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Using wavelet analysis to detect the influence of low frequency magnetic fields on human physiological tremor

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Abstract
The influence of extremely low frequency magnetic fields (ELF-MFs) on human physiological processes and, in particular, on motor activity is still not established with certainty. Using the wavelet-transform approach, changes in the characteristics of human finger micromovement are studied in the presence of a low intensity MF centred at the level of the head. Different approaches to nonstationary signal analysis involving real as well as complex wavelet functions are considered. We find evidence that ELF-MFs lead to more regular postural tremor and more homogeneous energy distribution.

Keywords: physiological tremor, magnetic fields, wavelet analysis, Hölder coefficients, local intermittency

1. Introduction

In our daily lives we are all exposed to different sources of extremely low frequency (ELF, below 300 Hz) and low intensity (below 2 mT) magnetic fields (MFs), such as personal computers, domestic electrical appliances, residential power installations, etc (Gandhi *et al* 2001, Gauger 1985). The influence of such ELF-MFs on the central and peripheral nervous system remains open and to some extent controversial. The main reason for this is the obvious problems of detecting ELF-MF effects in classical neurophysiological signals such as electroencephalograms or evoked potentials. Experimental recordings of the brain electrical activity are contaminated by the presence of the MF itself (Cook *et al* 2004), which significantly complicates attempts to reveal changes of the neurophysiological parameters.

Being a highly sensitive indicator of the activity of the nervous system, physiological tremor offers an opportunity to avoid this problem and thus to study, although indirectly, possible MF-induced effects on the activity of the central nervous system.

Tremor is a rhythmical involuntary oscillatory movement of a body part which depends on the recording conditions and the body part examined (Beuter *et al* 2003). It has a variable amplitude and a relatively stable frequency. It is now generally accepted that physiological tremor is a peripheral manifestation of a central oscillatory activity. According to McAuley and Marsden (2000) tremor has a multifactorial origin including central nervous system oscillatory activity, motor unit firing properties starting firing at around 8 to 10 Hz, limb mechanical resonance and reflex loop resonance (the stretch reflex is a negative feedback loop and the loop time is about 50 ms). Most of the normal physiological tremor frequency content is between 5 and 15 Hz, and it is influenced by many factors (temperature, smoking, stress, fatigue, etc) (Wachs and Boshes 1961). In general, however, healthy people demonstrate weak-amplitude physiological tremor with frequencies around 8–12 Hz (Elble and Koller 1990). Tremor appears to follow a continuum between its physiological and pathological manifestations. We have observed that, going in the direction of abnormality, tremor frequency decreases and its frequency content becomes more organized. That is, the more regular the signal, the more abnormal (sometimes pathological) is the tremor. The latter was discussed, for instance, in the work of Edwards and Beuter (1999). In addition, the lower the frequency of tremor, the more abnormal (sometimes pathological) is the tremor. Going in the direction of pathology, tremor amplitude usually increases and tends to fluctuate (Edwards and Beuter 1999).

If ELF-MFs influence human neurophysiological processes, this should be revealed as changes in the physiological tremor, especially during a postural maintenance task which leads to activation of neuromuscular processes. This situation may be realized, for instance, when a person maintains the index finger in a horizontal position (postural tremor). The effects of low intensity MF (1 mT, 50 Hz) on human motor behaviour were considered in a recent paper (Legros and Beuter 2005), using standard statistical analysis of the experimental data. This paper aimed to reveal any possible responses of ELF-MF in index finger microdisplacements. It was shown that the MF changes the energy distribution at low frequencies (2–4 Hz). A subsequent work (Legros *et al* 2006) exploiting the technique of wavelet analysis did not show any effect of the application of MFs on the local frequency organization of postural tremor. It was concluded, however, that the effects of ELF-MFs could be comparable to those of relaxation. This conclusion allows us to suppose that the ELF-MF can change correlation properties of postural tremor data. Note that quantification of the corresponding changes is limited by instability of the standard correlation analysis as applied to short noisy time series. A study of correlation properties based on the Hölder exponents (Muzy *et al* 1994) has a number of advantages in the latter case. In particular, a variance of the estimated characteristics can be significantly reduced (Dumsky 2005). Within the framework of the Hölder analysis, changes of signal characteristics can be described in terms of the 'smoothness' of tremor data. Additionally, we study other possible effects in postural tremor caused by the ELF-MF such as the homogeneity of the energy distribution. We show that the use of Hölder analysis and of a local intermittency measure allows us to reveal short-term changes in signal structure that occur during 5–10 s.

