Time Series Analysis for Deformation Monitoring

Prof. Dr.-Ing. W. Caspary
Universität der Bundeswehr München,
Neubiberg, Germany
Dr.-Ing. Th, Sutor
Deutsches Zentrum für Luft- und Raumfahrt,
Oberpfaffenhofen, Germany

This paper deals with a geodetic application of time series analysis. The observations forming the time series were taken at a power dam located in Canada. Prof. Chrzanowski, who has provided the data, has been conducting deformation measurements at this dam for many years. His analyses of these measurements have led to comprehensive deformation models and successful approaches to processing observational data which are exemplary and in use all over the world to monitor the behavior of comparable objects. Our modest contribution focuses on the special problem of deriving useful information from time series. As it turns out, the classical statistical methods fail, since the observations are contaminated by outliers. Only the introduction of robust estimation methods leads to some success. The result of our endeavor is only a very small contribution to the body of knowledge on deformations not at all comparable with the significant contributions of Prof. Chrzanowski.

Deformation Monitoring of a large dam

Large dams suffer deformations from a number of causes like changing water levels, seasonal temperature shifts and the immense weight of the structure itself. Starting with the construction of a large dam, precision measurements are regularly carried out in order to obtain a stable reference frame and to establish a database from which the future behavior of the structure can be predicted. A large variety of equipment is used for this purpose including classical geodetic instruments like EDM and theodolites, geotechnical sensors, e.g. plumb lines, extensometers and jointmeters. Nevertheless, individual characteristics of each dam require special measurement setups and examination procedures. As an example, for the purpose of this paper, serves the well known Mactaquac power plant which was built at the Saint Johns River in the years 1964 to 1968. The main part of it consists of a concrete dam, 42 meters high with the power house situated in front of it.

Figure 1: Bird's view of the dam [Chrzanowski et al., 1989]

Since 1975 strong deformations of the dam and widening expansion joints at the power house were observed. The displacements with steady rates also took place in the succeeding years leading to enormous deformations of the spill building. Local instabilities of the surrounding rocks, transfer of pressure through the stock pipes, tension within the structure itself and chemical processes were considered as causes and had to be rigorously investigated before exclusion. In the end it was found that the deformations were caused by an alkaline reaction of the used cement [Chrzanowski et al., 1991].

Figure 2: Cross section with placement of sensors [Chrzanowski et al., 1991].

Figure 2 shows a cross section of the dam and the powerhouse with the placement of the various sensors. At the expansion joints jointmeters are applied. The measurement principle of these gauges is rather simple. On one side of the gap three cones are arranged on a base plate, facing one single cone on the other side of the gap. By measuring all distances and applying simple geometric calculations the relative spatial movement can be determined. The accuracy is stated to be better than 0.1 mm [Wroblewicz/Solymar/Thompson, 1988]. Two of the thereby obtained time series are shown in figure 3.

Figure 3: Time series of jointmeter readings.

Time Series Analyis of Jointmeter Readings

To prove the performance of a newly developed autocorrelation estimator [Sutor, 1997] the available data sets originating from the described jointmeter measurements were utilized. One time series was chosen to serve as an example which will be analyzed throughout this section. As the first step a trend function and an additional periodical component were adjusted to the observations. In figure 4 the estimated trends are displayed together with the residuals after adjusting a cyclic function to the time series. The respective parameters are given at the right margin.

Figure 4: Jointmeter readings with estimated trends.

The classical non robust least squares estimation leads to a quadratic trend as the best fit to the observations while the robust method yields a Gaussian trend function. The trends were chosen from six trial functions under the condition that both, the empiric variance and the number of required parameters attain a minimum. All estimated coefficients are significant as can be seen from the corresponding standard deviations. Figure 5 depicts the obtained residuals after the estimated trend was removed from the original time series.

Figure 5: Residuals after elimination of trend

The studentized residuals of the least squares fit (left graph of figure 5) contain obviously outliers, while the robust residuals (right graph of figure 5) do not. The iteratively computed weights of the robust adjustment correspond with individual empirical standard deviations which efficiently control the influence of outlying observations, so that the deterministic components of the time series could be successfully estimated and removed. The two resulting residual vectors, plotted in figure 5, can now be considered as realizations of a stationary stochastic processes and can, hence, be analyzed with methods based on the well known theory of linear time invariant systems. This has been done in two different ways. The residuals of the least squares trend estimation have been treated further by non robust methods, while robust estimators have been applied to the robust residuals. In a first step the autocorrelation functions of the two series have been estimated. Figure 6 shows the result and gives a first impression of the overall stochastic behavior of the observations and enables a more detailed view of the micro structure.

