

Learning at the Ends: From Hand to Tool Affordances in Humanoid Robots

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Overview

We investigate the developmental transition from hand affordances (action possibilities by using the hands) to tool affordances (action possibilities by using tools). We propose a probabilistic model to learn hand affordances by exploring the environment, and we show how this model can generalize to estimate the affordances of previously unseen tools. We publicly release a dataset of hand affordances.

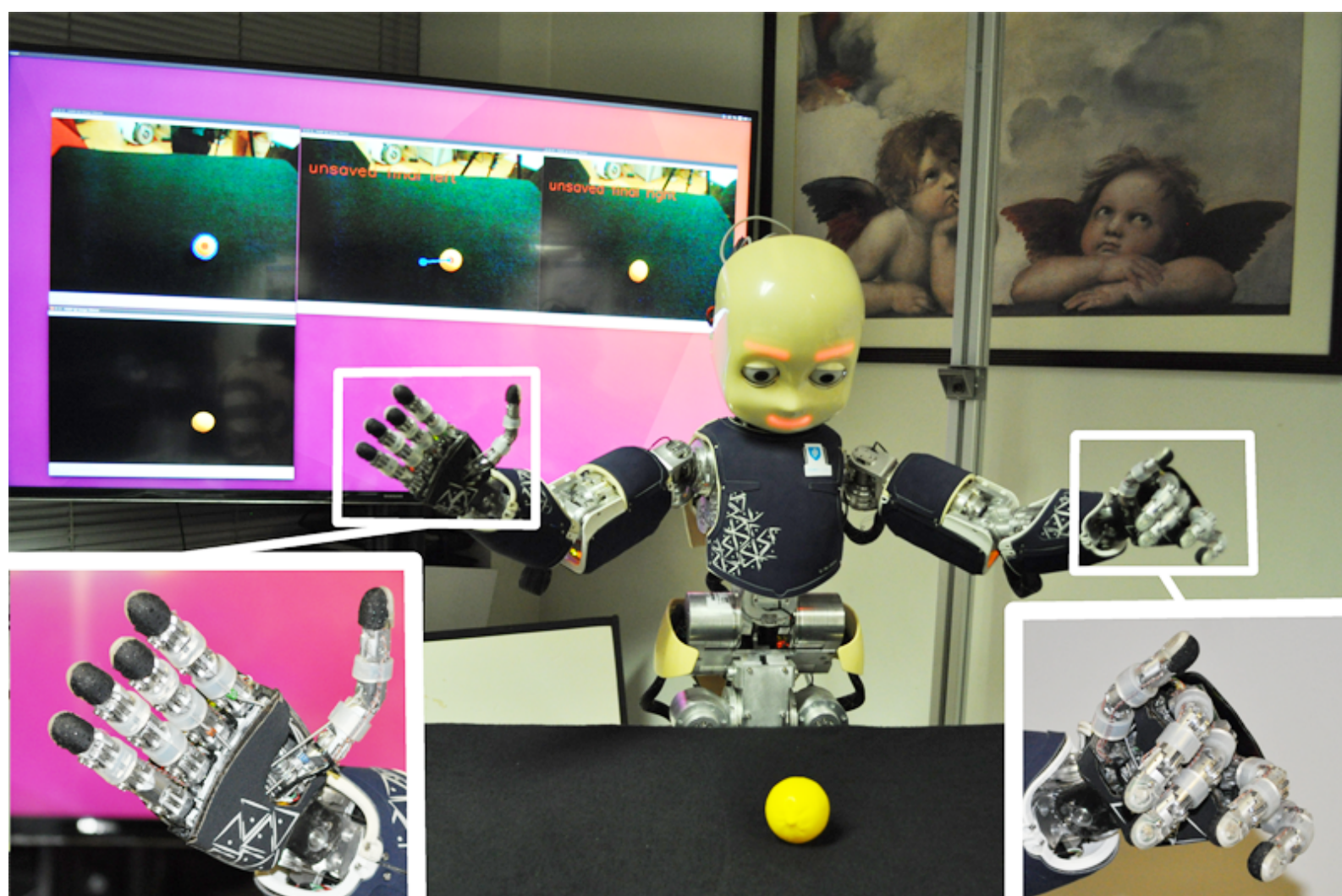
Motivation

- Our hands are our first tools, i.e., the first means to interact with world objects. From 16 months of age, we start developing functional tool use.