2. Experiments

Experiments were performed on volunteers from the personnel of a French electricity company 'Electricité de France' (24 men, aged between 20 and 50 years, the average age is 37.8 ± 8).

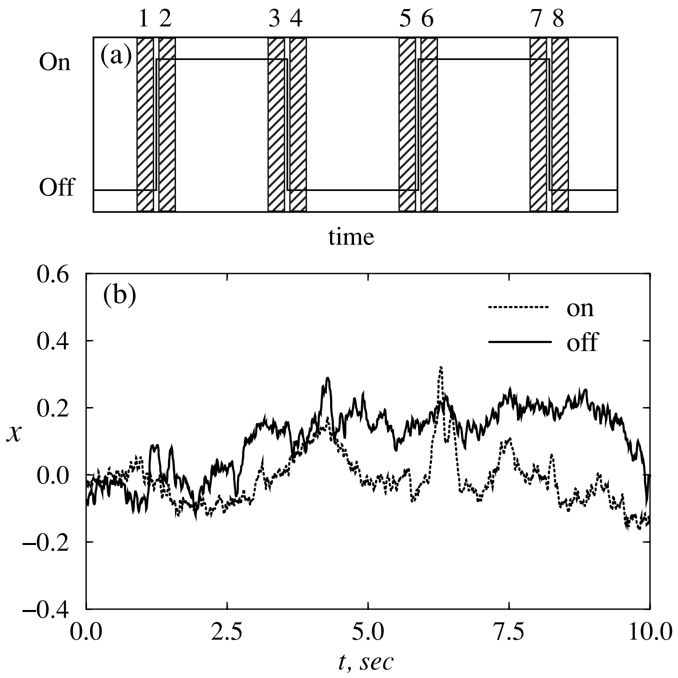

Figure 1. (a) Experimental sequence involving two 'off/on' and two 'on/off' transitions, (b) examples of experimental data corresponding to the states 2 and 4.

All participants completed a screening questionnaire testifying that they did not use drugs or any form of medication, had never experienced an epileptic seizure, had no limitation of hand or finger movements, did not suffer from chronic illness and did not carry cardiac or cerebral pacemakers. This information was verified by the company's occupational medicine service. The experimental protocol was approved by the Operational Committee for Ethics of the CNRS (Centre National de la Recherche Scientifique, France), life sciences section.

Aiming to reach identical environmental conditions, all subjects were tested at the same time of day (9.00 AM) and during a single session (Legros and Beuter 2005). The room temperature was constant (23 °C) and tests were done under natural lighting. Subjects were asked to refrain from smoking and coffee drinking in the morning of the test. They sat on a chair placed in the middle of the device that generated a homogeneous 50 Hz, 1.0 mT MF centred at the level of the head. The dominant forearm was placed in a prone position on an armrest and the hand was placed with the palm facing towards the ground on a moulded clay support. A small piece of white cardboard was fixed to the index finger nail. A Class II laser diode (Micro laser sensor LM100, series ARN12, Matsushita Electronic Work, Ltd), located vertically 8 cm above the piece of white cardboard and pointing towards the ground, transmitted a beam recording the vertical finger displacement with a resolution of 5 μm and a sampling rate of 1000 Hz. Subjects had to control their index finger's vertical position using a feedback line displayed on an oscilloscope: They had to maintain this feedback line superimposed as closely as possible on a static target line. All participants wore ear plugs and an anti-noise helmet to be isolated from environmental noise.

The ambient geomagnetic field was measured in the testing room with a handheld digital magnetometer μMAG-02WB (Macintyre Electronic Design Associates, Inc., Dulles, VA) and was 48.7 μT. It was oriented at 23.8° compared with the alternating MF generated by the exposure system. Since this is a static field, it does not induce any electrical current in the body and did not therefore influence the results. Background ambient alternating MF produced by surrounding electric and electronic sources was also measured with an EMDEX Lite monitor (ENERTECH Consultants, Campbell, CA) and was less than 0.01 μT. It is 100 000 times less than the field used in the experiment and could not then influence the results as well.

