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The remarkable coherence between two Italian far away recording stations points to a role of acoustic emissions from crustal rocks for earthquake analysis

Giovanna Zimatore,1,a) Gianpao Garilli,1 Maurizio Poscolieri,1 Claudio Rafanelli,1 Fabrizio Terenzio Gizzi,2 and Maurizio Lazzari2
1CNR-IDASC, Institute of Acoustics and Sensors “O. M. Corbino,” via Fosso del Cavaliere 100, Rome, Italy
2CNR-IBAM, Institute for Archaeological and Monumental Heritage, C/da S. Loja Zona Industriale Tito Scalo (Potenza), Italy

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We observed a remarkable near-to-unity correlation between the time series of Acoustic Emissions (AEs) collected at two stations approximately 300 km apart from each other and located along the Apennine belt (Italy). This finding prompted us to verify the hypothesis that AE signals can carry with them an indication of anomalies in a crustal stress trend, possibly related to earthquake occurrences. Thus, we checked the ability of Recurrence Quantification Analysis and Fractal Analysis as applied to AE to identify signal phase transitions before the crisis occurs. The sharp drop of the Percent of Determinism after its maximum value, and simultaneously with minimum values of the Fractal Dimension (D), few days before some seismic events take place, seems to point to the relevance of the proposed approach as precursor detection. Published by AIP Publishing.

In this paper, we propose a new approach to study impending seismic events. We applied two modern methods of nonlinear data analysis as Recurrence Quantification Analysis and Fractal Analysis to Acoustic Emissions. These ultrasonic signals are relevant in earthquake studies because they occur many days before the earthquake and not after as seismic waves. The unexpected coherence between two distant Italian stations went hand-in-hand with the convergence of two nonlinear dynamics inspired techniques like fractal analysis and recurrence quantification analysis allowing us to delineate a unique tectonic scenario. In our opinion, this is not only an achievement in geophysics but suggests a potentially useful data analysis style. The topical interest of this paper regards the proposal of possible physical indicators of impending earthquakes.

I. INTRODUCTION

It is well known that whenever two objects are in contact and slide with respect to each other, vibrations due to friction occur. Narrow-banded noise of train wheels running along tight curves, friction in bearings, and fracture process in a rigid body caused by a certain load (Kurz, 2015), as well as micro-scale events in molecular physics and, as regards what this paper discusses, active faults within seismogenic zones are some examples of this phenomenon.

Seismogenic zones are present along the whole Italian peninsula, mostly within the Apennine mountain range (Italy) which stretches for about 1,200 km, where frequent and severe earthquakes have occurred (Castello et al., 2004 and Gizzi et al., 2012).

The regional NW–SE striking sets include large seismogenic sources that caused major historical earthquakes (M ≤ 7, Rovida et al., 2011). The faults in the northern part of the study area dip to the southwest and those in the southern part dip to the northeast. Recently, Fracassi and Milano (2014) investigated the transfer zone and linkage between divergent extensional seismogenic fault systems on the border between the central and southern Apennines. The authors inferred that a reverse in dip polarity between the two normal fault systems could result due to the relative motion of the diverse tectonic units composing the border between the central and the southern Apennines.

Taking into account the described tectonic setting of the Italian peninsula, this paper builds upon the remarkable coherence observed between the Acoustic Emissions (AE) (Gregori and Paparo, 2003; Gregori et al., 2007 and Chelidze and Matcharashvili, 2007) time series recorded in two monitoring stations located in the central-southern Apennines. Recently, Wu et al. (2016) reported multiple-parameter anomalies associated with the Mw 6.3 2009 L’Aquila earthquake: among them the authors also mentioned changes in acoustic emission trends before this earthquake (Gregori et al., 2010).

The fact that two AE stations about 300 km apart gave rise to highly coherent time signals points to the fact that AEs are proxies of relevant “sliding dynamics”. We checked the hypothesis that these signals represent a sort of “precursor events” of earthquakes. To this goal, we analyzed AE by means of two very popular non-linear signal analysis tools, namely, Recurrence Quantification Analysis (RQA) and Fractal Analysis (FA). In particular, RQA is routinely used in biomedical sciences as well as in financial studies (Webber and Marwan, 2015).

