Time-Varying Delay Estimation using Common Local All-Pass Filters with Application to Surface Electromyography

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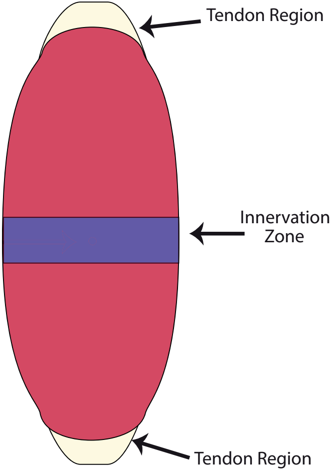
Outline

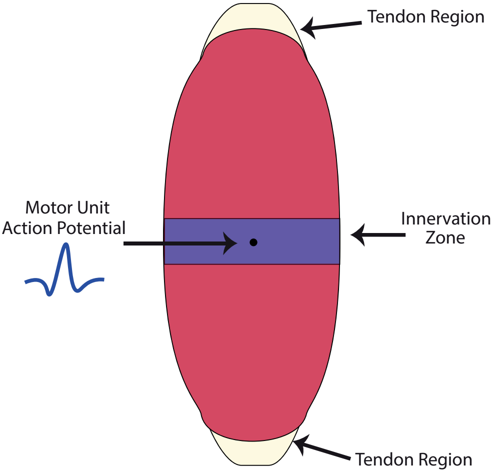
1. Introduction
   - Conduction velocity in surface electromyography (sEMG)
   - Equivalent to Time-Varying Delay Estimation
2. Estimating a Delay using All-Pass Filters
   - Shifting by a constant delay $\Longrightarrow$ All-pass filtering
   - Time-varying delay obtained from Local All-Pass (LAP) filters
   - Estimate delay common to a group of signals $\Rightarrow$ Common LAP
3. Evaluation Results
   - Synthetic sEMG data
   - Experimental data $\Longrightarrow$ High density sEMG recordings
4. Conclusions

Conduction Velocity



Describes the speed of propagation of motor unit action potentials (MUAPs) along the muscle

Conduction Velocity



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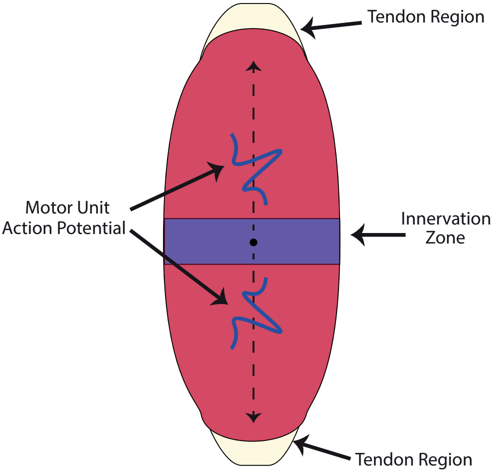

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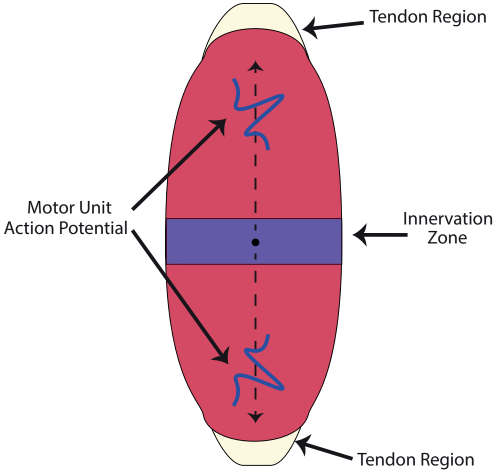

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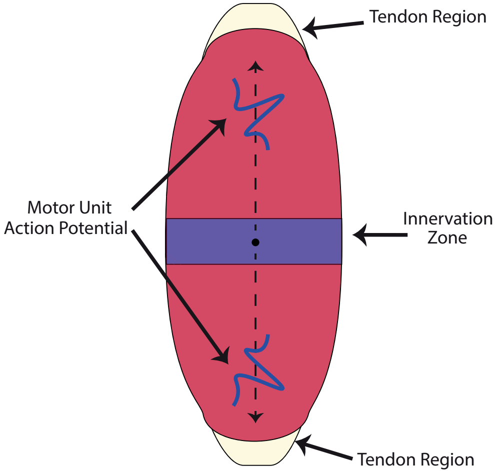
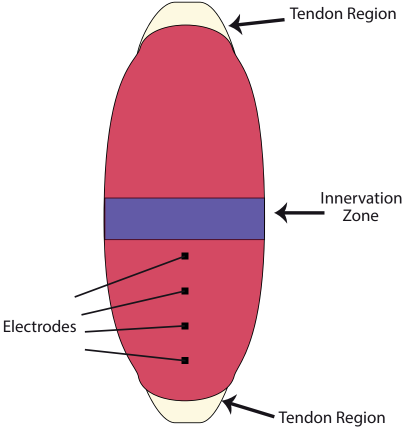


