

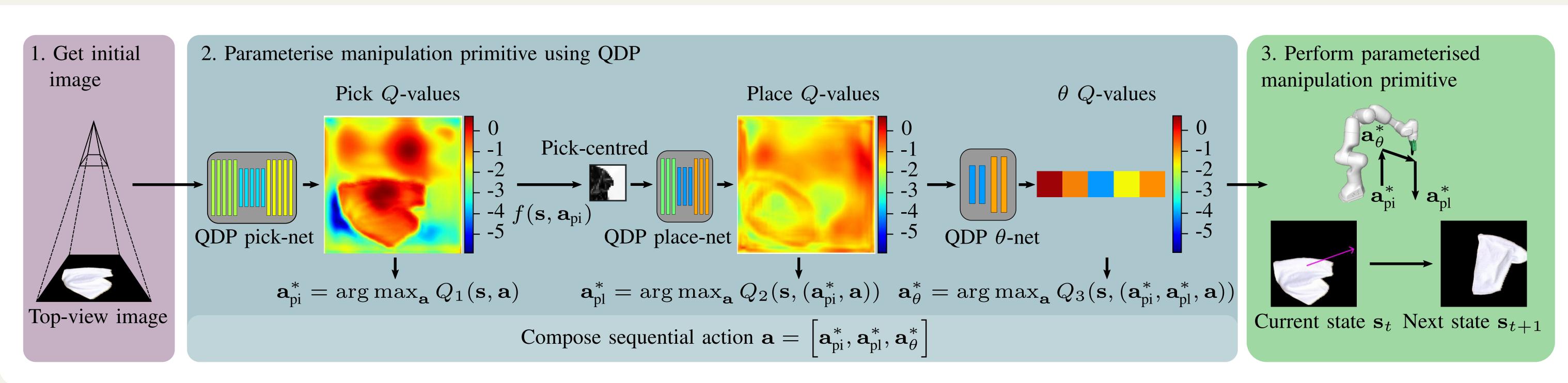
# QDP: Learning to Sequentially Optimise Quasi-Static and Dynamic Manipulation Primitives For Robotic Cloth Manipulation

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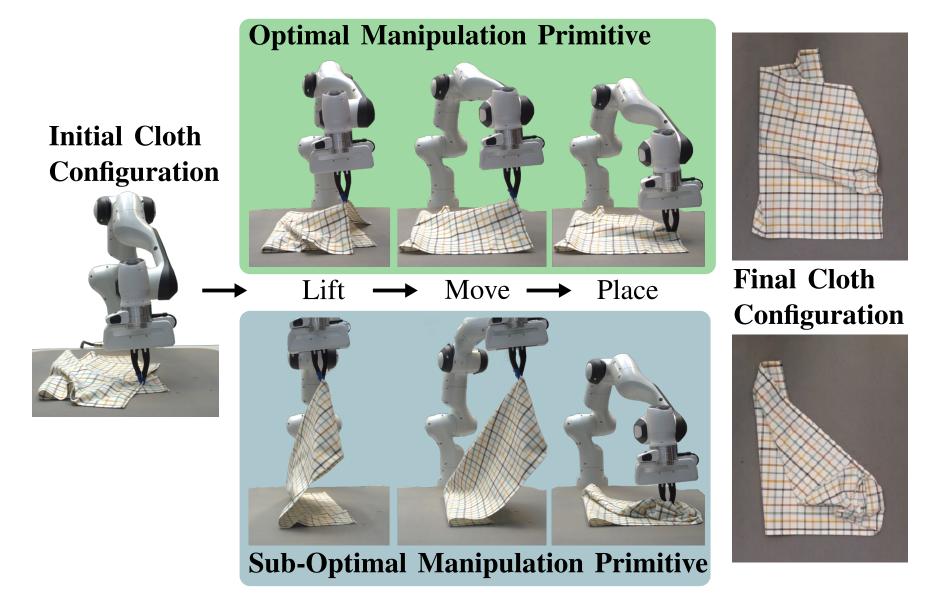
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Cloth manipulation performance is significantly affected by variables such as stiffness or density, and the **velocity** or **trajectory** of **quasi-static** and **dynamic manipulation primitives**, an aspect often **neglected**. To address this, we have developed the **Quasi-Dynamic Parameterisable** (QDP) method, which optimizes parameters like motion velocity alongside pick and place locations. Our method uses Sequential Reinforcement Learning to optimise the primitive parameters sequentially. Our results show that optimizing these parameters improves cloth unfolding performance by 20% in simulations, and real-world experiments prove the **benefits** of **adjusting velocity and height** for **cloths** of **different properties**.





**QDP** sequentially optimises the manipulation primitive parameter values to achieve better cloth configurations (*green*) compared to suboptimal parameter values (*blue*) for a manipulation primitive such as pick-and-place.



# **Manipulation Primitives**

### • Dynamic Quintic Polynomial:

Dynamic manipulation primitive which is defined by its velocity. This primitive follows a semi-circle shaped trajectory from  $\mathbf{a}_{pi}$  to  $\mathbf{a}_{pl}$  using a fifth order polynomial.

### • Pick-and-Place (P-n-P):

Quasi-static manipulation primitive with parameters  $\{h_{\theta}, t_{\theta}\}$ , where the height has the range of values  $h_{\theta} \in [0.1, 0.2, 0.3, 0.4, 0.5]$  m. to lift the cloth; and the time to move from  $\mathbf{a}_{pi}$  to  $\mathbf{a}_{pl}$  is within the range of  $t_{\theta} \in [10, 11, 12, 13, 14, 15]$  seconds.

