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Estimation of Correlation Functions by Random Decrement

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ABSTRACT

This paper illustrates how correlation functions can be estimated by the random decrement technique. Several different formulations of the random decrement technique, estimating the correlation functions are considered. The speed and accuracy of the different formulations of the random decrement technique is compared with the direct approach and an approach based on Fourier and inverse Fourier transformations. The investigations are based on the simulated response of a white noise loaded 2 degree of freedom system. Special attention is given to the significance of the length of the time series and the length of the correlation functions. The accuracy of the estimates with respect to the theoretical correlation functions and the modal parameters are both investigated. The modal parameters are extracted from the correlation functions using the polyreference time domain technique.

1 INTRODUCTION

The correlation functions of the response and the load of linear systems can be used for estimation of the modal parameters of the system, see e.g. Bendat & Piersol [1], [2]. In some situations it is only possible to measure the response of a structure. By assuming white noise loading the modal parameters of the structure can be extracted from the correlation functions between the measured response. This is the case in e.g. ambient testing of civil engineering structures.

Several different non-parametric methods to estimate the correlation functions exist. These are e.g. the direct approach or an approach based on Fourier and inverse Fourier transformations, see e.g Bendat & Piersol [1], [2]. Another method for non-parametric estimation of correlation functions is the random decrement (RDD) technique, see Vandiver et al. [3], Brincker et al. [4].

An RDD function is estimated by averaging time segments, which fulfil a trigger condition at the centre of the time segment. Different formulations of the trigger condition are possible, as described in section 2. The advantage of this approach is the speed since only addition is used in the estimation process. In this work only trigger conditions which pick out the correlation functions of the time series are considered. This assumes stationary and zero mean Gaussian time series, see Brincker et al. [4]. No assumption of the physical problem from which the time series are generated is needed, in this paper although damped mechanical systems are considered.

The aim of this paper is an investigation of the advantages and disadvantages of the RDD technique for estimation of correlation functions. The investigations are based on simulated responses of a 2-degree-of-freedom system loaded by white noise. The results of the RDD technique are compared with results obtained from the direct approach and the FFT-IFFT approach. The comparison of the methods is based on estimation time and the corresponding accuracy as a function of the number of time lags in the correlation functions and the length of the time series. The accuracy of the estimated correlation functions and the corresponding modal parameters are both taken into consideration. Modal parameters are extracted using the polyreference time domain technique (PTD), see Vold et al. [5]. All analyses are performed in the MATLAB environment on a PC-486. The RDD functions are implemented in C and linked to MATLAB.

2 THE RANDOM DECREMENT TECHNIQUE

The auto, $D_{XX}(\tau)$, and cross, $D_{YX}(\tau)$, RDD functions are defined as the expected value of the time series X and Y on condition that X fulfils a trigger condition.

$$D_{XX}(\tau) = E[X(t+\tau)|C_{X(t)}] \tag{1}$$

$$D_{YX}(\tau) = E[Y(t+\tau)|C_{X(t)}] \tag{2}$$

In eq. (1) and eq. (2) the trigger condition, $C_{X(t)}$ is used. A general trigger condition can be formulated as.

$$C_{X(t)} \sim [X(t) = a \ \wedge \ \dot{X}(t) = v] \tag{3}$$

Since measured time series are discrete, the RDD functions are estimated as the empirical mean. The number of trigger points is denoted N.

$$\hat{D}_{XX}(\tau) = \frac{1}{N}\sum_{i=1}^{N} X(t_i+\tau)|C_{X(t_i)} \tag{4}$$

$$\hat{D}_{YX}(\tau) = \frac{1}{N}\sum_{i=1}^{N} Y(t_i+\tau)|C_{X(t_i)} \tag{5}$$

In practice the trigger conditions are implemented as crossing problems, since a trigger condition formulated as in eq. (3) is fulfilled in the discrete time series with probability zero, see Brincker et al. [7]. The estimates of the RDD functions in eq. (4) and eq. (5) are unbiased.

