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Visual Motor Skills for Low Cost Robots

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Abstract— ***The robots which perform multiple functions are extensively operated by skilled operators. As hu- mans, a robot cannot observe its environment and learn the skills from it. We propose a novel algorithm that can make robots do tasks that are performed by other just by looking the demonstration of the task from image pixels without any external control. We use meta learning concept to apply the general intelligence to the robot. We experiment with a arm robot and manipulate it to perform tasks that are performed using human hand. The tasks include pushing and placing and the results are compared with other memory based techniques. We compare the results with the same experiments done with high precision industrial robots.***

1. INTRODUCTION

The robotic systems that operate today takes a lot of assistance humans and makes itself restrictive to be operated in only critically required applications. We are interested in robots which are much more intelligent and flexible not only in performing the given tasks but also to learn some important features of its environment such as the physical laws, uncertainity, possible outcomes of an action, etc. These learned features will help the robot to face unseen situations and act appropriately. Demonstrations are the effortless way of communicating without the help of language. Humans and animals have the ability to learn from a demonstration just by watching someone else perform the task. Is it possible to build robots with this ability? Machine learning terms this type of problems to be an *imitation learning* problem. But imitation constitute only a part of the problem and the major problem lies when the imitation is performed in the real world. The problem of *domain shift* that most of the imitation learning models face must be addressed in a effective way when it comes to robotics. *Domain shift* happens because the data is collected from real world which will not be identical, requiring the model

Figure 1. (a) Low cost robot using servos

to take different decisions for the same task. This can be viewed as a problem where the model encounters multiple tasks which are different and learning the environmental features will help it take the model better pre- dictions. *Meta learning* is sub field of AI which encounters this by proposing multiple methods. We analyze one of those approaches where the parameters of the model are directly learned from the data. We apply *Model Agnostic Meta Learning or MAML* in imitation learning setup and analyze how the model predicts actions based of raw RGB pixels. We also analyze how the model generalizes and responds to unseen situations.

2. RELATED WORK

Imitation learning approach this task of acquiring feature knowledge from human demonstrations for single task is presented. Since this accounts for single tasks there has been many attempts to naturally translate the human activities to corresponding robot actions. Some approaches this problem in the reinforcement learning setting by providing a reward based environment which helps the robot to track how well its performing where they learn a model to outputs the outcome human demonstrations for particular state action pair. There has been attempts to use the same setting with memory based recurrent networks like LSTM with soft attention models. Contextual policies policies also do the same by conditioning the task which will be given as the input. The meta learning approaches include *Chelsea Finn et al* where they use teleoperated robot to be the demonstrator and in *Yan Duan et al* the demonstration is done in the virtual reality setting to avoid the problem of domain shifting.

3. PROBLEM FORMULATION

The problem is learn a model directly which can perform a wide range of tasks just by looking at the video stream and the state of the robot configuration at each time step. The generalization of the model is obtained by training across multiple tasks with different objects and background. We also want figure out how well low cost robots perform with the probabilistic predictions of the model. We have a two dataset D_h and D_r representing human demonstrations and robot demonstrations respectively. Each dataset consists of multiple tasks T_{ih} and and T_{ir} each task is represented as

$$T_{i_h} = \{o_1, o_2, \dots o_{t-1}, o_t\}$$
$$T_{i_r} = \{s_1, o_1, a_1, \dots s_t, o_t, a_t\}$$

4. DOMAIN ADAPTIVE META LEARNING MODEL

We will have two datasets D_{tr} and D_{val} which corresponds to the D_h and D_r respectively. We will initially learn from the D_{tr} and update the parameters of the model based on certain inner objective for n gradient steps(in our case n = 1). The objective is given as

$$\phi = \theta - \alpha \nabla L(\theta, D_{tr})$$

Then the overall model is updated using the robot demonstrations from D_{val} by a meta objective of

$$\phi_{new} = \phi - \alpha \nabla L(\phi, D_{val})$$

It is important to note that the overall model is updated by the D_{val} which consists of the actual robot actions. The inner objective gives the sense of the visual perception of the task to the model. But the final action predictions are carried out by the outer objective. Thus the overall update rule for the model can be expressed as

$$\theta_{new} = \theta - \beta \nabla L(\theta - \alpha_1 \nabla L(\theta, D_{tr}), D_{val})$$

It turns out that the outer of the model is simply the behavior cloning loss which can be of any type like MDN, Euclidean distance or the L_1 distance. But the inner objective is not a standard loss and thus it has to be learned by the model. This loss will give insights to the model about the visual observations of the task. Thus the final objective is expressed as

$$\theta_{new} = \theta - \beta \nabla L_{BC}(\theta - \alpha_1 \nabla L_{\psi}(\theta, D_{tr}), D_{val})$$

The final Learned loss L_ψ and the learned parameters θ_{new} are returned as the model.