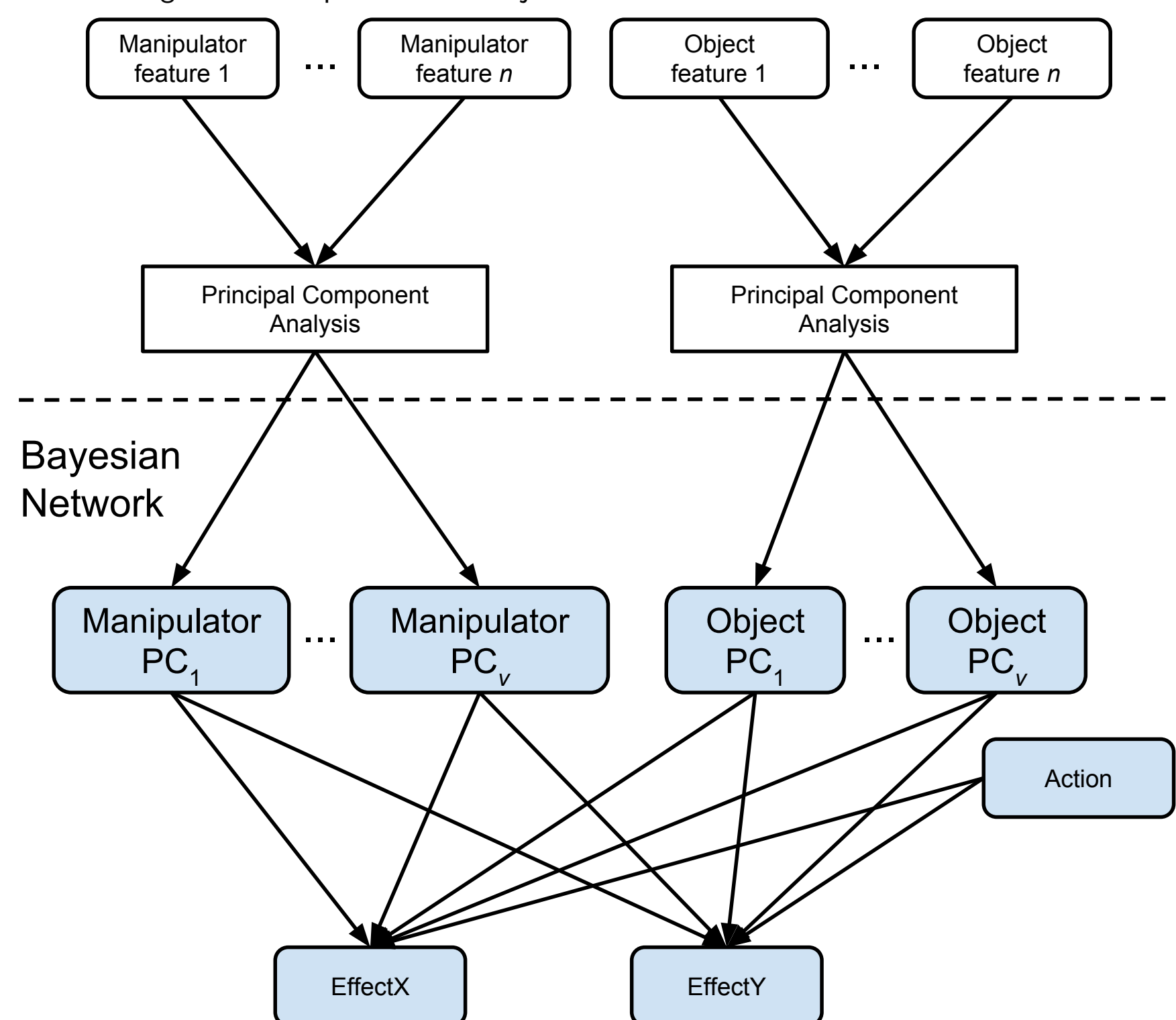


- What skills that an agent has acquired with its *bare hands* can be employed for *tool use* and reasoning?

