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Multifractal analysis based on the weak scaling exponent and applications to MEG recordings in neuroscience

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Stéphane Jaffard[‡], Guillaume Saës[‡]

Abstract : We develop the mathematical properties of a multifractal analysis of data based on the weak scaling exponent. The advantage of this analysis is that it does not require any a priori global regularity assumption on the analyzed signal, in contrast with the previously used Hölder or p -exponents. As an illustration, we show that this technique allows one to perform a multifractal analysis of MEG signals, which records electromagnetic brain activity, that was not theoretically valid using the formerly introduced methods based on Hölder or p -exponents.

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This article is dedicated to Akram Aldroubi: a true friend, a great scientist, and a fantastic salsa dancer!

1 Introduction

The purpose of this article is to develop the mathematical understanding of a newly introduced variant of multifractal analysis which does not require a priori regularity assumptions on the data to be analyzed, in contrast to all other multifractal analysis methods introduced in the past; furthermore, we show it at work on MEG signals, which record electromagnetic brain activity from SQUID sensors located around the patient's head. The reason for testing this new framework on such data is that MEG signals often don't meet the a priori regularity assumptions required by other methods. We start by recalling the purpose and aims of multifractal analysis from a signal processing viewpoint.

1.1 Multifractal analysis

Multifractal analysis supplies methods which associate to everywhere irregular signals classification parameters based on scaling invariance properties. It can be traced backed to the seminal work of N. Kolmogorov in the 1940s [48] where the *Kolmogorov scaling function* $\zeta_f(q)$ of a function f was introduced as

$$\forall q > 0, \quad \int |f(x+h) - f(x)|^q dx \sim |h|^{\zeta_f(q)} \quad (1)$$

in the limit of small scales $h \rightarrow 0$ (a more precise, but less eloquent definition is supplied by (12)). A first success of this tool is that it allowed to discard the possibility of modeling the velocity of fully developed turbulence at small scales by fBm; indeed this process has a linear scaling function, which is not the case for turbulence data, see [32] and ref. therein. Key steps concerning the understanding of the information supplied by the scaling function were obtained as a consequence of key ideas introduced by U. Frisch and G. Parisi in 1985 [60]: They interpreted the strict concavity of the scaling function as indicating the presence of different values taken by the pointwise regularity of the function analyzed. Let us be more precise: The pointwise Hölder exponent of a locally bounded function $f : \mathbb{R} \rightarrow \mathbb{R}$ is defined as follows.

Definition 1.1. *Let $f \in L_{loc}^\infty(\mathbb{R})$. Let $x_0 \in \mathbb{R}$ and $\alpha \geq 0$; f belongs to $C^\alpha(x_0)$ if there exist a polynomial P_{f,x_0} of degree less than α and $C, r > 0$ such that*

$$\forall x \in (x_0 - r, x_0 + r), \quad |f(x) - P_{f,x_0}(x - x_0)| \leq C|x - x_0|^\alpha.$$

The Hölder exponent of f at x_0 is $h_f(x_0) = \sup\{\alpha : f \in C^\alpha(x_0)\}$.

The multifractal spectrum of f is

$$\mathcal{D}_f(H) = \dim(\{x : h_f(x) = H\}), \quad (2)$$

where \dim denotes the Hausdorff dimension (and, by convention $\dim(\emptyset) = -\infty$).

The support of the spectrum is the set of values H for which $\mathcal{D}_f(H) \neq -\infty$.

The idea underlying the definition of the multifractal spectrum is that, for large classes of signals, pointwise regularity varies from point to point in an extremely irregular way, so that its precise determination is not a realistic goal, and one should rather focus on estimating more global quantities, such as the size of the sets of points where a given type of singularities shows up. U. Frisch and G. Parisi proposed a formula for estimating $\mathcal{D}_f(H)$ by means of a Legendre transform of ζ_f : they defined the *Legendre spectrum* of f as

$$\mathcal{L}_f(H) := \inf_q (1 + Hq - \zeta_f(q)), \quad (3)$$

and they developed heuristic arguments backing the idea that, in general, the Legendre spectrum coincides with the multifractal spectrum (when it is the case, the *multifractal formalism* is said to hold). Multifractal analysis (using several possible variants for the definition of the scaling function) has been tried and tested in numerous applications ranging from medical image processing [33, 69] to the modeling and prediction of natural phenomena [31, 50, 61] and brain activity in neuroscience [19, 20, 49, 26].

However, two limitations of this approach quickly appeared: First it is irrelevant for functions that are not locally bounded, in which case the Hölder exponent is no longer defined. This raised the problem of determining if the Kolmogorov scaling function yields some information for other concepts of pointwise regularity; we will come back to this question in Sec. 2. Another concern was the numerical instability of the computation of the scaling function when extended to negative values of q ; this concern is critical because, if one restricts the definition (3) to $q > 0$, then it yields at best the increasing hull of the multifractal spectrum. This problem already appeared for models as simple as the Brownian motion; Since its pointwise Hölder exponent takes the constant value $h_B(x) = 1/2$, it follows that its multifractal spectrum is supported by the unique value $H = 1/2$, whereas (3) yields a wrong decreasing part for \mathcal{D}_B : Its right hand side takes the value $3/2 - H$ for $H \in [1/2, 3/2]$, see [44, 12]. These limitations motivated several advances:

- This setting was soon extended to the analysis of probability measures: In that case, the pointwise regularity exponent h_μ of a measure μ is (informally) defined by

$$\mu([x - r, x + r]) \sim r^{h_\mu(x)} \quad \text{when } h \rightarrow 0; \quad (4)$$

in 1992, G. Brown, G. Michon and J. Peyrière proved that the corresponding formalism (obtained by adapting (3) to a relevant scaling function, such as (5) below) yields an upper bound for the multifractal spectrum when the infimum is taken on all (positive and negative) values of q , see [14].

- As regards functions, in order to eliminate the numerical instabilities met for $q < 0$, A. Arneodo and his collaborators introduced an alternative way to compute the scaling function: In 1991, they proposed to replace increments in (1) by a continuous wavelet transform, and the integral by a discrete sum computed over the local maxima of this transform [57].

- In 1997 a functional analysis interpretation of the scaling function for $q > 0$ (see (12) below) opened the way to determining when data can be modelled by locally bounded functions, and also to the first mathematical results concerning the validity of the multifractal formalism for functions [40].

1.2 Multiscale quantities and wavelet expansions

Definition (4) plays a key role in the derivation of the upper bound supplied by the multifractal formalism in the measure setting, where the scaling function $\eta_\mu(q)$ of a measure μ can be defined as follows. We will use the following notations for dyadic intervals:

$$\lambda (= \lambda_{j,k}) = \left[\frac{k}{2^j}, \frac{k+1}{2^j} \right] \quad \text{and} \quad 3\lambda = \left[\frac{k-1}{2^j}, \frac{k+2}{2^j} \right].$$

The *measure scaling function* of μ is defined by

$$\forall q \in \mathbb{R}, \text{ if } S_\mu(j, q) = 2^{-j} \sum_k (\mu(3\lambda_{j,k}))^q, \quad \eta_\mu(q) = \liminf_{j \rightarrow +\infty} \frac{\log(S_\mu(j, q))}{\log(2^{-j})}; \quad (5)$$

Denote by $\lambda_j(x)$ the unique dyadic interval of width 2^{-j} which contains x . Then (4) can be rewritten

$$h_\mu(x) = \liminf_{j \rightarrow +\infty} \frac{\log(\mu(3\lambda_j(x)))}{\log(2^{-j})}. \quad (6)$$

When such a relationship holds between a non-negative quantity defined on dyadic intervals and a pointwise regularity exponent, we will say that the multiscale quantity (here $\mu(3\lambda)$) is *associated* with the corresponding exponent (here h_μ). This notion is important because, when it holds, it follows that

$$\mathcal{L}_f(H) \leq \inf_q (1 + Hq - \zeta_f(q)), \quad (7)$$

see [42]. This is a strong motivation for the quest of multiscale quantities associated with pointwise regularity exponents. In the case of the Hölder exponent of a function, a first possibility is to consider its *oscillations*

$$\mathcal{O}_f(\lambda) = \sup_{x,y \in 3\lambda} |f(x) - f(y)|$$

(or higher order differences if Hölder exponents larger than one can be met in the data), see [44]. However, this method lacks of numerical accuracy. The state-of-the-art method makes use of *wavelet leaders* instead, which are defined as follows.

