A Tour of Information-Theoretic Principles for

Brain, AI, and Robot

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서 일 홍

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COGA-PLEX

advancing mobility through AI

나는 누구인가?

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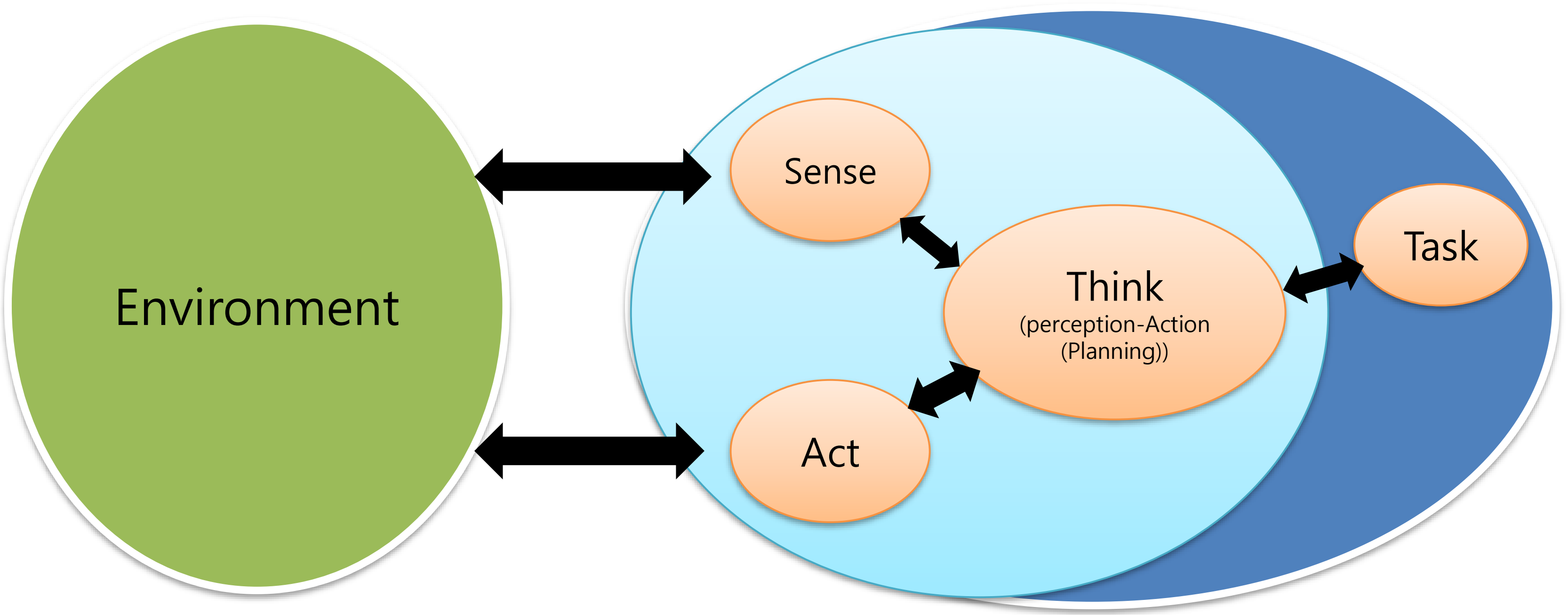
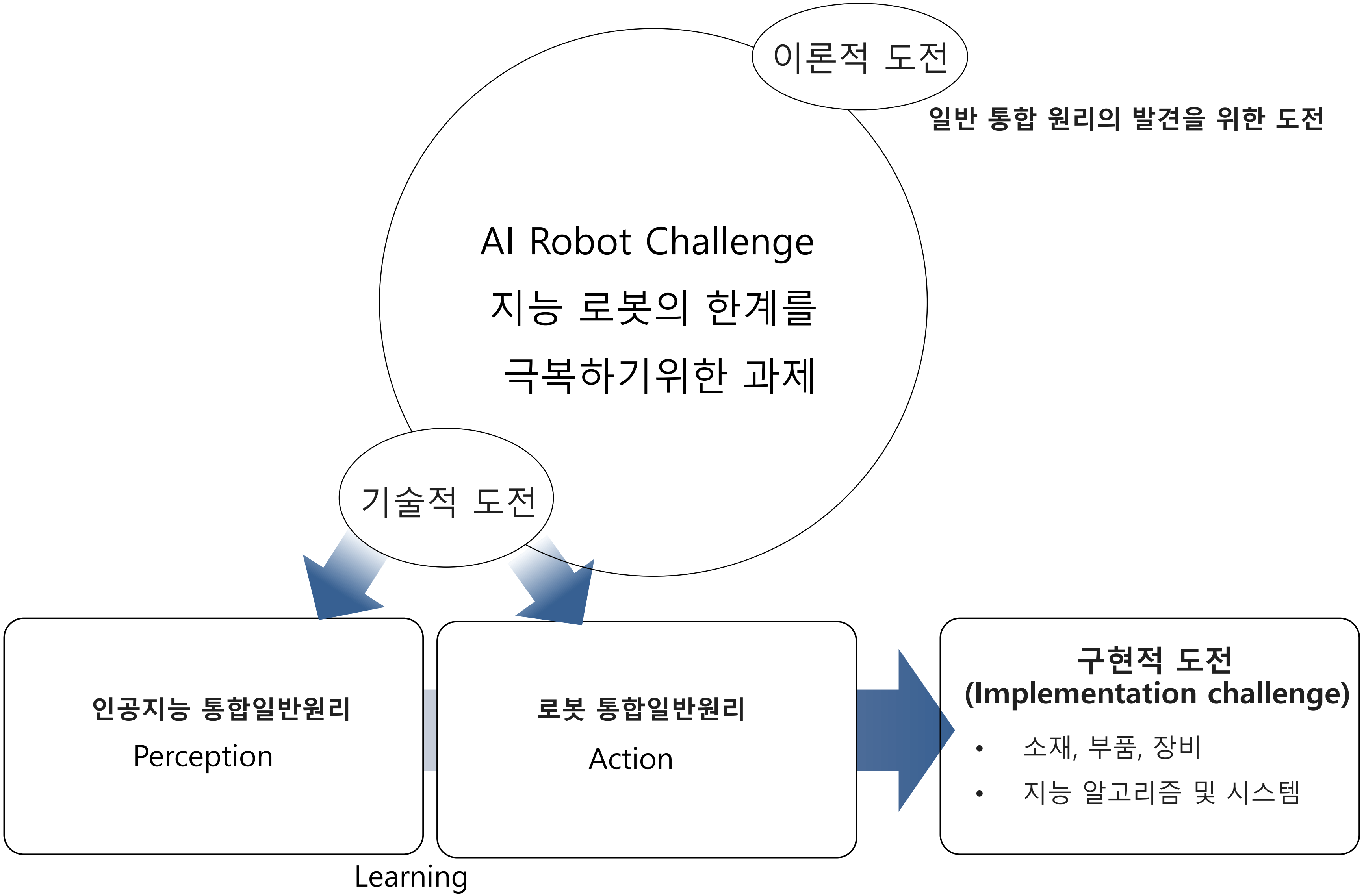
AI-ROBOT(생명체)

