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# IDENTIFICATION AND DAMAGE DETECTION ON STRUCTURAL SYSTEMS

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## Abstract

A short introduction is given to system identification and damage assessment in civil engineering structures. The most commonly used FFT-based techniques for system identification are mentioned, and the Random decrement technique and parametric methods based on ARMA models are introduced. Speed and accuracy are discussed. Finally some commonly used damage indicators are mentioned, and the problem of identifying damage from a set of damage indicators is discussed.

## Identification from dynamical response

Identification of physical properties from the dynamic response of structural systems - often called experimental modal analysis or system identification - is an area where a huge amount of research has been carried out, and where the interest for research results and practical applications is still increasing.

The growing interest for these techniques can be explained in different ways. One explanation is that computational possibilities in structural dynamics are getting better and new structural designs are introduced calling for a better and more detailed knowledge about the physical properties of the structures and how these properties are affected by damage and changes in load conditions. Another explanation is that by introduction of the computer in the measurement system, the possibility of handling large amounts of data became available, and the potential of the techniques were revealed.

The many possibilities of practical applications can be illustrated by studying one of the latest conference proceedings about experimental modal analysis, for instance one of the latest IMAC proceedings, see [15]. Only a few examples of applications will be mentioned here.

One of the first applications of structural dynamic measurement was in the 1940's where the problem of describing the loads on aircraft wings was studied and where especially the problems of flutter gave rise to experimental studies of the dynamical properties of aircraft

structures. Also, masts, chimneys and wind turbines are examples of structures where experimental studies of flutter and dynamic wind load might be wanted. Measurements on offshore structures loaded by sea waves have been performed in many locations for determination of sea loads and structural response, see e.g. Jensen [6].

Traditionally, identification of structural systems from their dynamical response has been based on the Fast Fourier Transform, Brigham [4]. The basic ideas were discovered in the forties by Danielson and Lanczos, [7], but the technique became known by the work of Cole and Tukey [8] and was implemented in larger scale from the the mid-sixties.

The standard technique is to estimate spectral density functions and fit these functions with a suitable rational spectrum model, Ewins [5]. Unfortunately, in typical cases in structural engineering, where the loading is unknown and unperiodic, the estimates based on this technique becomes biased due to leakage. However, the leakage problem might be removed by estimating correlation functions instead of spectral density functions, Brincker et al [13].

Another unparametric technique is the Random Decrement (RDD) Technique, Brincker et al [13]. The RDD technique is a fast technique for estimation of correlation functions for Gaussian processes by simple averaging.

The RDD technique was developed at NASA in the late sixties and early seventies by Henry Cole and co-workers [9-12], just a little later than the development of the FFT technique.

The basic idea of the technique is to estimate a co-called RDD signature. If the time series  $x(t)$ ,  $y(t)$  are given, then the RDD signature estimate  $\hat{D}_{XY}(\tau)$  is formed by averaging  $N$  segments of the time series  $x(t)$

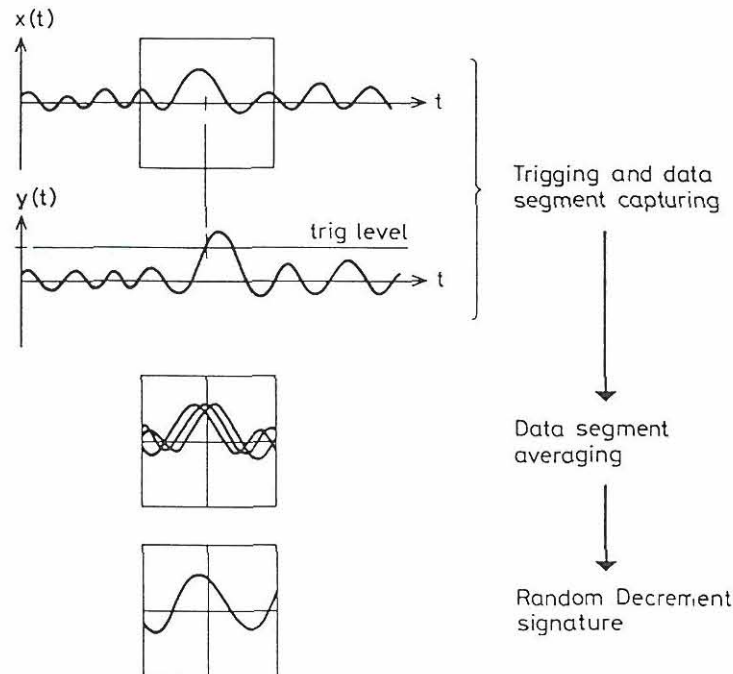
$$\hat{D}_{XY}(\tau) = \frac{1}{N} \sum_{i=1}^N x(\tau + t_i) | C_{y(t_i)} \quad (1)$$