Each experimental session lasted 65 min and included two sequences of postural tremor testing. A session was composed of 16 conditions of tremor testing, each lasting 62 s and spaced with a 3 min resting period in between. One sequence (real) contained four MF transitions with 4 min in between (two 'off/on' and two 'on/off', see figure 1(a)). Time series of 62 s centred on each MF transition were recorded. The other sequence (sham) was used as a control: during this sequence, the MF was never present, even in the so-called 'on' condition, but the time course of tremor recordings was similar to the real exposure sequence. A computer controlled the course of the experiment, which was conducted following a double blind, counterbalanced procedure (neither the subject nor the experimenter knew when the MF was present). The approach was designed to emphasize rapid changes occurring in physiological tremor induced by the application of low frequency MFs and to reduce the significance of possible confounding factors. The use of sham sequences as control conditions ensures the external validity of the results: because the subject has no information whether the MF is actually presented, it is possible to reveal actual changes of postural tremor induced by the MF. 'Sham' sequences allowed us to estimate a range of possible changes of different characteristics (not caused by the MF).

Velocity data obtained by numerical differentiation (simple backward difference) of the recorded time series of vertical finger position were used in subsequent analyses. The presence of MFs produced artefacts at the grid frequency (50 Hz). Since tremor occurs in the lower frequency domain, a low-pass filtering of the data was applied with a cut-off frequency 40 Hz (using a filter with infinitely sharp characteristics, obtained through fast Fourier transform followed by the inverse transform). Aiming to remove a slow nonstationarity (trend) from the experimental recordings, an additional high-pass filtering with the cut-off frequency 2 Hz was used at the stage of data preprocessing (applying a similar filtering procedure). A further numerical analysis of tremor data was performed based on custom programs written in C. Statistical tests are performed using Matlab (The Mathworks, Natick, MA).

3. Wavelet analysis

As previously mentioned, Legros and Beuter (2005) have recently studied the effects of MFs on physiological tremor using standard methods of statistical analysis. This included estimations of amplitude variations, of different characteristics of the probability density function and of the spectral power distribution. This study revealed some changes in the power spectra in the presence of ELF-MF. Preliminary wavelet analyses were performed in a preceding work (Legros *et al* 2006). In particular, this work suggested that the effects of ELF-MFs could be comparable to those of relaxation.

Let us emphasize, however, that the analysed data are quite nonstationary (figure 1(b)). This leads to a variety of problems concerning the interpretation of the results obtained by standard statistical methods. In particular, the presence of nonstationarity reduces the reliability of quantification of amplitude variations and broadens the probability density function. The complex inhomogeneous dynamics of living systems is often studied more effectively by using specialized tools whose efficiency does not depend on the requirement of stationarity. At present, one of the most efficient tools is probably wavelet analysis (Grossman and Morlet 1984, Chui 1992, Mallat 1998, Marsh *et al* 2005, Sosnovtseva *et al* 2005).

The wavelet transform of a signal $x(t)$ has the following form:

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^* \left(\frac{t-b}{a}\right) \mathrm{d}t, \tag{1}$$

where ψ is the basis function (the wavelet), and a and b are the scale and time displacement parameters. $W(a, b)$ are referred to as the wavelet coefficients. The choice of the basis function ψ depends on the aim of the research. Different functions have different features in both the time and the frequency domains. Hence, the proper selection of ψ gives an opportunity to reveal different aspects of the structure of the analysed process. The purpose of the following sections is to study features of tremor data with more refined wavelet-based tools such as Hölder analysis and a local intermittency measure (Astaf'eva 1996). As mentioned above, these tools allow us to reveal short-term changes in the signal structure.

3.1. Analysis based on real wavelets

Some features of the signal $x(t)$ do not depend on the basis function ψ. One such feature is the local regularity that is usually estimated within the framework of multifractals (Muzy *et al* 1993, 1994). This estimation is performed with real wavelets constructed, e.g., by differentiation of the Gaussian function:

$$\psi^{(m)}(\theta) = (-1)^m \frac{\partial^m}{\partial \theta^m} \left[\exp\left(-\frac{\theta^2}{2}\right)\right]. \tag{2}$$

In this paper we consider $m = 1$ ('WAVE' wavelet) and use $\psi^{(1)}(\theta)$ when computing the transform (1) with real wavelets. $\theta = \frac{t-b}{a\Delta t}$, where Δt is the sampling step ($\Delta t = 0.001$ s). The result of the wavelet transform (1) can be considered as a surface of coefficients $W(a, b)$ in a three-dimensional space. The most important information about this surface is contained in the skeleton, i.e. in the lines of local extrema of the coefficients $W(a, b)$ that can be extracted by fixing the scale a and changing the displacement parameter b. As illustrated in figure 2, the result is a number of lines in the b–$\log a$ plane. Some of these lines are very short and can be revealed only at small scales; other lines are much longer. Each line originates at a point b where the analysed signal $x(t)$ has some specific feature (singular behaviour for $a \to 0$). The statistical analysis of singularities in nonstationary processes can be performed with the 'wavelet-transform modulus maxima' (WTMM) technique (Muzy *et al* 1993). A detailed description of this approach and its application to experimental data may be found in the review by Muzy *et al* (1994).

