SEMANTIC SEGMENTATION FOR CHANGE DETECTION IN SATELLITE IMAGING

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ABSTRACT

The change detection is common and actual problem in the field of remote sensing. The classical approches using raw pixel informations are very sensitive to noise. In this study we propose the usage of additional semantic information for change detection. We use the semantic segmentation methods like geospatial Segment Anything Model and encoder based UNet to evaluate the predictions and tracing the semantic information as well as raw information in change detection. Later the multidimentional time series data is used via Vector Autoregression model to predict the future changes in the landscape. The observations which fall out of the prediction interval are considered as the changes in the landscape. The proposed method is evaluated on the dataset of the random locations across the Baltic region. The research is acompannied by the data and reproducable code at Github repository.

Index Terms— Deep learning, semantic segmentation, change detection, satellite imagery

1. INTRODUCTION

Change detection is a problem to object variations by observing them over the time. Satellite imagery is one of the domains where change detection is widely used. Remote sensing change detection is applied by using data from Earth-orbiting satellites and identifying the changes in the landscape structural permutations which have happened throughout a specific time track.

The change detection problem is analysed in classical mathematical modelling methods as algebraic analysis difference [1] or regression [2]. However, any methods based only on pixel intensity are very sensitive to noise. This common problem in computer vision, thus deep learning methods could be used to overcome this problem [3]. Deep learning methods for change detection could be divided to two groups based on different approach. First approach of usage of 3-channel RGB images, while second approach is based on multi-spectral imagery and contain more band information.

The RGB imagery approach is widely used in the field of remote sensing. The most popular method is based on U-Net [4] architecture. The U-Net architecture is used in the field of remote sensing for semantic segmentation [5] and change detection [6]. The U-Net architecture is also used in the field of remote sensing for change detection in combination with Siamese networks [7] demonstrating good results on cases like OSCD dataset [8]. Some recent methods apply deep learning models using bi-temporal images [9] or transformer based models [10].

The main challenges arise among approaches. The older satellite images does not enable to form bi-temporal images. The bi-temporal images are formed by using the same place image taken at different times. The relief displacement is also a problem in remote sensing [6]. The relief displacement is a problem that occurs when the same object is imaged from different angles. Finally the seasonality of weather conditions is also a problem in remote sensing when climate conditions are changing, thus the same place could be imaged in different seasonality and weather conditions.

The addressing of challenges in remote sensing the deep learning methods are suitable choice. While some successful feature extraction methods could be used using end-to-end models [11] it raises the computational challenges. To address this we focus on the semantic segmentation methods. Very common approach is the usage of U-Net models modifications for semantic segmentation [12]. On the other hand recent successful model for semantic segmentation is Segment Anything Model [13] which was adopted to remote sensing imaging [14].

The most common non-commercial application of change detection falls under climate monitoring. For this current resolution of satellite imagery is rather sufficient. The 10 to 60 meter resolution like from Sentinel-2 [15]. The land site change detection for coastal zone is analysed [16].

The change detection is significantly impacted on noises and quality of images [8] or non stationary objects in the images like [17]. Thus it encounter the problems on joining datasets [18]. The class imbalance is also the common challenge [19, 20, 17, 21], mostly since background class in general is not changing [18]. Finally, clouds an noises are also is challenge [22] as increased saturation [17] or distorted

*This project was funded by the European Union (project No S-MIP-23-44) under the agreement with the Research Council of Lithuania (LMTLT).

