TIME SERIES ANALYSIS: DYNAMICAL EVOLUTION OF SPECTRAL, DETERMINISTIC AND STOCHASTIC PARAMETERS FOR THE CHARACTERIZATION OF VOLCANIC ACTIVITY

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Contents

Summary

A volcano can be considered as a dynamical system, and each time series recorded at a volcano can be interpreted as one of its observables. It is therefore theoretically possible to extract, from a single time series, information about the underlying governing system. This is done through a procedure called "embedding" that is based on the intuitive statement that the only time series available carries with it information also about the time evolution of other parameters that we are not able to sample or observe. Carrying out this embedding procedure requires estimates of key parameters such as the optimal delay time and a proper embedding dimension.

Another independent, but conceptually similar procedure makes use of the Singular Spectral Analysis or Singular Value Decomposition. These and other related approaches can be used to conduct a data reduction phase, which condenses the amount of data to be analyzed and processed, while retaining the most of the information content. The resulting reduced data stream can be used for a number of purposes, such as characterizing different volcanic regimes, examining their relationship with external or internal events such as tectonic or volcano-tectonic seismic events, looking for precursors of paroxysmal eruptive phases etc. In this chapter the existing literature on this subject will be reviewed, and the prospects of future research will be discussed.

1. Introduction

Forecasting is a key issue in volcanology, both from the pure research point of view (e.g. for the validation of a model of a given phenomenon) and from the more practical point of view of civil defense (e.g. to reduce the potential impact of an eruption on society). Volcanic risk can, as any other (natural) risk (UNDRO, 1979), be separated into three factors, i.e. hazard, vulnerability and exposure. Hazard can be defined as the probability of occurrence of a potentially damaging event in a given temporal and spatial window. The vulnerability is then the extent to which a given object can suffer damage from this event. Finally, our estimate of the value of such element at risk leads us to the concept of exposure. The combination of these three factors is the risk, which measures the expected number of lives lost, persons injured, damage to property or disruption of economic activity due to a given (volcanic) event. While vulnerability to volcanic events can be hopefully reduced, volcanic hazard cannot in general be mitigated, and forecasts of volcanic hazards are, therefore, an essential input for risk assessment.

Very different time scales can be taken into account while evaluating volcanic hazard, spanning from minutes to thousands of years. We can assess volcanic hazards at short term (minutes to weeks), e.g. to study the evolution of an ongoing eruption or to plan safe touristic visits to a crater, at mid term (months to years), e.g. to monitor a volcano in order to detect the first signs of an upcoming eruption, or at long term (few years to hundreds of thousands of years), e.g. to choose a site suitable for a nuclear waste repository (Carniel et al., 2008b).

Although in principle any (geophysical) time series recorded on a volcano - e.g. geomagnetic and electromagnetic (Currenti et al., 2005; Hayakawa et al., 2009) or thermal (Harris et al., 2005; Marchese et al., 2006; Lovallo et al., 2007) - can be used with the methods described here, the continuous seismic noise, together with classical “discrete” seismicity, is recognized as the one with the widest application and one of the most informative (Carniel et al., 2008a). This “seismic noise”, while approaching an eruptive phase, usually shows a growing self-organization as it transforms into what is more properly called “volcanic tremor”, that has been recognized as extremely information-rich already about 40 years ago (Schick and Riuscetti, 1973).

Hints on which time series to choose for each time scale can also come from their persistence, which can be estimated with geostatistical tools (Jaquet and Carniel, 2001) also in a multivariate sense (Jaquet and Carniel, 2003). The variogram (Jaquet and Carniel, 2001) is in fact aimed at recognizing the “memory” of the system generating a given experimental time series and/or its variations with time. A time series that does not keep memory of its past cannot, in fact, provide information about the future of the evolving volcanic process, i.e. it cannot help to forecast an eruption. The geostatistical approach aims to identify this memory, if it exists, quantify its duration and exploit its potential in forecasting; this approach can be applied not only in the time but also in the space domain, in which these techniques were originally developed (Matheron, 1962). Such tools constitute therefore a powerful approach to the forecasting of volcanic eruptions, especially at medium–long term, based on a probabilistic formalism (Sparks, 2003). A statistical analysis of e.g. seismic activity, if combined with suitable modeling, can provide also interesting insights into the details of physical processes within the magma column (Bottiglieri et al., 2005; De Martino et al., 2011; Jaquet et al., 2006). The perspectives offered by the application of (geo)statistical models to volcanology were recently reviewed by Carniel et al., 2008b. In this review chapter we will therefore focus more on the deterministic approach. It is worthwhile to underline that the two approaches are not mutually exclusive and can on the contrary profit from a mutual integration.