Let ψ be an oscillating and well localized function, having its first r (≥ 1) vanishing moments and of class $C^{r-1}(\mathbb{R})$. The function ψ generates an *r-smooth orthonormal wavelet basis* when the $\{\psi_{j,k}(x) = 2^{j/2}\psi(2^jx - k)\}_{(j,k) \in \mathbb{Z}^2}$ form an orthonormal basis of $L^2(\mathbb{R})$. The discrete wavelet coefficients of a function f are defined by

$$c_{j,k} = 2^j \int_{\mathbb{R}} f(x)\psi(2^jx - k) dx, \quad (j, k) \in \mathbb{Z}^2. \quad (8)$$

Let λ denote the dyadic interval $\lambda = [\frac{k}{2^j}, \frac{k+1}{2^j})$; we will sometimes index wavelets and wavelet coefficients by dyadic intervals and write indifferently $c_\lambda = c_{j,k}$.

A first advantage of using wavelets is that they offer a numerically reliable extension of the Kolmogorov scaling function with a wider range of applicability: The *wavelet scaling function*, is defined as in (5), but replacing the multiscale quantity $\mu(3\lambda_{j,k})$ by the wavelet coefficients $c_{j,k}$. Let $q > 0$; the *q-structure functions* of f are

$$\forall j \geq 0, \quad S_f^w(j, q) = 2^{-j} \sum_k |c_{j,k}|^q;$$

The *wavelet scaling function* of f is

$$\zeta_f(q) = \liminf_{j \rightarrow +\infty} \frac{\log(S_f^w(j, q))}{\log(2^{-j})}. \quad (9)$$

Note that the definition of the wavelet scaling function does not require any assumption on the data: One just has to make sure that the wavelet used are smooth enough, in which case (8) is interpreted as a duality product between smooth functions (wavelets) and a tempered distribution f . Furthermore, it is independent of (smooth enough) wavelet basis which is used, see [40]. The scaling function thus obtained is still denoted by $\zeta_f(q)$ because it coincides with the Kolmogorov scaling function if $q > 1$ and if the Hölder exponent of f takes all its values below 1. It has many use cases:

- it can be used for classification;
- it allows us to determine for which type of pointwise exponents a multifractal analysis can be performed, see (12) below;
- it yields an upper bound of the increasing part of the *weak scaling spectrum*, see Def. 1.4 and Prop. 2.2 below.

The wavelet scaling function is ill-defined for negative qs ; indeed, the distribution of wavelet coefficients of real-life signals usually display a non-vanishing density around 0, hence wavelet coefficients of arbitrarily small size show up, and generate numerical instabilities when raised to a negative power. A way to mitigate this problem consists in considering the following alternative scaling function, see [42].

Definition 1.2. Let $f \in L_{loc}^\infty(\mathbb{R})$, and assume that a sufficiently smooth wavelet basis has been chosen. The wavelet leaders of f are

$$\forall (j, k) \in \mathbb{Z}^2, \quad l_f(j, k) = \sup_{\lambda' \subset 3\lambda} \{|c_{\lambda'}|\}.$$

The *wavelet leader scaling function* is

$$\forall q \in \mathbb{R}, \text{ if } S_f(j, q) = 2^{-j} \sum_k (l_f(j, k))^q, \text{ then } \eta_f(q) = \liminf_{j \rightarrow +\infty} \frac{\log(S_f(j, q))}{\log(2^{-j})}. \quad (10)$$

A numerical advantage of using wavelet leaders in the definition of the scaling function is that, in contradistinction with wavelet coefficients, their distribution vanishes around 0, see [13]. An additional key property is that, under a uniform regularity hypothesis on the data, wavelet leaders are *associated* with the Hölder exponent according to (6), see [42]; it follows that the corresponding Legendre spectrum (using the wavelet leader scaling function) yields an upper bound for the multifractal spectrum which holds without additional assumption.

However, large classes of signals cannot be modelled by locally bounded functions: In order to determine when this is possible, one computes the value taken by the *uniform Hölder exponent*, denoted by H_f^{\min} , which is defined through a log-log plot regression as follows

$$H_f^{\min} = \limsup_{j \rightarrow +\infty} \left(\frac{\log(\sup_k |c_{j,k}|)}{\log(2^{-j})} \right). \quad (11)$$

Note that this exponent has found an independent interest for classification, see e.g. [1] and Sec. 4. If $H_f^{\min} < 0$, then the data cannot be modelled by a locally bounded function, see [40], and it follows that a multifractal analysis based on the Hölder exponent cannot be performed; this situation is illustrated in Fig. 4 where a log-log plot regression of a MEG signal is performed, yielding a negative value for H_f^{\min} ; see also Fig. 5 where it is shown that most exponents H_f^{\min} which we have estimated on MEG data are negative. Nonetheless, if $\zeta_f(q) > 0$, then the data can be modelled by a function in L_{loc}^q . This follows from the following interpretation of the wavelet scaling function:

$$\zeta_f(q) = q \cdot \sup\{s : f \in L^{q,s}(\mathbb{R}^d)\}, \quad (12)$$

where $L^{q,s}(\mathbb{R}^d)$ denotes the Sobolev space of functions (or distributions) whose fractional derivative of order s belongs to L^q , see [40]. In that case, the following extension of the Hölder exponent introduced by A. Calderón and A. Zygmund can be used [17].

Definition 1.3. *Let $f \in L_{loc}^p(\mathbb{R})$ with $p \geq 1$. Let $x_0 \in \mathbb{R}$. A function f belongs to $T_\alpha^p(x_0)$ when there exist a polynomial P_{f,x_0} of degree less than α and constants $C, R > 0$ such that*

$$\forall r \in (0, R), \quad \left(\frac{1}{r} \int_{x_0-r}^{x_0+r} |f(x) - P_{f,x_0}(x - x_0)|^p dx \right)^{\frac{1}{p}} \leq Cr^\alpha.$$

The p -exponent of f at x_0 is $h_f^p(x_0) = \sup\{\alpha : f \in T_\alpha^p(x_0)\}$.

Appropriate multiresolution quantities associated with the p -exponent have been introduced in [47, 52]. They are referred to as p -leaders, and the corresponding multifractal formalism is currently used in signal and image processing, and even preferred to the leader based multifractal formalism due to its improved statistical performances, see [51] where it is shown that values of p close to $p = 2$ should be preferred. Note that the choice $p < 1$ allows one to analyze certain tempered distributions (by replacing the spaces L^p by the real Hardy spaces H^p in Def. 1.3), see [46, 43].

1.3 The weak-scaling exponent

In practice, the use of p -exponents does not cover all types of data that are met in real-world applications. This has been noticed for the analysis of the cadence of marathon runners [12] and it also happens when analyzing brain activity notably on MEG signals, as shown later on in Sec. 4. On the theoretical side, a simple example for which no p -exponent can be used is supplied by Gaussian white noise; indeed, the fact that its coefficients on any orthonormal basis are IID centered normal Gaussian variables easily implies that its wavelet scaling function is

$$\forall q > 0, \quad \zeta_X(q) = -\frac{q}{2},$$

so that it takes negative values only. We will see in Sec. 3 other examples of mathematical models for which no p -exponent can be used. These situations, which show up both in theory and applications, call for the use of another pointwise regularity exponent which would be defined without any a priori assumption. Such an exponent has been introduced by Y. Meyer in [55], with a different purpose. The initial motivation was to answer a problem which appeared in the mid 1980s: Indeed, it was commonly believed that the pointwise Hölder exponent of a function f can be characterized by the decay rate of its continuous wavelet transform in the *cone of influence* of the point considered; if translated to the discrete wavelet setting, this means that, for a given point x_0

$$\exists C, C' > 0 : \quad \text{if} \quad \left| \frac{k}{2^j} - x_0 \right| \leq \frac{C}{2^j} \quad \text{then} \quad |c_{j,k}| \sim 2^{-h_f(x_0)j} \quad (13)$$

(the $2[C] + 1$ wavelet coefficients closest to x_0 at each scale decay like $2^{-h_f(x_0)j}$). Such a statement was proved wrong, typical counterexamples being supplied by the chirps

$$|x - x_0|^\alpha \sin\left(\frac{1}{|x - x_0|^\beta}\right), \quad (14)$$

for $\alpha, \beta > 0$. However Yves Meyer showed that this property (essentially) characterizes the weak-scaling exponent, which can be defined as follows, see [55, 12] where equivalent definitions are also introduced.

Definition 1.4. *A tempered distribution $f : \mathbb{R} \rightarrow \mathbb{R}$ belongs to the two-microlocal space $C^{s,s'}(x_0)$ if its wavelet coefficients (in an r -smooth smooth wavelet basis with $r > \max(|s|, |s'|)$) satisfy*

$$\exists C, \quad \forall j, k, \quad |c_{j,k}| \leq C 2^{-sj} (1 + |2^j x_0 - k|)^{-s'}; \quad (15)$$

$f \in \Gamma^s(x_0)$ if there exists $s' > 0$ such that $f \in C^{s,-s'}(x_0)$.