Proposed Approach

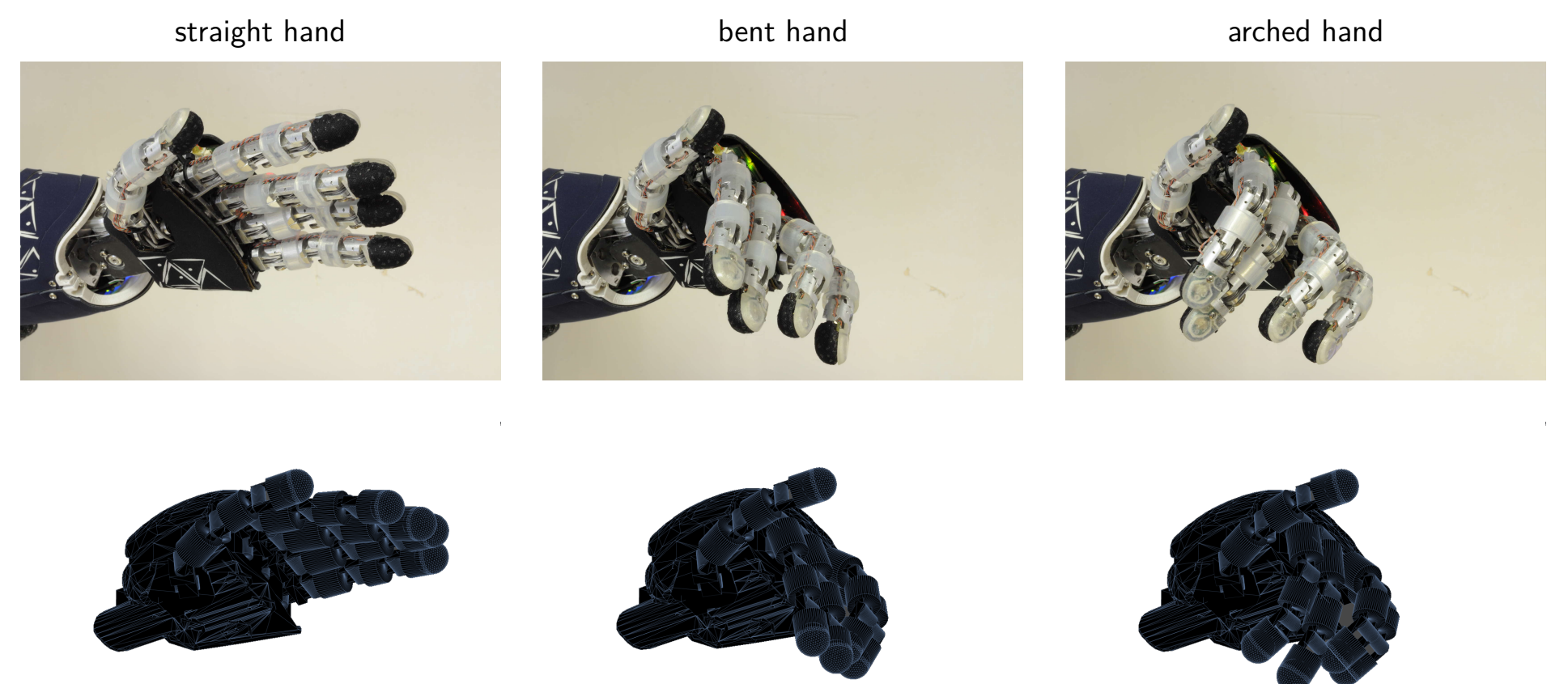


- Computational probabilistic model [2] to learn hand and object affordances.
- Robot interacts with environment by trying manipulative actions on objects on a table. Affordances learned as relationships between:
 - Manipulator features – shape features from Internal Model of Hands;
 - Object features – shape features from visual segmentation;
 - Actions – tap from left, tap from right, push farther, draw closer;
 - Effects – geometric displacement of objects.



