Perception for Autonomous Systems (PAZ)

Octavio Arriaga  
University of Bremen, Robotics Research Group  
ARRIAGAC@UNI-BREMEN.DE

Matias Valdenegro-Toro  
DFKI - Robotic Innovation Center, Bremen Germany  
MATIAS.VALDENEGRO@DFKI.DE

Mohandass Muthuraja  
RoBoTec PTC GmbH, Bremen Germany  
MOHANDASS@BREEDINGLEADERS.COM

Sushma Devaramani  
Hochschule Bonn-Rhein Sieg, Sankt Augustin Germany  
SUSHMA.DEVARAMANI@INF.H-BRS.DE

Frank Kirchner  
University of Bremen, Robotics Research Group  
DFKI - Robotic Innovation Center, Bremen Germany  
FRANK.KIRCHNER@DFKI.DE

Abstract

In this paper we introduce the Perception for Autonomous Systems (PAZ) software library. PAZ is a hierarchical perception library that allow users to manipulate multiple levels of abstraction in accordance to their requirements or skill level. More specifically, PAZ is divided into three hierarchical levels which we refer to as pipelines, processors, and backends. These abstractions allows users to compose functions in a hierarchical modular scheme that can be applied for preprocessing, data-augmentation, prediction and postprocessing of inputs and outputs of machine learning (ML) models. PAZ uses these abstractions to build reusable training and prediction pipelines for multiple robot perception tasks such as: 2D keypoint estimation, 2D object detection, 3D keypoint discovery, 6D pose estimation, emotion classification, face recognition, instance segmentation, and attention mechanisms.

Keywords: Robot Perception, Computer Vision, Deep Learning.

1. Introduction

Current research trends in machine learning and computer vision indicate that state-of-the-art models in the coming years would most likely include the use of differentiable libraries and deep learning (Goodfellow et al., 2016). Furthermore, deep learning has now been consolidated as an incremental discipline in which we hypothesize that small additive changes must also represent small incremental modifications to their software description. Additionally, the term design stamina hypothesis is used in software engineering to describe the capacity of software to quickly develop additional functionalities given that it contains an appropriate set of internal tools and abstractions (Fowler, 2018). Thus, one of the main goals of PAZ is to create internal software structures that satisfy the design stamina hypothesis for perceptual algorithms. We corroborate the successful direction of PAZ by using our hierarchical abstractions to build reusable components for multiple robot perception algorithms in multiple domains. More specifically, PAZ was used for creating complete training and inference pipelines for all tasks and models displayed in Figure 1.
Figure 1: Examples of multiple perception tasks and models implemented using PAZ: 1a) Probabilistic keypoint estimation (Neumann and Vedaldi, 2018) 1b) 6D head pose estimation 1c) 2D Object detection (Liu et al., 2016) 1d) Emotion classification (Arriaga et al., 2017) 1e) 2D Keypoint estimation (Wang et al., 2020) 1f) Instance segmentation (He et al., 2017) 1g) Keypoint discovery (Suwajanakorn et al., 2018) 1h) Haar Cascades (Viola and Jones, 2001) 1i) 6D Pose estimation 1j) Face recognition (Turk and Pentland, 1991) 1k) Attention (Jaderberg et al., 2015) 1l) Implicit pose estimation (Sundermeyer et al., 2018).

2. Related software

Similar software libraries are Detectron2 (Wu et al., 2019) the Object detection API from Tensorflow (Huang et al., 2017) and MMDetection (Chen et al., 2019). Detectron2 focuses in extending a single model, Mask-RCNN, while the Object Detection API and MMDetection focus primarily in optimizing models on the single task of 2D object detection. On the other hand, as shown in Figure 1, PAZ focuses in extending multiple models across a diverse set of perception tasks. This broad generality of tasks and models is possible due to our hierarchical-API, which allows users to re-use and construct entirely new functions in a modular scheme.

3. Hierarchical abstractions

In this section we review the main components of each of our hierarchical levels and their corresponding software abstractions. One important consideration to be made is that while we encourage the user to use our abstractions we don’t necessarily impose them. Thus, a PAZ user can use any of it’s functionality at any level without necessarily subscribing to a specific API.

3.1 High-level:

Our highest API level, pipelines, contains application-ready functions for 2D object detection, 2D keypoint estimation, 6D pose estimation, emotion classification, data-augmentation and image pre-processing. Our API allows the user to quickly instantiate out-of-the-box
functions that can be applied directly to an image. Listing 1 contains an example on how to instantiate a single-shot object detector from PAZ and apply directly to an image for an end-to-end prediction.

```python
from paz.pipelines import SSD512COCO

detect = SSD512COCO()

# apply directly to a numpy-array
inferences = detect(image)
```

Listing 1: High-level function

```python
from paz import processors as pr

augment = pr.SequentialProcessor()

augment.add(pr.RandomContrast())
augment.add(pr.RandomBrightness())
augment.add(pr.RandomSaturation())
augment.add(pr.RandomHue())

# apply it as a python function
image = augment(image)
```

