From autonomy to interaction - A pladoyer for a paradigm shift

Britta Wrede Applied Informatics **LOR-**Lab





• 3 Misconceptions of Robotics

• Some examples of how interaction influences learning

• Some Implications



"Robots should learn autonomously"

But

- Human infants learn through interaction
- Some actions can not be learned through observation and imitation [Csibra & Gergely, 2003]

• The meaning of an action in terms of goal, means and restrictions needs to be communicated by a tutor



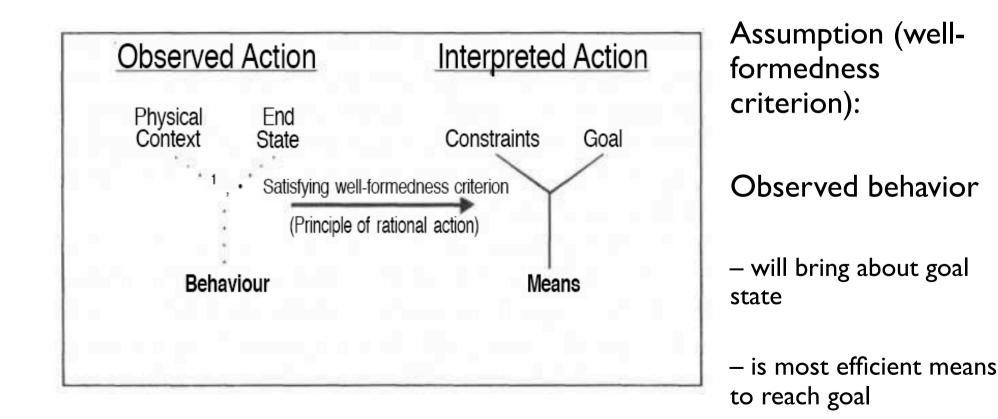
How to draw inferences about other's goal directed actions? [Csibra & Gergeley 2009]

Children

- primarily imitate causally efficacious means to achieve goals,
- **ignore** apparently unnecessary actions
- unless the demonstrator makes it manifest for them that these cognitively opaque aspects are relevant
- \Rightarrow ostensive behavior of tutor important

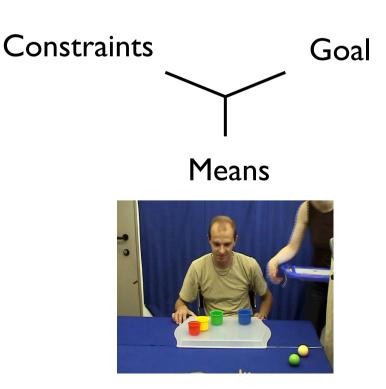


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Support for Interpreting Actions in Infant Directed Actions









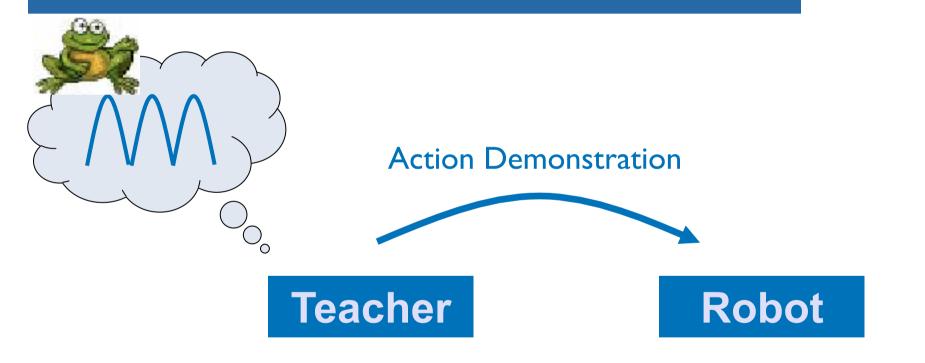
Misconception 2: stable representation = static representation