- **Perception**
  - 로봇(생명체)이 일하는 공간(환경)안에서
  - 로봇(생명체)이 이용 가능한 센서로부터 얻은 공간(환경) 정보로부터
  - 하고자 하는 작업 달성(생명유지)에 필요한 정보를 추출
- **Action**
  - 작업 달성(생명유지)를 위해서 환경에 적용할 최적의 적합한 행동을 실수없이 시의 적절하게
  - 배우거나, 선택하거나, 만들어 낼 수 있는 로봇(생명체)


Environment
Sense
Think
(perception-Action
(Planning))
Task
Act

AI Robot 분야의 기술적 도전



Information-Theoretic Principles for Brain, AI and Robot

자연지능 생명체(Brain)

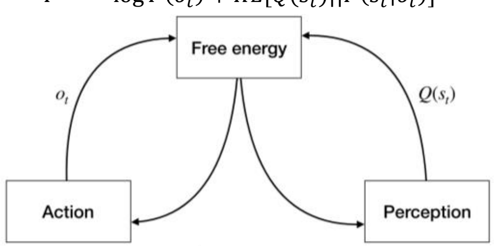
Perception <->Action

The Free Energy Principle

(=Surprise Minimization Principle)

Surprise $= -\log P(o_t)$

$$F = -\log P(o_t) + KL[Q(s_t)||P(s_t|o_t)]$$



$Q(\pi) = \sigma(\sum_{\rho \le t} F(\pi,\rho) + \sum_{\tau > t} G(\pi,\tau))$

$Q(s_t) = \arg\min_{Q} F$

Changing sensations through action to maximize evidence

Changing beliefs to minimize divergence

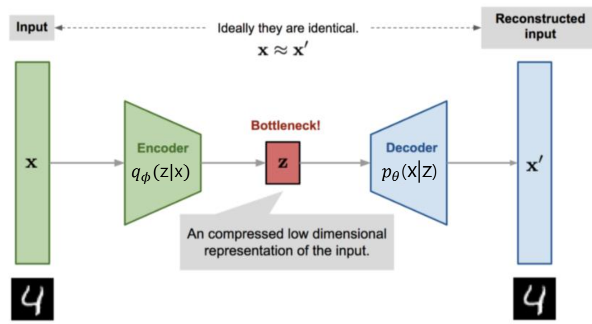
(Kare Fristone, Beren Millidge)

인공지능 통합 원리

Perception

The Information Bottleneck principle

$$\min_f I(f(x);x) - \lambda\, I(f(x);task)$$



$$L_i(\phi,\theta,x_i) = -\mathbb{E}_{q_\phi(z|x_i)}[\log(p_\theta(x_i|z))] + KL(q_\phi(z|x_i)||p(z))$$

(Naftali Tishbi, S. Soatto)

로봇 통합 원리

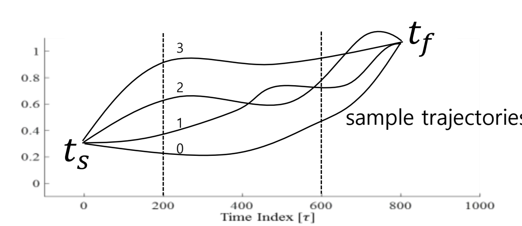
Action

The Path Integral Principle

$$R_t^i = q_\tau + \int_t^T q(\mathrm{X}_i) + \frac{1}{2}\boldsymbol{u}_t^T \boldsymbol{R} \boldsymbol{u}_t d\tau_t$$

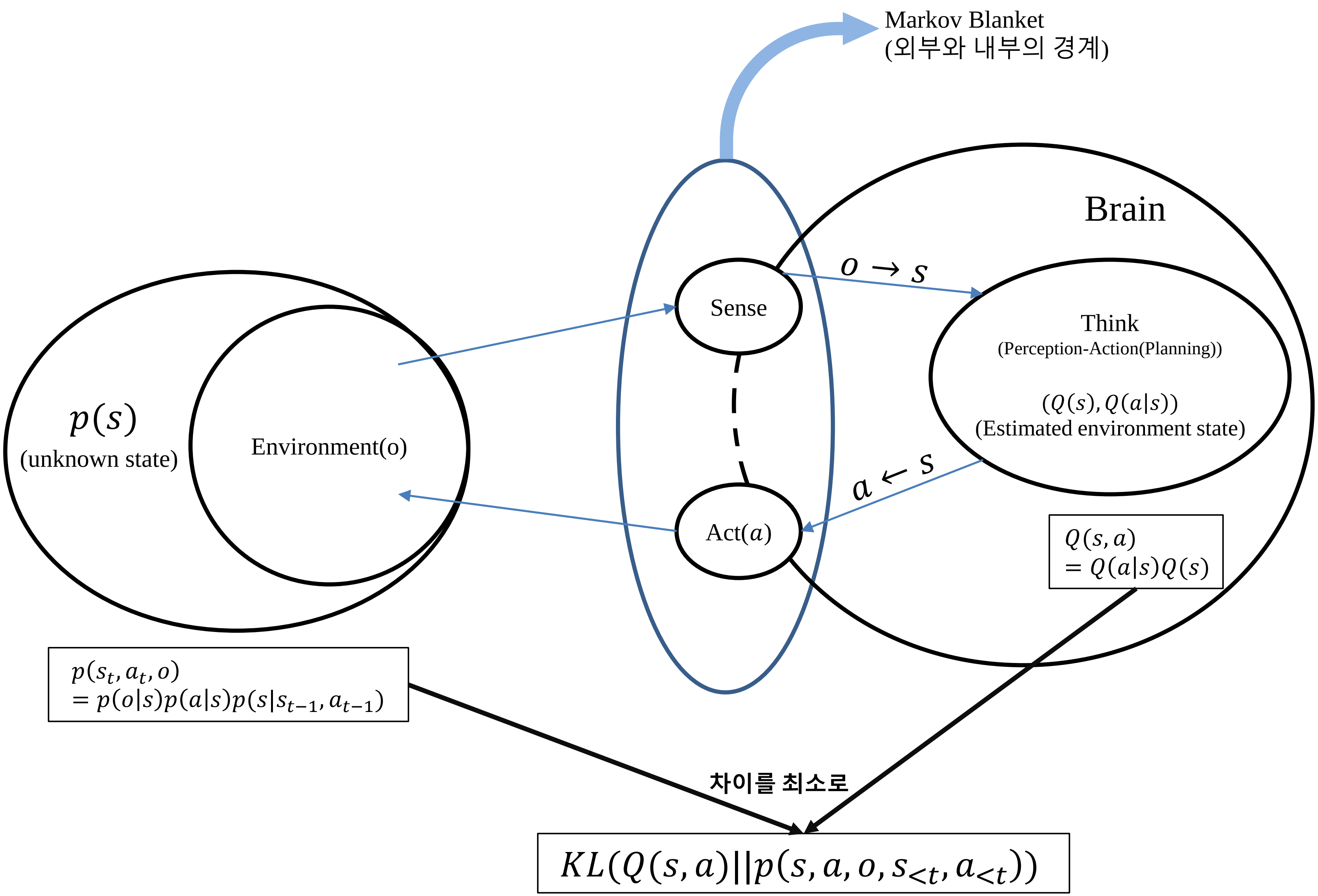
$$w_t^i = \exp(-\lambda R_t^i)$$

$$\boldsymbol{u}_t^{new} = \frac{\sum_i w_t^i \boldsymbol{u}_t^i}{\sum_i w_t^i}$$