$$E[\hat{D}_{YX}(\tau)] = \frac{1}{N}\sum_{i=1}^{N} E[Y(t_i+\tau)|C_{X(t_i)}] = D_{YX}(\tau) \tag{6}$$

So the only bias apparent in the RDD functions are introduced by implementation of the trigger condition $C_{X(t_i)}$. If the time series X and Y are stationary, zero mean and Gaussian, then the following general relation between the RDD functions and the correlation functions, R, and their time derivatives, R', exists:

$$D_{XX}(\tau) = \frac{R_{XX}(\tau)}{\sigma_X^2} \cdot a - \frac{R'_{XX}(\tau)}{\sigma_{\dot{X}}^2} \cdot v \tag{7}$$

$$D_{YX}(\tau) = \frac{R_{YX}(\tau)}{\sigma_X^2} \cdot a - \frac{R'_{YX}(\tau)}{\sigma_{\dot{X}}^2} \cdot v \tag{8}$$

These relationships are obtained by using the general trigger condition eq. (3), see Brincker et al. [4]. The correlation functions can be estimated by application of one of the following three special cases of the general trigger condition. The proportionality between the RDD functions and the correlation functions are derived from eq. (7) and eq. (8).

Every positive point trigger condition.

$$C_{X(t_i)} \sim [X(t_i) > 0] \quad \Rightarrow \quad D_{XX} \propto R_{XX}, \quad D_{YX} \propto R_{YX} \tag{9}$$

Level crossing trigger condition.

$$C_{X(t_i)} \sim [X(t_i) = a] \quad \Rightarrow \quad D_{XX} \propto R_{XX}, \quad D_{YX} \propto R_{YX} \tag{10}$$

Local extremum trigger condition.

$$C_{X(t_i)} \sim [X(t_i) > a \wedge \dot{X}(t_i) = 0] \quad \Rightarrow \quad D_{XX} \propto R_{XX}, \quad D_{YX} \propto R_{YX} \tag{11}$$

The result for the auto RDD function using level crossing trigger was first derived by Vandiver et al. [3]. All the above trigger conditions will be investigated in the numerical analysis in section 3. Since the RDD functions are estimated by averaging time segments, the speed of this approach is expected to be an advantage. Triggering at every positive point is the slowest trigger condition. Half of the points in the time series are trig points. The speed of this formulation could be increased by applying bounds to the positive points. E.g. all positive points between 1 and 2 times the standard deviation of the trigger time series could be used. This reduced estimation time will also, unfortunately, result in an increase of the uncertainty, since less trigger points is available. In these investigations the bounds are avoided, so that the every positive point trigger condition will provide an upper limit of the estimation time, which is independent of the statistical parameters of the time series. This is not true for the level crossing and the local extremum trigger condition.

3 NUMERICAL INVESTIGATION

The investigations are based on the response of a 2-degree-of-freedom system loaded by uncorrelated white noise. The responses are simulated by an ARMAV-model, which ensures covariance equivalence between the continuous and the discrete response, see Andersen et al. [6]. Uncorrelated white noise is added to the response. The noise is characterized by the signal-to-noise ratio given as the fraction between the standard deviations of the noise and the simulated response. The modal parameters are.

$$\begin{array}{llll} f_1 = 3.17\ Hz & \zeta_1 = 1.22\% & |\phi|^1 = [1\ 1.62] & \angle\phi^1 = [0\ 1.5] \\ f_2 = 4.92\ Hz & \zeta_2 = 3.50\% & |\phi|^2 = [1\ 0.62] & \angle\phi^2 = [0\ 177.6] \end{array} \tag{12}$$

All simulations are performed with a sampling frequency of 45 Hz. The accuracy of the estimates are defined as the error, E.

$$E = \frac{1}{(2 \cdot M + 1)} \cdot \sum_{m=-M}^{M} (R(m \cdot \Delta T) - \hat{R}(m \cdot \Delta T))^2 \tag{13}$$

Where R and $\hat{R}$ denote the theory and the estimate of the correlation functions, respectively, and ΔT is the sampling period. The accuracy calculated after eq. (13) contains contributions from both random and bias errors. To reduce simulation errors all results are based on 250 averages. For both level crossing and local extremum trigger condition the trigger level a is 1.5 times the standard deviation of the trigger time series.

