December 2018

The University of Texas at Austin

Grasping Affordance

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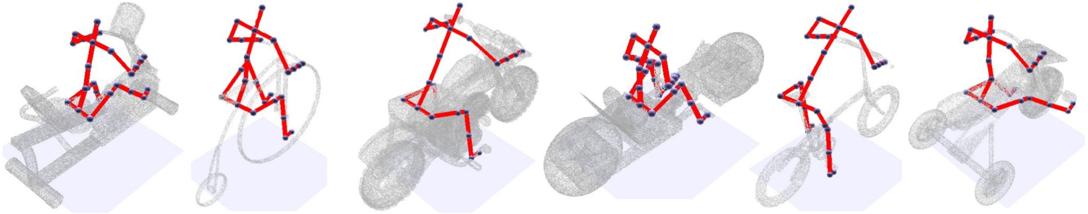
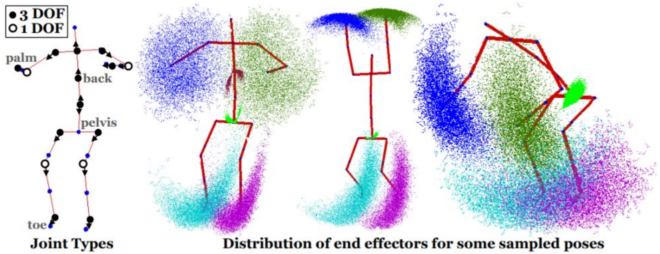
Introduction



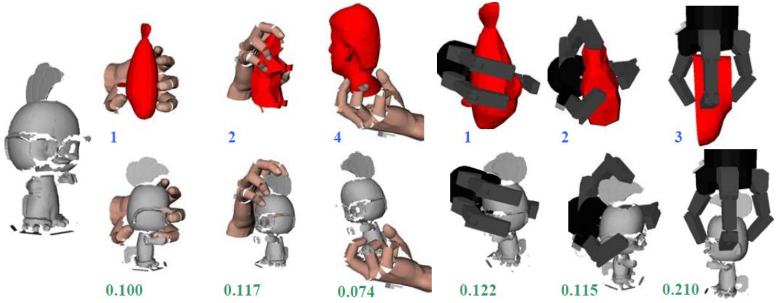
- Shape2Pose studies affordances of **human bodies** interacting with objects
- Affordances help understand semantics and function of novel objects
- Essentially, we want understand **how** an object is used
- We extend this work to **grasp** affordances along with more modern approaches

Existing Approaches



- Treated as an optimization problem over an energy function with geometric/prior knowledge of objects/poses
- Shape2Pose's energy function:
  - Feature compatibility using a random forest
  - Pose prior represented with mixtures of Gaussians over joint angles
  - (no deep learning)

Our Approach



- Dataset: Columbia Grasp Database
- Similar energy function formulation
- Pose prior and feature compatibility replaced with deep learning techniques

Formulation

$$E(q) = w_{\text{pose}} E_{\text{pose}}(q) + w_{\text{feat}} E_{\text{feat}}(q) + w_{\text{dist}} E_{\text{dist}}(q)$$

