This is an excerpt from the thesis "*Semi-Supervised Virtual Support Vector Machines with Self-Learning Constraint for Remote Sensing Image Classification*".

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Cartography M.Sc.

Master Thesis

Semi-Supervised Virtual Support Vector Machines with Self-Learning Constraint for Remote Sensing Image Classification

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Semi-Supervised Virtual Support Vector Machines with Self-Learning Constraint for Remote Sensing Image Classification

Submitted for the academic degree of Master of Science (M.Sc.) conducted at the Department of Aerospace and Geodesy Technical University of Munich

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Abstract

In real-world applications, it is difficult to collect labeled samples, and supervised learning methods rely on the quality of this labeled training data. Therefore, in this research, a semi-supervised learning approach is developed in order to benefit from the unlabeled samples that can be produced effortlessly. These semi-supervised methods are built on a popular machine learning technique called support vector machine, which is used to classify remote-sensing imagery in this thesis. Moreover, this work aims to enhance the accuracy of the methods in settings with very few labeled samples and deploy a constrained set of unlabeled samples with a self-learning strategy. Additionally, the aim includes model evaluation for existing support vectors and virtual samples. Moreover, the methodology is further extended with an active learning method. This extension involves uncertainty visualizations in order to increase the model accuracy by relabelling the uncertain samples in a prioritized way. To evaluate these models, experimental results were obtained over the city of Cologne, Germany, and the Hagadera Refugee Camp, Kenya from a very high spatial resolution multispectral data set. Results from newly proposed methods showed favorable performance properties, especially on the few labeled samples. Furthermore, the uncertainty of the models was compared with the active learning extension, and this extension also increased the accuracy.

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List of Abbreviations

SVM	Support Vector Machines
SV	Support Vectors
VSVM	Virtual Support Vector Machines
VSV	Virtual Support Vectors
VSVM-SL	Virtual Support Vector Machines with Self-Learning
QP	Quadratic Programming
VC	Vapnik–Chervonenkis
SRC	Structural Risk Minimization
S3VM	Semi-supervised Support Vector Machines
GIS	Geographic Information Science
AL	Active Learning
VSVM-SL-U	Virtual Support Vector Machines with Self-Learning with Unlabeled Samples
VSVM-SL-VU	Virtual Support Vector Machines with Self-Learning with Virtual Unlabeled Samples
SVM-SL-U	Support Vector Machines with Self-Learning with Unlabeled Samples
OA	Overall Accuracy
AA	Average Accuracy

1 Introduction

1.1 Motivation and problem statement

In the last decades, with the advent of high spatial and spectral resolution remote sensing data, land cover classification applications have become one of the main subjects in remote sensing (Lu et al., 2016). Consequently, it triggered the development of many methods to derive thematic classes from image data, and as an outcome, supervised methods became one of the most preferred classification approaches because of their robust and accurate information extraction properties (Geiß et al., 2019) Although it is overly challenging to determine the best method from numerous of existing approaches for a classification problem, Support Vector Machines (SVM) attracted attention regarding the classification of multispectral remote sensing images. As a working principle, SVM set suitable hyperplanes on different classes of labeled data and those samples are projected through a nonlinear transformation from input space to a higher-dimensional space. In that space, support vectors (SV), which are the samples closest to the separating surface, are determined in subject to the optimal hyperplane that maximizes the margin (Geiß et al., 2019; Burges, 1998). Therefore, SVM showed excellent performance due to their, (i) ability to manage high-dimensional feature space; (ii) relevant generalization properties (iii); the uniqueness of the solution (Tuia et al., 2009)

SVMs, as any other supervised method, rely on the quality of the labeled training data. However, this constrains the training set and requires extensive manual efforts regarding human-machine interaction. That is why active learning methods and semi-supervised learning approaches which use unlabeled samples will benefit the classification results, especially with respect to poorly sampled remote sensing applications (Izquierdo-Verdiguier et al., 2012). It is here where we combine self-learning constraints on Virtual Support Vector Machines (VSMV) with a semi-supervised approach to indicate useful information about the underlying data distribution which eventually achieves higher accuracies, especially with small amounts of training data.