3.1 Results: Correlation Functions

Figure 1 shows the total estimation time (in CPU) of the 4 correlation functions with 128 time lags as functions of the number of points in the time series.

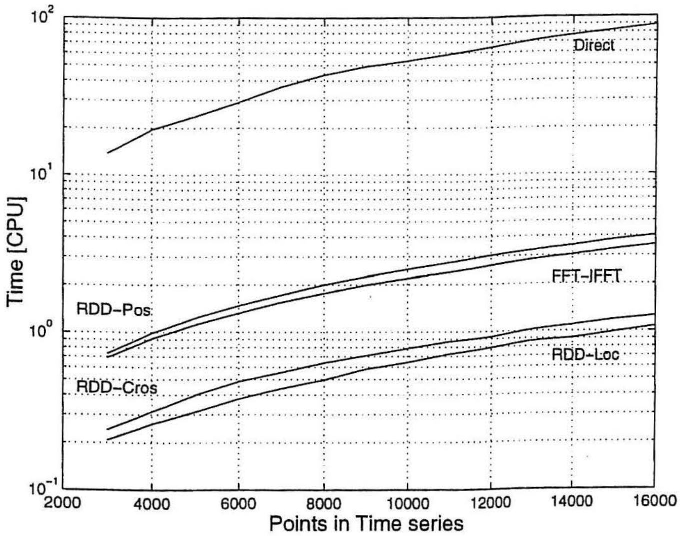

Figure 1: *Total estimation time of 4 correlation functions each consisting of 128 time lags. RDD-Cros = Level crossing. RDD-Pos = Every positive point. RDD-Loc = Local extremum.*

As expected, the direct approach is clearly the slowest approach. The reduced estimation time by using the FFT-IFFT approach is obvious. Trigger at every positive point has about the same estimation time as the FFT-IFFT approach. This trigger condition produces the highest estimation time possible for the RDD technique. Level crossing and local extremum trigger both results in shorter estimation times compared to the FFT-IFFT approach. The estimation times of these two formulations depend on the chosen trigger levels and the variance of the time series and the variance of the time derivative of the time series. Even though the estimation time would differ by using another trigger level or different system parameters, the results indicates that the RDD technique becomes faster than the FFT-IFFT approach if a strict trigger condition is chosen.

Figure 2 shows the estimation time of the correlation functions with varying number of time lags in the correlation functions. The number of points in the time series is 8000.

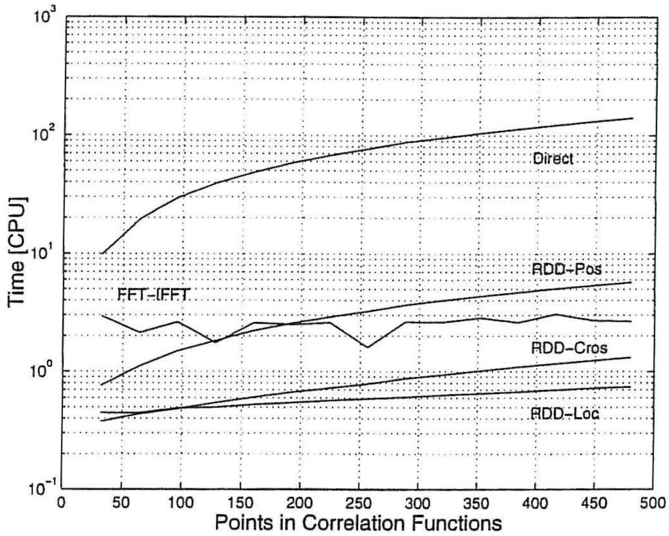

Figure 2: *Total estimation time of 4 correlation functions with varying number of time lags. Number of points in time series is 8000. RDD-Cros = Level crossing. RDD-Pos = Every positive point. RDD-Loc = Local extremum.*

