Change Detection in Dynamic Characteristics of Structural Systems from Earthquake Records

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Abstract: Major changes in the dynamic properties of structures are likely to occur and have been observed from the earthquake records obtained from several instrumented buildings.
An appropriate signal processing technique for analysing both the earthquake ground motion and the building response data, capable of identifying the time variations in the amplitude and frequency content is presented.
The discussed method implies an impulse invariant transformation for obtaining the discrete time equivalent model of the effective earthquake ground motion and of the structural system, represented by a parallel-form realization of second-order subsystems, corresponding to different modes of vibrations. The general procedure for change detection in the dynamic characteristics of the system is as follows:
(i) Segment the input signal in quasi-stationary data blocks and fit the AR filters to them.
(ii) Find the envelope of the standard deviations of the residuals derived from each data block at (i).
(iii) Divide the building response by the envelope function.
(iv) Filter the resulted building response, containing information about both the dynamic excitation environment and the behaviour of the structure, with the AR filters obtained at (i) above, corresponding to different time intervals.
(v) Segment the filtered response in quasi-stationary data blocks, each transition from one data block to another marking a change in the dynamic properties of the structural system concerned. For each quasi-stationary data segment, the time and frequency characteristics for diagnosis-making can be evaluated. The method was applied to strong motion records gathered from a 12-storey instrumented reinforced concrete building, during the August 30/31, 1986 Romanian earthquake. Some of these results are included in the paper.

Keywords: Detection of changes, spectral characteristics, autoregressive modelling, structural systems, earthquake ground motion.

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1. Introduction

The problem of detecting changes in signals and systems has been paid large attention in the last fifteen years. Conclusive surveys on and contributions to this subject, justifying its importance and describing different applications can be found in Willsky(1976), Mironovski(1980), Isermann(1984), Söderström and Kumamaru(1985), Basseville and Benveniste(1986), Smed and Carlsson(1988), Carlsson(1988), Basseville(1988), Patton, Frank and Clark(1989), Wahlberg(1989), Popescu and Demetriu (1990a).

The problem addressed in this paper is the detection of changes in the dynamic characteristics of a vibrating structure subject to a transient natural excitation. Examples of such vibrating structures are off-shore drilling platforms open to the waves, buildings or bridges exposed to wind or earthquakes, mechanical systems subject to fluid interactions, etc.

Basseville and colleagues (1984, 1987) originally approached change detection and diagnosis in modal characteristics of nonstationary signals for unmeasured natural excitation with application in vibration monitoring. This is based on instrumental statistics and on a statistical approach of detection.

Popescu and Demetriu (1991) propose an approach based on system identification and associate it with the Smed and Carlsson decision making methods. This procedure is applied to a large scale reinforced structure of which acceleration records were obtained during a high-level nonstationary earthquake excitation. The used structure models can be described in terms of their vibration modes (natural frequencies, modal damping ratios and mode shapes).

The method discussed in this paper works with an impulse invariant transformation for obtaining a discrete time equivalent model of the effective excitation and of the structural system. It is represented by a parallel-form realization of second-order subsystems, corresponding to different modes of vibrations. At the same time, a general procedure is used to segment a nonstationary data set into quasi-stationary data blocks, with each transition from a data block to another marking a change of the dynamic properties of the signal.

The paper is organized as follows. Section 2 presents the general combined earthquake-structure model used in the problem concerned. The change detection procedure for change detection in the effective excitation and in the structural system is presented in Section 3. Supporting numerical results produced by the investigation of a real structural system are reported in Section 4.

2. Combined Earthquake - Structure Model

The equation of motion for an N degree-of-freedom system subject to an earthquake ground motion, outlined as a linear planar, time invariant model with viscous damping can be written as:

$$M\ddot{x}(t) + C\dot{x}(t) + Kx(t) = -M.[1]\ddot{x}_g(t) \quad (1)$$

in which M, C and K are, respectively, the NxN mass, viscous damping and stiffness matrices. Vector $x(t) = [x_1(t), \dots, x_N(t)]^T$ denotes a relative displacement, dots mark a derivative with respect to time, [1] and vector $[1, t, \dots, 1]^T$ and $x_g(t)$ define the base acceleration.