The basic idea of the WTMM involves the construction of the so-called partition functions $Z(q, a)$ by extracting the skeleton from the surface $W(a, b)$ according to

$$Z(q,a) = \sum_{l \in L(a)} |W(a, b_l(a))|^q. \tag{3}$$

Here, $L(a)$ is the set of all lines of modulus maxima for the wavelet coefficients, i.e. the lines of maxima of the values $|W(a, b)|$ existing at the scale a. The value $b_l(a)$ defines the maximum related to the line l. The unit-less parameter q defines the range of scales being analysed as described below. As explained in the above cited review (Muzy *et al* 1994), the partition functions are assumed to demonstrate the following power-law dependence:

$$Z(q,a) \sim a^{\tau(q)}, \tag{4}$$

where $\tau(q)$ are the scaling exponents. The statistical analysis of singularities is performed in terms of the Hölder exponents $h(q) = \mathrm{d}\tau(q)/\mathrm{d}q$ and the singularity spectrum $D(h) = qh - \tau(q)$ (Muzy *et al* 1994). The Hölder exponents characterize the presence of correlations

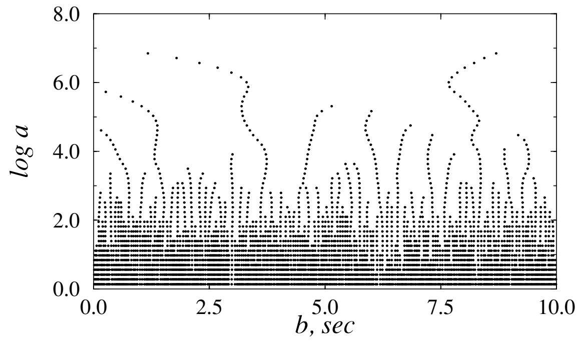

Figure 2. Skeleton computed for the signal shown in figure 1(b) ('on' condition). Each line originates at a point where the analysed signal $x(t)$ has singular behaviour at $a \to 0$. Here, we consider the range $\log a \in [0.1; 7.5]$. Aiming to reduce possible pitfalls of the Hölder analysis, further estimations of the scaling exponents are performed for the range $\log a \in [0.7; 4.0]$.

of different types in the analysed process, e.g., anti-correlated ($h < 0.5$) or correlated ($h > 0.5$) dynamics, absence of correlations ($h = 0.5$) and conformity of the signal $x(t)$ with classical examples of random processes: $1/f$ noise ($h = 1$), Brownian motion ($h = 1.5$), etc. In general, the 'smoother' the signal $x(t)$, the greater the exponents $h(q)$ are. When performing a study of correlation properties for short noisy data, the use of Hölder exponents can have some advantages over the classical correlation function, in particular, a higher stability of the estimated characteristics (Dumsky 2005). It is known that the wavelet-based methods have different limitations and pitfalls (Maraun and Kurths 2004, Veneziano *et al* 1995, Sosnovtseva *et al* 2005). In particular, the singularity spectrum $D(h)$ can lead to different misinterpretations of the actual dynamics (Veneziano *et al* 1995). Nevertheless, the averaged value of the Hölder exponents allows one to characterize even small changes of correlation properties. The partition function $Z(q, a)$ describes the power-law dependences (4) at $q < 0$ for weak singularities or small fluctuations and at $q > 0$ for strong singularities or large fluctuations. Aiming to estimate the scaling exponents $\tau(q)$, we use the range $\log a \in [0.7; 4.0]$.

3.2. Analyses based on complex wavelets

Today, spectral analyses of nonstationary processes are often performed with the wavelet transform (1), using a complex basis function ψ (Grossman and Morlet 1984, Chui 1992). The advantages of this approach in comparison with a classical spectral analysis based on a finite-time Fourier transform have been widely discussed (Chui 1992, Mallat 1998). If we only need to determine the time-averaged spectral components presented by the analysed signal, then the classical approach can be successfully applied. However, if we are interested in the temporal evolution of the rhythmic components, then the wavelets have clear advantages.

