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Wavelet analysis as a tool to characterise and remove environmental noise from self-potential time series

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Abstract

Multiresolution wavelet analysis of self-potential signals and rainfall levels is performed for extracting fluctuations in electrical signals, which might be addressed to meteorological variability. In the time-scale domain of the wavelet transform, rain data are used as markers to single out those wavelet coefficients of the electric signal which can be considered relevant to the environmental disturbance. Then these coefficients are filtered out and the signal is recovered by anti-transforming the retained coefficients. Such methodological approach might be applied to characterise unwanted environmental noise. It also can be considered as a practical technique to remove noise that can hamper the correct assessment and use of electrical techniques for the monitoring of geophysical phenomena.

Key words *self-potential signals – wavelet analysis*

1. Introduction

Environmental conditions act on self-potential variability driving non-stationary patterns which can highly distort background behaviours (for a discussion of self-potential electrochemical theory see *e.g.*, Pham *et al.*, 2001; and references therein). Such disturbances severely limit the possibility of studying the electrical variability of pure geophysical origin and correctly using self-potential measures for the monitoring of some geophysical phenomena. In particular, the relationship between electrical variability and seismic or volcanic activity, which might be useful in prediction studies of earthquakes and volcanic eruptions (*e.g.*, Sobolev, 1975; Massenet and Pham, 1985; Varotsos *et al.*, 1993; Cuomo *et al.,* 1996; Di Bello *et al.*, 1996; Park, 1996; Varotsos *et al.*, 1996; Uyeda *et al.*, 2000), can be strongly hidden by environmental disturbances such as meteorological variability and anthropic activities. Anthropic influences can be reduced by choosing monitoring sites in zones which are sufficiently far from industrial or urban areas, high power lines, and any source of human disturbance. This is possible just in theory, since for applied purposes we have to take into account that risk areas generally do not satisfy these requirements. In any case, even with optimal instrumental and ambient conditions, electric signals are sensitive to meteorological variability

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that can alter electrochemical phenomena. Therefore, studies related to the assessment of soil electric activity as a signature of geophysical phenomena for monitoring purposes cannot neglect the presence of inherent meteorological disturbances.

Self-potential signals are good examples of inhomogeneous signals containing both regularities and isolated singularities in the form of pulses, jumps, power or deltalike singularities. In order to single out unwanted interferences, our first task is to analyse electrical fluctuations retaining information on the localization of discontinuities and transient variations. To this purpose, wavelet analysis is a useful tool, able to carry out multiresolution studies and to enhance local features against long term dynamic structures. Formalization of wavelet theory was actually initiated by works on seismic signals (Goupillaud *et al.*, 1984; Grossmann and Morlet, 1984). Environmental perturbations in electrical signals might be singled out in the time-scale domain of the wavelet transform more easily than in the physical space. By transforming meteorological data, we locate the time-scale regions where the environmental stress acts. Then we transform the self-potential signal and, in the previously selected regions, we extract the excited wavelet coefficients. Such coefficients account for local fluctuations which are candidates for describing the electrical responses to the external disturbance. Excited coefficients can be filtered out and the signal can be recovered by anti-transforming the retained coefficients.

In this exploratory work, we focus on hourly electrical variability observed during rainy periods using hourly rainfall levels as support data. These levels are proxy data for the triggering action of rainfalls, since they are related to transient variations in the soil water content. The information stored in rain data concerns the strength of the external forcing and its duration but it does not provide indications on the evolution of possible subsequent long term soil responses. In dynamic terms, our support data allow us to investigate those short range self-potential fluctuations which strictly follow significant gradients of the soil water content. Of course, with additional support data, our methodological approach can be useful to pick up long range features as well.