Equation (1) represents a system of N coupled equations which can be uncoupled provided that the viscous damping is proportional (for example Rayleigh assumption C = aM + bK). Let us have $x = \Phi \,.\, y$ where y is the vector of the modal displacements and Φ is the modal matrix whose column vectors are the individual mode shapes Φ_r, ($r = 1, N_m$ ($N_m \leq N$)), i.e. $\Phi_r^T = [\,\Phi_{1r}, \Phi_{2r}, \dots, \Phi_{Nr}\,]^T$. By multiplying equation (1) by Φ^T, we obtain a set of NxN_m uncoupled equations as

$$\ddot{x}_i^r(t) + 2\,\xi_r \omega_r \dot{x}_i^r(t) + \omega_r^2\, x_i^r(t) = \rho_i^r\, \ddot{x}_g(t) \quad (2)$$

in which ω_r and ξ_r are the r-th vibration circular frequency and modal damping, respectively. ρ_i^r is the participation factor of the r-th mode at response point i, defined as

$$\rho_i^r = -\Phi_{ir} \frac{\Phi_r^T \cdot M \cdot [1]}{\Phi_r^T \cdot M \cdot \Phi_r} \quad (3)$$

The displacement at the level i is given by combining all the modal contributions:

$$x_i(t) = \sum_{r=1}^{N_m} x_i^r(t) \qquad (4)$$

The normal modes approach presented above is adopted here. It is assumed that the observed response is the sum of a finite number of modal responses, and each mode is modelled by a second order system. A block diagram of such an earthquake excitation - structure system is shown in Figure 1.

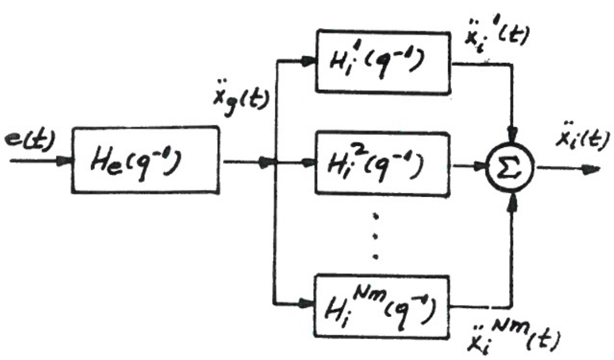

Figure 1. Block diagram of the earthquake excitation-structure system

The single-degree-of-freedom oscillator can be approximated by a transfer function of the form:

$$H^r(s) = \frac{K\omega_r^2}{s^2 + 2\xi_r \omega_r s + \omega_r^2} \qquad (5)$$

or of the discrete form:

$$H^r(q^{-1}) = q^{-1}\frac{b_1^r + b_2^r q^{-1}}{1 + a_1^r q^{-1} + a_2^r q^{-2}} \qquad (6)$$

Our analysis is practically interested in the evaluation of changes in ξ_r and ω_r, using the parameter estimates of the discrete model form. The transform relations are given by Åström and Wittenmark (1984).

The actual earthquake is represented by $H_e(q^{-1})$ which is assumed to be the transfer function of a finite-order linear, time-variant system , of which input is a white noise process e(t).

The accelerogram measured at the i level, $\ddot{x}_i(t)$, can be considered as the realization of a random process containing information about the dynamic excitation environment and the dynamics of the structure. This nonstationary time history is treated here as a realization of a discrete-time stochastic process, which is the output of a linear, time-variant system. The dynamic characteristics of such a system are changing with time and input.

3. Change Detection Procedure

The main hypothesis of the change detection procedure under discussion will be that the analysed signals: excitation and building response can be taken as nonstationary for a long period of time, but as quasi-stationary for short time intervals, marked by change instants.

