Pitfalls of high-pass filtering for detecting epileptic oscillations:

a technical note on 'false' ripples

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Abstract

Objectives

To analyze interictal High frequency oscillations (HFOs) as observed in the medial temporal lobe of epileptic patients and animals (ripples, 80-200 Hz and fast ripples, 250-600 Hz).

To show that the identification of interictal HFOs raises some methodological issues, as the filtering of sharp transients (e.g., epileptic spikes or artefacts) or signals with harmonics can result in "false" ripples.

To illustrate and quantify the occurrence of false ripples on filtered EEG traces.

Methods

We have performed high-pass filtering on both simulated and real data. We have also used two alternate methods: time-frequency analysis and matching pursuit.

Results

Two types of events were shown to produce oscillations after filtering that could be confounded with actual oscillatory activity: sharp transients and harmonics of non-sinusoidal signals.

Conclusions

High-pass filtering of EEG traces for detection of oscillatory activity should be performed with great care. Filtered traces should be compared to original traces for verification of presence of transients. Additional techniques such as time-frequency transforms or sparse decompositions are highly beneficial.

Significance.

Our study draws the attention on an issue of great importance in the marking of HFOs on EEG traces. We illustrate complementary methods that can help both researchers and clinicians.

1. Introduction

The past years have witnessed an increasing interest in fast oscillatory brain activity as measured by EEG, MEG or intracerebral EEG. In cognitive studies, gamma band oscillations have been proposed to play a major role in the integration of information ('binding by synchrony') or in attentional processes (Tallon-Baudry and Bertrand, 1999). In human partial epilepsies, fast oscillations have long been considered as a hallmark of epileptogenicity (Bancaud, 1974). These oscillations (also referred to as "rapid discharges" or "fast discharges") are commonly observed, either during ictal or during interictal periods.

Regarding ictal periods, the recordings of EEG signals using intracerebral electrodes have long revealed that seizure onset is often characterized by the occurrence of fast activity that may last up to several seconds in brain structures belonging to the epileptogenic zone (Bartolomei et al., 2008; Wendling et al., 2009).

The frequency spectrum of these discharges has been found to range from beta (13 -25 Hz) to gamma range (30-100 Hz) (Alarcon et al., 1995; Allen et al., 1992; Wendling et al., 2003). Higher frequencies (200-500Hz) have been also reported after high-pass filtering of the signals (Jirsch et al., 2006).

Regarding interictal periods, High Frequency Oscillations (HFOs) have been described both in humans and in epileptic animals using micro-electrode recordings (Engel et al., 2009).

Oscillations in the 80-200 Hz range, or "ripples", can be recorded from normal hippocampus, parahippocampal structures and neocortex of humans and animals (Grenier et al., 2003; Urrestarazu et al., 2007)In contrast, HFOs in the range of 250-600 Hz, or "fast ripples", are considered as pathologic, characterizing the epileptogenic tissue in mesial temporal lobe epilepsy (Bragin et al., 1999a; Bragin et al., 1999b; Bragin et al., 2002; Grenier et al., 2001, 2003; Traub, 2003).

Several recent studies using macro-electrodes have also reported HFOs either in isolation or in association with interictal spikes in several types of human epilepsies. They have been proposed to be a characteristic electrophysiological marker of the most epileptogenic tissues (Bagshaw et al., 2009; Jacobs et al., 2008; Urrestarazu et al., 2007; Urrestarazu et al., 2006; Worrell et al., 2008).

The study of interictal HFOs raises however some methodological issues, in particular when using classical filtering methods. Indeed, the usual technique for detecting such fast oscillatory activity is to filter EEG signals in high frequency bands, using either classical band-pass filters or time-frequency methods. The energy of the filtered signal in a given frequency band of interest is then typically considered to represent the amount of oscillatory activity within this band. However, some components of brain signals are not band-limited, i.e., their energy can spread over the entire frequency spectrum. This is particularly the case for sharp transients, such as epileptic spikes or impulse-like artefacts, or for non-sinusoidal oscillatory events that contain harmonics. Such events are said to be "broadband". In the ideal case of an impulse (i.e. a short duration transient signal), all frequencies are present with same energy. This property is in fact classically used to study the response in frequency of a system without need to scan all frequencies, or to characterize filters ("impulse response"). When passed through a band-pass filter, transient events result in a signal that is close to the impulse response of the filter, which is typically a short-duration oscillation. As a consequence, sharp transient events, after filtering, can result in "false" ripples that may easily be confounded with "genuine" ripples: both types of events correspond to a fast oscillatory activity in the frequency band defined by the filter. Some studies have explicitly taken into account this effect by enforcing ripples to have a minimum number of oscillations (Jacobs et al., 2009; Urrestarazu et al., 2007). Still, the range of shapes of false ripples in different configurations has not been quantified systematically.

