

From muscles to the brain: MU-based EEG filters

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Processing pipeline









Isometric HDEMG model: Convolutive







Convolutive EMG model: matrix form



Matrix of convolution kernels (MUAPs):



Extended vector of pulse sources:



A. Holobar, D. Zazula: Convolution Kernel Compensation, *IEEE Trans. Signal Proc.*, 2007

Data model: MUAPs of Biceps Brachii



Funded by

GA No. 101079392

the European Union









HYBRID

MU 6, 74 chs	MU 7, 48 chs	MU 8, 82 chs	MU 9, 90 chs	MU 10, 84 chs
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<u></u> 0.16 μV	<u></u> [0.23 μV	<u></u>	_0.18 μν	_0.16 μV

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_0.16 μV	_0.23 μV	<u></u> 0.35 μV	<u></u> _0.18 μV	-

_0.24 μV



JK Research

GA No. 10052152

and Innovation



MU 13, 84 chs					
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when whe whe whe					

	MU 14, 90	chs	
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	mhur muhur	mhr mhr -	-hrhr
_0.26 μV			

#### **Data model: MUAPs of Soleus**



---------------------I30  $\mu$ V

MU 2, 101 chs



MU 9, 30 chs

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MU 15, 37 chs

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**Ι**40 μV

#### MU 4, 78 chs



I50  $\mu$ V

MU 10, 28 chs								

**Ι**110 μV



MU 7, 72 chs ---------- ----- ----- ----- ----- ---------------------------------I60  $\mu$ V

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15	0 μV								

MU 8, 103 chs



MU 14, 25 chs

Ι140 μV

Ι100 μV

Ι100 μV



Ι140 μV



Ι150 μV





Convolution Kernel Compensation (CKC)

A. Holobar, D. Zazula: Convolution Kernel Compensation, IEEE Trans. Signal Proc., 2007

HDEMG model: $\vec{y}(n) = H\vec{t}(n)$

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Correlation matrixes

Correlation matrix of measurements: $C_y = \sum_n \vec{y}(n) \vec{y}(n)$

Correlation matrix of pulse trains: $C_t = \sum_n \vec{t}(n) \vec{t}(n)$

$$C_{y} = \sum_{n} \vec{y}(n) \vec{y}(n) \longleftarrow \vec{y}(n) = H\vec{t}(n)$$
$$C_{y} = HC_{t}H^{t}$$

MU Filter: $y(n_0)^T C_y^{-1}$



Data model: Correlation matrix of extended measurements

Biceps brachii $C_{\bar{v}}$





Soleus $C_{\bar{y}}$





Correlation matrix of pulse trains $C_{\bar{t}}$ **is (close to) diagonal**



HYBRID NEURO

Convolution Kernel Compensation (CKC)



A. Holobar, D. Zazula: Convolution Kernel Compensation, IEEE Trans. Signal Proc., 2007

HDEMG model: $\vec{y}(n) = H\vec{t}(n)$

HDEMG correlation matrix: $C_y = HC_t H^t$

Example 1: The first approximation of MU filter

MU Filter:
$$y(n_0)^T C_y^{-1}$$

MU spike train estimation: $y(n_0)^T C_y^{-1} y(n) = \vec{t}(n_0)^T C_t^{-1} \vec{t}(n)$

If MUs are asynchronous: $\vec{t}(n_0)^T \vec{t}(n)$



Data model: correlation matrix of pulse trains





Data model: correlation matrix of pulse trains





Convolution Kernel Compensation (CKC)



A. Holobar, D. Zazula: Convolution Kernel Compensation, IEEE Trans. Signal Proc., 2007

HDEMG model: $\vec{y}(n) = H\vec{t}(n)$

HDEMG correlation matrix: $C_y = HC_t H^t$

Example 2: The optimal MU filter -

MU Filter: $C_{\overline{t_i},y}^T C_y^{-1}$

MU spike train estimation: $c_{\vec{t}_i,y}^T C_y^{-1} y(n) = c_{\vec{t}_i,\vec{t}}^T C_t^{-1} \vec{t}(n)$

