Estimating Muscle Fibre Conduction Velocity in the Presence of Array Misalignment

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Outline

High Density Surface EMG (HD-sEMG)

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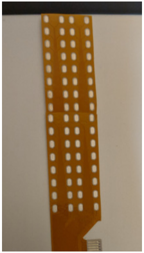
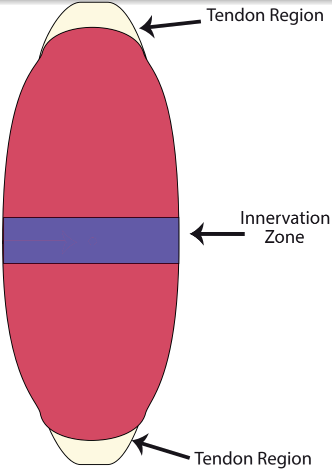


High Density Surface EMG (HD-sEMG)

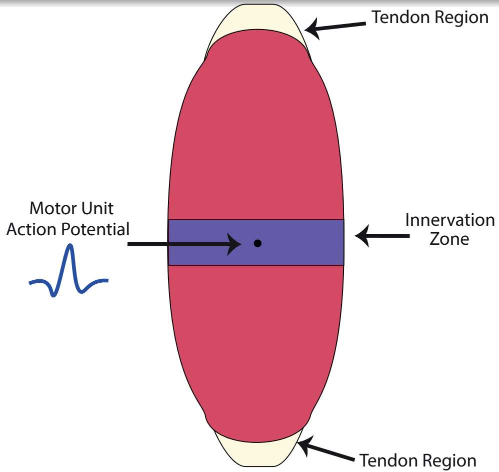
- Typically sEMG is recorded with bipolar electrodes
- Recent developments allow for high density recording arrays
- HD-sEMG provides spatial information otherwise unavailable

Conduction Velocity



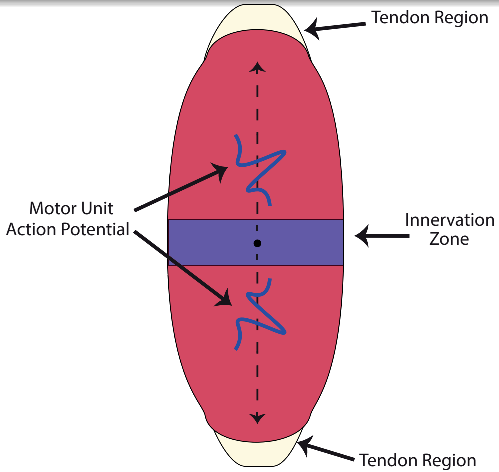
One such property is the muscle fibre conduction velocity

Conduction Velocity



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

Conduction Velocity



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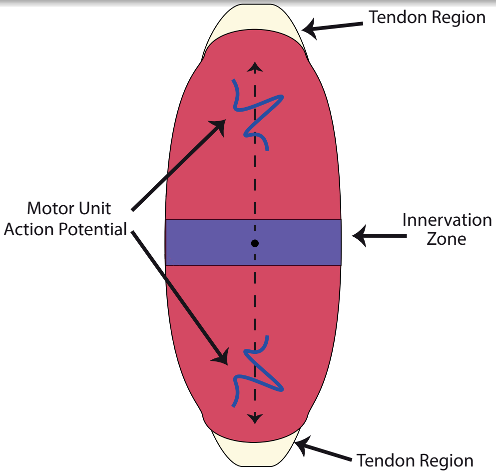

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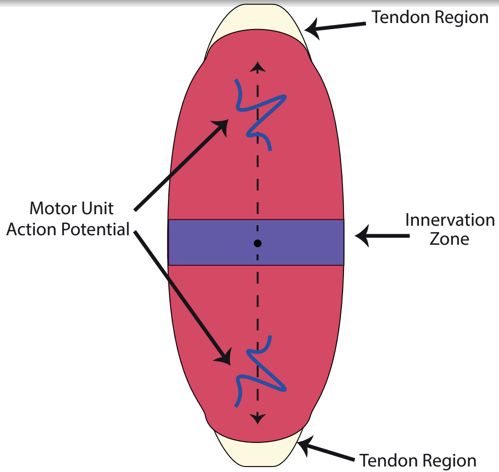
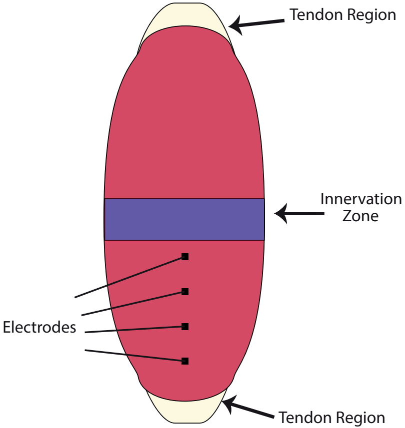


