Open set segmentation is a relatively new and unexplored task, with just a handful of methods proposed to model such tasks. We propose a novel method called CoReSeg that tackles the issue using class conditional reconstruction of the input images according to their pixelwise mask. Our method conditions each input pixel to all known classes, expecting higher errors for pixels of unknown classes. It was observed that the proposed method produces better semantic consistency in its predictions, resulting in cleaner segmentation maps that better fit object boundaries. CoReSeg outperforms state-of-the-art methods on the Vaihingen and Potsdam ISPRS datasets, while also being competitive on the Houston 2018 IEEE GRSS Data Fusion dataset. Official implementation for CoReSeg is available at: https://github.com/iannunes/CoReSeg.

Index Terms— semantic segmentation, open set, convolutional neural network, auto-encoder, open world

1. INTRODUCTION

In the last decade many computer vision tasks such as object classification [1], detection [2] and semantic segmentation [3][4] have greatly improved their performance. Semantic Segmentation is a fundamental task in computer vision field, and its objective is to assign a label to each pixel of the image [5]. Traditional Semantic Segmentation (SSeg) tasks use closed set models, since the produced segmentation models are conceived to learn and predict the same set of classes. However, assuming an open set of classes is more applicable in real-world scenarios, where classes not seen during training appear on the deploy phase. In such cases, the method must be able to identify the pixels of unseen or unknown classes while still correctly segmenting known classes [6][7][8], which is the definition of Open Set Semantic Segmentation (OS3).

OS3 is inherently harder than open set classification due to its dense labeling nature. This can explain the gap in the literature for OS3 methods, with only a handful of works tackling the issue [9]. According to Silva et al. [7] a dataset with all possible classes known in advance will hardly be found in practice, especially when dealing with remote sensing datasets. Silva et al. [7] adapted the well-known OpenMax algorithm [10] for patchwise OS3, resulting in the OpenPixel method. OpenPixel, however, has a major drawback of being extremely inefficient during both training and testing. A nonparametric statistical adaptive OS3 method was proposed by Cui et al. [9]. Employing the Mann-Whitney U test on a
closed set segmentation output to determine the existence of unknown classes in each image and uses an adaptive threshold that defines which pixels are defined as unknown.

The first fully convolutional architectures for OS3 were proposed by Oliveira et al. [8]. Open Fully Convolutional Network (OpenFCN) is a fully convolutional extension of OpenPixel [7] for dense labeling tasks. Open Principal Component Scoring (OpenPCS) [8] uses the intermediate feature activations from closed set networks to fit gaussian distributions in a low-dimensional projection, obtaining a likelihood score for OOD pixel detection.

The performance of all previously mentioned OS3 methods vary considerably across datasets and distinct hidden class scenarios. Thus, robustness is still lacking in OS3 algorithms, with qualitative results varying widely across tasks and poor semantic consistency along neighboring pixels in OS3 predictions. With these limitations in mind, we propose a novel end-to-end fully convolutional OS3 method named Conditional Reconstruction for Open Set Segmentation (CoReSeg). Figure 1 shows an overview of the information flow in CoReSeg, with reconstruction and closed set segmentation branches merging into one single open set prediction. We describe this novel development in Section 2 and present experiments and our conclusions along Sections 3, 4 and 5. Our experiments show that CoReSeg is capable of yielding OS3 predictions with superior semantic consistency, overall robustness and better average AUROC when compared to the state-of-the-art.

2. PROPOSED METHOD: CoReSeg

CoReSeg employs a pre-trained closed set neural network to generate a latent representation of the input image, which is then sent to a reconstruction decoder. This decoder also receives conditioning information, whose objective is to guide the reconstruction of the input image from its latent features conditioned to the desired class (or classes). An overview of this process is illustrated in Figure 2a.

Our method is inspired in some design choices proposed by Oza et al. [12], wherein the conditioning concerns the entire image, while for CoReSeg the conditioning is performed in a pixel-wise manner. The main idea of the conditioning procedure is that objects from known classes will be better reconstructed when their pixels are conditioned to the correct class, while unknown objects will present poor reconstructions, since there is no correct conditioning to these pixels.

