

内容安排的基本逻辑



第九讲、第十一讲

小波变换应用要点和综合案例

学习要点

- 连续小波变换CWT的应用要点
 - Morlet小波的参数选取（中心频率、窗口长度、波数）
 - 相位谱和幅度谱——特征提取
- 离散小波变换DWT的应用要点
 - 小波基函数选择：小波与被处理成分的相似性
 - 频率特性：被处理成分的频率特性、小波的频带
 - 局部处理：被处理成分的局部特性
 - 两类应用：
 - 信号处理（局部去噪）：脑电信号中的眼电去除 (Khatun, IEEE 2016)
 - 特征提取：睡眠脑电特征与睡眠分期
- 综合案例
 - 丙泊酚麻醉过程的脑电特性动态变化 (Purdon et al., 2013)

连续小波变换CWT的应用要点 ——以Morlet小波变换为例

Morlet小波 — 正弦函数与高斯函数的乘积

- 时域内，一个正弦函数与一个高斯函数的乘积对应一个Gabor函数，Morlet小波

$$Gabor(x) = g(x) \cdot f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-x^2}{2\sigma^2}} \cdot e^{i\omega_0 x}$$

- 其中正弦函数

$$f(x) = e^{i\omega_0 x} = \cos(\omega_0 x) + i\sin(\omega_0 x)$$

- 高斯函数

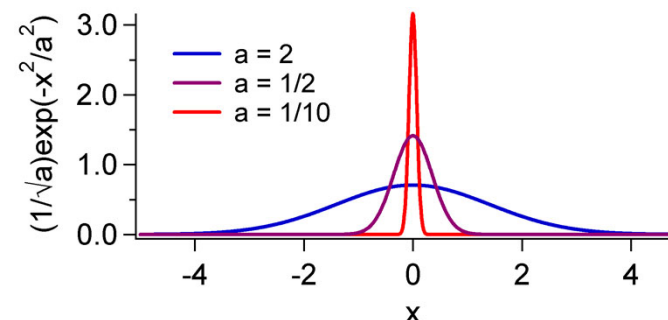
$$g(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-x^2}{2\sigma^2}}$$

Morlet小波的参数选择

- % Complex Morlet wavelet (Cohen2014, Fig. 6.2)
 - $fs = 100$; $t = -1:1/fs:1$; % the duration of the wavelet
 - $f = 5$; % Hz
 - $w = 2 * (5 / (2 * \pi * f))^2$; % the Gaussian width parameter
 - $gaussian = \exp(-t.^2/w)$; % the Gaussian function
 - $csw = \exp(1i * 2 * \pi * f * t)$; % the complex sine wave
 - $mwavelet = csw .* gaussian$; % the complex Morlet wavelet

如何选择 t 和 w ?

高斯函数的幅度?



Morlet小波对应的高斯窗口长度

- 针对高斯函数的幅度问题，用概率密度函数

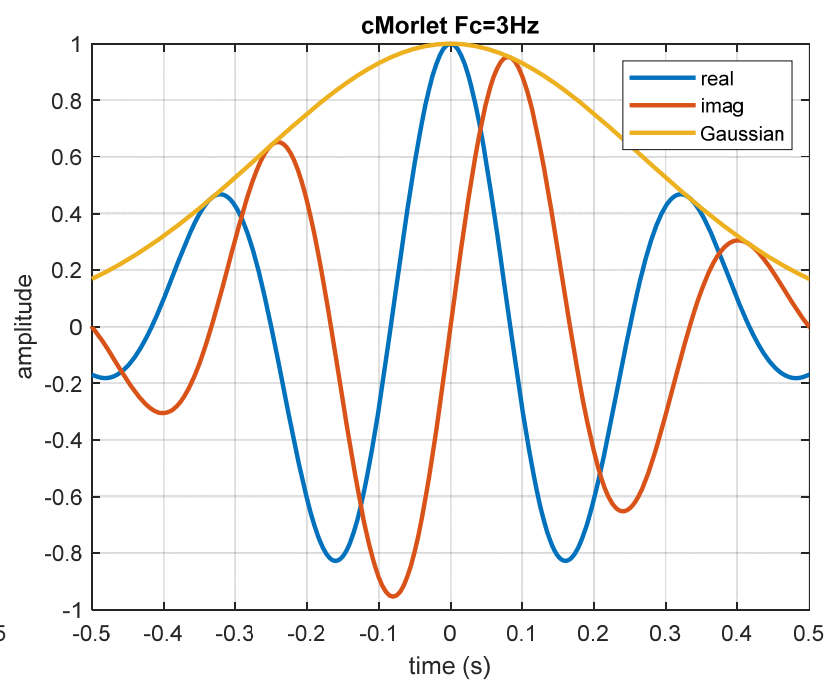
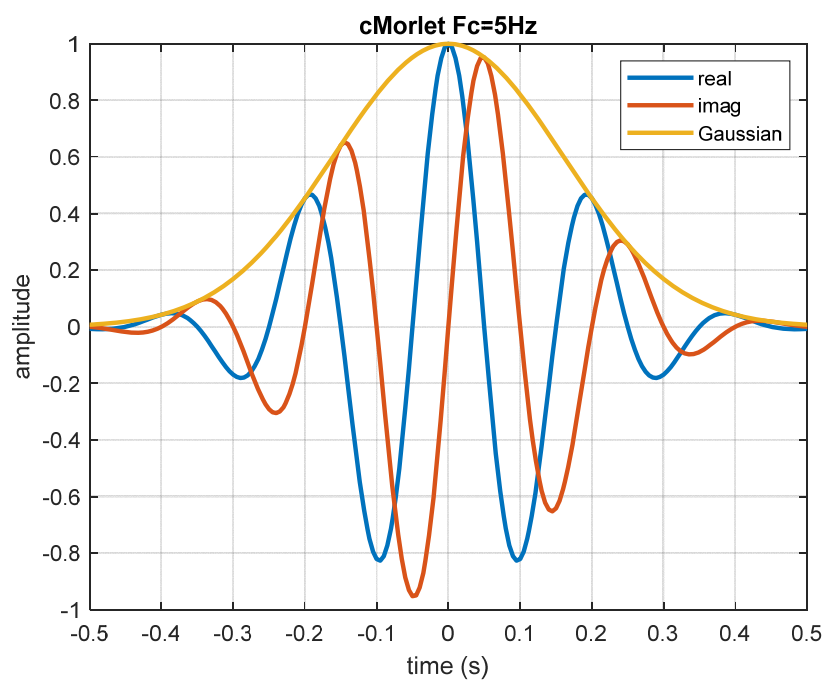
$$g(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}}$$

- 原程序中 `gaussian = exp((-t.^2)/w)`，令 $w=2\sigma^2$ ，则
- $\sigma = \text{sqrt}(w/2)$
- 改进定义：`gaussian = 1/(sqrt(w*pi))*exp((-t.^2)/w)`
- 如何选择t和w
 - 高斯窗口的傅里叶变换： $G(\omega) = e^{-\frac{\omega^2 \sigma^2}{2}}$
 - 信号分析的频率分辨率需求：例如在 $f=5\text{Hz}$ 的频率条件下， $\Delta f=0.5\text{ Hz}$ ，考虑频率域内的高斯的标准差为 0.25Hz ，则 $1/\sigma=0.25$ ，对应时域内的 $\sigma=4\text{秒}$
 - 考虑时域内高斯函数需要 $\pm 3\sigma$ 的位置之外衰减接近0，时间窗口长度 $t\text{Win} = 6*\sigma = 24\text{ s}$
 - 代入 $w=2\sigma^2$ ， $w=2*4^2 = 32$
 - w同时应该与待分析信号频率f的成反比例关系，表达为 $w=a/f^2$

方法一：分别定义高斯窗口的tWin和w

- Cohen2014 Fig.6.2对应的程序采用该方法
 - `fs = 100; t = -1:1/fs:1; % define tWin to be 2 seconds`
 - `f = 5;`
 - `w = 2*(5/(2*pi*f))^2; % the Gaussian width parameter`
 - `gaussian = exp((-t.^2)/w);`
 - `csw = exp(1i*2*pi*f*t);`
 - `mwavelet = csw .* gaussian;`
- 分析
 - 特点：tWin固定，w与中心频率 f^2 成反比
 - 存在的问题：高斯窗口参数w太大，在时间窗口tWin的范围内不衰减到0，不符合小波两端衰减到0的定义要求
 - 原因：由tWin固定，与w独立

固定 $t_{Win}=1s$ ，不同 F_c



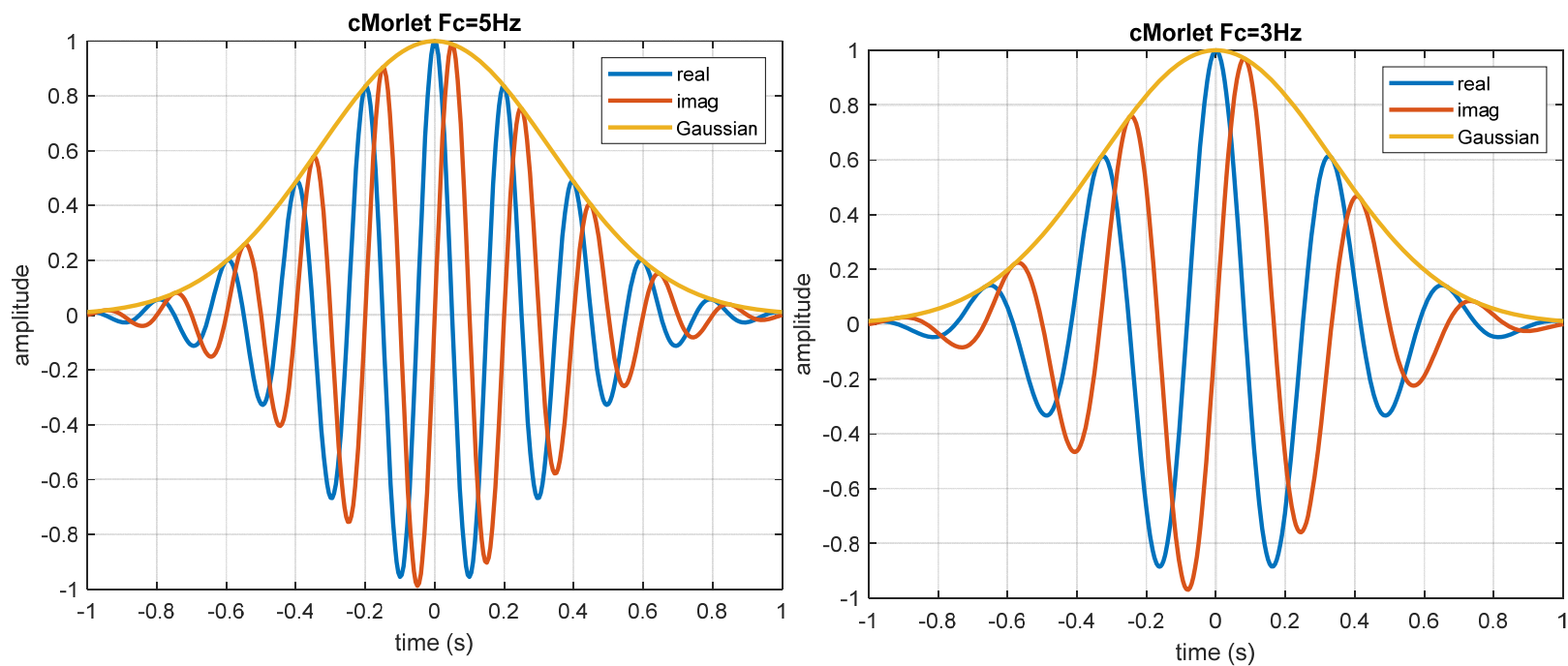
- 低中心频率对应较大的高斯窗宽度，在固定时间窗口内不能衰减到0

方法二：定义tWin满足分辨率需求

- 为了小波总是能衰减到0，采用固定的高斯窗口
- $F_{resol} = 0.5 \text{ Hz}$
- $tTick = -0.5/F_{resol}:1/F_s:0.5/F_{resol};$
- $\sigma = (1/F_{resol})/nSigma;$
- $w = 2*\sigma^2;$

