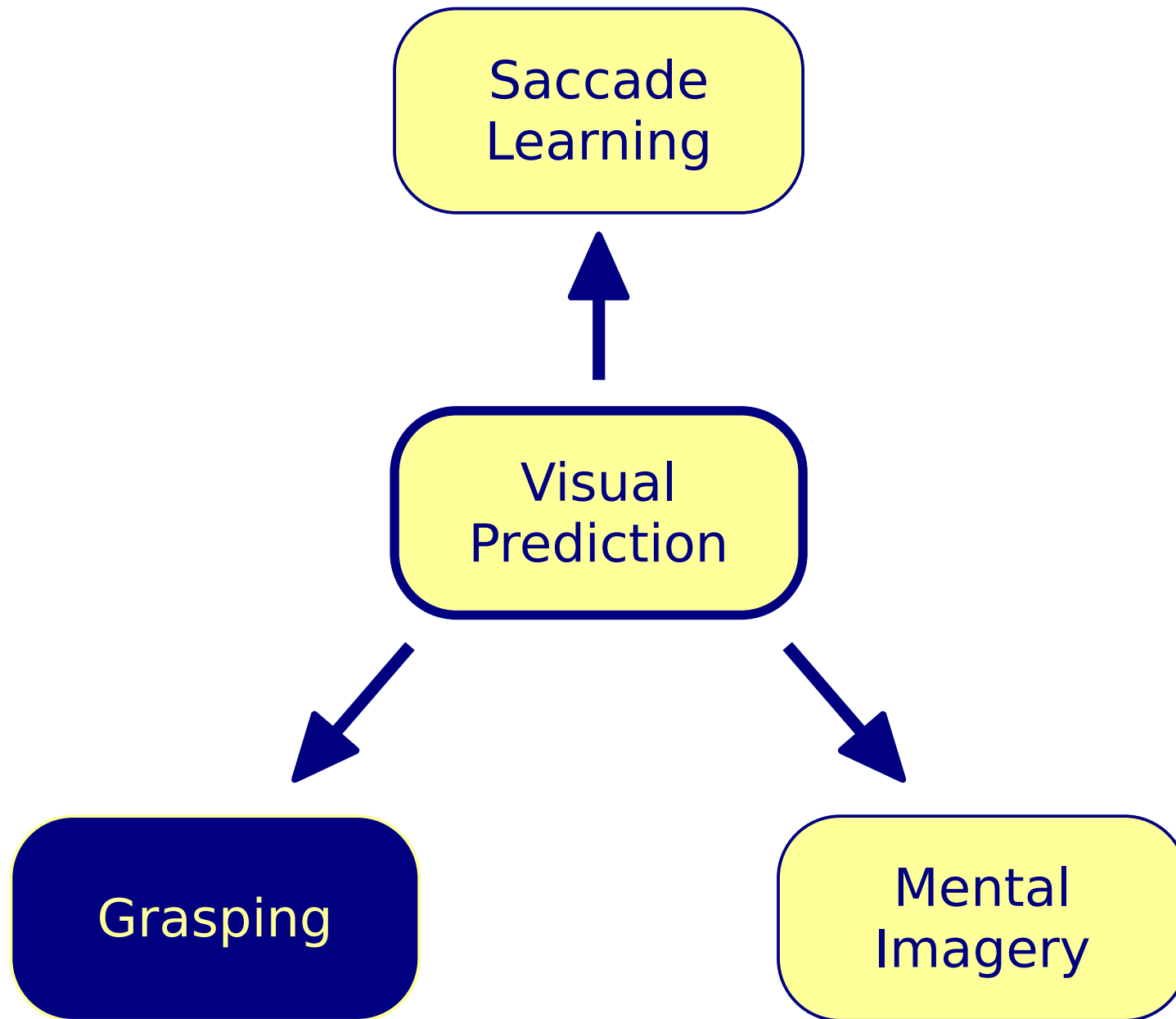


# Intermediate Discussion

- ▶ Successful saccade learning on retinal images
- ▶ Problem of the missing teacher signal solved by direct inverse modeling
- ▶ Problem of target re-identification solved by visual prediction

Link to “spatial representations and dynamic interactions”:

Visual prediction enables the agent to shift freely between different eye-centered frames of reference (“different” with respect to the gaze direction)

