Multiscale Adaptive Gabor Expansion (MAGE): Improved Detection of Transient Oscillatory Burst Amplitude and Phase

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ABBREVIATED TITLE:
MAGE Multiscale Adaptive Gabor Expansion

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Abstract

Since Denis Gabor's pioneering paper on the discrete Gabor Expansion (Gabor, 1946), time-frequency signal analysis has proven to be an important tool for many fields. In neurophysiology, time-frequency analysis has often been used to characterize and describe transient bursts in local field potential data. However, these transient bursts have a wide range of variable durations, suggesting that a time-frequency-scale dictionary composed of elementary signal "atoms" may prove useful to more accurately match recorded bursts. While overcomplete multiscale dictionaries are useful, generating a sparse code over such dictionaries is a difficult computational problem. Existing adaptive algorithms for discovering a sparse description are slow and computationally intensive. Here we describe the Multiscale Adaptive Gabor Expansion (MAGE), which uses an implicit dictionary of parametric time-frequency-scale Gabor atoms to perform fast parameter reassignment to accelerate discovery of a sparse decomposition. Using analytic expressions together with numerical computation, MAGE is a greedy pursuit algorithm similar to Matching Pursuit, restricted to a dictionary of multiscale Gaussian-envelope Gabor atoms. MAGE parameter reassignment is robust in the presence of moderate noise. By expressing a unknown signal as a weighted sum of Gabor atoms, MAGE permits a more accurate estimate of the amplitude and phase of transient bursts than existing methods.

KEYWORDS: Adaptive Gabor Expansion, Multiscale Time-Frequency Analysis, Time-Frequency Reassignment

1 Introduction

Bursts are brief periods of increased neural activity that reflect local network coordination, resulting in transient, non-stationary oscillations that exhibit high trial-to-trial variability. Mounting evidence suggests that transient bursts play an important functional role in neural coding (Lundqvist et al, 2018) and network coordination (Kirst et al, 2016). For example, Lundqvist and colleagues (Lundqvist et al, 2016) showed that the amount of information prefrontal neurons encoded about a stimulus in a working memory task was dependent on narrow-band oscillatory bursts in the gamma band (55-90 Hz). In particular, neurons encoded more information during periods of increased gamma power (greater than 2 standard deviations above the mean spectral power) compared to periods with baseline power levels. In their model, gamma bursts are signatures of cell assembly activation that are associated with informative spiking within single cells. Spikes from single neurons are more informative during bursts (high amplitude or spectral power) compared to inter-burst periods (mean to low power). Furthermore, the spike timing of individual cells relative to the phase of an ongoing high-frequency burst carries information about working memory load (Siegel et al, 2009). Similarly, Battaglia and colleagues showed that the amplitude and phase of burst activity that occurs in multiple areas is associated with the gating and flow of information within a distributed network (Palmigiano et al, 2017). In their simulations, small relative phase differences between bursts had a large impact on the direction and gain of information transmission. These studies highlight the importance of an accurate estimation of burst parameters, including ongoing amplitude and phase, in order to better understand the role that dynamic bursts play in perception, cognition, and action. However, the detection and accurate estimation of burst parameters is a difficult problem.

While a given burst may exhibit a stable instantaneous frequency for the duration of its occurrence, subsequent bursts may exhibit high variability in mean frequency, onset time relative to stimuli, or burst duration. This variability and non-stationarity can make it difficult to study burst dynamics with the traditional methods often used in electrophysiology studies. Traditional methods assume signal stationarity and model the variability of repeated experimental trials as a constant signal waveform embedded in stochastic noise. However, recent studies suggest that the ongoing local field potential (LFP) signal can be thought of as a non-stationary sequence of discrete, variable, and disjoint atomic bursts occurring within a stationary background of relatively low-power continuous ongoing activity. The goal of this paper is to describe a novel adaptive method for detecting transient bursts in non-stationary neurophysiological signals. Specifically, this method describes bursts as Gaussian-envelope Gabor atoms, using parameter reassignment and matching pursuit to generate a sparse atomic decomposition of neural signals. Given an initial set of Gabor parameters describing a burst in terms of time, frequency, scale, amplitude, and phase, this adaptive method returns improved parameters using fast refinement rules based on one-shot curve fitting, similar to the adaptive chirplet method of Yin and colleagues (Yin et al, 2002). Whereas their method used finite differences and 6 inner product operations to estimate the reassigned parameters, this method uses 4 inner product operations computing derivatives with

respect to the parameters for time, frequency, and scale (duration in time or bandwidth in frequency). For this reason, we term the method the Multiscale Adaptive Gabor Expansion, or MAGE. In the following we review some of the concepts involved in moving from linear, non-adaptive, and time-invariant signal processing of stationary signals to non-linear, sparse, and adaptive signal processing working on non-stationary signals using overcomplete frames or dictionaries. Next we derive the parameter reassignment rules at the core of MAGE before applying them to simulated and empirically-recorded data examples. The sensitivity and speciificy of MAGE are estimated under noiseless and noisy conditions. Finally, we consider some potential concerns or possibilities for applying MAGE to neurophysiological signals.