方法二：定义tWin满足分辨率需求

- $F_{resol}=0.5$ Hz



- 问题：在不同中心频率下对应的时间窗口长度一致，不能满足时间分辨率随着中心频率改变而改变的需要

方法三：tWin内的波数nCycles恒定

常用

• nCycles = 3;

→ 振荡周期个数

• tTick = (-0.5*nCycles/Fc):1/Fs:(0.5*nCycles/Fc)

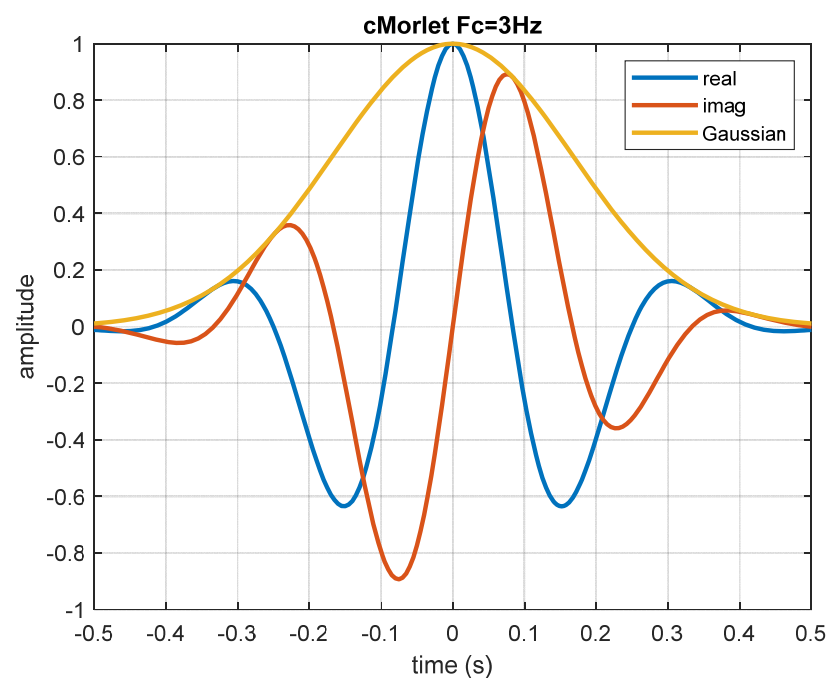
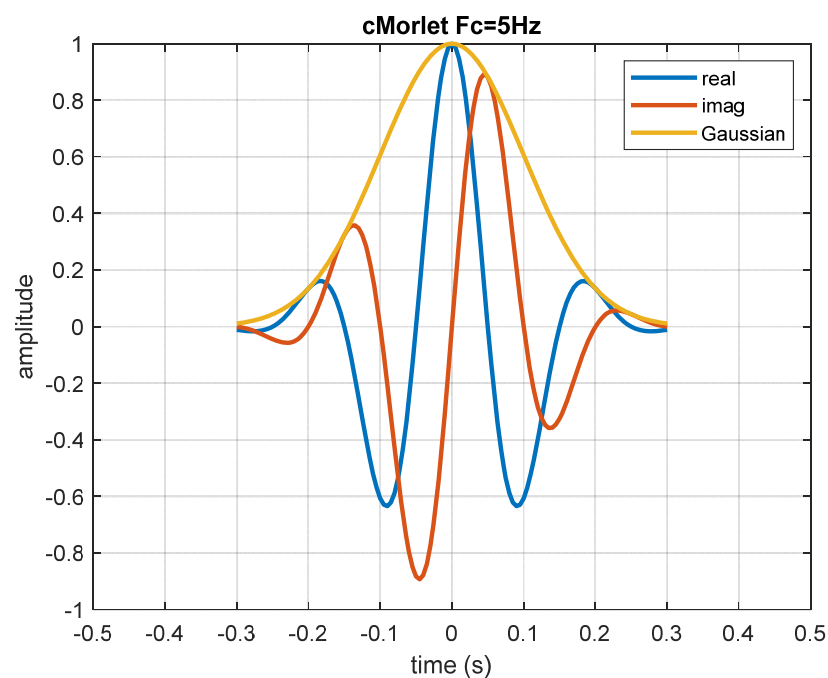
• sigma = nCycles/Fc/nSigma;

• w = 2*sigma^2;

• 注：程序中时间窗口tWin（tTick的范围）和高斯窗口w 同时随着Fc的变化而变化

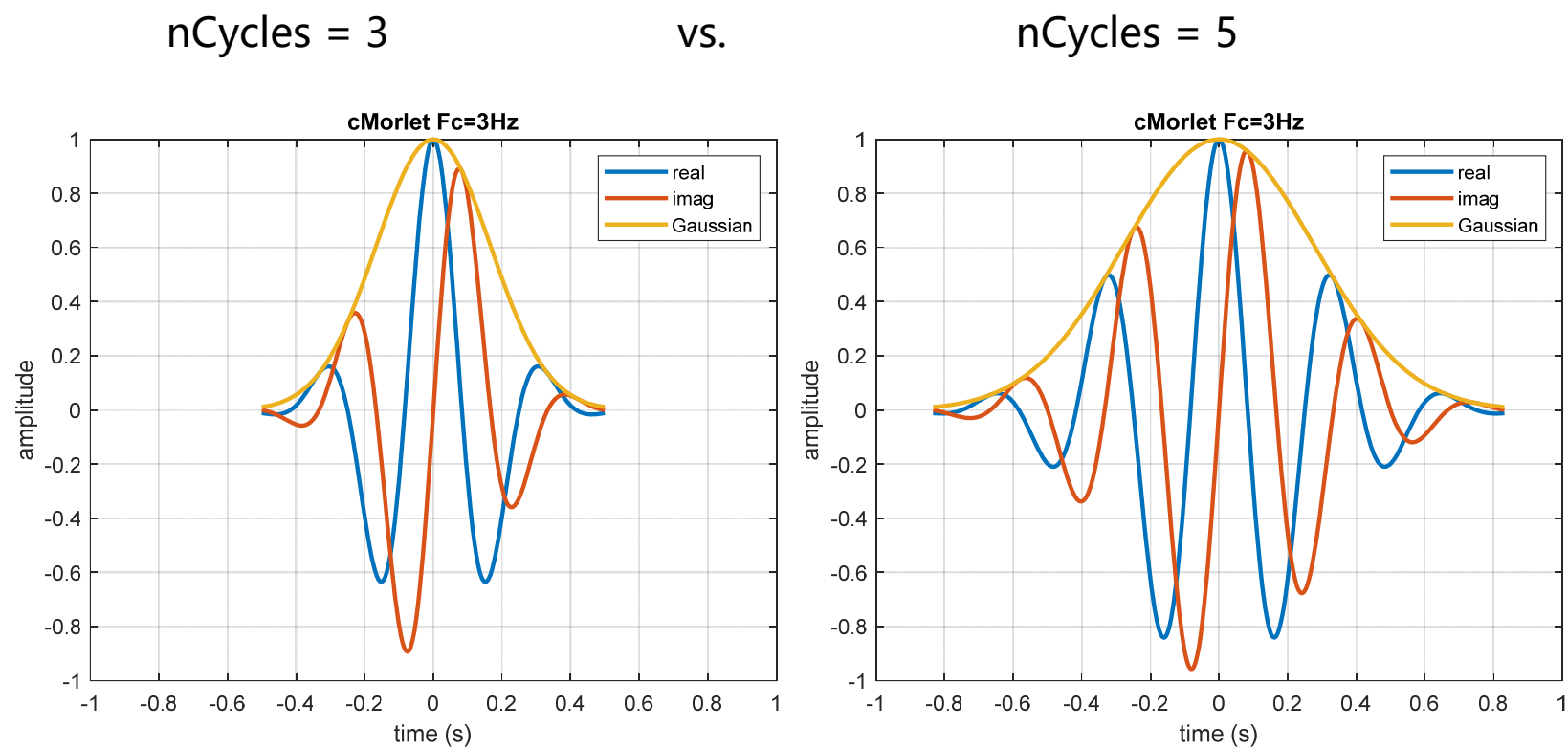
方法三：tWin内的波数nCycles一致

- $nCycles = 3$;



- 注：同时实现了时间窗口tWin和高斯窗口w随着Fc变化而变化

对方法三中波数nCycles的讨论



- $tTick = (-0.5 * nCycles / Fc) : 1 / Fs : (0.5 * nCycles / Fc)$, 对应不同长度的tWin

Morlet 小波分析中心频率取值范围

- 完全取决于对研究对象有兴趣的信号频率范围
- 例：睡眠脑电分析
 - 通常感兴趣的波是delta (0.5~4 Hz) , theta (4~8 Hz) , alpha (8~12 Hz) , beta (12~30 Hz) 波, 则中心频率应该取值的范围为0.5 Hz ~ 30 Hz
 - 考虑最低频率分辨率为0.5 Hz, 则最短的时间窗口长度为2s
 - 还要考虑在这个时间窗口内, 最好有3个或者稍多的波数 $nCycles \geq 3$
 - 综合考虑, 对于中心频率为0.5 Hz的信号, 则需要6秒钟的时间窗口长度

Morlet小波分析中心频率的步长

- 根据感兴趣的频率范围
- 时间窗口的宽度 – 频率分辨率的情况
 - 长时间窗口，高频率分辨率的情况下，可以减小步长
- 线性步长 vs. 对数步长
 - 两者仅仅是视觉上的效果不一样？
 - 线性步长在高频段重叠的频率越来越大
 - 对数步长
 - $nCycles = 3;$
 - $tTick = (-0.5 * nCycles / Fc) : 1 / Fs : (0.5 * nCycles / Fc)$
 - $\sigma = nCycles / Fc / nSigma;$
 - $w = 2 * \sigma^2;$
 - $gaussian = \exp(-t.^2 / w);$
 - 傅里叶变换的频率的 σ 随着频率升高而增大

正负半周的选择

小波变换的幅度和相位谱

- 连续小波变换

$$W_f(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} \psi\left(\frac{t-b}{a}\right) f(t) dt = \int_{-\infty}^{\infty} \psi_{a,b}(t) f(t) dt, a > 0$$

- Morlet小波

- gaussian = exp((-t.^2)/w);
- csw = exp(1i*2*pi*f*t);
- mwavelet = csw .* gaussian;

- 信号sigData的Morlet小波变换

- coefMT = conv(sigData, mwavelet, 'same');
- 幅度: abs(coefMT)
- 相位: angle(coefMT)