The procedure is as follows:

Step 1. Segment the excitation signal $\ddot{x}_g(t)$ into quasi-stationary data blocks and fit the AR filters to them; here, the acceptance of quasi-stationary is that, within a segment, the short-time spectral estimate does not change appreciably with time. The method described by Popescu and Demetriu (1990b) is based on the nonstationarity analysis procedure suggested by Kitagawa and Akaike (1978), and uses three autoregressive models : a global model AR_2, identified in a growing window, a model AR_0, identified for a data subset supposed to be stationary and a short term model, AR_1, identified in a sliding window (see Figure 2). Deciding on changing the dynamical properties of the signal involves an evaluation of the Akaike Information Criterion (AIC) for the global model, AIC_2, and for a combination of the latter two models, $AIC_{0,1} = AIC_0 + AIC_1$.

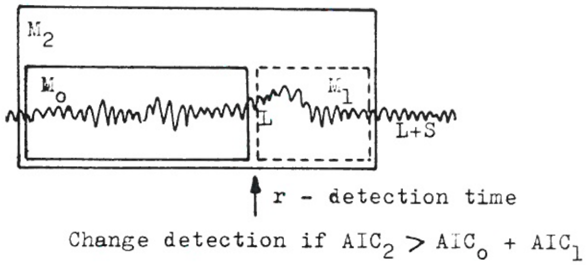

Figure 2. Change detection scheme

Let $\ddot{x}_g(1), \ddot{x}_g(2), \ldots, \ddot{x}_g(L)$ be a set of initial data considered quasi-stationary, and $\ddot{x}_g(L+1), \ldots, \ddot{x}_g(L+S)$, an additional data set of S observations, with S as a prescribed number. The segmentation procedure is as follows:

(i) Fit an autoregressive model AR_0

$$\ddot{x}_g(t) = \sum_{m=1}^{M_0} a(m)\ddot{x}_g(t-m) + e(t) \qquad (8)$$

with δ_0^2 the innovation variance, where M_0 is chosen as giving the minimum of the AIC criterion, for the set of data $\ddot{x}_g(1), \ddot{x}_g(2), \ldots, \ddot{x}_g(L)$:

$$AIC_0 = L.\log \sigma_0^2 + 2M_0 \qquad (9)$$

(ii) Fit an autoregressive model AR_1

$$\ddot{x}_g(t) = \sum_{m=1}^{M_1} a(m)\ddot{x}_g(t-m) + e(t) \qquad (10)$$

with δ_1^2 the innovation variance, and M_1 chosen as giving the minimum of the AIC criterion, for the set of data $\ddot{x}_g(L+1), \ldots, \ddot{x}_g(L+S)$

$$AIC_1 = S.\log \sigma_1^2 + 2M_1 \qquad (11)$$

(iii) Define the first competing model by "connecting" the autoregressive models AR_0 and AR_1. The AIC of this joint model is given by:

$$AIC_{0,1} = L.\log\sigma_0^2 + S.\log\sigma_1^2 + 2(M_1+M_2) \qquad (12)$$

(iv) Fit an autoregressive model AR_2,

$$\ddot{x}_g(t) = \sum_{m=1}^{M_2} a(m)\ddot{x}_g(t-m) + e(t) \qquad (13)$$

with σ_2^2 the innovation variance, where M_2 is chosen the same way as above, for the data set $\ddot{x}_g(1), \ddot{x}_g(2), \ldots, \ddot{x}_g(L), \ldots, \ddot{x}_g(L+S)$.

(v) Define the model AR_2 as the second competing model with the AIC criterion given by:

$$AIC_2 = (L+S).\log \sigma_2^2 + 2M_2 \qquad (14)$$

(vi) If AIC_2 is less than $AIC_{0,1}$ the model AR_2 is accepted for initial and additional sets of observations and the two sets of data are considered to be homogeneous (no change in signal characteristics is detected). If not so, we switch on to the new model AR_1 (a change in signal characteristics is detected at instant $r=L$). The procedure is repeated whenever a set of S new observations is given. It is so designed as to adapt to the change in signal characteristics. If the characteristics keep unchanged, the model will be improved by additional observations. An AR model has resulted for each quasi-stationary data segment. It will be used in the next step.