Internal Model of Hands

- Body schema: representation of the body that is constantly updated, useful for inferring limbs position in space and guiding motor actions.
- Graphically and geometrically precise appearance model of robotic hand, based on CAD model [3].

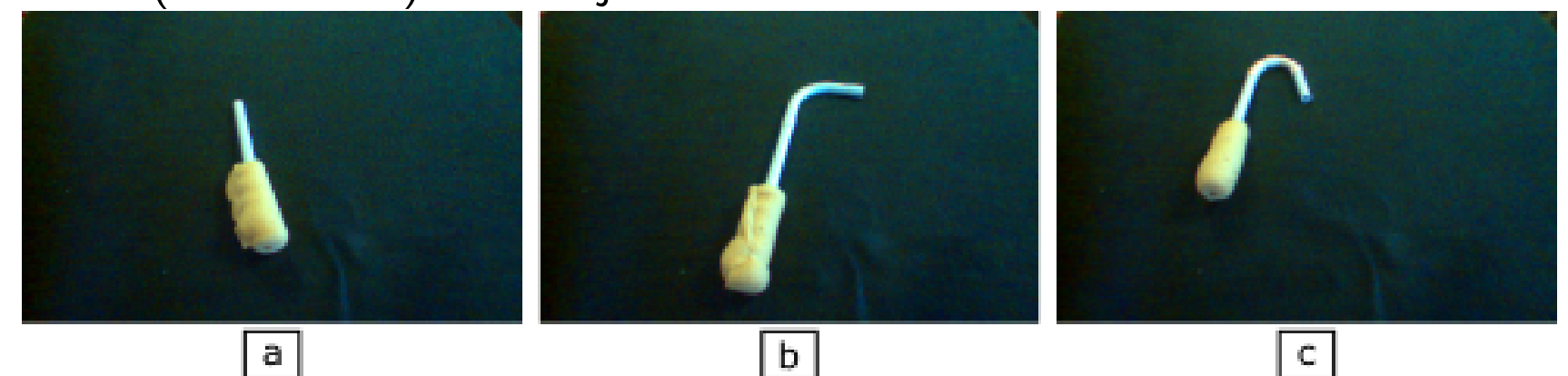


Hand Affordance Dataset

- We measure the horizontal and vertical displacement effects of objects when trying different {action, hand posture} combinations on them.
- 4 actions, 2 objects, 3 hand postures, multiple views → 42 000 affordances.
- Hand posture affordance dataset publicly available at <https://github.com/vislab-tecnico-lisboa/affordance-datasets>

Tool Selection Experiment

- The robot must select a tool between (a) stick, (b) rake, (c) hook to bring an object closer (*draw* action). The object cannot be reached with the bare hands.



- These tools were never seen before (zero-shot learning). Their affordances are evaluated merely based on the knowledge in the Hand Affordance Dataset.
- Percentage of experiments where each tool is selected in our Hand-to-Tool case (HT: train with hands, test with tools) vs Tool-to-Tool case (TT) [1]:

| action | stick | hook | rake |
|--------------|-----------------------------------|-----------------------------------|--------------------------------|
| tapFromRight | HT: 1.0 (TT: 1.0) | HT: 1.0 (TT: 1.0) | HT: 1.0 (TT: 1.0) |
| tapFromLeft | HT: 1.0 (TT: 1.0) | HT: 1.0 (TT: 1.0) | HT: 1.0 (TT: 1.0) |
| draw | HT: 0.5385 (TT: 0.1538) | HT: 0.6154 (TT: 0.1538) | HT: 1.0 (TT: 0.4615) |
| push | HT: 1.0 (TT: 1.0) | HT: 1.0 (TT: 1.0) | HT: 1.0 (TT: 1.0) |

References

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