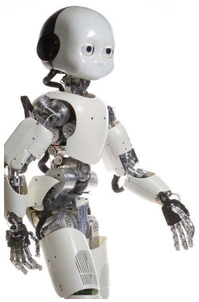
Motor skills and robots

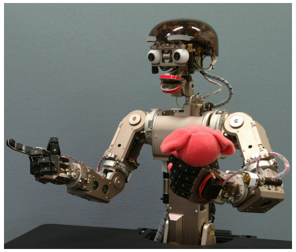
- Two basic set of skills ?
  - 3 m roll, 6 m sit-up, 8 m crawl, 1 y walk.. predictable
  - Family
- Child-size robots: Rich spectrum of physical behaviors, skill acquisition
- Use of humanoid robots, philosophy is different

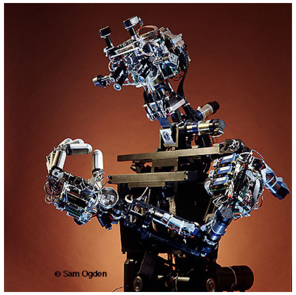


Humanoid robots used in DevRob







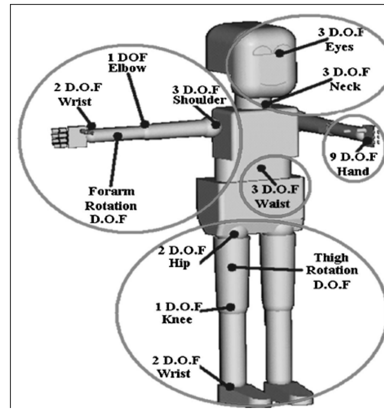





	Manufacturer	DOFs	Actuator type	Actuators position	Soft sensitive skin	Human-like appearance	Child size	Height/ weight	History (Model)	Main research references
iCub	IIT (Italy)	53	Electric	Whole-body	Yes	No	Yes	105 cm 22 kg	2008	Metta et al., 2008 Parmiggiani et al., 2012
NAO	Aldebaran (France)	25	Electric	Whole-body	No	No	Yes	58 cm 4.8 kg	2005 (AL-01) 2009 (Academic)	Gouaillier et al. 2008
ASIMO	Honda (Japan)	57	Electric	Whole-body	No	No	Yes	130 cm 48 kg	2011 (All New ASIMO)	Sakagami et al., 2002 Hirose & Ogawa, 2007
QRIO	Sony (Japan)	38	Electric	Whole body	No	No	Yes	58 cm 7.3 kg	2003 (SDR-4X-II)	Kuroki et al., 2003
CB	SARCOS (USA)	50	Hydraulic	Whole body	No	No	No	157 cm 92 kg	2006	Cheng et al., 2007b
CB^2	JST ERATO (Japan)	56	Pneumatic	Whole body	Yes	Yes	Yes	130 cm 33 kg	2007	Minato et al., 2007
Pneuborn-13 (Pneuborn-7II)	JST ERATO (Japan)	21	Pneumatic	Whole body	No	No	Yes	75 cm 3.9 kg	2009	Narioka et al., 2009
Repliee R1 (Geminoid)	ATR, Osaka, Kokoro (Japan)	9 (50)	Electric (Pneumatic)	Head (upper body)	No (Yes)	Yes (Yes)	Yes (No)	(150 cm)	2004 (2007)	Minato et al., 2004 (Sakamoto et al., 2007)
Infanoid	NICT (Japan)	29	Electric	Upper body	No	No	Yes		2001	Kozima, 2002
Affetto	Osaka (Japan)	31	Pneumatic and electric	Upper body	No	Yes	Yes	43 cm 3 kg	2011	Ishihara et al., 2011
KASPAR	Hertfordshire (UK)	17	Electric	Upper body	No	Yes	Yes	50 cm 15 kg	2008	Dautenhahn et al., 2009
COG	MIT (USA)	21	Electric	Upper body	No	No	No		1999	Brooks et al., 1999

iCub

- Open-source
- IIT – robotcup.org
- 3.5 y: 105 cm tall, 22 kg
- 53 dof, hands and upper torso
- Tendon-driven hand actuators
- 2 cameras, 1 microphone
- 3 gyroscopes, 3 accelerometers, compass
- 4 force/torque sensors
- Tactile:
  - Palm and fingertip
  - Distributed sensorized skin
- Position encoders
- YARP middleware

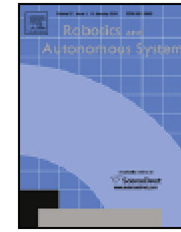


Robotics and Autonomous Systems 59 (2011) 580–595

Contents lists available at ScienceDirect

Robotics and Autonomous Systems

journal homepage: www.elsevier.com/locate/robot



Goal emulation and planning in perceptual space using learned affordances

Emre Ugur[a,b,c,*], Erhan Oztop[a,b,d], Erol Sahin[c]

[a] *NICT, Biological ICT Group, Kyoto, Japan*

[b] *ATR, Cognitive Mechanisms Labs., Kyoto, Japan*

[c] *Middle East Technical University, Department of Computer Engineering, KOVAN Research Lab., Ankara, Turkey*

[d] *Osaka University, School of Engineering Science, Osaka, Japan*

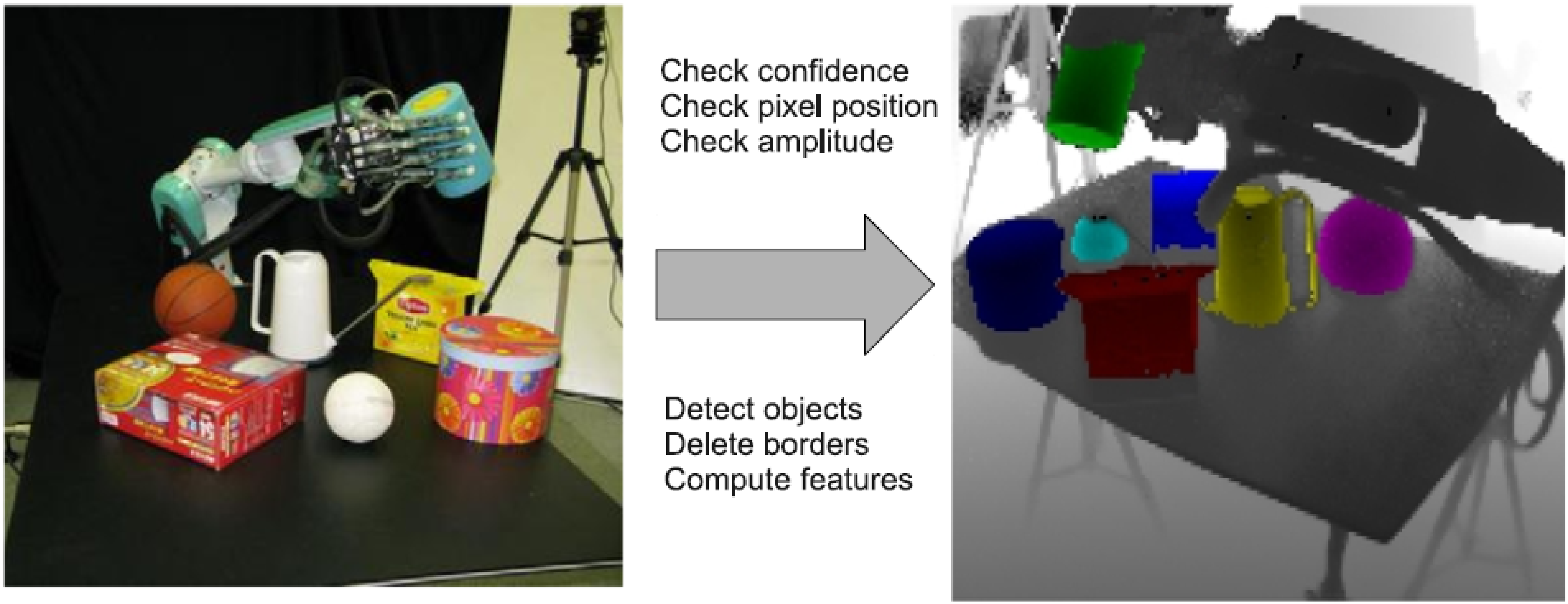
ARTICLE INFO

Article history:
Received 13 August 2010
Received in revised form
24 January 2011
Accepted 9 April 2011
Available online 17 April 2011

Keywords:
Affordance
Developmental robotics
Sensorimotor learning
Manipulation
Perception
Cognitive robotics

