Online 3D Deformable Object Classification for Mobile Cobot Manipulation

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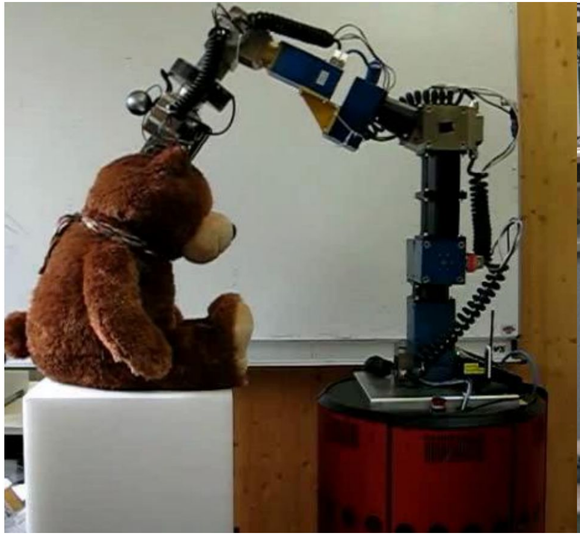
Assistive Mobile Cobots Can Be Used to Grasp Various Everyday Objects for Service Tasks



Courtesy: Frank, Barbara, et al, 2011

Courtesy: Google's robotics lab

Image: Our case

Some Objects Are Easily Deformed Due to Grasping Forces from Robots or from Human Factors

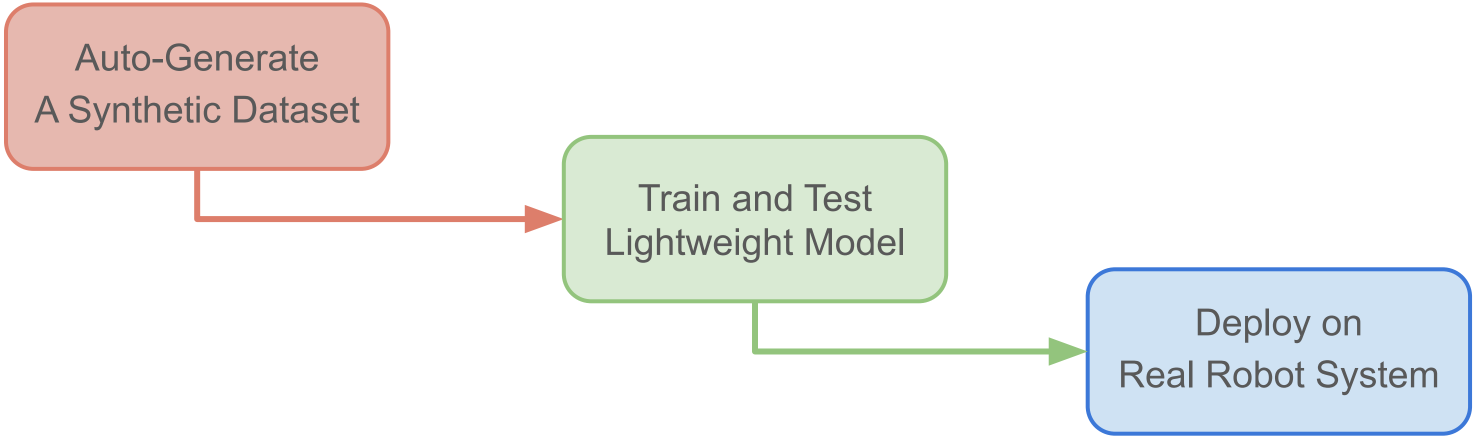
and machine learning (ML) models for vision are highly sensitive to input changes ⇒ misclassification problem

3D Deformable Object Classification for Mobile Cobots

Key Contributions:

- Generation pipeline for deformed objects from 3D scan.
- Lightweight ML model to classify objects with deformation artifacts.
- Guarantee online inference for mobile cobots.

Our Pipeline:



Scanning Real-World Deformable Objects

- The MakerBot Digitizer 3D scanner *(right)* is used to scan real-world objects.
- Our raw scans *(left)* include various-sized deformable objects (*e.g.*, tin cans, foam balls, and paper cups).