The weak-scaling exponent of f is

$$h_f^{ws}(x_0) = \sup\{s : f \in \Gamma^s(x_0)\}.$$

The multifractal weak scaling spectrum $\mathcal{D}_f^{ws} : \mathbb{R} \cup \{+\infty\} \rightarrow \mathbb{R}_+ \cup \{-\infty\}$ of f is the mapping defined by

$$\forall H \in \mathbb{R}, \quad \mathcal{D}_f^{ws}(H) = \dim_H(\{x \in \mathbb{R} : h_f^{ws}(x) = H\}).$$

Note that the weak scaling exponent can take any positive or negative value. In particular, this notion allows us to give a proper mathematical framework for defining pointwise singularities of arbitrary negative exponent. This is not a straightforward problem: for instance, it is well known that the usual *cusp singularities*

$$|x - x_0|^\alpha$$

no longer make sense if $\alpha < -1$ (they are ill-defined as Schwartz distributions, so that, for instance, their wavelet coefficients cannot be properly defined).

In this article, our purpose is to investigate techniques for the estimation of the function \mathcal{D}_f^{ws} , and to show its relevance for the analysis of MEG data.

In Sec. 2.1, we discuss the pertinence of the weak-scaling spectrum in order to perform the multifractal analysis of data. In Sec. 2.2 we show how the increasing part of the weak scaling spectrum can be estimated directly from wavelet coefficients. The estimation of the decreasing part requires the use of (θ, ω) -leaders as multiscale quantities which are introduced in Sec. 2.3. In Section 3, we illustrate these results by showing what this analysis yields for several classical mathematical models, such as fractional Gaussian noises, random wavelet series and multifractal random walks, thereby demonstrating the relevance and accuracy of the weak-scaling spectrum compared to previously introduced methods. Finally, in Sec. 4, we apply this technique to MEG recordings (time series), for which a multifractal analysis based on p -exponents cannot be systematically completed.

This article is partly review and partly research: Besides the introduction, the review part concerns Sec. 2, where we collect several results concerning the weak-scaling exponent which are scattered in the literature, and we complement them by new results. The other sections contain new material.

2 Mathematical tools for weak-scaling multifractal analysis

In this section, we collect results concerning the equivalent mathematical definitions of the weak-scaling exponent and its relevance for multifractal analysis. Furthermore, we discuss how this analysis can be performed in a numerically stable and tractable way.

2.1 When should the weak-scaling exponent be used?

Several criteria have been proposed to determine if a multifractal analysis based on the p -exponent can be worked out. A simple criterion that we already mentioned is that it is the case if, for this value of p , the wavelet scaling function satisfies $\zeta_f(p) > 0$, see [47]. Another criterion, which is derived from the *large deviation spectrum* of the wavelet coefficients, can be found in [12]. We now propose a new one, which can be applied if some information is available concerning the location of the singularities of the data.

Definition 2.1. Let $\delta < 1$ and $q > 0$. A tempered distribution $f : \mathbb{R} \rightarrow \mathbb{R}$ is (δ, q) -sparse if it can be written $f = f_1 + f_2$ with $f_1 \in L^q$ (or, when $q \leq 1$, if f_1 belongs to the Hardy real space H^q) and the wavelet expansion of f_2 in a given wavelet basis is such that, at generation j , f_2 has at most $C \cdot 2^{\delta j}$ nonvanishing wavelet coefficients.

Typical example of (δ, q) -sparse distributions are provided by lacunary wavelet series [41] or by distributions supported by a fractal set of upper box dimension $\delta < 1$. This last case is relevant e.g. for applications in urban modeling, where data are carried by the urban network, which is often modelled by a fractal set [29].

Recall that the Besov space $B_p^{s,\infty}$ can be characterized by the following wavelet condition:

$$\exists C, \forall j, \quad 2^{-j} \sum_k |c_{j,k}|^p \leq C 2^{-spj}.$$

Proposition 2.1. If f is a (δ, q) -sparse distribution, then there exist $\varepsilon, p > 0$ such that $f \in B_p^{\varepsilon,\infty}$, so that a multifractal analysis of f using p -exponents can be performed.

Proof: Since $f_1 \in L^q$, a p -exponent based multifractal analysis of f_1 can be performed for any $p \leq q$, so that we focus on f_2 . Since it is a tempered distribution, it is of finite order, so that there exists $A \in \mathbb{R}$ such that $f_2 \in C^A(\mathbb{R})$ (one can pick any $A < H_f^{min}$); thus, its wavelet coefficients satisfy

$$\exists C \quad \forall j, k, \quad |c_{j,k}| \leq C 2^{-Aj}.$$

If $A > 0$, then f_2 has a positive uniform Hölder regularity, and the result holds. Let us now assume that $A \leq 0$. Since f_2 has at most $C 2^{\delta j}$ nonvanishing wavelet coefficients,

$$\forall j \quad 2^{-j} \sum_k |c_{j,k}|^p \leq C 2^{(-1+\delta)j} 2^{-Apj},$$

so that

$$f_2 \in B_p^{s,\infty} \quad \text{for any} \quad s \leq \frac{1-\delta}{p} + A.$$

We now recall the following classical embeddings between Besov and Sobolev spaces

$$\forall s > s' > s'', \quad B_p^{s,\infty} \subset L^{p,s'} \subset B_p^{s'',\infty}.$$

It follows that p -exponents can be used as soon as $f \in B_p^{s,\infty}$ for an $s > 0$, and s can be picked positive as soon as

$$p < \frac{1-\delta}{-A}. \tag{16}$$

This proposition shows that sparsity conditions on the wavelet expansion can imply that a multifractal analysis based on some p -exponent can be performed for a $p > 0$, the value of which being given by (16). However, it has been documented that performing a multifractal analysis based on the p -exponent is robust for values of p close to 2, so that having recourse to values close to 0 may lead to numerical instabilities [51].

If no p -exponent can be used, i.e. if the wavelet scaling function satisfies

$$\forall p > 0, \quad \zeta_f(p) < 0,$$

then one can always perform on the data a preprocessing which consists in performing first a fractional integration of order s on the data; indeed if s is large enough, then the wavelet scaling function of the smoothed signal f^{-s} thus obtained becomes positive for some (or even all) values of p : the Sobolev interpretation of the wavelet scaling function, supplied by (12) implies that it suffices to take a fractional integral of order s larger than

$$s_0(p) = \frac{-\eta_f(p)}{p}.$$

Larger values of s will even shift the uniform Hölder exponent to positive values: since $H_{f^{-s}}^{min} = H_f^{min} + s$, it suffices to take a fractional integral of order larger than $-H_f^{min}$. It follows that a multifractal analysis based on the Hölder exponent will be possible. This technique has often been used (either explicitly or implicitly) in multifractal analysis. It is for instance a prerequisite before using the WTMM [57] (indeed, the continuous wavelet transform restricted at its local maxima may yield unbounded quantities if $H_f^{min} < 0$). Nonetheless, a fractional integration can alter the shape of the multifractal spectrum in a way that cannot be a priori predicted, so that, in general, it is not possible to derive information on the initial data from such an analysis. This has been documented in the case of *Lacunary Wavelet Series*, where, for a given p , the multifractal spectrum of $f^{(-s)}$ is a shifted *and dilated* version of the multifractal spectrum of f , see [3]. In Sec. 3 we will show other examples which illustrate this phenomenon, and therefore call for a direct analysis of the data without such a preprocessing.

2.2 An upper bound for the weak-scaling spectrum

The wavelet scaling function allows to derive the following upper bound of the weak-scaling spectrum see [45].

Proposition 2.2. *Let f be a tempered distribution defined on \mathbb{R} . Then its weak scaling spectrum satisfies*

$$D_f^{ws}(H) \leq \inf_{p>0} (Hp - \eta_f(p) + 1). \quad (17)$$

This result is natural if we remember the heuristic which motivated the introduction of the weak-scaling exponent: The size of the wavelet coefficients located in the “cone of influence” yield this exponent through a log-log plot regression; this means that, though wavelet coefficients are not multiscale quantities associated with the weak-scaling exponent in the sense supplied by (6), nonetheless they are “close” to be such, so that the corresponding upper bound still holds. However, this formula meets a severe limitation: Since the infimum is taken on positive ps only, the right hand side of (17) is increasing, and this bound can only estimate the increasing part of the spectrum. Actually, if this formula is applied to negative

ps, it does not yield a sharp estimate, as shown by the toy-example supplied by Brownian motion, see [44, 12].

