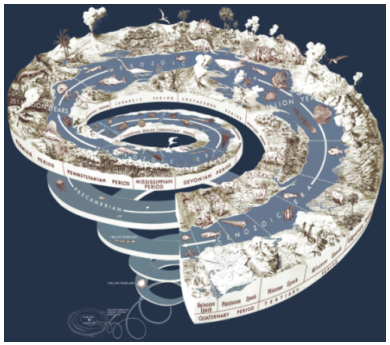
# Some Thoughts on Robot Intelligence

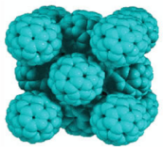
Hanyang University
Il Hong Suh

2012.4.17

4.5 Ga : 1.8 Ma =
1 day : 34.6 Sec

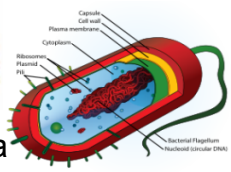


# Evolution of Species



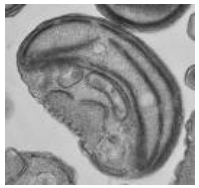
polymerization

Mitochondria



Bacteria

cyanobacteria



eukaryote

trilobite

fish

**Darwinian Creature**

**Skinnerian Creature**

4.5 billon y ears

4 billon ye ars

3.8 billon ears

Simple cel ls

Complex c ells

2 billon ye ars

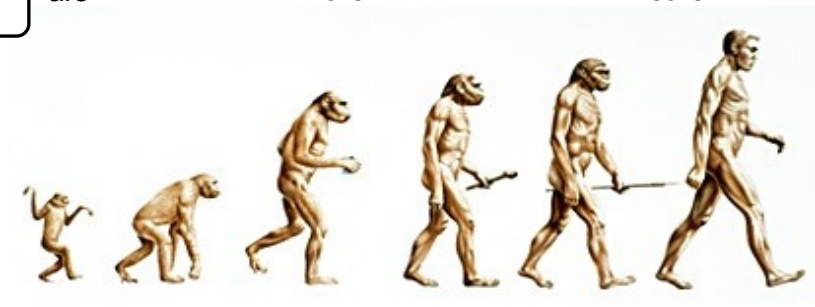
1 billon ye ars

700 million y ears

Amphibia

Dinosaur

Mammalia



Human

**Popporian Creature**

**Gregorian Creature**

542 million ears

Cambrian ex plosion

Australopithecus

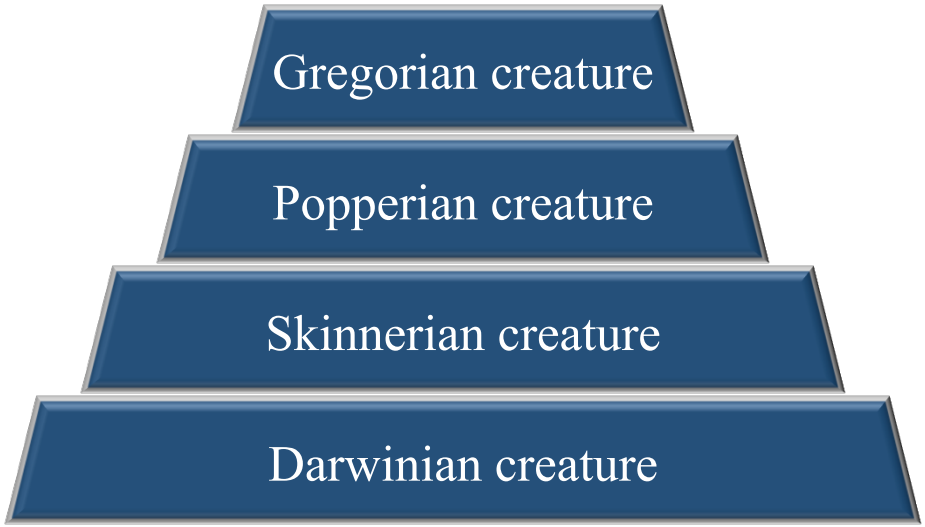
2.5 million years

1.8 million years

Origin of L anguage

# Four Kinds of Minds

- Tower of Generate-and-Test
  - By a process of evolution by natural selection
  - Important advances in cognitive power



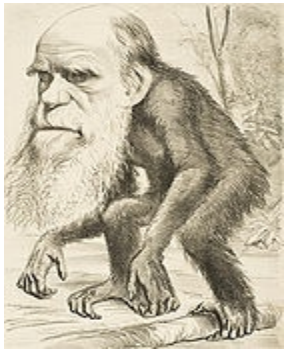

Tower of Generate-and-Test

Daniel Clement Dennett
(1942~ )

- American philosopher
- Evolution biology and cognitive science
- Kinds of Minds: Toward an understand of consciousness
- Darwin's Dangerous Idea: Evolution and the meanings of life
- Intentional stance(beliefs and desires)

# Darwinian Creature

- Darwinian evolution of species by natural selection
  - Generated by recombination and mutation of genes
  - Field-tested, and only the best designs survived

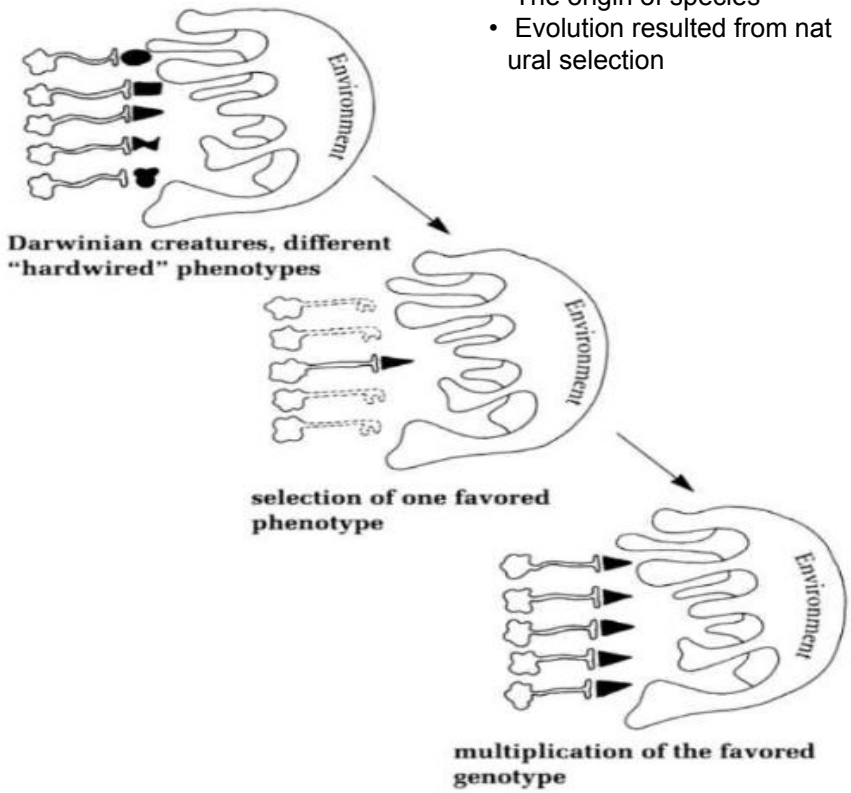


Charles Darwin
(1809~1882)

- English naturalist
- The origin of species
- Evolution resulted from natural selection

Sensory Signal
(Data)


Tower of Generate-and-Test



# Darwinian Creature

- Behavior-based Intelligence

Diving beetle senses waves of $1^{-9}$m

**Prediction**
Specialized sensor-based Simple Prediction
(**Simple bottom-up processing**)

**Intention**
Preservation of species

Gregorian creature

Popperian creature

Skinnerian creature

Darwinian creature

Tower of Generate-and-Test

**Perception**
1 or 2 High performance Specialized Sensors
(**Very Low entropy, Very simple data**)

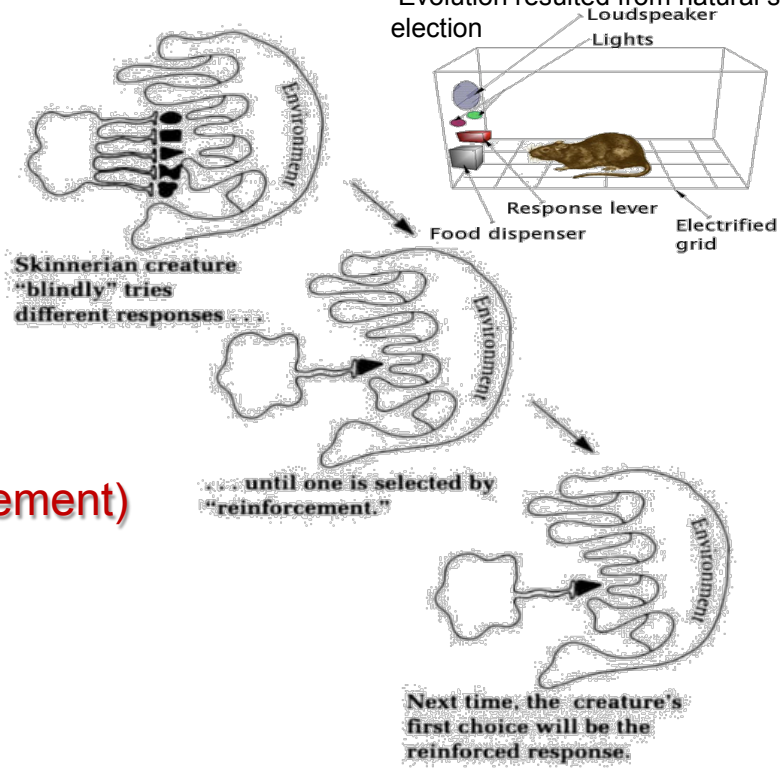
**Model/Learning**
Fixed & tightly coupled Sensory-motor Coordination / Natural selection

# Skinnerian Creature

- Property of phenotypic plasticity
- Simple sort of "experience"
  - Getting a positive or negative signal
  - Adjusted probability of that action

Burrhus Frederic Skinner
(1904~1990)

- American psychologist
- Operant conditioning (Skinner bo x)
- Evolution resulted from natural s election



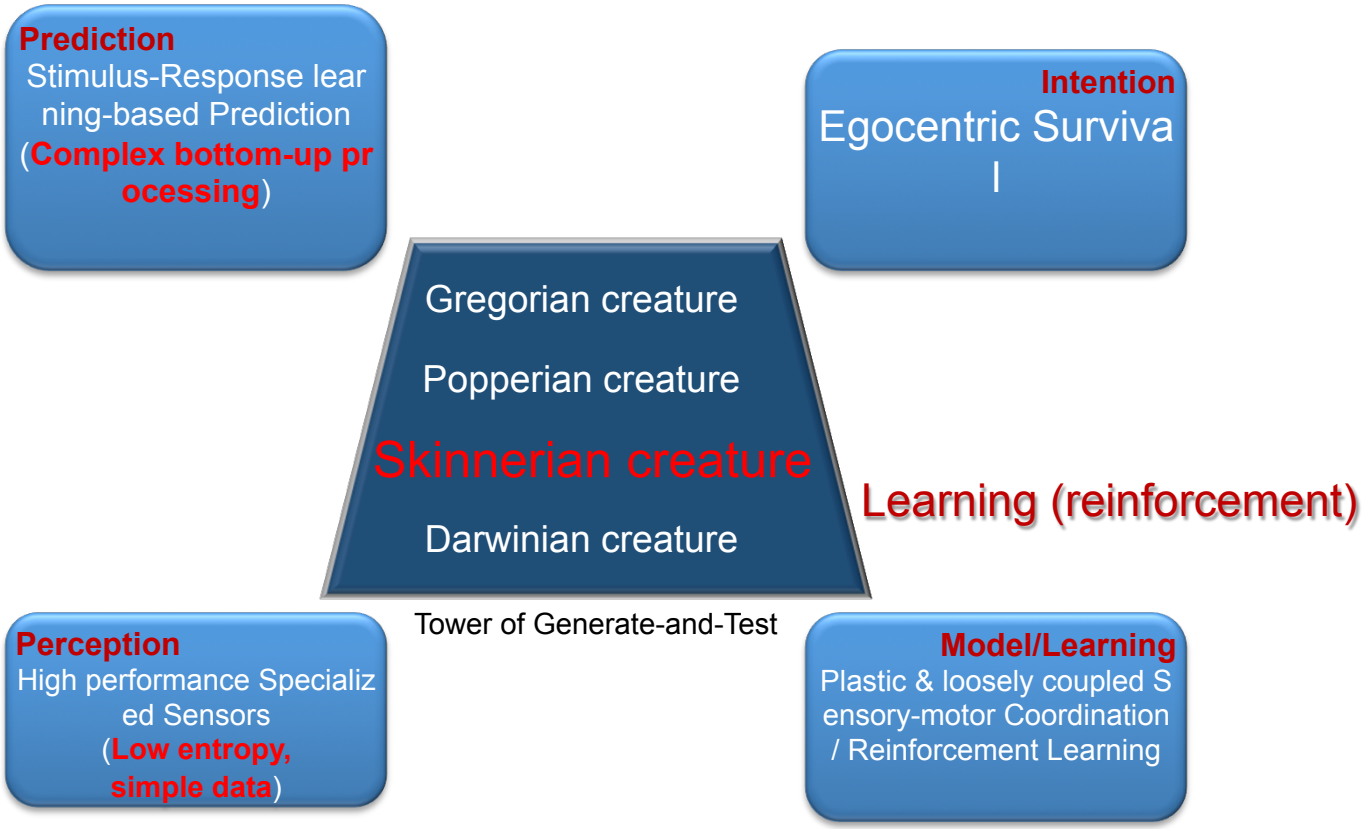

Related data


Tower of Generate-and-Test

Learning (reinforcement)

# Skinnerian Creature

- Operant conditioning, reinforcement



# Popperian Creature

- Preselection and prediction
- "Permits our hypothesis to die in our stead"
  - The inner environment contains about the outer environment and its regularities
- Filtered Pattern

Sir Karl Raimund Popper (1902~1994)

- Austrian and British philosopher
- Critical rationalism
- Scientific method by advancing empirical falsification

Filtered Pattern

Gregorian creature

Popperian creature

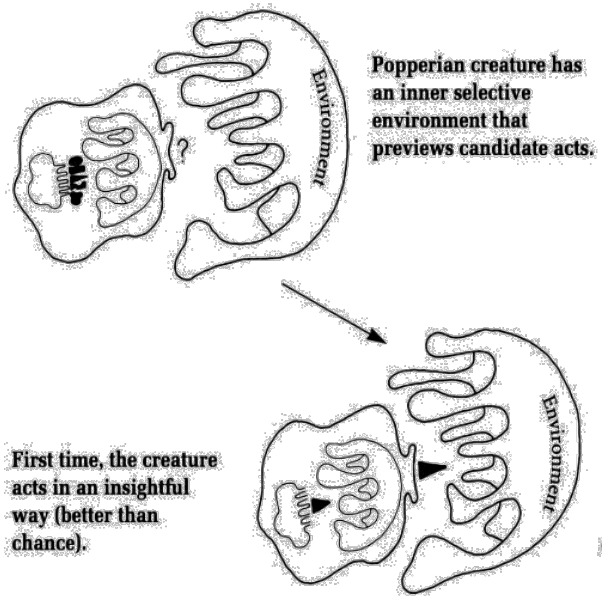
Skinnerian creature

Darwinian creature

Tower of Generate-and-Test

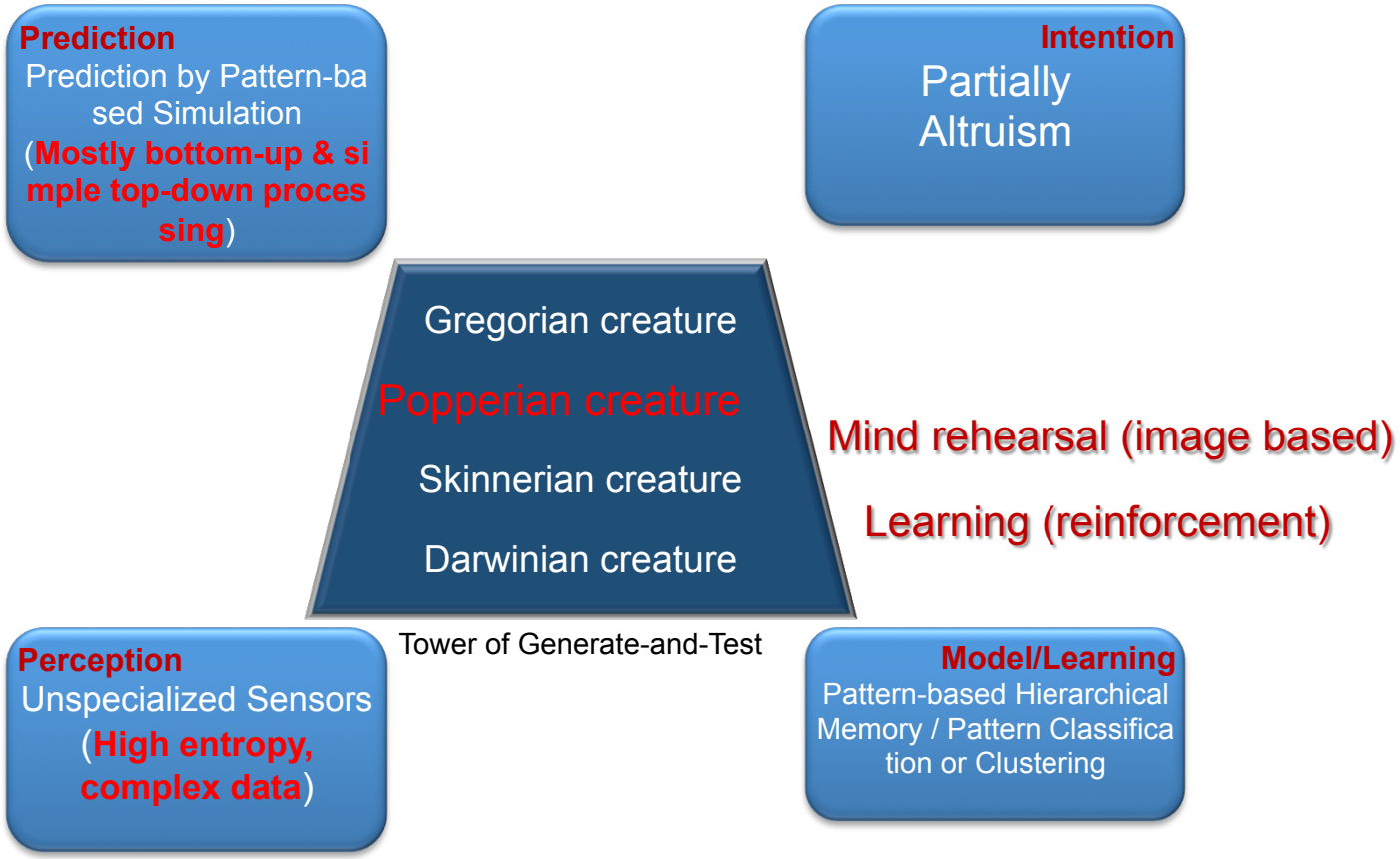
Mind rehearsal (image based)

Learning (reinforcement)



# Popperian Creature

- Pattern-based Prediction



# Gregorian Creature

- Mind tools: words
- Benefiting from the experience of others with the mind tools(words)
- Sharable and reusable Knowledge

Richard Langton Gregory (1923~)

- British psychologist
- Emeritus professor of neuropsychology at the university of Bristol
- Eye and Brain, Mind in Science
- the modern founder of the science of perception

Semantics, language

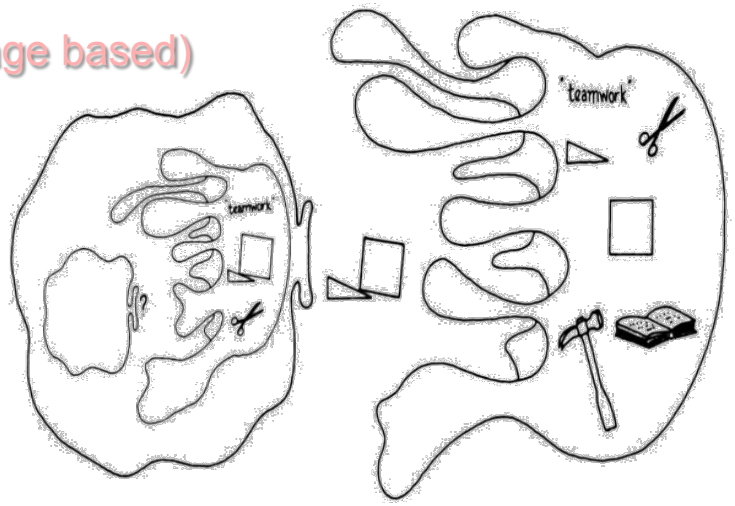

Tower of Generate-and-Test

Knowledge representation (sharing)

Imitation

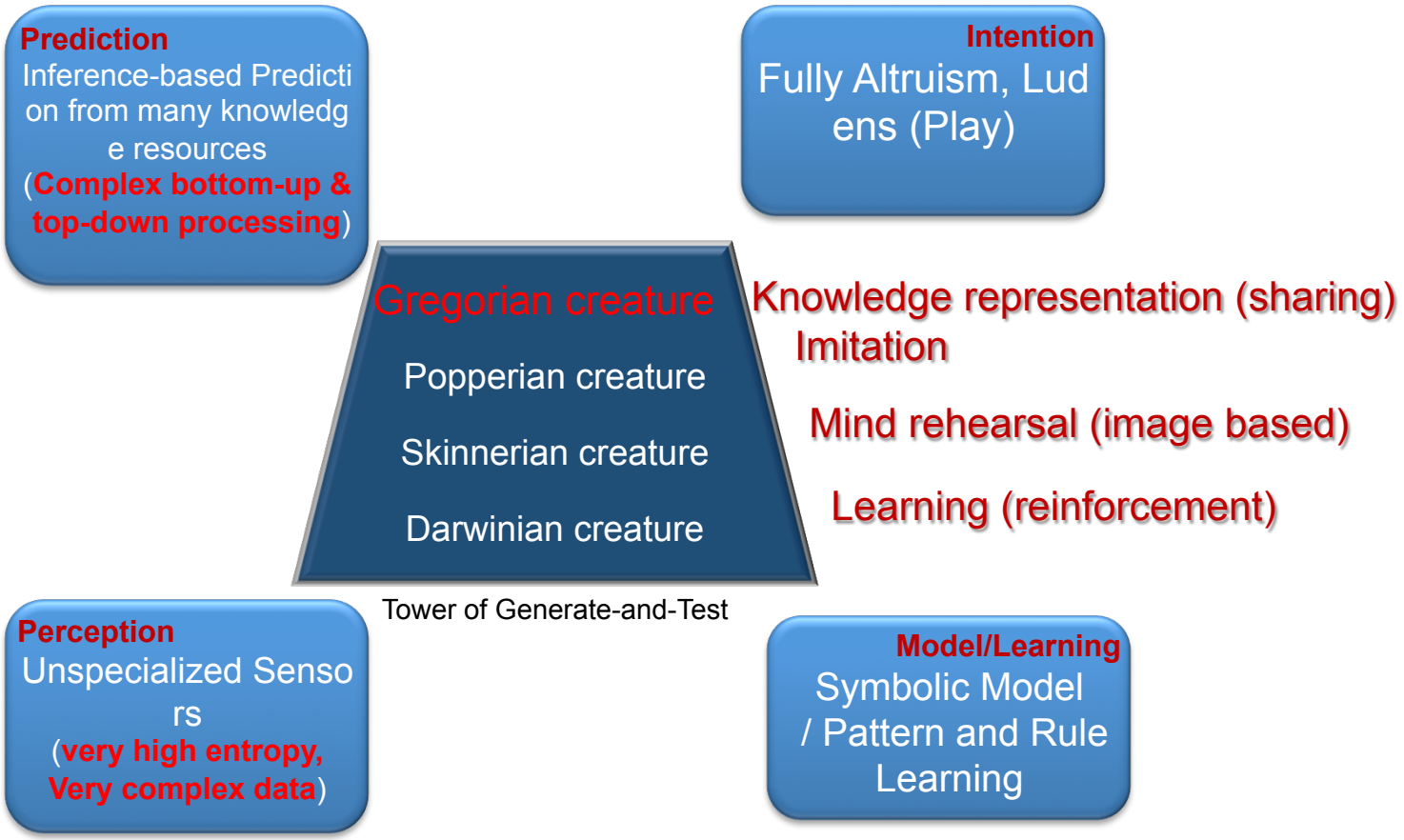
Mind rehearsal (image based)

Learning (reinforcement)