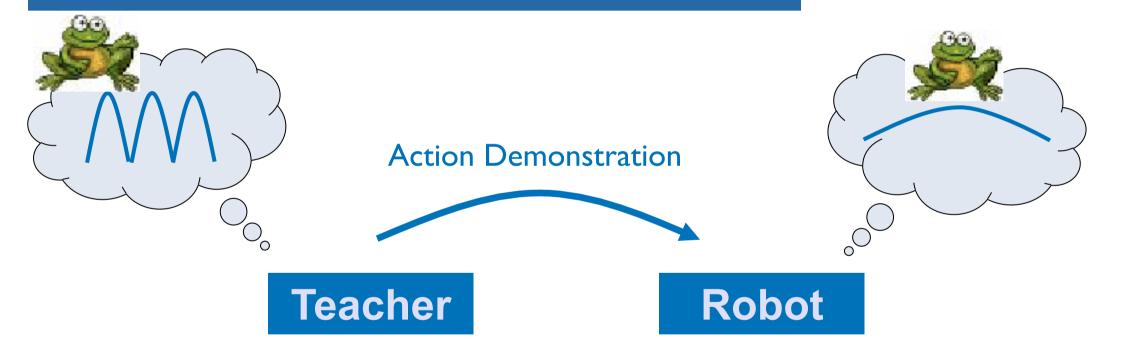
"A robot needs a stable representation in order to act in its environment"

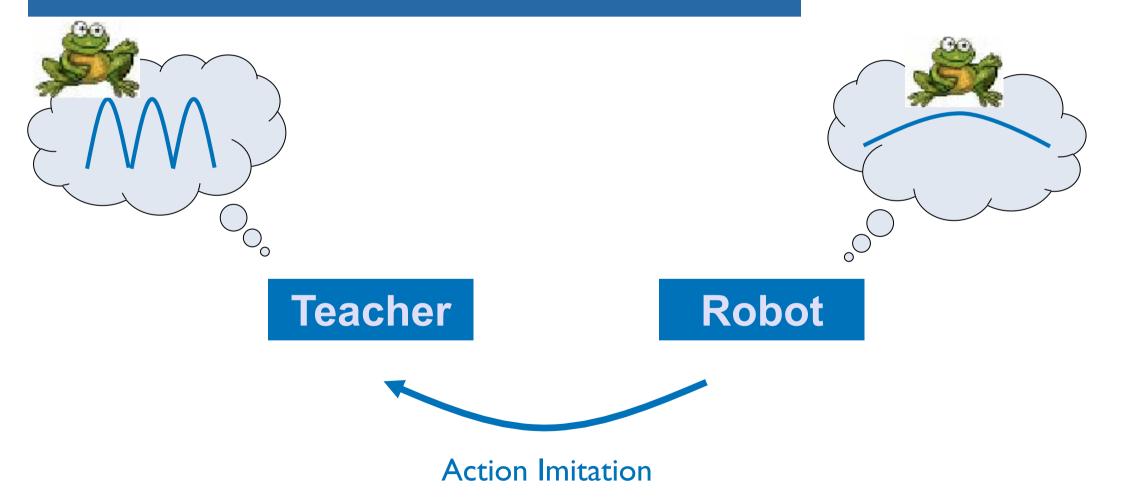
But

- Representations are emergent and shaped through interaction
- E.g. consider teaching a robot an action