Figure 6: Estimates of autocorrelation function

As already mentioned, a new robust estimator of the autocorrelation function has been developed by the authors. The main idea can be briefly described as follows. The influence of each individual observation on the autocorrelation estimate is analysed, then the original observations are appropriately reweighted in order to reduce the leverage effect of outlying values. As the right graph of figure 6 clearly shows, this robust estimation method uncovers periodicities in the time series which were not detected in the previous steps of the analysis. For the interpretation of these periodicities it would be desirable to have further information on the forces which cause the observed deformations, but since these are not available in this case, only conclusions from empirical modelling are possible. The dominant oscillation appearing in the right graph of figure 6 has a period around 25 observation intervals. Because the readings of the jointmeter were taken weekly, this period suggests a half year oscillation. The existence of additional, less strong oscillations can be conjectured from the close inspection of the robustly estimated autocorrelation function. But to get a more precise picture of the situation a (robust) estimation of the spectral density function is required. Less clear is the interpretation of the left graph of figure 6, originating from the non robust estimation of the autocorrelation function. It demonstrates the not at all satisfying properties of least squares estimation in the presence of outlying observations. An analysis of structural dependencies between the observations based on these estimates seems to be hardly possible and meaningful. Nevertheless, a certain systematic behavior can be observed for lags smaller than k=100. The interpretation will tend to assume random effects suggested by the overall plot.

The spectral density functions of the data sets plotted in figure 5 were estimated by the periodogram (non robust) and the so-called Blackman-Tukey estimator (robustified by the authors) [Caspary/Sutor, 1996]. Both methods are based on the estimates of the autocorrelation functions of figure 6. The periodogram uses the Wiener-Khintchin theorem to relate correlation function and density of the power spectrum, while the second method at first improves the estimate of the correlation function and then applies the fourier transformation. Both estimated spectral density functions are shown in figure 7.

Figure 7: Estimates of spectral density function

The left graph of figure 7 demonstrates the weakness of the non robust periodogram estimator. Since the observation vector contains a number of outliers the generally inferior statistical properties are amplified leading to an estimate of the spectral density function strongly suffering from distortions. In addition to this fault a so called line splitting appears rendering the interpretation even more difficult and risky. Especially in the low frequency range a localization of individual spectral lines is nearly impossible, and the micro structure of the observations which was by the track of robust methods already detected in the autocorrelation estimate (see figure 6) is here completely hidden by noise. In contrast, the robustified Blackman-Tukey estimator clearly unveils a number of oscillations whose periods are either a fraction or a multiple of one year. To confirm this outcome a cross-check with a dynamic model of the dam based on forces and environmental parameters would be desirable.

Literature

Caspary, W. and T. Sutor [1996]. "Robust Estimation in the Frequency Domain". *Proceedings of the Eighth International FIG Symposium on Deformation Measurements*, pp. 259-265. Kun Lung, Hong Kong.

Chrzanowski, A., Y. Chen, J. Secord, A. Szostak-Chrzanowski, D. Hayward, G. Thompson and W. Wroblewicz [1989]. "Integrated Analysis of Deformation Surveys at Mactaquac." *International Water Power & Dam Construction,* Vol. 41, pp. 17-22.

Chrzanowski, A., Y Chen, J. Secord and A. Szostak-Chrzanowski [1991]. "Problems and Solutions in the Integrated Monitoring and Analysis of Dam Deformations". *CISM Journal ACSGC*, Vol. 45, pp. 547-560.

Wroblewicz, Z., Z. Solymar and G. Thompson [1988]. "Deformation Monitoring Instrumentation at Mactaquac Generating Station, New Brunswick, Canada." *Proceedings of the Fifth International FIG Symposium on Deformation Measurements*. pp. 187-192. Fredericton, Canada.

Sutor, T. [1997]. "Robuste Verfahren zur Analyse linearer stochastischer Prozesse im Spektralbereich." Schriftenreihe Studiengang Vermessungswesen. Universität der Bundeswehr München, Heft 56.