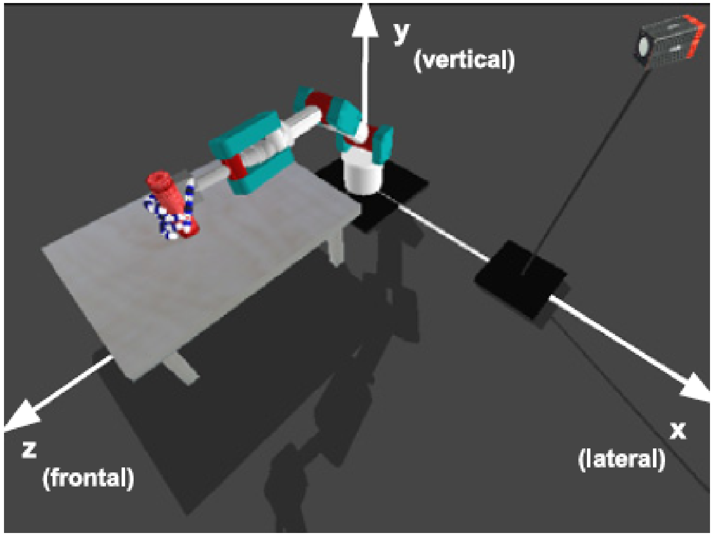
ABSTRACT

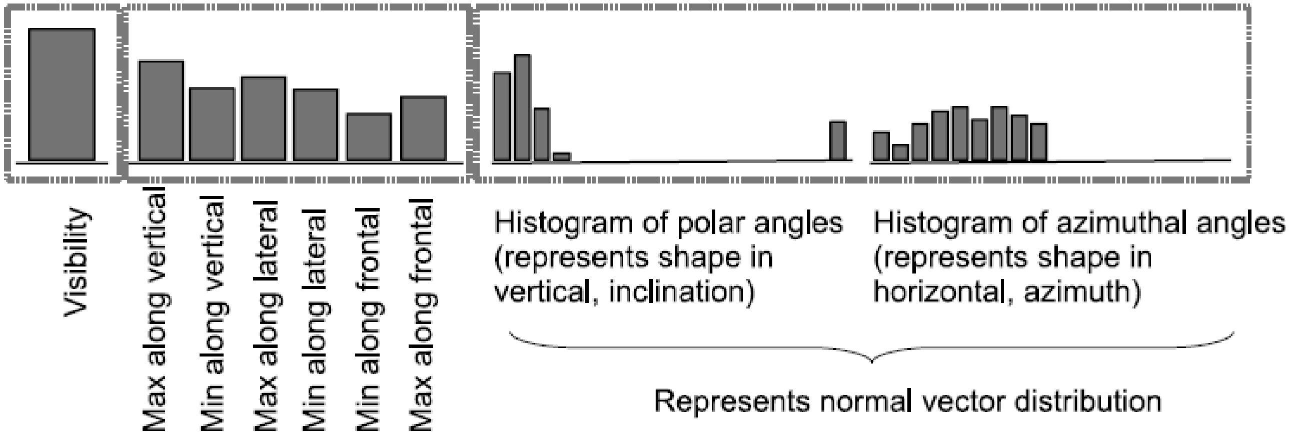
In this paper, we show that through self-interaction and self-observation, an anthropomorphic robot equipped with a range camera can learn object affordances and use this knowledge for planning. In the first step of learning, the robot discovers commonalities in its action-effect experiences by discovering effect categories. Once the effect categories are discovered, in the second step, affordance predictors for each behavior are obtained by learning the mapping from the object features to the effect categories. After learning, the robot can make plans to achieve desired goals, emulate end states of demonstrated actions, monitor the plan execution and take corrective actions using the perceptual structures employed or discovered during learning. We argue that the learning system proposed shares crucial elements with the development of infants of 7–10 months age, who explore the environment and learn the dynamics of the objects through goal-free exploration. In addition, we discuss goal emulation and planning in relation to older infants with no symbolic inference capability and non-linguistic animals which utilize object affordances to make action plans.



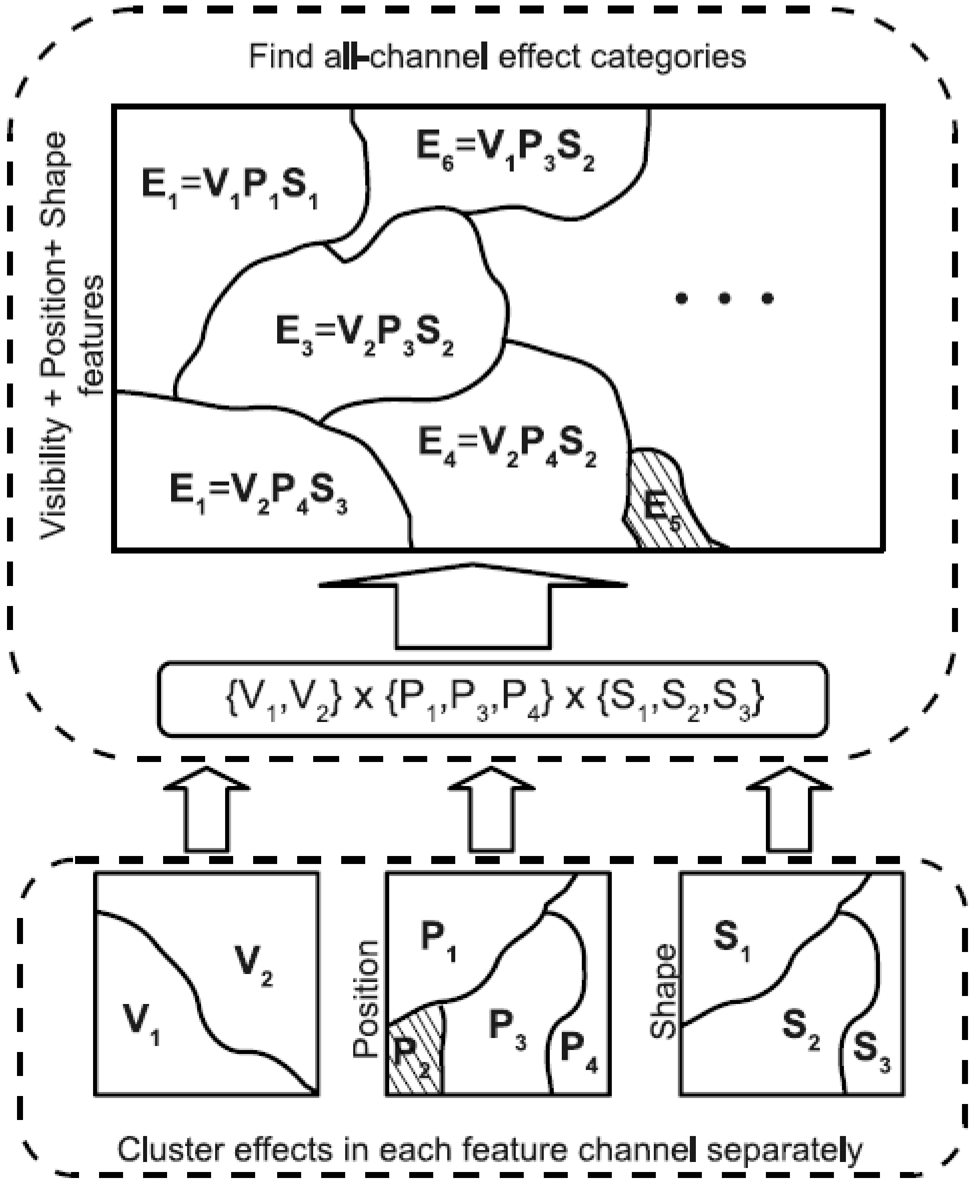
(a) Photograph of setup

(b) Range image

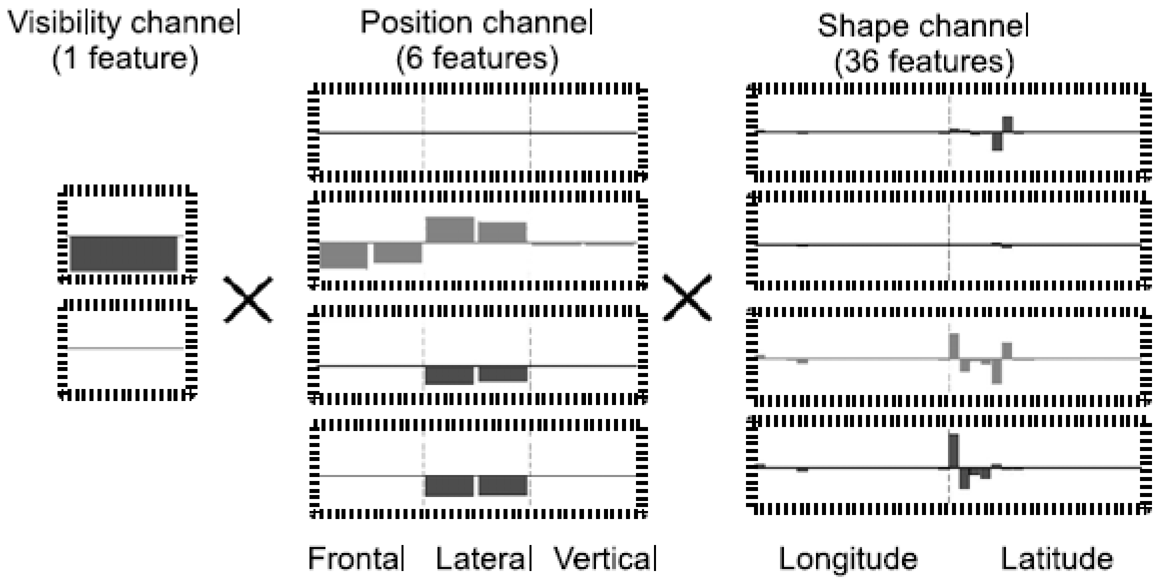

y
(vertical)
z
(frontal)
x
(lateral)