复Gabor函数与Chirp信号的卷积程序

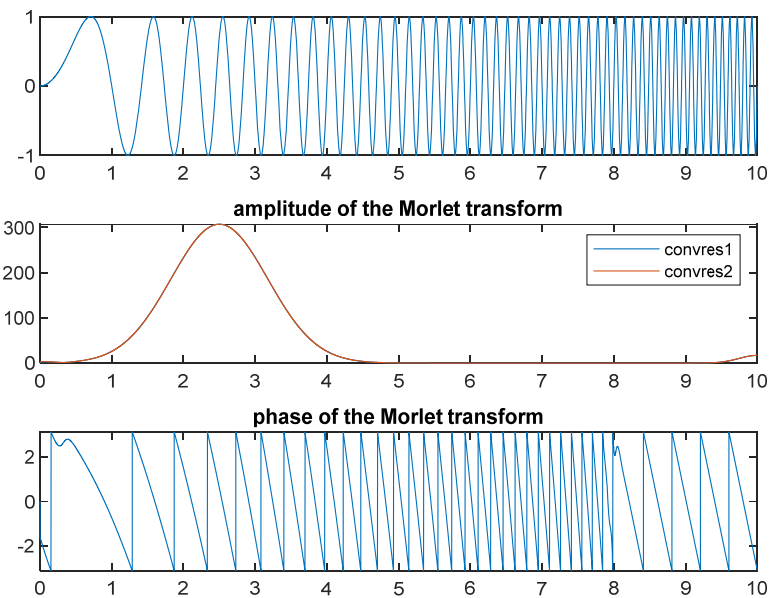
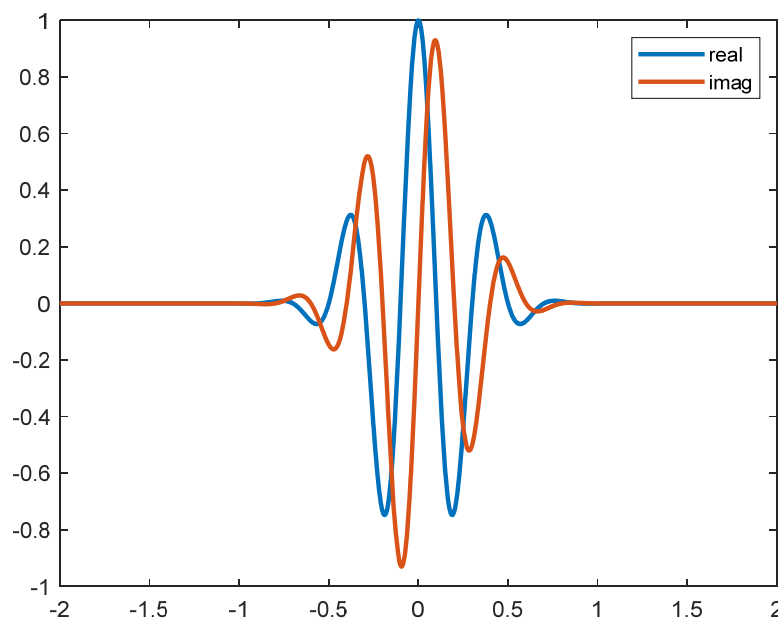
- % 产生Chirp信号
- Srate = 1000; f = [0 10]; t = 0:1/srate:(max(f)-min(f)); n = length(t);
- chirpTS = sin(2*pi.* linspace(f(1),f(2)*mean(f)/f(2),n).*t);
- % 产生中心频率为f0的复Morlet小波
- f0 = 2.5; w = 2*(4/(2*pi*f0))^2; wtime = -2:1/srate:2; % wavelet time
- cmw = exp(1i*2*pi*f0.*wtime) .* exp((-wtime.^2)/w);
- figure; plot(wtime, [real(cmw); imag(cmw)]', 'linewidth', 2); legend('real', 'imag');
- halfwavL = floor(length(wtime)/2); % half of the length of the wavelet
- chirpTSpad = [zeros(1, halfwavL) chirpTS zeros(1, halfwavL)]; % zero-pad chirp
- convres = zeros(size(chirpTSpad)); % run convolution
- for i = halfwavL+1:length(chirpTS)+halfwavL-1 % 逐点求卷积
- convres(i)=sum(chirpTSpad(i-halfwavL:i+halfwavL) .* cmw);
- end
- convres = convres(halfwavL:end-halfwavL-1); % 去除两端
- figure; subplot(311), plot(t, chirpTS); subplot(312), plot(t, **abs(convres)**)
- title('amplitude of the Morlet transform');
- subplot(313), plot(t, **angle(convres)**); hold on; title('phase of the Morlet transform');

Morlet小波与Chirp信号的卷积

- 时域内的卷积

- $f_0 = 2.5$ Hz;

Chirp信号的 $f = [0, 10]$



离散小波变换DWT的应用要点

DWT的应用要点

- 小波基函数选择
 - 小波基函数的多样性是相对傅里叶变换的显著特征之一
 - 为什么需要这么多种小波？应用时选择哪一种？
 - 一般考虑：小波与被处理成分的相似性
- 频率范围的选择
 - 被处理成分的频率特性
 - 小波的频带
- 局部处理
 - 被处理成分的局部特性：宽带低振幅噪声，还是偶发性高振幅伪迹？
 - 单层小波系数的处理
 - 多层小波系数的关系与处理

频率范围的选择

- 小波分解各层小波系数的频率范围
 - 回顾Mallat的DWT算法，信号分为高频（细节项）和低频（近似项）的迭代
 - 各层小波系数对应的频率范围由采样率 F_s 和分解的层数 k 完全确定
 - 试图计算采样率 $F_s=256$ Hz，分解到 $k=3$ 的近似项和细节项对应的频率范围
- 各类典型生理信号的频率范围
 - 脑电： δ 波（0.5~4 Hz）， θ 波（4~8 Hz）， α （8-12 Hz）， β （12-30 Hz）， γ （30-80 Hz或者更高的频率）
 - 眼电：1-14 Hz

$\frac{F_s}{2}$ 表

离散小波变换应用1

——基于SWT的局部去噪

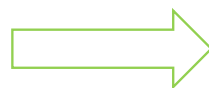
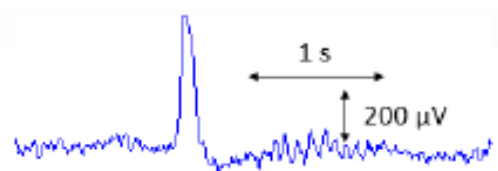
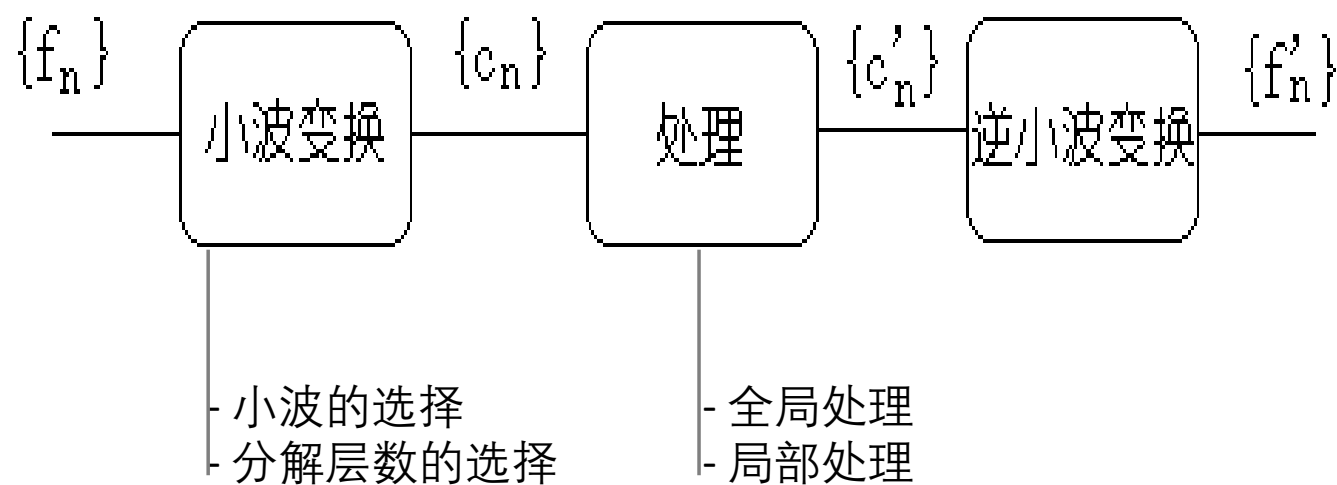
信号与噪声的关系

- 信号特性与处理方法的匹配



	噪声与信号 频谱不重叠	噪声与信号 频谱重叠
确定信号	滤波	叠加平均方法
随机信号	滤波	针对局部噪声 (非平稳随机过程) 小波变换

基于离散小波变换的信号处理



基于小波变换的局部噪声消除

- 信号与噪声特性分析
 - 有限带宽信号 vs. 宽频噪声，在不同小波尺度的表现不同
 - 偶发性噪声 – 不平稳 – 局部性
 - 例如脑电中的眼电伪迹仅仅发生在某些特定的事件段
 - 信号在邻近频带的相关性
 - 例如台阶信号的边沿部分，眼电伪迹等的邻近小波系数有相关性
 - 可以通过求类似于“与”的关系检测出来
- 基于小波变换的算法
 - 选择合适的小波函数
 - 选择合适的小波分解层数
 - 小波变换系数的上述某些特征进行特定处理
 - 例如根据某些噪声的局部性→对小波系数进行局部非线性处理
 - 对多种不同的信号和噪声/伪迹的混合特性，选用合适的信号处理流程
 - 算法具有灵活性，有机会发挥创造性

案例1：眼电去除的小波变换方法

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Comparative Study of Wavelet-Based Unsupervised Ocular Artifact Removal Techniques for Single-Channel EEG Data

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应用举例

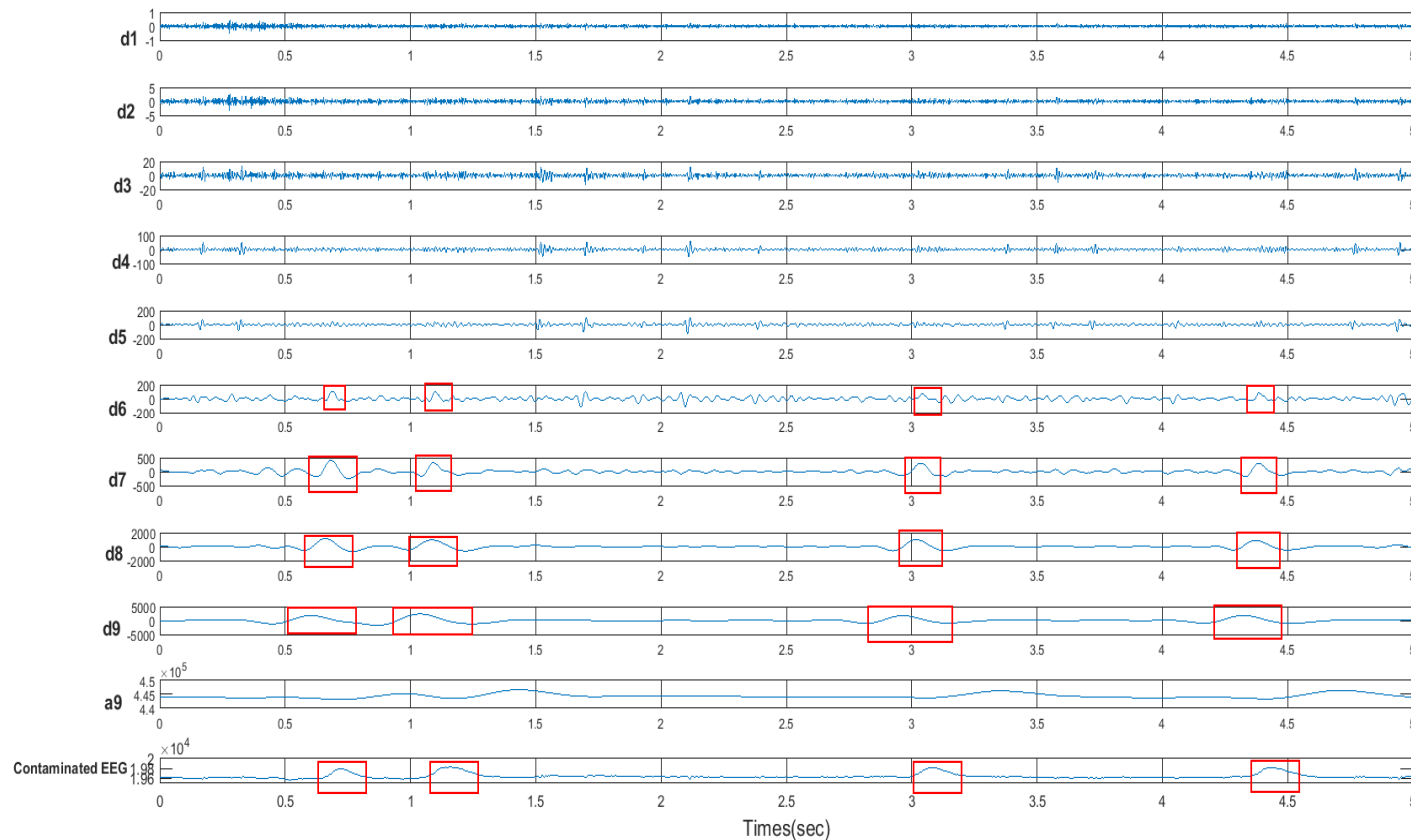
- 脑电中的混杂的眼电是脑电分析常常遇到的困难，消除脑电的眼电伪迹因此成为脑电分析的必要预处理步骤。离散小波变换是常用的眼电去除算法的核心。如何使用小波变换去除眼电？



算法要点

- 原则：信号特征决定算法及其参数的选取
 - 脑电能量分布在1-100 Hz之间，眼电信号是由于眼动和眨眼造成的，其主要能量分布于1-14 Hz之间。
 - 眼电信号的波形幅度高
 - 眼电发生的时间偶然
- 母小波的选择
- 小波分解的层数
 - 确定分解的总层数
 - 确定眼电所在的小波系数?
- 阈值的选择与非线性滤波
- 算法性能评价

实测数据分析举例 (Zhang et al.)

