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SHORT COMMUNICATION

NDVI Time Series Reconstruction Using Morphological Filtering

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Abstract

Time series of Normalized Difference of Vegetation Index (NDVI) values, derived from satellite data, are useful for monitoring the vegetation status and can form a basis for more advanced analysis. However, data in these time series is affected by noise caused primarily by atmospheric conditions and acquisition errors, resulting in glitches and prompting the need for developing reconstruction techniques that can efficiently remove the noise. A multitude of approaches have been developed so far, including a variety of temporal-based methods that include filtering techniques. In this letter, a morphological filter with a non-flat structuring element is proposed for NDVI time series reconstruction. This method is applied on two time series obtained from the Copernicus Global Land Service 300 m NDVI product. The experimental results prove the effectiveness of the proposed approach in producing high-quality NDVI reconstructions, highlighted by the significantly better root mean square error (RMSE) values obtained on the considered time series in comparison with three well-established techniques.

Keywords NDVI · Time series · Noise reduction · Copernicus

Introduction

Remote Sensing enabled a plethora of applications for the analysis of the surface of our planet, especially for agriculture [1]. The Earth Observation (EO) data provided by satellites may offer invaluable information for the land cover monitoring. Within the Space program of the European Union, Copernicus is the component dedicated to EO.

In precision agriculture, remote sensing techniques are used for the acquisition of information about the development stage and health status of the agricultural crops. Various parameters can be measured at various levels; usually indirect parameters, such as vegetation indices (VIs), are measured or computed from the multispectral reflectance information acquired by spectrophotometers. Perhaps the most used vegetation index is the Normalized Difference of Vegetation Index (NDVI), which considers the reflectance of red and near infra-red wavelengths [2].

From the time series of multispectral data, NDVI time profiles can be computed for the analyzed agricultural crops, each profile being characteristic to each type of crop. Due to various reasons (such as errors in the data acquisition process or the presence of thin clouds or water vapors in the atmosphere) the NDVI profiles are not smooth, but instead contain glitches and, in addition, they are sparse, because of unavailability of optical data in cloud-covered days. Consequently, in this letter we focus on NDVI time series reconstruction.

A series of NDVI time series reconstruction techniques have been proposed; these techniques can be classified in four categories [3]: temporal-based, frequency-based, spatial-based, and hybrid.

Temporal-based methods process a single pixel as a time series, ignoring any spatial correlation. This category of techniques can be further divided into four sub-categories [3]: filters (such as the Savitzky–Golay (SG) filter [4] and the changing-weight filter [5]), interpolation-replacement methods (maximum value compositing (MVC) [6] being an example), function-fitting methods (including Asymmetric Gaussian (AG) [7] and Double Logistic (DL) [8]) and

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deep learning models (one of the few models developed for NDVI is the deep stacking network (DSN) architecture [9]).

Mathematical morphology [10–12] is a powerful framework for non-linear signal and image processing and analysis. One of the more important components of this framework is morphological filtering [13], which is employed in various contexts, including noise reduction [14–16]. Morphological operations are applied using a *structuring element* (SE), which is a mask used for probing the signal. The most widely used version is that of a *flat* SE, i.e. a mask defined only by its size (equivalent to a simple analysis window), without any associated values. By contrast, a *non-flat* SE is defined also by its values, which further influence the local result of the morphological processing.

In this letter we propose a temporal-based NDVI reconstruction approach using morphological filtering with a non-flat SE. The approach is validated on two two-year NDVI time series extracted from the Copernicus Global Land Service (CGLS) 300 m NDVI product.

Methodology and Data

Morphological Filtering

Given a discrete signal $f[n]$ and a discrete SE $g[n]$, $n \in \mathbb{Z}$ the two fundamental morphological operators, erosion $\varepsilon_g(f)$ and dilation $\delta_g(f)$ are defined as:

$$\varepsilon_g(f)[n] = \bigwedge_{k \in \mathbb{Z}} \left(f[n+k] - g[k]\right) \tag{1}$$

$$\delta_g(f)[n] = \bigvee_{k \in \mathbb{Z}} \left(f[n-k] + g[k]\right) \tag{2}$$

where $\bigwedge$ and $\bigvee$ represent the infimum and supremum, respectively, of the considered set of values (minimum and maximum in the case of finite sets). Dilation can be viewed as a non-linear convolution, where the sum of products operation is replaced by a maximum of sums [17], while, in a similar fashion, erosion can be viewed as a non-linear correlation.

