EC1: The paper presents several flaws in the organization, in the methodological approach and in the presentation of the results. Unfortunately the English is not fluent and the clarity of the sentences and concepts is not always achieved. Even the abstract, which in principle has to outline clearly and synthetically the main findings of the study, seems quite obscure and does not convey clearly the information on what is the outcome of the presented research. For instance the starting paragraph of the Abstract "Existence of a self-affine long range persistence in the seismic noise time series evidences that the current state of system is not in the pure diffused regime and transition from coherent to incoherent motion is still on progress. Rate of this evolving transition can be indirectly linked to the degree of heterogeneity of medium" seems not well explained and it would be difficult for a reader to understand what exactly its meaning is. Please, be aware that at least the abstract should be developed in a manner that even a reader not strictly familiar with the topic of the paper can capture the general information. Unfortunately, the whole abstract fails in the characteristics of clarity, synthesis, clear explanation of the obtained results.

AC: The extended abstract has been revised as follows. We hope it conveys clearly the main points of paper.

Abstract. The diffusivity of incoming seismic noise is certainly a critical precondition for executing seismic interferometry. But higher than the narrow ~ (0.05 -0.3) Hz microseismic bandwidth, this diffusivity stems mostly from the heterogeneity of local site characteristics, therefore the heterogeneity level of sites should be assessed beforehand in order to make an accurate assessment of a Green's response. As evidenced by recent studies (e.g. Padhy 2016), it has become evident that seismic signals show a self-affine long-range persistence in their coherent parts (e.g. P or S body waves) which is slowly disappeared with the emergence of the incoherent diffused incoming wavefield (i.e. Coda waves). Pilz & Parolai (2014) showed that the rate of this evolving transition is closely linked to the heterogeneity level of medium in such a way that for a strong heterogonous medium less time will be needed for falling signal into the diffuse state. Therefore, learning the fractality of a seismic noise will indirectly provide the basis for a decision on the potential place for executing seismic interferometry. But this conclusion rests on this pillar that input incoming noise wavefield is always stationary, but there is obviously a degree of ambiguity surrounding such assumption. There may be

circumstances under which signals include: Intrinsic Non-Stationary Direct Waves, Intrinsic Non-Stationary Scattered Waves and External Non-Stationary Signals. In executing the fractal analysis, it is essential that the method chosen be consistently reliable to ensure us that the correct Hurst coefficient is being used for the interpretation. There is broad agreement on the appropriateness of Multifractal Detrended Fluctuation Analysis (MF-DFA) in studying multifractal scaling behaviour of signals, corrupted by External Non-Stationary Signals, but it fails to comply with the intrinsic non-stationarity of signals. In this paper, we used the method introduced by Borgnat et al., (2010) to recognize the inherent characteristics of signal in the pre-processing step, before the feeding data into the cycle of Fractal analysis. Based on this revised method we try to define the degree of heterogeneity of different sites, locating at the North-Western of Iran.

References:

Borgnat, P., Flandrin, P., Honeine, P., Richard, C., and Xiao, J.: Testing stationarity with surrogates: A time-frequency approach, IEEE Transactions on Signal Processing, 58, 3459-3470, 2010.

Hillers, G., and Ben-Zion, Y.: Seasonal variations of observed noise amplitudes at 2–18 Hz in southern California, Geophysical Journal International, 184, 860-868, 2011.

Margerin, L., Planès, T., Mayor, J., and Calvet, M.: Sensitivity kernels for coda-wave interferometry and scattering tomography: theory and numerical evaluation in two-dimensional anisotropically scattering media, Geophysical Journal International, 204, 650-666, 2015.

Padhy, S.: The Multi-fractal Scaling Behavior of Seismograms Based on the Detrended Fluctuation Analysis, in: Fractal Solutions for Understanding Complex Systems in Earth Sciences, Springer, 99-115, 2016.

Pilz, M., and Parolai, S.: Statistical properties of the seismic noise field: influence of soil heterogeneities, Geophysical Journal International, 199, 430-440, 2014.

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EC1: However, the authors say that after removing mean and trend (which trend? linear trend? a figure with the raw data would have been useful), they merged all the different length segments; but how such merging was performed? Then since the data present gaps "stemmed from the zeroed out spikes and overlaps" (what overlaps?), this gaps were filled with linear interpolation; but this interpolation is not clearly explained, and the number and the length of gaps is not specified: these details would be important to mention especially in a journal like NPG, where a relevant focus is given on the methodological aspect of presented study.