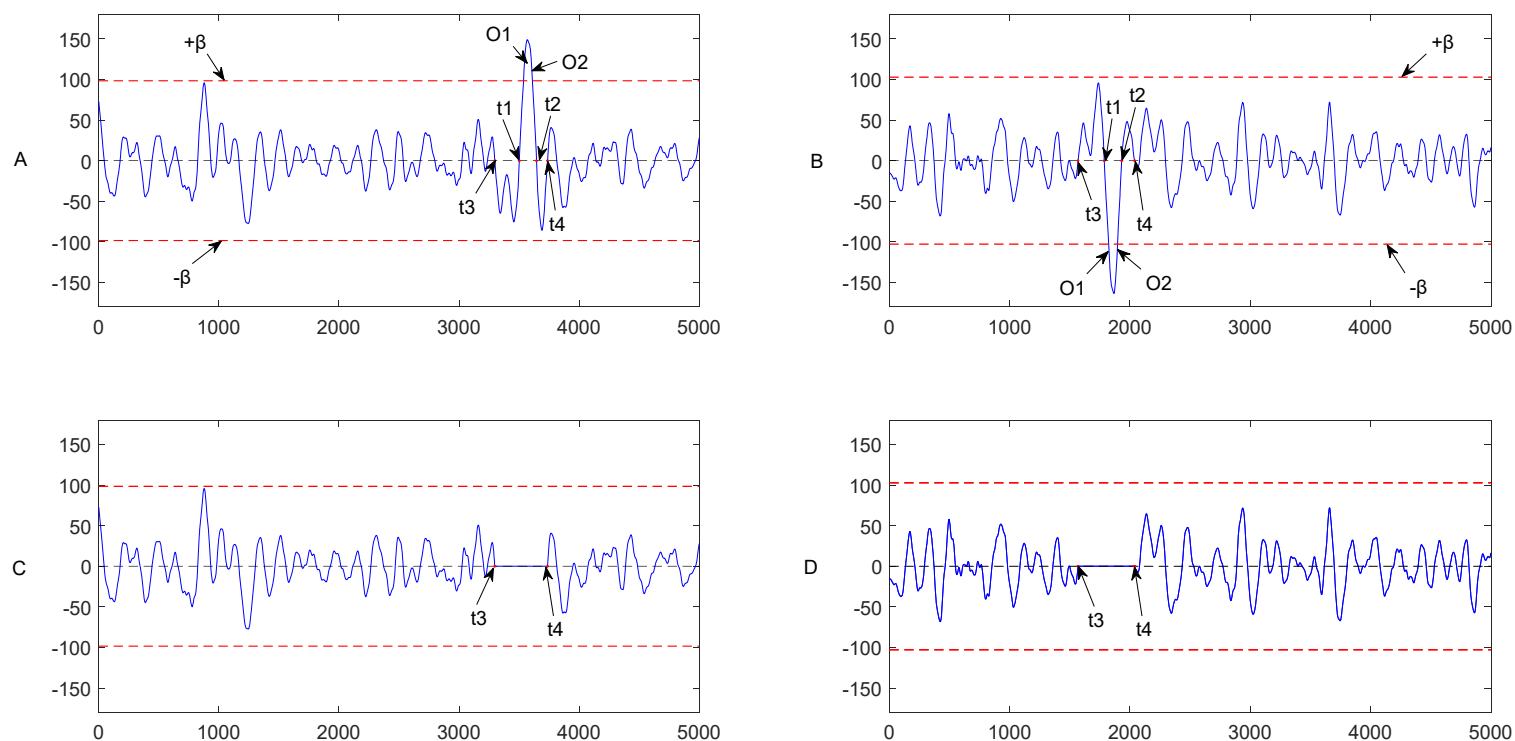


- 眼电波形特性，确定母小波，这里选择
- 根据采样率1000 Hz，眼电所在频率范围（1~14 Hz），小波分层数量
- 确定眼电所在层数：d6~d9

各层系数对应频率范围

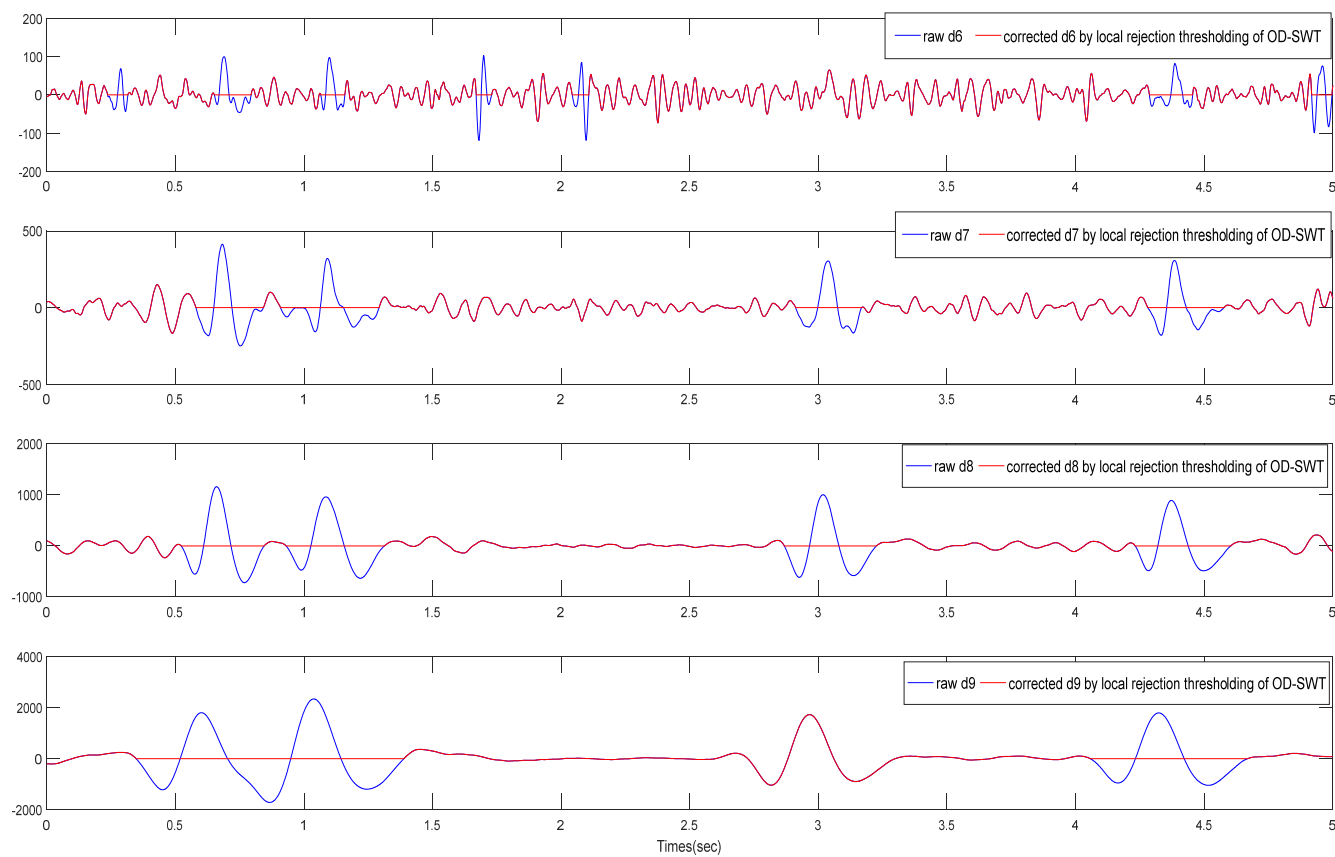
- 采样率1000 Hz
- The details coefficients
 - level 9: 0.975-1.95 Hz, level 8: 1.95-3.9 Hz, level 7: 3.9-7.8 Hz, level 6: 7.8-15.625 Hz, level 5: 15.625-31.25 Hz, level 4: 31.25-62.5 Hz, level 3: 62.5-125 Hz, level 2: 125-250 Hz, level 1: 250-500Hz
- The approximation coefficient
 - level 9: 0-0.975 Hz

阈值选择与非线性滤波 (Zhang et al.)