An extension of Prop. 2.2 for $p < 0$ is proposed in [44]. It is based on structure functions which are not derived directly from wavelet coefficients, but rather from ε -leaders, i.e. from multiscale quantities which are defined as local suprema of wavelet coefficients taken on small boxes of width $2^{\varepsilon j}$ around the corresponding location of the wavelet coefficients in the time-scale half-plane, and then taking a limit of the resulting scaling functions when $\varepsilon \rightarrow 0$. This formulation however is not fitted to applications, because of the double limit which is involved in this approach. This motivated the introduction of new multiscale quantities which we now describe; indeed, they do not present this double-limit drawback and they yield sharp upper bounds for the weak scaling spectrum (see Def. 1.4 below), which turn out to be equalities for several classes of models, see [12] and Sec. 3.

2.3 Multiscale quantities: (θ, ω) -leaders

We now define the local suprema of wavelet coefficients which are the multiscale quantities on which multifractal analysis for the weak-scaling exponent will be based.

A function $\theta : \mathbb{N} \rightarrow \mathbb{R}^+$ has *sub-polynomial growth* if it satisfies

$$\left\{ \begin{array}{l} \forall j \quad \theta(j+1) \geq \theta(j) \geq j \\ \frac{\log(\theta(j))}{\log(j)} \rightarrow 0 \quad \text{when } j \rightarrow +\infty; \end{array} \right. \quad (18)$$

typical examples are supplied by functions of logarithmic growth $j \rightarrow j + C(\log j)^a$ for an $a \geq 0$. Note that this definition is slightly more general than those introduced previously, see [12] and ref. therein.

A function $\omega : \mathbb{N} \rightarrow \mathbb{R}^+$ has *sub-exponential growth* if it is non-decreasing and such that

$$\left\{ \begin{array}{l} \omega(k) \rightarrow +\infty \quad \text{when } k \rightarrow +\infty \\ \frac{\log(\omega(k))}{k} \rightarrow 0 \quad \text{when } k \rightarrow +\infty; \end{array} \right. \quad (19)$$

typical examples are supplied by power-laws $k \rightarrow k^a$ for an $a > 0$.

We start by defining the sets of dyadic intervals on which the local suprema of wavelet coefficients will be taken.

Definition 2.2. *Let θ and ω be two functions with respectively sub-polynomial and sub-exponential growth, and let λ be a dyadic interval; the (θ, ω) -neighbourhood of λ , denoted by $V_{(\theta, \omega)}(\lambda)$ is the set of dyadic intervals λ' indexed by the couples (j', k') satisfying*

$$j \leq j' \leq \theta(j) \quad \text{and} \quad \left| \frac{k}{2^j} - \frac{k'}{2^{j'}} \right| \leq \frac{\omega(j)}{2^j}.$$

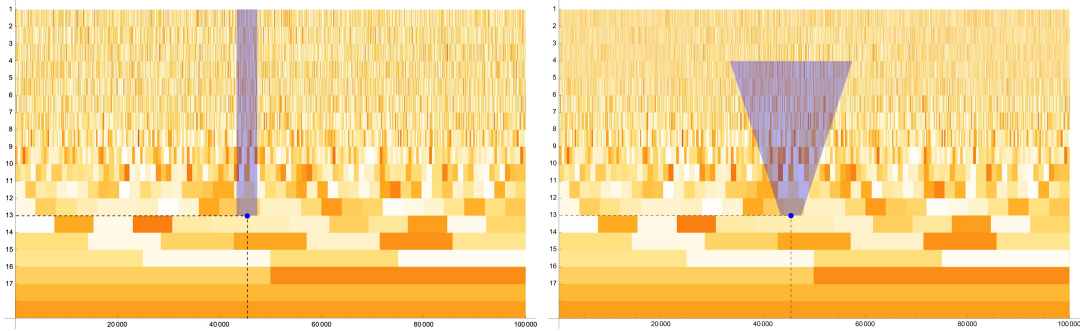


Figure 1: Selected wavelet coefficients for leaders (left) and (θ, ω) -leaders (right) for the determination of the corresponding multiresolution quantities.

We now introduce the (θ, ω) -leaders which will be the multiscale quantities on which the multifractal analysis of the weak-scaling exponent will be based, see Figure 1.

Definition 2.3. *Let f be a tempered distribution of wavelet coefficients $(c_{j,k})$; the (θ, ω) -leaders of f are defined by*

$$d_{j,k} = \sup_{(j',k') \in V_{(\theta,\omega)}(j,k)} |c_{j',k'}|. \quad (20)$$

The definition that we gave is slightly more general than the one proposed in [12]; its motivation is to solve some numerical problems met by the previous definition, while keeping its key mathematical properties. Indeed, it allows to define leaders such that the supremum in their definition is taken on a number of coefficients which can be chosen more evenly as a function of the scale, hence can display better statistical properties: Note that, for the definition we take, at generation j , this supremum is taken on

$$(2^{\theta(j)+1} - 1) \omega(j)$$

coefficients.

The definition of (θ, ω) -leaders yields an extension of the wavelet scaling function (9) to $p < 0$; indeed, one can easily check that, for $p > 0$, the following definition coincides with (9).

Definition 2.4. *Let f be a tempered distribution; its wavelet scaling function is defined by*

$$\forall p, \quad \zeta_f(p) = \liminf_{j \rightarrow +\infty} \frac{\log \left(\omega(j) \cdot 2^{-j} \sum_{k=l \cdot [2 \cdot \omega(j)]} |d_{j,k}|^p \right)}{\log(2^{-j})}. \quad (21)$$

The sum is taken over the multiples of $[2 \cdot \omega(j)]$ so that the contribution of one dyadic interval λ' is taken into account only once, inside one of the (θ, ω) -leaders. If the wavelet coefficients are computed over an interval of length L then, at the generation j , there are $\sim L2^j$ wavelet coefficients which are computed; since the supremum in the computation of

wavelet leaders is taken on $[2 \cdot \omega(j)] + 1$ coefficients of generation j , then the prefactor of normalization of the sum in (21) corresponds to the number of elements on which this sum is taken.

The following result was already derived in [44] in the case of ε -leaders and extended to (θ, ω) -leaders in [12]. One easily checks that it remains valid for the extension of (θ, ω) -leaders that we propose in the present paper.

Proposition 2.3. *Let f be a tempered distribution. Then its weak scaling spectrum satisfies*

$$\mathcal{D}_f^{ws}(H) \leq \inf_{p \in \mathbb{R}} (Hp - \zeta_f(p) + d). \quad (22)$$

In particular, if the wavelet scaling function of a distribution f is a linear function over \mathbb{R} , then its weak scaling exponent is constant.

3 Mathematical models

3.1 Fractional noises

Let us consider the example of Gaussian white noise. It is a Schwartz distribution, which is not a function. Since it has Gaussian IID coefficients on an arbitrary orthonormal basis, it follows that its wavelet expansion is

$$W(x) = \sum_{k \in \mathbb{Z}} \chi_k \varphi(x - k) + \sum_{j=0}^{\infty} \sum_{k \in \mathbb{Z}^d} \sum_i \chi_{j,k} 2^{j/2} \psi(2^j x - k), \quad (23)$$

where this equality has to be understood in the sense of distributions, and the χ_k and $\chi_{j,k}$ are IID centered reduced Gaussian random variables. A straightforward computation yields that its wavelet scaling function is

$$\forall p \in \mathbb{R}, \quad \zeta_W(p) = -\frac{p}{2}.$$

As a consequence of Prop. 2.3, the weak scaling exponent of the Gaussian white noise satisfies

$$\text{a. s. } \forall x \quad h_W^{ws}(x) = -\frac{1}{2}.$$

It follows in particular that this random distribution satisfies the multifractal formalism for the weak scaling exponent (i.e. equality holds between the multifractal and the Legendre spectrum).

3.2 Multifractal analysis of random wavelet series

Random wavelet series (RWS) were introduced in [4] where their multifractal analysis was performed. They offer an interesting field of investigation in order to compare the different

variants of multifractal analysis; indeed, their multifractal spectra differ depending if one uses the Hölder and the p -exponents, and it depends on the value of p that is chosen, see Theo. 3.1 below. We show in this section that a multifractal analysis based on the weak-scaling exponent yields yet another spectrum, which supplies more information on the parameters which characterize the RWS. We start by briefly recalling the construction of these processes.