### • Drag:

Quasi-static primitive which can be seen as a P-n-P primitive where  $h_{\theta}$  is equal to zero, and the time has the range of values as the P-n-P primitive.

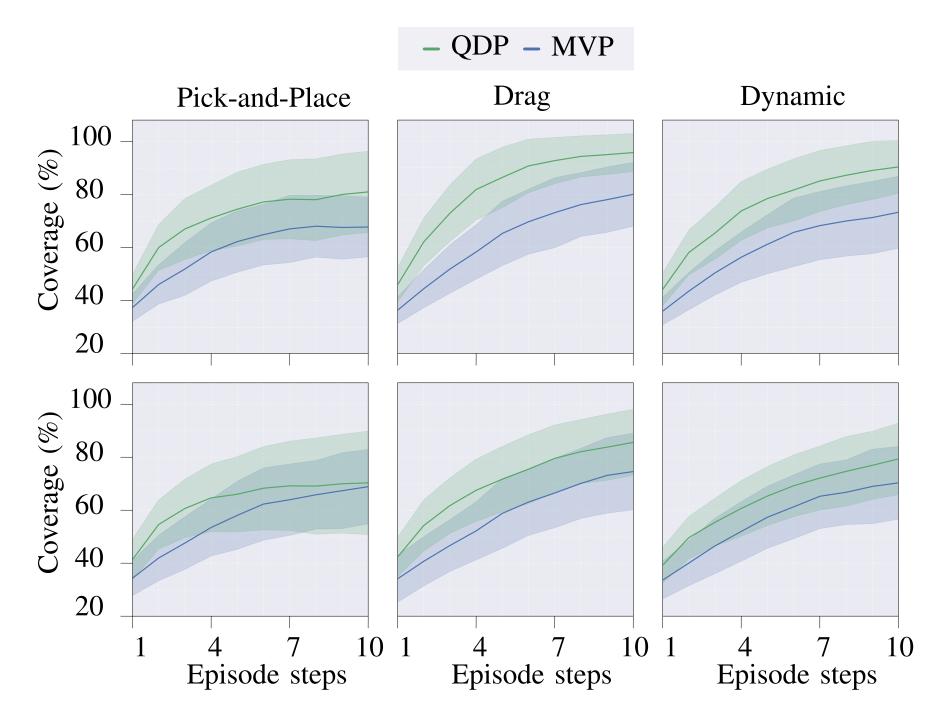
Real-world Results

## **Experimental Results**

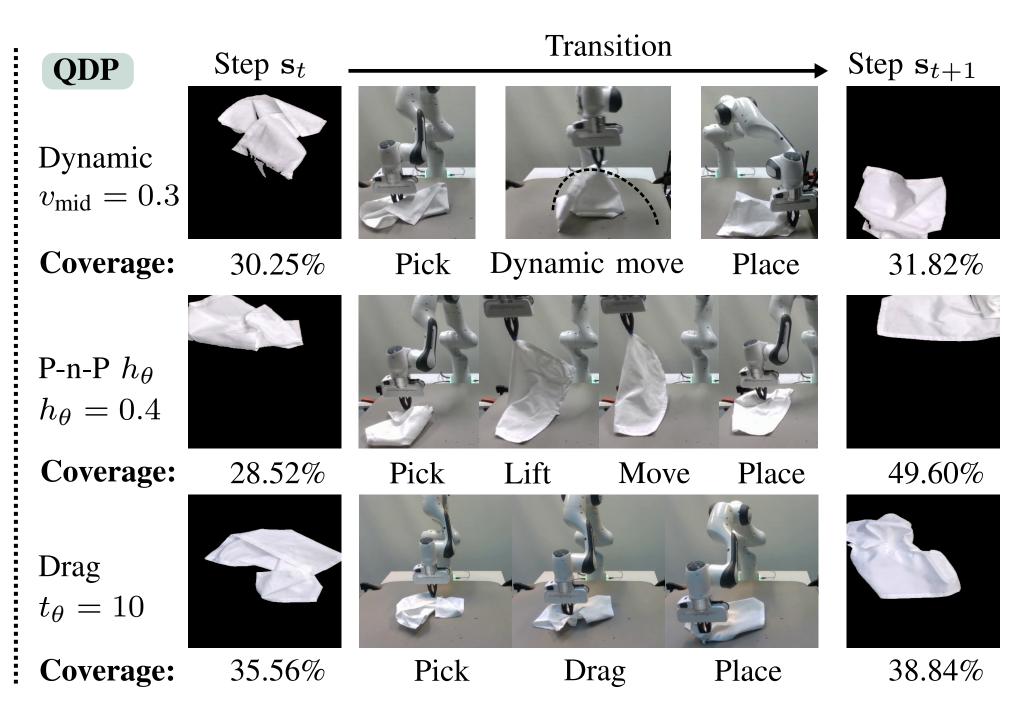
What do we analyse?

- The impact of learning to sequentially optimise parameters such as the height or velocity of pre-defined manipulation primitives
- The performance of QDP when transferred to the real-world in a zero-shot manner

### **Simulation Results**



### Transition Step $\mathbf{s}_{t+1}$ Step $\mathbf{s}_t$ MVP Dynamic $v_{ m mid}=0.1$ Dynamic move Pick **Coverage:** 30.01% 29.31% P-n-P $h_{\theta} = 0.2$ **Coverage:** 24.52% Move Place Pick 29.01% Drag $t_{\theta} = 10$ 30.00% 28.30% Pick **Coverage:** Place



The proposed sequential decision process allows a greater variety and complexity of primitives to be used. QDP paves the way to:

- a broader range of complex manipulation primitives,
- eliminating the human effort of fine-tuning or designing primitives,
- reducing computational requirements due to the sequential decision process.