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Analysis of multidimensional geophysical monitoring time series for earthquake prediction

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Abstract
A method is presented for detection of synchronous signals in multidimensional time series data. It is based on estimation of eigenvalues of spectral matrices and canonical coherences in moving time windows and extraction of an aggregated signal (a scalar signal, which accumulates in its own variations only those spectral components which are present simultaneously in each scalar time series). It is known that an increase in the collective behavior of the components of some systems and an enlarged spatial radius of fluctuations of their parameters could be regarded as an important precursor of an oncoming catastrophe, *i.e.* abrupt change of the system's parameter values. From that point of view, detection of synchronous signals in various geophysical parameters, measured at points of some network, covering a given area of the Earth's crust, is of interest for identifying precursors of strong earthquakes. Some examples are presented of the use of this technique in the processing of real geophysical time series.

Key words *collective behaviour – spectral matrices – canonical coherences*

1. Introduction

If we consider the problem of processing time series from geophysical monitoring systems, it is obvious that there is a major difference between data processing of seismic (*i.e.* rather «high-frequency») signals and of low-frequency geophysical time series, for example, measurements of crustal deformation, tilts, underground water well level variations, electrical resistivity of rocks, emanation of free gases from the Earth's interior, seismoacoustic intensity and so on. This difference consists of a lack of *a priori* purpose in low-frequency data processing. In contrast with seismic signals, for which the purpose traditionally is defined as detection and identification of seismic events (abrupt changes of amplitude and frequency structure of the recorded signals), for low-frequency geophysical signals the purpose is very fuzzy. The notion of «event» could not be directly transfered from seismology to low-frequency monitoring problems because many seismological terms arsing from the wave nature of seismic signals are of no relevance to the variations of chemical elements in underground water, for example. This fuzziness is intensified when there is a complex of heterogeneous and physically different results of observations coming from a number of spatially different points of a monitoring system. The only exception is the investigation of the response of some processes (deformations, tilts, water-well-level variations) on tidal influence, because there are rather elaborate theoretical models of their tidal response. But the tidal

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influence is very narrow-banded and most of the frequency range could not be touched by such an analysis. Moreover, for many processes the tidal response is negligible.

Thus, the analysis of complex low-frequency time series needs a special approach. This approach must be based on a definition of what kind of «signal» we want to extract from such observations, especially if the scalar components of a multidimensional time series, which composes the data flow from a monitoring system, have different physical senses and are measured in various scales.

Some papers (Lyubushin, 1993, 1994, 1998a,b; Lyubushin and Latynina, 1993; Lyubushin *et al.*, 1997) have elaborated a method for analysis of low-frequency multidimensional time series based on estimation of response functions, eigenvalues of spectral matrices and canonical coherences in moving time windows. The main thesis of this approach is the notion of a synchronous signal, which qualitatively could be defined as an increase in collective behaviour of the scalar components of the given heterogeneous data flow in some time intervals and some frequency bands. It is widely known that an increase in the collective behavior of constituent parts of some «big» system and enlraged spatial radius of fluctuations of its parameters could be regarded as an important «flag», a precursor of an oncoming catastrophe, *i.e.* of an abrupt change in parameter values (Gilmore, 1981; Nicolis and Prigogine, 1989). From that point of view detection of synchronous signals in various geophysical parameters, measured at points of some network, covering a rather big area of the Earth's crust, is of considerable interest for identifyng precursors of geocatastrophes, including strong earthquakes.

It must be noted that an idea of searching for the precursors of strong earthquakes as effects of cooperative behavior can be realized by different approaches. For instance in Johansen *et al.* (1996) this idea is realized as a search for the effects of log-periodic modulations in time series of different ion concentrations in groundwater. The idea of log-periodicity also comes from the most general properties of system behavior before catastrophes and has recently been developed intensively for earthquake prediction purposes and investigating the critical behavior of geological and even financial systems (Ouillon *et al.*, 1996; Sornette *et al.*, 1996). Searching log-periodicity means detecting (using time-frequency spectral analysis, wavelet analysis or simply nonlinear regression) from scalar time series a signal, which has a specific form of modulations with a more and more increasing frequency as the system approachs critical point. The main lack of such approach is that it can be applied only separately to each scalar time series but not to the whole multidimensional data flow from monitoring system.

Multidimensional analysis is not yet a widespread instrument for earthquake prediction data processing. For geophysical data analysis it is used usually as a classic factor or principal component analysis of covariational matrices in frames of expert systems for prediction and seismic hazard assessment (Feng *et al.*, 1984; Zhuang *et al.*, 1989). The main difference between these methods and the approach described below is that in the latter a cardinal point is the use of multidimensional spectral statistics for the quantitative description of interactions between geophysical fields and extracting effects of collective behavior, which evidently could strongly depend on frequency.