↬ Important factor in the study of muscle pathology, fatigue or pain

Estimating Conduction Velocity from sEMG

Estimate conduction velocity $\implies$ Delay estimation



$$g_1(t) = f(t) + e_1(t)$$
$$g_2(t) = f\big(t - \tau(t)\big) + e_2(t)$$
$$\vdots$$
$$g_N(t) = f\big(t - (N-1)\tau(t)\big) + e_N(t)$$

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

Estimating Conduction Velocity from sEMG

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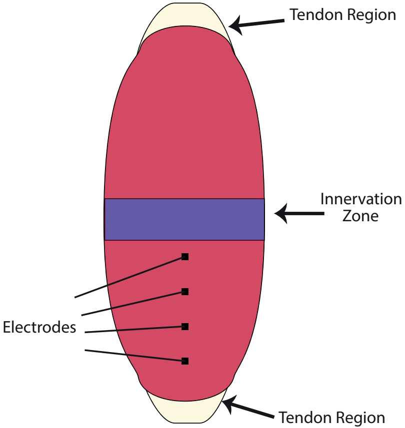

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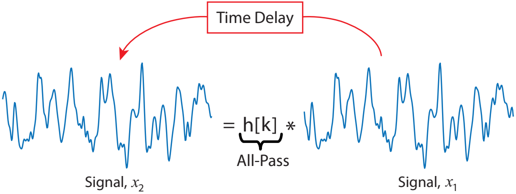
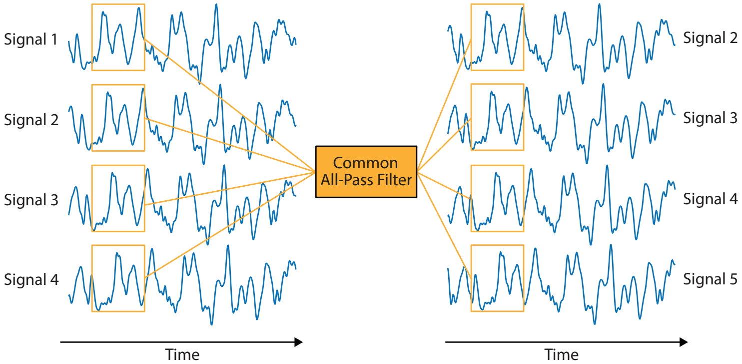


Estimating a common time-varying delay



Common Local All-Pass (CLAP) algorithm:

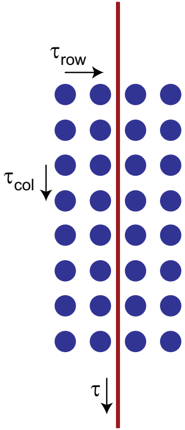
Assume delay is constant within a local region ⇒ Local All-Pass Filters

↬ Per sample estimate of the time-varying delay

↬ Robust and very accurate

C. Gilliam et al., *'Time-Varying Delay Estimation using Common Local All-Pass Filters with Application to Surface Electromyography'*, ICASSP 2018

Array Misalignment Problem



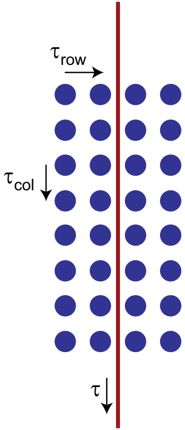
Aligned Array

In a perfect world....

Array is aligned with the muscle fibre

$\looparrowright \quad \tau(t) = \tau_{\text{col}}(t)$

Array Misalignment Problem



Aligned Array

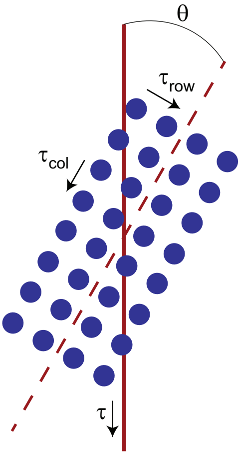
In a perfect world....

Array is aligned with the muscle fibre
$\looparrowright \quad \tau(t) = \tau_{\text{col}}(t)$

But...