Visibility
Max along vertical
Min along vertical
Max along lateral
Min along lateral
Min along frontal
Max along frontal
Histogram of polar angles (represents shape in vertical, inclination)
Histogram of azimuthal angles (represents shape in horizontal, azimuth)
Represents normal vector distribution

$$\boldsymbol{f}_{effect,o_i}^{(b_j)} = \boldsymbol{f}_{o_i}^{(b_j)} - \boldsymbol{f}_{o_i}^{()}$$



Find all-channel effect categories
Visibility + Position+ Shape features
$E_1=V_1P_1S_1$
$E_6=V_1P_3S_2$
$E_3=V_2P_3S_2$
. . .
$E_4=V_2P_4S_2$
$E_1=V_2P_4S_3$
E_5
$\{V_1,V_2\} \times \{P_1,P_3,P_4\} \times \{S_1,S_2,S_3\}$
V_1
V_2
Position
P_1
P_2
P_3
P_4
Shape
S_1
S_2
S_3
Cluster effects in each feature channel separately


Visibility channel
(1 feature)
Position channel
(6 features)
Shape channel
(36 features)
Frontal
Lateral
Vertical
Longitude
Latitude

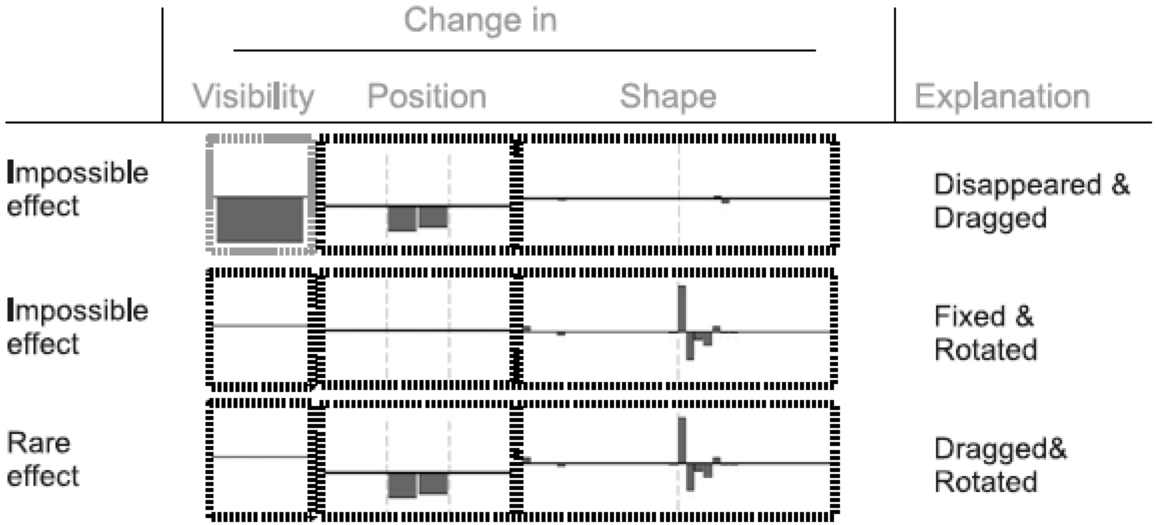
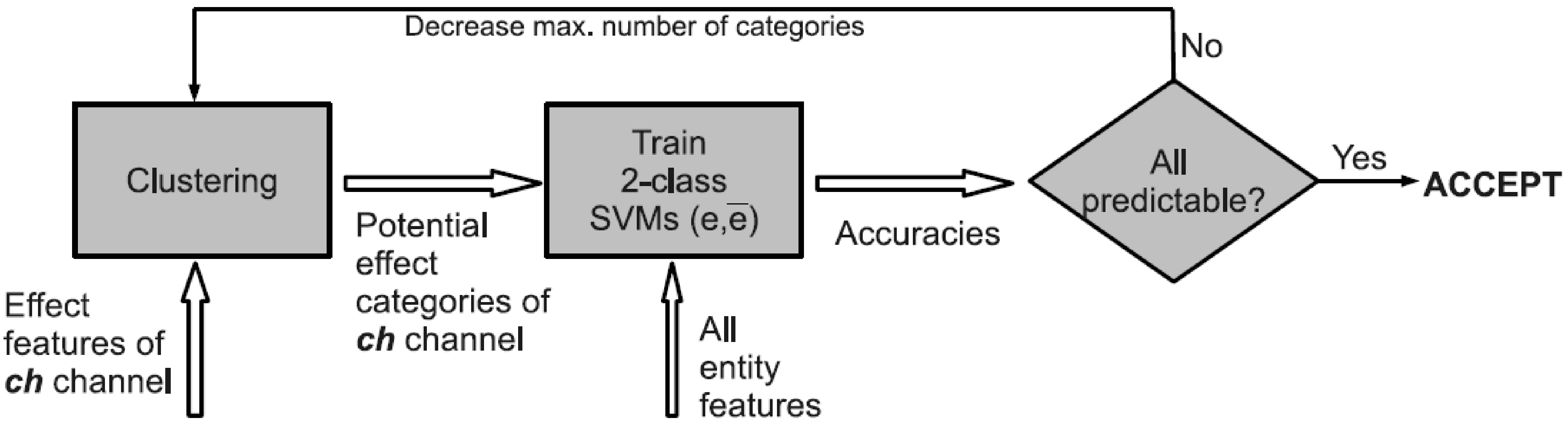
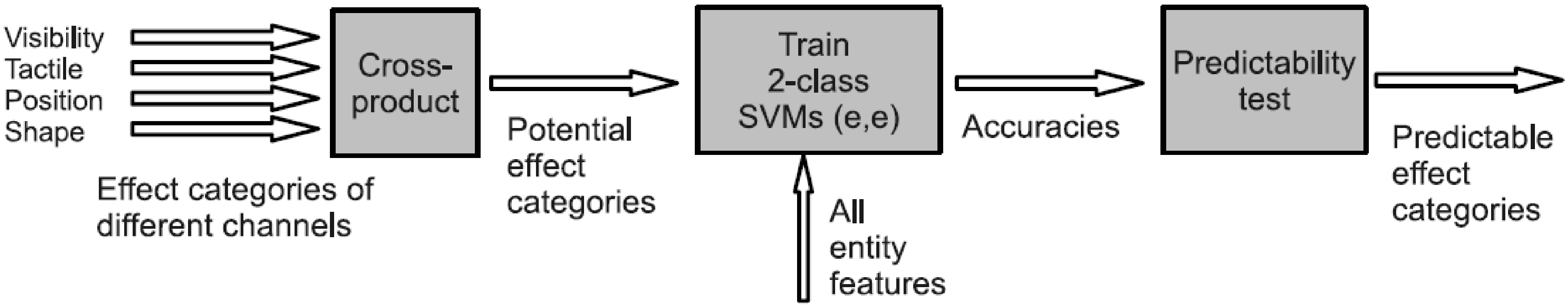


Fig. 5. Impossible or rare effect categories that are formed through Cartesian product of channel-specific categories for push-right behavior. Some of the categories can be created due to inaccuracies in simulator and some of them do occur very rarely.



(a) *Channel-specific effect category* discovery for each channel *ch* in the lower-level

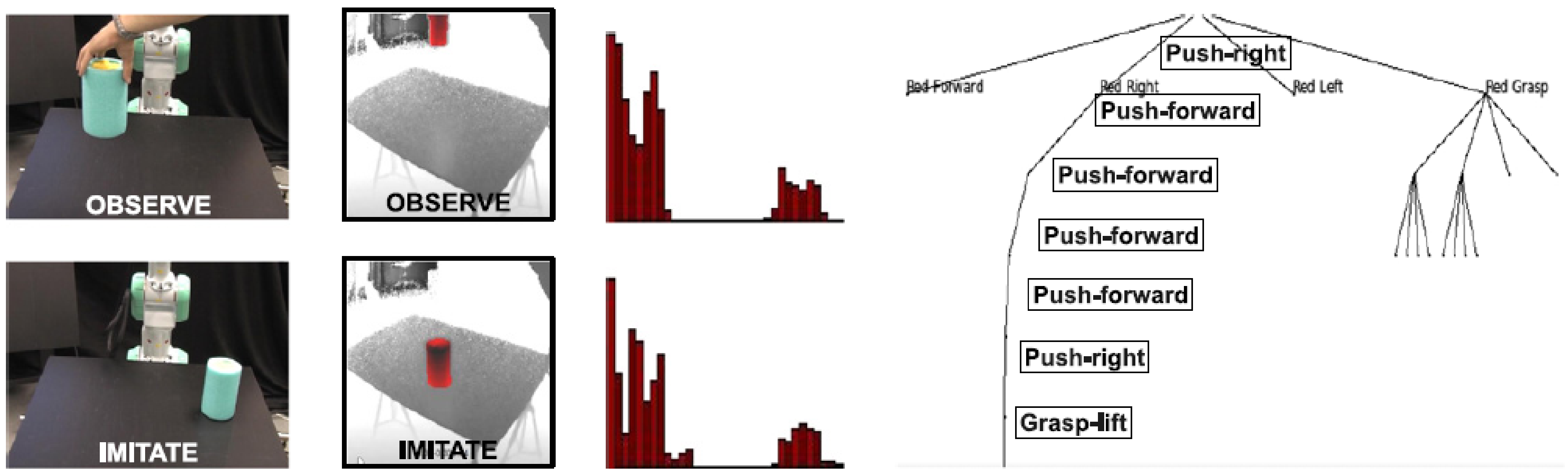


(b) *All-channel effect category discovery in the upper-level*

TABLE II

THE EFFECT CATEGORIES (CAT.) DISCOVERED BY 2-LEVEL CHANNEL-BASED CLUSTERING.

