Multiplexing and transient estimates in lung EIT instruments

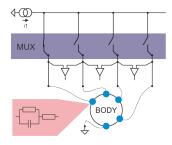
M. G. Crabb, P. Green, W. R. B. Lionheart, P. Wright

School of Mathematics, University of Manchester, UK
michael.crabb@manchester.ac.uk

June 23, 2016

Multiplexing in EIT instruments I

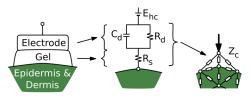
 Multiplexing is inherent to EIT. During current change, voltage amplitudes change and a transient can appear.



- Traditional approach is to settle to steady state. To achieve high frame rates, settling time after multiplexing is significant.
- Transient may not only take up significant amount of signal power, but also contain useful information about electrodes.

Contact impedance modelling I

 Model electrode as lumped capacitance (dead skin layer) C, in parallel with lumped resistance (ionic gel) R i.e. a parallel RC circuit [1, 2].



- 64 electrode system, f > 10 kHz injection and 30 fps, implies < 0.5 ms measurement time (5 full cycles per measurement).
- Typically $\tau \approx$ 0.1-0.2 ms, and significant amount of useful energy is lost.

Contact impedance modelling II



- In practice, contact may have several characteristic time constants, inductive effects, or imperfect capacitors $(Z(w) = \frac{1}{iC(\omega)^{\beta}}, 0 < \beta < 1)$, which will not have single exponential behaviours.
- Explore fitting exponential and polynomial transient models

$$U_{\mathbf{A}}^{\mathsf{EXP}}(t) = A_1 \cos(\omega t) + A_2 \exp(-\frac{t}{A_3}) \tag{1}$$

$$U_{\mathbf{A}}^{\mathsf{POLY}}(t) = A_1 \cos(\omega t) + \sum_{i=2}^{N} A_i t^i. \tag{2}$$

Simulating transients with Fourier series

• Assuming linear constitutive relations $D = \epsilon E$, $J = \sigma E$, and negligible magnetic induction. Maxwell's equations:

$$\nabla \cdot (\epsilon \frac{\partial E}{\partial t} + \sigma E) = 0, \qquad E = \nabla u \text{ for some } u.$$

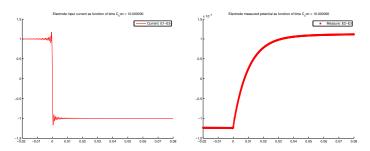
Let
$$u(x,t) = \sum_{\omega} u(x,\omega) e^{i\omega t}$$
,
$$\nabla \cdot ((\sigma + i\omega \epsilon) \nabla u(x,\omega)) = 0, \quad \text{for each} \quad \omega$$
 (3)

- Generalise CEM with frequency dependent impedance e.g. $\frac{1}{z(w)} = \frac{1}{R} + i(\omega)^{\beta} C$, $\beta \ge 0$.
- Given current $I(t): [-T, T] \to \mathbb{R}$, decompose using Fourier series into modes $\tilde{I}(w)$, solve (static) (3) with $\tilde{I}(\omega)$, and sum resulting $u(x,\omega)$ weighted by $e^{i\omega t}$

Square wave current simulation

• Conductive $(\sigma=1)/{
m permittive}$ $(\epsilon=0.01)$ medium and current

$$I(t) = egin{cases} 1 & t \leq 0 \\ -1 & t > 0. \end{cases}$$



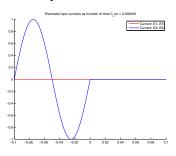
• Current discontinuity at t = 0 generates exponential decay in typical measured voltage, due to permittivity.

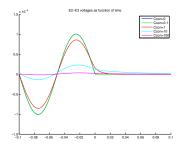
Sinusoidal current simulation I

ullet Conductive $(\sigma=1)/{
m permittive}$ $(\epsilon=0.01)$ medium and current

$$I(t) = egin{cases} \sin(10\pi t/T) & t \leq 0 \ 0 & t > 0. \end{cases}$$

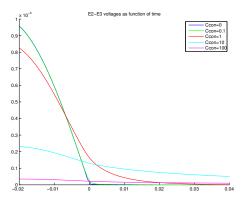
• Left/Right represents input current/measurement at t=0. Note decay of measurement at t=0.





Sinusoidal current simulation II

• Smooth current transition at t=0, hence decay of measured voltages is due to non-zero electrode capacitance.



• Smaller capacitances have higher amplitude and faster decay, since $\tau \approx \textit{CR}$ (approximate since effective τ will depend on bulk medium permittivity/conductivity.)

Signal Processing and data reduction

- Denote U(t) be raw voltage data, sampled uniformly (2 MHz), and passed through 16-bit ADC.
- \approx 3200 bits per cycle(0.1ms). 64 electrodes implies \approx 2 Gbits/s data rate.
- Instead, typically compress data at FPGA e.g. at ith-cycle

$$\begin{split} I_{i} &= \sum_{n=iT}^{(i+1)T} V(t_{n}) \sin(\omega t_{n}), \qquad Q_{i} &= \sum_{n=iT}^{(i+1)T} V(t_{n}) \cos(\omega t_{n}), \\ D_{i} &= \sum_{n=iT}^{(i+1)T} V(t_{n}), \qquad \qquad SS_{i} &= \sum_{n=iT}^{(i+1)T} V(t_{n})^{2}. \end{split}$$

where $T = \frac{2\pi}{\omega}$. Assume saturation flag for each cycle.

• \approx 22 bytes = 176 bits per cycle (0.1ms). 64 electrodes implies \approx 0.1 Gbits/s data rate (50 times data reduction.)