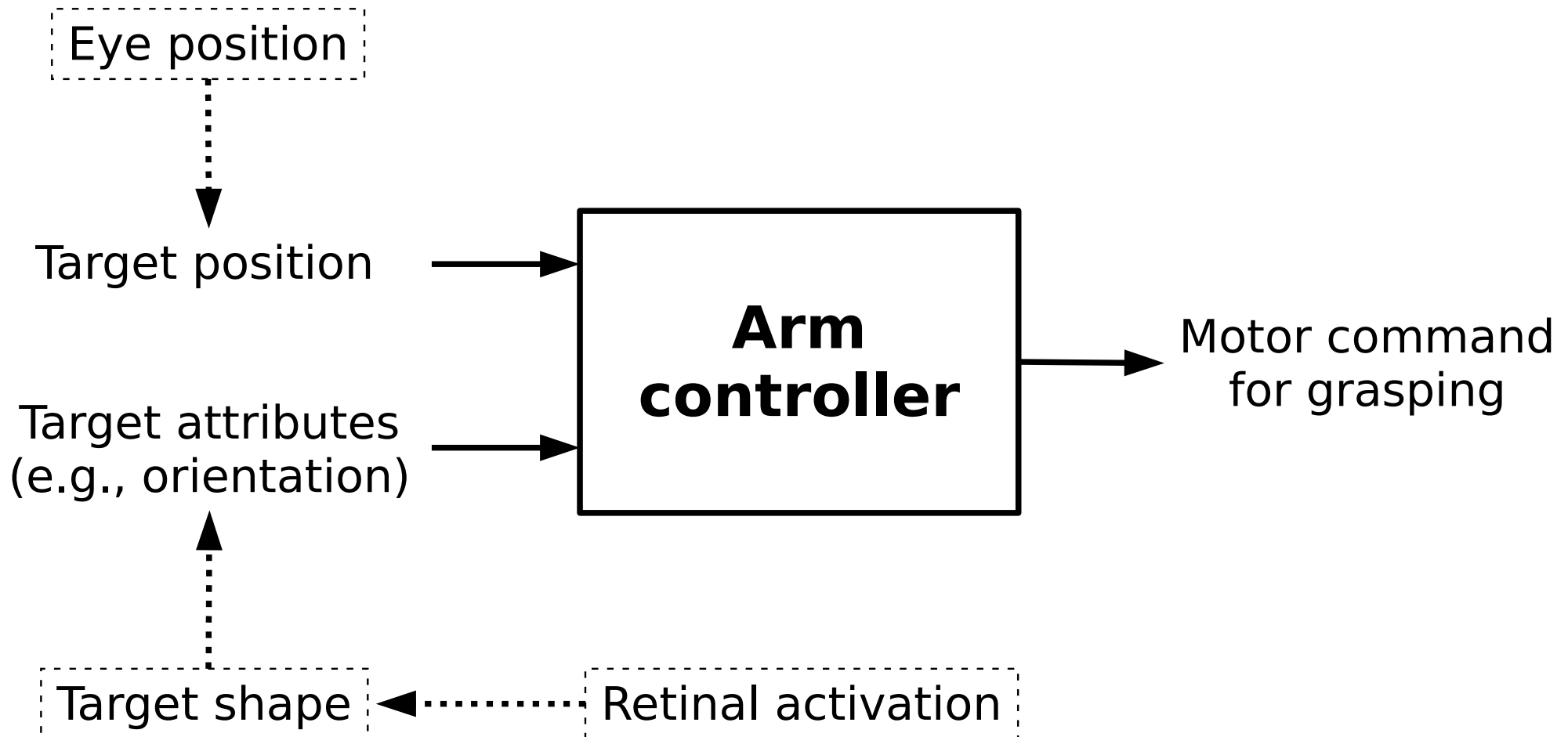


Schenck, Hoffmann, & Möller (2009)

