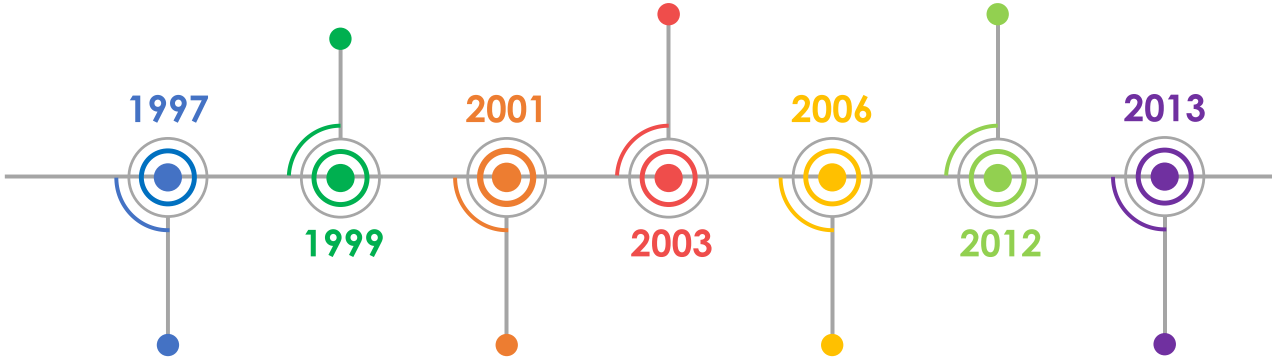
Decoding motor unit activity from high-density EMG signals: methodological considerations and recent advances

Aleš Holobar, University of Maribor, Slovenia

with MANY COAUTHORS around the globe

Presentation outline

- **Introduction to motor unit (MU) identification**: spatiotemporal properties of MU electrical activity
- **Spatial, temporal and MU filters**
- **Blind source separation approach to MU identification**: learning of MU filters and their application to HDEMG signals
- **Banks of MU filters and their efficiency** in different skeletal muscles: isometric conditions
- Banks of MU filters and their efficiency in different types of contractions: **isometric**, **dynamic and elicited contractions**



Surface EMG decomposition timeline & evolution of MU filters

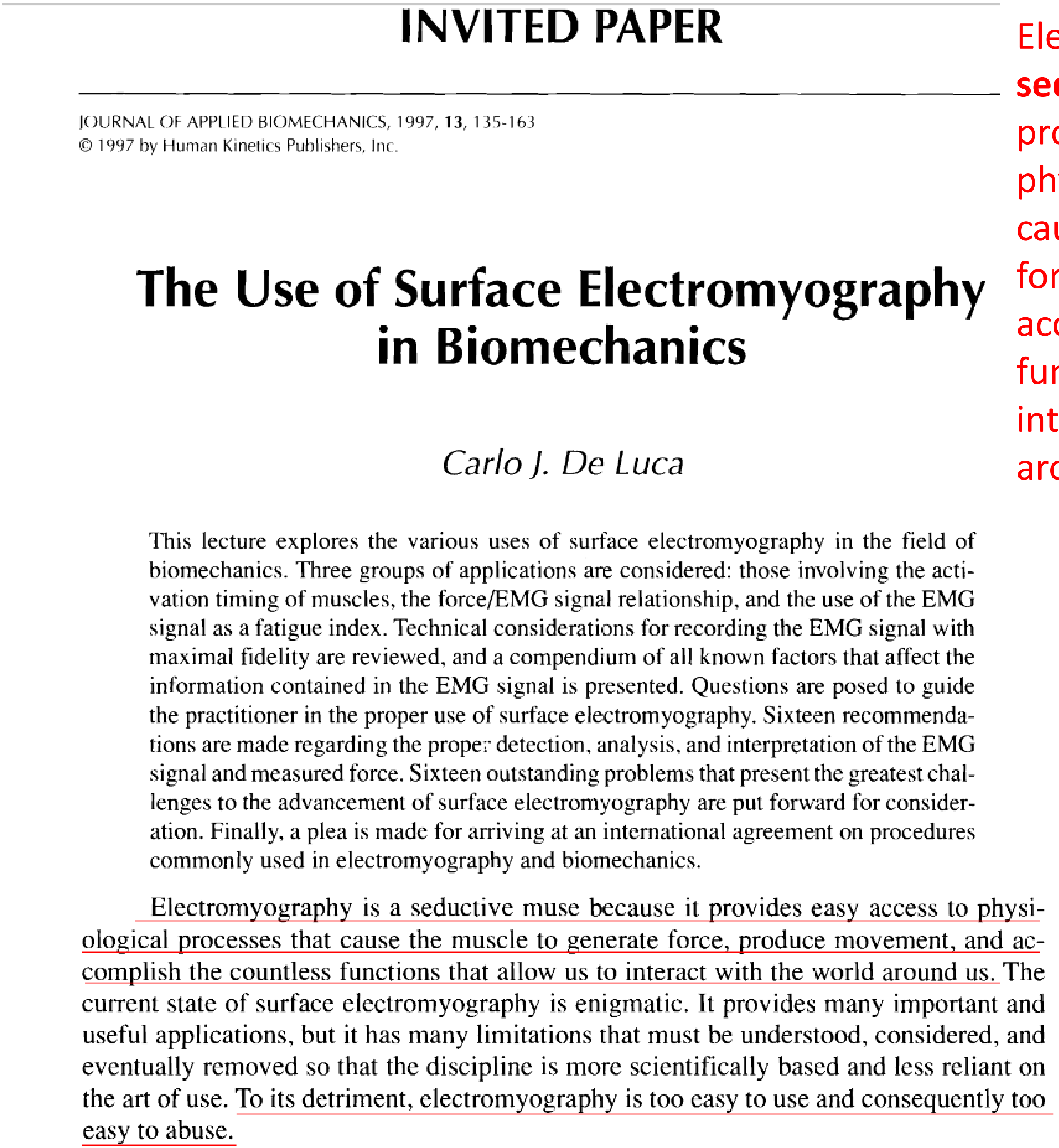
1997

Electromyography is a seductive muse

C.J. De Luca (Boston):

#ISEKtutorials

1997



INVITED PAPER

JOURNAL OF APPLIED BIOMECHANICS, 1997, **13**, 135-163

The Use of Surface Electromyography in Biomechanics

Carlo J. De Luca

This lecture explores the various uses of surface electromyography in the field of biomechanics. Three groups of applications are considered: those involving the activation timing of muscles, the force/EMG signal relationship, and the use of the EMG signal as a fatigue index. Technical considerations for recording the EMG signal with maximal fidelity are reviewed, and a compendium of all known factors that affect the information contained in the EMG signal is presented. Questions are posed to guide the practitioner in the proper use of surface electromyography. Sixteen recommendations are made regarding the proper detection, analysis, and interpretation of the EMG signal and measured force. Sixteen outstanding problems that present the greatest challenges to the advancement of surface electromyography are put forward for consideration. Finally, a plea is made for arriving at an international agreement on procedures commonly used in electromyography and biomechanics.

Electromyography is a seductive muse because it provides easy access to physiological processes that cause the muscle to generate force, produce movement, and accomplish the countless functions that allow us to interact with the world around us. The current state of surface electromyography is enigmatic. It provides many important and useful applications, but it has many limitations that must be understood, considered, and eventually removed so that the discipline is more scientifically based and less reliant on the art of use. To its detriment, electromyography is too easy to use and consequently too easy to abuse.

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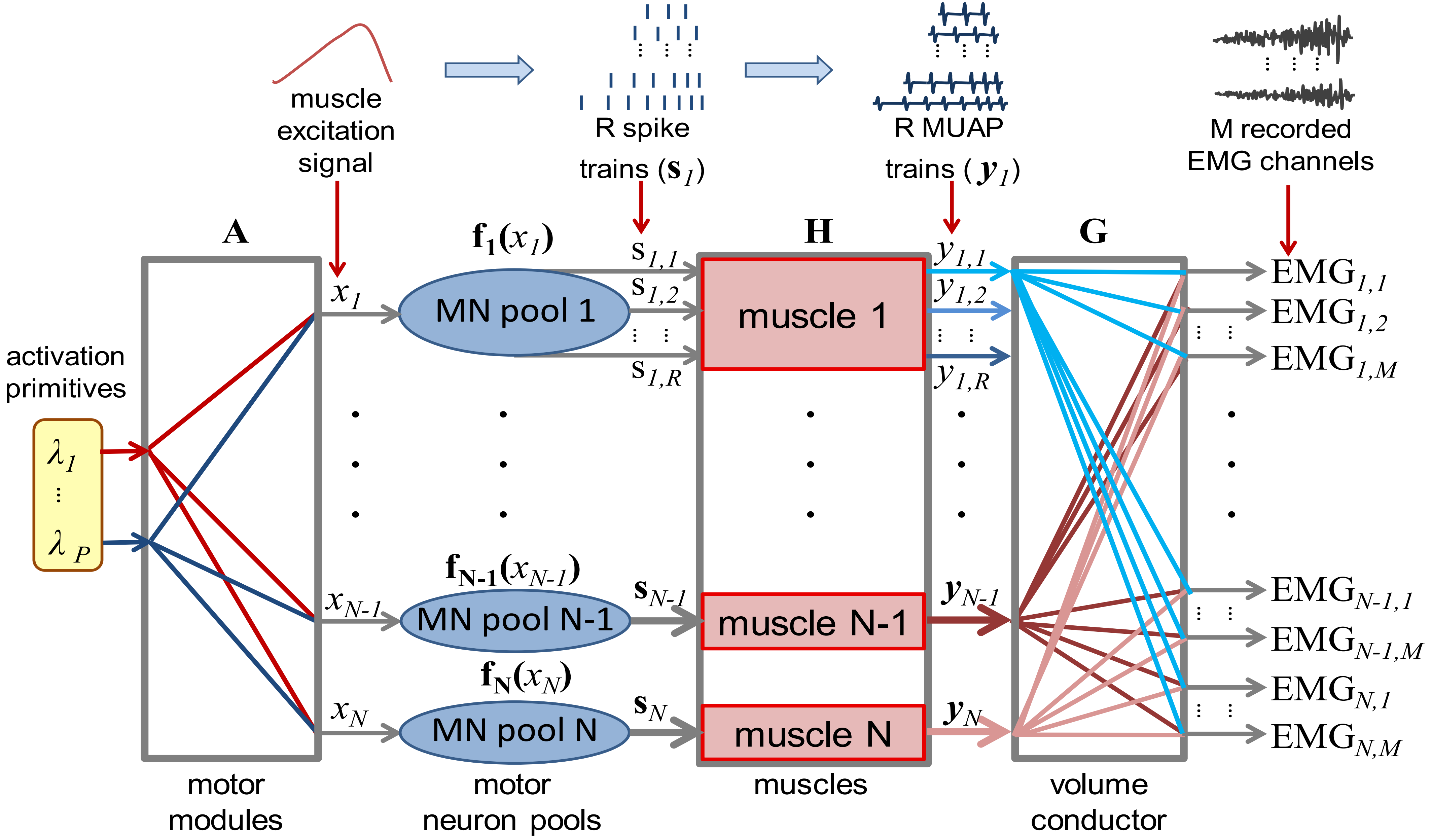
Surface EMG mixing models: signal-based approach



Holobar & Farina, *Physiol Measur* 2014

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Holobar & Zazula 2003,
2004, 2007

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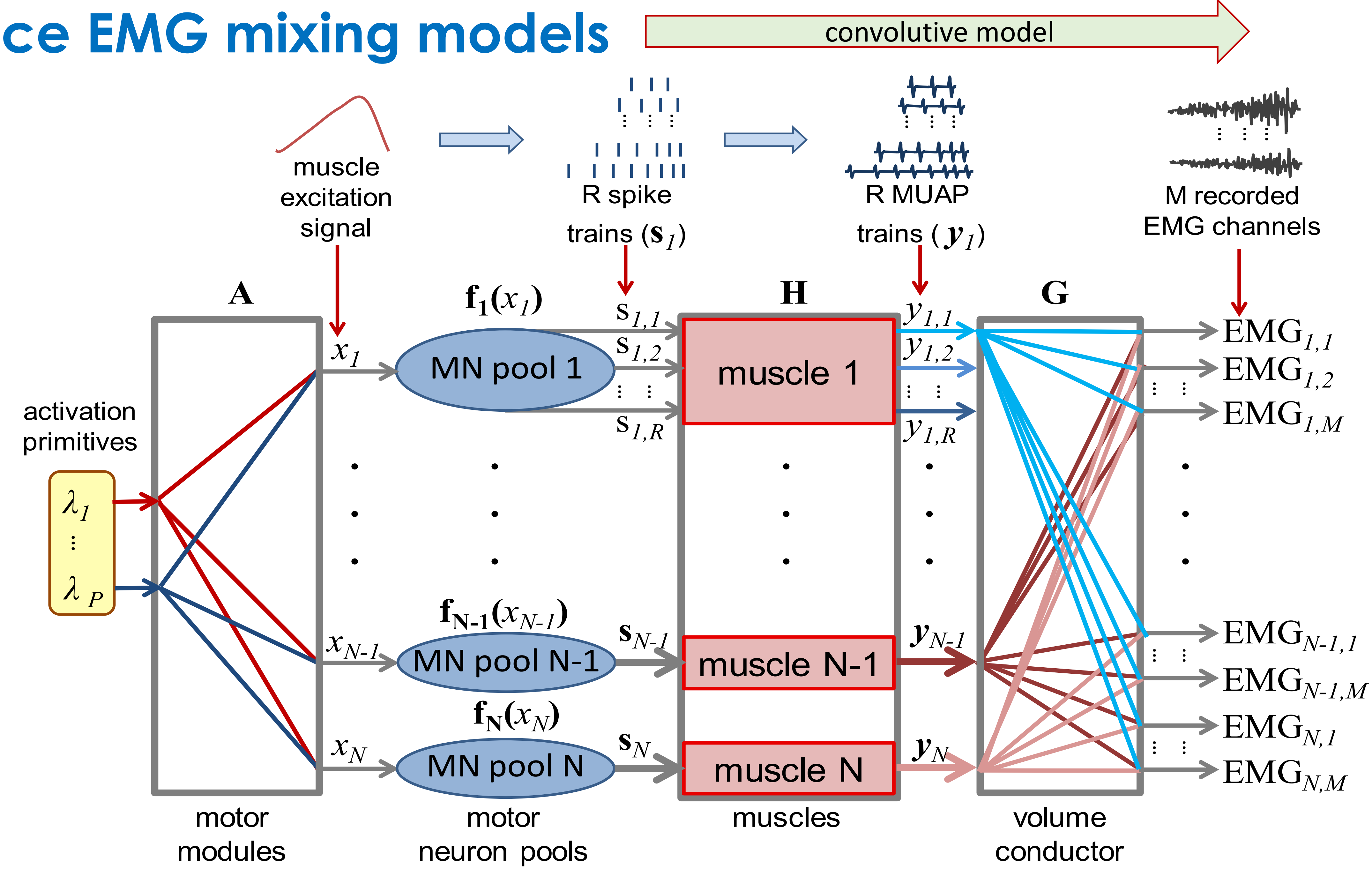
Surface EMG mixing models



Holobar & Farina, *Physiol Measur* 2014

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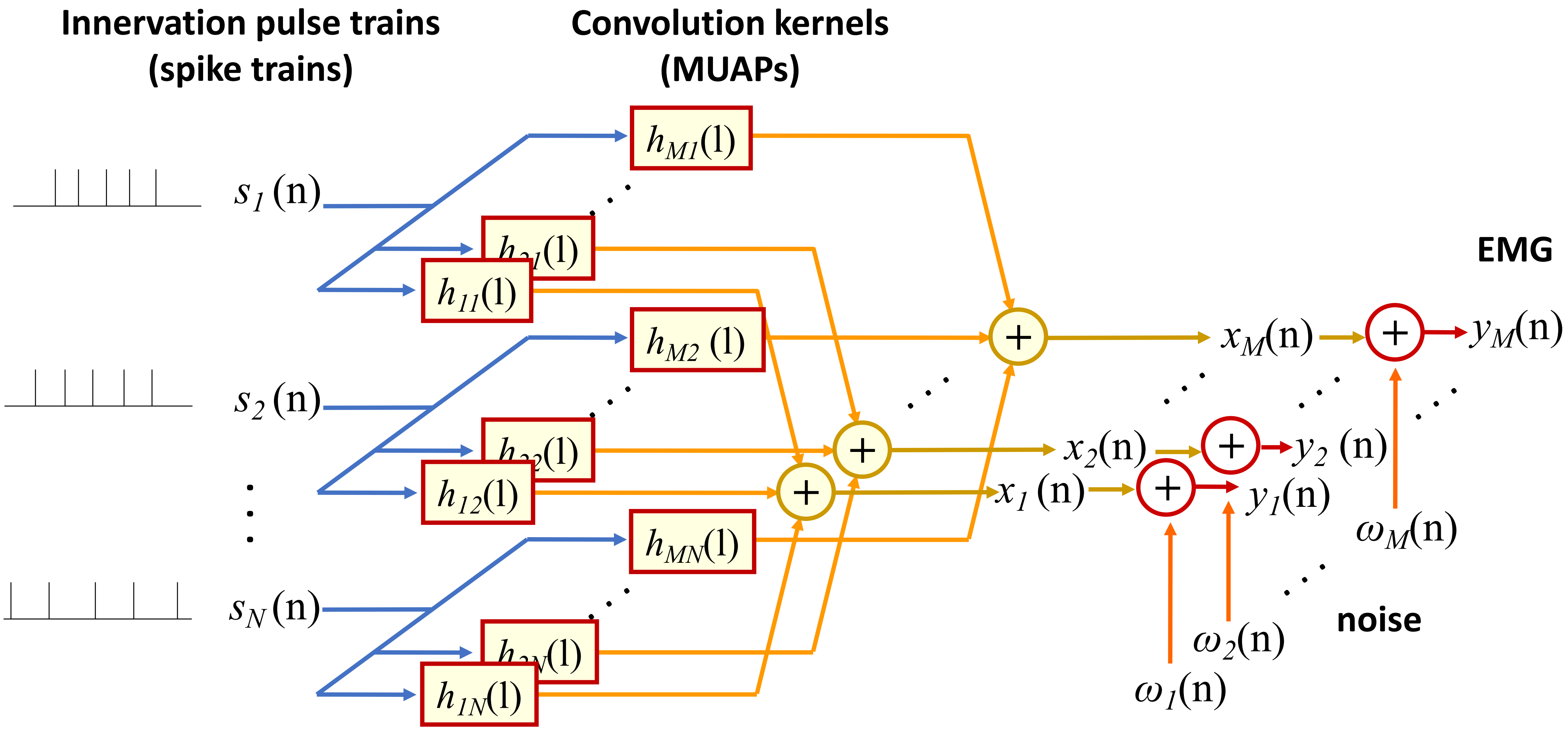
High-density EMG: convolutive model