Listing 2: Mid-level construction

3.2 Mid-level

The high-level API is useful for rapidly creating applications; however, it might not be flexible enough for the user’s specific purposes. Therefore, PAZ builds high-level functions using our a mid-level API which allows the user to modify or extend existing pipelines. The abstraction for this mid-level is referred to as a Processor. Processors are meant to perform small computations that can be re-used in other applications or entirely new algorithms. PAZ includes the SequentialProcessor abstraction to sequentially apply processors to a set of inputs. In Listing 2 we create a simple data-augmentation pipeline for image classification. Our sequential API reveals some of the flexibility and reusability of PAZ. If for example a user wishes to input a dictionary, or to add a new data augmentation function or a normalization operation one would only need to add a new processor. Furthermore, PAZ provides an abstract template class for creating any custom new logic. However, an important consideration that we would like to make is that the user can pass any python function to a pr.Sequential pipeline, and is not constrained to use our Processor base class. Another relevant aspect of our API is that it clearly depicts the processing steps of our data into well separated modules; thus, PAZ creates a programming bias to distribute computation into multiple simple functions. This allows users with limited experience either with programming or with a specific new algorithm to easily adapt, debug, or understand any aspect of it’s computation. We specifically consider this of great importance given the state of many ML research projects, that often prove difficult to continue their improvement.

3.3 Low-level

Processors allow us to easily compose, compress and extract away parameters of functions; however, most processors are build using our low-level API (backend). Our backend modules are found in: backend.boxes, backend.camera, backend.image, backend.keypoints and backend.quaternion. Each of these modules is meant to be expanded or entirely

1. The name processor describes the capacity to create both pre-processing and post-processing functions.
2. Similar abstractions have proven useful in the context of deep learning. Specifically in the sequential application of layers in Keras (Chollet et al. 2015).
replaced without affecting the functionality of the higher levels. For example, if a camera contains it’s own software API, one could wrap this camera-specific API with our `backend.camera.Camera` fields and methods in order to re-use our own specific camera utilities such as real-time prediction visualization or real-time prediction video-recording.

Furthermore, one could re-use any low-level functions without ever subscribing to our mid-level or high-level APIs or functionalities. In this case one uses PAZ as a collection of small modules without any meta-function construction. We believe that a user should have the possibility to choose which paradigms fits better to their case, ability or style; thus, we provide functionality and resources for each of these levels.

4. Additional functionality

**Built-in messages:** PAZ includes built-in messages of common prediction types made in perceptual systems. These built-in messages include `Box2D`, `Pose6D` and `Keypoints3D`. These types allow PAZ users to have an easier data exchange with other robotic frameworks such as ROS (Quigley et al., 2009) or ROCK (Joyeux, 2013) without having to install any additional software.

**Datasets:** PAZ provides a common interface to load multiple datasets related to object detection, image segmentation and image classification. The available datasets within PAZ are OpenImages (Kuznetsova et al., 2018), COCO (Lin et al., 2014), VOC (Everingham et al., 2010), YCB-Video (Xiang et al., 2017), FAT (Tremblay et al., 2018), FERPlus (Barsoum et al., 2016) and FER2013 (Goodfellow et al. 2013).

**Automatic batch dispatching:** Once a dataset has been loaded we can pass it to our batch dispatcher class (`SequenceProcessing`), along with any built-in or custom function for preprocessing or data augmentation. The batch dispatcher class instantiates a generator that is ready to be used directly with a `model.fit` scheme.

5. Software engineering

PAZ has only three dependencies: Tensorflow (Abadi et al., 2015), OpenCV (Bradski, 2000) and Numpy (Van Der Walt et al., 2011). Furthermore, it has continuous integration (CI) in multiple python versions (python 3.5, 3.6, 3.7 and 3.8). PAZ has unit-tests for all high-level application functions along with most of the major `backend` modules, and it currently has a test-coverage of 47%. Additionally, PAZ has automatic documentation generation directly from documentation strings.

6. Conclusions and future work

We presented a modular hierarchical software library for perceptual systems. We validated its applicability by creating training and prediction pipelines on a wide range of tasks and algorithms. Further directions and improvements of this software library include increasing the perceptual tasks, increasing the test coverage, and extending our backend functionality.
7. Acknowledgments

We would like to thank Alexander Fabisch for his insightful evaluation and thorough revision of our software. Furthermore, we would like to thank the internal DFKI software board for their evaluation metrics and helpful discussions. This work was supported through two grants of the German Federal Ministry of Economics and Energy during the Projects TransFIT and KiMMI-SF [BMWi, FKZ 50 RA 1703, and FKZ 50 RA 2022].

References

Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dandelion Mané, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. TensorFlow: Large-scale machine learning on heterogeneous systems, 2015. URL https://www.tensorflow.org/. Software available from tensorflow.org.

Octavio Arriaga, Matias Valdenegro-Toro, and Paul Plöger. Real-time convolutional neural networks for emotion and gender classification. arXiv preprint arXiv:1710.07557, 2017.