Deformable Object Generation Procedure

- Downsampling scanned objects
- Identifying graspable region
- Sampling handle points
- Taking handle points for multiple deformations
- Slicing the object for position of opposite handle point
- Defining inward orientation and deformation intensity for deformation
- Generating deformed meshes

(a) Scan Real-World Object (b) Downsample Point Cloud (c) Identify Graspable Region (d) Sample Handle Points (e) Slice Point Cloud (f) Deform based on Handle Points (g) Generate Deformed Mesh

As-Rigid-As-Possible (ARAP) Deformation with Smooth-Regularization

- Denote a mesh of *n* vertices as: $\mathcal{M} := (E, V, F)$
  with *E*, *V*, and *F* are sets of edges, vertices, and faces in *M*, respectively.
- We would like a deformed mesh, as follows:

  $$\mathcal{M}^{'} := (E^{'}, V^{'}, F^{'})$$

  with *E'*, *V'*, and *F'* are sets of edges, vertices, and faces in *M'*, respectively.

As-Rigid-As-Possible (ARAP) Deformation with Smooth-Regularization

- Without loss of generality, arrange vertices in the deformed mesh as follows:

$$\begin{cases} \mathbf{v}_i^{'} = \mathbf{c}_i = \mathbf{v}_i, & \text{for } i = 1, 2, ..., m \\ \mathbf{v}_i^{'} = T_i(\mathbf{v}_i)\ , & \text{for } i = m+1, m+2, ..., n \end{cases}$$

where:

$T_i(\cdot)$ represents the transformation from the original vertex,

$\mathbf{v}'_i$ is the transformed vertex of $\mathbf{v}_i$, and

$\mathbf{c}_i$ denotes a constraint point in M' that is invariant to vertex $\mathbf{v}_i$ in M.

As-Rigid-As-Possible (ARAP) Deformation with Smooth-Regularization

- The formula for ARAP deformation with smooth regularization is written as:

$$\boxed{\mathcal{E}(V')} = \sum_{i=1}^{n} \left\| \frac{1}{|\Omega_i|} \sum_{j \in \mathcal{N}(\mathbf{v}_i')} \omega_{\cot} \left(\mathbf{v}_i' - \mathbf{v}_j' \right) - R(\mathbf{v}_i') \cdot \delta(\mathbf{v}_i) \right\|_2^2 + \sum_{i=m+1}^{n} \left\| \mathbf{v}_i' - \mathbf{c}_i \right\|_2^2 + \sum_{i=1}^{n} \sum_{j \in \mathcal{N}(\mathbf{v}_i')} \alpha_{smooth} \cdot S(\mathcal{M}) \left\| R(\mathbf{v}_i') - R(\mathbf{v}_j') \right\|_2^2,$$