(Bert Kappen, Stefan Schaal)

Free-Energy(Surprise) Principle:



Free Energy(Information)

$$= KL\,(Q(s,a)\parallel p(s,a,o,s_{<t},a_{<t})$$

$$= KL\big(Q(a|s)Q(s)\parallel p(o|s)p(a|s)p(s|s_{t-1},a_{t-1})\big)$$

$$= \underbrace{-\int Q(s)\log(o|s)}_{\text{Auto Encoder}} + \underbrace{KL(Q(s)\parallel p(s|s_{t-1},a_{t-1}))}_{\text{Prection of Dynamics(Equivariance property 포함)}}$$

$$+\underbrace{E_{Q(s)}[KL[Q(a|s)\parallel p(a|s)]]}_{\text{KL-control theory(⇒ Maximum Entropy Reinforcement Learning)}}$$

KL-Control Theory

$$-KL(Q(a|s) \parallel p(a|s)) = \int Q(a|s)\log p(a|s) + H(Q(a|s))$$

$$Ergodicity \Rightarrow p(a|s) \propto \sigma[e^{-\delta \overbrace{G(s,a)}^{\text{surprise}}}]$$

KL minimization $\Rightarrow$ maximum Entropy Reinforcement Learning

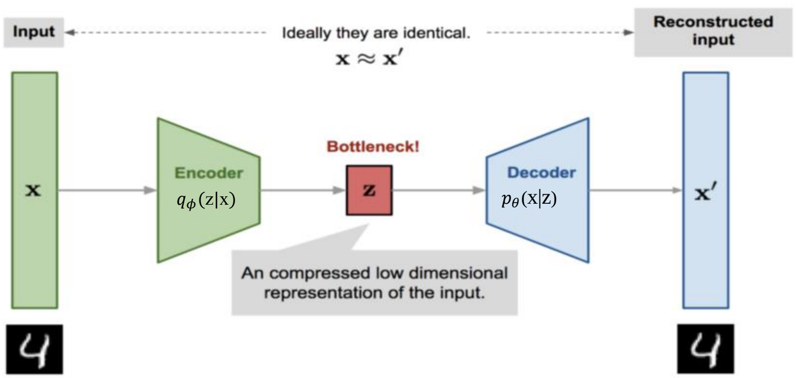
- 미래에 기대되어지는 보상의 합을 최대로 하는 행동 (내가 기대하고 상황이 틀리지 않도록 하는 행동을 배우거나 시행한다)을 시행하되, 가급적 여러가지 행동을 해 보아야 한다.

Information Bottleneck Principle

인공지능 통합 원리
Perception

The Information Bottleneck principle

$$\min_f I(f(x);x) - \lambda\, I(f(x);task)$$



$$L_i(\phi,\theta,x_i) = -\mathbb{E}_{q_\phi(z|x_i)}\left[\log\left(p_\theta(x_i|z)\right)\right] + KL\left(q_\phi(z|x_i)||p(z)\right)$$

Path Integral Principle

(Control as Inference)

KL control theory

The control computation is 'reduced' to a (graphical model) inference problem.

Dynamics: $p_{xy}^{t}(\pi)$
Cost: $C(\pi^{0:T}) = \langle R \rangle$ → DP → Bellman Equation

↓ restricted class ↓ approximate J

Free dynamics: q_{xy}^{t}
$C = KL(p||q\exp(R))$ → approx inference → Optimal π

Optimal solution:

$$p(x^{1:T}|x^0 = \frac{1}{Z} q(x^{1:T}|x^0)\exp(R(x^{0:T}))$$

Path integral control can be obtained as a special case of the KL control formulation.

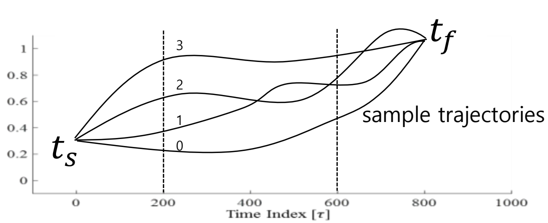
Path Integral Control Theory

Optimal Control (Hamilton-Jacobi -Bellman Equation) $\Leftrightarrow$ Sampling of Path and Integral of cost along the paths