Figure 2 shows the same tendency as figure 1. If a strict RDD formulation, such as level or local extremum triggering is used, the RDD technique becomes faster than the FFT-IFFT approach. If only a few number of time lags is needed, the RDD technique becomes faster than the FFT-IFFT approach. Furthermore the difference in the estimation time between the different trigger conditions reduces with a decreasing number of time lags in the correlation functions. This can be explained by the fact that the averaging process (see eq. (4) and eq. (5)) and the detection of trigger points (see eq. (3)) both contribute to the total estimation time. For estimates with a large number of time lags the averaging process is dominant. With a decreasing number of time lags in the estimates, the detection of a trigger point becomes correspondingly more dominant. On average the number of trigger points for local extremum trigger was 225 and for level crossing 430. For a large number of time lags local extremum trigger is faster. But for a small number of time lags level crossing trigger is faster. This is expected since detecting a local extremum is more time consuming than detecting a level crossing.

The estimation times in the above figures also reflect the speed of the computer for performing multiplication and addition. Figure 3 shows the quality (see eq. (13)) of the different methods as a function of the number of points in the time series. Figure 4 shows the results of the same investigation performed on time series with 20% noise added. The direct approach has been omitted due to the high estimation time.

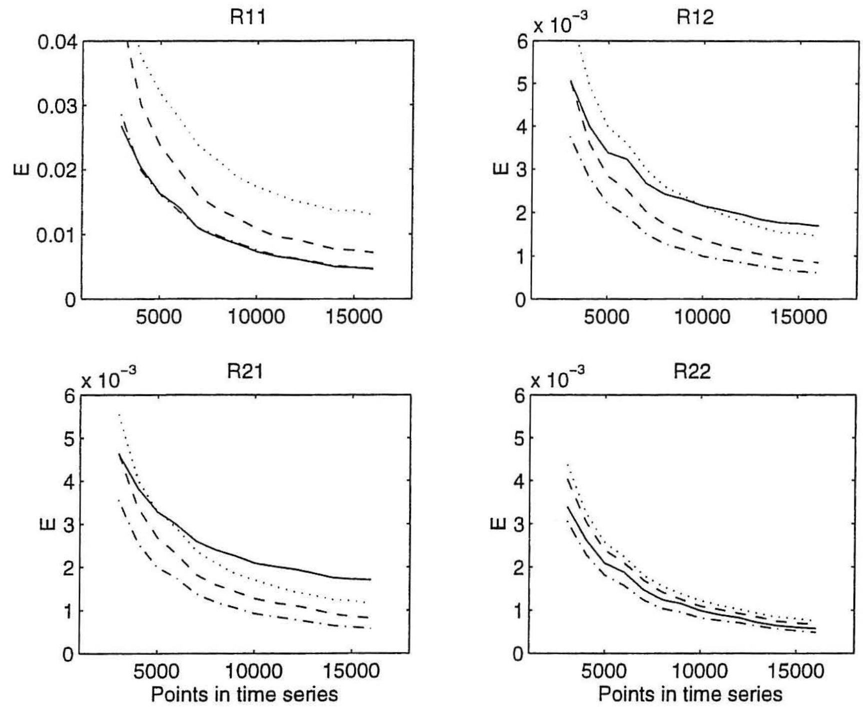

Figure 3: *Accuracy, E, of correlation functions with varying time series length. 128 points in correlation function.* ——— *=FFT-IFFT,* · · · ·*=RDD-Loc,* – · – · –*=RDD-Pos,* – – – – – –*=RDD-Cros.*

