A Case Study for a Multitemporal Segmentation Approach in Optical Remote Sensing Images

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***Abstract*—Continuous observations from remote sensors provide high temporal and spatial resolution imagery, and better remote sensing image segmentation techniques are mandatory for efficient analysis. Among them, one of the most applied segmentation techniques is the region growing algorithm. Within this context, this paper describes a study case for a multitemporal segmentation that adapts the traditional region growing technique. Our method aims to detect homogeneous regions in space and time observing a sequence of optical remote sensing images. Tests were conducted by considering the Dynamic Time Warping distance as the homogeneity criterion to grow regions. A case study on high temporal resolution for sequences of Landsat-8 vegetation indices products provided satisfactory outputs.**

Keywords–Multitemporal Segmentation; Image Processing; Geoprocessing; Remote Sensing; Dynamic Time Warping.

I. INTRODUCTION

As satellite products have a repetitive data acquisition and its digital format is suitable for computer processing, remote sensing data have become the main source for application of change detection and observation of land use and land cover during the last decades [1]. Satellite image analysis plays a key role for detecting land use/cover changes in different biomes. The extensive amount of remote sensing data, combined with information from ecosystem models, offers a good opportunity for predicting and understanding the behaviour of terrestrial ecosystems [2].

If the satellite image analysis is performed using only per-pixel techniques, inherent information of the objects in the scene is discarded, such as shape, area and statistical parameters. In order to exploit this information, there are segmentation algorithms, which partition images in regions whose pixels present similar properties [3] [4]. Using a homogeneity criterion between the image pixels, the identified regions are treated as objects from which characteristics can be extracted to be used in the analysis.

Change detection based on time series is advantageous compared to the pure observation of image sequences, since the series takes into account information regarding temporal dynamics and changes in the landscape rather than just observing the differences between two or more images collected on different dates [2]. With the amount of multitemporal and multiresolution images growing exponentially, the number of image segmentation applications is recently increasing and, simultaneously, new challenges arise. Hence, there is a need to explore new segmentation concepts and techniques that make use of the temporal dimension [5] [6].

Many of the recent segmentation processes based on objects have paid attention to high image spatial resolutions whereas, so far, there are few studies adapted to multitemporal data [7]. In this paper, we describe a case study for a segmentation applied to time series of remote sensing images. The algorithm integrates regions in order to detect objects that are homogeneous in space and time. This approach aims to overcome the dlimitations of the snapshot model [8], that analyses each time step independently. The technique adapts the segmentation based on spatial region growing [9]. A case study was conducted using time series of Landsat-8 Operational Land Imager (OLI) scenes by applying multitemporal segmentation using the Dynamic Time Warping measure [10] as the homogeneity criterion.

With this context, this work can contribute to the segmentation of remote sensing data in geographic information systems from the construction of thematic maps as output of the segmentation process, since it is possible to generate a layer of information from the input data, representing homogeneous regions with similar properties over time.

The rest of the paper is organized as follows. In Section II, we present a brief description of remote sensing image segmentation and related works applied in change detection. In Section III, we discuss the use of satellite image time series. The Dynamic Type Warping is described in Section IV. The methodological procedures are depicted in Section V. In Section VI, we discuss the results obtained in this work. Finally, we describe the conclusion and future work in Section VII.

II. REMOTE SENSING IMAGE SEGMENTATION

Segmentation is a basic and critical task in image processing whereby the image is partitioned into regions, also called objects, whose pixels are similar considering one or more properties [8]. Overall, it is expected that the objects of interest are automatically extracted as a result of segmentation. Features can be extracted from these objects and used later for data analysis.

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One of the most applied segmentation techniques in remote sensing is the region growing algorithm [9]. This is a simple iterative approach that groups pixels or sub-regions into larger regions depending on how similar they are, using some similarity criteria. The technique starts with a set of pixels called *seeds* and, from them, grows regions by adding neighbour pixels with similar properties.

The threshold definitions in region growing segmentation are a key step due to their direct influence on the accuracy of the output. The similarity threshold analyses if the pixel value difference or the average difference of a set of neighbouring pixels is smaller than a given threshold. The area threshold is another common parameter and it takes into account the minimum size of the regions that will be individualized by the algorithm. Setting these values enables the user to control the outcome in an interactive way, depending on the goal and study area. In general, the threshold is reached after several tests among possible combinations of the algorithm. The tests continue until the result of the segmentation is suitable for a particular purpose.

Several segmentation techniques applied in change detection are still derived from the traditional snapshot model [6], observing only the differences between discrete dates [11]–[13]. However, a thorough literature review revealed just a few studies that adapted methods based on objects for applications with multitemporal data [7].