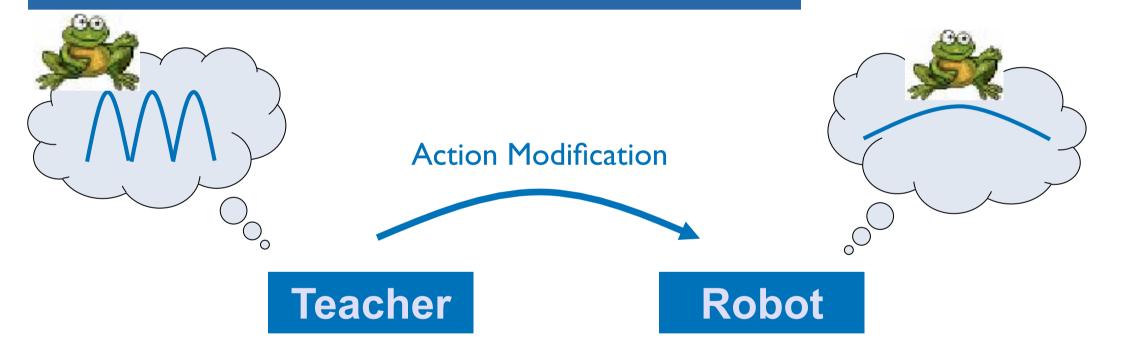


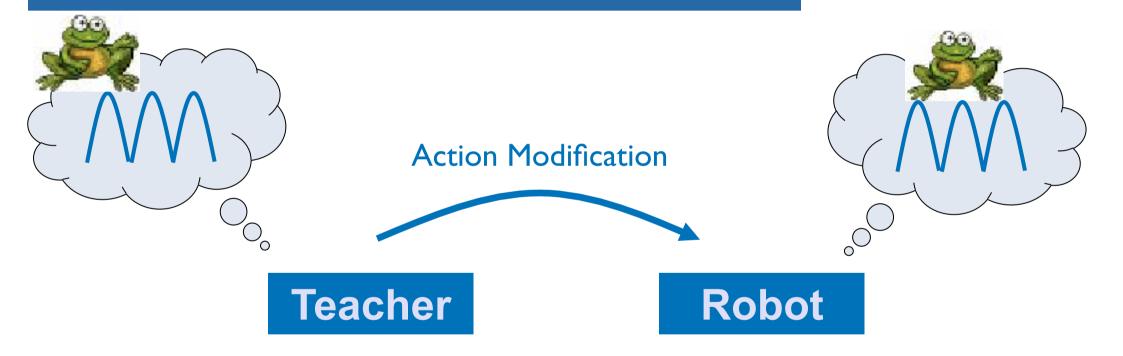


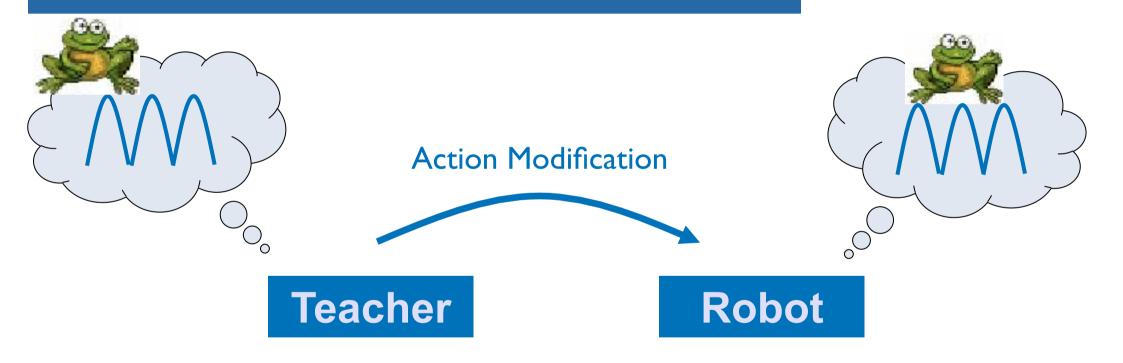




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- stable representation may produce variable action demonstrations
- learner's representation needs to be flexible



"Interaction is not necessary but may be used for giving commands"

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But

- Interaction is bi-directional
- Feedback of the learner is important

Analysing Infants' Feedback and its effect on the tutor's behavior



Anna-Lisa Vollmer Karola Pitsch

Feedback of infants changes with infant's age (and capabilities)

Pre-lexical infants:

- Gazing behavior displays the infant's state of attention
- \Rightarrow Tutor attracts attention by e.g. waving
- \Rightarrow Tutor exaggerates movement

Early lexical infants:

- Anticipate next actions with the direction of gaze
- \Rightarrow Tutor's movements not exaggerated