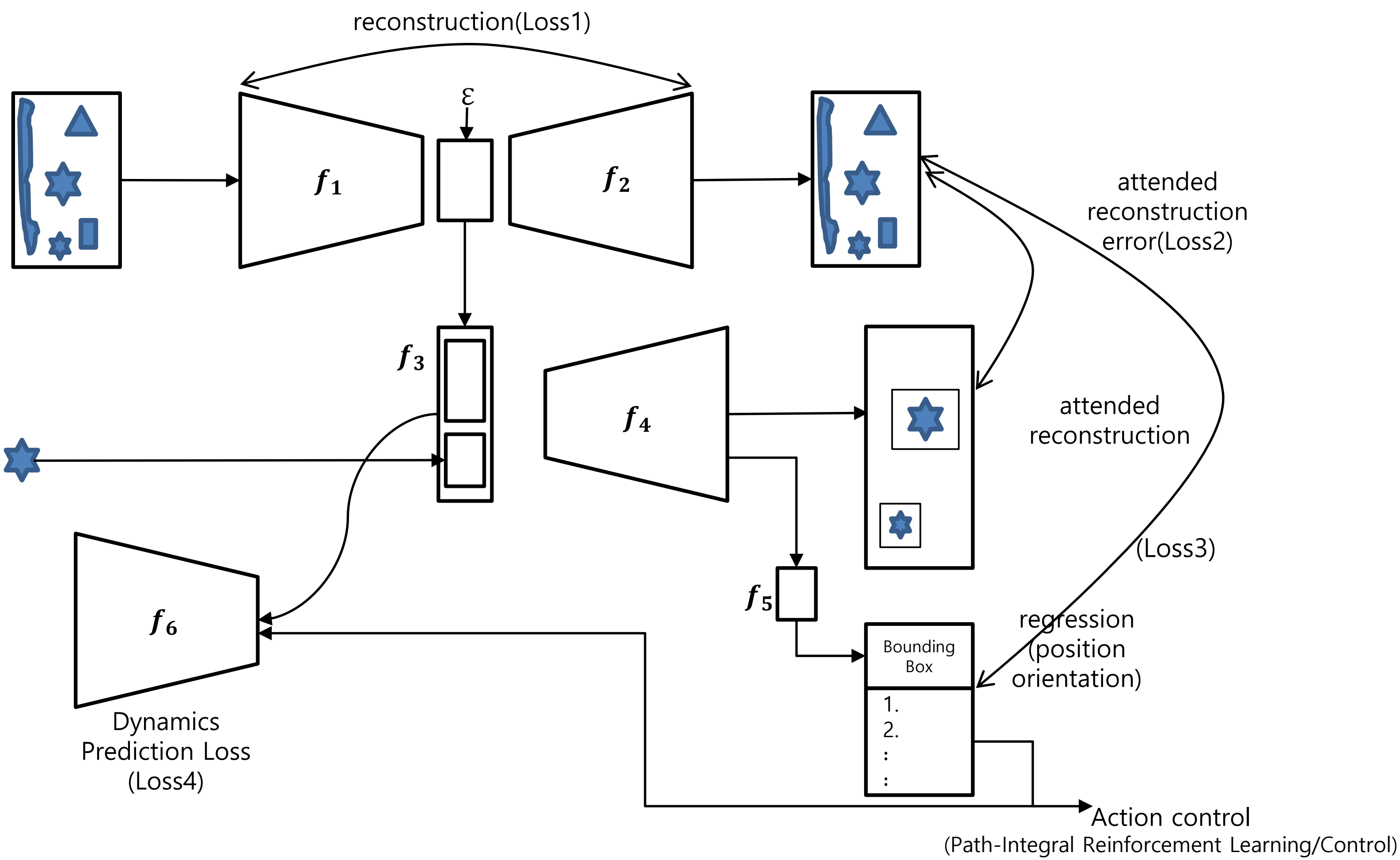
$$R_t^i = q_\tau + \int_t^T q(\mathrm{X}_i) + \frac{1}{2}\boldsymbol{u}_t^T \boldsymbol{R} \boldsymbol{u}_t d\tau_t$$

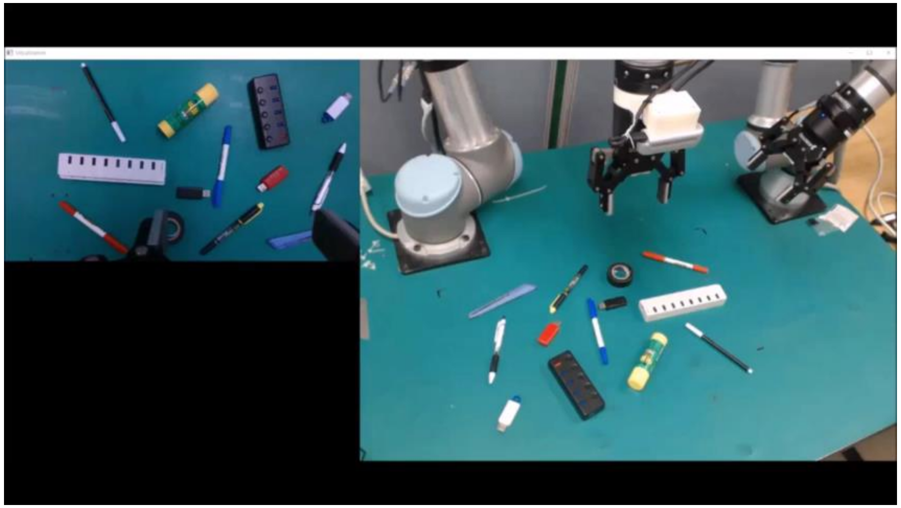
$$w_t^i = \exp(-\lambda R_t^i)$$

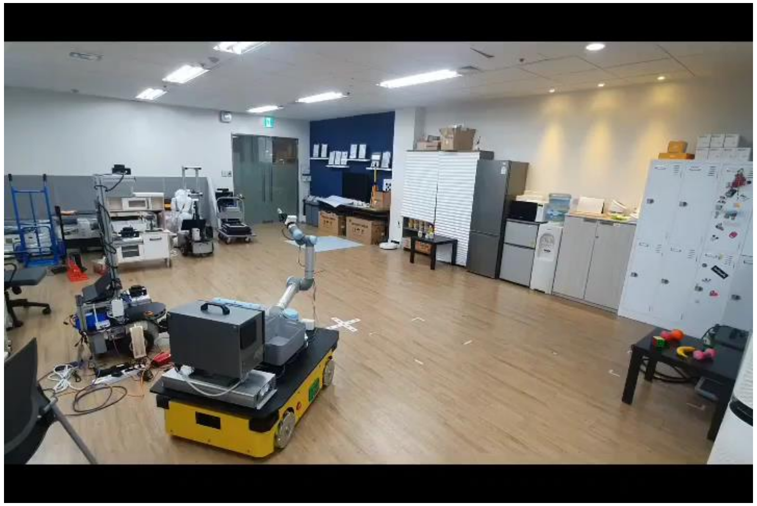
$$\boldsymbol{u}_t^{new} = \frac{\sum_i w_t^i \boldsymbol{u}_t^i}{\sum_i w_t^i}$$



Conceptual Diagram of FEP-based Robot Learning/Control







Additional Information-Theoretic Principles

- **Complexity-Information Theory (Suh, Lee and Cho – Motion Significance/Complexity)**
  - **언제, 어디에 집중(Attention)해야 하는가?**

- **Empowerment Theory**
  - **Maximum information-channel capacity**

COGAPLEX

(2017년 8월~)