AC: This question is of utmost importance and we will definitely add the detail of data processing. Our datasets include different-length segments (they are less than several seconds. As seen in the top panel of Figure 1, the first and end samples of each segments are accompanied by small-length "glitches". Further, some segments are affected by unusual trends which shows little consistence with regard to the exception of before and after it. Therefore, using the absolute-running-mean normalization can surgically remove narrow data glitches and unusual trends of a special segment (the below panel of Figure 1). The length of sliding window should be adaptively selected as small as possible to preserve the overall long-range mean and correlation of time series.

Missing data caused by removing these glitches is replaced by interpolated data as described at the Obspy Official website

https://docs.obspy.org/packages/autogen/obspy.core.trace.Trace.__add__.html#obspy.core.trace.Trace.__add__

(Part 4, from Handling gaps section named: "Traces with gaps and given fill_value='interpolate' ").

The length of interpolated sample is just one-sample so they potentially cannot effect on the long-range correlations. According to the Chen et al., (2002), shown at its Fig (2)-page 4, effects of the ''cutting'' procedure on the scaling behavior of correlated signals is not considerable with less than 10% of the points removed.

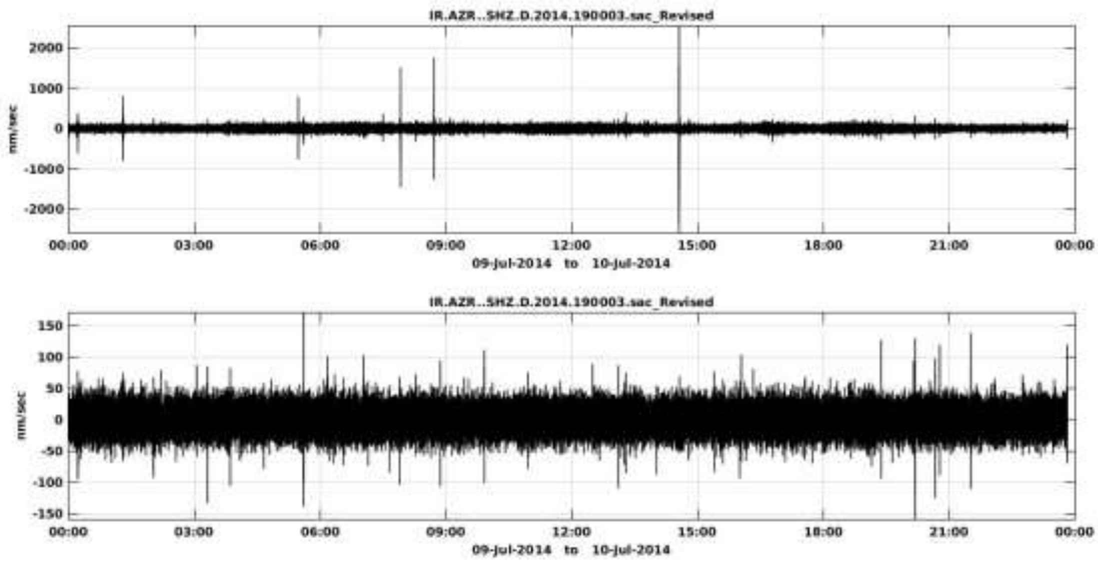

Fig (1) Above: An example for Merged 24-hour length signal which accompanied by small-length "glitches". Below: It depicts the signal shown in top panel after removing the small length glitches and replacing them with interpolated signals.

References:

Chen, Z., Ivanov, P.C., Hu, K. and Stanley, H.E., 2002. Effect of nonstationarities on detrended fluctuation analysis. Physical Review E, 65(4), p.041107.

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EC1: An explanatory table indicating name, geographic coordinates, elevation of Stations should be attached. Such lack of clarity is also evidenced in the description of the dataset. It is not mentioned how many stations have been analysed, although one can guess them from Fig. 1; but probably an explanatory table indicating name, geographic coordinates, elevation, and maybe some simple statistical characteristics, would have been useful to add to make the text clearer.

AC: We asserted below table as Table 1.

Station	Latitude (N˚)	Longitude (E˚)	Altitude (m)
AZR	37.678	45.984	2273
BST	37.701	46.889	2112
HRS	38.318	47.042	2137
MRD	38.713	45.702	2142
SHB	38.283	45.619	2290
SRB	37.825	47.663	1958
TBZ	38.235	46.15	1550

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EC1: Some flaws also exist in the methodology. For instance it would have been more correct to link the persistence/antipersistence of a signal to the succession of the increments rather than of the signal values.

AC: Thank you for notification. We will correct that mistake, at the original paper.