Channel	Cat.	Prototype vector	2-category accuracy	Predic-table?	Accep-ted?
Visibility	2 cat.	-1 0	90.6 % 90.6 %	√ √	√
Tactile	3 cat.	0.40 0.11 0.00	79.73 % 64.42 % 68.82 %	√ X X	X
	2 cat.	0.38 0.04	80.15 % 80.15 %	√ √	√
Position	3 cat.	[9, 2, 1] [0, 0, 0] [12,-4,12]	67.00 % 81.14 % 79.20 %	X √ √	X
	2 cat.	[2, 1, 0] [12,-3,12]	78.2 % 78.2 %	√ √	√
Shape	3 cat.	Large Large Small	73.47 % 69.77 % 71.27 %	X X X	X
	2 cat.	Large Small	70.5 % 70.5 %	X X	X
	1 cat.	NA.	NA.	√	√



(a) Snapshots. (b) Range images. (c) Features. (d) Search tree and generated final plan.

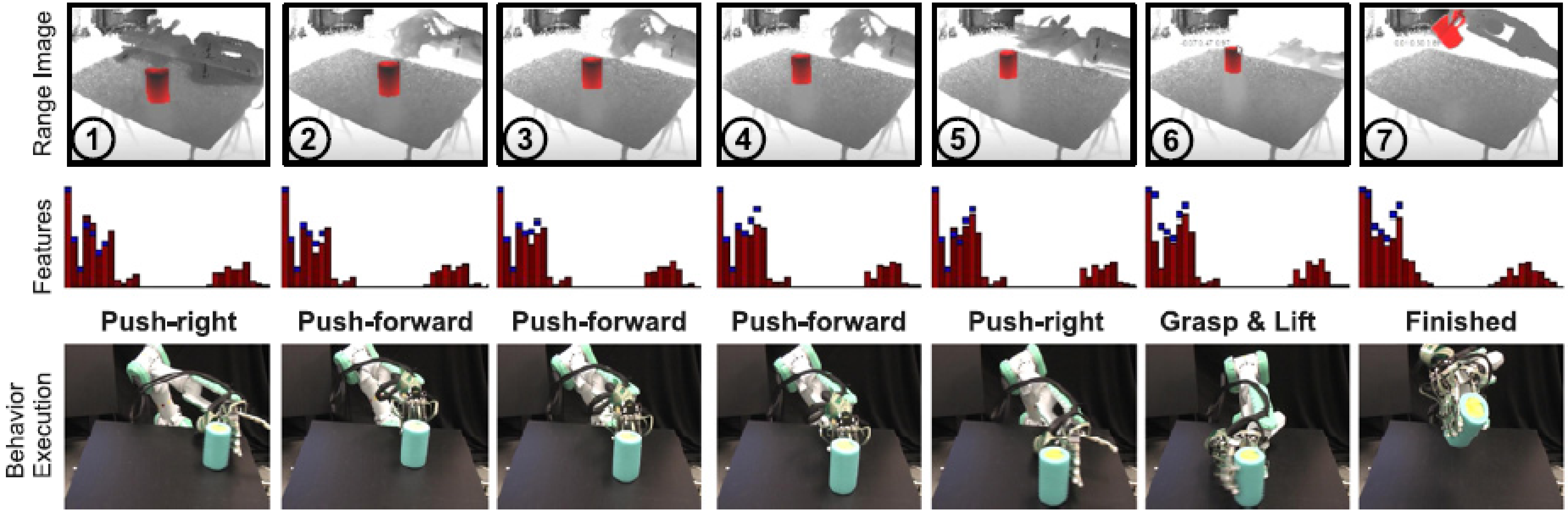


Fig. 13. The execution steps of a 7-step plan that was generated to bring the object to the observed position in Fig. 12(a) top.

- Find effect categories through clustering
- Initial feature → effect categories

Learning Object Affordances: From Sensory--Motor Coordination to Imitation

View Document

4
Author(s)

Luis Montesano ; Manuel Lopes ; Alexandre Bernardino ; JosÉ Santos-Victor

View All Authors

Abstract | Authors | Figures | References | Citations | Keywords | Metrics | Media

Abstract:
Affordances encode relationships between actions, objects, and effects. They play an important role on basic cognitive capabilities such as prediction and planning. We address the problem of learning affordances through the interaction of a robot with the environment, a key step to understand the world properties and develop social skills. We present a general model for learning object affordances using Bayesian networks integrated within a general developmental architecture for social robots. Since learning is based on a probabilistic model, the approach is able to deal with uncertainty, redundancy, and irrelevant information. We demonstrate successful learning in the real world by having an humanoid robot interacting with objects. We illustrate the benefits of the acquired knowledge in imitation games.

Published in: IEEE Transactions on Robotics (Volume: 24, Issue: 1, Feb. 2008)

Learning Object Affordances: From Sensory–Motor Coordination to Imitation

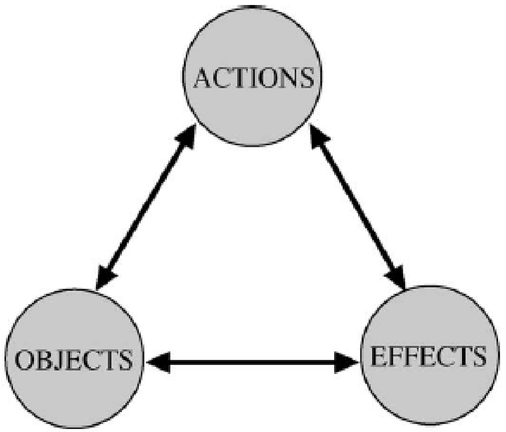
Luis Montesano, Manuel Lopes, Alexandre Bernardino, *Member, IEEE*, and José Santos-Victor, *Member, IEEE*

***Abstract*—Affordances encode relationships between actions, objects, and effects. They play an important role on basic cognitive capabilities such as prediction and planning. We address the problem of learning affordances through the interaction of a robot with the environment, a key step to understand the world properties and develop social skills. We present a general model for learning object affordances using Bayesian networks integrated within a general developmental architecture for social robots. Since learning is based on a probabilistic model, the approach is able to deal with uncertainty, redundancy, and irrelevant information. We demonstrate successful learning in the real world by having an humanoid robot interacting with objects. We illustrate the benefits of the acquired knowledge in imitation games.**

***Index Terms*—Affordances, biorobotics, cognitive robotics, humanoid robots, learning.**

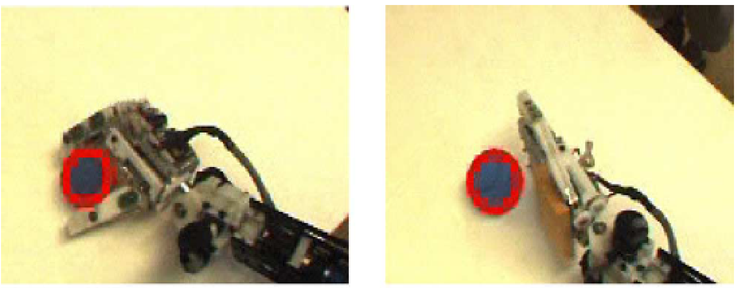
I. Introduction

HUMANS can solve many complex tasks on a routine basis, e.g., by selecting, amongst a vast repertoire, the actions to exert on an object to obtain a certain desired effect. A painter



inputs	outputs	function
(O, A)	E	Predict effect
(O, E)	A	Action recognition & planning
(A, E)	O	Object recognition & selection

Fig. 1. Affordances as relations between (A)ctions, (O)bjects, and (E)ffects that can be used to address different purposes: predict the outcome of an action, plan actions to achieve a goal, or recognize objects or actions.



(a) (b)

Fig. 2. Examples of actions as seen by the robot. (a) Grasping.(b) Tapping.

