Evaluating distance measures for image time series clustering in land use and cover monitoring

Karine Reis Ferreira[1], Lorena Santos[1], and Michelle C. A. Picoli[1]

Brazilian National Institute for Space Research (INPE)
São José dos Campos, São Paulo, Brazil
karine.ferreira@inpe.br, lorena.santos@inpe.br, michelle.picoli@inpe.br

Abstract. Time series derived from Earth observation satellite images have been widely used for land use and cover classification and change detection. Clustering is a common technique performed to discovery intrinsic patterns on time series data sets, by grouping similar time series together based on a certain similarity measure. This short paper describes an ongoing work on evaluating distance measures for remote sensing image time series clustering using Self-Organizing Maps (SOM), specifically to land use and cover monitoring. We present an experiment to evaluate three similarity measures, Dynamic Time Warping (DTW), Euclidean (ED) and Manhattan (MD). In this experiment, we show that ED and ED are more accurate than DTW for remote sensing image time series clustering in land use and cover application.

Keywords: remote sensing image time series, time series clustering, similarity measures, land use and cover monitoring

1 Introduction

Nowadays, the big amount of Earth observation satellite images freely available has motivated the use of time series analysis for land use and cover classification and change detection [3]. Time series derived from remote sensing images have been widely used for detecting agricultural intensification [8], forest disturbance [4], ecological dynamics [7], and phenological change detection [10].

Clustering is a common technique performed to discovery intrinsic patterns on time series data sets [1]. Time series clustering is a unsupervised method that groups similar time series together into homogeneous collections based on a certain similarity measure. According to Ding et al. [2], the similarity measure is a key aspect for achieving effectiveness in time series analysis. Time series represent sequences of values ordered over time. Thus, the distance between time series needs to be carefully defined in order to reflect the fundamental similarity of these sequences. Ding et al. [2] evaluated 9 similarity measures and their variants, testing their effectiveness on 38 time series data sets from different application domains, and concluded that on small data sets, *elastic* measures, e.g. Dynamic Time Warping (DTW), can be significantly more accurate than L_n-*norm*, e.g. Euclidean and Manhattan distances.

This paper presents an ongoing work on evaluating similarity measures for remote sensing image time series clustering using the Self-Organizing Maps (SOM) neural network [6]. In a previous work, we describe the use of SOM method with Euclidean distance to assess land use and cover samples and to evaluate which time series of spectral bands and vegetation indexes are best suitable for the separability of land use and cover classes [9]. However, more studies are necessary to evaluate which distance measure has the best accuracy for clustering such time series using SOM. Thus, in this work, we analyse the SOM method with three distinct distance measures, the Manhattan distance (MD), the Euclidean Distance (ED) and the *elastic* measure DTW. Differently from Ding et al. [2], our experiment shows that ED and MD distances are more accurate than DTW for remote sensing image time series clustering in land use and cover application.

2 Similarity measures for time series

Distance metrics aid to identify how the data is similar or dissimilar with each other. Given two time series $x = [x_1, \ldots, x_i, \ldots, x_n]$ and $y = [y_1, \ldots, y_i, \ldots, y_n]$, the Euclidean distance (ED) between these two time series is:

$$ED = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2} \tag{1}$$

The Manhattan distance (MD) between these two time series is:

$$MD = \sum_{i=1}^{N} |x_i - y_i| \tag{2}$$

The *elastic* DTW measure aligns similar sequences in time series that match even if they are out of phase in the time axis [5]. The first step of DTW is to compute a cost matrix Ψ, $n \times n$, given by the squared distance between each point of the two time series:

$$\Psi_{i,j} = (x_i - y_j)^2. \tag{3}$$

From Ψ,the best matching between two time series can be found, and the an optimal path that minimizes the cost warping is obtained. The warping path is a contiguous set of matrix elements that defines a mapping between the time series:

$$d_{i,j} = \Psi_{i,j} + \min \begin{cases} d_{i-1,j} \\ d_{i-1,j-1} \\ d_{i,j-1} \end{cases} \tag{4}$$

Figure 1 shows two time series X and Y. The distance measures between these two time series are: DTW = 0, ED = 4.242 and MD = 6. We can note that DTW measure considers that, even though the time series are out of phase in time axis, X and Y are matching and the distance between them is zero (DTW = 0). On the other hand, ED and MD distances reveal a significant difference between these two time series.