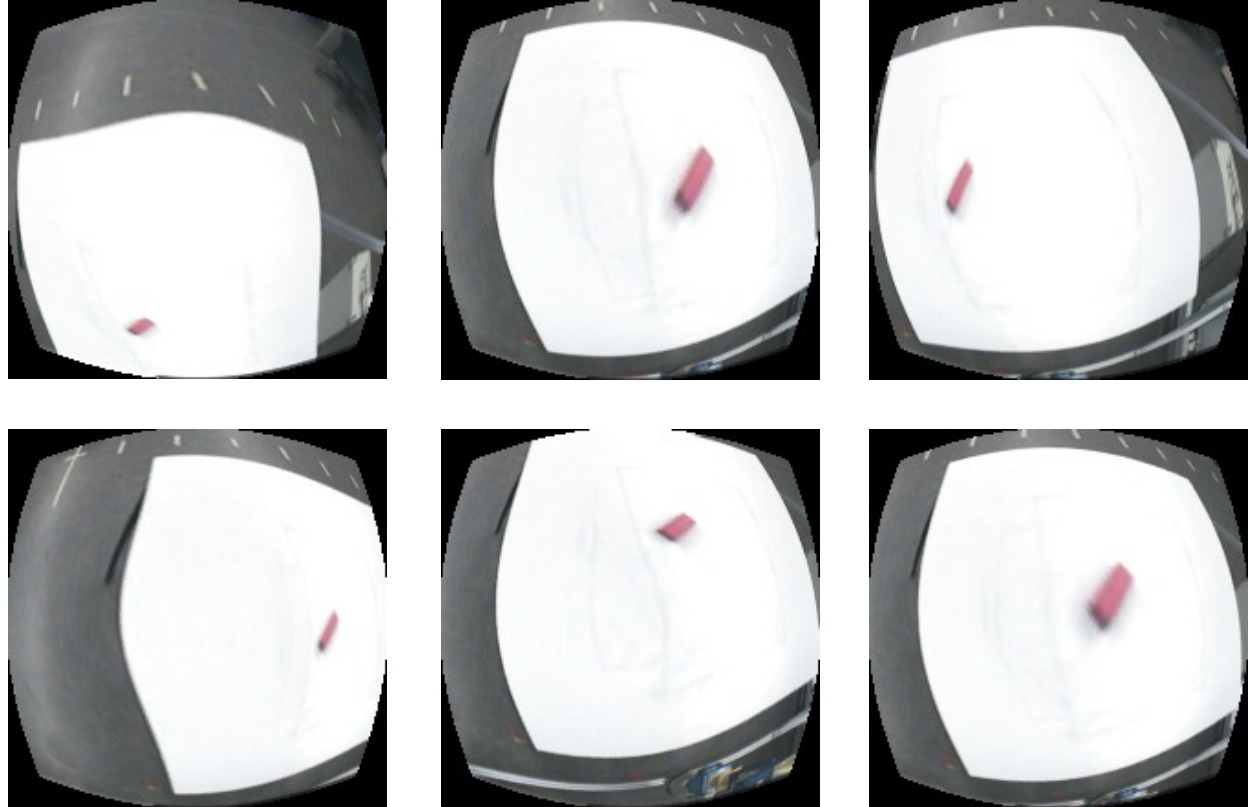
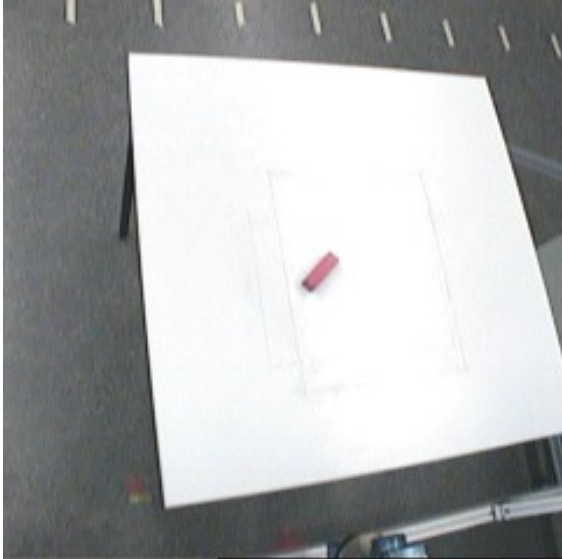
# Grasping to Extrafoveal Targets