2. Data Reduction

For each time scale, several independent approaches can be followed while analyzing even the very same raw geophysical data, as different parameters can show complementary information (Carniel and Tarraga, 2006). The single methodologies constitute therefore a first “data reduction” stage aimed at generating the inputs for a final evaluation stage. The basic idea is that we want to extract, from one or more experimental time series, the most significant information while maintaining a very limited set of parameters. These can be then computed in separate time windows and their time evolution investigated individually to identify the existence of specific regimes, precursors, etc. These data reduction methodologies can include classical (but still powerful!) evaluations of intensity and energy that can be then used for forecasts based e.g. on the Failure Forecast Method (FFM) concept (Voight, 1988). The idea is simply to integrate some positive quantity of the time series along each time window. This quantity can be for instance the absolute value of the amplitude of the signal; this choice produces a (seismic) intensity, which is known also as RSAM – Realtime Seismic Amplitude Measurement (Endo and Murray, 1991). On the other side, the squared value of the amplitude can be taken, producing the so called RSEM – Realtime Seismic Energy Measurement. Alternatively, some spectral-filtered versions of these quantities can be computed, defining what is called SSAM - Spectral Seismic Amplitude Measurement (Rogers and Stephens, 1995) or SSEM - Spectral Seismic Energy Measurement respectively.

Power law accelerations in the mean rate of strain, earthquakes, tremor and other precursors have been widely reported prior to volcanic eruptions as predicted by several theoretical models. The FFM linearizes this power law trend and has been used in both hindcasts and forecasts (Tarraga et al., 2006; Tarraga et al., 2008a). More recently, Bell et al. (2011) have suggested that a Generalized Linear Model (GLM) method - a generalization of least squares linear regression which can account for a non-Gaussian distribution of errors from the mean (e.g. Poisson) and for a functional relation (e.g. power law) between the mean of the distribution and a basic linear model - could provide higher quality forecasts that converge more accurately to the eventual failure time.

Hammer and Ohrnberger (2012) also claim to find better predictions of volcanic activity with respect to FFM by following a different approach, namely modeling the earthquake rate as a random walk process embedded in a potential function linked to the moving average of the random walk's trace. Other methods are based on classification heuristics such as the ones derived from the artificial neural networks (Lippmann, 1987) domain (e.g. Falsaperla et al., 1996; Carniel, 2005; Langer et al. 2006).

Finally, the combination of the results provided by these different approaches, which can be carried out with a Bayesian approach (Aspinall et al., 2003), with Markov models (Aspinall et al., 2006; Beyreuther et al., 2008), event trees (Newhall and Hoblitt, 2002; Marzocchi et al., 2006) or event bushes (Pshenichny et al., 2009), is a noteworthy problem on its own. Actually, the combination of the different, possibly even contradicting, results is as important as the methods used to generate them, but we will not investigate in detail this issue here.