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EC1: It is correct the observation of the referee about what the authors did, ignoring the small part of the signal at its end that remains out during the calculation of the fluctuation function, since in

most of the studies such small part at the end of the signal has not ignored but included recalculating the fluctuation function starting from the end of the signal.

AC: Actually, we followed a process similar to the one outlined in the "Casetra, et al., 2007, and Pilz & Parolai (2014) ". Your comment is greatly appreciated in this regard, but the similar approach has been taken, geared towards improving the efficiency of their introduced method. We also considered the 3D soil displacement instead of its three components given by Casetra, et al., (2007) as:
"Moreover, we consider the 3D soil displacement instead of its three components because we are interested in studying the global soil motion under the effect of seismic noise; considering and comparing the motion in each component separately (H/V spectral ratio, etc.), could be done in a next paper (Casetra, et al., 2007, p. 259)".

In any case, we feel that your comment is well-founded and that there needs to be reflection on the matter in the advanced processing.

References:

Caserta, A., Consolini, G. and De Michelis, P., 2007. Statistical features of the seismic noise-field. *Studia Geophysica et Geodaetica*, *51*(2), pp.255-266.

Pilz, M. and Parolai, S., 2014. Statistical properties of the seismic noise field: influence of soil heterogeneities. *Geophysical Journal International*, *199*(1), pp.430-440.

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Also the use of the multitaper spectrogram (Borgnat et al., 2010) seems not correctly performed or at least not clearly carried out, raising issues on the correctness of the obtained results.

AC: Maybe I was not quite clear enough in explaining the theoretical aspect of Testing Stationary of Signal, so was maybe not something one would want to do too

A signal is stationary over a given observation scale if its spectrum undergoes no evolution in that scale. This assumption leads Bayram and Baraniuk, (2000) to use Multitaper Spectrograms (MS) for studying the time-dependent features of signals as

$$w_x(t,f) = \frac{1}{K}\sum_{k=0}^{K}\left|\int x(\tau)\mathrm{h}_k(-t)e^{-j2\pi f\tau}d\tau\right|^2 \qquad (1)$$

where $\{\mathrm{h}_k(\tau - t), k = 1, \dots, K\}$ stands for the first K Hermite functions, which are used as the short-length windows. Bayram and Baraniuk (2000) used the Hermite functions $\mathrm{h}_k^H(t)$ as the sliding windows since they give the best time-frequency localization and orthonormality in the time-frequency domain. Hermite functions can be obtained recursively, as follows

$$\mathrm{h}_k^H(t) = \pi^{\frac{-1}{4}}\left(2^k k!\right)^{\frac{-1}{2}} e^{\frac{-t^2}{2}} H_k(t) \tag{2}$$

where $\{H_k(t), \mathrm{t} \in \mathrm{N}\}$ represents Hermite polynomials, defined by

$$H_k(t) = 2tH_{k-1}(t) - 2(k-2)H_{k-1}(t) \tag{3}$$

in which $H_0(t) = 1$ and $H_1(t) = 2t$. These family of windows are mutually orthonormal with elliptic symmetry and maximum concentration in the time-frequency domain. To define the global spectrum of signal, we should take the average of MS as (Xiao et al., 2007)

$$\langle w_x(t,f)\rangle_N = \frac{1}{N}\sum_{t=0}^{N} w_x(t,f) \tag{4}$$

For a stationary signal $w_x(t,f)/w_x^{av}(t,f)$ remains almost unchanged at the whole recording window, but in practice fluctuations in this ratio is inevitable. These fluctuations can be defined by a dissimilarity function as

$$c_t^x = D\left(w_x(t,f), w_x^{av}(t,f)\right),\ t = 0, \dots, N \tag{5}$$

The significance of fluctuations can also be assessed by using surrogates (Borgnant et al., 2010). A surrogate is artificially produced in such a way that mimics statistical properties of real data. Isospectral surrogates have identical power spectra as the real signal but with randomized phases (Theiler et al., 1992). Once a collection of J synthesized isospectral surrogates, $\{s_j(t), j = 1, \dots, J\}$, are generated, the dissimilarity between local, $w_{s_j}(t,f)$, and global spectra, $w_{s_j}^{av}(t,f)$, for surrogates can be evaluated by (Borgnant et al., 2010)

$$\left\{c_t^{s_j} = D\left(w_{s_j}(t,f), w_{s_j}^{av}(t,f)\right),\ t = 0, \dots, N,\ j = 1, \dots, J\right\} \tag{6}$$

