**Automatic Target Recognition Literature Review**

**Preston Hart**

**Automatic Machine Learning for Target Recognition**

There are two loops for operating Automatic target recognition (ATR) within the bounds of deep learning and machine learning; data to models and models to products. One requires the use of a machine to read empirical data which could be processed on board or offloaded to a server. The other requires user refinement of the model outputs to aid in optimal decision making. Challenges with Dl/ML currently include data sparsity and model drift, which stems from these algorithms only being fed empirical data and not a mix of empirical and artificial test data.

Also, models trained on one type of target or with data coming from one type of sensor/camera run into complications when the target is changed or a sensor/camera is replaced or swapped since the data coming into the model could be drastically different than previous training data. Conceptual Neural Networks (CNN) have been used alongside multimodal datasets to help with such issues. CNN's specifically apply low, mid, and high-level filters to abstract away image data into integrated shapes needed to identify unique features of an image. DL/ML methods in the form of CNNs reached a 98.7% accuracy threshold after applying some additional filters to the interconnected neural networks for the image data being processed. Some different types of Dl/ML tools: Caffe, DIGITS, Python, LMDB

Erik Blasch, Uttam K. Majumder, Todd Rovito, Peter Zulch, Vincent J. Velten,

"Automatic machine learning for target recognition," Proc. SPIE 10988,

Automatic Target Recognition XXIX, 109880L (14 May 2019); doi:

10.1117/12.2519221

Source: <https://www.spiedigitallibrary.org/conference-proceedings-of-spie/10988/109880L/Automatic-machine-learning-for-target-recognition/10.1117/12.2519221.full?SSO=1>

**UAV environmental perception and autonomous obstacle avoidance: A deep learning and depth camera combined solution**

Currently, advanced sensors on UAVs are only able to accomplish limited object recognition due to external factors such as range and lighting conditions. A color image is filtered through a conceptual Neural Network to determine the objects’ profile, and then that profile’s 3D depth information is pulled out to create a complete mapping of the object. YOLO V3 was used as the CNN fitler to create the object's profile. The depth data that is extracted from the object's profile is analyzed to eliminate irregularities by measuring the distances of the grey point values of the images from two different points, the bounding box center of the image and the gravity center of the object. After extensive testing of combing the CNN model with depth data of the image 91.9% of the tested images were perceived correctly and on average was taking 53.33ms to process and make a prediction on the object. However, there were diminishing returns on the side of the depth data as the drones got further away from the object. The camera used in this testing to achieve great depth data was the Intel RealSense D435 depth camera.

Dashuai Wang, Wei Li, Xiaoguang Liu, Nan Li, Chunlong Zhang,

UAV environmental perception and autonomous obstacle avoidance: A deep learning and depth camera combined solution, Computers and Electronics in Agriculture, Volume 175, 2020, 105523, ISSN 0168-1699, doi: https://doi.org/10.1016/j.compag.2020.105523.

Source: <https://www.sciencedirect.com/science/article/pii/S0168169920303379?casa_token=sjgTImh-ZH8AAAAA:dxOYx5rOpt3QIC10zk0OJgTLcoL9SxxSMvUKMDq5PxcfzVOr60O_4r_rA3hYcihLoGxlIuEwesqW>

**Power Line Recognition and Tracking Method for UAVs Inspection**

This article looks to provide an object detection solution for an unmanned aerial vehicle in the specific aera of electrical equipment. The goal was to hone in and detect the power transmission lines while blocking out background noise that has caused the UAVs in the past to detour off of their proposed field of view. By focusing on the power line’s linear shape bilateral filtering within the object recognition algorithm was used to help create better edge detection. In order to better track the power lines, image sequences were fed into the algorithm rather than searching single frames independently. The bilateral filtering requires an image/camera to rotate in intervals of 15 degrees in order to create the sequence of images for the algorithm to remember as different frames are analyzed. This process specific to a linear object significantly reduced the amount of time spent trying to identify the power lines.

F. Tian, Y. Wang and L. Zhu, "Power line recognition and tracking method for UAVs inspection," *2015 IEEE International Conference on Information and Automation*, 2015, pp. 2136-2141, doi: 10.1109/ICInfA.2015.7279641.

Source: <https://ieeexplore.ieee.org/abstract/document/7279641?casa_token=Vv1zjcskWpkAAAAA:SH8_qRz5R5IZIvbtbQmEP1ZCeqeyJ_ihEw3fJx2DcwBomI93y3TdRm88Ma-ZdPfyF7nng0f2qb1P>

**Person detection with opencv and calculating provide location using PTZ of camera**

Source: <https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.505.7146&rep=rep1&type=pdf>