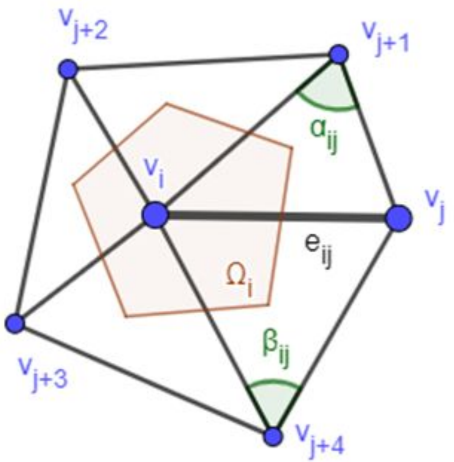
we want to optimize this

differential term

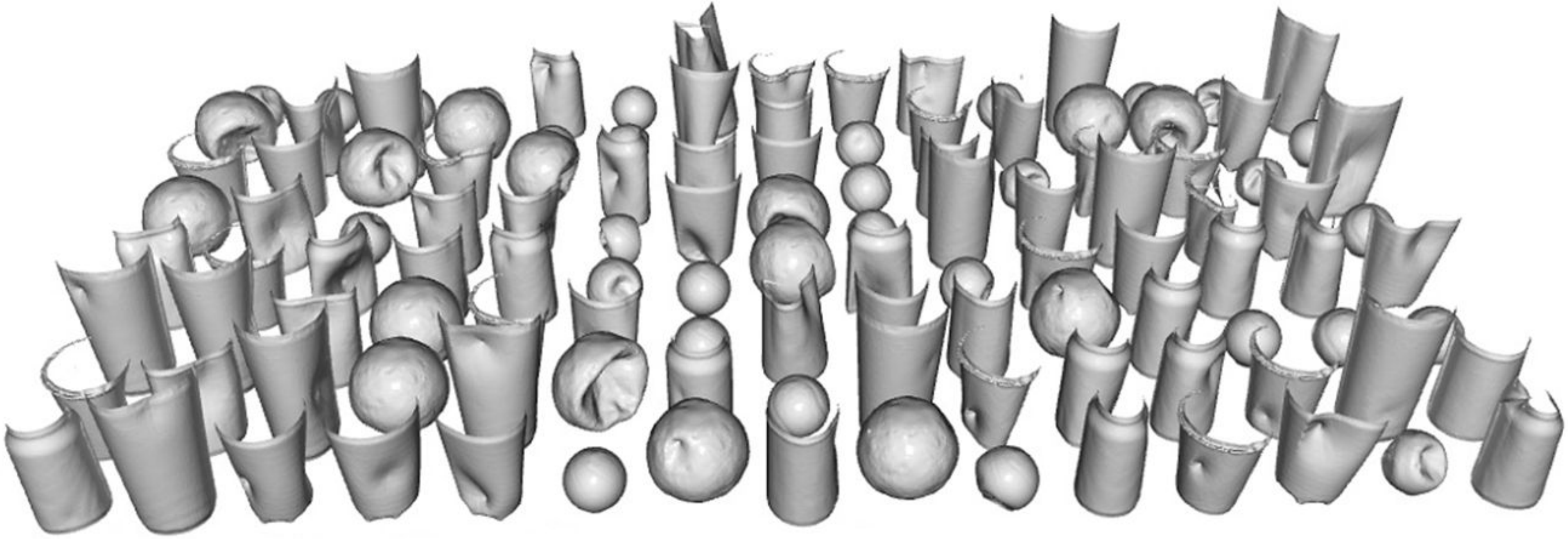
smooth regularization term

$$\text{with } \delta(\mathbf{v}_i) = \frac{1}{|V|} \sum_{i=1}^{|V|} \frac{1}{|\Omega_i|} \sum_{j \in \mathcal{N}(\mathbf{v}_i)} \omega_{\cot}(\mathbf{v}_i - \mathbf{v}_j)$$

$$\text{and } \omega_{\cot} = (\cot \alpha_{ij} + \cot \beta_{ij})/2$$

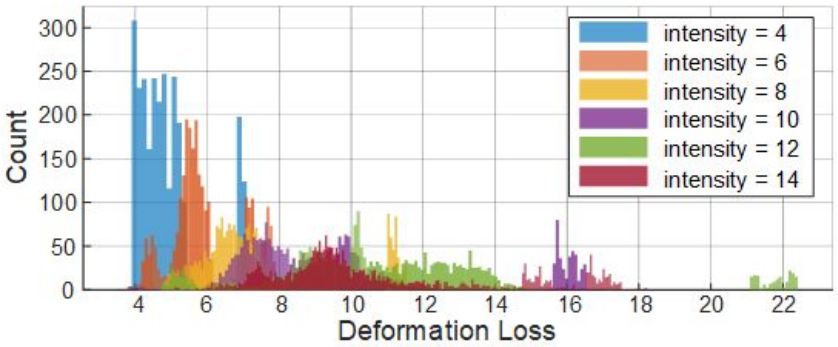


Demonstration of A Subset of the Auto-Generated 3D Deformable Object Dataset



The objects are viewed using Open3D.

How Well the Dataset Distributes In Terms of Deformation Loss?

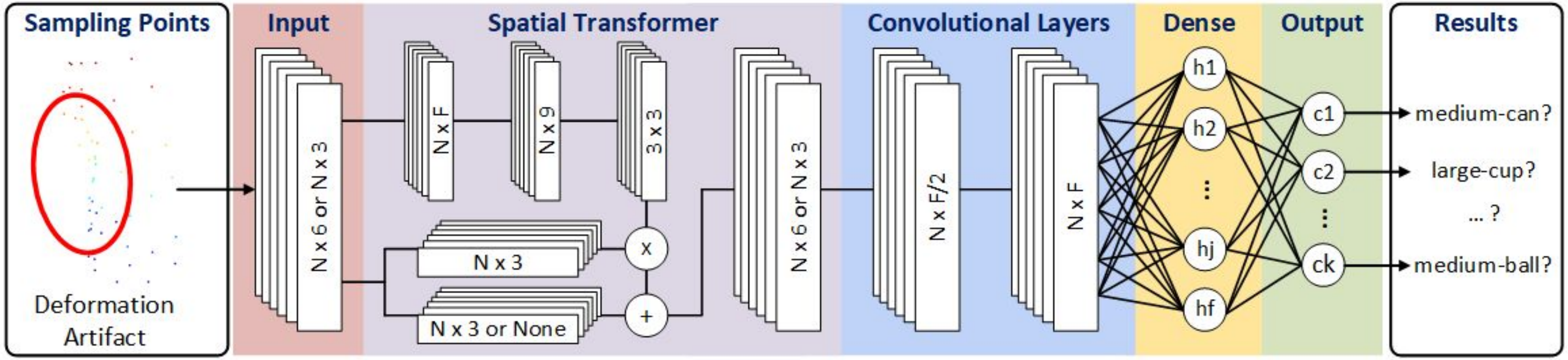


Well-distribute across the domain.