2. Observational data

We analyse self-potential signals measured by means of a new geoelectrical monitoring network installed in a seismic active area of the Southern Apennine Chain (Italy). We focused on the analysis of self-potential data measured by the remote station prototype developed at the beginning of 1999 at the Institute of Methodologies for Environmental Analysis of the National Research Council (IMAA/CNR) Geophysical Laboratory, located in Tito Scalo (PZ). For further details on the monitoring network and the description of the experimental equipment, we refer to Balasco *et al.* (2002). Pluviometric measures were supplied by the Istituto Idrografico of Catanzaro.

Figure 1a,b shows two examples of self-potential time series recorded in rainy periods. The signal in fig. 1a is very erratic on short time scales and does not exhibit significant long range trends. Similarly to earthquakes, pluviometric measures can be regarded as realizations of a «point process» (Cowpertwait, 1994) that is a succession of discrete events we will call «rain events». Rain events in fig. 1a induce evident perturbations which seem to follow the triggering action of the rainfalls rather strictly. The first three consecutive small events induce a slight variation in the mean electric potential values (a trend over a period of ~ 1 day), whereas a cluster of more important events drives a rather sharp and large variation. This last perturbation persists for a time which is almost equal to the rainy period.

In fig. 1b, a cluster of rain events located at a time distance of a very few hours is likely to be responsible for the concomitant strong potential variation shown in the plot (~ 100 mV). Differently from the previous example, this transient is superimposed on a non stationary background. After that the rainfalls stop, the signal decrease is followed by an increase presumably due to the progressive drying process. The increase asymptotically restores the signal morphologies observed before the rainfalls but with mean values which are greater than those observed immediately before the rainfalls. Erratic short range variability with anti-persistent features is ubiquitous, as already highlighted in recent works (Cuomo *et al.*, 2000; Colangelo *et*

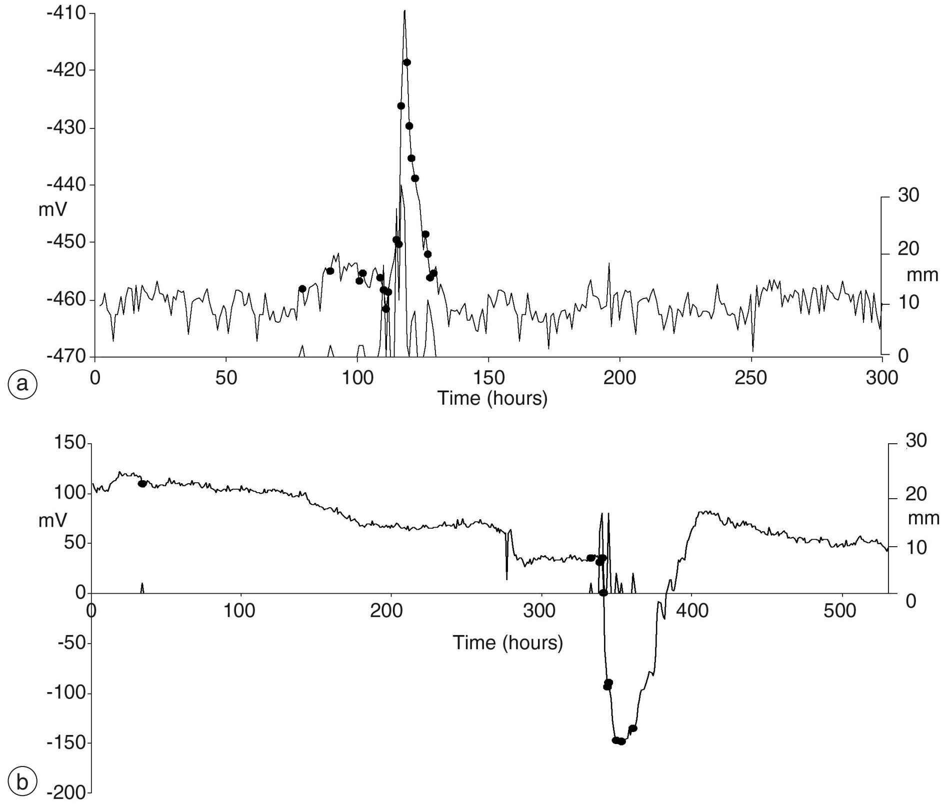

Fig. 1a,b. Two examples of hourly measures of self-potential and contextual hourly rainfall levels: a) measures recorded from 20.11.1999 to 03.12.1999; b) from 08.05.1999 to 29.05.1999. The vertical axis on the left side in the plot refers to self-potential while the axis on the right side refers to rain.