1.1 From linear, time-invariant processing of stationary signals to sparse, adaptive decomposition of non-stationary signals via overcomplete dictionaries

Signal processing often requires us to characterize an unknown signal $f(t)$. One way to do so is to compare the unknown signal $f(t)$ to a dictionary of known references signals G, where each element $g_k(t) \in G$ is a time-frequency signal "atom" that captures some feature of interest, such as localization in time, frequency, or scale. The inner product is a useful procedure for directly comparing an unknown target signal $f(t)$ and a known probe signal $g(t)$:

$$\langle f, g \rangle = \int_{-\infty}^{\infty} f(t)\overline{g(t)}\, dt \tag{1}$$

where $\overline{z}$ is the complex conjugate of $z \in \mathbb{C}$.

The more similar f is to g, the larger the magnitude of the inner product. Conversely, if f and g are dissimilar, their inner product will tend toward zero. Therefore, the set of inner products of the signal f against the dictionary G – that is, the set $\{\langle f, g_k \rangle | g_k \in G\}$ – describes how similar the unknown signal is to every atom in the dictionary and provides a simple measurement technique for generating structured data about the unknown signal: which reference or probe atoms best describe the unknown target signal, what part of the target signal different atoms capture, and the relative importance of different atoms for accurate and robust signal reconstruction.

A surprising number of signal processing transforms can be characterized in this way, as an ordered set of inner products with a parametric dictionary (Qian and Chen, 1993; Qian and Chen, 1994; Yin et al, 2002). These include 1-dimensional transforms such as the Fourier, Laplace, and fractional Fourier Transforms, 2-dimensional transforms such as the Short-Time Fourier and Wavelet Transforms, and 3-dimensional transforms such as the multi-scale Gabor transform (Cohen, 1995; Grochenig, 2000; Qian, 2001).

1.1.1 From orthogonal bases to sparse overcomplete dictionaries

If the dictionary G spans the same space as the unknown target signal f while each dictionary atom is orthogonal to every other atom (that is, $m \neq n$ implies $\langle g_m, g_n \rangle = 0$

for all $g_m, g_n \in G$), then G forms a basis for f. In this case, the analysis and synthesis of f assumes the form:

$$c_k = \langle f, g_k \rangle \text{ (analysis via orthogonal dictionary)} \tag{2}$$

$$f = \sum_k c_k g_k = \sum_k \langle f, g_k \rangle g_k \text{ (synthesis via orthogonal dictionary)} \tag{3}$$

The expansion of a signal over orthogonal dictionaries has proven to be very useful in many domains, most notably in signal compression and communication. However, in other domains such as biomedical imaging, the primary goal is to *characterize* a novel signal, rather than to *transmit* it elsewhere; in this case orthogonal dictionaries may miss signal features that we would like to describe. That is, while an orthogonal basis still provides for perfect reconstruction, describing a single feature of the target signal may require a weighted sum of several different dictionary atoms.

Therefore, for cases where signal characterization is the primary goal, it may be more appropriate to use an *overcomplete* dictionary, also known as a redundant frame. As with a basis, a frame spans the space of the signal – but unlike a basis, frame (or dictionary) atoms need not be orthogonal. Relaxing the orthogonality constraint allows us to include a larger variety of signal atoms in the dictionary, increasing the likelihood that one of the atoms will prove to be a good match to a part of the target signal. As before with the orthogonal dictionary, analysis is simple:

$$c_k = \langle f, g_k \rangle \text{ (analysis via overcomplete dictionary } G) \tag{4}$$

In many cases, such as biomedical research, the goal of signal processing is to generate the set of coefficients $\{c_k\}$ which are then examined directly for some feature of interest – that is, in many cases there is no need to explicitly reconstruct the original signal f from the set of dictionary inner products. If desired, synthesis can still be performed using a synthesis dictionary $G^\dagger$ (distinct from the analysis dictionary G), where $GG^\dagger = G^\dagger G = I$:

$$f = \sum_k c_k g_k^\dagger = \sum_k \langle f, g_k \rangle g_k^\dagger \text{ (synthesis via overcomplete dictionary } G^\dagger) \tag{5}$$

In general, however, synthesis becomes more complicated in the overcomplete setting, in that for a given analysis dictionary G, the synthesis dictionary $G^\dagger$ is not unique.