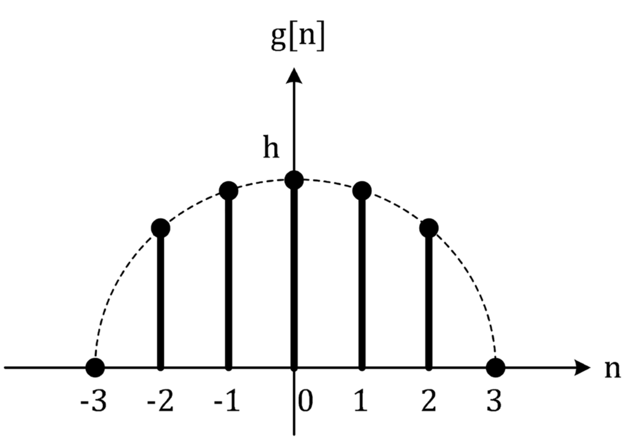


Fig. 1 Elliptic SE with $r = 3$

The *closing* operator $\phi_g(f)$ is defined as the erosion of the previously dilated signal:

$$\phi_g(f) = \varepsilon_g(\delta_g(f)) \tag{3}$$

Closing is a morphological filter used for filling small valleys/glitches in a signal. This makes it an appropriate choice for NDVI time series reconstruction, since noise caused by clouds and atmosphere tends to reduce NDVI values [5], manifesting as glitches in the time series. Furthermore, the closing operator is idempotent:

$$\phi_g(\phi_g(f)) = \phi_g(f) \tag{4}$$

meaning that it is sufficient to apply the operator only once, with further applications bringing no changes to the result, which is a useful property for a filter.

A flat SE is defined as:

$$g[n] = \begin{cases} 0 & n \in B \\ -\infty & n \notin B \end{cases} \tag{5}$$

where B represents a set of points which defines the neighbourhood which is taken into consideration. If this type of SE is employed in equation (1) or (2), each resulting value is a value from the input signal belonging to the neighbourhood B centred in n.

Since NDVI time series are generally not constant over long intervals (for instance due to crop growth and senescence), employing a flat SE, which would induce some degree of repetition of the output values when noise is encountered, is not particularly appropriate for reconstruction. In order to obtain output values that are not necessarily in the input set, a non-flat SE has to be used, defined by other values besides 0 and $-\infty$. We propose using an elliptic SE with semi axes r and h, which can be described by equation (6). Figure 1 presents an elliptic SE with $r = 3$ ($-\infty$ values are not depicted).

$$g[n] = \begin{cases} h\sqrt{1 - \frac{n^2}{r^2}} & n \in \{-r, ..., r\} \\ -\infty & n \notin \{-r, ..., r\} \end{cases} \tag{6}$$

Taking all of the above in consideration, the proposed reconstruction approach consists of applying morphological closing using an elliptic SE in order to remove glitches in the NDVI time series.

Data and Performance Metric

For the validation of the proposed approach, two pixels (NDVI time series) were extracted from the CGLS 300 m NDVI product [18]. The time series cover a two-year period, from 1 July 2021 to 21 June 2023, with 3 values for each month, resulting in a total of 72 values for each of the two time series. The two pixels are located at $46.60° N, 21.08° E$ (Szabadkígyós, Hungary)—referred to as pixel $\#1$ and $46.19° N, 21.28° E$ (Arad, Romania)—pixel $\#2$. They were chosen on the basis that all the values in the two-year series are of high quality (i.e. no bit is set in the quality flag layer for any value in the two-year series), the selected areas being the only two areas in the region with pixels that satisfy this property for the considered time interval.

In order to assess the reconstruction performance of the proposed filter, a framework proposed in [19] and [5] was employed. It consists of modelling ideal NDVI time series through smoothing and then applying various amounts of noise. In the present case, the ideal NDVI time series were obtained from the chosen pixels by averaging the results of filtering the time series with the Asymmetric Gaussian (AG), Double Logistic (DL) and Savitzky–Golay (SG) methods, all included in the freely available TIMESAT 3.3 software package [20]. Noise was introduced by reducing a number of randomly chosen values in the ideal time series by random percentages between 5 and 50% with 5% increments. The percentages of modified values were 10% (low level of noise), 40% (moderate) and 70% (high level of noise). Figure 2 presents the two time series in the original version (values from the NDVI product), ideal version (obtained from the original through smoothing) and moderate noise version (the ideal version in which 40% of the values are replaced with noise).