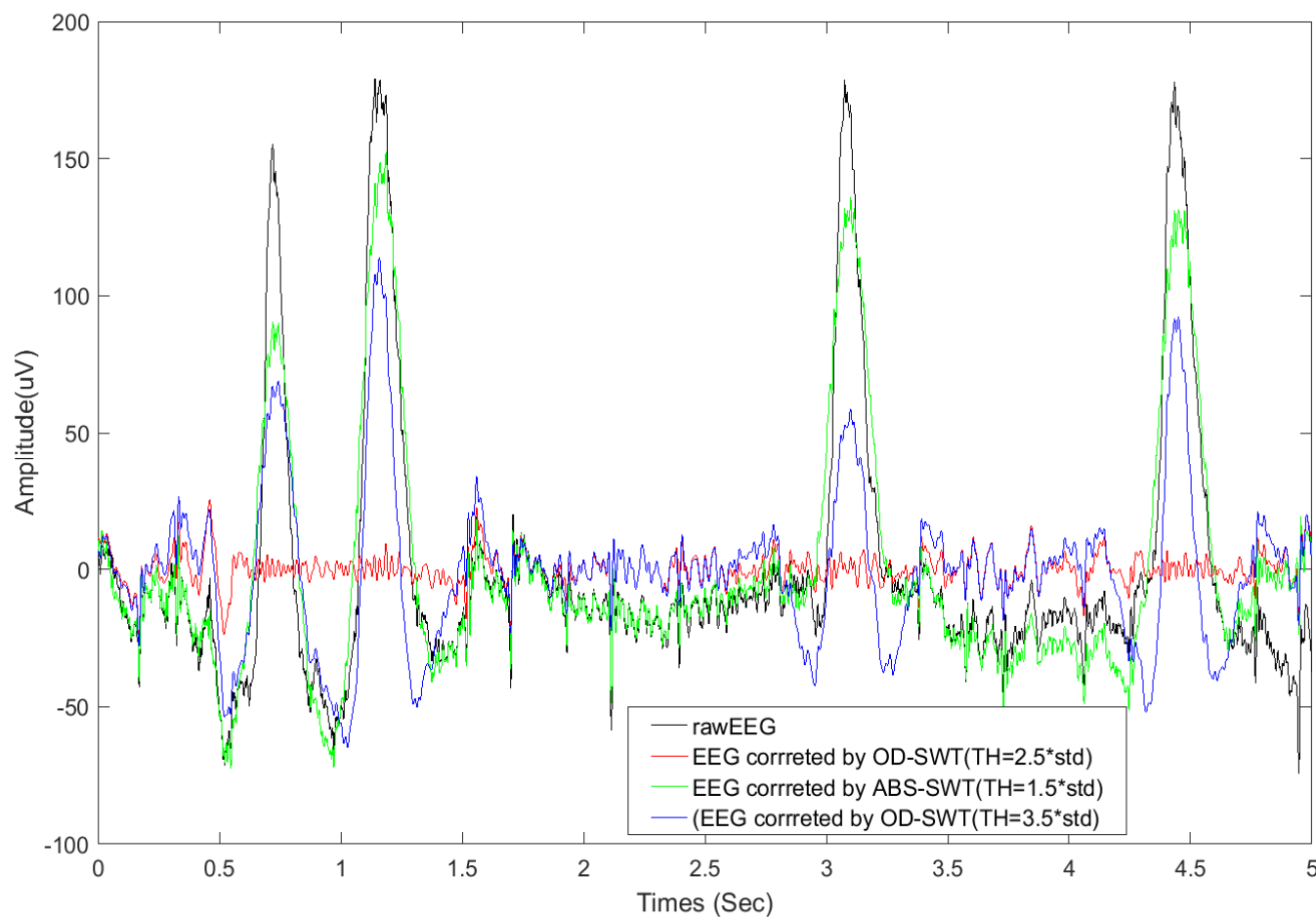


- 小波系数的非线性处理：超过阈值附近区域的小波系数置零

算法结果举例



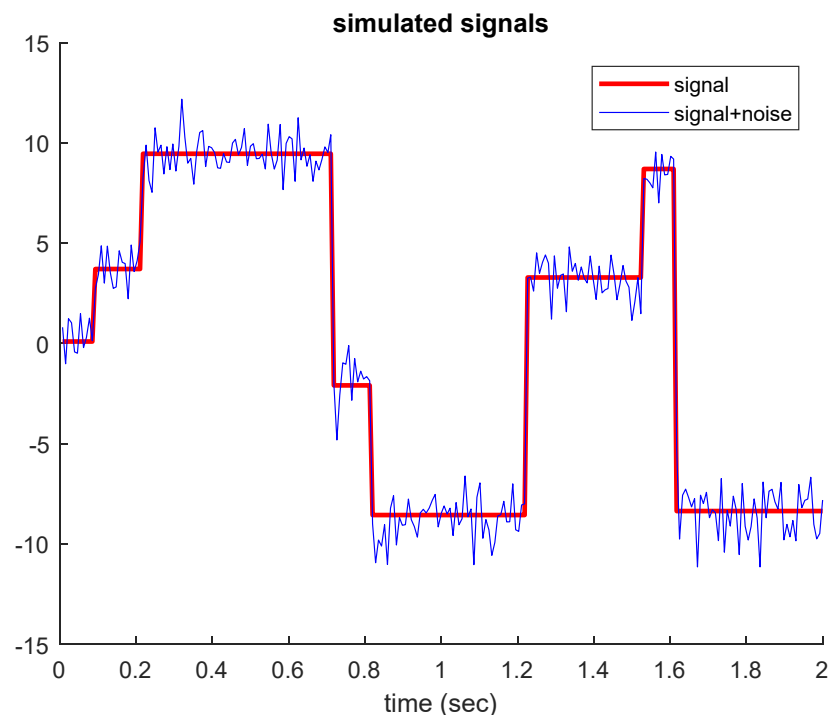
算法结果与参数选择的关系



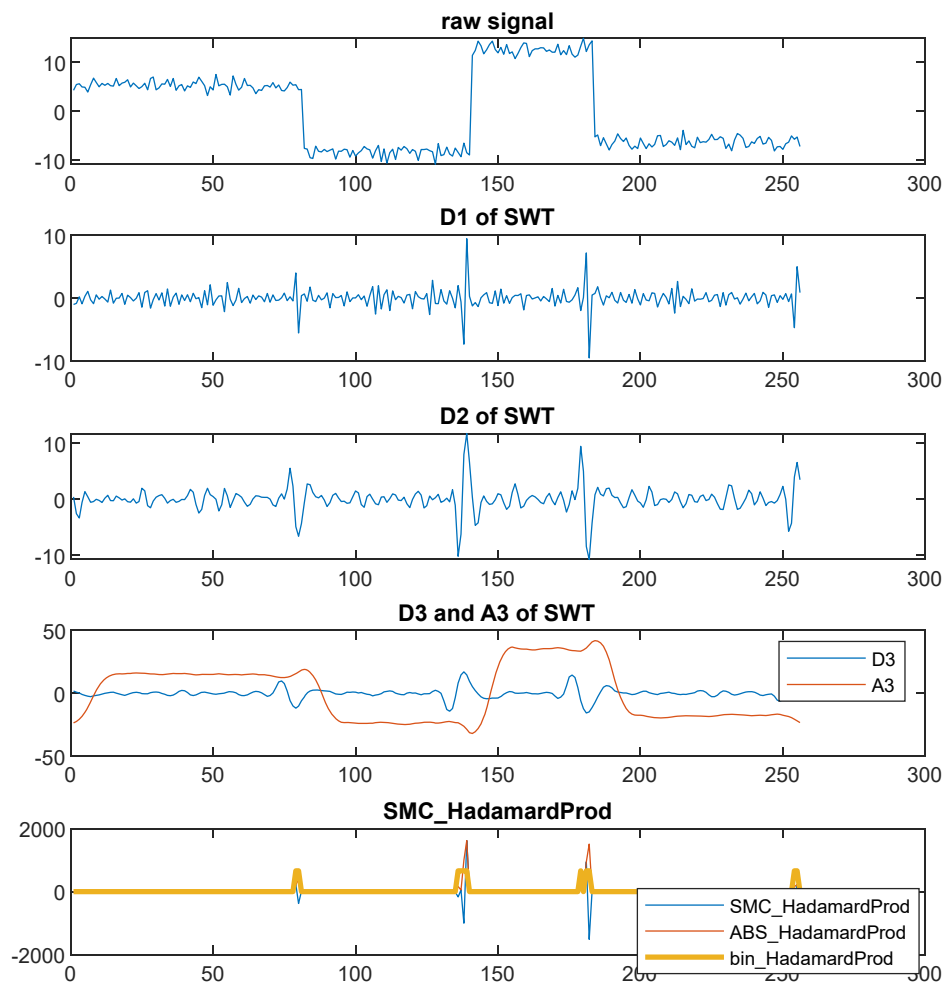
- 观察不同参数得到的结果
- 学习呈现结果的方法，便于比较

案例2：保留陡峭边缘的信号去噪

- Ex09swt_dwt.m中仿真方波的信号是需要提取的目标信号，而需要去除其它成分。实现该信号处理的方法与眼电去除算法的异同。



瞬态变化对应多尺度小波系数



保留瞬变边缘的方法

- `K = 3;`
- `SWC_K = swt(targetSig, K, 'db3');`
- `figure,`
- `ax(1) = subplot(K+2, 1, 1); plot(targetSig); title('raw signal');`
- `SMC_HadamardProd = ones(1, length(targetSig));`
- `for i=1:K`
 - `ax(1+i)=subplot(K+2, 1, 1+i); plot(SWC_K(i, :));`
 - `title(['D', num2str(i), ' of SWT']);`
 - `SMC_HadamardProd = SMC_HadamardProd.*SWC_K(i, :);`
- `end`
- `hold on; plot(SWC_K(K+1, :));`
- `title(['D', num2str(K), ' and ', 'A', num2str(K), ' of SWT']);`
- `legend(['D', num2str(K)], ['A', num2str(K)]);`
- `ax(K+2) = subplot(K+2, 1, K+2); plot(SMC_HadamardProd);`
- `title('SMC_HadamardProd', 'interpreter', 'none');`
- `xlim([0, dataLen]); linkaxes(ax, 'x');`

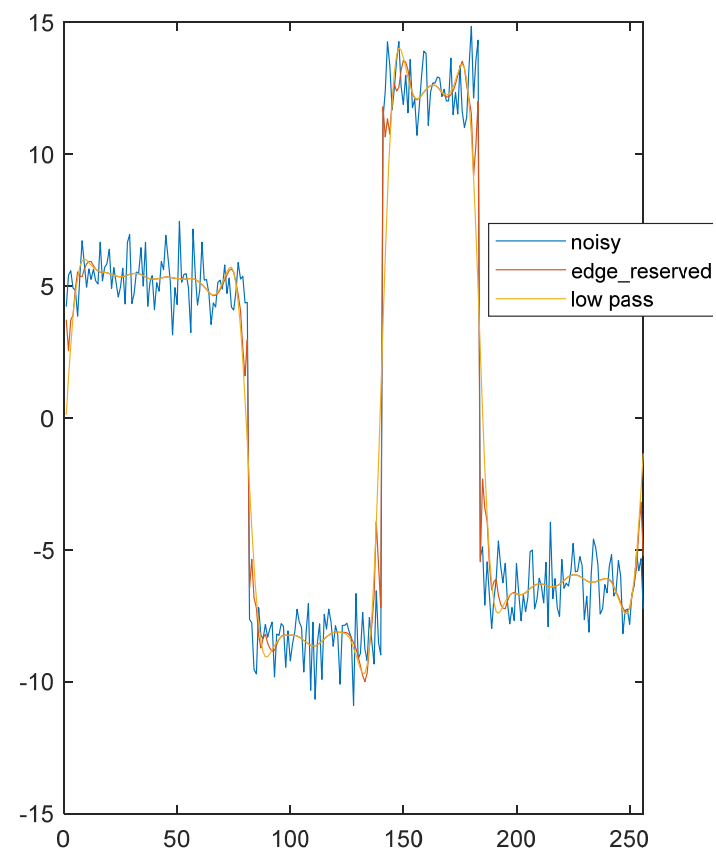
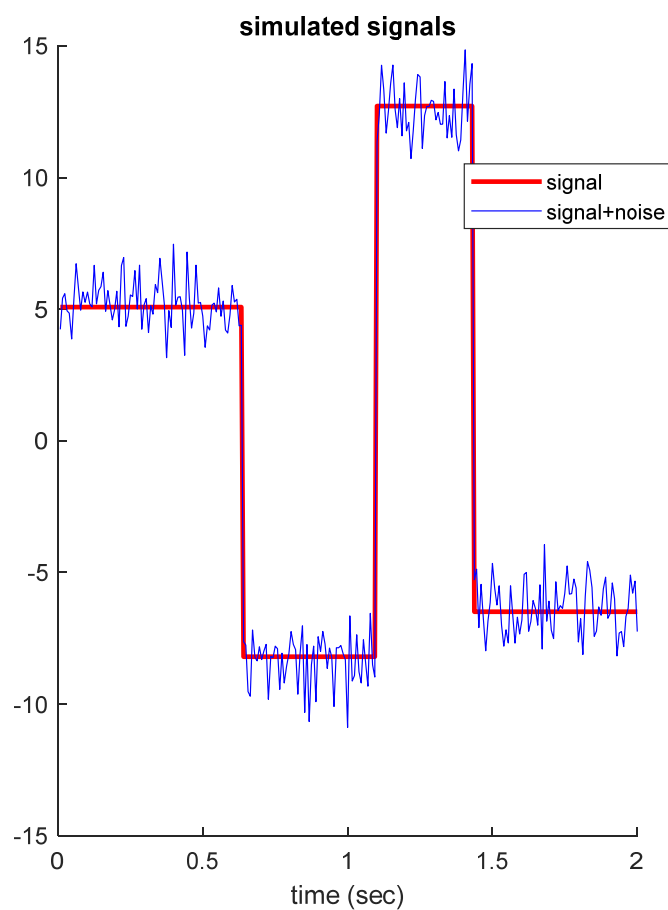
确定边缘所在的时间区间