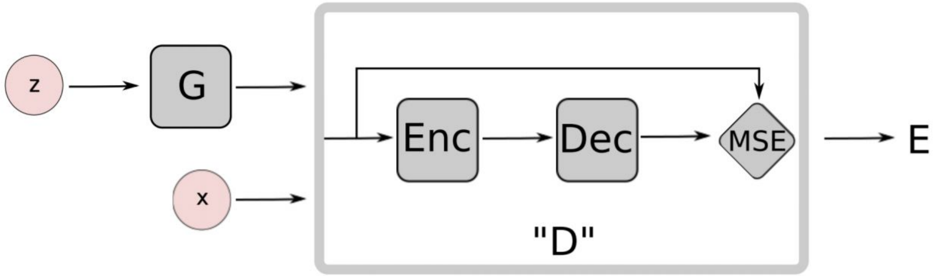
q : Hand configuration

E_{pose} : Pose Prior

E_{feat} : Feature compatibility

E_{dist} : Distance

Pose Prior

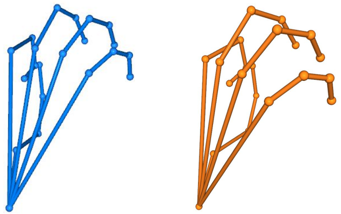


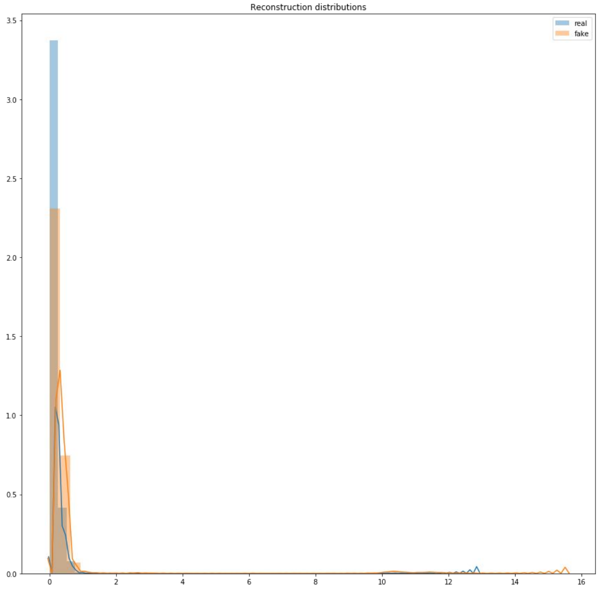
- Represented with EBGAN
- EBGAN
  - GAN with the discriminator treated as an energy
  - Discriminator represented with autoencoder
  - Autoencoder reconstruction loss is the energy
  - Real samples = low energy, fake samples = high energy

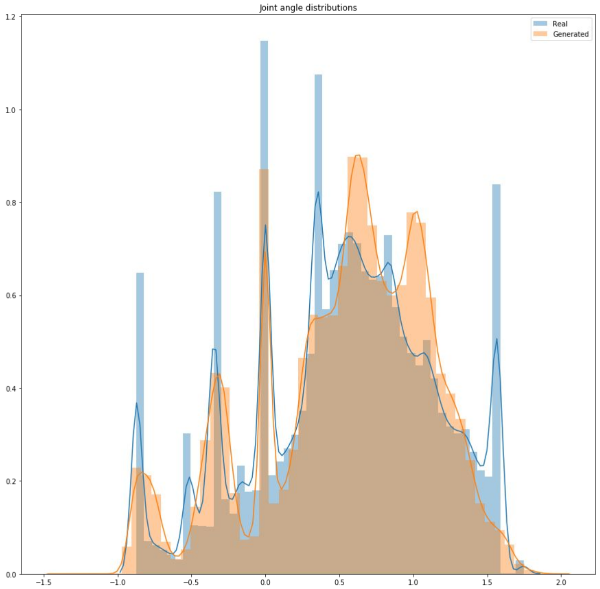
$$\mathcal{L}_D(x, z) = D(x) + [m - D(G(z))]^+$$