2. Method

Let $\vec{Z}(t)$ be an l-dimensional time series of measurements from a monitoring system (t – discrete time index), $S_{ZZ}(\omega)$ – its spectral matrix for the frequency value ω (this complex matrix is nonnegative and hermitian, an so its eigenvalues are real and nonnegative), $\lambda_1(\omega)$ – maximal eigenvalue of spectral matrix. According to the spectral method of principal components (Brillinger, 1975), $\lambda_1(\omega)$ is a power spectrum of some hypothetical scalar time series $W_1(t)$ (a first principal component time series), constructed by multichannel filtration of the initial time series $\vec{Z}(t)$, by using as a frequency filter an eigenvector of spectral matrix $S_{ZZ}(\omega)$, corresponding to the maximal eigenvalue $\lambda_1(\omega)$. A first principal component time series carries maximum information about joint behavior of the scalar components of the vector time series $\vec{Z}(t)$ (for Gaussian time series). Thus, if for some frequency bands the value of $\lambda_1(\omega)$ increase considerably relative to neighbor background fluctuations, this means that for such values of frequency ω the collective behavior also increases.

Let now the l-dimensional vector $\vec{Z}(t)$ be split into two vectors: an m-dimensional vector $\vec{X}(t)$ and an n-dimensional vector $\vec{Y}(t)$, where $l = n + m$. Without restriction of generality let $m \leq n$. This splitting could have the following physical meaning: $\vec{X}(t)$ is composed of the results of measurements of some geophysical field at m point and $\vec{Y}(t)$ is composed of observations of another field at n points. Now we want to know for which frequency values ω the interaction between these two fileds is maximal or minimal. Another situation, that could be reflected in such a decomposition, is two points of obervations: at one point there are records of variations of m different geophysical parameters and at another point of n parameters. Let us now ask a question: how can we describe the interaction between the two geophysical regions, represented by these two points, in various frequency bands, using all available information?

To aswer us such a question, a notion of maximal canonical coherence is useful (Brillinger, 1975). Let us consider the matrix $U(\omega)$, which is a following product of inverted spectral and cross-spectral matrices

$$U(\omega) = S_{xx}^{-1}(\omega) \cdot S_{xy}(\omega) \cdot S_{yy}^{-1}(\omega) \cdot S_{yx}(\omega). \quad (2.1)$$

It can be seen that when both series are not vectors but scalars, then $U(\omega)$ becomes the usual squared spectrum of coherence. It can be shown that the eigenvalues of $U(\omega)$ are real, nonnegative and ≤ 1. These eigenvalues can be interpreted as the squared spectrum of coherence between some scalar time series, which are called *canonical components* of the initial time series $\vec{X}(t)$ and $\vec{Y}(t)$. Let $\mu_1^2(\omega)$ be the maximal eigenvalue of $U(\omega)$ (*i.e.* the maximal canonical coherence). Then if for some values of frequency the maximal canonical coherence increases considerably and approaches the value of 1, it means that for this frequency the statistical relation between the two vector time series is strong.

Let us now introduce a notion of component-wise canonical coherence $\nu_i^2(\omega)$ (Lyubushin, 1998a) as a maximal canonical coherence in a situation, when the time series $\vec{X}(t)$ is composed only of the i-th scalar component of the time series $\vec{Z}(t)$ ($m = 1$) and $\vec{Y}(t)$ of all the other components of $\vec{Z}(t)$ ($n = l-1$). The value of $\nu_i^2(\omega)$ describes the «strenght» of the relation between variations with frequency ω of the i-th component and the set of all other components. Computing the average value of all component-wise canonical coherences gives a spectral statistic that describes the «strenght» of joint relations between all components of $\vec{Z}(t)$ at a given frequency ω

$$\rho^2(\omega) = \frac{1}{l}\sum_{i=1}^{l} \nu_i^2(\omega). \quad (2.2)$$

It is evident that $0 \leq \rho^2(\omega) \leq 1$ and, hence, the closer the value of $\rho^2(\omega)$ is to 1, the stronger are the effects of collective behavior of the scalar components of $\vec{Z}(t)$ at a given frequency ω.

We must keep in mind that the interactions between geophysical processes and fields are nonstationary. That is why the computation of each statistic, describing the effects of interaction and collective behavior, must be carried out not over the whole time interval of observation, but in a moving time window. This gives a possibility not only to describe the changeability in the Earth's crust, but to detect anomalies, which could be precursors of earthquakes, for example.

