Chapter 20
Dynamical Changes Induced by Strong Electromagnetic Discharges in Earthquakes' Waiting Time Distribution at the Bishkek Test Area (Central Asia)

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Abstract From 1 August 1983 to 28 March 1990 at the Bishkek electromagnetic (EM) test site (Northern Tien Shan and Chu Valley area, Central Asia), strong currents, up to 2.5 kA, were released at a 4.5 km long electrical (grounded) dipole by discharge of MHD or large batteries. This area is seismically active and a catalogue with about 14100 events from 1975 to 1996 has been analyzed. The seismic catalogue was divided into three parts: the first, 1975–1983, with no EM experiments; the second, 1983–1988, during EM experiments; and the third part, 1988–1996, after the experiments. Qualitative and quantitative time series non linear analysis was applied to waiting times of earthquakes to the above three sub-catalogue periods. Qualitative and quantitative methods used include iterated function systems (IFS), Lempel-Ziv algorithmic complexity measure (LZC), correlation integral calculation, recurrence quantification analysis (RQA), and Tsallis entropy calculation. General features of temporal distribution of earthquakes around the test area reveal properties of dynamics close to low dimensional nonlinearity. Strong EM discharges lead to the increase of extent of regularity in earthquakes' temporal distribution. After cessation of EM experiments, the earthquakes' temporal distribution becomes much more random than before the experiments. To avoid non-valid conclusions, several tests were applied to our data set: differentiation of the time series was applied to check the results that were not affected by non-stationarity, followed by surrogate data approach in order to reject the hypothesis that dynamics belongs to the colored noise type. Small earthquakes, below the completeness threshold, were added to the analysis in order to check the robustness of the results.

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20.1 Introduction

The dynamics of seismic process is far from being clearly understood and modeled; under a multidisciplinary approach during last years, several aspects have arisen showing that seismicity is certainly not a pure random process. Magnitude, waiting time and spatial distribution of earthquakes present features of self-similarity or fractal character, as evidenced by several authors [Turcotte, 1997; De Rubeis *et al.,* 1993]. On the other hand, seismicity cannot be deterministically explained although efforts to show its quasi periodic character have been numerous. A direct consequence of this situation is the almost complete impossibility to precisely predict earthquakes [Main, 1999; Geller *et al*., 1997].

In the last years, nonlinear dynamics has offered several tools to analyze and characterize the seismicity. These qualitative and quantitative tools may help to distinguish between a purely random process and a complicate process driven by a finite, limited set of rules. The enormous gap between "simple" linear deterministic models and random, complicate and strongly unpredictable processes seems to be filled with these new analytical tools. The aim is to render tractable, in a certain way, phenomena and data, otherwise not clearly depicted.

In the present work, the influence of strong EM discharges on earthquakes temporal distribution has been investigated.

Experiments on triggering effect of MHD (magnetohydrodynamic) soundings on the microseismic activity of the region have been performed in 1975–1996 by IVTAN (Institute of High Temperatures of Russian Academy of Sciences) in the Central Asia test area [Tarasov, 1997; Tarasov et al., 1999; Jones, 2001]. During these experiments, deep electrical sounding of the crust was carried out at the Bishkek test site in the years 1983 to 1989. The source of electrical energy was MHD generator, and the load was an electrical dipole of 0.4 Ohm resistance with electrodes located at a distance of 4.5 km from each other. When the generator was fired, the load current was 0.28–2.8 kA, the sounding pulses had durations of 1.7 to 12.1 s, and the energy generated was mostly in the range of 1.2–23.1 MJ [Volykhin et al., 1993].

Evidences of some relationships between EM discharges and seismic activity have been pointed out under a statistical aspect and in a time range of days after EM experiments [Tarasov, 1997]. Here the general dynamical aspect is considered. A good seismic catalogue of the area has been available well before, during and well after this period. A simple causal relationship between the two processes is not clearly evident. Relations appear to be present but the data noise is also relevant. It is useful to investigate if the seismic dynamics, in periods before, during and after EM experiments is influenced by the introduction of strong electric current into the ground.

20.2 Methods

Investigation was performed according to general scheme of time series nonlinear analysis [Abarbanel et al. 1993; Sprott and Rowlands, 1995; Kantz and Schreiber, 1997; Goltz, 1998; Hegger and Kantz, 1999]. In general, data analysis can be performed firstly under a more qualitative and visual approach and successively a more quantitative methodology can be applied.

Qualitative approach includes a visual inspection of the reconstructed phase space. Namely, p-dimensional phase space from the scalar time sequences was reconstructed by the method of time delay [Packard et. al, 1980, Takens, 1981]. According to Takens theorem, it is possible to catch the essential dynamical properties of a system by a reconstruction of its phase space by only one variable. Two- and three-dimensional phase space portraits, encapsulating the essential dynamical properties of the analyzed complex process, were used as qualitative tests. Other qualitative tools have also been used, such as Iterated Function Systems (IFS) [Jeffrey, 1992] and Recurrence Plots (RP) [Eckman et al. 1987].

Generally, the recurrence analysis is a graphical method designed to locate hidden recurring patterns and structure in time series. The recurring pattern (RP) is defined as:

$$R_{i,j} = \Theta(\varepsilon_i - \|\bar{x}_i - \vec{x}_j\|), \tag{20.1}$$

where ε_i is a cut-off distance (often $\varepsilon = 0{\cdot}1\sigma$,with σ the standard deviation), and $\Theta(x)$ is the Heaviside function. According to Eckman et al. (1987), the values one and zero in this matrix are commonly visualized as black and white. The black points indicate the recurrences of the investigated dynamical system revealing their hidden regular and clustering properties. By definition, RP has black main diagonal (line of identity) formed by distances in matrix compared to each other. In order to understand RP it should be stressed that it visualizes distance matrix which represents autocorrelation in the series at all possible time (distance) scales. As far as distances are computed for all possible pairs, elements near the diagonal on the RP plots correspond to short range correlation, whereas the long range correlations are revealed by the points distant from the diagonal. Hence, if the analyzed dynamics (time series) is deterministic (ordered, regular), then the recurrence plot shows short line segments parallel to the main diagonal.

Qualitative patterns of unknown dynamics presented as fine structure of RP are often too difficult to be considered in detail. Therefore, one uses a modern quantitative method of analysis of complex dynamics for RP approach (Recurrence Quantitative Analysis or RQA) [Zbilut and Webber, 1992]. RQA is especially useful to overcome the difficulties often encountered dealing with nonstationary and rather short real data sets. As a quantitative tool of complex dynamics analysis, RQA defines several measures mostly based on diagonally oriented lines in the recurrence plots: recurrence rate, determinism, maximal length of diagonal structures, entropy, trend etc. In the present work, recurrence rate $RR(t)$ and determinism $DET(t)$ measures, based on an analysis of diagonal oriented lines in the recurrence plot, have been calculated [Weber and Zbilut, 1994; Marwan et al., 2002].

Generally speaking, the recurrence rate $RR(t)$ is the ratio of all recurrent states (recurrence points) to all possible states and is therefore the probability of the recurrence of a certain state. Stochastic behavior causes very short diagonals, whereas deterministic behavior causes longer diagonals.

The ratio of recurrence points forming diagonal structures to all recurrence points is called the determinism, $DET(t)$. $DET(t)$ is the proportion of recurrence points forming long diagonal structures consisting of all recurrence points. Again, stochastic and heavily fluctuating data cause none or only short diagonals, whereas deterministic systems cause longer diagonals.