- ▶ Usually: Saccades precede arm movements for reaching and grasping
  - Target objects are projected onto the fovea
- ▶ Arm movements towards extrafoveal target objects are possible, but with less precision (e.g., Vercher et al., 1994)

# Arm Control Scheme



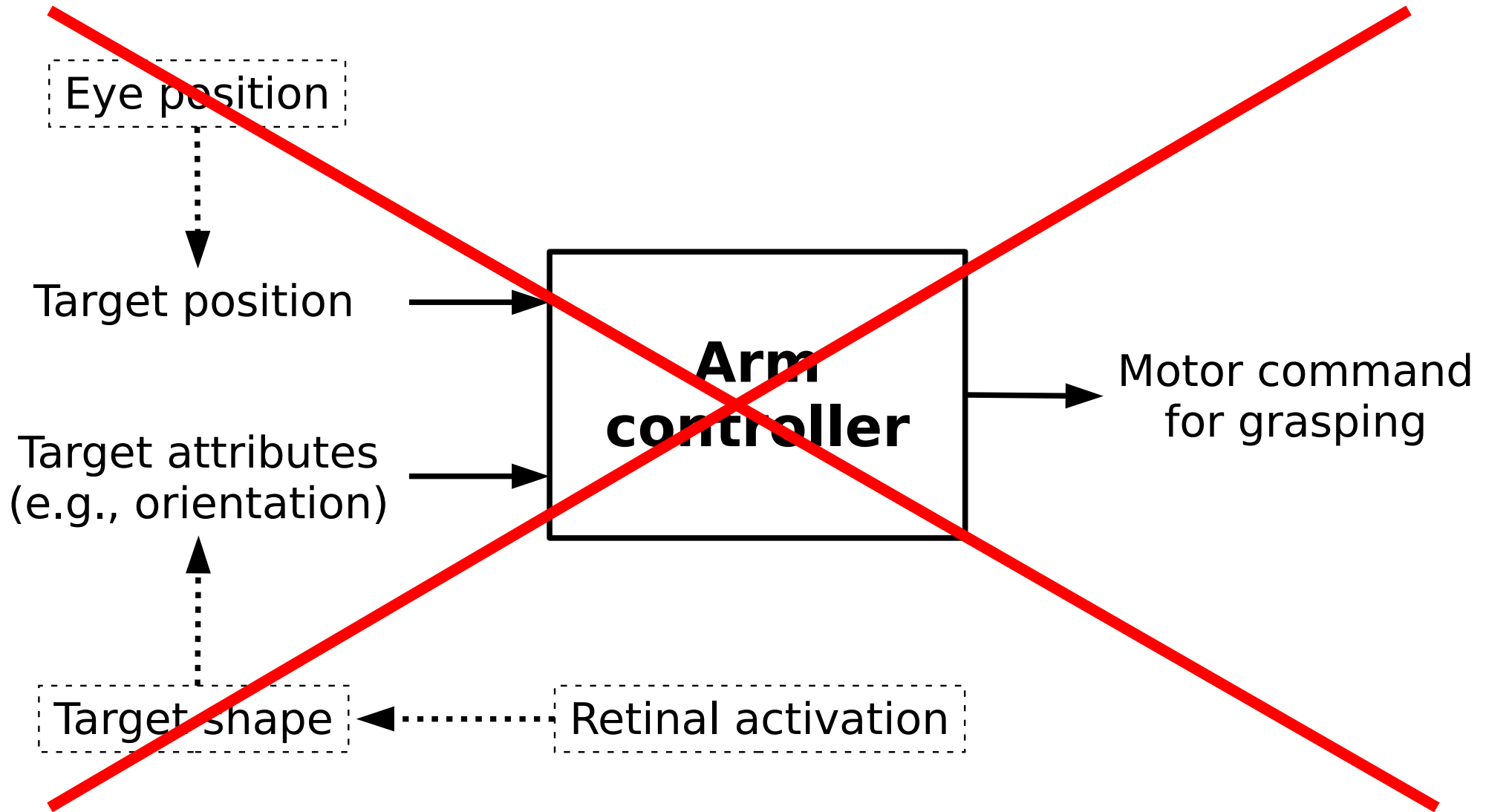
# Retinal Variance



- Depending on retinal position, sensor activation differs considerably!