Let τ be a time coordinate of the moving time window, for example, its center or right-hand end (which is more convenient for prediction purposes), L the number of samples in a time window, and δt the sampling time interval. Computing statistics $\lambda_1(\omega)$, $\mu_1^2(\omega)$ and $\rho^2(\omega)$ not over the whole interval of observation, but in a moving time window, we will obatin a set of two-parameter functions

$$\lambda_1(\tau,\omega),\ \mu_1^2(\tau,\omega),\ \rho^2(\tau,\omega). \quad (2.3)$$

The time window and the sampling time interval define a frequency band, which could be investigated with the help of statistics (2.3)

$$2\pi/((L-1)\delta t) \le \omega \le \pi/\delta t. \qquad (2.4)$$

Suppose that for some time intervals and frequency bands (τ, ω) the value of one of the functions (2.3) considerably exceeds the level of its statistical background fluctuations. Then we shall say that a synchronous signal is observed for this (τ, ω). Two of the functions, $\lambda_1(\tau, \omega)$ and $\rho^2(\tau, \omega)$, are intended for detection of the same effect – increased collective behavior of the scalar components of a single multidimensional time series (whereas $\mu_1^2(\tau, \omega)$ deals with two multidimensional series). A question arises – which statistic is the «best» one? Unlike $\rho^2(\tau, \omega)$, which always lies in the interval [0,1], $\lambda_1(\tau, \omega)$ has no upper bound. Thus it could arise that one sufficiently large peak of values of $\lambda_1(\tau, \omega)$ would overshadow other peculiarities of $\lambda_1(\tau, \omega)$ with more moderate amplitudes. For this reason $\rho^2(\tau, \omega)$ is preferred for time-frequency analysis. But $\lambda_1(\tau, \omega)$ has a positive quality: a better clustering of characteristic vectors of time windows, which are computed as energy values of the principal component in nonoverlapping frequency bands $[\Omega_k, \Omega_{k+1}]$, covering the frequency range (2.4):

$$r_k^{(\tau)} = \int_{\Omega_k}^{\Omega_{k+1}} \lambda_1(\tau, \omega)\, d\omega, \quad k = 1, \ldots, q. \qquad (2.5)$$

Applying formula (2.5) to the evolution of the first maximal eigenvalue of the spectral matrix gives a sequence of q-dimensional vectors $\vec{r}^{(\tau)}$, which constitute some «cloud». If this cloud could be divided into a number of distinguishable clusters, it can be interpreted as implying the existence of some distinguishable «modes» of interaction between the monitored processes. Some of these «modes» or clusters may be «dangerous» in the sense that they precede geocatastrophes. If so, then precursors of strong earthquakes could be found by identifying time windows τ when the vector $\vec{r}^{(\tau)}$ belongs to a «dangerous» cluster.

Finally, let us introduce the notion of aggregated signal (Lyubushin, 1998b). Qualitatively an aggregated signal could be defined as a scalar signal, that accumulates in its own variations only those spectral components, which are present simultaneously in each scalar time series of the multidimensional signal to be analyzed. Moreover, an algorithm of aggregation suppresses those spectral components, which are presented in any one of the scalar components but absent in the others (these components could be called *local disturbance* signals). The main purpose of constructing an aggregated signal is to bring out the common trends in low-frequency geophysical network data series, which indicate an increase in collective behavior.

To formalize the notion of aggregated signal let us exclude the i-th scalar component $Z_i(t)$ from the multidimensional time series $\vec{Z}(t)$ and try filter the $(l-1)$-dimensional series $\vec{X}^{(i)}(t)$ composed of the other components, so that the filtered scalar signal $C_i^{(z)}(t)$ has a maximal canonical coherence with $Z_i(t)$ for each frequency value. For this purpose we must use, as a frequency filter for $\vec{X}^{(i)}(t)$, an eigenvector, corresponding to the maximal eigenvalue of the matrix $U(\omega)$, where the series $Z_i(t)$ is taken as $\vec{Y}(t)$, and $\vec{X}^{(i)}(t)$ as $\vec{X}(t)$. It is clear that this eigenvalue equals $\nu_i^2(\omega)$. If $Z_i(t)$ contains some noise, which is present only in this component and absent from the other components of $\vec{Z}(t)$, then the noise will be absent from $C_i^{(z)}(t)$ as a consequence of its construction. At the same time, $C_i^{(z)}(t)$ retains all spectral components of $Z_i(t)$ which are common to the other scalar components of $\vec{Z}(t)$, *i.e.* to the $(l-1)$-dimensional signal $\vec{X}^{(i)}(t)$. Let us call $C_i^{(z)}(t)$ a canonical component of the scalar time series $Z_i(t)$.

Now let us define an aggregated signal $A_z(t)$ of the multidimensional time series $\vec{Z}(t)$ as the first principal component of the multidimensional series $\vec{C}^{(z)}(t)$, composed of the canonical components $C_i^{(z)}(t)$ of each of the scalar time series from the initial series $\vec{Z}(t)$.

The difference between $A_z(t)$ and a «simple» first principal component $W_1(t)$ must be emphasized. In both cases the signals are constructed by multichannel frequency filtering, using spectral matrix eigenvectors corresponding to maximal eigenvalues, as a filter. But for $W_1(t)$ the spectral matrix is that of the initial series $\vec{Z}(t)$, whereas for $A_z(t)$ the spectral matrix is that of $\vec{C}^{(z)}(t)$. Although in both cases detection of common spectral compoents takes place, the aggregated signal $A_z(t)$ has advantages in comparison with $W_1(t)$, because the algorithm of aggregation eliminates individual noise completely, whereas they could «penetrate» into $W_1(t)$, especially when the noise has the character of intense monochromatic signals.