An Iterated Function System (IFS) is an iteration of Hutchinson operator for every finite set of functions in some space which maps a set of points to another set of points. If Hutchinson operator is repeatedly applied to a compact set, in the limit it will render the unique attractor of the IFS [Peitgen et al., 1992]. For the purpose of time series analysis, IFS attractors can be used as a qualitative measure of self similarity of analysed dynamics (the greater the order in time series, the more regular the structures in the IFS attractor). We use the IFS as an additional qualitative tool for detection of hidden structure in the analysed time series [Sprott and Rowlands, 1995].

These tests enable to accomplish first qualitative visual inspection of unknown dynamics and helps to uncover general properties of analyzed process. Qualitative analysis allows revealing possible existence of specific attractors, e.g., strange ones which point to the deterministic chaotic behavior.

Among others, for quantitative analysis of earthquakes dynamics, correlation integral calculation of the reconstructed phase space of temporal distribution has been performed [Abarbanel et al., 1993; Kantz and Schreiber, 1997; Hegger and Kantz, 1999]. This approach is based on the idea of correlation sum. Correlation sum $C(r)$ of set of points in the vector space is defined as the fraction of all possible pairs of points which are closer to each other than a given distance r. The basic formula useful for practical application is

$$C(r) = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} \Theta(r - \|x_i - x_j\|), \tag{20.2}$$

where $\Theta(x)$ is the Heaviside step function, $\Theta(x) = 0$ if $x < 0$ and $\Theta(x) = 1$ if $x \geq 0$, $\|x_i - x_j\|$ is the Euclidian norm, $i = j$ being excluded. For fractal systems, if the time series are long enough and r is small, the $C(r) \propto r^{\nu}$relationship is correct. Commonly, such a dependence is correct only for the restricted range of r values, called the scaling region. Correlation dimension ν or d_2 is defined as

$$\nu = d_2 = \lim_{r \to 0} \frac{\log C(r)}{\log(r)}. \tag{20.3}$$

In practice, d_2 value is found from the slopes of $\log C(r)$ versus $\log r$ curves for different phase space dimensions. The correlation dimension of unknown process is the saturation value of d_2, which does not change by increasing the phase space dimension.

In order to reduce possible spurious conclusions about considered dynamics, noise reduction and surrogate testing methodologies were used [Kantz and Schreiber,1997; Hegger and Kantz, 1999].

The entropy calculation according to Tsallis [1988, 1998] has also been used as a measure of the complexity in earthquakes time distribution

$$S_q = k\frac{1}{q-1}\left(1 - \sum\nolimits_{i=1}^{w} p_i^q\right), \tag{20.4}$$

where p_i are the probabilities of the separate configurations (W) and q is intrinsic parameter with a value greater than zero which demonstrates the correlation between subsystems.

Besides, as an additional quantitative test for relatively short time series, Lempel-Ziv's algorithmic complexity measure (LZC) was calculated [Lempel and Ziv, 1976]. The LZC is based on the transformation of the original one-dimensional time series into a finite symbol sequence and is defined as $C_{LZ} = \lim\limits_{N\to\infty} \sup\frac{L(n)}{N}$, where N is the length of original time series, and $L(N) \sim N_w(N)(\log_b N_W(N) + 1)$ is the total length of encoded sequence, with $N_w(N) \leq N$ being the total number of code words. Being one of the tools for nonlinear analysis of time series, LZC is especially suitable for relatively short real data sets because it is not so demanding as concerns the time series length as other methods [Zhang and Thakor, 1999; Matcharashvili and Janiashvili, 2001].

20.3 Data and Analysis

In the present study nonlinear analysis has been performed on about 14100 time intervals (in seconds) between earthquakes contained in the IVTAN catalogue (1975–1996). In the original catalogue, the energy of the events was expressed as energy class, which we converted to magnitude using the following relation:

$$m = \frac{E-4}{1.8} \tag{20.5}$$

where m is magnitude and E is the energy class.

Completeness of the catalogue was investigated first by considering the realization of the Gutenberg-Richter relationship at low magnitudes: departure from a straight line was interpreted as a lack of completeness at low magnitudes. As a result, the catalogue was considered complete, under the sole magnitude aspect, for $m \geq 1.7$. The Gutenberg-Richter b-value was found to be equal to 0.83 with a reasonably good fit. Earthquakes with magnitude higher than 6 seem to show behavior typical of characteristic events.

A second test was oriented to check the time completeness. As is well known, a catalogue's completeness changes with time, usually as a result of improving seismic-network performance (e.g., by increasing the number of stations), leading to greater magnitude sensitivity. The completeness analysis was performed by employing the method of Mulargia *et al.* (1987). The method consists in separating all events into magnitude classes and plotting separately the cumulative number of events versus time. Assuming that during the considered time interval the seismicity had a constant rate, the flat behavior in the beginning of the time period may be due to a lack of data; this is normal for low-magnitude ranges.

Only for magnitudes higher than 2.0 our catalogue is complete over the entire time period (number of earthquakes $n = 5297$). If a lower magnitude limit is desired, the time period from year 1980 is more appropriate (Fig. 20.1). As a result of the analysis performed, a relatively complete catalogue was obtained with a lower magnitude threshold of 1.7 from the year 1980.

For the present study, the catalogue has been analyzed under the time aspect, specifically on inter-event (waiting) times. The catalogue subset of waiting times was used according to the completeness analysis, i.e., the whole time span and $m>2.0$. Successively, in order to confirm the results and to test their robustness, all data used were selected by the same procedure.

20.4 Results and discussion

In Fig. 20.2, the results of qualitative analysis of waiting times sequences above the mentioned threshold are presented. The results of IFS clumpiness test presented in Fig. 20.2 a, c, e, [Jeffrey, 1992; Sprott and Rowlands, 1995] and the recurrence plot analysis in Fig. 20.2 b, d, f [Zbilut and Webber, 1992] reveal that after the beginning of the experiments some structure in plots is visible, which points to the increased amount of functional interdependence in earthquake temporal distribution.

As to the quantitative approach, the variation of correlation dimension vs. dimension of phase space where the reconstructed dynamics is embedded (embedding dimension) is presented in Fig. 20.3. The integral time series (5297 time intervals) for the whole period of observation (1975-1996) containing time intervals sequences between all events above the threshold reveals clear low correlation dimension ($d_2 = 1.22 \pm 0.43$) (asterisks). Shorter time series were also considered. Namely, 1760 waiting times data before (1975-1983), 1953 waiting times during MHD experiments (1983-1988) and 1584 waiting times of the period after experiments (1988-1992). Time series before and especially during MHD experiments also have low correlation dimension ($d_2 < 5$). Namely, $d_2 = 3.83 \pm 0.80$ before and $d_2 = 1.04 \pm 0.35$ during experiments. On the other hand, in opposite to what was mentioned above, after cessation of experiments (Fig. 20.3, triangles) correlation dimension of waiting times sequences noticeably increases ($d_2 > 5.0$), exceeding low dimensional threshold ($d_2 = 5.0$). This means that after termination of experiments the extent of regularity or extent of determinism in process of earthquake temporal distribution decreases. The considered process becomes much more random both qualitatively (Fig. 20.2. e, f) and quantitatively (Fig. 20.3, triangles). For clarity, results for random number sequence are also shown in Fig. 20.3 (diamonds).