Lexical infants:

• Give systematic feedback according to the structure of the action including instructions for the tutor's next actions

 \Rightarrow Tutor changes behavior



Interaction is important for learning

- Learning needs to be both: autonomous and interactive
- Representations need to be both: stable and flexible
- Feedback of the learner influences how the next demonstration will be carried out
- Learner needs to be sensitive to tutor's ostensive signals





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 - Tutoring
 - Acoustic Packaging

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Tutoring

Tutoring plays an important role in learning [Csibra & Gergely, 2009]:

Learners are sensitive to tutoring cues

Learners prefer tutoring behavior (child-directed speech & action)

Tutoring enhances learning

Quantitative Analyses:

What are the characteristic modifications in infant-directed tutoring and how can they be used for learning?

Are these modifications similar in robot-directed tutoring?

How to benefit from these modifications?



What is Tutoring?

Ostensive cues that are characteristic for teaching:

- Contingency
- Motherese
- Motionese

Contingency

Reciprocity between physical events or social events

What aspects does contingency contain? [Watson, 1984]

Temporal Contingency

Sensitivity to reciprocal responsiveness and coordination of temporal parameters

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Spatial Relation

Sensitivity to covariation of place of behavior and place of effect

Sensorial Relation

Covariation between magnitude of sensory effect of own behavior (proprioeption) and sensory consequences



Innate Contingency Detection Module [Gergely & Watson, 1999]

How to perceive stimulus-response contingencies effectively?

Sufficiency Index (SI) P(stimulus (=perceived effect) | response (=own action)) P(moving_mobile | movement_of_right_leg)

Necessity Index (NI) 1 – P (stimulus | no_response) 1 – P (moving_mobile | no_movement_of_right_leg)

Learning causality or relatedness:

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If SI=1 and NI=1 then perfect contingency (= perceived causality) If NI > SI, then reduce response class (e.g. right leg instead of both legs) If NI < SI, then expand response class (e.g. both legs instead of right leg)

r Cognition and Robotics

Contingency

Perfect Contingency

Detection of Causality, e.g. learning of body schema

Nearly Perfect Contingency

Detection of Social Interaction

Contingency during Infant Development

2 months: preference of perfect contingency

3 months: preference of imperfect contingency (not in autistic children) [Bahrick & Watson, 1985] Universität Bielefeld CoR-Lab – Research Institute for Cognition and Robotics

Tutoring



Anna-Lisa Vollmer

Katrin Lohan

Motionese (velocity, pace, roundness and range of hand trajectories)



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 Hand movements are slower, less round and have more range in infant-directed tutoring

Motionese strongest in ARI

Contingency (nmb and length of eye-gaze bouts)







• More contingency in infant-directed tutoring

• Contingency weakest in ARI (impaired!)

Feedback-behavior of robot relevant for tutoring behavior





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 - Tutoring Detect ostensive cues in order to determine when to imitate

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• Acoustic Packaging

• Some implications

Acoustic Packaging [Brand et al., 2007]

Children need to discover meaningful action units

Language helps to divide a sequence of events into units

Prerequisite: synchrony between language and events

Described as acoustic packaging (AP) [Hirsh-Pasek and Golinkoff 1996]

AP can provide a bottom-up action segmentation

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Analysis of Parent-Infant Interaction

Characteristics of child-directed actions (Motionese)

- Trajectories more straight, less smooth, e.g., higher arches
- Modulations at trajectory onset
- Lower velocity

Characteristics of Child-Directed Speech (Motherese)

- More structure
 - More and longer pauses
 - Different intonation patterns
- ²⁷ Repeated checking of learners attention



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A Computational Model of Acoustic Packaging