COGAPLEX
advancing mobility through AI

COGnition + A

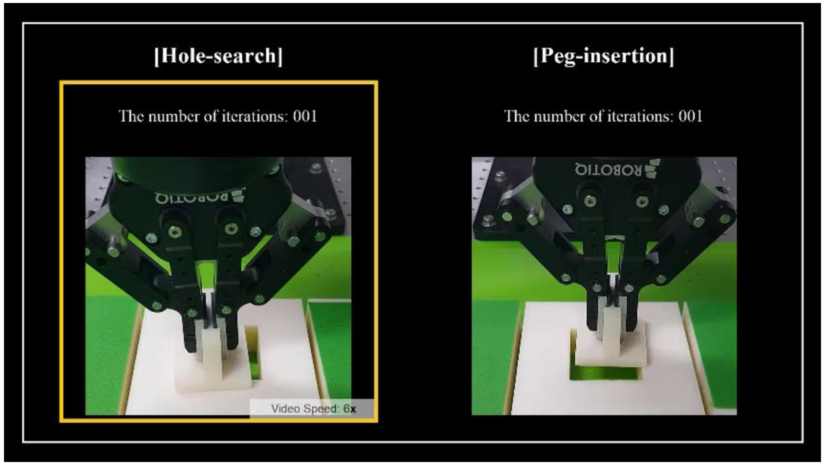
= Key to open comPLEX world

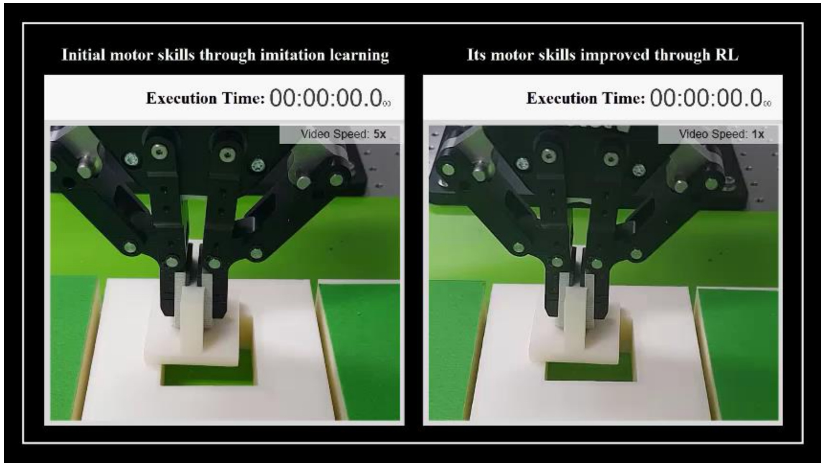
Robot Manipulation

Robot Navigation

AI-Manipulation Examples:

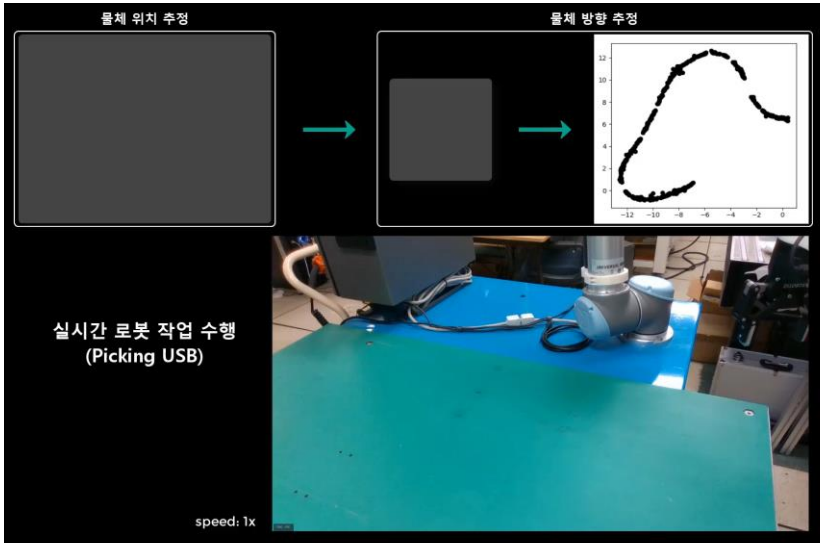
- **Imitation Learning and Reinforcement Learning in Fitting Task**

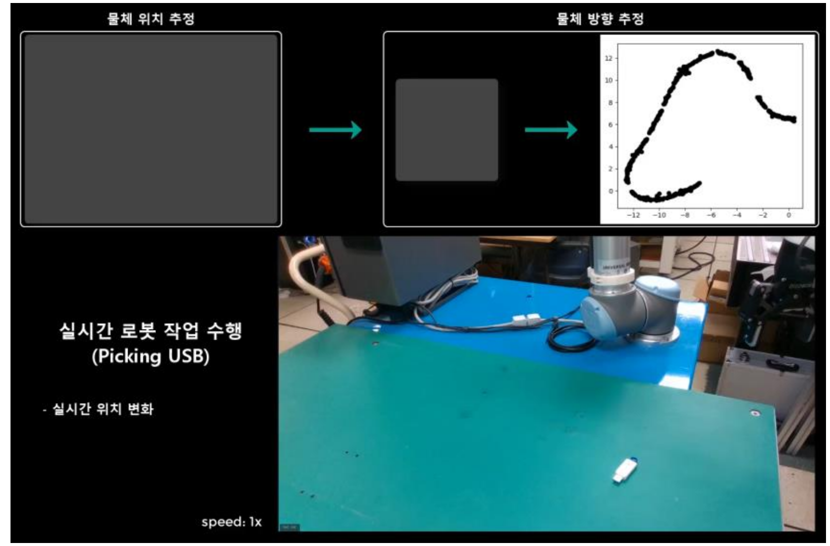


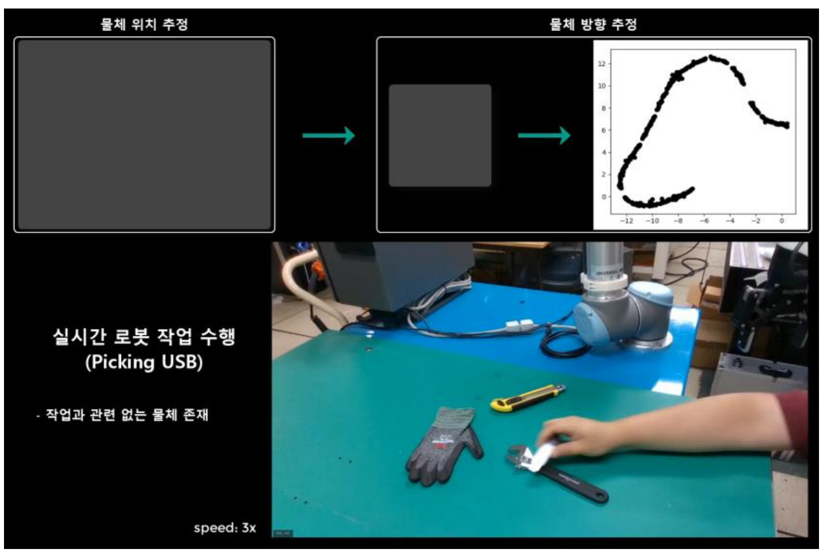


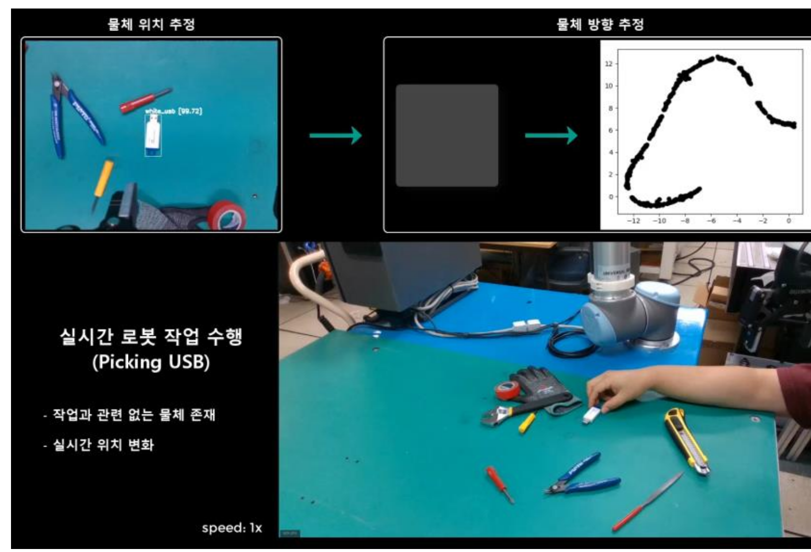
- **Assembly sequence: Set-top box – Power Cable – HDMI Cable**