The found low correlation dimension of waiting interval time series is in good accordance with the previously published results for the Caucasus [Matcharashvili,

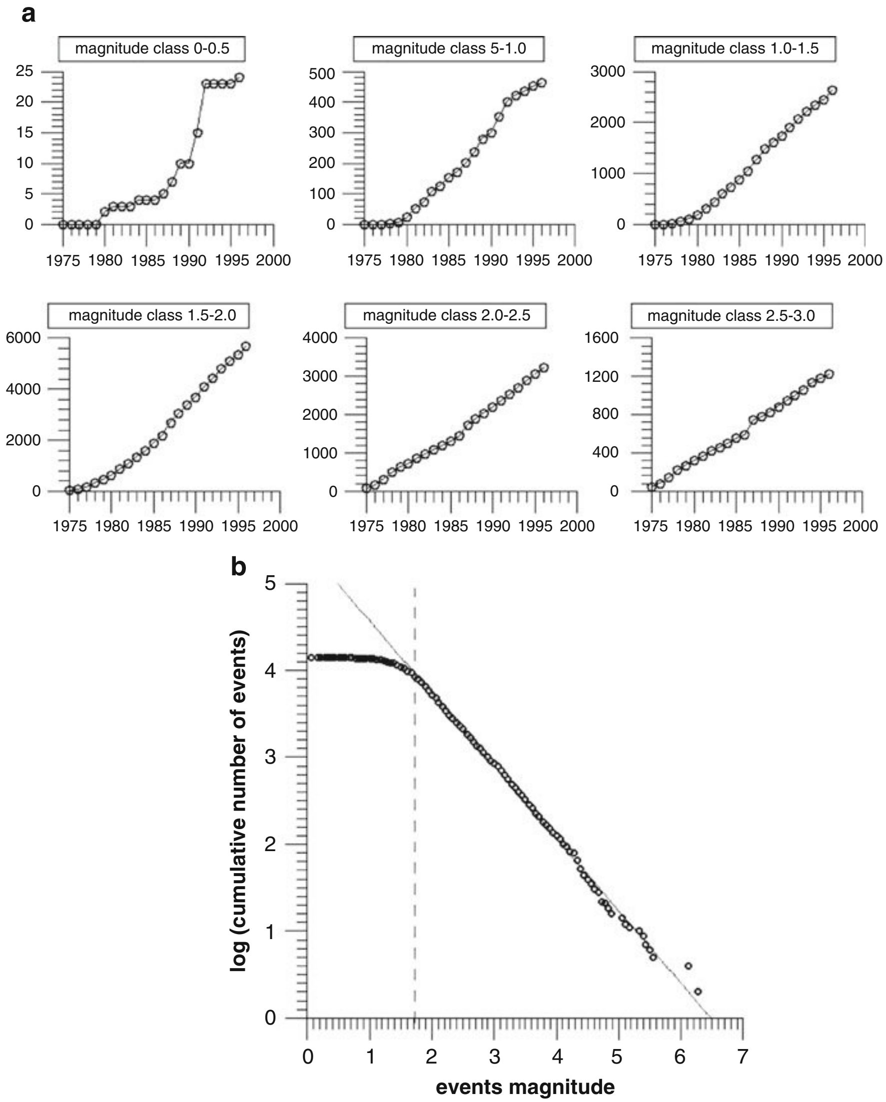


Fig. 20.1 **(a)** Cumulative number of events versus time for magnitude class step = 0.5. Note that cumulative number of events is rescaled among magnitude classes. **(b)** Log cumulative number of earthquake versus magnitude (Gutenberg-Richter relation); values of regression fit the equation $Y = -0.83\times X + 5.40$. Coefficient of determination, R-squared = 0.995

et al., 2000] as well as with the results of Goltz [1998] for other seismoactive regions.

This result together with qualitative analysis results shown in Fig. 20.2, provide evidence that after the beginning of EM discharges the temporal distribution of

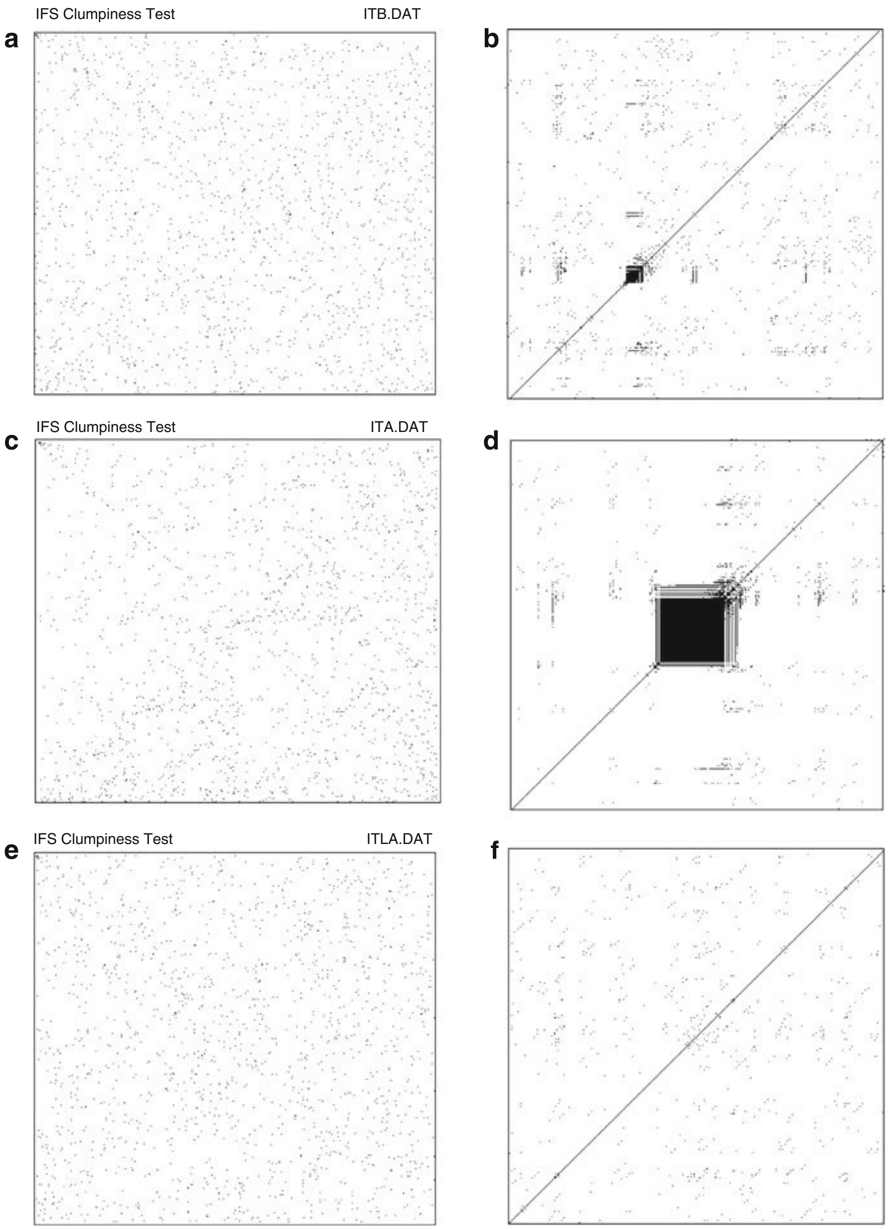


Fig. 20.2 Qualitative analysis of temporal distribution of earthquakes (complete catalogue, $M \geq 1.7$) before the beginning of EM experiments (1975-1983), during experiments (1983-1988) and after accomplishing of experiments (1988-1992). IFS-clumpiness test for inter-event time interval sequences: **(a)** before experiments, **(c)** during experiments, **(e)** after experiments. Recurrence plots analysis of waiting times sequences: **(b)** before experiments, **(d)** during experiments, **(f)** after experiments. Note diagonal lines in IFS plot and compact structure in RP during experiments