Requires very careful placement of array
$\looparrowright$ Impractical

Array Misalignment Problem



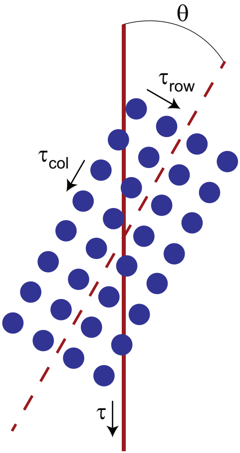
Misalignment Example

In reality...

Array and muscle fibre misalignment

$$\tau(t) = \tau_{\text{col}}(t) + j\tau_{\text{row}}(t)$$
$$= |\tau(t)|\,(\cos\theta + j\sin\theta)$$

Array Misalignment Problem



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In reality...

Array and muscle fibre misalignment

$$\tau(t) = \tau_{\text{col}}(t) + j\tau_{\text{row}}(t)$$
$$= |\tau(t)| (\cos\theta + j\sin\theta)$$

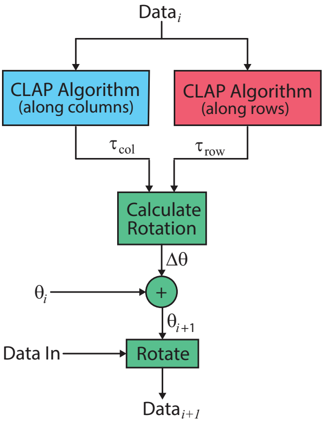
Delay along the columns

Underestimates Delay

$\Downarrow$

Overestimates Conduction Velocity

Parametric Estimation of Array Misalignment

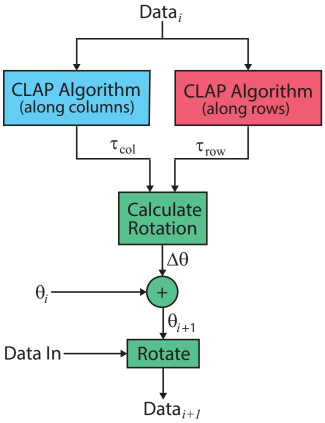


Parametric model:

$$|\tau(t)|\,(\cos\theta + j\sin\theta) = \tau_{\text{col}}(t) + j\tau_{\text{row}}(t)$$

↬ Misalignment angle constant in time

Parametric Estimation of Array Misalignment



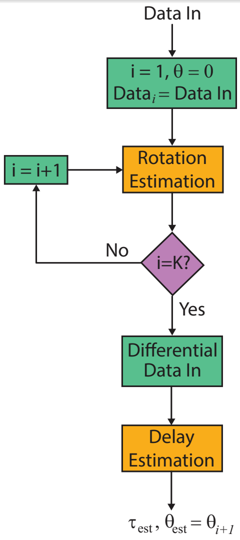
Parametric model:

$$|\tau(t)| (\cos\theta + j\sin\theta) = \tau_{\text{col}}(t) + j\tau_{\text{row}}(t)$$

Our approach:

1. Estimate delays $\tau_{\text{col}}(t)$ and $\tau_{\text{row}}(t)$
2. Calculate rotation using circular mean $\Delta\theta = \arg\left(\sum_t \tau_{\text{col}}(t) + j\tau_{\text{row}}(t)\right)$
3. Update current estimate of θ
4. Correct data using the rotation

Parametric Estimation of Array Misalignment



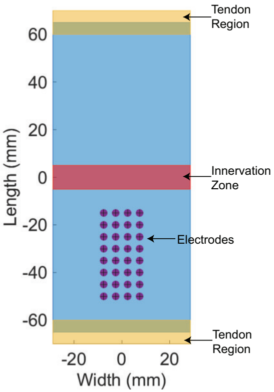
Iterative framework:

1. Perform rotation estimation and correct data
2. Repeat process to refine angle estimate θ_{est}
3. Perform CLAP estimation along columns of corrected data

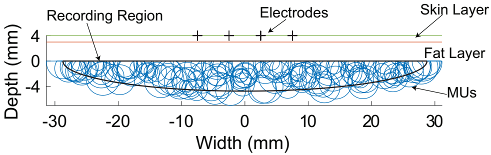
sEMG Model

↬ To test the proposed approach a model of sEMG as a combination of action potentials from many motor units was used

Muscle surface



Muscle volume



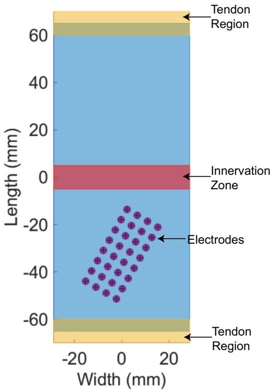
- MUAPs observed by an electrode depend upon
  - Size of the MU (number of fibres)
  - Size & shape of electrodes
  - Distance of electrode from innervation zone
  - Distance of MU from electrode

D. Farina & R. Merletti, *'A novel approach for precise simulation of the EMG signal detected by surface electrodes'*, IEEE Trans. Biomed.