Figures

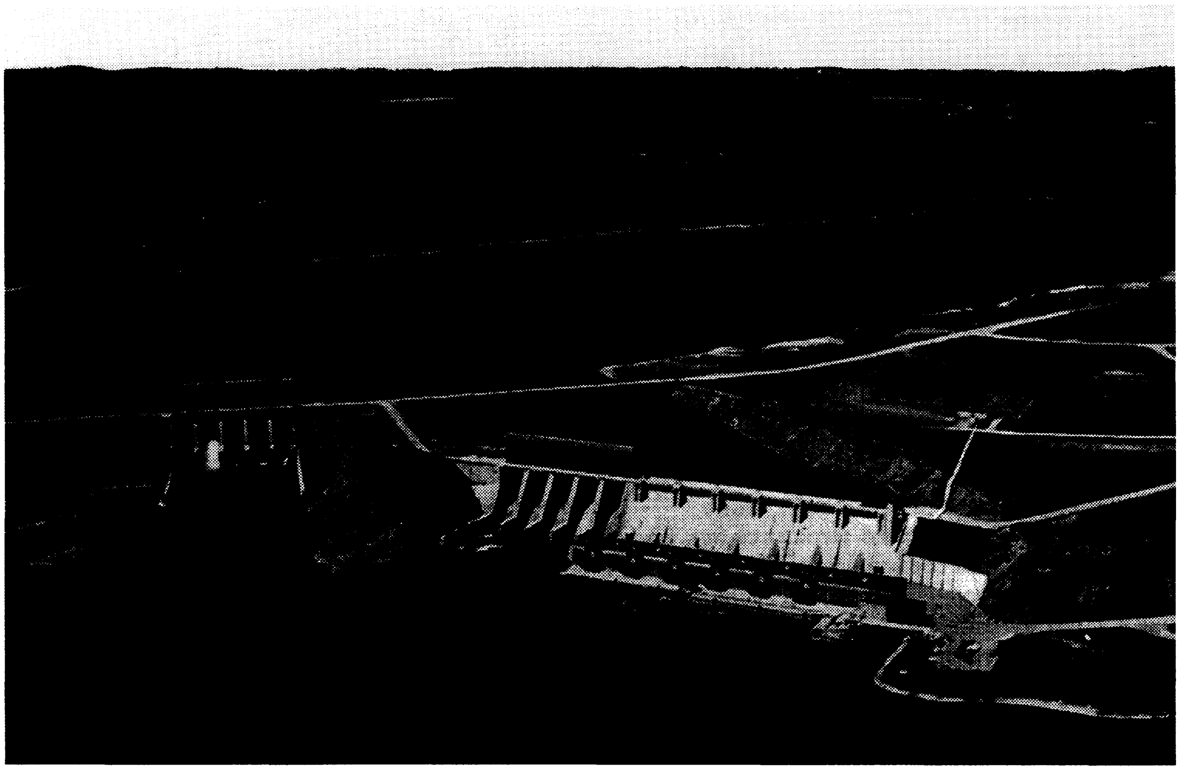


Figure 1: Bird's view of the dam [Chrzanowski et al., 1989]