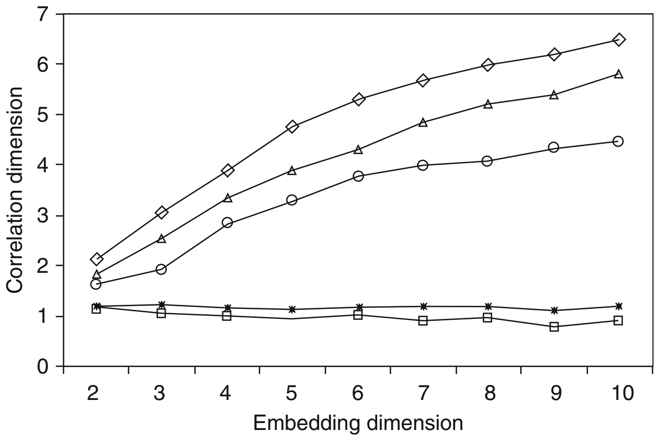


Fig. 20.3 Correlation dimension versus embedding dimension of waiting times sequences (complete catalogue): (a) asterisks–integral time series (1975-1996), (b) circles–before the beginning of experiment (1975-1983), (c) squares–during experiments (1983-1988), (d) triangles–after experiments (1988-1992), (e) diamonds correspond to random number sequence

earthquakes around IVTAN test area becomes more regular, or events of corresponding time series become functionally much more interdependent.

At the same time, the absence of typical phase space structure (not shown here), IFS and recurrence plot attractors (Fig. 20.2) do not allow to consider the process as deterministically chaotic.

In order to reduce effects of possible noises, we analyzed waiting time series after noise reduction procedure [Shreiber, 1993; Kantz and Schreiber, 1997]. Namely, we used methodology of nonlinear noise reduction (which in fact is phase space nonlinear filtering) instead of common linear filtering procedures. The latter, as it is well known, may lead to destroying the original nonlinear structure of analyzed complex processes [Hegger and Kantz, 1999; Schreiber, 2000]. Nonlinear noise reduction relies on the exploration of reconstructed phase space of considered dynamical process instead of frequency information of linear filters [Hegger and Kantz, 1999; Schreiber, 1993; Kantz and Schreiber, 1997].

Correlation dimension vs. embedding space dimension of noise-reduced time series is presented in Fig. 20.4. As follows from the obtained results, correlation dimensions are not essentially affected by unavoidable noises. Therefore, the results assure that the differences found in d_2-phase space dimension (P) dependence before, during, and after experiments (Fig. 20.3) are indeed related to dynamical changes in temporal distribution of earthquakes after the beginning of MHD discharges experiments.

When describing unknown dynamics of waiting times fluctuation, differentiation of original time series can be useful to avoid improper conclusions related to the effects of trends or non-stationarity in data sets, even when those are not clearly visible (as in the case of considered time series) [Goltz, 1998]. As it is shown in Fig. 20.5, differentiation of our time series, according to Goltz [1998], does not lead

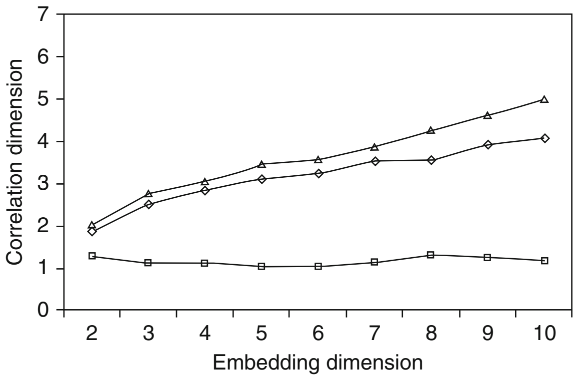
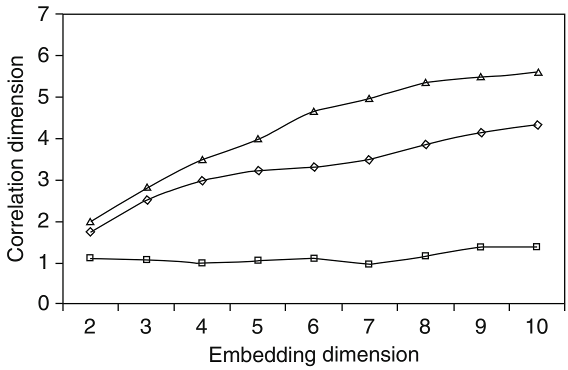


Fig. 20.4 Correlation dimension versus embedding dimension of waiting times sequences (complete catalogue) after noise reduction: (a) diamonds–before experiments, (b) squares–during experiments, (c) triangles–after experiments

Fig. 20.5 Correlation dimension versus embedding dimension of differenced waiting times sequences (complete catalogue). (a) diamonds–before experiments, (b) squares–during experiments, (c) triangles–after experiments



to significant changes of the obtained results (see Fig. 20.3). So our results could not be affected by trends or non-stationarity in the data sets used.

Analysis of differenced time series may be important also in the sense of inherent dynamical structure testing [Prichard et al., 1994]. Namely, the test is based on the finding that estimated nonlinear measure (correlation dimension in our case) for the differentiated series is larger than that estimated for original data, if the structure of their dynamics is caused by a linear stochasticity. At the same time, for chaotic (low dimensional) processes these measures are the same. From this point of view, the analysis of differentiated time series before detailed surrogate testing provides first additional evidence that variation of waiting times has inherent nonlinear structure indeed, and that their dynamical properties are not caused by linear relationships between data. Indeed, curves of Figs. 20.3 and 20.5 are characterized by comparable values of correlation dimension.

Moreover, in order to have a basis for more reasonable rejection of spurious conclusions caused by possible linear correlations in considered data sets, we have used the surrogate data approach to test the null hypothesis that our time series are generated by a linear stochastic process [Theiler et al., 1992; Rapp et al., 1993, 1994; Kantz and Schreiber, 1997]. In other words, we would like to reject reliably the possibility that the revealed dynamics belongs to the colored noise type. Namely, Random Phase (RP) and Gaussian Scaled Random Phase (GSRP) surrogate sets for waiting times series were used [Matcharashvili et al., 2000]. The RP surrogate sets are obtained by destroying the nonlinear structure through randomization of phases of Fourier transform of original time series and then performing a backward transformation. The GSRP surrogate sets were generated in a three-step procedure. At first, a Gaussian set of random numbers was generated, which has the same rank structure as the original time series. After this phase, randomized surrogates of these Gaussian sets were constructed. Finally, the rank structure of original time series was reordered according to the rank structure of the phase randomized Gaussian set (Theiler, 1992).