학습된 Embedding space 를 이용한 USB 파지 (위치/방향의 변화 고려)

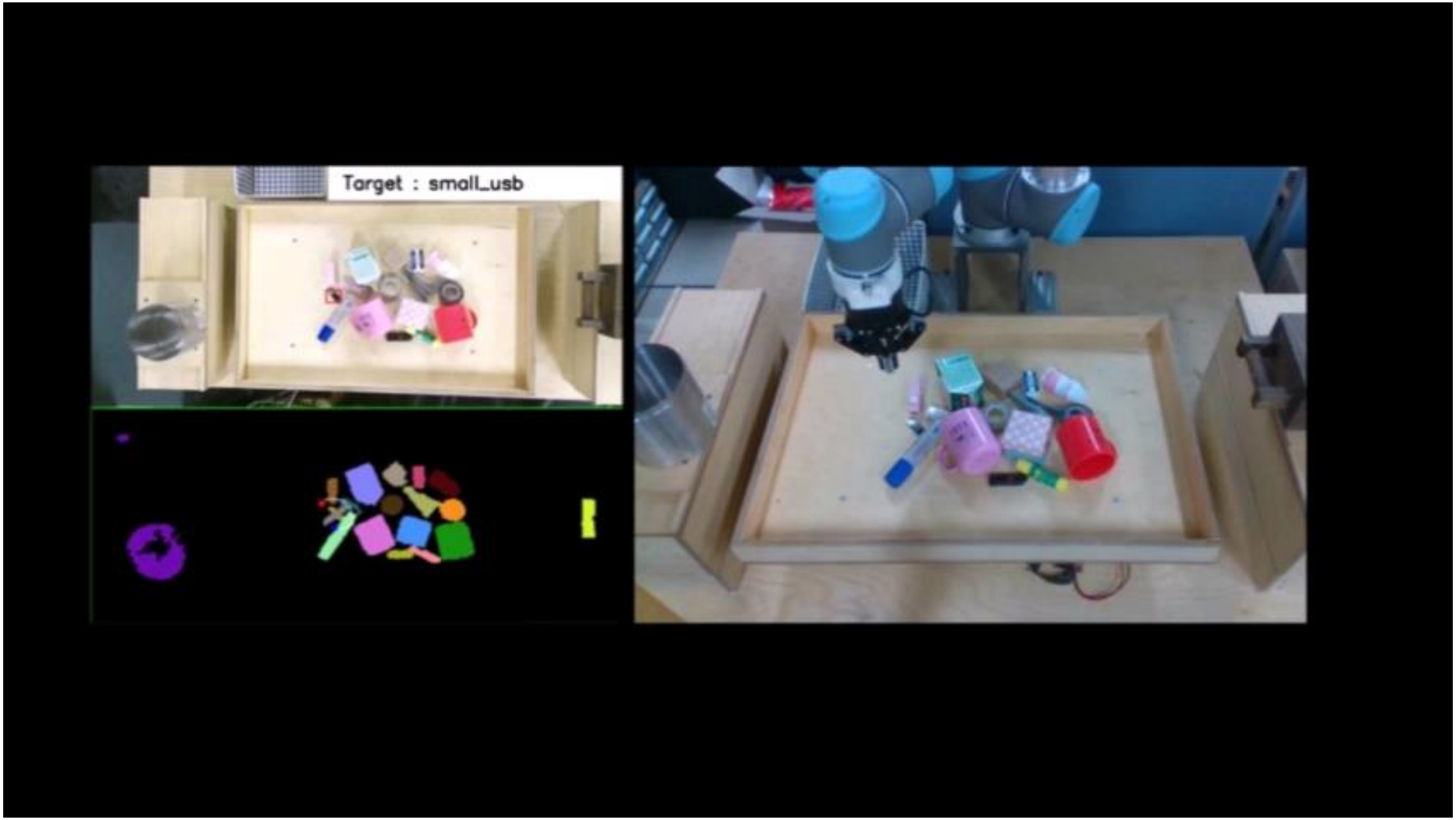






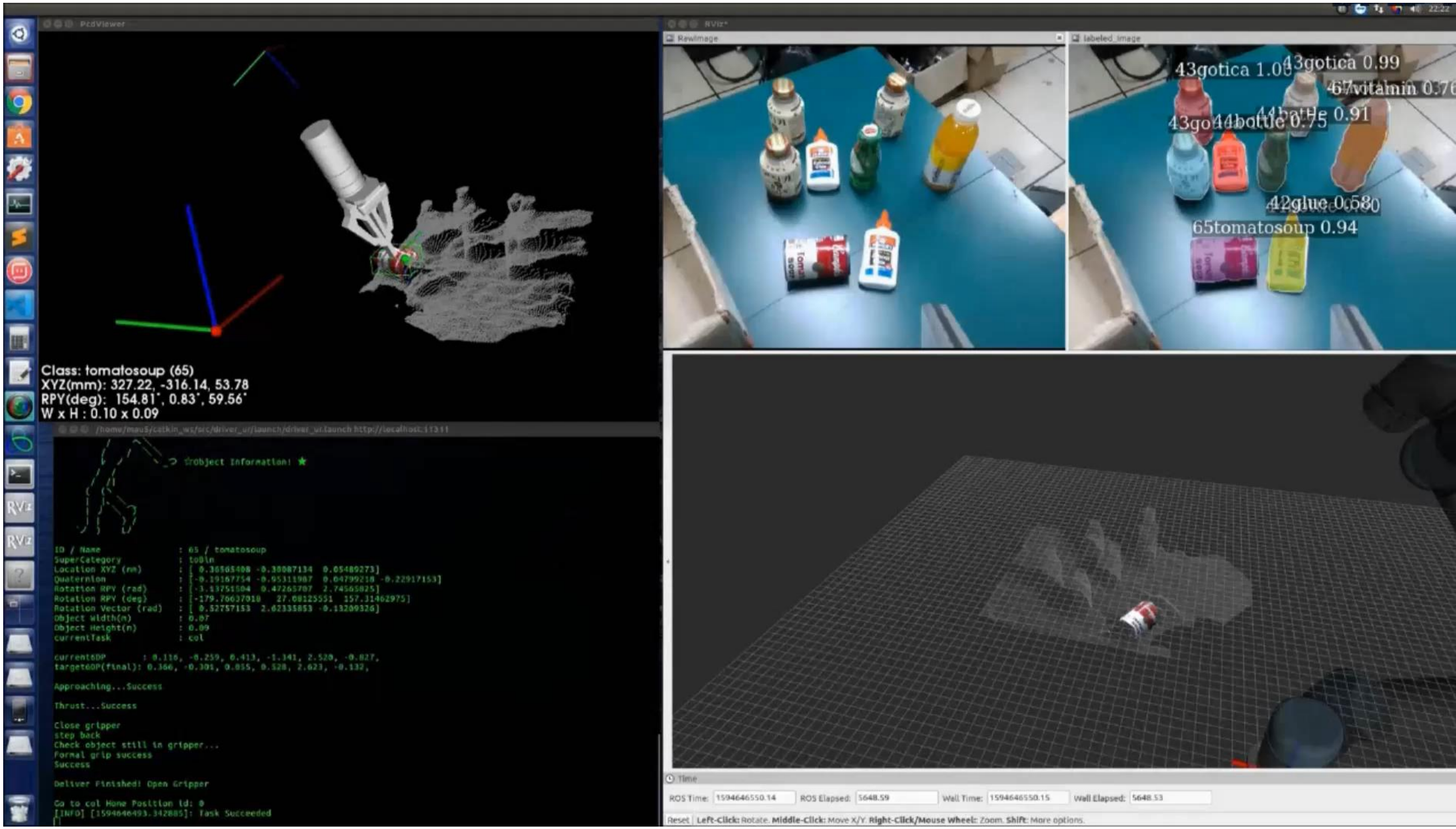