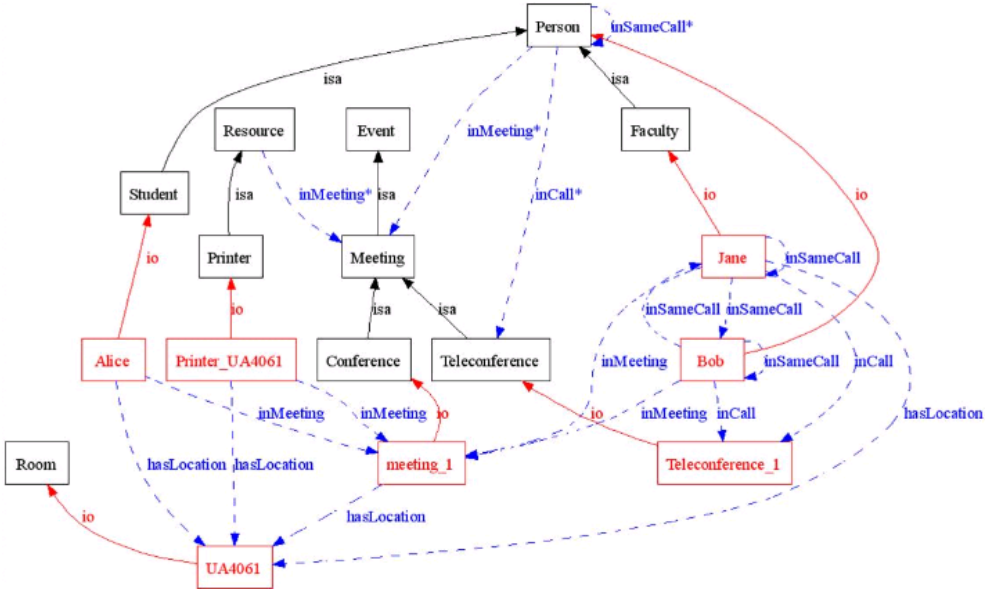


# Gregorian Creature

- Imitation & Symbol-based Prediction



# Gregorian Creature : Semantic Representation

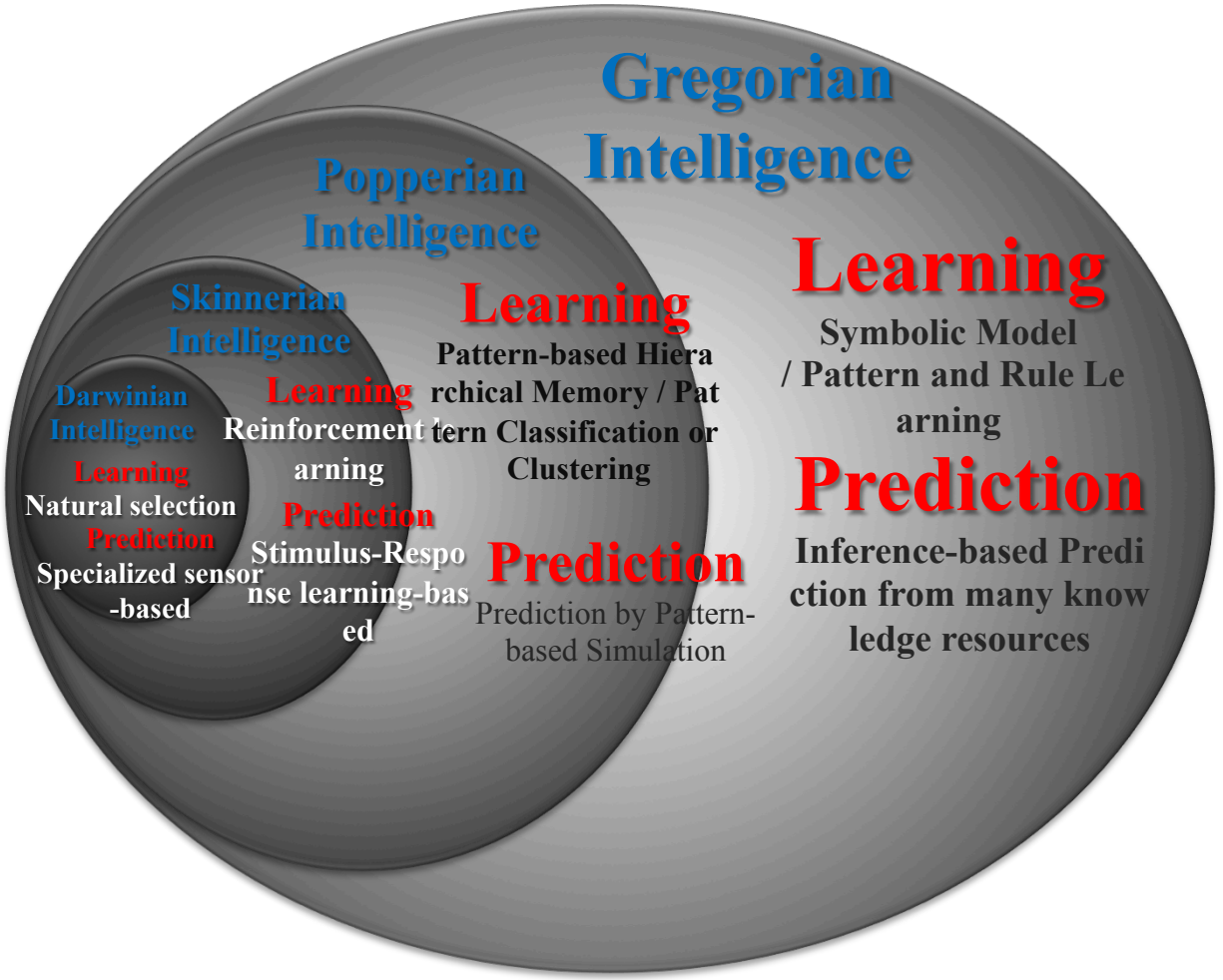

- Important resource for language processing
- Reducing the amount of data to be stored in memory
- Strongly invariant to scene variations
- Logical inference using relations between concepts

• • •

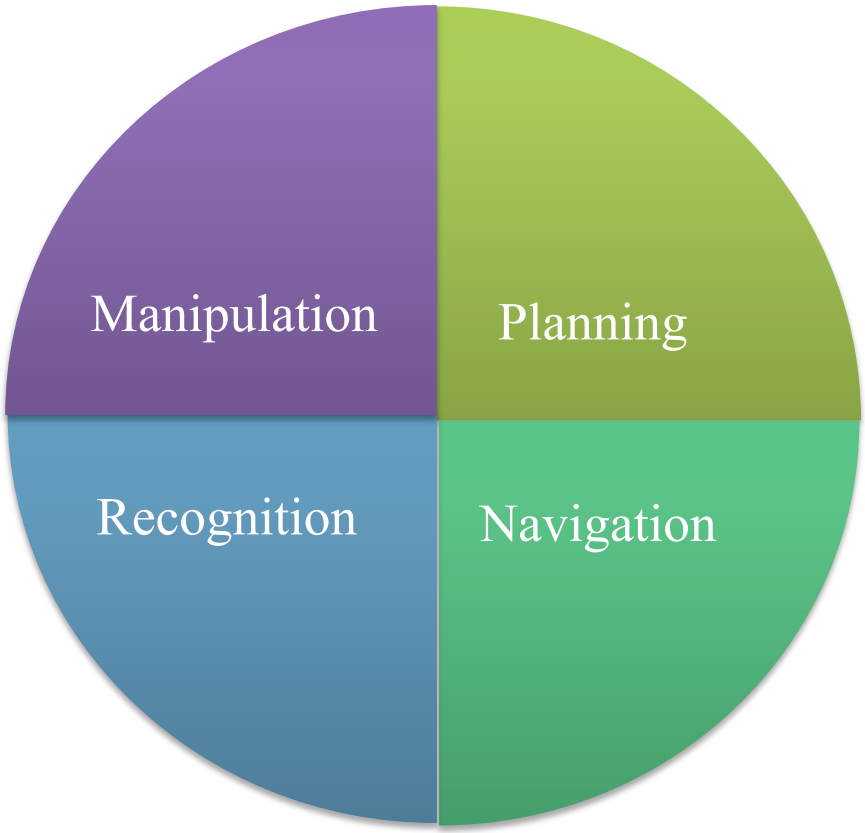
# Characteristics of Four Kinds of Mind (Intelligence)

| Level | Darwinian Level | Skinnerian Level | Popperian Level | Gregorian Level |
|---|---|---|---|---|
| Perception | 1 or 2 High performance Specialized Sensors **very simple data, very low entropy** | Some High performance Specialized Sensors **simple data, low entropy** | Unspecialized Sensors **complex data, high entropy** | Unspecialized Sensors **very complex data, very high entropy** |
| Prediction | Specialized sensor-based Simple Prediction | Stimulus-Response learning-based Prediction | Prediction by Pattern-based Simulation | Inference-based Prediction from many knowledge resources |
| Model / Learning | Fixed & tightly coupled Sensory-motor Coordination / Natural selection | Plastic & loosely coupled Sensory-motor Coordination / Reinforcement Learning | Pattern-based Hierarchical Memory / Pattern Classification or Clustering | Symbolic Model / Pattern and Rule Learning |

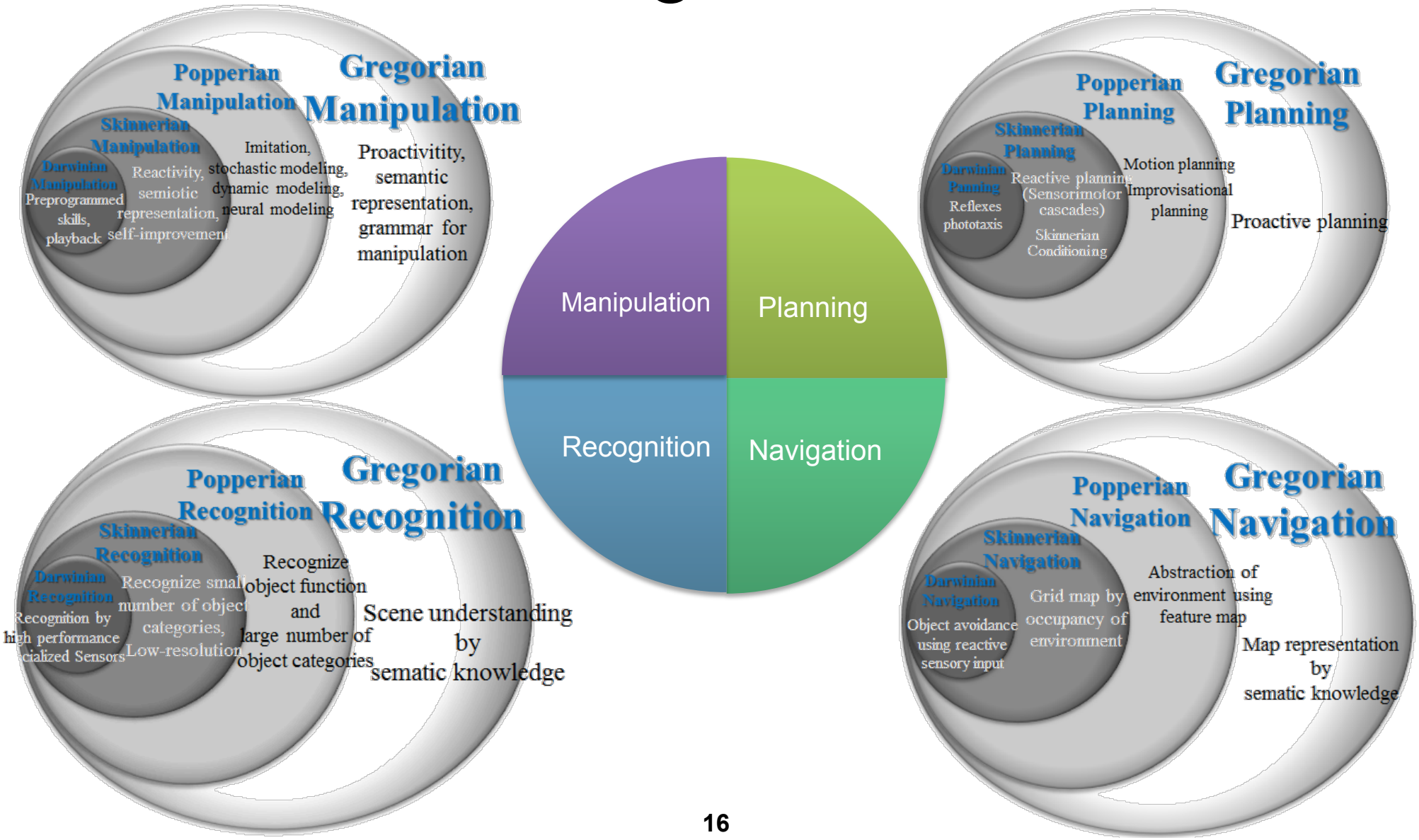
# Subsumption of Four Kinds of Mind (Intelligence)



# Fundamental Mind Functions



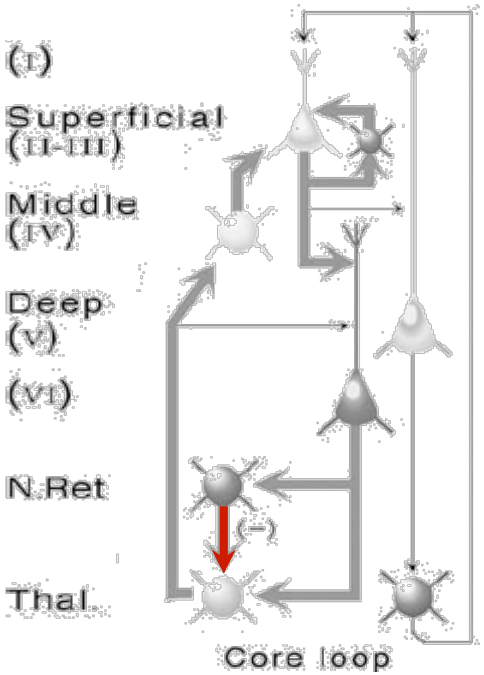
# Can We Develop Mind Functions in the Brain of Gregorian Creature?

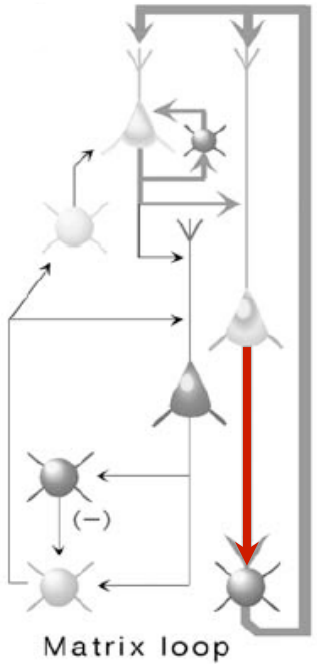


# Three Fundamental Information Processes in Human Brain

**Red : feedback**
**Green :feed-forward**

Thalamocortical system
(Learning is processed by **feedback**)



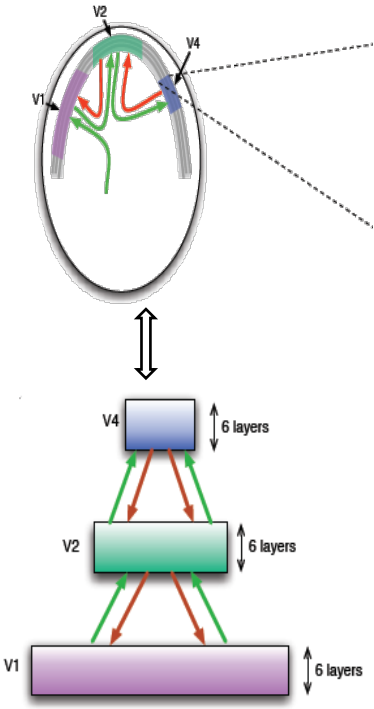



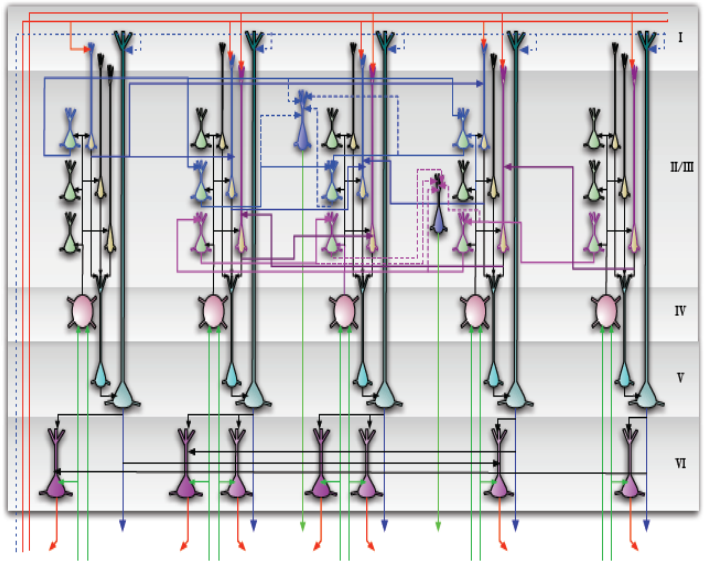

**Category learning**

**Sequential learning**

**Language, grammar learning !**

Prediction is processed by **top-down** infor mation



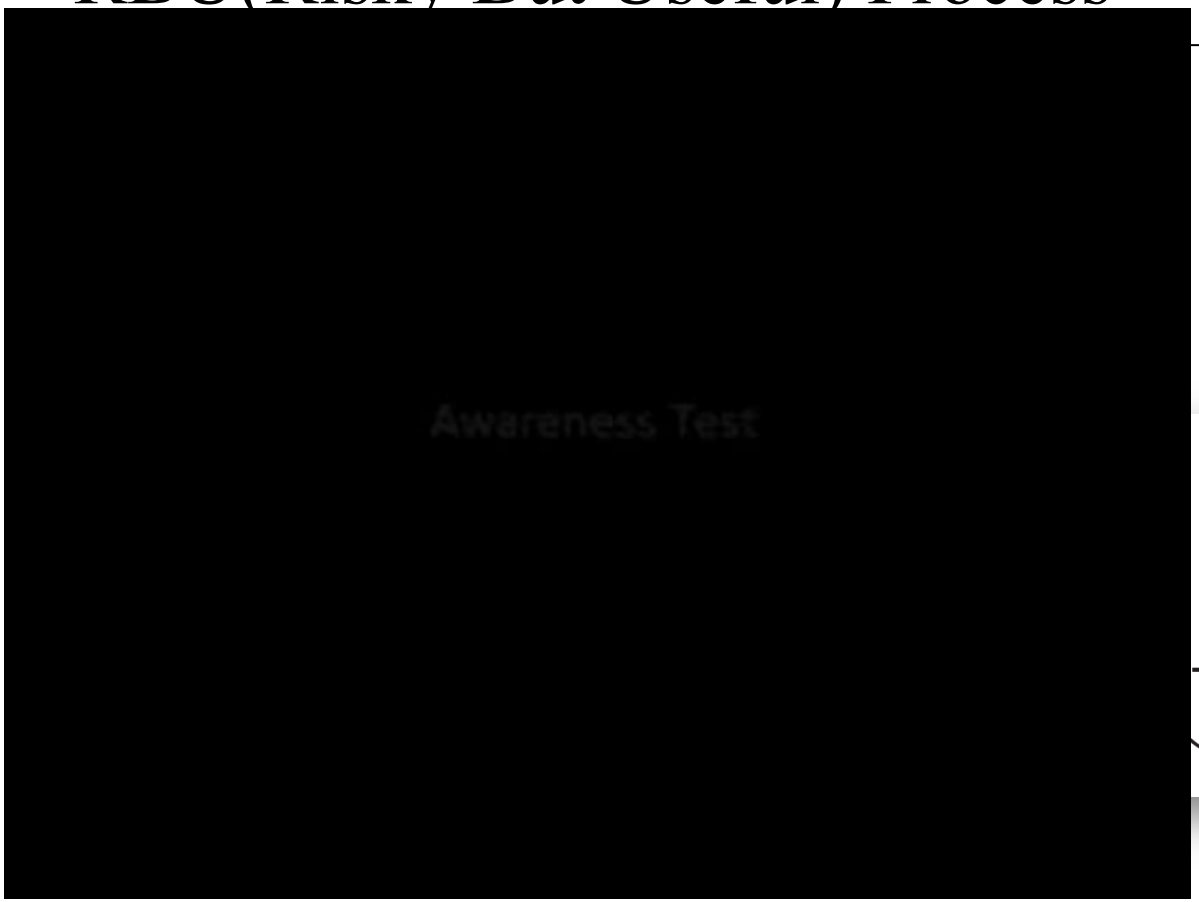



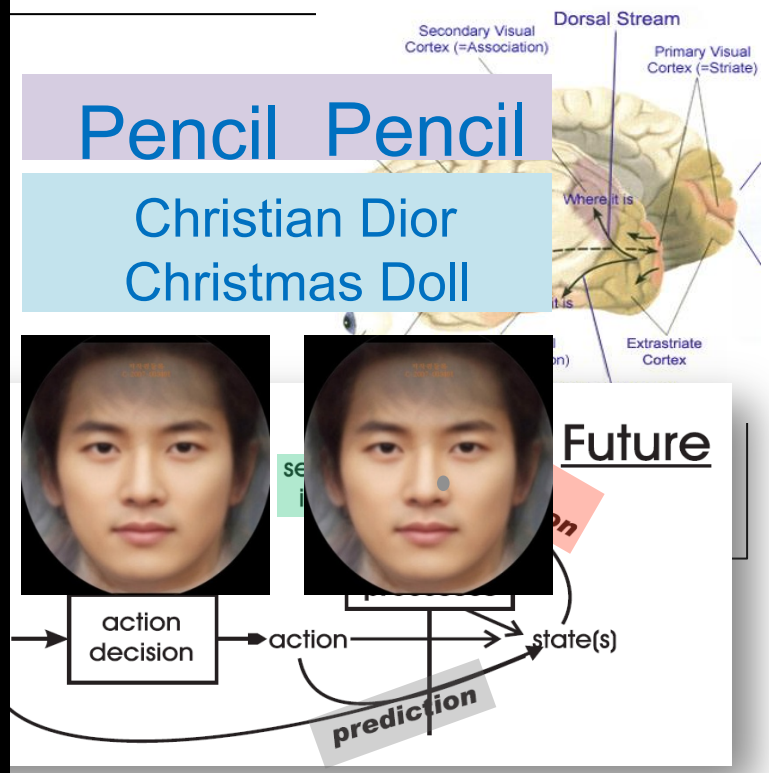

Granger R, Engines of the Brain: The computational instruction set of human cognition, AI Magazine (2006)

D. George amd J. Hawkins, Towards a mathematical theory of cortic al micro-circuits, PLoS Computational Biology, 2009.

# What Is Key Property in Information Processes of Gregorian Brain

## RBU(Risky But Useful) Process




(M. Butz et al. 2003.)

INCORL
Intelligence and Control for Robots Laboratory

# RESEARCHES ON FOUR MIND FUNCTIONS IN INCORL

## Planning

- Reactive planning
- Improvisational planning
- Proactive planning

## Navigation

- Semantic SLAM and navigation
- L-SLAM

## Recognition

- Oriented edge-selective band-pass filtering

## Manipulation

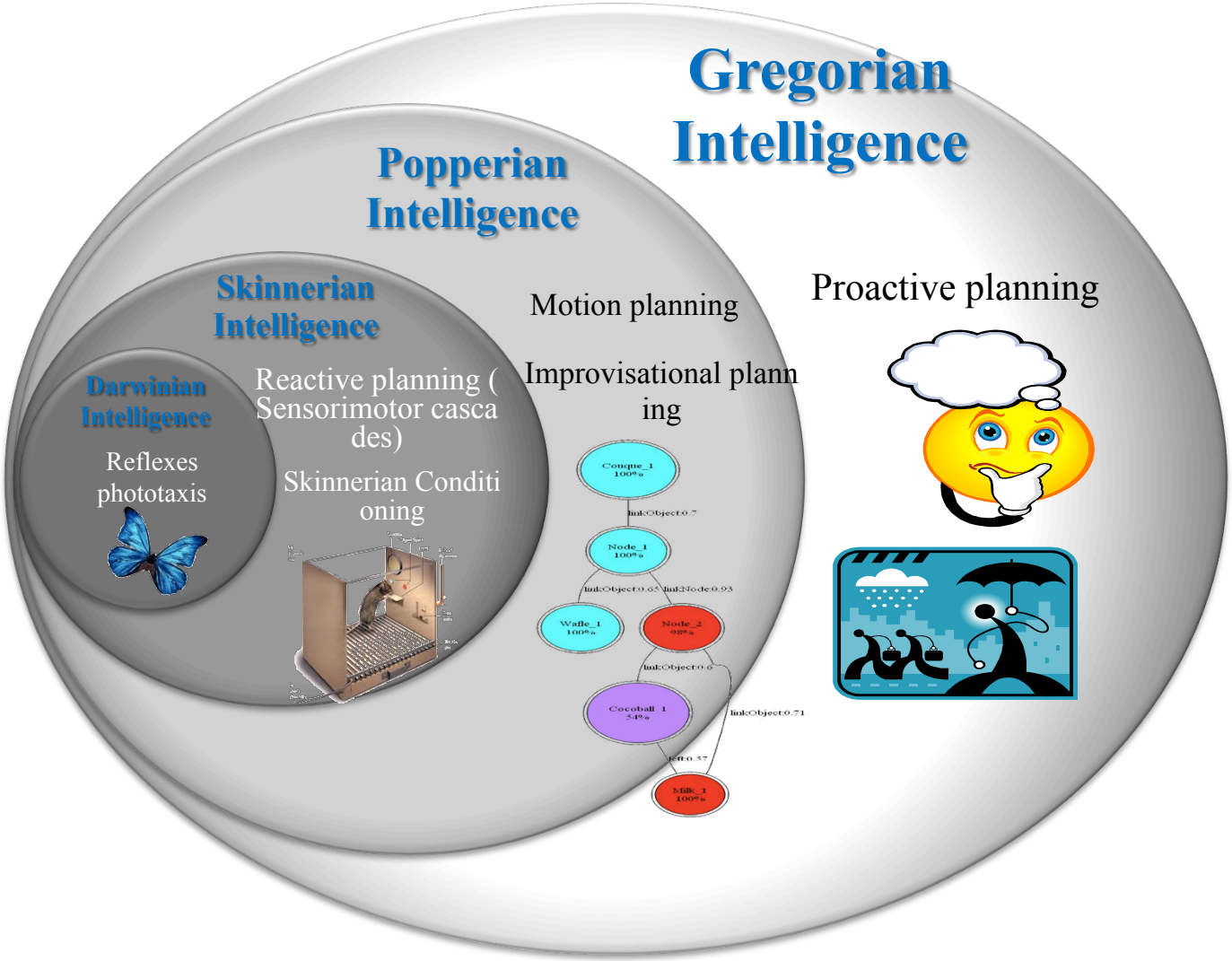
- Skill Learning

# List of Contributors

- Post Doctor
  - Sang Hoon Lee
    - Recognition
  - Gi Hyun Lim
    - Planning
- PhD Student
  - Guoxuan Zhang, Jin Han Lee, Dong Wook Ko
    - Navigation
  - Woo Young Kwon, Sang Hyoung Lee
    - Manipulation
  - Young Bin Park, Gwang Geun Ryu, Deok Hyeon Cho, Se Hyung Lee
    - Recognition
  - Seung Woo Hong
    - Planning