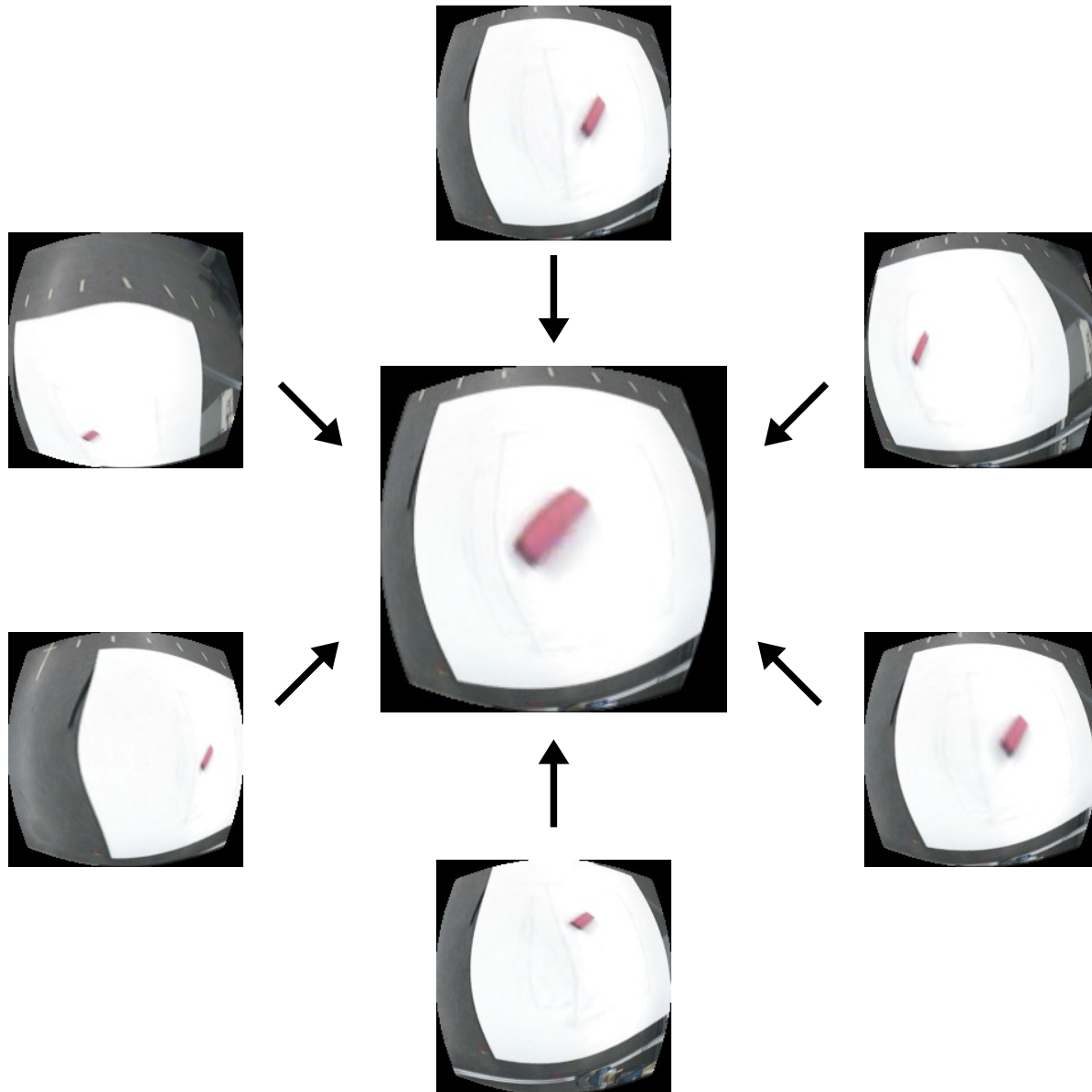
# Arm Control Scheme



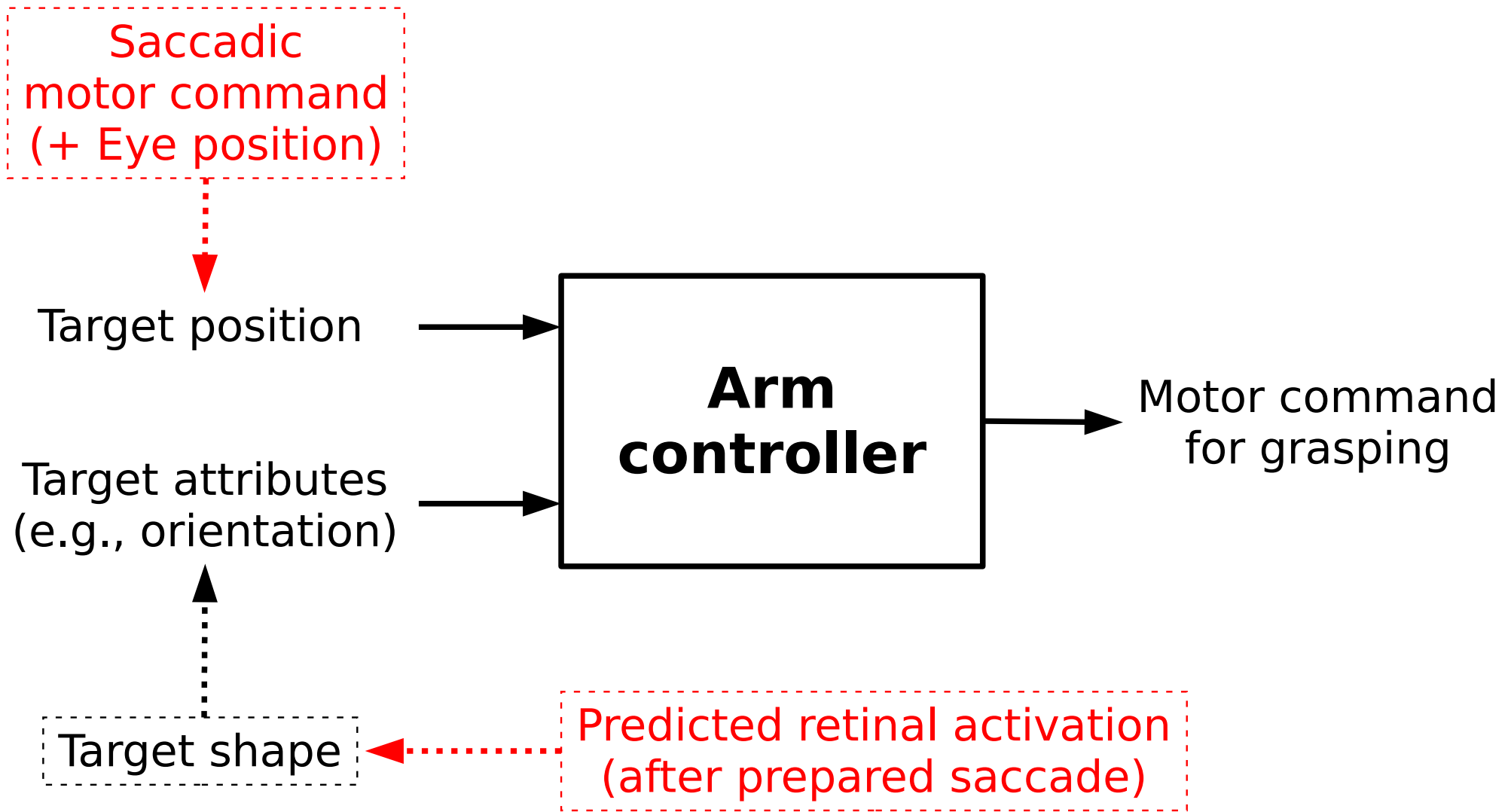
# Premotor Theory

- ▶ Spatial attention: Consequence of *preparation* of goal-directed movements (Rizzolatti et al, 1994)
  - Attention shifts are accompanied by the preparation of eye movements
- ▶ Additional hypothesis:
  - The preparation of eye movements triggers a prediction of the retinal images after the movement