Piece-Picking(In Cluttered Environment)(2D)

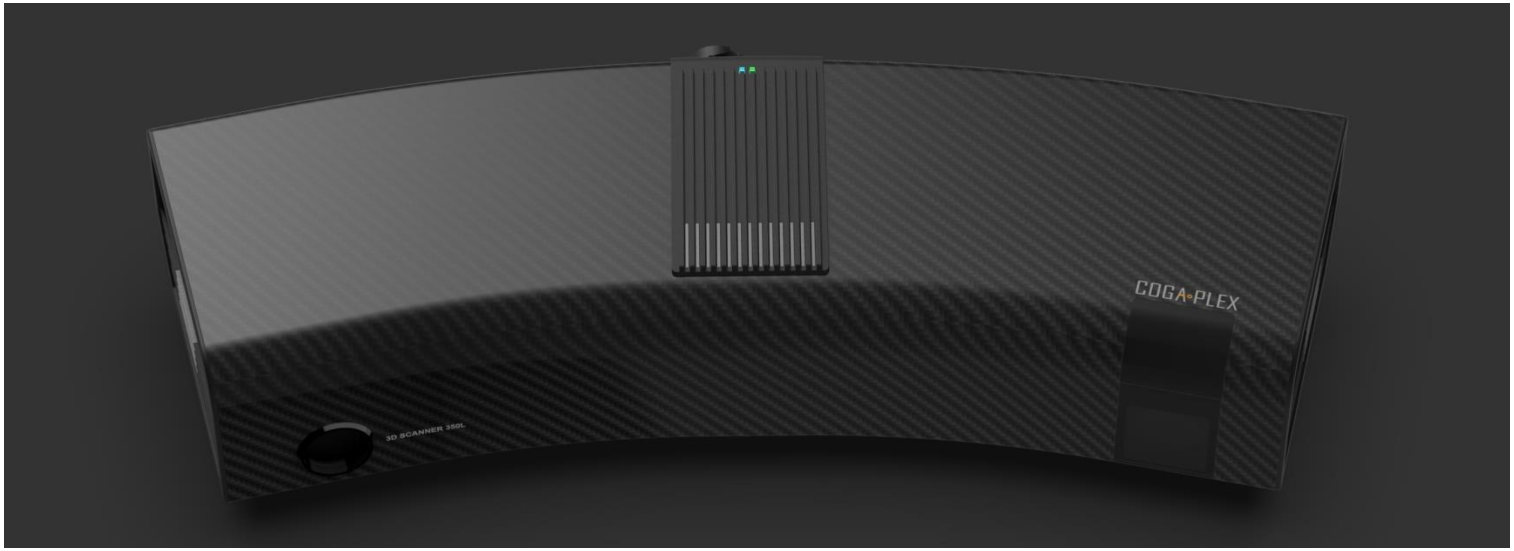


Piece-Picking(3D)