The goal of the present study was to quantify the impact of broadband activity on high-pass filtered signals, for different frequency bands, and to present strategies for reducing the influence of such activity.

In a first step, we quantify some features of oscillatory artefacts ('false ripples') obtained by high-pass filtering of simulated spikes or non-sinusoidal oscillations. Then, we present both true and false ripples in recordings in an animal model. Finally, we explore possible methods for distinguishing true ripples from false ripples.

2. Materials and Methods

The construction of simulated signals as well as the processing of signals were performed with the Matlab software (Mathworks, Natick, MA).

2.1. Simulated signals

Four types of events were simulated: Gaussian spikes, sinusoidal oscillation, triangular spikes, triangular oscillation. The signals were superimposed on EEG background activity (Figure 1). Signals were sampled at 2048 Hz, with a total length of 500 ms. The width (temporal duration) of spikes was set to 1 ms, 5 ms, 15 ms and 30 ms. The width of oscillations was set to 25 ms, and the frequency to 140 Hz. The background EEG activity was obtained from a neural mass model (Wendling et al., 2005) to ensure a physiologically-plausible spectrum. Its mean was set to 0 and its standard deviation was 1. The amplitude of aforementioned events was set to 10 (a.u.).

2.2. Real signals

Experimental data were obtained from epileptic adult male Wistar rats (pilocarpine model of temporal lobe epilepsy) (for a detailed description of the method, see Chauviere et al., 2009).

Rats were anesthetized with a mixture of ketamine (1mg/kg) and xylasine (0.5mg/kg). They were stereotaxically implanted with thirteen 50μm-tungsten electrodes (located in the median septum, the septo-hippocampal nucleus, two in CA1, in CA3, in the dentate gyrus, the entorhinal cortex, the perirhinal cortex, the thalamus, the posterior cingulate cortex, the supramammillary nucleus, the subiculum and in the ventral hippocampus), two stainless-steel screws in the frontal cortex and two other screws in the cerebellum as references electrodes. The 50μm-wires electrodes were glued to home-made microdrives that allow for implantation of each electrode separately.

After two weeks allowing recovery, rats received intraperitoneally (ip) injections of pilocarpine hydrochloride (310 mg kg^{-1}), and 30 min after an ip injection of scopolamine (1mg/kg). After pilocarpine injection, status epilepticus (SE) was detected and monitored by LFP continuous recordings in all the structures. Then, after a latent period (around 10 days after SE), animals display spontaneous and recurrent seizures (Chauviere et al., 2009).

A multi-channel data acquisition system (Cheetah System, Neuralynx, USA) was used to record local field potentials and multi-unit activity of epileptic rats. Then, the data were down-sampled at 2.5 kHz by a Neuralynx's software. Traces were inspected for local field potential high-frequency oscillations (ripple and fast ripples), when the rat was in quiet-immobility or sleep states in its home cage. A video-system (Video Track, Neuralynx, USA)

was used to quantify behaviour during recording sessions. All experimental protocols conformed to the French Public Health Service policy on the use of animal models.

2.3. Conventional Filtering

Signals were high-pass filtered with a series of FIR (finite impulse response) filters with band edge set at 40 Hz (gamma band), 80 Hz (ripple band) and 250 Hz (fast ripple band). Moreover, signals were low-pass filtered at 600 Hz in order to emulate an anti-aliasing filter. We used windowed linear-phase FIR digital filters (*fir1* function of Matlab). We used a Kaiser window (specification computed with *kaiserord* function). For the high-pass filter, the specifications for a given cut-off frequency f0 were: 5% of ripple in the passband, a stop band ripple of $10^{-(A/20)}$ at f0/2, with A in dB (i.e., an attenuation of A dB per octave).

We performed forward followed by reverse filtering (*filtfilt* function), in order to avoid latency shifts in the filtered signals. The spectra of filtered spikes and noise were computed by averaging the FFTs computed over 20 realizations of each event type; a Hanning window was used on each realization.