al., 2001). In these two cases, although correspondence between rain and signal anomalies appears rather evident, the strength and direction of the variations as well as duration of transients seem to be concerned with local dynamics.

3. The problem and the analysis rationale

3.1. *The dynamic problem*

The physical-statistical investigation of observational signals, aimed to reveal their underlying dynamics, is constrained by many factors, the main one being the nature itself of the dynamics. The presence of complex mechanisms related to many sources, possible nonlinear interactions among different perturbations, noises, make it very hard to solve the problem with simple tools. Unfortunately, we cannot *a priori* assume that disturbances induce simple effects. Ideally we can globally decompose the signal into smooth and fast components. In this picture, we split the dynamics on the basis of the frequency content: low frequencies account for long range variations whereas high frequencies account for generally erratic short range fluctuations (noise). Stationary noises in the context of linear dynamics are negligible because their effects have no significant consequences of dynamic value. Differently, externally induced abrupt changes and transient phenomena complicate the understanding of the electrical dynamics and its sources. The local character of these effects can alter the global dynamic outlook of the phenomenon, short and long time scales can interact and the simple global picture described above does not work well.

3.2. *The signal processing problem*

Mathematical transformations are usually applied to experimental data to obtain dynamic information that does not clearly appear in raw data. It is well known that pure traditional tools, such as the standard Fourier transform, are not suited for the analysis of non stationary signals. The Fourier transform of a signal with a local disturbance spreads the information concerning this singularity in all its coefficients so any filter will distort both the spectrum and the recovered signal. We need instead analysis tools able to carry out both global and local investigations allowing us to single out features at various temporal scales retaining information on the localization of discontinuities. Starting from traditional methods, some techniques have been developed, such as the short time Fourier transform (see *e.g.*, Portnoff, 1981), to carry out scale and time analysis simultaneously. In order to account for non stationary patterns, a temporal window is shifted along the series and the signal fluctuations are analysed separately within the series segments selected by the window. The width of the window is independent of the time scale so these methodologies are single-resolution. Transients in self-potentials may generally exist at different scales. When one cannot previously estimate the duration of the local patterns, a flexible window width is recommended. Wavelet analysis overcomes such problems since it is able to provide multiresolution time and frequency characterisation. It breaks up a signal in waveforms of duration matched to the scale. Such waveforms may be irregular and asymmetric, so providing a wide collection of functions to investigate shape, duration and arrival time of transients.

3.3. *Rationale*

We use the wavelet transforms of support time series as independent «markers» to select those time-scale regions where we expect that important features of the signal are mainly driven by environmental forcing. In the wavelet transform of the signal, such features are represented by anomalous (usually high absolute value) wavelet coefficients which we consider excited by external forcing. Owing to the multiresolution character of the wavelet analysis, the complexity of the patterns described in the physical space is separated in a multi-layer simpler descriptor. At any scale and time, we search for those excited coefficients that match significant coefficients of the marker. At this preliminary stage, we do not focus on the extensive study of electrical responses to different rainfall dynamics or on filtering strategies which can be more or less sophisticated depending on the specific needs. We merely aimed to evaluate the possibility of discriminating in a simple way wavelet coefficients accounting for meteorology induced morphological distortions by following the fingerprints of suited support data. We simply filtered the selected wavelet coefficients substituting their values with values randomly extracted form the distribution of the coefficients estimated at the scale concerned immediately before the rainfalls. This procedure is only mildly invasive because it preserves all the other coefficients and therefore all those details that, at any scale and time, cannot be directly associated with the given forcing, also during transients.