1.2 Research identification

1.2.1 Research objectives

To eventually enhance the accuracy properties of the Virtual Support Vector Machines with the self-learning (VSVM-SL) method in settings with very few labeled samples, the goal is to deploy a constrained set of unlabeled samples for model learning and for very high spatial resolution multispectral remote sensing images. As a result, the training set which the model is learning will be enriched by informative unlabeled samples. Those are jointly evaluated and selected with respect to existing support vectors and virtual samples. In addition, the generation of spatial visualization for the uncertainty of results is done by checking the distance of SVMs hyperplane from the model and further monitoring how the uncertainty changes with the newly developed methods. The spatial visualization will be displayed as land cover classification maps showing corresponding thematic uncertainty. Subsequently, these spatial visualizations will benefit the active learning process by providing human-machine interaction on relabeling uncertain samples in a prioritized way and will use those samples to relearn the model and eventually obtain higher accuracies.

RQ1: To what extent does the new Virtual Support Vector Machines with self-learning constraints on a semi-supervised scheme (VSVM-SL- Unlabeled Samples) method provide better classification accuracy with few labeled samples when compared to other/older methods such as SVM, VSVM, and VSVM-SL?

- Comparison analysis will be made between newly proposed semi-supervised methods to previous methods by comparing overall and average accuracies, kappa value, and F1 score.
- Line graphs will be used in order to see mean kappa values and overall accuracies of the methods.

RQ2: Does visualizing the uncertainties of the models improve human-monitored active learning approaches on relabeling uncertain samples?

- Model quantifies the certainty of unlabeled samples by checking the distance of SVM hyperplane and shows which land cover classes they belong to. Consequently, this helps the user to label those uncertain samples and bring them back to model.
- Therefore, a case study will be applied in order to assess the effects and overall performance of relabeling with visualization of uncertainty on active learning. Accuracy results of newly developed methods plus the uncertainty visualizations will be compared to the results of newly developed methods without the uncertainty visualizations.

1.3 Innovation aimed at

The innovation of the research aims at developing a semi-supervised classification method based on a self-learning strategy. This will provide results with higher accuracy on sparsely sampled remote sensing imageries and will be adaptable in the future to the classification of hyperspectral data. These innovations are aimed at bringing a new outlook with the extension and combination of methods on remote sensing and the cartography fields.

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In future works, the same methodology can be applied for classifying hyperspectral data within an adequate processing framework. Additionally, an active learning approach with uncertainty visualizations can be integrated into all settings of the data sets. Moreover, this approach can be further adapted to the supervised methods as well. At last, a combination of the semi-supervised methods and active learning approach can be integrated better in a collaborative learning scheme.

6 References

Bastin, L., P. F. Fisher, and J. Wood
2002. Visualizing uncertainty in multi-spectral remotely sensed imagery. *Computers & Geosciences*, 28(3):337–350.

Bennett, K., A. Demiriz, et al.
1999. Semi-supervised support vector machines. *Advances in Neural Information processing systems*, Pp. 368–374.

Blaschke, T.
2010. Object based image analysis for remote sensing. *ISPRS journal of photogrammetry and remote sensing*, 65(1):2–16.

Bruzzone, L. and L. Carlin
2006. A multilevel context-based system for classification of very high spatial resolution images. *IEEE transactions on Geoscience and Remote Sensing*, 44(9):2587–2600.

Bruzzone, L., M. Chi, and M. Marconcini
2006. A novel transductive svm for semisupervised classification of remote-sensing images. *IEEE Transactions on Geoscience and Remote Sensing*, 44(11):3363–3373.

Burges, C. J.
1998. A tutorial on support vector machines for pattern recognition. *Data mining and knowledge discovery*, 2(2):121–167.

Cortes, C. and V. Vapnik
1995. Support-vector networks. *Machine learning*, 20(3):273–297.

Demir, B., C. Persello, and L. Bruzzone
2010. Batch-mode active-learning methods for the interactive classification of remote sensing images. *IEEE Transactions on Geoscience and Remote Sensing*, 49(3):1014–1031.

Ding, S., Z. Zhu, and X. Zhang
2017. An overview on semi-supervised support vector machine. *Neural Computing and Applications*, 28(5):969–978.

Dópido, I., J. Li, P. R. Marpu, A. Plaza, J. M. B. Dias, and J. A. Benediktsson
2013. Semisupervised self-learning for hyperspectral image classification. *IEEE transactions on geoscience and remote sensing*, 51(7):4032–4044.

Fernández-Delgado, M., E. Cernadas, S. Barro, and D. Amorim
2014. Do we need hundreds of classifiers to solve real world classification problems? *The journal of machine learning research*, 15(1):3133–3181.

Foody, G. M.
2009. On training and evaluation of svm for remote sensing applications. In *Kernel methods for remote sensing data analysis*, Pp. 85–109. Wiley.