X4



3D Perception

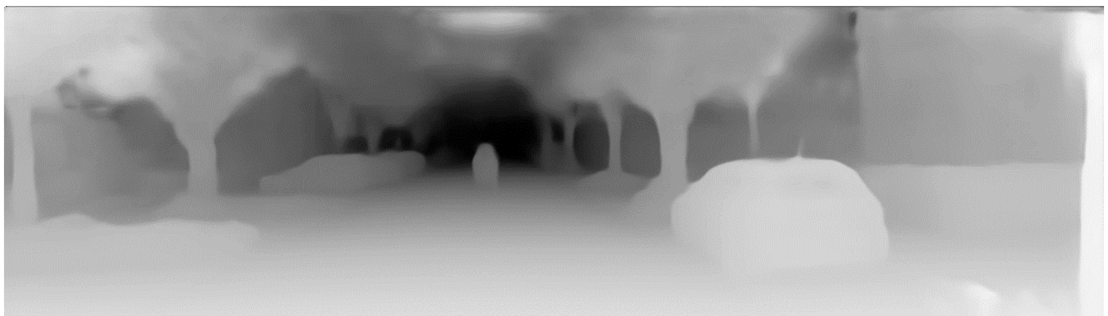


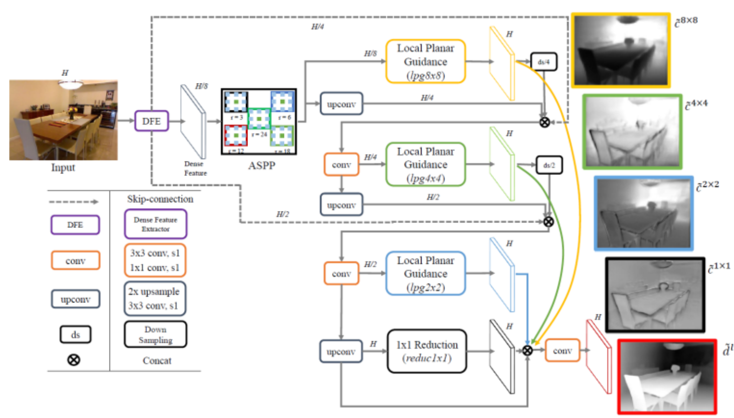
RoBoEYE CoPicK-3D Vision

3D scanning

자동차 조립 공정 (글라스 장착) X2

3D Perception: Monocular Depth Estimation





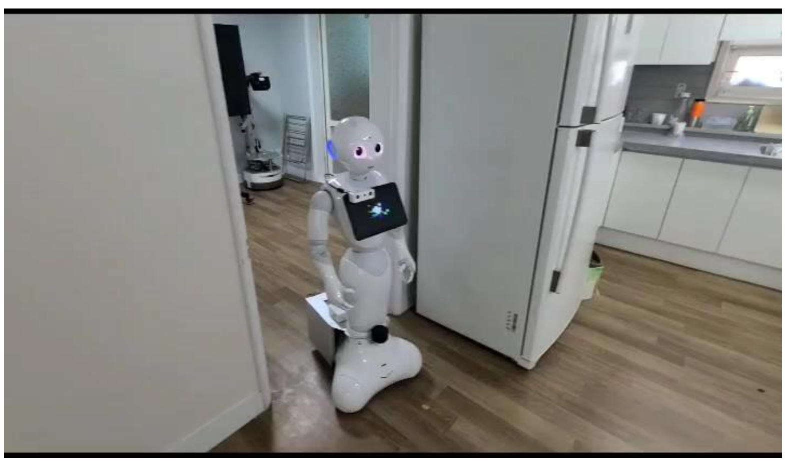
	Method	Setting	Code	SILog	sqErrorRel	absErrorRel	iRMSE	Runtime	Environment	Compare
1	BTS		code	11.67	2.21	9.04	12.23	0.1 s	GPU @ 2.5 Ghz (Python + C/C++)	
	J. Lee, M. Han, D. Ko and I. Suh: From Big to Small: Multi-Scale Local Planar Guidance for Monocular Depth Estimation. arXiv:1907.10326 2019.									
2	DL_61 (DORN)		code	11.77	2.23	8.78	12.98	0.5 s	GPU @ 2.5 Ghz (Python + C/C++)	
	H. Fu, M. Gong, C. Wang, K. Batmanghelich and D. Tao: Deep Ordinal Regression Network for Monocular Depth Estimation. IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2018.									
3	DL_SORD_SL			12.39	2.49	10.10	13.48	0.8 s	GPU @ 2.5 Ghz (Python + C/C++)	
	R. Diaz and A. Marathe: Soft Labels for Ordinal Regression. The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2019.									
4	BTS-256			12.47	2.70	9.92	13.42	0.1 s	GPU @ 2.5 Ghz (Python + C/C++)	
5	VNL		code	12.65	2.46	10.15	13.02	0.5 s	1 core @ 2.5 Ghz (C/C++)	
	Y. Wei, Y. Liu, C. Shen and Y. Yan: Enforcing geometric constraints of virtual normal for depth prediction. 2019.									
6	DS-SIDENet_ROB			12.86	2.87	10.03	14.40	0.35 s	GPU @ 2.5 Ghz (Python)	
	H. Ren, M. El-Khamy and J. Lee: Deep Robust Single Image Depth Estimation Neural Network Using Scene Understanding. IEEE Conference on Computer Vision and Pattern Recognition Workshop (CVPRW) 2019.									
7	DL_SORD_SQ			13.00	2.95	10.38	13.78	0.88 s	GPU @ 2.5 Ghz (Python + C/C++)	
	R. Diaz and A. Marathe: Soft Labels for Ordinal Regression. The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2019.									
8	PAP			13.08	2.72	10.27	13.95	0.18 s	GPU @ 2.5 Ghz (Python + C/C++)	
	Z. Zhang, Z. Cui, C. Xu, Y. Yan, N. Sebe and J. Yang: Pattern-Affinitive Propagation Across Depth, Surface Normal and Semantic Segmentation. The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2019.									
9	GN-NET			13.35	2.88	10.22	13.61	0.12 s	1 core @ 1.5 Ghz (Python)	
10	VGG16-UNet			13.41	2.86	10.60	15.06	0.16 s	GPU @ 2.5 Ghz (Python + C/C++)	
	X. Guo, H. Li, S. Yi, J. Ren and X. Wang: Learning monocular depth by distilling cross-domain stereo networks. Proceedings of the European Conference on Computer Vision (ECCV) 2018.									
11	AcED			13.45	3.63	10.61	13.94	0.5 s	GPU @ 2.5 Ghz (Python)	
12	DORN_ROB			13.53	3.06	10.35	15.96	2 s	GPU @ 2.5 Ghz (Python)	
	H. Fu, M. Gong, C. Wang, K. Batmanghelich and D. Tao: Deep Ordinal Regression Network for Monocular Depth Estimation. IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2018.									
13	MonoS		code	14.04	3.26	11.01	15.57	0.1 s	1 core @ 2.5 Ghz (Python)	
14	BMMNet			14.37	5.10	10.92	15.51	0.074 s	GPU @ 2.0 Ghz (Python + C/C++)	
15	CARN			14.44	3.63	13.33	17.75	0.1 s	GPU @ 2.5 Ghz (Python)	

Depth Estimation Network

KITTI Benchmark Depth Prediction

AI-Navigation Examples:

서빙고



Pepper Service Robot

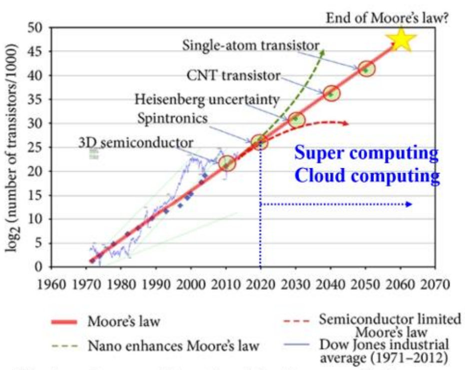
Logistic Robot

맺음말

Human Brain-Level AI is still missing.
Human Brain-Level AI-Robot is still missing.

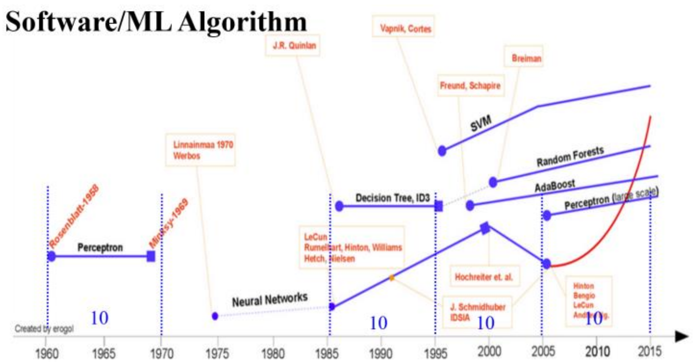
뇌 정보 이론 기반 반도체	뇌 정보 이론 기반 ML	뇌 정보 이론 기반 Smart Actuator

Computing power



Rate of growth : double / every 1.5 years

Software/ML Algorithm



Rate of growth : breakthrough / 10 years

Artificial body(sensor/actuator)

- **Rate of growth :** double / 10 years
- **Soft Robotics**

In 2045

- **Computing power:** 1,000,000 times growth
- **Software/ML Algorithm:** Over 3 breakthroughs
- **Artificial body(sensor/actuator):** 10 times growth