The numerical procedure for AR model fitting could be the method of the least squares realized by Householder transformation (Söderström, Stoica, 1989). This approach proves a very simple procedure of handling other new observations.

It is well-known that the Akaike method tends to overestimate the true model order (even for $N \rightarrow \infty$), while the other methods provide consistent order estimates. However, for a finite number of data points, Akaike's method is expected to take a smaller risk in underestimating the order. That is why we would rather have it than the other methods.

Step 2. The variance of e(t), corresponding to different time intervals, is stabilized by dividing it by its envelope function given by standard deviations of residuals, of each model obtained for quasi-stationary data blocks.

The resulted residuals can be assumed to be a stationary and normally distributed process with mean zero and variance 1. At this stage, the autocorrelation function of the residuals must also be estimated, for confirming the lack of correlation.

Step 3. Divide the building response by the envelope function determined above.

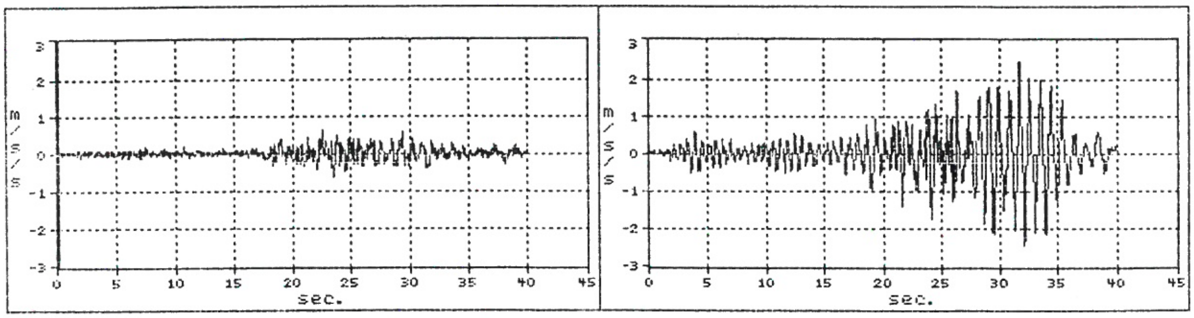

Figure 3. Transversal acceleration
a) base acceleration
b) 12th level acceleration

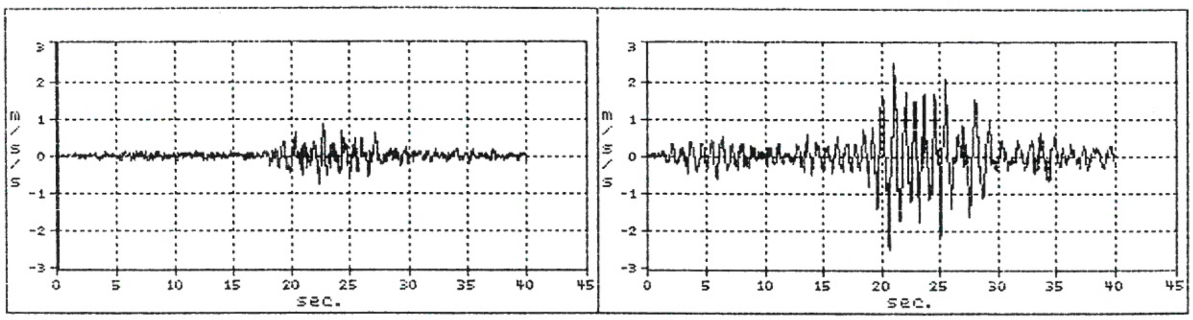

Figure 4. Longitudinal acceleration
a) base acceleration
b) 12th level acceleration