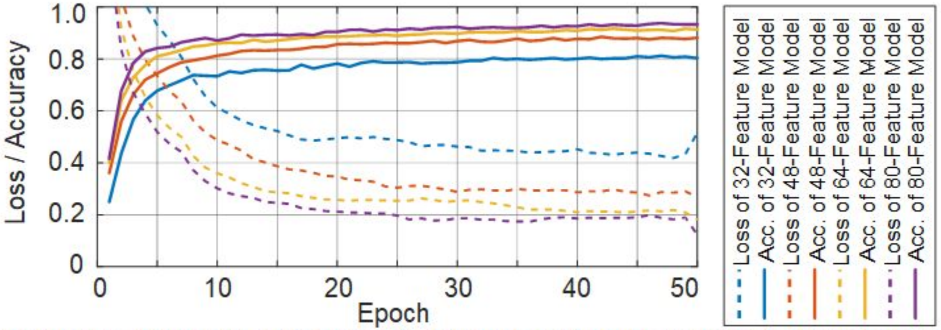
- The deformation loss is computed as weighted losses of:
  - Chamfer distance loss
  - Mesh edge loss
  - Mesh normal loss
  - Laplacian smoothing loss
- **Intensity** represents the inward displacement of handle points during the ARAP deformation.

Classification Network for 3D Deformable Objects

- Takes sampling points with *deformation artifact* as input.
- Passes through a spatial transformer, two convolutional layers, and one fully-connected (dense) layer.
- **Spatial transformer** is used to find the representation that is invariant to *permutations*, *rotations*, and *translations* in point clouds.
- Returns probabilities among classes at the output layer.



Training Performances of Designed Networks

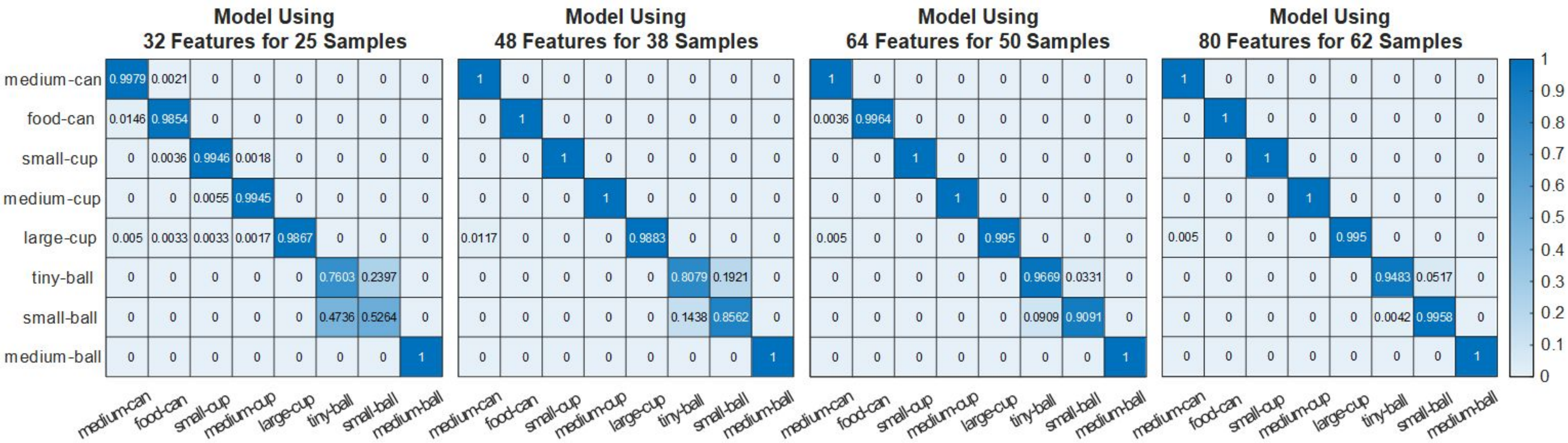


Training performance of deformable object classifier with multiple feature choices

