Unsupervised Domain Adaptation for semantic segmentation of dwellings with Unbalanced Optimal Transport

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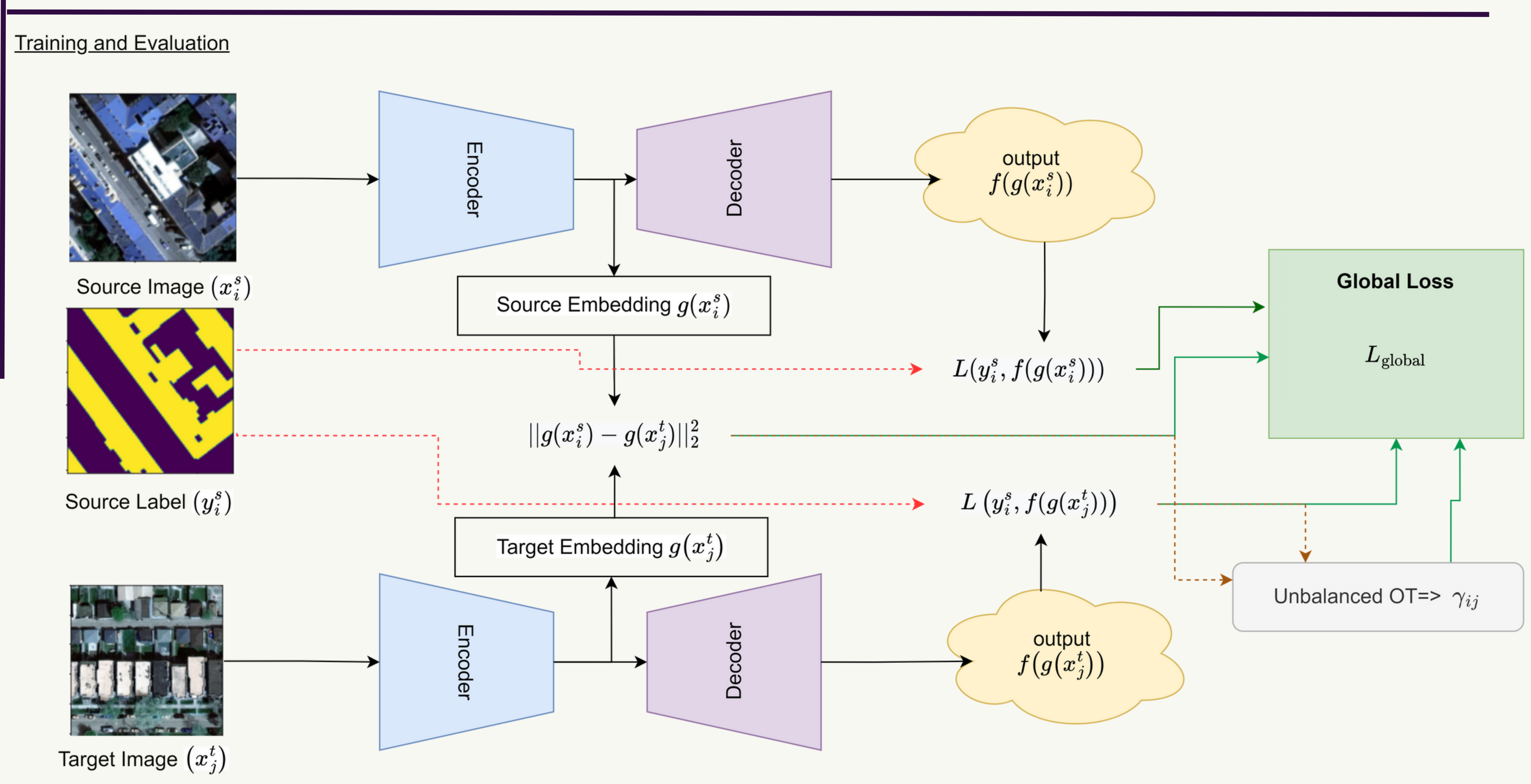
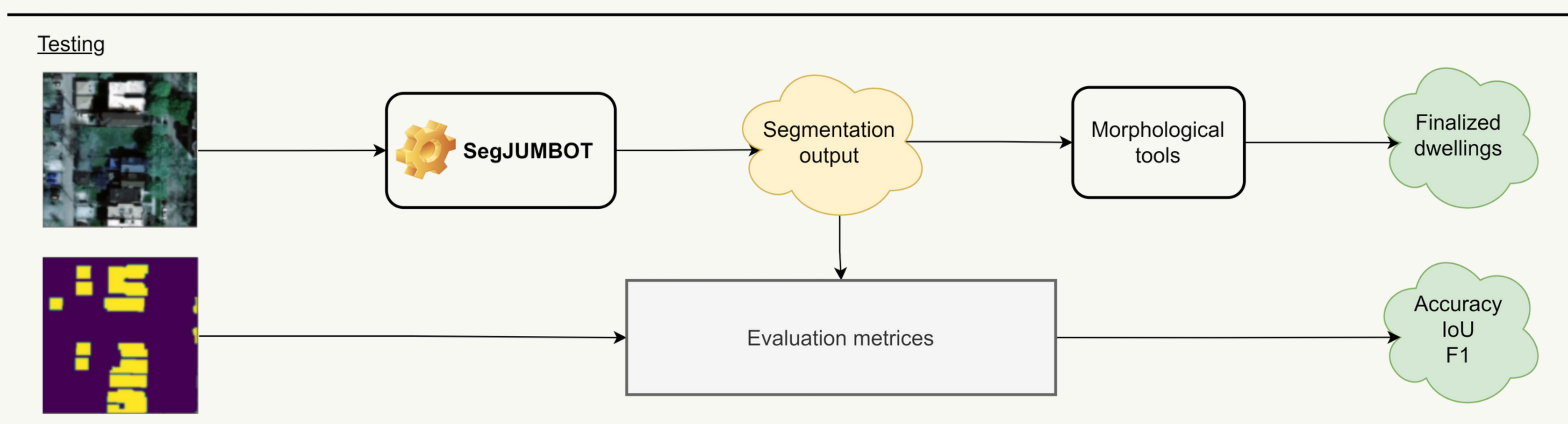
INTRODUCTION