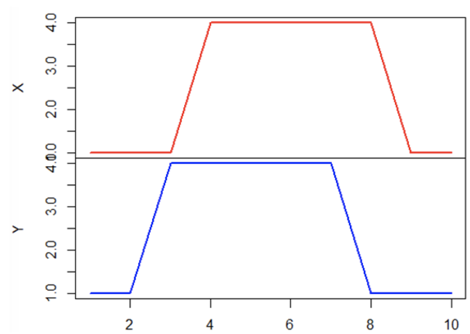

Fig. 1. Time series: $X = \{1,1,1,4,4,4,4,4,1,1\}$ and $Y = \{1,1,4,4,4,4,4,1,1,1\}$. The distance measures between X and Y are: DTW = 0; ED = 4.242 and MD = 6.

3 Experiment and results

In this work, we performed an experiment using 2115 ground samples located in the Mato Grosso state, Brazil, as shown in Figure 2. These samples are divided in nine land cover classes: (1) Forest, (2) Cerrado, (3) Pasture, (4) Soybean-fallow, (5) Fallow-cotton, (6) Soybean-cotton, (7) Soybean-corn, (8) Soybean-millet, and (9) Soybean-sunflower. For each sample, we extracted six time series associated to its location from the MODIS sensor images (MOD13Q1 product) of NASA, provided every 16 days at 250-meter spatial resolution. The six time series are the original spectral bands (1) BLUE, (2) RED, (3) Near-Infrared (NIR), and (4) Mid-Infrared (MIR), and the vegetation indexes (5) Normalized Difference Vegetation Index (NDVI) and (6) Enhanced Vegetation Index (EVI).

The main goal of this study is to evaluate which distance measure, ED, MD or DTW, has the best accuracy for clustering the time series of the nine land cover classes using the SOM method. SOM is an unsupervised neural network suitable for time series clustering [6] [1]. It allows mapping from a high-dimensional space to a low-dimensional space, preserving the data topology while reducing computational cost. It is composed by input and output layers, where the input layer is the sample data to be clustered and the output layer is a set of neurons.

To evaluate the separability of the clusters, we performed SOM for each distance metric combining different time series of spectral bands and vegetation indices. We tested three combinations: (1) Case I: NVDI and EVI; (2) Case II: NDVI, EVI, NIR and MIR; (3) Case III: NDVI, EVI, NIR, MIR, RED and BLUE.

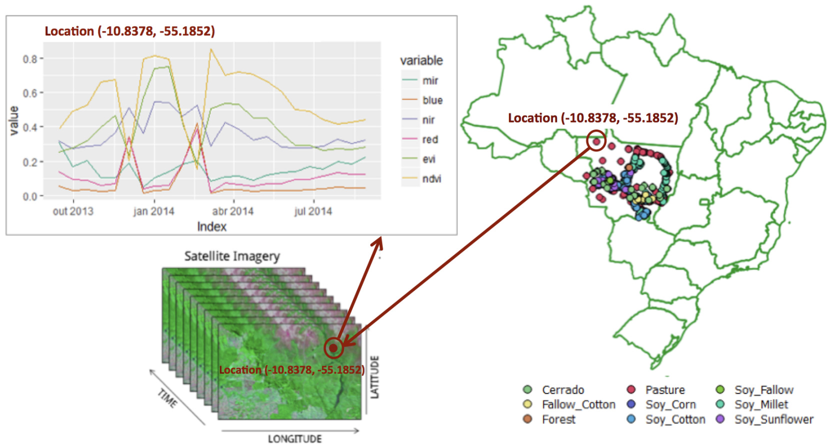

Fig. 2. Remote sensing image time series associated to land use and cover ground samples in Mato Grosso state, Brazil.