where the time series  $y(t)$  at the times  $t_i$  satisfies the trig condition  $C_{y(t_i)}$ , and  $N$  is the number of trig points. The trig condition might be for instance that  $y(t_i) = a$  (the level crossing condition) or some similar condition. The algorithm is illustrated in figure 1. In eq. (1) a cross signature is estimated since the accumulated average calculation and the trig condition are applied to two different time series. If instead the trig condition is applied to the same time series as the data segments are taken from, an auto signature is estimated.

In figure 2 estimation times are compared for direct estimation of the correlation function (using the definition), for estimation using the unbiased FFT and for using the RDD technique. As it appears, the RDD technique is faster than the FFT, for short estimates, up to 100 times faster.

The two techniques just mentioned are based on the same idea: to compress the data in a short interface function and then extract the physical parameters from this function by fitting an analytical model. However, information will be lost in the data compression





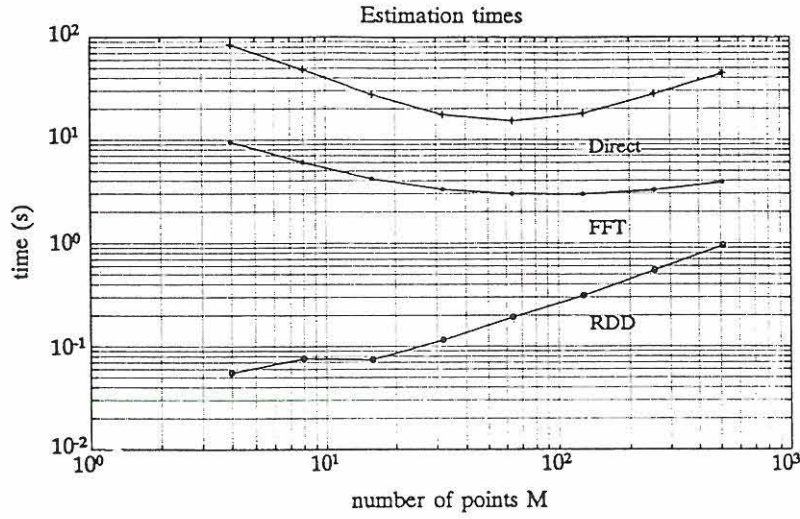
**Figure 1.** Determination of the Random Decrement signature.

process, because it is not possible to contain all the detailed information hidden in the time series in the estimates of correlation functions or spectral density functions.

Therefore, system parameters estimated from interface functions, will show larger variance than parameters estimated by effective fitting of models directly to the time series.

When fitting models directly to the time series, "blackbox" models in discrete time like Auto Regressive Moving Average (ARMA) models or oversized Auto Regressive (AR) models (also denoted method of maximum entropy) are frequently used, Ljung [1], Söderström and Stoica [2], Pandit and Wu [3]. These techniques have been developed mainly for applications in electrical engineering, but they are considered to be very accurate - in practice the closest one can get to unbiased effective estimators. For applications in structural engineering see e.g. Jensen [6]. In these techniques the parameter identification is based on nonlinear optimization and therefore the techniques require a relatively large computation power. However if the computation time and the time for transferring and storage of the large amounts of data can be accepted, these techniques will be an obvious choice.