In Fig. 20.6, the results are shown of surrogate testing of waiting time sequences before (a) and during (b) experiments, using d_2 as a discriminating metric. For each of our data sequences, we have generated 75 of RP and GSRP surrogates. There are several ways to measure difference between the discriminating metric measure of

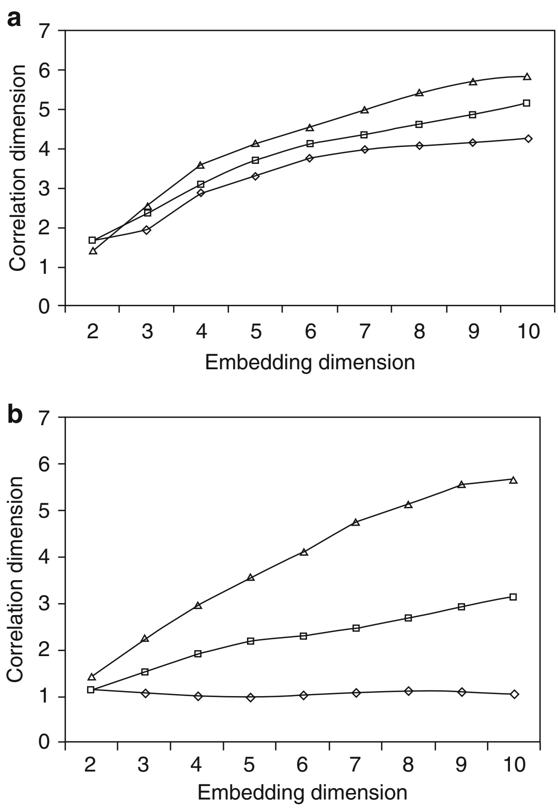


Fig. 20.6 Correlation dimension versus embedding dimension of original (diamonds) and surrogate (squares–GSRP, triangles–RP) waiting time sequences: (**a**) before the beginning of experiments, (**b**) during experiments

original (given by M_{orig}) and surrogate (given by M_{surr}) time series [Rapp, 1994]. Investigators often use the significance criterion $S=|\langle M_{surr} \rangle - M_{orig}|/\sigma_{surr}$, where σ_{surr} is the standard deviation of M_{surr} [Theiler, et al, 1992].

The significance criterion S, according to Theiler et al. [1992], for analyzed time series before experiments is significant: 22.4 ± 0.2 for RP and 5.1 ± 0.7 for GSRP surrogates. Consequently, after the beginning of experiments the null hypothesis that the original time series is a linearly correlated noise was rejected with significant value of S criterion: 39.7 ± 0.8 for RP and 6.0 ±0.5 for GSRP surrogates.

These results can be considered as a strong enough evidence to prove that the analyzed time series are not a linear stochastic noise and that the corresponding processes of earthquakes' temporal distribution before and especially during experiments are characterized by inherent low-dimensional nonlinear structure.

According to the IVTAN catalogue, each considered time period contains one large ($M \approx 6.1$–6.3) earthquake. Therefore, in order to refine whether the above results are caused by special properties of a separate large earthquake or reflect total changes in dynamics caused by EM discharges, we have analyzed waiting time sequences (above the appropriate threshold) after each largest event. Namely, 1000 consecutive waiting time intervals after 03.24.78 $M = 6.1$ ($K = 15.0$), 01.24.87 $M = 6.3$ ($K = 15.3$) and 798 time intervals after 12.30.93 $M = 6.1$ ($K = 15.0$) events were analyzed. It is important to note that each of these relatively short time series is localized in the corresponding time periods named "before", "during" and "after" experiments.

It becomes clear from the results of IFS-clumpiness and RQA analysis (Fig. 20.7) that qualitatively this situation is like that shown in Fig. 20.2, i.e., after the beginning of experiments the dynamics becomes more regular and after accomplishing of experiments the dynamics is most random-like.

Quantitatively, it is shown in Fig. 20.8 that these short time series generally reveal that after the experiments the dynamics has also become more random than before. Some differences are noticeable in saturation values of correlation dimension (in Fig. 20.8) before (circles, $d_2 = 3.1 \pm 0.4$) and during (squares, $d_2 = 2.1 \pm 0.7$) experiments. The latter may be caused by the fact that the data length was too limited for proper nonlinear analysis of these time series (untypical shape of the curve at high embedding dimensions) as well as by artificially increased fraction of aftershocks in short time series, which contains only the events after the largest earthquake.

In any case, our main conclusion about low-dimensional dynamical structure of earthquake temporal distribution during experiments and increasing randomness after termination remains valid even for periods of separate large earthquakes.

The above conclusion about the increase of regularity in earthquakes temporal distribution after beginning of experiments is to some degree also confirmed by results of Lempel and Ziv's algorithmic complexity (C_{LZ}) measure calculation [Lempel and Ziv, 1976]. Indeed, C_{LZ} is larger when the necessary code words are longer, i.e., when regular patterns of analyzed time series are minor.

Indeed, measured values of Lempel-Ziv's complexity before, during, and after experiments for original time series above the threshold are $C_{LZ} = 0.99 \pm 0.07$; $C_{LZ} = 0.87 \pm 0.05$; $C_{LZ} = 1.00 \pm 0.08$, respectively.

