Selection and evaluation of kinematic models for InSAR time series: is there more in stock?

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Can we....

...detect a hazardous building in Bangladesh, before it collapses?

...indicate when a landslide becomes catastrophic?

...predict a sinkhole before the collapse?

...indicate when this bridge will break?
Monitoring the movement, or kinematic behavior, of millions of InSAR measurement points is feasible from earth orbiting satellites.
Linear velocity map

Web portal Skygeo

TU Delft
Linear velocity map
Linear velocity map
Linear velocity map
Observations: time series

Kinematic time series

\[ E\{y\} = t \cdot v \]

Design matrix: \([t_1 \ t_2 \ ...]\)

Linear velocity \([\text{mm/y}]\)
Kinematic time series

\[ E\{y\} = t \cdot v \]

Not optimal functional model
Problem formulation

• Data sets are too large for manual analysis
  --- Automatic detection needed

• How to parameterize the time series?
  --- Find the optimal kinematic model for each point

• How?
Find the optimal kinematic model

- Fitting a polynomial model **NO!**
- Polynomial model: good fit, but:
  1. Model is not realistic → not physically interpretable
  2. Tendency towards ‘overfitting’
  3. Model does not take stochasticity into account
Finding the optimal kinematic model

• Choosing from a library of physically realistic models, e.g.,
  --- Steady-state, Temperature-dependent, Exponential decay, Break-point, Temporal offsets and outliers, … This library can be extended when more information is available

• Conditions:
  --- No overfitting
  --- Follow Ockham’s razor with Einstein’s addition:
    “Everything should be kept as simple as possible…,
    …but not simpler”
  --- Avoid that a model with more parameters will fit the data better
Methodology

Baarda’s method of testing (‘B-method’):

“the probability of accepting any particular alternative hypothesis should be equal”

*This probability is known as the ‘(discriminating) power of the test’
Flow chart

- Start with a ‘steady-state’ model as most straightforward $H_0$.

**Huygens (~1640):** whether a point is in rest or in uniform motion is not observable.

**Newton 1st law (1687):** Without any external force, a point is in rest or in uniform motion.

- Stochastic model, chosen conservatively

- Type-1 error, chosen to be large (~25%)
  (this implies that in a lot of cases we will engage in evaluating alternative hypotheses, rather than sticking to $H_0$. Note that the final outcome may still be that $H_0$ is sustained)
What if $H_0$ is rejected?

Test many (100’s) of alternative models:
- By testing them against $H_0$
- Compute test statistic, divide by critical value \( \rightarrow \) ‘test ratio’
- $H_a$ with highest test ratio rejects $H_0$ most significantly \( \rightarrow \) best fit considering Ockham-Einstein-Baarda criterion
- Compute a-posteriori sigma
Real Terrasar-X data \((m = 127, \ 2009-2013)\) results: (Rotterdam, the Netherlands)
Real Terrasar-X data (m = 127) results: pointwise

Class: Linear
Real Terrasar-X data ($m = 127$) results: **pointwise**

Class: Linear + temperature-related
Real Terrasar-X data ($m = 127$) results: pointwise

Class: Exponent
Real Terrasar-X data (m = 127) results: pointwise

Class: Linear + jump
Real Terrasar-X data \((m = 127)\) results: \textit{pointwise}

\begin{itemize}
\item \textbf{Class: Exponent + temperature-related}
\end{itemize}
Real Terrasar-X data \((m = 127)\) results: pointwise

Class: Exponent + jump
Real Terrasar-X data ($m = 127$) results: pointwise

Class: Linear + temperature-related + jump
Real Terrasar-X data (m = 127) results: pointwise

Class: Exponent + temperature-related + jump
Real Terrasar-X data ($m = 127$) results: *pointwise*

Class: Linear + temperature-related

Class: Linear

Class: Exponent

Class: Exponent + temperature-related

Class: Linear + jump

Class: Exponent + jump
Real Terrasar-X data \( (m = 127) \) results: pointwise

Class: Linear + temperature-related

The **MDV** of the temperature-related parameter = 0.12 [mm/K], when \( \lambda_0 = \lambda(\alpha_0 = 1(1/127), q = 1, \gamma_0 = 50\%) = 8.23 \). This implies that for a specific target, if the temperature dependent parameter is 0.12 [mm/K], it will be found with a likelihood of 50%. A greater value of this parameter will be detected with a higher likelihood.
Real Terrasar-X data ($m = 127$, 2009-2013) results:
(Rotterdam, the Netherlands)
Bridge --- Botlekbrug: stable or no (significant) deformation

Class: Linear
Bridge --- Botlekbrug: stable or no (significant) deformation

Class: Linear + temperature-related
Bridge --- Botlekbrug: stable or no (significant) deformation

Class: Linear + seasonal
Real Terrasar-X data ($m = 127$, 2009-2013) results:
(Rotterdam, the Netherlands)
Turnout

Class: Linear
Turnout

Class: Linear + temperature-related + jump

Class: Linear + jump
Turnout

When?

Class: Linear + seasonal + jump

Class: Linear + jump
Turnout

Class: Linear + seasonal + jump

Class: Linear + jump
What does this all mean?

1. The ‘steady-state’ model (linear) is systematically challenged.
2. In the InSAR community, we have to change the representation, parameterization and visualization of our results.
3. Velocities can be biased → this is corrected for now.