Probably the most popular complex basis function is the Morlet wavelet whose simplified expression can be written in the form

$$\psi(\theta) = \pi^{-1/4} \exp(\mathrm{j}2\pi f_0\theta) \exp\left[-\frac{\theta^2}{2}\right]. \tag{5}$$

Function (5) is used in our study when performing analysis based on complex wavelets. The transformation (1) represents a two-dimensional decomposition of a scalar time series with the frequency ($f = f_0/(a\Delta t)$) and time (b) treated as independent quantities. Unlike the

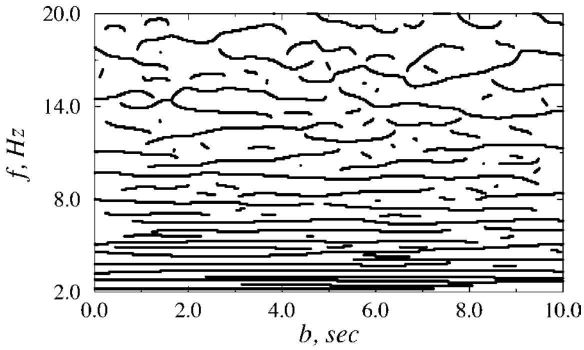

Figure 3. Time-frequency spectrum illustrating the complex structure of spectral components for the signal shown in figure 1(b) ('on' condition).

case of a real function ψ, analyses based on the complex wavelet (5) typically deal with the energy density $E(f, b) = |W(f, b)|^2$ instead of the wavelet coefficients $W(a, b)$. The energy density also represents a surface in a three-dimensional space whose sections at fixed time moments $b = t^*$ correspond to the local energy spectrum. The main information about the surface $E(f, b)$ is associated with the dynamics of its local maxima, i.e. with the time evolution of instantaneous frequencies of the main rhythmic components. Their extraction can be realized by analogy with the skeleton in section 3.1. The difference, however, consists in the fixation of the displacement parameter b and the choice of local peaks of the surface $E(f, b)$ under variation of the scale parameter a (or the frequency f). As a result, the instantaneous frequencies of all rhythms that are present in the analysed signal will be detected. An example is shown in figure 3, where we consider the range $f \in [2; 20]$ Hz. The required range of a is estimated depending on the chosen frequencies.

In addition to the local spectra there are a number of other characteristics estimated from the energy density including, e.g., the measure of local intermittency (local deviations from the average value of energy at each scale). The latter quantifies the inhomogeneity of the energy distribution (Astaf'eva 1996):

$$I(f, b) = \frac{E(f, b)}{\langle E(f, b) \rangle}. \tag{6}$$

Here, the angular brackets denote averaging over time, i.e. over the parameter b. As a characteristic of the inhomogeneity, we suggest using the standard deviation of the measure $I(f, b)$ from its mean value $\langle I(f, b) \rangle = 1$. When dealing with noise-like processes such as physiological tremor data (figure 1(b)), averaging within some window in the frequency domain may be useful to smooth out strong variations of the measure $I(f, b)$.

4. Results

4.1. Analysis of local regularity with real wavelets

Because of the ability of neural systems to adapt to external signals on a variety of different time scales, our study of the ELF-MF-induced effects on physiological tremor is performed using short time intervals after the 'off/on' transitions (states 2 and 6 in figure 1(a)) and after the 'on/off' transitions (states 4 and 8). These short time periods involve transient processes, and the application of specialized tools for nonstationary data analysis is, therefore, needed.