- %%由二值化的bin_HadamardProd变量确定
-
- `ABS_HadamardProd = abs(SMC_HadamardProd);`
- `bin_HadamardProd = zeros(1, length(targetSig));`
- `idx = find(ABS_HadamardProd > 0.3 * std(ABS_HadamardProd));`
- `bin_HadamardProd(idx) = 1;`
- `hold on; plot(ABS_HadamardProd);`
- `hold on; plot(bin_HadamardProd * 4 * std(ABS_HadamardProd), 'linewidth', 2);`
- `legend('SMC_HadamardProd', 'ABS_HadamardProd', 'bin_HadamardProd', 'interpreter', 'none');`

保留边缘，去除高频噪声

- %% SMC processing
- SWC_proc = SWC_K;
- SWC_proc(1, :) = SWC_K(1, :).*bin_HadamardProd;
- SWC_proc(2, :) = SWC_K(2, :).*bin_HadamardProd;
- SWC_proc(3, :) = SWC_K(3, :).*bin_HadamardProd;
- sigProc = iswt(SWC_proc, 'db3');
- figure, plot(targetSig); hold on; plot(sigProc);
-
- %% in comparison to the all-zeros for hi-frequency noise
- SWC_proc2 = SWC_K;
- SWC_proc2(1, :) = 0;
- SWC_proc2(2, :) = 0;
- SWC_proc2(3, :) = 0;
- sigProc2 = iswt(SWC_proc2, 'db3');
- hold on; plot(sigProc2);
- legend('noisy', 'edge_reserved', 'low pass', 'interpreter', 'none');

保留边缘的高频噪声去除



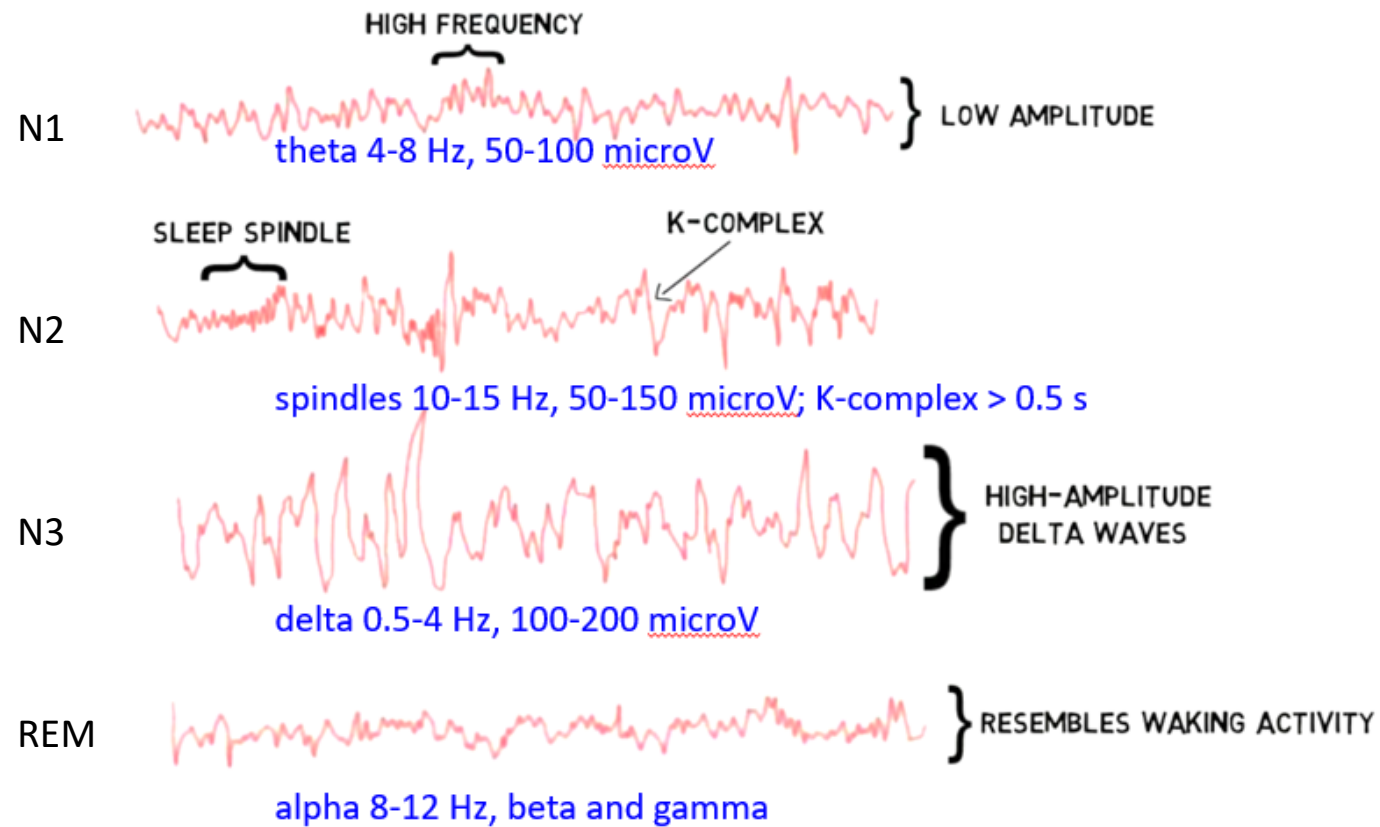
离散小波变换应用2

——基于SWT的时频特征提取

案例：睡眠脑电信号特征提取

- 睡眠脑电特征是睡眠分期的关键依据
- 随着睡眠阶段的变化，睡眠脑电具有非平稳特性
- 基于小波变换的时频特征提取，判断睡眠深度的变化

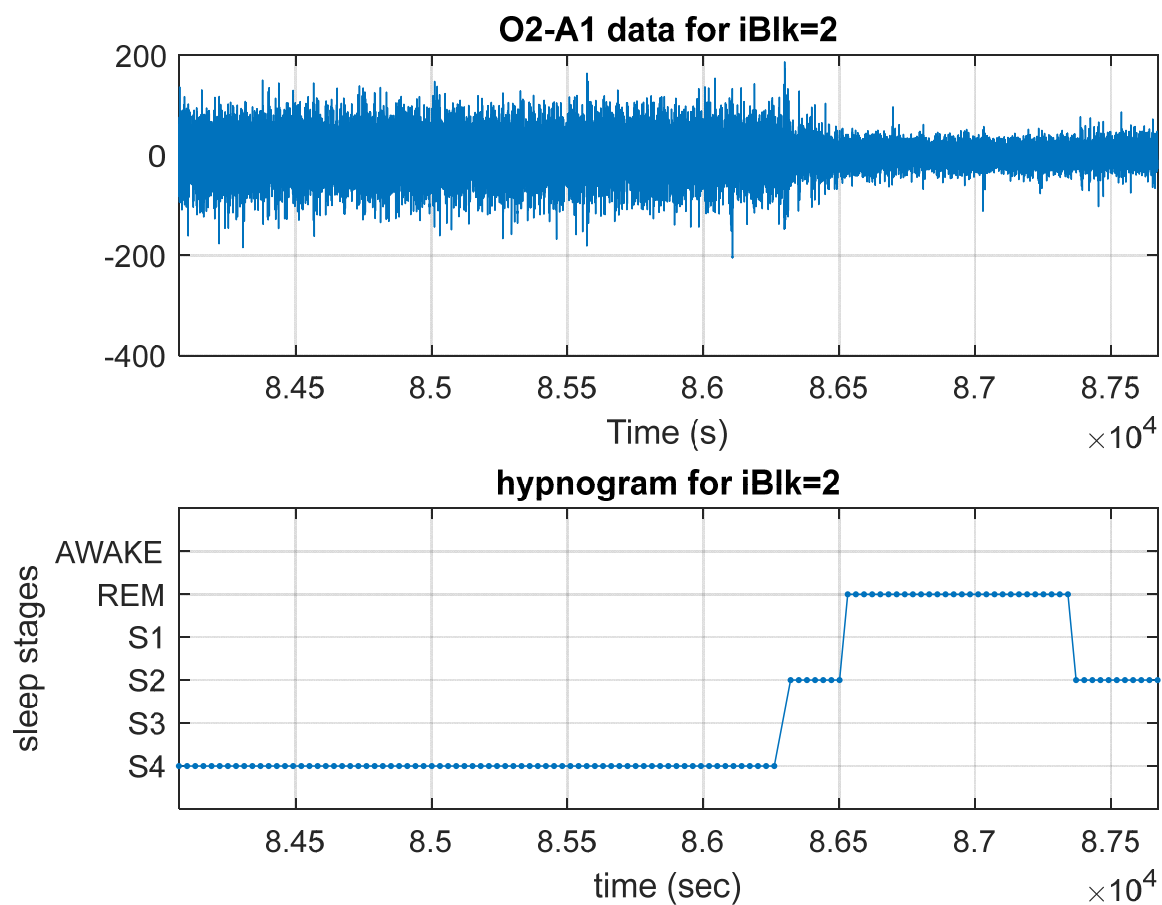
睡眠阶段与脑电特征



案例数据可视化

- `load('Ex9_n7_iBlk2_O1A2_hyp.mat');`
- `% sampRate = 128; % for n7 only confirmed`
- `% save('n7_iBlk2_O1A2_hyp.mat', 'tTick_PSG_iBlk', 'chData_iBlk', ...`
- `% 'tTick_hypnogram_iBlk', 'hypHeight_iBlk', 'sampRate');`
-
- `figure; % show the raw data`
- `subplot(2, 1, 1); plot(tTick_PSG_iBlk, chData_iBlk);`
- `xlabel('Time (s)'); title([chLabel, ' data for iBlk=', num2str(iBlk)]);`
- `xlim([tTick_PSG_iBlk(1), tTick_PSG_iBlk(end)]); grid on;`
-
- `subplot(2, 1, 2); plot(tTick_hypnogram_iBlk, hypHeight_iBlk, '-');`
- `yticks([1:6]); yticklabels({'S4', 'S3', 'S2', 'S1', 'REM', 'AWAKE'});`
- `xlabel('time (sec)'); ylabel('sleep stages'); grid on;`
- `xlim([tTick_hypnogram_iBlk(1) tTick_hypnogram_iBlk(end)]); ylim([0 7]);`
- `title(['hypnogram for iBlk=', num2str(iBlk)]);`

