Institute of Photogrammetry and GeoInformation

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Master Thesis

Improving pseudo-labels for domain adaptation to train fully convolutional neural networks for aerial image classification

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Abstract

The pixel-wise classification of aerial images and additional data such as digital surface models are the key part of automatic production of maps. Fully convolutional neural networks (FCN) have handled the task of the pixel-wise classification of aerial images and additional data very well. To meet the requirement of FCN which is to have a great many labelled training samples to perform well, semi-supervised domain adaptation (SSDA) can be used to adapt a model that is trained with labelled images in one domain to classify unseen images from another domain. Where the model trained initially with labelled images is called source domain. A target domain in which no labelled images are available. In this work, the trained models in the source domain are being adapted to the target domain in an iterative process by jointly using the labelled images from the source domain and unlabelled images from the target domain, resulting in a classifier for the target domain. To achieve an improvement on the performance of the classifier in the iterative re-training process after adaptation, the selection of correct pseudo-labels is crucial. Re-training with incorrectly predicted labels leads to degraded adaptation result. The present master thesis studies possible approaches from three different ways to cleanse pseudo-labels with low predicted probabilities that are treated as noise, for the re-training process. These different aspects are object feature, predicted probability of pseudo-labels and spatial smoothness in a combination with predicted probability of pseudo-labels. The object feature in this work regards to size feature, elongation and fill factor. Based on the assessment of different criteria of the three approaches, noisy pseudo-labels are rejected for the re-training procedure. Each cleansing approach yields certain improvement of overall accuracy, of evaluation of source-trained models on the test set of respective target domain without adaptation. The approach which leads to highest increment in the overall accuracy and evaluation of other quality matrices is used to adapt four obtained models from the source training to the other domains. Evaluating the obtained models after the source training on the test set of other domains delivers an average overall accuracy of 71.1%. The adaptation with the rejection of noisy pseudo-labels for the re-training process results in an average accuracy of 71.6%. The joint training scheme of the re-training procedure achieves better adaptation results compared to the case which leverages pseudo-labels exclusively.