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a)Author to whom correspondence should be addressed. Electronic mail: giovanna.zimatore@uniroma1.it
II. MATERIALS AND METHODS

A. Acoustic emission (AE)

In order to evaluate the crustal stress propagation, two Acoustic Emission (AE) time series, acquired at two monitoring stations, were considered: Savoia di Lucania (Potenza, Italy; 40.57° N, 15.56° E, hereafter Savoia) and Orchi (Perugia, Italy; 43.02° N, 12.78° E), located both along the Apennine axial zone of the central-southern Italy. The distance between the two stations is about 320 km and the AE sensors are fastened to a natural rock in Orchi and to the head of a pile wall at the top of a monitored historic landslide adjacent to the urban area of Savoia. Figure 1 shows the location of the two AE monitoring sites and the epicenters of some peculiar earthquakes occurred during the AE registering time period, on a Google Map. On this map, tectonic, faults, and paleoseismological information are also depicted according to the Database of Individual Seismogenic Sources (DISS, 2015) (http://diss.rm.ingv.it/diss/) released by National Institute of Geophysics and Volcanology (INGV). The earthquake data were obtained from the ISIDe (Italian Seismological Instrumental and Parametric Database) Seismic Catalog of INGV, by selecting the events with a Magnitude greater than 3.0 and localized within 300 km radius circles, each of them having the center on one of the AE sites (http://iside.rm.ingv.it/iside/standard/index.jsp, accessed on Feb.16/2016).

AE records were sampled with two piezoelectric sensors centered on two frequency bands of 150 kHz (called high frequency, labeled as HF-AE) and 25 kHz (low frequency, labeled as LF-AE), respectively. The signals were sampled at 3 kHz and the data were recorded as RMS (Root Mean Square) amplitude every 30 s producing an AE time series (Concerning data acquisition and handling, refer Gregori and Paparo (2003)). As example, Figure 2 shows the pattern of both HF-AE and LF-AE recorded at Savoia and Orchi stations from September 18th, 2014 to February 9th, 2015 (154 days = 3696 h = 3696 points). The AE time series exhibit a very high correlation in time with a Pearson r coefficient equal to 0.95 as for the HF-AE component (mean value of 150 points, considering only common points, that is neglecting points recorded only in one location) in spite of the distance and the different regional and local geotectonic settings.

In Gregori et al. (2016), it is well explained that “every local rigid crustal component must release some acoustic emission (AE). Therefore, when some AEs are detected at a given site - and whenever they appear correlated with the seismic activity occurred somewhere else - the detected AE signal is originated by a local source, while it is not propagated from the earthquake epicenter”.

It is worth noting that AE sensors were located on the top of a suitable solid body in order to detect strictly local phenomena, although being the consequence of some large-scale stress.

The above result is consistent with the hypothesis that cracking phenomena always start with releasing AE signals at very high frequency (about 800 kHz). The high frequency regime then changes into intermediate frequencies (≈160–200 kHz) originating when some small pores yield.
followed by acoustic pulses emitted at lower frequencies (i.e., $\approx 25$ kHz), when pores yield and coalesce into larger micro-cavities. Eventually, at later time, an earthquake follows ($< 5$ Hz) when the large scale mechanical structure of the system yields.

Moreover, it is important to underline that the AE signal amplitudes cannot be uniformly calibrated since they vary according to the acoustic impedance, which is in turn related to local crustal stress conditions and particularly sensitive to involved rocks characteristics, fracture density, and water content. This feature asks for the use of scale-invariant techniques only based on internal autocorrelation structure of the signals, such as RQA and FA methods.

