# Estimation of Suitable Action to Realize Given Novel Effect with Given Tool Using Bayesian Tool Affordances

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**Abstract**

We present the concept of ***Bayesian Tool Affordances*** as a solution to estimate the suitable action for the given tool to realize the given novel effects to the robot. We define *Tool affordances* as the "awareness within robot about the different kind of effects it can create in the environment using a tool". It incorporates understanding the bi directional association of executed *Action*, functionally relevant features of the *Tool* and the resulting effects. We propose Bayesian leaning of Tool Affordances for prediction, inference and planning capabilities while dealing with uncertainty, redundancy and irrelevant information using limited learning samples. The estimation results are presented in this paper to validate the proposed concept of ***Bayesian Tool Affordances.***

## Introduction

To enable robot to perform everyday tasks with human competence requires intelligent use of tools. Conventional approaches focused learning tool manipulation based on the models they chose to define the tool with. Kemp and Edsinger (2006) proposed *geometric approach* to learn tool manipulation by focusing on detection and control of task relevant features which is tip of the unknown tool rigidly grasped by the robot . The drawback is that experience of learning of one tool cannot be applied to another tool since no notion of distinctive novelty of tools has been established. Stoytchev (*2005*, *2007*) proposed *non-geometric approach* to encode the characteristics of the tool in the resulting effects without providing any explicit geometrical model of the tool to the robot. Sinapov and Stoytchev (*2008*) proposed classification of different types of tools upon the similarity of outcomes generated. But the drawback is that the approach requires robot to experiment and learn with each target object before classifying the tool and the learning requires large number of training samples. Brown (*2009*) proposed *relational model approach* to represent the structure and relationships between tool parts and/or the tool, target object, and environment. But the drawback is that learning approach does not handle uncertainty, redundancy and irrelevant information. All of the above approaches do not focus on learning the bi-directional association (shown in Fig1) required for prediction, inference and planning.

Thus we present an integrated solution of ***Bayesian learning** of **Tool Affordances*** to solve the problem of autonomous tool manipulation. Bayesian framework has been chosen due to its probabilistic semantics, casual inference and prediction capabilities required solving the problems mentioned in related works. To validate the proposed concept, we perform an experiment for the robot to estimate suitable Action for the given Tools and desired novel effects.

## Learning Bayesian Tool Affordances

Robot performs self-exploration using pre-programmed Actions to manipulate target object, an approach similar to Stoytchev (*2005).* Effects are represented in task space as direction vector and relative displacement of target object. Similar to *geometric approach* we abstract away details of the tool and focus on relevant features of the tool and similar to *non-geometric approach* encode the relevant features in the action outcomes. For example functionality of knife and scissor depends on its sharp edge, of a spoon depends on the oval shaped head at the end of handle. Thus we introduce novel concept of *functional part* as "the relevant geometrical features that define the functionality of the tool for a given task". Using *functional parts* robot can understand the effects of several tools that share the same functional part and experience of learning of one tool can be applied to other tools. Bayesian Network offers a flexible way to store data in discrete or continuous nodes and enable learning using limited samples. Its probabilistic semantics deals with uncertainty, redundancy, and irrelevancy and allows robot to infer and predict the queried information given some evidence.

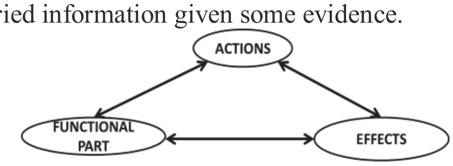



Fig1: Model of Tool Affordances encoding bi directional association.

Table 1: Formalism of Tool Affordances. The salient changes between observations over time are Effects (**E**).

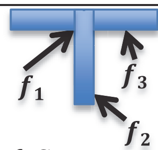
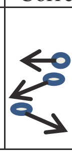
| Actions : **A** | Functional Parts :**F** | Effects : E<br>$E_i \in \{ e_1, e_2 \}$ |
|---|---|---|
| $A_1$:Contract Arm<br>$A_2$:Slide Arm Left<br>$A_3$:Pull Diagonally 1<br>$A_4$:Pull Diagonally 2 | <br>$f_1$ $f_3$ $f_2$<br>$f_1$:Corner<br>$f_2$:Vertical<br>$f_3$:Horizontal | $e_1$: $RelPos_{target}$ : Relative displacement of target object after manipulation<br>$e_2$: $trajectory_{target}$ : Direction of target traversal |

Table 2: Data representing Tool Affordances (refer Table 1)

| A,F | **Effect** | Corresponding Target direction |
|---|---|---|
| $Epoch1: A_1, f_3$<br>$Epoch2: A_2, f_2$<br>$Epoch3: A_3, f_1$<br>$Epoch4: A_4, f_1$ | $E_1$<br>$E_2$<br>$E_3$<br>$E_4$ |  |