Modelling Array Misalignment

Array misalignment changes the relationship between electrodes and the MUs

Muscle surface



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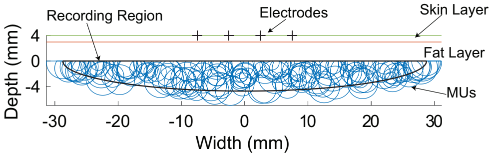

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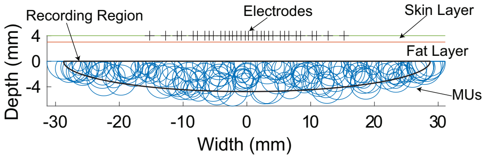

Weighted Conduction Velocity

- MU areas are determined by the number of fibres & fibre density
- MUs with larger area have a faster conduction velocity

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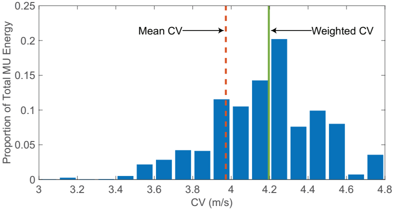

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- Distribution becomes skewed due to larger number of fibres belonging faster motor units

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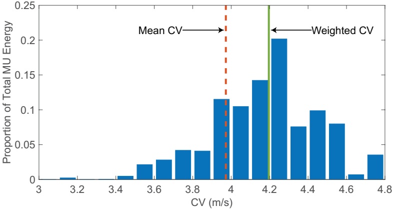

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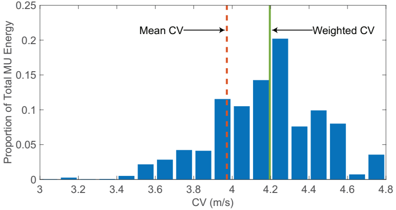

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Weighted Conduction Velocity

To account for this a weighted CV is used

- The total energy E is the summation of the energies of all MUs
- The energy e_i is the energy of the signals from MU i
- Giving the weighted CV

$$wCV = CV_1 \frac{e_1}{E} + CV_2 \frac{e_2}{E} + \dots$$

Fixed Conduction Velocity

Simulation Scenario

- Each MU has a fixed muscle fibre conduction velocity
- CVs are drawn from Gaussian distribution with $\mu = 4$ m/s and $\sigma = 0.3$ m/s
- Weighted CV used as an ensemble measure of the CV observed by the sEMG
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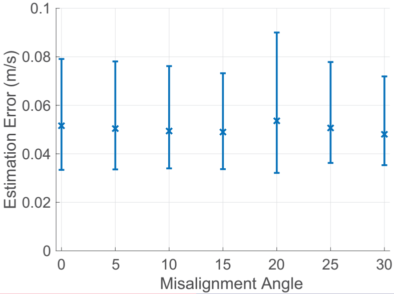
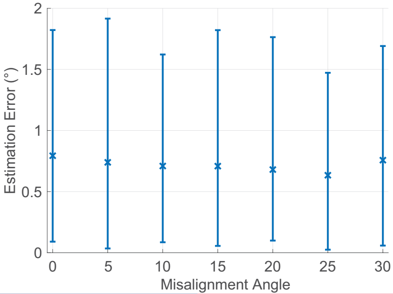
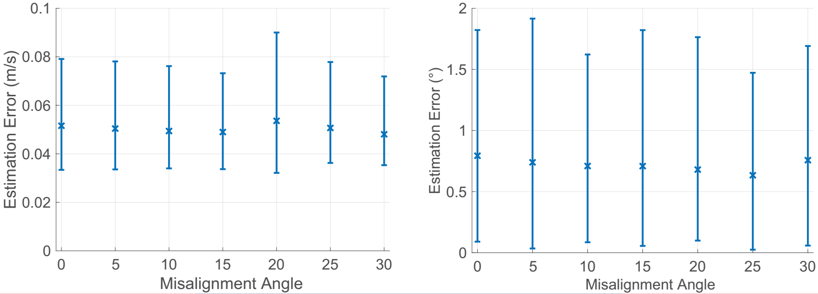




Fixed Conduction Velocity

Results

- Estimates were accurate and robust
- Errors were relatively consistent across the different misalignment angles.
- The average mean absolute error was consistent across angles
- 95% of the estimates have an error of less than 2°.