It is necessary to point out that an aggregated signal is constructed by the operation of projection of Fourier transformations of time series on the eigenvector of various spectral matrices. Eigenvectors are defined with sign uncertainty, and therefore phases of aggregated signals are defined with uncertainty $\pm \pi$. This peculiarity can give rise to a wish to «invert» a plot of the aggregated signal if the inverted signal seems to compare more naturally with plots of the initial data time series. The inversion is very simple: differ the series (to give a series of increments), then change the sign of each increment and sum them back again.

Estimation of spectral matrices can be done either by averaging multidimensional periodograms or by using a vector autoregression model (Marple, 1987). The second approach is preferable for estimation in short time-windows because it provides better discrimination of neighboring frequency components. Before estimating the spectral matrix in each time-window the following preliminary operations are carried out: each scalar time series is substituted by a series of its first successive differences (in order to increase stationarity inside the time-window) and then it is scaled to unit variance. The last operation is intended to eliminate the difference in scale between the various physical units in which the different processes are measured.

The are three main reasons why synchronous signals arise in geophysical measurements:

1) The existence of a single external source of disturbances with large spatial radius of correlation, which influences all the measured processes, for example, variations of atmospheric pressure or tidal variations.

2) The most interesting reason, which was already discussed, consolidation of small Earth crust blocks into a big one in the area of preparation of a future geocatastrophe.

3) The postseismic reaction of most of the processes after rather strong earthquakes (this kind of synchronization is the most evident and simple for detection).

Reason (1) should be removed before estimating statistics (2.3) or calculating aggregated signals. It can be removed with the help of methods of multidimensional compensation for the influence of measurable external disturbances factors (Lyubushin, 1993; Lyubushin and Latynina, 1993).

3. Examples of applications

Figures 1 to 3 illustrate the use of statistics (2.3) and (2.5) in the processing of hydrogeochemical time series, measured by Yu.M. Khatkevich (Institute of Volcanology, Petropavlovsk-Kamchatsky) on a system of boreholes during the time period 1986-1992 on Kamchatka, not far from the town of Petropavlovsk-Kamchatsky. Characteristic linear size of the network is about 50 km. The time series were obtained with a sampling-time interval of 3 days, with 821 samples in each time series. Such a big sampling-time interval does not allow us to investigate «high» frequencies and forces us to use moving time-windows with a small number L of samples within it. The next defect of these data is low precision, which manifests itself in the existence of a rather long time «plateau» of constant values. Nevertheless, using the described method gives some interesting results on the connection of synchronous signals with seismic regime (Lyubushin *et al.*, 1997). During the period of observations 7 earthquakes occurred near the network. The epicenters of these events are at distances of 100 to 150 km from the center of the network, near the Pacific Ocean coastline. Among these seismic events two are rather strong:

– Event #2: 06 October 1987, $M = 6.6$, depth = 34 km (644-th day from the beginning of 1986).

– Event #7: 02 March 1992, $M = 7.1$, depth = 40 km (2253-th day from the beginning of 1986).

Statistics (2.3) were computed in moving time-windows of length 100 samples (300 days), with a mutual shift of 20 samples (60 days).

Figure 1 presents the function $\lambda_1(\tau, \omega)$, computed for the 5-dimensional time series of intensity of emanation of free gases (Ar, CH4, CO2, He, N2) from one of the boreholes. Synchronous signals (2) can be seen before event #2 on low frequencies and before event #7 near the frequency 0.07 day^{-1}. Also a post-seismic synchronization can be seen (3) after the strongest event #7.

Figure 2 illustrates the idea of computing the sequence of characteristic vectors (2.5) for the case $q = 2$, *i.e.* one component of the vector is a high-frequency energy and another a low-frequency. The cloud of vectors strictly divides into two clusters. Note that vectors preceding the strongest earthquakes belong to one cluster («right-hand»), which could be called «dangerous». After event #7, the vector's trajectory «jumps out» of the cloud but returns to the side of the dangerous cluster. This fact could be interpreted as forewarning rather strong shocks in the future. This conclusion was confirmed later: in 1993 two earthquakes occurred with magnitudes 7.3 (8 June) and 7.0 (13 November).

Figure 3 is a $\mu_1^2(\tau, \omega)$-diagram between the 4-dimensional time series of concentrations of silicon acid and the 5-dimensional time series of concentrations of negative ions of carbon acid in various boreholes. The most interesting peculiarity of this diagram is a long-term precursor of event #7 in the frequency band [0.03, 0.05] day^{-1}. It is interesting that neither the 4-dimensional time series nor the 5-dimensional, nor the general 9-dimensional one, taken alone and using statistics $\lambda_1(\tau, \omega)$ or $\rho^2(\tau, \omega)$ detect such a long preseismic signal. In this case the most subtle and latent effects could be detected only by investigating interactions between processes.