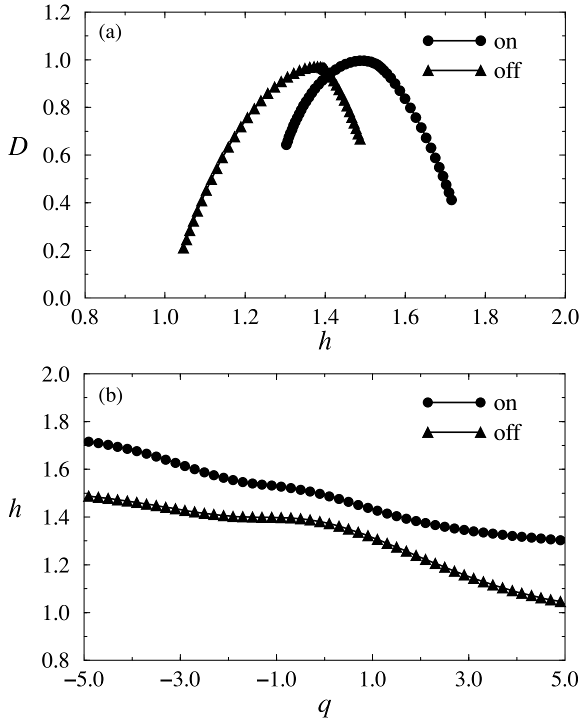

Figure 4. Differences in a local regularity in velocity data between the 'on' and 'off' conditions for the sequence 'real' (a representative example from one subject). Singularity spectra (a) and Hölder exponents (b) are estimated for the signals in figure 1(b). The shift of the singularity spectrum means changes of the correlation properties of the analysed time series. An increase of $h(q)$ means that the process becomes 'smoother' (it is close to the Brownian motion in the 'on' condition from the viewpoint of statistical characteristics). The results are obtained using the 'WAVE' wavelet.

Figure 4 illustrates an example of possible changes in physiological tremor during the exposure, namely, changes of a local regularity and correlation properties. Here, the analysed velocity data in the 'off' condition can be treated as an inhomogeneous random process resembling a normal Brownian motion at small time scales and as $1/f$ noise at larger time scales. The transition to the 'on' condition increases the values of the Hölder exponents (figure 4(a)), resulting in the displacement of the singularity spectrum (figure 4(b)). This indicates that the signal becomes 'smoother'.

The characteristics of physiological tremor varied among the participants. Nevertheless, the above effect (an increase of h during the 'on' condition) could be observed in the group average (figure 5, black circles). Although this effect is fairly weak as compared to the standard deviation for a group, we can therefore conclude that the presence of low intensity MFs leads to 'smoother' processes. Note that similar changes of the local regularity were not observed for the 'sham' sequence where the MF was not present, even during the 'on' condition (figure 5, white circles). We have applied an ANOVA statistical test to the experimental results with $p = 0.05$. This has shown MF-induced changes of signal structure for 'real' sequences ($F = 3.32$) and absence of clear changes for 'sham' sequences ($F < F_{\mathrm{cr}} = 2.56$), where F_{cr} is a critical value estimated from the table of F-distributions for the chosen p.

Consideration of other basis functions, e.g., the 'MHAT' wavelet ($m = 2$ in (2)) leads to similar conclusions. We did not find notable changes in the structure of the skeleton

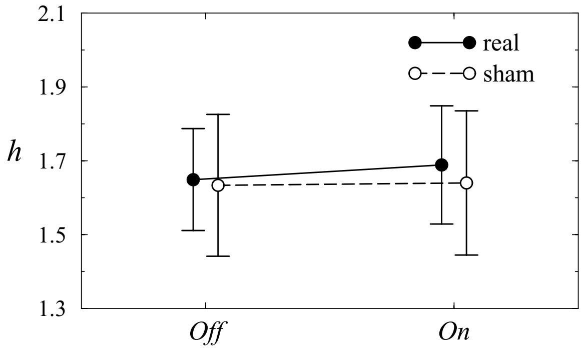

Figure 5. Changes observed in the local signal regularity. The circles indicate mean values over a group of 48 data sets collected from 24 individuals. The error bars denote inter-individual variations (standard deviation). A slight increase of the Hölder exponent can be detected for the 'real' sequence (mean value of h increases by 2.7%). The 'sham' sequence shows no effect (the difference between the 'off' and 'on' conditions is about 0.5%).

between the 'on' and 'off' states ($F < F_{cr}$), i.e. in the number of lines L of the local extrema (for the same function ψ); the existing distinctions occurred only in the scaling behaviour of the partition functions $Z(q, a)$ and they can therefore be identified from the singularity spectra.

4.2. Data analysis with complex wavelets

Complex wavelet functions provide an opportunity to perform a local spectral analysis of nonstationary processes and to estimate the global energy spectrum, an analogue to the classical power spectrum. We have attempted to observe variations in tremor signal by computing the spectral powers in different ranges of the energy density $E(f, b)$. This analysis has not revealed significant differences and we have, therefore, focused our attention on estimating the local intermittency (6). For this purpose, the wavelet transform (1) was computed with the resolution 0.1 Hz, $f_0 = 5$. The standard deviation (σ_I) of the measure $I(f, b)$ was estimated in the frequency range 2–15 Hz within the 'sliding' window of width 2 Hz. As illustrated in figure 6(a), this allowed us to reduce strong variations of the considered characteristics and to obtain a rather smooth dependence $\sigma_I(f)$. Moreover, inspection of the figure shows that the energy distribution becomes more homogeneous in the 'on' condition, i.e. a transition to a more ordered dynamics is observed.