4. Some basic concepts of wavelet analysis

At present, there is an extensive literature concerning wavelet analysis and its applications, from classical papers (*e.g.*, Mallat, 1984; Daubechies,1992) to more recent textbooks (*e.g*., Percival and Walden, 2000). Here we limit ourselves to some background concepts useful for understanding this paper.

Wavelet analysis uses functions (wavelets), which are localised both in time and in frequency (or scale, in the rigorous wavelet formalism). In practice, the only basic requirement for regarding a function as a plausible wavelet is that it is an oscillating function which has limited duration, zero mean with an inherent pass-band like spectrum. The wavelet transform takes a one-dimensional time signal into a two-dimensional transformed function of time and scale. Therefore it resolves features at various scales without losing information on time localization. Such intrinsic ability to *zoom in* on short-lived high frequency phenomena is simply achieved by introducing a scale parameter s which adapts the width of the wavelet kernel to the resolution required (thus changing its frequency contents) at locations which are determined by a parameter t_0. Dilated (changing s) and translated (changing t_0) versions are obtained from a wavelet prototype ψ (mother wavelet). By iteratively dilating the wavelet and shifting it along the signal we obtain a multiscale information of the temporal properties of the signal. Dilated and translated versions of the mother wavelet are obtained by the action U

$$U(s, t_0)\,\psi(t) = \psi\left(\frac{t - t_0}{s}\right)$$

where $s,\ t_0 \in R$ and $s > 0$ for the Continuous Wavelet Transform (CWT). The wavelet transform W_f of a function $f(t)$ is then obtained projecting the function on the dilated and translated wavelets

$$W_f(s, t_0) = \frac{1}{s}\int f(t)\,U^*(s, t_0)\,\psi(t)\,dt$$

where (*) denotes complex conjugation. CWT is obtained by continuously shifting scalable functions which do not form an orthogonal basis. For many applied purposes we use the Discrete Wavelet Transform (DWT, Daubechies, 1992). Discrete wavelets are not continuously scalable and translatable but are scaled and shifted in discrete steps. In the DWT formalism the wavelet representation is

$$\psi_{j,k}(t) = \psi\left(\frac{t - kt_0 s^j}{s^j}\right).$$

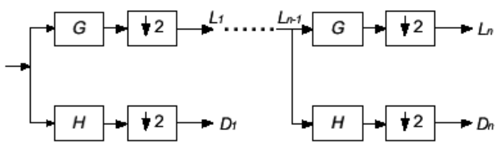

Fig. 2. Multilevel wavelet transform. The symbol ↓2 indicates down-sample by two.

The parameters j and k are integers and $s > 1$ ($s = 2$ for the usual dyadic sampling) is a fixed dilation step. The translation parameter t_0 depends on this dilation step: for $t_0 = 1$ we have a dyadic sampling of the time axis as well. Wavelet series decomposition transforms signals in series of wavelet coefficients. In discrete wavelet analysis, the signal is decomposed in approximation and details. The process can be iterated. The original signal is decomposed in successively lower resolution components so producing a wavelet decomposition tree. Figure 2 shows the generic form of a one-dimensional (1D) wavelet transform. The signal is passed through H (a low-pass filter) and G (a high-pass filter), and then down-sampled by a factor of two. This process is considered one level of the transform and can be repeated for a finite number of levels n. The resulting outputs, D_i ($i = 1, 2, \ldots, n$) and L_n, are called wavelet coefficients, and are details and approximation respectively. When we use orthogonal wavelet basis functions, we can reconstruct an arbitrary signal by anti-transforming its wavelet coefficients.