In order to objectively assess the reconstruction results, the widely-used root mean square error (RMSE) was employed [21], defined as:

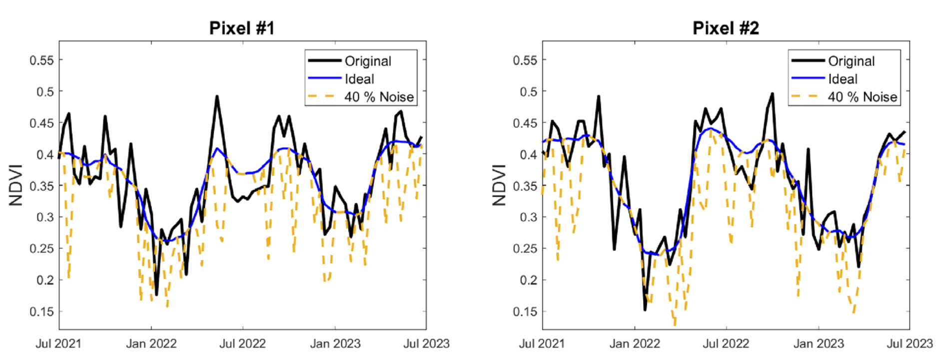
$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(f[n] - f'[n])^2} \tag{7}$$

where $f[n]$ and $f'[n]$ represent the ideal and the noisy/filtered time series, respectively, and N is the number of values in the time series. A lower RMSE value indicates a greater similarity between the two time series and, thus, a better result.

Results

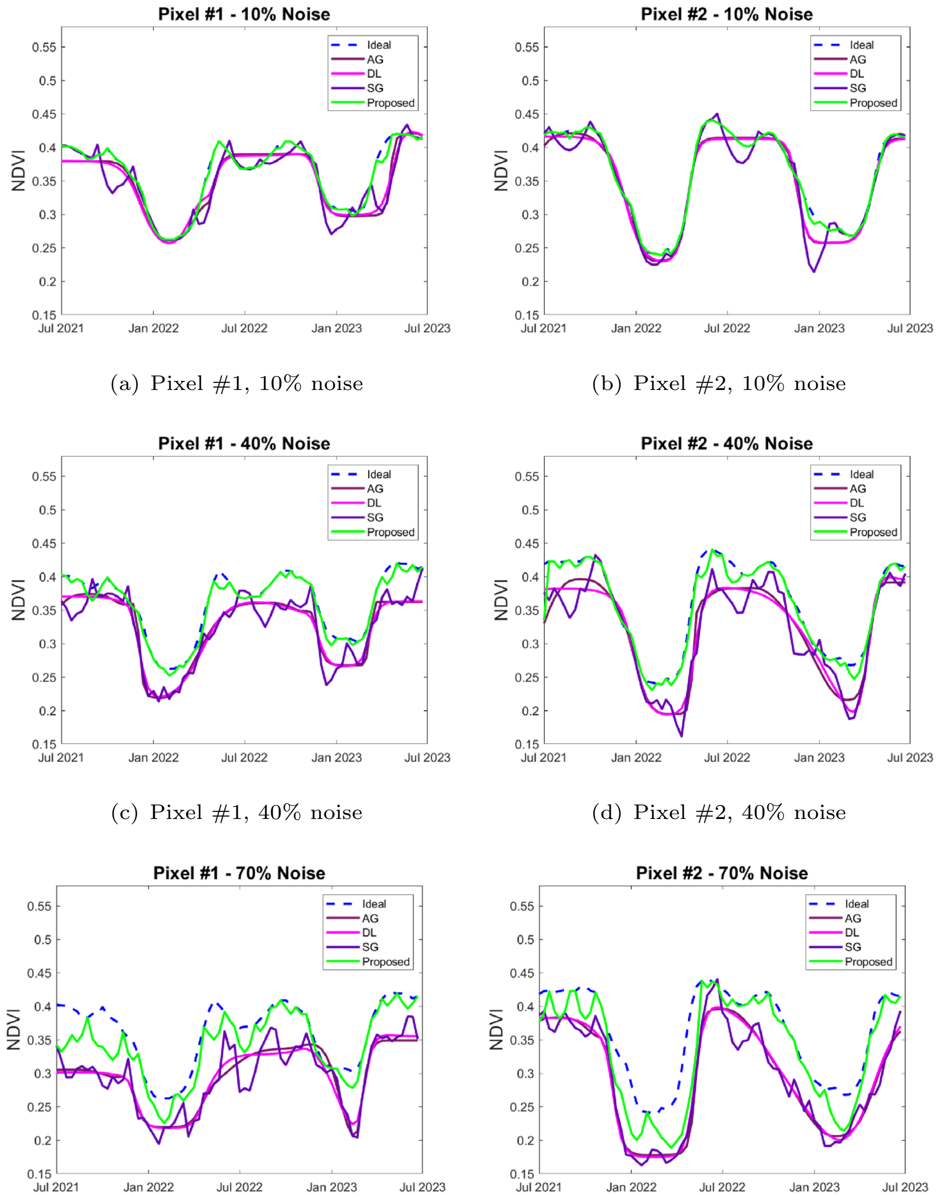
In a comparative analysis, the proposed approach was implemented in MATLAB and applied using $r = 5$ and $h = 0.5$ as empirically-chosen parameters for the elliptic SE. The other methods used in the analysis are AG, DL and SG, implemented in the TIMESAT software. Figure 3 presents the results obtained by all the methods on the two time series affected by low, medium and high levels of noise, along with the ideal time series in dotted lines (the noisy curves are not depicted for the sake of clarity). The graphs show that, in all cases, the proposed approach produces the results that are the closest to the ideal curves, with particularly good results for low and medium levels of noise; the other employed methods, particularly the function fitting methods, tend to underestimate the ideal curve more as the level of noise increases.