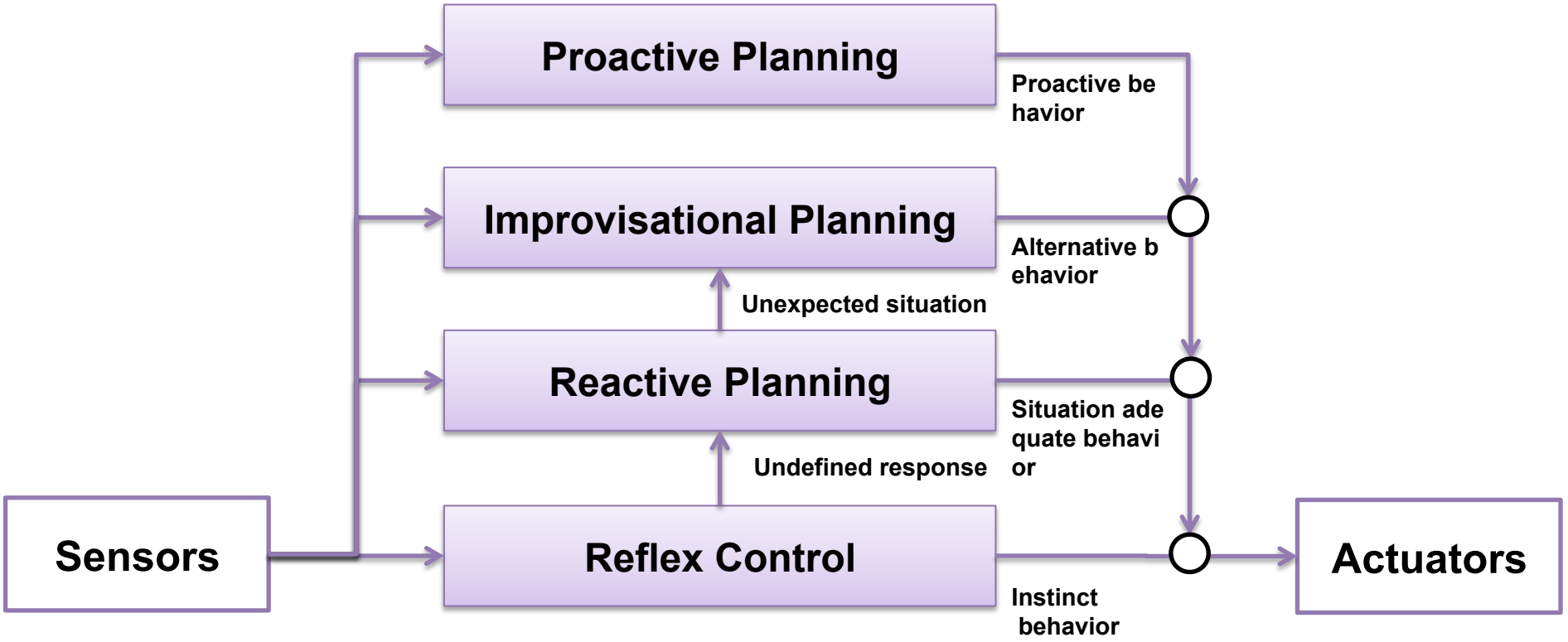
# PLANNING

# Four Kinds of Planning



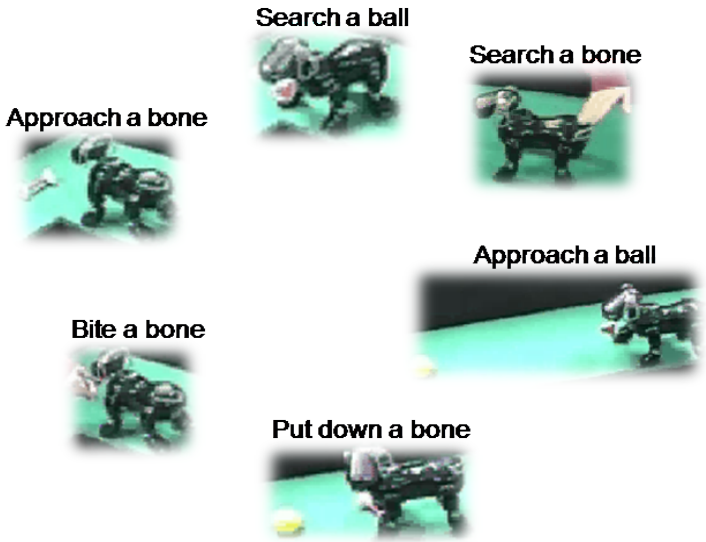
# Future plan

- Integrated framework for Gregorian-level planning including



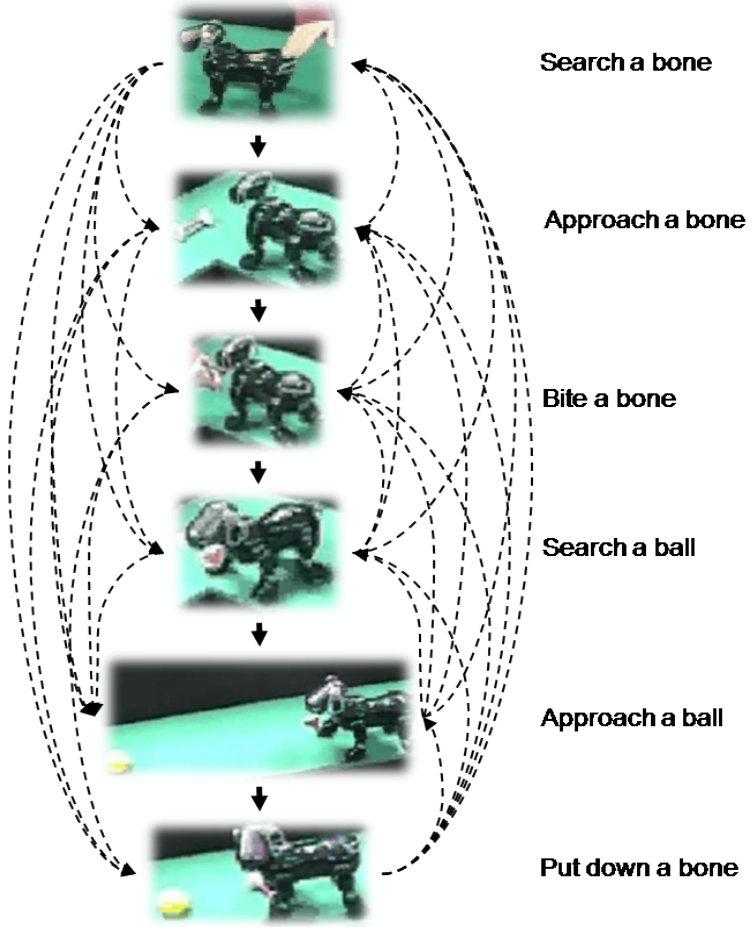
# REACTIVE PLANNING

# Reactive Control vs. Goal-Oriented Control Based on Reactive Planning



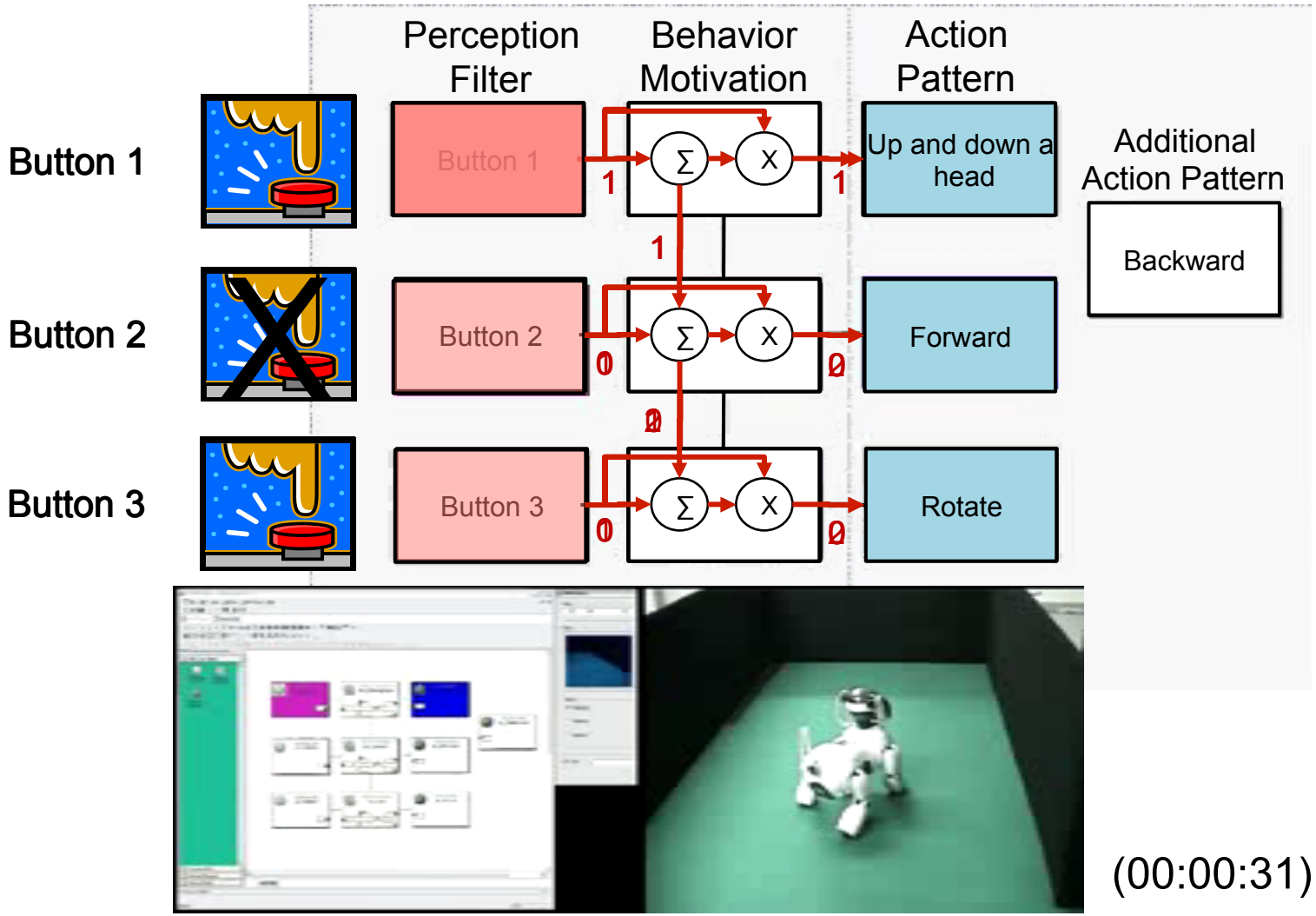

Reactive but not goal-oriented

Every possible state sequence of a task
(fully connected finite state machine)




Goal-oriented as well as Reactive

# An Example of Reactive Planning



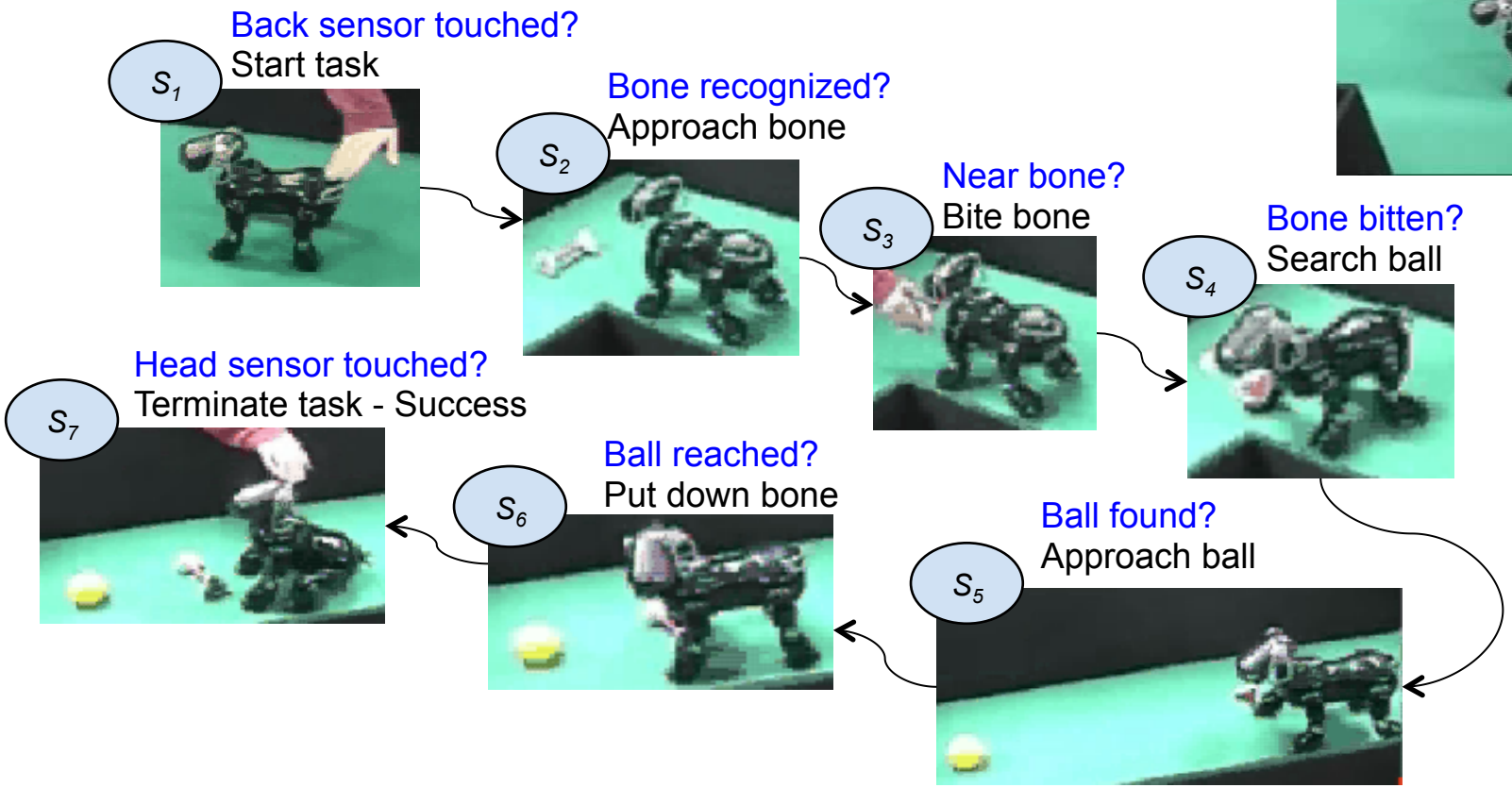

(00:00:31)

[References]
I. H. Suh, S. Lee, W. Y. Kwon, and Y. -J. Cho, "Learning of Action Patterns and Reactive Behavior Plans via a Novel Two-Layered Ethology-Based Action Selection Mechanism," 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp.1232-1238, August 2-6, 2005, Edmonton, Canada

# Reactive Plan Scenario

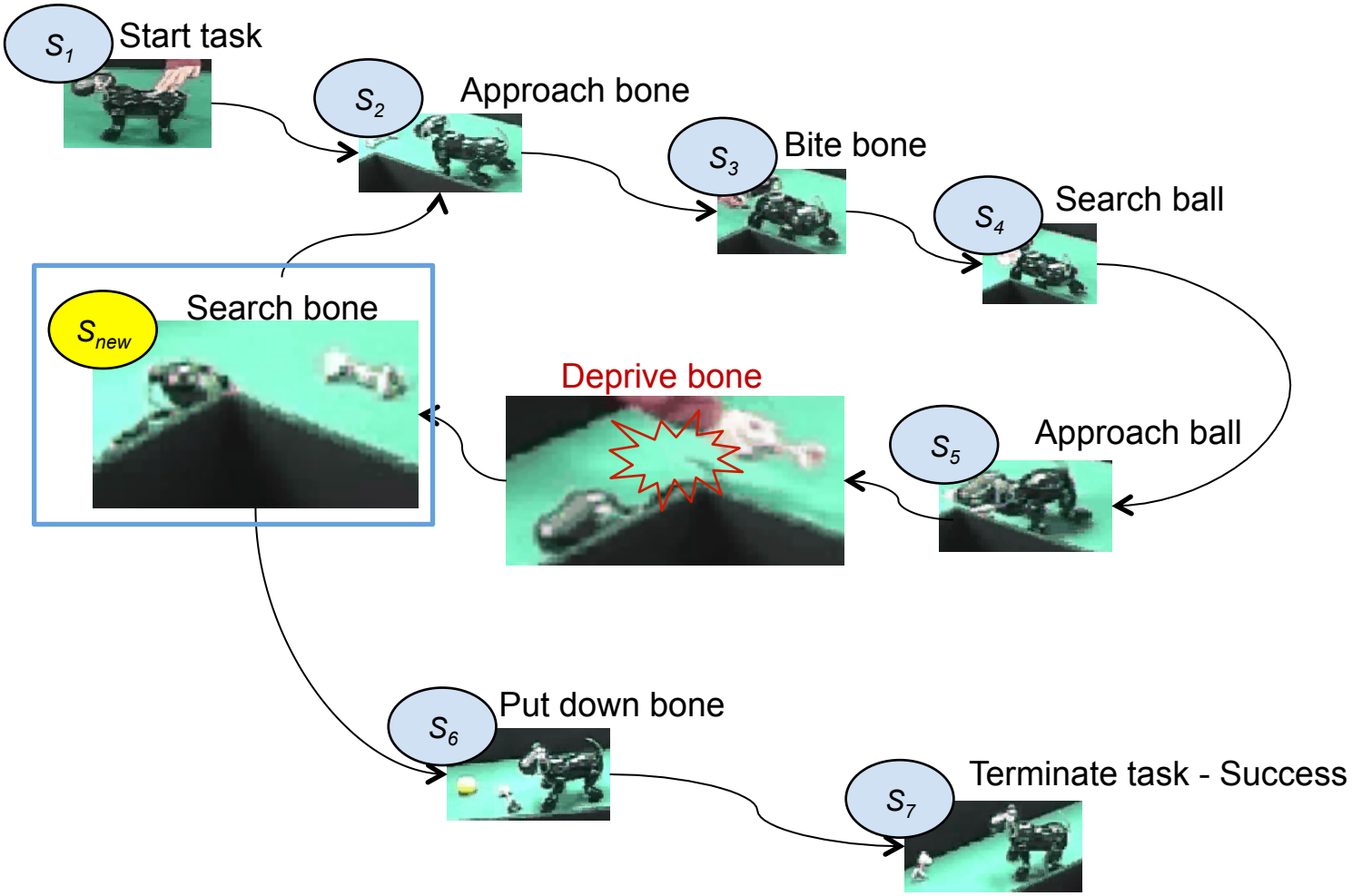
- Task: Bite a bone and put down the bone in front of the ball (Here, the ball is a food storage space)

(X2, 00:00:28)

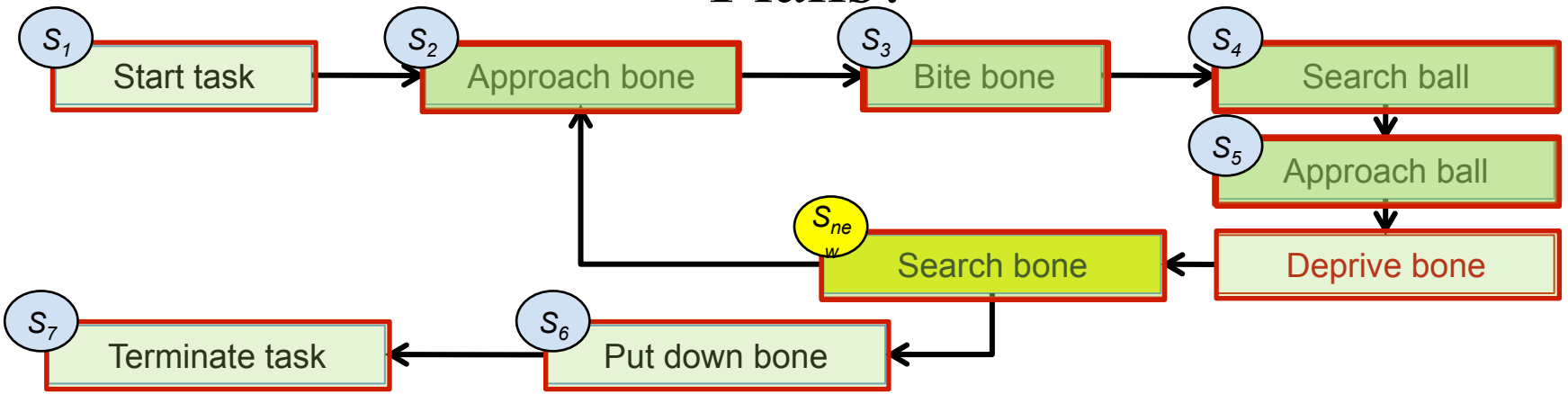


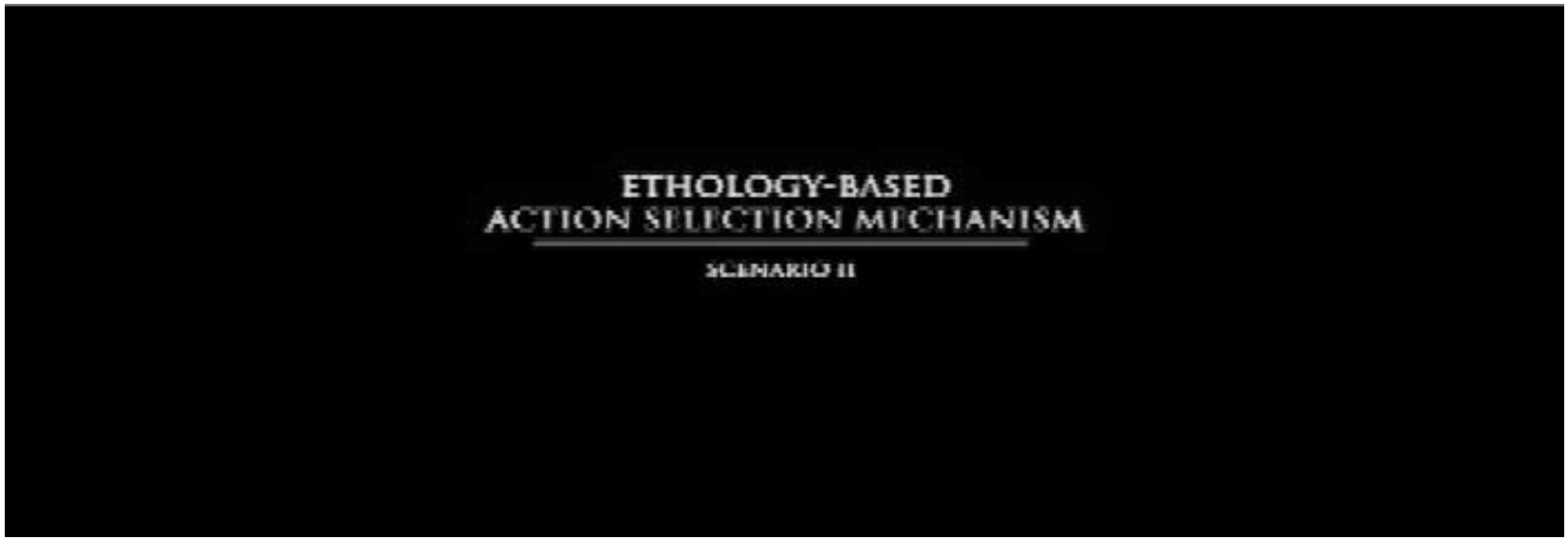
# How the AIBO Reactively Can Use Embodied Plans?

When the AIBO loses the bone by human disturbance…



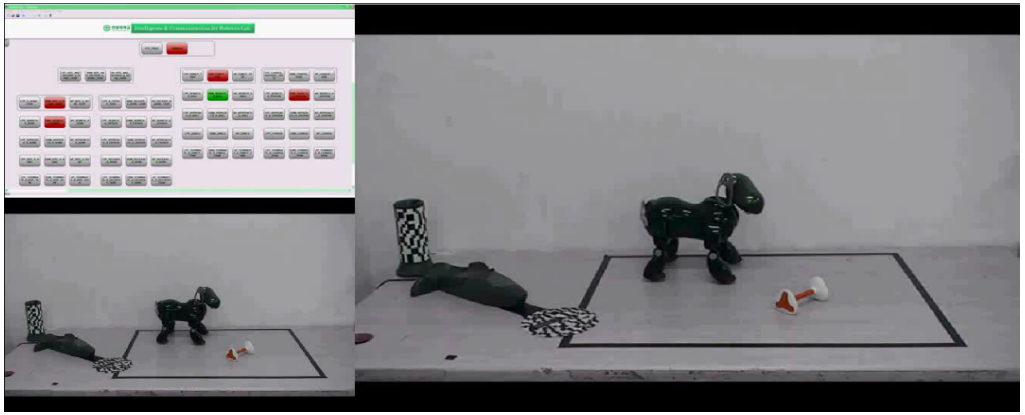
# Video Clip: How the AIBO Reactively Can Use Embodied Plans?