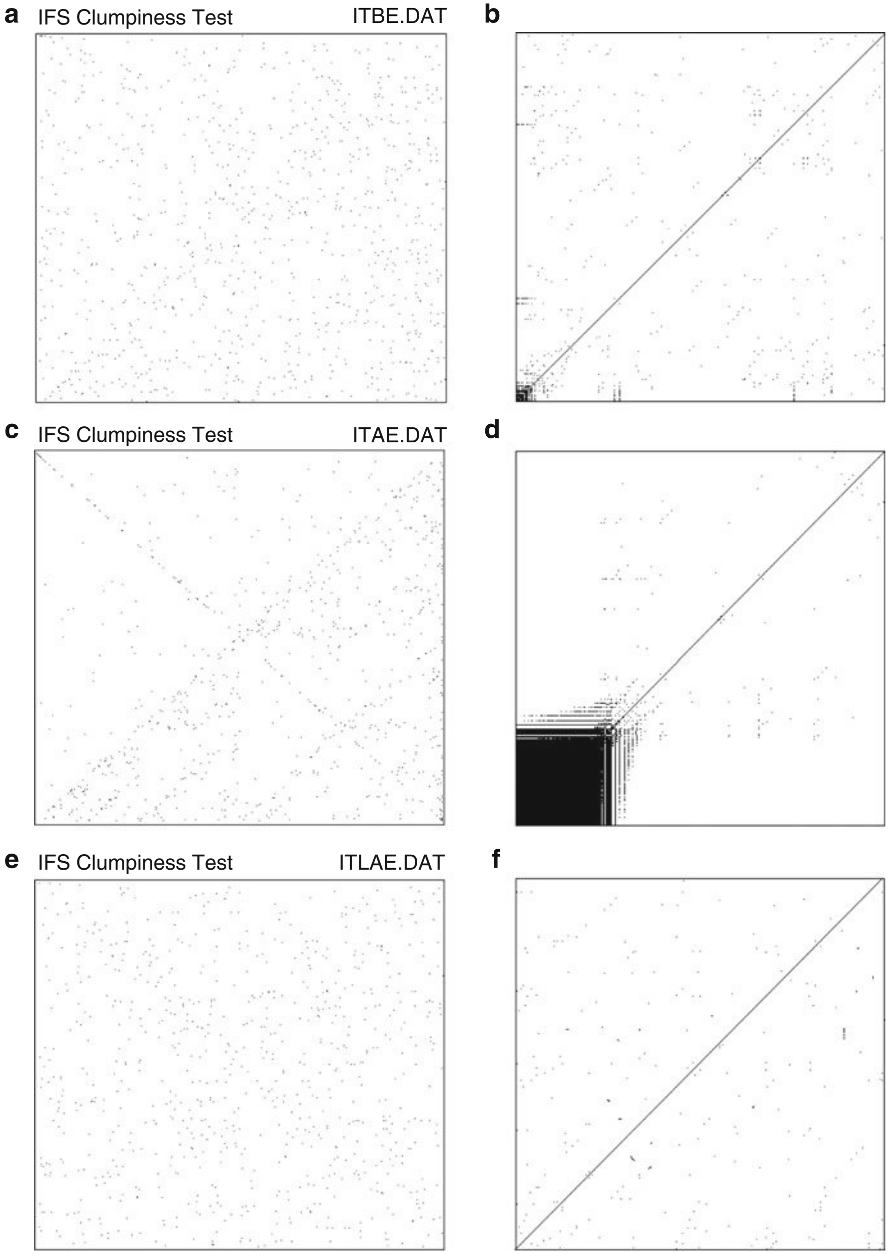


Fig. 20.7 Qualitative analysis of 1000 data waiting times sequences (complete catalogue), after largest events before the beginning of EM experiments (1975-1983), during experiments (1983-1988) and after accomplishing of experiments (1988-1992). IFS-clumpiness test for inter-event time interval sequences: (**a**) before experiments, (**c**) during experiments, (**e**) after experiments. Recurrence plots analysis of waiting times sequences: (**b**) before experiments, (**d**) during experiments, (**f**) after experiments

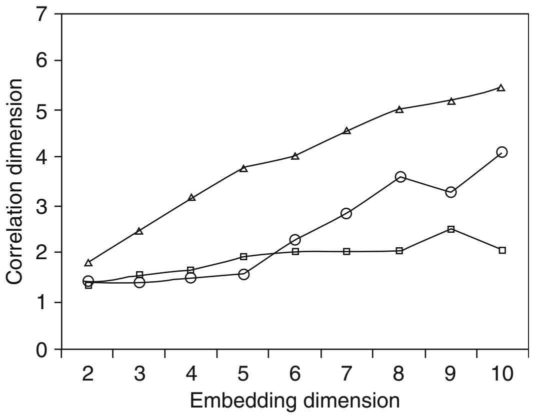


Fig. 20.8 Correlation dimension versus embedding dimension of 1000 data waiting times sequences (complete catalogue) after largest events: (a) circles–time period before beginning of experiments (1975-1983), (b) squares–time period during experiments (1983-1988), (c) triangles–time period after accomplishing of experiments (1988-1992).

The same conclusion follows also from quantitative RQA results; namely $RR(t) = 9.6$, $DET(t) = 3.9$ before the experiments, $RR(t) = 25$, $DET(t) = 18$ during, and $RR(t) = 3$, $DET(t) = 1.5$ after the experiments.

The increasing order in earthquake temporal distribution under the influence of EM is confirmed for short time interval sequences above the threshold after the largest earthquakes. Indeed, Lempel-Ziv's complexity measure values were: $C_{LZ} = 0.98 \pm 0.08$; $C_{LZ} = 0.74 \pm 0.05$; $C_{LZ} = 1.00 \pm 0.09$ before, during, and after MHD runs, respectively (note that $C_{LZ} = 0.04$ for periodic and $C_{LZ} = 1$ for random processes). Also, the increasing order in temporal distribution is documented by RQA results for the above-mentioned short time series; namely $RR(t) = 9.8$, $DET(t) = 6.5$ before the experiments, $RR(t) = 19.5$, $DET(t) = 49.3$ during, and $RR(t) = 7.1$, $DET(t) = 1.6$ after the experiments.

In other words, for the situation where the shape of d_2 (Fig. 20.8) is not informative for finding changes in dynamics, possibly due to too short time series, Lempel- Ziv and RQA analysis reveals the increase of regularity. The conclusion from Tsallis entropy calculation is the same. As it is shown in Fig. 20.10, normalized to the averaged S value calculated for randomized data sets, the entropy decreases for time series 2, i.e., the extent of regularity in the earthquake temporal distribution increased during MHD runs.

On the basis of results of previous research it is known that small earthquakes play a very important role in general dynamics of earthquake temporal distribution [Matcharashvili et al., 2000]. Therefore, we have additionally carried out an analysis of time series containing all the waiting time sequences available from the whole catalogue, including those between small earthquakes below the magnitude threshold. This test is also valid for checking the robustness of results in case of adding a new, not necessarily complete set of data to our original set. The total number of events in the whole catalogue increased up to 14100, while in the complete catalogue for the three above-mentioned periods (before, during and after MHD experiments) there were about 4000 data in each one.

The results of IFS and recurrence plots tests of these time series are shown in Fig. 20.9. Noticeable qualitative differences in waiting time distribution dynamics during, as well as after accomplishment of experiments is obvious.

The results of correlation dimension calculation for these time series are presented in Fig. 20.11. Practically, there are no differences from results obtained for the case with $m > 2.0$ (Fig. 20.3). Namely, according to Fig. 20.11, integral time series (14100 time intervals) for the whole period of observation (1975–1996) reveals a clear low correlation dimension ($d_2 = 2.40 \pm 0.71$) (diamonds). Time series before the beginning of experiment (squares) is characterized by correlation dimension $d_2 = 3.50 \pm 0.63$ which still is below the accepted low dimensional threshold ($d_2 = 5.0$). During experiments (Fig. 20.11, triangles), the correlation dimension of time interval sequence decreases noticeably ($d_2 = 1.71 \pm 0.09$) as compared to the situation before. After termination of experiments, the correlation dimension of waiting time interval sequences increases noticably ($d_2 > 5.0$), exceeding low dimensional threshold ($d_2 = 5.0$). As in the case of complete catalogue, this means that after termination of experiments the extent of determinism in process of earthquake temporal distribution decreases. The considered process becomes much more random, both qualitatively (Fig. 20.9. c, f), and quantitatively (Fig. 20.11 circles).

Both the complete and whole catalogues of waiting time sequences reveal low-dimensional nonlinear structure in temporal distribution of earthquakes before and especially during experiments, which was confirmed by 70 surrogate testing analyses (Fig. 20.12). The significance criterion S for analyzed time series before the experiments gives: 32.3 ± 0.2 for RP and 5.3 ± 0.6 for GSRP surrogates; consequently, after the beginning of experiments the null hypothesis that the original time series is a linearly correlated noise was rejected with significant value of S criterion: 46.2 ± 0.5 for RP and 6.5 ± 0.7 for GSRP surrogates.

The correlation dimension vs. embedding space dimension of noise-reduced time series of the whole catalogue is presented in Fig. 20.13. It is clear from this picture that calculated values of correlation dimension are not affected by noises as for the complete catalogue. The results show that the differences found in the d_2-phase space dimension (P) relationship before and during experiments in both catalogues are indeed caused by dynamical changes in temporal distribution of earthquakes during EM experiments.

We also analyzed waiting time sequences after each largest ($M \approx 6.1$–6.3) event for the whole catalogue, namely, 1000 consecutive waiting time sequences after 03.24.78 $M = 6.1$ ($K = 15.0$), 01.24.87 $M = 6.3$ ($K = 15.3$) and 12.30.93 $M = 6.1$ ($K = 15.0$) events. As it is shown in Fig. 20.14, these short time series generally reveal dynamical characteristics similar to those of the time series obtained from the complete catalogue. The differences which are noticeable in saturation values of correlation dimension before (circles, $d_2 = 2.0 \pm 1.1$ in Fig. 20.14) and during (squares, $d_2 = 3.2 \pm 0.8$, Fig. 20.14) experiments may be caused both by the shortness of these time series or by the influence of increased fraction of aftershocks.

Thus, conclusions concerning the influence of hot and cold EM runs on general characteristics of the dynamics of earthquakes' temporal distribution remain valid for small earthquakes too.