Alternatively, given a large overcomplete dictionary, one can use an iterative pursuit algorithm to generate a sparse signal description.

1.1.2 Sparse Signal Representation via the Matching Pursuit algorithm

Recall that given an overcomplete dictionary G, any signal can be described as a sum of weighted atoms:

$$f(t) = \sum_{k=1}^{\infty} c_k g_k(t), \tag{6}$$

where $m < n$ implies $|c_m| \geq |c_n|$. For greedy algorithms such as Matching Pursuit (Mallet and Zhang, 1993), each coefficient c_k is extracted sequentially. That is, we can express any signal $f(t)$ as a filtered signal f_N and a residual signal r_N:

$$f_N = \sum_{k=1}^{N} c_k g_k \tag{7}$$

and

$$r_N = \sum_{k=N+1}^{\infty} c_k g_k \tag{8}$$

where

$$f(t) = f_N(t) + r_N(t), \|r_N\|_2 < \epsilon \tag{9}$$

More formally, we can describe the Matching Pursuit algorithm as a function that takes in the unknown signal s to be decomposed, the dictionary D of known signal atoms, and the number N of atoms to be extracted:

$[G, c, r] = \text{MP}[D, s, N]$ (Matching Pursuit Algorithm)
Inputs:
D: dictionary of normalized signal atoms; $\|g\|_2 = 1$ for all $g \in D$
s: unknown signal to be decomposed
N: number of signal atoms to extract from s
Outputs:
G: ordered list (sub-dictionary) of extracted atoms; $G = \{g_k\}_{k=1}^{N} \subset D$
c: ordered list of coefficients; $c \in \mathbb{C}^N$
r: residual signal; $r = s - \sum_{k=1}^{N} c_k g_k$
Initialization:
$G^{(0)} = \emptyset$
$c^{(0)} = \emptyset$
$r^{(0)} = s$
Main loop:
for $k = 1$ to N do
$g_k = \text{argmax}_{g \in D} |\langle r^{(k-1)}, g \rangle|$ (select best atom from dictionary)
$G^{(k)} = \{G^{(k-1)}, g_k\}$ (update list of extracted atoms)
$c^{(k)} = \{c^{(k-1)}, \langle s, g_k \rangle\}$ (update list of coefficients)
$r^{(k)} = r^{(k-1)} - \langle s, g_k \rangle \; g_k$ (update residual)
end for
return $G^{(N)}, c^{(N)}, r^{(N)}$

That is, Matching Pursuit finds the next best atom to extract by computing the inner product of the unknown signal s with all atoms in the dictionary D:
1. $\rho_\gamma = \langle r^{(k-1)}, g_\gamma \rangle$ for all $g_\gamma \in D$ (compute inner product of signal with dictionary atoms)

2. $\gamma^* = \text{argmax}_\gamma |\rho_\gamma|$ (find index of best atom)
3. $g_k = g_{\gamma^*}$
4. $g_k = \text{argmax}_{g \in D} |\langle r^{(k-1)}, g \rangle|$ (select best atom from dictionary):

Unfortunately, steps 1 and 2 are often computatonally expensive. One solution to this computational burden is to restrict the dictionary D to only use atoms of a known parametric form, and use the analytic expression for the atom waveform and rather than storing an explicit numerical waveform. Similarly, for some parametric dictionaries the inner product also has an analytic form and can be used to speed up the discovery of the best-fit atom in matching pursuit.

1.1.3 The dictionary of multiscale Gaussian-envelope Gabor atoms

One signal atom that is very useful in time-frequency analysis is the Gaussian function $\varphi(t)$:

$$\varphi(t) = 2^{1/4} e^{-\pi t^2} \tag{10}$$

Recall that a signal $s : \mathbb{R} \to \mathbb{C}$ is finite-energy if and only if

$$\|s\|_2^2 = \langle s, s \rangle = \int_{-\infty}^{\infty} s(t)\overline{s(t)}\, dt = \int_{-\infty}^{\infty} |s(t)|^2\, dt = E_s < \infty \tag{11}$$

Direct integration shows that φ has unit energy,

$$E_{\varphi,t} = \langle \varphi, \varphi \rangle = \int_{-\infty}^{\infty} |\varphi(t)|^2\, dt = 1 \tag{12}$$

We can use the Gaussian energy density function to compute the average time of the signal:

$$\mu_{\varphi,t} = \int_{-\infty}^{\infty} t|\varphi(t)|^2\, dt = 0, \tag{13}$$

Similarly, we can compute the time-domain variance:

$$\sigma_{\varphi,t}^2 = \int_{-\infty}^{\infty} (t - \mu_{\varphi,t})^2 |\varphi(t)|^2\, dt = \frac{1}{4\pi}. \tag{14}$$