An ARMA model is a parametric model given by



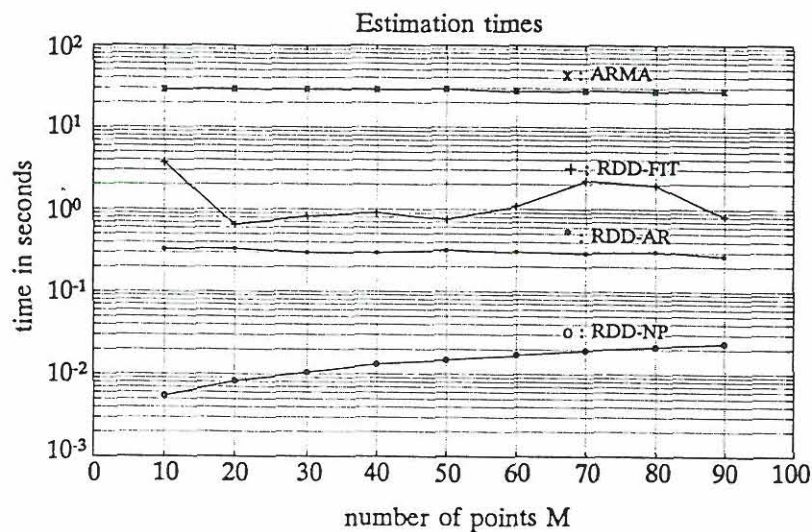
**Figure 2.** Times for calculation of autocorrelation function estimates by the Random Decrement technique (RDD), the Fast Fourier Transform (FFT) technique and the direct technique.

$$y(t) + a_1 y(t-1) + \dots + a_{n_a} y(t-n_a) = e(t) + c_1 e(t-1) + \dots + c_{n_c} e(t-n_c) \quad (2)$$

where the zero mean Gaussian white noise sequence  $e(t)$  is filtered through a filter, described by the parameters  $a_i$  and  $c_i$  to give the response  $y(t)$ . the right-handside is the autoregressive part (AR), and the left-handside is the moving average part (MA). It can be shown, that any structural system with  $n$  degrees of freedom can be modelled as an ARMA( $2n$ ,  $2n-1$ ) model, Pandit et al [3], i.e.,  $2n$  AR parameters and  $2n-1$  MA parameters. When the model order has been chosen, and the parameters has been estimated by non-linear optimization, any system parameter can be calculated by closed form solutions. Further, since the covariance matrix of the parameter set is estimated together with the parameter vector itself, confidence limits on any physical parameter might easily be calculated.

In practice however, the choice between the different techniques is governed by a trade-off between accuracy and speed, and sometimes it is beneficial to accept a small increase in variance for a large decrease in the time used in the estimation process.

The difference in estimation time might be quite large. To illustrate the difference the slowest, but most accurate technique (ARMA) is compared to the fastest possible at the moment (RDD), figure 3. Eigenfrequency and damping is estimated for a single degree



**Figure 3.** Estimation times for different techniques as a function of the length  $M$  of the one-sided auto correlation estimate.