The performance of a deep learning-based methods can severely drop when they are used outside of the trained domain, which is often the case for rapid segmentation tasks. Unsupervised Domain Adaptation has been proposed as a possible solution for such an issue as it tries to adapt a classifier trained on a specified domain with labels to help predict in a different domain without labels. Inspired by recent success of optimal transport in the context of domain adaptation, we propose a new unsupervised domain adaptation technique for semantic segmentation (SegJUMBOT). This method addresses the domain shift problem by leveraging the unbalanced minibatch-based optimal transport framework for semantic segmentation of large remote sensing datasets.

OBJECTIVE

Advance the method of (Ackaouy et al., 2020) by introducing an unbalanced optimal transport approach proposed by Fatras et al. (2021) coined as SegJUMBOT.





METHODOLOGY

We considered a state-of-the-art U-Net architecture with ResNet34 as the backbone for this semantic segmentation problem. In this model, we map a sample *(x)* to the latent space representation *(z)*, which is then mapped to the label space *(y)*. To define a proper cost function to measure how two samples are related, we define such a cost as a linear combination of a distance in the embedding space and a distance between the labels, thus defining a distance between joint distributions. In practice, we used the POT (Python Optimal Transport) package to solve the corresponding problem, and follow the same procedure as (Fatras et al., 2021) to perform differentiation.

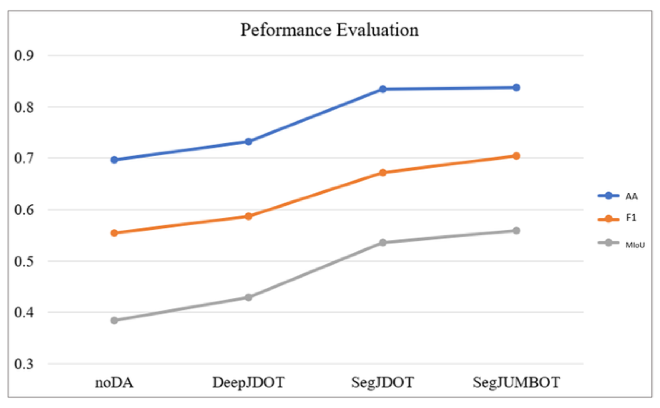
Both source and target datasets share the same encoder and decoder weights. The total loss is a combination of domain alignment loss using deep embedded features from encoder and target loss using outputs from decoder and ground truth from labeled source dataset.