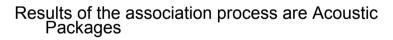
Segmentation of input cues

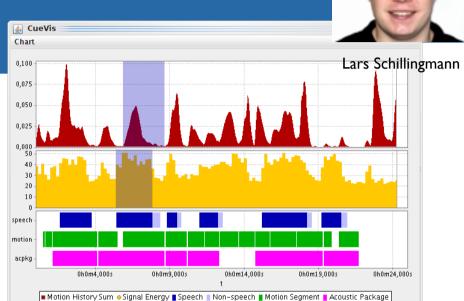
Acoustic temporal segmentation

Visual temporal segmentation

Cue fusion

Temporal association of multi-modal input streams





Acoustic Package Speech Acoustic Package Motion 28

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Evaluation

Videos from Motionese corpus (11 AAI, 11 ACI) and from babyface study (11 ARI)

Analysis

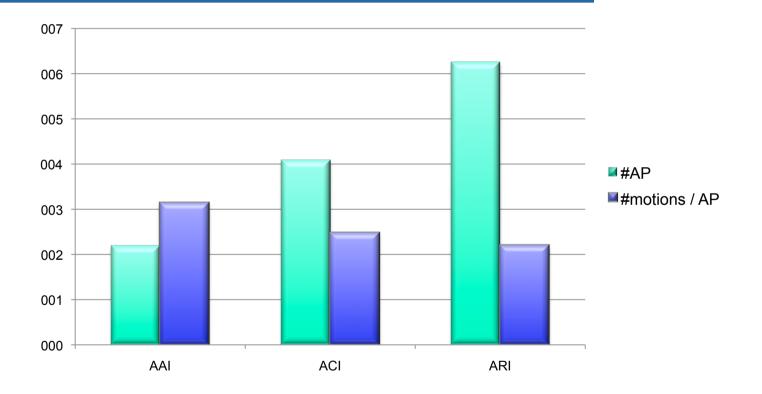
- Automatic detection of Acoustic Packages
- Measurements:
 - number of Acoustic Packages (#AP)
 - mean number of motions per Acoustic Package (#motions / AP)

Hypothesis

- ACI more structured than AAI
- More #AP and less #motions / AP in ACI

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Results



- Sig. more Acoustic Packages in ACI and ARI
- Sig. less Motions per Acoustic Packages in ACI and ARI



Evaluation showed AP is able to reflect differences between adult-adult and adult-child interaction

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Goals

Generating feedback events

Providing learning units for further processes

Challenges

How to generate Feedback?

What is visually interesting?

What is acoustically interesting?

³¹ How to discriminate human motion against object motion?

Detecting Moving Colored Objects

Detecting changing regions

Masking delayed image with Motion History Image Labeling

Clustering in YUV color space

Ranking according to color distance (U,V) to centroid of all clusters

Heuristical filtering

Detecting background by region growing on current frame

Skin color filtering

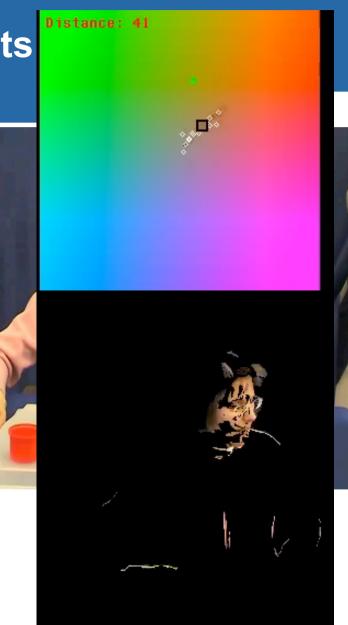
Deviation of Pixels

Density: Pixels / Variance ratio

Trajectory accumulation

Multiple hypothesis

Ranked by average color distance to centroid



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Acoustic Prominence

Relative ranking of syllables within an utterance

Syllable Segmentation

Mermelstein algorithm

Features [Tamburini, Wagner 2007]

