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SEASONAL FOREST DISTURBANCE DETECTION USING SENTINEL-1 SAR & SENTINEL-2 OPTICAL TIMESERIES DATA AND TRANSFORMERS

Adugna Mullissa[1], *Johannes Reiche*[2], *Sassan Saatchi* [1,3]

[1] CTREES.org, Pasadena, CA 91105, United States
[2] Laboratory of Geo-Information Science and Remote Sensing, Wageningen University, the Netherlands
[3] NASA, Jet Propulsion Laboratory, Pasadena, CA 91105, United States
amullissa@ctrees.org

ABSTRACT

Tropical seasonal forests make up 40% of the globally available forest stock and play an essential role in regulating the variability in the global carbon cycle. Therefore, there is a strong need to persistently monitor seasonal forest changes to understand the forest carbon fluctuation and to better conserve biodiversity and enforce laws. In this regard, the advent of the European Space Agency (ESA) Copernicus program avails a dense time-series of both Synthetic Aperture Radar (SAR) and optical images, globally and free of charge, that enables the exploitation of these images for near real-time forest monitoring. Detecting seasonal forest changes in dense time-series, however, is complicated by fluctuation in the detected signal that is induced by forest phenology change. Therefore, forest disturbance detection methods should account for these seasonal fluctuations to make an accurate inference about forest disturbances. In this regard, deep learning approaches designed for sequential data such as Transformers can be used to implicitly learn the natural forest seasonality pattern in the signal to detect forest disturbances. This abstract demonstrates the efficacy of Transformers to detect seasonal forest disturbance in a seasonal dry-forest region in Bolivia.

***Index Terms*—** Sentinel-1, Sentinel-2, Deep Learning, Transformers

1. INTRODUCTION

The advent of temporally dense optical and SAR images, such as Sentinel-1 SAR and Sentinel-2 optical images with global coverage has been important for timely detection of forest disturbances. However, the exploitation of these images for seasonal forest disturbance detection is complicated by the presence of seasonal signal variations in the time-series images [1].

Traditionally, to detect seasonal forest disturbance, deseasonalization is applied to the time series first to remove the seasonal forest component [1] before forest disturbance algorithms are applied. The seasonal component is usually assumed to follow a sinusoidal pattern, therefore a harmonic model is fitted to the data to remove the seasonal component. However, to fit a robust model a dense image timeseries is required which can be challenging for optical images due to missing data because of cloud cover. Furthermore, seasonal shifts (e.g. due to climate change) introduce imperfections in the fitted model introducing errors in disturbance detection.

Deep learning approaches designed for sequential data promise to mitigate the effect of seasonality by implicitly learning the seasonality patterns to make forest disturbance predictions. In this regard, recurrent neural networks are deep learning methods that are suited for time series data with the long short term memory (LSTM) and gated recurrent unit (GRU) being notable variants [2] [3].

Recent attention based time series deep learning methods such as Transformers [4] have become popular in natural language processing (NLP) domain because of its ability to learn semantics by understanding the relationship between words in a sentence. This concept can be transferred to the image time series domain to understand the relationship between images in the series that defines the natural dynamics of seasonal forests.

Therefore, in this manuscript, we demonstrate a Transformer based deep learning approach that predicts seasonal forest disturbance from both Sentinel-1 and Sentinel-2 time series images in a seasonal forest setting.

2. METHODOLOGY

2.1. Architecture

We use a Siamese Transformer architecture (Figure 1) to train a model that can detect seasonal forest disturbance. We se-

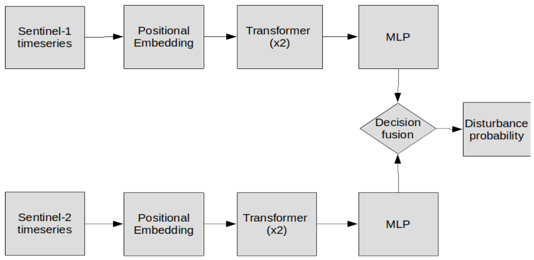

Fig. 1. The proposed architecture.

Fig. 2. Cumulative seasonal forest disturbance inferred from the proposed method for the year 2020 over the study area.

lected to use a Siamese approach because of the difference in the severity of seasonality in the optical and SAR data. We apply the same transformer encoder architecture to both streams and fusion is implemented at the decision level. Therefore, the deep learning objective can be formulated as:

$$\arg\min_{\theta} \sum L(f_\theta([S_1, S_2]), R). \tag{1}$$

Here, $[S_1, S_2]$ are the input Sentinel-1 and Sentinel-2 image time series, R is the binary forest non-forest maps we will use as reference data and f_θ is the deep learning network parameterized by the learned parameters θ. The Loss function (L) in (1) is a binary cross-entropy loss function.