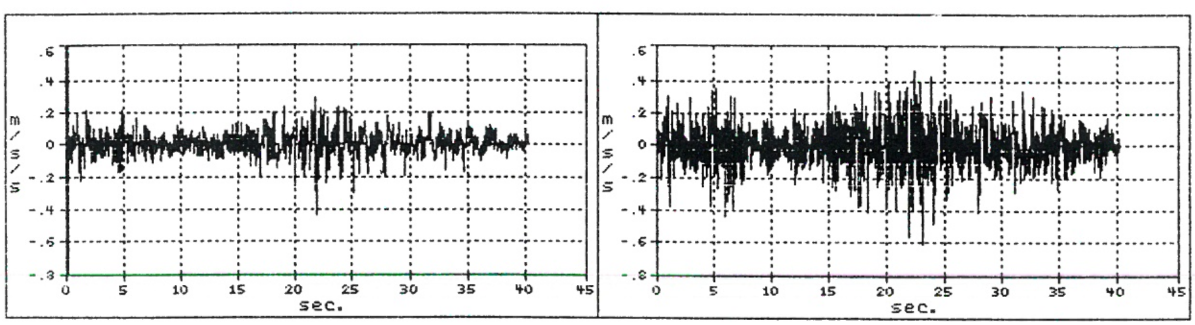

Figure 5. Vertical acceleration
a) base acceleration
b) 12th level acceleration

Step 4. Filter the resulted building response, containing information about the dynamics of excitation as well as the dynamics of the structure, with the AR filters obtained at Step 1 above, corresponding to the quasi-stationary time intervals of the excitation signal.

If the series of the model residuals obtained at Step 2 can be assimilated to a white noise process, the filtered response will only contain information on the dynamic properties of the analysed structure. This signal can be considered as the output of a linear, time-variant filter having as input a white noise signal, also stationary and normally distributed.

Step 5. Segment the filtered response into quasi-stationary data blocks, using the procedure described at Step 1 above. Each transition from a data block to another will make a change in the dynamic properties of the system. For each quasi-stationary data segment, the characteristics of the system in time and frequency domain can be evaluated for diagnosis-making.

Starting from the resulted AR models, it is possible to evaluate the structural modes of vibrations for each quasi-stationary data segment.

4. A Case Study

The previously described procedure was applied to strong motion records obtained in a 12-storey reinforced concrete building, during the August 30/31, 1986 Romanian earthquake. The transversal (N-S), longitudinal (E-W) and vertical components of the acceleration recorded at the basement and the roof levels of the structure have been analysed. The excitation acceleration and the response acceleration for all components are sampled at 0.02 seconds and are represented in Figure 3, Figure 4 and Figure 5 respectively.

Calculations of the Fourier amplitude spectrum of these records have indicated that their frequency content is mainly in the range of 0-5 Hz. for transversal and longitudinal components and in the range of 0-12 Hz. for the vertical components. Therefore, the transversal and longitudinal data were lowpass filtered using a zero-phase, second-order Butterworth filter, with the cut-off frequency of 5 Hz.; the vertical components were lowpass filtered with a similar filter with cut-off of 12 Hz. After a preliminary analysis of the excitations components, for different lengths of sliding windows, we find the length of 100 data (2 sec.) as best suited for this application.

Using the segmentation procedure described in the previous section, the excitation components were divided into data segments after detecting change instants; also, the AR models, of a maximum order of 20, were determined for these quasi-stationary data segments: 7 for the transversal component, 8 for the longitudinal component and 10 for the vertical component.

The building response components, after having been divided by the envelope of the standard deviation of the excitation components and filtered with the AR models are given in Figure 6.

The autocorrelation functions of the normalized residuals of the excitation components are given in Figure 7. Practically, a lack of correlation of all these functions can be noticed.

The nonstationary analysis procedure applied in this case reveals the change instants in the dynamic characteristics of the system; these change instants are marked by vertical lines in Figure 6. Figure 8 presents the evolution of the power spectral density of the quasi-stationary data segments for all components. The AR models obtained at this phase can be used to estimate the modal characteristics of the structure for each direction.

5. Conclusions

A practical method for change detection in the dynamic characteristics of structural systems from earthquake records was presented and investigated in a case study.

On the basis of the results reported here, it is tentatively concluded that this approach is capable of adequately detecting main change instants in the dynamic characteristics of structural systems using AR modelling.

