Assessment of interpolation and approximation algorithms for high temporal and spatial resolution image time series

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High spatial and temporal resolution imagery

New opportunities: High spatial and temporal resolution (Sentinel-1 and Sentinel-2), global coverage. Vegetation status monitoring, early crop mapping, change detection.
New challenges: Efficiently describe and exploit the temporal behavior (phenology).
Think pixels, not images.

La loi cherchée peut se représenter par une courbe. L'expérience nous a fait connaître certains points de cette courbe. En vertu du principe que nous venons d'énoncer nous croyons que ces points peuvent être reliés par un trait continu. Nous traçons ce trait à l'œil. Des nouvelles expériences nous fourniront des nouveaux points de la courbe. Si ces points sont en dehors du trait tracé d'avance, nous aurons à modifier notre courbe, mais non pas à abandoner notre principe. Par des points quelconques, si nombreux qu'il soient, on peut toujours faire passer une courbe continue. Sans doute, si cette courbe est trop capricieuse, nous serons choqués (et même nous soupçonerons des erreurs d'expérience), mais le principe ne sera pas directement mis en défaut.

Henri de Poincaré, La Valeur de la Science

Needs in temporal processing

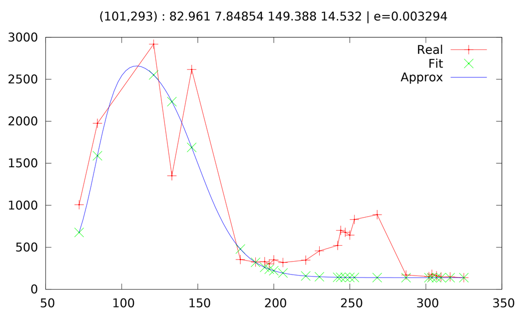
- Tools are needed for
  - **Approximation:** for modeling and feature extraction.
  - **Gapfilling:** clouds, shadows.
  - **Regular time sampling:** multi-year comparison.
  - **Denoising, artifact suppression:** smoothing, etc.
- These techniques are easily available through software packages as the free of cost TIMESAT[2], or as the free (libre) R packages providing BFAST[1] or STL[3].
- Most of **these techniques were designed to work with the medium and low spatial resolution sensors** and therefore assume either daily revisit (in order to being able to denoise), several growing seasons of vegetation, or regularly sampled (time composites) in order to estimate analytical models.

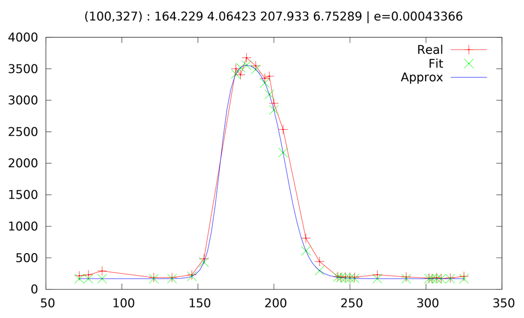
Approximation, parametric modeling

Goal: Fit an analytical (parametric) model in order to extract phenological features from the time series.

Double logistic

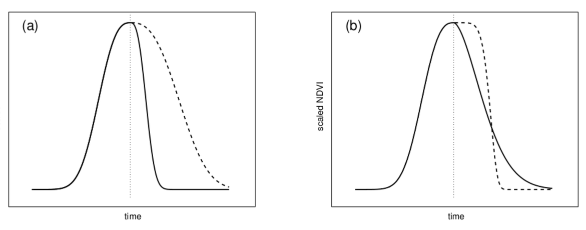
$$y(t) = K * \left(\frac{1}{1 + exp(\frac{x_0 - t}{x_1})} - \frac{1}{1 + exp(\frac{x_2 - t}{x_3})} \right)$$





Asymmetric Gaussians

$$g(t; x_1, \cdots, x_5) = \begin{cases} \exp\left[-\left(\frac{t - x_1}{x_2} \right)^{x_3} \right] & t > x_1 \\ \exp\left[-\left(\frac{t - x_1}{x_4} \right)^{x_5} \right] & t < x_1 \end{cases}$$



Other models:

- Degree-day

$$y(t) = K * \left(\frac{1}{1 + e^{-b*(t - T_i)}} - e^{a*(t - T_f)} \right)$$

- Grosenbauch family [4]

$$y = \beta_1 + \beta_2 [e^{(\beta_3^2 - 1)z} - \beta_3 z]^{\beta_3 \beta_4 + 1}$$