↬ Important factor in the study of muscle pathology, fatigue or pain

Estimating Conduction Velocity from sEMG

Estimate conduction velocity $\Longrightarrow$ Delay estimation



- Using high-density electrode arrays:
  - Measure the propagation of the signal

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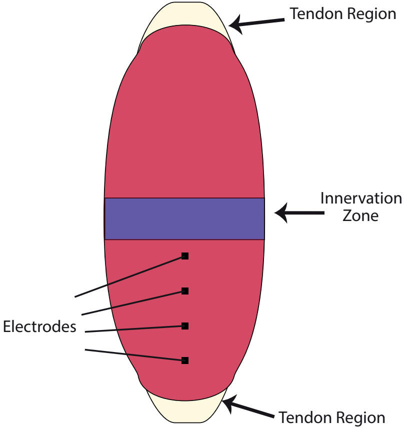

- Using high-density electrode arrays:
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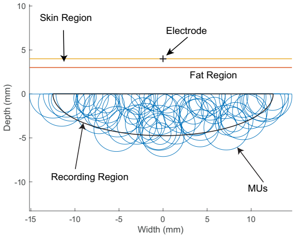
- Difficulties:
  - sEMG contains many MUAPs



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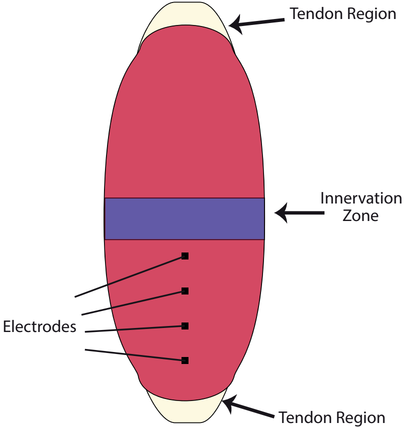
Estimate conduction velocity $\implies$ Delay estimation



- Using high-density electrode arrays:
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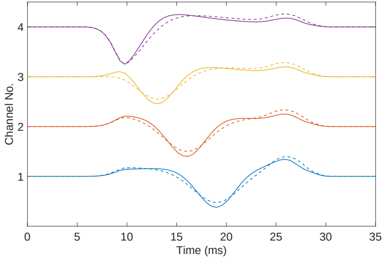
- Difficulties:
  - Non-constant MUAP shape



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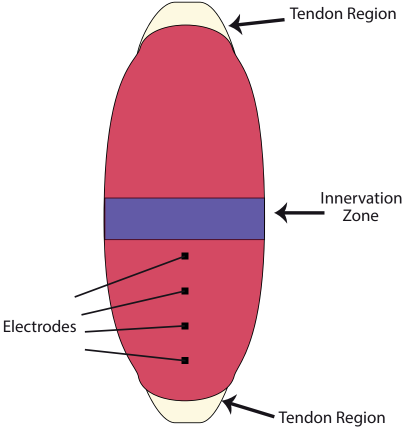

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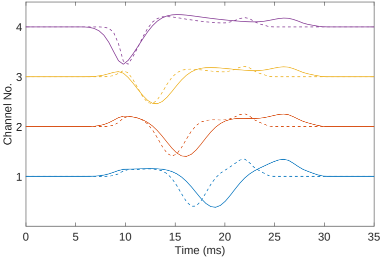

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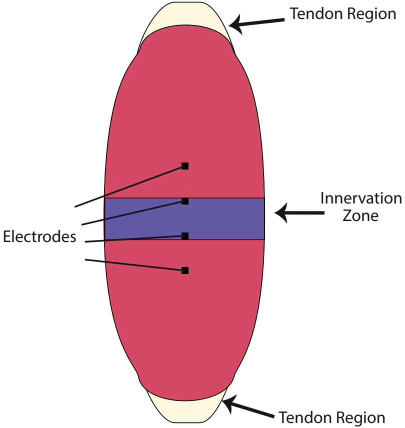