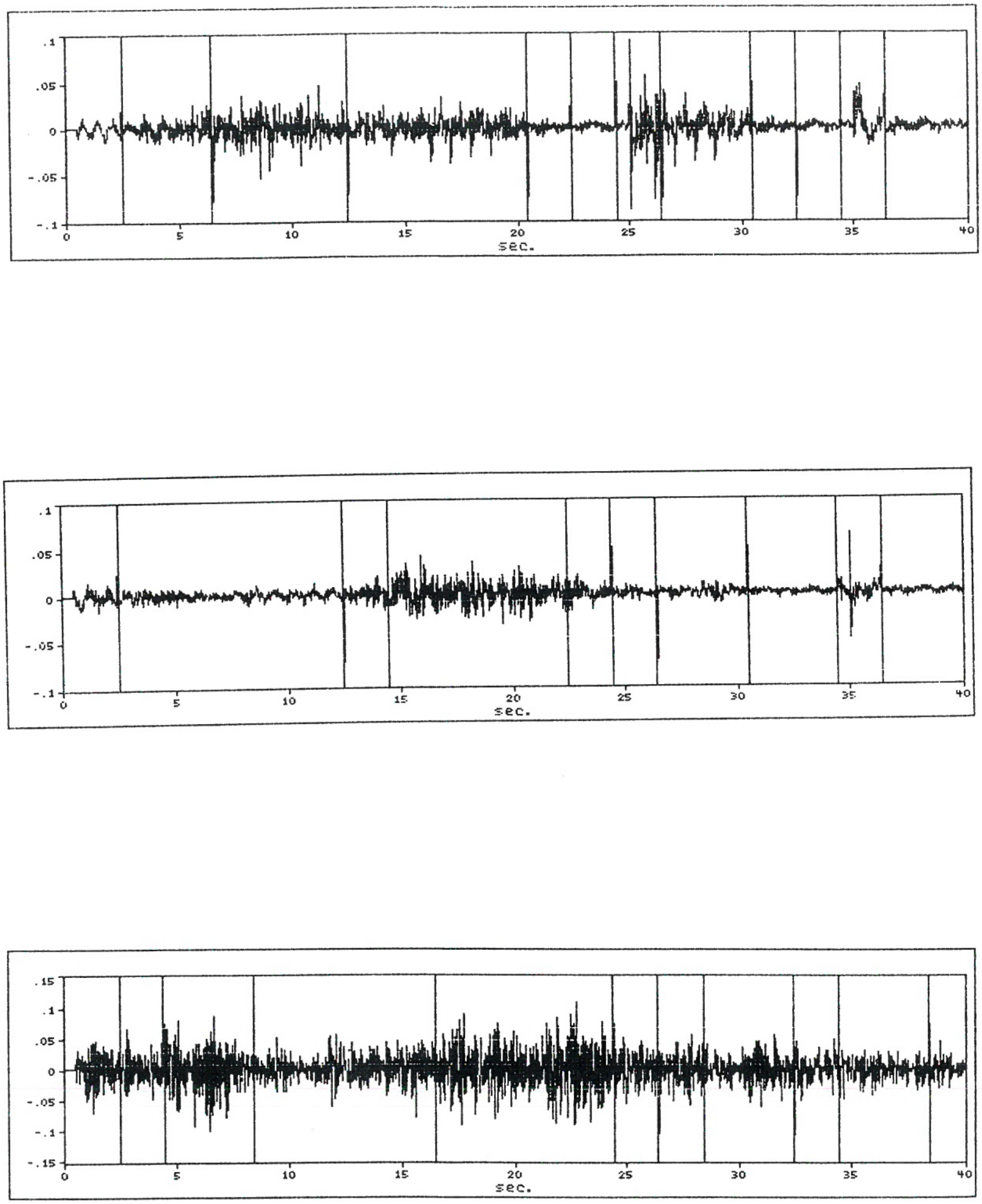

Figure 6. Change instants in the dynamic characteristics
a) Transversal direction
b) Longitudinal direction
c) Vertical direction