In order to test the effect of the type of filter that is used, we also designed IIR (infinite impulse response). This effect was tested on a Gaussian spike (of width 10 ms) with 6 different configurations: FIR filters with an attenuation of 24, 48 or 96 dB/oct and butterworth IIR filters with the same attenuations (*butter* Matlab function, order computed with *buttord*).

2.4 Spectral analysis

In order to compute the spectrum of the different simulated event (spikes or oscillations), we averaged for each signal the FFTs computed on 20 realisations. FFTs were computed on a 150 ms window comprising the events. Apodization was performed with a Hanning window.

2.5. Time-frequency analysis and Matching Pursuit

The time-frequency analysis was performed by convolving the signals with Morlet wavelets (or Gabor atoms), i.e. sinusoidal waves with a Gaussian envelope (oscillation parameter = 5). These waveforms have a high compactness in the time-frequency domain and represent a good trade-off between time and frequency resolution. We used an in-house modification of the *awt* function of the WAVELAB Matlab toolbox (http://www-stat.stanford.edu/~wavelab/).

The Matching Pursuit (MP) procedure (Mallat and Zhang, 1993) aims at iteratively identifying atoms in a signal. The atoms are drawn from a 'dictionary', i.e. a set of elementary waveforms. A classical dictionary consists in a set of oscillating waves (Gabor atoms), with a varying number of oscillations (Bénar et al., 2009; Durka and Blinowska, 1995; Tallon-Baudry et al., 1996). This is a redundant representation, as atoms are typically drawn from a large dictionary. It however results in a more concise representation than conventional time-frequency analysis, as fewer elements are needed to describe a given waveform. Moreover, MP can help disentangling elements with overlapping time-frequency support (Durka et al., 2005). We used the implementation of the MP available at http://eeg.pl/mp.

3. Results

3.1. Quantification of false ripples in simulated signals

Figure 1 shows the results when simulated signals are filtered with different cut-off frequencies.

For the spikes, clear spurious oscillations, or "false ripples", are produced in the gamma band (>40 Hz) for width of 15 and 30 ms (graph B3 et B4 in figures 1a and 1b), in the ripple band (>80 Hz) for a width of 15 ms (graph C3), and in the fast ripple band (>250 Hz) for a width of 5 ms (graph D2). For the short width (1 and 5 ms), except for fast ripple at 5 ms, signal keeps a "spike-like" shape (graphs B1, B2, C1, C2, D1). For the triangular spikes (figure 1b), there is some residual signal for the large width (C4, D3, D4), but the signal appearance is also less oscillatory.

For the sinusoidal oscillation at 140 Hz, there is some residual oscillation at the same frequency in the ripple band (Figure 1a, graph D5), due to the fact that (i) the short-duration oscillation has some spread in frequency and (ii) the filter response is not a perfect step (a perfect step would produce more oscillations in response to transient signals, see study below on the level of attenuation). For the triangular oscillation, there is a false fast ripple due to the harmonic at 3×140=420 Hz (Figure 1b, graph D5).

The signal-to-noise ratio of the spurious oscillation can be explained by the relative shape of the spike spectra and of background noise, as shown in Figure 2. For the Gaussian spikes, the spectrum is Gaussian with a width inversely proportional to the spike width. Therefore, for

small widths, the signals retain a high energy for high frequencies. The spread in frequency of the sinusoidal oscillation, due to its finite length, is visible in Figure 2a.

For the triangular spikes, the spectrum shows many secondary lobes, with the same inverse relationship between the width of the spike and the spread of the spectrum. The first harmonic of the triangular oscillation can be seen in figure 2b.

We then assessed the influence of the filter type on the shape of the filtered signal, for one example of input signal (Gaussian spike, 5 ms width). The level of attenuation of the filter (24, 48 or 96 dB/oct, see Figure 3a for the filter responses) had an impact on the number of oscillations, with a higher number for higher attenuation (Figure 3b). Moreover, the IIR filters have a tendency to oscillate more than FIR filter, especially for a high attenuation level (Figure 3b, IIR 96 dB/oct). Given the additional advantage that FIR filters have linear phase properties, this result confirms that FIR filters should be preferred (Urrestarazu et al., 2007).