Emad Barsoum, Cha Zhang, Cristian Canton Ferrer, and Zhengyou Zhang. Training deep networks for facial expression recognition with crowd-sourced label distribution. In ACM International Conference on Multimodal Interaction (ICMI), 2016.

Gary Bradski. The opencv library. Dr Dobb’s J. Software Tools, 25:120–125, 2000.

Kai Chen, Jiaqi Wang, Jiangmiao Pang, Yuhang Cao, Yu Xiong, Xiaoxiao Li, Shuyang Sun, Wansen Feng, Ziwei Liu, Jiarui Xu, et al. Mmdetection: Open mmlab detection toolbox and benchmark. arXiv preprint arXiv:1906.07155, 2019.

François Chollet et al. Keras. https://keras.io, 2015.

Mark Everingham, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (voc) challenge. International journal of computer vision, 88(2):303–338, 2010.

Martin Fowler. Refactoring: improving the design of existing code. Addison-Wesley Professional, 2018.

Ian Goodfellow, Yoshua Bengio, and Aaron Courville. Deep Learning. MIT Press, 2016. http://www.deeplearningbook.org.

Ian J Goodfellow, Dumitru Erhan, Pierre Luc Carrier, Aaron Courville, Mehdi Mirza, Ben Hamner, Will Cukierski, Yichuan Tang, David Thaler, Dong-Hyun Lee, et al. Challenges in representation learning: A report on three machine learning contests. In International conference on neural information processing, pages 117–124. Springer, 2013.
Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision*, pages 2961–2969, 2017.

Jonathan Huang, Vivek Rathod, Chen Sun, Menglong Zhu, Anoop Korattikara, Alireza Fathi, Ian Fischer, Zbigniew Wojna, Yang Song, Sergio Guadarrama, et al. Speed/accuracy trade-offs for modern convolutional object detectors. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 7310–7311, 2017.

Max Jaderberg, Karen Simonyan, Andrew Zisserman, et al. Spatial transformer networks. In *Advances in neural information processing systems*, pages 2017–2025, 2015.

Sylvain Joyeux. Rock: the robot construction kit, 2013.

Alina Kuznetsova, Hassan Rom, Neil Alldrin, Jasper Uijlings, Ivan Krasin, Jordi Pont-Tuset, Shahab Kamali, Stefan Popov, Matteo Mallochi, Tom Duerig, et al. The open images dataset v4: Unified image classification, object detection, and visual relationship detection at scale. *arXiv preprint arXiv:1811.00982*, 2018.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *European conference on computer vision*, pages 740–755. Springer, 2014.

Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng-Yang Fu, and Alexander C Berg. Ssd: Single shot multibox detector. In *European conference on computer vision*, pages 21–37. Springer, 2016.

Lukáš Neumann and Andrea Vedaldi. Tiny people pose. In *Asian Conference on Computer Vision*, pages 558–574. Springer, 2018.

Morgan Quigley, Ken Conley, Brian Gerkey, Josh Faust, Tully Foote, Jeremy Leibs, Rob Wheeler, and Andrew Y Ng. Ros: an open-source robot operating system. In *ICRA workshop on open source software*, volume 3, page 5. Kobe, Japan, 2009.

Martin Sundermeyer, Zoltan-Csaba Marton, Maximilian Durner, Manuel Brucker, and Rudolph Triebel. Implicit 3d orientation learning for 6d object detection from rgb images. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 699–715, 2018.

Supasorn Suwajanakorn, Noah Snavely, Jonathan J Tompson, and Mohammad Norouzi. Discovery of latent 3d keypoints via end-to-end geometric reasoning. In *Advances in neural information processing systems*, pages 2059–2070, 2018.

Jonathan Tremblay, Thang To, Balakumar Sundaralingam, Yu Xiang, Dieter Fox, and Stan Birchfield. Deep object pose estimation for semantic robotic grasping of household objects. *arXiv preprint arXiv:1809.10790*, 2018.

Matthew Turk and Alex Pentland. Eigenfaces for recognition. *Journal of cognitive neuroscience*, 3(1):71–86, 1991.
Stefan Van Der Walt, S Chris Colbert, and Gael Varoquaux. The numpy array: a structure for efficient numerical computation. *Computing in Science & Engineering*, 13(2):22, 2011.

Paul Viola and Michael Jones. Robust real-time face detection. In *null*, page 747. IEEE, 2001.

Jingdong Wang, Ke Sun, Tianheng Cheng, Borui Jiang, Chaorui Deng, Yang Zhao, Dong Liu, Yadong Mu, Mingkui Tan, Xinggang Wang, et al. Deep high-resolution representation learning for visual recognition. *IEEE transactions on pattern analysis and machine intelligence*, 2020.

Yuxin Wu, Alexander Kirillov, Francisco Massa, Wan-Yen Lo, and Ross Girshick. Detectron2, 2019.

Yu Xiang, Tanner Schmidt, Venkatraman Narayanan, and Dieter Fox. Posecnn: A convolutional neural network for 6d object pose estimation in cluttered scenes. *arXiv preprint arXiv:1711.00199*, 2017.