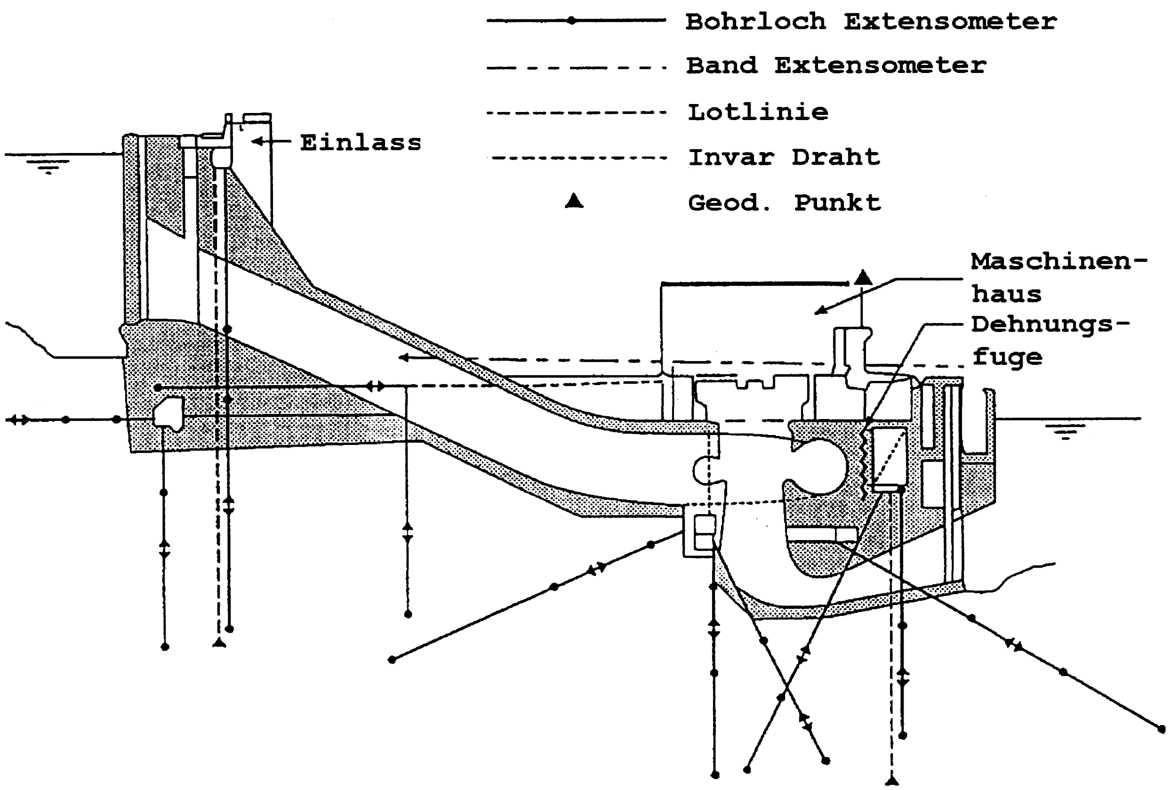


Figure 2: Cross section with placement of sensors [Chrzanowski et al., 1991].

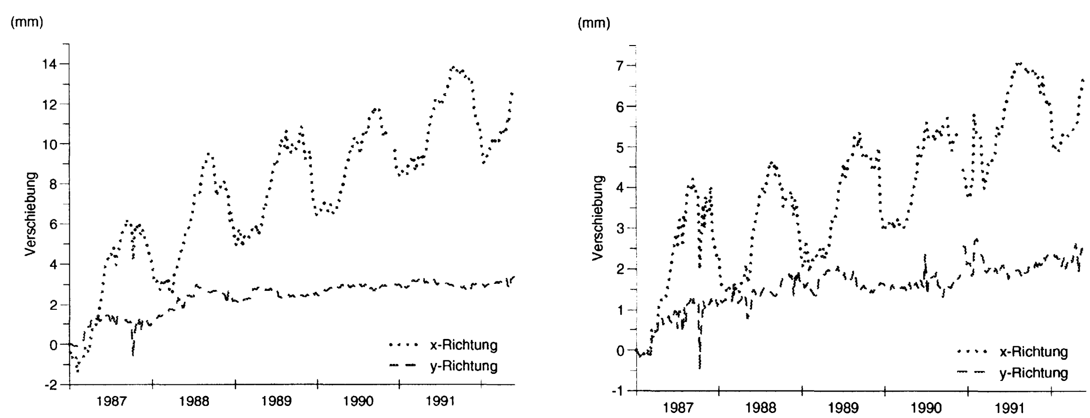
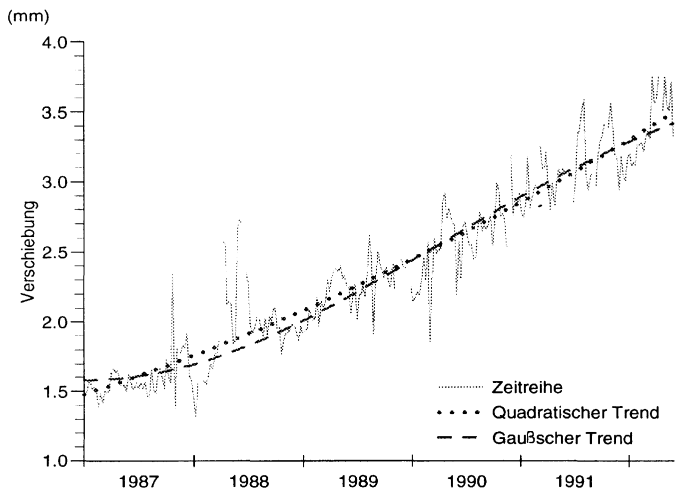


Figure 3: Time series of jointmeter readings



Least squares adjustment

Parameter	Value	Std. Dev.
a	8.E-6	1.0E-6
b	5.E-3	0.4E-3
K	1.47	0.02

Quadratic Trend (s^2=0.020)