RESULTS

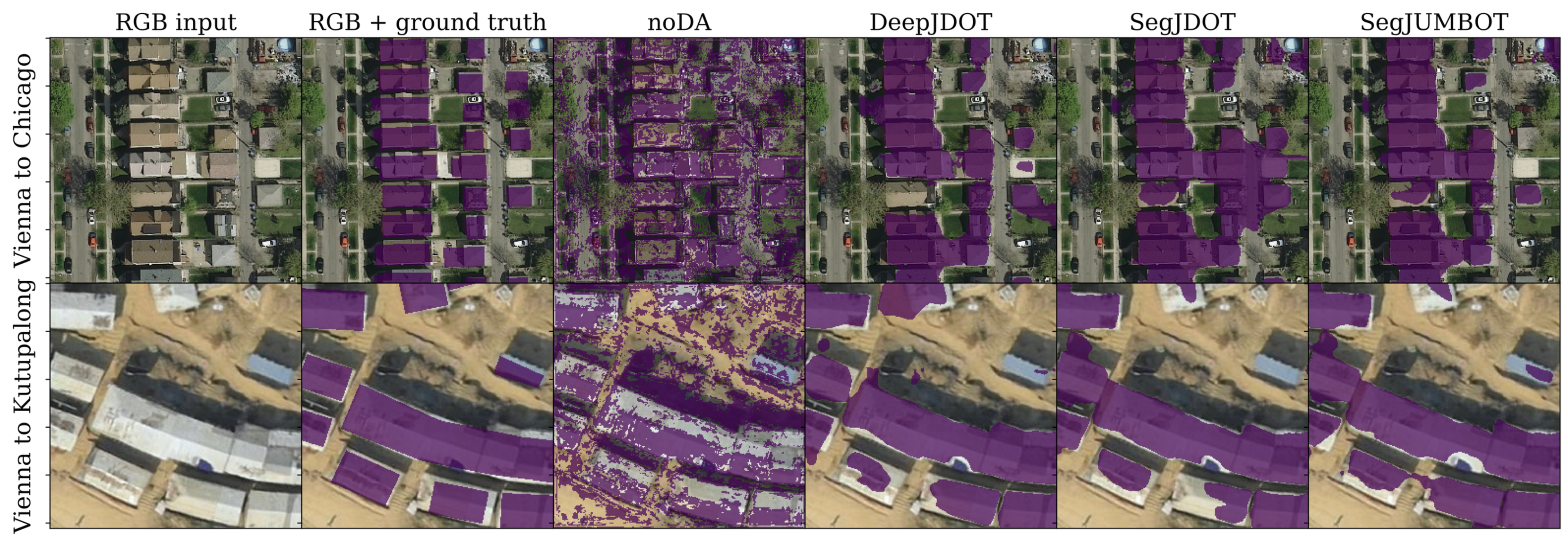
The quantitative performance analysis reveals that the DeepJDOT framework provided a slight improvement compared to the model without DA. Improvement with large margin was seen with the SegJDOT-based method and even higher with our hybrid method (SegJUMBOT).

The SegJDOT-based model and the finalized hybrid models(SegJUMBOT) were observed to have similar results when visually evaluating the segments. Though they could generally represent the dwellings, in some cases, they were unable to depict the gaps between the buildings and instead presented clusters of buildings as a single segment. This could be attributed to the spatial complexity of dwelling patterns in FDP where some of image patches have contagious or connected dwellings which are even tough for manual delineation. Moreover, contrary to dwelling characteristics in target dataset, the building characteristics in the source dataset are relatively homogeneous and well spaced within image patches.

Type	Source	Target	MIoU	F1	AA
Source only	Vienna	Vienna	0.557	0.715	0.838
		Chicago	0.384	0.555	0.697
		Kutupalong	0.235	0.369	0.513
DeepJDOT	Vienna	Chicago	0.428	0.586	0.732
		Kutupalong	0.385	0.536	0.718
SegJDOT	Vienna	Chicago	0.536	0.672	0.835
		Kutupalong	0.425	0.576	0.760
SegJUMBOT	Vienna	Chicago	**0.559**	**0.704**	**0.838**
		Kutupalong	**0.622**	**0.767**	**0.842**



Performance metrics during test phase from all the considered models



Comparative visual output of all the trained models on images from (first row) the INRIA dataset (Vienna → Chicago task) (second row) FDP site (Vienna → Kutupalong task)

CONCLUSION

With the SegJUMBOT framework, we have demonstrated the applicability of the unbalanced optimal transport-based method for unsupervised domain adaptation for semantic segmentation of dwellings. A relative improvement of approx 27% was observed in the testset, while 107 % relative improvement was observed while transferring a model over a different geographical region of varying scene and dwelling morphological properties.

RELATED LITERATURE

Antoine Ackaouy, Nicolas Courty, Emmanuel Vall ée, Olivier Commowick, Christian Barillot, and Francesca Galassi. Unsupervised Domain Adaptation With Optimal Transport in Multi-Site Segmentation of Multiple Sclerosis Lesions From MRI Data. Frontiers in Computational Neuroscience, 14:19, mar 2020. ISSN 16625188.

Nicolas Courty, Remi Flamary, Devis Tuia, and Alain Rakotomamonjy. Optimal Transport for Domain Adaptation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(9):1853–1865, sep 2017.

Kilian Fatras, Thibault S éjourn è, R èmi Flamary, and Nicolas Courty. Unbalanced minibatch optimal transport; applications to domain adaptation. In International Conference on Machine Learning, pp. 3186–3197. PMLR, 2021.

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