Nucleus duration

Spectral emphasis

Pitch movements

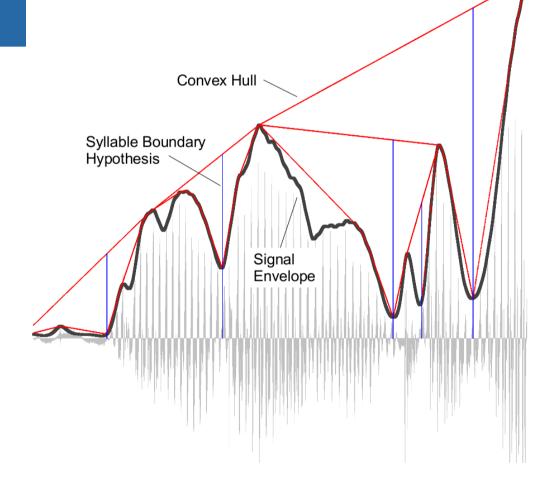
Overall intensity

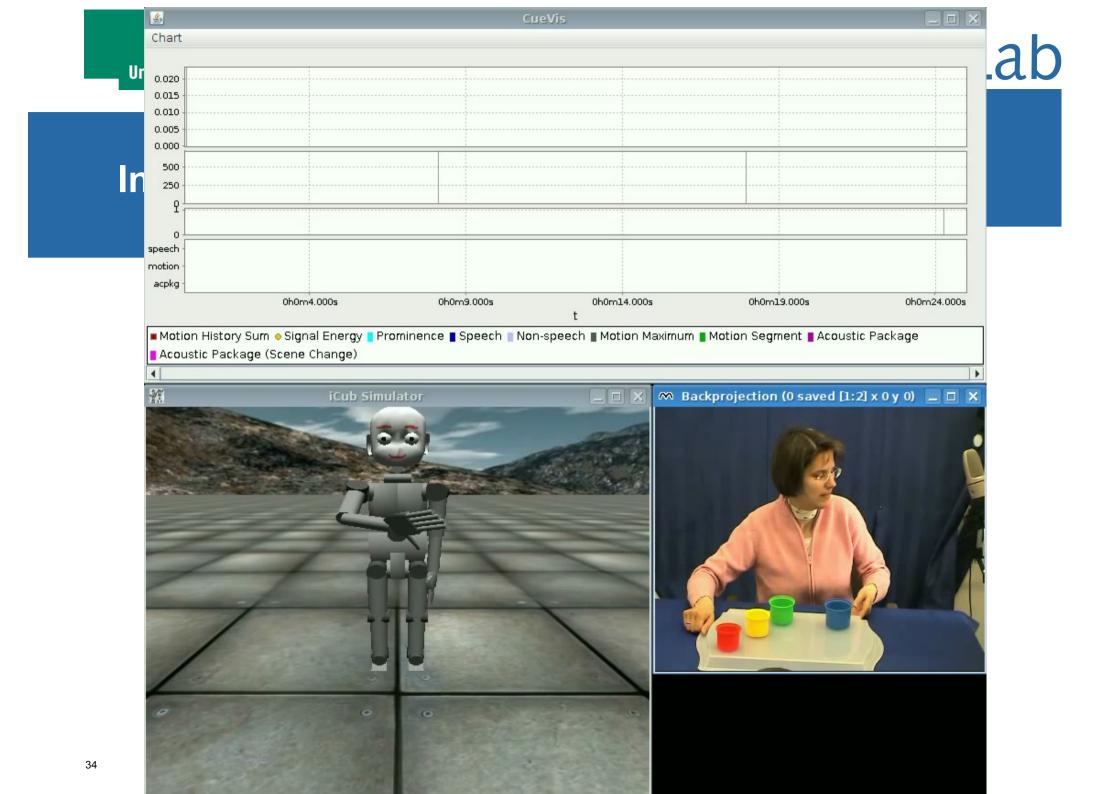
Currently used: Spectral emphasis

Examples with 3 syllables context











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 - Acoustic Packaging Detect stucture in demonstration to determine what to imitate

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• Some implications



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- Some implications
 - Modeling Dialog on a Robot in order to provide feedback