Definition 3.1. *Let $(\psi_{j,k})_{j,k \in \mathbb{Z}^2}$ be a smooth orthonormal wavelet basis. A RWS associated with this basis is a stochastic process of the form*

$$X_t = \sum_{j \geq 0} \sum_{k \in \mathbb{Z}} c_{j,k} \psi_{j,k}(t) \quad (24)$$

such that its wavelet coefficients $c_{j,k}$ are independent and, at each scale j , share a common law μ_j . Additionally, these laws satisfy

$$\text{a.s.} \quad \exists C > 0, \exists A \in \mathbb{R}, \forall j \geq 0, \forall k \in \{0, \dots, 2^j\}, \quad |c_{j,k}| \leq C 2^{-Aj}. \quad (25)$$

Note that this notion is not canonical, but depends on the wavelet basis chosen. Since we are interested in regularity properties of the sample paths of X_t , we need not care about possible terms corresponding to $j < 0$ which would yield a smooth contribution to (24), and we do not consider such a component in the following. Note that the assumption (25) only implies that the sample paths of the process are well defined as a Schwartz distribution; more precisely, it implies that the process X has some uniform regularity: the wavelet characterization of the Hölder spaces implies that a.s. the sample paths of X locally belong to the Hölder space C_{loc}^A . A simple sufficient condition implying that the sample paths are continuous (and thus that the Hölder exponent can be used in order to estimate pointwise regularity) is to pick $A > 0$ in (25). Another condition implying that the sample paths belong to L_{loc}^p is given below, see Prop. 3.1.

The a.s. multifractal properties of the sample paths of RWS depend on a quantity called the *wavelet large deviation spectrum* introduced in [4], and which we now recall. Let $j \geq 0$ be given and denote by ρ_j the common probability measure of the 2^j random variables $X_{j,k} := -\log_2(|c_{j,k}|)/j$. Thus ρ_j satisfies

$$\mathbb{P}(|c_{j,k}| \geq 2^{-\alpha j}) = \rho_j((-\infty, \alpha]).$$

Definition 3.2. *Let X_t be a RWS. Let*

$$\forall \alpha \in \mathbb{R}, \quad \text{let} \quad \rho(\alpha, \varepsilon) := \limsup_{j \rightarrow +\infty} \frac{\log_2(2^j \rho_j([\alpha - \varepsilon, \alpha + \varepsilon]))}{j},$$

and, for $\alpha = +\infty$,

$$\rho(A) := \limsup_{j \rightarrow +\infty} \frac{\log_2(2^j \rho_j([A, +\infty)))}{j},$$

The wavelet large deviation spectrum of X is

$$\text{if } \alpha < +\infty, \text{ then} \quad \rho(\alpha) := \inf_{\varepsilon > 0} \rho(\alpha, \varepsilon), \quad (26)$$

$$\text{if } \alpha = +\infty, \text{ then } \quad \boldsymbol{\rho}(+\infty) := \inf_{A>0} \boldsymbol{\rho}(A). \quad (27)$$

The support of the wavelet large deviation spectrum is

$$\text{supp}(\boldsymbol{\rho}) = \{\alpha : \boldsymbol{\rho}(\alpha) \geq 0\}.$$

Note that $\boldsymbol{\rho}$ is defined on $\mathbb{R} \cup \{+\infty\}$ and takes values in $[-\infty, 1]$. As in [4], in order to evacuate degenerate cases of little interest, we suppose that $\boldsymbol{\rho}(\alpha)$ takes a positive value for at least one (finite) value of α .

The following result follows from the determination of the wavelet scaling function of RWS in [4]; it supplies a sufficient condition for the use of the Hölder exponent or the p -exponent in the multifractal analysis of X_t .

Proposition 3.1. *Let $p \in (0, +\infty)$. If*

$$\forall \alpha \in \mathbb{R}, \quad \boldsymbol{\rho}(\alpha) < p\alpha + 1 \quad (28)$$

then the sample paths of X_t almost surely belong to L_{loc}^p . Furthermore, if

$$\exists \varepsilon > 0 : \quad \forall \alpha < \varepsilon, \quad \boldsymbol{\rho}(\alpha) = -\infty$$

(or, equivalently, if (25) holds for an $A > 0$), then the sample paths of X_t almost surely belong to L_{loc}^∞ .

Let

$$W = \{\alpha : \forall \varepsilon > 0, \quad \sum_{j \in \mathbb{N}} 2^j \boldsymbol{\rho}_j([\alpha - \varepsilon, \alpha + \varepsilon]) = +\infty\}, \quad H_X^{\min} := \inf_{\alpha} W, \quad (29)$$

and

$$H_X^{\max}(p) := \left(\sup_{\alpha} \frac{\boldsymbol{\rho}(\alpha)}{\alpha + 1/p} \right)^{-1}.$$

The following result yields the multifractal p -spectra of the sample paths of RWS. The case $p = +\infty$ corresponds to the Hölder exponent.

Theorem 3.1. *Let X be a random wavelet series, and assume that (28) holds. With probability one, the sample paths of X share the following properties:*

- *The support of their multifractal p -spectrum is $\mathcal{S}_X = [H_X^{\min}, H_X^{\max}(p)]$;*
- *their multifractal p -spectrum $\mathcal{D}_X(H)$ is given by*

$$\forall H \in \mathcal{S}_X, \quad \mathcal{D}_X^p(H) = H \sup_{\alpha \leq H} \boldsymbol{\rho}(\alpha) \frac{H + 1/p}{\alpha + 1/p}; \quad (30)$$

- *for almost every t ,*

$$h_X(t) = H_X^{\max}. \quad (31)$$

- the Legendre p -spectrum is the concave hull of the multifractal spectrum.

The last statement is a weak formulation of the multifractal formalism. This theorem is proved in [4] in the case of the Hölder exponent and in [3] for the p -exponent in the case of lacunary wavelet series (i.e. when $\boldsymbol{\rho}$ take only one non-negative value). Its extension to the general case of the p -exponent of RWS follows from adapting the ideas developed in [4] inside the framework supplied by p -exponents as shown in [3].

We now consider the setting supplied by the weak scaling exponent.

Theorem 3.2. *Let X be a random wavelet series. The weak scaling multifractal spectrum of X is given by*

$$\forall H \in \mathbb{R}, \text{ a.s.}, \quad \mathcal{D}_X^{ws}(H) = \boldsymbol{\rho}(H) 1_W(H).$$

Sketch of proof: This theorem follows from several results of [4]. Let $\varepsilon > 0$ and denote by E_α^ε the limsup of the ε -neighbourhoods of the dyadic intervals λ such that the corresponding wavelet coefficient $c_{j,k}$ satisfies $c_{j,k} \sim 2^{-\alpha j}$. First, note that outside of the set

$$\bigcup_{\alpha} E_\alpha^\varepsilon$$

h_X^{ws} takes the value $+\infty$. Letting $\varepsilon \rightarrow 0$, we obtain that the support of the spectrum is included in the support of 1_W . Let now α be fixed; for any $\varepsilon > 0$, the set of points x where $h_X^{ws}(x) = \alpha$ is included in

$$F_\alpha^\varepsilon = E_\alpha^\varepsilon - \bigcup_{\beta \neq \alpha} E_\beta^\varepsilon,$$

and a simple box-counting argument yields that

$$\dim(F_\alpha^\varepsilon) \leq \boldsymbol{\rho}(\alpha) + o(1)$$

(where the $o(1)$ has to be understood as a limit when $\varepsilon \rightarrow 0$). Taking the limit when $\varepsilon \rightarrow 0$, it follows that $\mathcal{D}_X^{ws}(H) \leq \boldsymbol{\rho}(H) 1_W(H)$. The lower bound is obtained as in [4], using an ubiquity-type argument.

3.3 Multifractal random walk (MRW)

Multifractal random walks are Gaussian processes defined as integrals of infinitely divisible stationary multifractal cascades with respect to fractional Brownian motion [5, 2]. They have met a huge success as models of phenomena of multiple natures and as models on which the numerical algorithms for estimating multifractal spectra have been tested. By construction, such processes display only *canonical singularities* in the sense defined in [3], i.e. their Hölder, p -exponents and weak-scaling exponents coincide (whenever they are well defined) as a consequence of the following property: when applying a fractional integral of order α , the pointwise exponent of such processes is increased by exactly the quantity α . This implies that the numerically estimated spectra of the sample paths of MRWs using wavelet leaders, p -leaders or (θ, ω) -leaders should yield the same result, and these spectra should be shifted

by α to the right when a fractional integral of order α is applied. Figure 2 shows that the spectrum always is correctly obtained in the case of an analysis based on the weak scaling exponent. This is in sharp contradistinction in the cases of the Hölder and the p -exponents where the analysis yields a wrong spectrum when the admissibility condition for the use of the corresponding exponent is not satisfied.