Recall the definition of the Fourier transform $\mathcal{F} : L^2(\mathbb{R}) \to L^2(\mathbb{R})$ and its inverse $\mathcal{F}^{-1} : L^2(\mathbb{R}) \to L^2(\mathbb{R})$:

$$\mathcal{F}s = \mathcal{F}[s(t)] = (\mathcal{F}s)(\nu) = \hat{s}(\nu) = \int_{-\infty}^{\infty} s(t) e^{-2\pi i \nu t}\, dt \tag{15}$$

$$\mathcal{F}^{-1}\hat{s} = \mathcal{F}[\hat{s}(\nu)] = (\mathcal{F}\hat{s})(t) = s(t) = \int_{-\infty}^{\infty} \hat{s}(\nu) e^{2\pi i \nu t}\, d\nu \tag{16}$$

which we take here as already extended to be bounded, linear, unitary operators. Applying the Fourier Transform to the time-domain Gaussian function, we find the frequency-domain expression

$$\mathcal{F}\varphi = \mathcal{F}[\varphi(t)](\nu) = \hat{\varphi}(\nu) = 2^{1/4}e^{-\pi\nu^2} \tag{17}$$

From this we determine the frequency-domain energy, mean frequency, and frequency-domain variance:

$$E_{\hat{\varphi},\nu} = \langle\hat{\varphi},\hat{\varphi}\rangle = \int_{-\infty}^{\infty} |\hat{\varphi}(\nu)|^2\, d\nu = 1 \tag{18}$$

$$\mu_{\hat{\varphi},\nu} = \int_{-\infty}^{\infty} \nu|\hat{\varphi}(\nu)|^2\, d\nu = 0 \tag{19}$$

$$\sigma^2_{\hat{\varphi},\nu} = \int_{-\infty}^{\infty} (\nu-\mu_{\varphi,\nu})^2|\hat{\varphi}(\nu)|^2\, d\nu = \frac{1}{4\pi} \tag{20}$$

Here we see why Gaussian functions are so useful in time-frequency analysis. Recall that for any signal s,

$$\sigma_{s,t}\sigma_{s,\nu} \geq \frac{1}{4\pi} \tag{21}$$

meaning that there is a lower limit on how concentrated a signal can simultaneously be in both the time- and frequency-domains. In general, if the energy of s is concentrated in time, then the energy of s is spread out in frequency, and vice versa. However, Gaussian-type functions make this inequality an equality; that is,

$$\sigma_{\varphi,t}\sigma_{\varphi,\nu} = \frac{1}{4\pi} \tag{22}$$

meaning that Gaussian functions are maximally localized in time and frequency. There exist no signals which have a tighter concentration of energy in the time-frequency plane. Therefore, if you want to decompose an unknown signal by describing in terms of simple, known time-frequency "atoms," then Gaussian functions are an excellent choice, given their strong energy concentration.

1.1.4 The translation, modulation, and dialation operators

To be able to move φ to any location in the time-frequency plane, we introduce two operators $T_x, M_x : L^2(\mathbb{R}) \to L^2(\mathbb{R})$, where $t, x \in \mathbb{R}$, $f(t) \in L^2(\mathbb{R})$.

The translation operator

$$T_x f = T_x[f(t)] = (T_x f)(t) = f(t-x) \tag{23}$$

shifts or translates the signal f in time, while the modulation operator

$$M_x f = M_x[f(t)] = (M_x f)(t) = f(t)\exp[2\pi i x t] \tag{24}$$

shifts or modulates the signal f in frequency. Applying these operators to φ permit us to shift the mean time and mean frequency of the localized signal atom. That is, given the simple reference function φ as a fundamental signal "atom" which is well-localized in time and frequency, together with the operators T_x and M_x that move signal atoms in time and frequency, we can fully tile an unknown signal within the

time-frequency plane, comparing small segments of this unknown signal to time- and frequency-shifted version of the known reference signal φ. To describe an unknown signal f, we can compute the inner product of it with the dictionary $\{T_\tau M_\omega \varphi\}$. This is the origin of the continuous STFT (where $\tau, \omega \in \mathbb{R}$) as well as its sampled counterpart, the Gabor expansion (where $\tau = am$ and $\omega = bn$ for small, fixed $a, b \in \mathbb{R}$ and $m, n \in \mathbb{Z}$).

However, time- and frequency-shifts alone do not capture all signal features of interest. Complex signals such as the local field potential recorded in neuroelectrophysiology often involve components that reflect different durations or scales – some signal sub-components may rise and decay quickly while others evolve more slowly.