In Matcharashvili et al. (2011), AEs were studied in order to define their relationships with impending seismic events. Furthermore, the dynamic pattern of seismicity was revealed by the application of nonlinear dynamics tools to time series from acoustic emissions during natural stick-slip, regional seismicity of Caucasian mountains and regional seismicity in Central Asia (Chelidze and Matcharashvili, 2007; 2015). Then, Ramirez-Rojas et al. (2015) studied the properties of the seismicity that occurred in Mexico in the period 2006–2014, by considering the occurrence of events as sequences of Magnitudes (time series) and determining the recurrence plots. They showed that, by using the Visual Recurrence Analysis (VRA) (Kononov, 2016), it is possible to get dynamical features of the seismicity. Moreover, some authors of this paper claimed the usefulness of feasible tools for seismic precursors’ identification in previous studies (Gregori et al., 2005; 2007; 2010).

### B. RQA general description

The great part of dynamic techniques for numerical series analysis builds upon the projection in a multi-dimensional space of an initially one-dimensional time-dependent signal, through the technique of embedding (Webber and Zbilut, 1994). RQA, following this method, reveals the “hidden” periodicities characterizing the dynamics of the system, so highlighting interesting nonlinear features of seismic processes. Models of earthquake faults were recently studied by Franović et al. (2016) from the perspective of nonlinear dynamics theory, offering a theoretical frame consistent with our data analysis perspective. As a matter of fact, AE signals’ analysis highlighted phase transitions, subtle periodicities, and recurrence phenomena invisible to traditional methods (e.g., Fourier analysis).

This is made possible by the lack of any assumption of stationarity or minimum length of the signal, as commented in the application of RQA in the analysis of time series of oto-acoustic emissions from ears (Zimatore et al., 2000; 2002).

RQA defines the overall complexity of the signal in terms of quantitative indexes deriving from the so-called ”Recurrence Plots“ (RP)

An RP is nothing else than the distance matrix between all pair-wise comparison of the rows of embedding matrix of the signal thresholded by means of a selected radius ($r$): if two $i,j$ rows have a mutual distance lower than $r$, a dot (correspondent to a recurrence) is inserted in the $i,j$ (and $j,i$) position in RP, otherwise the position is left empty.

To build the recurrence plot, the time behaviour of the original signal was represented by a series of $n$ points equally spaced in time (e.g., $\{a_1, a_2, \ldots, a_n\}$, where $a_i$ represents the value of the signal corresponding at the $i$-th time position). Then, the series was arranged in successive columns (the column number is defined by the “embedding dimension,” $N$), each-one obtained by applying a delay in time (lag parameter, $\tau$) to the original sequence, this way an “embedding vector” was created, as in equation 1.

$$
\begin{bmatrix}
  a_1 & a_{1+t} & \ldots \\
  a_2 & a_{2+t} & \ldots \\
  \vdots & \vdots & \ddots \\
  a_n & 0 & \ldots \\
\end{bmatrix} = 
\begin{bmatrix}
  e_{1,1} & e_{1,2} & \ldots & e_{1,N} \\
  e_{2,1} & e_{2,2} & \ldots & e_{2,N} \\
  \vdots & \vdots & \ddots & \vdots \\
  e_{n,1} & 0 & \ldots & e_{n,N} \\
\end{bmatrix}
$$

Finally, the recurrence plot was built, drawing a black dot (named recurrent point) in the represented space if the distance between the corresponding rows, e.g., the distance between the $i$-th and the $j$-th row is \(\sqrt{\sum_{k=1}^{N} (e_{ik} - e_{jk})^2}\), of the embedding vector was lower than a fixed value (radius). In the obtained plot, the horizontal and vertical axes represented the relative position of the $n$ points into the AE time series, Zimatore (2011b). The main diagonal is called line of

![Graphical representation of AE time series pattern of both HF-AE (panel (a)) and LF-AE (panel (b)) recorded at Savoia (blue) and Orchi (red) stations.](image-url)
identity (LOI) and vertical segments (respectively, dots) represent phase space trajectories which remain in the same phase space region for some time whilst diagonal lines represent trajectories which run parallel for some time. Determinism (DET) measures the relative occurrence of the diagonal lines and is represented, graphically, by calculating the fraction of recurrence points that form diagonal lines parallel to the line of identity (LOI). RQA measures were then calculated on the basis of the number and the location of dots in the matrix (Marwan et al., 2007).