Amplitude estimation - Full data course I

- Classical approach and FFT: Reduce gain on current driven electrode just after measurement, and wait for a number of cycles until transient has effectively disappeared.
- Exponential/Polynomial model: Denote M = EXP or POLY from in (2). Objective is to determine parameter $\{A_i\}_{i=1}^N$ and formulate as (non-linear) optimisation problem [3]

$$\mathbf{A} = \arg\min_{\mathbf{A}'} \sum_{i=1}^N (U(t_i) - U_{\mathbf{A}}^{\mathbf{M}}(t_i))^2$$

 MATLAB function lsqnonlin.m is used to solve this (and subsequent) optimisation problems.

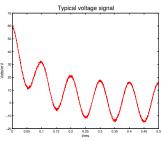
Simulated transient signal

Without loss of generality consider phase-corrected signal

$$V(t) = A\cos(\omega t) + f(t) + n(t),$$

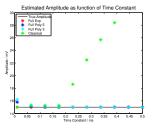
where n(t) is white Gaussian noise and f(t) is transient (assumed here to be $B \exp(-t/C)$).

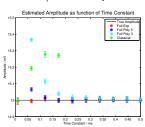
• Simulation parameters: Frequency f=10 kHZ, 5 full cycles (0.5ms measurement time), 2 MHz sampling rate, with 16-bit ADC. Initial/final amplitude 60/15 mV and noise variance $\sigma^2=0.5$ mV.



Full data results - Sinusoidal amplitude estimation

- Sinusoidal amplitude estimation as a function of $\tau \in [0, 0.5]$ over 20 noise realisations.
- Red/Blue/Magenta/Green Exponential/3rd order polynomial/ 5th order polynomial models/FFT respectively.

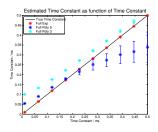




- FFT gives poor estimates for $\tau > 0.05$. Exponential model estimates very well, and polynomial model estimates well for $\tau > 0.1$.
- Amplitude estimates at $\tau = 0.2278s$:
 - Exponential 15.001 ± 0.013 mV. 5^{th} order polynomial 14.997 ± 0.014 mV. FFT 18.637 ± 0.015 mV.

Full data results - Time constant estimation

• Time constant estimation as a function of $\tau \in [0, 0.5]$.



- Time constants also estimated very well with exponential model. 3^{rd} and 5^{th} order polynomial estimates time constants better for $\tau > 0.3$ and $\tau < 0.3$ respectively.
- Time constant estimates at $\tau = 0.2278s$:
 - Exponential 0.2272 ± 0.0002 ms. 5^{th} order 0.2144 ± 0.0156 ms.

Data reduction optimisation

- What information can be obtained given I, Q, S, D values (and saturation flags) from FPGA?
- Assume transient is purely exponential, integrating exponential model (2) analytically over ith cycle gives

$$D(\mathbf{A})_{i} = -\frac{A_{2}}{A_{3}} \left(\exp\left(-\frac{T(i+1)}{A_{3}}\right) - \exp\left(-\frac{Ti}{A_{3}}\right) \right)$$

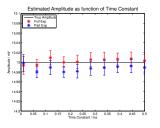
$$I(\mathbf{A})_{i} = A_{2}A_{3} \exp\left(-\frac{iT}{C}\right) \left(1 - \exp\left(-\frac{T}{A_{3}}\right)\right) / \left((1/A_{3})^{2} + \omega^{2}\right) + A_{1}T/2$$

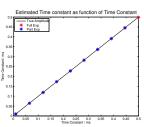
- Equivalent integrals computable for n^{th} order polynomial model. However, n extra integrals $Vt_i^n := \int_{\text{cycle}i} V(t)t^n dt$ must be computed at FPGA, which will require, \approx 48 bits per cycle per moment (\approx 30 Mbits/s).
- Let $M(\mathbf{A})_i = [D(\mathbf{A})_i, I(\mathbf{A})_i]$, and $M_i = [D_i, I_i]$ be measured data and s first cycle without saturation, then

$$\mathbf{A} = \arg\min_{\mathbf{A}'} \sum_{i=s} (M(\mathbf{A}')_i - M_i))^2$$

Partial data results - Amplitude estimation

- Left/Right represent amplitude/time constant estimation for exponential model over 20 noise realisations.
- Red/Blue represent Full/Partial data respectively.





- For exponential model partial data results are only marginally worse than full data results.
- Amplitude estimate for $\tau = 0.2278s$:
 - \bullet Full 15.001 \pm 0.013mV. Partial 14.982 \pm 0.018mV.
- Time constant estimate for $\tau = 0.2278s$:
 - \bullet Full 0.2272 \pm 0.0002ms. Partial 0.2277 \pm 0.0002ms.

Conclusions and Future Work

Conclusions

- Transient behaviour is significant when attempting high frame rates at kHZ frequencies.
- Given full time samples of voltage data, one can extract both sinusoidal amplitude and information of exponential transient, both with an exponential and polynomial model.
- Typically small set of data (e.g. I, Q, S, D) are computed per clock cycle, and sinusoidal amplitude can be extracted almost as well with this ≈ 50 times smaller data set.

Further Work

- Improved models of electrode-skin interfaces e.g. Jossinet et al. [2] to improve model fits.
- Algorithm presented here is inherently offline. Can fitting be performed on FPGA to extract sinusoidal component?

References I





Karjalainen M, Antsalo P, Mäkivirta A, Peltonen T, Välimäki V 2002, Estimation of Model Decay Parameters from Noisy Response Measurements *J. Audio End. Soc.* **50**(11) pp. 867-878