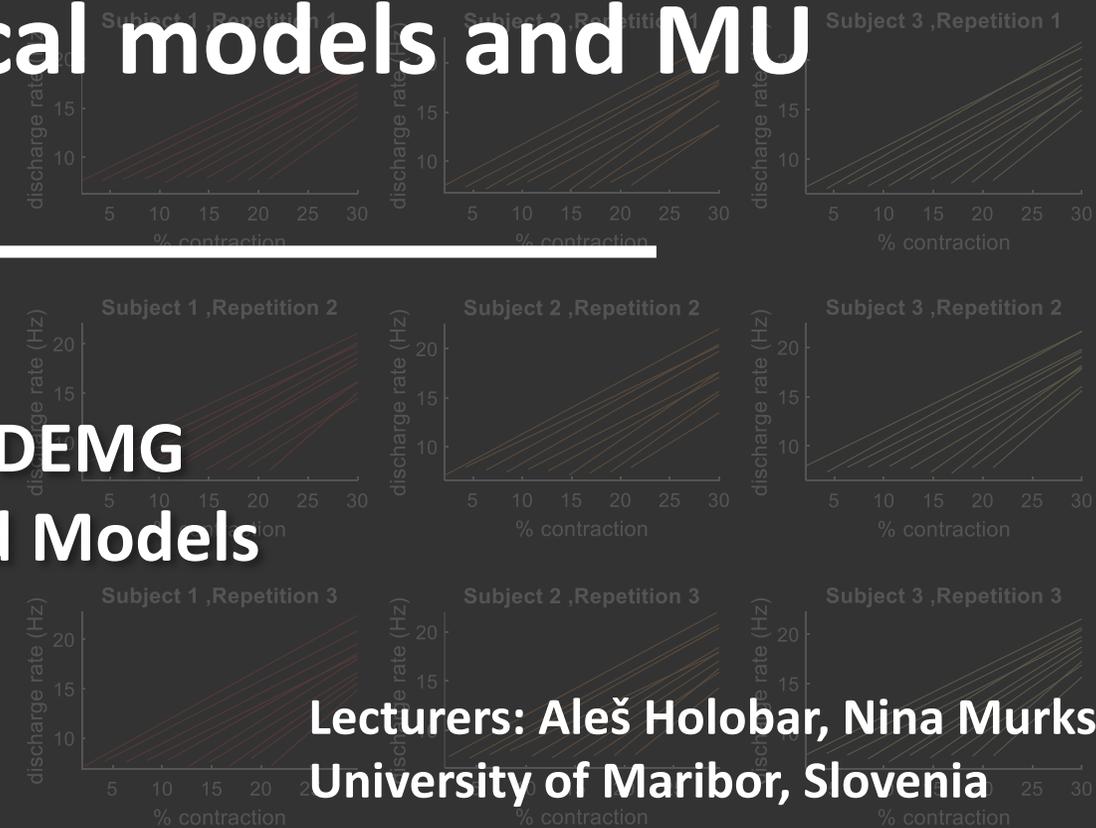


WEBINAR: Validation of results: statistical models and MU identification accuracy

Gentle introduction to:

- Accuracy of MU identification from HDEMG
- Regression analysis with Linear Mixed Models
- Bayesian Linear Regression Models



**Lecturers: Aleš Holobar, Nina Murks
University of Maribor, Slovenia**



Hybrid neuroscience based on cerebral and muscular information for motor rehabilitation and neuromuscular disorders



HybridNeuro focuses on development of Hybrid Neural-machine Interfaces, which record cerebral and muscular signals, and aims to improve the objectivity, precision and personalisation of monitoring and rehabilitation of neuromuscular disorders, such as stroke.



This project has received funding from the European Union's Horizon Europe Research and Innovation Programme under grant agreement no. 101079392 and from the UK Research and Innovation (UKRI) government's Horizon Europe funding guarantee scheme under grant agreement no. 10052152.



Hybrid neuroscience based on cerebral and muscular information for motor rehabilitation and neuromuscular disorders

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- 4 Workshops
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- 1 Massive open online course (MOOC) on Hybrid Neuroscience
- 1 International HybridNeuro Hub
- 12 National/international events

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February 6th –9th 2024

Universitat Politècnica de Catalunya, Barcelona, Spain



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NEURO**

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“A journey into brain activity”

From EEG and related potentials to connectivity and source modeling

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Day 2: ERP and MRCP studies and movement intention for device control.

Day 3: Source localization and brain connectivity.

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Hybrid Workshop
(online and In-person event).
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to be covered by participants

Summer school on Hybrid Neural Interfaces

July 8th-12th 2024, Maribor, Slovenia

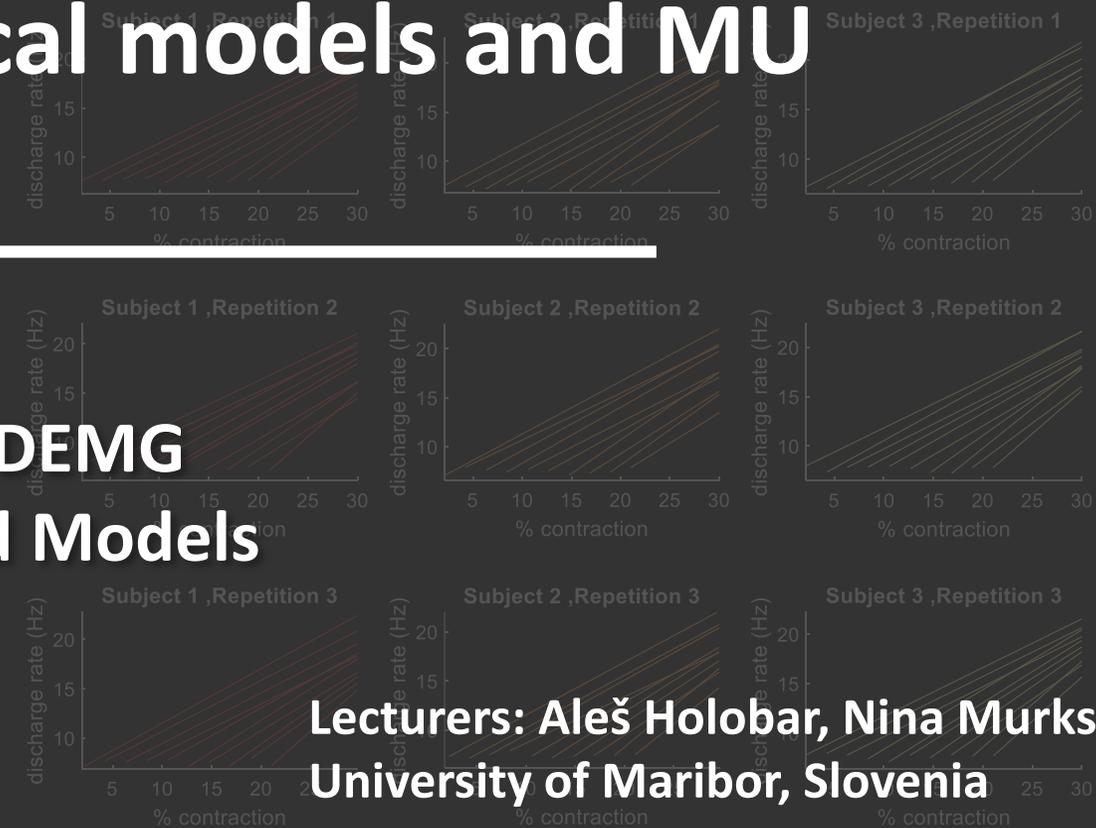
- Surface & intramuscular HDEMG
- Identification of neural codes
- EEG & functional brain connectivity
- Corticomuscular coupling
- Movement augmentation
- Hybrid Neural Interfaces in practice
- Keynote lectures
- Practical examples
- Student 2 student explanations
- Present your project
- Ask top experts
- Active consultations

WEBINAR:

Validation of results: statistical models and MU identification accuracy

Gentle introduction to:

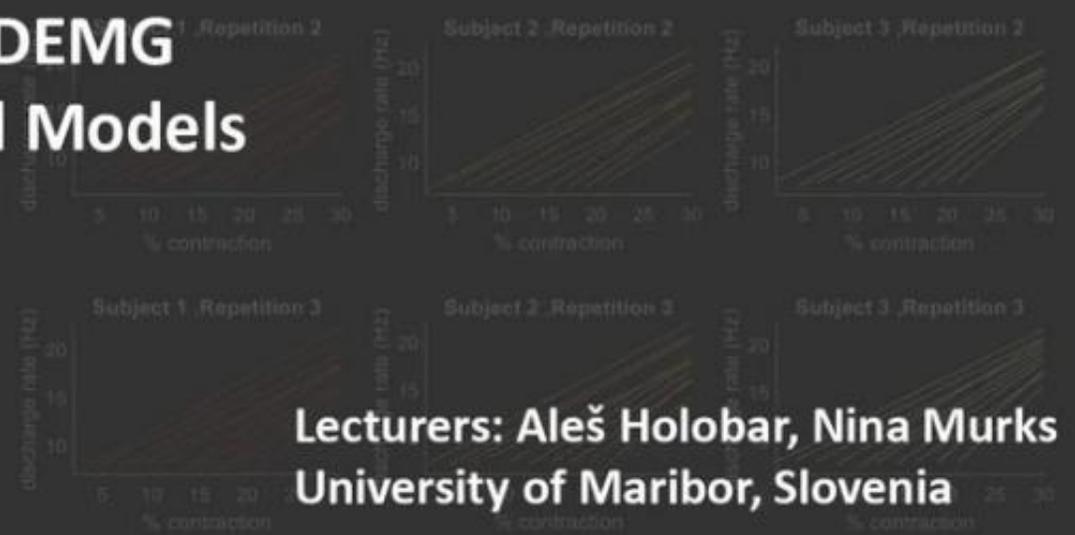
- Accuracy of MU identification from HDEMG
- Regression analysis with Linear Mixed Models
- Bayesian Linear Regression Models



Lecturers: Aleš Holobar, Nina Murks
University of Maribor, Slovenia

- Accuracy of MU identification from HDEMG
- Regression analysis with Linear Mixed Models
- Bayesian Linear Regression Models

- Use cases & examples in MATLAB & R
- Synthetic & experimental data
- Free registration



Lecturers: Aleš Holobar, Nina Murks
University of Maribor, Slovenia



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Access the webinar content showcased here:

MATLAB Code

- Experimental EMG
- Synthetic EMG

R Code

- Experimental EMG
- Synthetic EMG

Data

- Experimental EMG
- Synthetic EMG
- Large Synthetic EMG

Presentation

- Slides

Files on the HybridNeuro website

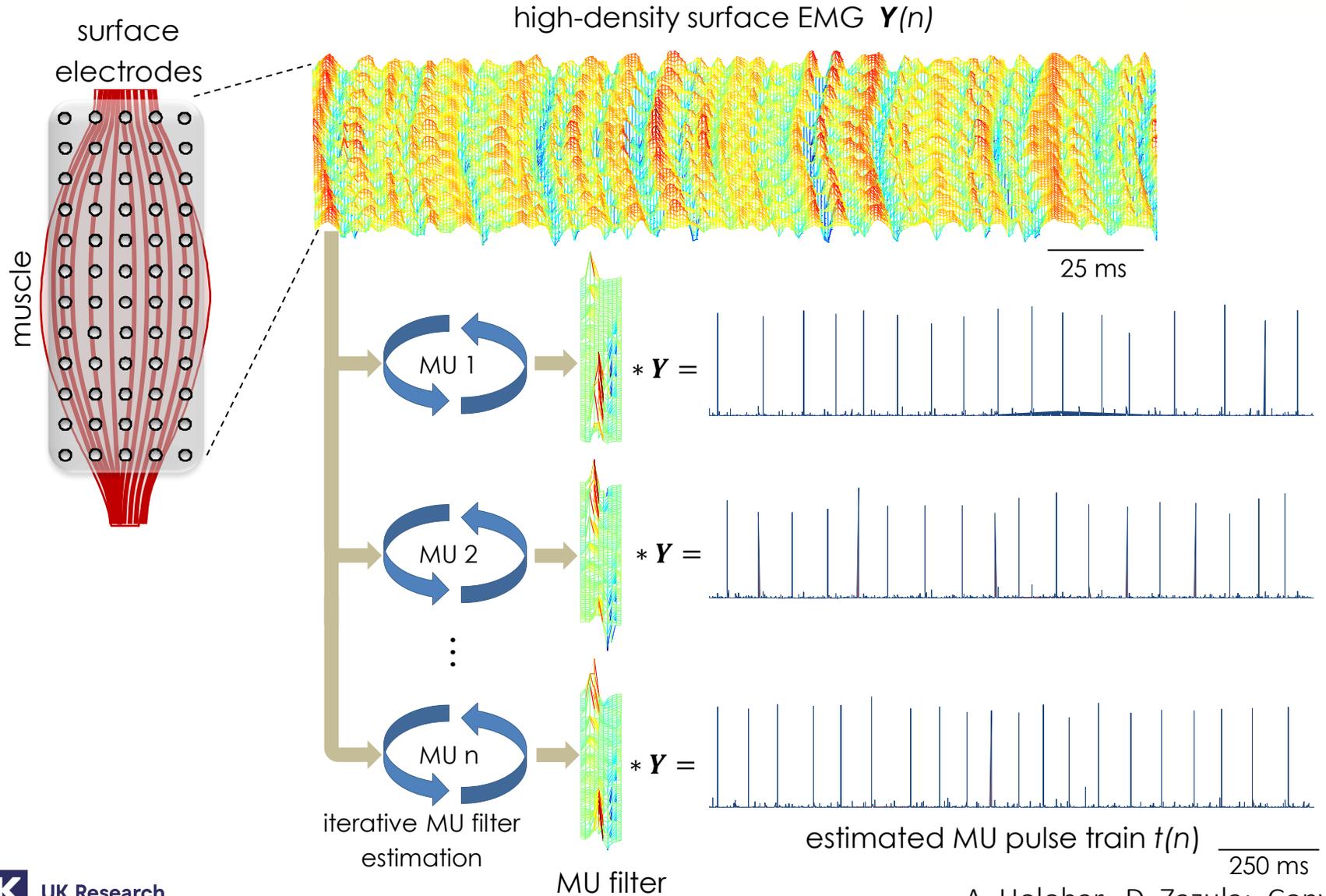


- **MATLAB:**
 - **MATLAB_code_SyntheticEMG.m:** Generation of synthetic data and preliminary statistical analysis
 - **MATLAB_code_ExperimentalEMG.m:** Analysis of experimental data

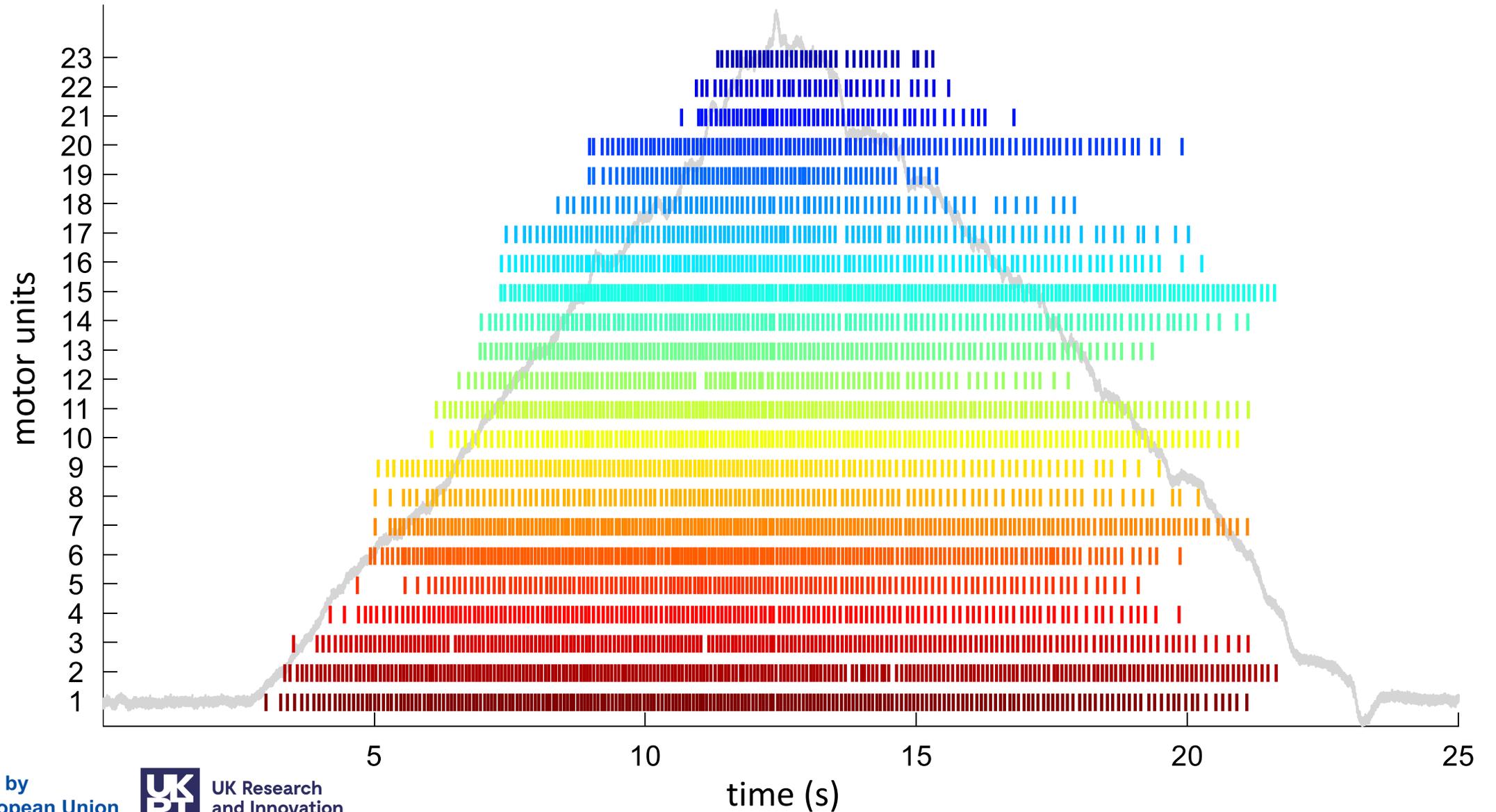
- **DATA:**
 - **DATA_SyntheticEMG.cvs:** synthetic data (15 subjects, 3 contraction repetitions, 15 MUs per subject, no missed MUs – balanced tests...)
 - **LARGE_DATA_SyntheticEMG.cvs:** synthetic data (20 subjects, 3 Contraction repetitions, 20 MUs per subject, no missed MUs – balanced tests...)
 - **DATA_ExperimentalEMG.cvs:** experimental data (19 subjects, 3 contraction repetitions, MUs tracked across contraction repetitions)

- **RSTUDIO:**
 - **R_code_SyntheticEMG.R:** Analysis of synthetic data
 - **R_code_ExperimentalEMG.R:** Analysis of experimental data