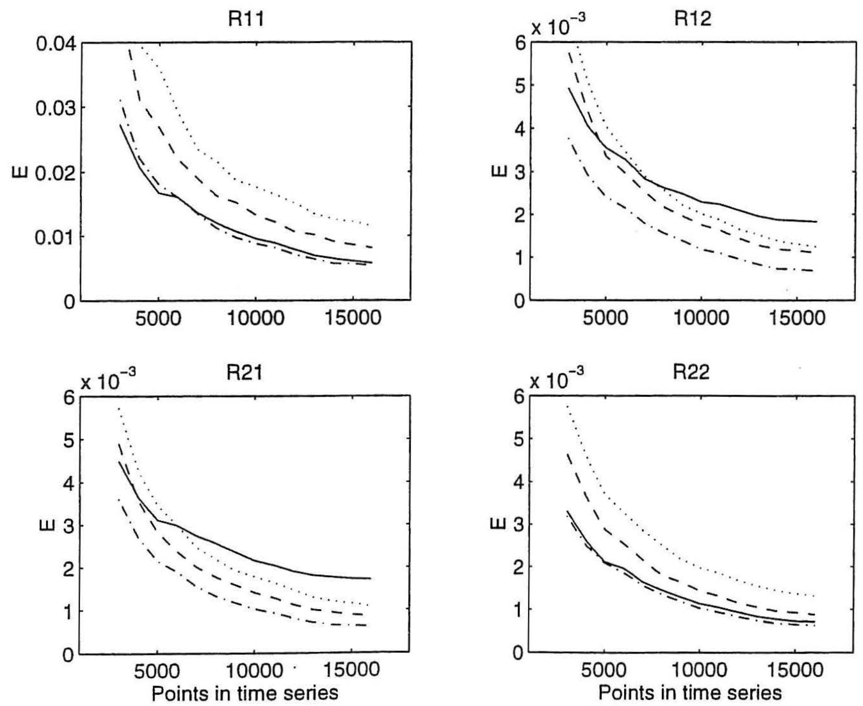

Figure 4: *Accuracy, E, of correlation functions with varying time series length. 128 points in correlation function.* ——— *=FFT-IFFT,* · · · · *=RDD-Loc,* – · – · –*=RDD-Pos,* – – – – – –*=RDD-Cros.*

As expected, the results show that, the error of all 4 approaches converges towards zero with increasing length of the time series. The effect of adding noise is a slower convergence rate, but the results still have a high accuracy compared with the noise free analysis. The every positive point trigger condition gives the lowest error, whereas the local extremum trigger condition has the highest error.

Figure 5 and figure 6 show the quality of the 4 approaches as a function of the number of points in the correlation functions. The results are based on 8000 points in the time series.