Some object-based techniques aim at performing the segmentation generating one output for each time instance and then comparing the objects changes over time [13]–[17]. In other studies, the objects are defined in the first image, and then their differences are analysed in subsequent image [12] [18] [19].

Another approach has included the time as an additional factor within the segmentation, being used with the spatial and spectral image features [7]. However, many studies that applied this segmentation approach have used a limited number of multitemporal images [20]–[24] and they did not make use of time series of high temporal resolution images [6].

III. Satellite Image Time Series

Detection of changes based on time series is advantageous compared to the analysis of each image in a sequence independently, since the series take into account information regarding temporal dynamics and changes in the landscape rather than just observing the difference between two or more images collected on different dates [2]. However, a large amount of time series data has been generated over the past years, which forces the remote sensing community to rethink processing strategies for satellite time series analysis and visualization.

The time series of vegetation indices, for example, can be used to analyse seasonality for cover monitoring purposes. In the analysis and characterization of vegetation cover, for example, vegetation indices are used for seasonal and inter-annual monitoring of biophysical, phenological and structural vegetation parameters. Figure 1 illustrates the time series generation of a given vegetation index for a pixel $p(x, y)$. For each pixel, a time series can be observed, representing the variation of the vegetation index over time.

Vegetation indices represent improved measures of spatial, spectral and radiometric surface vegetation conditions. One of most used indices is the Normalized Difference Vegetation Index (NDVI), based on the reflectance of red and near-infrared wavelengths [25].

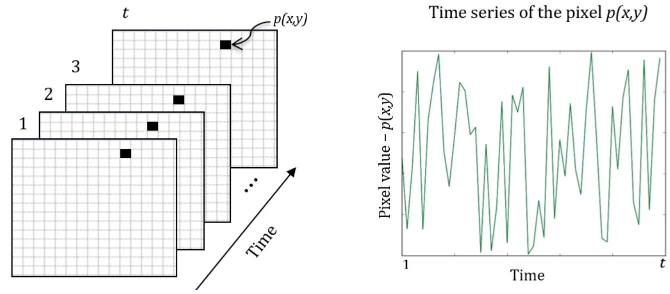

Figure 1. Example of a time series for the pixel $p(x, y)$.

IV. Dynamic Time Warping

Dynamic Time Warping (DTW) is one of the most used measures to quantify the similarity between two time series [26]. Originally designed to treat automatic speech recognition [10] [27], DTW measures the optimal global alignment between two time series and exploits temporal distortions between them.

The choice of a good similarity measure plays a key role since it defines the way to treat the temporality of data. The main change detection analysis in remote sensing images consists in comparing the data to estimate the similarity between them [28]. In many cases, the similarity is computed using a distance measure between two instances.

Among the known distances, DTW has the ability to realign two time series, so that each element of the first series is associated with at least one of the second series. With DTW, two time series out of phase can be aligned in a nonlinear form (Figure 2). Providing the cost of this alignment, DTW highlights similarities that the Euclidean distance is not able to capture, comparing shifted or distorted time series [28].

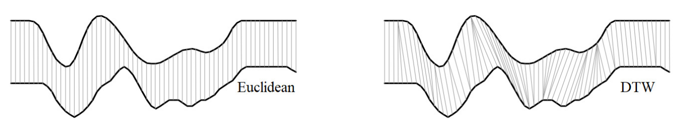

Figure 2. DTW nonlinear alignment allows a more intuitive distance to be calculated. Source: Adapted from [29].

Let A and B be two time series of length m and n, respectively, where $A = \langle a_1, a_2, \cdots, a_n \rangle$ and $B = \langle b_1, b_2, \cdots, b_m \rangle$. The first step for calculating the DTW measure between A and B is to build a matrix of size $n \times m$, where each matrix element (i, j) corresponds to a distance measured between a_i and b_i. This distance, $\delta(a_i, b_j)$ can be calculated using different metrics, such as the absolute difference $d(a_i, b_i) = |a_i - b_i|$ or the Euclidean distance.

The values of the matrix elements are calculated from left to right and from bottom to top. The algorithm adds the distance value δ of the elements in that position of each series. The elements receive the lowest value from the previous adjacent elements to the left, down and diagonal, as in (1).

$$D\left(a_i, b_j\right) = \delta\left(a_i, b_j\right) + \min \begin{cases} D\left(a_{i-1}, b_{j-1}\right), \\ D\left(a_i, b_{j-1}\right), \\ D\left(a_{i-1}, b_j\right) \end{cases} \tag{1}$$

Once the matrix is completely filled, the next step is to find the best path between the start and end values of the matrix that results in the optimal alignment value. For this, the search for the path starts from $D(a_n, b_m)$ (top right), always adding the lowest element in the neighborhood, until the first element at bottom left.