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

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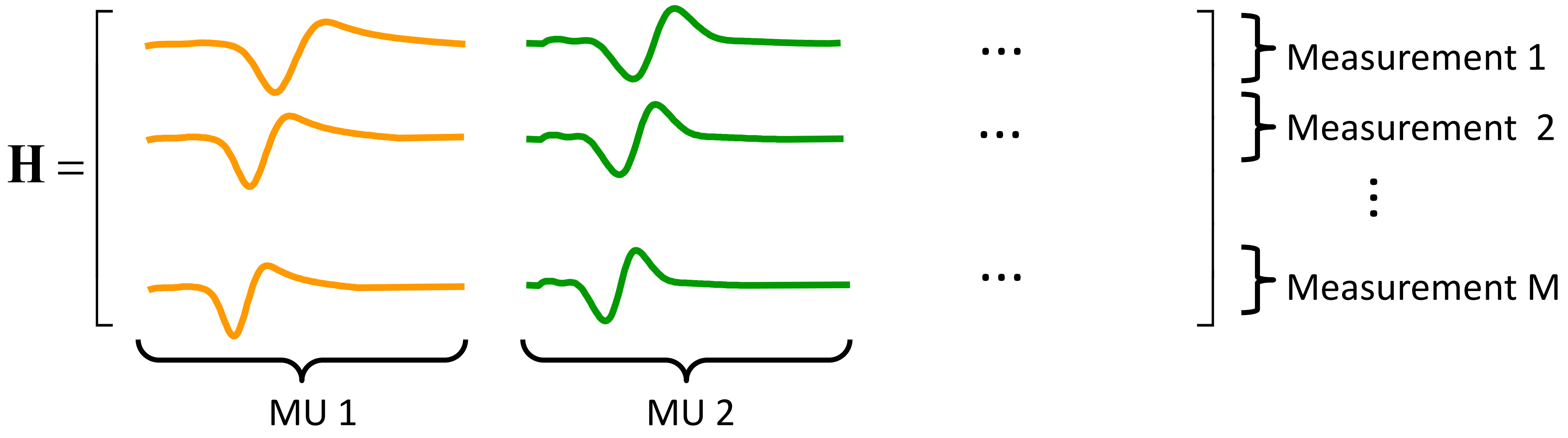
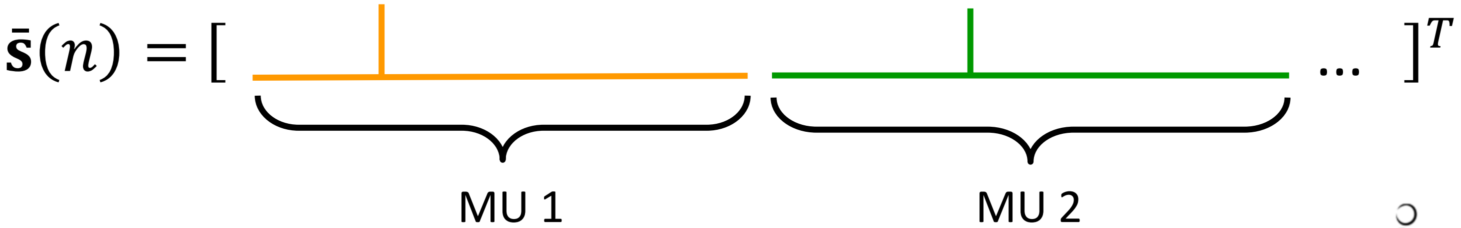
Convolutive EMG model: matrix form

$$\boxed{\mathbf{x}(n) = \mathbf{H}\bar{\mathbf{s}}(n)}$$

- **Matrix of convolution kernels (MUAPs):**



- **Extended vector of pulse sources:**



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

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Convolution Kernel Compensation (CKC)

HDEMG model: $\mathbf{x}(n) = \mathbf{H}\bar{\mathbf{s}}(n)$

HDEMG correlation matrix: $\mathbf{C}_{\mathbf{x}} = \mathbf{H}\mathbf{C}_{\bar{\mathbf{s}}}\mathbf{H}^T$

MU filter: $\mathbf{c}_{\bar{\mathbf{s}}_i,\mathbf{x}}^T \mathbf{C}_{\mathbf{x}}^{-1}$

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

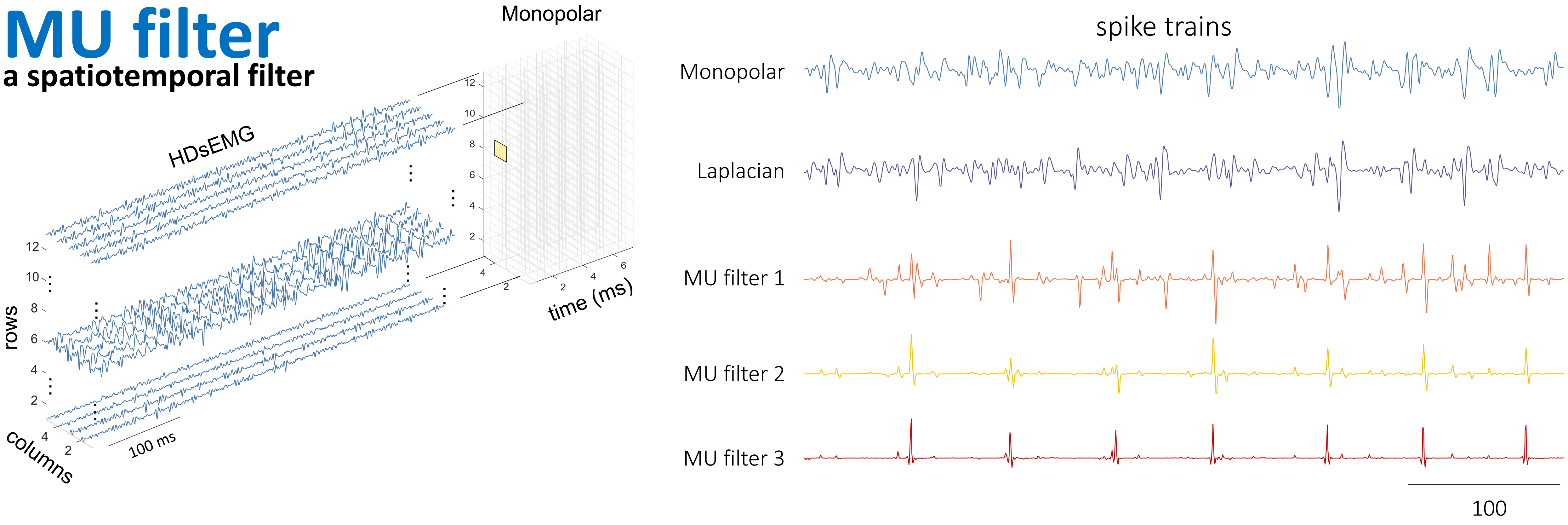
$$= \mathbf{c}_{\bar{\mathbf{s}}_i,\bar{\mathbf{s}}}^T \mathbf{H}^T\mathbf{H}^{-T}\mathbf{C}_{\bar{\mathbf{s}}}^{-1}\mathbf{H}^{-1}\mathbf{H}\bar{\mathbf{s}}(n)$$

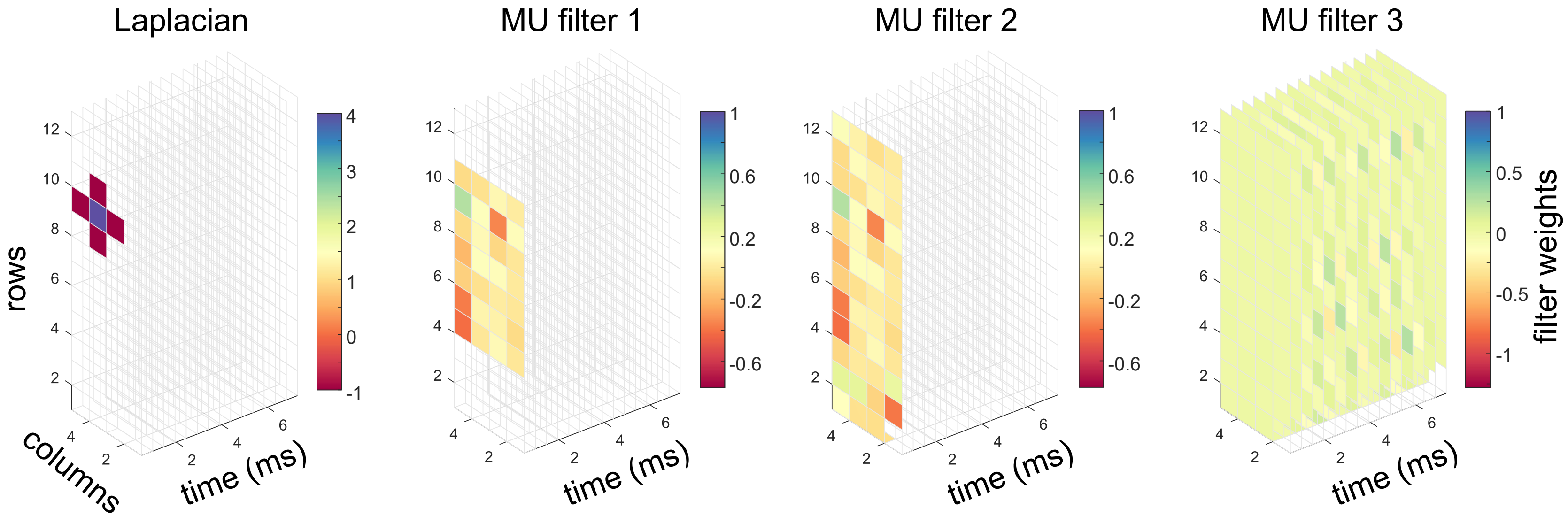
$$= \bar{s}_i(n)$$

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

MU filter

a spatiotemporal filter





Škarabot et al. The Journal of Physiology, 2023

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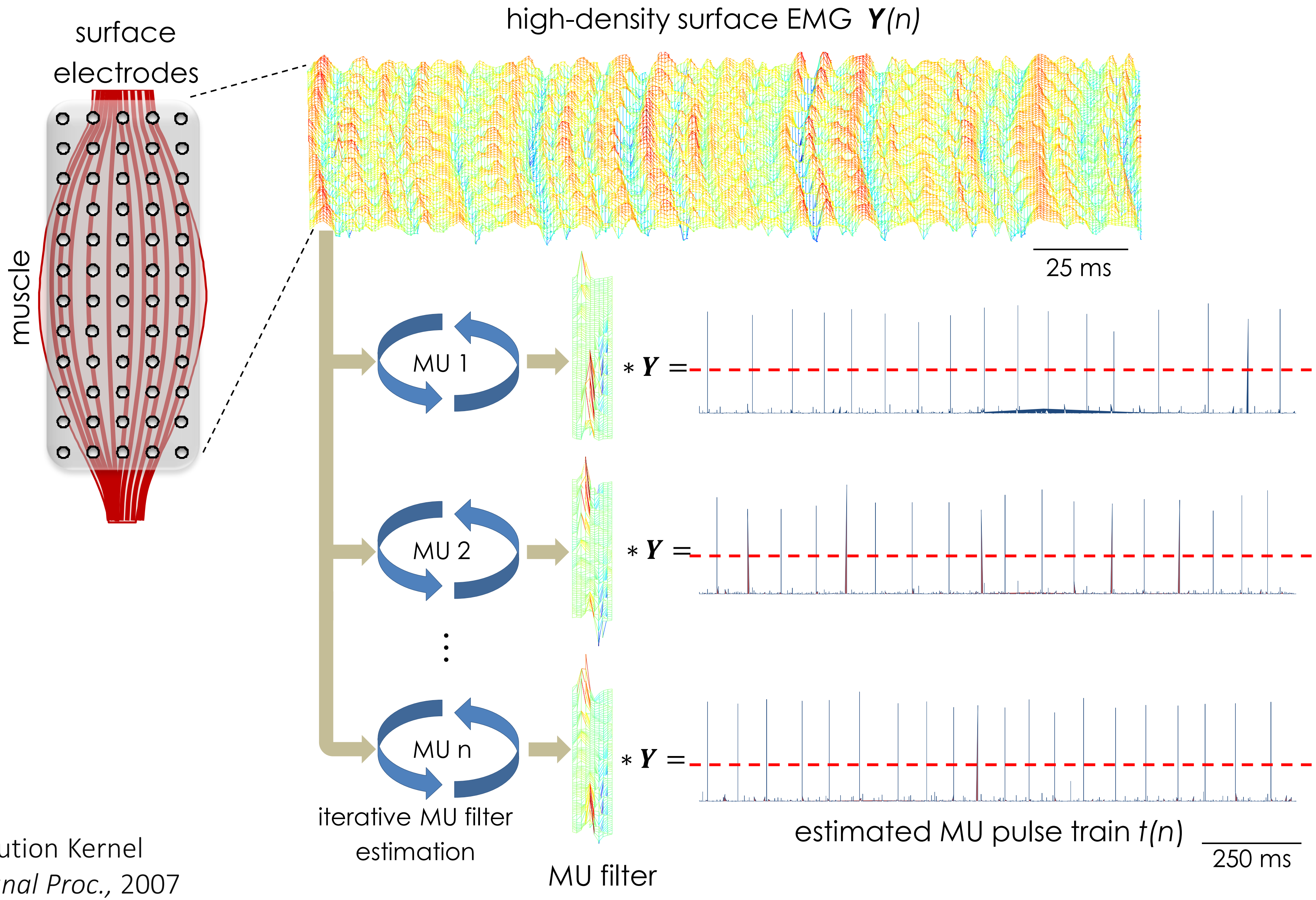
Identification of MU spike trains



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Surface EMG decomposition timeline & evolution of MU filters

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Holobar & Zazula 2003, 2004, 2007

2006

Template matching & surface EMG decomposition
De Luca et al. 2006

2011

Cumulative spike train
Negro & Farina 2011

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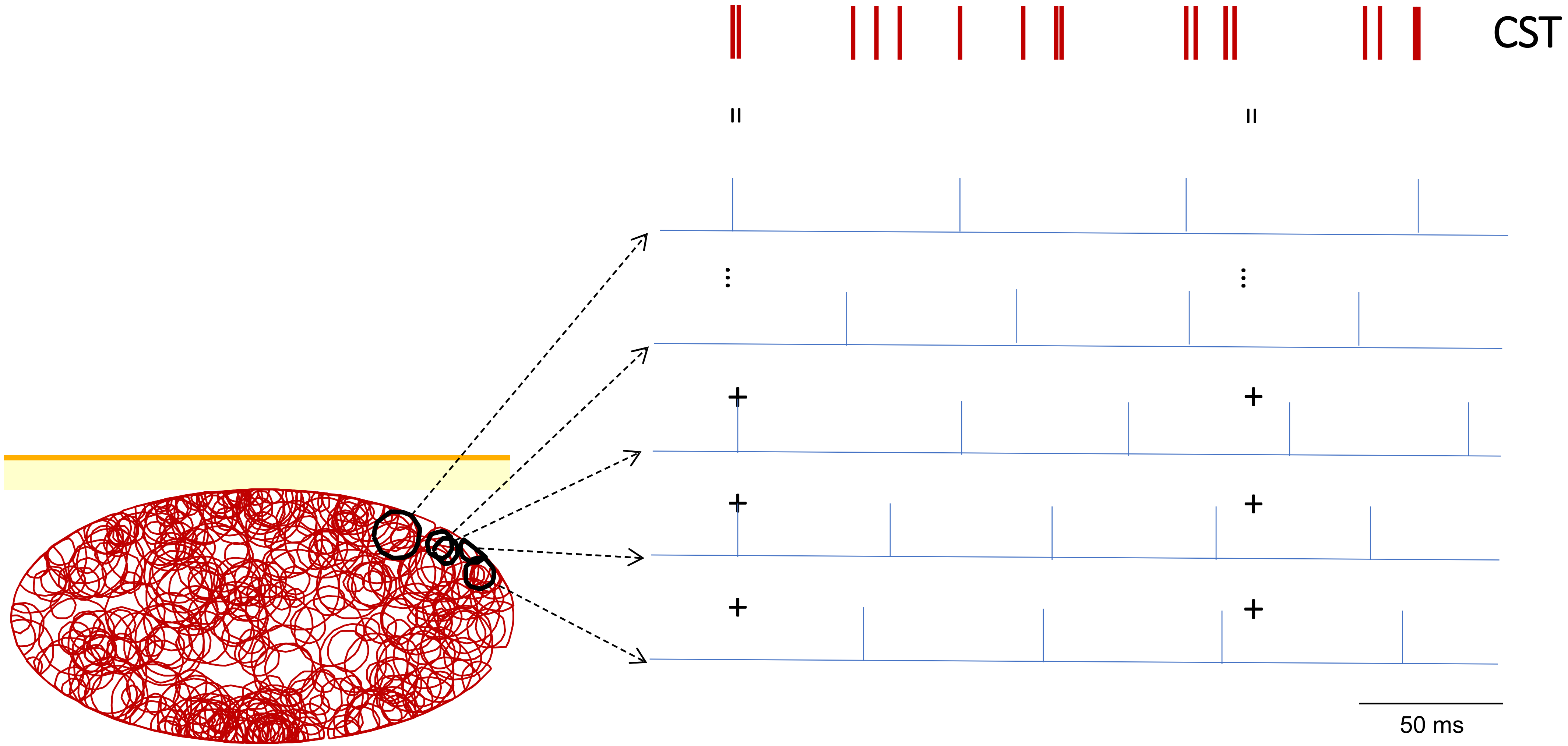
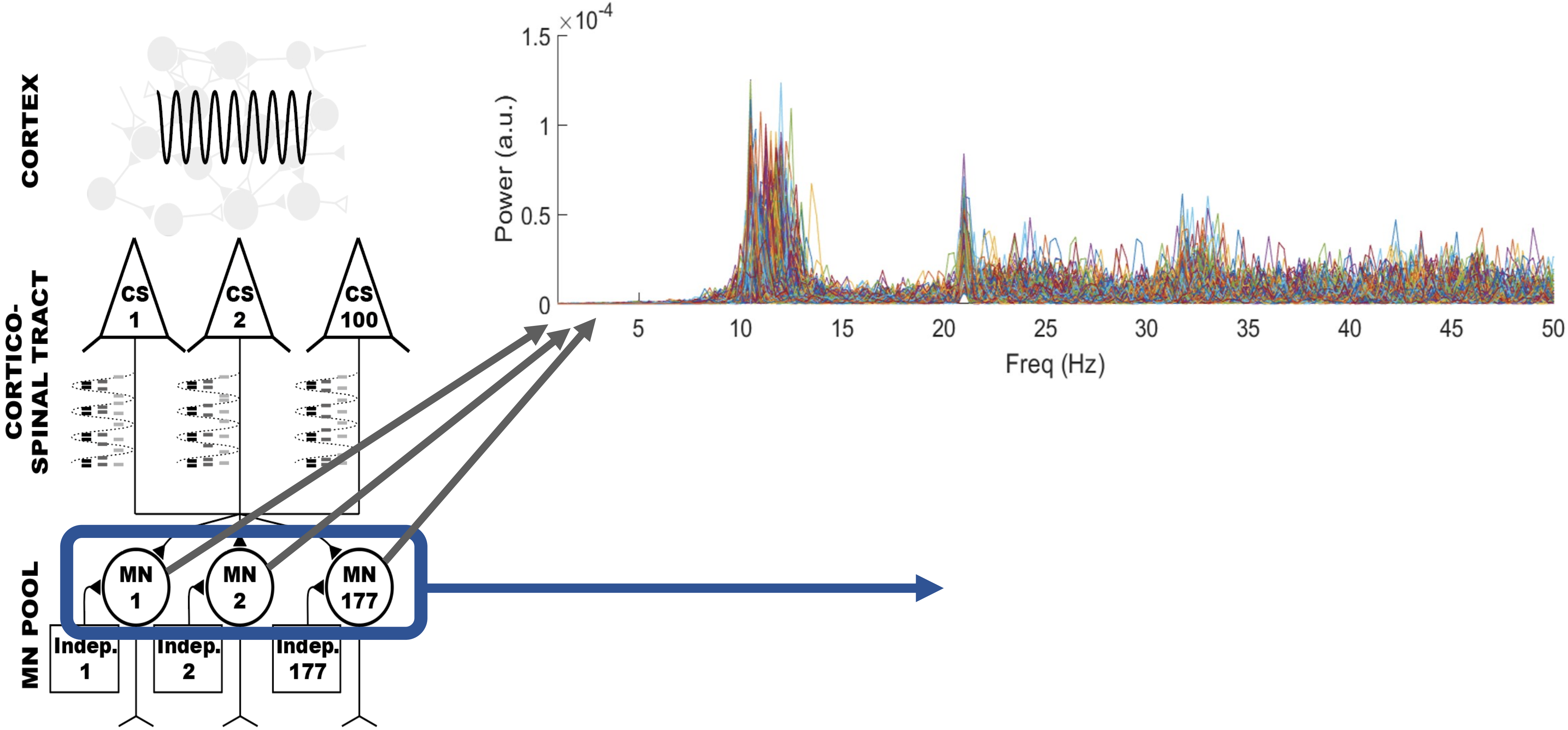
MUs & Cumulative Spike Train (CTS)