- Using high-density electrode arrays:
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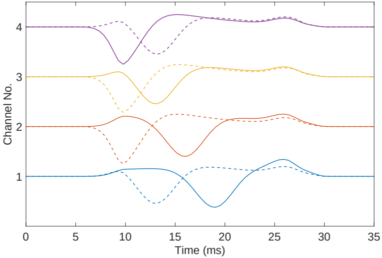
- Difficulties:
  - Array placement



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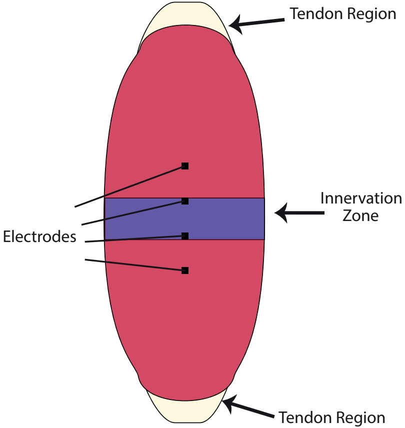

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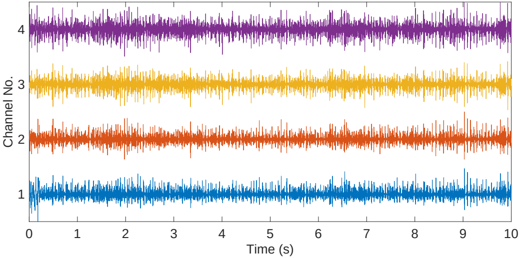

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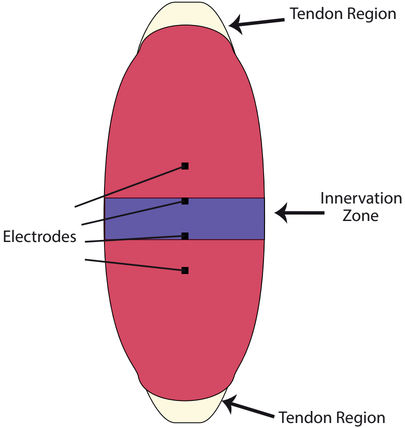

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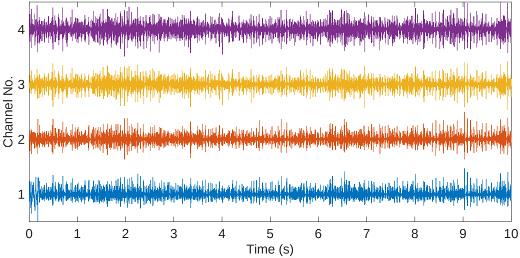

↬ Time-varying delay estimation with unknown waveforms

Time-Varying Delay Estimation

The problem:

Multi-channel recordings:

$$\begin{cases} g_1(t) = f(t) + e_1(t) \\ g_2(t) = f\big(t - \tau(t)\big) + e_2(t) \\ g_3(t) = f\big(t - 2\,\tau(t)\big) + e_3(t) \\ \qquad\vdots \\ g_N(t) = f\big(t - (N-1)\tau(t)\big) + e_N(t) \end{cases}$$

where

- $g_n(t)$ is the signal from the nth electrode
- $f(t)$ is the signal of interest
- $\tau(t)$ is the time-varying delay
- $e_n(t)$ is Gaussian noise

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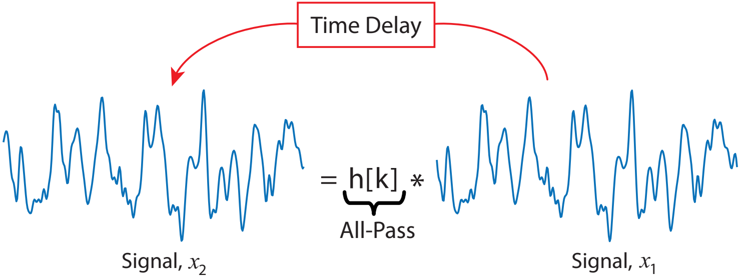
Our Approach:

Common Local All-Pass Filter algorithm:

- ↬ Robust and very accurate
- ↬ Automatically identify Innervation Zone
- ↬ Uses all of the electrode signals