CoReSeg has 3 sequential stages to be further explained in the following paragraphs: 1) Closed Set Training, 2) Conditional Reconstruction, and 3) Open Set Pixel Recognition. 

Closed Set Training: CoReSeg requires a pre-trained closed set segmentation model to generate latent features that will be later used as input to the reconstruction decoder. For this reason, the first necessary step is to train a U-net [4] in a traditional closed set scenario, where only the known classes are learned. We call the encoder of this U-net the Closed Set Encoder, and its output is the desired latent representation for the conditional reconstruction training to be performed later. The resulting model will be used in both Open Set Training and Deploy phases. Also, the weights of this closed set U-net will not change after its initial training, which means that the semantic segmentation layers are frozen during the training of the rest of CoReSeg’s framework.

Conditional Reconstruction: Conditional Reconstruction training aims at reconstructing the image that serves as input
to the closed set semantic segmentation block of the framework from its latent representation. The reconstruction is conducted by a conditioning input, which, in the case of a semantic segmentation task, is comprised by a mask providing a class for each pixel. The conditional reconstruction block of the framework can be viewed as an AutoEncoder where the conditioning layers are the encoder and the reconstruction layers are the decoder. Figure 2a shows how these different parts of the training are connected to each other.

In order to train the model to reconstruct the image taking into account the conditioning input, CoReSeg uses for each input image 2 different masks to condition the reconstruction. The first mask is the one correctly labeled for the image (match mask, $y_m$). The second one is the label from a different image (non-match mask, $y_{nm}$), which means that it incorrectly conditions the pixels from the input image. The use of a non-match mask is important to make sure the network is actually learning to condition the input while not simply reconstructing the image from the latent representation.

We employ the L1 loss in the reconstruction step. The final reconstruction loss $L$ is computed as follows:

$$L = L_1(x, x_m) + \alpha \ast L_1(x, x_{nm}),$$  

where $x$ is the input image, $x_m$ and $x_{nm}$ are the reconstructions conditioned on $y_m$ and $y_{nm}$, respectively, while $\alpha$ weights the importance of each term.

Aiming to enforce the conditioning, the encoder from the conditional reconstruction block applies a transformation to the intermediate features from the frozen Closed Set Encoder layers ($e_i$). The result of this transformation is then used as input on the corresponding layer of the reconstruction decoder ($d_i$). In Figure 2a, this process is represented by the $f_i(e_i)$ blocks and it is performed for both match and non-match conditioning masks. The transformation responsible for the conditioning is the FiLM method proposed by Perez et al. extended to work in a pixelwise problem. More specifically, in order to use the pixelwise FiLM, the conditional reconstruction decoder is composed by two auxiliary encoders: $\beta$ and $\gamma$. Both encoders have the same shape as $e_i$ and $d_i$. In order to apply the transformation, we perform the following operation $\gamma_i \odot e_i + \beta_i$, where $\beta_i$ and $\gamma_i$ are the $i^{th}$ blocks of the conditional reconstruction encoder, and $e_i$ is the output of the $i^{th}$ block from the Closed Set Encoder. This procedure allows us to perform pixelwise FiLM conditioning on $e_i$.

The reconstruction decoder uses as a main input the latent representation of the input image from the Closed Set Encoder. Furthermore, each layer of the reconstruction decoder receives two additional inputs concatenated to the previous layer activation: (i) the corresponding FiLM transformation ($f_i$) from the conditional reconstruction encoder, and (ii) the raw feature maps from the corresponding Closed Set Encoder ($e_i$). These concatenations can also be viewed in Figure 2a.

**Open Set Pixel Recognition.** During deploy – shown in Figure 2b – we cannot provide match and non-match masks for the conditional encoder, as the labels for these samples are not available. So, to define which pixels are known and unknown CoReSeg tries to condition every pixel for each known class. Then, for each pixel the minimum loss for $k \in \{1, 2, \ldots, K\}$ is computed and selected – where $\{1, 2, \ldots, K\}$ is the set of known classes. Pixels that were conditioned to the right class yield a small minimum error, while unknown pixels result in higher loss values for each one of the reconstructions, since none of them match the right expected class. At last, a threshold operation defines which pixels are known and unknown. We use error quantiles to set thresholds and find the best performance for the model. If the minimum reconstruction loss of a pixel is below the threshold, its class is deemed as known and set to the closed set predicted output, and otherwise it is set as unknown.