Foody, G. M. and A. Mathur
2004. A relative evaluation of multiclass image classification by support vector machines. *IEEE Transactions on geoscience and remote sensing*, 42(6):1335–1343.

Geiß, C., P. A. Pelizari, L. Blickensdörfer, and H. Taubenböck
2019. Virtual support vector machines with self-learning strategy for classification of multispectral remote sensing imagery. *ISPRS journal of photogrammetry and remote sensing*, 151:42–58.

Geiß, C., P. A. Pelizari, H. Schrade, A. Brenning, and H. Taubenböck
2017. On the effect of spatially non-disjoint training and test samples on estimated model generalization capabilities in supervised classification with spatial features. *IEEE Geoscience and Remote Sensing Letters*, 14(11):2008–2012.

Goodchild, M. F.
2008. Imprecision and spatial uncertainty.

Hughes, G.
1968. On the mean accuracy of statistical pattern recognizers. *IEEE transactions on information theory*, 14(1):55–63.

Izquierdo-Verdiguier, E., V. Laparra, L. Gómez-Chova, and G. Camps-Valls
2012. Encoding invariances in remote sensing image classification with svm. *IEEE Geoscience and Remote Sensing Letters*, 10(5):981–985.

Kinkeldey, C.
2014. A concept for uncertainty-aware analysis of land cover change using geovisual analytics. *ISPRS International Journal of Geo-Information*, 3(3):1122–1138.

Kinkeldey, C., J. Mason, A. Klippel, and J. Schiewe
2014. Evaluation of noise annotation lines: using noise to represent thematic uncertainty in maps. *Cartography and Geographic Information Science*, 41(5):430–439.

Li, Y.-F. and Z.-H. Zhou
2014. Towards making unlabeled data never hurt. *IEEE transactions on pattern analysis and machine intelligence*, 37(1):175–188.

Lu, X., J. Zhang, T. Li, and Y. Zhang
2016. A novel synergetic classification approach for hyperspectral and panchromatic images based on self-learning. *IEEE Transactions on Geoscience and Remote Sensing*, 54(8):4917–4928.

Lucieer, A.
2004. *Uncertainties in Segmentation and their Visualisation*. PhD thesis, Utrecht University and International Institute for Geo-Information Science ....

Melgani, F. and L. Bruzzone
2004. Classification of hyperspectral remote sensing images with support vector machines. *IEEE Transactions on geoscience and remote sensing*, 42(8):1778–1790.

Mountrakis, G., J. Im, and C. Ogole
2011. Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(3):247–259.

Murphy, C. E.
2015. Intellectual highlighting of remote sensing imagery for better image map design. In *Proc. 27th Int. Cartographic Conf.*

Pan, C., J. Li, Y. Wang, and X. Gao
2018. Collaborative learning for hyperspectral image classification. *Neurocomputing*, 275:2512–2524.

Song, X., Z. Duan, and X. Jiang
2012. Comparison of artificial neural networks and support vector machine classifiers for land cover classification in northern china using a spot-5 hrg image. *International Journal of Remote Sensing*, 33:3301–3320.

Tuia, D. and J. Munoz-Mari
2012. Learning user's confidence for active learning. *IEEE Transactions on Geoscience and Remote Sensing*, 51(2):872–880.

Tuia, D., F. Ratle, F. Pacifici, M. F. Kanevski, and W. J. Emery
2009. Active learning methods for remote sensing image classification. *IEEE Transactions on Geoscience and Remote Sensing*, 47(7):2218–2232.

Tuia, D., M. Volpi, L. Copa, M. Kanevski, and J. Munoz-Mari
2011. A survey of active learning algorithms for supervised remote sensing image classification. *IEEE Journal of Selected Topics in Signal Processing*, 5(3):606–617.

Ul Haq, Q. S., L. Tao, F. Sun, and S. Yang
2011. A fast and robust sparse approach for hyperspectral data classification using a few labeled samples. *IEEE Transactions on Geoscience and Remote Sensing*, 50(6):2287–2302.

Volpi, M., D. Tuia, F. Bovolo, M. Kanevski, and L. Bruzzone
2013. Supervised change detection in vhr images using contextual information and support vector machines. *International Journal of Applied Earth Observation and Geoinformation*, 20:77–85.

Wang, X. and P. M. Pardalos
2014. A survey of support vector machines with uncertainties. *Annals of Data Science*, 1(3-4):293–309.