The network consists of positional embedding layer and two transformer encoder blocks each consisting of layer normalization, Multi-head attention blocks and multi-layer perceptrons (MLP) in both the Sentinel-1 and 2 branches. Finally a decision fusion module combines the probability from each data stream in an AND condition to derive inference probabilities. The architecture used in this manuscript is implemented using the TensorFlow deep learning framework in a Python 3.9 environment and trained on Google Colab platform using a Tesla T4 GPU.

2.2. Dataset

The proposed Transformers architecture is trained and tested using an analysis ready Sentinel-1 SAR ground range detected (GRD) time series in both the VV and VH polarizations [5] and Sentinel-2 normalized burn ratio (NBR) vegetation index time series synthesized in the dry Chaco eco region in Bolivia that is characterized by a multi-layer deciduous dry forest structure that typically consists of a canopy, shrub and herbaceous layer, at a nominal ground sampling distance of 10m. We opted to use NBR instead of the original Sentinel-2 multi-spectral bands because of the NBR's sensitivity to low reflectance pixels. We have derived surface reflectance values prior to estimating NBR values. we have also applied cloud and shadow masking to the Sentinel-2 timeseries prior to model training. The study area's upper left coordinates are -63.166^0 lon, -17.792^0 lat and the lower right coordinates are -61.166^0 lon, -19.792^0 lat. The datasets were acquired from January 2019 to December 31, 2020. The Sentinel-1 SAR sensor acquires data in C band for both the VV and VH polarizations, whereas the Sentinel-2 images are acquired in the visible, near infrared and short wave infrared ranges. We synthesized the reference data by taking the intersection between the globally available Hansen forest loss dataset and the Landsat based GLAD alerts [6] [7].

2.3. Network training

The input data to the network was prepared by random sampling of timeseries pixels from the training area for both the Sentinel-1 SAR image in both VV and VH polarization and the NBR time series derived from Sentinel-2 images. We split the sampled data into 90% training, 10% validation and 10% testing data.

The network was trained using Adam optimization method. We initialized the parameters randomly using the improved Xavier initialization. Batch normalization was used for every dense layer outside the Transformer encoder layer layer except the prediction layer. To minimize training and validation errors, we applied hyper-parameter tuning using the Keras tuner package [8] using Hyperband method to select the optimal number of neurons for the embedding dimension, number of heads in the self attention module and the optimal learning rate. The training data consisted of 2784 randomly selected labeled timeseries pixels. During training a mini-batches of 16 samples and a weight decay factor of 5×10^{-4} was used.

3. RESULTS

The optimally trained model contained 320 units in the dense layers within the MLP, an embedding dimension of 224 and a learning rate of 0.01. To evaluate the performance of the proposed Transformer architecture, we synthesized a Sentinel-1 SAR image in both VV and VH polarization and a Sentinel-2 NBR timeseries for the year 2020 to derive the cumulative disturbance for the selected area (Figure 2). This testing data was prepared from an area that was disjointed from where the training data was synthesized. We qualitatively compared the results of cumulative disturbance prediction with a high resolution Planet scope image. We also performed quantitative assessment by deriving the precision, recall and F-1 score of the model on the independent test data. The proposed method achieved high accuracy with a precision of $99\% \pm 1\%$, recall of $83\% \pm 6\%$ and an F-1 score of $89\% \pm 4\%$ for forest disturbances (Table 1). This indicated the proposed approach is able to detect seasonal forest disturbances with a high accuracy. This was also confirmed when comparing the predicted disturbance map with that of a high resolution Planet scope images (Figure 2).

Table 1: The precision, recall and F-1 score of the proposed method on independent test data.

Class	Precision	Recall	F-1 score
Disturbance	0.99 ± 0.01	0.83 ± 0.06	0.89 ± 0.04

Overall, the proposed architecture provided promising results in detecting disturbances from seasonal forests at the cost of computational complexity. However, the limited dataset used in the experiments and missing data from the Sentinel-2 timeseries due to cloud cover and shadows posed a challenge to the overall efficacy of the model.

4. CONCLUSIONS

In this abstract, we demonstrated the use of a Transformer based architecture for the detection of seasonal forest disturbance. We used a Siamese transformer architecture to implicitly learn the seasonality pattern, which distinctly didnot rely on traditional manual deseasonalization approaches.

In future work, we will further improve the efficacy of the method by minimizing overfitting by using a diverse set of training dataset. Furthermore, we will improve the generalization capability of the model and address the effect of missing data in the Sentinel-2 time-series by using different gap estimation and filling approaches. Finally, we'll explore different fusion approaches to further improve the robustness of the proposed method.

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