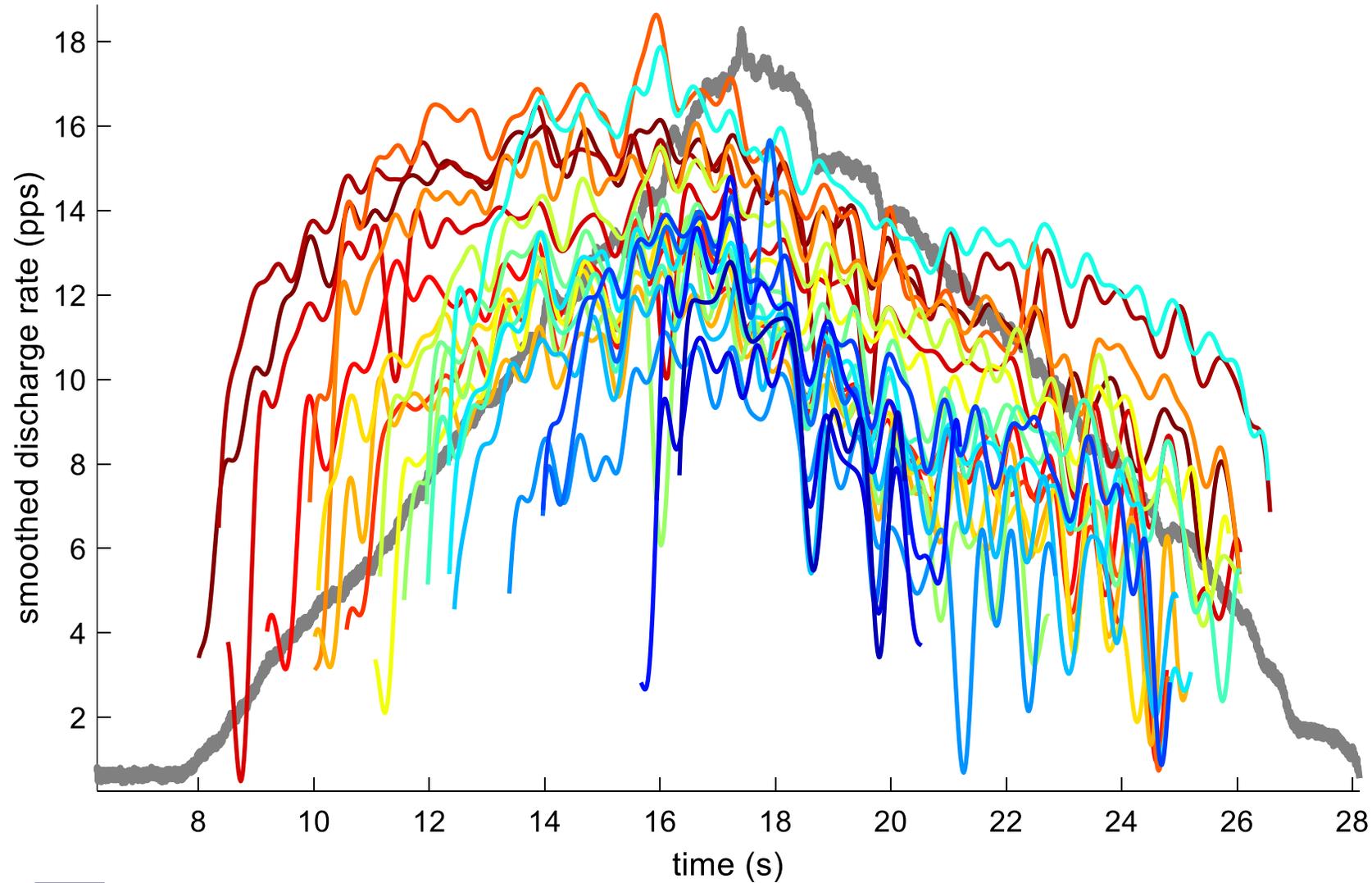
Identification of MU spike trains: MU filter



MU discharge patterns

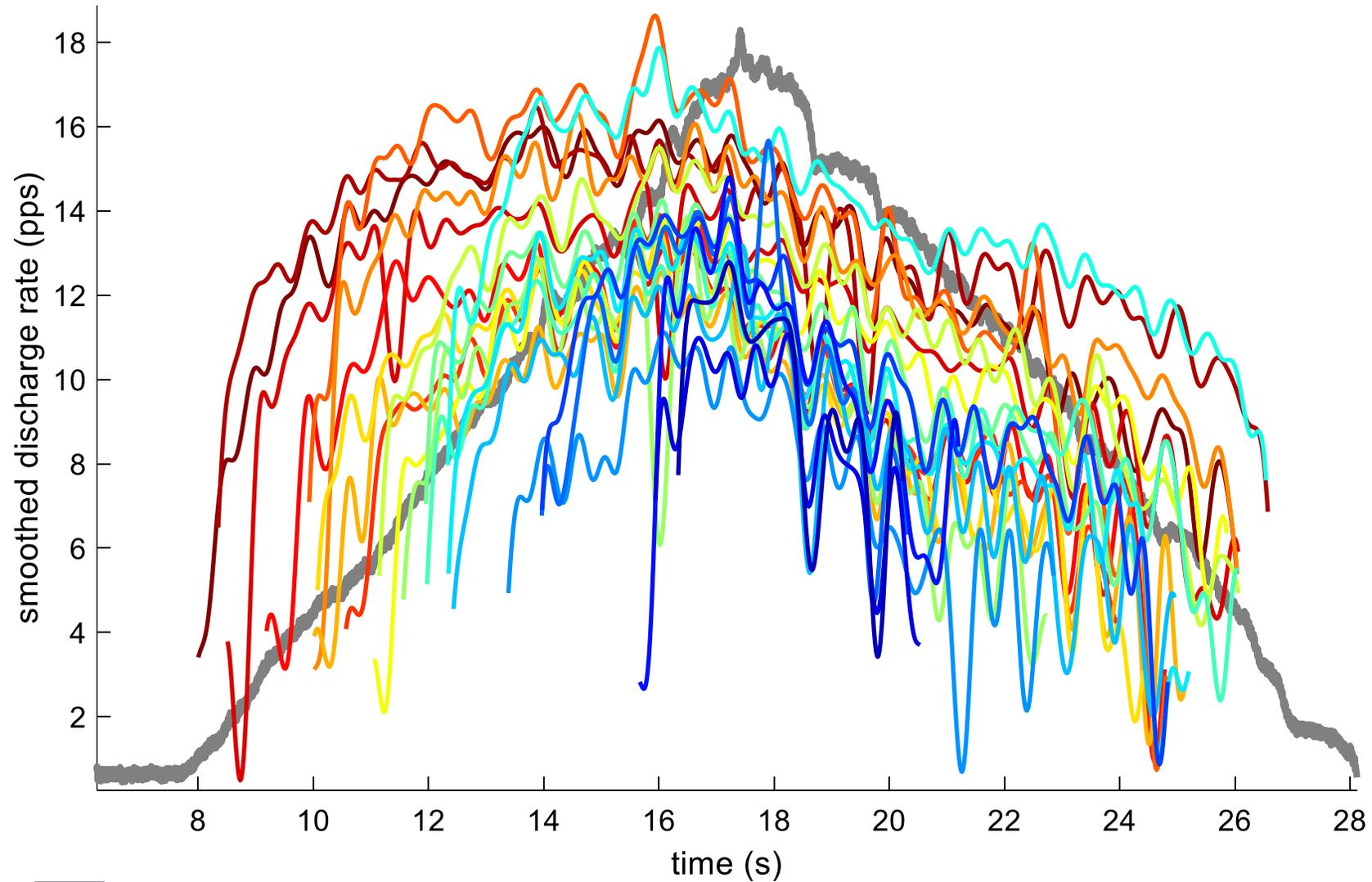


MU discharge rates

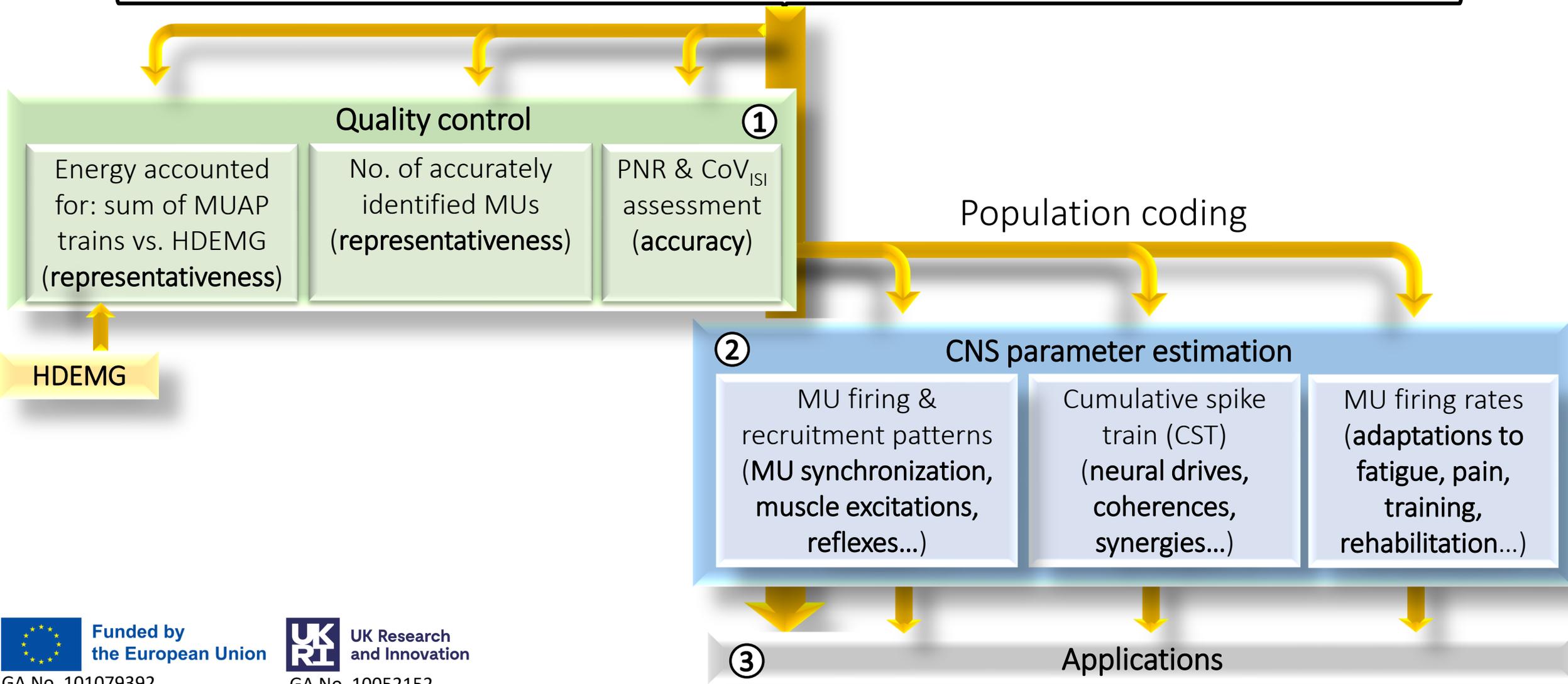
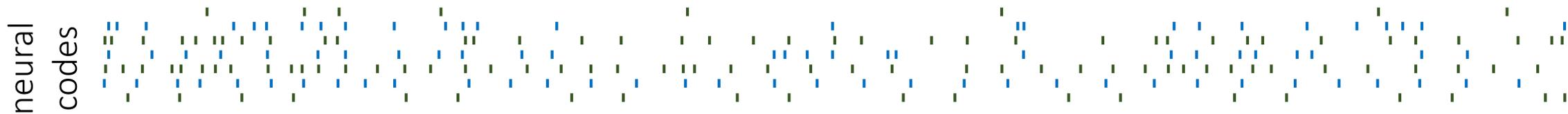


In Wilkinson notation:

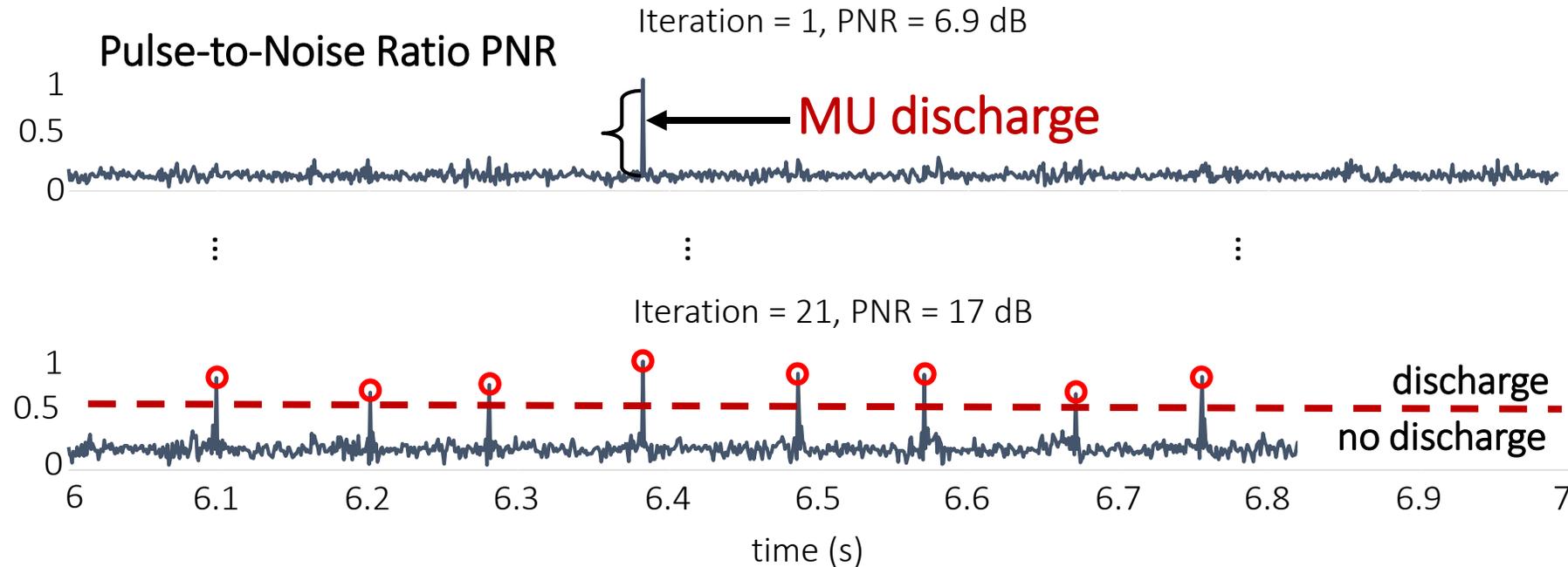
$\text{MaxDR} \sim 1 + \text{RecThr} + \text{RecDR} + (-1 + \text{RecThr} | \text{SubID}) + (-1 + \text{RecThr} | \text{ContRep}) + (-1 + \text{RecThr} | \text{SubID:MUId})$



Information extraction pipeline



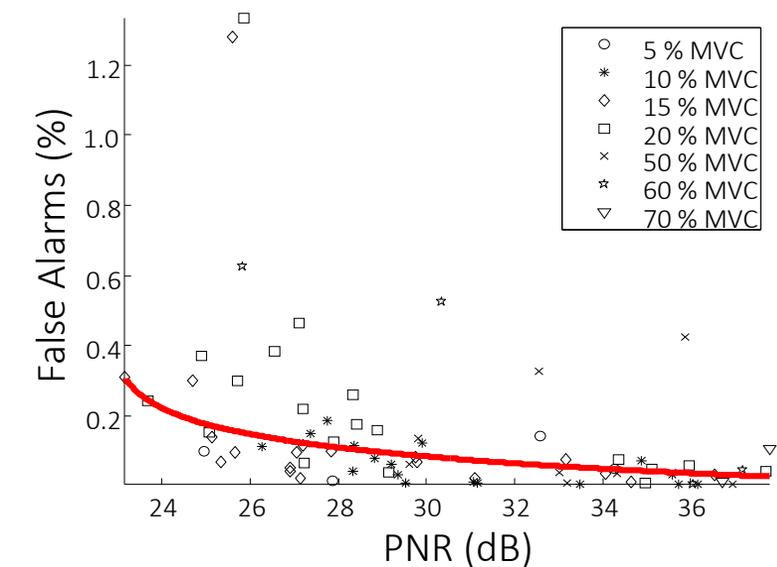
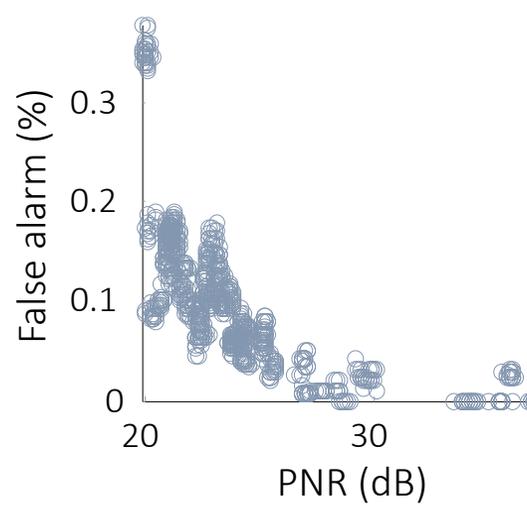
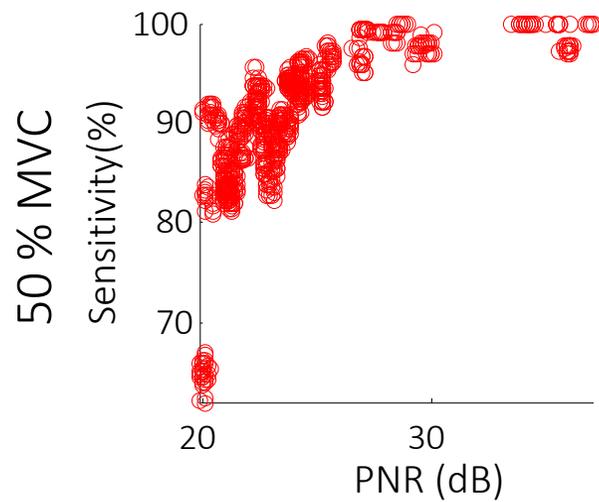
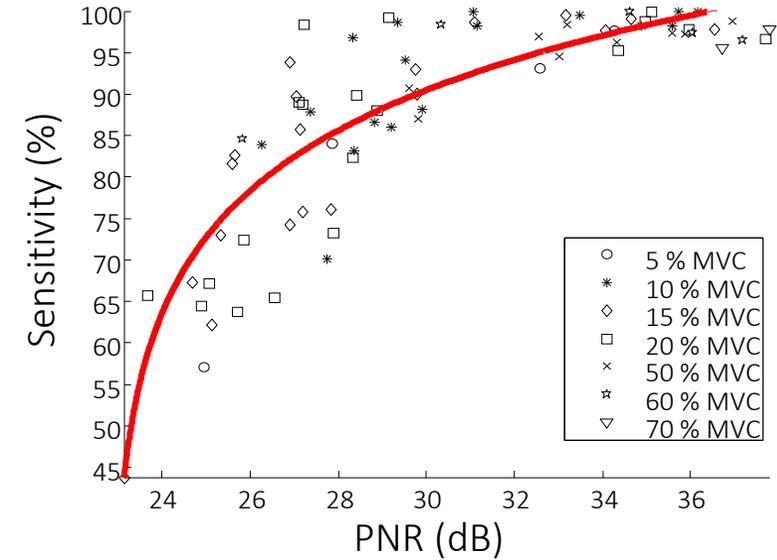
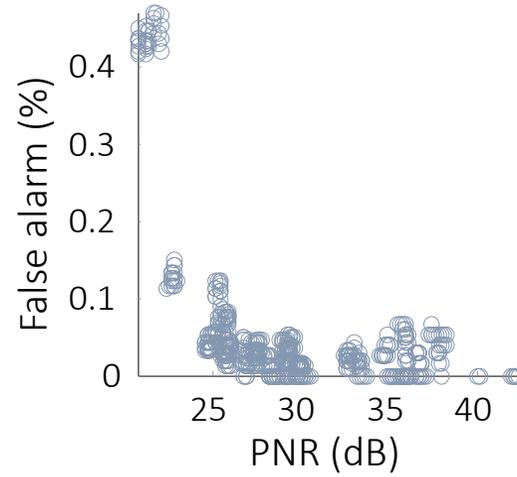
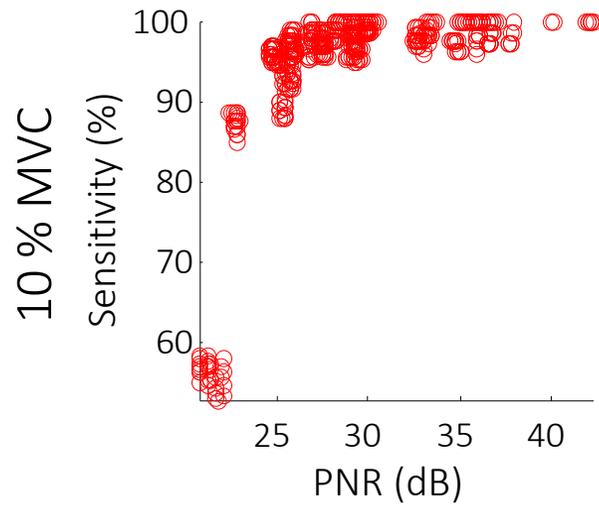
BSS-based identification of MU firings



