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

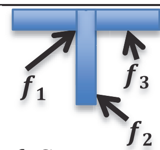
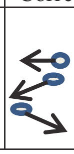
Actions : **A**	Functional Parts :**F**	Effects : E $E_i \in \{e_1, e_2\}$
A_1:Contract Arm A_2:Slide Arm Left A_3:Pull Diagonally 1 A_4:Pull Diagonally 2	 f_1:Corner f_2:Vertical f_3:Horizontal	$e_1 : RelPos_{target}$: Relative displacement of target object after manipulation $e_2 : trajectory_{target}$: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

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

A,F	**Effect**	Corresponding Target direction
$Epoch1: A_1, f_3$ $Epoch2: A_2, f_2$ $Epoch3: A_3, f_1$ $Epoch4: A_4, f_1$	E_1 E_2 E_3 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.

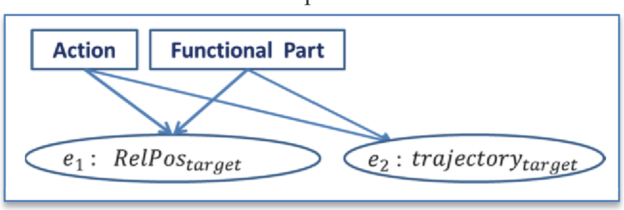


Fig2: The Bayesian Network structure for Tool Affordances.

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.

1. www.[illegible].com

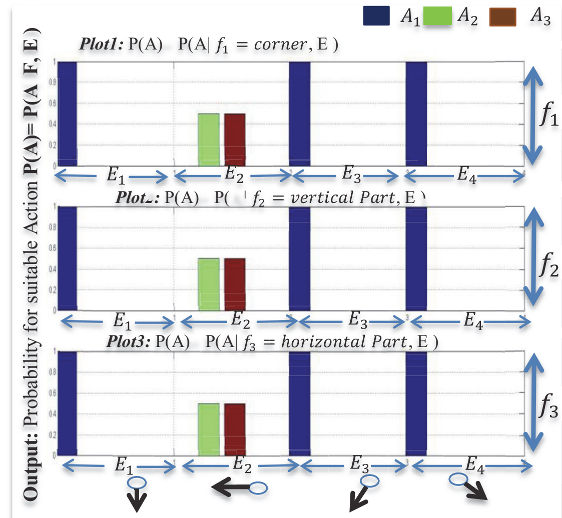


Fig3: Inputs to *Bayesian Tool Affordances* are effects E_1 to E_4 (horizontal axis) and functional parts f_1, f_2, f_3 (vertical right axis) during evaluation and vertical left axis represent the probability of the Actions given Effects and functional part as evidence

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.