We can examine variations in scale by introducing another operator $D_x : L^2(\mathbb{R}) \to L^2(\mathbb{R})$, where the dialation operator

$$D_x f = D_x[f(t)] = (D_x f)(t) = e^{-\frac{x}{4}} s(te^{-\frac{x}{2}}) \tag{25}$$

dialates or re-scales the input domain of f while preserving the signal energy.

Given the Gaussian function φ together with the translation, modulation, and dialation operators defined above, we can generate an overcomplete dictionary $G = \{T_a M_b D_c \varphi | a, b, c \in \mathbb{R}^3\}$. This dictionary tiles the time-frequency plane, in that for each time-frequency coordinate (a, b) we can find an atom centered at that location – in fact, centered at each time-frequency point (a, b) is a continuous family of atoms that span all possible scales or durations specified by the duration parameter c. Furthermore, since the Gaussian φ satisfies the uncertainty principle relation as an equality, each such atom provides the most compact time-frequency energy concentration possible.

Specifically, let

$$\phi_k = (t_k, \nu_k, s_k) \in \mathbb{R}^3 \tag{26}$$

represent the (time, frequency, scale) parameters for a given atom $g_k \in L^2(\mathbb{R})$. Then

$$g_k = T_{t_k} M_{\nu_k} D_{s_k} \varphi, \tag{27}$$

$$g_k(t) = g(t|\phi_k) = g(t|t_k, \nu_k, s_k) = T_{t_k} M_{\nu_k} D_{s_k} \varphi(t), \tag{28}$$

such that

$$g_k(t) = \sqrt[4]{2} \exp\left[-\frac{s_k}{4} - \pi e^{-s_k} (t - t_k)^2 + 2\pi i \nu_k (t - t_k)\right]. \tag{29}$$

Applying the Fourier Transform to g_k results in

$$\hat{g}_k(\nu) = \hat{g}(\nu|\phi_k) = \hat{g}(\nu|t_k, \nu_k, s_k) = \sqrt[4]{2} \exp\left[\frac{s_k}{4} - \pi e^{s_k} (\nu - \nu_k)^2 - 2\pi i \nu t_k\right]. \tag{30}$$

Given these time- and frequency-domain formulas of the atom g_k, we can calculate the total energy, the mean time, and the mean frequency of the Gabor atom:

$$E_k = \langle g_k, g_k \rangle = \langle \hat{g}_k, \hat{g}_k \rangle = \int_{-\infty}^{\infty} |g_k(t)|^2 \, dt = \int_{-\infty}^{\infty} |\hat{g}_k(\nu)|^2 \, d\nu = 1, \tag{31}$$

$$\mu_{k,t} = \int_{-\infty}^{\infty} t |g_k(t)|^2 \, dt = t_k, \tag{32}$$

$$\mu_{k,\nu} = \int_{-\infty}^{\infty} \nu |\hat{g}_k(\nu)|^2 \, d\nu = \nu_k. \tag{33}$$

This shows that the generative parameters (t_k, ν_k) correspond to the measured values of mean time and mean frequency.

Finally, as a measure of signal duration, we can calculate the time-domain and frequency-domain variance:

$$\sigma_{k,t}^2 = \int_{-\infty}^{\infty} (t - \mu_{k,t})^2 |g_k(t)|^2 \, dt = \frac{\exp[s_k]}{4\pi}, \tag{34}$$

$$\sigma_{k,\nu}^2 = \int_{-\infty}^{\infty} (\nu - \mu_{k,\nu})^2 |\hat{g}_k(\nu)|^2 \, d\nu = \frac{\exp[-s_k]}{4\pi}. \tag{35}$$

Showing that the duration parameter s_k captures the variance in signal energy in both the time and frequency domains.

1.1.5 Inner product relation between Gabor atoms

Using the parametric formula for g_k given above, we can identify an analytic expression for the inner product between two Gabor atoms:

$$\rho = \langle g_t, g_p \rangle = \int_{-\infty}^{\infty} g_t(t) \overline{g_p(t)} \, dt = \Phi(t_t, \nu_t, s_t, t_p, \nu_p, s_p) = A_\rho \exp[i\theta_\rho], \tag{36}$$

where

$$A_\rho = \sqrt{\operatorname{sech}\left[\frac{s_\Delta}{2}\right]} \exp\left[-\frac{\pi e^{-s_p} t_\Delta^2}{1 + e^{s_\Delta}} - \frac{\pi e^{s_p} \nu_\Delta^2}{1 + e^{-s_\Delta}}\right], \tag{37}$$

$$\theta_\rho = -\frac{2\pi t_\Delta \nu_\Delta}{1 + e^{-s_\Delta}} - 2\pi \nu_p t_\Delta, \tag{38}$$