Pulse-to-Noise Ratio (PNR):

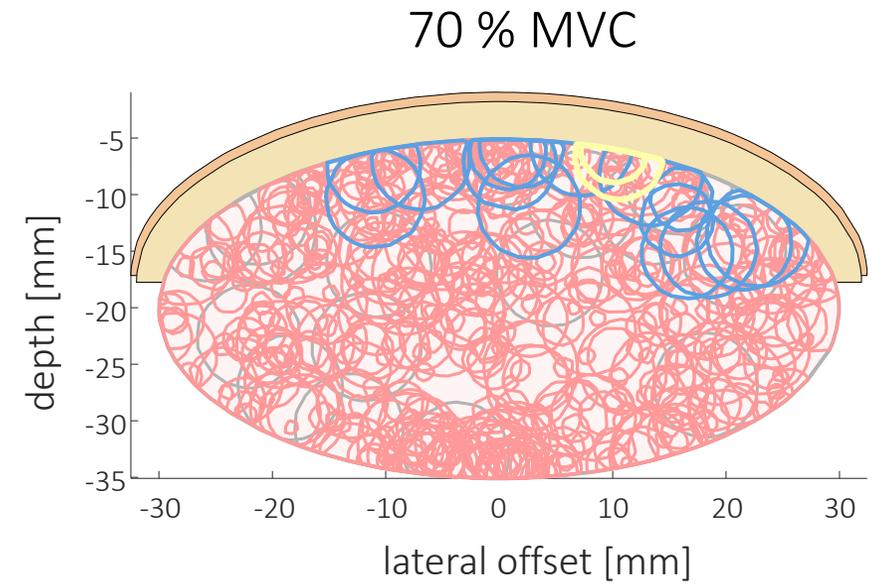
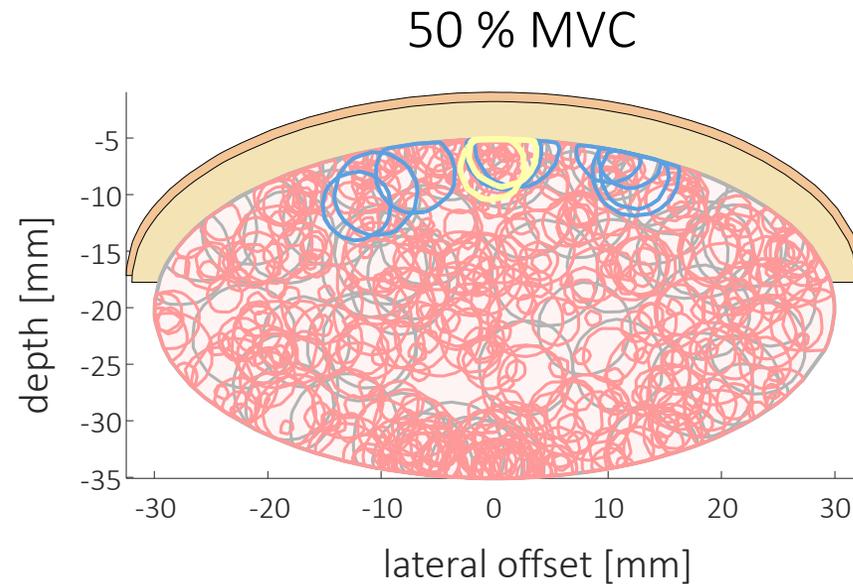
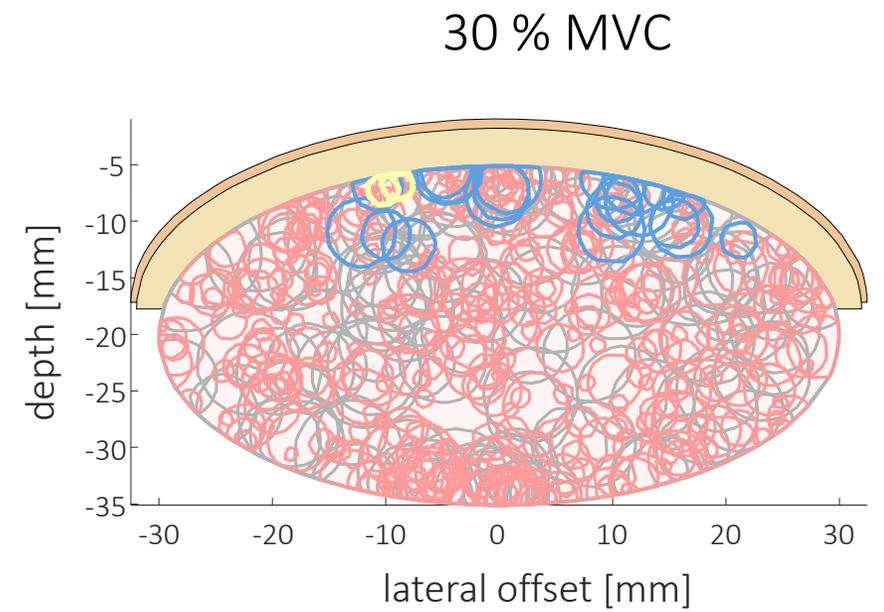
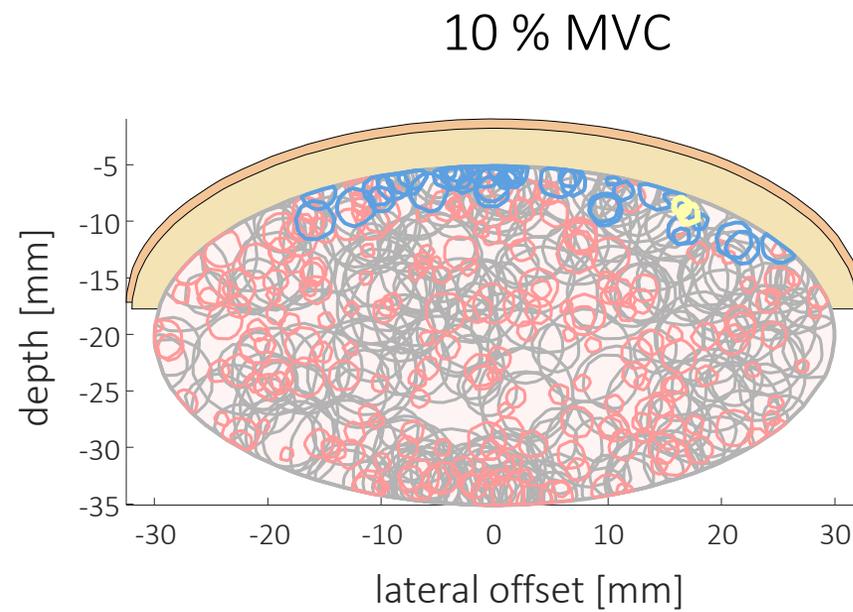
- applied to EVERY identified motor unit
- no additional experimental costs
- reliable indicator of accuracy of motor unit identification

Synthetic EMG, experimental surface & intramuscular EMG



MU merging

Divjak et al. ICNR2020

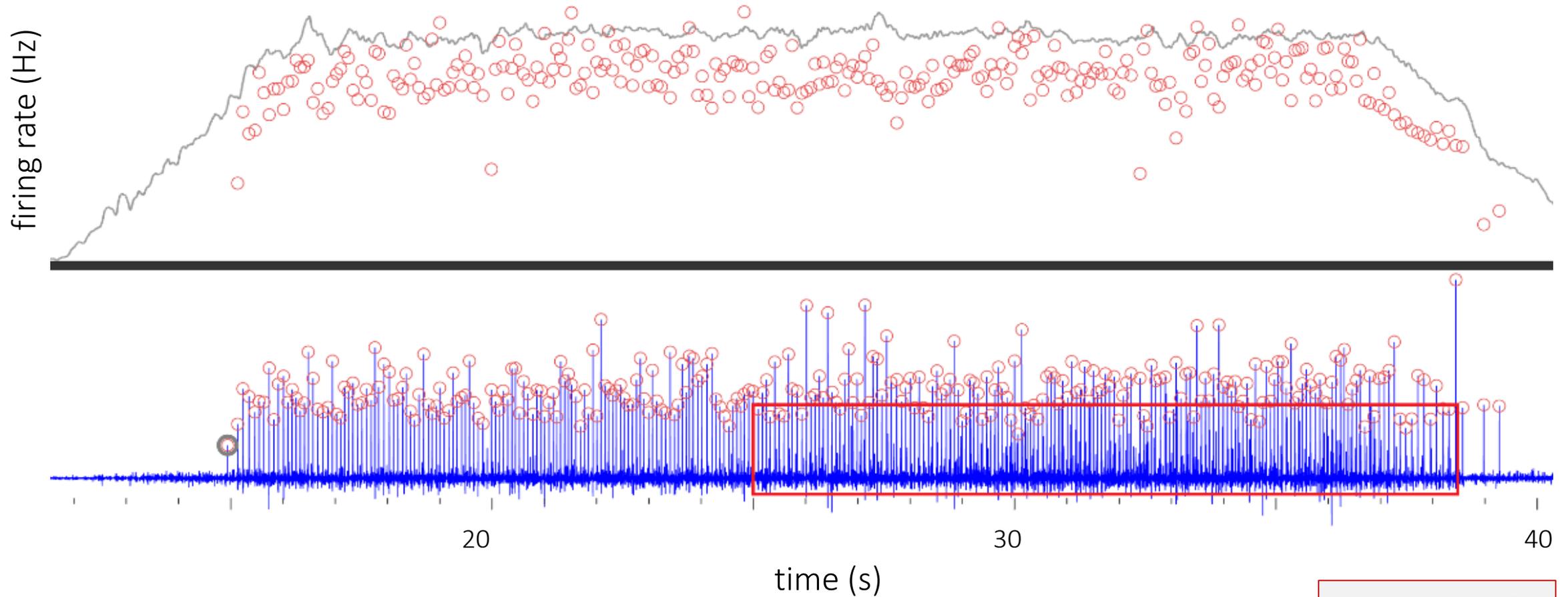


○ active MU

○ unmerged identified MU

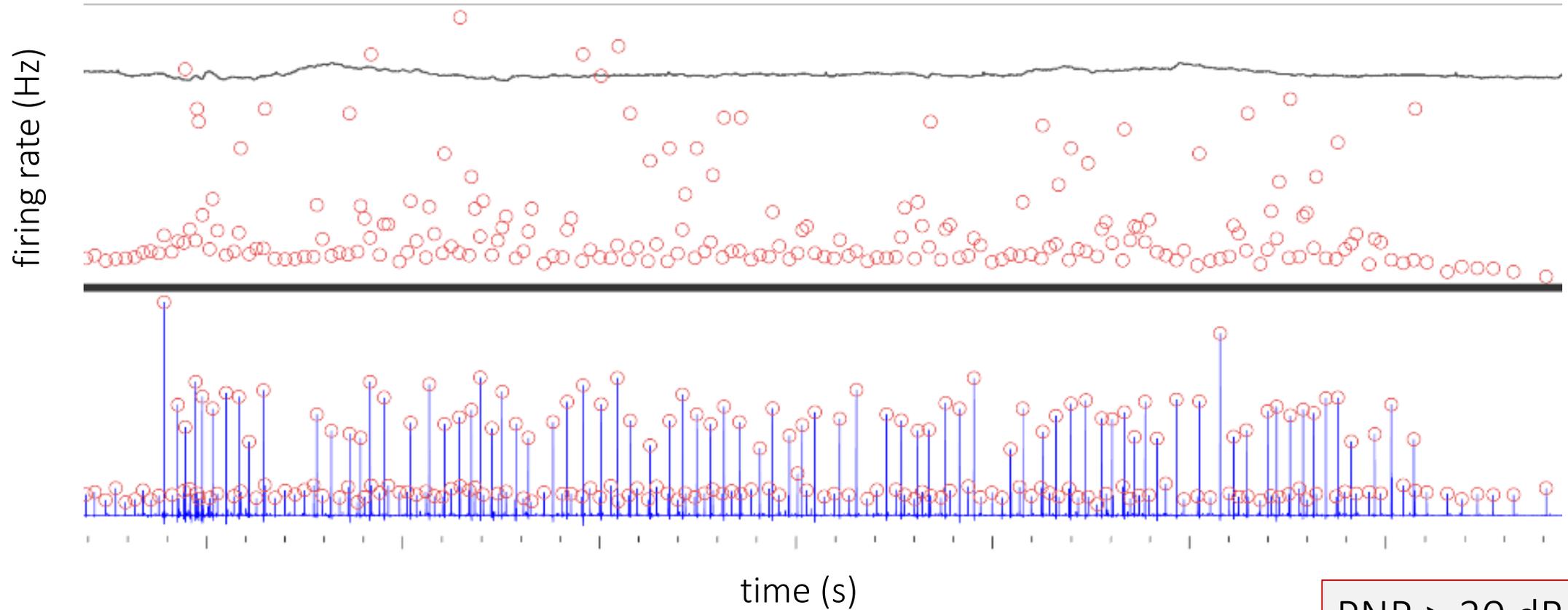
○ merged identified MU

MU merging, low CoV_{ISI} is not enough



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

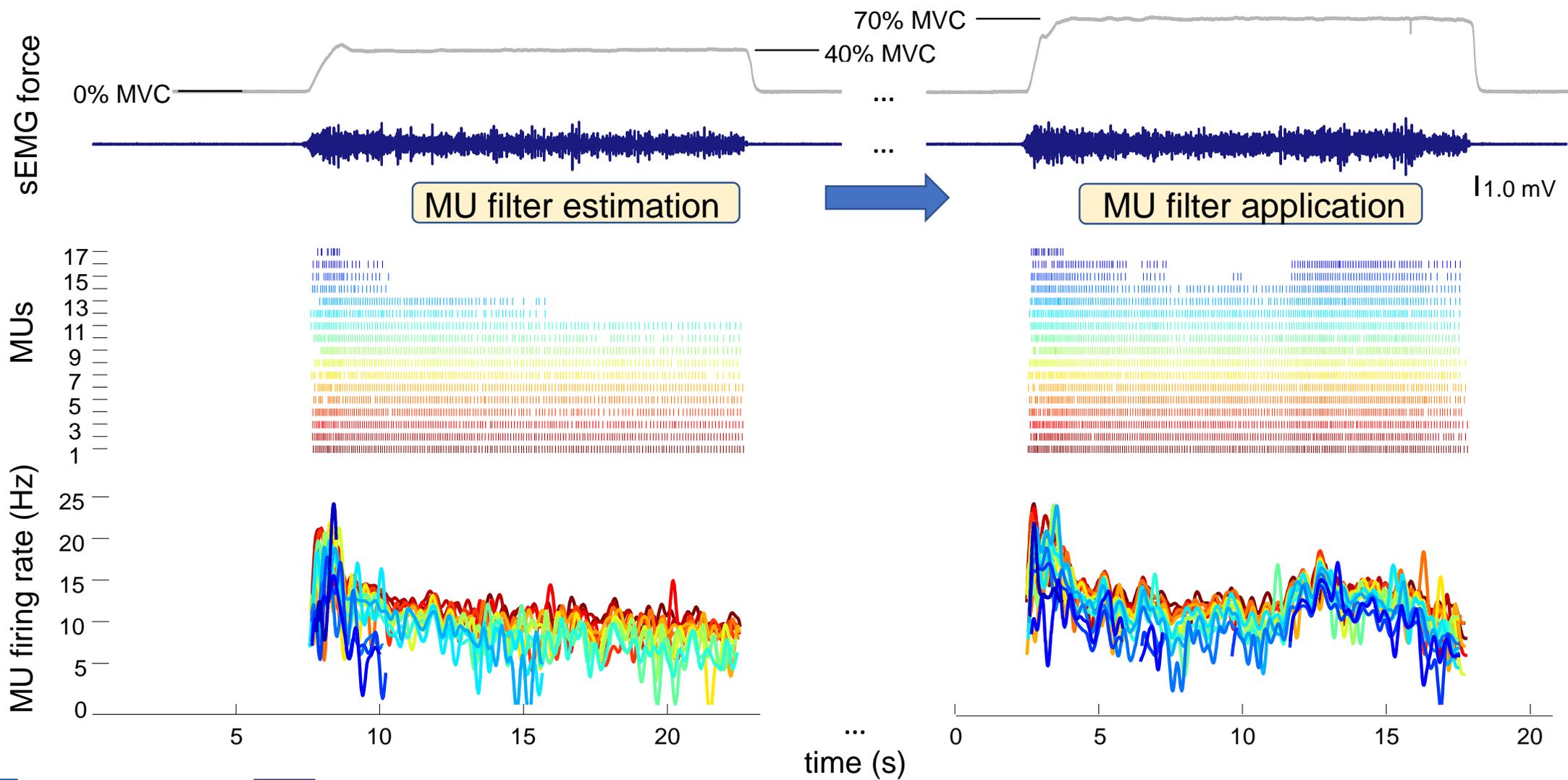
MU merging, high PNR is not enough



PNR > 30 dB
 CoV_{ISI} > 0.5

... but pathology plays with the regularity of MU firing.

