CHANGE DETECTION IN TIME SERIES

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Summary

Time series are analysed to detect changes and predict future behaviour. Monitoring of the surface or subsurface in Geoscience provides such time series. As new data becomes available, changes of regime are detected. They should be identified as early as possible with as few false positive as possible.
In this paper, we define the ideas of regime and change of regime in a time series. We then give an overview of the Bayesian method used to detect these changes. The principles are illustrated with an application for the detection of a mine tailings dam failure using InSAR satellite data.

Change detection in time series

Introduction

Time series have often been analysed to detect changes and predict future behaviour. In such datasets, data points are collected at intervals over a period and measurements are therefore received one-by-one. The problem is then to identify breakpoints or change-points in the time series, indicating a change in the evolution trend or change of regime. This identification should occur as early as possible in the sequence, and several techniques have been developed to do so (Oosterbaan et al., 1990; Adams and MacKay, 2007).

In Geoscience, with the development of new monitoring solutions, there is an increasing number of possible applications of these techniques for surface and subsurface change analysis. One can think of monitoring of production fields (Michou et al., 2013), Permanent Reservoir Monitoring systems, gas storage, and, more recently, the surveillance of CO_2 storage. The applications are not limited to subsurface monitoring, as they are also developed for structural and shallow surface surveillance (Cai, 2022) using in-situ sensors but also with remote sensing data like satellite images, an example that will be developed in this paper. With these examples, there is often a lot of spatial redundancy in the measurements, suggesting the need for specific pre-processing of the measurements, both spatially and temporally. The spatial redundancy facilitates the robustness of the early detection, particularly to reduce false positives.

In the first section, we will define the ideas of regime and change of regime in a time series. We will then give an overview of the Bayesian method used to detect the changes of regime. The principles will be illustrated with an application for the detection of a dam failure using InSAR satellite data.

An example of time series

In this example (Michou et al., 2013), the continuous land seismic reservoir monitoring provided daily active seismic measurements over a heavy oil pad produced with thermal EOR.

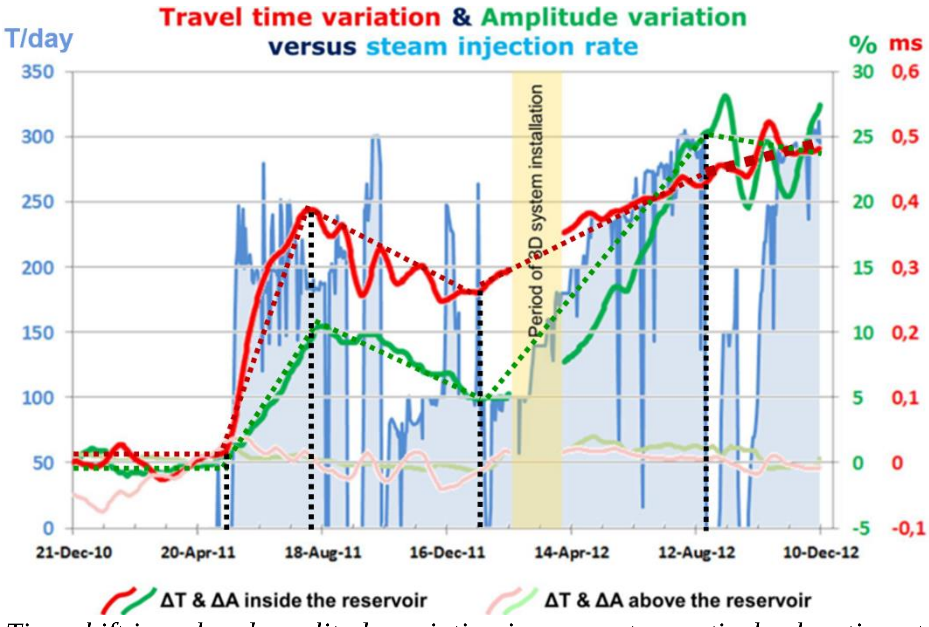

__Figure 1__ Time shift in red and amplitude variation in green at a particular location at the top of the reservoir near the injection well over a two-year period. The steam injection rate is represented in blue. Most of the variability of the seismic measurements through time can be modeled with a succession of five linear models with four changes (dotted lines).

Figure 1 shows the two-way-time (TWT) and amplitude changes at the top of the reservoir through the monitoring period at a particular location. The temporal evolution of the attributes shows monotonous trends with some slope changes occurring at times corresponding to changes in the steam injection. As a first approximation, these measurements can be modeled with a succession of linear regimes. Dates at which the slope changes occur are common for both time shifts and amplitude variations. This kind of modeling is similar to the blocking of wireline logs within layers and is not limited to linear models between change points. In the case of linear models, the methodology is also called segmented regression with breakpoints (Oosterbaan et al., 1990).

