

Exposure Consequences - Statistics and Figures

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1 Overview

This document collects statistics and figures to be used in the manuscript on the exposure consequences project.

1.1 Figures

These are the planned figures. Figure one will not be included here, and can in fact simply be re-used from the previous manuscript.

1. Setup & Task (goal: visualize the experiment)
 - A: Setup (side view)
 - B: Rotated training (top view)
 - C: No-cursor reaches (top view)
 - D: Localization (top view)
2. Reach Aftereffects (goal: show motor changes are there, are robust and compare to classic)
 - A: Exposure reach aftereffects (initial & later)
 - B: Classic & Exposure reach aftereffects (initial only? or all?)
3. Localization
 - A: Exposure, active and passive (goal: small/no difference between active and passive)
 - B: Classic, active and passive (goal: larger difference between active and passive, different generalization?)

Maybe:

4. Correlation
 - A: Exposure, active and passive localization predicting reach aftereffects
 - B: Classic, active and passive localization predicting reach aftereffects

1.2 Tables

We expand the table used in the previous manuscript to include this paradigm as well.

1. Task order & trial numbers (goal: clarify task order and show similarity between classic and exposure experiment - so probably after Fig 1)

1.3 Source scripts

The scripts doing the statistics and figures are in separate R files. They allow many options, but here we will only see / do the ones that we think should go to the manuscript.

First we load those other scripts:

```
source('shared.R') # functions used everywhere
source('nocursor.R') # functions for no-cursor reach data
```

Loading required package: nlme

Loading required package: car

```
source('localization.R') # functions for localization data
source('relateLocalizationNoCursors.R') # functions that correlate the two kinds of data
```

1.4 Topics

In the manuscript we'll first show that there are motor changes after exposure training (with the no-cursor data) and then compare that with the classic. Second is the localization: a) localization shifts after exposure b) the shifts are the same/different from those after classic c) the effects are different across the workspace d) this pattern is indistinguishable / different from that after classic. A third topic might be if localization shifts can predict no-cursor changes, which we'll call the "correlation" topic. Here we'll also follow this order:

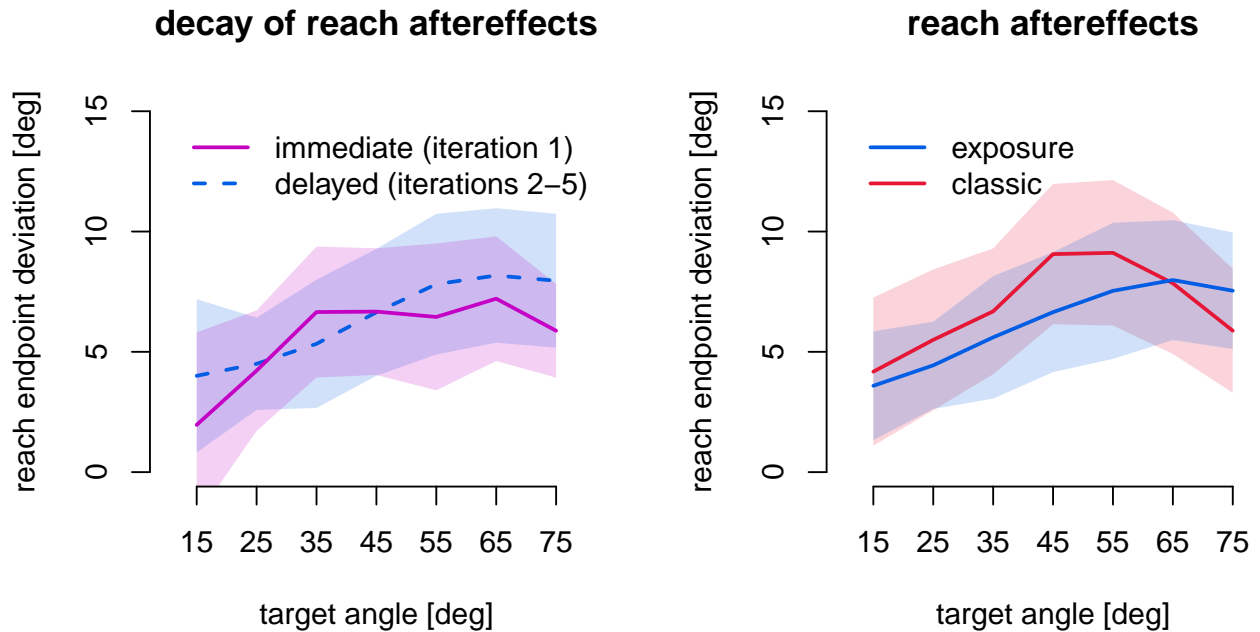
1. Reach aftereffects
2. Localization
3. Correlations