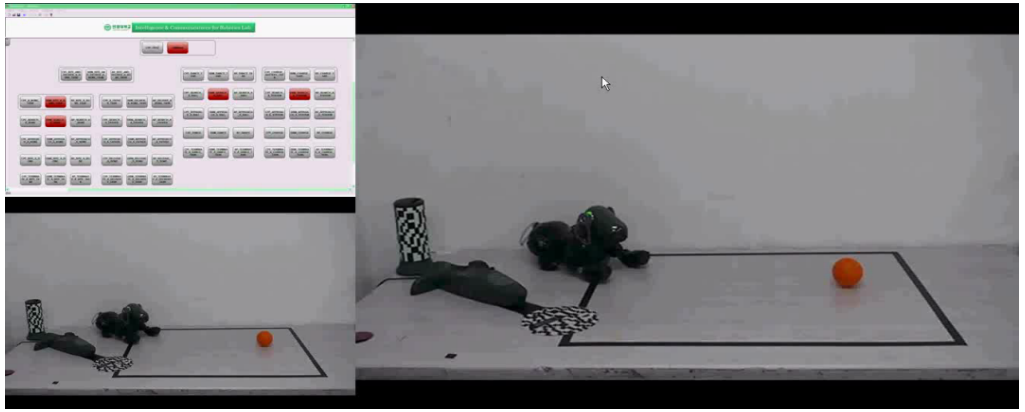


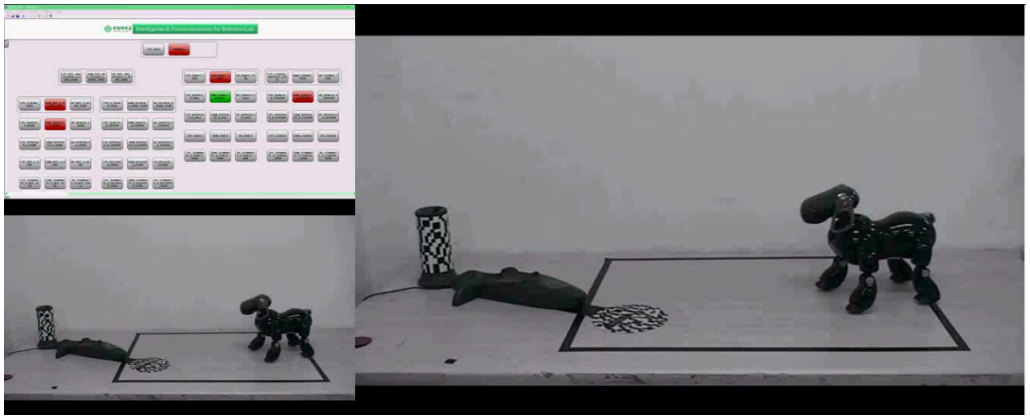




(X4, 00:00:45)

# Reactive Planning anda Action Selection



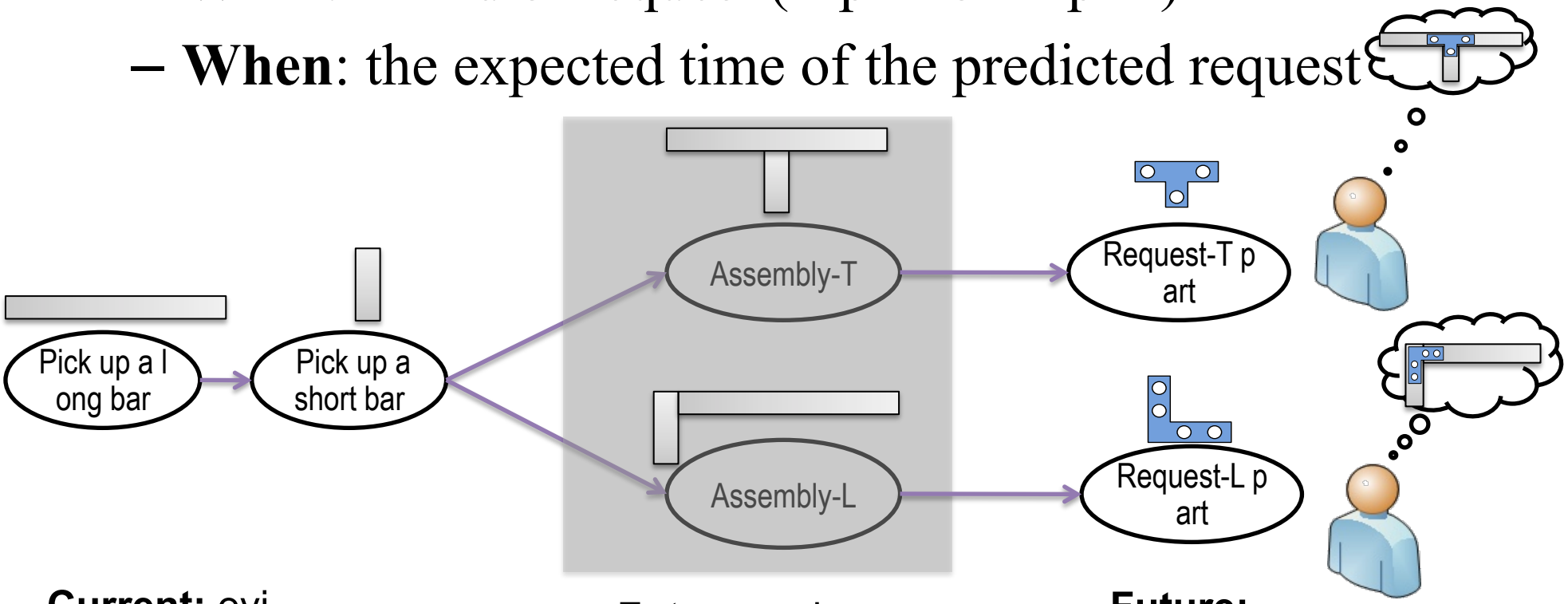




# PROACTIVE PLANNING

# Proactive Assistant Robot Using Temporal Prediction of Future Events

- Two kinds of predictions
  - **What**: a kind of request (T-part or L-part)
  - **When**: the expected time of the predicted request

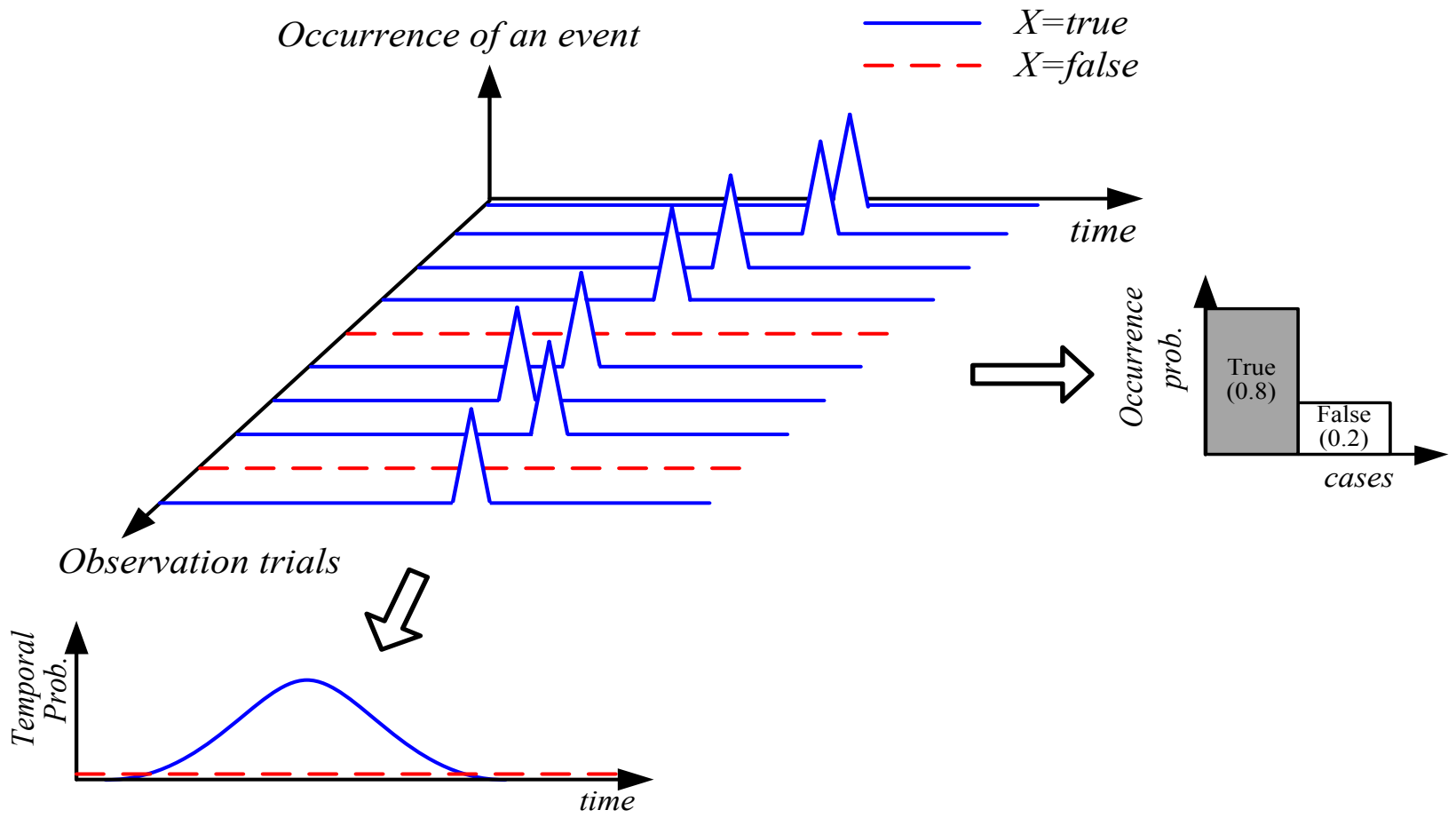



**Current:** evi dences

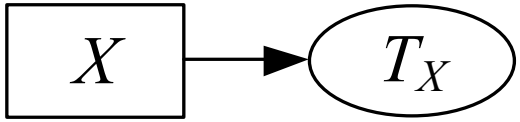
**Future:** unk nown

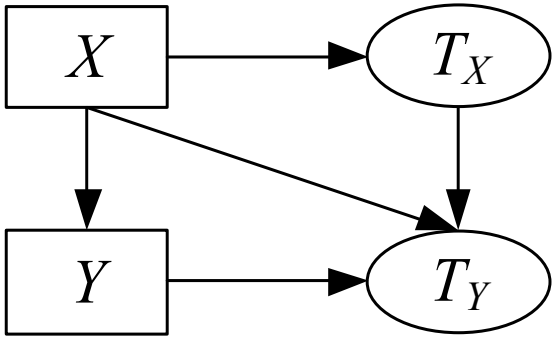
**Future:** query(kinds of part and t he time)

# Separation of Uncertainty and the Time of the Same Event



# Hybrid Bayesian Network Representation of Temporal Event




(a) An hybrid Bayesian network representation of a temporal event, **X**

(b) An hybrid Bayesian network representation of relationship, **X→Y**

$$P\left(X = x_i, t_1 < T_X < t_2\right)$$

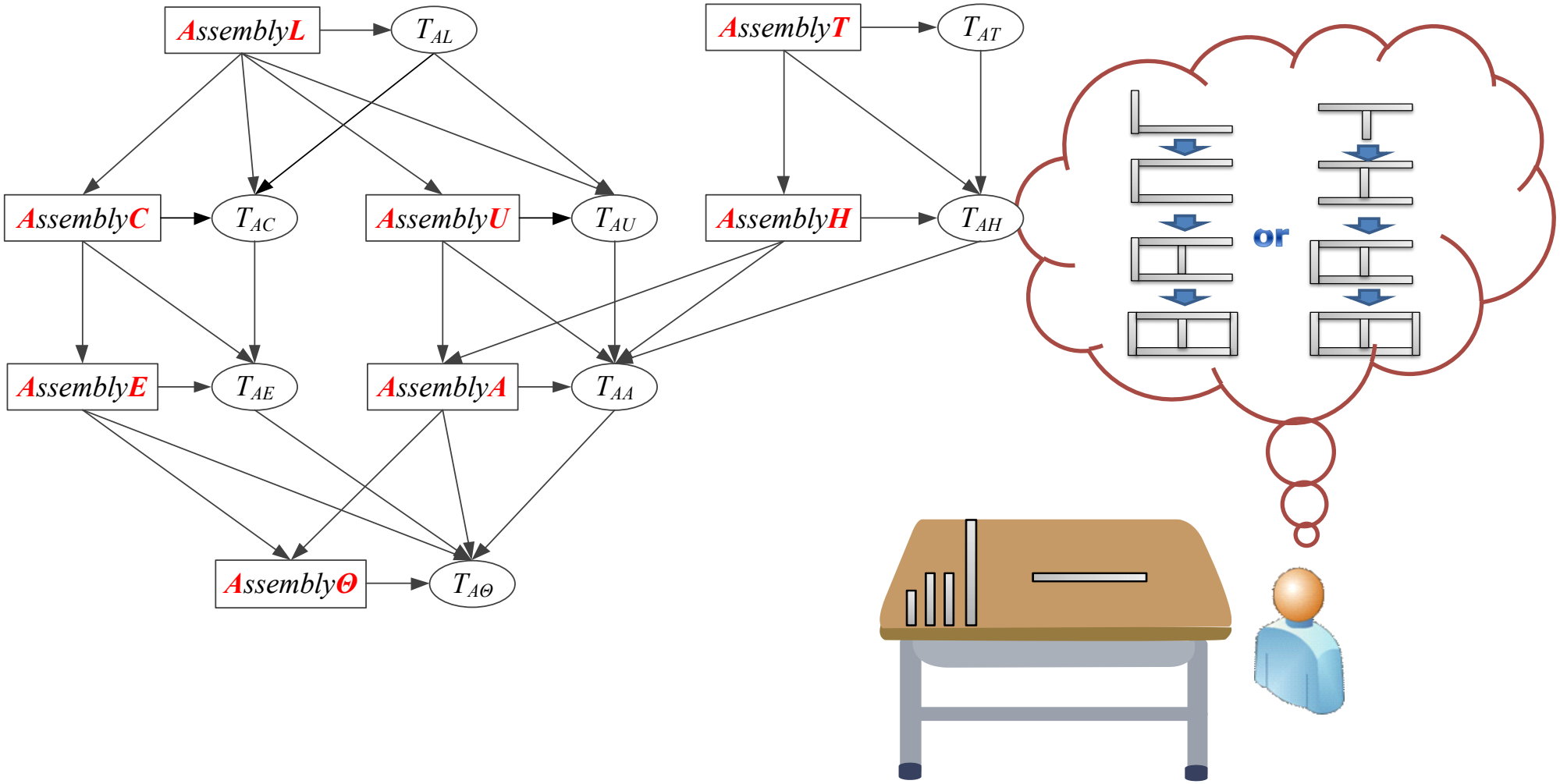
$$= P\left(X = x_i\right) \int_{t_1}^{t_2} f_{X_i}\left(t_X\right) dt_X$$

$$P(Y = y_i, t_1 \le T_Y \le t_2 \mid X = x_j, T_X = t_X)$$

$$= P(Y = y_i \mid X = x_j) \int_{t_1}^{t_2} f_{Z_k}(t_Y - t_X) dt_Y$$

Temporal probability of an event = **causal** x **temporal**

# Temporal Bayesian Network



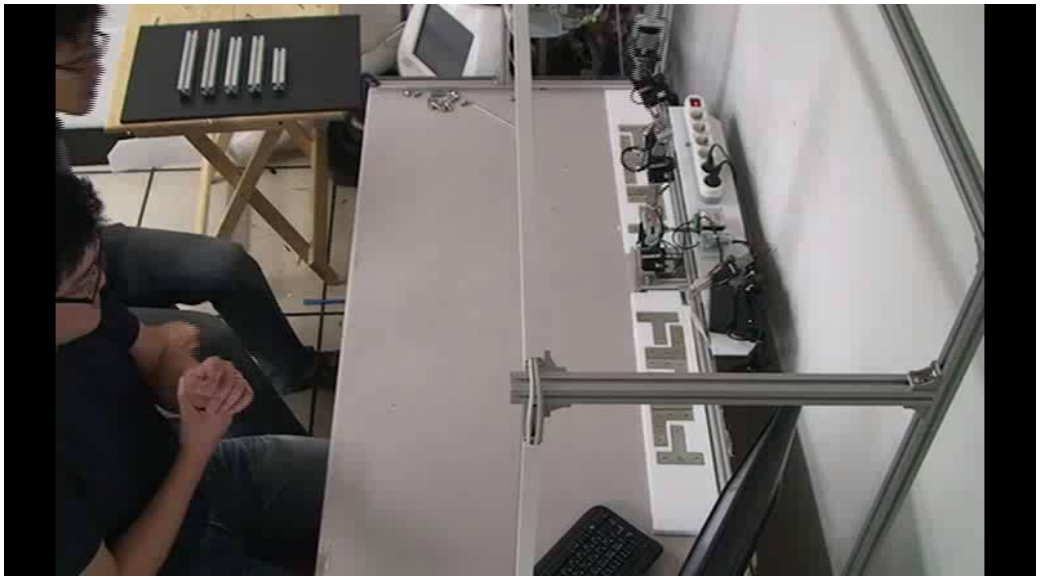

[References]
Woo Young Kwon and Il Hong Suh. 2011. "Towards proactive assistant robots for human assembly tasks", In Proceedings of the 6th in ternational conference on Human-robot interaction. ACM, pp.175-176, New York, NY, USA, 2011.

# Demonstration of A Manufacturing Assistant Robot

**On Demand assistance**
**(training mode)**


6x [01:05]

**Proactive assistance**



6x [00:42]

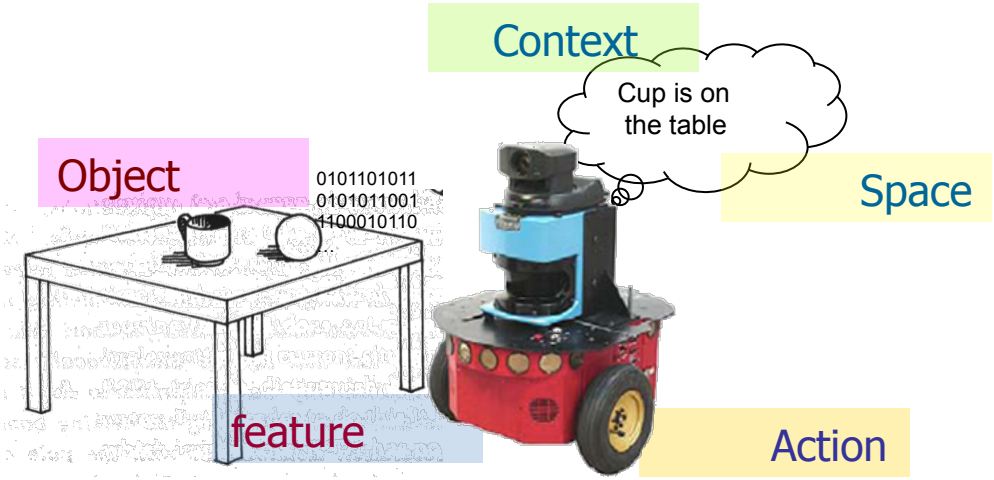
# IMPROVISATIONAL PLANNING

# Issues of Semantic Robot Intelligence

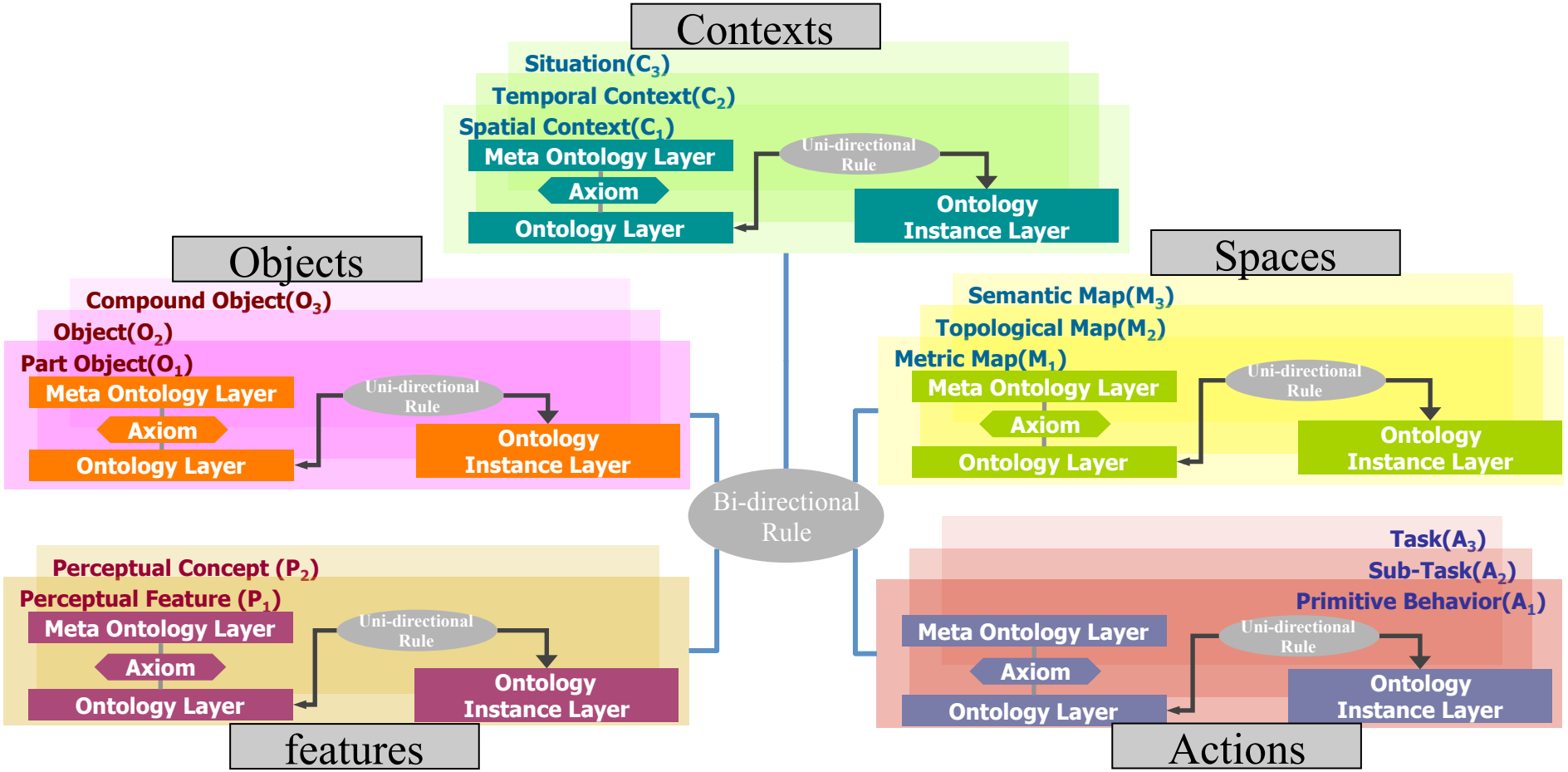
- Unified robot knowledge to integrate low-level data to high-level knowledge to interact with humans
- Robust knowledge instantiation and update with imperfect sensing data such as misidentification of object recognition
- Suggestion of alternative actions even with incomplete knowledge

# Requirements for Robot Knowledge

- Robot has to perceive environments with features, model a world with object and space where it exists, plan and perform some sequence of actions and be aware of contexts
- Each data class includes from low level to high level. Those different level of data representation needs to be connected with each other