MU filter reused – pairwise comparisons



EXAMPLE 1:

MU tracking across different contraction levels

Frančič & Holobar, IEEE Access 2021

No. of tracked MUs
Synthetic HDsEMG, SNR = 20 dB

	application 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

Frančič & Holobar, IEEE Access 2021

Frequently, MUs cannot be tracked across conditions

Paired tests not possible

No. of tracked MUs
Tibialis Anterior (TA)

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



Simulated data

Full control of simulation parameters & grand truth known

In Wilkinson notation:

MaxDR ~ 1 + RecThr+RecDR+ (-1 + RecThr|SubID) + (-1 + RecThr|ContRep) + (-1 + RecThr|SubID:MUid)

Simulated data: Model in MATLAB



```
NoSubjects = 15; % play with the number of Subjects (e.g. NoSubjects = 5...)
NoRepetitions = 3; % Number of contraction repetitions per subject
NoMUs = 15; % play with the number of MUs (e.g. NoMUs = 5, NoMUs = 15...)
portionOfMissedValues = 0.0; % portion of missed MUs (0 for 0%, 0.5 for 50 %)

% FIXED FACTORS
C = 30; % maximum contraction level & intercept
mean_recThSlope = -0.3; % mean slope of recruitment threshold factor
mean_recDRSlope = -1; % mean slope of discharge rate factor
recTh_recDR_interactionSlope = 0.0; % interaction between recruitment threshold
and recruitment discharge rate

% RANDOM FACTORS - UNIFORM DISTRIBUTION!!! (use randn for Normal distribution)
S = 0.2*(rand(1,NoSubjects) - 0.5); % random effect per subject
R = 0.025*(rand(NoRepetitions,NoSubjects) - 0.5); % random effect per repetition
M = 0.025*(rand(NoRepetitions,NoSubjects,NoMUs) - 0.5); % random effect per MU
```

Simulated data: MATLAB script



```
for Si = 1:NoSubjects
    for Ri = 1:NoRepetitions
        for Mi = 1:NoMUs
            % two factors
            RecThr(end+1,1) = Mi/NoMUs*0.7*C+0.1*rand();
            RecDR(end+1,1) = 7+rand();

            % coefficients
            DRintercept(end+1,1) = C;
            recThSlope(end+1,1) = mean_recThSlope + S(1,Si) + R(Ri,Si) + M(Ri,Si,Mi);
            recDRSlope(end+1,1) = mean_recDRSlope;

            % MaxDR generation
            MaxDR(end+1,1) = DRintercept(end,1) + recDRSlope(end,1)*RecDR(end) +
            recThSlope(end,1)*RecThr(end) +
            recTh_recDR_interactionSlope*RecDR(end)*RecThr(end) + 0.5*randn(1);

        end
    end
end
```

Simulated data: MATLAB script

```
for Si = 1:NoSubjects
    for Ri = 1:NoRepetitions
        for Mi = 1:NoMUs
```

In Wilkinson notation (with some simplifications):

MaxDR ~ 1 + RecThr+RecDR+ (-1 + RecThr|SubID) + (-1 + RecThr|ContRep) + (-1 + RecThr|SubID:MUID)

```
% coefficients
```

```
DRintercept(end+1,1) = C;
```

```
recThSlope(end+1,1) = mean_recThSlope + S(1,Si) + R(Ri,Si) + M(Ri,Si,Mi);
```

```
recDRSlope(end+1,1) = mean_recDRSlope;
```

```
% MaxDR generation
```

```
MaxDR(end+1,1) = DRintercept(end,1) + recDRSlope(end,1)*RecDR(end) +
```

```
recThSlope(end,1)*RecThr(end) +
```

```
recTh_recDR_interactionSlope*RecDR(end)*RecThr(end) + 0.5*randn(1);
```

```
end
end
end
```

Fixed effects/factors
Random effects/factors


residuals

Use MATLAB code to generate the simulated data: MATLAB script

Play with:

- number of subjects: `NoSubjects = 15`
- number of contraction repetitions: `NoRepetitions = 3`
- number of MUs: `NoMUs = 15;`
- portion of missed Mus: `portionOfMissedValues = 0.0`
- distribution of random factors: `S = 0.2*(rand(1,NoSubjects) ...`
- standard deviation of residuals: `...+ 0.5*randn(1)`

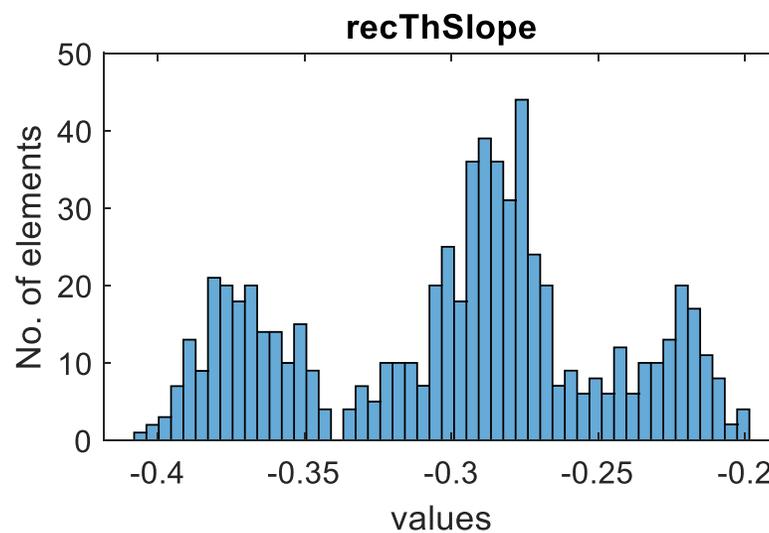
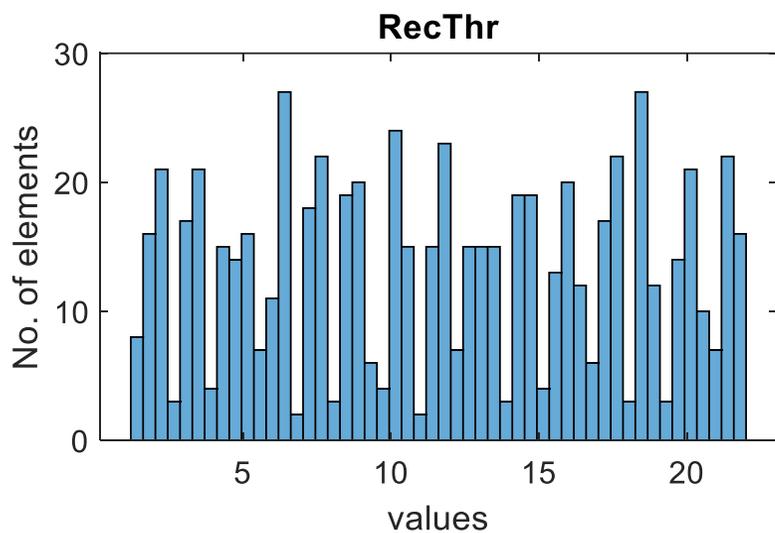
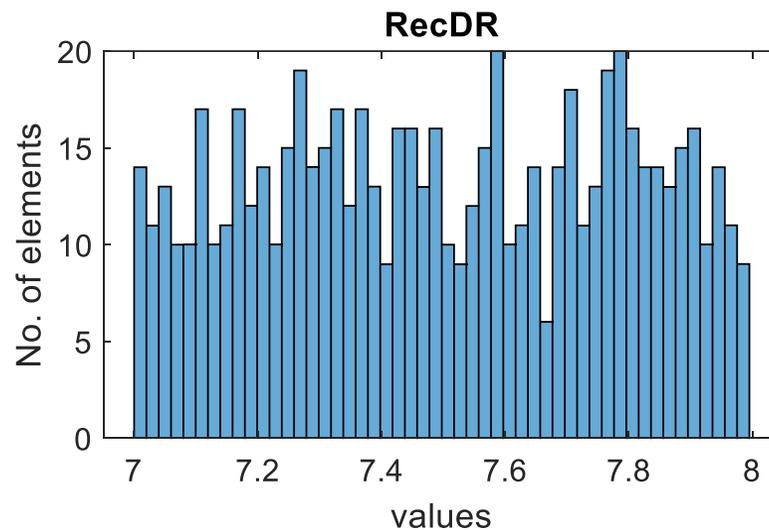
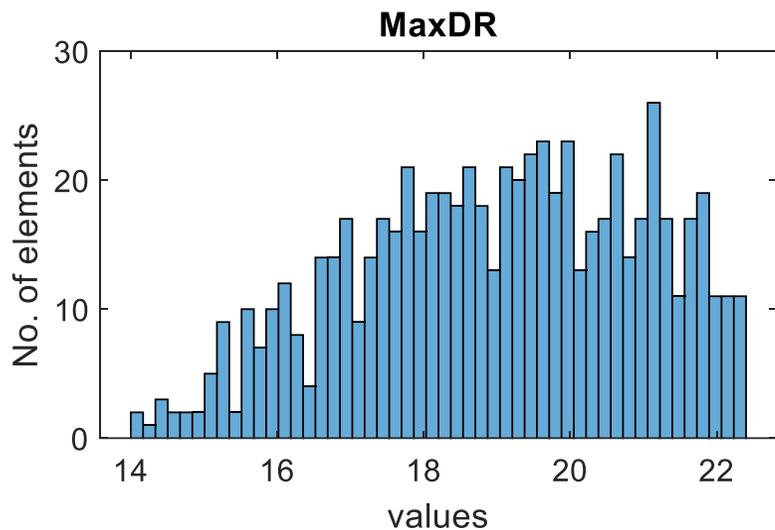
Generated synthetic data



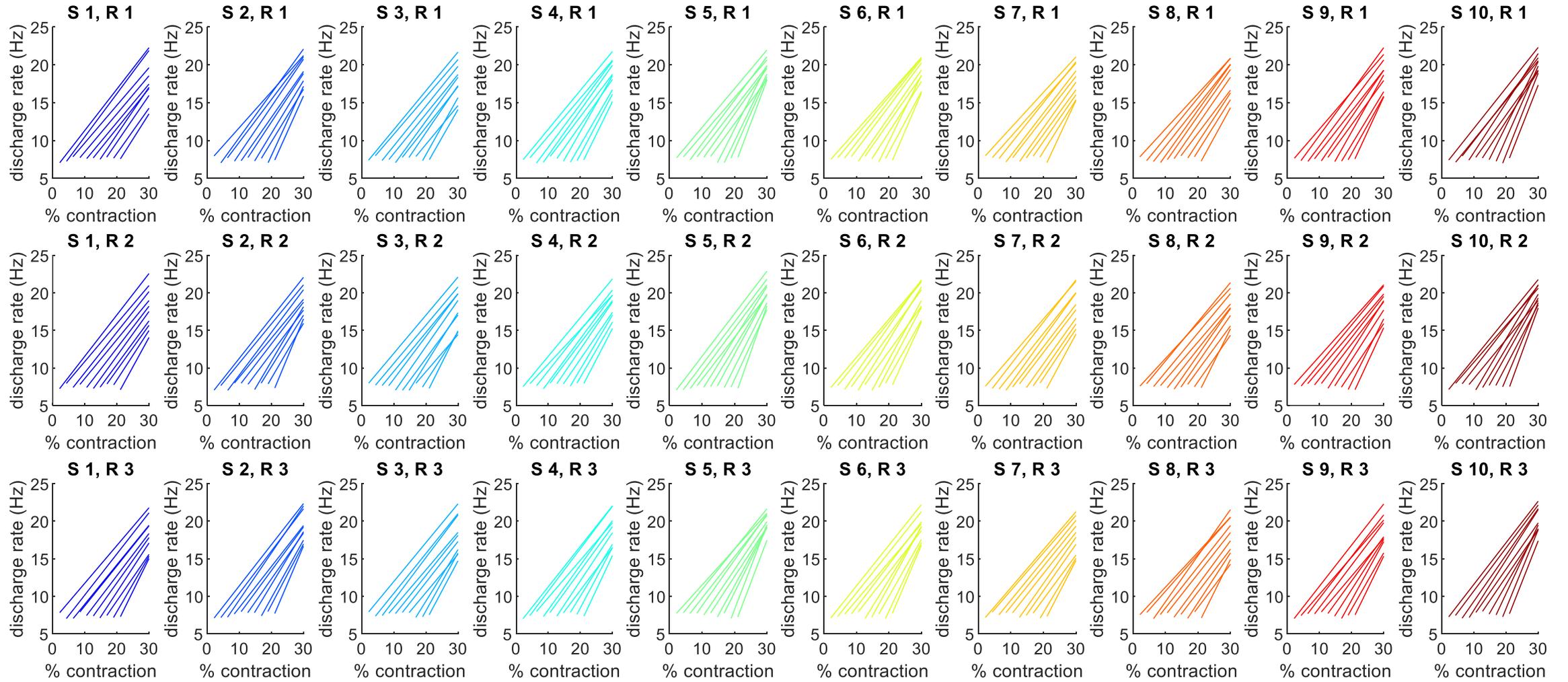
	SubID	ContRep	MUId	RecThr	RecDR	MaxDR
1	1	1	1	1.304582	7.809072	21.69751
2	1	1	2	2.217251	7.490311	21.89127
3	1	1	3	3.477377	7.564893	20.60219
4	1	1	4	5.111151	7.361645	20.87282
5	1	1	5	5.609156	7.127993	21.18084
6	1	1	6	7.242648	7.229332	20.36605
7	1	1	7	8.026397	7.187388	20.26364
8	1	1	8	9.160058	7.882963	18.96820
9	1	1	9	9.677212	7.819587	19.13943
10	1	1	10	10.832018	7.545053	18.73962
11	1	1	11	11.889022	7.700884	18.68902
12	1	1	12	13.502939	7.909991	17.93430
13	1	1	13	14.150664	7.329819	18.27405
14	1	1	14	14.736652	7.620602	17.36552
15	1	1	15	16.302724	7.746850	17.29255
16	1	1	16	16.922055	7.069719	16.69830
17	1	1	17	18.499537	7.925429	17.01645
18	1	1	18	19.771736	7.393052	15.97765
19	1	1	19	20.159837	7.010169	16.12223
20	1	1	20	21.240958	7.286717	15.67633
21	1	2	1	1.906525	7.028672	23.07511
22	1	2	2	2.485699	7.812762	21.07494
23	1	2	3	4.059424	7.664201	21.26823
24	1	2	4	5.058551	7.517004	20.18698
25	1	2	5	5.890015	7.920506	20.34778
26	1	2	6	7.178889	7.076835	19.80120

Showing 1 to 27 of 1,200 entries, 6 total columns

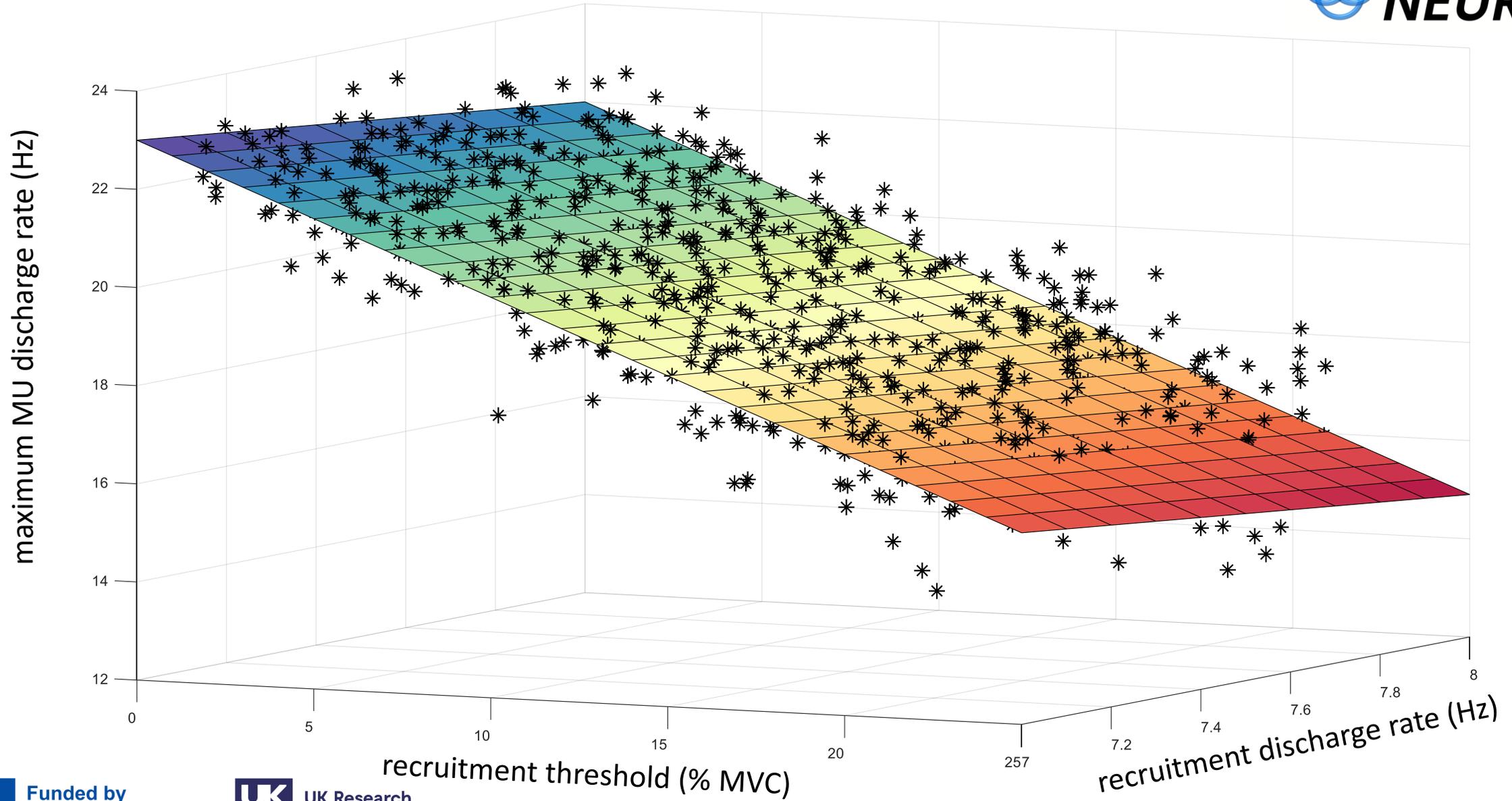
Simulated data: MATLAB script



Simulated data



Simulated data



Simulated data: different LMEs

```
MaxDR ~ 1 + RecThr + RecDR
```

Rstudio

```
lme2 <- lm(MaxDR ~ 1 + RecThr + RecDR, data = emg.data)
summary(lme2)
```

```
### plot residuals with qq-plot
```

```
qqnorm(residuals(lme2))
qqline(residuals(lme2))
```

```
### Visual check of model various assumptions
```

```
check_model(lme2)
```

MATLAB

```
lme2 = fitlme(Table1, 'MaxDR ~ 1 + RecThr + RecDR')
```

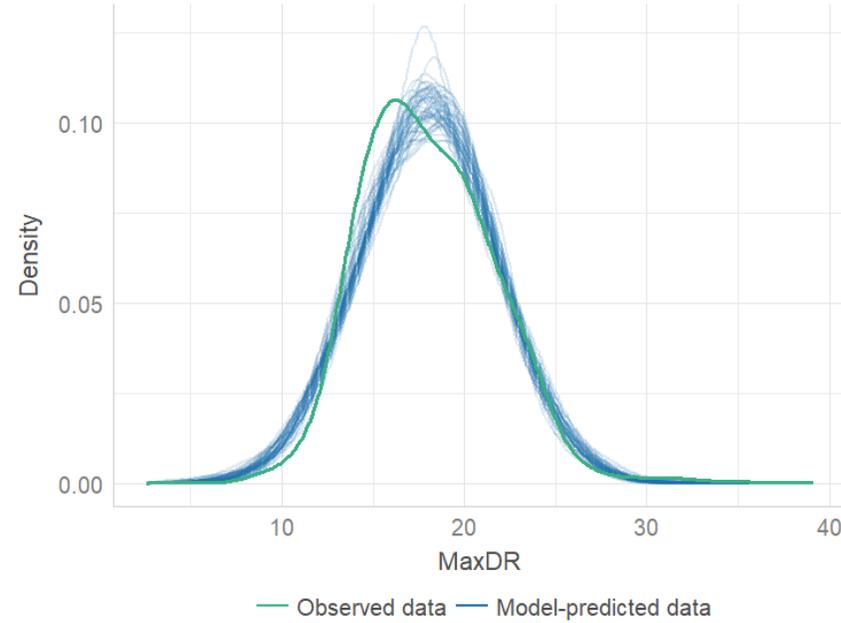
```
% Visual check of model various assumptions
```

```
figure; subplot(2,2,1); plotResiduals(lme2, 'probability');
subplot(2,2,2); plotResiduals(lme2, 'lagged');
subplot(2,2,3); plotResiduals(lme2, 'histogram');
subplot(2,2,4); plotResiduals(lme2, 'caseorder');
compare(lme1, lme2)
```

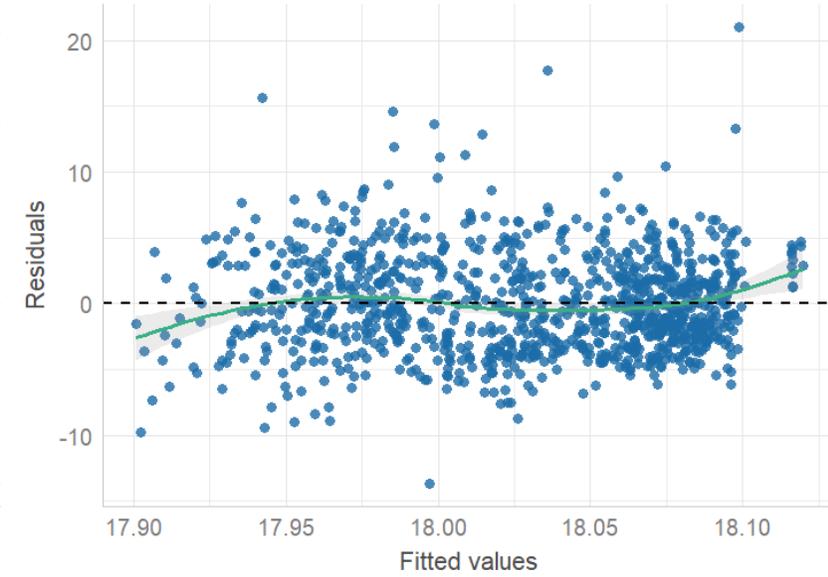
check_model...