The simple visual inspection of RPs allows us to grasp some interesting features of the dynamics. The rapid decrease of the number of dots moving away from the main diagonal (corresponding to the equivalence in time) is an indication of a highly non-stationary signal. The presence of long diagonal lines parallel to main diagonal could suggest the existence of a quasi-periodic behavior or, as in this paper, periods of similar evolution of a dynamical system at different times; the length of diagonal lines is related to the divergence behavior of the system. Finally, the identification of square-like arrangements of dots are the image in light of “resting” phases in which the series does not change (Pascual et al., 1999 and Giuliani et al., 1998).

In this paper, we focused on how percent of determinism (DET, corresponding to the percentage of recurrences happening at consecutive epochs) changes along time. Rapid shifts from high to low (and vice versa) DET values are usually indicators of regime changes and phase transitions (Trulla et al., 1996 and Marwan et al., 2007). It is worth noting that the increase in correlation (High DET means high autocorrelation) is a universal marker of crisis in fields ranging from physiology to finance (Gorban et al., 2010).

C. Application of RQA to acoustic emissions

The sampling rate of AE is 2 samples/min, in this work, as in Zimatore et al. (2011a), an average on 120 points as a first smoothing of the recorded AE signals, has been reckoned; in the following analysis 1 point corresponds to 1 hour; in the whole time period, we study 154 days = 3696 hours = 3696 points on both the time series excluding the missing points when the sensor did not work as is explained in the following. The lack of data comes from technical problems in the registration (Savoia sensor not working) and missing points are only consecutive points, excluded in this study.

The optimization procedure consists of finding the input parameter that permits us to observe in a dataset the main feature of different signals as different; this procedure suggested the following RQA measurement parameters: the delay (lag) is set to 1; the embedding dimension to 10, the cut-off distance (radius) to 15% of mean distance between all pairs of points in time and line (minimal number of consecutive recurrences to score a determinism line) set to 8. Embedding dimension is set to 10 because this value is well inside the linearity scaling of all the RQA measures.

RQA is computed across consecutive distance matrices corresponding to consecutive and overlapping sliding windows (epochs) along the series, and this mode of analysis is called RQE (Recurrence Quantification by Epochs). The occurrence of an abrupt change of DET in adjacent windows corresponds to a transition in the dynamical regime of the signal.

RQE analysis was carried out by adopting the same parameters setting as for the global mode (in this paper, when an epoch coincides with all points of the time series, the result is called RQA), plus the definition of windows having a length of 150 points (1 point ≈ 1 hour) and shifting of 1 point between consecutive windows, respectively.

RQA software, RQE.exe and RQC.exe version 8.1, are those included in RQA 14.1 (Webber, 2012).

The statistics were calculated using a commercial statistical package (Systat, v.10.2, Chicago, IL).

D. Fractal analysis

The estimation of the AE fractal dimension (D) in turn can be intended as seismic precursor Paparo et al. (2002). The purpose is to monitor the stress propagation that crosses different regions, in order to envisage where and when it can eventually trigger a catastrophe of the system (Barton and La Pointe, 1995). Fractal Analysis (FA) was performed by means of Box Counting Method (BCM) (López Pumerega et al., 2012). In this work, the D values were calculated for each day and plotted as a function of the time. For each D value, we use 12 points in the Richardson’s diagram in order to obtain a good fit.

A unitary fractal dimension (D = 1) suggests that the AE events do not correlate at all; conversely, when the AE sources distribution results progressively organized, D progressively decreases towards D = 0 meaning that the system evolves towards a more organized structure Gregori (1998) and Paparo et al. (2004).

The main reason for the choice of the Fractal Box Counting method (BCM), with respect to other approaches, is that this is often the first technique tried on physical data, probably because it seems so simple a concept. Unfortunately, there are some limitations to BCMs; this method requires a large number of data points in order to produce correct dimension (Dubuc et al., 1989) reported instabilities in the method when the number of data points used was small). In this context, the authors found the second reason for concentrating on BCM: many alternatives for physical data are based on similar mathematical limiting processes and may suffer from similar difficulties. In general, FA works only with big datasets and also with an appropriate signal. In nature this almost always happens (crustal stress is always present, or even the fluids feeding a volcano).