3. Spectral Parameters

Spectral analysis remains at the core of any processing of a (set of) time series. Fast Fourier Transforms (FFT) and their variations (e.g. Welch, 1967; Elliot and Rao, 1982) provide methods to determine the importance of each single frequency or frequency band in the construction of a given signal. The FFT assumes a stationarity of the signal and provides therefore information that describes the time series in its entirety, eliminating any time evolution in its frequency content. This assumption is neither appropriate nor very useful, and the classical solution is to divide our signal into time windows of suitable duration, compute the spectrum for each, and examine how the frequency content changes with time, building what is known as a *spectrogram*. This presents a paradox, as we are computing spectra (assuming stationarity) and then studying their time evolution (negating the same stationarity assumed before), a paradox however that nobody would abandon because it is a simple and powerful tool, although a theoretically questionable one. The way of presenting the resulting information is not unique, and has also evolved with the years exploiting newly available graphical visualization possibilities. We can stack each spectrum to build a 3D-like figure (e.g. Carniel et al., 1996), present a 2D-like figure using contour lines (e.g. Carniel and Iacop, 1996) or a now more classical color spectrogram (e.g. Carniel et al., 2006a), which is basically a matrix where horizontal and vertical coordinates represent time and frequency respectively (although not necessarily in this order) and the amplitude of each element of the matrix is somehow color-coded using a given color map. Although the information presented is the same in all these cases, transitions between different regimes potentially at very different time scales (e.g. Ripepe et al., 2002; Harris et al., 2005; Carniel et al., 2003) can be made more evident by choosing the right presentation. In this respect, the type of normalization used is of uttermost importance to determine if a change will be visible or not. Spectrograms can in fact be normalized using all the values in the matrix at once, clearly highlighting amplitude variations but often masking variations in low-amplitude time windows if one time windows has much greater amplitude than the others. An alternative is to normalize the spectrogram independently in each time window. This choice completely throws away any information about the amplitude time variations – which have therefore to be presented in another graph, e.g. using the already cited RSAM derived parameters – but often highlights much better the possible subtle time evolution of the *relative* importance of different frequency bands.

Related to the spectral analysis, other techniques aim to characterize the system with a few but most significant spectral parameters. In other words, instead of (re)presenting the full spectrogram, one reduces each column to one or more scalar parameters. Time evolution of the frequency content can be then analyzed e.g. by computing only three scalar parameters (dominant frequency, average frequency and spectrum standard deviation), derived from the normalized spectrogram over time windows of suitable duration, as proposed e.g. by Carniel and Di Cecca (1999). The normalization is carried out in order to look at the relative energy distribution within this frequency range and not at the absolute values. The dominant frequency is the central frequency of the spectrogram bin where the maximum is found in a given time window. The average frequency is computed by weighting the central frequency of each bin by its relative value, so that it represents the barycenter of the spectral distribution. Finally, the spectrum standard deviation measures how disperse the spectrum is in each time window. Moving averages of the resulting time evolution can also be carried out in order to smooth the graphs.

Other spectral techniques aimed at highlighting the appearance of "unusual" frequencies are being included in routine seismic noise analyses of volcanic seismic signals (Arambula-Mendoza et al., 2011), such as the minimum spectrum, proposed by Vila et al. (2006). The Base Level Noise Seismic Spectrum (BLNSS), or simply minimum spectrum, was initially proposed to monitor the health of instrumentation and to observe correlation between seismic noise and seasonal conditions but was then retuned as a tool for the analysis of volcanic activity (Vila et al., 2006). The method consists in comparing the amplitude of all spectral components of a series of spectra obtained from contiguous segments of data. By selecting the minimum value for each frequency, a new spectrum is constructed in which transient signals are eliminated if the calculation is carried out long enough. This 'minimum' spectrum represents the normal background seismicity spectrum acquired with a healthy instrument or network. Deviations from this minimum spectrum, with the appearance of higher weights at given frequencies, can indicate either a problem in the acquisition system or a change in the natural dynamical regime, e.g. a volcanic unrest.

In the following sections, we will concentrate on the data reduction techniques based on the deterministic approach, the theory of non linear dynamical systems (e.g. Carniel and Di Cecca, 1999) and the embedding (Packard et al., 1980), and we will use in most of the cases the volcanic tremor to illustrate the application of the methodologies to a series of case studies taken from the recent literature.