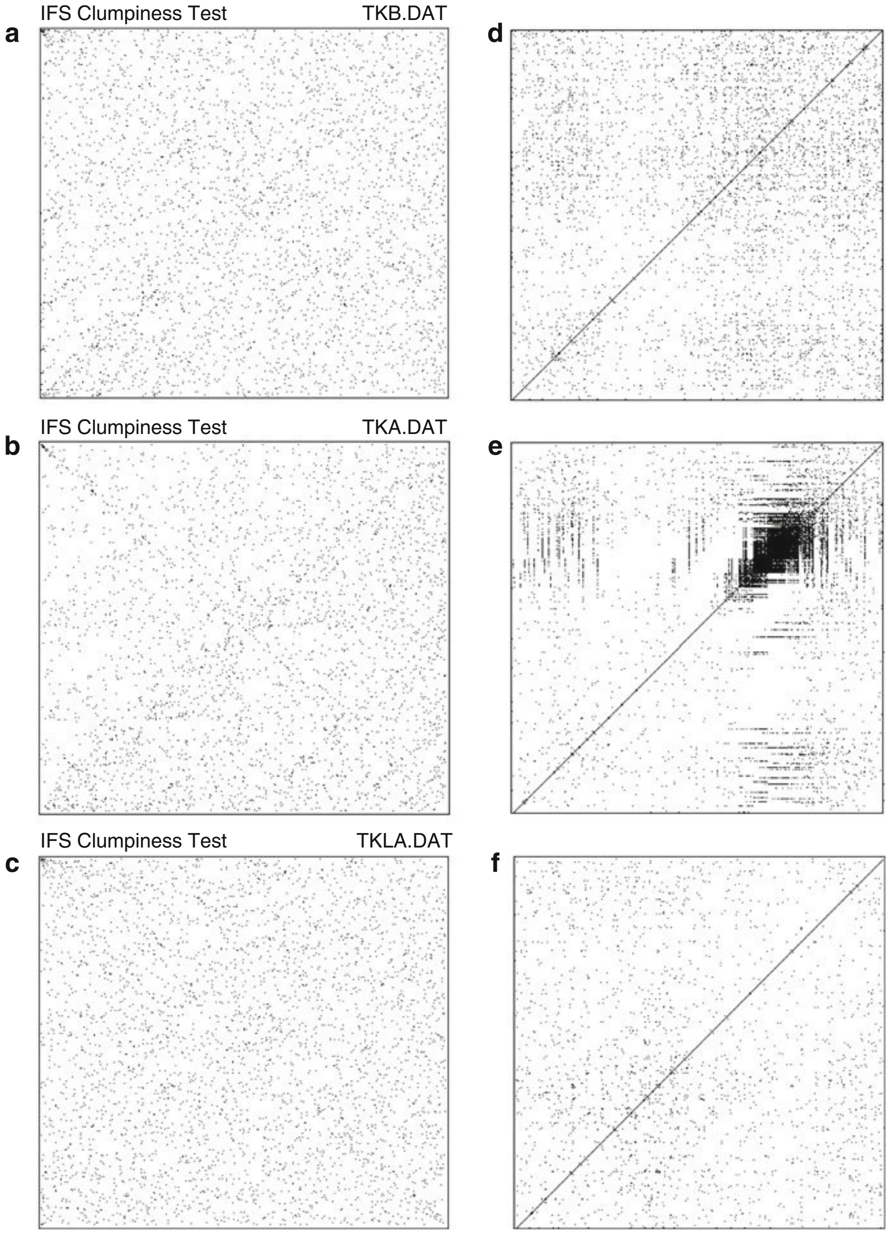


Fig. 20.9 Qualitative analysis of temporal distribution of earthquakes including small events (whole catalogue, all events) before the beginning of EM experiments (1975-1983), during experiments (1983-1988) and after accomplishing of experiments (1988-1992). IFS-clumpiness test for waiting times sequences: (**a**) before experiments, (**c**) during experiments, (**e**) after experiments. Recurrence plots analysis of inter-event time interval sequences: (**b**) before experiments, (**d**) during experiments, (**f**) after experiments

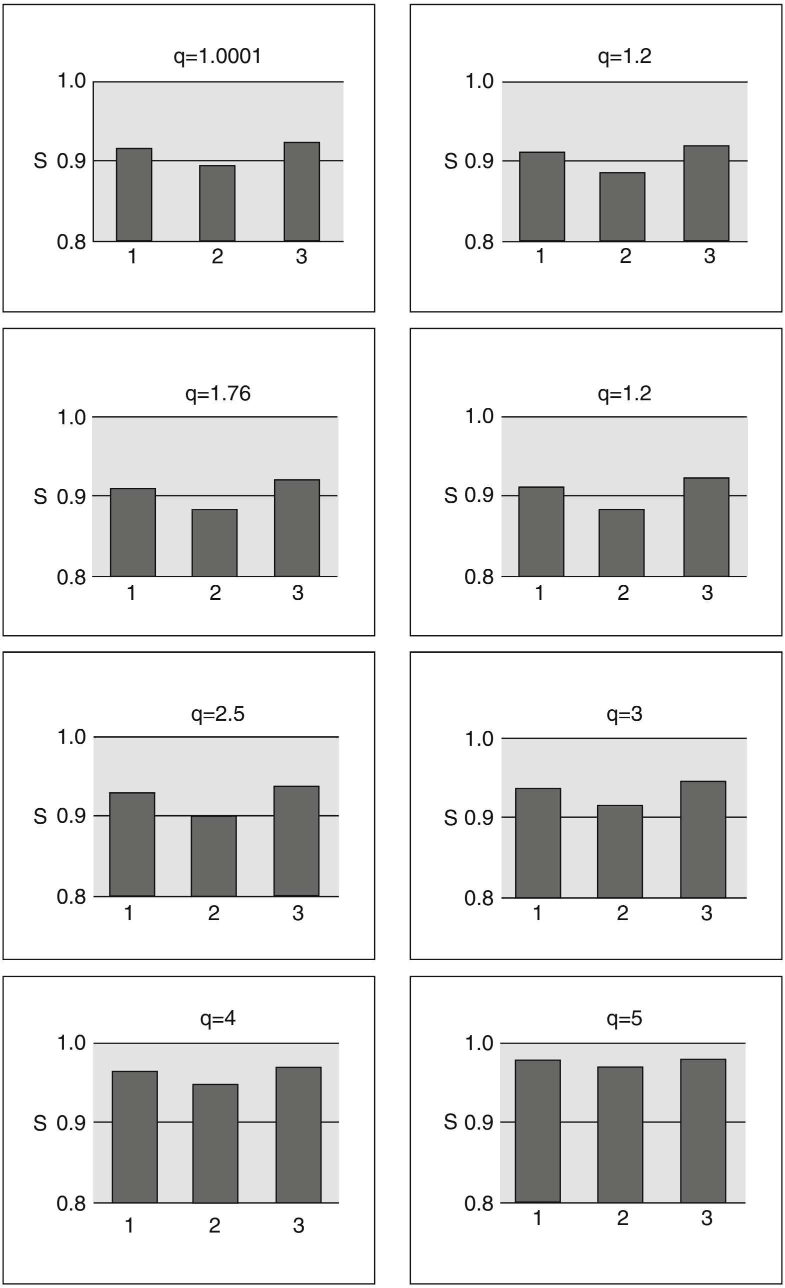


Fig. 20.10 The Tsallis entropies calculated for 3 windows (1–before, 2–during and 3–after MHD runs) for various entropic indexes q