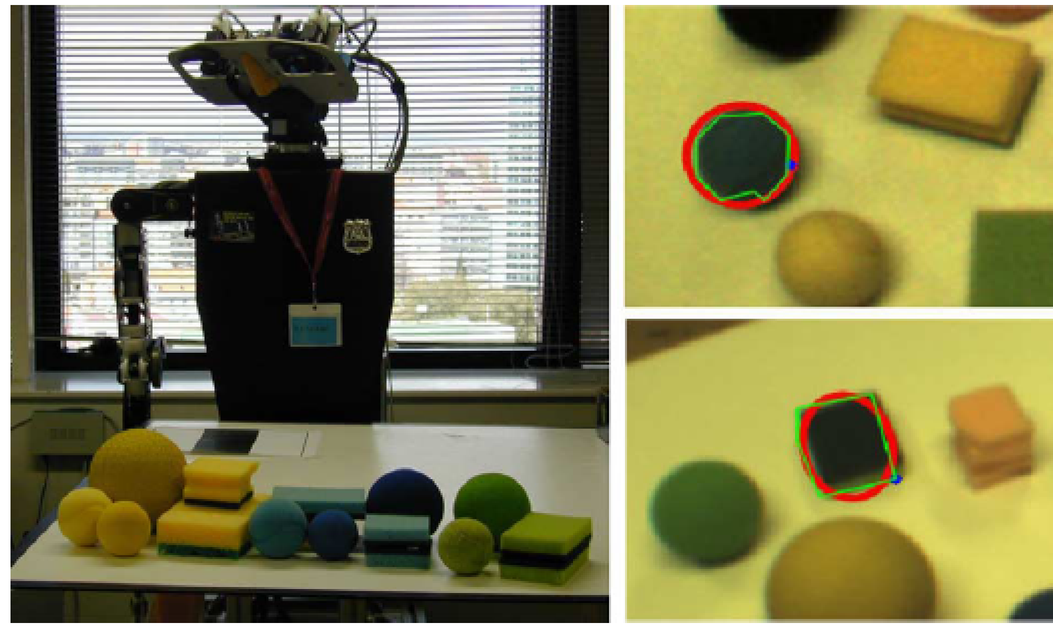
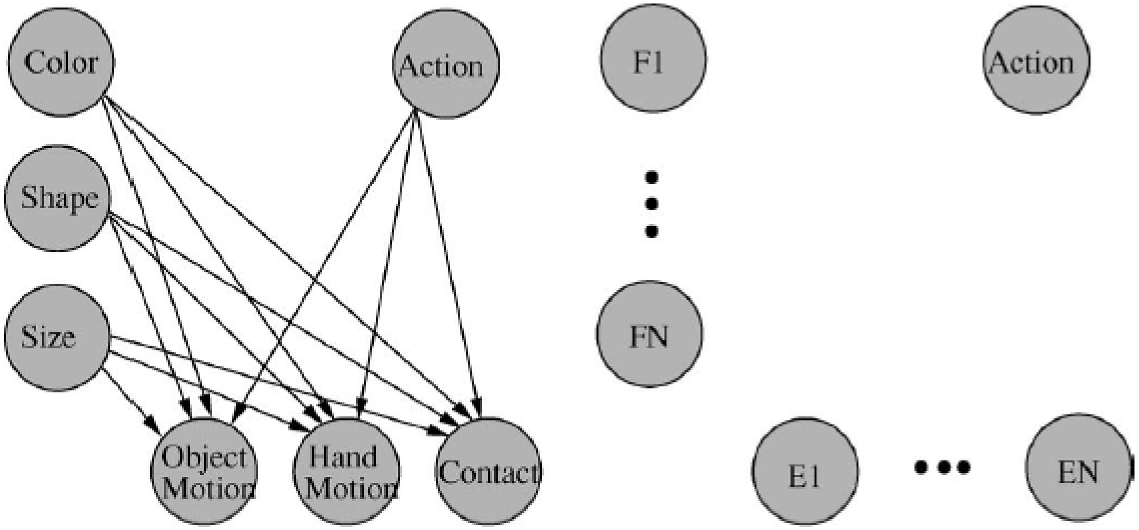


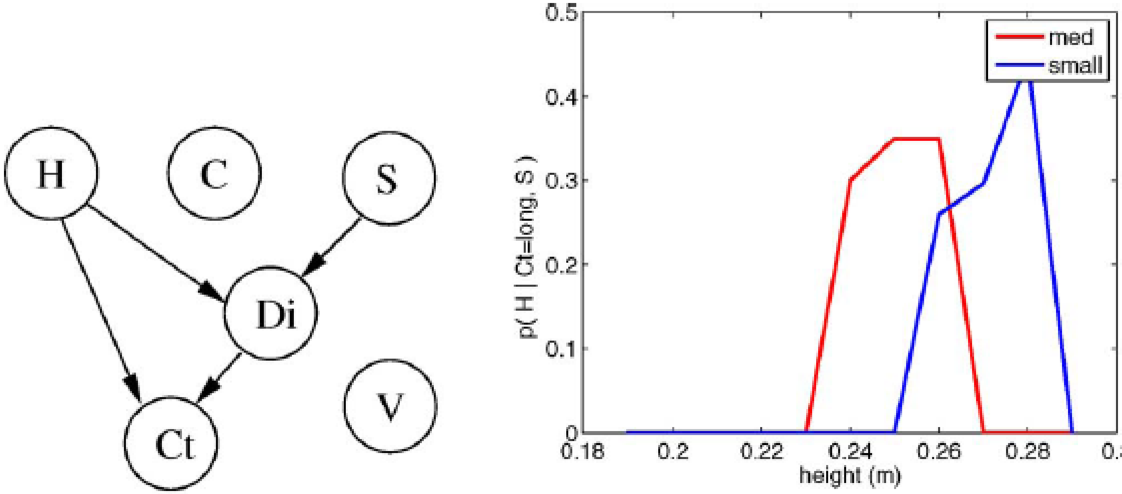
Fig. 3. Experimental setup. The Robot's workspace consists of a white table and some colored objects with different shapes (left). Objects on the table are represented and categorized according to their size, shape and color, e.g., the "ball" and "square" class (right).



(a) (b)

TABLE II
SUMMARY OF VARIABLES AND VALUES

Symbol	Description	Values
A	Action	*grasp, tap, touch*
H	Height	discretized in 10 values
C	Color	$green_1$, $green_2$, *yellow, blue*
Sh	Shape	*ball, box*
S	Size	*small, medium, big*
V	Object velocity	*small, medium, big*
HV	Hand velocity	*small, medium, big*
Di	Object-hand velocity	*small, medium, big*
Ct	Contact duration	*none, short, long*



(a) (b)

Fig. 7. Tuning the height for grasping a ball. (a) Dependencies discovered by the learning algorithm. The action and shape for this example are fixed and color does not have an impact on the effects. Node labels are shown in Table II. (b) CPD of height given the robot obtained a long contact (successful grasp).

What, when how to learn

Question: What is the best strategy to learn?

- Optimize learning to maximize reward? Optimize task-performance? Learn from mistakes?

Intrinsic Motivation (IM)

Homeostasis is the property of a system in which variables are regulated so that internal conditions remain stable and relatively constant.

IM behaviors have no clear goal, purpose or biological function; performed for their own sake.

- Serving the need of hunger (homoeostatic need) is considered extrinsic.

Advantages:

- Task-independent,
- Re-use of skills?
- IM is open-ended

Questions in IM: What to explore next?

- **Novel situations** that have not been experienced before.
- Situations that are **easy to learn**?
- Situations that **add a lot of information** to the world model?

Intrinsic Motivation (IM)

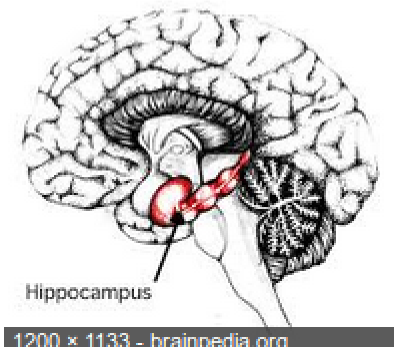
Knowledge based view (focus: properties of the environment)

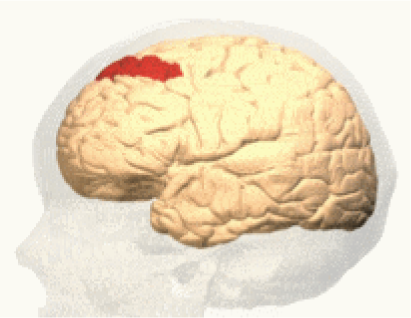
- detect novel or unexpected features, objects or events in the environment
- depends on current state of knowledge
- motivated to expand the knowledge base
- *Novelty-based IM:*
  - *Mismatch between experience and knowledge base*
  - *Low/moderate/high level of novelty, which one to go?*
- *Prediction-based IM*
  - *Explore unfamiliar "edges" of its knowledge base. Curiosity & surprise*
  - *Probe the environment, if does not behave as expected, explore more!*

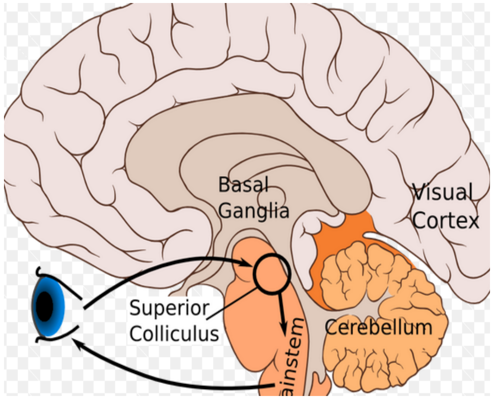
Competence based view (focus: self, abilities, skills it possess)

Intrinsic Motivation – Neural Bases

- Hippocampus
  - Novel experience → activates a recurrent pathway to VTA → release of dopamine for new memory traces in hippocampus.
    - Over repeated presentations → response diminishes → habituation
- Frontal Eye Field (FEF)
  - Activity is anticipatory
  - Increased activity when there is mismatch
- Superior colliculus (SC)
  - Short-term increase in dopamine
  - Detects ongoing actions unexpected consequences
  - Increase the repetition likelihood