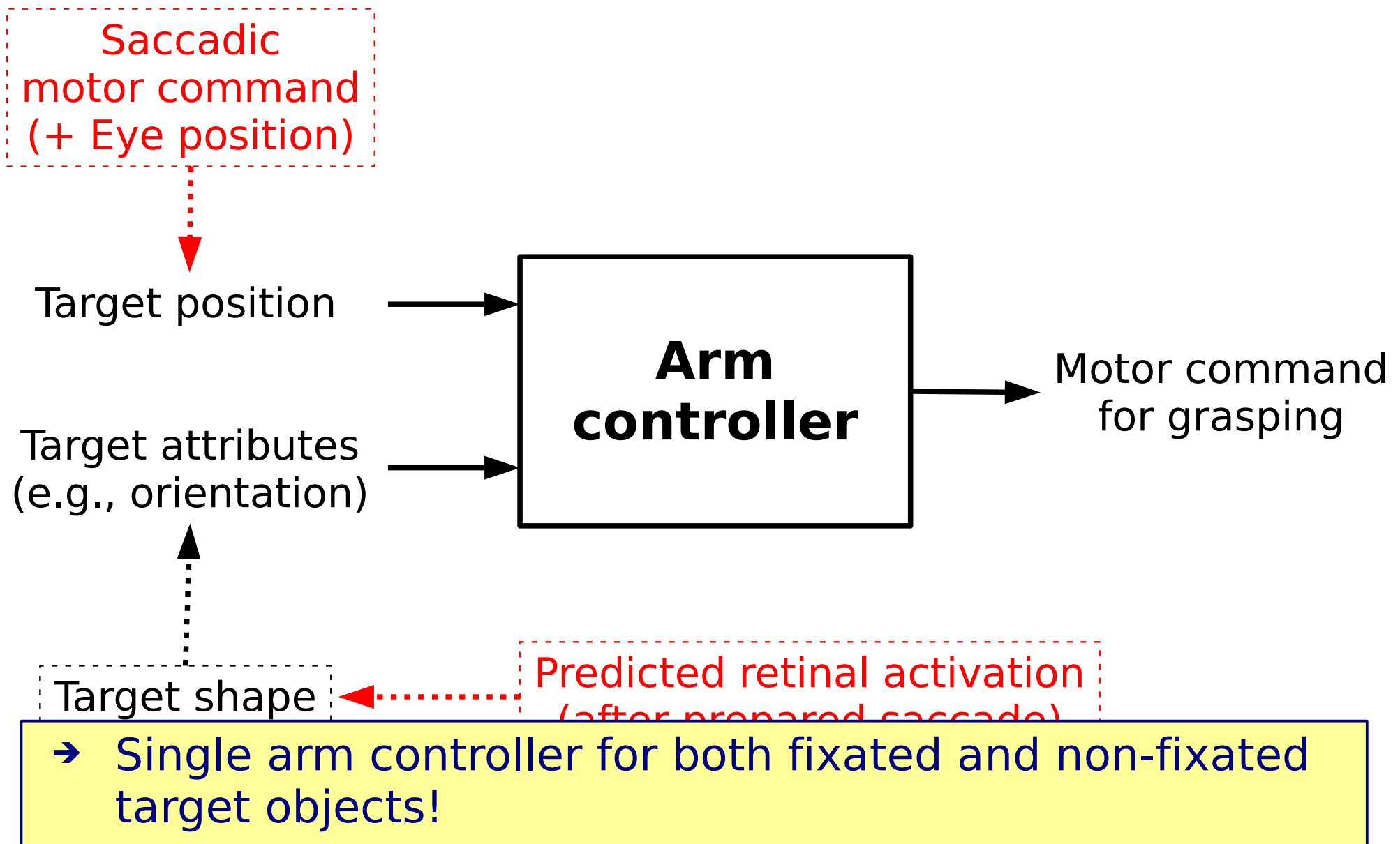
# Retinal Invariance Through Visual Pred.