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The results indicate that the proposed nonlinear approach can be used to dynamically characterize the volcanic phenomena and to recognize possible pre-eruptive temporal patterns]

Marchese, F., N. Pergola and L. Telesca, (2006). Investigating the temporal fluctuations in satellite advanced very high resolution radiometer thermal signals measured in the volcanic area of Etna (Italy), *Fluctuation Noise Lett*., 6, L305-L316 [The temporal fluctuations of the thermal signal detected by RST over a long series (1995-2005) of Advanced Very High Resolution Radiometer (AVHRR) satellite data, have been characterized by means of the correlation function and the power spectrum analysis, showing the presence of correlation structures in the thermal time series recorded in the crater area]

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Matheron, G. (1962). *Traité de géostatistique appliquée*. Tome 1, Editions Technip, Paris, 334 pp. [George Matheron is the father of spatial statistics. In this book he presents his first results on regionalized random variables]

Mineva A, Popivanov D., (1996). Method for single-trial readiness potential identification, based on singular spectrum analysis. *J Neurosci Method* 68,91–9. [The advantages of the singular spectrum analysis (SSA) for short and noisy time series are presented. The case study is the analysis of EEG activity after the onset of a voluntary motor act, aiming to distinguish different dynamical stages of the movement preparatory process].

Newhall, C.G. and Hoblitt, R. P. (2002). Constructing event trees for volcanic crises. *Bull Volcanol* (2002) 64:3–20, DOI 10.1007/s004450100173 [Event trees allow to discuss probabilities – empirical or mathematically estimated - of the outcomes of volcanic unrest. Their use during volcanic crises can help a critical analysis of volcanic hazard and its comparison with more familiar risks]

Packard, N.H., Crutchfield, J.P., Farmer, J.D. and Shaw, R.S., (1980). Geometry from a time series. *Phys. Rev. Lett*., 45, 9: 712-716. [A milestone of the dynamical analysis of time series. The proposed embedding techniques are applied to problems of turbulent fluid flows as case studies]

Pshenichny, C.A., S.I. Nikolenko, R. Carniel, P.A. Vaganov, Z.V. Khrabrykh, V.P. Moukhachov, V.L. Akimova-Shterkhun, A.A. Rezyapkin, (2009). The event bush as a semantic-based numerical approach to natural hazard assessment (exemplified by volcanology), *Computers & Geosciences*, 35, 5, 1017-1034 [The event bush is a formalism for organizing knowledge in the geosciences, particularly for hazard assessment. The paper presents basic principles, guidelines for application and examples, including the connection with Bayesian Belief Networks]

Ripepe, M., Harris, A.J.L., and Carniel, R., (2002). Thermal, seismic and infrasonic evidences of variable degassing rates at Stromboli volcano. *Journal of Volcanology and Geothermal Research*, 118: 285-297. [Time series analyses of thermal, infrasonic and seismic data led to identify two styles of gas puffing activity at Stromboli volcano. The first is characterized by frequent, rapidly rising puffs, the second by less frequent, slowly rising puffs. Variations in puffing activity can be used to track changes in the rate at which the shallow system is supplied by fresh, gas-rich magma]

Rogers, J. A. and Stephens, J. A. (1995). SSAM Real Time Seismic Spectral Amplitude Measurement on PC and its application to volcano monitoring. *Bull. Seism. Soc. Am*. 85: 632-639. [The idea to integrate some positive quantity of the time series in a given time window led first to the computation of a seismic intensity, which is known as RSAM – Realtime Seismic Amplitude Measurement. In this paper, a spectral-filtered version of this quantity is proposed, defining what is called SSAM - Spectral Seismic Amplitude Measurement]

Schick R., Riuscetti M. (1973). An analysis of volcanic tremor at South-Italian volcanoes. *Zeit. Geophysik*, 39, 262-274. [The authors propose a model where volcanic tremor energy is correlated with the velocity of gases escaping through the summit crater conduits. The observed steadiness of the frequency peaks is related to at least one oscillator, excited by gas bubbles uprising in the magma]