Detection of regime changes within the time series

The benefit of monitoring is to detect the changes of regime as early as possible (Fearnhead and Liu, 2007), so that actions can be taken if needed to prevent any risk. To do so, the Bayesian technique Bayesian Online Change Detection (BOCD), as explained by Adams and MacKay (2007) and Alami et al. (2020), was developed.
All possible time values are envisaged as possible change points. A model and its associated probability is computed for each possible time value. The set of models is updated as new measurements become available. In Figure 2 below, two alternate models are represented on the left, with and without change, and the associated probability through time is represented on the right (with dark areas the most probable). The model without change (regime 1), corresponding to a single linear regime starting at time 0, is the most probable until time 50. The model with a change of regime at time 40 (regime 2) becomes more probable from time 50 and beyond.

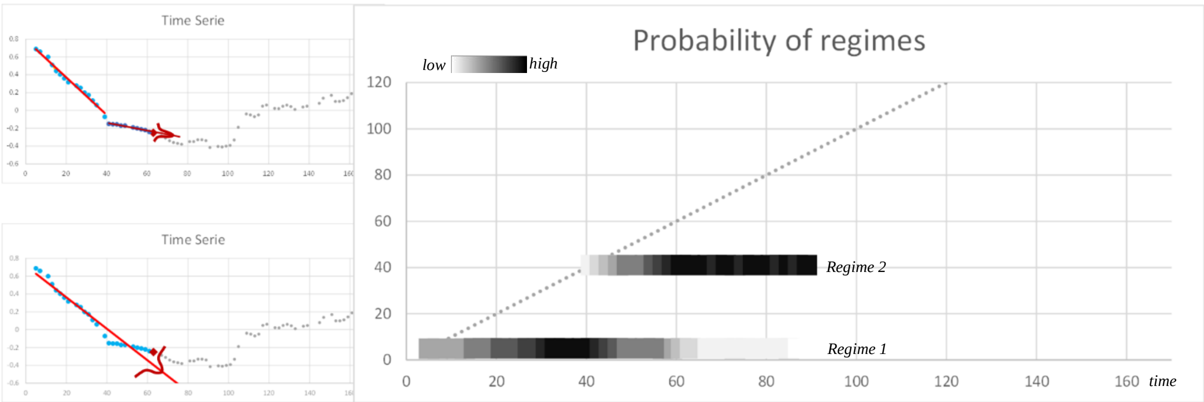

Figure 2 *Example of change of linear regime. A model without change is shown on the lower left graph, a model with a change is illustrated on the upper left graph. The graph on the right illustrates the probability of each regime through time, represented in shades of grey, where higher probabilities are darker. The vertical axis is the beginning of the regime considered.*

In detection mode, one critical aspect is the delay of detection of regime change. It occurs when the probability of a new regime becomes larger than the probability that the previous one continues. In the case of redundant spatial measurements, the delay of detection can be reduced by looking simultaneously into neighbouring time series.

Application to the detection of the Cadia mine tailings dam failure

The main waste products from many mining operations are in the form of tailings, typically a wet slurry of finely ground rock particles. These often contain toxic substances, and therefore must be carefully managed to avoid environmental damage and impacts on population. In many cases, tailings are stored in dammed impoundments known as tailings storage facilities (TSFs).
Across the industry, there is a legacy of older and poorly maintained TSFs. In recent years, a series of sometimes catastrophic failures have concentrated the attention of both operators and regulators on ensuring the structures are properly monitored for signs of instability.

InSAR is a remote monitoring technique using satellite radar to measure displacements at centimetric to millimetric accuracy, at typical intervals of around 6-12 days. InSAR is already widely used within the mining industry for both pit stability and TSF monitoring, with the aim of detecting incipient instability early enough to prevent or mitigate the impacts of a failure. However, the increasingly large volume of near-real-time data means manual interpretation and surveillance are becoming impractical, and automated detection and alerting of potential precursors are essential.
This work uses a known failure event captured by InSAR measurements to evaluate the performance of the BOCD algorithm for operational monitoring, including the timeliness and reliability of the detection and the level of false positives. The failure occurred at Cadia mine (New South Wales, Australia) on March 9th 2018, with InSAR revealing a notable change in behaviour across that section of the TSF in the months leading up to the failure.