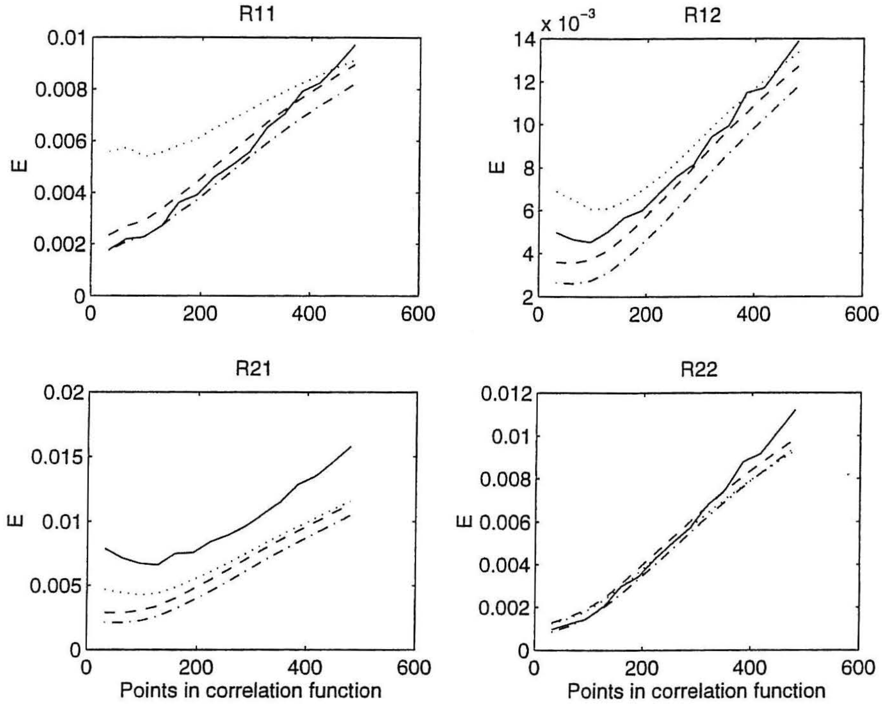

Figure 5: *Accuracy, E, of correlation functions with increasing number of time lags. 8000 points in time series.* ——— *=FFT-IFFT,* · · · ·*=RDD-Loc,* — · — · —*=RDD-Pos,* — — — — — —*=RDD-Cros.*

All 4 approaches have increasing accuracy with an increasing number of points in the time series. In general the RDD technique with local extremum trigger condition gives the highest error. The general difference between the results from the noise free responses and the responses with 20% noise added is only a slight increase in the error. It is interesting that although the absolute error is different for the 4 approaches, the rate of increase in the errror with increasing number of points in the correlation functions is the same.

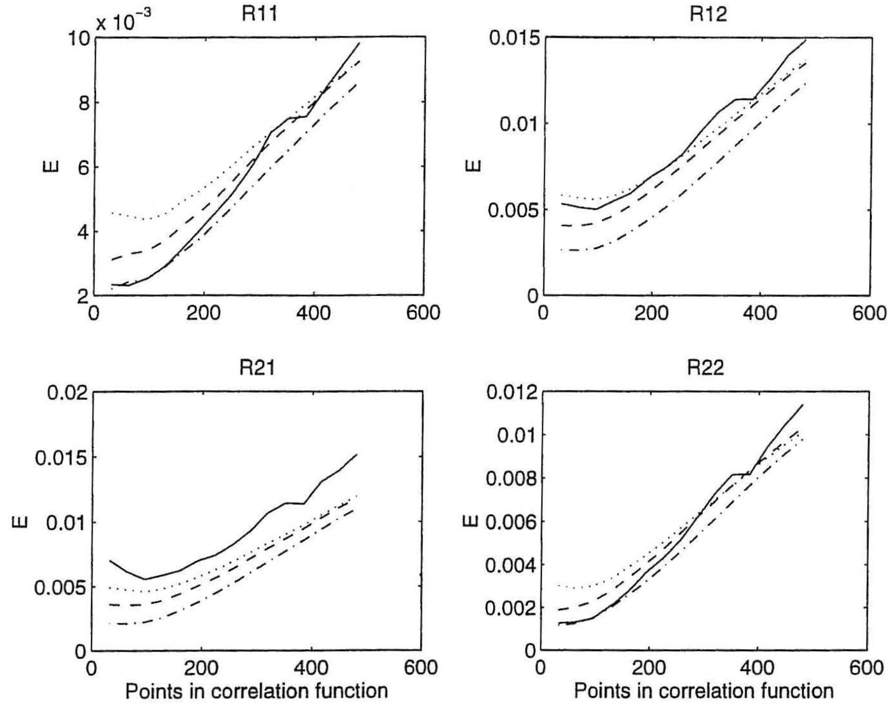

Figure 6: *Accuracy, E, of correlation functions with increasing number of time lags. 8000 points in time series.* ——— *=FFT-IFFT,* · · · ·*=RDD-Loc,* – · – · –*=RDD-Pos,* – – – – – – –*=RDD-Cros.*

3.2 Results: Modal Parameters

The modal parameters are extracted from the correlation functions by PTD, see Vold et al. [5] and [8]. 32 points from the correlation functions are used in the estimation procedure.