The FA analysis has been carried out by means of a code written entirely in C++, which can be assembled in a series of modules. Each of these modules is able to elaborate different steps of the entire analysis.

For the processing of the data, the following steps were carried out:

1. Eliminating outliers, which are extreme values (either small or large) that can largely influence statistical analysis. Eliminating outliers can be performed by means of the interquartile range (IQR), which can be used as a
measure of how spread-out the values are. Statistics assumes that the values are clustered around some central value. The IQR indicates how spread out the middle values are; it can also be used to detect when some of the other values are too far from the central value. These too far away points are called outliers, because they lie outside the range in which are expected. If the lower quartile is Q1 and the upper quartile is Q3, then the difference (Q3 - Q1) is called the interquartile range or IQR. An outlier is any value that lies more than one and a half times the length of the box from either end of the box. That is, if a data point is below Q1 - 1.5 × IQR or above Q3 + 1.5 × IQR, it is viewed as being too far from the central values to be reasonable.

2. Application of a weighted moving average (WMA) to AE data, carried out over a given pre-chosen time lag. The weight is defined by a triangular function, aimed at reducing the role of the side lobes of a simple non-weighted running average. In this work, a time lag of 101 data was chosen, which is shifted every 30 s until the end of the dataset, calculating the weighted average for each shift.

3. Calculation of the residuals, which were calculated subtracting the weighted average values from the original dataset. Once that \( \text{rms} \) of all residuals was evaluated, a threshold equal at \( 0.4 \times \text{rms} \) was set for the next step.

4. Definition of a point-like process, which is identified with the time instants of all relative maxima of the residual data series, when the peak value of a relative maximum is \( >0.4 \times \text{rms} \). By means of this process, using the BCM, the fractal dimension D was computed, considering the AE phenomena by the occurrence of AE values above the analysis threshold level as YES and as NO for lower levels Barton and La Pointe, (1995). Moreover, a time lag \( \mu \), called "ruler", is defined such that the whole temporal window is divided into an integer number of rulers; "+1" is added to the counter \( G(\mu) \) whenever a time lag \( \mu \) contains at least one data above the specified threshold. Then, it is possible to plot \( G(\mu) \) versus \( \mu \) in a log–log graph, called Richardson’s diagram. The slope H of the interpolating line of this graph is equal to the fractal dimension changed in sign, \( D = -H \). Use at least 12 points in the Richardson’s diagram, and it allows to get a good estimate of the fractal dimension. The D values were calculated for each day and plotted as a function of time.

III. RESULTS

A. Signals correlation

The reconstructed amplitude dynamics of hourly means of AE signals recorded at Orchi and Savoia stations were investigated and a very strong correlation (HF-AE Orchi vs Savoia correlation scores Pearson \( r = 0.95 \) intercept \( = 0.00052 \pm 0.00013 \), slope \( = 1.899 \pm 0.0081 \), was found (Fig. 3). Due to the lack of data, the regression line is only the graphical description of the linear relation computed
by least squares estimation of the correlation HF-AE using only the points in common between the two series.

This strong correlation (the equation is merely the cosine between two vectors correlated) derives from a common crustal stress, a very strong dynamic relation that forces the two signals as order parameter. In order to understand if and how earthquakes are related to the phase transition of the signals, the AE time series main descriptors (DET and D) and main seismic events (magnitude M > 3) are compared in the following paragraph.

B. Percent of determinism, DET

Figure 4 reports RQE analysis carried on HF-AE time series from the two different Orchi and Savoia stations from September 18th, 2014 to February 9th, 2015 (154 days ≈ 5

<table>
<thead>
<tr>
<th>Start point</th>
<th>0</th>
<th>500 (a)</th>
<th>1000 (b)</th>
<th>1500 (c)</th>
<th>2000 (d)</th>
<th>2500</th>
<th>3000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date (2014)</td>
<td>September 18</td>
<td>October 09</td>
<td>October 29</td>
<td>November 19</td>
<td>December 10</td>
<td>December 31</td>
<td>January 21 (2015)</td>
</tr>
</tbody>
</table>

TABLE I. Start point-Date correspondences.
months); the input parameters chosen are described in details in Subsection II C.