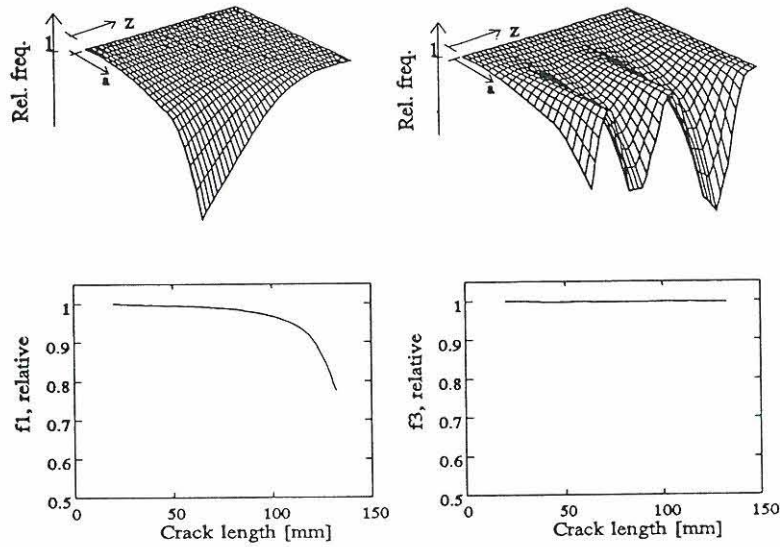
of freedom system. In figure 3 three different curves are shown for the RDD technique, fitting of the theoretical correlaton function (RDD-FIT), fitting an AR model the the correlation function estimate (RDD-AR) and using a simple non-parametric technique to estimate the two quantities (RDD-NP). As it appears the estimation time differ by a factor of 1000-5000.

## Damage Detection

One of the interesting applications of structural system identification is damage detection. When a specimen or even a large complex structure is damaged, the damage will cause a change of the dynamic properties. For instance if a structural member is cracked, the crack will decrease the stiffness and thereby decrease the eigenfrequencies of the structure and it may increase the damping due to local plasticity and thereby change the energy flow and the overall damping of the structure.

It is important to emphasize however, that there is no safe way at the moment for an accurate damage identification. The problem of finding out what kind of changes a certain damage might cause is usually not a great problem. The opposite problem however, the problem of identifying a certain damage for a given change of the structural response is a very difficult task - and at the present time - a problem that has not been solved.





**Figure 4.** Result for a cantilever beam with box section ( $80 \times 40$  mm). Upper figures: Variation of the first and the third natural frequency with crack position  $z$  along the beam and crack length  $a$ . Lower figures: Experimental results for a certain crack location.

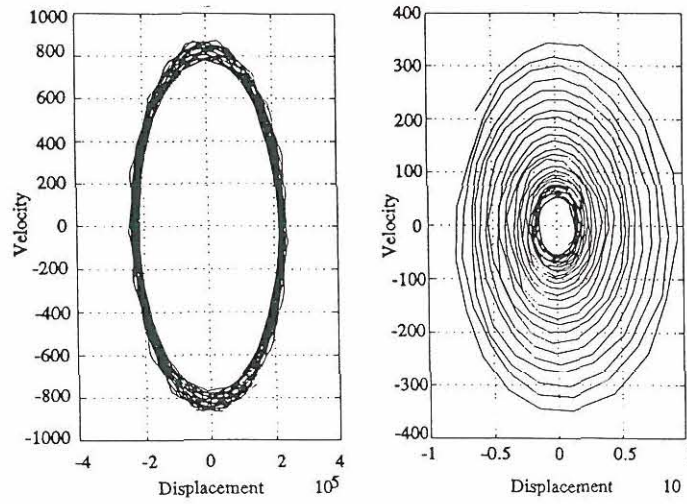
In practise therefore, the application of these techniques is limited to cases where it is of importance to know whether or not significant structural changes has taken place, and if some changes has taken place - to be able to indicate the type and location of a possible damage.

A fine review of the different damage indicators is given by Rytter [14]. Some examples will be given here.

The simplest and most important damage indicators are may be the changes of the eigenfrequencies. The eigenfrequencies can easily be measured with large accuracy, and if the eigenfrequencies are sensitive to the kind of damage in quistion, they might be well suited as damage indicators. The sensitivety is illustrated in figure 4.

Also the damping ratios might be used as damage indicators. In figure 5 is shown a phase-plan plot for a beam in the undamaged and the damaged state (a small crack develloped). The test results show clearly a large increase in damping.