***E.g.*, 64-feature model means the neural network having F equals 64.**

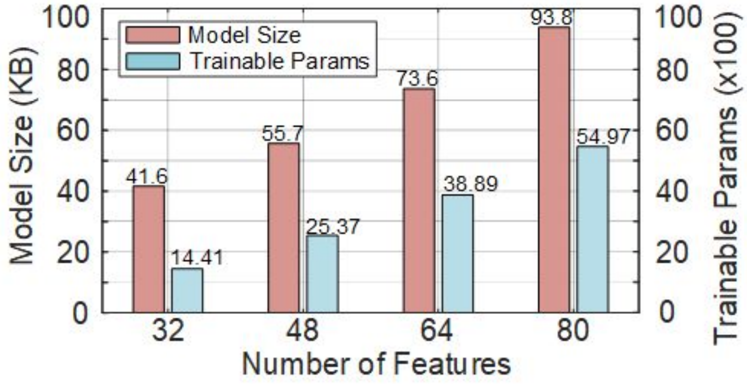
- The training stage converges relatively fast on the NVIDIA RTX 4090 (24 GB) GPU:
  - batch size of 256
  - 50 epochs
  - 10 minutes of training time
  - approx. 90% of accuracy on validation set

Testing Performances of Designed Networks



The more features the network learned,
the better accuracy it achieves.

Trainable Parameters and Model Sizes

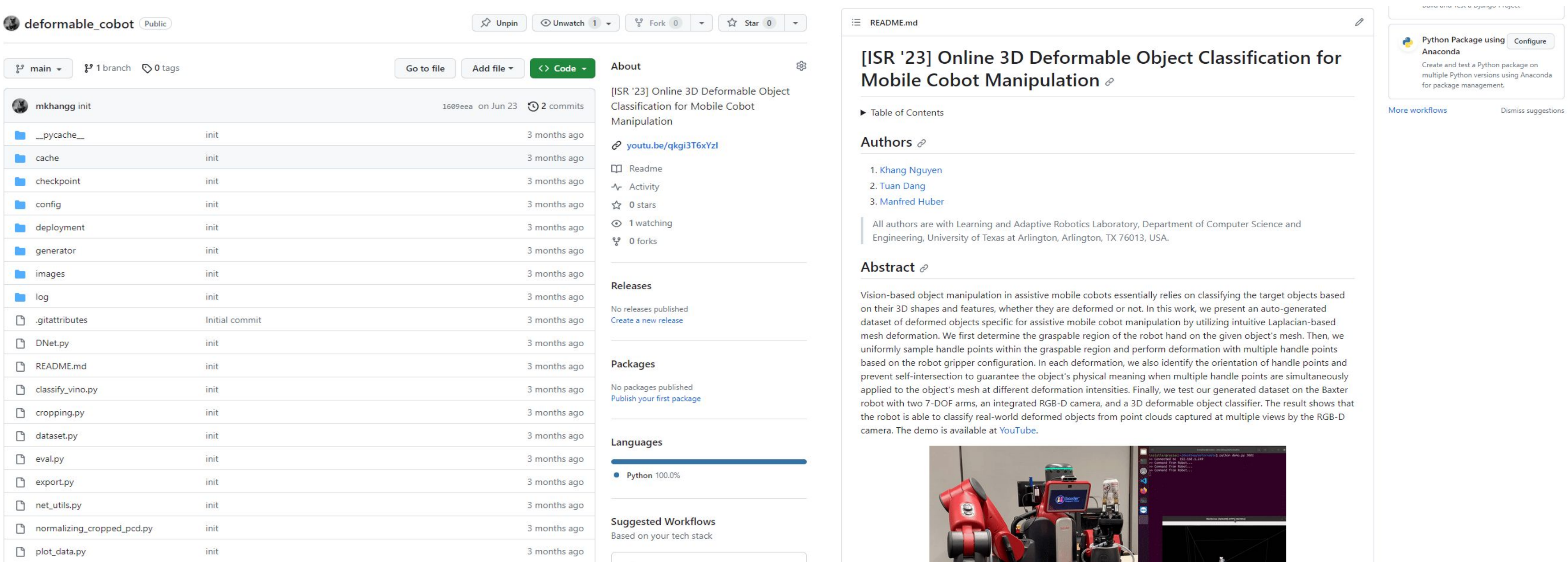


- The best model from our observation:
  - 80 features are learned
  - about 100 KB
  - about 5,500 trainable parameters

Suitable for on-robot deployment!

GitHub Repository

- *Link*: https://github.com/mkhangg/deformable_cobot



Demonstration Video

Click to see the demo video.

Thank you for listening!

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