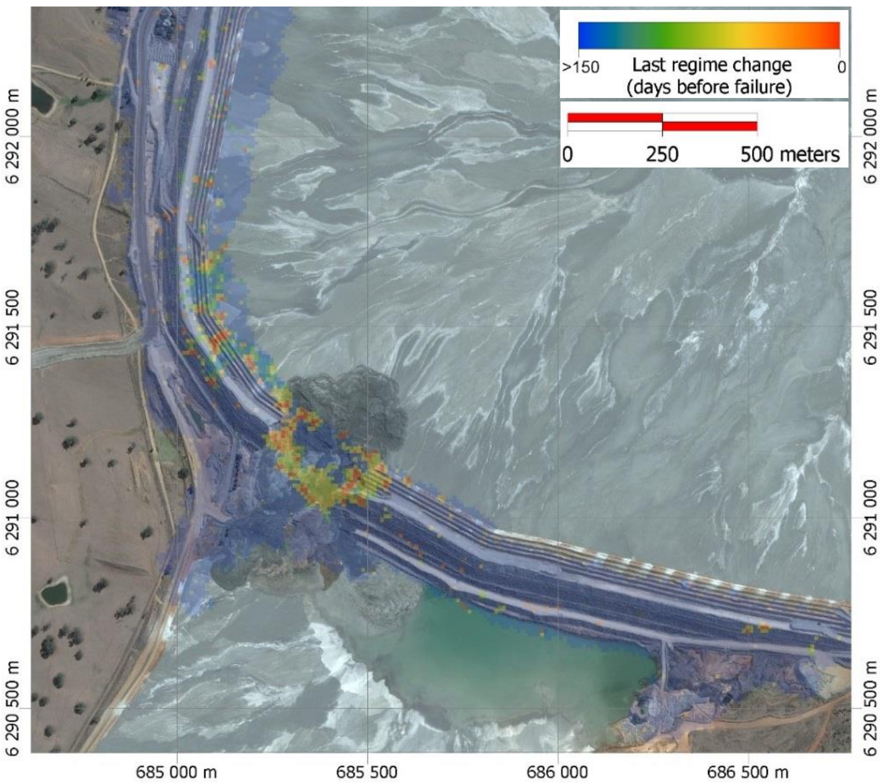

Figure 3 *Number of days since last change of regime, at the time failure occurred. Background image © CNES 2018, Distribution AIRBUS DS.*

The satellite information is only available in areas where the surface is stable enough, excluding areas filled with water and areas where vegetation is present. More than 50 000 time series are available over a 3-year period before the failure. Figure 3 shows the number of days since the last change of regime is detected before the failure, with blue indicating that the last change of regime occurred more than 150 days before the failure and orange/red indicating that it happened in the weeks before the failure. A very high density of orange/red points is located precisely at the failure location. This was observed after applying the BOCD technique directly on raw data. Improvements were obtained when applying some data analysis and pre-processing to reduce the number of false positives.

Figure 4 shows the result of spatial and temporal analysis and processing applied to reduce the number of false positives. The time series displayed on the left, showing the deformation as a function of time, is typical of the failure area. The changes in the last hundred days before failure are visible in the raw data in blue, but the detection is possible earlier in the filtered version in orange. Data processing reduces the level of noise and therefore improves the detectability of regime change. It also translates into a reduction of the number of change points and therefore a reduction of the number of false positives (see Figure 4, right).

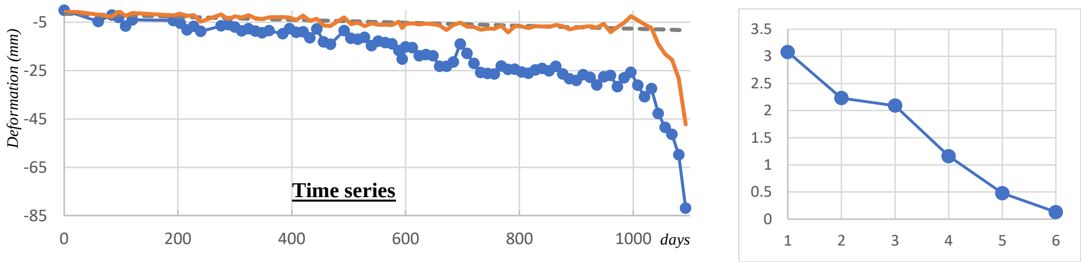

Figure 4 *On the left is one of the time series of the deformation (in mm) in the dam failure area. The original time series is in blue, the processed one in orange. On the right is the average number of point changes per time series after each processing step illustrating the drastic reduction in false positive detection.*

Conclusions

Several technologies are currently used or being developed to offer long-term subsurface monitoring solutions, including 4D seismic PRM, InSAR, DAS optical fibers, and Muons, to name a few. For all these applications, there is a common need to create an automatic change detection solution with a traffic light system to prevent potential risks. The work presented in this paper using an automatic detection of spatio-temporal anomalies with a Bayesian or ML approach is a first step towards integrated solutions. The main challenges of these methods are to reduce the number of false positive detections and improve the delay of detection so that remediate actions can be taken in due time. Careful detailed analysis and data-specific processing, considering both spatial and temporal variations, will be key to address these challenges.

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