By analogy with the Hölder exponents, the values of σ_I demonstrate essential variations between subjects (figure 6(b)). Nevertheless, the ordering effect is only observed for the 'real' sequence when the MF was present in the 'on' condition; it does not occur for the 'sham' sequence (see figure 6(b)). The ANOVA statistical test ($p = 0.05$) gives the values of $F = 3.92$ for 'real' sequences and $F = 1.53$ for 'sham' sequences. In other words, only in the first case did we obtain significant distinctions ($F > F_{cr}$). Changes of the probability distribution in the second case are fairly small and probably caused by random factors.

Changes of tremor characteristics can also be reflected in the local peaks of the two-dimensional wavelet spectrum (figure 3). An increase in the number of points in this figure has multiple interpretations. On one hand, the increase may be caused by the appearance of additional spectral components. On the other hand, it may be associated with a higher stability of the existing rhythmic contributions (if a rhythm disappears during some time periods, its stabilization will result in the absence of interruptions). This is why an increase or reduction

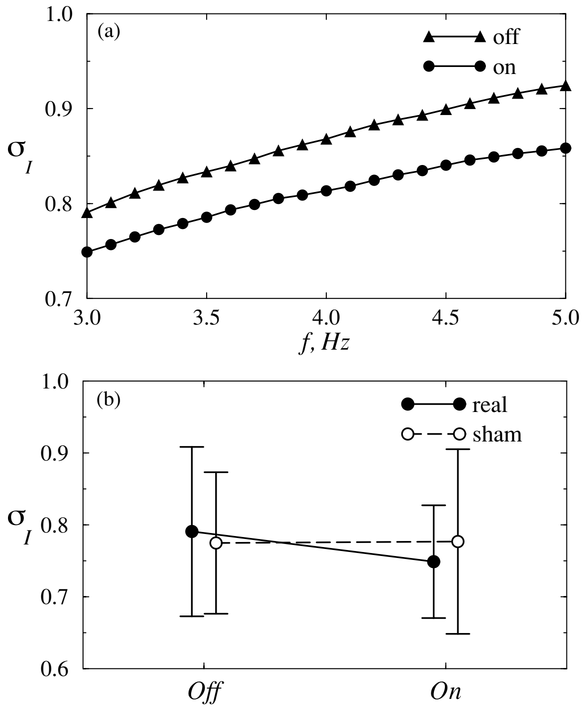

Figure 6. Averaged standard deviations of the local intermittency measure (a representative example from one subject, the 'real' sequence) (a) and the results for all subjects (b). A reduction of the value σ_I can be considered as an ordering effect that is observed only for the 'real' sequence (the difference between the 'off' and 'on' conditions is ≈5.3% for the 'real' sequence and ≈0.6% for the 'sham' sequence). The error bars denote inter-person variations (standard deviation).

in the number of local spectral peaks in figure 3 cannot be treated in terms of the complexity measures. It is suggested to consider this number as a highly sensitive characteristic even to small changes in the structure of the analysed time series.

This characteristic was estimated in two steps. First, the difference between the numbers of local spectral peaks in the 'on' and 'off' conditions was calculated before each of the four MF transitions (each number of local peaks was estimated within a sliding window of 2 Hz). Further, we have looked for a sign of this difference ('+' if the difference increases and '−' if it decreases). By averaging over a group, the probability (P) of increase in the number of local spectral peaks for the 'on' condition was defined (i.e. a relative number of time series for which such an increase takes place). Second, we analysed how this probability was changed after the MF transition. Figure 7 illustrates the results obtained for the range 2–5 Hz. Such a range was considered because of previous works which suggested an effect of the MF on the proportion of tremor low frequencies, going in the direction of a higher proportion of oscillations in the 2–4 Hz frequency band induced by the exposure (Legros and Beuter 2005, 2006). We can see that the probability increases after the MF transition (figure 7, black circles). A similar effect does not occur for the 'sham' sequence: the estimated values of P are close to 0.5, reflecting the absence of clear distinctions in the structure of wavelet spectra between the 'on' and 'off' states. The value $P = 0.5$ means that the number of local spectral peaks increases in the 'on' condition for about half of the recordings and is reduced for the other half of the time series (figure 7, white circles). Additionally, we performed the corresponding analysis for other