Negro & Farina, JP 2011, Holobar & Farina: Physiological Measurement, 2014

Inputs sampled by single neurons vs. population



courtesy of Prof. D. Farina, Imperial College London

Negro et al. *J Physiol* 2009; Farina et al., *J Physiol* 2014; Farina & Negro, *Exerc Sports Sci Rev* 2015

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High MU synchronization: pathological tremor
Holobar et al. 2012

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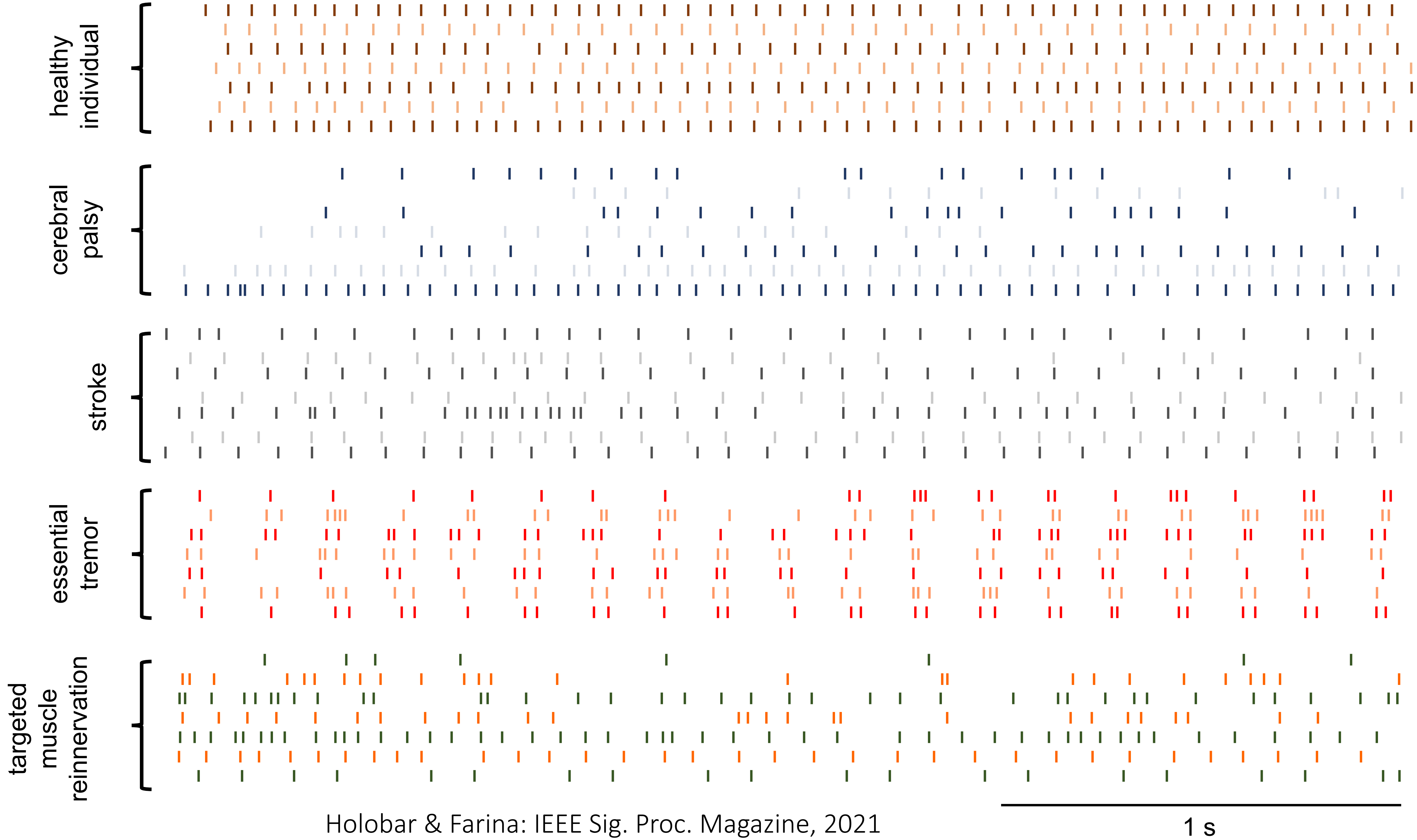

Holobar & Farina: IEEE Sig. Proc. Magazine, 2021

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Template matching & surface EMG decomposition
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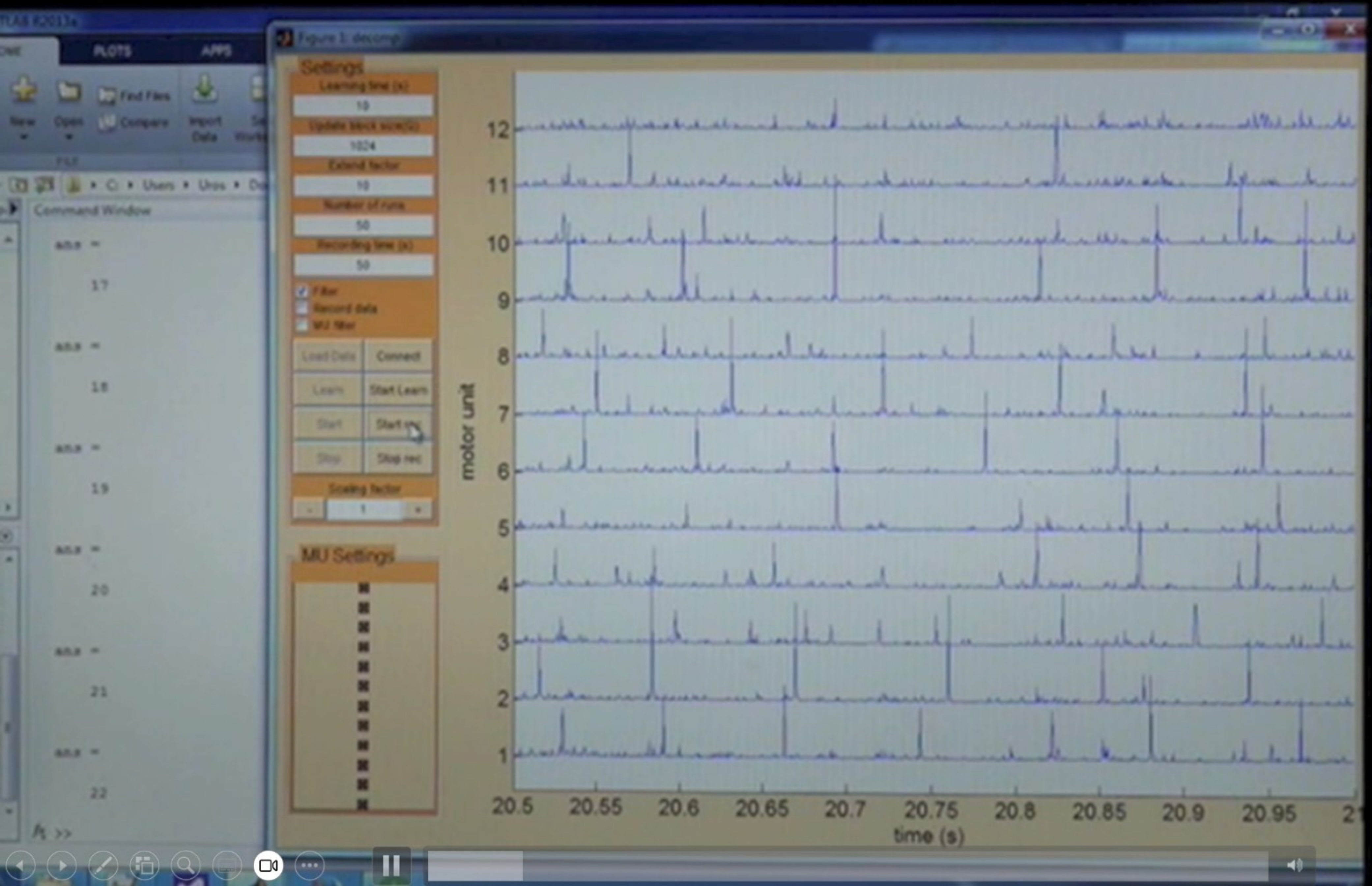
2011-2012

Cumulative spike train
Negro & Farina 2011

High MU synchronization: pathological tremor
Holobar et al. 2012

2013

Realtime Convolutive EMG decomposition (CKC, BSS)
Glaser et al. 2013



Settings

Learning time (s): 10

Update block size(s): 1024

Extend factor: 10

Number of runs: 50

Recording time (s): 50

☑ Filter

☐ Record data

☐ MU filter

Scaling factor: 1

```
ans =

    17

ans =

    18

ans =

    19

ans =

    20

ans =

    21

ans =

    22
```

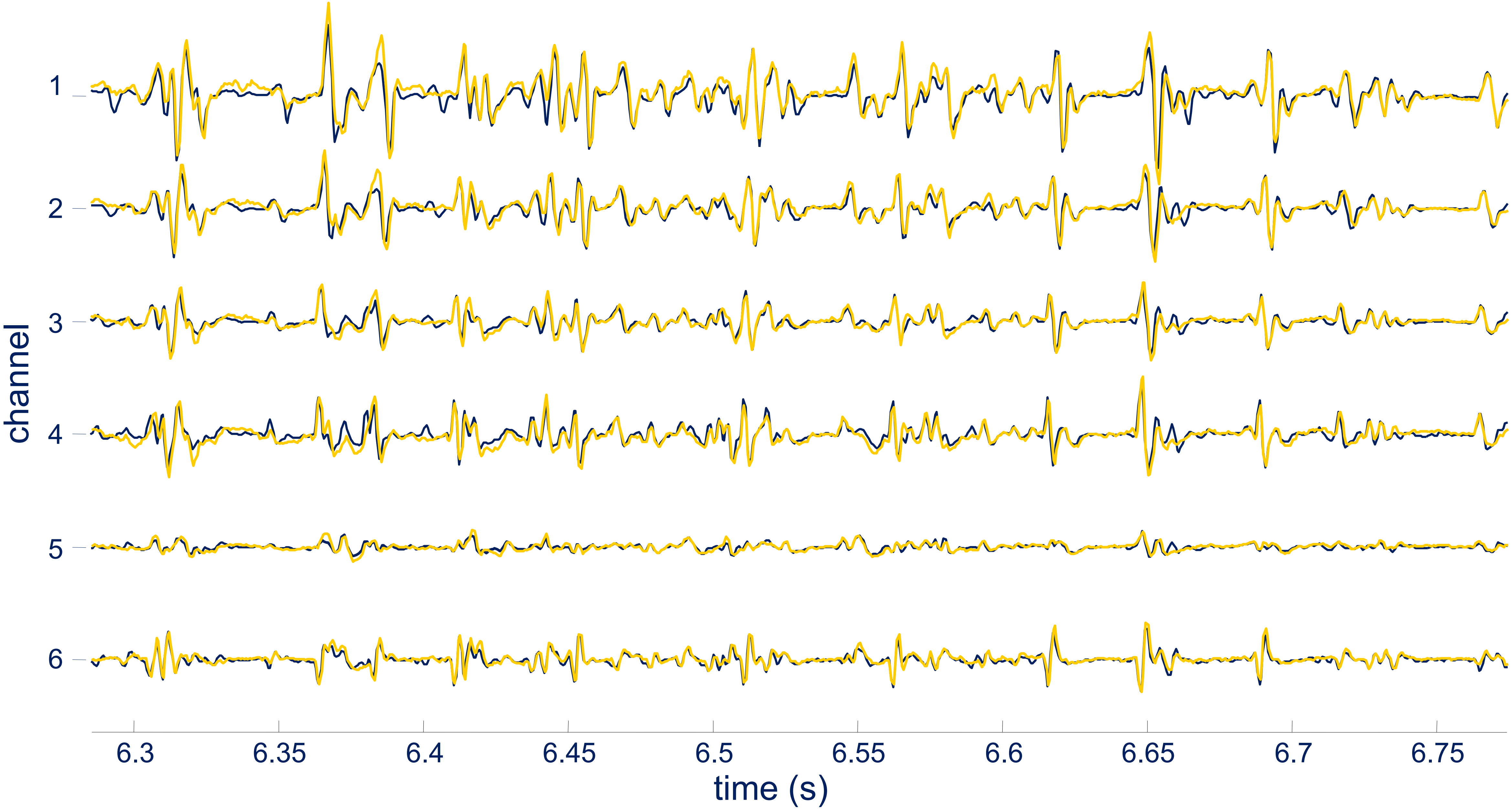
Surface EMG decomposition timeline & evolution of MU filters

2014

MU identification accuracy (Pulse-to-Noise Ratio – PNR)
Holobar et al. 2014

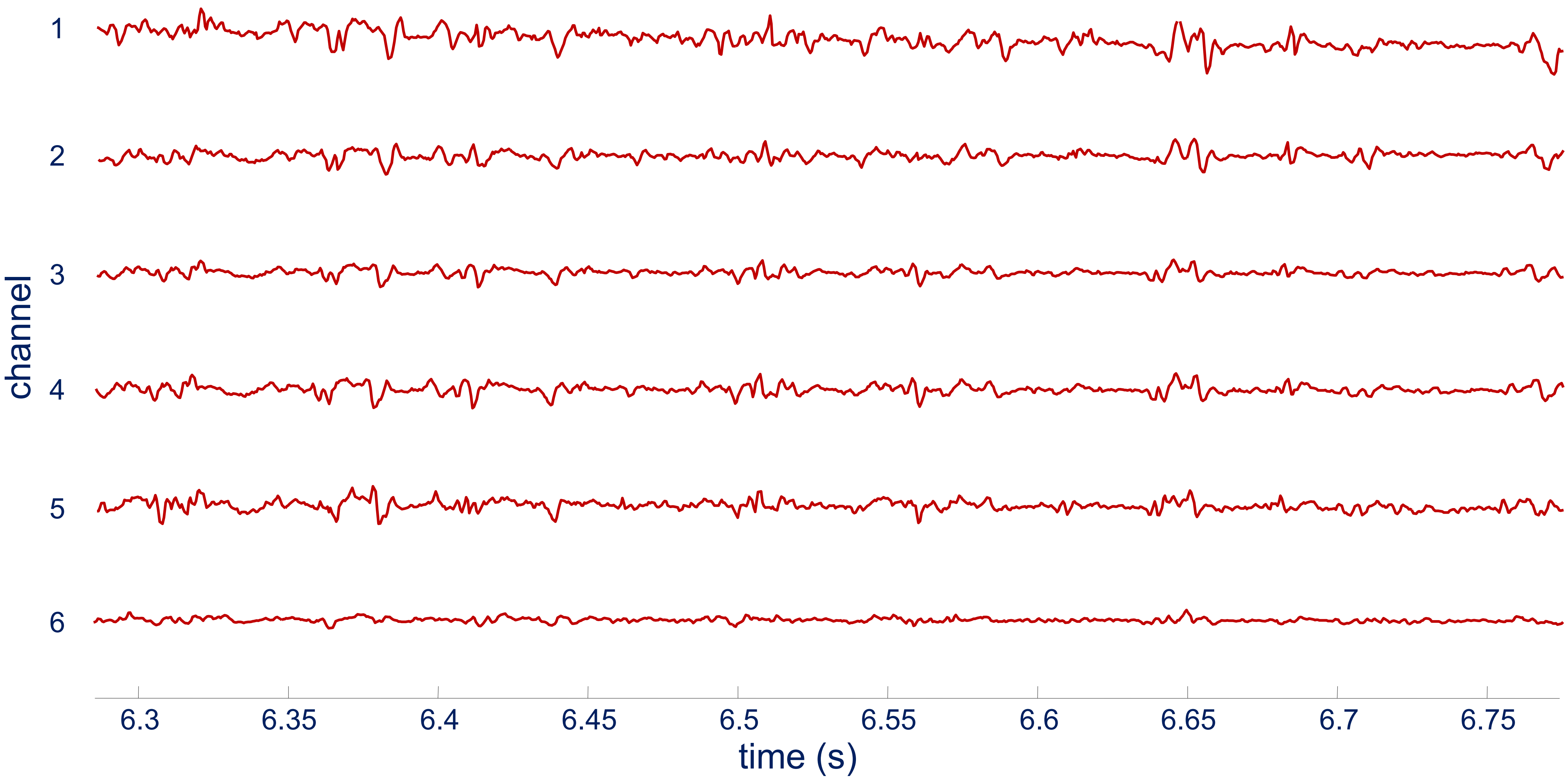
Abductor pollicis brevis: 10 % MVC

(Identified MUs account for 31 % - 57 % of signal energy)

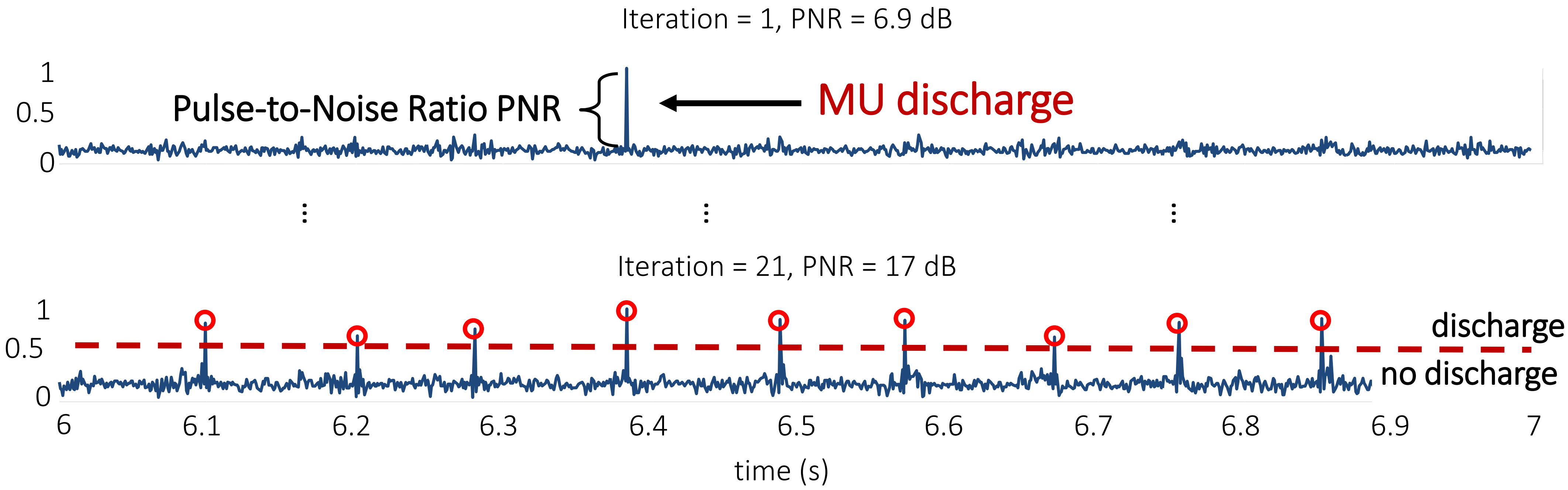


Residual after subtraction of MUAP trains

(Identified MUs account for 31 % - 57 % of signal energy)



Pulse-to-Noise Ratio (PNR)



Pulse-to-Noise Ratio (PNR):

- applied to EVERY identified motor unit
- no additional experimental costs
- reliable indicator of accuracy of motor unit identification