All-Pass Filter Framework - Concept 1

Constant delay $\tau \implies$ Filtering Signal 1 with All-Pass Filter h



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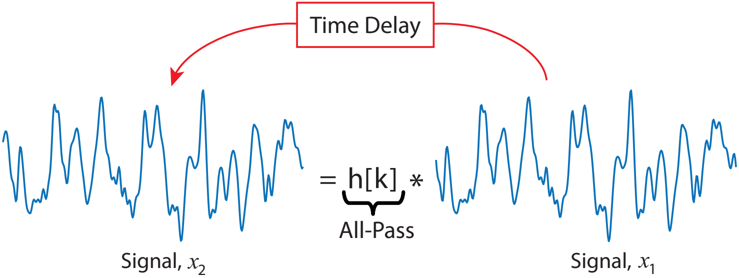

Shifting in Frequency:

$$X_2(\omega) = \underbrace{X_1(\omega)\, \mathrm{e}^{-j\tau\omega}}_{=\ \text{Filtering Operation}} \xrightarrow{\text{Define Filter}} \underbrace{H(\omega) = \mathrm{e}^{-j\tau\omega}}_{=\ \text{All-Pass}}$$

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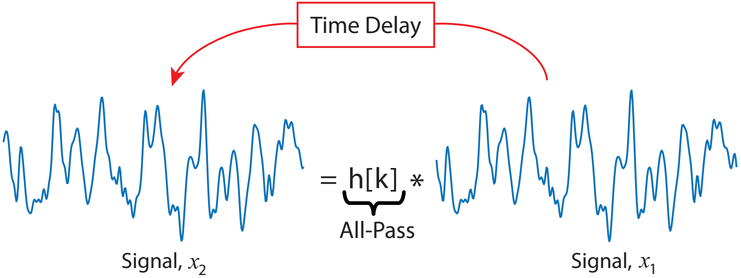

↬ Estimation of All-Pass Filter = Estimation of time delay
↬ No assumption on the size of the delay

All-Pass Filter Framework - Concept 2

Any all-pass filter has a rational structure $\implies H(\omega) = \dfrac{P(\omega)}{P(-\omega)}$

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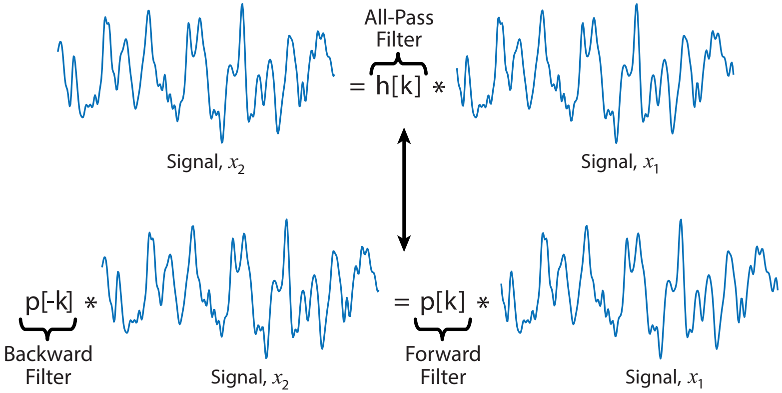

↬ Linearise All-Pass Filtering

All-Pass Filter Framework - Concept 3

Approximate p with a few known real filters

$$p_{\text{app}}[k] = \sum_{l=0}^{L-1} c_l p_l[k] \quad \Longrightarrow \quad \text{Estimate coefficients } c_l$$

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A good choice of filters $\Longrightarrow$ Span the derivatives of an isotropic function

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$$p_0[k] = \exp\left(-\frac{k^2}{2\sigma^2}\right) \quad \text{where} \quad \sigma = \frac{R}{2} - 0.2$$

$$\text{First derivatives} \quad \Longrightarrow \quad p_1[k] = k\, p_0[k]$$

↬ Filters are scalable $\Longrightarrow$ Estimate both large and small delays

↬ Linked to R, the half support of the filters

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Finally....

$$\text{Set } c_0 = 1 \quad \Longrightarrow \quad \text{Need to estimate 1 coefficients}$$

$\looparrowright$ Solve using Least Mean Squares $\Longrightarrow$ Linear system of equations