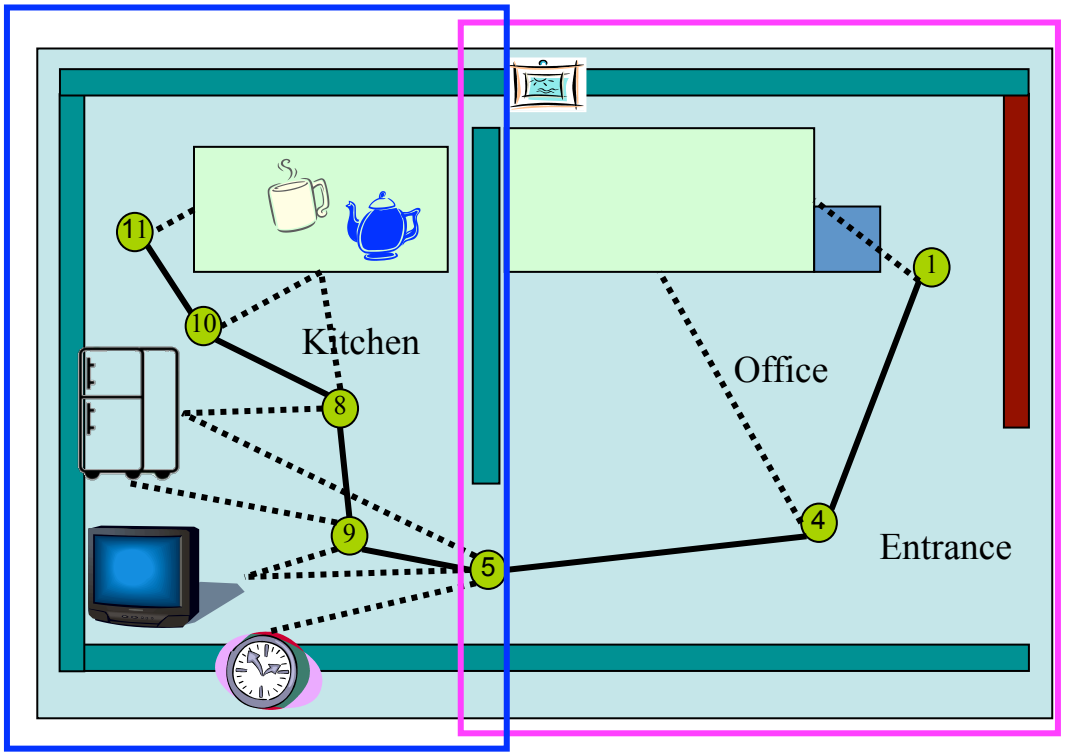


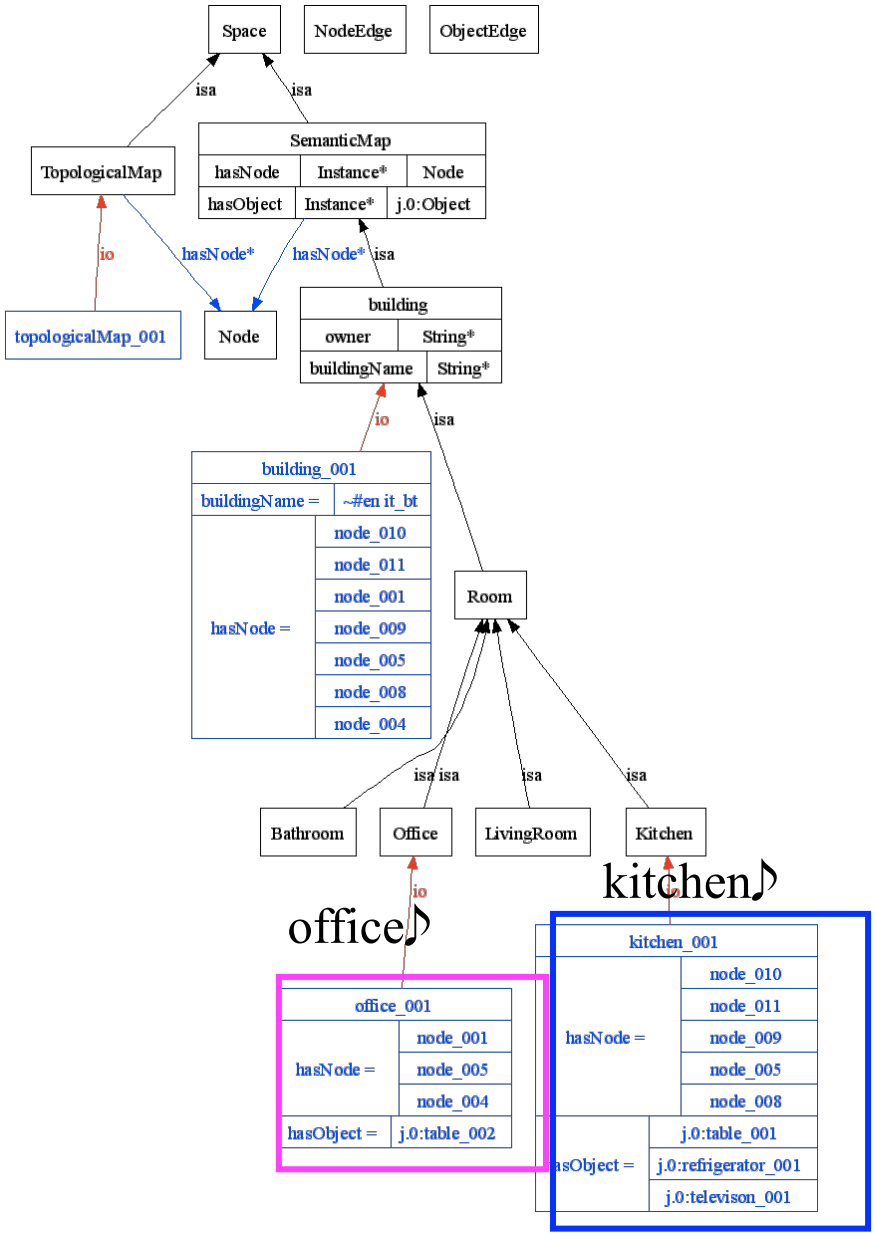
# Robot-centered Ontology



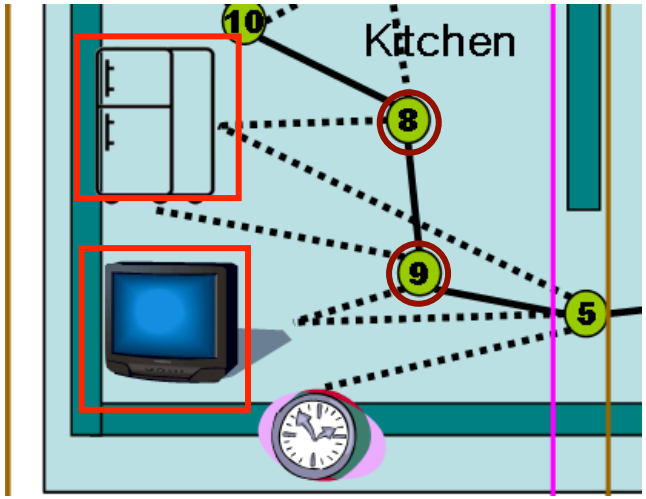

[References]
Gi Hyun Lim, Il Hong Suh, Hyowon Suh, "Ontology-Based Unified Robot Knowledge for Service Robots in Indoor Environments", S ystems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on , vol.41, no.3, pp.492-509, May 2011

# Example of Semantic Map



# Applications of Semantic Map

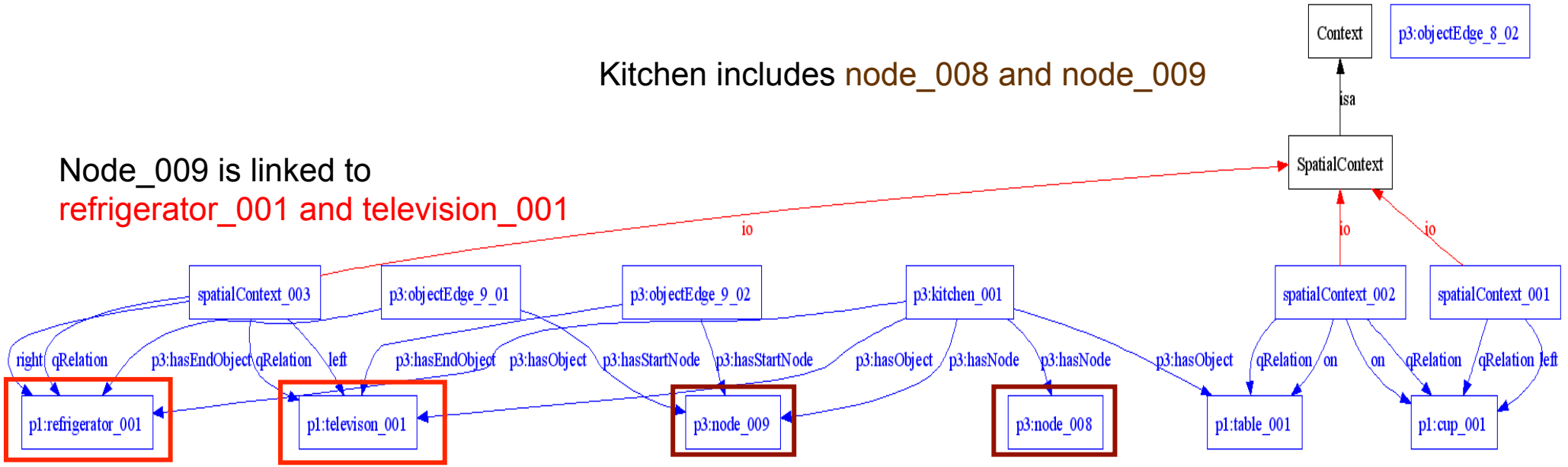



## Is it on the way to kitchen?

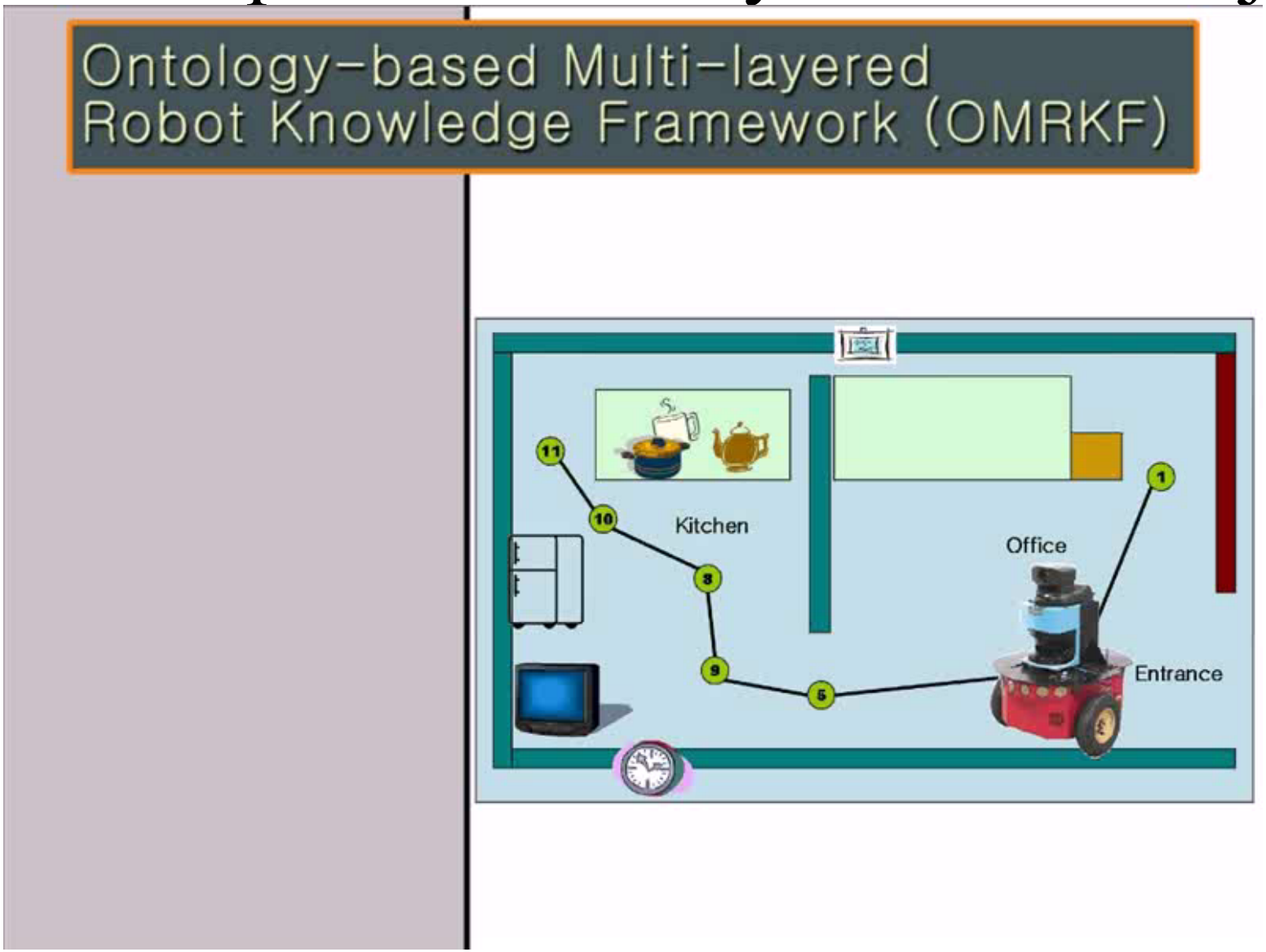
```
If A exists and A is linked to Target_node
   and A is recognized
  then Robot is on the right way to Target_node.
```

Kitchen includes node_008 and node_009

Node_009 is linked to
refrigerator_001 and television_001

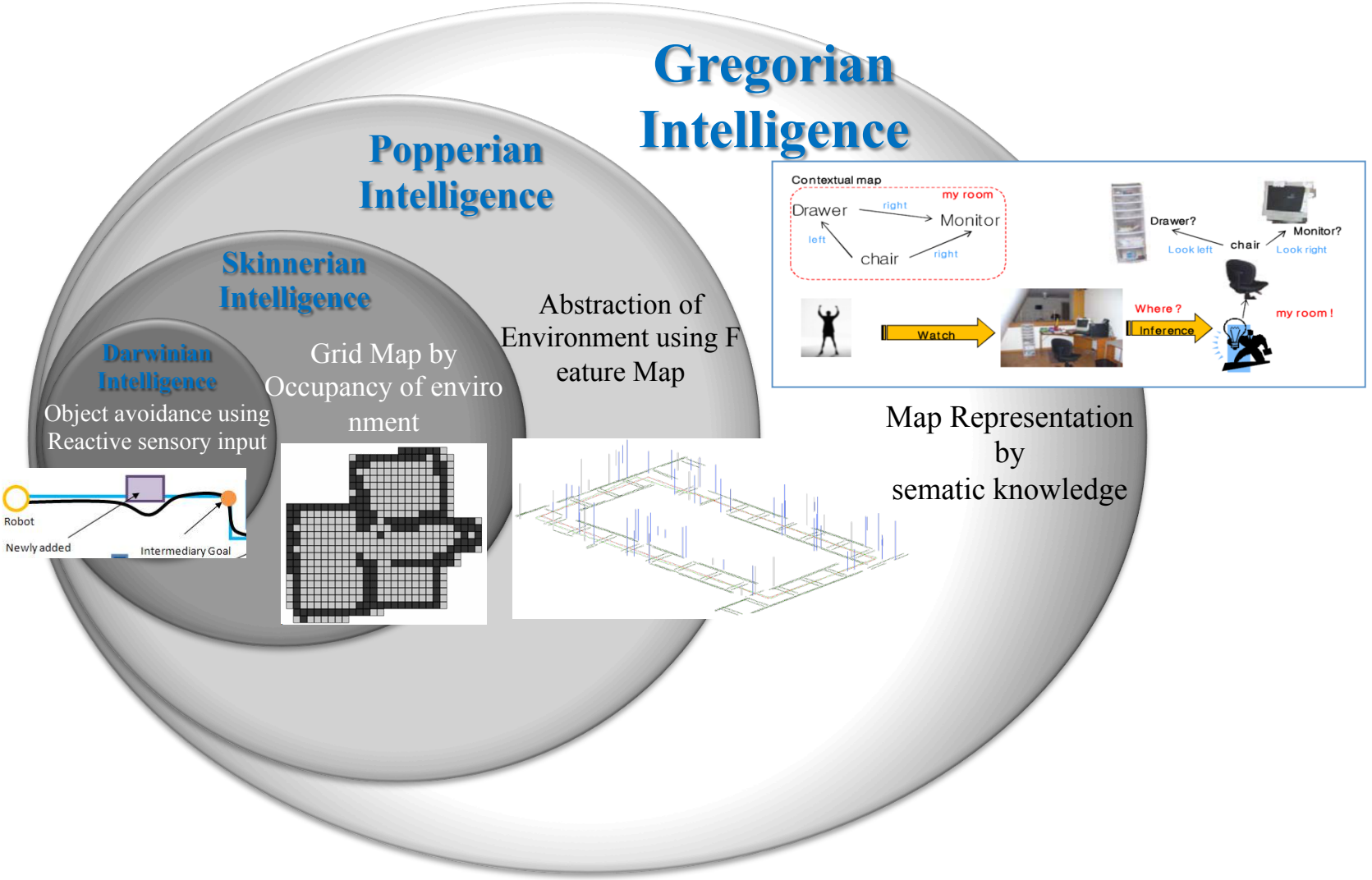


# Video Clip: Find Partially Occluded Object



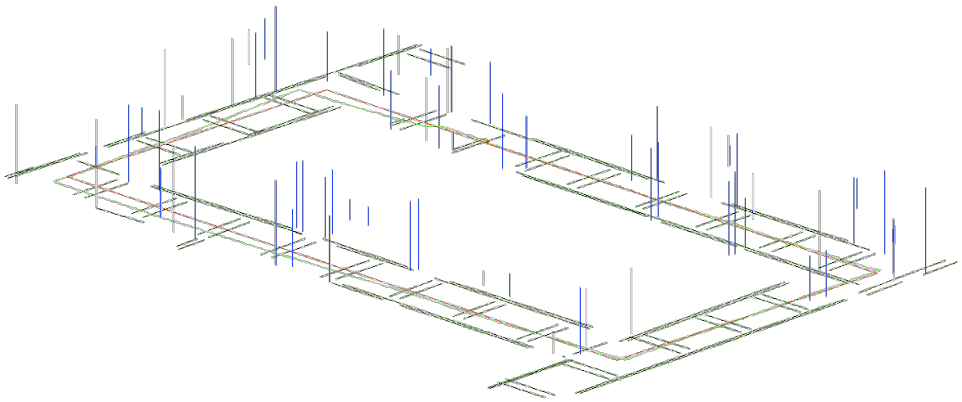
# NAVIGATION

# Four Kinds of Navigation

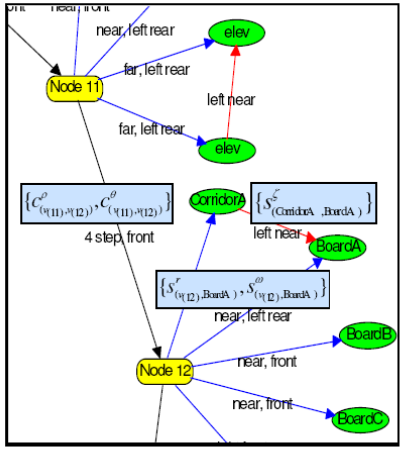


# Navigation

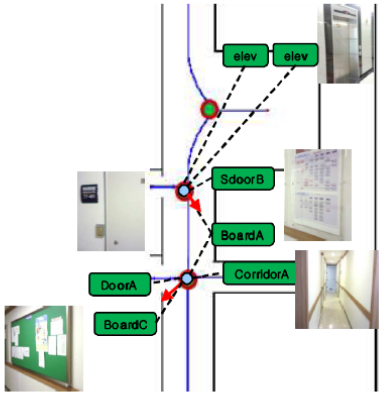
## Line SLAM (L-SLAM)



## Semantic SLAM



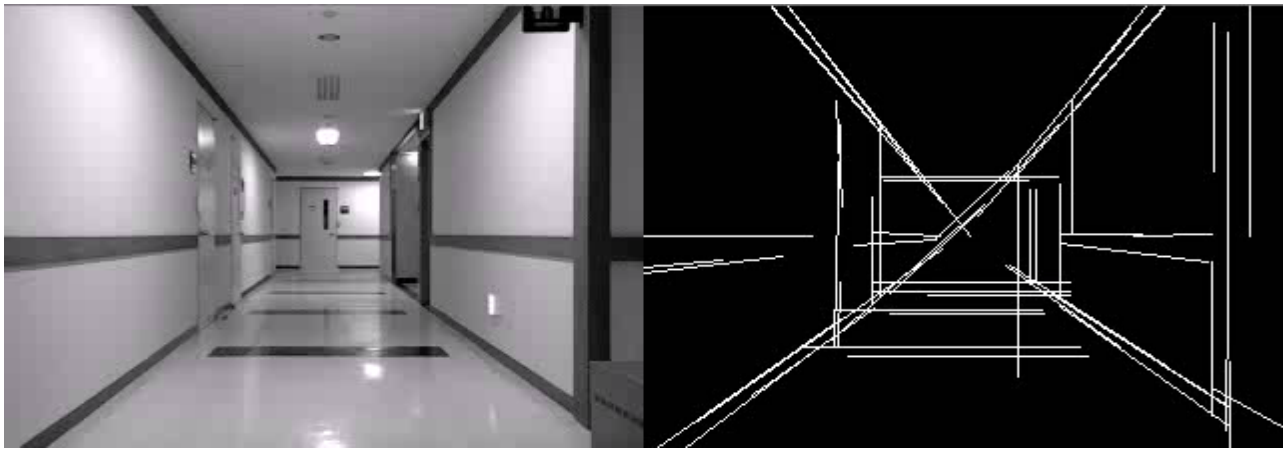

(b)

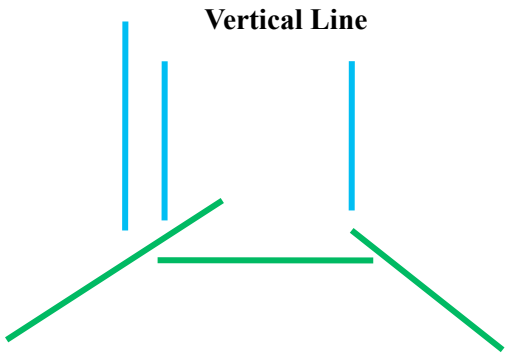


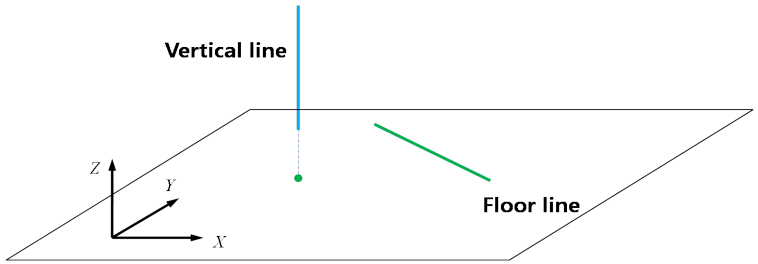

(c)

# L-SLAM

# Line-based Monocular SLAM



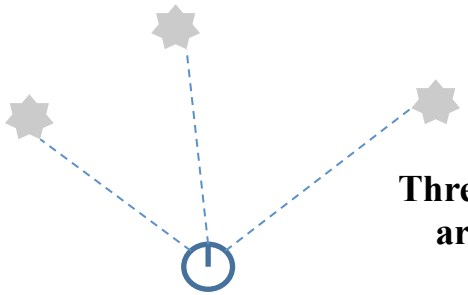


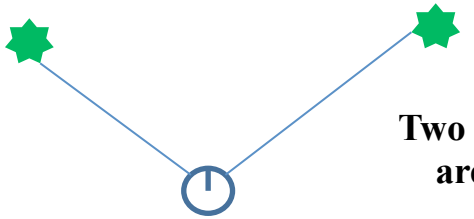

- G. Zhang, I. H. Suh, “SoF-SLAM: Segments-on-Floor-based Monocular SLAM,” in Proc. of The IEEE/RSJ International Conference on Intelligent Robots and Systems, Taiwan, 2010.
- G. Zhang, I. H. Suh, “Building a Partial 3D Line-based Map using a Monocular SLAM,” in Proc. of The IEEE International Conference on Robotic s and Automation, Shanghai, China, 2011.

# Sensor RBU Revision

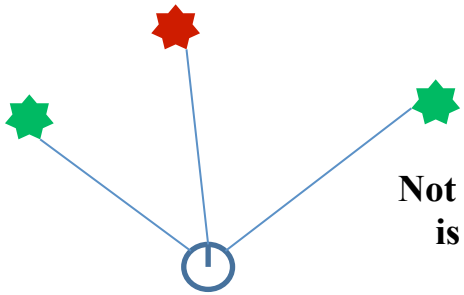
- RBU: Risky But Useful



**Three landmarks are in map.**



**Two landmarks (green) are observed.**

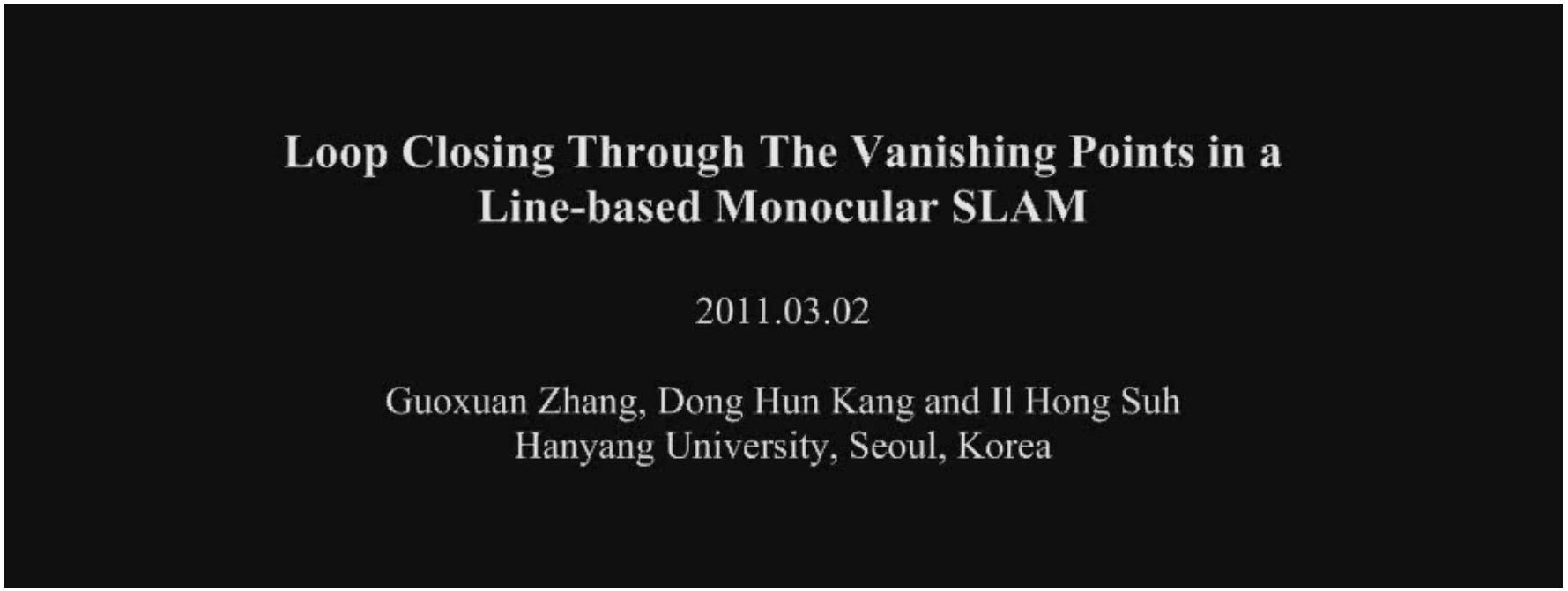


**Not observed (red) landmark is generated.**

**: Detected Vertical Line**

**: Generated Vertical Line**

# Demo Video Clip



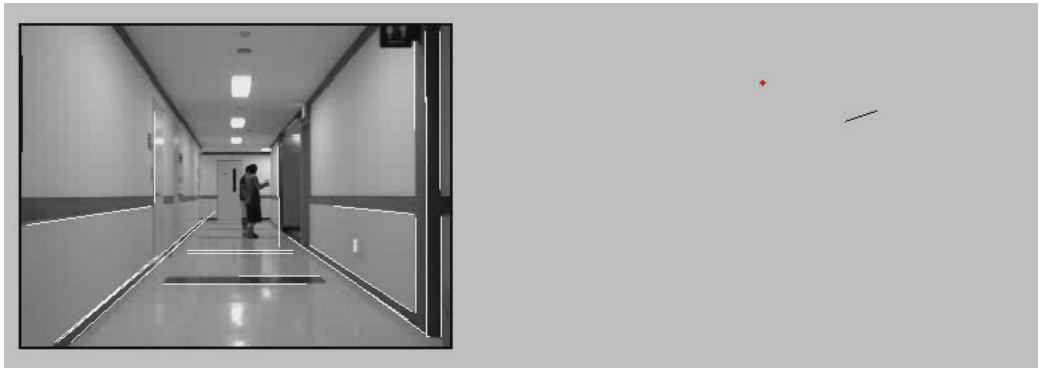

[ 00:01:09 ]

- G. Zhang, D. H. Kang, and I. H. Suh, “Loop Closure Through Vanishing Points in a Line-based Monocular SLAM,” Accepted for The IEEE Inter national Conference on Robotics and Automation, 2012.