Shaw, R., (1984). *The Dripping Faucet as a Model Chaotic System*, Aerial Press, Santa Cruz, CA.. [The book investigates the relationship between a chaotic dynamical system and its production of information. The model is simple – a dripping faucet – but its behavior is very complex, leading to important questions about the predictability of even simple dynamical systems]

Sparks, R.S.J., (2003). Forecasting volcanic eruptions. *Earth Planet. Sci. Lett*., 210, 1–15 [Forecasting is a fundamental objective of volcanology and is becoming more and more quantitative, based on understanding of the underlying physical processes. However, the coupling of highly non-linear and complex kinetic and dynamic processes leads to a rich range of behaviors and to intrinsic uncertainties that need to be expressed in probabilistic terms]

Takens, F., (1981). *Detecting strange attractors in turbulence, in Dynamical Systems and Turbulence*, Lecture Notes in Mathematics, 898, 336-381, Springer, Berlin. [A milestone in the dynamical analysis of time series. Takens presents here procedures to decide whether one can attribute certain experimental data, as in the onset of turbulence, to the presence of strange attractors]

Tárraga, M., Carniel, R., Ortiz, R., Marrero, J.M. and García, A., (2006). On the predictability of volcano-tectonic events by low frequency seismic noise analysis at Teide-Pico Viejo volcanic complex, Canary Islands, Nat. Hazards *Earth Syst. Sci*., 6: 365-376. [FFM is used on low frequency seismic noise at Tenerife to forecast tectonic events. To avoid subjectivity, forecasts are generated automatically and validated by Bayes theorem. A "forecast gain" measures quantitatively what is gained in probabilistic terms by applying the forecast]

Tárraga M., Carniel R., Ortiz R., García A. (2008a). The Failure Forecast Method. Review and application for the realtime detection of precursory patterns at reawakening volcanoes. Chapter 13 In: Gottsmann, J. and Marti, J (eds.): *Caldera volcanism: Analysis, modelling and response, Developments in Volcanology*, Elsevier, Vol. 10, 447-469, doi:10.1016/S1871-644X(07)00013-7 [A review of the FFM and its application to volcanology, with a special focus to the possible use of FFM in the analysis of reawakening volcanoes and caldera unrest, with Tenerife as a case study]

Tárraga, M., Carniel, R., Ortiz, R., García, A., Moreno, H., (2008b). A dynamical analysis of the seismic activity of Villarrica volcano (Chile) during September-October 2000. *Chaos, Solitons & Fractals* 37: 5. 1292-1299 [A spectral, dynamical and statistical analysis of the tremor recorded at Villarrica during September and October 2000, in order to characterize the effects of a tectonic event recorded on 20 September 2000]

Tárraga, M., De La Cruz-Reyna, S., Mendoza-Rosas, A.T., Carniel, R., Martínez-Bringas, A., García, A. and Ortiz, R., (2012). Dynamical parameter analysis of continuous seismic signals of Popocatépetl volcano (Central Mexico): A case of tectonic earthquakes influencing volcanic activity. *Acta Geophysica*, 60, 3, 664-681, DOI: 10.2478/s11600-012-0020-1 [The influence of major regional tectonic earthquakes on Popocatépetl is evaluated through the changes of spectral and dynamical parameters of seismic data at the volcano. Recognition of these earthquake-related changes can enter decision making for volcanic alert levels]

Telesca, L., M. Lovallo, R. Carniel, (2010). Time-dependent Fisher Information Measure of volcanic tremor before 5 April 2003 paroxysm at Stromboli volcano, Italy, *Journal of Volcanology and Geothermal Research*, 195, 78-82 [Dynamics of Stromboli volcanic tremor before a paroxysm was studied with the FIM, suggesting that the signal varies between disordered (small FIM) and ordered (large FIM) states. FIM is also a good potential detector of regime changes and possible precursors]

UNDRO (1979). Natural disasters and vulnerability analysis. Office of the United Nations Disaster Relief Co-ordinator (UNDRO), Report of Expert Group Meeting (9–12 July 1979), UNDRO, Geneva [In 1979, UNDRO convened an international Expert Group Meeting on the major natural hazards, to review UNDRO's work in vulnerability analysis, defining concepts and developing methodologies for applying the results in disaster-prone developing countries. This is the report of that meeting, summarizing six years of research]