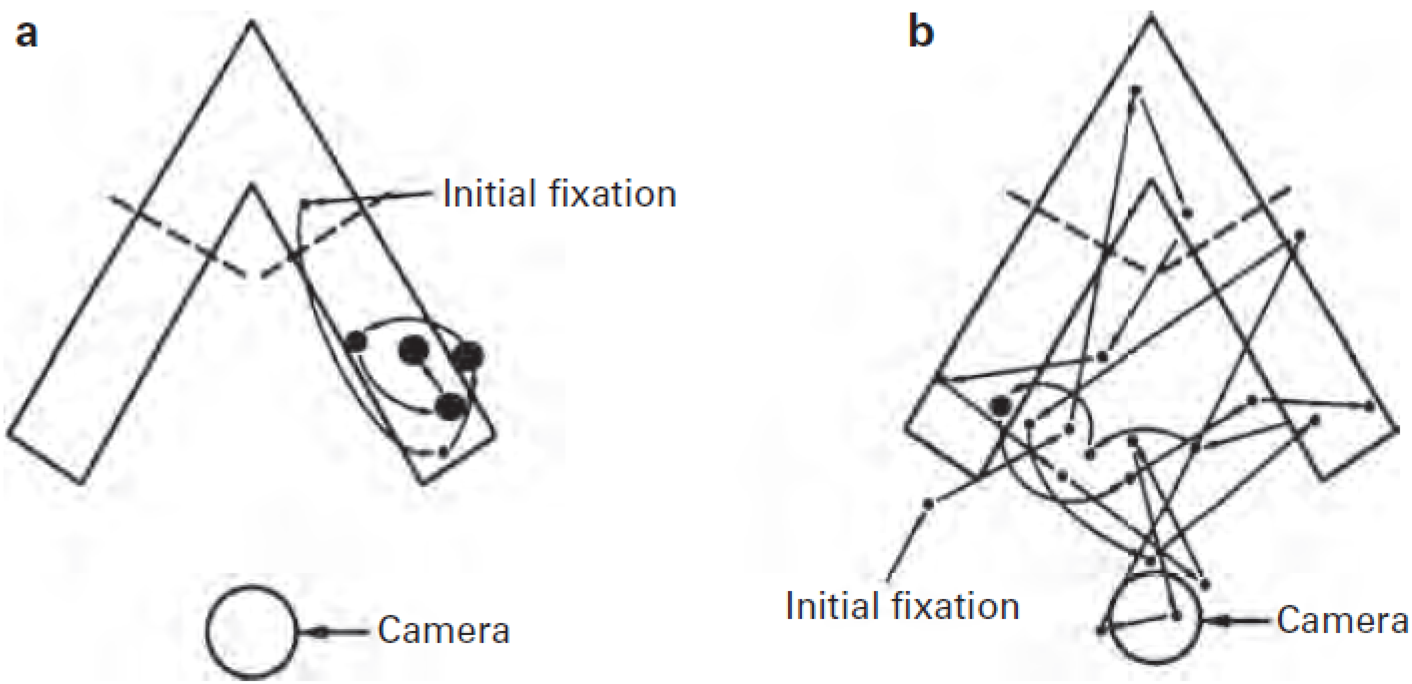




Neuron. 2005 Jun 2;46(5):703-13. The hippocampal-VTA loop: controlling the entry of information into long-term memory. Lisman JE(1), Grace AA.

Novelty in Infants, 1 - visual exploration

- Bronson, 1991
- 2 and 12 month olds
- 2 differences?
- Interpretation? Only attention to novel areas?
  - Related to both novelty and control of the eyes.



Novelty in Infants, 2 - novelty detection

- Habituation: the decrease in response to a stimulus as a result of repeated presentation
- How can you detect novelty with this?

- Habituation – dishabituation
- Present male faces repeatedly, infants habituate.
- Present female faces in the post-habituation phase.
- Significant increase in looking time: something novel!

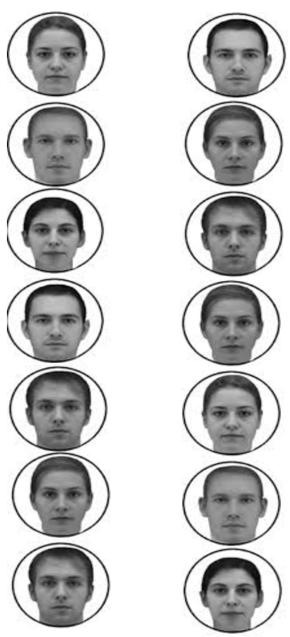
Review two paradigms to measure infant perception

- Preferential looking

(Fantz, 1956, infant looking chamber)

Trial #

1
2
3
4
5
6
7



- Habituation-dishabituation

Trial # (Habituation - dishabituation)

1
2
3
4
5

.

.

Trial # (Dishabutiation)

1
2
3

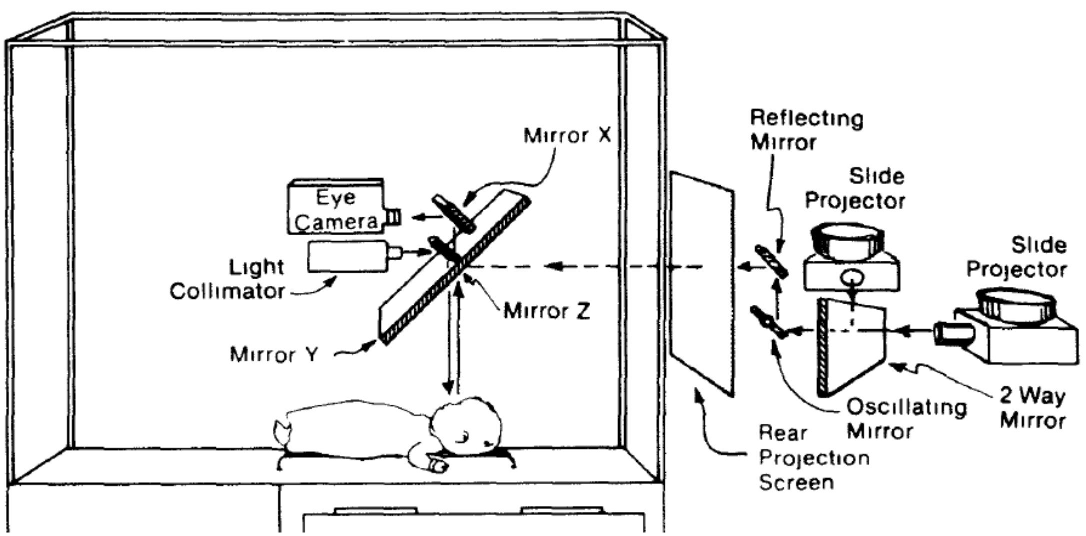
Novelty in Infants, 2 - novelty detection

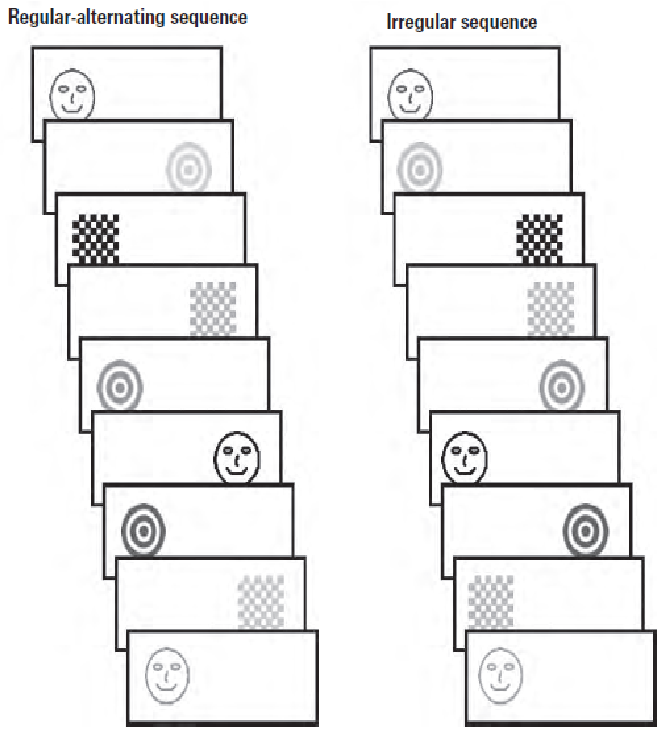
- Change in novelty preference in infants:
  - 0-2 months: prefer familiar objects
  - 3-6 months: shift toward novel objects
  - 6-12 months: robust performance for novel objects
- How to explain familiarity → novelty preference?
- Evgeny Sokolov, the stimulus-model comparator theory
  - Gradually create an internal model of the observed stimuli
  - Compare the stimulus with the model,
  - If match, then inhibit the response.
- Limited visual processing does not allow stable model construction

Intrinsic Motivation in Infants

Knowledge-based in Infants: Prediction

- In anticipation of an event → action based on outcome (e.g. gaze shift)
  - What actions?
- Studied with visual expectation paradigm (VexP)
- 2-month-olds learn to predict the upcoming locations of the images in regular patterns, cannot deal with complex patterns. But 3-month-olds