# Revised Arm Control Scheme

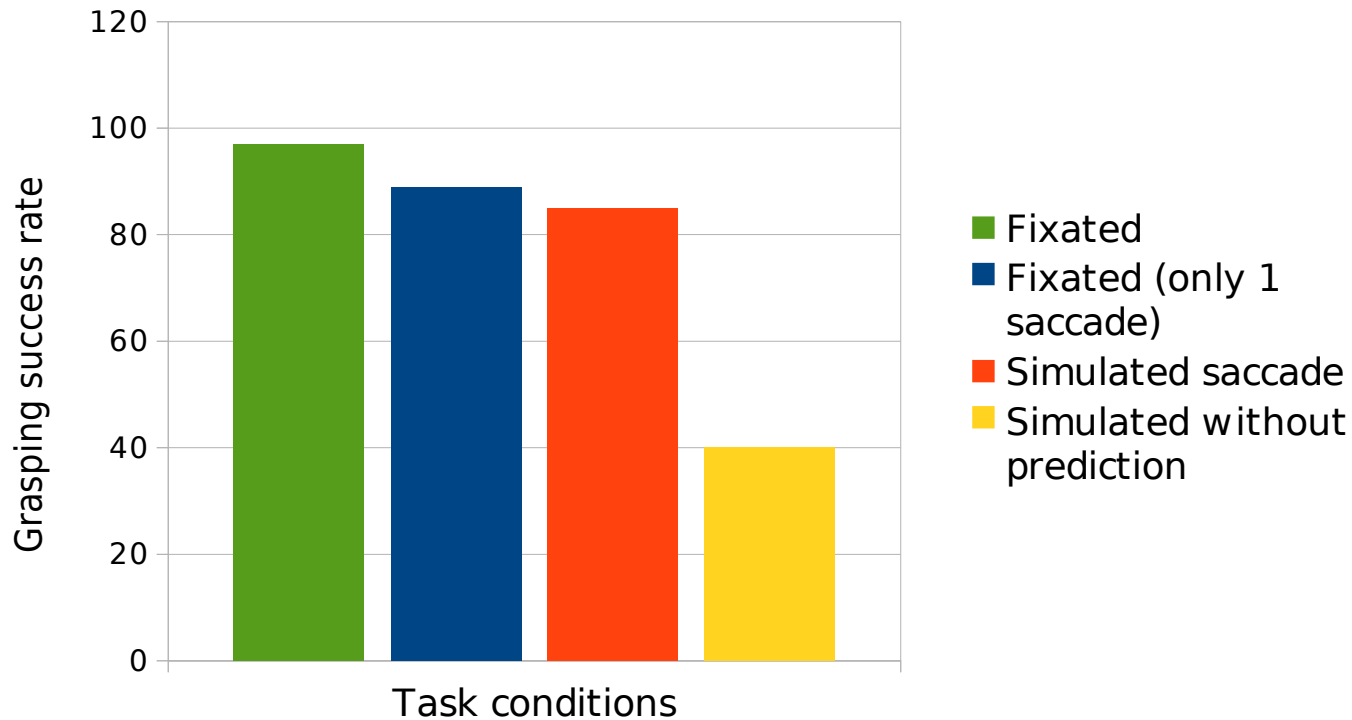


# Revised Arm Control Scheme



# Experimental Results

- ▶ Grasping performance over 100 trials in four different experimental conditions

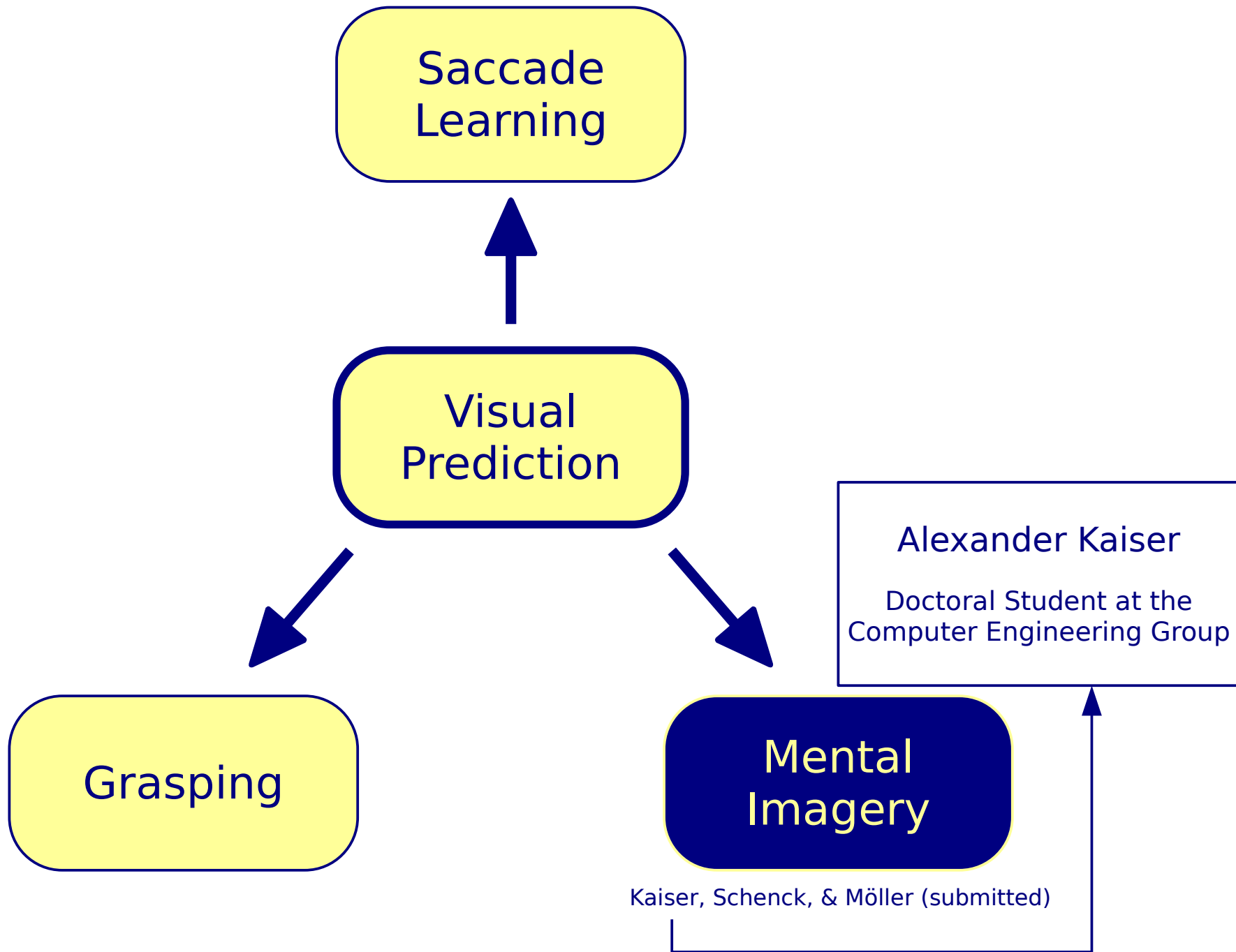


# Intermediate Discussion

- ▶ Model successful in grasping to extrafoveal targets
  - Real-world robotic test
- ▶ Visual prediction might be an important component of visuomotor coordination in this task domain

