PHYSCON 2009, Catania, Italy, September, 1–September, 4 2009

CLUSTERING OF INFRASONIC EVENTS AS TOOL TO DETECT AND LOCATE EXPLOSIVE ACTIVITY AT MT. ETNA VOLCANO

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Abstract
Active volcanoes characterized by open conduit conditions effectively generate sonic and infrasonic signals, whose investigation provides useful information for both monitoring purposes and study of the dynamics of explosive phenomena. At Mt. Etna volcano (Italy) a clustering algorithm based on spectral features and amplitude of the infrasonic events was developed. It allows to recognize the active vent with no location algorithm and by using only one station. Moreover, a waveform inversion procedure was coded, based on genetic algorithm, that enables us to quantitatively investigate the infrasound source parameters.

Key words
Infrasound, volcanoes, clustering, Self-Organizing Map, K-means, source modelling

1 Introduction

During the last decade, new insights into explosive volcanic processes have been achieved by studying infrasonic signals (e.g. Vergniolle and Brandeis, 1994). In fact, infrasonic activity on volcanoes is generally evidence of open conduit conditions and can provide important indications on the dynamics of the explosive processes. Unlike the seismic signal whose wavefield can be strongly affected by topography (Neuberg and Pointer, 2000) and path effects (Gordeev, 1993), the infrasonic signal maintains almost unchanged its features during the propagation. In most of cases the infrasonic signals are related to the internal magma dynamics, as the acoustic resonance of fluids in the conduit, triggered by explosive sources; this implies propagation of sound waves in both magma and atmosphere (Garces and McNutt, 1997). Other studies relate the source of sound to the sudden uncorking of the volcano (Johnson and Lees, 2000), the local coalescence within a magma foam (Vergniolle and Caplan-Auerbach, 2004) and the Strombolian bubble vibration (Vergniolle et al., 2004). In this paper we illustrate an unsupervised clustering of infrasound events, able to recognise the active vent without location algorithm. Moreover, a method to quantitatively investigate the source mechanism is shown.

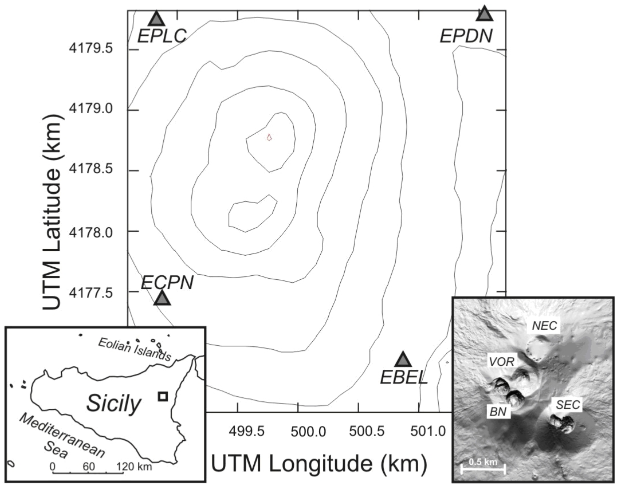

Figure 1. Map of the summit area of Mt. Etna with the location of the four infrasonic sensors (triangles), composing the permanent infrasound network. The digital elevation model in the lower right corner shows the distribution of the four summit craters (VOR=Voragine, BN=Bocca Nuova, SEC=South-East Crater, NEC=North-East Crater).

2 Infrasonic features clustering

The time period September-November 2007 was characterised at Mt. Etna volcano (Italy) by explosive activity and intense degassing. During this time interval infrasonic signals were recorded by an infrasonic network, composed of 4 sensors azimuthally distributed around the summit area (Fig. 1). By a triggering procedure, about 1000 infrasonic events were found, consisting in amplitude transients with short duration (from 1 to over 10 s), impulsive compression onsets and peaked spectra with most of energy in the frequency range 1-5 Hz (Fig. 2). Generally, in order to reduce the size