3.2. False ripples in real signals

Figure 4 presents six events observed in real unfiltered data, along with the signals filtered in the ripple and fast ripple bands, and the time-frequency representation. The first event (graph A1) is a "spike with no visible oscillation" (according to the nomenclature introduced by Urrestarazu and colleagues (Urrestarazu et al., 2007)): even with close visual inspection, there is no visible superimposed fast oscillatory activity. The second and third events are a ripple and a fast ripple respectively (graphs A2 and A3), without spike. The fourth and fifth discharges are a combination of spikes and ripples (A4 and A5). The last event is a transient sharp artefact.

As shown in rows 2 to 5 of Figure 4, when these different events are used as input signals of high-pass filters, the output signals are oscillatory, except for the ripple filtered at 250 Hz (graph C2, where there is an increase of energy but no clear pattern) and the sharp artefact (graph B6, where the shape of the signal stays sharp after filtering).

It can be seen in the last row that the ripples and fast ripples produce 'blobs' in the time-frequency representation: at 140-190 Hz for the ripple (graph D2), at 400 Hz for the fast ripple and 80-140 Hz for the following ripple (D3), around 200 Hz for the ripple on top of a spike (D4), at 450-600 Hz and 140-190 Hz for the fast ripple and ripple on top of a spike (D5).

For the first spike (A1), there is no visible high-frequency blob. Still, there are oscillations in the filtered signals, that resemble those in the visible oscillations: the oscillation for a filter at 80 Hz (B1) is similar to that following the fast discharge (B3, between 10 and 40 ms), and the oscillation for the signal filtered at 250 Hz (C1) resembles that in the fast discharge (C3), although with much shorter duration and number of cycles. These oscillations may be considered as 'false ripples' (see next section).

For the artefact (A6), one can see in the time-frequency representation (D6) that its energy spreads over the whole frequency range, resulting in an elongated shape. Similarly to the spike, there is a short oscillation in the signal filtered at 250 Hz, but with a much higher signal-to- noise ratio, again a possible 'false ripple', similarly to those illustrated in Figure 1.

For the ripple in column 4, note that there is a secondary blob in the time-frequency representation around 400 Hz, which could be a harmonic of the main blob at around 200 Hz (see next section).

3.3. Reproducing false ripples

We investigated the possibility that some oscillations in the filtered signal were not actual oscillations but instead by-products of the filtering process, or 'false ripples'.

In Figure 5a, we show the real spike along with a simulated spike with the same characteristics, both on an expanded time scale. The simulated spike was obtained by linear interpolation with three fixed points, followed by a smoothing (moving average on 4 points). This ensured that there was no oscillation on this signal, by construction. The filtered traces and the time-frequency representation are very similar in the real and simulated signals, indicating that the observed oscillations are indeed 'false' ripples.

We have reproduced the non-sinusoidal ripple of Figure 4 (graph A4) with an asymmetric oscillation s(t) given by

$$s(t)=A \cos(2\pi f_0 (t+1.3\cos(2\pi f_0 t))/F_s), \tag{1}$$

with f_0=220 Hz and F_s sampling frequency. The fact that the oscillation is not purely sinusoidal produces an harmonic, visible in the time-frequency plane, and resulting in a fast oscillation in the signal filtered at 400 Hz. This can be considered as another type of 'false' ripple: the

actual event is an oscillation at 220 Hz, but filtering the traces at 400 Hz gives the false impression that the oscillation is at 440 Hz.

3.4. Masking effects in the time-frequency decomposition.

As discussed in section 3.2., the last row of Figure 4 shows that true oscillations are visible as "blobs" in the time-frequency plane. The pure spike (A1) and the artefact (A6) produce a single elongated shape with no visible superimposed band-limited blob.

However, the fact that the blob corresponding to the pure spike is of high amplitude and extends into the high frequency bands could mask a true oscillation.

We illustrated this masking effect in Figure 6. There, an interpolated spike (based on the first spike of Figure 4, as in Figure 5a) is added to the ripple (A2 in Figure 4) oscillation, with varying time shifts. In column 1, 2 and 4, a ripple is visible between 140 and 190 Hz (white arrows). For the shift in columns 2, this oscillation is partly masked by the spike. Similarly, the oscillation at a lower frequency (black arrow) is masked in column 3.

3.5. Atomic decomposition using the matching pursuit approach

The second row of Figure 7 depicts the atoms found by MP decomposition on real signals (atoms that reproduce 99 % of the energy of the signal). In this representation, the pure spike (with no oscillation) stays confined in the part of the plane below 100 Hz, whether the oscillations are detected as atoms in the ripple and fast ripple bands. It is then possible to filter the data by selecting only the oscillatory atoms that are above a given frequency (here, 50 Hz). This MP-based filtering permits to recover the real oscillatory activity corresponding to high-frequency atoms, while avoiding false ripples for the spike and the artefact, as shown in the bottom row of Figure 7.