In this work, a dyadic wavelet decomposition is carried out down to level $n = 3$ that corresponds to a scale $2^3 = 8$ h (the coarsest time resolution of our analysis). This time scale appeared sufficient for investigating relatively fast variations in the given signals. We used the daubechies 3 (asymmetric) wavelet. Nevertheless trials with different wavelet functions did not imply remarkable differences in our analysis.

5. Results

Figure 3a,b shows the rain and self-potential wavelet coefficients estimated for the signal of

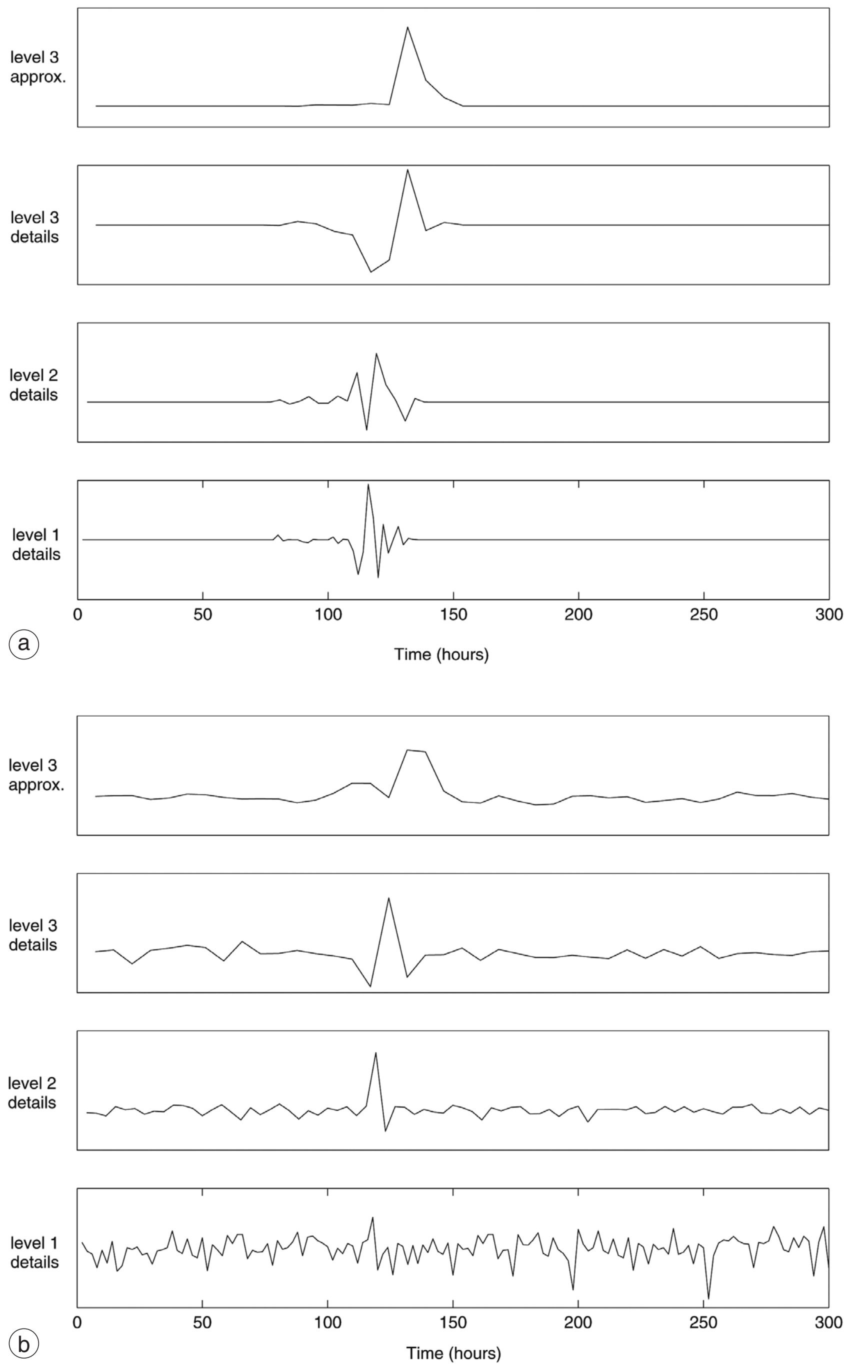

Fig. 3a,b. Wavelet coefficients (a) for rainfall measures and (b) for self-potentials relative to the signal reported in fig. 1a.