- normality of residuals
- normality of random effects
- heteroscedasticity
- homogeneity of variance
- multicollinearity

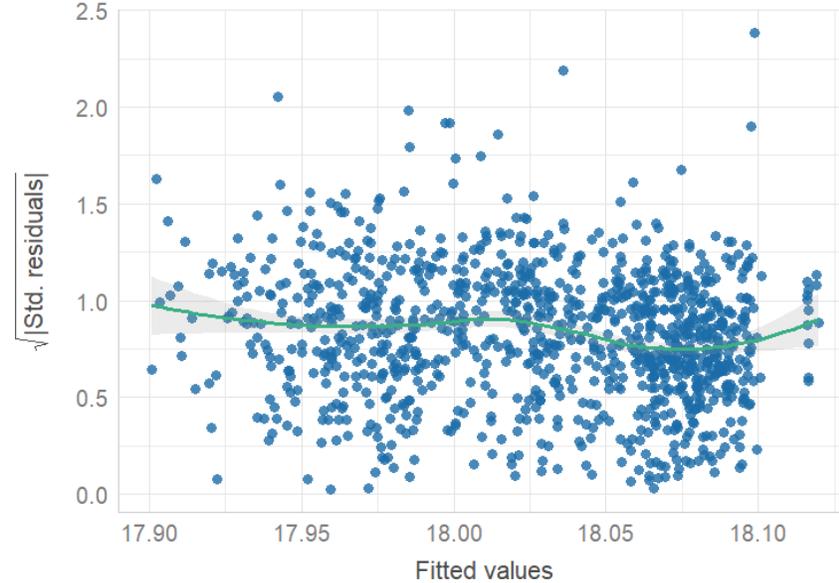
Posterior Predictive Check
Model-predicted lines should resemble observed data line



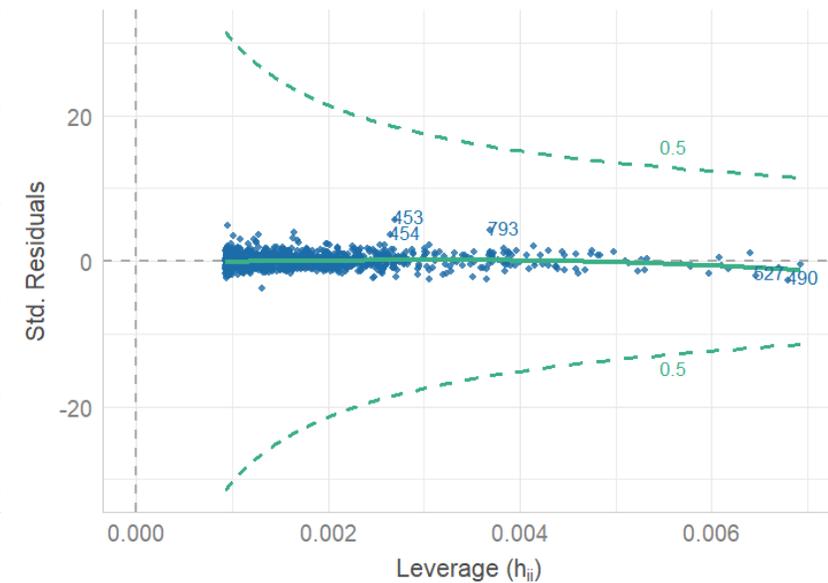
Linearity
Reference line should be flat and horizontal



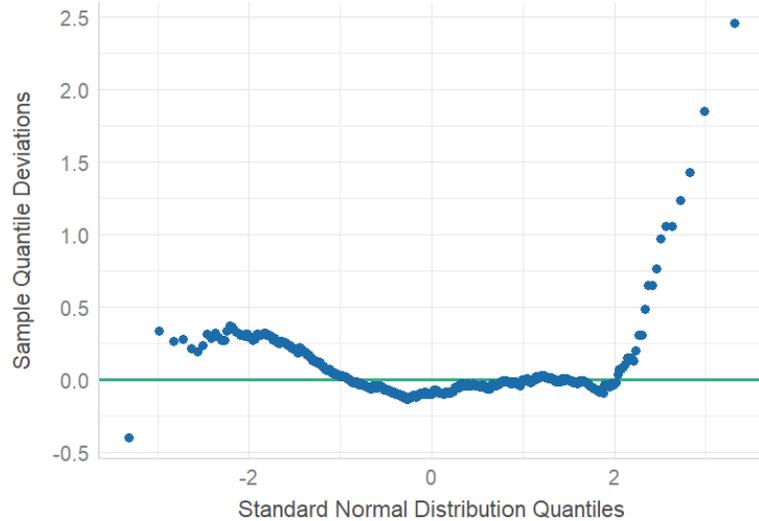
Homogeneity of Variance
Reference line should be flat and horizontal



Influential Observations
Points should be inside the contour lines



Normality of Residuals
Dots should fall along the line



Simulated data: different LMEs



MaxDR ~ 1 + RecThr

Rstudio

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	22.500201	0.060776	370.21	<2e-16 ***
RecThr	-0.299514	0.004616	-64.89	<2e-16 ***

MATLAB

Name	Estimate	SE	tStat	DF	pValue	Lower	Upper
{ '(Intercept) ' }	22.5	0.060686	370.76	673	0	22.381	22.619
{ 'RecThr ' }	-0.29951	0.0046091	-64.983	673	3.3361e-292	-0.30856	-0.29046

Ground truth:

{ '(Intercept) ' }	30.00
{ 'RecThr ' }	-0.30
{ 'RecDR ' }	-1.00

MaxDR ~ 1 + RecThr + RecDR

Rstudio

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	28.805324	0.704397	40.894	<2e-16 ***
RecThr	-0.300113	0.004365	-68.748	<2e-16 ***
RecDR	-0.839625	0.093489	-8.981	<2e-16 ***

MATLAB

Name	Estimate	SE	tStat	DF	pValue	Lower	Upper
{ '(Intercept) ' }	28.805	0.70283	40.985	672	5.8802e-185	27.425	30.185
{ 'RecThr ' }	-0.30011	0.0043557	-68.901	672	8.0329e-307	-0.30867	-0.29156
{ 'RecDR ' }	-0.83962	0.093281	-9.0011	672	2.2713e-18	-1.0228	-0.65647

Simulated data: different LMEs in Rstudio



MaxDR ~ 1 + RecThr + RecDR + (1 | ContRep) + (1 | SubID) + (1 | MUIid)

Rstudio

Fixed effects:	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	30.085862	0.392933	380.566120	76.57	<2e-16 ***
RecThr	-0.300210	0.002223	660.004042	-135.04	<2e-16 ***
RecDR	-1.010187	0.048070	660.204111	-21.02	<2e-16 ***

MATLAB

Name	Estimate	SE	tStat	DF	pValue	Lower	Upper
{ '(Intercept) ' }	30.086	0.39291	76.572	672	0	29.314	30.857
{ 'RecThr' }	-0.30021	0.0022231	-135.04	672	0	-0.30458	-0.29585
{ 'RecDR' }	-1.0102	0.048071	-21.014	672	9.592e-76	-1.1046	-0.9158

Ground truth:

{ '(Intercept) ' }	30.00
{ 'RecThr' }	-0.30
{ 'RecDR' }	-1.00

MaxDR ~ 1 + RecThr + RecDR + (RecThr | ContRep) + (RecThr | SubID) + (RecThr | MUIid)

Rstudio

Fixed effects:	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	30.03710	0.16927	654.57554	177.45	< 2e-16 ***
RecThr	-0.30053	0.01319	15.67415	-22.78	1.95e-13 ***
RecDR	-1.00322	0.02243	655.64726	-44.73	< 2e-16 ***

MATLAB

Name	Estimate	SE	tStat	DF	pValue	Lower	Upper
{ '(Intercept) ' }	30.034	0.16931	177.39	672	0	29.702	30.367
{ 'RecThr' }	-0.3005	0.013158	-22.837	672	7.012e-86	-0.32634	-0.27466
{ 'RecDR' }	-1.0029	0.02246	-44.652	672	2.936e-203	-1.047	-0.95879

Simulated data: Bayesian regression

MaxDR ~ 1 + RecThr + RecDR

Rstudio

```
blr1 <- brm(MaxDR ~ RecThr+RecDR, data = emg.data,  
            prior = c(set_prior("normal(0,3)", class = "b"),  
                      set_prior("cauchy(0,2.5)", class = "sigma")),  
            family = gaussian(), seed = 123123)  
  
summary(blr1, waic = TRUE)
```

MATLAB

```
NoPredictors=2;  
  
PriorMdl1 = bayeslm(NoPredictors,ModelType="diffuse", VarNames=["RecThr" "RecDR"]);  
PriorMdl1 = bayeslm(NoPredictors,ModelType="mixconjugateblm", VarNames=["RecThr" "RecDR"]);  
plot(PriorMdl1); set(gcf,'Position',get(0,'ScreenSize'))  
  
X = Table1{Table1.ContLev==30 & Table1.PNR>PNRthreshold,PriorMdl1.VarNames(2:end)};  
y = Table1{Table1.ContLev==30 & Table1.PNR>PNRthreshold,"MaxDR"};  
PosteriorMdl1 = estimate(PriorMdl1,X,y);  
plot(PosteriorMdl1,PriorMdl1); set(gcf,'Position',get(0,'ScreenSize'))
```

Simulated data: Bayesian regression

MaxDR ~ 1 + RecThr + RecDR

Converged or not?

Rstudio

Population-Level Effects:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
Intercept	28.80	0.71	27.41	30.21	1.00	3666	2806
RecThr	-0.30	0.00	-0.31	-0.29	1.00	5574	3248
RecDR	-0.84	0.09	-1.03	-0.65	1.00	3656	2727

Family Specific Parameters:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sigma	0.69	0.02	0.65	0.72	1.00	3745	3395

MATLAB

	Mean	Std	CI95	Positive	Distribution	Regime
Intercept	28.2943	0.6873	[26.942, 29.637]	1.000	Empirical	1
RecThr	-0.2999	0.0044	[-0.308, -0.291]	0.000	Empirical	1
RecDR	-0.7720	0.0912	[-0.950, -0.592]	0.000	Empirical	1
Sigma2	0.4707	0.0259	[0.422, 0.524]	1.000	Empirical	NaN

Ground truth:

{ '(Intercept) ' }	30.00
{ 'RecThr' }	-0.30
{ 'RecDR' }	-1.00

Simulated data: Bayesian regression



MaxDR ~ 1 + RecThr + RecDR + ContRep SubID + MUIid

Rstudio

Population-Level Effects:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
Intercept	29.51	0.66	28.20	30.81	1.00	3889	2832
RecThr	-0.29	0.09	-0.46	-0.12	1.00	2246	2293
RecDR	-0.88	0.09	-1.05	-0.70	1.00	3941	2635
SubID	-0.06	0.01	-0.07	-0.05	1.00	4695	2770
ContRep	0.02	0.03	-0.04	0.08	1.00	4041	2858
MUIid	-0.01	0.12	-0.26	0.22	1.00	2241	2351

Ground truth:

```
{ '(Intercept) ' } 30.00
{ 'RecThr'       } -0.30
{ 'RecDR'       } -1.00
```

Family Specific Parameters:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sigma	0.64	0.02	0.61	0.68	1.00	3778	2491

MATLAB

	Mean	Std	CI95	Positive	Distribution
Intercept	29.5166	0.6693	[28.204, 30.829]	1.000	t (29.52, 0.67^2, 6.7e+02)
RecThr	-0.2917	0.0877	[-0.464, -0.120]	0.000	t (-0.29, 0.09^2, 6.7e+02)
RecDR	-0.8795	0.0877	[-1.051, -0.707]	0.000	t (-0.88, 0.09^2, 6.7e+02)
SubID	-0.0567	0.0057	[-0.068, -0.045]	0.000	t (-0.06, 0.01^2, 6.7e+02)
ContRep	0.0185	0.0303	[-0.041, 0.078]	0.730	t (0.02, 0.03^2, 6.7e+02)
MUIid	-0.0118	0.1227	[-0.252, 0.229]	0.462	t (-0.01, 0.12^2, 6.7e+02)
Sigma2	0.4124	0.0226	[0.370, 0.459]	1.000	IG(334.50, 0.0073)

Simulated data: Bayesian regression



MaxDR ~ 1 + RecThr+RecDR+ (-1 + RecThr|ContRep) + (-1 + RecThr|SubID) + (-1 + RecThr|MUID)

Rstudio

Group-Level Effects:

~ContRep (Number of levels: 3)

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sd(RecThr)	0.01	0.02	0.00	0.04	1.01	592	1301

~MUID (Number of levels: 15)

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sd(RecThr)	0.00	0.00	0.00	0.00	1.01	423	371

~SubID (Number of levels: 15)

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sd(RecThr)	0.06	0.01	0.04	0.09	1.06	55	460

Population-Level Effects:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
Intercept	30.03	0.18	29.68	30.37	1.02	392	1278
RecThr	-0.30	0.02	-0.33	-0.27	1.04	130	374
RecDR	-1.00	0.02	-1.05	-0.96	1.02	330	1178

Family Specific Parameters:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sigma	0.16	0.00	0.15	0.17	1.02	249	834

MATLAB

Model not supported

Ground truth:

{ '(Intercept) ' }	30.00
{ 'RecThr' }	-0.30
{ 'RecDR' }	-1.00



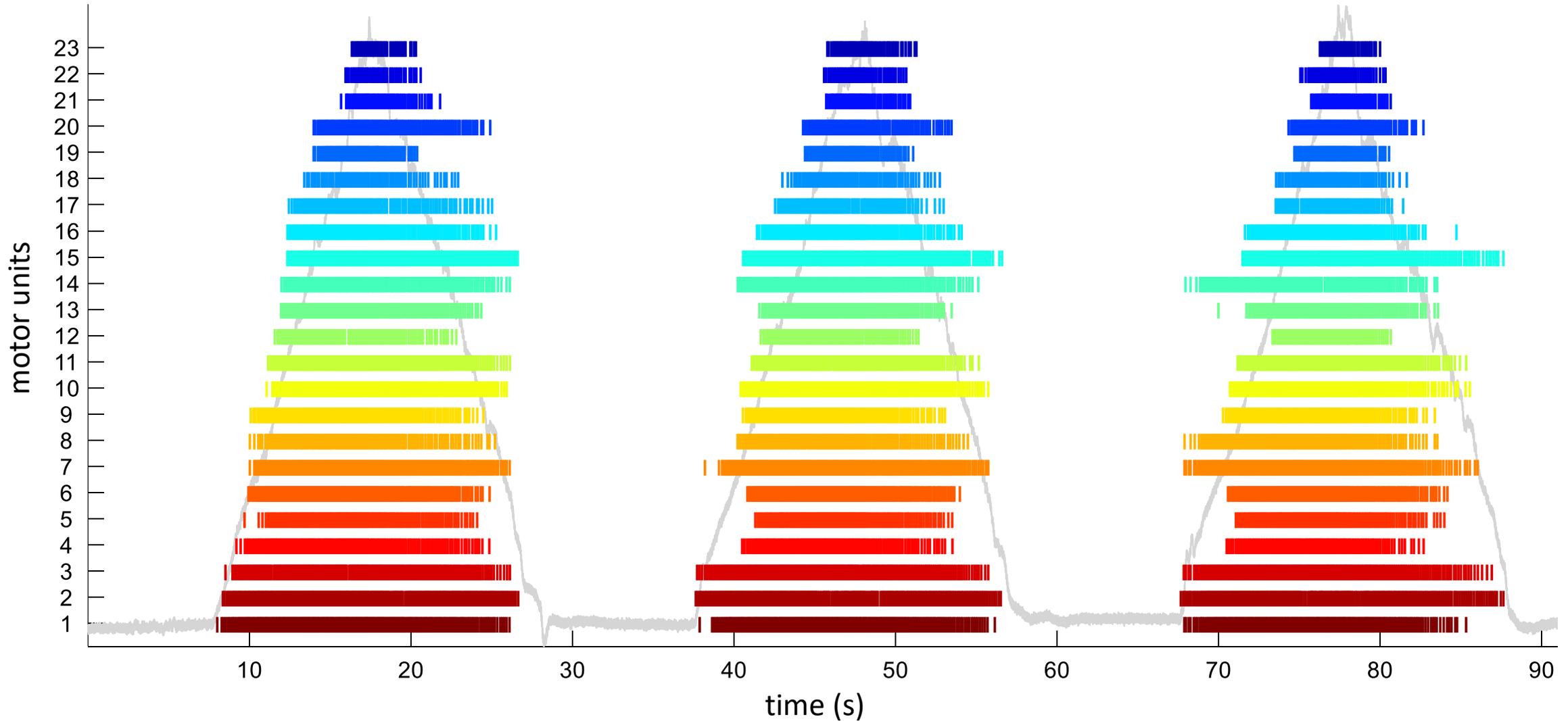
Experimental data

Tibialis anterior, healthy subjects, 30% ramp contractions

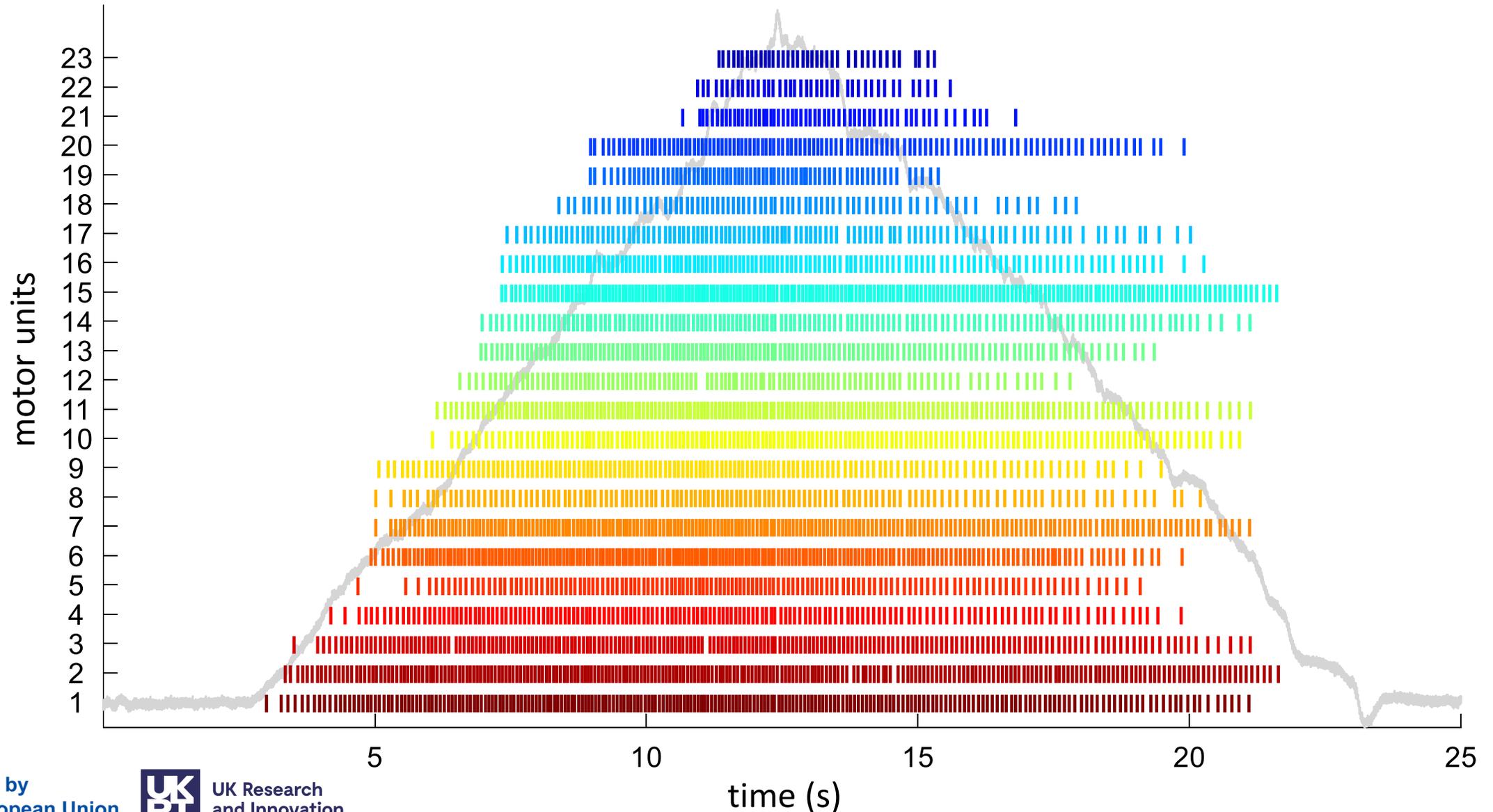
Experimental data

- 19 healthy subjects
- Tibialis anterior muscle
- HDEMG signals
 - 64 channels
 - Sampling: 16 bit resolution and 2048 Hz of sampling rate
- Decomposition
 - Convolution Kernel Compensation (CKC)
 - Manually edited by two experts, only accurately identified motor units (MU) kept for analysis

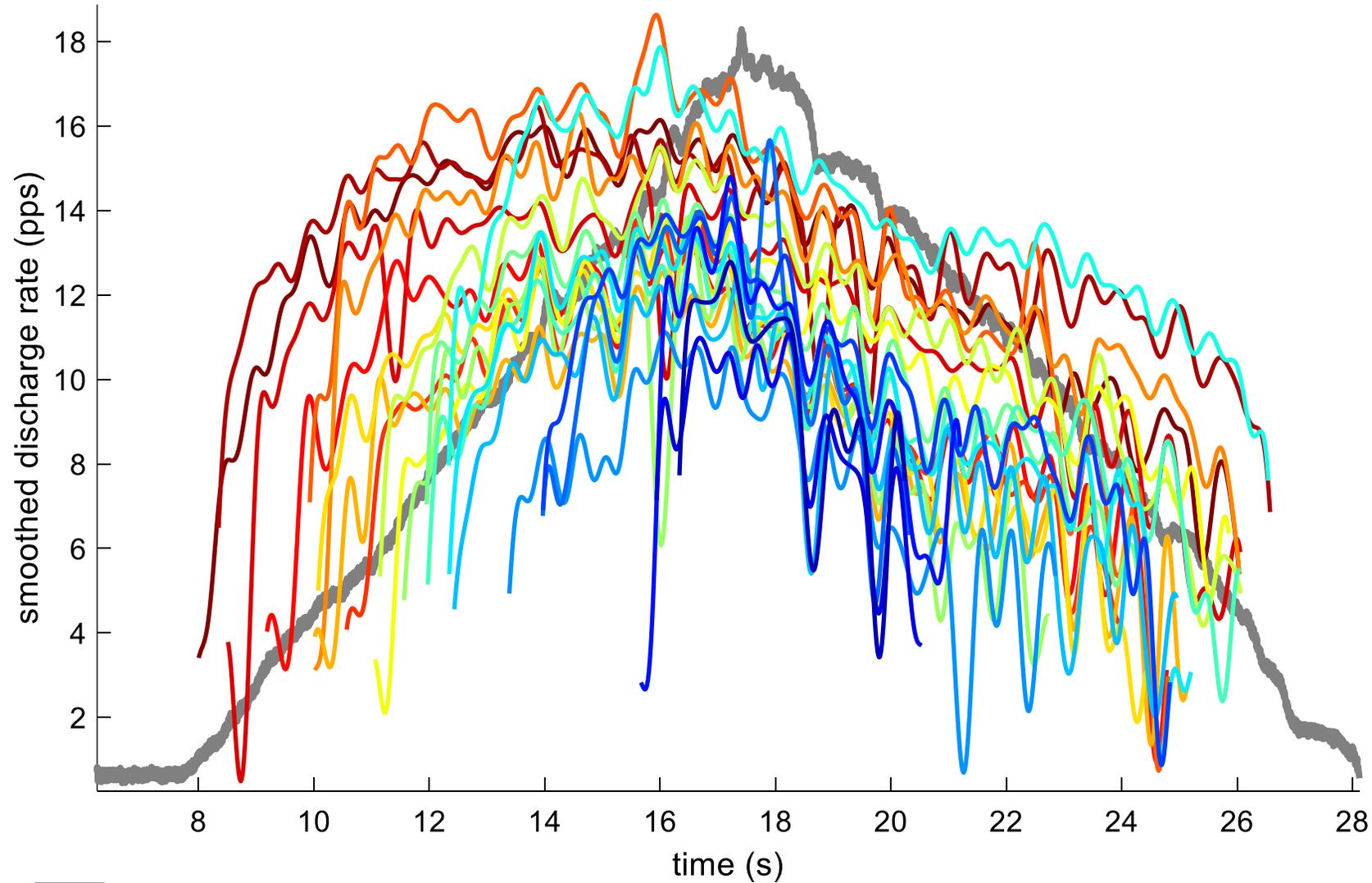
Experimental data: MU tracked across contractions, variations in MU recruitment threshold



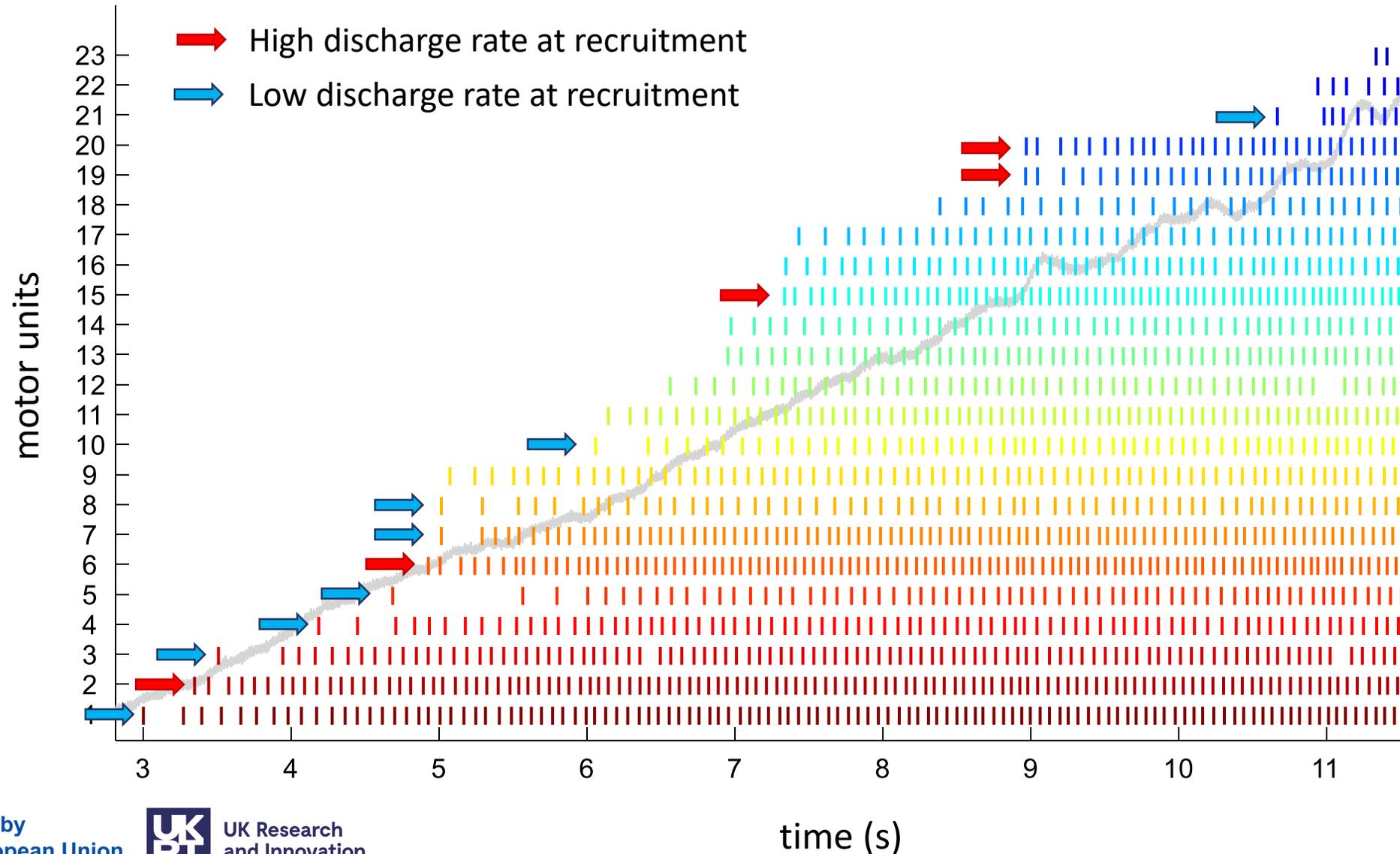
Experimental data: variability of MU recruitment discharge rate



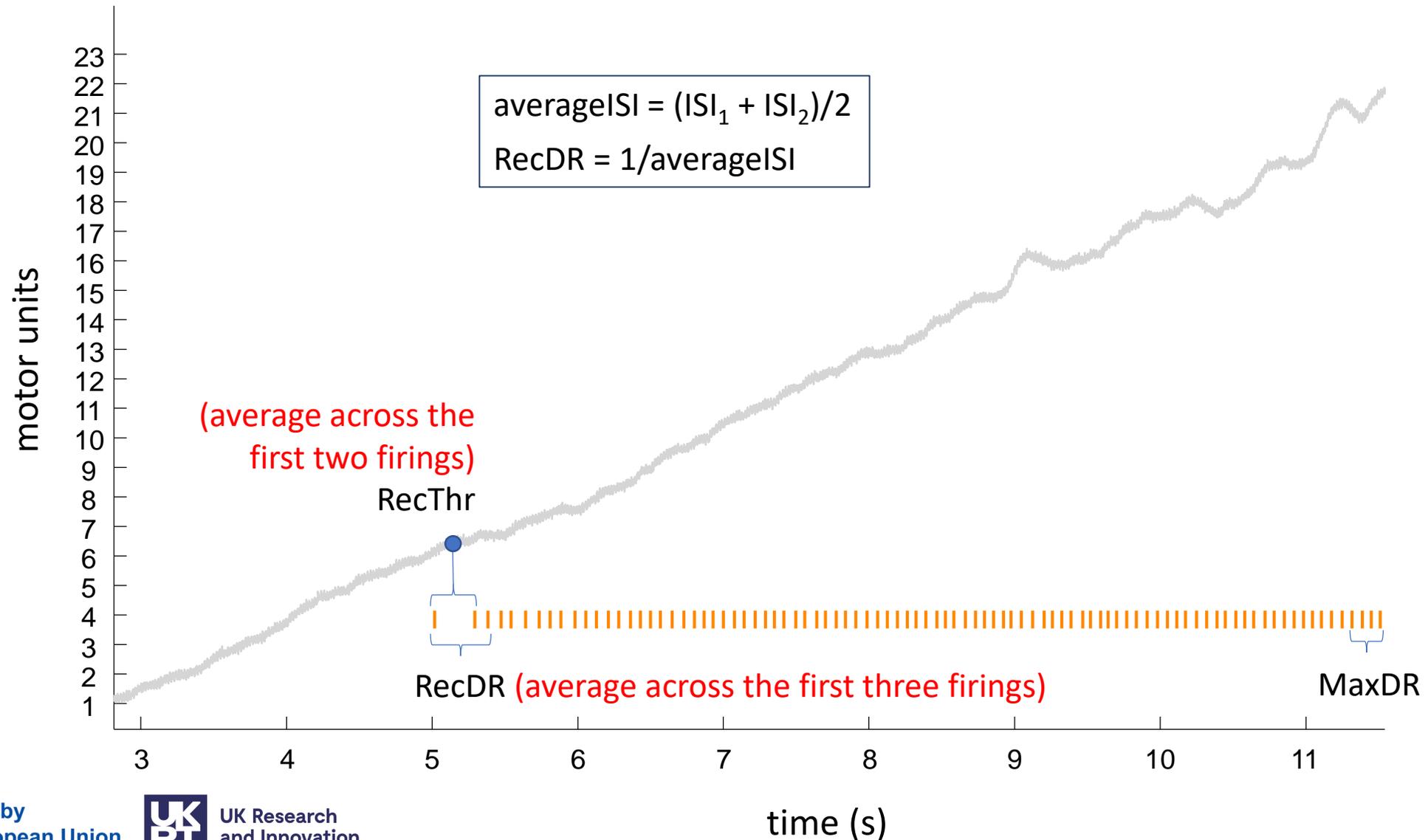
Experimental data



Experimental data: variability of MU recruitment discharge rate



Experimental data: discharge rate and recruitment threshold calculations



Extracted data from experimental HDEMG

	SubID	ContLev	ContRep	MUID	RecThr	RecDR	MaxDR	PNR
1	1	30	1	1	0.6569055	7.335337	16.341819	25.91926
2	1	30	1	2	1.2383117	6.933358	15.925919	34.64867
3	1	30	1	4	1.9663557	10.367114	16.429530	31.07783
4	1	30	1	5	2.2390207	6.711693	15.387350	33.61697
5	1	30	1	7	3.8457452	7.212698	18.038826	33.71810
6	1	30	1	8	3.8825443	5.421191	14.658741	38.74707
7	1	30	1	9	3.9298414	5.149425	13.334769	39.86485
8	1	30	1	10	4.0012238	8.989763	15.940111	30.63242
9	1	30	1	11	4.3347160	6.607963	13.761101	34.93147
10	1	30	1	12	5.6329045	7.506767	13.223399	34.20745
11	1	30	1	15	9.4745756	7.632033	15.508550	30.69901
12	1	30	1	16	9.8373421	7.623913	14.182222	35.78660
13	1	30	1	17	9.9524461	7.566303	14.236357	33.57780
14	1	30	1	18	9.9524461	6.939700	14.002998	26.22607
15	1	30	1	19	9.9855810	8.212448	16.460278	33.74459
16	1	30	1	20	10.5830719	7.531014	13.934777	29.21554
17	1	30	1	21	11.5181735	7.383080	14.850754	25.98349
18	1	30	1	22	11.9682065	9.002758	12.781504	29.92432
19	1	30	1	23	12.2822505	5.789410	11.277619	34.08185
20	1	30	1	24	15.5528515	7.055209	14.593718	28.18759
21	1	30	1	25	15.5579976	4.528634	12.954859	27.72613
22	1	30	1	26	15.9778303	6.594490	13.636291	39.86824
23	1	30	1	27	15.9947253	9.981402	16.909188	27.32570
24	1	30	1	28	21.3873306	10.284329	14.310285	34.51161
25	1	30	2	1	0.2818675	8.765103	16.838501	25.24965
26	1	30	2	2	1.3257065	8.308624	12.678760	34.25484
27	1	30	2	4	2.2317743	9.353130	16.550371	28.55214
28	1	30	2	5	0.7520789	7.210378	15.319340	33.70748
29	1	30	2	6	8.8643727	8.878025	16.724040	26.22825