A. Holobar, D. Zazula: *IEEE TSP* 2007

Holobar, Minetto & Farina. *JNE* 2014

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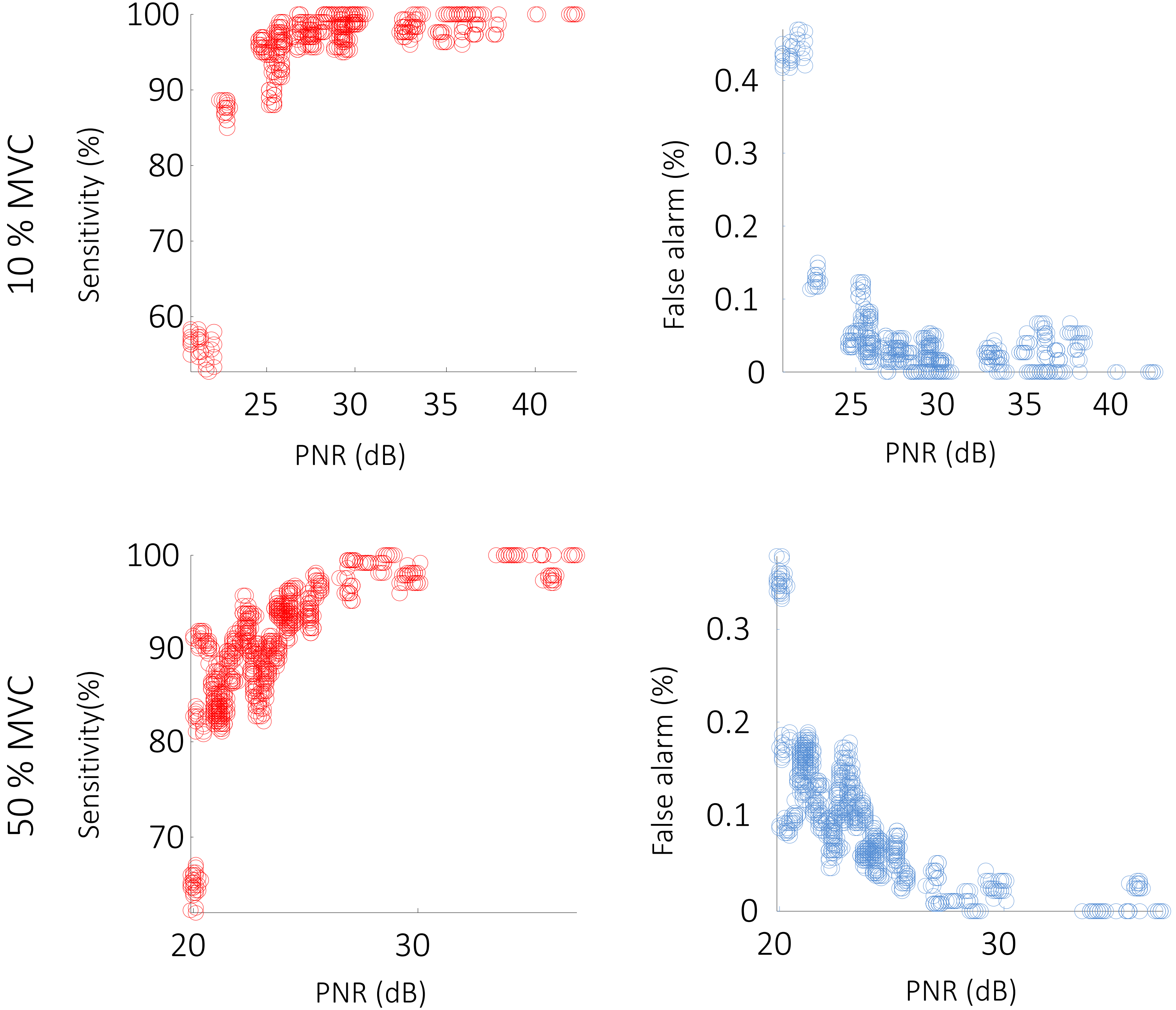
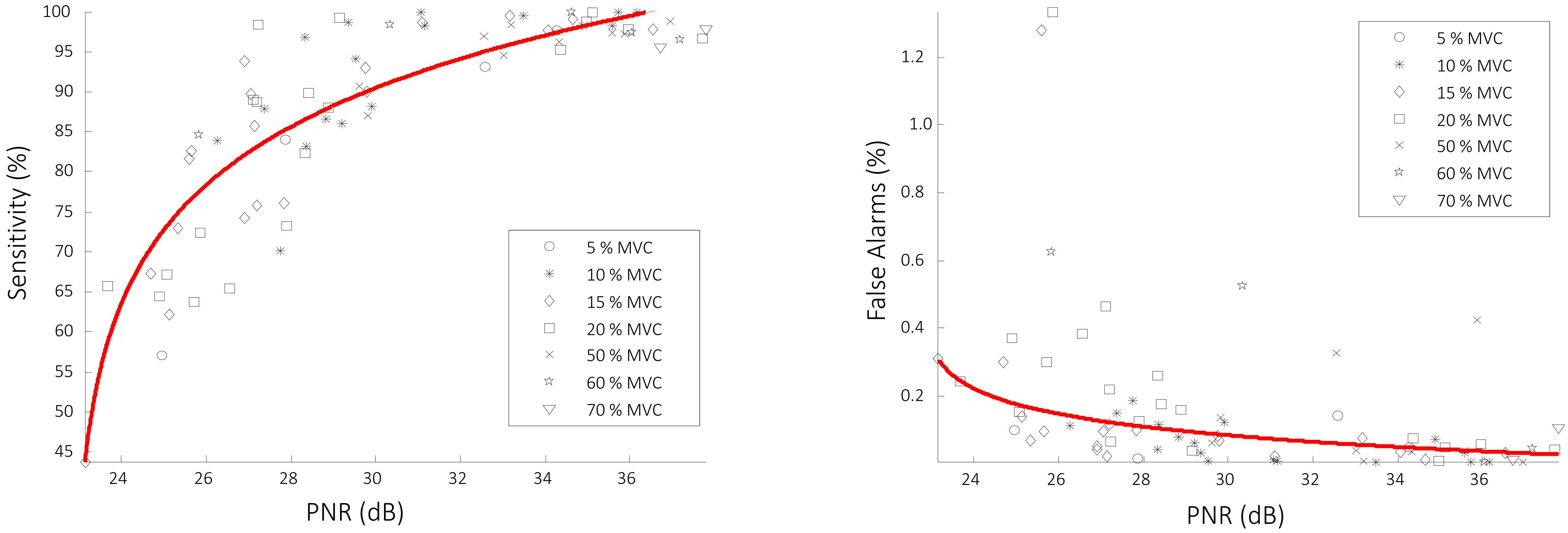
Synthetic surface EMG

SNR = 15 dB



Holobar, Minetto & Farina. *JNE* 2014

Experimental surface & intramuscular EMG



Holobar, Minetto & Farina. *JNE* 2014

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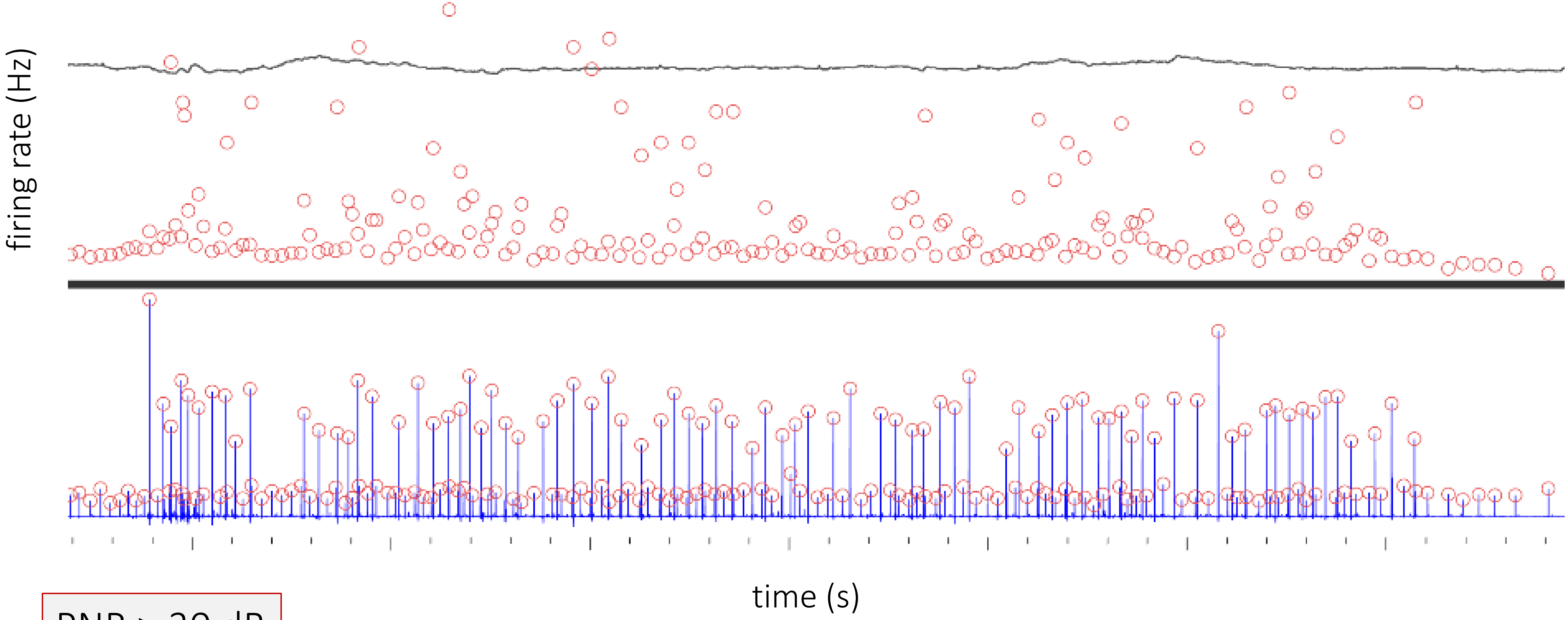
MU merging: high PNR is not enough



PNR > 30 dB
$\text{CoV}_{\text{ISI}} > 0.5$

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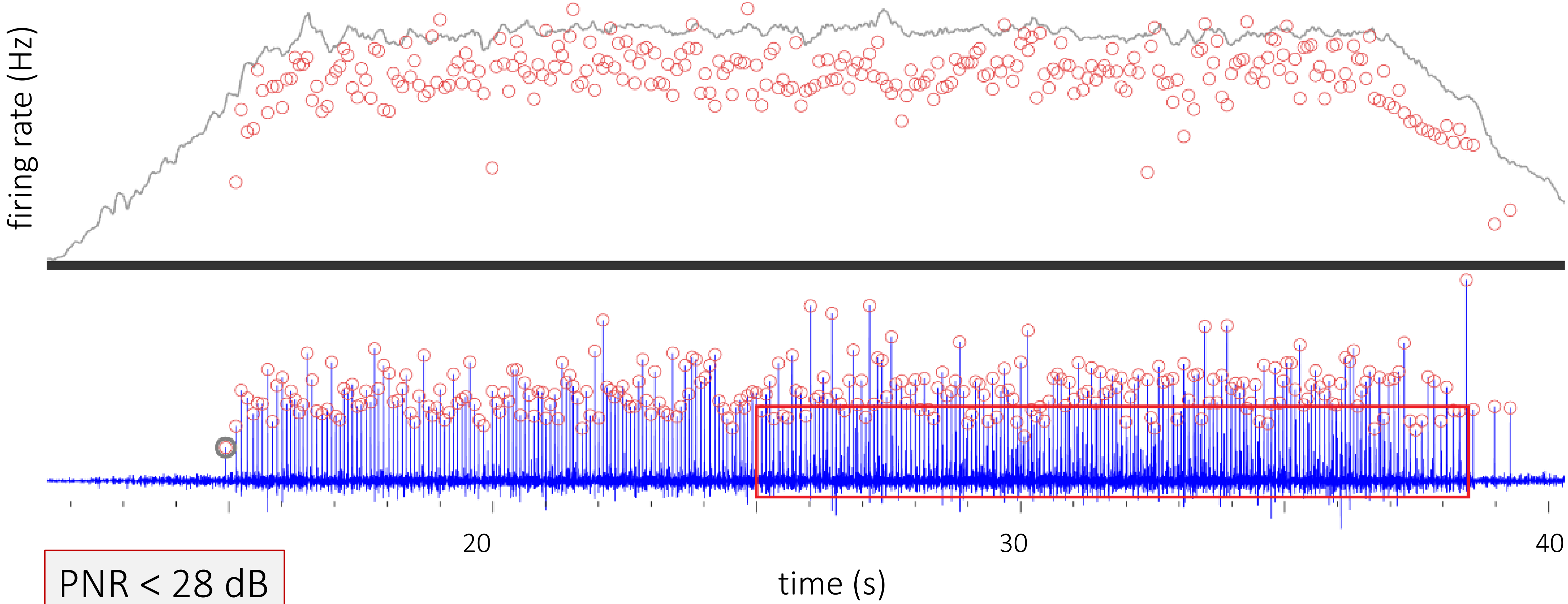
MU merging: low CoV$_{ISI}$ is not enough



PNR < 28 dB
CoV$_{ISI}$ < 0.3

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Surface EMG decomposition timeline & evolution of MU filters

2014

MU identification accuracy (Pulse-to-Noise Ratio – PNR)
Holobar et al. 2014

2015

fastICA framework
Maoqi et al. 2015

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Dynamic surface EMG – template matching
De Luca et al. 2015

2016

High-density intramuscular EMG decomposition (BSS)
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Dynamic surface EMG – convolutive BSS
Glaser et al. 2017

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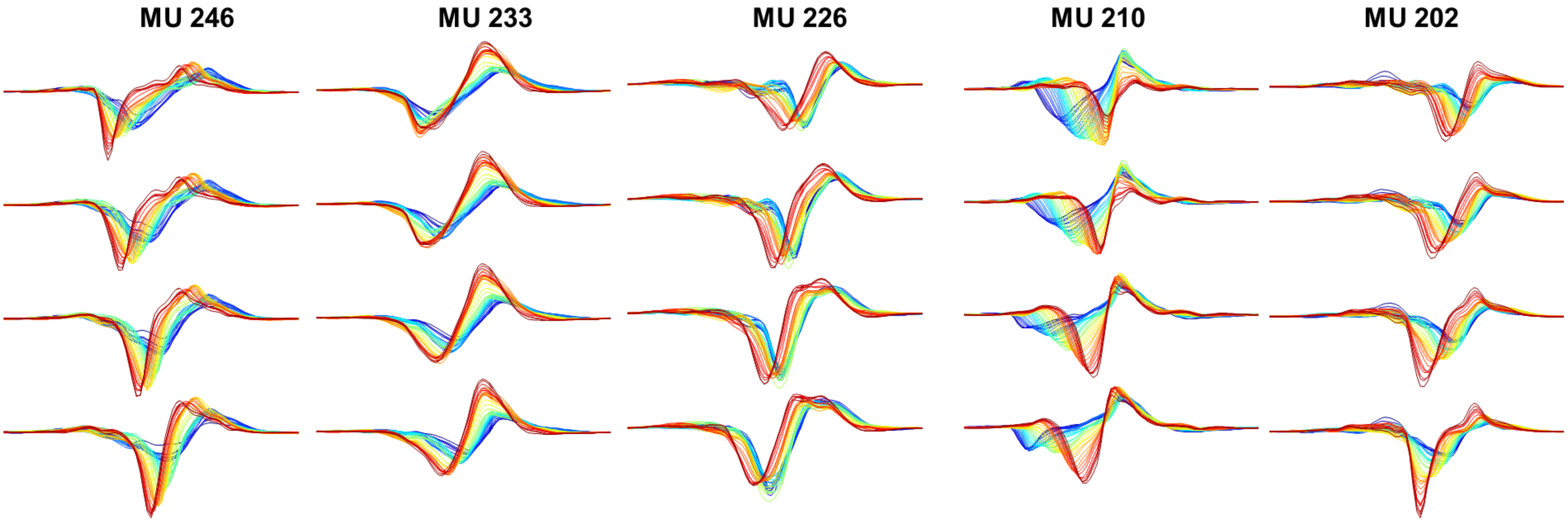
Shortening of Biceps Brachii



V. Glaser & A. Holobar, 2018

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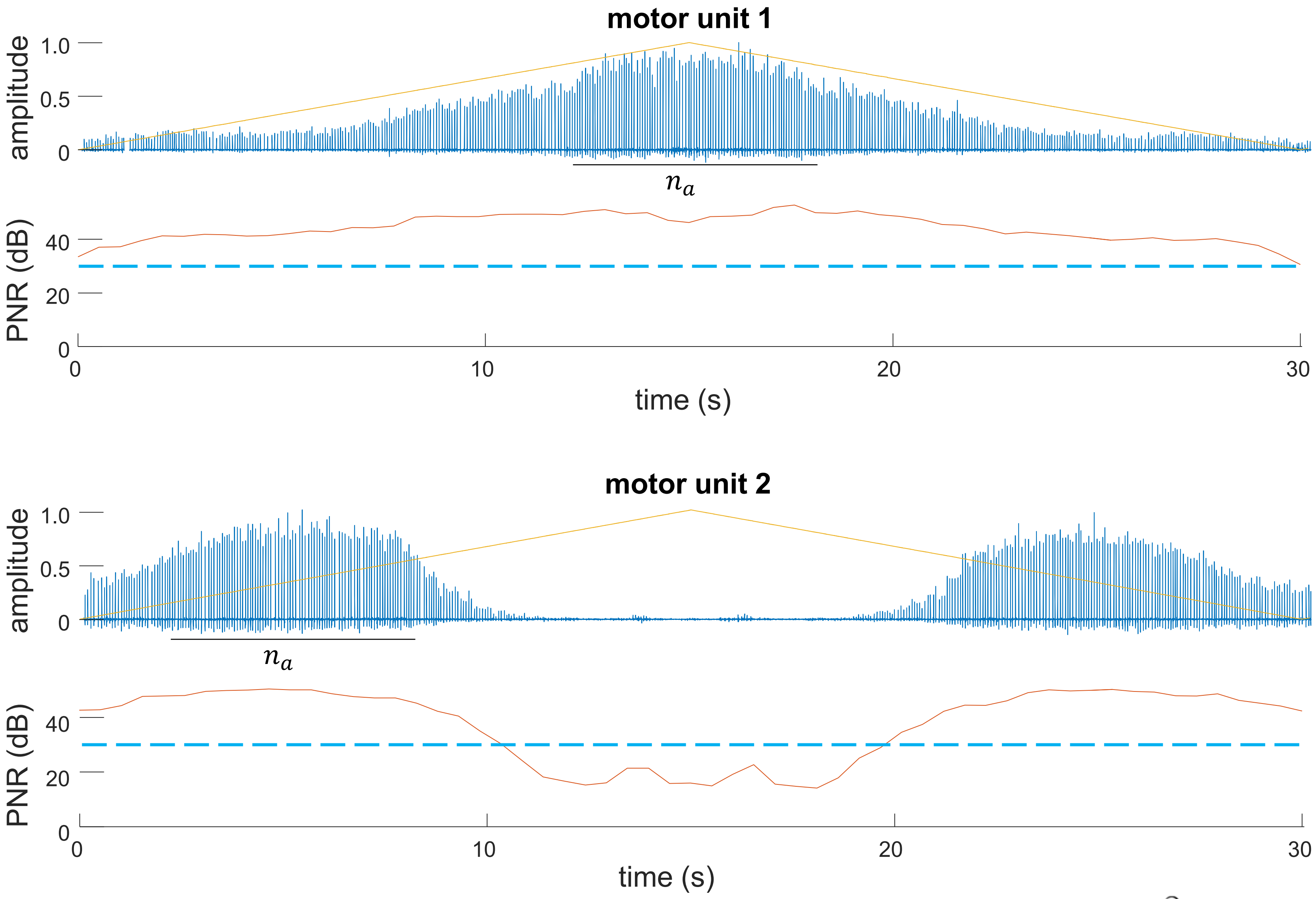
Impact of shortening on MU spike identification



