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Sandia National Laboratories

RAPID CONSTRAINED OBJECT MOTION ESTIMATION USING DEEP NEURAL NETWORKS

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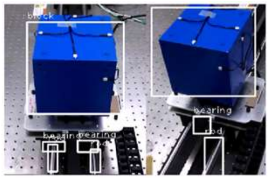
Problem & Motivation

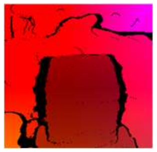
- Autonomous manipulation in unstructured environments is a complex challenge.
- Key for interaction: grasping object dynamics for task-specific manipulation.
- Existing methods lag in quick and precise motion prediction of mechanical systems.
- **Our goal: refine object motion estimation through centroid localization in semantically labeled objects.**

Research Highlights

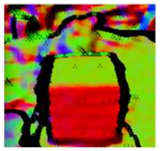
- Introduces a rapid RGB-D data algorithm for object labeling and centroid tracking for motion model estimation.
- Case Study: simplified cube on a linear rail to validate the approach.
- Showcases a scalable approach to object motion model estimation for manipulation.
- Compares strengths and limitations of algebraic methods and DNNs in motion estimation.



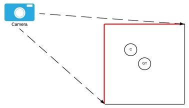
Object detection with bounding boxes and labels.



Depth Map



Surface Normal Map



Centroid Estimation

Edge Map

Resulting Surface Map

Object Detection & Segmentation

- Utilizes YOLO for region of interest identification via bounding boxes.
- Applies bounding boxes to bearings, rods, and cubes in depth maps.

Instance Segmentation

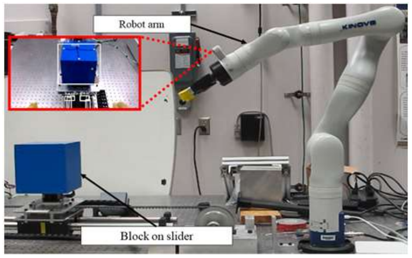
- Analyzes surface normal on depth maps for each point.
- Uses normal map gradients to discern object edges from the background.

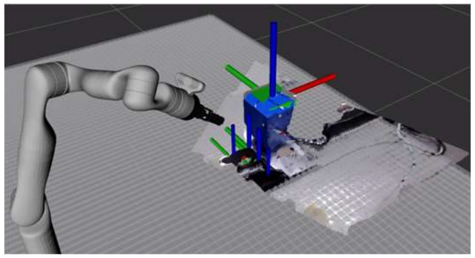
Centroid Estimation

- Computes instantaneous centroid by averaging points on the region of interest.
- Potential drift due to background noise and occlusion effects.

Filtering and Tracking

- Employs minimum-oriented bounding boxes for object framing.
- Implements Kalman filtering for improved object tracking.





Motion Model Estimation

- Normalized geometric motion model highlighting constraint locations and permissible motion directions.
- Identifies constraints by associating bearings with the block, under a single-block assumption.
- Determines the closest rod pairs and matches them with the nearest average bearings.

Algebraic Approach

- Calculate the pair of vectors with minimum angle between the vectors representing cube to bearings and rods.

$$m = arg\min_{k \in S} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \arccos\left(\frac{(b_i^k - r_i^k) \cdot (b_j^k - r_j^k)}{|b_i^k - r_i^k| \cdot |b_j^k - r_j^k|}\right)$$

- Averaging and normalizing this vector gives the angle of motion of the block.

$$v = \frac{1}{n} \sum_{i=1}^{n} b_i^m - r_i^m$$

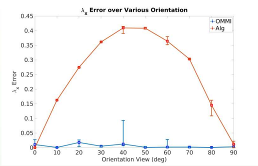
- Motion Model

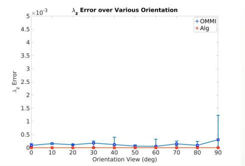
$$\lambda = diag(1 - |v_1|, 1 - |v_2|, 1 - |v_3|, 1, 1, 1)$$

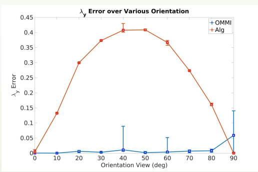
Deep Neural Network Approach

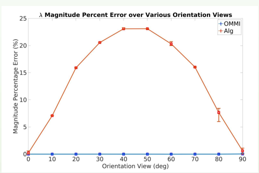
- Input features: 7 inputs including constraint ID and positions of far/near constraints.
- Architecture: 25 hidden layers with 100 neurons each, employing relu and linear activations.
- Optimization: Utilizes Adam optimizer with Mean Squared Error and physics-informed loss functions.
- Training: Conducted on synthetic datasets representing varied constraint locations in 3D, over 600 epochs.

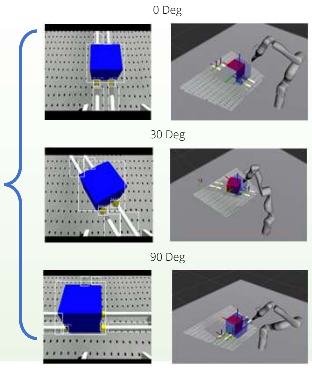
$$J = \frac{\alpha}{N} \sum_{i=1}^{N} (\hat{\lambda}_i - \lambda_i)^2 + \frac{\beta}{N} \sum_{i=1}^{N} (\|\hat{\lambda}_i\| - \|\lambda_i\|)^2$$







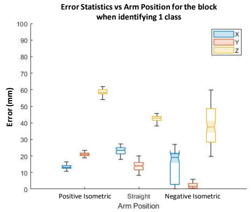


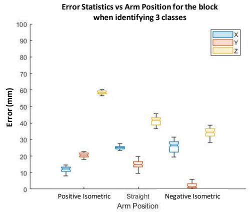


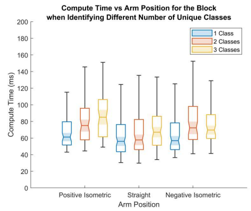
Hardware Experiment & Results

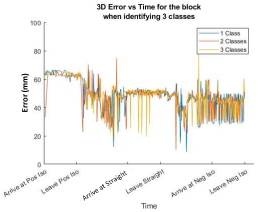
- **Setup:** Centroid estimation algorithm trialed with a cube on a linear rail using Kinova Gen3 7-DOF manipulator.
- **Testing:** Varied end-effector positions (isometric, straight, negative isometric) to assess motion model.
- **Results:**

1) Multiple classification didn't compromise accuracy, showed sublinear increase in estimation time.
2) Model estimation error was negligible at $1.23 \times 10^{-4}\ rad$.
3) Noted noise and peak error during movement or imprecise centroid detection.









Statistical Comparison: Algebraic vs. DNN Approaches

- **Evaluation:** Compared both approaches using variable block orientations (0 – 90 deg orientation).
- **Algebraic shortcomings:** Lacks capability to assess constraint directionality.
- **Accuracy:** Algebraic method more precise with 0/90 deg views, performance degrades with angle variation.
- **DNN strengths:** demonstrates greater adaptability/scalability, suitable for more complex systems.

Summary

- **Innovation:** Developed a rapid RGB-D data processing algorithm for accurate object labeling and centroid estimation.
- **Case Study:** Validated using a simplified cube on a linear rail setup.
- **Advantages:** Presents a scalable, multi-class approach for estimating object motion models, enhancing manipulation tasks.
- **Comparative Insights:**
  - Algebraic Method: Highly precise in certain views but cannot evaluate constraint directionality.
  - DNN Method: Offers enhanced adaptability and scalability, suitable for complex system analysis.

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