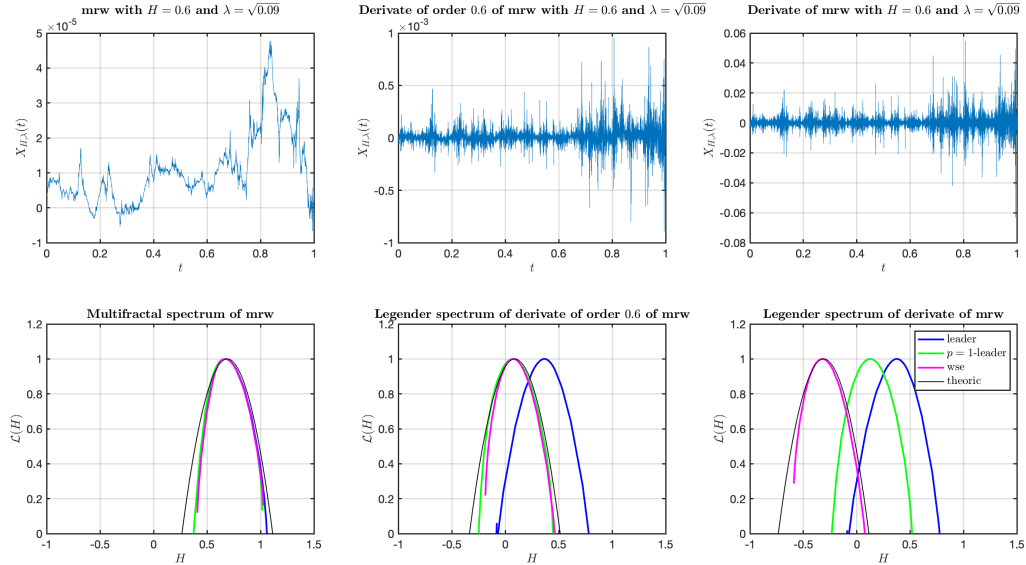


Figure 2: Legendre spectrum estimation of multifractal random walk (mrw) by leaders, p -leaders and (θ, ω) -leaders coefficients (left), Legendre spectrum estimation of derivate of order 0.6 of MRW (center), derivate of order 1 of MRW (right).

4 Multifractal analysis of brain activity measured in MEG

4.1 Scale-free dynamics in brain activity

Scale-free dynamics has been reported in spontaneous brain activity [39] and in electrophysiological recordings, such as magnetoencephalography (MEG), electroencephalography (EEG) and local-field-potentials (LFP) [39, 28, 49]. The presence of scale-free dynamics in the brain was originally demonstrated in the infra-slow frequency range of the broadband spectrum (from 0.01 Hz to 1 Hz [39, 16, 37, 10]) but also in the slow power fluctuations of narrow-band neuronal oscillations [30, 54, 56, 59, 26]. Empirical work has revealed that scale-free dynamics of brain activity was modulated by levels of wakefulness (*vs.* sleep) [71, 39, 24, 64], consciousness (*vs.* anesthesia) [38, 8], aging and neurodegenerative diseases [63] as well as task performance [15, 39, 36, 20, 74, 75, 56, 59, 53, 49].

The intuition behind the scale-free concept is that the relevant information in the temporal dynamics of a given signal is coded within the relations that tie together temporal scales, rather than solely in the power of neuronal oscillations in specific bands. However, its origin remains poorly understood. Brain activity recorded with MEG or EEG is more comparable to LFP, and slow dynamic fluctuations probably reflect the up and down states of cortical networks compared to spiking activity *per sec* [6]. Hence, although fast neuronal activity or avalanches can endogenously produce scale-free infra-slow brain dynamics nearby the critical regime [26], a careful statistical assessment remains necessary to draw conclusions on the nature of observed scale-free dynamics [11, 66, 21].

4.2 Models for scale-free brain dynamics

Scale-free dynamics recorded in electrophysiology (MEG, EEG) has generally been quantified using a $1/f^\beta$ power spectrum model on a wide continuum of frequencies. As a result, empirical assessment has often used Fourier-based spectrum estimation. As an alternative, self-similarity provides a well-accepted model for scale-free dynamics that encompasses, formalizes, and enriches traditional Fourier $1/f^\beta$ spectrum modeling, with models such as fractional Brownian motion (fBm) or fractional Gaussian noise (fGn) [58, 39, 20, 18]. The parameter of self-similarity, or Hurst exponent H , matches the spectral exponent β as $\beta = 2H - 1$ for fGn and as $\beta = 2H + 1$ for fBm. In the context of brain activity, H indexes how well neural activity is temporally structured (through its autocorrelation). Furthermore, although H has been estimated using Detrended Fluctuation Analysis (DFA) [54, 15, 36, 35, 59, 8], it is now well documented that wavelet-based estimators provide significant theoretical improvements and practical robustness over DFA, notably by disentangling true scale-free dynamics from non-stationary smooth trends [68, 65, 9, 20, 18]. For a review of statistically relevant estimations of the self-similarity parameter, interested readers are also referred to [7].

Often associated with Gaussianity, self-similarity alone does not fully account for scale-free dynamics. The main reason is that self-similarity restricts the description of neural activity to second-order statistics (autocorrelation and Fourier spectrum) and hence to additive processes. However, multiplicative processes have been proposed to provide more appropriate descriptions of neural activity [16]. Independently of, and in addition to self-similarity, multifractality provides a framework to model these nonadditive processes [62, 63, 67]. Multifractality can be conceived as the signature of multiplicative mechanisms or as the intricate combination of locally self-similar processes. For example, if a cortex patch (i.e. the anatomical resolution of MEG recordings) is composed of several small networks each characterized by a single self-similar parameter H , the multifractality parameter (say M) constitutes an index that captures the diversity of H s and their interactions within the patch. Qualitatively, the multifractality parameter M quantifies the occurrence of transient local burstiness or non-Gaussian temporal structures, not accounted for by the autocorrelation function or by the Fourier spectrum (hence, neither by H nor β). To meaningfully and reliably estimate M , it has been theoretically shown that the wavelet-based analysis must be extended to wavelet-leaders [72] and more recently to wavelet p -leaders [52]. The purpose of this section is to show that such p -leader formalism can fall short in certain situations in MEG time se-

ries analysis such as the presence of oscillating singularities, such as the chirps (14), or when $\zeta_X(p)$ is negative for all values of $p > 0$ so that a multifractal analysis based on p -exponents cannot be worked out, for any value of p .

4.3 Motivations for WSE-MFA in MEG

The development of the weak-scaling multifractal analysis is instrumental for a reliable and automated analysis of MEG times series. This statement actually results from the following key observations. First, from sensor to sensor, MEG signals have a varying amount of regularity, some embodying oscillating singularities. Therefore fractional integration or order s has different effects on different time series. Optimizing the order s in a sensorwise manner is not tenable in practice and would mean that the input signals cannot be analyzed in a homogeneous way, or that, part of the neuronal activity is lost if we adopt the same fractional order everywhere. Second, as MEG recordings are real data, we don't have access to ground truth parameters ($H_{min}, \eta(q)$) and their estimates may be biased. The WSE multifractal analysis therefore allows us to get rid of such inherent limitations of the standard wavelet p -leader formalism.

4.4 MEG data set

Magnetoencephalography (MEG) measures magnetic field magnitude and gradient near the surface of the skull of human subjects. The commonly received interpretation for the genesis of magnetic currents observed in MEG is that the postsynaptic currents of large neuronal assemblies of pyramidal neurons in the cortex that fire together in a synchronized manner form current dipoles whose induced magnetic field is strong enough to overcome the noise and be measured by SQUID sensors. We picked an ordinary resting-state recording from an openly available dataset [70] to showcase the common shortcomings of wavelet leaders and p -leaders in the context of state-of-the-art multifractal analysis of MEG signals. The time series were sampled at 1793 Hz, and at recording time were high-pass filtered at 0.1 Hz. We additionally low-pass filtered the data with a cutoff at 3 Hz.

4.5 MEG signal preprocessing

MEG signals are naturally noisy, as sensors record every magnetic field variation, whether coming from the brain or from physiological noise sources (e.g. eye blink, heartbeat, motion) and external ones (e.g. power line). We followed the standard processing pipeline in order to remove the noise component in the data, making use of mne-python [34]:

1. Bad MEG sensors are identified visually.
2. Signals coming from outside the area where the head is present are suppressed via the temporal Signal-Space Separation method (tSSS). Bad channels are interpolated in the process, and head movement is cancelled by shifting to a reference position.

3. Biological artifacts due to blinking and heartbeats are removed via Independent Component Analysis (ICA). Independent components (spatial filters) that correlate to heartbeats and blinks are identified, then the measurement is reconstructed, without the noise components.

Further projection of the signals onto the cortical surface (also called source localization in the field) is possible, however it is not necessary to illustrate the problems associated with low regularity in the recorded time signals: They are already present in the sensor space.

Prior art. The low frequency fluctuations of electrophysiological time series have been shown to be approximately scale free in MEG/EEG [22, 23, 74]. In particular, multifractality in MEG signals has been demonstrated to be increased in multiple brain areas during a visual discrimination task as compared to the resting state [76, 49] and through a multi-perceptual learning paradigm [77, 73]. Additionally, multifractality has been observed during epileptic seizures [25] and reproduced from computational models of neural field dynamics [26].