Borgnat et al., (2010) merged the Kullback-Leibler distance,

$$D_{KL}(A,B) = \int_{\Omega} \left(A(f) - B(f)\right)\log(A(f)/B(f))\, df \tag{7}$$

and log-spectral distance, $D_{KL}(A,B)$,

$$D_{LSD}(A,B) = \int_{\Omega} |\log(A(f)/B(f))|\ df \tag{8}$$

in the following combined form

$$D(A,B) = D_{KL}(A,B).\left(1 + D_{LSD}(\tilde{A},\tilde{B})\right) \tag{9}$$

In these equations A and B are two positive distributions and $\tilde{A}$ and $\tilde{B}$ indicate their normalized versions to the unity over the domain. The dissimilarity function $D(A,B)$ enables us to differentiate an amplitude-modulated or frequency-modulated non-stationary signal from a stationary one. Statistical variance $\Theta_1 = var(c_n^x)_{n=1,\ldots,N}$ gives the variance of c_n^xs. Similarly, for each one of J synthesized surrogates we can define a separate variance as

$$\left\{\Theta_0(j) = var\left(c_n^{s_j}\right)_{n=1,\ldots,N}, \; j = 1, \ldots, J\right\} \tag{10}$$

These Θ_0s can be assumed as a set of realizations of Gamma probability distribution with the following description

$$\mathrm{P(x; a, b)} = \frac{1}{b^a \psi(a)} x^{a-1} \exp\left(-{}^{x}/_{b}\right) \tag{11}$$

As a null hypothesis original signals is supposed to be stationary but if it violates the predefined threshold γ, null hypothesis is rejected and non-stationarity is assumed, that is

$$\mathcal{J}(x) = \begin{cases} 1 \; if \; \Theta_1 > \gamma: \; non-stationarity \\ \quad 0 \; if \; \Theta_1 < \gamma: \; stationarity \end{cases} \tag{12}$$

The threshold value for γ is considered as a confidence level of 95% for probability distribution under the maximum likelihood sense. By comparing Θ_1 and the estimates of Θ_0, one can define the degree of stationarity. Quantitatively, these difference can be evaluated by index of non-stationarity (INS) (Xiao et al., 2007):

$$\text{INS} = \sqrt{\Theta_1 / \frac{1}{J} \sum_{n=1}^{J} \Theta_0(j)} \tag{13}$$

Further, note the result of stationarity test depends on the window length of spectrogram, $\mathrm{T_n}$. This dependence can be analyzed by the scale of non-stationarity (SNS). It informs us that in which one/ones of considered values for $\mathrm{T_n}$ the given threshold in Eq. (10) has been exceeded (Xiao et al., 2007):

$$\text{SNS} = \frac{1}{\mathrm{T}} \arg\max_{\mathrm{T_n}} \{\mathrm{INS(T_n)}\} \tag{14}$$

References:

Bayram, M. and Baraniuk, R.G., 2000. Multiple window time-varying spectrum estimation. *Nonlinear and Nonstationary signal processing*, pp.292-316.

Xiao, J., Borgnat, P., Flandrin, P. and Richard, C., 2007, August. Testing stationarity with surrogates-a one-class SVM approach. In *Statistical Signal Processing, 2007. SSP'07. IEEE/SP 14th Workshop on* (pp. 720-724). IEEE.

Borgnat, P., Flandrin, P., Honeine, P., Richard, C. and Xiao, J., 2010. Testing stationarity with surrogates: A time-frequency approach. *IEEE Transactions on Signal Processing*, *58*(7), pp.3459-3470.

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EC1: The authors apply a complex signal pre-processing for searching the stationary windows to apply MFDFA. Besides the logical observation of the referee that the algorithm of the MFDFA is already developed in a way to remove the non-stationarities (thus making probably quite unuseful or unnecessary that pre-processing), it would have been, instead, much more useful, to apply the MFDFA directly to the signals (as obtained after the procedure described in section 2) and then to such stationary segments (and thus, after the pre-processing) to check if any difference would have been existed and to see if an improvement would have been obtained in the results, especially in relationship with the geophysical implications.