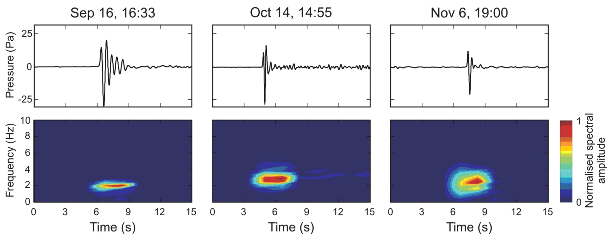

Figure 2. Infrasonic events recorded by EBEL station and corresponding Short Time Fourier Transform.

of certain information (signals, data, etc), definition of peculiar features or properties by a "feature extractor" may be useful. In our case, we can use both the spectral characteristics, computed by Sompi method (Kumazawa et al., 1990) and consisting in dominant frequency and quality factor, and the peak-to-peak amplitude, as features to describe the infrasonic events. Then, in order to investigate prospective similarities or differences among the features extracted from the infrasonic signals, we plotted the frequency, the quality factor and the peak-to-peak amplitude, in the x-axis, y-axis and z-axis, respectively, and obtained the so-called 'feature space' (Fig. 3). In order to discover cluster in the feature space, the Self-Organizing Map (SOM) was chosen. SOM is a neural network based

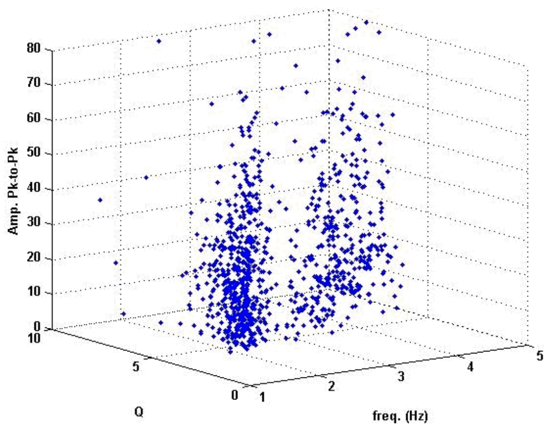

Figure 3. feature space of about 1000 of infrasound events, recorded by EBEL station. In x-, y- and z-axes the frequency, the quality factor and the peak-to-peak amplitude (Pa), respectively, are reported.

on unsupervised learning (Kohonen, 1995) useful in data visualization and exploration. The SOM maps high-dimensional input vectors onto two-dimensional grid of prototype vectors that are easier to visualize and explore than the original data. The fundamental of the SOM is the competition between the nodes in the output layer. The fundamental of the SOM is the competition between the nodes in the output layer. The U-matrix is a common tool for visual inspection of SOM. It visualizes distances between neighbouring map units, and thus shows the cluster structure of the map: high values of the U-matrix indicate a cluster border while uniform areas of low values indicate clusters themselves. In Fig. 4a the SOM U-matrix after training algorithm is presented. Each group of neurons constitutes a cluster. In the obtained U-matrix we can see three dark blue regions, that correspond to low values in the U-matrix, and hence to clusters in the data. These regions are separated by lighter colours. Thus through the visual inspection of the U-matrix we can recognise three clusters in the feature space.By studying the final U-matrix map, and the underlying features planes of the map, a number of cluster can be identified by K-means algorithm (Dubes and Jain, 1976). The best clustering structure, which was obtained by the K-means algorithm, is selected using Davies-Bouldin index (Davies and Bouldin, 1979). This index uses the

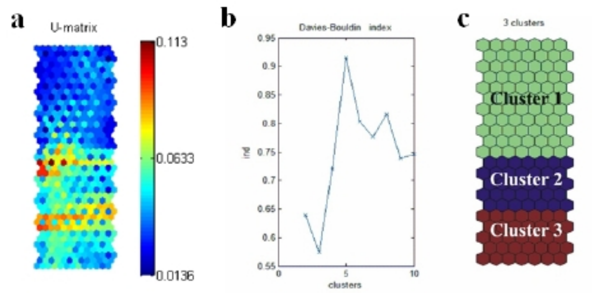

Figure 4. (a) U-matrix, (b) Davies-Bouldin index and (c) best clustering structures.