V. Glaser & A. Holobar, 2018

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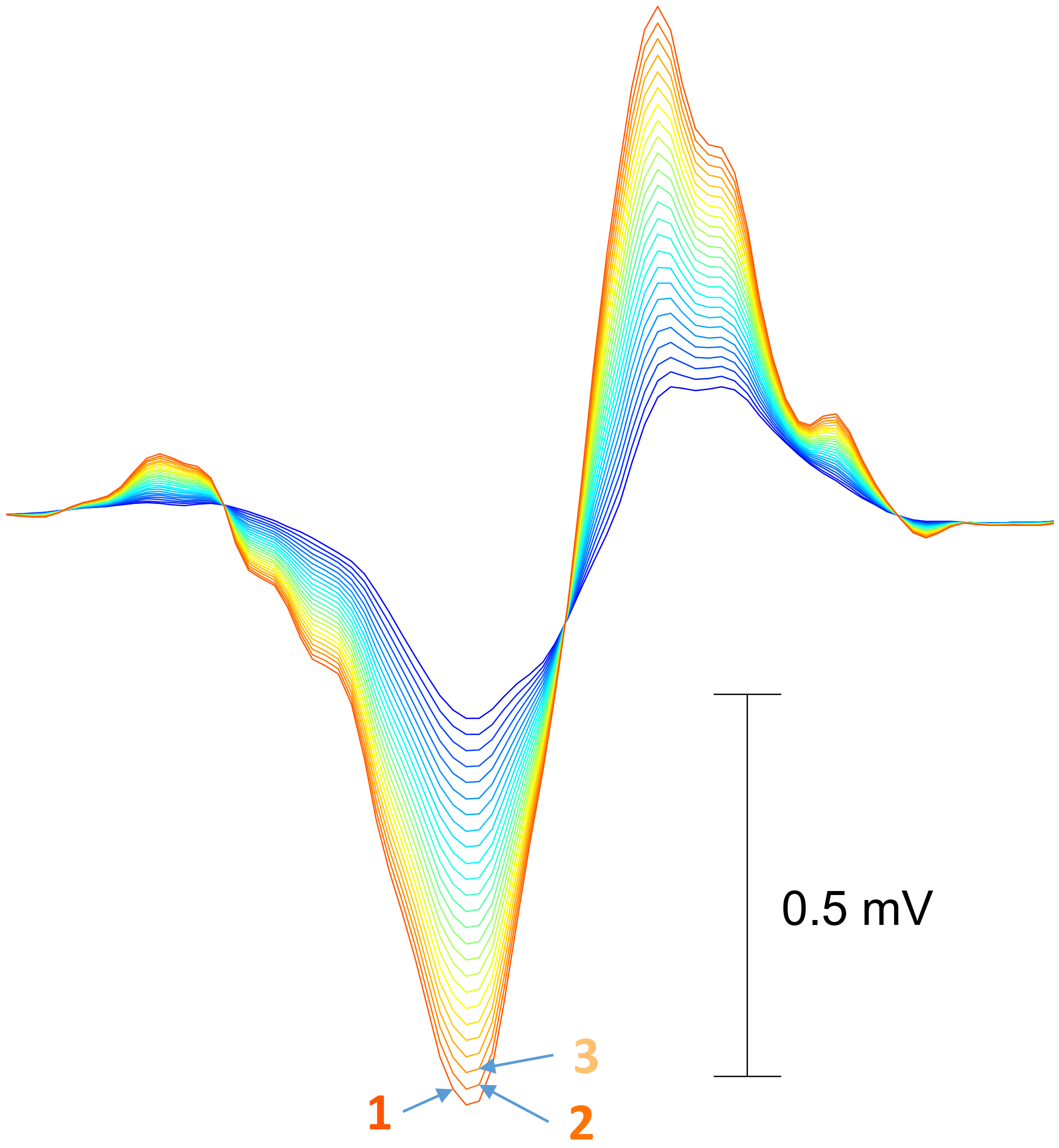
MUAP shape prediction on each HDEMG channel

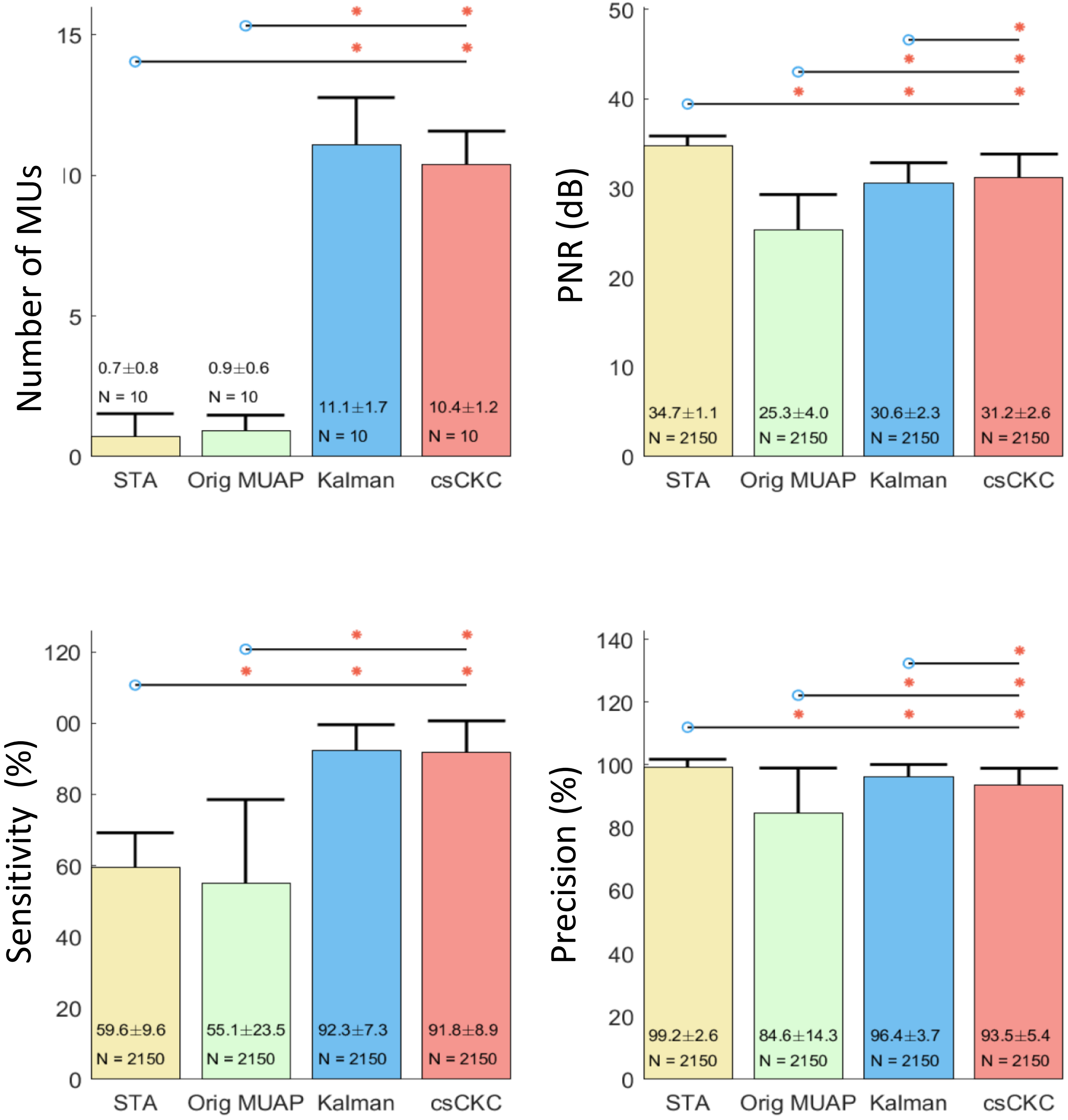


We can predict the change of MUAP based on already identified changes.

We can integrate this prediction into MU filter estimation (Kalman filter based prediction of MU filters).

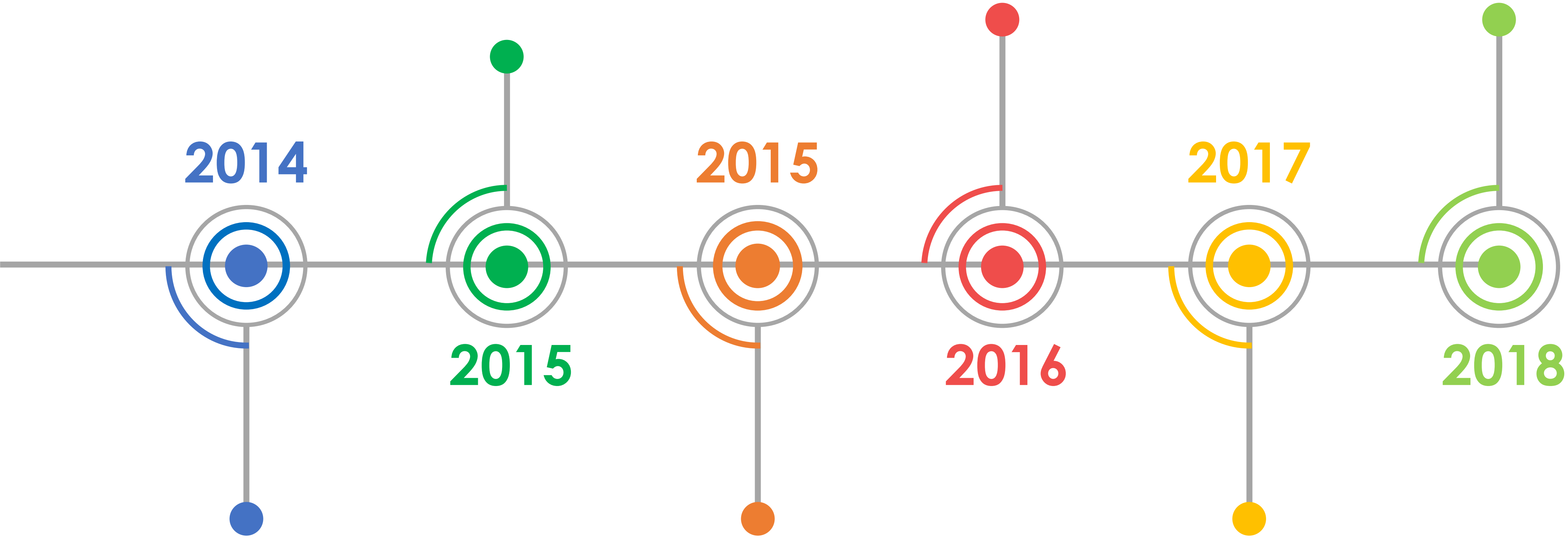
Kramberger & Holobar, IEEE Access 2021

MU tracking (in dynamic and/or fatiguing contractions)



Kalman - Kramberger & Holobar, IEEE Access 2021
csCKC - Glaser & Holobar, IEEE TNSRE 2019

Surface EMG decomposition timeline & evolution of MU filters



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Extension to Convolutive model of EEG
Holobar et al. 2018

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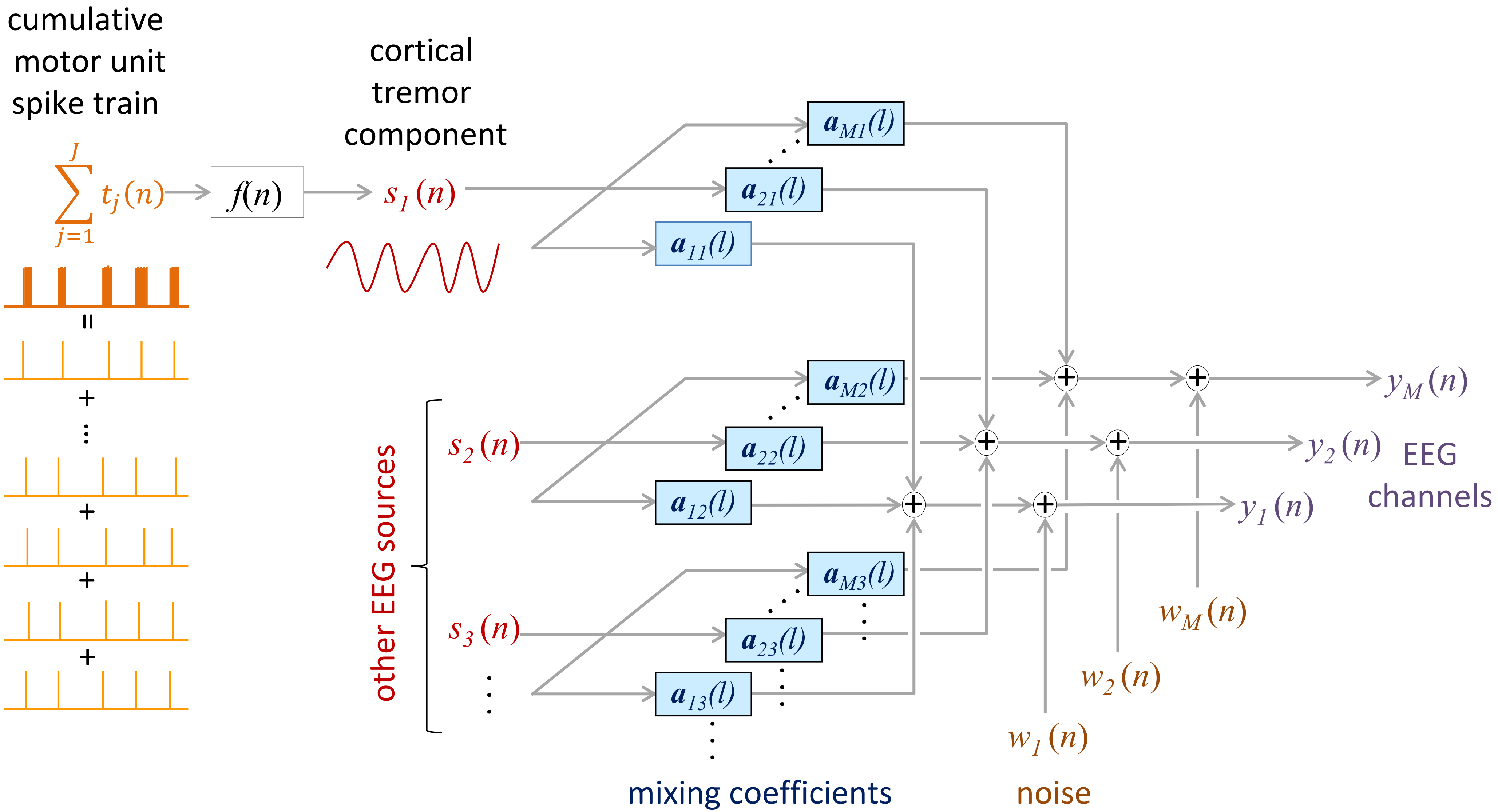
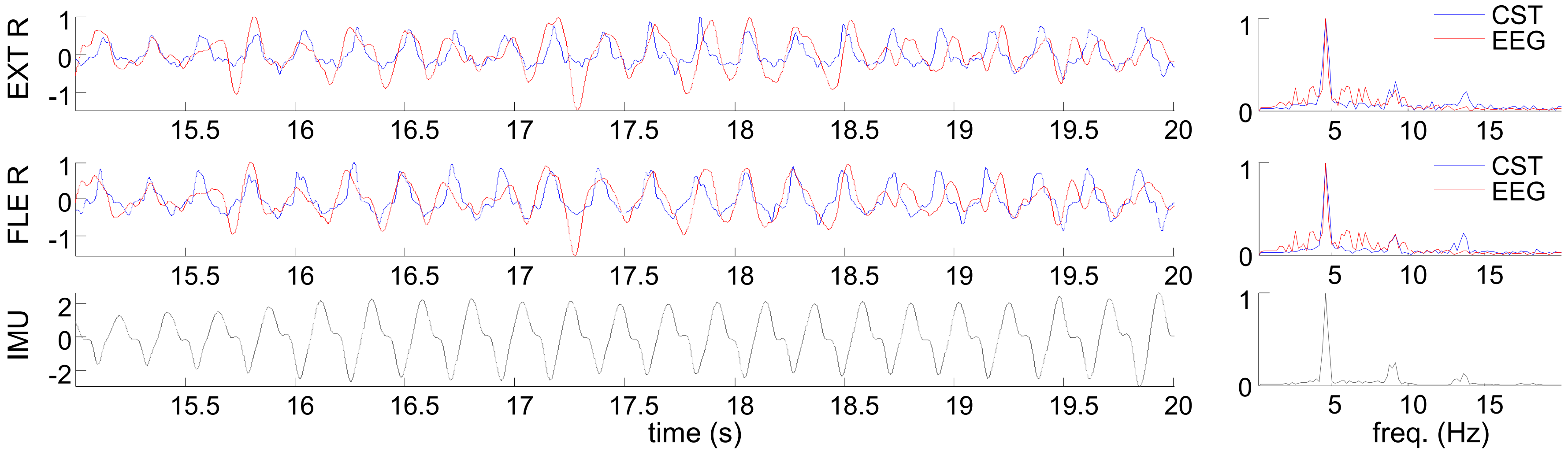
EMG to EEG filter transfer



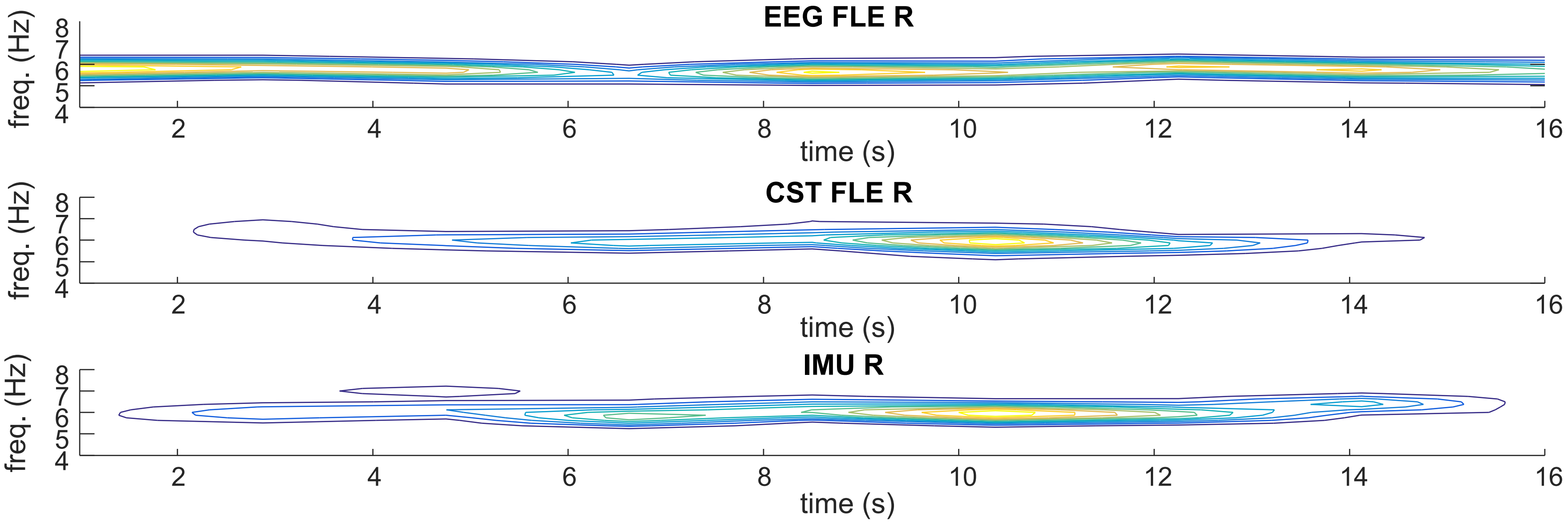
Holobar et al. 2018

EMG to EEG filter transfer: pathological tremor

A)