Moreover, the earthquakes of magnitude greater than 3 on the Richter scale occurred inside a circle area of radius equal to 300 km, centered around each AE station, are shown. Note that the minima of DET that occur quite in simultaneity for the two stations are highlighted by five numbered black ellipses; considering the minima of DET of HF-AE recorded from Orchi station, it is possible to count that the 65% of seismic events (24 of 37) fall in correspondence of these dramatic drop of DET values; the fifth minimum around (January 8, 2015) is less evident (DET = 70%), the minimum around October 30, 2014 is skipped because is not in simultaneity for the two stations, the minimum around November 20, 2014 is skipped because there is a lack of Savoia data.

To quantify the coincidence of minima of DET with the seismic events, 28 not overlapped 75 hours wide windows are considered and a statistical inferential test (Mann-Whitney U Test) is reckoned to evaluate the correlation between the number of seismic events occurred in each window and the number of seismic events fallen into minima of DET. Every selected time period (of the five minima) is considered at half the height of the difference between the

**FIG. 6.** Qualitative Comparison between Distance Matrix (DM) of time series HF-AE from Savoia (left) and Orchi (right) in two different frames shown in Table I: I (top) and F (bottom). On the horizontal axis the real time (day/month) is also reported. DM is obtained by Visual Recurrence Analysis 4.3 (Kononov, 2016).
highest and lowest DET values (Sum of Minima for Orchi plus Savoia; sum of events). The U-value is 310; the result is significant at \( p < 0.05 \). Moreover, a Chi-Square for 2 x 2 Contingency Table is calculated (Sum of Minima for Orchi plus Savoia yes-no; sum of events yes-no) in 16 not overlapped 150 hours wide windows. The chi-square value is 4.7727. The \( p \)-value is 0.028914. This result is significant at \( p < 0.05 \).

Note that DET changes before the crisis: DET is very high (greater than 2 standard deviation estimated over the whole interval) about ten days before the occurrence of significant events, falls in DET really reflect transient state changes and can be better observed in panels (a)–(d) of Fig. 5 over the time as explained in Table I.

C. Recurrence plots

The four RPs point to different qualitative behavior of the underlying signal. Panel (a) is clearly subdivided into two different regimens from 0 to approximately 350 and from 350 onward. This implies the presence of a singularity or a transition at point 350 Poscolieri et al. (2012); it is worth noting that the second phase is highly non stationary (recurrences concentrated in the vicinity of main diagonal) with respect to the previous phase. Panel (b) shows a highly modular structure with clustered phases corresponding to the square-like portions of the graphs. Panels (c) and (d) show more regular pattern.

To better highlight the regular pattern of RP corresponding to the final period in comparison with the first period, two different frames (I and F) are considered. The Distance Matrix (DM) is shown in Fig. 6 (see Table I), because they allow the visual understanding of the completely different texture common to both Orchi and Savoia that cannot be appreciated by mean classical RPs (see Marwan et al. (2007)). The periods corresponding to panels (a) and (b) of Fig. 5 are in the frame I, while panel (d) corresponds to the frame F, as indicated in Fig. 4. Three events along the same fault occurred in the final period (frame F) (see red flags in Fig. 1 and the points that fall inside the black ellipse in Fig. 7) in an area located approximately in the middle between the two AE monitoring stations: such a regular pattern in RP of frame F is a proof of the reliability and the robustness of the obtained results.

D. Fractal dimension, D

The correlation dynamics of systems subjected to external stressors Gorban et al. (2010) reveals that an increase in correlation precedes the onset of a crisis. Our results show that AE signals DET increases (Fig. 4) and, at the same time, D decreases.

This implies that both RQA and Fractal Analysis detect an increase in AE signal autocorrelation; it is thus crucial to check if this correlation increase is followed by a crisis. In this respect, it is worth noting that the “correlation increase” in Gorban’s model Gorban et al. (2010) is reversible and not necessarily dynamics ends up into a transition.