实例：受试者n7睡眠的第二个小时数据



平稳小波变换及可视化

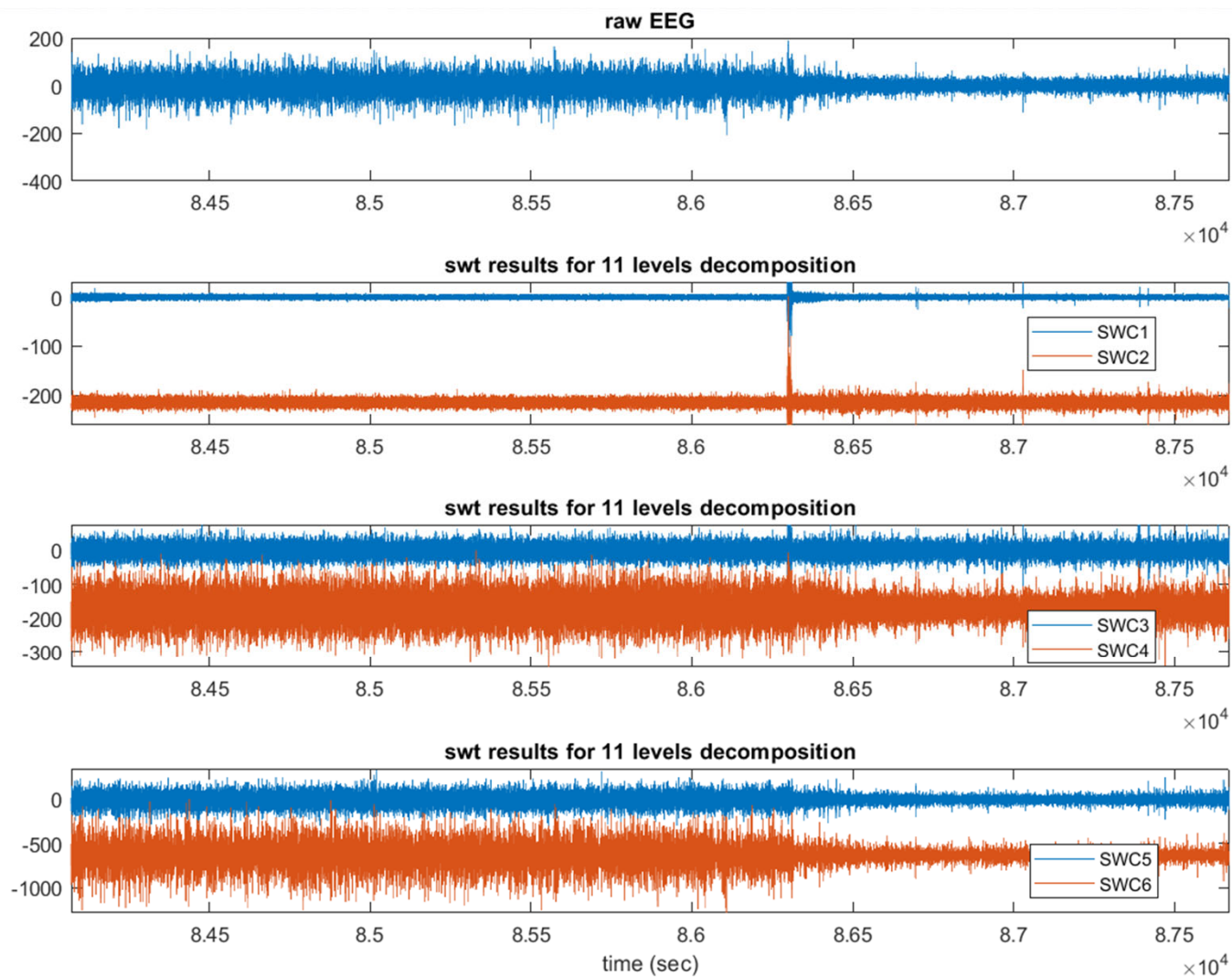
- `SWC = swt(chData_iBlk, 11, 'db3');` % 11级小波分解
- `figure; hold on; axID(1) = subplot(4, 1, 1); plot(tTick_PSG_iBlk, chData_iBlk);`
- `title('raw EEG');` % 原始数据
- `xlim([tTick_PSG_iBlk(1), tTick_PSG_iBlk(end)]);`
- %% 分解1-6层的小波系数, 分3子图展示
- `axID(2) = subplot(4, 1, 2); plot(tTick_PSG_iBlk, SWC(1, :));`
- `hold on; plot(tTick_PSG_iBlk, SWC(2, :)-max(SWC(2, :)));`
- `legend('SWC1', 'SWC2');` `title('swt results for 11 levels decomposition');`
- `xlim([tTick_PSG_iBlk(1), tTick_PSG_iBlk(end)]);`
- `axID(3) = subplot(4, 1, 3); plot(tTick_PSG_iBlk, SWC(3, :)); hold on; plot(tTick_PSG_iBlk, SWC(4, :)-max(SWC(4, :)));`
- `legend('SWC3', 'SWC4');` `title('swt results for 11 levels decomposition');`
- `xlim([tTick_PSG_iBlk(1), tTick_PSG_iBlk(end)]);`
- `axID(4) = subplot(4, 1, 4); plot(tTick_PSG_iBlk, SWC(5, :)); hold on; plot(tTick_PSG_iBlk, SWC(6, :)-max(SWC(6, :)));`
- `legend('SWC5', 'SWC6');` `title('swt results for 11 levels decomposition');`
- `linkaxes(axID, 'x');` `xlabel('time (sec)');`
- `xlim([tTick_PSG_iBlk(1), tTick_PSG_iBlk(end)]);`

平稳小波变换及可视化

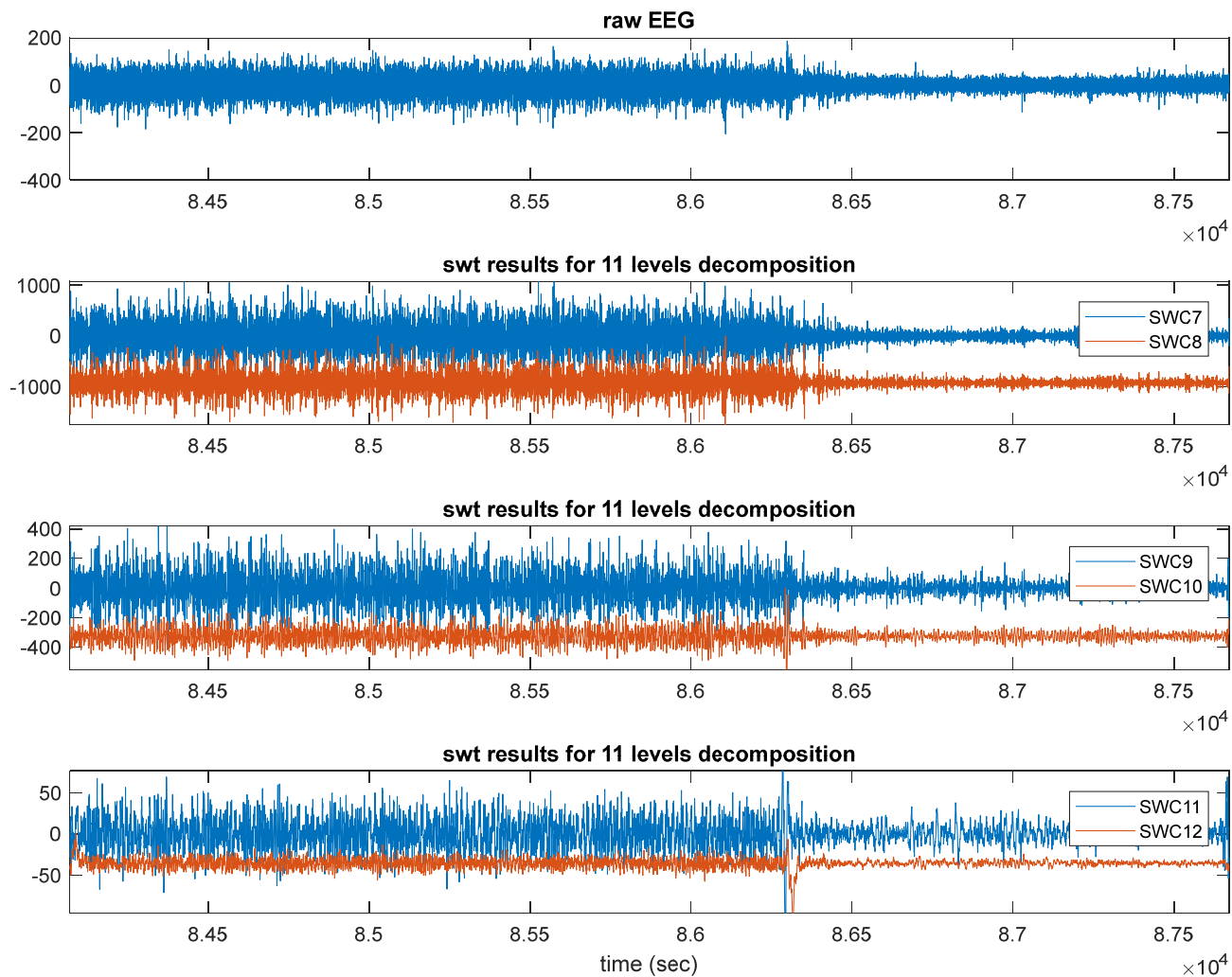
- figure;
- axID2(1) = subplot(4, 1, 1); plot(tTick_PSG_iBlk, chData_iBlk);
- title('raw EEG'); % 原始数据

- %% 分解7-11层的细节项小波系数和第11层近似项，分3子图展示
- axID2(2) = subplot(4, 1, 2); plot(tTick_PSG_iBlk, SWC(7, :)); hold on; plot(tTick_PSG_iBlk, SWC(8, :)-max(SWC(8, :)));
- legend('SWC7', 'SWC8'); title('swt results for 11 levels decomposition');
- axID2(3) = subplot(4, 1, 3); plot(tTick_PSG_iBlk, SWC(9, :)); hold on; plot(tTick_PSG_iBlk, SWC(10, :)-max(SWC(10, :)));
- legend('SWC9', 'SWC10'); title('swt results for 11 levels decomposition');
- axID2(4) = subplot(4, 1, 4); plot(tTick_PSG_iBlk, SWC(11, :));
- hold on; plot(tTick_PSG_iBlk, SWC(12, :)-max(SWC(12, :)));
- legend('SWC11', 'SWC12'); title('swt results for 11 levels decomposition');
- % axID2(4) = subplot(4, 1, 4); plot(tTick_PSG_iBlk, SWC(13, :));
- % hold on; plot(tTick_PSG_iBlk, SWC(13, :)-max(SWC(13, :)));
- % legend('SWC13', 'SWC14');
- linkaxes(axID2, 'x'); xlabel('time (sec)'); xlim([tTick_PSG_iBlk(1), tTick_PSG_iBlk(end)]);

原始数据与1-6层分解



原始数据与7-12层分解



小波系数幅度特征分析

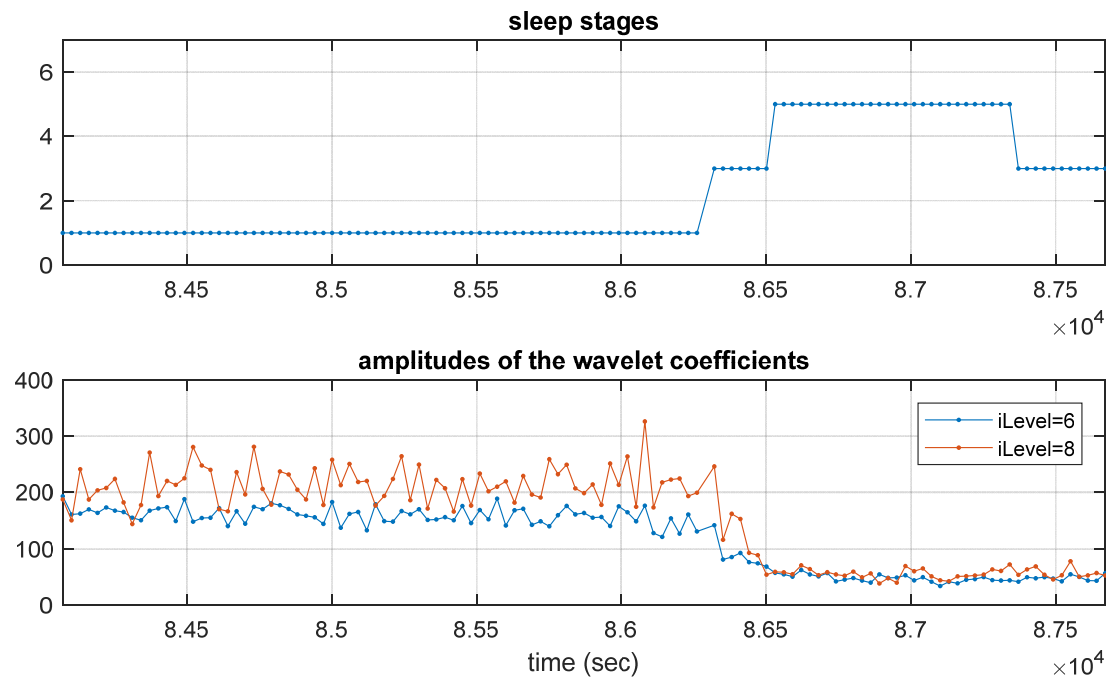
- %% extract the amplitude features % using the std of every 30 seconds of data
- seg30Len = 30*sampRate; % 确定窗口长度对应的数据点数
- iLevel1 = 6; coefLk = SWC(iLevel1, :); nSegs = dataLen/seg30Len;
- for iSeg = 1:nSegs
- ampLk(iSeg) = std(coefLk((iSeg-1)*seg30Len+1 : iSeg*seg30Len));
- end
- figure; axID(1) = subplot(2, 1, 1); plot(tTick_hypnogram_iBlk, hypHeight_iBlk, '.-');
- ylim([0 7]); title('sleep stages'); grid on;
- axID(2) = subplot(2, 1, 2); plot(tTick_hypnogram_iBlk, ampLk, '.-');
-