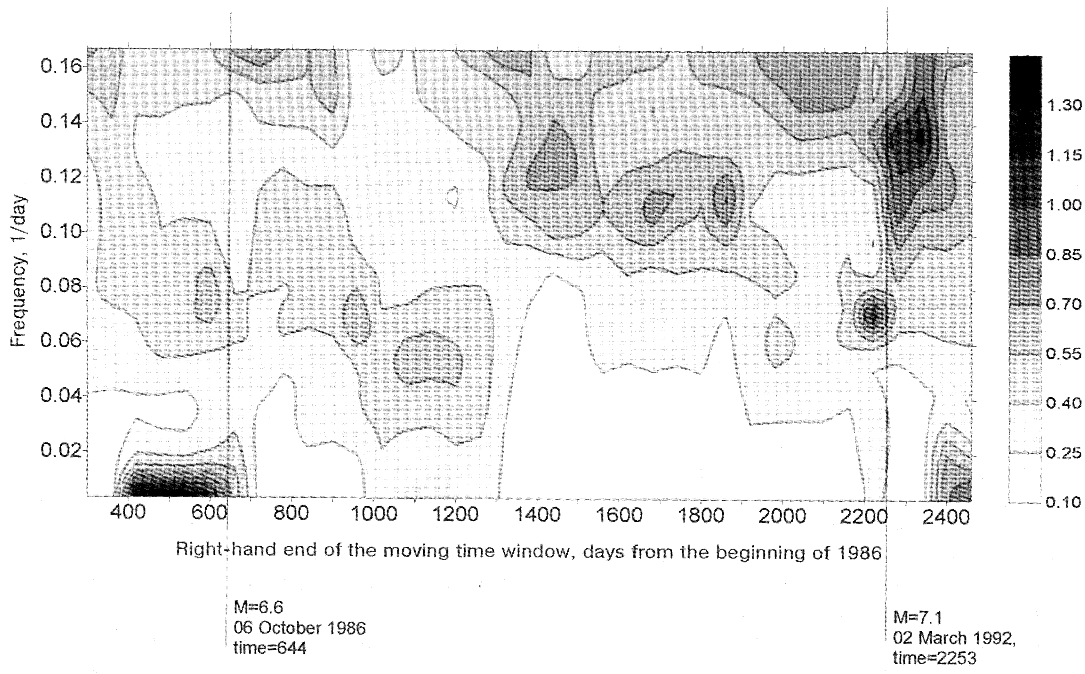

Fig. 1. Evolution of the maximal eigenvalue of spectral matrix of 5-dimensional time series of intensity of emanation of different free gases from a borehole in Kamchatka, estimated in a moving time-window of length = 300 days, taken with shift = 20 days. Vertical lines = time moments of the two strongest earthquakes during the period of observation (1986-1992).