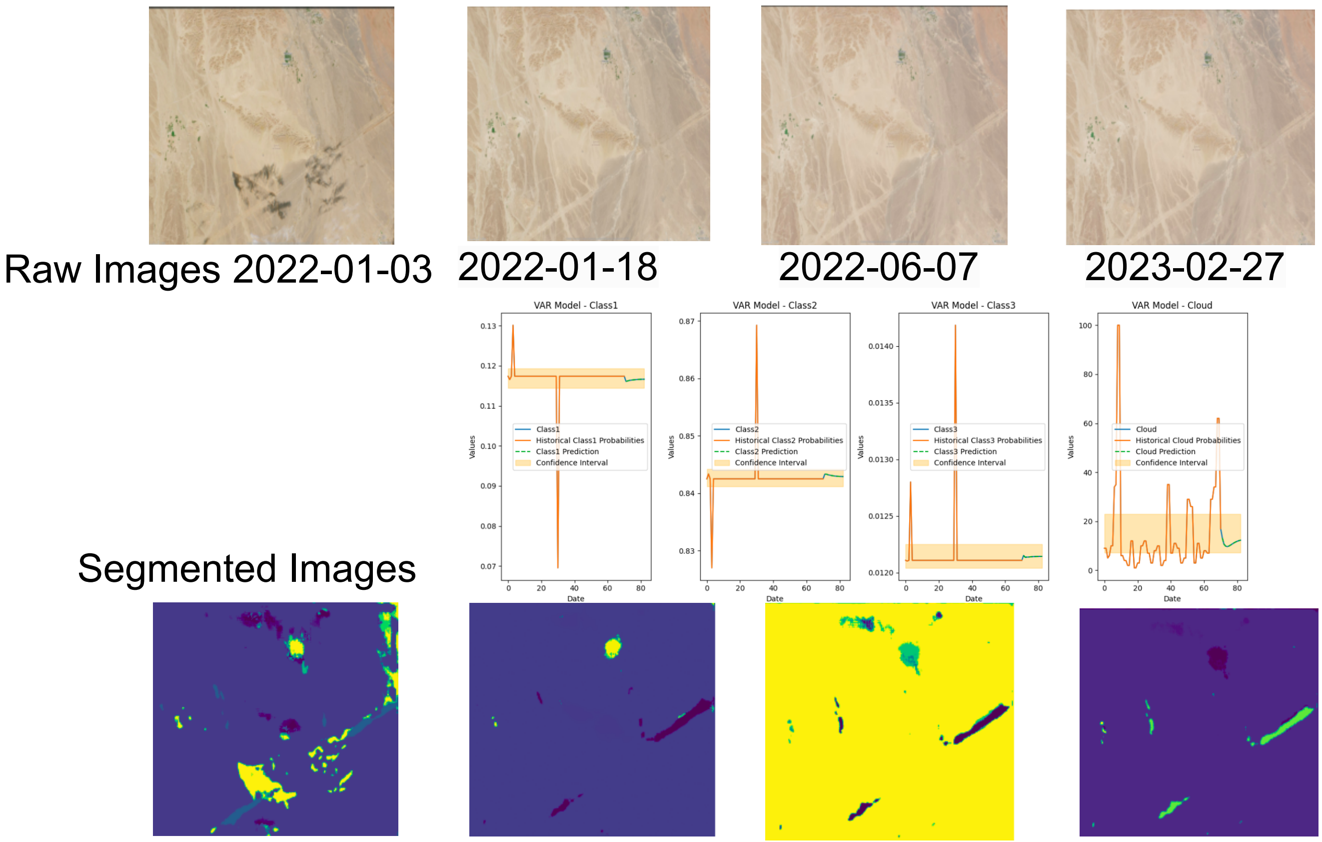

Fig. 1. The illustrative example of confidence interval of prediction of the VAR model, which is used to detect the changes in the landscape.

colours [23].

The work is organized as follows. In Section 2 we discuss the proposed methodology. In Section 3 we discuss the dataset. In Section 4 we discuss the results. In Section 5 we discuss the conclusions.

2. METHODOLOGY

2.1. Semantic segmentation

The semantic segmentation is of computer vision problem of assigning a class label to each pixel in an image from a predefined set of classes. Let's assume the input of format $\mathbf{X} \in \mathbb{R}^{c \times w \times h}$ of image consistent of tensor $\mathbf{X}$ with c - number channels, and width/height w, h respectively. The semantic segmentation mask $\mathbf{X} \in \mathbb{R}^{L \times w \times h}$ contain L number of classes, where each pixel is assigned to one of the classes. Such models could predict the class of each pixel in the image [12]. In our experiments we used the UNet like model[1]. The pre-trained model had Building, Land, Road, Vegetation, Water and Unlabeled classes. For the generic segmentation models like Segment Anything Model [13] provide object mask prediction confidence score.