Link to “spatial representations and dynamic interactions”:

Visual prediction (in combination with a saccade controller) enables (kind of) invariance of the retinal representation with respect to the gaze direction



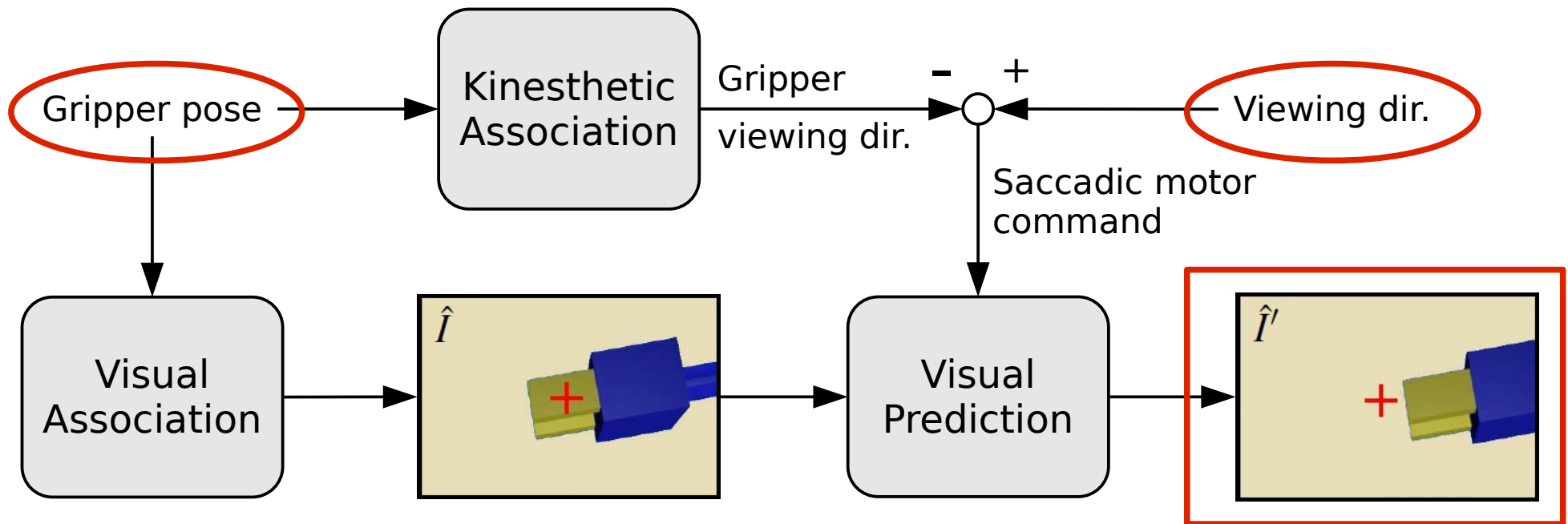
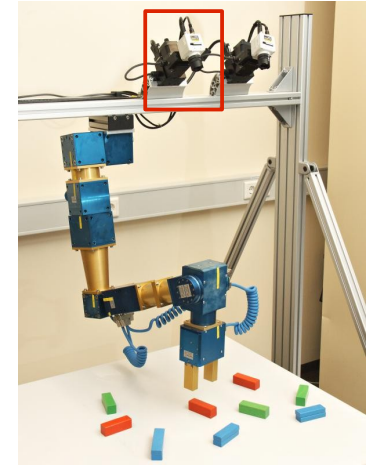


# Mental Imagery for Motor Simulation

- ▶ Simulation theories: Simulation of action sequences and their accompanying sensory or system states as basis for perception and cognition (e.g., Hesslow, 2002; Möller, 1999; Ziemke et al., 2005)
- ▶ Covert (simulated) sensory and motor states: “Mental images”
- ▶ **Here:** Mental images of visual gripper states (to be used in forthcoming cognitive architectures)

# Overall Model

- ▶ Input: Gripper pose, viewing direction
- ▶ Output: Image of the gripper (simulated “mental” image)



# Sorry, further slides...

- ▶ ... on this topic removed since this work has been recently submitted for publication (decision pending)

# Intermediate Discussion

- ▶ Model successful in generating “mental images” of visual gripper states
- ▶ Holistic approach: The image is generated as a whole in its original “raw” format, not on the basis of single features
- ▶ Need for visual prediction results from the decomposition of the overall problem in a visual association and a prediction part

Link to “spatial representations and dynamic interactions”:

Visual prediction allows to generalize from a purely foveal representation (target fixated) to other gaze directions

# Summary and Open Questions

# Summary: Three Studies

- ▶ Visual prediction in the context of saccade learning
  - Purpose: Facilitates target re-identification
- ▶ Visual prediction in the context of grasping
  - Purpose: Transforms extrafoveal visual representations of target objects into foveal representations
- ▶ Visual prediction in the context of mental imagery
  - Purpose: Facilitates the generation of “mental images” by simplifying the visual association task

# Open Questions

- ▶ Algorithms to learn visual prediction for motor tasks with many degrees of freedom?
- ▶ Visual prediction for movements where depth information is relevant?
- ▶ Multi-step visual prediction – stability, precision?

**Thank you for your attention!**