Hybrid Execution Models of Parameterised Actions for Explainable and Diagnosable Robot Action Execution

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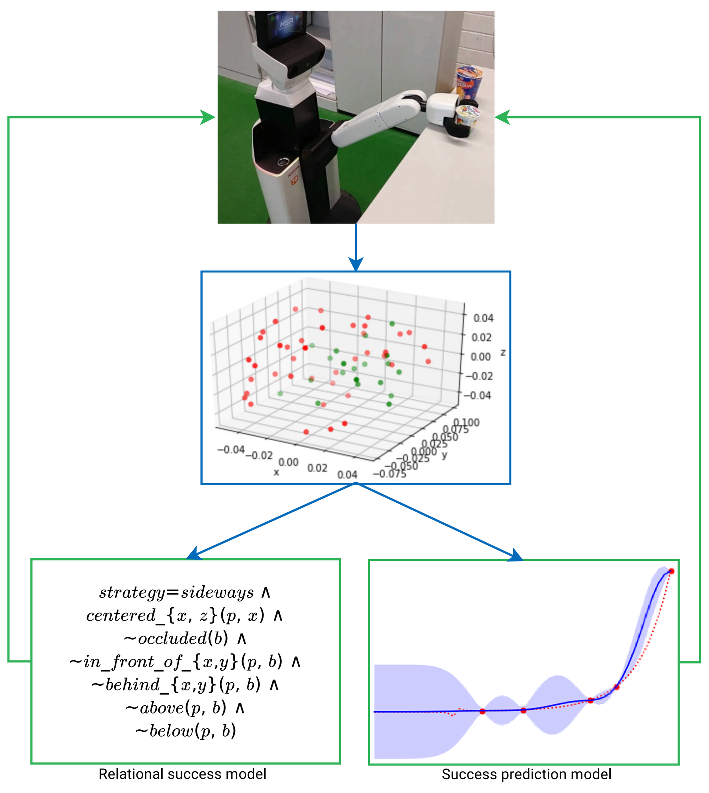
Overall Objective

Increase the interpretability of robot action execution so that execution failures can be analysed - important for users so that they understand the reasons for failures, but also for robots so that they can learn from failures more effectively

Execution Model Representation [1]



- **Execution model** represents execution-specific action knowledge
- Formally defined as $M = (R, F)$ with R **relational** and F **continuous**
- **Qualitative action modes** represented by a collection of relational models: $R = (R_1, ..., R_m)$
- Optional action constraints incorporated as inputs to F
- Execution parameters sampled from F and verified by R

Relational success model R:

- Extracted from a predefined set of qualitative attributes
- Models semantic execution-specific knowledge
- Learned from successful execution examples

Success prediction model F:

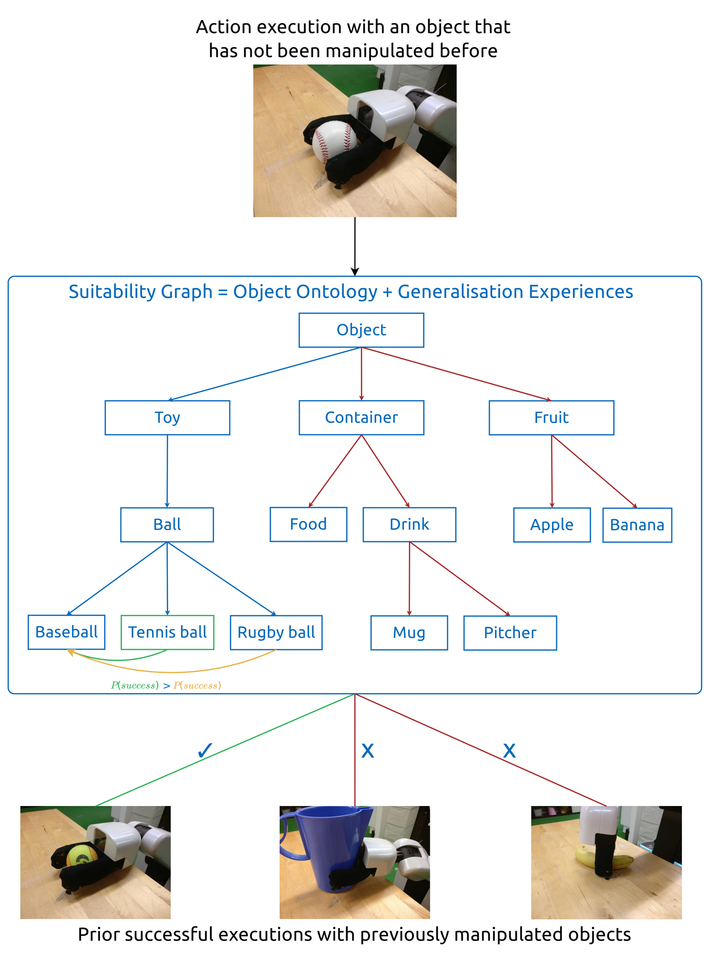
- Represented by a Gaussian Process regression model [2]
- Predicts execution success given action parameters
- Learned from positive and negative execution examples