B)



Holobar et al. 2018

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Extension to Convolutive model of EEG
Holobar et al. 2018

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Rapid contractions
Del Vecchio et al. 2019

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Surface EMG decomposition timeline & evolution of MU filters

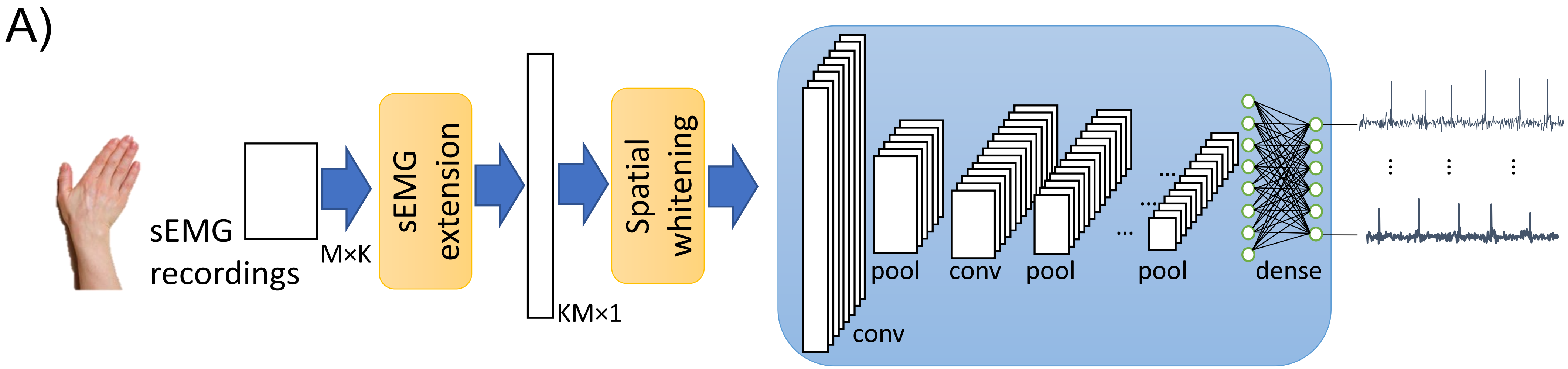
2020

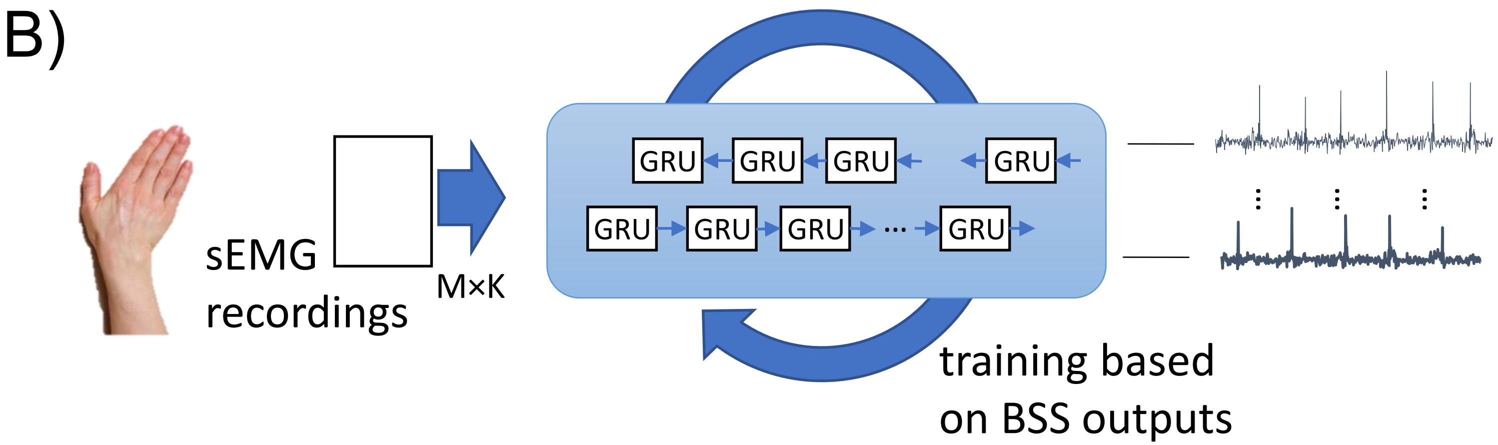
MU identification in newborns
Del Vecchio et al. 2020

2020

Deep learning & surface EMG decomposition
Clarke et al. 2020
Urh et al. 2020

MU identification from HDEMG by deep NNs





Clarke et al. 2020, Urh et al. 2020, Holobar & Farina: IEEE Sig. Proc. Magazine, 2021

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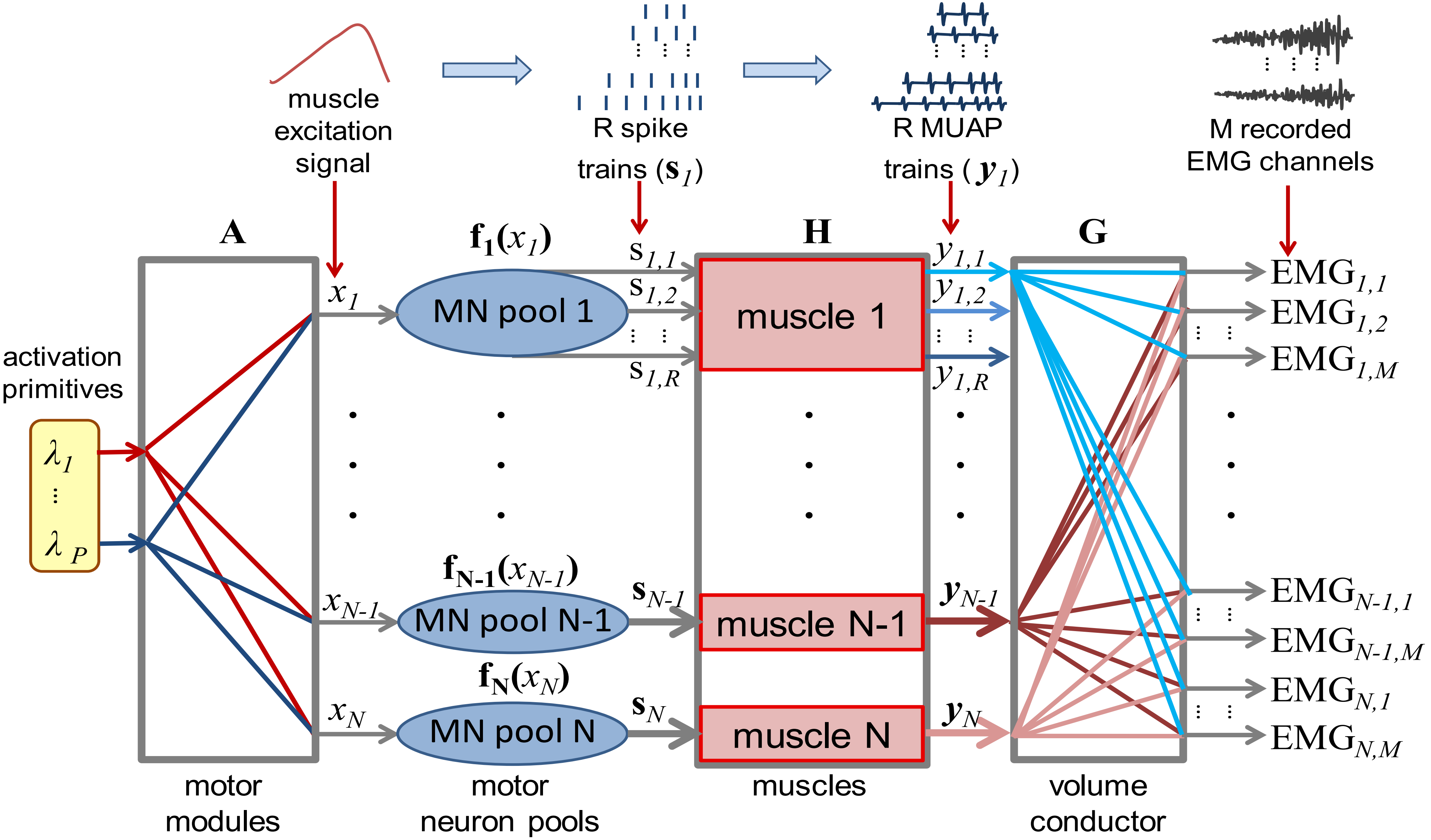

Holobar & Farina, *Physiol Measur* 2014

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Banks of MU filters & MU filter transfer
Francic et al. 2021

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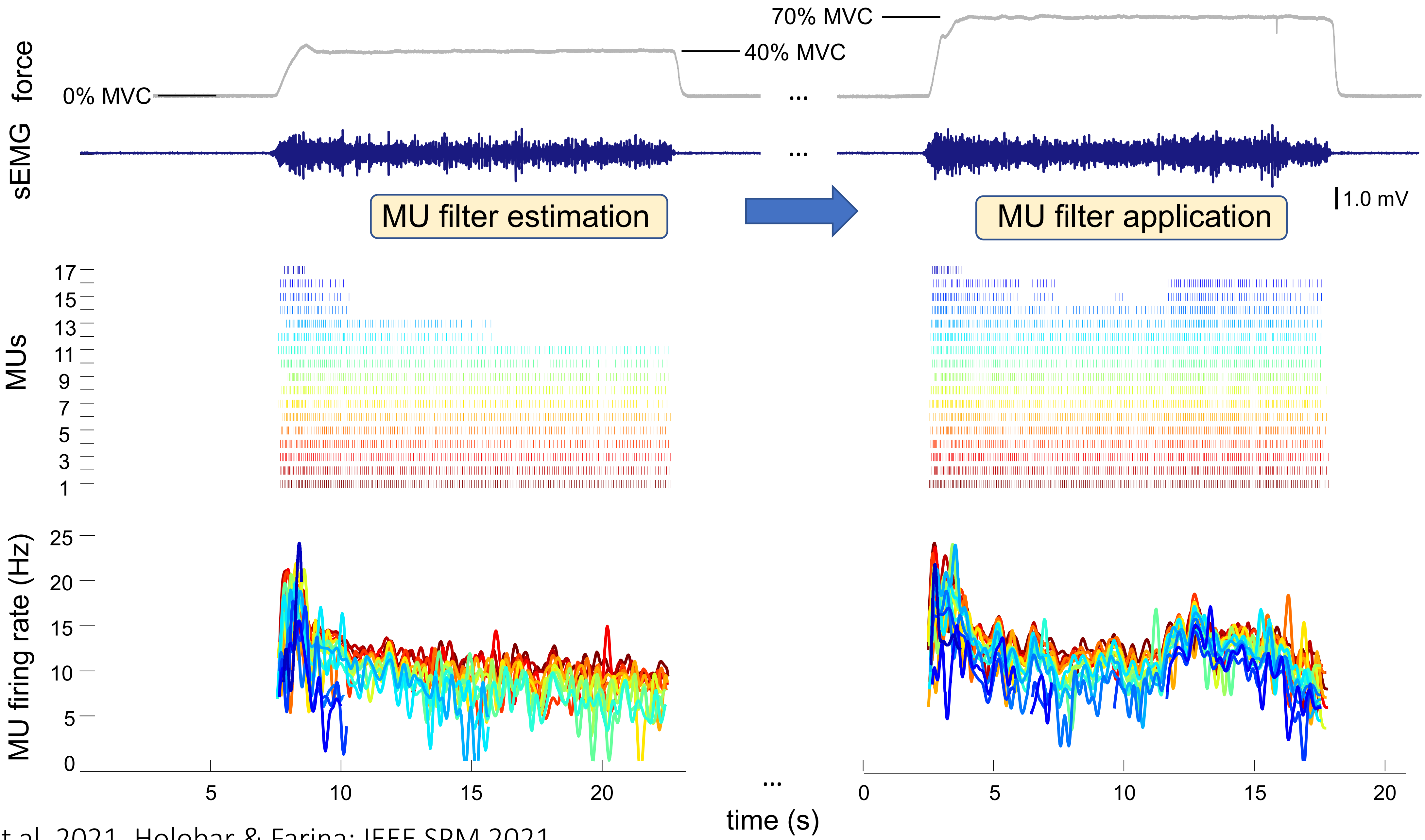
MU filter reused – pairwise comparisons



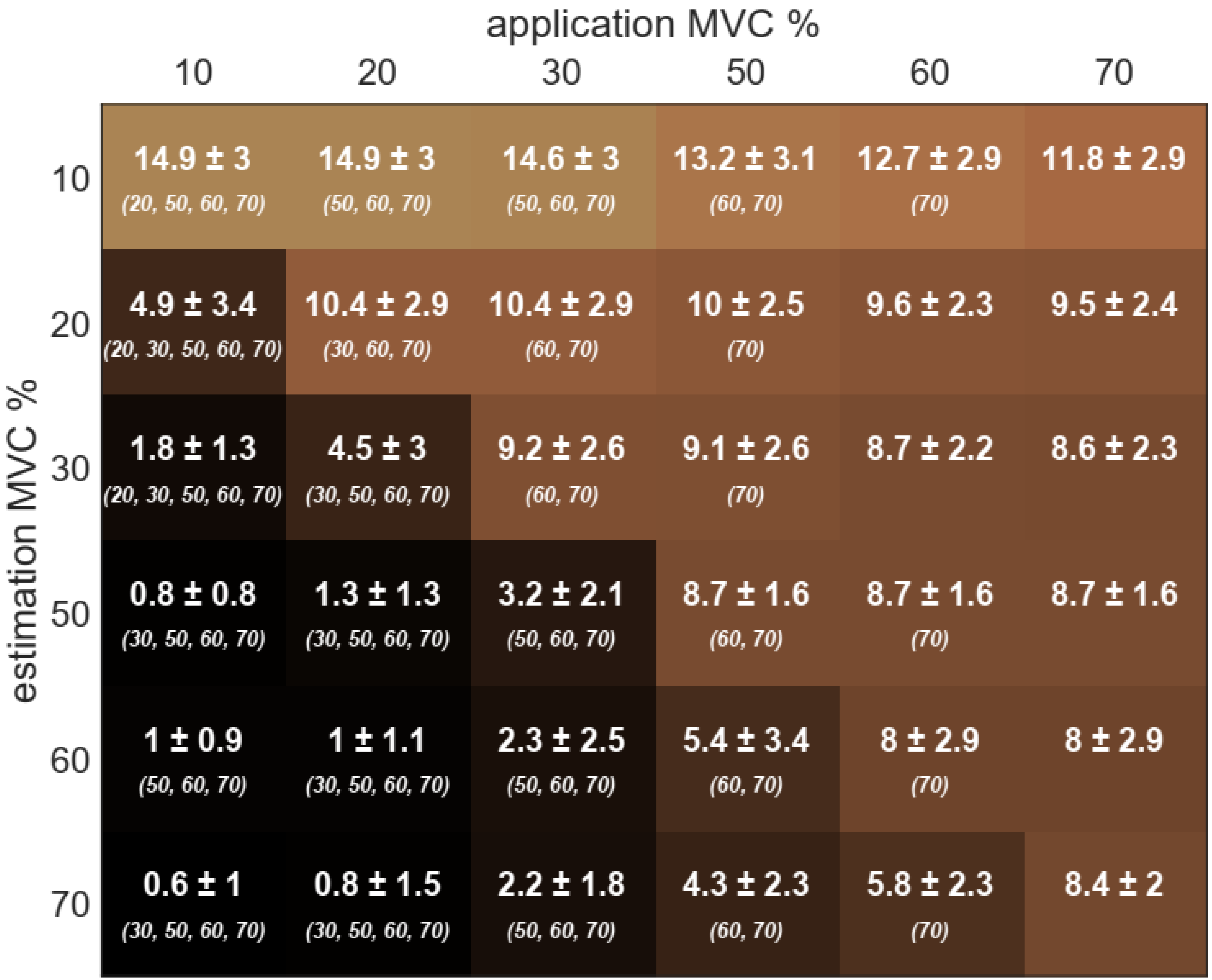
Francic et al. 2021, Holobar & Farina: IEEE SPM 2021

EXAMPLE 1:

MU tracking across different contraction levels

No. of tracked MUs

Synthetic HDsEMG, SNR = 20 dB



application MVC %

estimation MVC %

	10	20	30	50	60	70
10	14.9 ± 3 *(20, 50, 60, 70)*	14.9 ± 3 *(50, 60, 70)*	14.6 ± 3 *(50, 60, 70)*	13.2 ± 3.1 *(60, 70)*	12.7 ± 2.9 *(70)*	11.8 ± 2.9
20	4.9 ± 3.4 *(20, 30, 50, 60, 70)*	10.4 ± 2.9 *(30, 60, 70)*	10.4 ± 2.9 *(60, 70)*	10 ± 2.5 *(70)*	9.6 ± 2.3	9.5 ± 2.4
30	1.8 ± 1.3 *(20, 30, 50, 60, 70)*	4.5 ± 3 *(30, 50, 60, 70)*	9.2 ± 2.6 *(60, 70)*	9.1 ± 2.6 *(70)*	8.7 ± 2.2	8.6 ± 2.3
50	0.8 ± 0.8 *(30, 50, 60, 70)*	1.3 ± 1.3 *(30, 50, 60, 70)*	3.2 ± 2.1 *(50, 60, 70)*	8.7 ± 1.6 *(60, 70)*	8.7 ± 1.6 *(70)*	8.7 ± 1.6
60	1 ± 0.9 *(50, 60, 70)*	1 ± 1.1 *(30, 50, 60, 70)*	2.3 ± 2.5 *(50, 60, 70)*	5.4 ± 3.4 *(60, 70)*	8 ± 2.9 *(70)*	8 ± 2.9
70	0.6 ± 1 *(30, 50, 60, 70)*	0.8 ± 1.5 *(30, 50, 60, 70)*	2.2 ± 1.8 *(50, 60, 70)*	4.3 ± 2.3 *(60, 70)*	5.8 ± 2.3 *(70)*	8.4 ± 2