and the difference between target and probe Gabor parameters are given by

$$t_\Delta = t_t - t_p, \tag{39}$$

$$\nu_\Delta = \nu_t - \nu_p, \tag{40}$$

and

$$s_\Delta = s_t - s_p. \tag{41}$$

Thus, the inner product between two gabors can be computed numerically or analytically. This is useful once we recall that, as in Matching Pursuit, any signal can be decomposed into a weighted sum of atoms and a residual signal:

$$\langle s, g_p \rangle = \langle \sum_{k=1}^{N} c_k g_k, g_p \rangle = \sum_{k=1}^{N} c_k \langle g_k, g_p \rangle \tag{42}$$

Since the derivate operator is conjugate linear, we also have

$$x_p \in \{t_p, \nu_p, s_p\}, \tag{43}$$

$$\frac{\partial}{\partial x_p}\langle s, g_p\rangle = \frac{\partial}{\partial x_p}\sum_{k=1}^{N} c_k\langle g_k, g_p\rangle = \sum_{k=1}^{N} c_k\frac{\partial}{\partial x_p}\langle g_k, g_p\rangle \tag{44}$$

$$\frac{\partial}{\partial x_p}\langle g_t, g_p\rangle = \langle g_t, \frac{\partial}{\partial x_p} g_p\rangle = \langle g_t, z_{x_p} g_p\rangle \tag{45}$$

$$\frac{\partial}{\partial x_p}\langle s, g_p\rangle = \sum_{k=1}^{N} c_k\langle g_k, \frac{\partial}{\partial x_p} g_p\rangle = \sum_{k=1}^{N} c_k\langle g_k, z_{x_p} g_p\rangle \tag{46}$$

for some z_{x_p}. To compute z_{x_p}, recall that the derivative of the inner product of two gabors with respect to a given Gabor parameter is equal to the inner product of a gabor atom with a derivative atom. That is, we can the exchange the derivative and inner product operators.

1.1.6 Derivation of MAGE parameter reassignment rules

Recall that our goal is to derive parameter reassignment rules such that if we are given a coarse parameter estimate of a target Gabor atom, then our reassignment rules will give us the parameters for a Gabor atom nearer to the target (ideally in one step). Since the operators in the prior sections are conjugate linear, we can exchange the order of operators to generate analytic expressions that are easier to deal with, as when we replace the derivative of an inner product between two Gabor atoms with the inner product between a target Gabor and a derivative kernel. Finally, we note that these derivative atoms have an analytic form, allowing us to rearrange and simplify to produce our reassignment rules.

Note that the 1st derivative of probe Gabor atom with respect to the center time parameter t_p is

$$\frac{\partial}{\partial t_p} g_p(t) = z_{t_p}(t) g_p(t), \tag{47}$$

where

$$z_{t_p}(t) = 2\pi\left(e^{-s_p}\left(t - t_p\right) - i\nu_p\right), \tag{48}$$

The 1st derivative of probe Gabor atom with respect to the center frequency parameter ν_p is

$$\frac{\partial}{\partial \nu_p} g_p(t) = z_{\nu_p}(t) g_p(t), \tag{49}$$

where

$$z_{\nu_p}(t) = 2\pi i(t - t_p), \tag{50}$$

The 1st derivative of probe Gabor atom with respect to the duration parameter s_p is

$$\frac{\partial}{\partial s_p} g_p(t) = z_{s_p}(t) g_p(t), \tag{51}$$

where

$$z_{s_p}(t) = \pi e^{-s_p}(t - t_p)^2 - \frac{1}{4}, \tag{52}$$

Let m stand for numerically-measured inner product values. Note that

$$m_0, m_{x_p} : \mathbb{R}^3 \to \mathbb{C}, \tag{53}$$

$$m_0(\phi_p) = \langle s(t), g_p(t|\phi_k) \rangle = \langle s, g_p \rangle, \tag{54}$$

$$m_{x_p}(\phi_p) = \frac{\partial}{\partial x_p} \langle s(t), g_p(t|\phi_k) \rangle = \langle s, \frac{\partial}{\partial x_p} g_p \rangle. \tag{55}$$