Dialog Modeling for Robots: The PaMini Framework



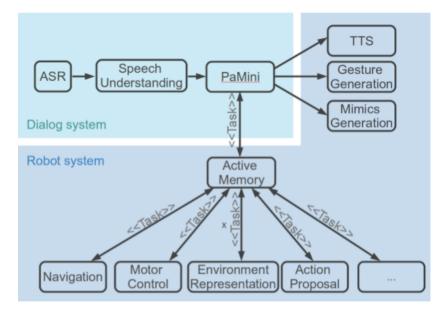
Julia Peltason

- Concepts
 - Modeling Robot Tasks: Task State Protocol
 - Modeling Dialog States: Interaction Patterns
- Usability Test



The Task-State Protocol

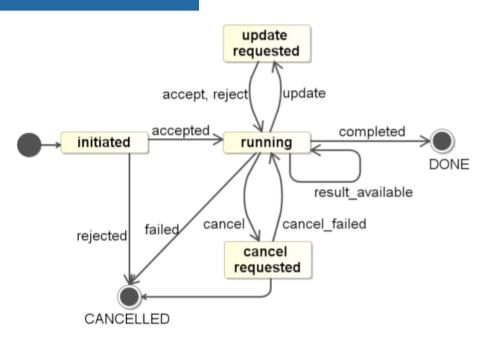
- Complex application back-end on robots
 - Multiple compoments
 - Temporally extended actions
 - ...that may fail
- A uniform interface for coordination needed



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The Task-State Protocol

- Fine-grained interface to robotic subsystem
 - Tight integration of action and perception
 - Basis for verbalizing the robot's actions and internal state
- Supports task update during execution
- Gives the robot the ability to react to comments and corrections on-the-fly.



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Interaction Patterns

Dialog modeling on robots often relies on simple command-control techniques.

- Roboticists want to build HRI scenarios,
- but they do not want to bother about subtleties of dialog modeling

Interaction Patterns

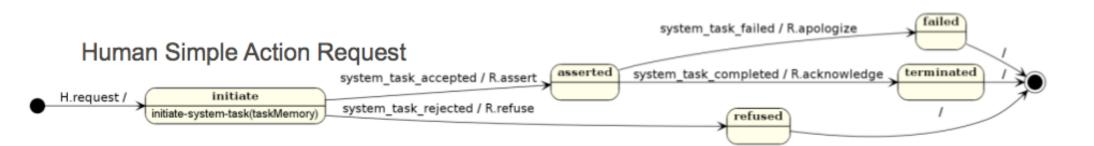
- describe recurring conversational structures
- provide configurable building blocks of interaction
- support rapid prototyping

Interaction Patterns

Transducer-like notation

- Input: human dialog acts or task events
- Outputs: robot dialog acts
- Actions: task and variable updates

Defined at an abstract level and configured for specific situations



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Usability Evaluation: Do interaction patterns ease dialog modeling?

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- Usability test: performance measure + think-aloud
- 2 groups: roboticists, non-roboticists
- 5 tasks with increasing complexity; 1 hour time-limit

| Task | Description | #DA | Challenge | Interaction Pattern |
|------|------------------------|-----|---|------------------------------------|
| 1 | Greeting | 2 | | Interaction Opening |
| 2 | Parting | 2 | | Interaction Closing |
| 3 | Following | 11 | Task communication | Cancellable Action Request |
| 4 | Low Battery warning | 1 | Task communication, Variable definition, Parameterized output | Notification |
| 5 | Acquire name | 6 | Task communication, Variable definition, Task update | Correctable Information Request |

Usability Evaluation: Do interaction patterns ease dialog modeling?

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Results & Observations

- All participants were able to solve task 1-3
- Half of participants were able to solve task 5 partially
- Roboticists slightly faster
- Steep learning curve
- Roboticists rely on task events, Non-Roboticists rely on dialog acts



Paradigm shift towards interaction necessary:

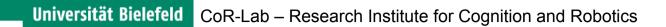
- Autonomy neccessary but not sufficient for learning
- Learning implies interacting

Implications

 Dialog modeling on robots requires abstraction from action and dialog steps

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• System integration necessary



Merci beaucoup!