Difficulties and aims. Electrophysiological recording time series are difficult to handle due to the presence of locally highly irregular singularities. The low minimal regularity of MEG time series has required large fractional integration coefficients ($s \geq 1.5$) to make a p -leaders analysis feasible with $p = 2$ (the value which heuristically yields the best statistical robustness).

The lowest regularity time series is the one which sets the global integration level, as a single value of s for the whole data set is required to have comparable estimates to perform statistical analysis later on.

Single outlier low-regularity time series may be ignored, annotated as bad channels and interpolated. However this carries a loss in statistical power during subsequent analyses, and should remain exceptional.

Lifting the current requirement of high fractional integration to perform multifractal analysis in neural recordings would enable a gain in sensitivity to unveil multifractality, and therefore higher statistical power in MEG data analysis. Higher statistical power then implies being able to better determine the functional relevance of multifractality and its modulation between different experimental conditions, stimuli of patient conditions.

4.6 Multifractal analysis

Multifractal analysis of MEG signals was performed using the open source Python Toolbox `pymultifrac`¹ [27].

In order to perform the multifractal analysis, we begin by computing the discrete wavelet transform of preprocessing MEG time series to obtain the wavelet coefficients $c_{j,k}$ across time scales $j \in [j_{\min}, j_{\max}]$ and time points $k/2^j$, and then an estimate of the value taken by the exponent H_f^{\min} defined by (11).

¹<https://github.com/neurospin/pymultifrac>

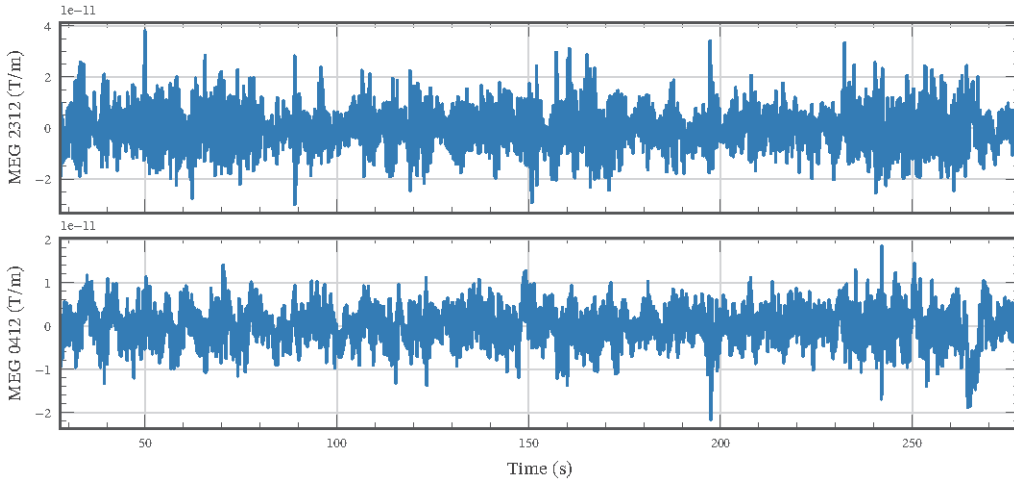


Figure 3: Representation of the simultaneous measurements of the two gradiometers : MEG 2312 and MEG 0412, on a single subject. On the x-axis, we have time in seconds and on the y-axis the magnetic field gradient in T/m.

Based on previous works on MEG signals [76, 49], the appropriate scales for analysis are between $j_{\min} = 10$ and $j_{\max} = 14$. However, the challenge with noisy signals is to obtain sufficiently good log-log linear regression to perform a reliable analysis. In this regard, we will calculate the residual mean squared error (RMSE) that we make on our estimates:

$$RMSE = \sqrt{\sum_{j=10}^{14} \left(\log_2 \left(\sup_k |c_{j,k}| \right) - (H_f^{\min} j + b) \right)^2},$$

where $y = H_f^{\min} j + b$ is the linear regression estimate between the scale $j_{\min} = 10$ and $j_{\max} = 14$. Across all 306 signals, we manage to obtain good estimates of H_f^{\min} with an $RMSE < 0.6$ for 191 of them. Figure 4 shows a best-case example of the estimation of H_f^{\min} .

Figure 5 shows the different values of H_f^{\min} that are accurately estimated. Since a large proportion is negative, the next step is to determine the wavelet scaling function and find values of $p > 0$ for which $\eta(p) > 0$, which will allow to perform the multifractal analysis with p -leaders [47, 52]. This is illustrated in Figure 6, which shows how these values are obtained by log-log regressions. On other hand, if there is no such value of $p > 0$ where the wavelet scaling function is positive, one must have recourse to the use of the WSE.

If $\eta(p) > 0$ for some p , then using the p -leader formalism is possible to estimate a Legendre spectrum, however that may not always be the case on real world data. Indeed, we can observe on the wavelet scaling function of multiple signals, (Figure 7) that there are indeed some time series for which, for some values of p one gets $\eta(p) > 0$, meanwhile others are such that, for all values of p , one gets $\eta(p) < 0$.

Let us discuss the results shown in Figure 8, where the spectra for the sensors MEG 2312 and MEG 0412 are shown after subtracting out the integration order s . On the left, we observe the case for which estimating both leader and 2-leader spectra requires fractional

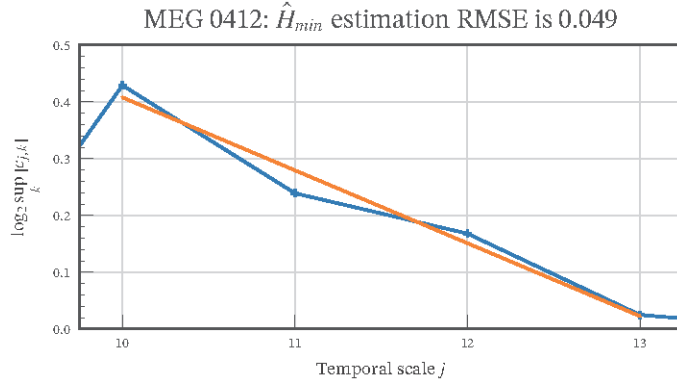


Figure 4: Estimation of the H_f^{\min} value using a log-log regression on the supremum of the wavelet coefficients. In this graph, we can observe that the RMSE is approximately 0.05 and gives a value here of $H_f^{\min} \approx -0.13 < 0$.

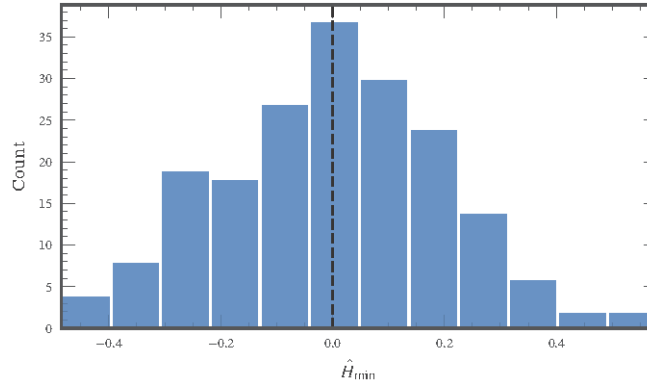


Figure 5: For the 191 signals for which the \hat{H}_{min} estimation is relevant, we observe that in most cases $\hat{H}_{min} < 0$. The several estimates of \hat{H}_{min} which are negative prevent us to perform the classical multifractal analysis using wavelet leaders.

integration ($s = 1$), whereas the WSE-based spectrum is determined without fractional integration. The leader and 2-leader spectra agree, but since they are both determined via fractional integration, there is still the possibility that while they concur, they do not provide the most accurate estimation of the multifractal spectrum. On the right, we observe the case where only the leaders need to be integrated, and $\eta(2)$ is positive, enabling the use of 2-leaders without fractional integration. In this case, the leader and 2-leader spectra disagree; one possible explanation is that this is due to the presence of oscillating singularities in the signal.