Figure 3 shows the spectral-temporal patterns and the amplitudes of the EVI index time series of the ground samples of four land use and cover ground samples: soybean-corn, soybean-cotton, soybean-sunflower and soybean-millet. It shows the spectral-temporal patterns of these time series during the Brazilian crop season that begins at September and spans to August of the next year. We can observe that these agricultural crops have a very similar spectral-temporal response. This similarly is due to the plant's own phenology and to the agricultural calendar of the state of Mato Grosso that relates the planting periods to the rainy season, and the harvest periods with the dry season.

Table 1 presents the cluster accuracy generated by SOM for each distance measure and for each set of time series (Cases I, II and II). To generate these clusters, we created a 2D SOM grid of neurons and initialized their weight vectors randomly. The SOM parameters that we used were: grid size = 25×25, learning rate = 1, and number of iterations = 100. Then, for each time series, the algorithm finds the 2D grid neuron which has the smallest distance to the time series, based on its weight vector. After the match, the neuron's weight vector and those of its neighbors are then updated. After all time series are associated with neurons, each neuron is labelled using a majority vote, taking the most frequent class from the time series associated with it. A neuron labelled as class X is part of the cluster X. The accuracy of the cluster X is calculated based on the percentage of time series associated to the class X in neurons labelled as class X.

We can observe in Table 1 that the best general accuracy is 93% generated by the Euclidean and Manhattan distances both in Case II, using the time series NDVI, EVI, NIR and MIR. Because the spectro-temporal patters of the crops are very similar, as shown in Figure 3, DTW distance can not distinguish them well and so can not produce clusters with good accuracy.

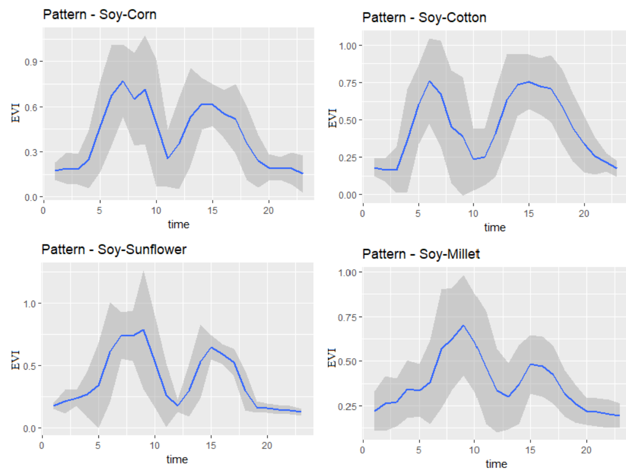

Fig. 3. Spectro-temporal patterns of the EVI index time series.

Table 1. Cluster accuracy for each distance measure and for each case (I, II and III)

	Euclidean			Manhattan			DTW		
	I	II	III	I	II	III	I	II	III
Cerrado	84	97.3	93.3	92.8	97.2	95.6	88	97.5	98.0
Fallow-Cotton	72.2	85.7	78.9	69	80.9	73.9	66	73.68	76.1
Forest	100	99.3	89.9	99.2	99.2	97.1	98	98.5	96.5
Pasture	92.7	97.3	93.7	94.9	95.9	96.9	92.1	98.9	98.9
Soy-Corn	82.0	84.0	85.4	84.6	84.9	86.5	70.1	74.3	80.2
Soy-Cotton	94.6	95.5	93.5	95.45	97.3	96.82	74.8	85.7	92.0
Soy-Fallow	97.8	100	98.9	100	97.7	100	73.6	88.8	98.9
Soy-Millet	85.5	90.3	88.2	87.5	92.8	88.5	72.2	85.1	100
Soy-Sunflower	77.1	76.9	72.9	73.21	86.0	75.9	-	50	63.2
Accuracy	**88.1**	**93**	**90**	**91.2**	**93**	**92.9**	**80.8**	**88.5**	**91.1**

In Table 1, we can observe that DTW in Case I can not distinguish the crop Soy-Sunflower from the others. That is, it is not able to create a group or cluster to represent the Soy-Sunflower crop. The confusion matrix of DTW in Case I is shown in Table 2 where we can observe the confusion between the classes Soy-Sunflower (9) and Soy-Corn (5). In this case, the majority of time series of the Soy-Sunflower class is in the cluster of the class Soy-Corn class.