The DTW measure has been the subject of studies for geoprocessing and analysis of satellite images time series. Petitjean et al. [26] [28], for example, used DTW to compare time series affected by clouds. Maus et al. [30] presented a weighted version of DTW for land cover and land use classification.

V. Methodology

The proposed spatio-temporal segmentation by region growing is diagrammed in Figure 3. Our proposed method

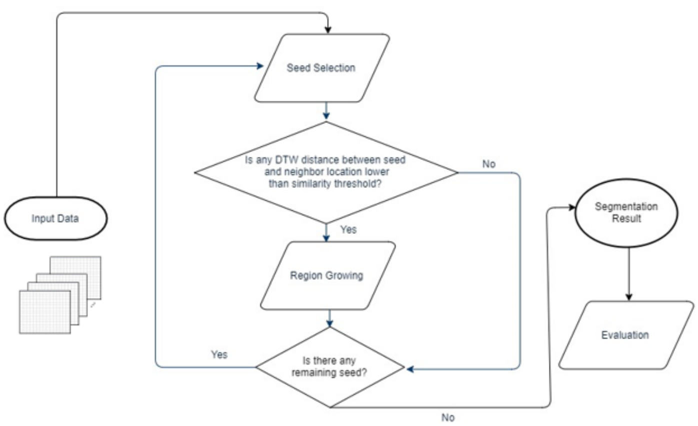

Figure 3. Flowchart of the proposed methodology.

adapts the traditional region growing technique in order to detect regions that present similar properties over time. The methodology uses the DTW distance as a part of the region growing process. The algorithm can be expressed by the following steps:

1) Select a sequence of images as input data.
2) Set similarity and area thresholds.
3) Determine the seed set.
4) Compute the DTW distance between the time series of the seeds and their neighbors. If the absolute difference between the DTW value of the time series of the seed and the time series of the neighbor is less than the similarity threshold, the neighbor is considered similar and it is added to the region.
5) Continue examining all the neighbors until no similar neighbor is found. Label the obtained segment as a complete region.
6) Observe the next unlabelled seed and repeat the process until all the pixels are labelled in a region.
7) For each segment whose size is less than the area threshold value, merge the segment with the neighbouring segment with the largest common boundary.

A case study was conducted by considering the DTW measure as homogeneity criterion in the algorithm. For each image, each pixel corresponds to a NDVI value, so that the values of this ordered sequence of images result in a time series. These collected time series are used in DTW calculation between the seed and its neighbouring pixels. The user determines the length and periodicity of the time series from the input data. The segmentation algorithm was written using R language.

For the acceptance or rejection of a given threshold in a remote sensing image segmentation result, the resulting segments were compared with a remote sensing image at the same location of the scene in the end of the time series. The seed set, processing order and location of the seeds were set randomly by the algorithm. The similarity threshold was reached using the same seed set and processing order of the seeds in all tests.

VI. Results and Discussion

Our technique was used to evaluate a central-western area in Brazil. The study area encompasses a region in the state of Mato Grosso (MT), located in Nova Cannã do Norte City, illustrated in Figure 4. A sequence of 27 images obtained from NDVI Landsat-8 OLI between April 10, 2016 and May 31, 2017 were used, with temporal resolution of 16 days. All images have a dimension of 155×132 pixels, with spatial resolution of 30 m.

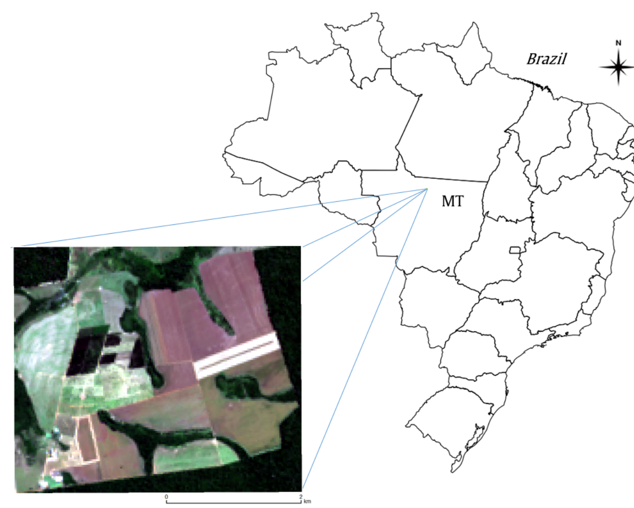

Figure 4. Study area. Landsat-8 (R4G3B2) imagery of the study area.