The matching pursuit is therefore an interesting alternative to classical filtering or to wavelet analysis, as it permits to disentangle events with overlapping representation in the time-frequency domain. Still, the MP algorithm has also some limitations.

The main limitation is the fact that a given signal may not be perfectly fitted by a few atoms. This means that in some cases the atomic information can be difficult to interpret: a high frequency atom can be either describing a part of the actual high frequency oscillation or a high-frequency contribution caused by a transient event. Moreover, the subtraction procedure within the MP algorithm will almost inevitably leave some residuals: the part of the atom that

is not fitted to the signal will be left in the subtracted signal, and will have to be explained at subsequent iteration by a correction term.

This leads to the second important limitation of MP: the difficulty of choosing the number of atoms. Indeed, too few atoms could miss some true oscillations, while too many atoms will end up in the last iterations as correction terms to the imperfect subtraction of the first iterations. A way to choose the number of atoms is to set a threshold on the proportion of energy that needs to be explained by these atoms. In the preceding tests, the threshold was set to 99%: the energy of the reconstructed signal (using all atoms) is 99% that of the original signal. In figure 8, we present the decomposition of the interpolated spike (i.e., with no oscillation by construction, see 3.3) with an energy threshold of 99.99%: this threshold is so high that the MP needed to have correction atoms, which happen to be high-frequency oscillating atoms. This means that the threshold on the number of atoms needs to be carefully chosen in order not to overfit the data (i.e., not to fit noise).

4. Discussion

In this study, we have shown that the high-pass filtering of epileptic transients or non-sinusoidal oscillations may lead to spurious oscillations (referred to as 'false ripples' in the present work) that are similar to real oscillatory discharges while simply reflecting the impulse response of the filter or the harmonic nature of the signal. This can lead to false detection of HFOs, in particular in cerebral tissues where interictal spiking is abundant, and therefore to inappropriate interpretation of results. There are several strategies for handling the filtering artefacts in the detection and classification of epileptiform events.

The first strategy is to carefully review each epileptic transient, along with the filtered signal, in order to assess the presence of simultaneous oscillations by visual inspection. However, such review is tedious and time-consuming, and it is possible that some actual small oscillations escape visual inspection. Moreover, visual inspection only results in a classification of events as oscillatory or not, but does not permit to finely quantify the fluctuations in the energy of oscillatory activity. A criterion can be introduced on the minimum number of cycles in the filtered oscillation in order to reject false ripples. This criterion would have indeed permitted to avoid classifying the spurious oscillations for fast transients as true ripples. Still, our results show that one has to ensure that a given filter has an

impulse response that oscillates less than the chosen number of cycles. Moreover, this criterion does not permit to reject the false ripples produced by harmonics of non-sinusoidal signals.

The second strategy is to use time-frequency or wavelet transforms, where a transient event and an oscillation have different signatures: a transient signal produces a large-band elongated blob, whereas the representation of an oscillation is more restricted in frequency. Moreover, a non-sinusoidal oscillation produces several blobs at harmonic frequencies. Still, there can be an overlap between the time-frequency representations of spikes and oscillations, which may not permit to disentangle the two.

The third strategy is to use an atomic decomposition, such as that provided by the Matching Pursuit algorithm (Mallat and Zhang, 1993). We have shown in the present study that such representation allows for effective extraction of real oscillatory activity, with limited influence from transient spike events. The decomposition also permits to parameterize the discharges (Durka, 2004), which may allow to assess the clinical importance of parameters such as sharpness of the spike. Although promising, this method still has some limitations like, for example the possible distortions introduced by the subtractive approach. Improvement may arise from simultaneous estimation of the atoms, which is proposed by the basis pursuit method (Chen et al., 1998), or mixed norm sparse decomposition . In these methods, the level of background noise is explicitly taken into account, which may avoid over-fit of the data. Another improvement would be to use a multi-channel (Durka et al., 2005; Gribonval et al., 2007) or multi-trial decomposition (Bénar et al., 2009; Sieluzycki et al., 2009), which could help improving the signal-to-noise ratio for events that are spread across channels. The multichannel decomposition would also have the advantage of using different spatial structures of spikes and oscillations, when present, as additional information for separating these activities.