[1]https://github.com/ayushdabra/dubai-satellite-imagery-segmentation

2.2. Vector Autoregression

The vector autoregression (VAR) is a model used to capture the linear interdependencies among multiple time series data. The VAR model is generalization of the univariate autoregressive model (AR) [24]. The VAR model is used to forecast tasks. The VAR model is defined as follows:

$$y_t = \beta + \sum_{i=1}^{p} \Omega_i y_{t-i} + \epsilon_t$$

where y_t is a $k \times 1$ vector of endogenous variables at time t, β is a $k \times 1$ vector of bias, Ω_i is a $k \times k$ matrix of coefficients for i-th lag, p is the order of the VAR process, and ϵ_t is a $k \times 1$ vector of error terms at time t. The confidence interval of VAR models could be used either dynamic, either fixed. In our case use t distribution confidence interval which is same for each time steps. The critical value for the confidence level α, in our experiments we used $\alpha = 0.05$. The VAR model was used using `Python` package `statsmodel`.

3. DATASET

The investigation of change detections was applied on covering wide range of diverse cases. We randomly chose 100 coordinates over Baltic region (53,53100 - 59,69747 latitude values and 20,49722 - 28,22760 longitude) using uniform distribution. After that, we used COPERNICUS/S2 satellite in Google Earth Engine API for collect images of random chosen coordinates over 2022 - 2023 time period. In our experiments, we used pixel intensities of B4, B3 and B2 bands which are represents red, green and blue colors. For each coordinates, we made predictions using `geospatial` Segment Anything Model [14] and collect IOU and score values. Class probabilities are collected using UNet model. Cloud Probabilities collected using Google Earth Engine API. In such the dataset for each coordinate consist of 11 features of Raw Pixel Intensity of B4, Pixel Intensity of B3, Pixel Intensity of B2, IOU, Scores, Probabilities of 6 classes and Cloud Probabilities.

4. RESULTS

For each point, we collected sentinel-2 RGB images using scale 10 zoom rate. Then, having surounding enviroment around the segmentation predictions was made using relevant models for each images. Such enables to have semantic information for each investigative pixel. After creating our dataset, we used VAR model for selected index and forecast $h = 12$ steps. The experiment we calculating root mean square error (RMSE), akaike information criterion(AIC) and confidence intervals for each feature using t distribution.

The Fig. 1 presents the general pipeline of approach. The segmented image semantic information are added to vector time series models, thus while raw image data seems unchanged significantly, the semantic information allows to be additional control mechanism for quality assessment. Cloud probability are often used to remove untruthfull images, the same could be done by tracking unchanged situations. The illustrative case in Fig. 1 can be seen for index 6 in the Table 1 below. Also one can be seen in Table 1 that some testing images have high variation in raw data or some data was not overlaped (black/empty image) over specific flight and 0 observation fell in confidence interval.

5. CONCLUSION

In the study we investigate the estimation of non-changing temporal situations in satellite imagery. The publication propose the addition of additional semantic information usage for tracking changes. The raw and semantic information modelled by vector auto-regressive models. The experiments demonstrated succesfull usage of the method. The identified change-detection cases often related to data obscures of not visible areas. The publication is complimented with reproducible repository of method pipeline in Github.

Table 1. Summary Table

Index	Lat	Lon	RMSE	AIC	Fall In CI
0	57.9822	27.5759	0.206	-105.333	0
1	54.8303	21.8945	2.98e-15	None	0.9761
2	59.1785	24.5851	0.02	-112.393	0.4444
3	57.2123	24.1739	0.008	-58.051	0.5
4	55.4973	23.1317	5.84e-04	None	0.988
5	59.5876	25.7885	0.029	-114.48	0.3048
6	57.2948	22.5929	3.07e-04	-205.4	0.9761
7	53.6124	27.2380	5e-04	-51.1965	0.4352
8	54.6356	22.8023	0.115	-136.188	0
9	56.6370	20.7791	0.098	None	0

Note: RMSE and Fall In CI columns are values for Class2

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