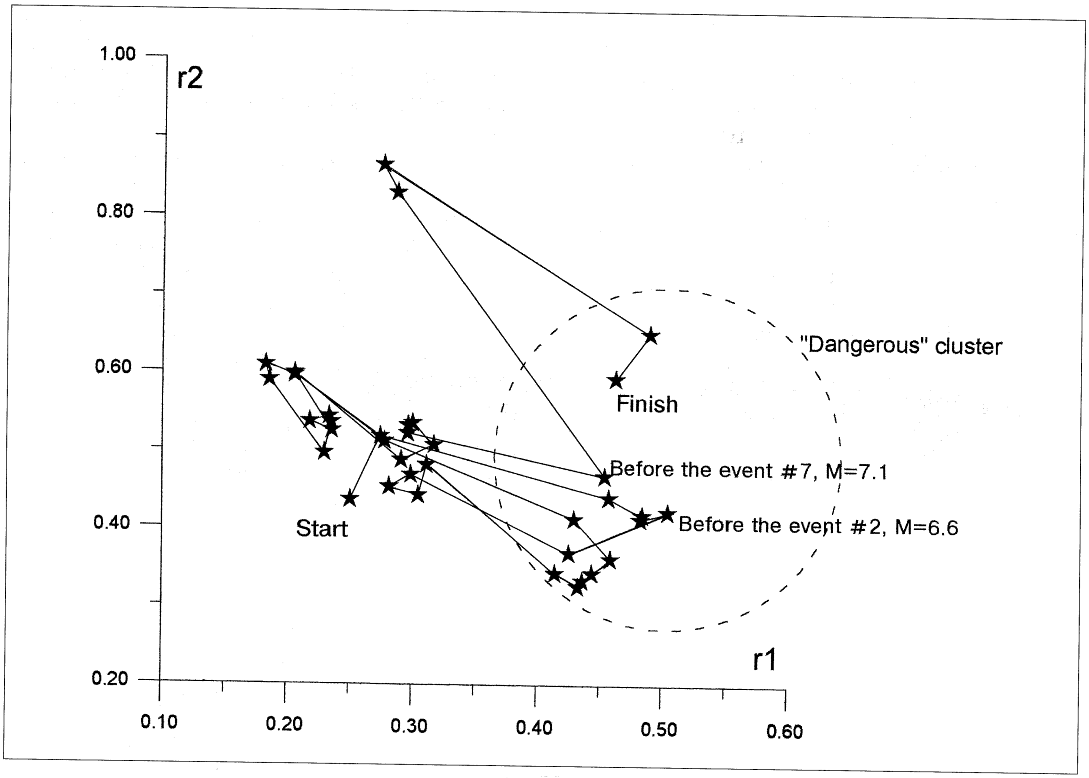

Fig. 2. Trajectory of characteristic vectors, computed using formula (2.5) for $q = 2$, for evolution of the maximal eigenvalue of the spectral matrix of the 5-dimensional time series of intensity of emanation of different free gases (fig. 1).

Figures 4 and 5 present the results of applyng the aggregated signals technique. A set of initial data consists of 10 time series, representing the results of synchronous observations for the following geophysical values:

– Rock electroresistivity – 3 time series, plots 1-3 on fig. 4.

– Tilts – 3 time series, plots 4-6 on fig. 4.

– Underground water well level variations – 4 time series, plots 7-10 on fig. 4.

The initial time series were kindly placed at our disposal by Prof. Zhang Zhaocheng, Center for Analysis and Prediction of Earthquakes, State Seismological Bureau, China. A characteristic linear size of the observational network is about 200 km. The time-period of observation is 8 years, from 1 January 1972 to 31 December 1979. The sampling-time interval $\delta t = 1$ day. Thus the length of each time series is 2922 samples. During this time interval a catastrophic Tang-Shan earthquake occurred on 28 July 1976, $M = 7.8$. This event coincided with the 1671-th day from the beginning of 1972 and it has a most explicit reaction on plot 9 of water-well level variations.

A visual analysis of plots 1-10 on fig. 4 does not allow us to detect precursory features for the Tang-Shan earthquake. A question arises as to whether some latent information exists in these results of observations, which could indicate their usefulness for prediction purposes. We try to give a positive answer to this question using different variants of aggregated signals.

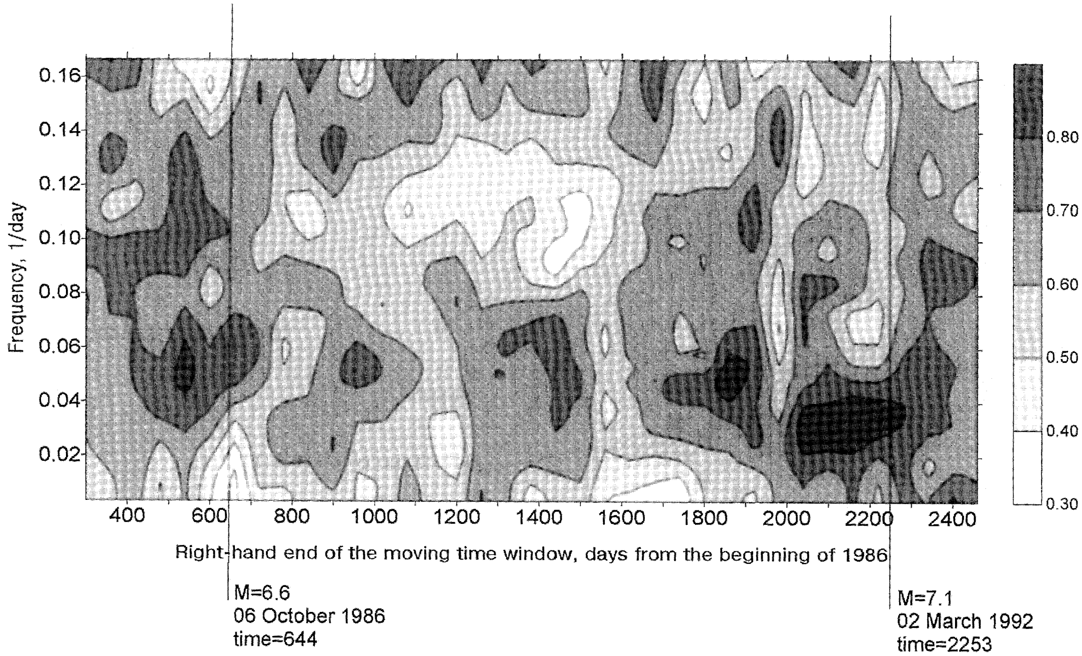

Fig. 3. Evolution of the maximal canonical coherence between 4-dimensional time series of concentrations of silicon acid and 5-dimensional time series of concentrations of negative ions of carbon acid in various boreholes in Kamchatka, estimated in a moving time-window of the length = 300 days, taken with shift = 20 days. Vertical lines = time moments of the two strongest earthquakes during the period of observation (1986-1992).