If MUs are asynchronic:
$$c_{\vec{t}_i,\vec{t}}^T \vec{t}(n)$$



MU filter estimation & optimization







Processing pipeline









DEMUSE tool

KC: pic_sol_6.otb+ - BR2023-SO	L				-		×
Properties About CKC							د د
load signals	ter	mporal filter: 20 - 500	Hz 🛛 🗹 diff mode				
		spatial filter	No filter 🗸				
load results	save results	✓ remove line interfer.	auto sel. chs.(%) 95				1 3
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load MU firings	save MU firings						< 11
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decompose	stop decomposing	draw	decomp. runs: 30				9
redecompose	batch decompose	✓entire signal	epoch offset (s): 0				8
	batch MU track		epoch length (s): 261.81				7
CKC inspector			decompose sections	5 📃 🗖			6
							5
							4
plot signals	plot spectra	selected MU	: MU 1 🗸				3
plot MU firings	plot MU PTs	sort MUs by	∕no sort				2
plot MU firing rates	plot MUs statistics		MU up MU down				1
animate MUAPs	plot MUAPs	■all MUs	delete MU		Δ	$\land \land$	
plot MUAP trains	plot MUAP residual		delete empty MUs	1 2	3	4 5	





CKC inspector



MU spike outliers removal





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MU spike outliers removal





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Adding missed firings





Adding missed firings





Iterative spike-based MU optimization



Iterative spike-based MU optimization



Merged MU





MU 1





MU 2





Five steps of consideration for deleting MU



- 1. PNR < 24 dB.
- 2. At least 3 different heights in amplitude of PT.
- 3. Irregular and strange MUAP shapes.
- 4. The IDR panel doesn't have a clear firing pattern during different phases of contraction (ramp up, hold, ramp down).
- 5. MU has < 10 firings.



MUs that should be deleted





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MUs that should be deleted





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MUs that should be deleted



Applying MU filter to the EEG (CKC)



MU spike train estimation: $\hat{t}_i(n) = \mathbf{c}_{\bar{t}_i, EMG}^T \mathbf{C}_{EMG}^{-1} EMG(n)$



EEG component estimation: $\hat{s}_i(n) = \mathbf{c}_{cst, EEG}^T \mathbf{C}_{EEG}^{-1} EEG(n)$



EMG to EEG filter transfer: convolutive EEG model







$$t_j(n) = \sum_{k=0}^{K_j} \delta\left(n - k\frac{f_s}{f_j} - d_j - \Delta d_{jk}\right)$$

j=1,...,J,

- d_i is the common firing time lag due to the transmission from cortex,
- Δd_{jk} is MU firing time variability, $\Delta d_{jk} \sim N(0, \sigma_{\Delta d_j})$,
- f_i is the motor unit discharge frequency,
- f_s is the sampling frequency
- K_i is the number of discharges in the observed time interval.

The EEG signals were simulated as comprising ten (J = 10) mutually orthogonal sinusoids $s_j(n)$ and their first higher harmonics as input signals:

$$s_j(n) = a(n) \cdot \left(B \cdot sin(2\pi f_j n - \phi_j) + H_1 \cdot sin(4\pi f_j n - \phi_j) \right),$$

The amplitude B was set equal to 1, whereas the amplitude of the first harmonic, H_1 , was varied across simulations and set to 0, 0.2, 0.4, 0.6, 0.8 and 1























Experimental conditions

Holobar et al. Front. Neurol., 2018





wrist

EEG/EMG synchronization







EEG-EMG Coherence

Holobar et al. Front. Neurol., 2018



FC1

10

20

1

0.75

0.25

0.5

0

0



1

0.75

0.25

0.5

0

0

FC2

10

20







FC3

10

20

coherence

0.75

0.5

0

0

0.25





0.75

0.5

0

0

0.25

FCz

10

20







Inverse tomography and MU related EEG activity







Questions?



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