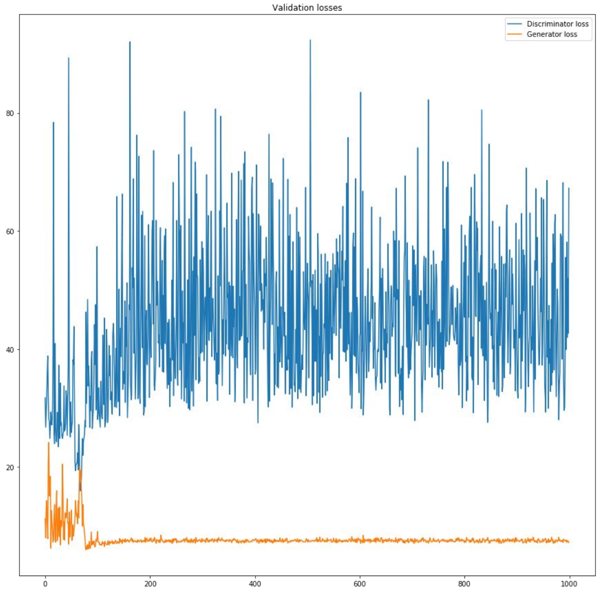
$$\mathcal{L}_G(z) = D(G(z))$$

Pose Prior results



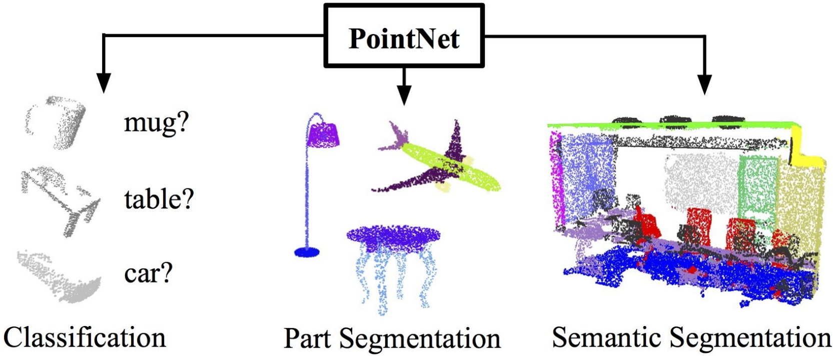


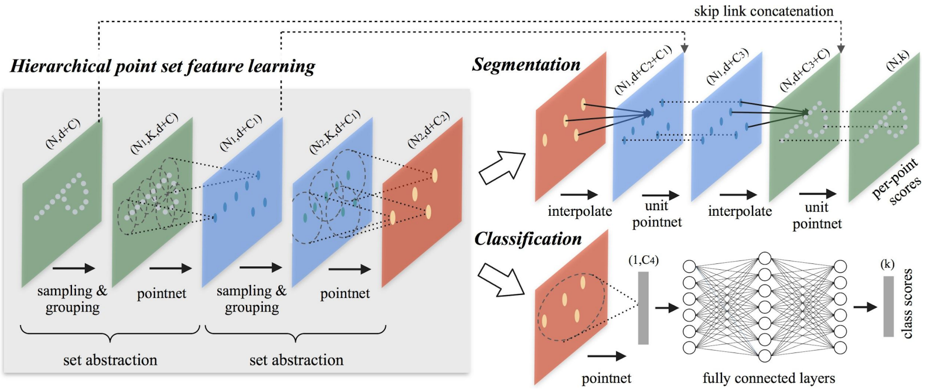




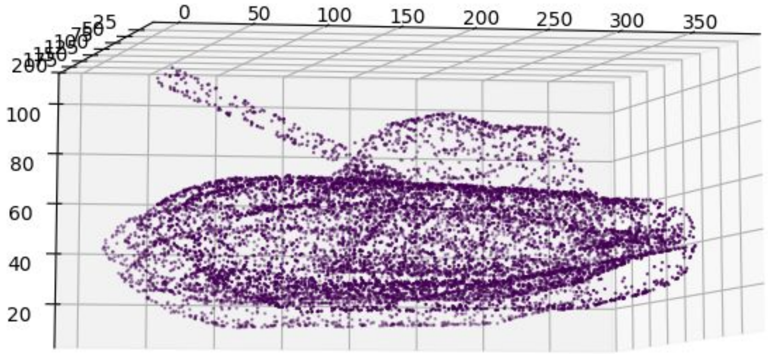
Feature Compatibility

- Parameterized by PointNet++
- Goal: predict the log probability that each point on the mesh is the nearest point to each joint/end effector on the hand





Feature Compatibility Results



- Note that the side is more likely to have contact points
- However many contact points are equally valid since you can hold shapes in many different orientations (which is expressed in the dataset)

Distance

$$E_{\text{dist}}(\mathbf{q}) = \max_{1 \leq i \leq k} ||\mathbf{p}_i - x_i(\mathbf{q})||_2^2 \tag{3}$$

$$\text{where } \mathbf{p}_i = \arg \min_{\mathbf{p}' \in \text{Object}} ||\mathbf{p}' - x_i(\mathbf{q})||_2^2 \tag{4}$$

Energy will assign higher scores to configurations near the object

Optimization

- Evolution strategies

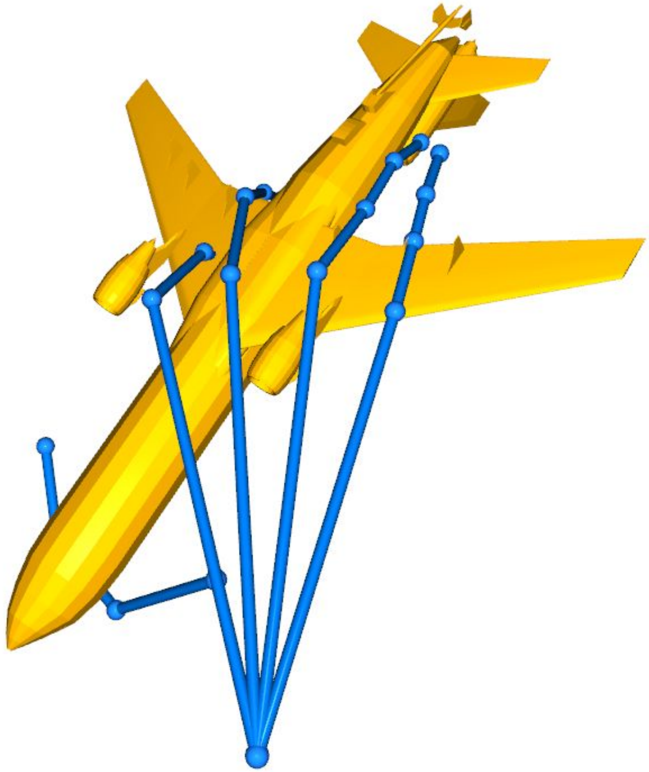
Algorithm 1 Evolution Strategies

```
Input: Learning rate α, noise standard deviation σ, initial policy parameters θ_0
for t = 0, 1, 2, ... do
    Sample ε_1, ... ε_n ~ N(0, I)
    Compute returns F_i = F(θ_t + σε_i) for i = 1, ..., n
    Set θ_{t+1} ← θ_t + α (1/(nσ)) Σ_{i=1}^{n} F_i ε_i
end for
```

$$\theta_{t+1} \leftarrow \theta_t + \alpha \frac{1}{n\sigma} \sum_{i=1}^{n} F_i \epsilon_i$$

Results

- Some good grasps
- Ideas for improvement



Questions?