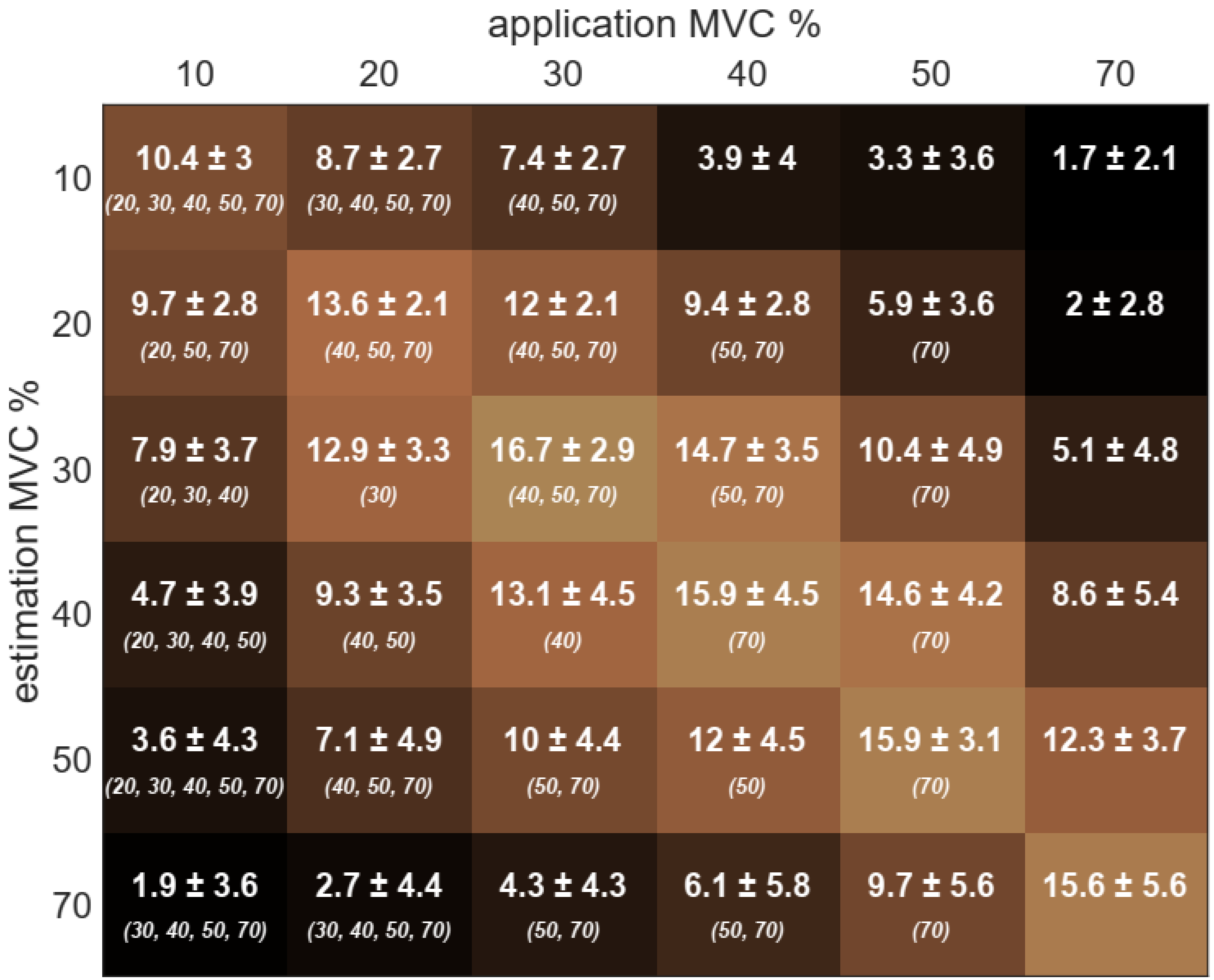
Frančič & Holobar, IEEE Access 2021

EXAMPLE 2:

MU tracking across different contraction levels

No. of tracked MUs

First Dorsal Interosseous (FDI)



	10	20	30	40	50	70
10	10.4 ± 3 *(20, 30, 40, 50, 70)*	8.7 ± 2.7 *(30, 40, 50, 70)*	7.4 ± 2.7 *(40, 50, 70)*	3.9 ± 4	3.3 ± 3.6	1.7 ± 2.1
20	9.7 ± 2.8 *(20, 50, 70)*	13.6 ± 2.1 *(40, 50, 70)*	12 ± 2.1 *(40, 50, 70)*	9.4 ± 2.8 *(50, 70)*	5.9 ± 3.6 *(70)*	2 ± 2.8
30	7.9 ± 3.7 *(20, 30, 40)*	12.9 ± 3.3 *(30)*	16.7 ± 2.9 *(40, 50, 70)*	14.7 ± 3.5 *(50, 70)*	10.4 ± 4.9 *(70)*	5.1 ± 4.8
40	4.7 ± 3.9 *(20, 30, 40, 50)*	9.3 ± 3.5 *(40, 50)*	13.1 ± 4.5 *(40)*	15.9 ± 4.5 *(70)*	14.6 ± 4.2 *(70)*	8.6 ± 5.4
50	3.6 ± 4.3 *(20, 30, 40, 50, 70)*	7.1 ± 4.9 *(40, 50, 70)*	10 ± 4.4 *(50, 70)*	12 ± 4.5 *(50)*	15.9 ± 3.1 *(70)*	12.3 ± 3.7
70	1.9 ± 3.6 *(30, 40, 50, 70)*	2.7 ± 4.4 *(30, 40, 50, 70)*	4.3 ± 4.3 *(50, 70)*	6.1 ± 5.8 *(50, 70)*	9.7 ± 5.6 *(70)*	15.6 ± 5.6

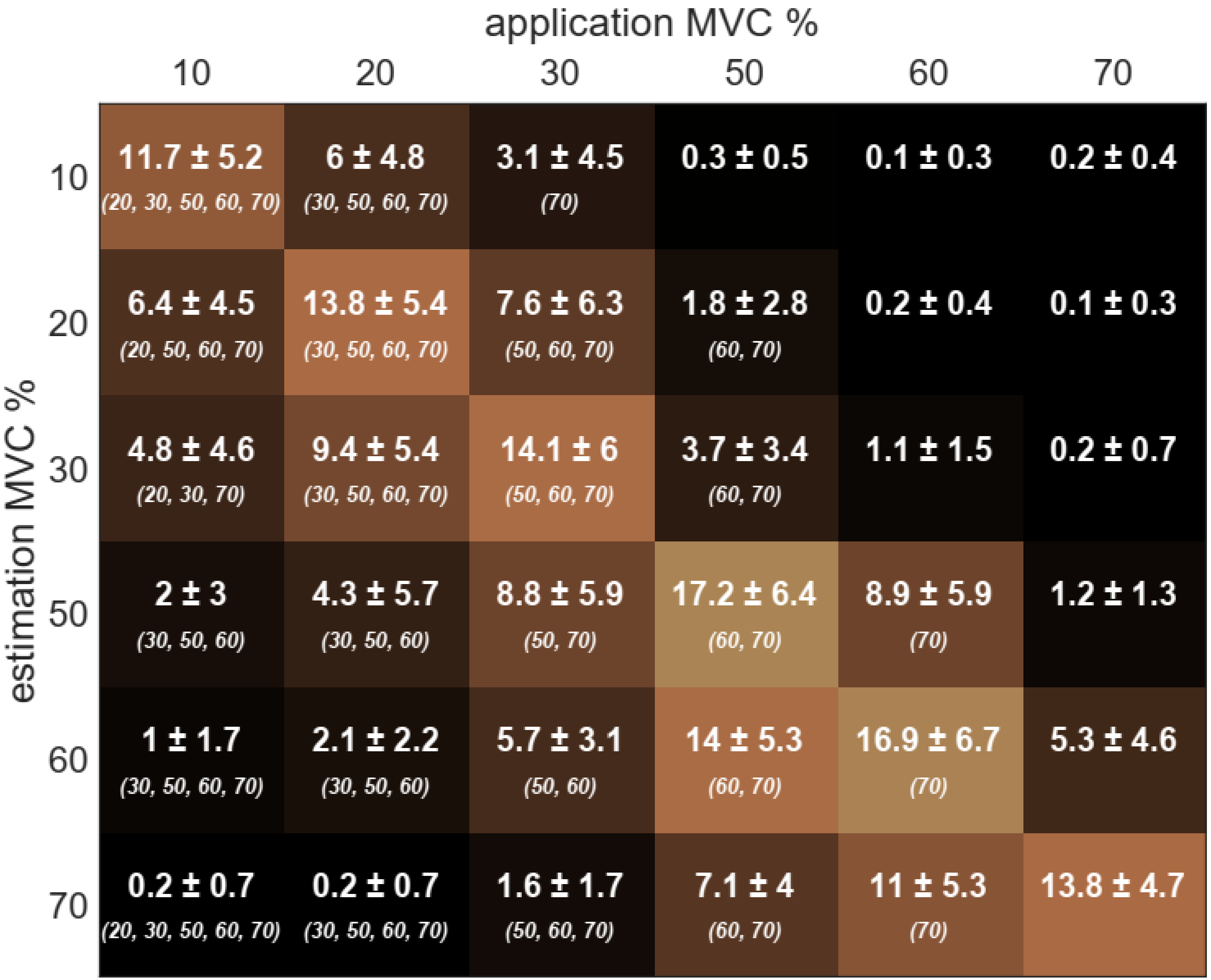
Frančič & Holobar, IEEE Access 2021

EXAMPLE 3:

MU tracking across different contraction levels

No. of tracked MUs

Tibialis Anterior (TA)



application MVC %

estimation MVC %

estimation MVC % \ application MVC %	10	20	30	50	60	70
10	11.7 ± 5.2 *(20, 30, 50, 60, 70)*	6 ± 4.8 *(30, 50, 60, 70)*	3.1 ± 4.5 *(70)*	0.3 ± 0.5	0.1 ± 0.3	0.2 ± 0.4
20	6.4 ± 4.5 *(20, 50, 60, 70)*	13.8 ± 5.4 *(30, 50, 60, 70)*	7.6 ± 6.3 *(50, 60, 70)*	1.8 ± 2.8 *(60, 70)*	0.2 ± 0.4	0.1 ± 0.3
30	4.8 ± 4.6 *(20, 30, 70)*	9.4 ± 5.4 *(30, 50, 60, 70)*	14.1 ± 6 *(50, 60, 70)*	3.7 ± 3.4 *(60, 70)*	1.1 ± 1.5	0.2 ± 0.7
50	2 ± 3 *(30, 50, 60)*	4.3 ± 5.7 *(30, 50, 60)*	8.8 ± 5.9 *(50, 70)*	17.2 ± 6.4 *(60, 70)*	8.9 ± 5.9 *(70)*	1.2 ± 1.3
60	1 ± 1.7 *(30, 50, 60, 70)*	2.1 ± 2.2 *(30, 50, 60)*	5.7 ± 3.1 *(50, 60)*	14 ± 5.3 *(60, 70)*	16.9 ± 6.7 *(70)*	5.3 ± 4.6
70	0.2 ± 0.7 *(20, 30, 50, 60, 70)*	0.2 ± 0.7 *(30, 50, 60, 70)*	1.6 ± 1.7 *(50, 60, 70)*	7.1 ± 4 *(60, 70)*	11 ± 5.3 *(70)*	13.8 ± 4.7

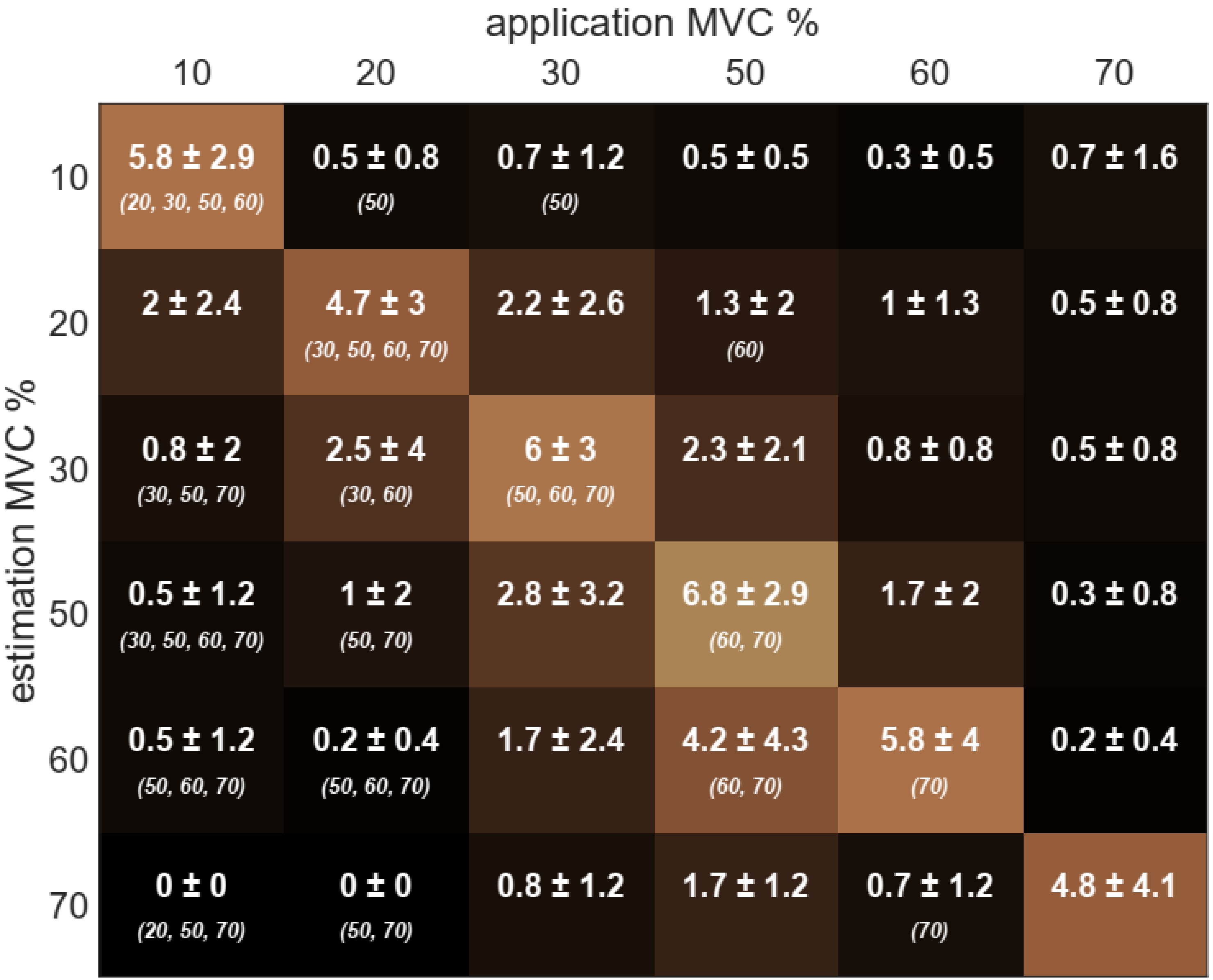
Frančič & Holobar, IEEE Access 2021

EXAMPLE 4:

MU tracking across different contraction levels

No. of tracked MUs

Biceps Brachi (BB)



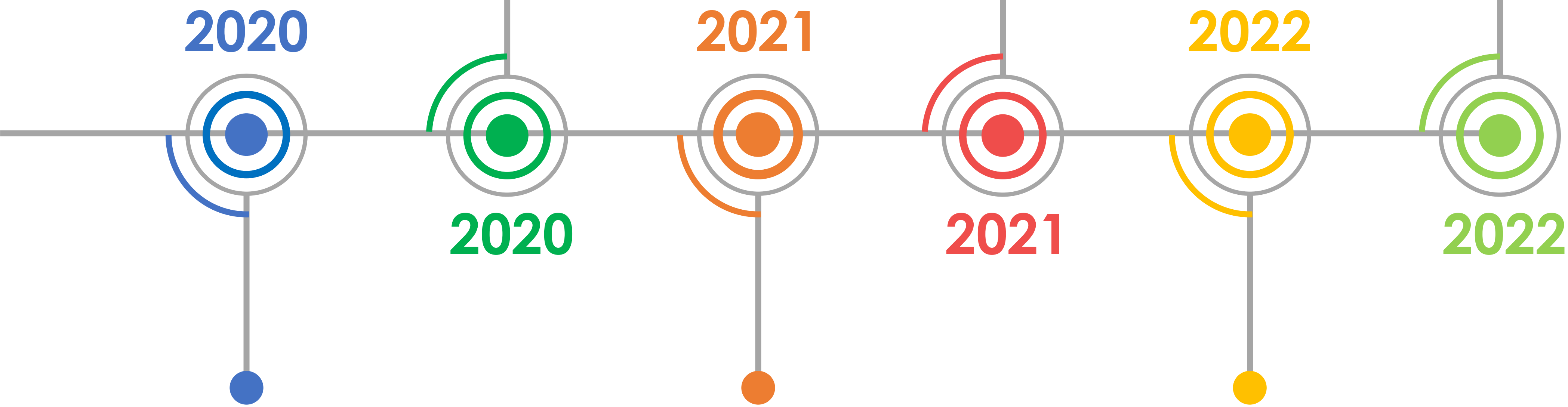
application MVC %

estimation MVC %

	10	20	30	50	60	70
10	5.8 ± 2.9 *(20, 30, 50, 60)*	0.5 ± 0.8 *(50)*	0.7 ± 1.2 *(50)*	0.5 ± 0.5	0.3 ± 0.5	0.7 ± 1.6
20	2 ± 2.4	4.7 ± 3 *(30, 50, 60, 70)*	2.2 ± 2.6	1.3 ± 2 *(60)*	1 ± 1.3	0.5 ± 0.8
30	0.8 ± 2 *(30, 50, 70)*	2.5 ± 4 *(30, 60)*	6 ± 3 *(50, 60, 70)*	2.3 ± 2.1	0.8 ± 0.8	0.5 ± 0.8
50	0.5 ± 1.2 *(30, 50, 60, 70)*	1 ± 2 *(50, 70)*	2.8 ± 3.2	6.8 ± 2.9 *(60, 70)*	1.7 ± 2	0.3 ± 0.8
60	0.5 ± 1.2 *(50, 60, 70)*	0.2 ± 0.4 *(50, 60, 70)*	1.7 ± 2.4	4.2 ± 4.3 *(60, 70)*	5.8 ± 4 *(70)*	0.2 ± 0.4
70	0 ± 0 *(20, 50, 70)*	0 ± 0 *(50, 70)*	0.8 ± 1.2	1.7 ± 1.2	0.7 ± 1.2 *(70)*	4.8 ± 4.1

Frančič & Holobar, IEEE Access 2021

Surface EMG decomposition timeline & evolution of MU filters



MU identification in newborns
Del Vecchio et al. 2020

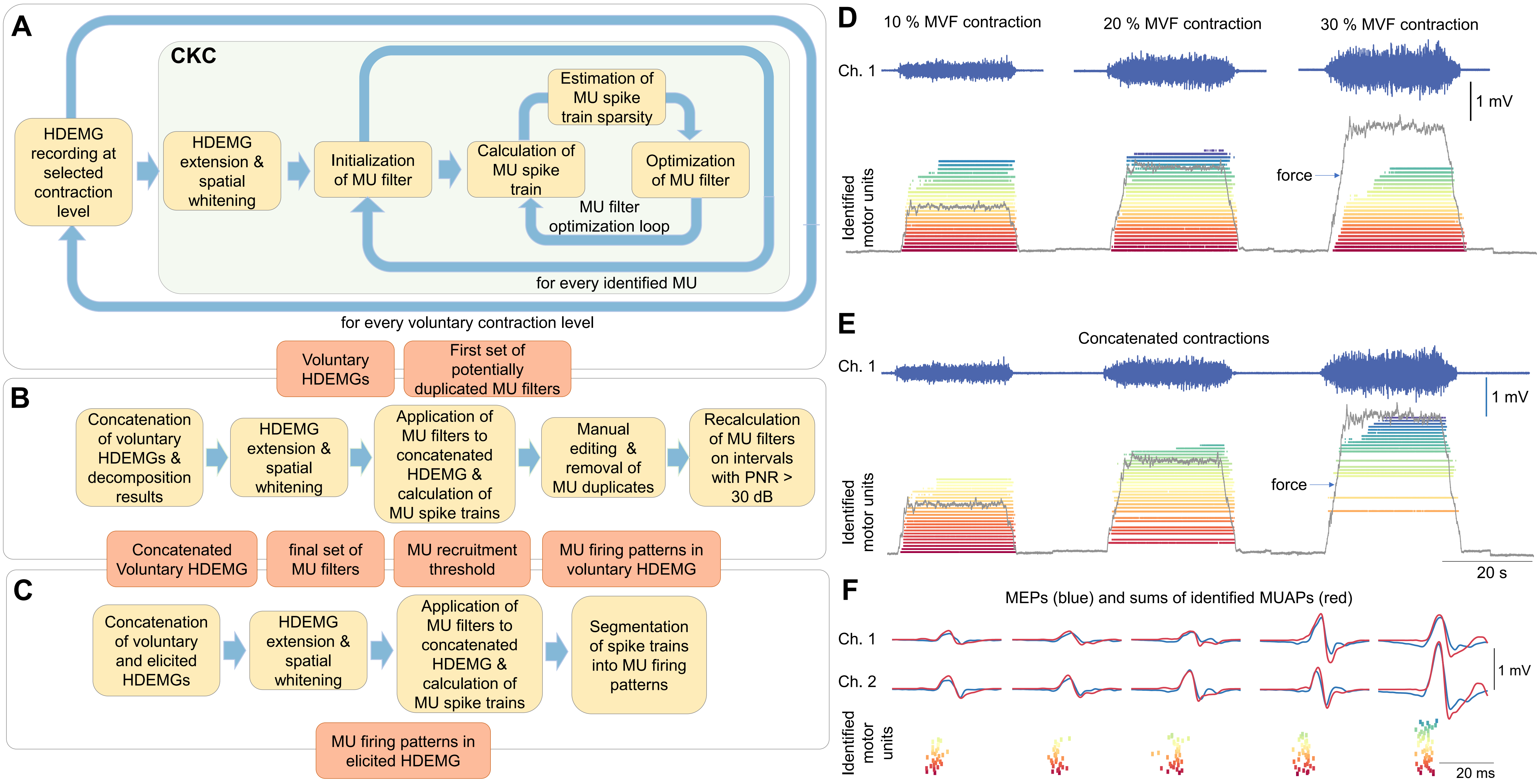
Deep learning & surface EMG decomposition
Clarke et al. 2020
Urh et al. 2020