The study was conducted in the Gamada Farm, which is supervised by the Brazilian Agricultural Research Corporation (EMBRAPA). Wet and dry seasons are well defined in the region. The dry season occurs from May to August, whereas about 95% of the annual rainfall is concentrated between September and April. During the analysed year, the farm contained areas of native forest and pasture, in addition to regions with several types of crops, such as sugarcane, maize, rice and soybean. This area was chosen because it presented regions with homogeneous properties in the described period, according to information provided by EMBRAPA.

After several tests, the similarity and area thresholds were chosen so that the agricultural, pasture and native forest areas could be separated from the other neighboring targets. The expected segmentation output includes segmented areas with similar geo-objects presenting homogeneity over time. The similarity threshold was defined empirically, based on visual inspection of the results. For the segmentation result presented in Figure 5, the similarity threshold was set to 0.061. The processing time using this threshold value was 143 seconds. The area threshold was used to eliminate sliver polygons that the algorithm generates in boundary areas. This is due to the low spatial resolution of the images that influences the pixel values in edge areas. In addition, we set this threshold to 60,000 m^2 to disregard small regions derived from noise caused by the high presence of cloud cover in the image sequence.

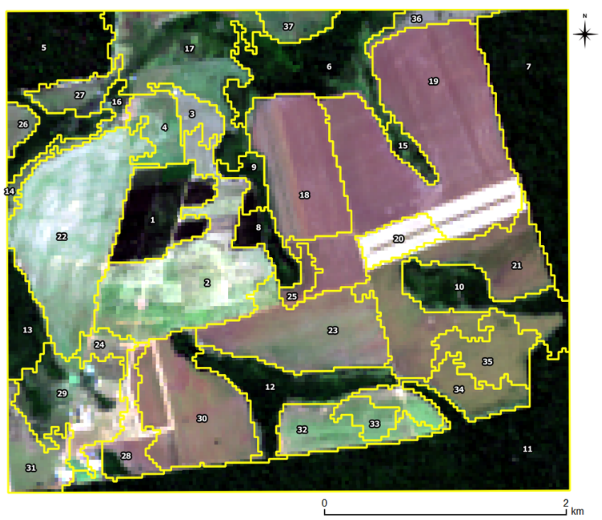

Figure 5. Segmentation output (yellow outlines) for the study area. The segments are superimposed on a Landsat-8 image (R4G3B2).

Evaluating the result of an image segmentation is difficult because, currently, no standard assessment techniques exist [31]. For this test, we compared the segmentation result to a Landsat-8 image, evaluating the output based on photo-interpretation of the satellite image. Visually, the proposed method was able to create similar-shaped segments, representing similar-sized groups of geo-objects, such as native forests, croplands and pasture areas.

The farm contains a region of Integrated Crop-Livestock-Forestry (ICLF) system. At the time of the study, Gamada Farm had crop rotation consisted of Brachiaria pasture grass (*Urochloa Brizantha*) interchangeable with soybean, rice+soybean, maize+soybean, Brachiaria+soybean, pasture, sugarcane and native forest. The region containing the ICLF system was detected by our technique, corresponding to the segment labelled 1 in Figure 5.

Additionally, our algorithm was able to create segments that presented regions with similar seasonal dynamics over the analysed period, distinguishing pastures regions (segments 2-4), native forest areas (5-17) and croplands (18-37). It is important to notice that some large agriculture areas were divided into sub-regions. Some of them were regions with different harvest periods and the method performed this separation between the areas during the analysed year.

However, since the proposed method is based on region growing technique, the algorithm contains some disadvantages. Different seed sets, for example, cause different results in segmentation. In addition, there is the dependence of processing order of the seeds, which is particularly noticeable when the regions are small or have some similar properties. In addition, DTW calculation demands a high computational cost.

The case study was encouraging and demonstrates the potential of the proposed multitemporal segmentation in dealing with time series generated by images of optical remote sensing images. However, one factor that reduces the quality of the segments is the noise in the time series derived from cloud cover.

VII. Conclusion

The proposed multitemporal segmentation brings a new way of interpreting data by means of analysing contiguous regions in time. In order to illustrate the potential of the method, we presented a study case on NDVI time series derived from Landsat-8 OLI products. We compared the segments generated by the proposed algorithm based on photo-interpretation, observing similarities between the segmentation results and the superimposed image.

Further analysis is needed to apply this approach in regions with higher temporal resolutions and to test different indices and spatial resolutions of Landsat-like image time series. However, the DTW computation and the use of the temporal dimension increases the complexity of processing compared with the segmentation of satellite images which considers only a single date.

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