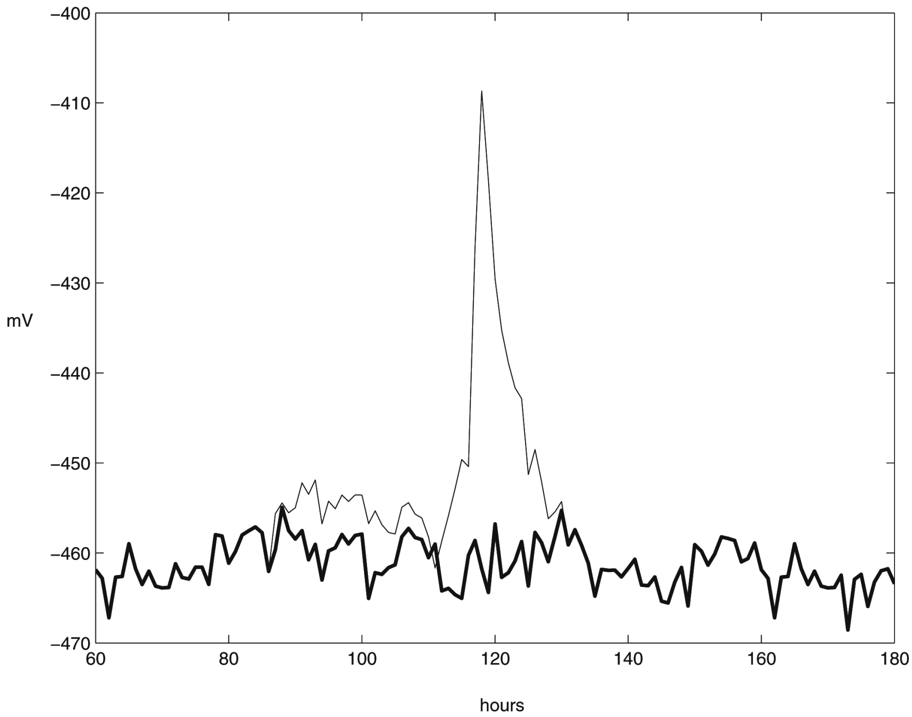

Fig. 4. Original (black line) and recovered (bold line) signals for the time series of fig. 1a.

fig. 1a. Correspondence between significant rain wavelet coefficients (fig. 3a) and excited signal coefficients (fig. 3b) is generally very good. We need no particular comparison criterion; a naked eye view is sufficient to understand that rain data are suited to locate the time-scale regions where the self-potential variability is altered. It is interesting to observe the signal coefficients (fig. 3b) at level 1 (scale = 2 h) in correspondence with the cluster of rainfalls (100-150 h). If we exclude a slighthy excited coefficient associated with the largest events, the coefficients at this scale do not appear particularly sensitive to rainfalls. This suggests that, when triggered, the rain effects are played on time scales longer that two hours. If a smoothing filter is used to remove the meteorological anomaly, these fine scale details may be averaged out. Our procedure instead retains these details. Figure 4 shows a *zoom in* representation of the original signal (fig. 1a) and the recovered signal. The two signals differ just during the rainfalls. It is interesting to see that no remarkable difference can be detected between the reconstructed signal during the external event and that of the real fluctuations observed before and after it. As stressed above, fine scale details are not synthetic. Our filter removes just excited coefficients so restoring the background behaviour. This fact highlights the mildly invasive character of our reconstruction.