小波系数幅度特征分析

- `iLevel2 = 8; coefLk = SWC(iLevel2, :);`
- `nSegs = dataLen/seg30Len;`
- `for iSeg = 1:nSegs`
- `ampLk(iSeg) = std(coefLk((iSeg-1)*seg30Len+1 : iSeg*seg30Len));`
- `end`
- `hold on; plot(tTick_hypnogram_iBlk, ampLk, '.-');`
- `title(['amplitudes of the wavelet coefficients']); legend(['iLevel=', num2str(iLevel1)], ['iLevel=', num2str(iLevel2)]);`
- `linkaxes(axID, 'x'); grid on; xlabel('time (sec)'); xlim([tTick_PSG_iBlk(1), tTick_PSG_iBlk(end)]);`

统计特征分析

- 小波系数的幅度、相位、复杂度（熵）等特征
- 小波系数的幅度特性为例
 - 按照AASM的标准：每30秒时间窗内数据的标准差（点数为 $F_s * 30 = 128 * 30$ ）；比较不同睡眠阶段的系数幅度特征



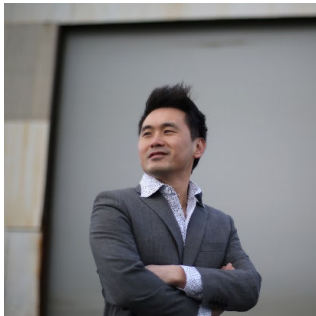
小结

- 连续小波变换
 - 最常用的Morlet小波，中心频率，窗口长度-波数
- 离散小波变换的应用要点
 - 根据采样率和待消除噪声的频率特性，确定小波，确定分解的层数和噪声对应的小波系数
- 基于swt的噪声消除算法
 - 两类案例：脑电中的偶发性眼电信号去除；保留瞬变边界的高频噪声去除
- 基于swt的医学信号时频特征提取
 - 信号的小波分解 → 小波系数的统计特征
 - 以不同睡眠阶段的脑电信号的不同小波系数的幅值特征为例

丙泊酚麻醉过程的脑电特性动态变化 (Purdon et al., 2013)

丙泊酚麻醉过程的脑电

- Purdon PL, ..., Brown EN. **Electroencephalogram signatures of loss and recovery of consciousness from propofol.** Proc Natl Acad Sci U S A. 2013 Mar 19;110(12):E1142-51.



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Degrees

PhD, Statistics, Harvard University, 1988

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AM, Statistics, Harvard University, 1984

Abstract

- Unconsciousness is a fundamental component of general anesthesia (GA), but anesthesiologists have **no reliable ways to be certain that a patient is unconscious**. **To develop EEG signatures** that track loss and recovery of consciousness under GA, we recorded high-density EEGs in humans during gradual induction of and emergence from unconsciousness with propofol. The subjects executed an auditory task at 4-s intervals consisting of interleaved verbal and click stimuli to identify loss and recovery of consciousness. During induction, subjects lost responsiveness to the less salient clicks before losing responsiveness to the more salient verbal stimuli; during emergence they recovered responsiveness to the verbal stimuli before recovering responsiveness to the clicks. The median frequency and bandwidth of the frontal EEG power tracked the probability of response to the verbal stimuli during the transitions in consciousness. Loss of consciousness was marked simultaneously by an increase in low-frequency EEG power (<1 Hz), the loss of spatially coherent occipital alpha oscillations (8–12 Hz), and the appearance of spatially coherent frontal alpha oscillations. These dynamics reversed with recovery of consciousness. The low-frequency phase modulated alpha amplitude in two distinct patterns. During profound unconsciousness, alpha amplitudes were maximal at low-frequency peaks, whereas during the transition into and out of unconsciousness, alpha amplitudes were maximal at low-frequency nadirs. This latter phase–amplitude relationship predicted recovery of consciousness. Our results provide insights into the mechanisms of propofol-induced unconsciousness, establish EEG signatures of this brain state that track transitions in consciousness precisely, and suggest strategies for monitoring the brain activity of patients receiving GA.

提出问题、解决问题、创造价值

提出问题， 设定研究目标

- 现存问题： Unconsciousness is a fundamental component of general anesthesia (GA), but anesthesiologists have **no reliable ways to be certain that a patient is unconscious.**
- 研究目标： **To develop EEG signatures** that track loss and recovery of consciousness under GA

解决问题的方法

- we recorded high-density EEGs in humans during gradual induction of and emergence from unconsciousness with propofol
- The subjects executed an auditory task at 4-s intervals consisting of interleaved verbal and click stimuli to identify loss and recovery of consciousness.

为什么这两个方面的观察——逻辑？

- 麻醉深度-意识
- 意识-行为
- 行为-脑电活动

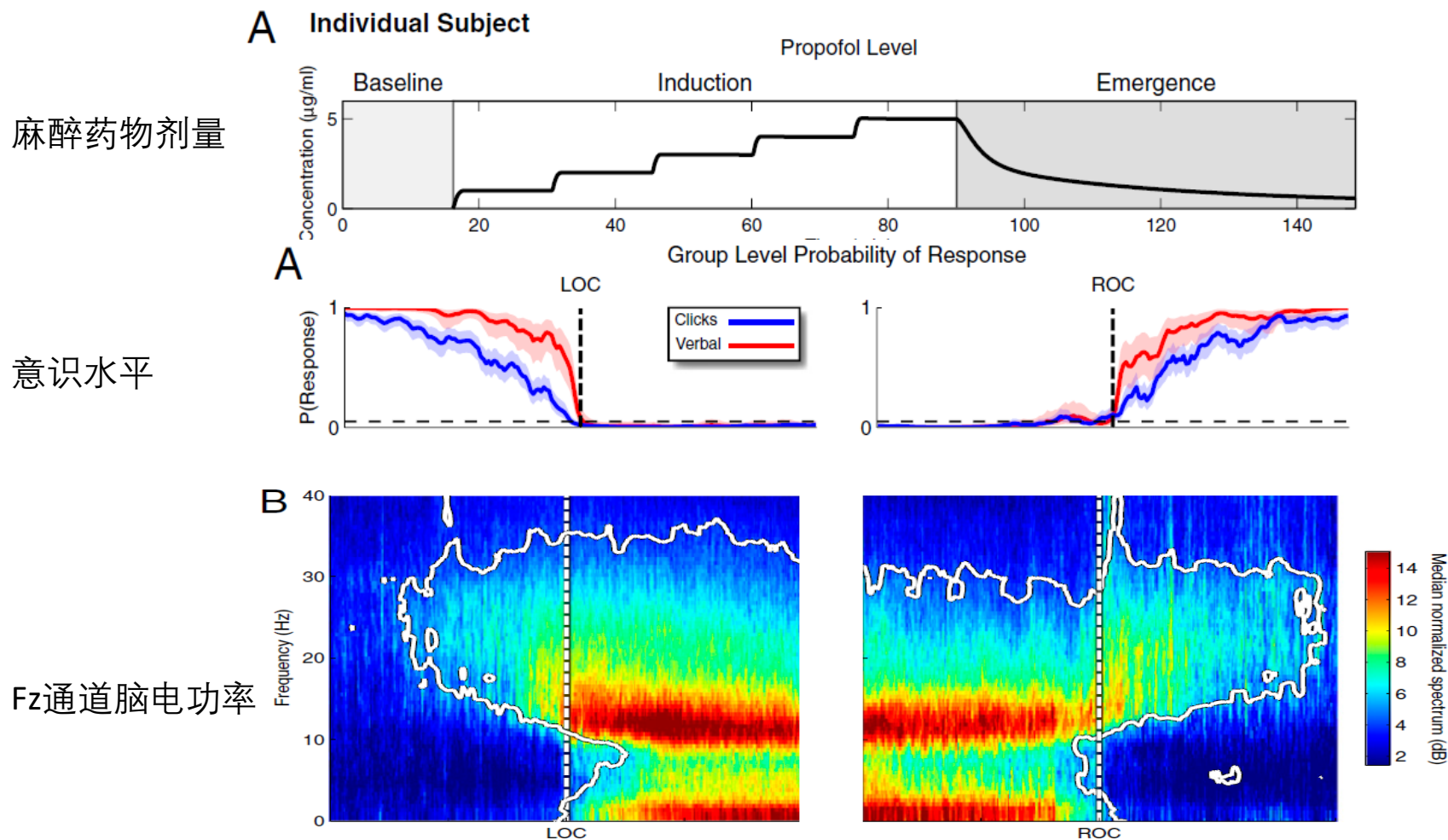


麻醉深度和脑电

结果

- During induction, subjects lost responsiveness to the less salient clicks before losing responsiveness to the more salient verbal stimuli; during emergence they recovered responsiveness to the verbal stimuli before recovering responsiveness to the clicks.
- The median frequency and bandwidth of the frontal EEG power tracked the probability of response to the verbal stimuli during the transitions in consciousness.
- Loss of consciousness was marked simultaneously by an increase in low-frequency EEG power (<1 Hz), the loss of spatially coherent occipital alpha oscillations (8–12 Hz), and the appearance of spatially coherent frontal alpha oscillations. These dynamics reversed with recovery of consciousness.
- The low-frequency phase modulated alpha amplitude in two distinct patterns. During profound unconsciousness, alpha amplitudes were maximal at low-frequency peaks, whereas during the transition into and out of unconsciousness, alpha amplitudes were maximal at low-frequency nadirs. This latter phase–amplitude relationship predicted recovery of consciousness.

主要结果



研究技术

- 实验设计
- 脑电信号记录，行为信号记录
- 脑电功率谱估计与特征提取：中位数频率，带宽
- 脑电的分量提取：1 Hz以下的低频成分，8-12 Hz的alpha波
- 脑电特征与行为的关系：脑电特征与麻醉深度

价值创造

- Our results provide insights into the mechanisms of propofol-induced unconsciousness, establish EEG signatures of this brain state that track transitions in consciousness precisely, and suggest strategies for monitoring the brain activity of patients receiving GA.

更具体内容——阅读原文

标题和作者及单位信息

Electroencephalogram signatures of loss and recovery of consciousness from propofol

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Contributed by Nancy J. Kopell, January 3, 2013 (sent for review September 22, 2012)

课程小结

关于课程目标的设想

- 构建智能医学仪器学科知识体系的一个关键模块
 - 生物医学信号（采集、处理、分析、解释、决策、控制）
- 科研思维和方法的启蒙
 - 科学问题的提出 → 科学假设的建立 → 实验设计与数据搜集 → 数据/信号处理与分析 → 分析结果的理解 → 基于证据的结论
- 为下学期医学信号处理实验课程项目做好理论准备
 - 下学期的课程将完成一个小型研究项目

结束语

- 祝大家期末考试取得理想的成绩
- 学无止境，终生学习
- 保持好奇心，保持责任感，以生物医学信号处理与分析为技术基础，探索生命的规律，为临床应用提供理论和技术支持