**Real-Time Demo**

[ 00:00:44 ]

# Additional Experiments

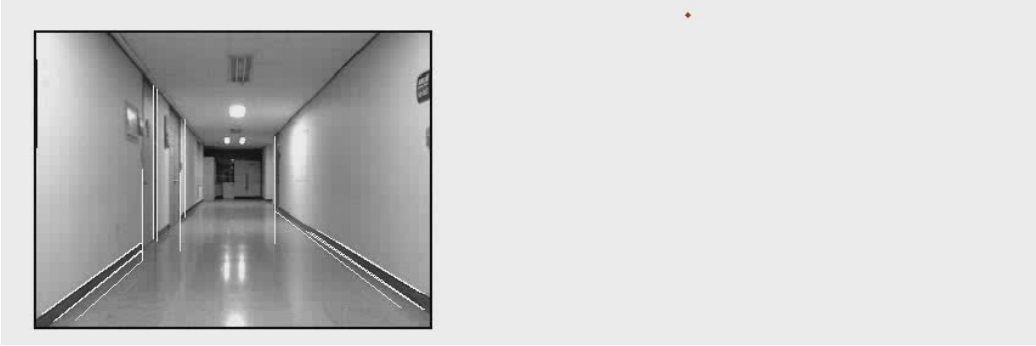


With Human Disturbance

[ 00:02:06 ]

Triangular Building

[ 00:01:09 ]



Without Perpendicular Floor Line

[ 00:00:47 ]

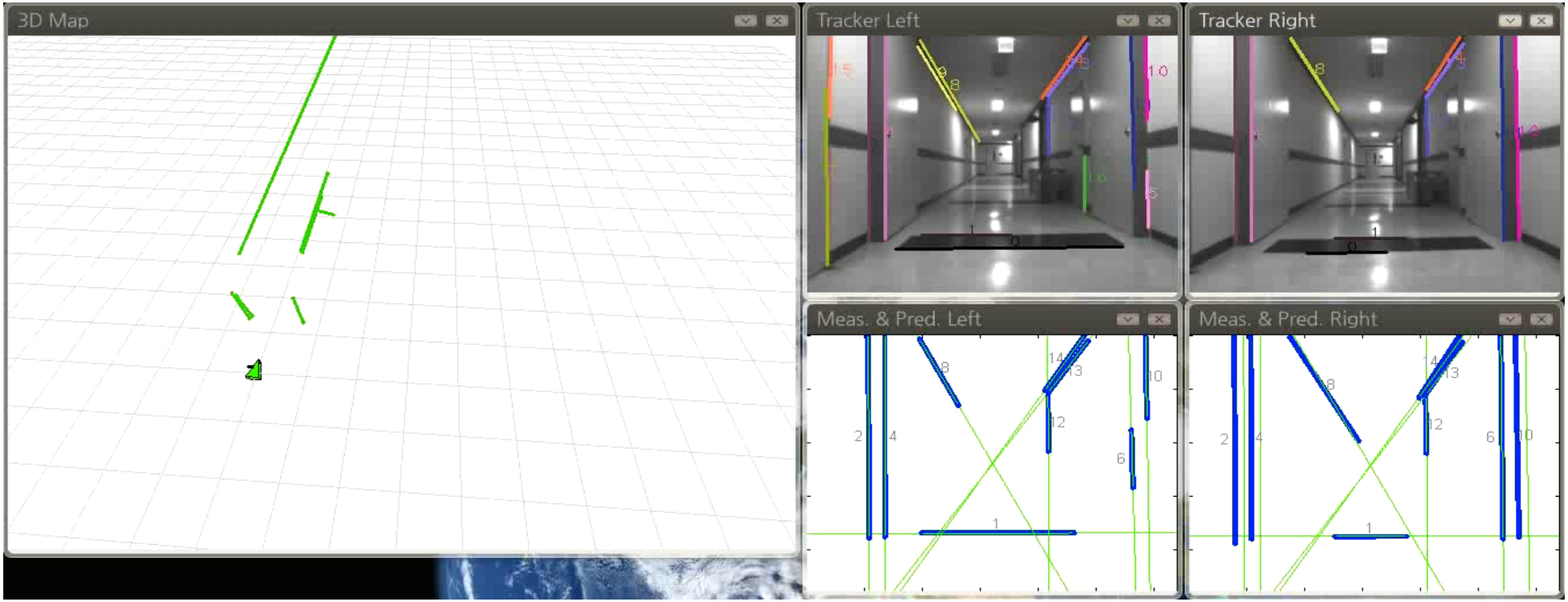
# SLAM in Crowd Indoor Environment (Hospital)


**Characteristics of Line-based Indoor SLAM System:**

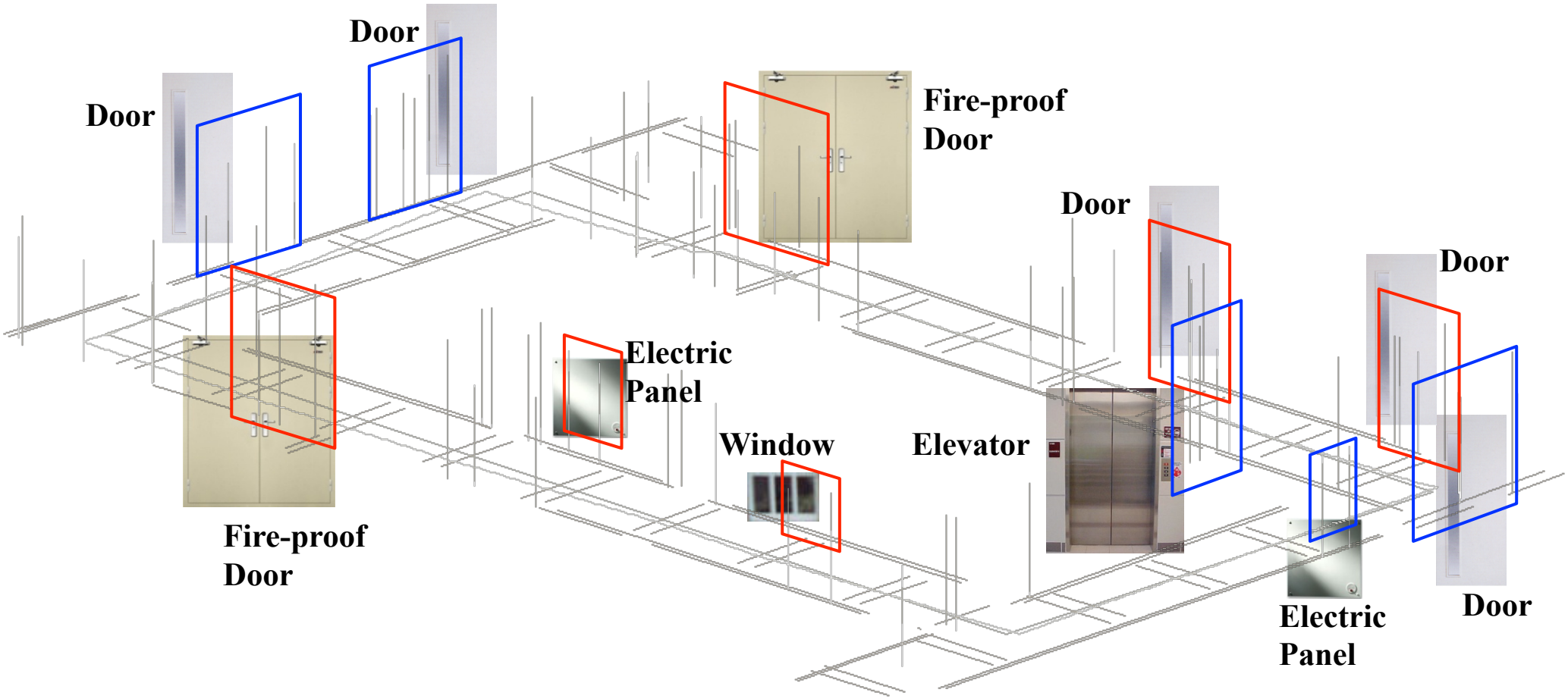
- Can effectively eliminate passers-by since lines are rarely extracted from human bodies.
- Robust for concurrently moving objects (passers-by)


- S. M. Hwang, G. Zhang and I. H. Suh, "Simultaneous Localization and Mapping using 3D Lines", 2012 IEEK(The Institute of Electronics Engineers of Korea) Autumn Conference, November 26, 2012, Daejeon, Korea.

# Stereo Line-SLAM



# Ongoing Work: Semantics SLAM



# SEMANTIC SLAM AND NAVIGATION

# Human Navigation Strategies

- **Human Navigation (In cognitive psychology)**
  - **Path Integration**

  - **View-dependent place recognition**


**Ego-Centrism**

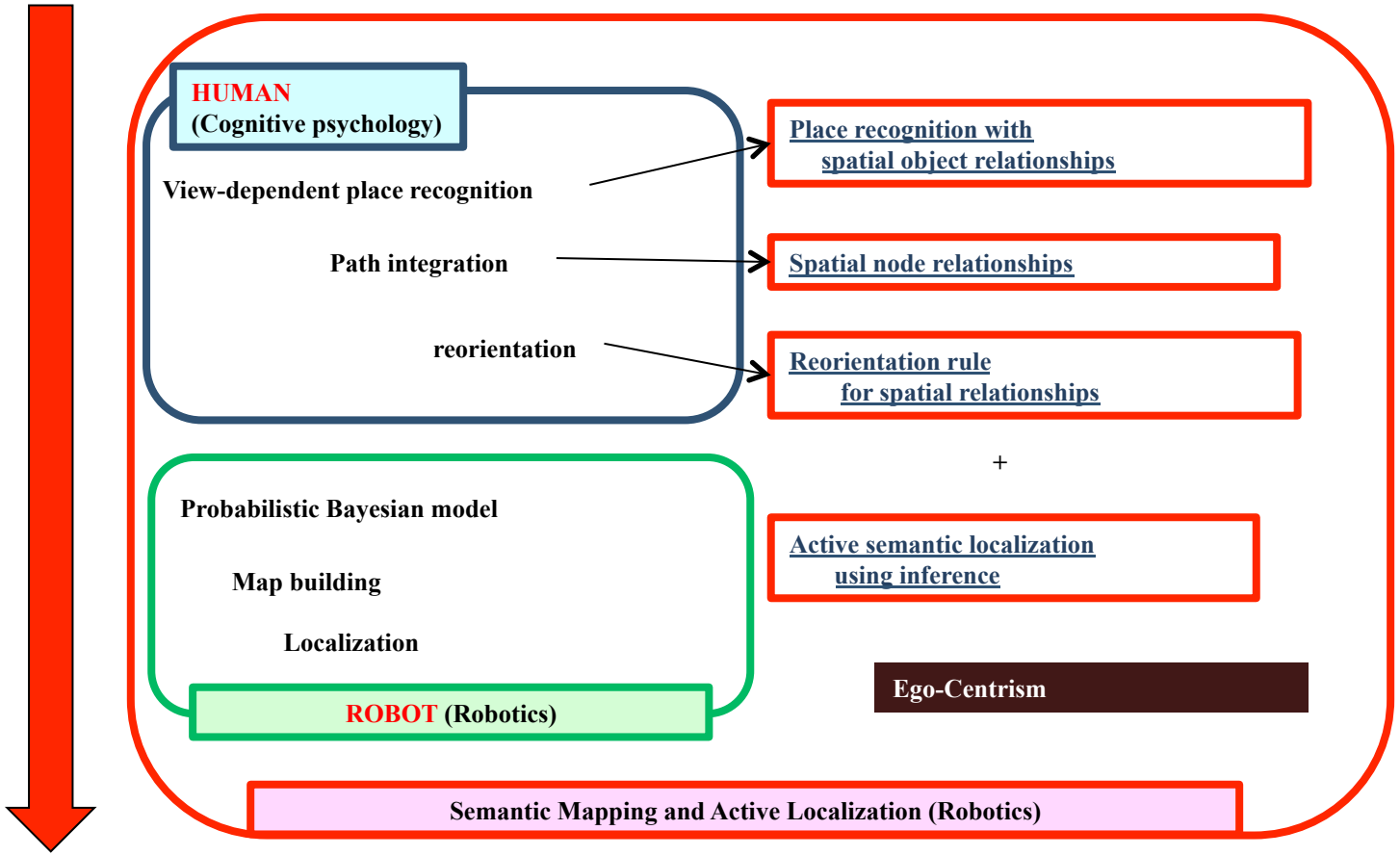
  - **Reorientation**

  - **Action**

R. Wang and E. Spelke, "Human spatial representation: Insights from animals," *Trends in Cognitive Sciences*, 6(9), pp. 376-382, 2002.

# Our Semantic SLAM

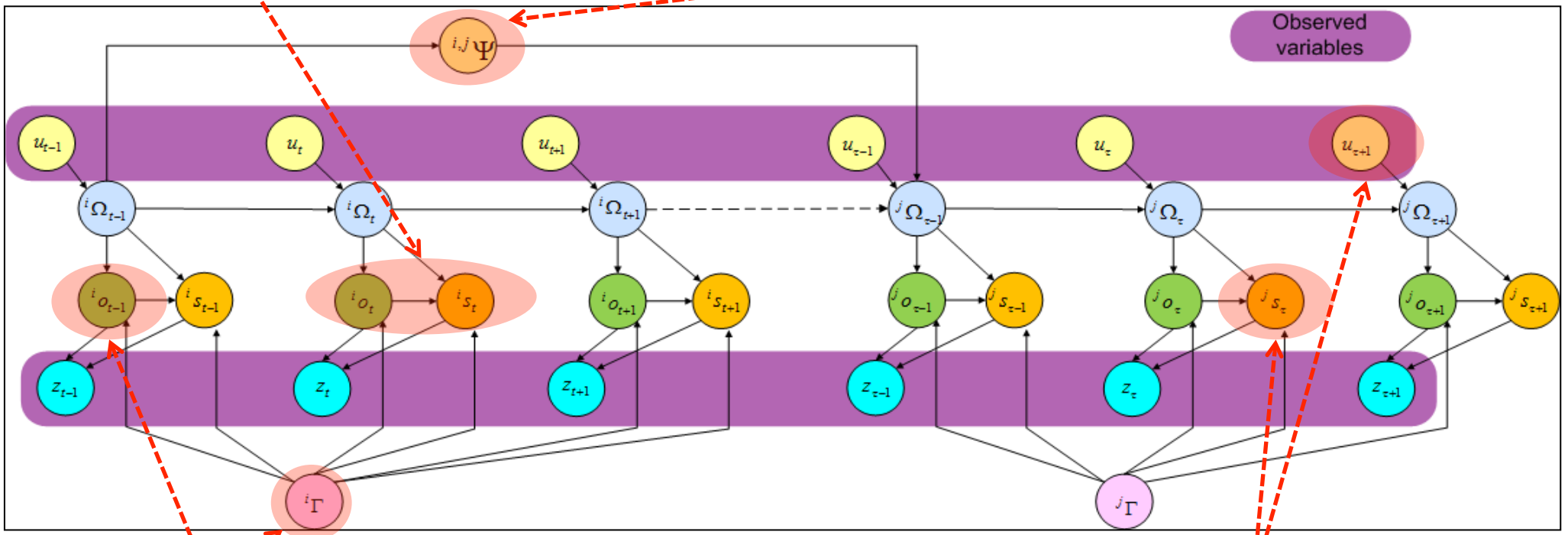
Topological + Semantic Map with high-cost and high-performance sensor




Topological + Semantic Map with low-cost and low-performance sensor

# Bayesian Model for Semantic SLAM

- **View-dependent place recognition**
  → **The likelihood of the spatial relationship**
- **Path Integration**
  → **Relative link in the topological map**

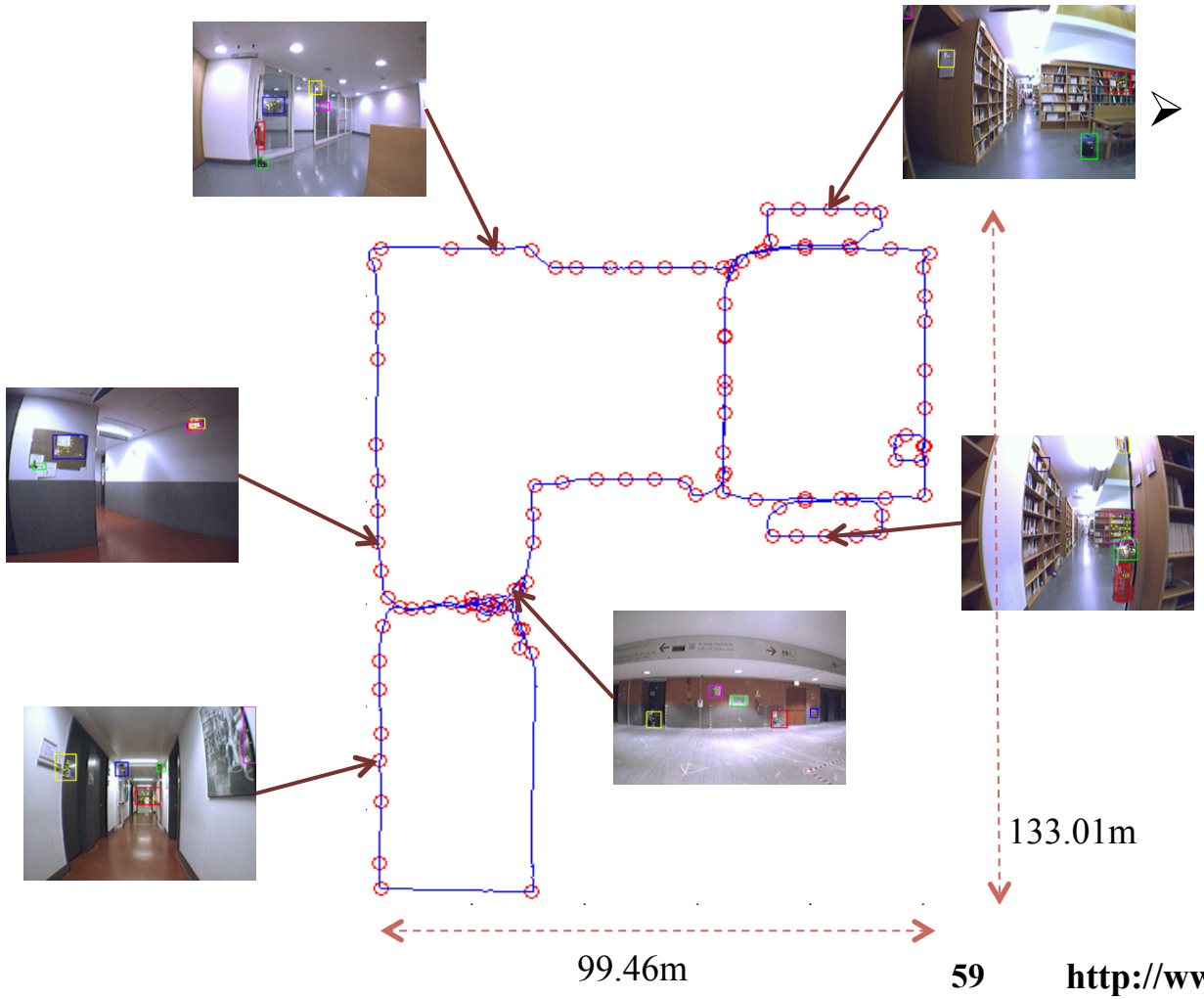



- **Reorientation**
  → **Local coordinate**
- **Action**
  → **Active Localization Using Symbolic Inference**


- C. Yi, I. H. Suh, G. H. Lim, and B. U. Choi, Semantic Mapping and Active Localization for Service Robots, IEEE Transactions on Systems, Man, and Cybernetics, Part A, submitted.
- C. Yi, I. H. Suh, G. H. Lim, and B. U. Choi, Bayesian robot localization using spatial object contexts, Proceedings of the 2009 IEEE/RSJ international conference on Intelligent robots and systems, pp. 3467-3473, 2009.
- C. Yi, I. H. Suh, G. H. Lim, and B. U. Choi, Active-semantic localization with a single consumer-grade camera, Proceedings of the 2009 IEEE international conference on Systems, Man a nd Cybernetics, pp. 2161-2166, 2009.

# Semantic Mapping and Localization with Open Dataset

- Automatic landmark detection using saliency (corner)
- Automatic node detection using Bayesian surprise




➢ Result of detection

Node number: 113

Landmark number: 289

The Rawseeds Project

"Raw seeds can be consumed as they are... or be the start for the growth of new results."

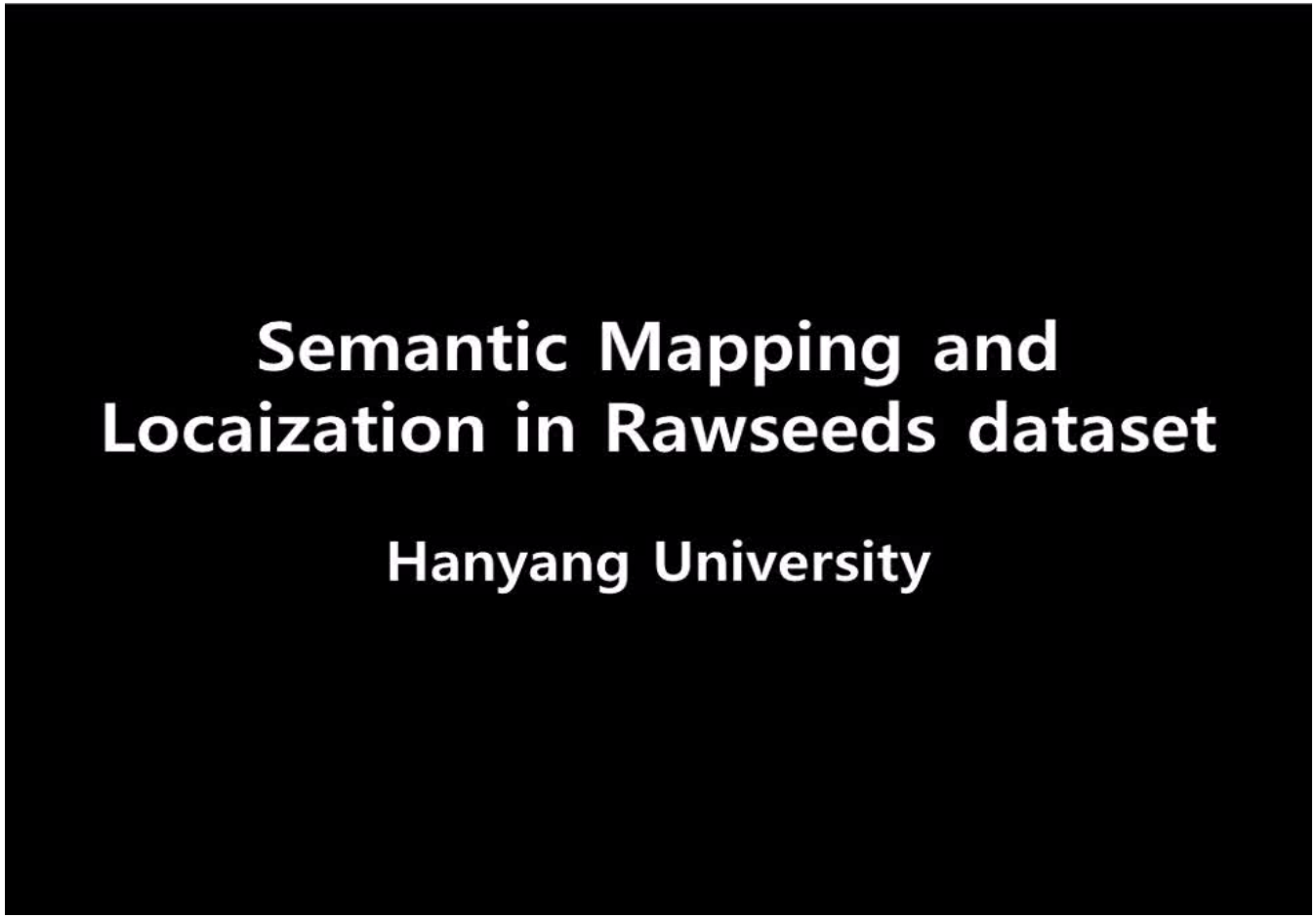


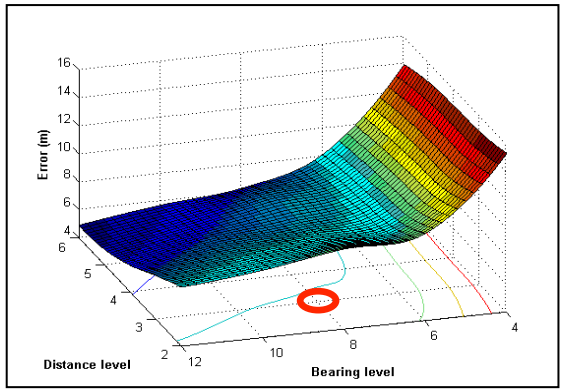
http://www.rawseeds.org/rs/datasets/view/6

# Experimental results of Open Dataset

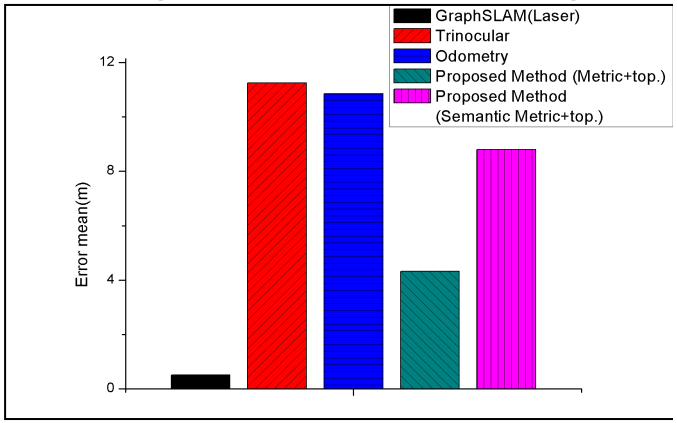
The Rawseeds Project

"Raw seeds can be consumed as they are... or be the start for the growth of new results."