The problem for the signal of fig. 1b is slightly more difficult because hourly rainfall levels in this case are not optimal support data. Figure 5a,b shows the estimated self-potential and rain wavelet coefficients. By comparing the coefficients at the same level of approximation or detail, we again observe a good agreement, but the excited regions for the signal are slightly longer that those detectable in the wavelet

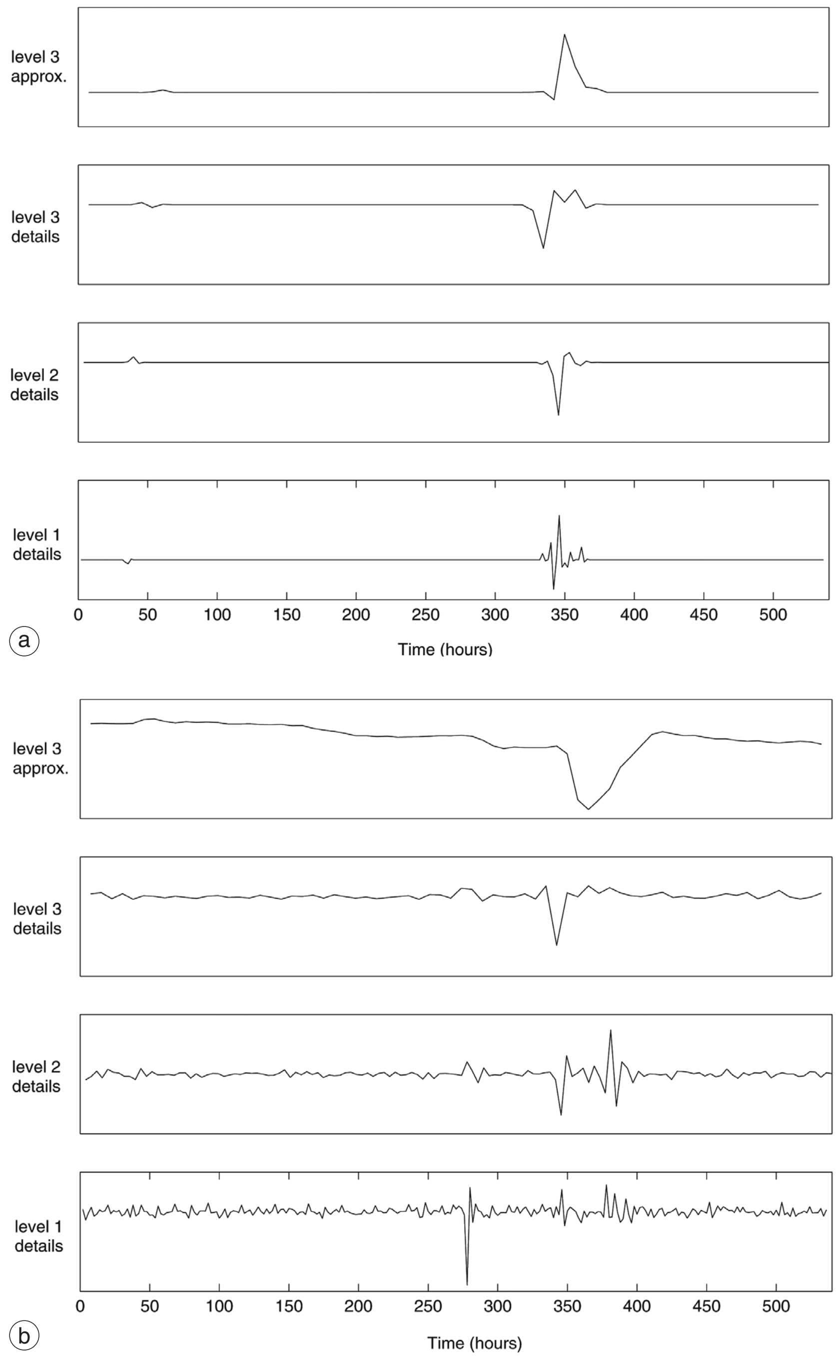

Fig. 5a,b. Wavelet coefficients (a) for rainfall measures and (b) for self-potentials relative to the signal reported in fig. 1b.