Algorithm 1 Domain Adaptive Meta Learning

INPUT: $D_h D_r$
Initialize: $\alpha\beta$
while training **do**
  Sample $T \sim p(T)$ from D_h
  Update $\phi = \theta - \alpha\nabla L_\psi(\theta, T)$
  Sample $T \sim p(T)$ from D_r
  Update $\phi_{new} = \phi - \beta\nabla L_{BC}(\phi, T)$
end while

5. *TEMPORAL LOSS*

The loss term L_ψ is directly learned from the data. This loss gives the model on the visual information about the task like the color of the object and depth of the objects, etc. This will indeed affect the final predictions of the robot. But the final predictions are based on the behaviour cloning loss which takes in the robot configurations into account. L_ψ is learned by using *Temporal Convolutions* which takes in multiple frames of the video and produces a correlated output. The *Temporal Convolutions* are usually referred as 1-D convolutions.

6. *MODEL ARCHITECTURE*

The model is a Convolutional Neural Network which maps the RGB images to the output robot angles. We use the convolutional layers to get the visual information from the camera frames. We use 4 convolutional layers with filter size of 3*x*3 with number of filters in each layer is equal to 60. The strides vary based on the receptive area of the experiment.

We then use *spatial softmax* to get the 2D feature points from the convolutional filters. We then use dense layers to predict the output actions. We use a temporal loss for the inner objective by 1*x*1 Convolutions. We use Behaviour cloning loss for the output actions. Mixed Density Networks(MDN) can also be used to predict the output actions by for placing experiments.

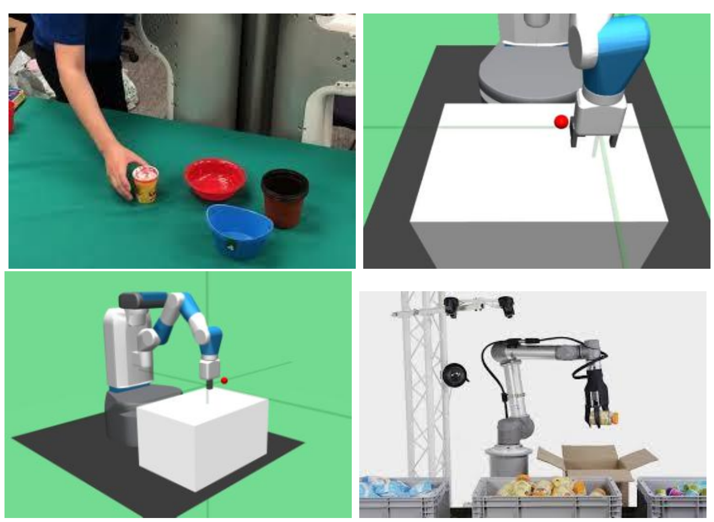

Figure 2. (a)Human performing demo (b)simulated pushing (c)simulated pushing at different angle (d) Real robot performing the same task by watching human

7. EXPERIMENTS

The Experiments aim to answer questions like, How well the robot learns about the environment? How low cost robots perform with these Machine learning algorithms? and What are the things that make the robot fail in complete a task? The experiments compare different approaches from other works.

7.1 Real World Placing

The real world placing is done with a low cost hobbyist robotic arm with 5DOF. The data is collected by teleoperation using mobile app. The total setup costs about $180 thus making it cheap and affordable for all applications. We compare our approach with LSTM policies and DAML with PR2 robot with our low cost robot.

7.2 Simulated Pushing

Simulated pushing experiment uses the *MuJoCo* Physics engine to simulate the environment. The demonstrations are given as with the help of kinect sensor. The actions are read using teleoperation based on the motion sensor values.

Models	Simulated Pushing	Real World Placing
LSTM	34.25%	33.3%
Meta learner(**ours**)	84.2%	77.6%

8 CONCLUSION

We have provided a method to make robots learn from its environment and act based on the needs. We also compared the model with industrial robot with the low cost hobbyist robots. This can further improved by generalizing the movements of the robots instead of tasks. More complex tasks can be used to experiment with and thus producing more advanced models. This can also be used beyond human imitation and enhanced towards humanoid robots.

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