Neural Autoencoder for Change Detection in Satellite Image Time Series

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***Abstract*—This paper introduces a new algorithm for satellite image time series change detection. This algorithm is based on image subtraction analysis and does not directly work on raw images, but on their feature representation version. The change detection method is totally unsupervised and does not need any labeled data.**

***Index Terms*—satellite image processing, change detection, deep learning, unsupervised learning, neural networks, convolutional autoencoder with fully-connected layers, feature extraction**

I. Introduction

Change detection in satellite images has applications in many different areas these days. Among them, there are numerous ecological applications such as the analysis and preservation of the stability of ecosystems or the detection and the analysis of such phenomena as deforestation and droughts, the studies of economical development of cities, the analysis of vegetation state for different agricultural purposes, etc.

In the case of supervised image analysis, change detection is a relatively simple process. Using reference data, we perform the classification of the images of interest and then we compare the classified images in order to detect change of classes. Often, we do not dispose of a database with labeled data that can be used as a reference during the image analysis. It is explained by the variety of objects presented on satellite images, by the non-homogeneity of images captured by the different satellites (different resolutions, number of bands, bands wavelength, etc) and by the cost of creating such database.

The easiest approach for unsupervised change detection between images is the analysis of subtraction or ratio of two images. This approach can work on low-resolution images, but with growing image resolution, we start to detect different image features and a class presentation is not anymore limited to just pixels values. Often these features are not completely superposed on the images, so the analysis of raw image subtraction or ratio can not be considered as a suitable method.

To resolve this problem, it was proposed to use neural network methods to perform analysis and extraction of textures. The use of neural autoencoder allowed us to transform raw images in their feature representation versions. These encoded images contain all the essential information about the original ones where the non-homogeneous areas of the original image are presented by new homogeneous features.

In the sequel we propose a new unsupervised temporal change detection algorithm that is based on the analysis of subtraction of encoded images. All the algorithm steps are completely non-supervised and do not need any labeled data. As a plus, it is possible to analyze the nature of changes and obtain a map with different changes types (cyclic, permanent).

II. Related work

A. Changes detection

As it was already mentioned before, the easiest unsupervised algorithm to detect changes is to analyze the image subtraction or image ratio, but this method is not suitable for high-resolution images. Different approaches for change detection are available. For example, in [1] authors propose hotspot detection in order to detect changes between two images. In [2] the object-based changes detection was proposed. In these algorithms, as well as in many others, authors detect changes without further analysis of the nature of these changes. The advantage of our algorithm is that it detects different types of changes (seasonal and permanent). Detection of seasonal changes is done on two different levels : on a single difference image and in a time series in order to understand its behavior.

B. Neural network autoencoders

Among different neural network models, autoencoders have found the application in many domains. In image processing, the autoencoders are used mostly for feature extraction, image segmentation, image compression/data reprojection and image reconstruction.

All the autoencoders are composed of encoding and decoding pass. During the encoding pass, the initial image is being transformed into a set of textures or into a feature vector. Then during the decoding pass, this data is being transformed back to the image that should resemble as much as possible to the initial image. Then we optimize the model parameters and do as much encoding-decoding passes as needed to optimize and stabilize the model.

Despite the fact that we can use autoencoders for unsupervised analysis (when no classified data is needed), in remote sensing, the autoencoders are mostly used for supervised

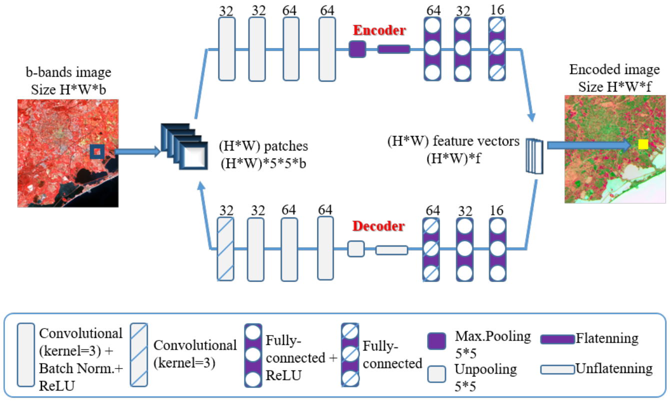

Fig. 1: Convolutional autoencoder with fully-connected layers.

purposes along with classic convolutional networks as they can drastically approve the quality of feature extraction [4], [3], [5]. The advantage of our autoencoder is that it can be used as a standalone algorithm for feature extraction with further use of extracted features for unsupervised purposes.

III. Proposed algorithm

We have an image time series of k images. Let $Im_1, Im_2, ..., Im_k - 1, Im_k$ be the images of this time series taken on dates $T_1, T_2, ..., T_k - 1, T_k$. The size of every image is $H*W*b$, where H is the height, W is the width and b is the number of spectral bands. The main steps of our algorithm are the followings:

1) Perform the image homogenization in order to minimize the difference in images luminosity caused by different atmospheric conditions.
2) Encode the images in their feature representation versions.
3) Perform the image subtraction for every pair of t_n and t_{n+1} images.
4) Analyze k-1 subtracted images in order to detect seasonal and permanent changes.

In order to encode the image in its feature representation version with f features, we use convolutional autoencoder with fully connected layers presented on Figure 1.

To perform pixel-wise encoding we clip the initial image in $H*W$ patches of size 5*5 pixels. Then we perform pixel-wise feature encoding and feature extraction for every patch of the image. The patches are encoded in feature vectors of size f and these vectors correspond to the central pixels of the patches. Once we encode the images, we perform image subtraction and, using the corresponding clustering method and histogram analysis, we can cluster the types of changes.

IV. Experimental framework

A. Data

In our work, we use Spot-5 satellite images of the city of Montpellier, France that belongs to the archive Spot World Heritage*. We kept red, green and near-infrared bands that have 10 meters pixel resolution. Note that our algorithm is generic and supposed to work on any satellite image dataset.

B. Results

The example of an encoded image subtraction is presented on Figure 2. Seasonal changes (for example, blue and dark-red) are easily detected even on a single image as they are numerous and belong have the same properties. The non-seasonal changes are less numerous and some of the are presented on this image in lemon yellow color.

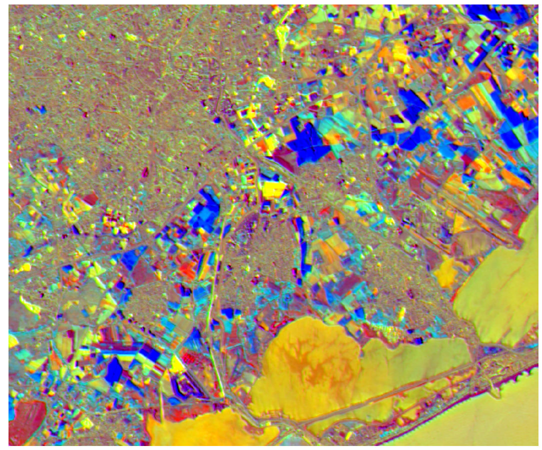

Fig. 2: Subtraction of two encoded images.

V. Conclusion

In this paper we proposed the main steps of an unsupervised change detection algorithm based on the subtraction of encoded feature images. This method permits to detect and cluster seasonal and permanent changes in order to better understand their nature.

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