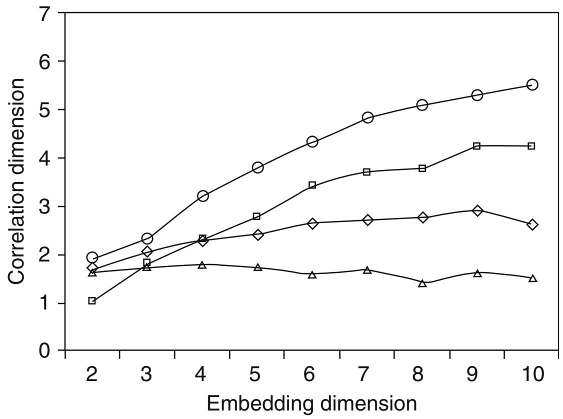


Fig. 20.11 Correlation dimension versus embedding dimension of waiting times sequences of the whole catalogue:
(a) diamonds–integral time series (1975-1996),
(b) squares–before the beginning of experiment (1975-1983),
(c) triangles–during experiments (1983-1988),
(d) circles–after experiments (1988-1992)

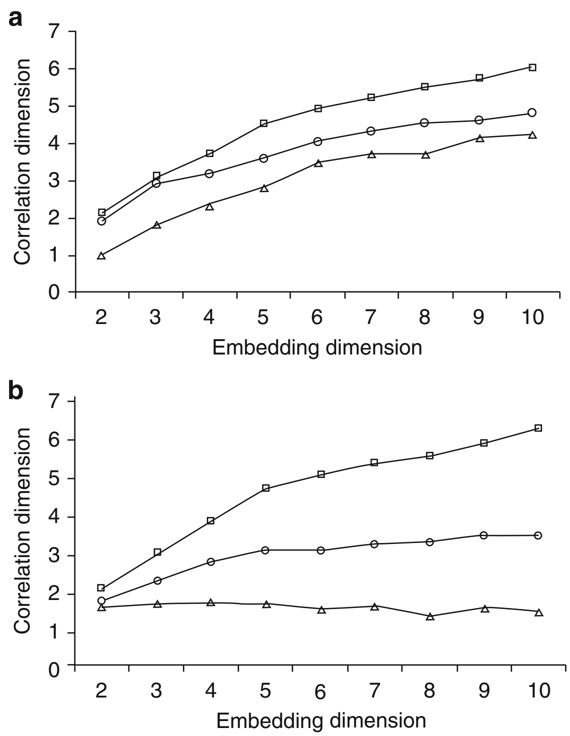


Fig. 20.12 Correlation dimension versus embedding dimension of original waiting time sequences of whole catalogue (triangles) and their surrogates (circles–GSRP, squares–RP): (**a**) before the beginning of experiments, (**b**) during experiments

It is interesting to note that on the laboratory scale the effect of triggering and synchronization of acoustic emission during a slip imposed by strong EM field is well documented in numerous experiments [Chelidze et al, 2002; Chelidze and Lursmanashvili 2003; Chelidze et al, 2005].

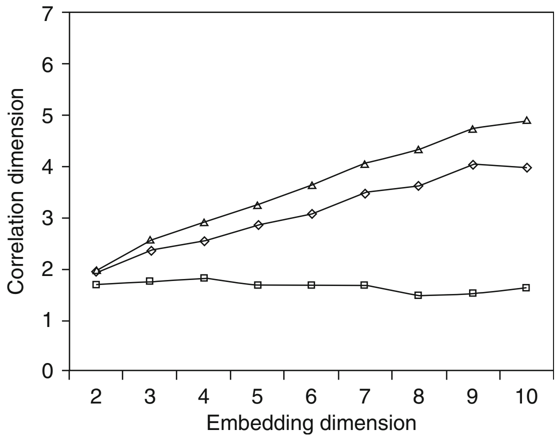


Fig. 20.13 Correlation dimension versus embedding dimension of inter-event time interval sequences of whole catalogue after noise reduction:
(a) diamonds–before experiments,
(b) squares–during experiments.
(c) triangles–after experiments

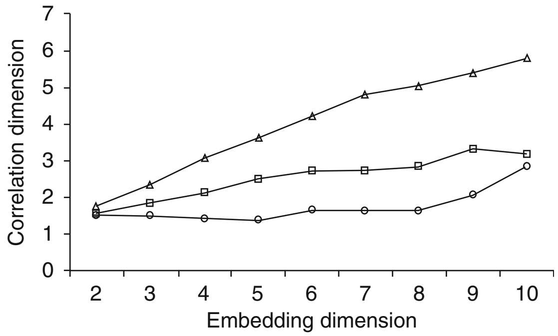


Fig. 20.14 Correlation dimension versus embedding dimension of 1000 data waiting times sequences of the whole catalogue after largest events: (a) circles–time period before the beginning of experiments (1975-1983), (b) squares–time period during experiments (1983-1988), (c) triangles–time period after accomplishing of experiments (1988-1992)

20.5 Conclusion

The question whether electromagnetic experiments on a specific site can influence the dynamics of a seismic region is complex. A complete answer to it, if any could be given, would involve a repeated set of analyses for different seismic regions over a long period of time with and without EM experiments. A theoretical explanation showing the cause-and-effect relationships between the two phenomena is also fundamental. This paper has addressed the question under statistical aspect involving nonlinear dynamics methods. These methods have been chosen because there are not trivial, simple and direct relations between the two phenomena: this means that relations are of complicated nature. Moreover, seismicity is very probably a critical process with a *per se* complicate evolution: under given conditions, possible relations must not be direct and simple. With nonlinear methods, the time evolution of seismicity has been investigated looking at relations with EM experiments. Waiting times constitute the aspect analyzed. The whole time period has been divided into three parts, the middle being the one when EM experiments took place.

The phase space attractor, reconstructed with delay time technique, shows low correlation dimension values for the whole time period; this indicates, at least, the presence of few seismicity-driving processes. The same analysis on the three sub-catalogues confirms the result, with the exception for the period after the EM experiments: strong EM discharges lead to the increase of extent of regularity in earthquakes temporal distribution, while after the EM influence ceases, the earthquakes' temporal distribution becomes much more random than before the experiments. This is the main result of the analysis and it has been confirmed by changing the conditions of the analysis itself. Non-linear noise reduced time series has confirmed such results, as also surrogate testing did. The middle period contains a large seismic event (January 24, 1987 $M = 6.3$ derived from energy class $K = 15.3$); this event has certainly a well-identified aftershocks activity and this can be a strong factor influencing the time dynamics. The root question is: is this event with its related sequence responsible of the change of the dynamics of analyzed data? If the answer would be yes we are forced to answer immediately the new question: is this earthquake related to the EM experiments? But it must be noted that inside the other two periods there are also important events of comparable magnitudes and the analysis has been conducted on the three sequences of catalogue after each strong event separately. General confirmation of results has been shown. Same results have been revealed with the use of the whole catalogue, regardless of the completeness criteria.

This analysis is certainly not exhaustive: the seismic catalogue covers a broad area and all complete data were used, with no distinction for space location of seismic events. The energy aspect has not been fully considered: all events were considered equal, regardless of their magnitude. These are strong simplifications and the results must be considered under these constrains. However, the results appear to be consistent: EM experiments influence seismic time dynamics to some extent, increasing the regularity of waiting times. After the EM experiments, seismic waiting times have increased their random character to a level higher than before experiments.

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