within-cluster distance and the between-clusters distance. The Davies-Bouldin index is suitable for evaluation of K-means partitioning because it gives low values indicating good clustering results. Fig. 4b shows the Davies-Bouldin index where the best clustering corresponds to the number of three clusters and then it has been projected onto the SOM (Fig. 4c). According to Cannata et al. (2009a), a cluster (called cluster 1) was related to the degassing activity of the North East Crater, while the other two (called clusters 2 and 3) to two different explosive activities of the South East Crater (Fig. 4c and 5).

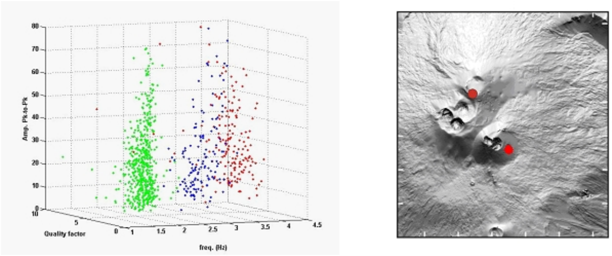

Figure 5. (a) Infrasonic feature space (green, blue and red dots indicate cluster 1, 2 and 3 respectively). (b) Location of the vents, source of infrasound.

3 Infrasonic source modelling

Once the events are characterised and the active vents located, the source processes can be studied. The detected infrasonic events are similar to the signals described in Ripepe and Marchetti (2002) and Vergniolle et al. (2004), and explained as generated by the vibration of a large gas bubble, before it bursts. Therefore, in order to quantitatively investigate the source mechanism of the infrasonic events, a waveform inversion procedure was developed. Using the equations reported in Vergniolle et al. (2004), we were able to calculate synthetic waveforms. Then, by optimization algorithms, we can constrain the values of the three unknown parameters, radius, length of the bubble and initial overpressure (indicated by R, L and ΔP, respectively) that allow finding the best fit between synthetic and measured waveforms. Optimization method chosen to look for the best fit between observed and synthetic signals is the Genetic Algorithm. Examples of waveform inversion are reported in Fig. 6.

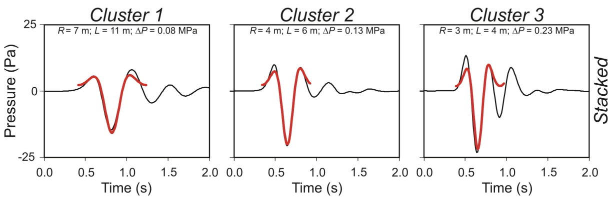

Figure 6. Comparison between the stacked waveforms of the three clusters of infrasonic events (black) and the synthetic ones (red). The source parameters obtained by the waveform inversion are reported at top of the plots.

4 Conclusions

At active volcanoes the detection and location of explosive activity is generally obtained by videocameras and thermal sensors. However, the efficiency is strongly reduced or inhibited in case of poor visibility caused by clouds or gas plumes. In these cases the detection and characterization of explosive activity by infrasounds is very useful (i.e Cannata et al., 2009b) and some techniques, based on infrasound signals recorded by arrays or networks, were developed to locate the source of this signal and then the active vent (e.g. Ripepe and Marchetti, 2002). All these techniques require that most of the stations properly work and the noise is low. At Mt. Etna the events at a single vent for a certain type of activity maintain stable their features (Cannata et al. 2009a). Therefore, once the link between event characteristics and vent is known we can understand which crater is active and which volcanic activity is going on by simply extracting the features of the infrasonic signal at a single station. In the light of it, a clustering based on spectral features and amplitude of the infrasonic events was developed. It allows to recognize the active vent with no location algorithm and by using only one station. Moreover, a waveform inversion procedure was coded, based on genetic algorithm, that enables us to quantitatively investigate the infrasound source parameters.

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