Hampel (bounded influence)

Parameter	Value	Std. Dev.
a	18.E-6	2.0E-6
b	-2.4	0.11
K	3.98	0.11

Gaussian Trend (s^2=0.019)

Figure 4: Jointmeter readings with estimated trends

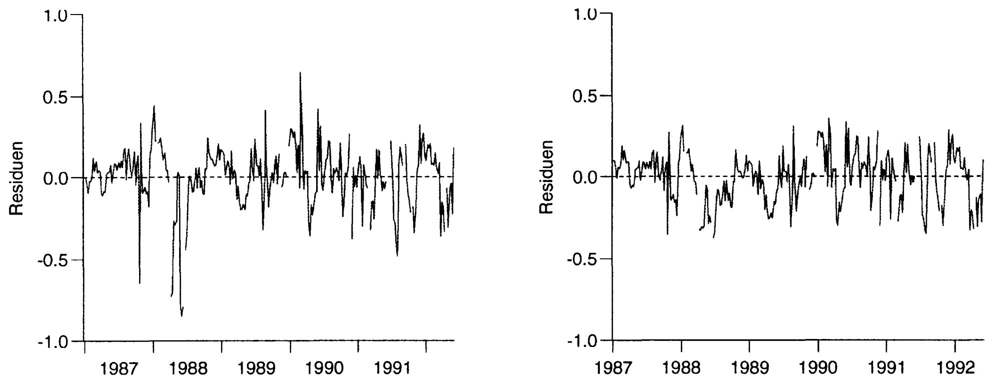


Figure 5: Residuals after elimination of trend

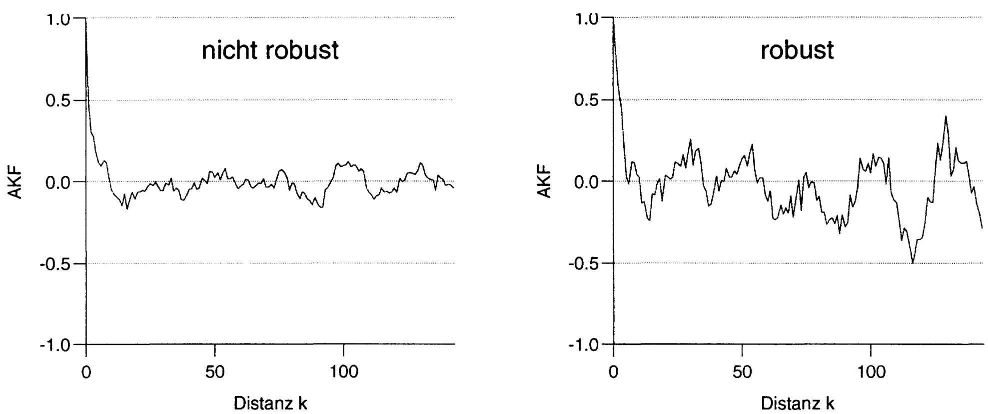


Figure 6: Estimates of autocorrelation function

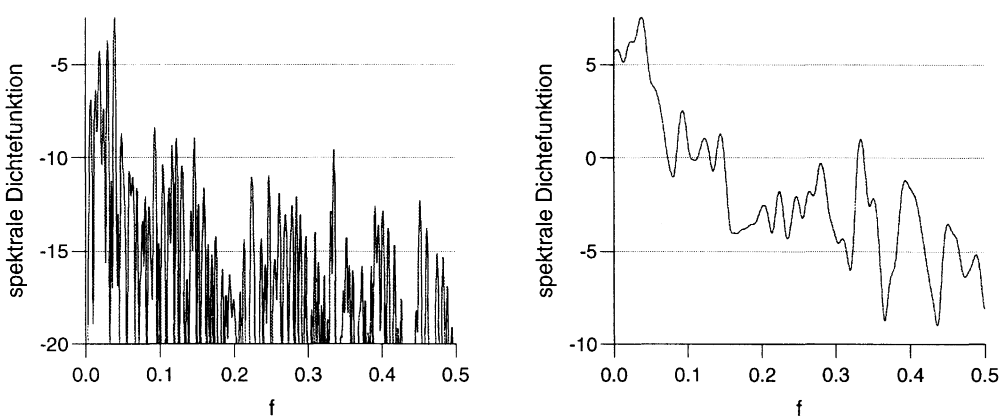


Figure 7: Estimates of spectral density function