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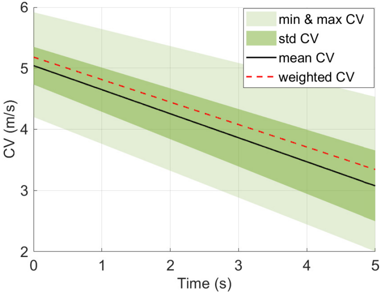
- Initial distribution: $\mu = 5$ m/s and $\sigma = 0.3$ m/s
- Final distribution: $\mu = 3$ m/s and $\sigma = 0.7$ m/s



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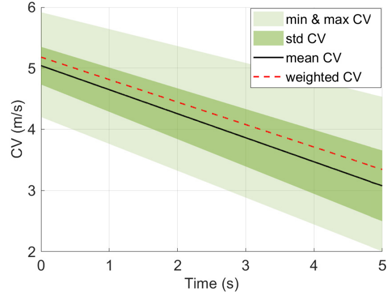
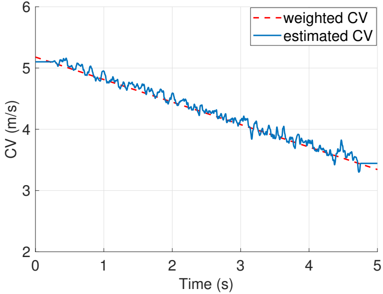
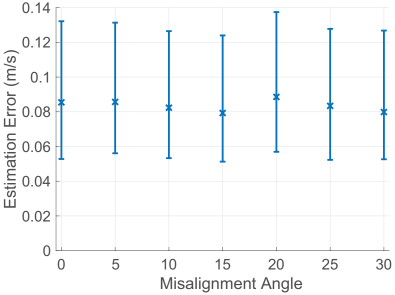


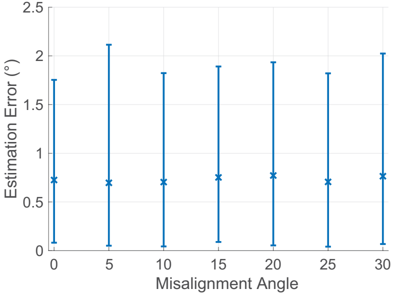


CLAP algorithm successfully tracks weighted CV

Time-Varying CV with Array Misalignment

Now we add array misalignment to the time-varying CV estimation





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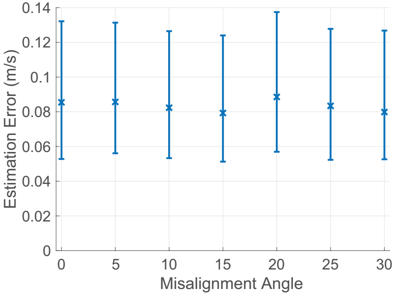

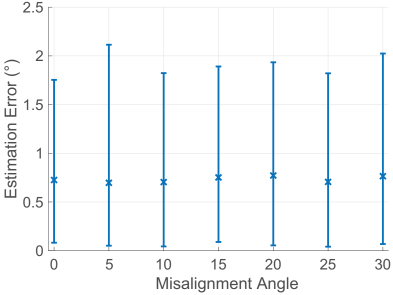

Results

- Average errors & angle estimates consistent across different misalignment angles
- Slightly higher errors than for the fixed MFCV
- Average angle errors less than 1°

Conclusions

- Muscle fibre conduction velocity estimation
  - Can be modelled as a TVD
  - Need to accurately place electrodes for sEMG recordings is a limitation
- Our approach
  - An extension of our earlier work for estimating MFCV
  - Allows misalignment between muscle fibres & electrode array
  - Models the misalignment as a rotation of the array
  - Iteratively fits the misalignment angle
- Practical solution to MFCV estimation
  - Estimates misalignment angle & delay in the direction of the fibres
  - Accurately estimates MFCV without perfect alignment of the array with the muscle fibre
- Future Work
  - Apply a parametric iterative fitting to improve the delay estimation

The End

Thank you for listening