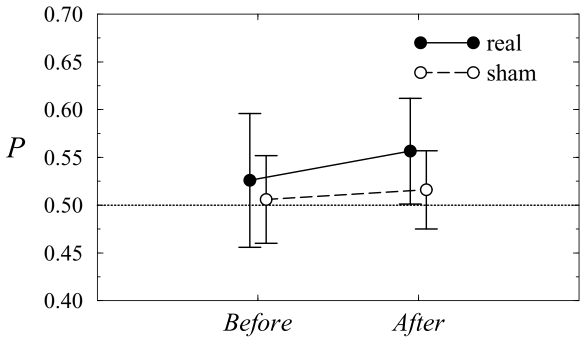

Figure 7. Probability of an increase in the number of spectral peaks in the 'on' condition relative to the 'off' state before and after the MF transitions (results for all subjects). The value $P = 0.5$ signals that distinction is impossible.

values of the parameter f_0 in (5), namely, for $f_0 = 3$ and $f_0 = 7$. The obtained results are rather similar to those presented in figure 7.

5. Conclusions

Effects of strong magnetic fields on human motor behaviour have been previously reported in scientific publications. In particular, the works of Britton *et al* (1993) and Pascual-Leone *et al* (1994) showed effects of transcranial magnetic stimulation (TMS) on human tremor. It has been shown that TMS can reset pathological tremor in patients with essential tremor and with Parkinson's disease. However, these studies use MF several orders of magnitude larger than the MF used in our study, and there is no evidence that the same brain mechanisms are involved. The significance of a low-intensity MF remains unclear. According to Schnitzler *et al* (2006), human brain functions including tremor are heavily contingent on neural interactions at the single neuron and the neural population or system levels. These authors go on to suggest that coupling of oscillatory neural activity provides an important mechanism to establish neural interactions. It is possible to record whole-head magnetoencephalography (MEG) during tremor with high spatial and temporal resolution and show noninvasively a coherence between what is occurring in the brain and muscle activations (Rothwell 1998). MEG has revealed the presence of a physiological cerebral network of structures associated with the production of tremor. This is especially true for Parkinsonian tremor which is associated with an extensive cerebral network including primary motor and lateral premotor cortex, supplementary motor cortex, thalamus/basal ganglia, posterior parietal cortex and secondary somatosensory cortex. These structures are entrained at the tremor or twice the tremor frequency (Schnitzler *et al* 2006, Pollok *et al* 2003). This network appears to represent the neurophysiological substrate of physiological tremor. In this network, the activity of large populations of neurons produces fluctuating local field potentials (LFP) which in turn can entertain various degrees of synchronization between interacting neural structures. LFP are vector sums of the intercellular currents of a population of cells. To our knowledge, it has never been shown that extremely low frequency and low intensity magnetic fields (ELF-MF) had a measurable effect on physiological tremor. But at this population scale, it is entirely plausible that ELF-MF may alter or interfere with the neuromagnetic signals associated with the physiological tremor. It is well known that there exists a wide range of sensitivity among neurons to imposed fields. Some neurons can change the frequency of their spontaneous firing by very small changes in their membrane potentials due to external fields of less than a few millivolts per centimetre (Terzuolo and Bullock 1956, Bullock 1986).

The purpose of the present paper was to study whether the characteristics of postural physiological tremor are sensitive to the influence of low intensity (1.0 mT) and low frequency (50 Hz) magnetic fields. Considering the nonstationarity of the analysed processes, our investigations were performed by means of modern wavelet analyses with different basis functions (real and complex) and a variety of refinements (Hölder coefficients, local intermittency measure and number of spectral peaks). We found evidence to show that application of a low-intensity MF leads to the following effects:

- an increase in the local regularity of the tremor data and, as a consequence, changes of its correlation properties;
- a reduction of the standard deviation of the local intermittency measure, i.e. a more homogeneous distribution of the energy;
- an increase in the number of the local spectral peaks in the range 2–5 Hz.

The obtained results are in agreement with the previous finding (Legros *et al* 2006) that the effects of ELF-MFs could be comparable to those of relaxation. All of these effects are fairly weak. Nevertheless, the results are consistent among the various tests and they suggest that ELF-MFs actually can have an influence on human neurophysiological processes or, at least, on physiological tremor, which we have used as a highly sensitive indicator of neuromotor pathway responsiveness.

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