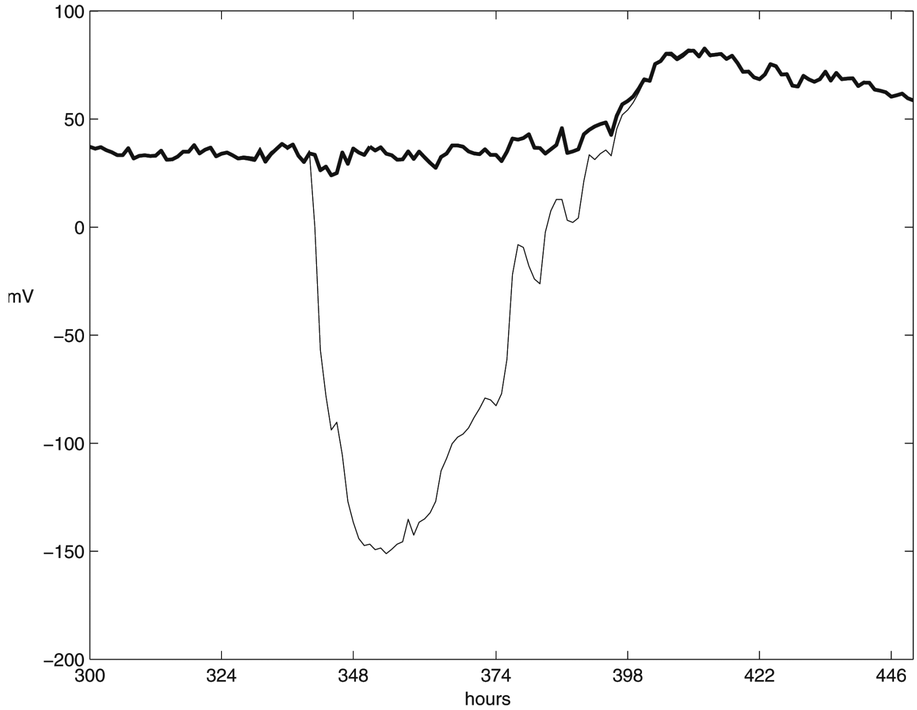

Fig. 6. Original (black line) and recovered (bold line) signals for the time series in fig. 1b.

transform of the rainfalls. As already observed in Section 2, the triggering action of the rainfalls seem to be followed by slower responses of the soil. In this case, our support data do not provide sufficient information to understand where the transient ends. In order to recover the signal, we made the operational hypothesis that the excited coefficients relative to the 24 h after the end of the rainfalls were relevant to the meteorological stress as well. As shown in fig. 6, the morphology of the recovered signal in the rainy period traces patterns which are similar to those observed in dry periods. About 24 h after the end of the rainfalls, the recovered signals adapts itself to intersect the observational data.

6. Conclusions

The main idea we present in this paper is that the joint multiresolution wavelet analysis of self-potential signals and support data related to environmental forcing can represent a suitable basis to extract environment-induced electrical fluctuations. Wavelet transform translates the complexity of mixed global behaviours and transient patterns described by the electrical signals in simpler time sequences of coefficients over several resolutions or scales. We focused on hourly self-potential variability driven by rainfalls by exploiting hourly rainfall level measures as support data. Such data, transformed in the wavelet domain, were used to mark the time-scale regions where rainfalls act influencing self-potential variability. We showed that in these regions excited wavelet coefficients of the signal are detectable and they well account for local alterations ascribable to the rain. Moreover, these coefficients can be filtered out, removing distortions with a mildly invasive technique. We think that our methodological approach is promising. However, the reliability of the recovering procedure is strictly related to the quality of the support data and their ability to represent the actual mechanisms we are interested in.

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