	Noise	f_1	σ_{f_1}	f_2	σ_{f_2}	ζ_1	σ_{ζ_1}	ζ_2	σ_{ζ_2}
Theory	0	3.165	-	4.917	-	1.22	-	3.50	-
RDD-Lev	0	3.166	0.008	4.909	0.026	1.29	0.24	3.53	0.52
RDD-Loc	0	3.166	0.008	4.913	0.022	1.30	0.24	3.54	0.49
RDD-Pos	0	3.166	0.007	4.914	0.021	1.27	0.23	3.52	0.40
FFT-IFFT	0	3.167	0.007	4.913	0.021	1.29	0.23	3.50	0.67
RDD-Lev	20	3.165	0.007	4.924	0.029	1.28	0.24	4.05	0.67
RDD-Loc	20	3.167	0.007	4.928	0.027	1.24	0.23	3.73	0.60
RDD-Pos	20	3.166	0.007	4.918	0.020	1.25	0.23	3.58	0.42
FFT-IFFT	20	3.166	0.008	4.916	0.019	1.27	0.22	3.53	0.41

Table 1: *Estimated mean value and standard deviation of eigenfrequencies* [Hz] *and damping ratios [%] using 4 different approaches.*

It is possible to extract the modal parameters of the system from the correlation functions estimated by all 4 approaches. The effect of adding noise to the responses is an increase in the standard deviations of the modal parameters. The most accurate modal parameters are extracted from the correlation functions estimated by every positive point

	Noise	Φ^1	σ_{Φ^1}	Φ^2	σ_{Φ^2}	$\angle\Phi^1$	$\sigma_{\angle\Phi^1}$	$\angle\Phi^2$	$\sigma_{\angle\Phi^2}$
Theory	0	1.616	-	0.620	-	1.525	-	177.6	-
RDD-Lev	0	1.606	0.018	0.617	0.052	1.559	0.739	175.0	3.833
RDD-Loc	0	1.647	0.019	0.647	0.048	1.428	0.739	175.8	2.896
RDD-Pos	0	1.614	0.013	0.617	0.029	1.551	0.471	177.4	1.979
FFT-IFFT	0	1.616	0.014	0.620	0.037	1.565	0.509	176.6	2.601
RDD-Lev	20	1.605	0.021	0.624	0.071	1.527	0.874	174.9	3.908
RDD-Loc	20	1.626	0.022	0.619	0.057	1.612	0.944	175.2	3.407
RDD-Pos	20	1.613	0.015	0.619	0.033	1.543	0.554	176.8	2.293
FFT-IFFT	20	1.614	0.016	0.617	0.036	1.512	0.519	176.6	2.495

Table 2: *Estimated mean value and standard deviation of mode shapes using 4 different approaches.*

trigger condition and the FFT-IFFT approach. The variance of these estimates is generally lower than the variance for the two other approaches.

4 CONCLUSION

Three different approaches for non-parametric estimation of correlation functions have been investigated: The direct approach, The FFT-IFFT approach and the random decrement technique. The main issue was illustration of advantages and disadvantages of different formulation of the Random Decrement technique. The investigations are based on simulated response of a 2-degree-of-freedom system loaded by white noise.

The direct approach was clearly the slowest approach. For a small number of points in the correlation functions the random decrement technique is the fastest approach no matter how this approach is formulated. For a large number of points only a strict formulation of the random decrement technique is faster than the FFT-IFFT approach.

Triggering at every positive point and the FFT-IFFT produces the most accurate estimates of the modal parameters compared to the level crossing and the local extremum trigger condition. More information about the influence of applying bounds to the every positive point trigger condition is needed. Applying bounds will increase the estimation time but also increase the uncertainty. Furthermore, the local extremum trigger condition did not produce as accurate results as expected. This trigger condition should be powerful, since the contribution from the velocity is conditioned to be zero. More work with this trigger condition is needed to investigate if a time shift bias is introduced, see Brincker et al. [7]

5 ACKNOWLEDGEMENT

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