Plot 11 in fig. 4 presents the behavior of aggregated signals of all 10 data time series. A prolonged precursory «bay-like» amplitude anomaly can be seen, which begins about 1500 days before the event. In order to check the stability of the obtained results, various aggregated signals were constructed, of which plots are presented in fig. 5. First of all, we exclude series 9 from analysis, because it presents the results of water-well-level observations at a station which is the closest to the hypocenter of the earthquake and thus has a large postseismic reaction. Plot «Z-9» in fig. 5 demonstrates the behavior of aggregated signal after removing series 9. It can be seen that a prolonged precursor remains and moreover, its relative amplitude even increases.

Other plots in fig. 5 represent various aggregated signals, constructed over sets of 8 time series, when besides series 9, other series are excluded one by one from processing but then, after testing a current set of series, they return for processing. The meaning of plot designations in fig. 5 is transparent: for example «Z-9-2i» means that the aggregated signal was created for 8 time series, leaving out series 9 and 2 and then the result was inverted («i»). One can see from these graphics that all of them contain long-term low-frequency precursory anomalies before the Tang-Shan earthquake. Some of them could be called «more successful» (Z-9-3, Z-9-4, Z-9-7) and some «less successful» (Z-9-1i, Z-9-5, Z-9-6). Nevertheless even for «less successful» cases a precursory anomaly exists, but it is masked by seasonal variations, which could easily be removed by frequency filtering (even «by eye»). Thus, the results of the multi-dimensional analysis of complex geophysical observations in North China show that they have a general collective