Vila, J., Macià, R., Kumar, K., Ortiz, R., Moreno, H., Correig, A.M., (2006). Analysis of the unrest of active volcanoes using variations of the Base Level Noise Seismic Spectrum. *Journal of Volcanology and Geothermal Research*, 153, 11–20 [A tool for monitoring the unrest of active volcanoes is presented: the Base Level Noise Seismic Spectrum (BLNSS). The base level activity can be determined by continuous monitoring of the minimum amplitude of all spectral components. Case studies are presented with data recorded at Soufriere Hills, Llaima and Villarrica volcanoes]

Voight, B., (1988). A method for prediction of volcanic eruptions. *Nature*. 332, 10: 125-130 [Failure Forecast Method is presented, based on the behavior of materials in terminal stages of failure, measured by an observable quantity such as strain. Drawing on analogies between failure mechanics and eruption processes at volcanoes, the paper provides a consistent analytical basis for eruption prediction]

Welch, P.D., (1967). The Use of Fast Fourier Transform for the Estimation of Power Spectra: A Method Based on Time Averaging Over Short, Modified Periodograms, *IEEE Transactions on Audio Electroacoustics*, AU-15, 70–73 [The use of FFT in power spectrum analysis is described, proposing an optimized method involving sectioning of the record and averaging modified periodograms of the sections]

Zeileis, A., Leisch, F., Hornik, K., Kleiber, C., (2002). strucchange: an R package for testing for structural change in linear regression models. *J. Stat. Softw.* 7 (2), 1–38. [The paper reviews the tests for structural change in linear regression models - from the generalized fluctuation test framework as well as from the F test framework – as implemented in the freely available R package "strucchange"]

Zeileis, A., (2005). A unified approach to structural change tests based on ML scores, F statistics, and OLS residuals. *Econom. Rev.* 24 (4), 445–466. [Three classes of structural change tests - based on maximum likelihood scores (Nyblom–Hansen test), on F statistics (sup F, ave F, exp F tests), and on OLS residuals (OLS-based CUSUM and MOSUM tests) - are unified by embedding them into the framework of generalized M-fluctuation tests. It is then shown how the tests can be extended to a monitoring situation]

Biographical Sketch

Roberto Carniel was born in Trieste (Italy) 1965, got his Laurea degree in Computer Science from the University of Udine, Italy in 1989 and his Ph.D. in Computational Mathematics from the University of Padova, Italy in 1993. Since 1991 he is a Researcher of Applied Geophysics at the University of Udine. Since 1992 he is a member - and since 1997 the Secretary - of the Working Group "Seismic phenomena associated with volcanic activity" of the European Seismological Commission. Since 2007 he is the EU Representative in the IASPEI/IAVCEI Joint Commission on Volcano Seismology. In 2008/09 he was a visiting temporary researcher at the UNAM - Universidad Nacional Autonoma de Mexico, Mexico DF. He will spend the summer 2012 as a visiting temporary researcher at the Earthquake Research Institute. University of Tokyo, Japan. His main research interests include geophysical - and non geophysical - time series analysis. In particular he studies the dynamical evolution of spectral, deterministic and stochastic parameters, also in relation to the occurrence of paroxysmal events (search for precursors, forecasting), for the characterization of volcanic regimes at different time scales, also with a multi-parametric approach, and the automatic detection of significant changes in the dynamics. He also developed a series of pre-processing techniques for the fast evaluation of site effects (local seismic spectral amplification). He authored more than 60 peer-reviewed papers in ISI journals. Since 2008, he is Associate Editor for Volcanology of the international ISI journal "Geofisica Internacional" published by UNAM, Mexico. Since 2011, he is a member of the Editorial Board of the international ISI journal "Journal of Volcanology and Geothermal Research", published by Elsevier, The Netherlands for which he also edited two special issues.