To perform this experiment, we used the Kohonen R package [11] and extended it with the DTW distance. The experiment presented in this work shows that Euclidean and Manhattan distances are more accurate than DTW for remote sensing image time series clustering in land use and cover application.

Table 2. Confusion Matrix - Case I - DTW

	1	2	3	4	5	6	7	8	9
Cerrado	379	0	1	20	0	0	0	0	0
Fallow_Cotton	0	2	0	0	3	19	5	5	0
Forest	8	0	130	0	0	0	0	0	0
Pasture	36	1	1	330	0	0	0	2	0
Soy_Corn	1	0	0	3	289	73	2	30	0
Soy_Cotton	0	0	0	1	33	343	15	7	0
Soy_Fallow	0	0	0	0	0	0	81	7	0
Soy_Millet	2	0	0	4	51	16	6	156	0
Soy_Sunflower	0	0	0	0	36	7	1	9	0

References

1. Aghabozorgi, S., Shirkhorshidi, A.S., Wah, T.Y.: Time-series clustering–a decade review. Information Systems **53**, 16–38 (2015)
2. Ding, H., Trajcevski, G., Scheuermann, P., Wang, X., Keogh, E.: Querying and mining of time series data: experimental comparison of representations and distance measures. Proceedings of the VLDB Endowment **1**(2), 1542–1552 (2008)
3. Gomez, C., White, J.C., Wulder, M.A.: Optical remotely sensed time series data for land cover classification: A review. ISPRS Journal of Photogrammetry and Remote Sensing **116**, 55–72 (2016)
4. Kennedy, R.E., Yang, Z., Cohen, W.B.: Detecting trends in forest disturbance and recovery using yearly Landsat time series. Remote Sensing of Environment **114**(12), 2897–2910 (2010)
5. Keogh, E., Ratanamahatana, C.A.: Exact indexing of dynamic time warping. Knowledge and Information Systems **7**(3), 358–386 (2005)
6. Kohonen, T.: The self-organizing map. Proceedings of the IEEE **78**(9), 1464–1480 (1990)
7. Pasquarella, V.J., Holden, C.E., Kaufman, L., Woodcock, C.E.: From imagery to ecology: leveraging time series of all available landsat observations to map and monitor ecosystem state and dynamics. Remote Sensing in Ecology and Conservation **2**(3), 152–170 (2016)
8. Picoli, M., Camara, G., Sanches, I., Simoes, R., Carvalho, A., Maciel, A., Coutinho, A., Esquerdo, J., Antunes, J., Begotti, R., Arvor, D., Almeida, C.: Big earth observation time series analysis for monitoring brazilian agriculture. ISPRS Journal of Photogrammetry and Remote Sensing **145**, 328 – 339 (2018)
9. Santos, L.A., Ferreira, K.R., Picoli, M., Camara, G.: Self-organizing maps in earth observation data cubes analysis. International Workshop on Self-Organizing Maps pp. 70–79 (2019)
10. Verbesselt, J., Hyndman, R., Zeileis, A., Culvenor, D.: Phenological change detection while accounting for abrupt and gradual trends in satellite image time series. Remote Sensing of Environment **114**(12), 2970 – 2980 (2010)
11. Wehrens, R., Buydens, L.M., et al.: Self-and super-organizing maps in r: the kohonen package. Journal of Statistical Software **21**(5), 1–19 (2007)