Showing 1 to 29 of 1,071 entries, 8 total columns

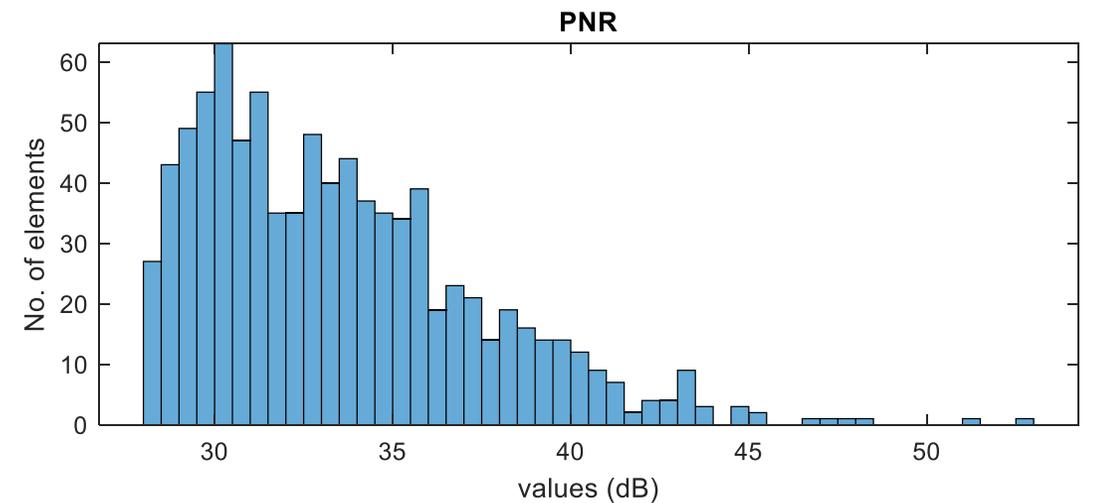
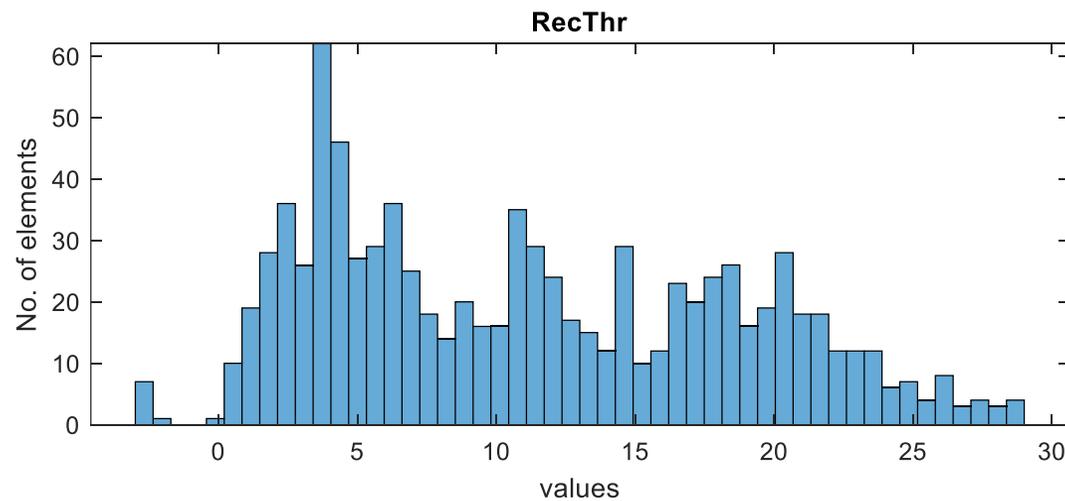
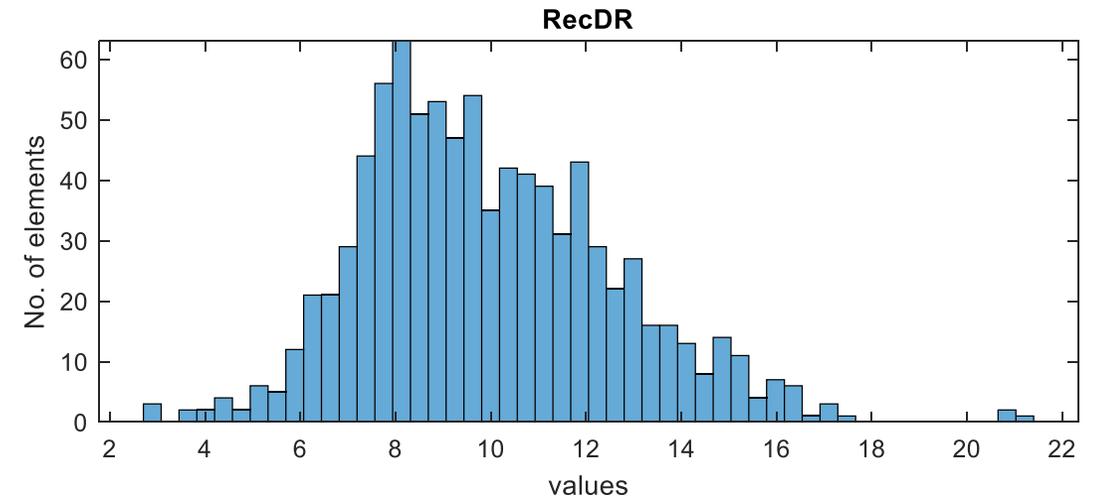
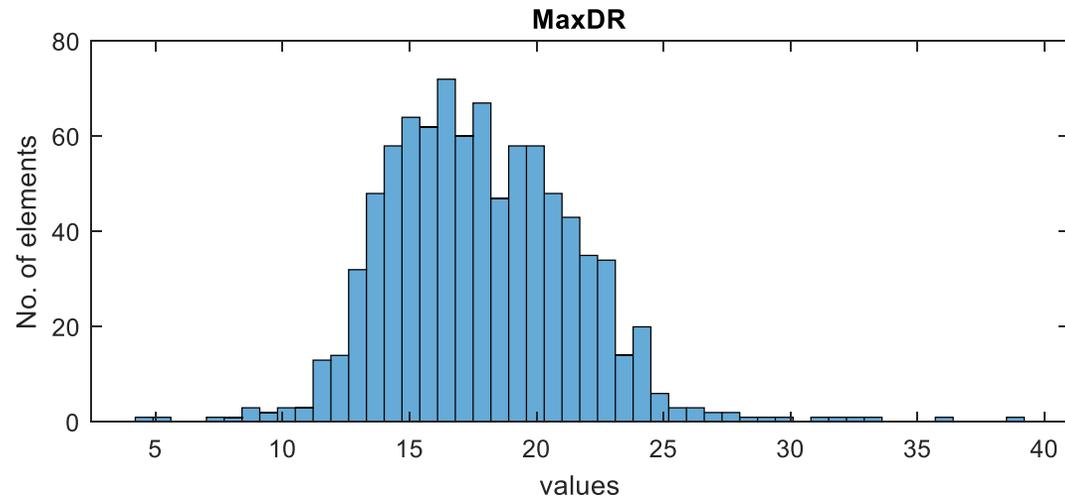


Funded by the European Union

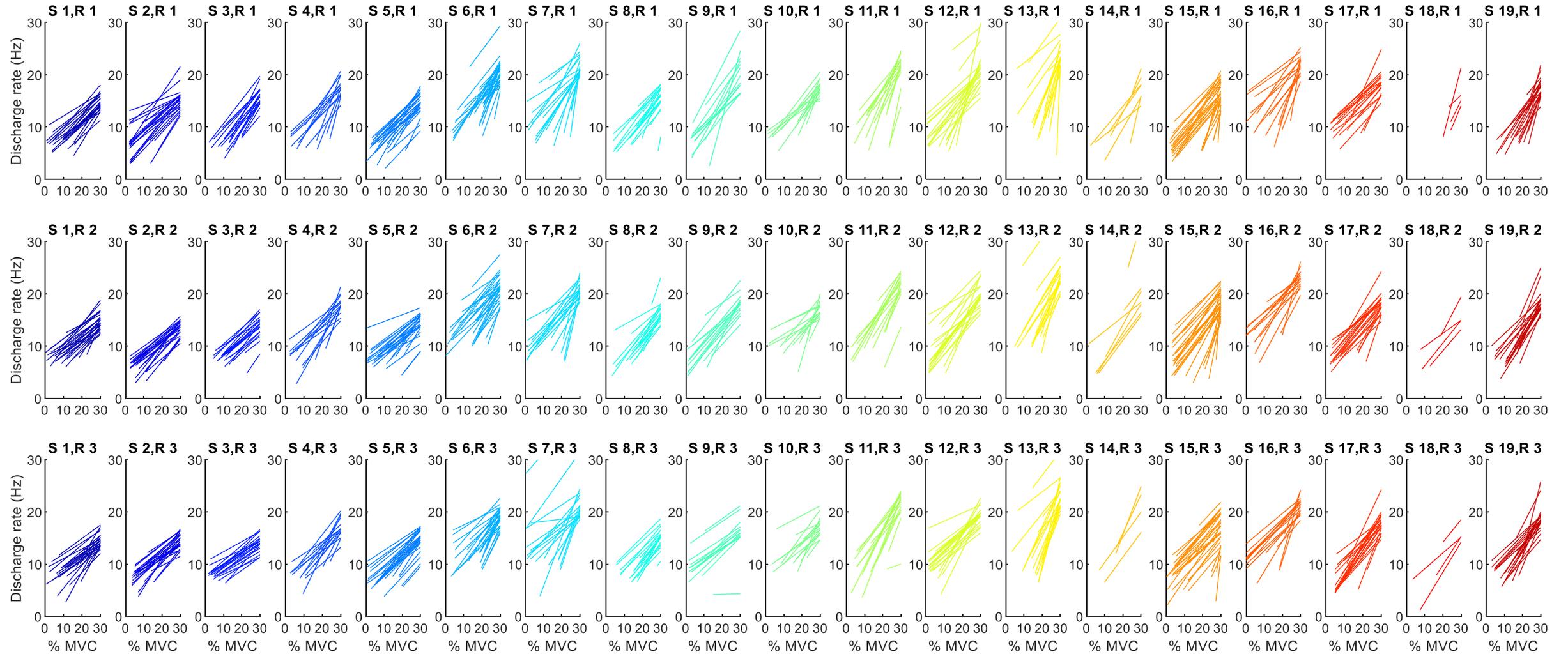


UK Research and Innovation

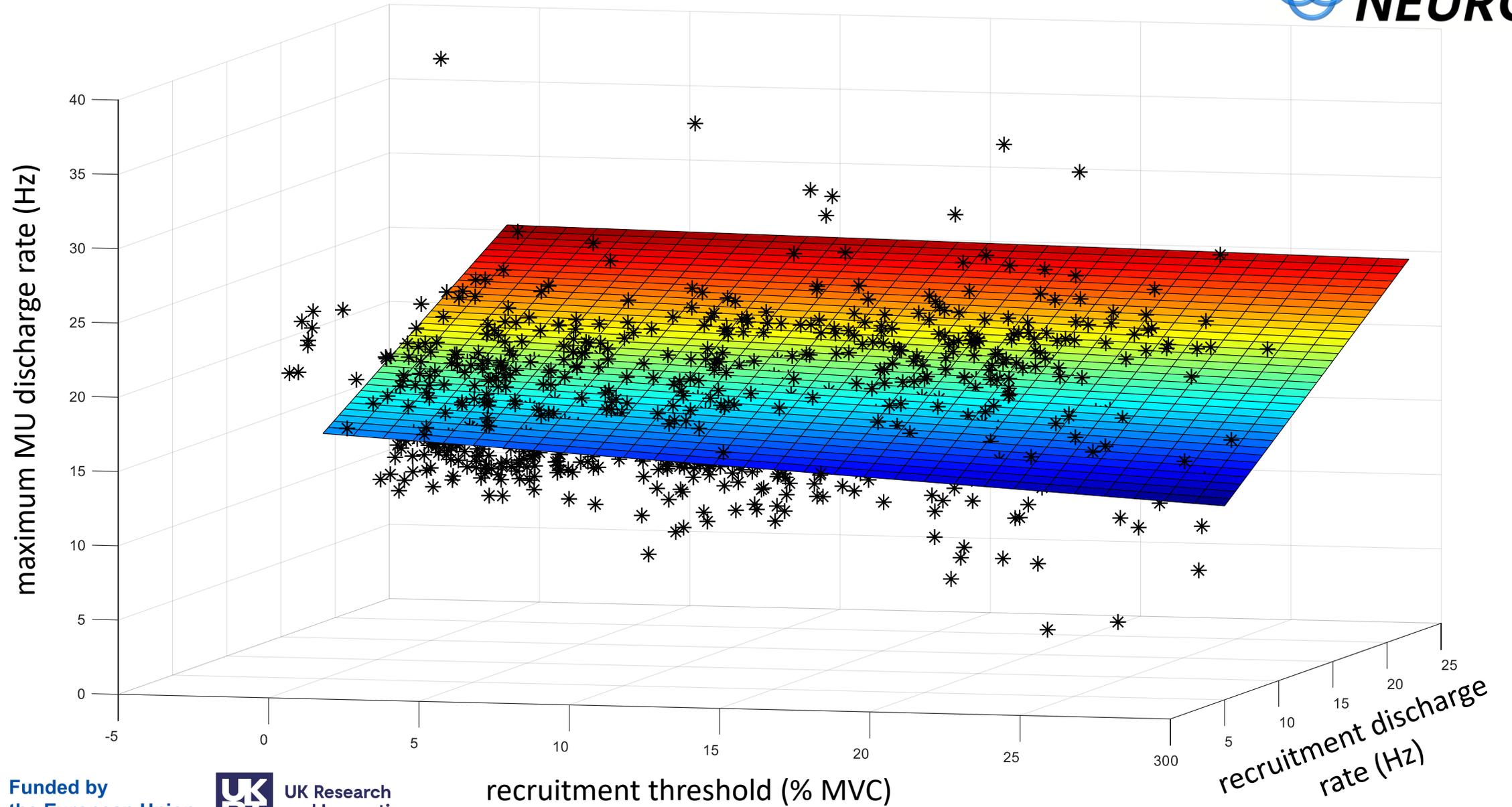
Extracted data distributions



Experimental data



Simulated data



Experimental data: different LMEs in MATLAB

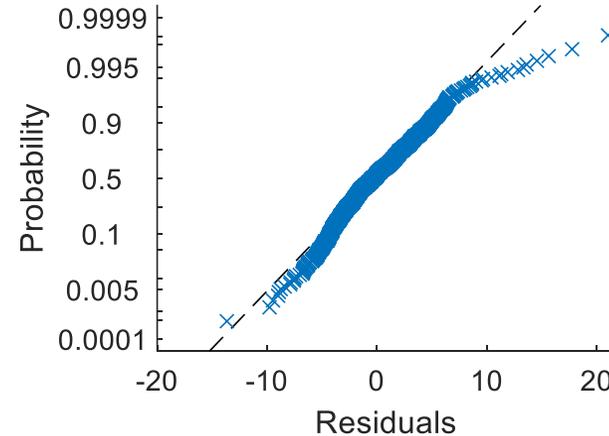


MaxDR ~ MaxDR ~ 1 + RecThr

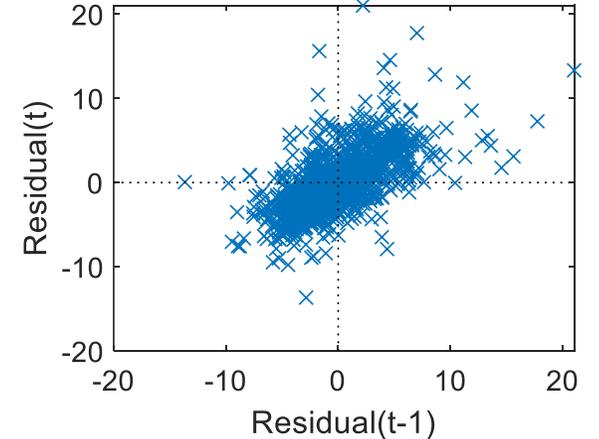
MATLAB

Name	Estimate	SE	tStat	DF	pValue	Lower	Upper
{ '(Intercept) ' }	18.1	0.19524	92.707	1069	0	17.717	18.483
{ 'RecThr ' }	-0.0069234	0.015477	-0.44734	1069	0.65472	-0.037292	0.023445

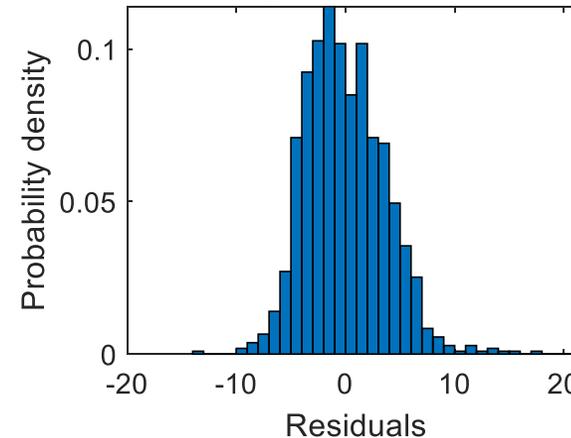
Normal probability plot of residuals



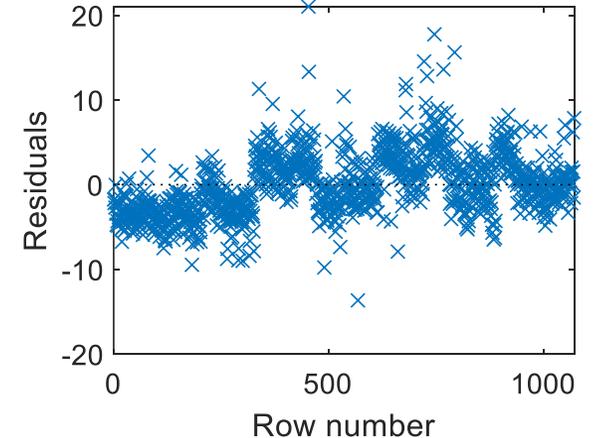
Plot of residuals vs. lagged residuals



Histogram of residuals



Case order plot of residuals



Ground truth unknown!

Experimental data: different LMEs in Rstudio



MaxDR ~ MaxDR ~ 1 + RecThr

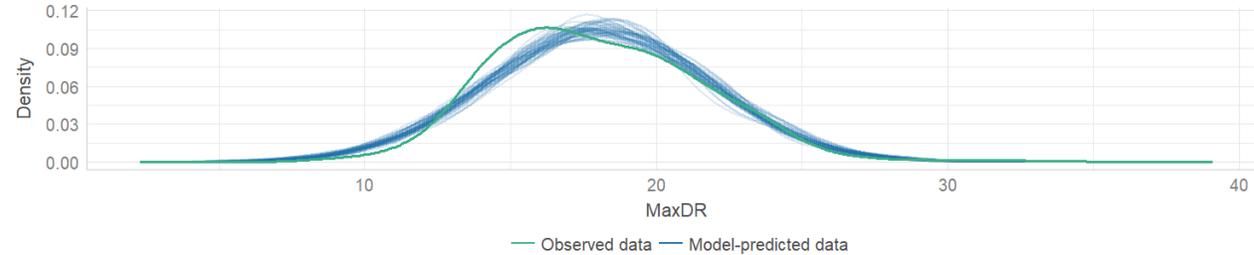
Rstudio

Coefficients:	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	18.100383	0.195426	92.620	<2e-16 ***
RecThr	-0.006923	0.015491	-0.447	0.655

Ground truth unknown!