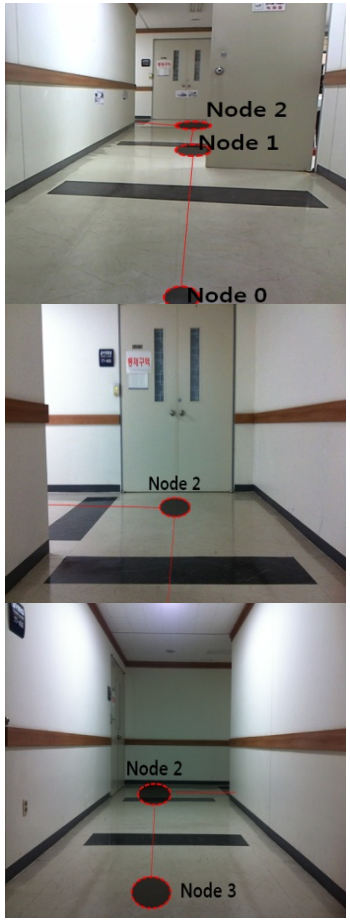

**Final mean error based on changes in distance and bearing**



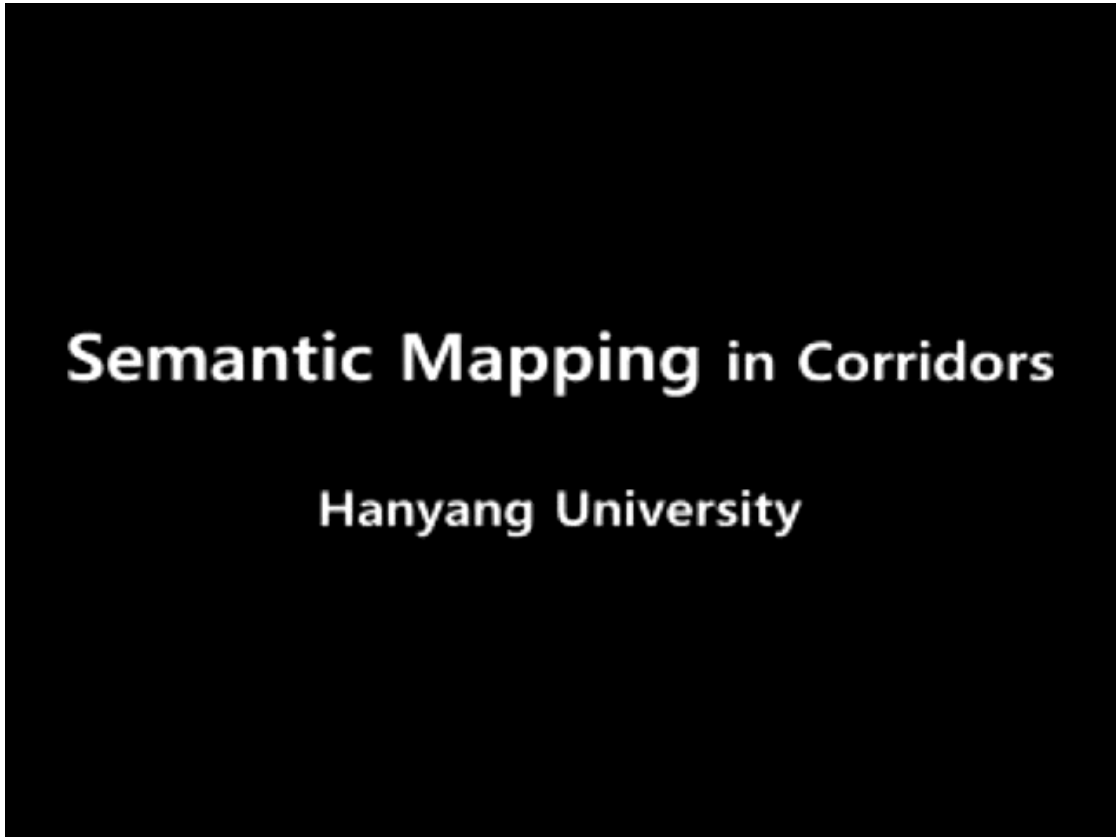

**Comparison of results**


- C. Yi, I. H. Suh, G. H. Lim, and B. U. Choi, Human Navigation-Inspired Semantic Map-building and Localization, Proceedings of the 2012 IEEE/RSJ international conference on Intelligent robots and systems, submitted.

# Semantic Mapping and Navigation in Real Environment (Corridors)




Semantic Mapping &Navigation



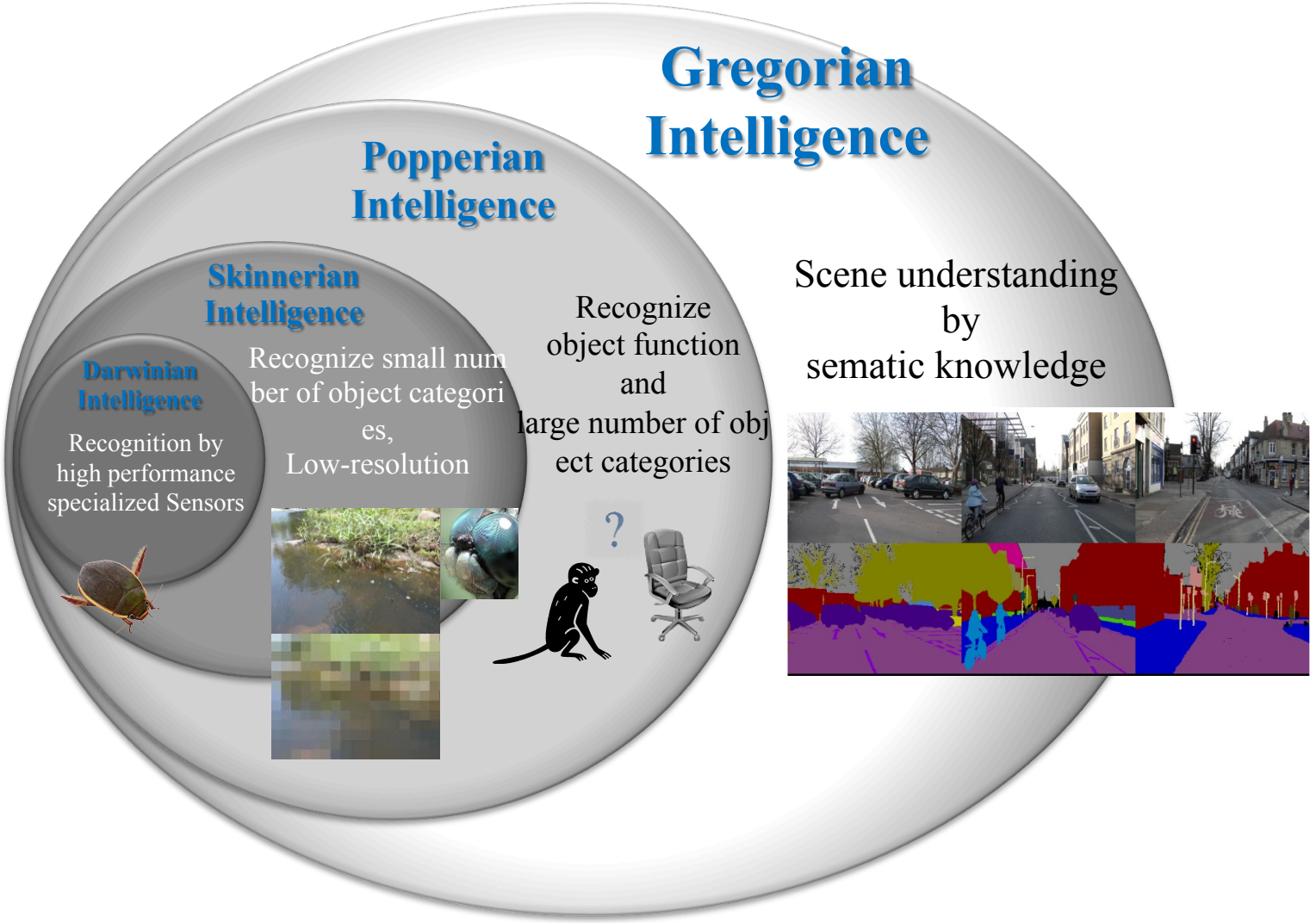

8X

Corridor environment

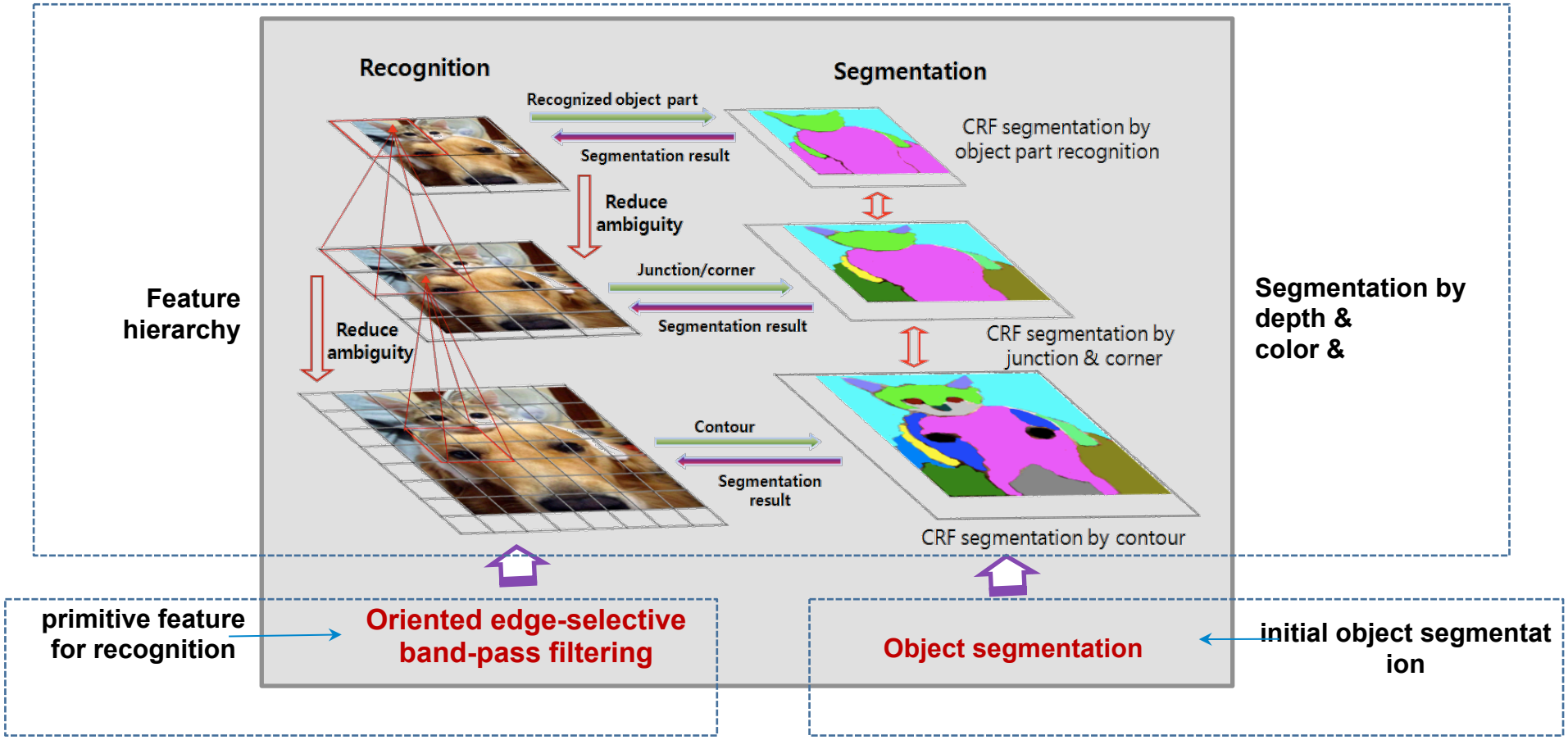

- D. W. Ko, C. Yi, I. H. Suh, and B. U. Choi, Semantic Mapping and Navigation with Visual Planar Landmarks, Proceedings of the 2012 IEEE/RSJ international conference on Intelligent ro bots and systems, submitted.

# RECOGNITION

# Four Kinds of Recognition



# HIRS (Hierarchical, Interactive Recognition & Segmentation) framework



# ORIENTED EDGE-SELECTIVE BAND-PASS FILTERING

# Edge Detection vs. Edge Orientation Estimation


Original image

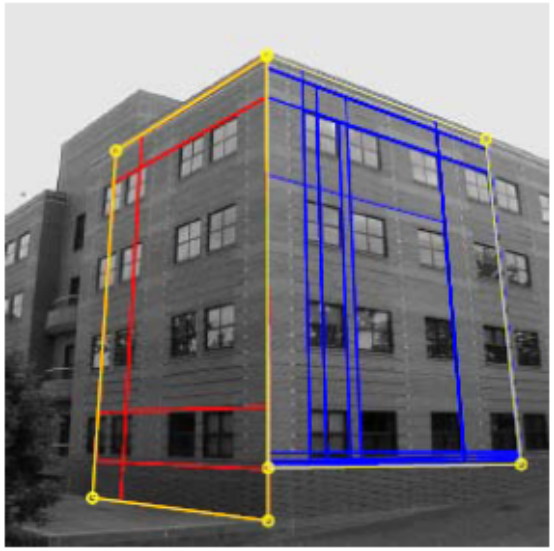
Edge detection
(Canny edge detection)

Edge orientation
estimation

Horizontal

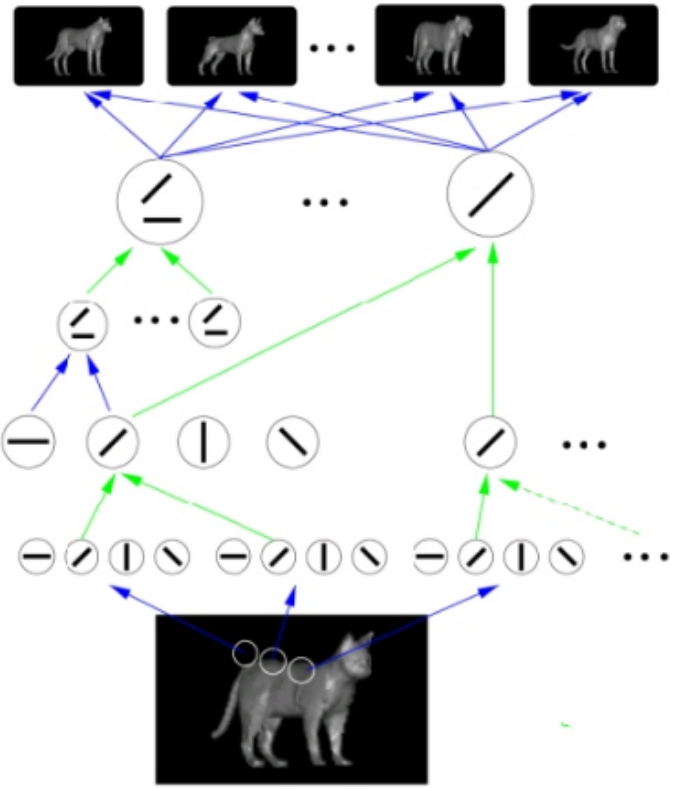
Vertical

# Why Is Edge Orientation Estimation Important to Recognize Objects?



Rectangle detection

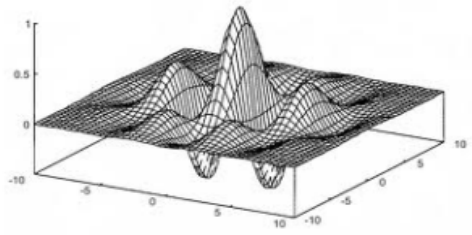
Eye, eyebrow and mouse recognition



Visual processing in human brain

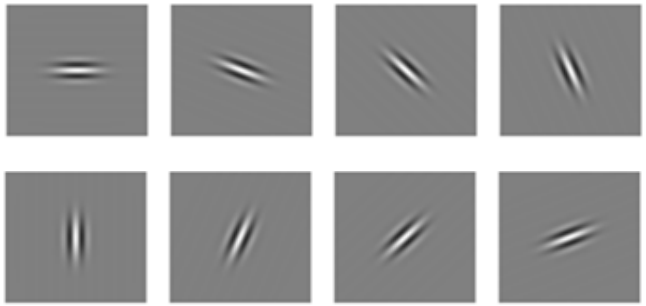
# Edge Orientation Analysis : Filter-based Approach

## Gabor filtering

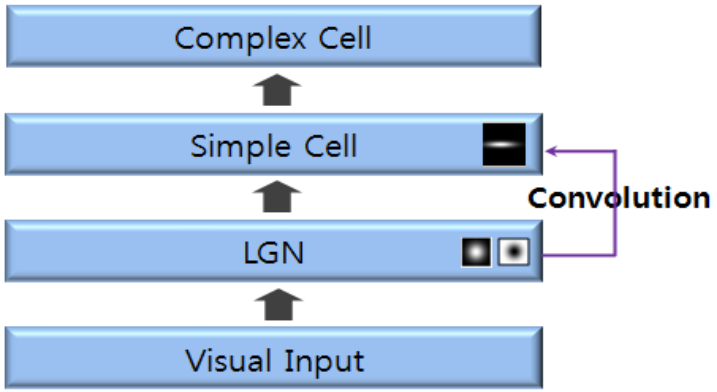


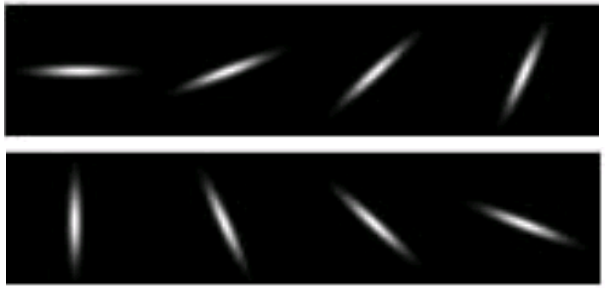
$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) =$$

$$\exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \cos\left(2\pi\frac{x'}{\lambda} + \psi\right)$$