A: Drawer handle grasping B: Fridge handle grasping C: Object pulling

Action	Random	F only	R and F
A	15	34	**41**
B	14	33	**44**
C	7	24	**38**

- **Relational model introduces conceptual constraints into the execution process**
- **Verifying parameters using the relational model increases the execution success**

Model Generalisation Over Object Classes [3]



- **Objective**: Generalise model $M_{\tilde{o}}$ learned for class $\tilde{o}$ to another class o
- An **object ontology** and **generalisation trials** guide generalisation
- Class generalisation preferences represented in a **suitability graph**
- Suitabilities $P_t(\tilde{o}|o, S)$ defined by a distribution of the form

$$P_{t+1}(\tilde{o}|o, S) = \eta\, s(o, \tilde{o}) P(S|\tilde{o}, o) P_t(\tilde{o}|o, S)$$

- Class o^* selected for generalisation maximises the suitability over the related objects C_o:

$$o^* = \arg\max_{\tilde{o} \in C_o} P_{t+1}(\tilde{o}|o, S = 1)$$

Object similarity $s(o, \tilde{o})$:

- Guides generalisation based on relations in an ontology
- Calculated using the Wu-Palmer similarity measure [4]

Success probability $P(S|\tilde{o}, o)$:

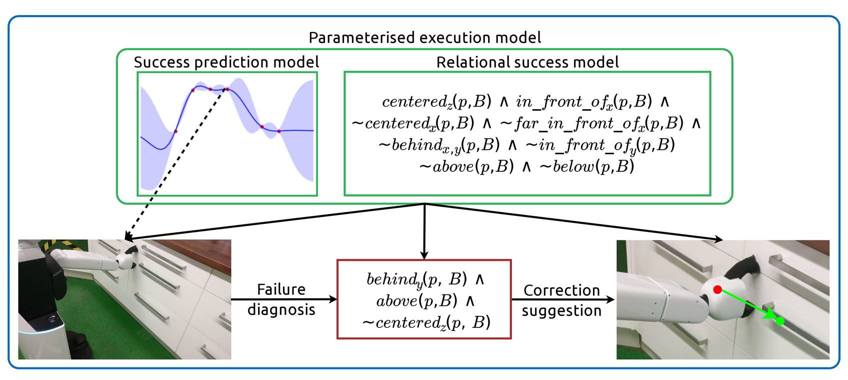
- Represented by a Beta distribution $\mathrm{Beta}(\alpha_{o_{\tilde{o}}}, \beta_{o_{\tilde{o}}})$ [5]
- Posterior updated based on the generalisation outcomes

A: Object grasping B: Object stowing

Action		Pitcher	Glass	Baseball
A	#models	2	1	1
	o^*	/	mug	tennis ball
	N^+	1	8	8
B	#models	1	1	1
	o^*	sugar box	/	tennis ball
	N^+	8	1	10

Model encourages adaptive generalisation and informs about the need for additional learning

Execution Failure Diagnosis [6]



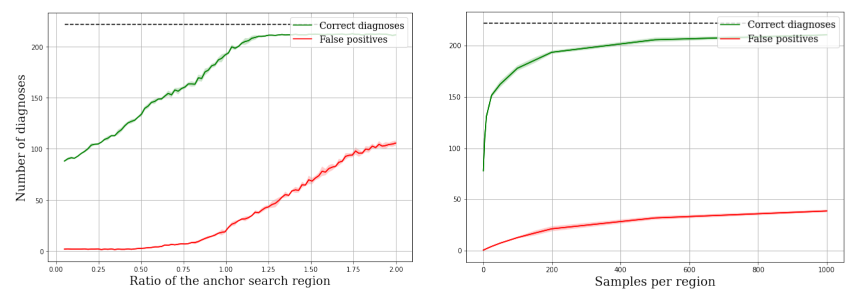
- Failure diagnosis found as a **violation of the relations in R**
- Violation enables finding an alternative set of **corrective parameters**

Violation search:

- Failed parameters perturbed until violations are found
- Perturbation done using sampling from a diagonal Gaussian

Experience correction:

- Failed parameters sampled away from region of violation
- Sampling done from a Gamma distribution



Diagnoses with different sampling region sizes Diagnoses with varying samples per region

Violation search parameters and the relations in R affect diagnosability

Future Work

- Automatic or lifelong learning of relations for increasing the diagnosis quality
- Extending the diagnosis framework to deal with failures propagated over time
- Including object affordances in the generalisation framework
- Extending the generalisation framework to deal with a dynamic ontology

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