Figure 9 shows the impact of the analysis parameters on the estimated spectra. In order to get consistent measures of multifractality between multiple sensors, a global integration order s is chosen for all sensors based on the lowest value of H_f^{\min} estimated. The top row shows the impact of using increasing values of s on the estimated spectra of the MEG 0412 sensor, for both leaders and 2-leaders. As we recall here $\hat{H}_{min} = -0.13$ it appears that integrating

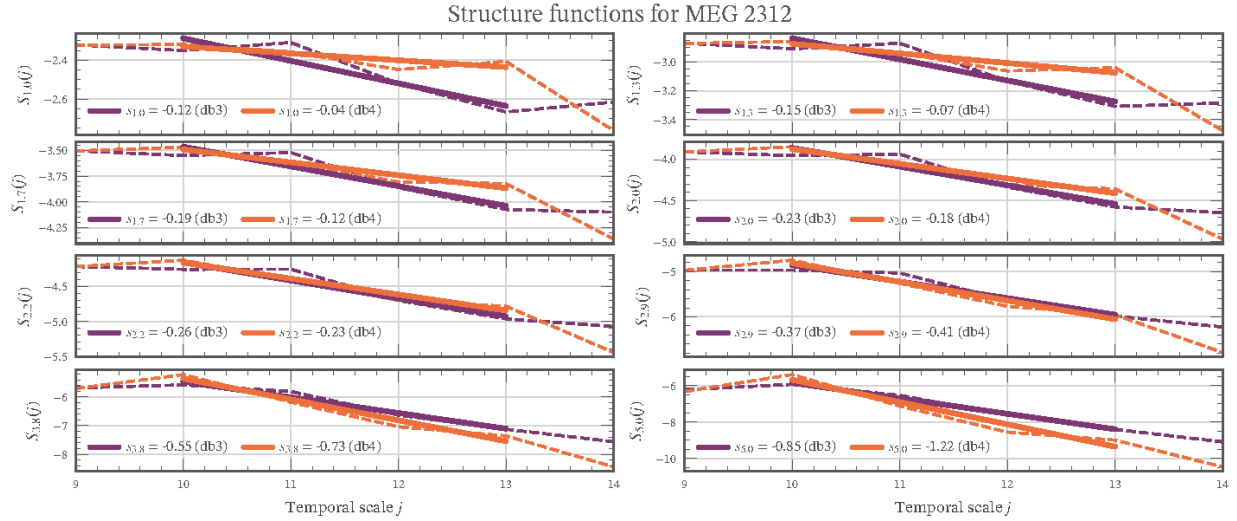


Figure 6: We provide different q -structure functions in order to estimate the value of $\eta(q)$ for the sensor MEG 2312.

using $s = 1$ (as would be typical in a MEG experiment) gives distorted spectra compared to smaller values of s that are closer to the expected level of integration required. This means that in practice fractional integration will affect the estimated spectra in unpredictable ways, which depend on the underlying minimum regularity. In that scenario, it is desirable to use WSE as they dispense dealing with the issue of fractional integration entirely.

The bottom row of Figure 9 shows the impact of the choice of the parameter θ involved in the definition of the (θ, ω) -leaders on the final spectra. It appears that, though, mathematically, this choice is asymptotically irrelevant, in practice changing θ leads to different spectra, and a precise statistical analysis of this phenomenon, which shows up before the asymptotic regime is attained, remains to be done in order to be able to obtain perfectly reliable results. The p -leader plots for different p shows that the estimated Legendre spectra are more consistent with the results in the top row when using smaller value of p , however decreasing p below 1 comes with issues of stability of the estimates.

To summarize, we have analyzed 306 signals of which only 191 showcase multifractality with good linear regressions. However, out of the 191 signals, 89 have an estimated $\hat{H}_{min} < 0$, within which there are 38 signals for which analysis using 2-leaders is not feasible. The analysis by WSE now makes it possible to overcome this obstacle.

5 Conclusion

Estimating H_{min} via linear regression is difficult in the context of limited or noisy data, and may lead to incorrect guesses about the degree of fractional integration required to obtain sensible Legendre spectra. Furthermore, in some experimental cases, $\eta(p)$ varies on a signal-by-signal basis, which in the absence of WSE-based analysis would require either different fractional integration coefficients, or more realistically to suffer from over-integrating part of

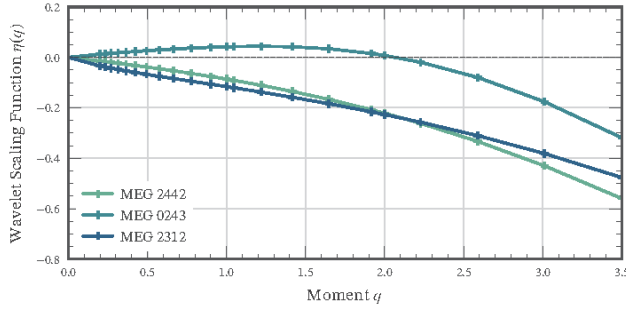


Figure 7: The wavelet scaling function of distinct sensors during the same recording is shown to reflect different behaviors. For two sensors shown here, $\eta(q) < 0$ for all positive q : this means that no p -leader based analysis is possible without having to rely on integrating the time series.

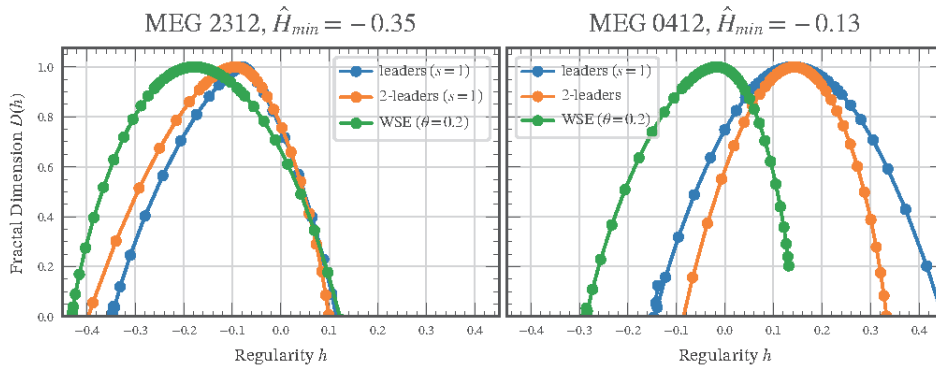


Figure 8: Estimation of Legendre spectra with 3 different methods, the leaders (in blue), the $p = 2$ -leaders (in orange), and WSE (in green). When used, the integration order s is reported in the figure legend. On the left are presented spectra estimated from a signal with $\hat{H}_{min} \ll 0$, and on the right results derived from a signal with comparatively higher \hat{H}_{min} .

the time series.

The WSE formalism mitigates these difficulties in dealing with time series of varying H_{min} , by providing a homogeneous method to deal with time series that have heterogeneous multifractal properties.

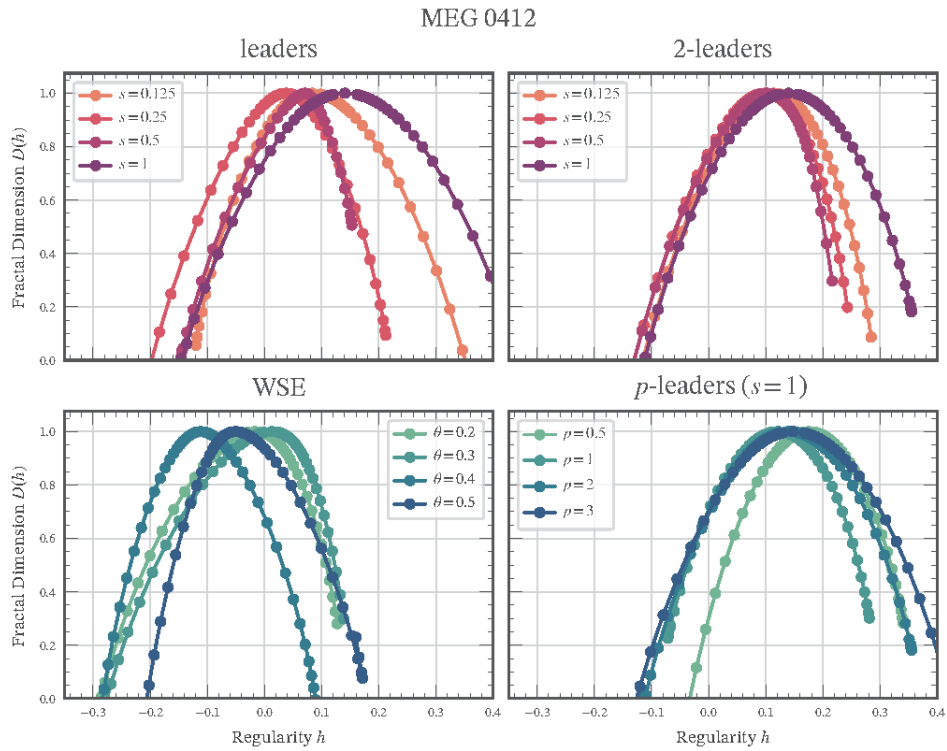


Figure 9: Spectra derived from the MEG 1833 sensor, for varying parameter values. The leaders (top left) and p -leaders ($p = 1, 2$, right column) spectra are depicted with varying fractional integration coefficient (s) from 0.25 to 1.25. The WSE-based spectra for varying values of θ are depicted on the bottom left.

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