### 3. EXPERIMENTAL SETUP

Three datasets were selected to evaluate the proposed method: Vaihingen and Potsdam datasets; and the Houston GRSS 2018 Data Fusion dataset. As the selected datasets for this work are intended for closed set segmentation, we emulate open set environments using the Leave One Class Out (LOCO) protocol. As the final model for the open set pixel recognition process, we choose the model with the best AUROC result calculated on the validation set.

**Vaihingen and Potsdam:** Both datasets have images with 4 spectral channels IR-R-G-B paired with the normalized digital surface model (nDSM). The semantic maps contain 6 classes: impervious surfaces, building, low vegetation, high vegetation, car and miscellaneous. All experiments were conducted using the IR-R-G-nDSM channels as input, leaving the Blue channel out. We separated images from the original training/test set used by OpenPCS to serve as a validation set: area 23 for Vaihingen; and areas 3,11 and 6,14 for Potsdam. For both datasets we tested 5 different scenarios in which one class was selected as UUC for each case.

**Houston:** For this work only the RGB spectral channels and DSM image were used. The image fusion procedure we employed was the same as described in OpenPCS. On Houston we tested 2 different scenarios: 1) Vegetation, wherein the UUC is composed by healthy grass, stressed grass, evergreen trees, and deciduous trees; and 2) Building, in which the UUCs are residential and non-residential buildings.

### 4. RESULTS AND DISCUSSION

As presented in Table 1 for Vaihingen and Potsdam, CoReSeg attained the best average AUROC result. CoReSeg reached a higher and more uniform performance between the different tested UUCs.
Fig. 3: Visual results for Potsdam (UUC Impervious Surfaces, top row) and Vaihingen (UUC Building, bottom row) using the LOCO protocol for the closed set model, Softmax with thresholding, OpenPCS and CoReSeg.

Table 1: Classwise AUROC and average (Avg.) AUROC in Vaihingen and Potsdam. Numbered columns stand for: 1 – Impervious Surfaces, 2 – Building, 3 – Low Vegetation, 4 – High Vegetation and 5 – Car.

Table 2: AUROC of Vegetation (Veg.) and Building (Build.) UUCs, as well as the average (Avg.) AUROC in Houston.

As shown in Table 1, until this work the state-of-the-art performance for both Vaihingen and Potsdam was achieved by OpenPCS with WRN-50. CoReSeg achieves better average results across classes, even though WRN-50 has the best AUROC for 3 UUCs in Vaihingen and 2 UUCs in Potsdam. When the UUC is Low Vegetation (2) or High Vegetation (3) almost all models and backbones have difficulties in identifying the OOD pixels. One possible reason for this poor performance is their high intraclass variability, hampering the characterization of OOD pixels.

For the Houston dataset, OpenIPCS with DN-121 achieved the best performance as shown in Table 2. The proposed method was not able to outperform the state-of-the-art results given by OpenIPCS with DN-121. We hypothesize that this might be linked to the size of the training set on Houston, which is considerably smaller than Vaihingen and Potsdam.

5. CONCLUSION

CoReSeg outperformed, in all tested scenarios, the other models using the same closed set backbone. For Vaihingen and Potsdam datasets, CoReSeg established new state-of-the-art performance achieving the best average performance. Adapting other closed set backbones to CoReSeg is a challenge. The architecture uses spatial information from the Closed Set Encoder as input to the reconstruction decoder. Adapting a backbone with a different architecture will likely also imply changes in the CoReSeg architecture.

In our future work we consider: adapting other closed set
backbones to work with the CoReSeg method; modifying the conditioning mechanism to better characterize each class; test on time series, sparsely labeled and not urban datasets.

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