Figure 7 shows the correlation between D for Orchi and Savoia HF-AE data and the seismic events. At high frequencies, there is a greater correlation than at low frequencies. The black dots represent earthquakes comprised in a circle of 300 km radius around Orchi, while the red squares represent those comprised in a circle of 300 km radius around Savoia. Inside the black oval are highlighted four earthquakes falling in the overlapping zone of circles. Three of these events of magnitude 4.0 (18 km depth), 3.7 (336 km depth), and 3.3 (5 km depth) seem to be aligned along the same fault.

As previously observed for DET (Fig. 4), it is possible to note that the earthquakes were preceded by local minima of D (lower than 2 standard deviations estimated over the whole interval) and that the values of D decrease simultaneously for both stations since the first week of Dec. 2014, in particular, for HF-AE (see frame F of Table I and Figure 6). 28 not overlapped, 75 hours wide, windows are considered and a statistical inferential test (Mann-Whitney U Test) is reckoned to evaluate the correlation between the number of maxima observed in D occurred in each windows and those observed in the time periods evidenced by five numbered minima of DET (see Figs. 4 and 7). The U-value is 342. Therefore, the result is significant at \( p < 0.05 \).

E. Det and D comparison for precursors

If the two time series, DET and D, are compared, it is possible to observe that DET and D follow the same trend,
moving away from randomness, perhaps driven by the same geotectonic phenomenon (see Figs. 4 and 7). The lowest values of D are reached about ten days before the earthquake as it was found for highest values of DET and this evidence occur in two stations apart from each other approximately 300 kilometers.

This appears as a clear example of a progressive and long lasting precursor. These results seem to point out that the AE technique can provide information about the similar temporal evolution of the tectonic system with respect to an incoming earthquake.

Fig. 8 reports the time series of both DET and D on HF-AE recorded in Orchi station. The maxima of DET are marked by a star; there is a mild evident, even albeit mild, relation between these maxima and minima of D. It is worth noting that DET exhibits a much better discrimination power than fractal dimension even due to the much clearer definition of maxima.

This evidence, together with the strong Pearson correlation between the raw data (par.A-Fig. 3), could mean that, in the period under analysis, the central-southern Apennines tectonic structure was subjected to the same global stress fields and the two AE stations registered similar strains.

Of course, additional studies to confirm these hypotheses are required. However, the results support the suggestion that the RQA and Fractal techniques may be used as precursors of impending seismic events Pso colieri et al. (2012) and Zimatore et al. (2011a).

IV. CONCLUSIONS

This work proposes the fundamental role of Acoustic Emission from crustal rocks for earthquake analysis that can detect anomalies in crustal stress behavior.

This study investigated the AE time series gathered from two monitoring stations in Italy and the remarkable correlation between signals from two stations is a possible indication of impending seismic events.

The application of the RQA and FA methods to the AE time series appears useful for pinpointing peculiar recurrence patterns and to monitoring quantitative changes in dynamics of temporal distribution, loss of synchronization of dynamic mechanism or spatial irregularities occurring in time.

The almost simultaneous abrupt trend change of Fractal (D) and RQA (DET) variables before the earthquake occurrences seems to suggest that these indexes might be considered as possible precursors.

What the authors want to emphasize is that the two inherently different analysis techniques when applied to different datasets, coming from distant stations distinguished to have unique tectonic scenarios, reveal the same analytical trend.

These are preliminary but encouraging results and the authors wish to point out that the proposed method might be useful in the future for the detection of incoming earthquakes. However, the authors are aware that in order to confirm the preliminary results discussed in this paper and improve the methodology itself, it is necessary to arrange a wider AE station network over the Italian territory so as to gain benefits of having longer time series on which performing statistical analyses.

Finally, it will be possible to optimize the analytical approach and confirm the potential capability of AE as being possible precursor of seismic events, but more generally in many other applications in the field of prevention of geological hazards and structural responses of buildings and infrastructures.

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