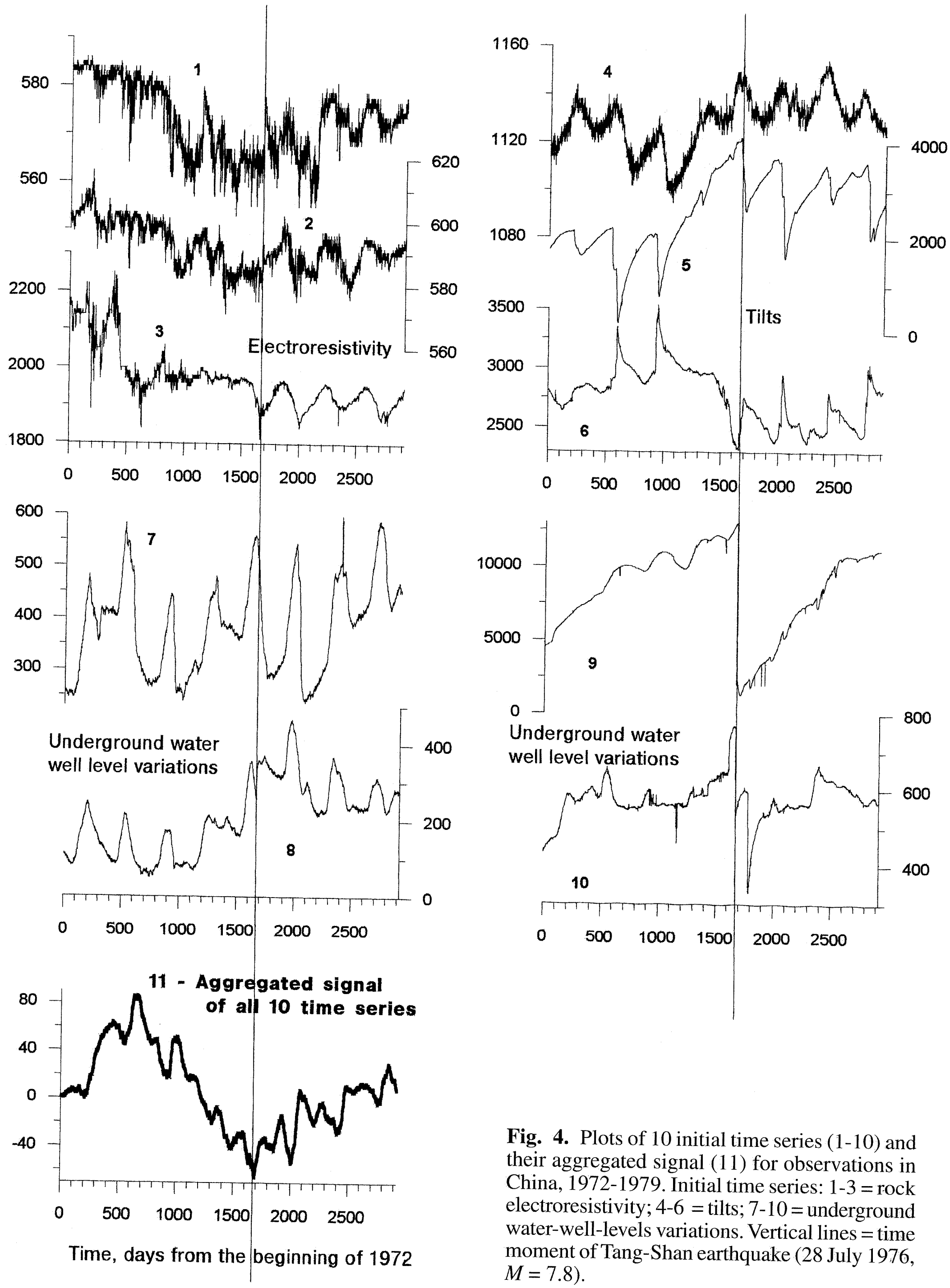

Fig. 4. Plots of 10 initial time series (1-10) and their aggregated signal (11) for observations in China, 1972-1979. Initial time series: 1-3 = rock electroresistivity; 4-6 = tilts; 7-10 = underground water-well-levels variations. Vertical lines = time moment of Tang-Shan earthquake (28 July 1976, $M = 7.8$).

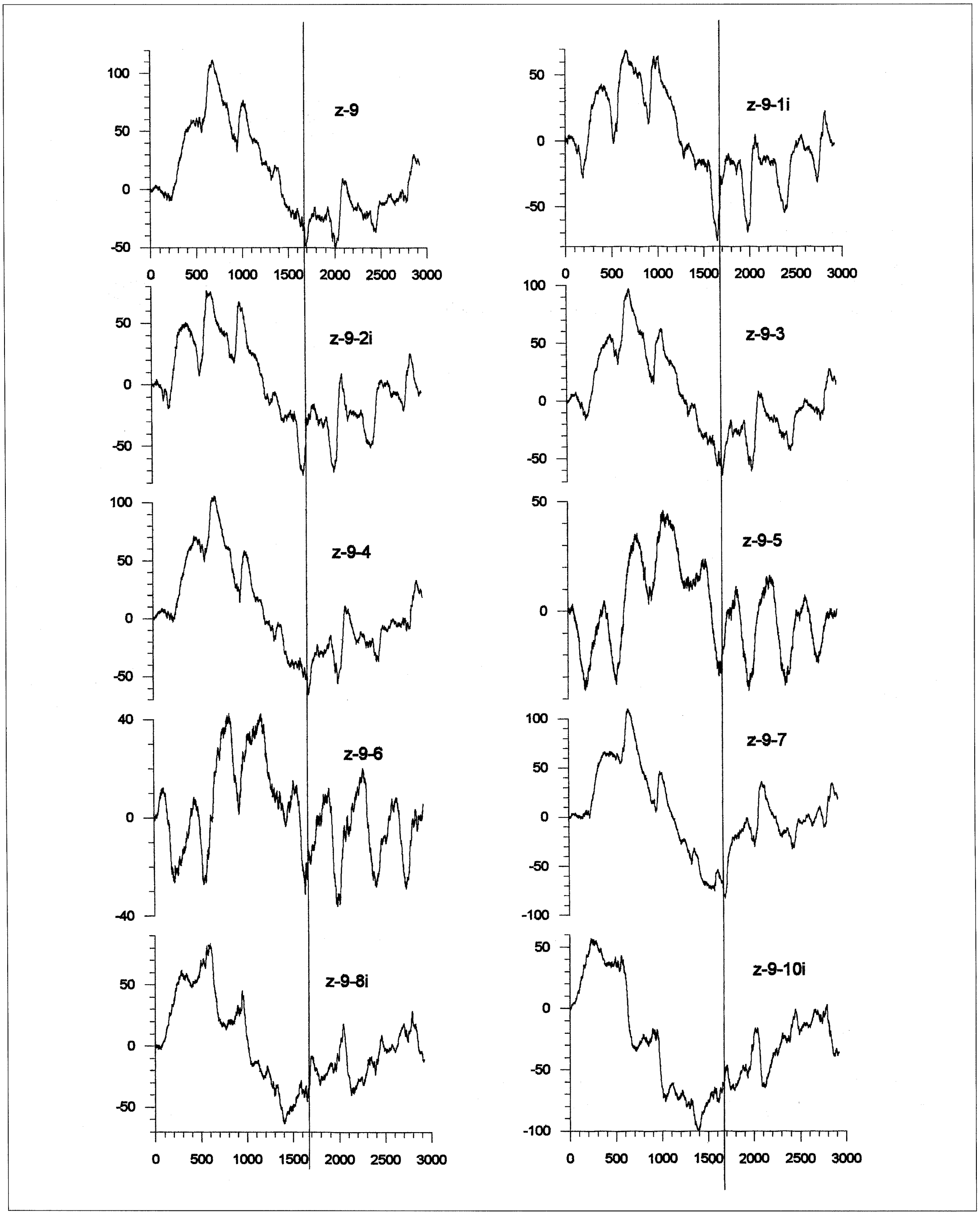

Fig. 5. Different variants of aggregated signals for observations in China. Vertical lines = time moment of Tang-Shan earthquake.

component, which reflects processes of strong earthquake preparation. This component can be extracted using the aggregated signals technique.

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