**Experiments, Results and Discussion**

For each pair of *Action* and *functional Part* shown in Table 2, a total of 240 times target object is manipulated. Target object which is a cube is placed randomly at different positions within the workspace to include variations in the data .A random force corresponding to each Action is applied on the tool resulting in target displacement using *functional part* and effects are recorded. The entire process is simulated using $WEBOTS^1$. The structure of *Bayesian network* is shown in Fig2. For learning 160 samples of $Epoch1, Epoch2$ $and Epoch3$ are used while remaining 80 samples are kept for evaluation along with 80 samples of $Epoch4$, which represent the novel effects. Thus in total we have 320 evaluation samples.

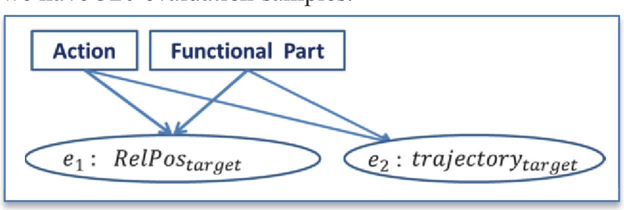



Fig2: The Bayesian Network structure for Tool Affordances.

Box represents nodes storing discrete data and ovals the continuous data. We use Maximum Likelihood parameter estimation (Christopher M. Bishop 2007) to adjust weight parameters along the connection during learning and Junction Tree algorithm (C. Huang and A. Darwiche 1996) for inference during evaluation.

The estimation of suitable Action to realize given effects using the given *functional part* is shown in Fig3. It shows that robot estimates Action $A_1$ using all given functional parts to bring the novel effect $e_4$ which seems quite likely by looking at the pictogram depicting corresponding target direction as shown in Table 2.

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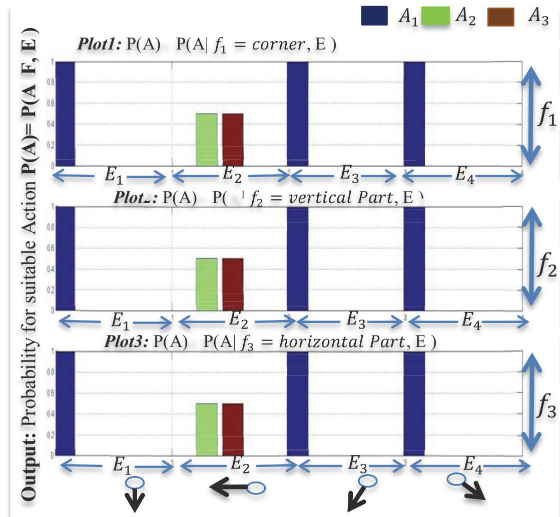


Fig3: Inputs to *Bayesian Tool Affordances* are effects $E_1$ to $E_4$ (horizontal axis) and functional parts $f_1, f_2, f_3$ ( vertical right axis ) during evaluation and vertical left axis represent the probability of the Actions given Effects and functional part as evidence

## Conclusion and Future Work

We proposed the concept of learning *Bayesian Tool Affordances* focusing of *functional parts* of the tool to solve the problem of autonomous tool manipulation. We addressed the problem of estimation of suitable Action given the desired effects and the *functional parts*. In future, we plan to study how robot can find functional parts using a combination of eye gaze, interactive communication, and imitation and computer vision.

## References

Brown, S. (2009). *A relational approach to tool-use learning in robots*. Ph.D. thesis, School of Computer Science and Engineering, The University of New South Wales, Sydeney.

C. Huang and A.Darwiche (1996) . Inference in belief networks: A procedural guide . International Journal of Approximate Reasoning, 15(3) : 225-263

Christopher M. Bishop (2007) . Pattern Recognition and Machine Learning (Information Science and Statistics ) . Springer.

Kemp, C. C., & Edsinger, A. (2006). Robot manipulation of human tools: Autonomous detection and control of task relevant features. In *Proceedings of the fifth international conference on development and learning, special session on classifying activities in manual tasks*

Stoytchev, A. (2005). Behaviour-grounded representation of tool affordances. In *Proceedings of IEEE International Conference on Robotics and Automation (ICRA)*, pp. 3071-3076

Stoytchev, A. (2007). *Robot tool behaviour: A developmental approach to autonomous tool use*. Ph.D. thesis, College of Computing, Georgia Institute of Technology, Atlanta.

Sinapov, J., & Stoytchev, A. (2008). Detecting the functional similarities between tools using a hierarchical representation of outcomes. In *Proceedings of the IEEE conference on development and learning (ICDL 2008)*, France.