Analytically, we have

$$\frac{\partial}{\partial x_p} \langle g_t, g_p \rangle = \zeta_{x_p} \langle g_t, g_p \rangle, \tag{56}$$

for

$$x_p \in \{t_p, \nu_p, s_p\}. \tag{57}$$

$$\zeta_{t_p} = \frac{2\pi \left(i e^{s_p} \nu_p + i e^{s_t} \nu_t + t_t - t_p \right)}{e^{s_p} + e^{s_t}}, \tag{58}$$

$$\zeta_{\nu_p} = \frac{2\pi e^{s_p} \left(e^{s_t} \left(\nu_t - \nu_p \right) - i \left(t_t - t_p \right) \right)}{e^{s_p} + e^{s_t}}, \tag{59}$$

$$\zeta_{s_p} = \frac{8\pi i \left(t_t - t_p \right) e^{s_p + s_t} \left(\nu_t - \nu_p \right) + e^{2s_t} \left(1 - 4\pi e^{s_p} \left(\nu_t - \nu_p \right)^2 \right) + e^{s_p} \left(4\pi \left(t_t - t_p \right)^2 - e^{s_p} \right)}{4 \left(e^{s_p} + e^{s_t} \right)^2}. \tag{60}$$

This allows us to define a reassignment function for each Gabor parameter:

$$(t, \nu, s) -> (t_t^*, \nu_t^*, s_t^*) \tag{61}$$

$$s_t^* = s_p + \log \left[\frac{2\pi e^{s_p}}{e^{s_p} \left(e^{s_p} \Re[\zeta_{t_p}]^2 - 4\pi \Re[\zeta_{s_p}] + \pi \right) - \Re[\zeta_{\nu_p}]^2} - 1 \right], \tag{62}$$

$$\nu_t^* = \nu_p + \frac{\left(e^{-s_p} + e^{-s_t^*} \right) \Re[\zeta_{\nu_p}]}{2\pi}, \tag{63}$$

$$t_t^* = t_p + \frac{\left(e^{s_p} + e^{s_t^*}\right) \Re[\zeta_{t_p}]}{2\pi}. \tag{64}$$

where $\Re[z], \Im[z]$ stand for the real and imaginary parts of a complex number z.

Interestingly, not all derivatives are needed, since the derivative of the inner product of two Gabor atoms with respect to center time and center frequency are related, with the imaginary part of one correponding to the real part of the other. That is, the relation of ζ_{t_p} to ζ_{ν_p} is:

$$\Re\left[\zeta_{t_p}\right] = -\Im\left[\zeta_{\nu_p}\right] e^{-s_p}, \tag{65}$$

and

$$\Re\left[\zeta_{\nu_p}\right] = \Im\left[\zeta_{t_p}\right] e^{s_p} - 2\pi e^{s_p} \nu_p. \tag{66}$$

Thus, given an initial probe Gabor g_k that has a moderate inner product magnitude with an unknown signal s, MAGE provides parameter reassignment formulas that may represent a Gabor with a better fit to the unknown signal. Given a moderately good initial probe Gabor, the reassignment function $(t, \nu, s) -> (t_t^*, \nu_t^*, s_t^*)$ suggests the next test point in time-frequency-scale space.

1.1.7 From Matching Pursuit to the Multiscale Adaptive Gabor Expansion (MAGE)

This gives us an update function for parameter reassignment which we can include within the Matching Pursuit algorithm to produce MAGE:

Multiscale Adaptive Gabor Expansion (MAGE) Algorithm:
$[\Phi, C, r] = \text{MAGE}[s, N]$
Inputs:
s: unknown signal to be decomposed, $s \in L^2(\mathbb{R})$
N: number of signal atoms to extract from s
Outputs:
Φ: ordered list of Gabor atom parameters; $\Phi = \{\phi_k\}_{k=1}^N, \phi_k = (t_k, \nu_k, s_k) \in \mathbb{R}^3$
C: ordered list of coefficients; $C = \{c_k\}_{k=1}^N, c_k \in \mathbb{C}$
r: residual signal; $r = s - \sum_{k=1}^N c_k g_k = s(t) - \sum_{k=1}^N c_k g(t|\phi_k)$
Initialize:
$\Phi^{(0)} = \{\}$ (empty list)
$C^{(0)} = \{\}$ (empty list)
$r^{(0)} = s$
Main loop:
for $k = 1$ to N do
$\phi_k = \text{argmax}_\phi |\langle r^{(k-1)}, g(t|\phi)\rangle|$ (find parameters of best dictionary atom)
$(t_t^*, \nu_t^*, s_t^*) < -(t, \nu, s)$ (apply analytic parameter reassignment formula)
$g_k = g(t|\phi_k)$ (generate atom)
$c_k = \langle r^{(k-1)}, g_k\rangle$ (compute coefficient)
$r^{(k)} = r^{(k-1)} - c_k g_k$ (update residual)
$C^{(k)} = \{C^{(k-1)}, c_k\}$ (update coefficient list)
$\Phi^{(k)} = \{\Phi^{(k-1)}, \phi_k\}$ (update atom parameter list)