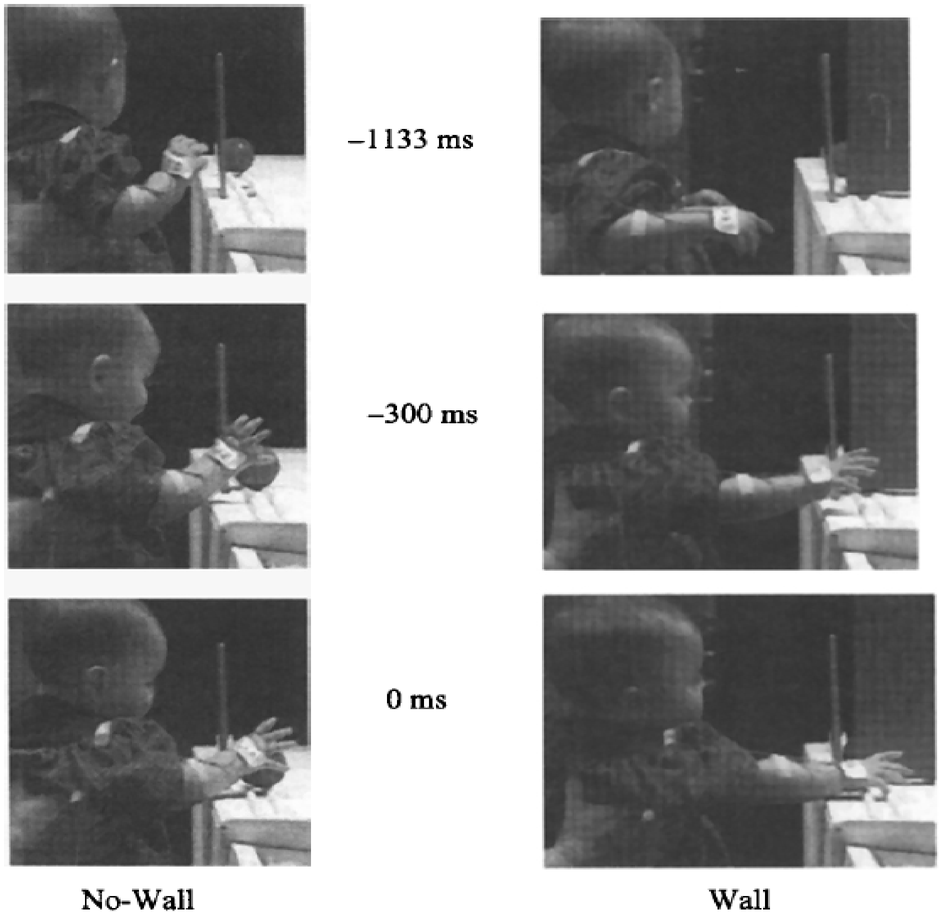
Haith, Marshall M., Cindy Hazan, and Gail S. Goodman. "Expectation and anticipation of dynamic visual events by 3.5-month-old babies." Child development (1988): 467-479.

Intrinsic Motivation in Infants

Knowledge-based in Infants: Prediction

- In anticipation of an event → action based on outcome (e.g. gaze shift)
  - What actions?
- Tracking a ball occluded on the way
- 3 months old: fail – narrow screen?
- 6 months old: succeed

- Screen + wall
- Track and reach



Berthier, Neil E., et al. "Using object knowledge in visual tracking and reaching." Infancy 2.2 (2001): 257-284.

Competence-based IM in Infants

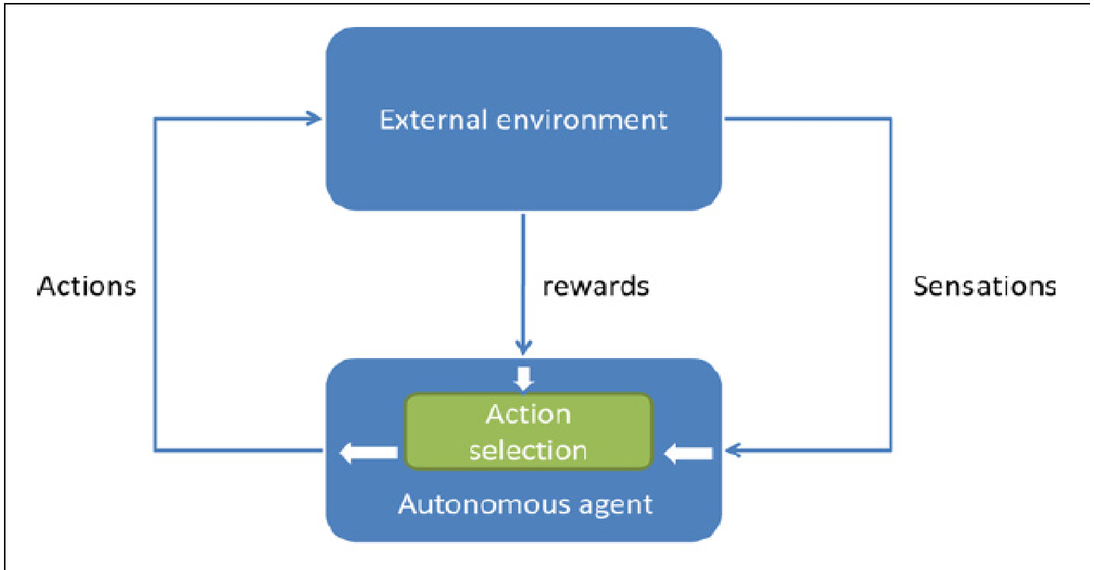
- Reminder: what was that?
- Early emerging component: self-efficacy
- How to study?
- Contingency perception method – baby in the crib
- Video display of self&other – e.g. leg
  - 3 months old – perfect match to self and then others – autism spectrum disorder
- Spontaneous play behavior

Age	Type of play	Example
0-2 years	Functional or sensorimotor	Gross activity: Running climbing, swinging kicking dropping objects
1-5 years	Constructive	Fine motor skills for building: Stacking blocks, connecting pieces of train rack
2-6 years	Pretend or symbolic	Cooking breakfast
6+ years	Rule-based	Checkers

IM-based robots in RL framework

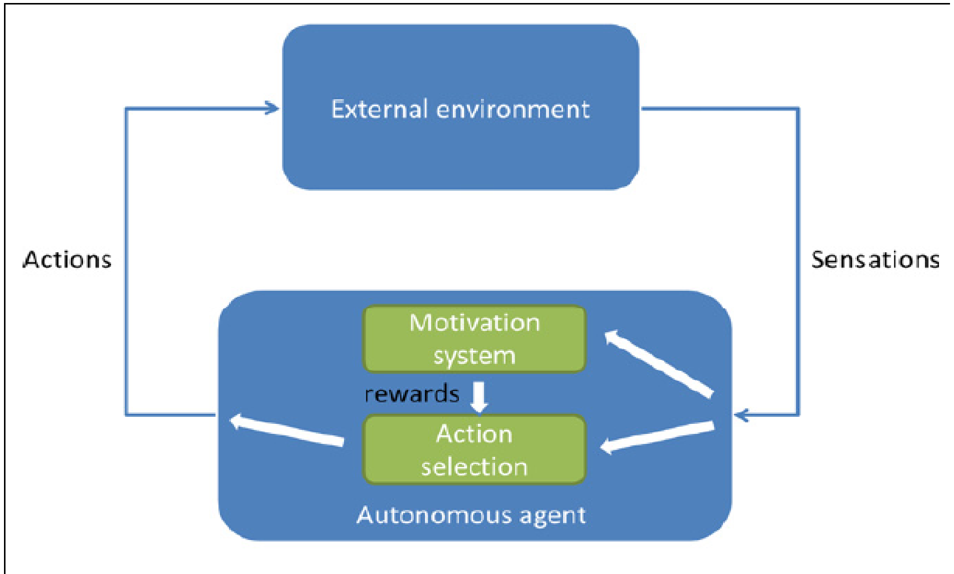
IM behaviors have no clear goal, purpose or biological function; performed for their own sake.

- Serving the need of hunger (homoeostatic need) is ?
- Battery charge act is intrinsic or extrinsic motivated ?
- Intrinsic motivated action?



Externally motivated behavior

Reward originates from environment: externally motivated



Internally motivated behavior

Internally motivated

Oudeyer, Pierre-Yves, and Frederic Kaplan. "What is intrinsic motivation? a typology of computational approaches." Frontiers in neurorobotics 1 (2007): 6.

A taxonomy of IM-based architectures by Oudeyer and Kaplan (2007)

Rewarding IM-based robots based on Novelty Amount

- Choose novel events that the robot is uncertain about

$$e^k\text{: kth sample from all possible set of events}$$

$$P(e^k,t)\text{: estimated probability of observing event at time t}$$

$$r(e^k,t) = C \cdot (1 - P(e^k,t))$$

- Above, uncertainty motivation. Seek novel and unfamiliar events.