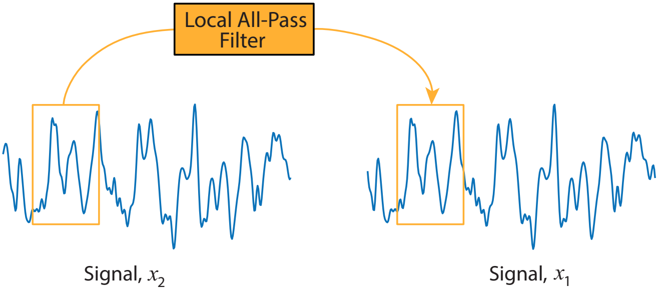
$$\min_{\{c_l\}} \sum_{k \in \mathbb{Z}} \left| p_{\text{app}}[k] * x_1[k] - p_{\text{app}}[-k] * x_2[k] \right|^2$$

$\looparrowright$ Extract estimate of delay from All-Pass Filter

Local All-Pass (LAP) Algorithm

Central Assumption:

Assume delay is constant within a local region ⇒ Local All-Pass Filters



At central sample ⟹ Estimate local all-pass filter

↬ Extract delay from the estimate of the filter

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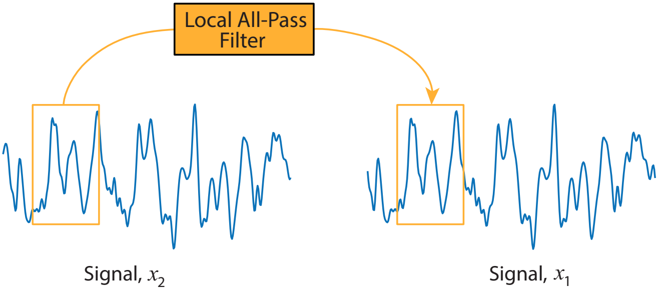

Move region (one sample change) $\implies$ Estimate new all-pass filter

Very efficient to solve $\implies$ Convolutions and fixed-point multiplication

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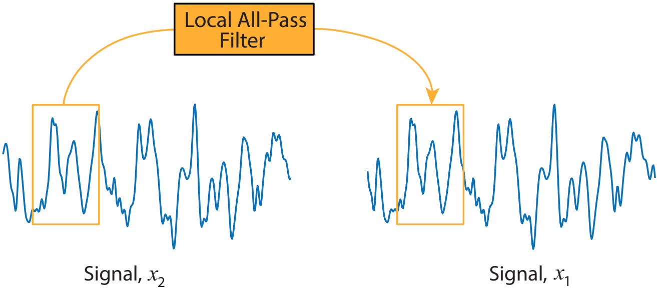

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$\looparrowright$ Size of the region $= R$, half support of the filters

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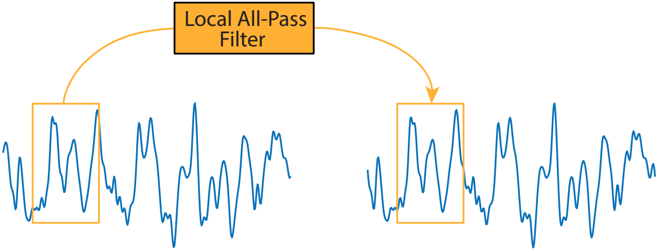

Signal, x_2 Signal, x_1

End Result:

↬ Per sample estimate of the time-varying delay

Estimating a Common Time-Varying Delay

The ensemble of signals:

$$\left.\begin{aligned} x_1(t) &= f(t) \\ x_2(t) &= f\big(t - \tau(t)\big) \\ x_3(t) &= f\big(t - 2\tau(t)\big) \\ &\vdots \\ x_N(t) &= f\big(t - (N-1)\tau(t)\big) \end{aligned}\right\}$$

Characterised by time varying delay

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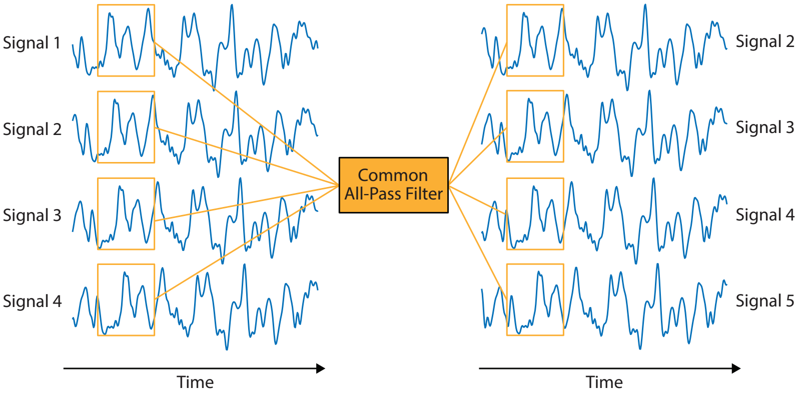
Key Observation:

Same time-varying delay $\tau(t)$ between each pair of signals
$\looparrowright$ Adapt LAP to multiple signals

Common Local All-Pass Filter

Our approach:



Within local regions $\Longrightarrow$ Estimate a common All-Pass Filter

Common Local All-Pass Filter

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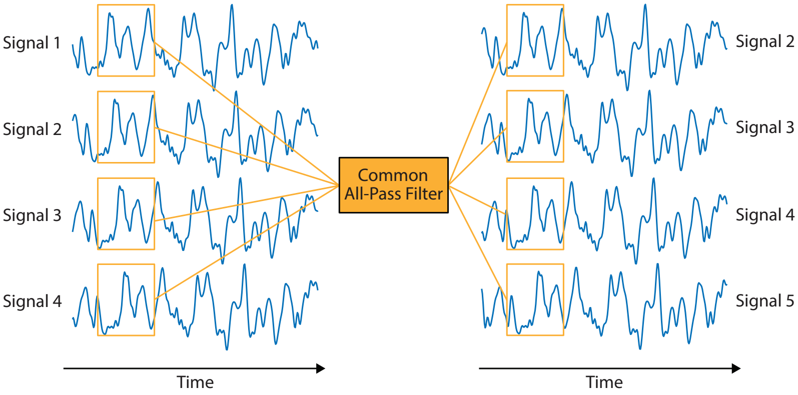
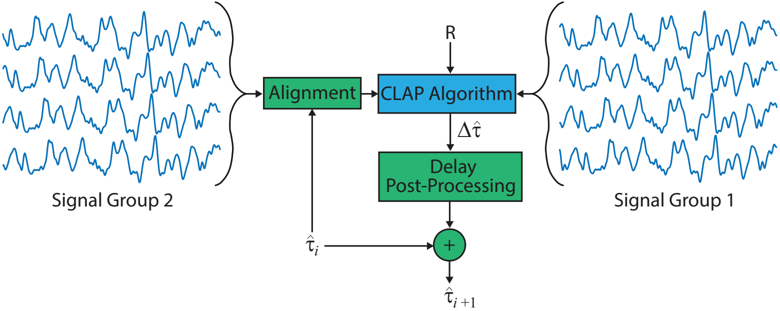


Common Local All-Pass (CLAP) Algorithm

Estimate a single time-varying delay common across a group of signals

Multi-Scale Framework

Iterative framework:



Estimate faster variations in the delay $\Longrightarrow$ Change R (size of filters)

Multi-Scale Framework

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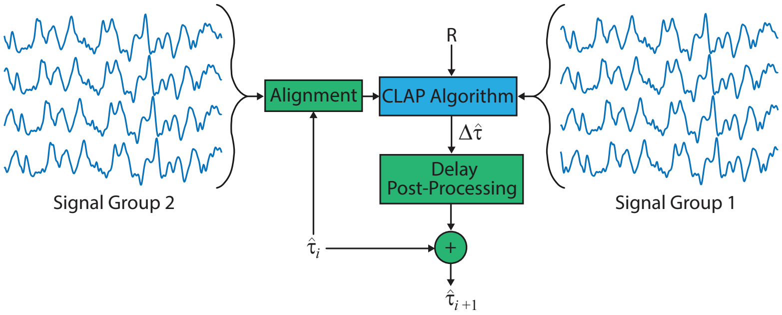

Alignment $\Rightarrow$ Warp signals using delay estimate

Post-Processing:
- Inpainting $\Longrightarrow$ Remove erroneous delay estimates
- Smooth estimate using Gaussian filtering

Application to sEMG

Step 1:

sEMG signals likely to suffer from a common source of corruption across all channels

Use single differential of signals: $x_n(t) = g_{n+1}(t) - g_n(t)$

Application to sEMG

Step 2:

Automatic identification of the Innervation Zone

Innervation Zone

Point where motor neurons innervate the muscle fibres
$\looparrowright$ MUAPs propagate out from zone to tendons