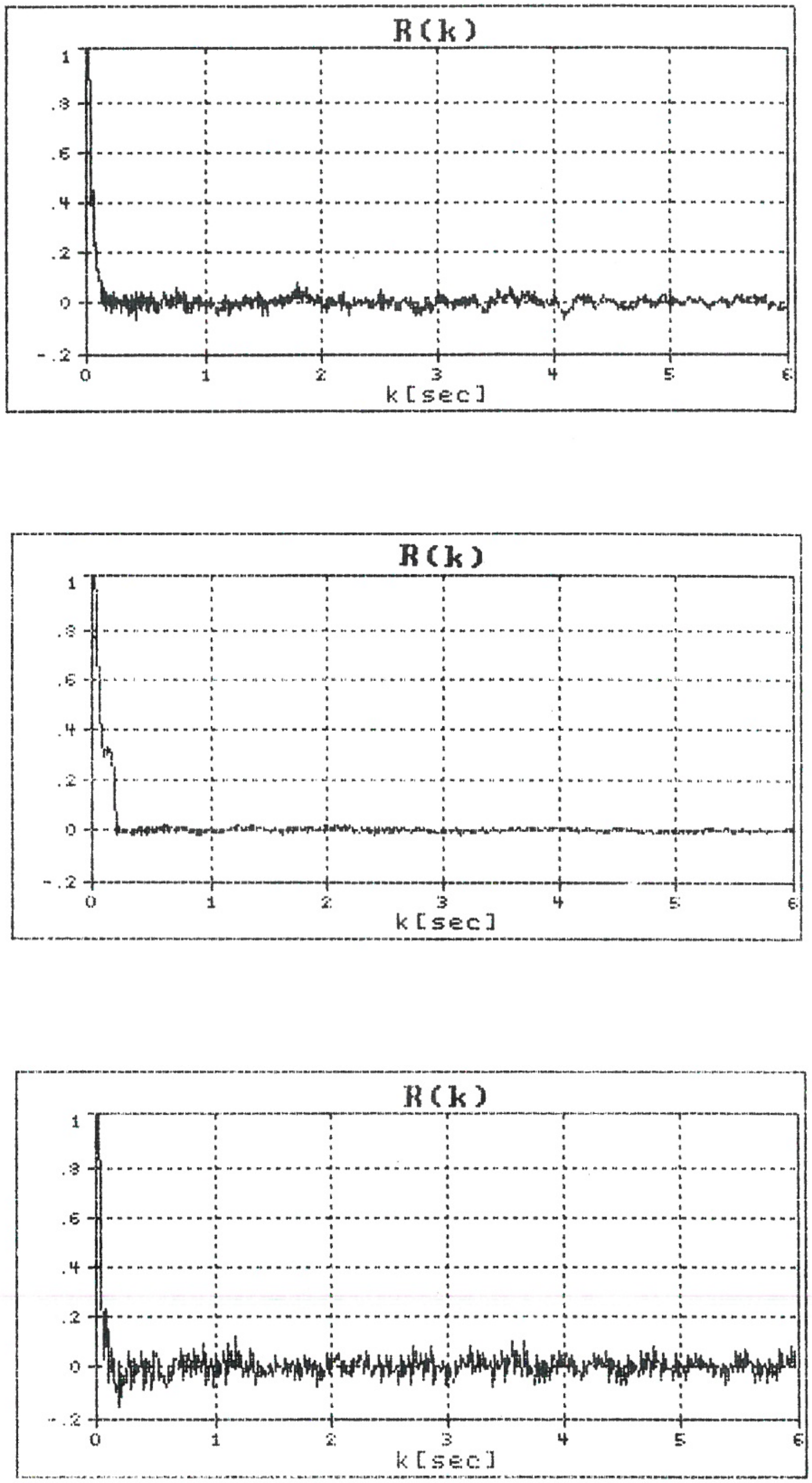

Figure 7. Autocorrelation functions of residuals
a) Filtered transversal base acceleration
b) Filtered longitudinal base acceleration
c) Filtered vertical base acceleration