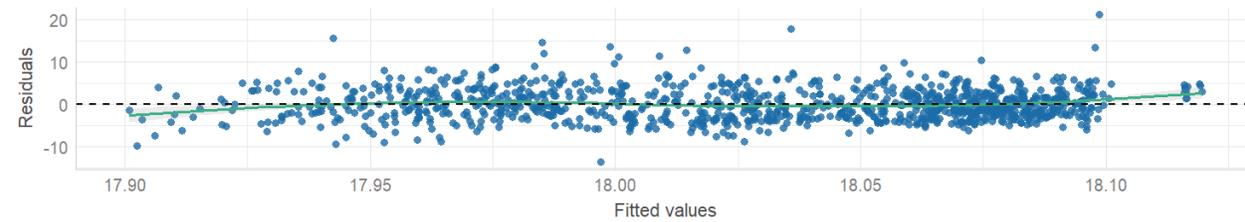
Posterior Predictive Check

Model-predicted lines should resemble observed data line



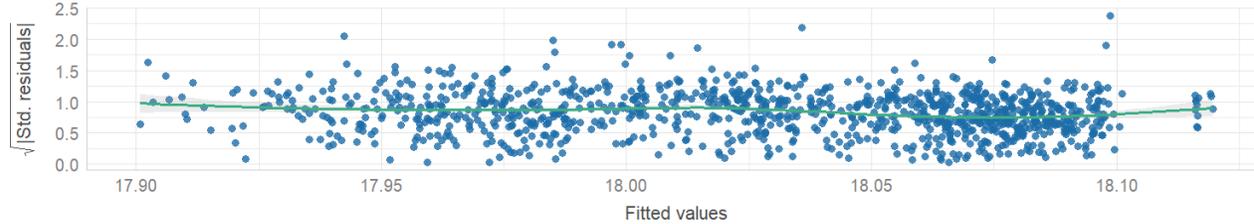
Linearity

Reference line should be flat and horizontal



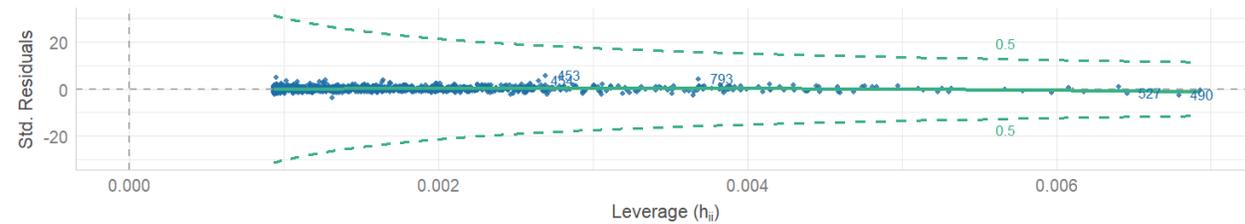
Homogeneity of Variance

Reference line should be flat and horizontal



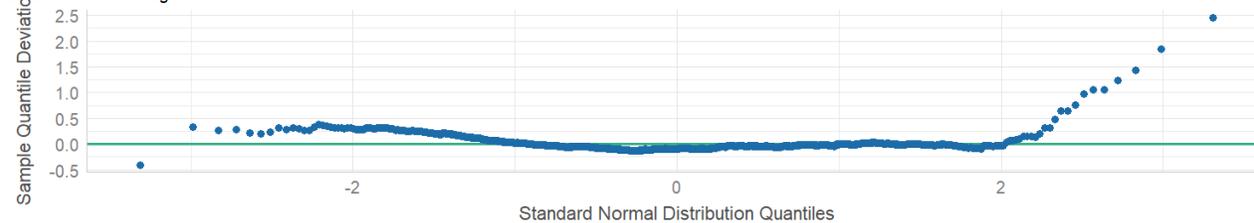
Influential Observations

Points should be inside the contour lines



Normality of Residuals

Points should fall along the line



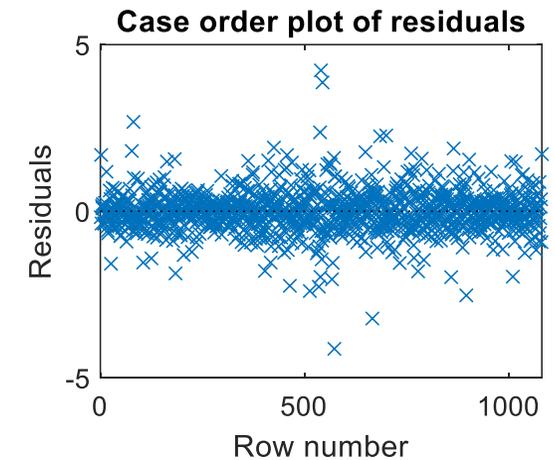
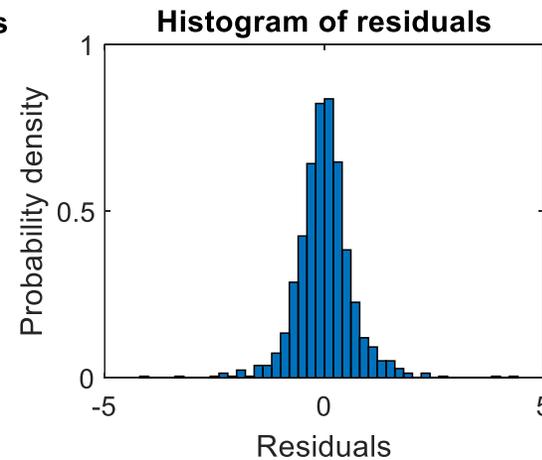
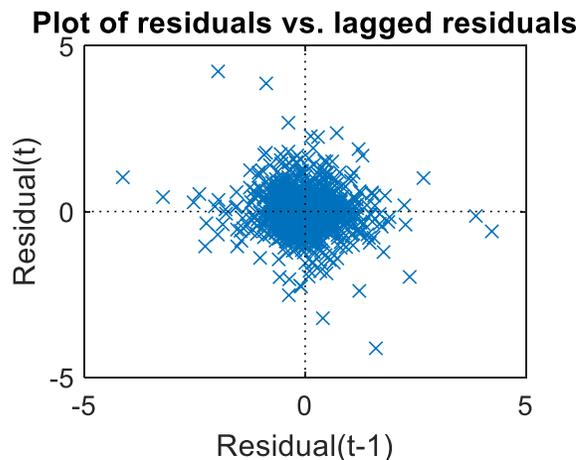
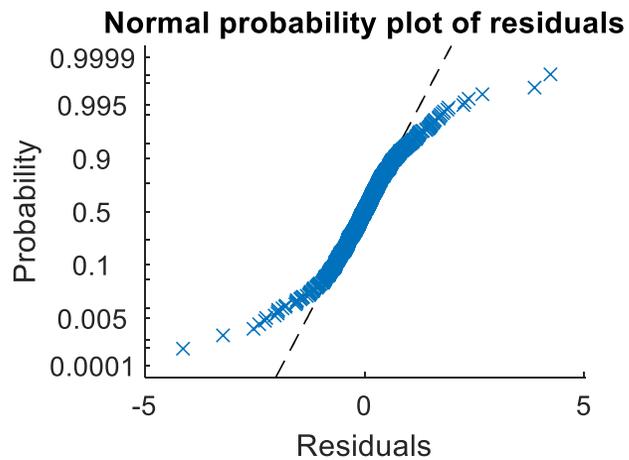
Experimental data: different LMEs in MATLAB



MaxDR ~ 1 + RecThr*RecDR+(-1 + RecThr|ContRep) + (-1 + RecThr|SubID)+ ' ...
 ' (-1 + RecThr|SubID:MUid) + (-1 + RecDR|ContRep) + (-1 + RecDR|SubID)+ (-1 + RecDR|SubID:MUid)

MATLAB

Name	Estimate	SE	tStat	DF	pValue	Lower	Upper
{ '(Intercept) ' }	15.996	0.3341	47.878	1067	5.5495e-268	15.34	16.652
{ 'RecThr' }	0.0027776	0.042105	0.065967	1067	0.94742	-0.079841	0.085396
{ 'RecDR' }	0.29774	0.064784	4.596	1067	4.8222e-06	0.17063	0.42486
{ 'RecThr:RecDR' }	-0.0089509	0.0029048	-3.0815	1067	0.0021126	-0.014651	-0.0032512



Ground truth unknown!

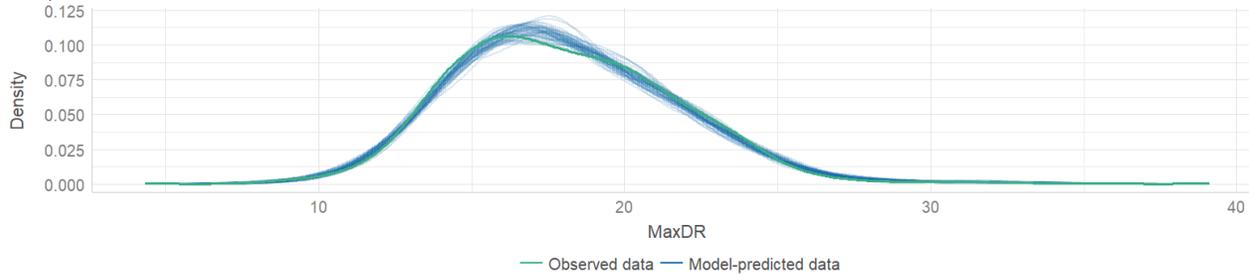
Experimental data: different LMEs in Rstudio



$$\text{MaxDR} \sim 1 + \text{RecThr} * \text{RecDR} + (1 + \text{RecThr} | \text{SubID}) + (1 + \text{RecThr} | \text{SubID} : \text{ContRep}) + (1 + \text{RecThr} | \text{SubID} : \text{MUI}) + (1 + \text{RecDR} | \text{SubID} : \text{ContRep}) + (1 + \text{RecDR} | \text{SubID} : \text{MUI})$$

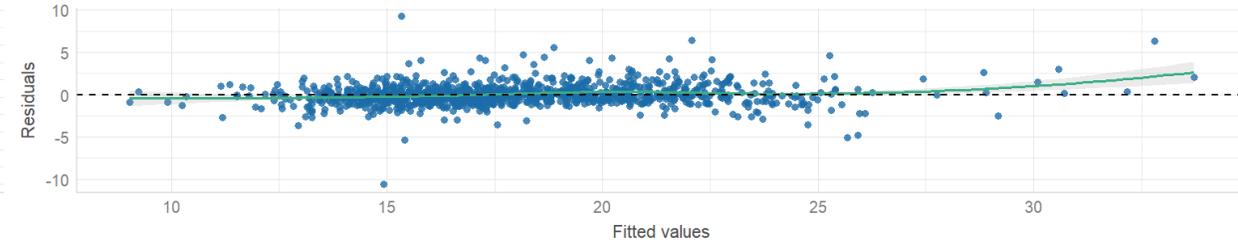
Posterior Predictive Check

Model-predicted lines should resemble observed data line



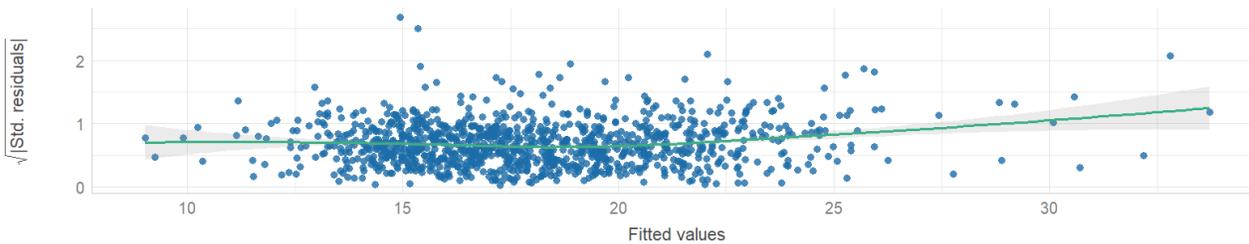
Linearity

Reference line should be flat and horizontal



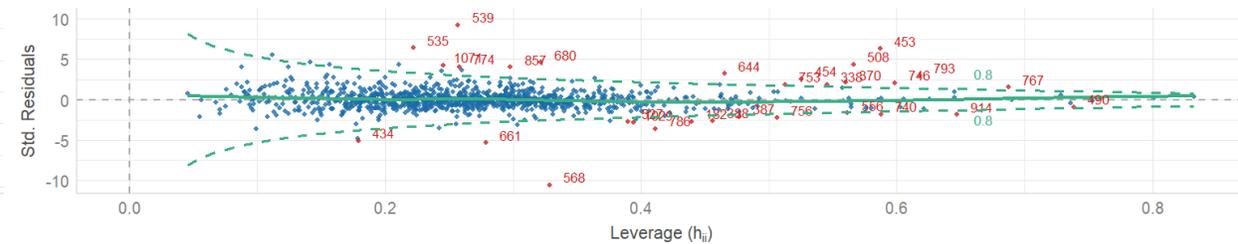
Homogeneity of Variance

Reference line should be flat and horizontal



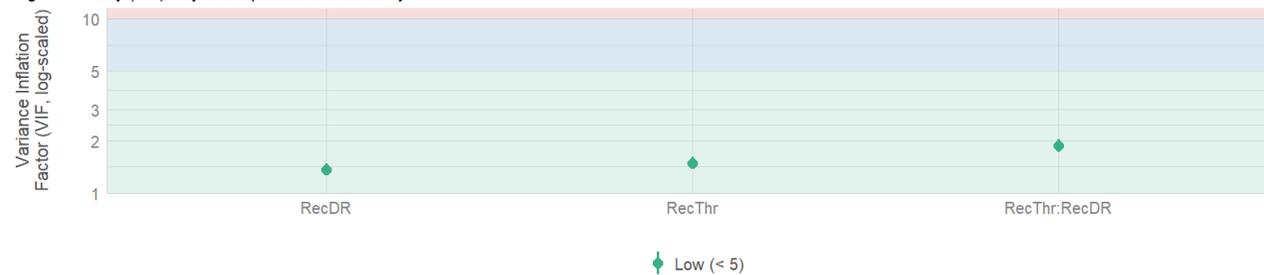
Influential Observations

Points should be inside the contour lines



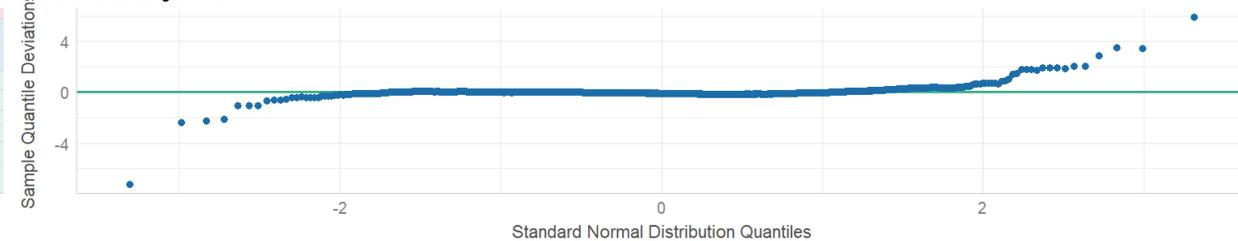
Collinearity

High collinearity (VIF) may inflate parameter uncertainty



Normality of Residuals

Points should fall along the line



Experimental data: different LMEs in Rstudio



MaxDR ~ 1 + RecThr*RecDR+(-1 + RecThr|ContRep) + (-1 + RecThr|SubID)+ ' ...
 ' (-1 + RecThr|SubID:MUID) +(-1 + RecDR|ContRep) + (-1 + RecDR|SubID)+ (-1 + RecDR|SubID:MUID)

MATLAB

Name	Estimate	SE	tStat	DF	pValue	Lower	Upper
{ '(Intercept) ' }	15.996	0.3341	47.878	1067	5.5495e-268	15.34	16.652
{ 'RecThr ' }	0.0027776	0.042105	0.065967	1067	0.94742	-0.079841	0.085396
{ 'RecDR ' }	0.29774	0.064784	4.596	1067	4.8222e-06	0.17063	0.42486
{ 'RecThr:RecDR ' }	-0.0089509	0.0029048	-3.0815	1067	0.0021126	-0.014651	-0.0032512

Rstudio

	Estimate	Std. Error	df	t value	Pr(> t)	
(Intercept)	15.995797	0.334103	918.950516	47.877	< 2e-16	***
RecThr	0.002786	0.042110	43.998670	0.066	0.94756	
RecDR	0.297771	0.064787	44.772357	4.596	3.51e-05	***
RecThr:RecDR	-0.008952	0.002905	953.703114	-3.082	0.00212	**

Ground truth unknown!

 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Experimental data: Bayesian linear regression



```
MaxDR ~ 1 + RecThr * RecDR + (-1 + RecThr | ContRep) + (-1 + RecThr | SubID) +  
(-1 + RecThr | SubID:MUid) + (-1 + RecDR | ContRep) + (-1 + RecDR | SubID) + (-1 + RecDR | SubID:MUid)
```

Rstudio

Population-Level Effects:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
Intercept	16.02	0.36	15.32	16.71	1.00	3181	3359
RecThr	0.00	0.05	-0.10	0.10	1.00	1306	1812
RecDR	0.29	0.09	0.11	0.46	1.00	984	1362
RecThr:RecDR	-0.01	0.00	-0.01	-0.00	1.00	3161	2940

Ground truth
unknown!

Family Specific Parameters:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sigma	1.48	0.04	1.39	1.57	1.00	1852	2455

MATLAB

Model not supported

Summary of introduction to...

- Model assumptions important, but not always easy to reach
- Visual check of model assumptions requires experiences
- Different programming languages come with different support to linear regression models
 - Rstudio, MATLAB, Python, JASP...
- Numerous packages in Rstudio – time needed for their testing and selection
- Different schools of thinking:
 - Linear Mixed Effect
 - Bayesian Linear Regression
- Comparison of different data models
 - AIC & BIC for Linear Mixed Effect models
 - WAIC & LOO for Bayesian Linear Regression models
- Simulated data can serve as an easy-to-use platform for testing of different assumptions.

Literature

- Winter, B., 2013. **A very basic tutorial for performing linear mixed effects analyses.** *arXiv preprint arXiv:1308.5499*, pp.1-22.
- G. K. Hajduk, **Introduction to linear mixed models**, <https://ourcodingclub.github.io/tutorials/mixed-models>
- H. Schielzeth et al. **Robustness of linear mixed-effects models to violations of distributional assumptions**, <https://doi.org/10.1111/2041-210X.13434>
- S. A. Baldwin et al., **An introduction to using Bayesian linear regression with clinical data**, <https://doi.org/10.1016/j.brat.2016.12.016>
- M. Franke et al. **A tutorial on contrast coding for (Bayesian) regression**, <https://michael-franke.github.io/Bayesian-Regression/practice-sheets/01e-contrast-coding-tutorial.html>
- E. Makalic et al. **High-Dimensional Bayesian Regularised Regression with the BayesReg Package**, arXiv:1611.06649 [stat.CO] [Version 1.9.1.0](#) (105 KB) by [Statovic](#)
- **Stan** <https://mc-stan.org/> (different programming languages supported, R, Matlab...)

February 6th –9th 2024

Universitat Politècnica de Catalunya, Barcelona, Spain



**HYBRID
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WORKSHOP BCN24

“A journey into brain activity”

From EEG and related potentials to connectivity and source modeling

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Day 2: ERP and MRCP studies and movement intention for device control.

Day 3: Source localization and brain connectivity.

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Hybrid Workshop
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**HYBRID
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	DAY	Tuesday 6th	Wednesday 7th	Thursday 8th	Friday 9th
		<i>EEG signal acquisition and preprocessing</i>	<i>ERP and MRCP studies and movement intention for device control</i>	<i>Source localization and brain connectivity</i>	<i>Networking with hospitals, companies, and research centers</i>
Presentations	09:30-10:00		Related cortical potentials measured by EEG: ERPs and MCRPs		What HybridNeuro Hub can do for you and you for it
	10:00-10:30	Presentation of HybridNeuro Action and UPC	Computerized computing tasks: cognitive and motor exercises	EEG source imaging: a practical review	Hospitals and companies presentations (I part)
	10:30-11:00				
	11:00-11:30	COFFEE BREAK	COFFEE BREAK	COFFEE BREAK	COFFEE BREAK
	11:30-12:30	Types of EEG artifacts and how to handle with them	ML and DL methods for movement imaginary BCI: Challenges and future directions	Introduction to functional Brain connectivity	Hospitals and companies presentations (II part)
	12:30-13:30	Artifact rejection and reduction by signal processing	Neuro-interfaces for interacting with robotics exoskeletons	Brain networks analysis using graph theory parameters	Round Table: How to look for synergies between scientists, companies, and hospitals
13:30-15:00	LUNCH	LUNCH	LUNCH	LUNCH	
HoT	15:00-17:00	Artifact reduction using software packages	A MRCP study: experiment preparation, recording and analysis	Practicing brain source localization and functional connectivity	



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- Identification of neural codes
- EEG & functional brain connectivity
- Corticomuscular coupling
- Movement augmentation
- Hybrid Neural Interfaces in practice
- Keynote lectures
- Practical examples
- Student 2 student explanations
- Present your project
- Ask top experts
- Active consultations



Questions?



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This project has received funding from the European Union's Horizon Europe Research and Innovation Programme under grant agreement no. 101079392 and from the UK Research and Innovation (UKRI) government's Horizon Europe funding guarantee scheme under grant agreement no. 10052152.