- Information gain motivation:
- Choose events that result in decrease in total uncertainty

$$H(E,t)\text{: total entropy}$$

$$H(E,t) = -\sum_{e^k \in E} P(e^k,t) ln(P(e^k,t))$$

$$r(e^k,t) = C \cdot (H(E,t) - H(E,t+1))$$

- What if do not change much?
  - Somehow need to limit maximum novelty (see next slide)

Rewarding IM-based robots based on Prediction Error

- Reward events that are unpredictable

$SM(t)$: sensorimotor context upto time t

$\Pi(SM(t))$: prediction of next context

$$r(SM(t)) = C \cdot E_r(t)$$

where

$$\Pi(SM(t)) = \tilde{e}^k(t+1)$$

$$E_r(t) = ||\tilde{e}^k(t+1) - e^k(t+1)||$$

- Reward event that provide maximum change in prediction error
  - Maximum Learning Progress

$$r(SM(t)) = E_r(t) - E'_r(t)$$

where

$$E'_r(t) = ||\Pi'(SM(t) - e^k(t+1))$$

Jurgen Schimidhuber:
http://people.idsia.ch/~juergen/

- The robot can get lost! Beyond its “current”limits!

$$\mathrm{r}\ (\mathrm{SM(t)}) = \mathrm{C}_1 \cdot e^{-C_2 \cdot ||E_r(t) - E_r^{\sigma}||^2}$$

Thresholded to moderate novelty

Rewarding IM-based robots based on Competence

- Focus is skills, skills have goals (g_k), goal-directed behaviors occur in episodes (t_g)
- Difference between expected goal and observed result

$$I_a(g_k, t_g) = ||\widetilde{g_k(t_g)} - g_k(t_g)||$$

- Reward?
- (mis) achievement of the intended goal. Favor large differences between attempted and achieved goals

$$r(RM(t), g_k, t_g) = C \cdot I_a(g_k, t_g)$$

- Maximizing-incompetence motivation? Goals well-beyond skill level.
- Favor improvement!

$$r(RM(t), g_k, t_g) = C \cdot (I_a(g_k, t_g - \Theta) - I_a(g_k, t_g))$$

$$r(SM(t)) = E_r(t) - E'_r(t)$$

Robots with prediction driven IM

where

$$E'_r(t) = ||\Pi'(SM(t) - e^k(t+1))$$

Recall Schmidhuber's *learning process* based IM

http://people.idsia.ch/~juergen/

- Reward based on changes in the prediction error over time
- LP = difference in consecutive prediction errors
- The actions are rewarded because they leed improvement in prediction.

Oudeyer et al. Intelligent Adaptive Curiosity

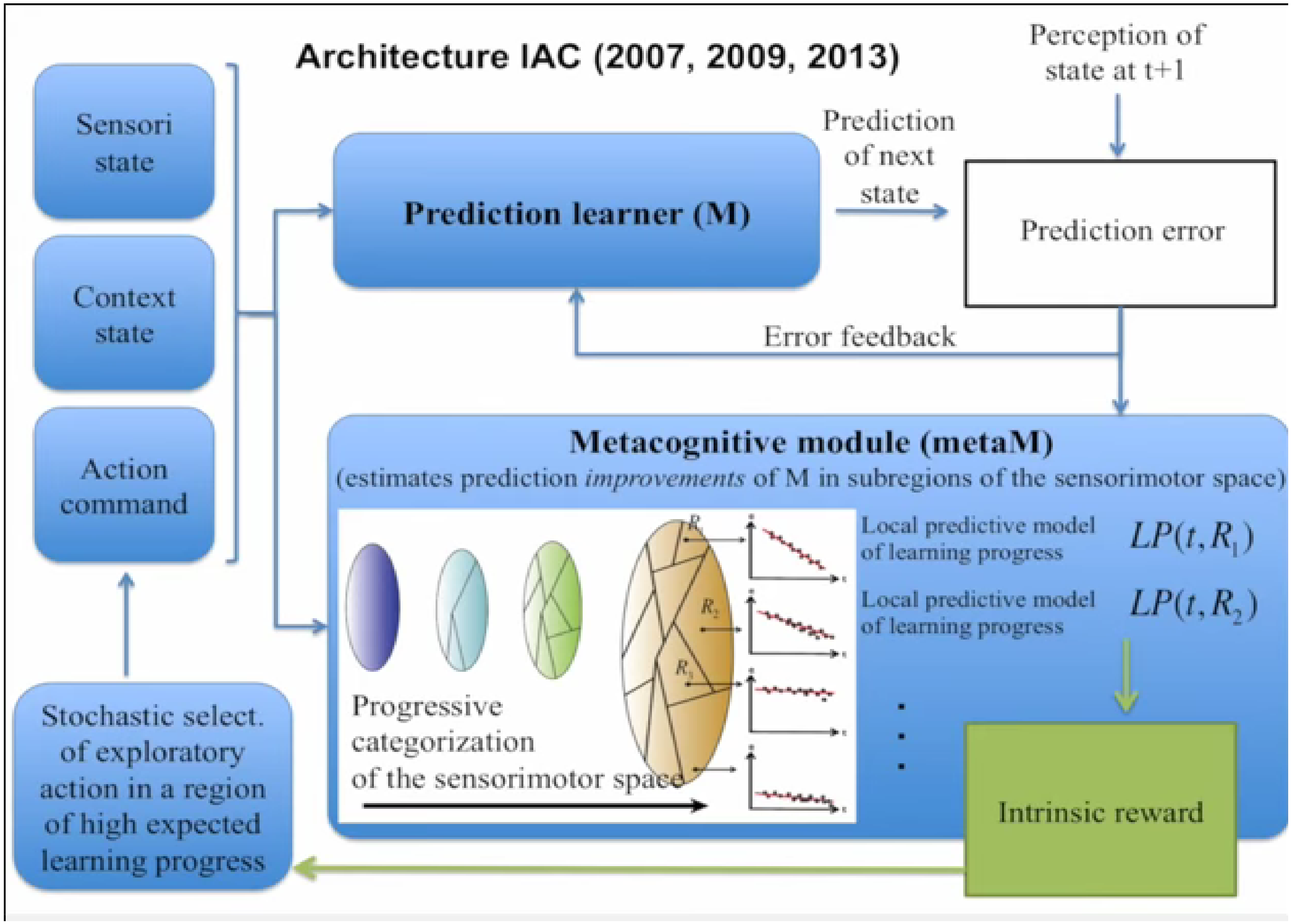
- Life-long learning in continuous high-dimensional sensorimotor spaces
- *Playground Experiments*

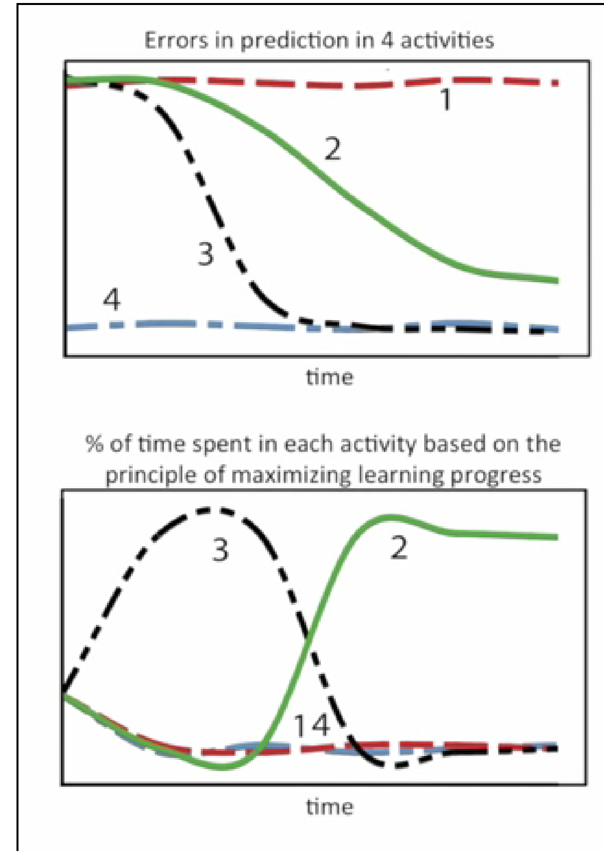
Robots with prediction driven IM

- Environment
  - An elephant toy on the ground
  - A hanging toy
  - An adult robot which automatically imitates if the infant is looking and speaking
- 4 parametrized motor primitives
  - turn head in various directions
  - Open/close mouth while crouching with varying strengths
  - Vocalizing with various pitches and lengths
  - Rocking leg with various angles and speed
- Sensory perception:
  - Visual (salient visual properties)
  - Auditory (other robot)
  - Tactile (something in mouth)

Oudeyer, Pierre-Yves, et al. "The playground experiment: Task-independent development of a curious robot." Proceedings of the AAAI Spring Symposium on Developmental Robotics. Stanford, California, 2005.

Robots with prediction driven IM





Oudeyer, Pierre-Yves, et al. "The playground experiment: Task-independent development of a curious robot." Proceedings of the AAAI Spring Symposium on Developmental Robotics. Stanford, California, 2005.

Robots with prediction driven IM

No hard-coded strategy

Stage-like development

1. Unorganized babbling (with combined primitives)
2. Explore each primitive randomly
3. Act towards areas with objects, e.g. localize to elephant, rock towards the adult robot
4. Shift focus to contingent action-object pairs

Emergence of communication

Oudeyer, Pierre-Yves, et al. "The playground experiment: Task-independent development of a curious robot." Proceedings of the AAAI Spring Symposium on Developmental Robotics. Stanford, California, 2005.