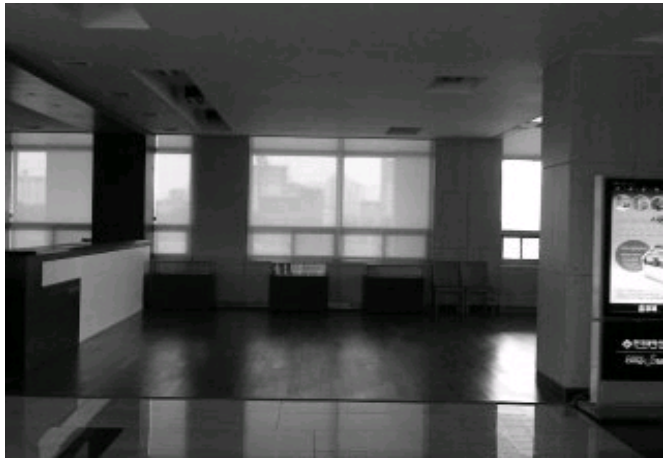


## Neumann filtering



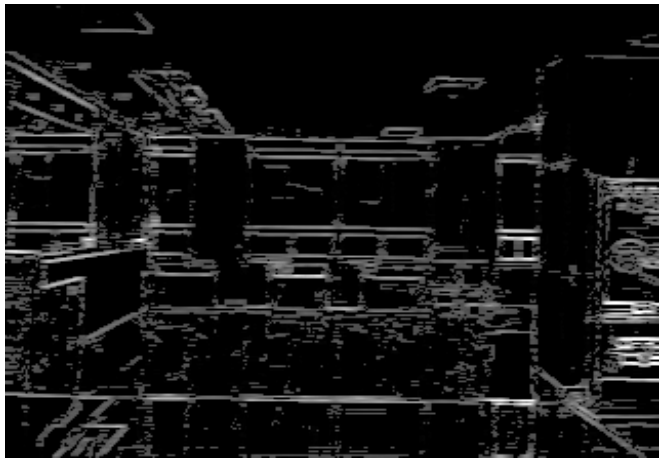
# Filter-based Approach : Problem



**Original image**

**Filtering Horizontal edge**

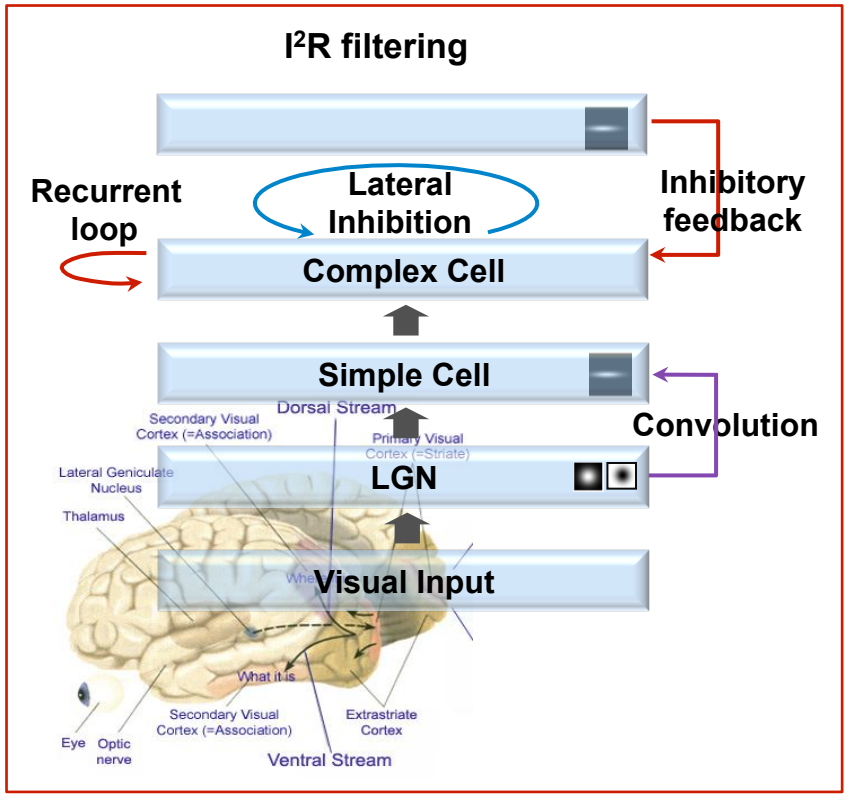
**Ideal condition**

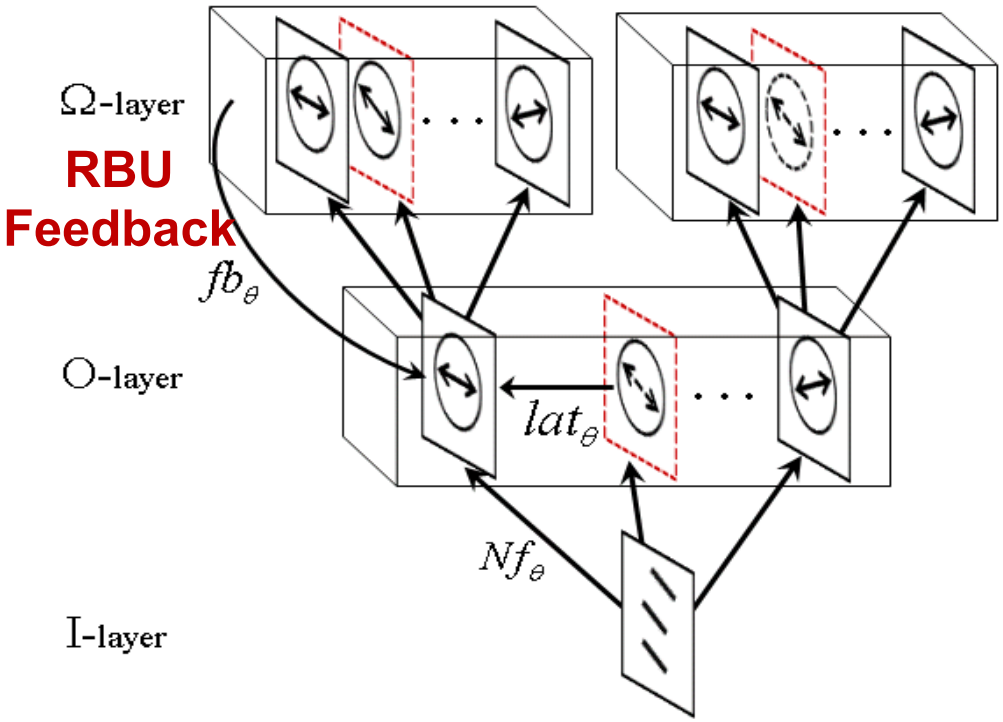


**Gabor filtering**

# Oriented Edge-Selective Band-Pass Filtering Based on RBU Theory

**I²R filtering :** Lateral **I**nhibition, **I**nhibitory Feedback, **R**ecurrent Connection



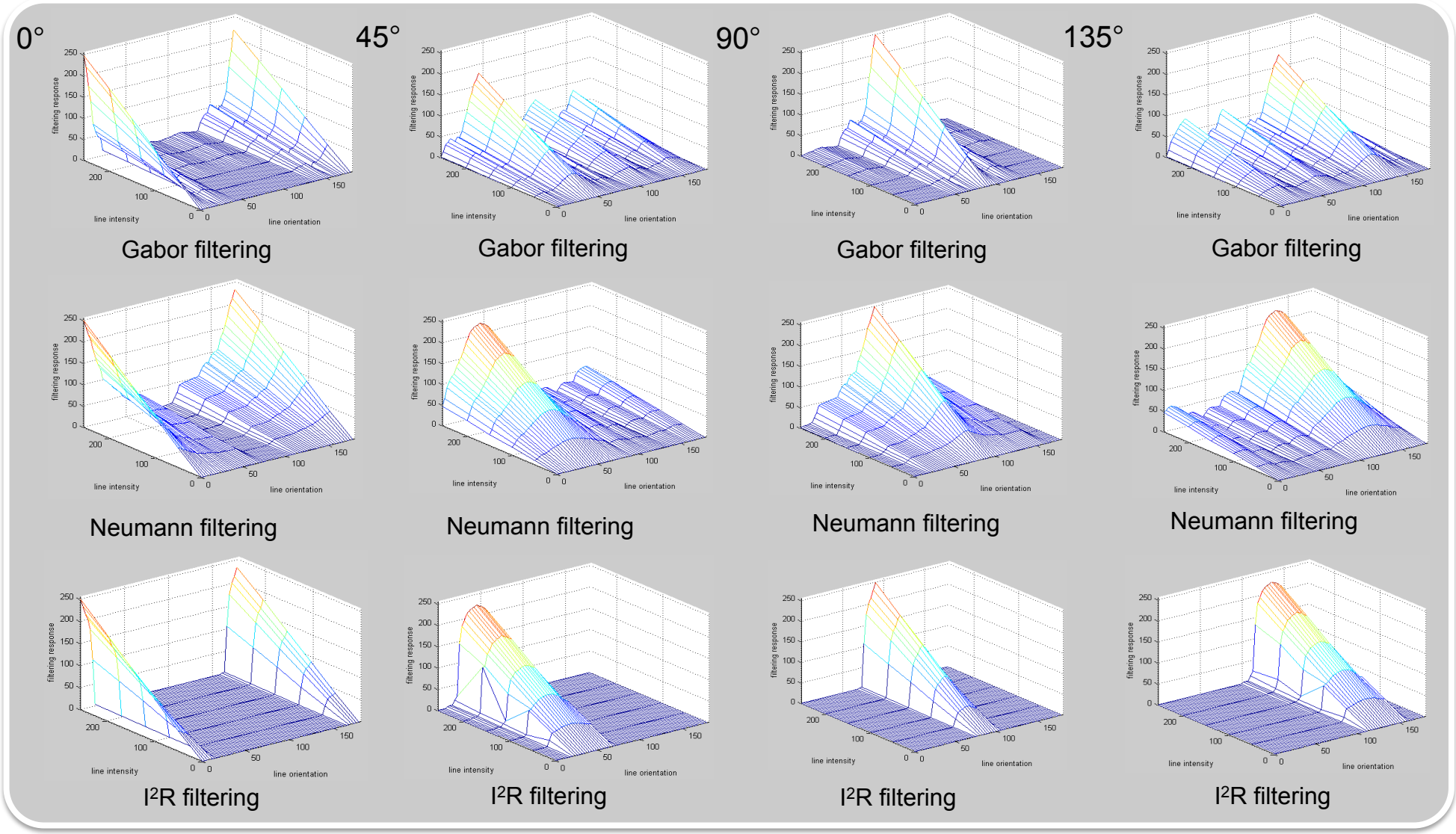



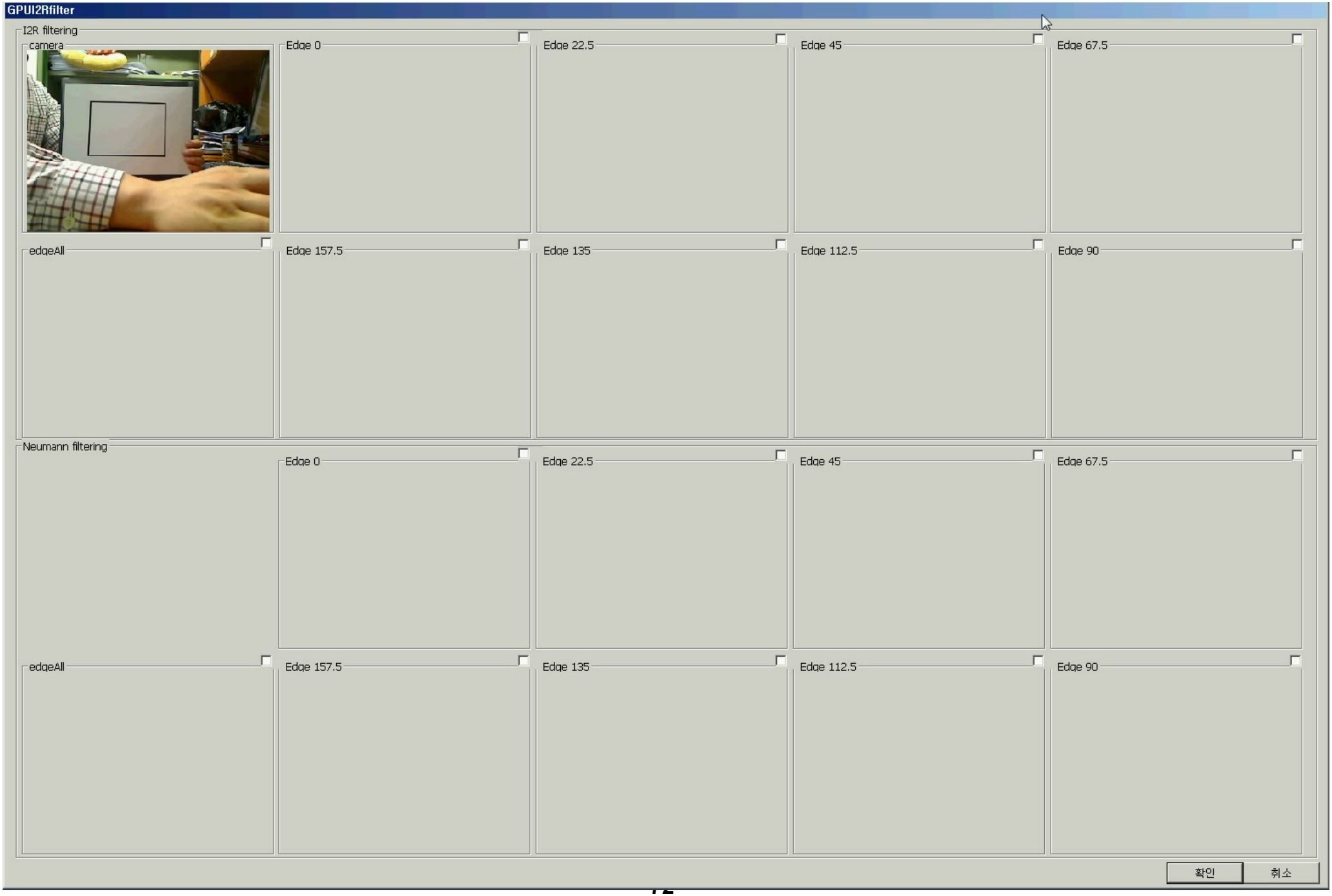


[References]

1. Lateral and Feedback Schemes for the Inhibition of False-positive Responses in Edge Orientation Channels, (*ICRA2012*)
2. Oriented Edge-Selective Band-Pass Filtering, *IEEE transactions on Image Processing*, Submitted

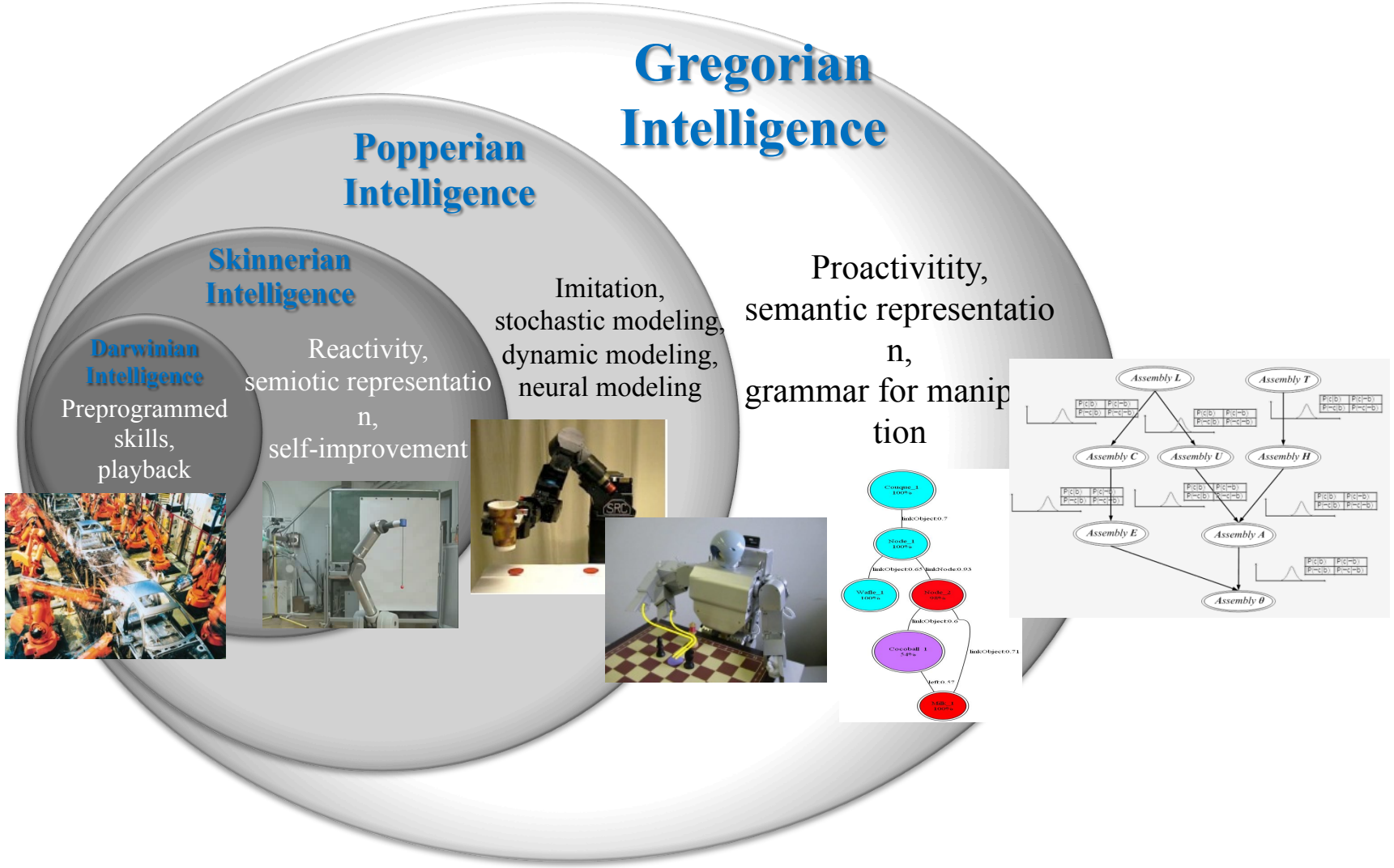
# Experimental Result




GPUI2Rfilter
I2R filtering
camera
Edge 0
Edge 22.5
Edge 45
Edge 67.5
edgeAll
Edge 157.5
Edge 135
Edge 112.5
Edge 90
Neumann filtering
Edge 0
Edge 22.5
Edge 45
Edge 67.5
edgeAll
Edge 157.5
Edge 135
Edge 112.5
Edge 90
확인
취소

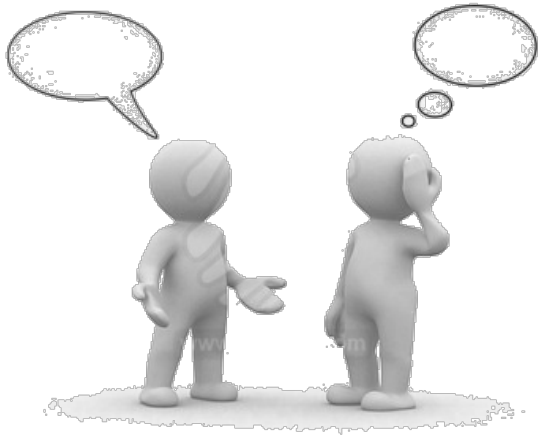
# MANIPULATION

# Four Kinds of Manipulation



# Gregorian Manipulation

: Generation of New Sentences using Words



sentences

"HEISABOY"

"SHEISNOTAGIRL"

words

HE | IS | A | BOY

SHE | IS | NOT | A | GIRL

reorganization

New sentence

"HE IS NOT A GIRL"

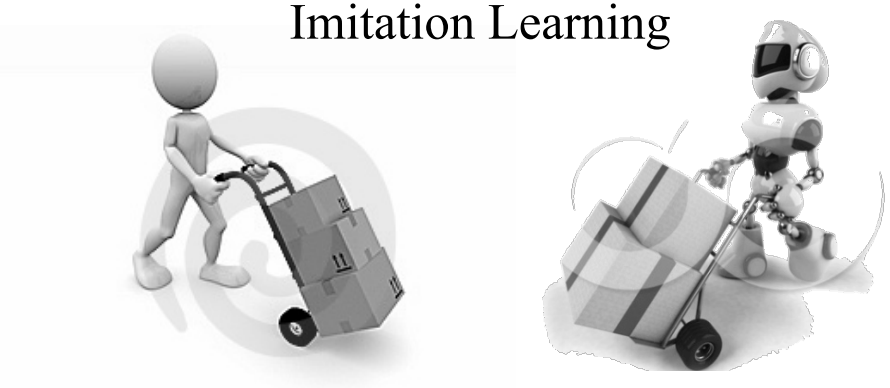
Reusability → Primitives (Words)

Pre- and Post-conditions

# Sapient Manipulation by Imitation

Semantic Manipulation → Learning Basis Skills → Efficient Reusability and Improvability

Imitation Learning



1. Acquiring training data by user –friendly Interaction easily and quickly
2. Learning new skills using the training data

State of the Art

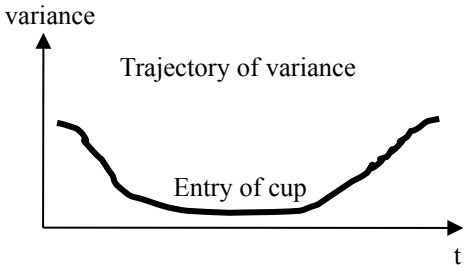


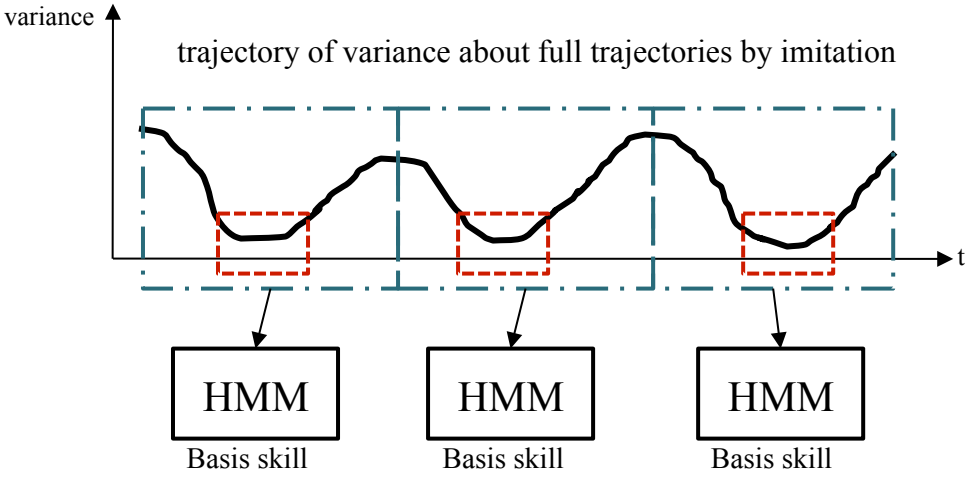

- Little Consideration of Primitives

# Learning and Improvement of Basis Skills by Imitation

## Efficient Reusability

By using segmentation based on variance




## Efficient Improvability

# Learning and Improvement of Basis Skills by Imitation

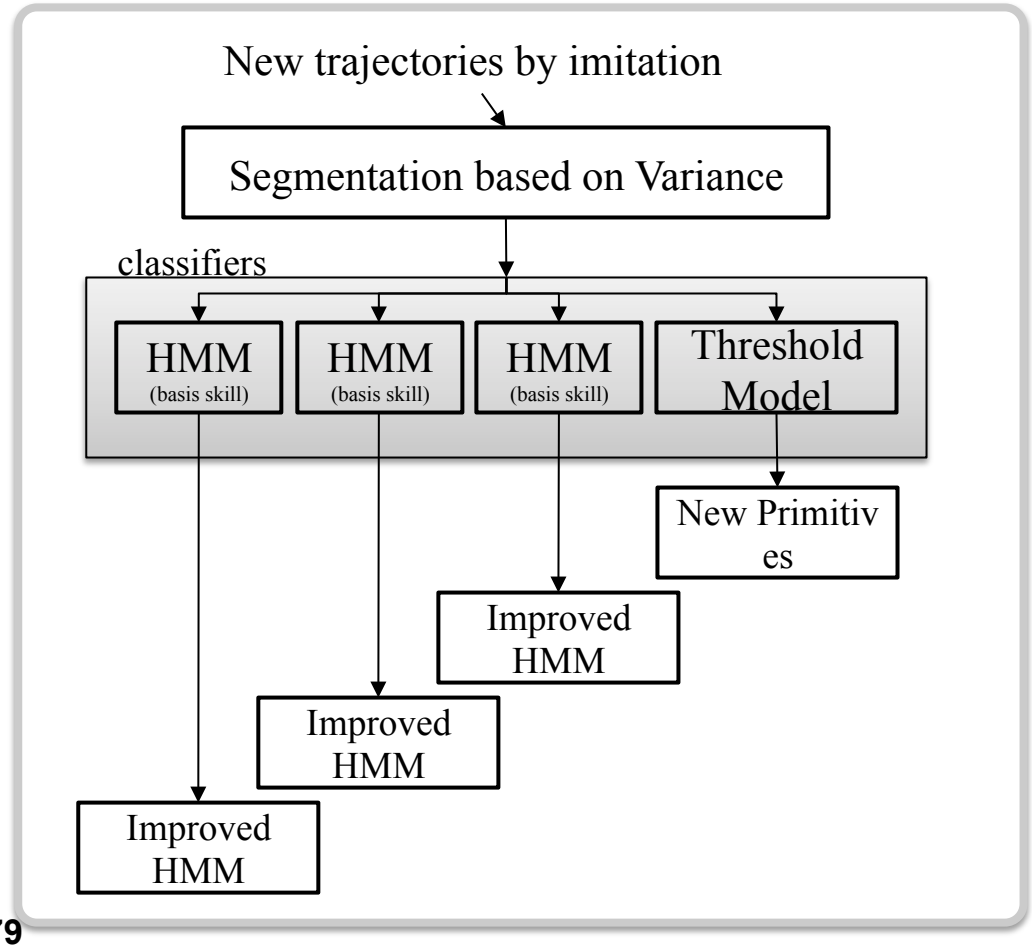
- Video Clip – Assistant Chef Robot (Making Rice)


x2, [0:01:04]

# Learning and Improvement of Basis Skills by Imitation

Efficient Reusability

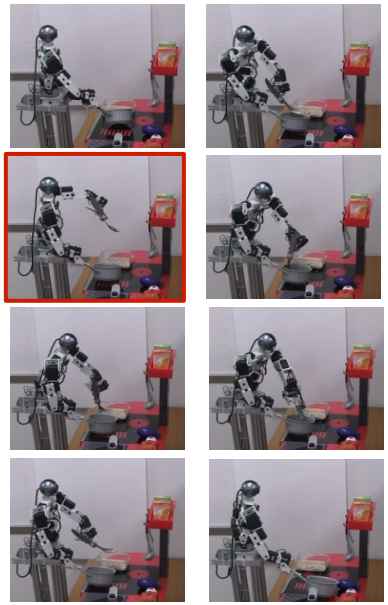
Efficient Improvability

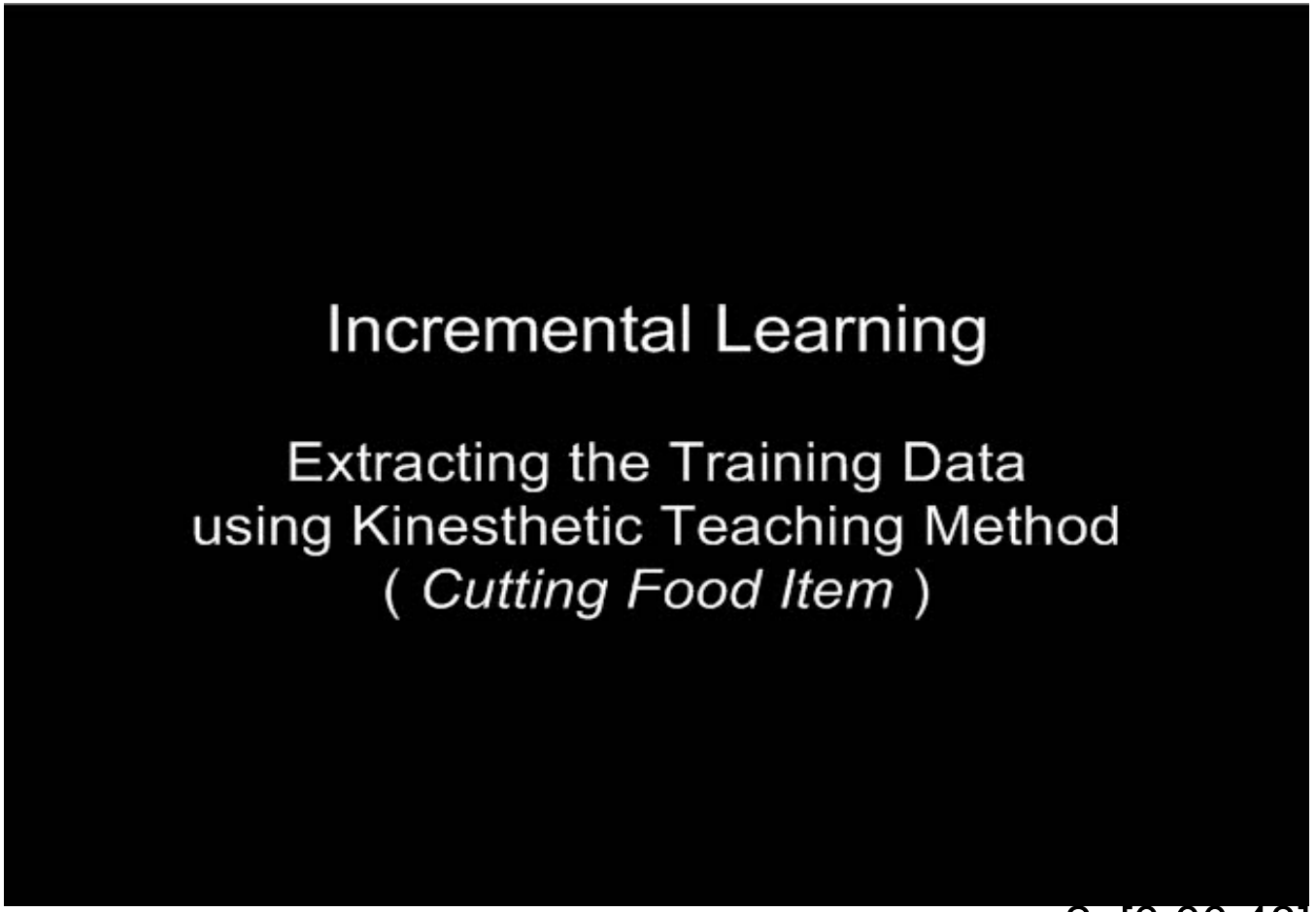


# Learning and Improvement of Basis Skills by Imitation

- Video Clip – Assistant Chef Robot (Cutting Food Item)

Eight Existing Basis Skills






x2, [0:00:43]

Four New Basis Skills

# Conclusion (Future Works in INCORL)

- **S**ervice-**O**riented dependable **S**ituated **H**uman **R**obot **I**nteraction (SOS-HRI)

- Application scenario
  - **Know**ledgeable and **S**ituation **A**dequate **K**itchen **A**ssistance **R**obot (Know-SAKAR)