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Point where motor neurons innervate the muscle fibres
↬ MUAPs propagate out from zone to tendons

$$
\begin{aligned}
x_{n-2} &= x_{n-1}(t + \tau(t)) \\
x_{n-1} &= x_n(t + \tau(t)) \\
x_n &\longrightarrow \text{Innervation Zone} \\
x_{n+1} &= x_n(t - \tau(t)) \\
x_{n+2} &= x_{n+1}(t - \tau(t))
\end{aligned}
$$

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Innervation Zone

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Solution:

- Run LAP pair-wise on adjacent signals & calculate mean delay
- Find point where the sign of the delay changes
- Reverse order of processing for signals above the zone

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Point where motor neurons innervate the muscle fibres
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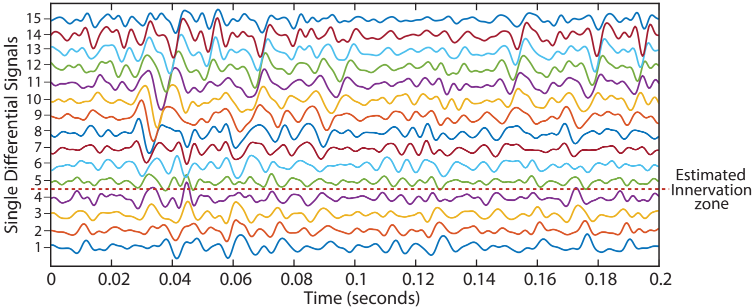

Evaluation on Synthetic sEMG Data

Synthetic Data Model[1]:

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Synthetic Data Model[1]:

1st Channel:
White Gaussian noise filtered using FIR filter with EMG-like spectral properties[2].

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Model of Conductance Velocity:

$$\mathsf{CV}(t) = 4 + 2\sin(2\pi\, 0.2t/F_s)$$

where $F_s = 2048\,\mathsf{Hz}$ is the sampling frequency

Biologically plausible $\implies$ Velocities range between $2\,\mathsf{m/s}$ to $6\,\mathsf{m/s}$

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$$\looparrowright \quad \tau(t) = F_s \frac{\Delta e}{\text{CV}(t)}$$

where $\Delta e = 5\,\text{mm}$ is the inter electrode distance

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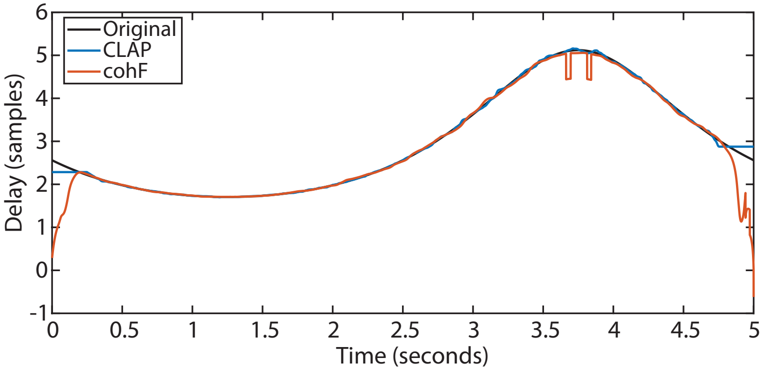
Evaluation on Synthetic sEMG Data - Results

Noiseless Data:

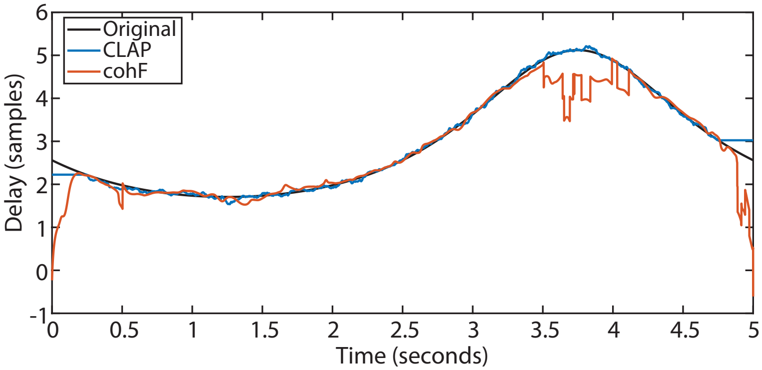


Estimation using 6 signals and window size of $0.25\,\text{s}$ (512 samples)

cohF = Fourier Phase Coherency (same window size)

