Progress Report

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1 Long-Term Goals

- Agile Manufacturing

2 Mid-Term Goals

- Bayesian Pose Estimation
- ARIAC
- Pose Estimation Survey

3 To Do

- Dissect Kendall's [1]: in progress.
- Write a literature review for [1]: in progress.
- Dissect BayesOD [2]: in progress.
- Write a literature review for [2]: Done.
- Implement PoseCNN, DOPE, and BayesOD.
- Look into transfer learning.
- Read and write a review for [3]: Done.
- Look into domain randomization and adaptation techniques.
- MoreFusion [4]: Wrote a literature review. Done.
- Reading list: [5] and [6].
- Read [7].
- Search for recent pose estimation survey papers.
- Generate new data set for PoseCNN and DOPE using UE4.
- Read more papers on deep pose estimation.
- Learn to use UE4.

4 Progress

Following items are listed in order of priority:

- Pose Estimation with BNN's: I am currently working on dissecting [1] and write a review for it simultaneously. Next, I will expand the review I have written for BayesOD and add more details as I look into the source code. My goal is to do some research every morning and to end that with a page of written material. I will focus on Bayesian vision as it offers probabilistic predictions by using per pixel Bayesian inference rather than deterministic output predictions based on MLE parameters as currently used by CNN's.

- Bayesian Uncertainty, [1]: Current pose estimation models with performance comparable with state of the art such as [8], [9], [4], and [10] all use CNN's.

  Although use of CNN's remains a powerful tool as a mean to compute rich feature maps by taking advantage of color channels; it has its short comings, mainly that predictions are deterministic even though the model is probabilistic.

  Classical neural networks and CNN's use maximum likelihood to calculate network weights and biases which derive network outputs. Such models are represented by conditional PDF $p(\mathbf{y}|\mathbf{x},\theta)$ trained on data $D = \{\mathbf{x}_i, \mathbf{y}_i\}_{i=1}^{N}$ and converging to a set of learned parameters $\theta = \{\mathbf{W}, \mathbf{b}\}$ where

  $$p(D|\theta) = \prod_{i=1}^{N} p(\mathbf{y}_i|\mathbf{x}_i, \theta)$$

  defines that PDF. For training these models, parameters $\mathbf{W}$ and $\mathbf{b}$ are learned through back-propagation using Maximum Likelihood Estimate (MLE) method, as defined by

  $$\theta_{\hat{MLE}} = \underset{\theta}{argMax} \sum_{i=1}^{N} ln\ p(\mathbf{y}_i|\mathbf{x}_i, \theta)$$

  On the other hand, Bayesian Neural Networks or BNN's infer posterior probability distribution frame by frame by marginalizing new likelihood over the distribution of parameters, hence converging to steady state posterior distribution. Moreover, Bayesian deep learning tools presented in [1] and [11] allows for study and analysis of *aleatoric* and *epistemic* uncertainties together in one frame work.

Aleatoric:

Epistemic:

Learned attenuation:

- ARIAC: For now, I will focus on implementing pose estimation and BayesOD implementations.
- TensorFlow [12]: I am still working through chapter 2.
- Project Alpe with Nolan: On pause for right now.
- UR5e:
- Fellowship:
- System Identification Presentation:

5 Plans

Following items are listed in order of priority:

- (On pause) Continue with ROS Industrial tutorials and documentation.
- (On pause) Resume Robotic Perception course as soon as possible.
- (On pause) Read Digital Image Processing by Gonzalez and Woods.

References

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[12] B. Planche and E. Andres, "Hands-on computer vision with tensorflow 2," 2019.