Motor neuron synergies
Tanzarella et al. 2021
Hug et al. 2021
Avrillon et al. 2023

Banks of MU filters & MU filter transfer
Francic et al. 2021

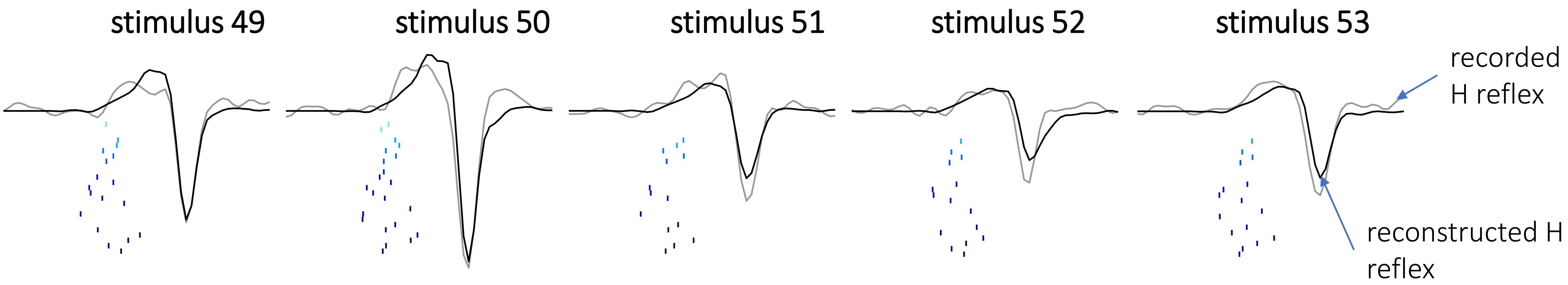
Fully automatic high-density intramuscular EMG decomposition
Muceli et al. 2022

Decomposition of elicited contractions:
H reflexes: Kalc et al. 2022a
M waves: Kalc et al. 2022b
TMS: Škarabot et al. 2023

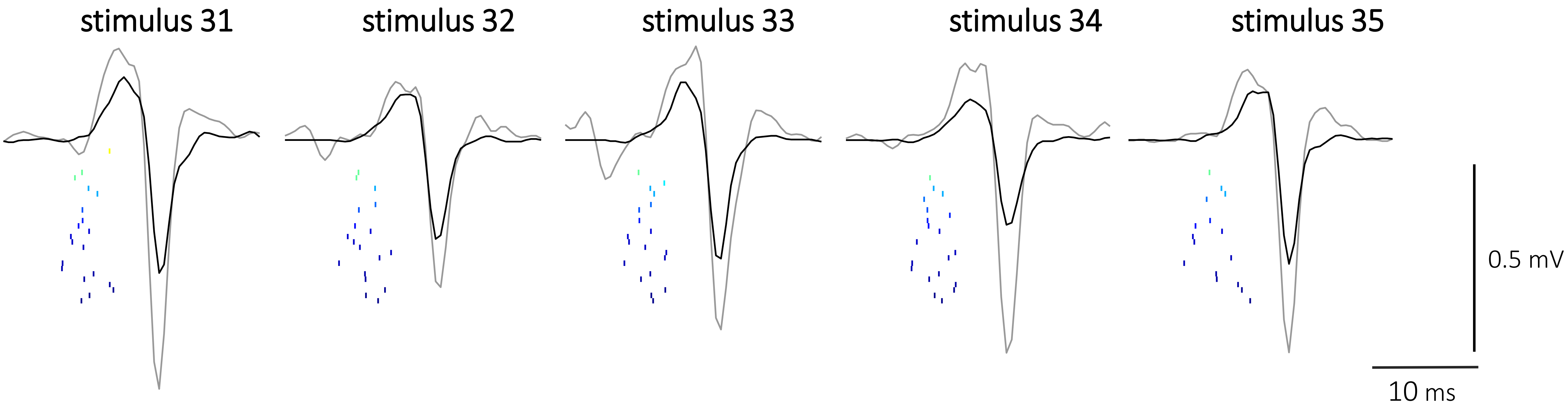


Škarabot et al. The Journal of Physiology, 2023.

H – REST

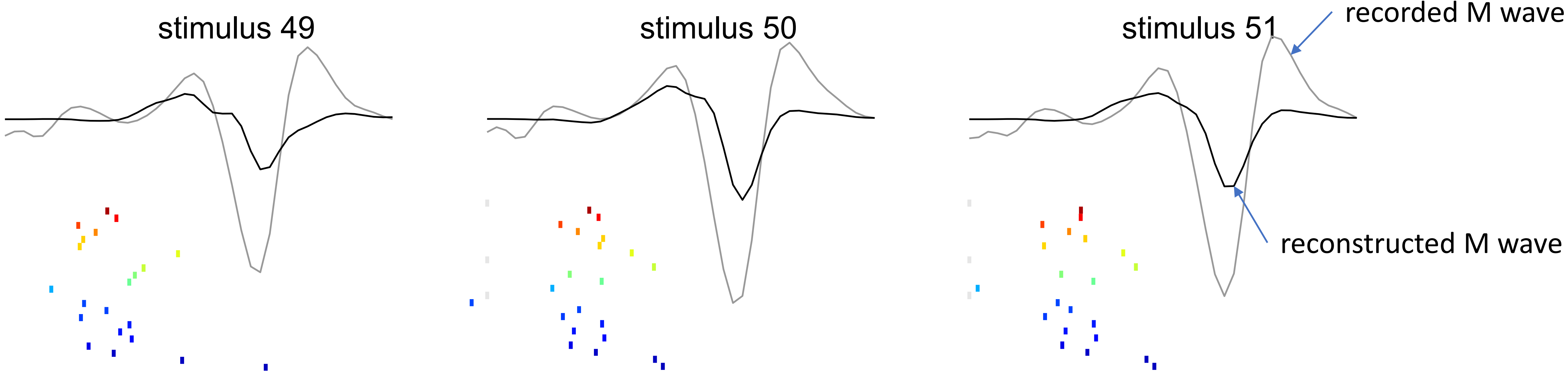


H – 10% MVC (C10)

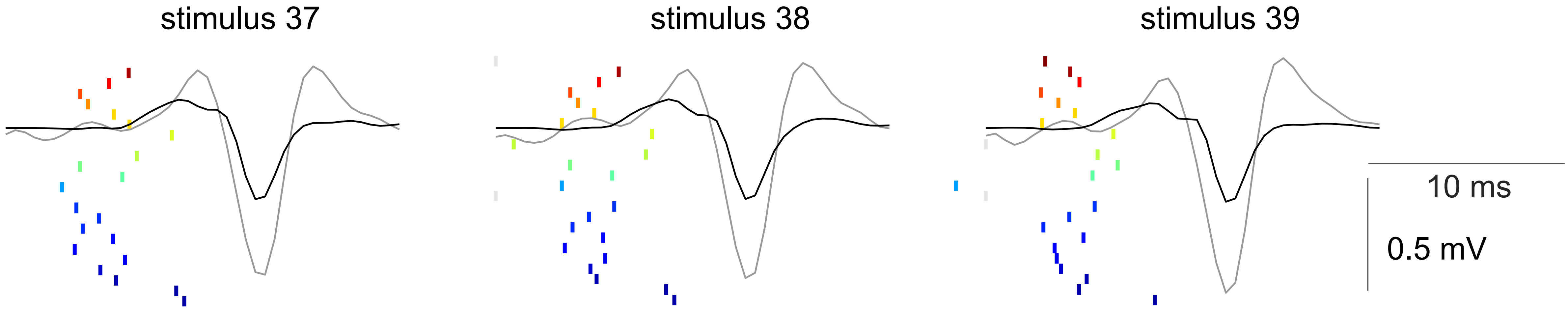


Kalc et al. Identification of motor unit firings in H-reflex of soleus muscle…, IEEE TNSRE 2022

M wave, REST

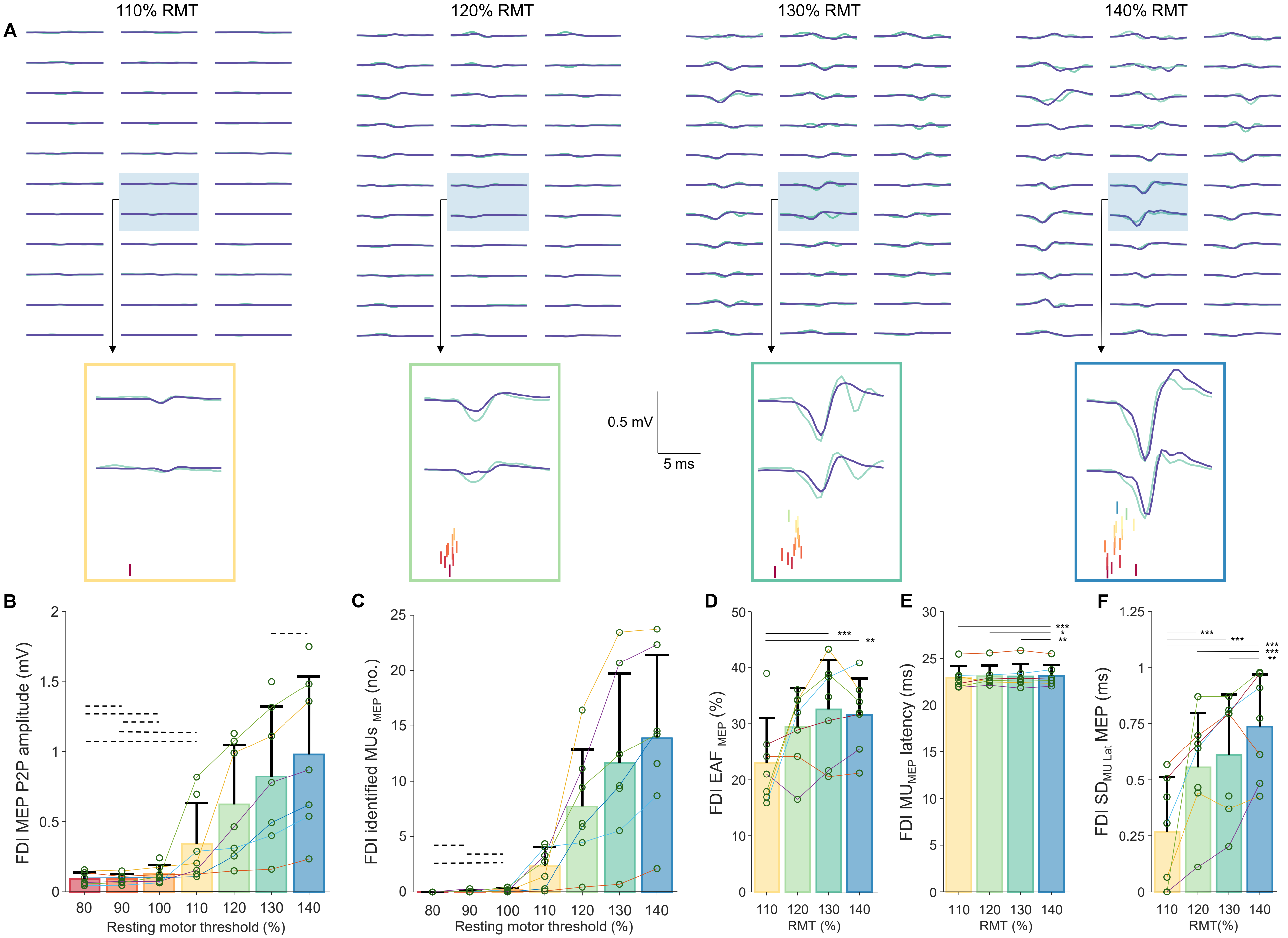


M wave, C10



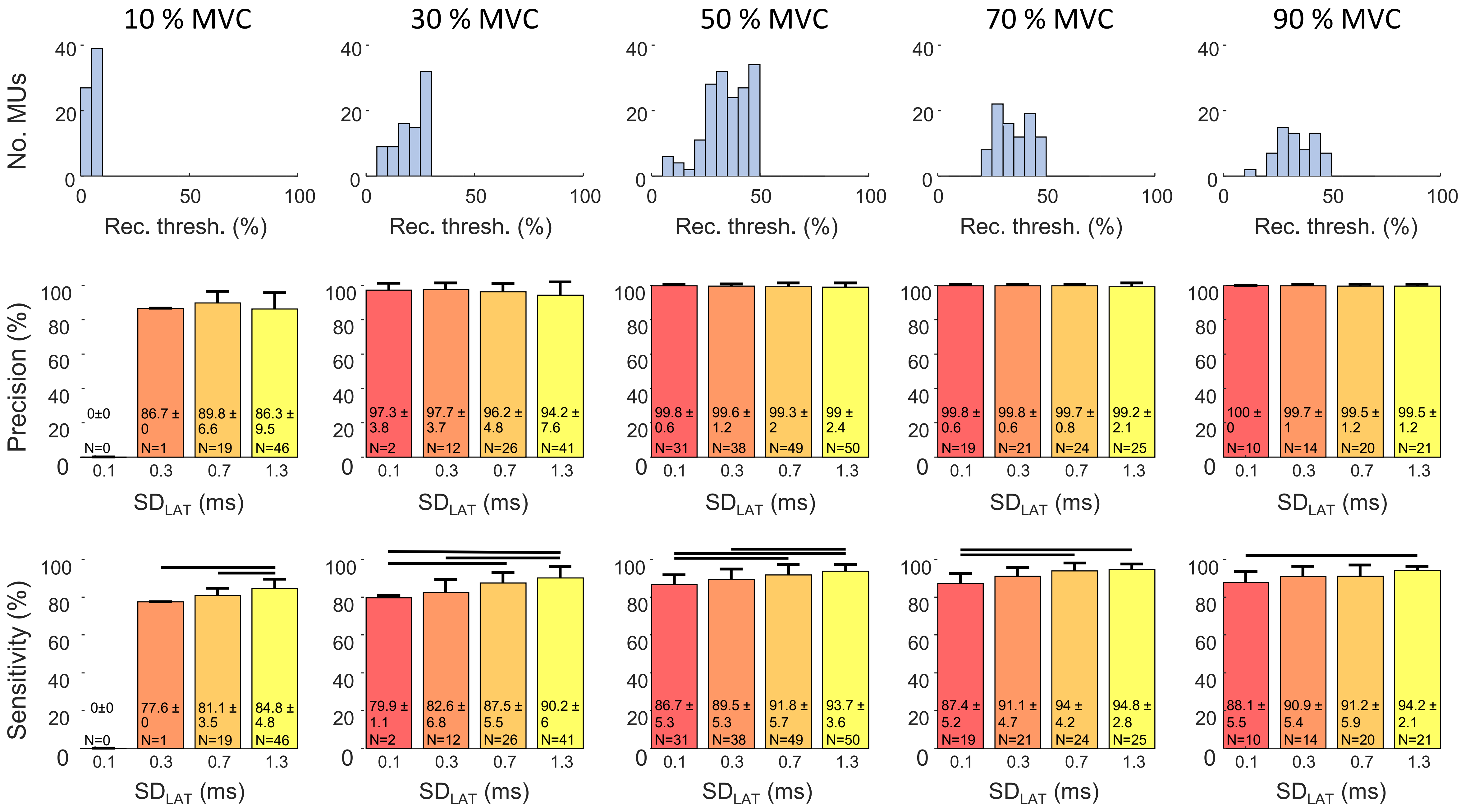
Kalc et al. Motor unit identification in the M waves recorded by high-density electromyogram, IEEE TMBE 2022

TMS & elicited CMAPs, FDI



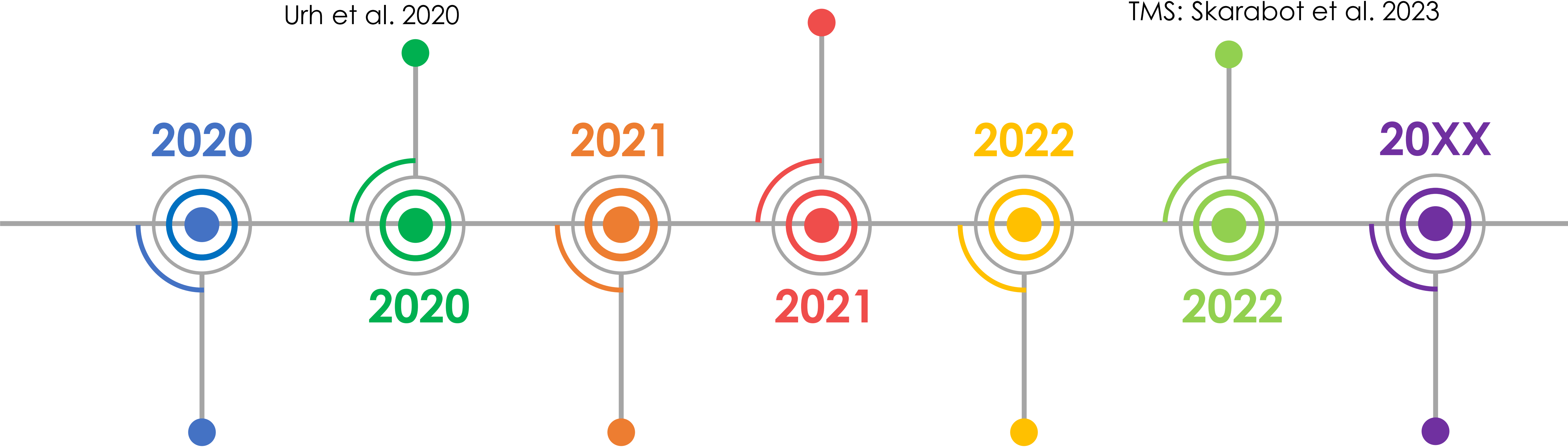
Škarabot et al. The Journal of Physiology, 2023.

Different voluntary contractions & elicited contraction at 50% MVC



Kalc et al. Identification of motor unit firings in H-reflex of soleus muscle…, IEEE TNSRE 2022

Surface EMG decomposition timeline & evolution of MU filters



2020

MU identification in newborns
Del Vecchio et al. 2020

2020

Deep learning & surface EMG decomposition
Clarke et al. 2020
Urh et al. 2020

2021

Motor neuron synergies
Tanzarella et al. 2021
Hug et al. 2021
Avrillon et al. 2023

2021

Banks of MU filters & MU filter transfer
Francic et al. 2021

2022

Fully automatic high-density intramuscular EMG decomposition
Muceli et al. 2022

2022

Decomposition of elicited contractions:
H reflexes: Kalc et al. 2022a
M waves: Kalc et al. 2022b
TMS: Škarabot et al. 2023

20XX

Exciting future awaits us
Many different authors

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Nahiduzzaman: Animated PowerPoint Timeline Slide Design Tutorial
https://www.youtube.com/watch?v=InyqaOFRwKw&t=59s (CC BY 3.0)

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