Evaluation on Synthetic sEMG Data - Results

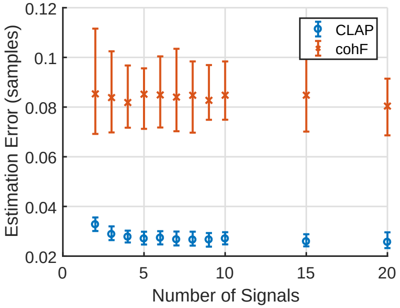
SNR $= 10\,$dB:



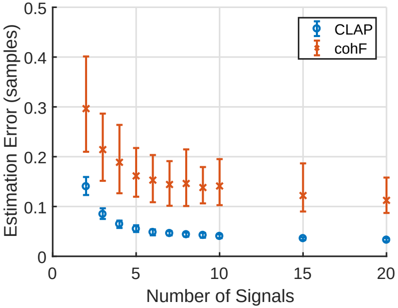
Estimation using 6 signals and window size of $0.25\,$s (512 samples)

cohF = Fourier Phase Coherency (same window size)

Synthetic sEMG Data - Varying Number of Signals



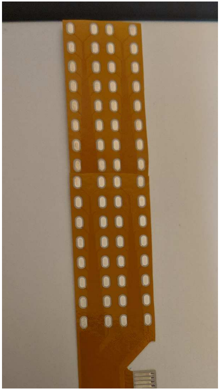
SNR $= 30\,$dB



SNR $= 10\,$dB

Error bars $= 5^{\text{th}}$ and 95^{th} quantiles
Values averaged over 100 realisations of the data

Evaluation on Experimental HD-sEMG Data



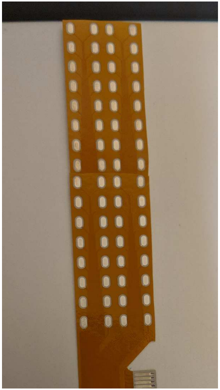
Electrode Array

Example of set up

4 $\times$ 16 HD-sEMG array placed on biceps brachii (parallel to muscle fibres)

Participants pull on fixed cable $\Rightarrow$ 40% & 80% max voluntary contractions

Evaluation on Experimental HD-sEMG Data



Electrode Array

Example of set up

Validate CLAP algorithm performance using surrogate data

Surrogates generated by iterative amplitude adjusted FFT

Evaluation on Experimental HD-sEMG Data - Results

Subject	MVC	Surrogates		Data	
		Avg $\bar{\tau}$	Var $\bar{\tau}$	$\bar{\tau}$	CV (m/s)
1	40%	-0.001	0.000	2.503	4.89
	80%	-0.003	0.000	2.363	5.20
2	40%	-0.001	0.000	2.320	5.28
	80%	0.000	0.002	2.399	5.11
3	40%	0.001	0.000	1.690	7.26
	80%	-0.002	0.001	1.726	7.13

$\bar{\tau}$ = Time averaged delay and MVC = Maximum Voluntary Contraction

100 surrogates per dataset

Evaluation on Experimental HD-sEMG Data - Results

		Surrogates		Data		
Subject	MVC	Avg $\bar{\tau}$	Var $\bar{\tau}$	$\bar{\tau}$	CV (m/s)	Change CV (m/s^2)
1	40%	-0.001	0.000	2.503	4.89	-0.001
	80%	-0.003	0.000	2.363	5.20	-0.029
2	40%	-0.001	0.000	2.320	5.28	-0.005
	80%	0.000	0.002	2.399	5.11	-0.017
3	40%	0.001	0.000	1.690	7.26	-0.001
	80%	-0.002	0.001	1.726	7.13	-0.017

$\bar{\tau}$ = Time averaged delay and MVC = Maximum Voluntary Contraction

100 surrogates per dataset

Conclusions

- Muscle conduction velocity estimation
  - Equivalent to time-varying delay estimation
  - Using HD-sEMG $\Longrightarrow$ Delay estimation across multiple channels
- Framework for estimating a delay using all-pass filters
  - Delay estimate $\Longrightarrow$ Local All-Pass Filters
  - Multiple channels $\Longrightarrow$ Common Local All-Pass Filters
  - Estimate a single time-varying delay common across a group of signals
- Demonstration of the CLAP algorithm
  - Able to automatically estimate the Innervation Zone
  - Synthetic data $\Longrightarrow$ Robust and accurate
  - Experimental data $\Longrightarrow$ Biologically plausible CV values & validated via surrogate testing

The End

Thank you for listening