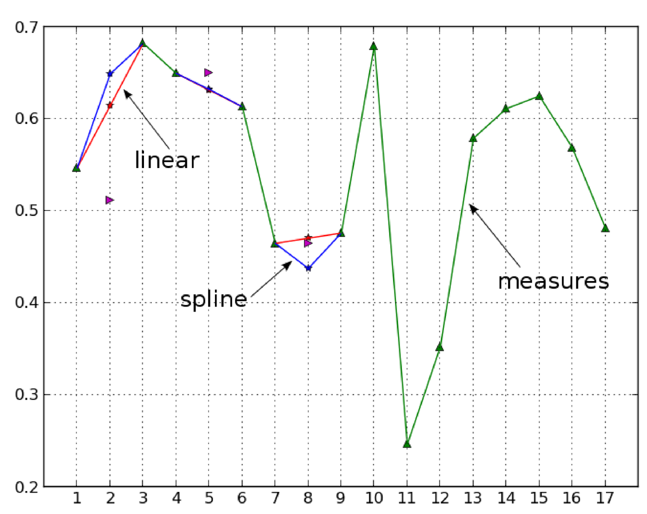
Crucial issues: in order for the parameter optimization to converge, a **heuristic-based initialization of the parameters** and an **iterative estimation of primary and secondary phenological cycles** are needed.

Interpolation and gapfilling

Goal: Obtain values to replace missing observations or observations which are considered to be unusable (clouds, saturations, shadows).

Linear, polynomial interpolation:

- Linear
- Savitzky-Golay



Interpolating splines:

- The (cubic) spline interpolation is a piece-wise continuous curve, passing through each of the measured values. There is a separate (cubic) polynomial for each interval, each with its own coefficients.
- In order to make the interpolation as smooth as possible, we require that the first and second derivatives also be continuous.

Interpolation and gapfilling are also useful to **resample the data to match other time series**: different years, different sensors, etc.

Learning schemes:

- No need to wait for a clean acquisition after a missing value → **real-time**.
- Kohonen's Self Organizing Map (SOM) with missing values in order to replace missing data with values coming from a pixel with a similar time series.
- Non-local Means (NLMeans) filtering: takes a mean of all pixels in the image, weighted by how similar these pixels are to the target pixel. The similarity (distance) function takes into account missing dates in the time series.

Filtering, denoising and smoothing

Goal: Obtain a smoother time series by replacing the measured values which are considered to be close to what should have been measured by the sensor.

Linear and nonlinear filtering:

- Moving average: Replace the current measure by a (weighted) average of the measures inside a temporal window.
- Median filter: Like the moving average, but use the median instead of the mean in order to be robust to outliers.

Local fitting:

- Savitzky-Golay: Replace the current measure by the value of a polynomial function fitted to the measures inside a temporal window.
  - usually a quadratic function is used;
  - mean squares fitting is applied.

Global fitting: Like the local fitting, but the temporal window contains the whole series.

- Polynomial: use mean squares fitting to obtain the coefficients of a polynomial of high degree. Can oscillate if the degree is to high.
- Smoothing splines: like interpolating splines (see above) but with a penalty for each knot for lack of smoothness (integral of the second derivative, for instance).

Free software implementations

- Parametric approximation: https://bitbucket.org/inglada/phenotb
- Interpolation and gapfilling: https://bitbucket.org/inglada/temporalgapfilling
- Filtering and smoothing and many other tools: http://www.orfeo-toolbox.org
- Orfeo Toolbox will progressively integrate all these tools in its **Multitemporal module**.

References

[1] Verbesselt, J., Hyndman, R., Newnham, G., and Culvenor, D. (2010). Detecting trend and seasonal changes in satellite image time series. Remote Sensing of Environment, 114, 106-115.

[2] Jönsson, P. and Eklundh, L., 2004, Timesat - a program for analyzing time-series of satellite sensor data, Computers and Geosciences, 30, 833-845.

[3] R. B. Cleveland, W. S. Cleveland, J.E. McRae, and I. Terpenning (1990) STL: A Seasonal-Trend Decomposition Procedure Based on Loess. Journal of Official Statistics, 6, 3–73.

[4] L. R. Grosenbauch, Generalization and reparametrization of some sigmoid or other nonlinear functions. Biometrics 21, 708âĂŞ714, 1965.