end for
return Φ, C, r

Including parameter reassigment rules within Matching Pursuit, as we do to develop MAGE, is justified for several reasons. First, recall that most matching pursuit algorithms use an explicit dictionary of sampled waveforms, such that Matching Pursuit only explores a discrete subset of parameter values corresponding to dictionary atoms. MAGE, however, performs its parameter reassignment in a continous parameter space relatively unaffected by issues of sampling or regularity of the search grid (eg, rectangular vs. triangluar-quincunx). This means that initial sampling grid can be fairly coarse to speed up the numerical computation, while relying on the MAGE parameter reassignment to generate a more refined estimate. Second, the analytic Gabor inner product relation used in the derivation of the reassignment rules can be used to quickly determine if a Gabor inner product value needs to be updated or not, greatly speeding up the Matching Pursuit algorithm. Third and finally, multiple probe Gabors (with different specific noise interference terms) can be used to estimate the parameters for the same target Gabor, implementing a simple form of noise reduction.

1.2 Application of MAGE to synthetic and empirically-recorded data examples

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1.2.1 Example 1: synthetic data with known ground-truth

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1.2.2 Example 2: empirically-recorded electrophysiology data

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1.3 Sensitivity and specificity under noiseless and noisy conditions

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1.4 Discussion and Conclusion

While the theoretical foundations of Matching Pursuit and similar adaptive algorithms is well established (Mallet and Zhang, 1993; Qian and Chen, 1994), fast and practical numerical implementations remain an open research topic. One of the most useful options right now is the Matching Pursuit Toolkit or MPTK (Krstulovic and Gribonval, 2006), a C++ open source toolkit which maintains a list of atoms that are local maxima in amplitude space and updates only those atoms that have a large inner product with the last atom extracted. MAGE can be seen as a similar augmentation of Matching Pursuit, where the known analytic expressions for Gaussian-envelope Gabor atoms is used to estimate the location of the best local maximum in parameter space, even

if it is off of the Matching Pursuit search grid. That is, Matching Pursuit finds the best Gabor atom in its set of regularly sampled atoms (initial coarse estimate step in sampled discrete space), which is then input into the MAGE reassignment rules to find an improved estimate (fast parameter refinement step in continuous parameter space). This fast refinement is a non-iterative parameter reassignment, although an iterative version of MAGE may be useful for denoising. Since MPTK partitions its search tree using time alone (no need to update atoms that do not overlap), it would be interesting to see if MAGE could be incorporated into MPTK, since the inner product relation between any two Gabor atoms can be used to partition the search space in time, frequency, and scale rather than just time alone.

Another concern is the relation between empirically-observed bursts and the parametric model of Gabor time-frequency-scale atoms. Gabor atoms are essentially Gaussian-windowed sinusoids, but recent studies have reminded researchers of the often non-sinusoidal nature of empirically-recorded electrophysiological brain signals (Cole and Voytek, 2017). One response to this concern is to note that the mean time and mean frequency are well-defined concepts for any finite-energy signal (Cohen, 1994). Recall that the center time and center frequency parameters correspond to the mean time and mean frequency, respectively, of any Gabor atom. Similarly, the time-domain variance and the frequency-domain variance of any finite-energy signal can be estimated from the numerical vector representing a sampled version of it, and these values can be used to estimate the Gabor atom scale parameter. So up to the level of 2nd order signal statistics, parametric Gabor atoms and non-parametric (empirically-recorded) signals can be matched. Additionally, data-driven learning methods such as single-channel Independent Component Analysis (ICA; Bell and Sejnowski, 1995) and Kernel-Singular Value Decomposition (k-SVD; Elad, 2010) can be used to further refine a non-parametric description of a burst once the best-fit parametric Gabor atom has been identified. For example, Brockmeier and Principe (2016) show that alternating Matching Pursuit with data-driven kernel-learning via k-SVD and ICA generate a small set of waveforms with consistent clustering properties that permit experimenters to express human EEG via a sparse code. In this regard, MAGE could be used as an initial step in data-driven kernel learning techniques used to identify segments of raw data containing high-power bursts, thus making learning more efficient.

The goal of this paper was to introduce an improved version of fast parameter refinement, similar to that suggested by [Yin et al, 2002]. As with their algorithm, MAGE is performing a curve-fitting operation in order to suggest an atom with a better fit to a signal to be filtered. The fast refinement algorithm of Yin et al uses finite differences to compute points for curve fitting. The spacing between points is an arbitrary hand-tuned parameter which MAGE does away with by using derivatives. Importantly, these derivatives are used to compute values for curve fitting, and are not used for an iterative hill-climbing optimization. Also, while the Yin algorithm uses 6 points for curve fitting, MAGE uses 4 points, which reduces the number of multily-add operations required.

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