In summary, review of epileptic oscillations should be performed very cautiously, keeping in mind the limitations of each method and the possible occurrences of 'false' ripples. It is likely that the best strategy will be a combination of different methods, like those presented here, which could avoid misclassifying false ripples are true epileptic oscillations. Still, further work is needed to quantify the performance of the different strategies (like wavelet analysis or sparse decomposition) for automatic detection (Gardner et al., 2007) and classification of true epileptic ripples.

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FIGURES

Figure 1: Simulated spikes and filtered traces, with a Gaussian waveform (Figure 1a) or a triangular waveform (Figure 1b), along with simulated oscillations (with sinusoidal and triangular waveforms repectively). The filters are FIR filters with a slope of 48 dB/oct. For the spikes, many filtered signals have an oscillatory aspect: these are 'false' ripples produced by the filtering process. For the triangular oscillation (last column of figure 1b), the third harmonic of the oscillation is visible in the signal filtered at 250 Hz (graph D5), illustrating another type of 'false' ripple.

Figure 2: Power spectra of the simulated spikes and oscillations. (a) Gaussian spikes and sinusoidal oscillation, (b) triangular spikes and oscillation. The spectrum of the simulated realistic background noise is shown as a continuous line, it decays smoothly as a 1/f process. For the Gaussian spikes, the energy decays monotonously with frequency, with a slope inversely proportional to the duration of the spike. The triangular events have spectra with harmonics. In particular, the triangular oscillation has high energy in the fast ripple band (>250 Hz).

Figure 3: Technical features of implemented filters. (a) frequency response of the IIR and FIR filters. The order of the filters is shown in the legend. (b) Effect of the filter type (finite impulse response, FIR, or infinite impulse response, IIR) and of the level of attenuation (24, 48 or 96 dB/oct) on the output signals. The filtered signals oscillate more with a higher attenuation. On top of having non-linear phase properties (not shown), the IIR filter oscillates more than the FIR, especially for a high attenuation (96 dB/oct, fourth row).

Figure 4: Results of filtering different types of epileptic discharges in real data, along with the time-frequency representation. (1) pure spikes (with no visible oscillation), (2) and (3) ripple and fast ripple repectively, (4) and (5) a mixture of spike and oscillations (6) sharp artefact. Several cut-off frequencies of the high-pass filter were used. The oscillations result in blobs in the time-frequency plane (last row). The spike results in oscillations in the ripple and fast ripple bands (B1 and C1 resp.), that are not visible as blobs in the time-frequency representation, and may therefore be a "false" ripple.

These false ripples are similar to true ripples as seen for example in B3 and C3, although with shorter duration and number of cycles. The artefact leads to a spurious oscillation in the fast ripple band.

Figure 5: Comparison of the results of filtering real signals and simulated signals. (a) spike of Figure 4 (graph A1) along with an interpolated spike, with no oscillation by construction. The filtered data and time-frequency representations are similar, indicating that the oscillation is mostly an artefact of the filtering procedure, i.e. a 'false' ripple. (b) a non-sinusoidal oscillation (ripple A2 from figure 4). The oscillations have harmonics, which lead to an oscillation at double frequency in the filtered signal, another type of "false" ripple.

Figure 6: Test of the interaction of the interpolated spike of Figure 5a and the oscillation of Figure 4 (graph A2) in the time-frequency plane, for different values of the shift between the signals. One oscillation (white arrow) is visible in columns 2, 3, 4 but in column 2 it is masked by the spike. The other oscillation (black arrow) is partly masked in column 4.

Figure 7: First row: real signals as in Figure 4. Second row: result of a Matching Pursuit (MP) decomposition. Each atom is represented by a blob showing its time-frequency extent. Third row: result of MP-based filtering, performed by keeping only the atoms above 80 Hz. In column 2 to 5, MP filtering was able to extract the real oscillation, while avoiding false ripples for the pure spike (columns 1 and 2) and the sharp artefact (column 6).

Figure 8: Illustration of overfitting of the data with Matching Pursuit (MP). First column: MP decomposition of the interpolated spike of Figure 5a (i.e., with no oscillation by construction), explaining 95% of the signal. Second column: MP decomposition explaining 99.99% of the signal. In the second case, correction atoms are needed to explain the data with high reconstruction accuracy, leading to a false ripple after MP-based filtering.

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