AC: The background seismic noise, at all moments and over different realizations, is generally assumed to be a temporarily-stationary process with certain second-order statistical properties e.g., mean value, variance and autocorrelation functions. Also, other sources of non-stationarity (e.g. segments with different properties, random outliers or spikes with different amplitudes, etc.) are mostly viewed as superimposed external transient signals. In general, there is broad agreement on the appropriateness of MFDFA to get a better handle on the detrimental effects of simple types of superimposed intermittent non-stationarities, associating with exterior long period trends, e.g. polynomial, sinusoidal, and power-law functions, but In connection with this point, we must make it absolutely clear that inherent non-stationarity of signals should never be confused with the concept of non-stationarity made by external perturbations. We wish to draw your attention to the paragraph "III. ANALYSIS OF SUNSPOT TIME SERIES" of Movahed (et al., 2005) which explains the reasons why further attention must be taken in the analysing the inherent stationarity of signals in the pre-processing step, before feeding them into the cycle of Fractal analysis. The importance of this issue is strikingly apparent for seismic signals, since a seismic time series inherently may lose their stationarity within finite time intervals and theses intervals at various frequency ranges or temporal length are different. The experimental estimates obtained by Gorbatikov & Stepanova, (2008) shows that, at the microseismic range of frequency, signals are mostly quasi-stationarity, but this stationarity may not be preserved for very long periods of time. For instance, this interval might be lengthen to the several day or be shorten to the 1–1.5 h , while Wang et al., (2014) showed that for frequencies above than 1 Hz signals, the stationarity range of signal is just in the range of several seconds. Therefore, the choice for signal length in executing MFDFA may appear of utmost importance, in such a way that, choosing an extreme short window length might lead to non-informative, and potentially misleading results. In certain circumstances, reproducible non-Stationary ballistic waves e.g. the waves induced by the interaction of wind and topography, or the waves generated by the near surface micro cracks may make matters worse by inducing large variability in the characteristics of seismic noise signals. Furthermore, Meng, et al., (2015) showed that the incoherent coda waves might be intrinsically non-Stationary, as well. This might be due to the occurrence of multiple scattering in an instable perturbed medium which Margerin et al., (2016) named it "the active scattering". When the time series is stationary its behavior can be considered as a fractal Gaussian noise (fGn), while for a no-stationary signal the concept of fractal Brownian motion (fBn) should be used instead (Qian, 2003; Ge and Leung, 2013). The stationarity of fGn signals can be characterized by two parameters, σ^2, the variance, and H, the Hurst coefficient, while a fBm process has a time dependent variance. Not surprisingly, on the basis of the class to which signals belong, different techniques may be required for processing. Seismic time series appear occasionally in the quasi-stationary state. In those cases, reproducible seismic signals could fall into the one of the following states: macroscale, mesoscale or microscale state (Borgnat et al. 2010), therefore, more accurate method is needed in order to properly assess the state of this quasi-stationarity. Failure to match signal class with the appropriate method of fractal analysis results in serious error in the estimating H and an incorrect interpretation of stationarity/non-stationarity of signal lead to misleading results (Chen et al., 2002; Eke, et al., 2002; Movahed et al., 2006). To this end, the Dispersional analysis (Disp) is recommended to use for alysing the fractionality of fGn signals, while bridge detrended scaled windowed variance analysis (bdSWV) is suitable for fBm signals (Eke et al., 2000). MFDFA can also be used sepately for both fGn and fBn (see, Delignieres et al., 2006). Based on this explanations, We want to underline that the degree of stationarity of signal should be known at the pre-processing step before making our choice between fGn and fBm process. However, these classes might not be a-priori known, so signal summation conversion method (SSC) is advised to use as a discriminating method (Eke et al., 2000). Based on this approach, a preliminary interpretation may be available by fitting a straight line of slope $-\beta$ on a log–log plot of the periodogram. Based on this method, signals can be categorized into the fGn or fBn, according to the value of β. Eke et al., (2000) placed emphasis on this point that tthe periodogram is only applicable for differentiating if β falls into the category $-1<\beta<0.38$ (for an obvious stationary case) or if falls into the range of $1.4 <\beta<3$ (for an obvious non-stationary case), but there is no certainty that this method fully comply with the complicated characteristics of signals in the range of $3.8<\beta<1.4$ where stationary and non-stationary mixed into each other. Therefore, it is essential to provide another reliable framework for a regular monitoring the stationarity of signals. In this paper, we do make a point that the length of signal directly impacts on the reliability of Long-range autocorrelations assessment. The importance of this factor was previously the subject of other investigations such as Delignieres et al., (2006) and Warlop et al., (2017).

References

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AC: I am also skeptical about the obtained results, because it seems that the calculation of the slopes of the fluctuation functions in Fig. 3 was performed considering all the available shown scales; if so, this is clearly wrong, because the fluctuation functions for any q are not linear in log-log scales. So, if the geophysical interpretation of the results are based on such wrong calculations of the slopes

of the fluctuation functions, also all the geophysical implications, rather poorly described by the way, would be not convincing.

EC: We tested the process for different time length, different seasons, different weather conditions, and also night and day times. All of results will be added at the final paper. We confirmed the suitability of this method.