The RMSE values obtained by all the methods are depicted in Table 1, with the values for the noisy series provided as reference. Confirming the results depicted in the graphs, the proposed method obtains the best RMSE results in all cases by a significant amount, indicating its suitability for high quality NDVI reconstruction.



(a) Pixel $\#1$ (b) Pixel $\#2$

Fig. 2 Time series for pixel #1 and #2—original, ideal and corrupted with 40% noise



(a) Pixel #1, 10% noise

(b) Pixel #2, 10% noise

(c) Pixel #1, 40% noise

(d) Pixel #2, 40% noise

(e) Pixel #1, 70% noise

(f) Pixel #2, 70% noise

Fig. 3 Reconstruction results obtained using Asymmetric Gaussian (AG), Double Logistic (DL), Savitzky–Golay (SG) and the proposed method, along with the ideal time series. Left column: Pixel #1, right column: Pixel #2. Top: low level of noise, middle: medium level of noise, bottom: high level of noise

Table 1 RMSE values computed for the reconstruction methods applied on the two time series; the best results are presented in bold

Method/noise level	Pixel #1			Pixel #2		
	10%	40%	70%	10%	40%	70%
Noisy	0.0430	0.0645	0.0878	0.0314	0.0668	0.0912
AG	0.0252	0.0407	0.0708	0.0152	0.0439	0.0744
DL	0.0238	0.0402	0.0693	0.0155	0.0442	0.0728
SG	0.0281	0.0428	0.0712	0.0206	0.0474	0.0753
Proposed	**0.0042**	**0.0077**	**0.0271**	**0.0035**	**0.0132**	**0.0390**

Conclusions

In this letter, a reconstruction method for NDVI time series is proposed, consisting of morphological closing with an elliptic structuring element. The method was applied in the reconstruction of two two-year time series obtained from the Copernicus Global Land Service 300 m NDVI product. The reconstructions produced by the proposed method were compared to those obtained by three well-known reconstruction techniques implemented in the TIMESAT software (asymmetric Gaussian function fitting, double logistic function fitting and the Savitzky–Golay filter). The results show that the proposed approach is the most effective at removing the noise and producing a time series that is close to the ideal one. Another advantage of the method is its simplicity in definition and implementation. Future development includes a study on the optimal choice of parameter values for the elliptic SE, experimenting with other SE shapes and conducting more experiments with various NDVI time series.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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