If one has estimated a large number of damage indicators  $d_i$  together with their corresponding standard deviations  $\sigma_i$ , a simple unified damage measure might be defined by taking the sum



**Figure 5.** Phase-plan plots for a cantilever beam with box section ( $80 \times 40$  mm) in the undamaged state (left) and in the damaged state (right).

$$D = \frac{|d_1 - d_{10}|}{\sigma_1} + \frac{|d_2 - d_{20}|}{\sigma_1} + \dots \quad (3)$$

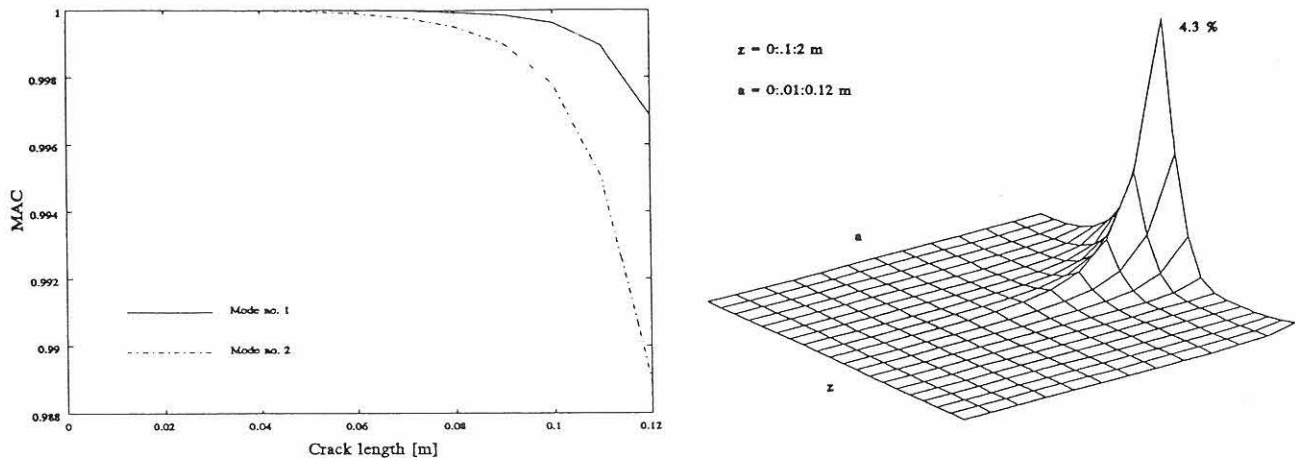
where  $d_{i0}$  is the damage indicators corresponding to the undamaged (virginal) state.

Mode shapes might be included. One way to do this is to use the modal assurance criterion calculating a so-called MAC matrix for two eigenvectors. A so-called COMAC vector might also be calculated. Some experimental results are shown in figure 6.

A certain class of damage indicator are of great importance however. This is the class of parameters indicating an increase in the non-linear behaviour of the structure. Consider the phase-plan plot in figure 5. The damaged beam show a clear unsymmetry in the phase plan plot indicating a change in stiffness when the bending change sign. The phenomenon is due to the opening and the closing of the crack. Other non-linear indicators are new peaks appearing in the power spectrum and changes in the response statistics.

The most important findings in the latest year is probably the use of neural networks in the damage detection problem. Neural networks are computational models loosely inspired by the neuron architecture and operation of the human brain. Many different types of neural networks exist. Among these the multilayered neural network trained by means of the back-propagation algorithm are currently given greatest attention by application developers.





**Figure 6.** Result for a cantilever beam with box section ( $80 \times 40$  mm). Left figure: MAC values for mode 1 and 2. Right figure: COMAC values for mode 1 and 2.

When the neural networks are used in damage detection, the networks are trained by introducing different kinds of damage in the structure and calculating the corresponding changes in the actual damage indicators. Then, after training the network, it might be used for identifying the kind of damage for a given set of damage indicator obtained from measurements. The method has proven to be successful on real structures, Kirkegaard et al [15], Rytter et al [16].

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