List of References

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1 Army

Hall et al. (2018) - *Probabilistic Object Detection: Definition and Evaluation*

*Summary:*A probabilistic object detection metric (PDQ - Probability-based Detection Quality) was proposed, thus defining the new task of defining probabilistic object detection metrics. The ability of deep CNNs to quantify both *epistemic* and *aleatoric uncertainty* is paramount for deployment safety-critical applications. PDQ aims to measure the accuracy of an image object detector in terms of its label uncertainty and spatial quality. This is achieved through two steps. First, a detector must reliably quantify its *semantic uncertainty* by providing full probability distributions over known classes for each detection. Next, the detectors must quantify spatial uncertainty by reporting *probabilistic bounding boxes*, where the box corners are modeled as normally distributed. A loss function was constructed to consider both label and spatial quality when providing a final detection measure. The primary benefit of this method is that it provides a measure for the level of uncertainty in a detection.

Is it possible to replace the probabilistic metric with a possibilistic one? Could this be more effective at handling outlying cases?

Mahalanobis and McIntosh (2019) - *A comparison of target detection algorithms using DSIAC ATR algorithm development data set*

*Summary:*The authors provided an initial characterization of detection performance on the DSIAC dataset using the *Faster R-CNN* algorithm and *Quadratic Correlation Filter (QCF)*. Performance was evaluated on two datasets, "easy" and "difficult", where the difficulty was determined by number of pixels on target and local contrast. Under difficult conditions, the Faster R-CNN algorithm achieved noteworthy performance, detecting as much as 80% of the targets at a low false alarm rate of 0.01 FA/Square degree. The dataset was limited by a lack of background diversity.

Tanner and Mahalanobis (2019) - *Fundamentals of Target Classification Using Deep Learning*

*Summary:*A shallow CNN was utilized for ATR on the DSIAC MWIR dataset. The goal of the study was to determine the range of optimal thresholds which would optimally separate the target and clutter class distributions defined by the CNN predictions (output of softmax), as well as determine an upper bound on the number of training images required for optimizing performance. The shallow CNN (5 layers) and a Difference of Gaussians (DoG), which finds regions of high intensity on dark backgrounds were used to detect and classify targets. The CNN could correctly classify 96% of targets as targets and as few as 4% of clutter as targets. It was found that the DoG detector failed when the targets were small (long range) or if the overall image was bright (infrared taken during the daytime). It was also determined that guessing the bright pixels were at the center of the targets was a bad assumption. (The brightest part of a target is not necessarily at its center.)

2 Manifold/ Representation Learning

van der Maaten et al. (2007) - *Dimensionality Reduction: A Comparative Review*

Summary:

Jindal and Kumar (2017) - *A Review on Dimensionality Reduction Techniques*

Summary:

Bengio et al. (2012) - *Unsupervised Feature Learning and Deep Learning: A Review and New Perspectives*

Summary:

Tenenbaum et al. (2000) - *A Global Geometric Framework for Nonlinear Dimensionality Reduction*

Summary:

Roweis and Saul (2000) - *Nonlinear Dimensionality Reduction by Locally Linear Embedding*
Summary:

Saul and Roweis (2001) - *An introduction to locally linear embedding*
Summary:

Belkin and Niyogi (2003) - *Laplacian Eigenmaps for Dimensionality Reduction and Data Representation*
Summary:

Bishop et al. (1998) - *GTM: The Generative Topographic Mapping*
Summary:

Delaporte et al. (2008) - *An introduction to diffusion maps*
Summary:

Theodoridis and Koutroumbas (2008b) - *The Karhunen-Loeve Transform*
Summary:

Theodoridis and Koutroumbas (2008a) - *Kernel PCA*
Summary:

Tipping and Bishop (1999) - *Probabilistic Principal Component Analysis*
Summary:

Lawrence (2003) - *Gaussian Process Latent Variable Models for Visualisation of High Dimensional Data*
Summary:

Lawrence (2005) - *Probabilistic Non-linear Principal Component Analysis with Gaussian Process Latent Variable Models*
Summary:

Gorban and Zinovyev (2008) - *Elastic Maps and Nets for Approximating Principal Manifolds and Their Application to Microarray Data Visualization*
Summary:

Lee et al. (2016) - *Learning Representations from Multiple Manifolds*
Summary:

Frigui and Gader (2009) - *Detection and Discrimination of Land Mines in Ground-Penetrating Radar Based on Edge Histogram Descriptors and a Possibilistic K-Nearest Neighbor Classifier*
Summary:

Fritzke (1994) - *A Growing Neural Gas Network Learns Topologies*
Summary:

Kohonen (1990) - *The self-organizing map*
Summary:

Lopez-Rubio and Palomo (2011) - *Growing Hierarchical Probabilistic Self-Organizing Graphs*
Summary:

Palomo and Lpez-Rubio (2016) - *Learning Topologies with the Growing Neural Forest*
Summary:

Palomo and Lpez-Rubio (2017) - *The Growing Hierarchical Neural Gas Self-Organizing Neural Network*
Summary:

Rauber et al. (2002) - *The growing hierarchical self-organizing map: exploratory analysis of high-dimensional data*
Summary:

Sun et al. (2017) - *Online growing neural gas for anomaly detection in changing surveillance scenes*

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Chiang and Gader (1997) - *Hybrid fuzzy-neural systems in handwritten word recognition*
Summary:

3 Manifold Regularization

Tsang and Kwok (2007) - *Large-Scale Sparsified Manifold Regularization*
Summary:

Ren et al. (2017) - *Unsupervised Classification of Polarimetirc SAR Image Via Improved Manifold Regularized Low-Rank Representation With Multiple Features*
Summary:

Belkin et al. (2006) - *Manifold Regularization: A Geometric Framework for Learning from Labeled and Unlabeled Examples*
Summary:

Ratle et al. (2010) - *Semisupervised Neural Networks for Efficient Hyperspectral Image Classification*
Summary:

Li et al. (2015) - *Approximate Policy Iteration with Unsupervised Feature Learning based on Manifold Regularization*
Summary:

Meng and Zhan (2018) - *Zero-Shot Learning via Low-Rank-Representation Based Manifold Regularization*
Summary:

4 Multiple Instance Learning

-
Summary:

-
Summary:

5 Fusion

6 Outlier/ Adversarial Detection

7 Segmentation

Caselles et al. (1997) - *Geodesic Active Contours*
Summary:

Álvarez et al. (2010) - *Morphological Snakes*

*Summary:*The authors introduce a morphological approach to curve evolution. Snakes or curves iteratively solve partial differential equations (PDEs). By doing so, the shape of the snake deforms to minimize the internal and external energies along its boundary. The internal component keeps the curve smooth, while the external component attaches the curve to image structures such as edges, lines, etc. Curve evolution is one of the most widely used image segmentation/ object tracking algorithms. The main contribution of the paper is a new morphological approach to the solution of the PDE associated with snake model evolution. They approach the solution using only inf-sup operators which has the main benefit of providing simpler level sets (0 outside the contours and 1 inside).

Márquez-Neila et al. (2014) - *A Morphological Approach to Curvature-Based Evolution of Curves and Surfaces*

Summary:

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