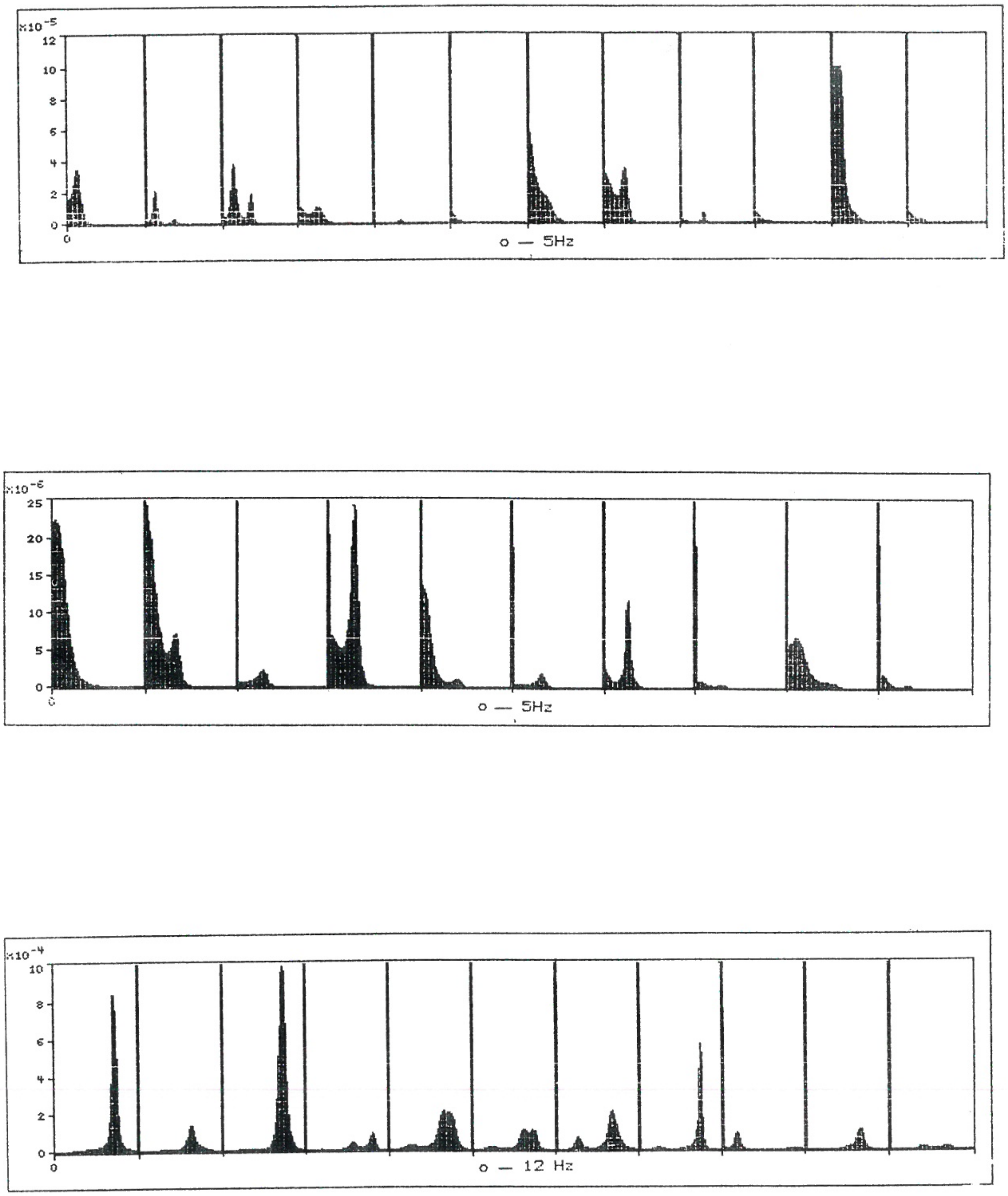

Figure 8. Evolution of power spectral density for quasi-stationary data segments
a) Transversal direction
b) Longitudinal direction
c) Vertical direction

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