Towards the Homogenization of GNSS Tropospheric Delay Time Series

STATUS AND RECENT DEVELOPMENTS

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Motivation and Introduction

ALL STARTED WITH...
Context and Motivation

COST Action GNSS4SWEC ‘Advanced Global Navigation Satellite Systems tropospheric products for monitoring severe weather events and climate’

WG3 “Use of GNSS tropospheric products for climate monitoring”

- It turned out that several groups were showing results from time series analyses, sometimes based on the same datasets.

- They were dealing/struggling with the homogenization of their datasets.
Common Homogenization Activity

Common dataset: IGS “repro1” troposphere products

- ZTD $\rightarrow$ IWV
- Daily Observations
- 120 Stations
- Period: 1995-2010

Screened and converted to Integrated Water Vapor (IWV) by O. Bock.

From A. Klos

Motivation and Introduction
Dataset and Reference Series

Targeted dataset: IGS “repro1” troposphere products

CCJM: Ogasawara, Japan

→ We will look for break points/change points in the ERA-interim-GPS IWV differences series.
Dataset and Reference Series

How to assess performance of the homogenization tools?
Generating Synthetic datasets

**Blind Homogenization Benchmarking Activity**

- **Real IWV Diff. (ERAI-GPS)**
  - Manual Homogenization
  - IGS log files
  - Power Spectra Density Analysis
  - Noise Analysis
  - Non-climatic Trend Analysis

- **Synthetic IWV Diff.**
  - Characterization of the number and amplitude of offsets (randomly inserted)
  - Significant Frequencies (annual, semi-annual…)
  - Noise Model: AR(1) + W.N.
  - Characterization of non-climatic trends (reference series)
Synthetic Datasets Variants

**Blind Homogenization Benchmarking Activity**

We wanted to assess the performances of the homogenization tools w.r.t. dataset characteristics

**EASY**
- Seasonal signals
- Offsets
- White noise (WN)

**LESS COMPLICATED**
Similar to EASY but +
- Autoregressive process of the first order (noise model = AR(1)+WN)

**FULLY COMPLICATED**
Similar to LESS but +
- Gaps (up to 20% of missing data)
- Non-climatic Trend (Ref. Series)
Participating Homogenization Tools

WG Contribution Summary

- 8 homogenization operators
- 13 break detection methods (daily+monthly)
- Applied on EASY/LESS/FULLY complicated synthetic datasets

4 main types of break detection methods:

- 1-test with cutting algorithm
- Maximum Likelihood (ML) multiple break methods
- Singular Spectrum Analysis (SSA)
- Non-parametric methods
Homogenization Tool Performance

ESTIMATED OFFSET CLASSIFICATION AND TIMING - SCORES AND SKILLS
Did I find a true break point?

Assessing breakpoint identification requires defining a time window

We work with daily but also monthly time series → define a time window of 2 months
Estimated Offsets Classification

- False Alarms: False Positive
- Matches: True Positive
- Misses: False Negative
- True Negatives

Estimated Break

True Break

Matched Break

N days

False Alarms

Matches

Misses

Time
From Classification to Score and Skill Analysis

Green zone == Good performance == if ((TP + TN > 40%) && (FP < 40%) && (FN < 40%))

Ternary graph adapted from Gazeaux et al. 2013

Potliaux E. et al. - Eric.Potliaux@oma.be - EGU 2019 G.A. Symposium, Vienna, Austria - 7-12 April 2019
Score and Skill Analysis

Performance Summary – Ternary Graphs

→ Good performance for the majority of the tools for the easy and less complicated dataset
Score and Skill Analysis

Performance Summary – Ternary Graphs

→ Performance decreases drastically for almost all the tools when adding gaps and a trend in the benchmark time series.
Homogenization Tool Performance

IMPACT ON THE TARGETED APPLICATION(S)
Impact on the targeted application(s)

**CRMSE and Trend Analysis - Principle**

- For each synthetic dataset, each homogenization tool contribution, and each time series we have

\[
CRMSE \equiv \sqrt{\frac{1}{N} \sum_{i=1}^{N} [(X_{i,\text{orig}} - \bar{X}_{\text{orig}}) - (X_{i,\text{corr}} - \bar{X}_{\text{corr}})]^2}
\]

\[
\text{Abs. Trend Bias} \equiv \text{abs}(\text{Trend}_{\text{orig}} - \text{Trend}_{\text{corr}})
\]
CRMSE and Trend Analysis

Synthetic Dataset “EASY” (Arithmetic mean over all stations)

CRMSE Improvements: 40% → 84%
Trend Bias Improvements: 69% → 95%
CRMSE and Trend Analysis

Synthetic Dataset “LESS COMPLICATED” (Arithmetic mean over all stations)

CRMSE Improvements: 43% → 77%
Trend Bias Improvements: 72% → 94%
CRMSE and Trend Analysis

Synthetic Dataset “FULLY COMPLICATED” (Arithmetic mean over all stations)

CRMSE Improvements: 18% → 34%
Trend Bias Improvements: 17% → 36%
First Conclusions and Future Steps

- **EASY and LESS Complicated:**
  - Most considered homogenization perform well in terms of scores and skill (timing of the offset), and show a large improvement in terms of CRMSE and trend bias (application side).

- **FULLY complicated (+gaps and trends):**
  - There is a drastic decrease in improvement, for all methods, with a large increase of false alarms (scores and skill, timing of the offset), and also a very reduced improvement in terms of CRMSE and trend bias. Reason is unclear (gap or trend) and must be further investigated.
  - The variation of performances within a single method increase when looking at individual time series.

- **Next major steps?**
  - Prepare next benchmark & blind homogenization test campaign?
  - Determine a proper strategy for correcting the (real) IGS repro 1 dataset and apply it (and possibly to other datasets e.g. the EPN repro 2).
Thank you...