2 Reach Aftereffects

Here is a plot, probably Figure 2:

```
plotReachAftereffects()
```

```
removed 133 outliers, kept 96.6%
removed 133 outliers, kept 96.6%
removed 131 outliers, kept 96.7%
removed 133 outliers, kept 96.6%
```



For Panel B: Earlier I used the initial block for this plot, but after discussion, we decided to use all data: there's no significant difference between the initial and other blocks, but using all data allows more accurate estimates.

Messages of the figure:

- Panel A: there are substantial and persisting reach aftereffects
- Panel B: that are somewhat lower than those in classic (but not that much? but only for some targets?)

These claims require analyses.

2.1 Is there an effect of exposure training on reach aftereffects?

First, we show that no-cursor reaches change direction immediately after exposure training (iteration 1):

```
exposureNoCursorChange()
```

removed 133 outliers, kept 96.6%

LME with session and target as fixed effects, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: endpoint_angle

	Chisq	Df	Pr(>Chisq)
(Intercept)	1.3733	1	0.2413
rotated	74.5681	1	<2e-16 ***
target	8.1406	6	0.2280
rotated:target	7.1149	6	0.3104

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

So this shows that whether or not the feedback was rotated mattered for the reach deviations in the exposure training group, i.e.: there are reach aftereffects.

2.2 Do the motor changes persist during localization?

The second analysis is to show that the reach aftereffects aren't all that different for first and later iterations of the rotated no-cursor tasks. (The baseline is always all aligned iterations of the task.)

```
exposureAftereffectsPersistent()
```

```
removed 133 outliers, kept 96.6%
removed 133 outliers, kept 96.6%
```

LME with session and target as fixed effects, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: endpoint_angle

	Chisq	Df	Pr(>Chisq)
(Intercept)	62.8173	1	2.268e-15 ***
iteration	1.6077	1	0.2048197
target	26.7191	6	0.0001634 ***
iteration:target	3.4796	6	0.7466863

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

So there is no effect of iteration here, which means the reach aftereffects are the same for the first iteration and the average across the other four iterations. We now also have enough power to see an effect of target angle (the generalization curve is not flat), but more importantly the effect of iteration is also not dependent on target.

2.3 Are reach aftereffects comparable between classic and exposure training?

Finally, we want to see if there is a difference between the reach aftereffects observed after exposure training and those after classic training.

```
exposureClassicReachAftereffects()
```

```
removed 133 outliers, kept 96.6%
removed 131 outliers, kept 96.7%
```

LME with training type and target as fixed effects, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: endpoint_angle

	Chisq	Df	Pr(>Chisq)
(Intercept)	81.4115	1	< 2.2e-16 ***
training	0.2353	1	0.6276
target	49.4121	6	6.166e-09 ***
training:target	7.6785	6	0.2626

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

I'd have expected there to be some difference between the two training types, perhaps only in interaction with target, but that's not the case apparently.

The absence of an interaction between training and target could be interpreted to mean that the generalization of reach aftereffects is the same after both kinds of training. Here are the confidence intervals for the peaks

of both:

```
getPeakConfidenceInterval('classic',part='all',CIs=c(.95))
```

CLASSIC

removed 131 outliers, kept 96.7%

Loading required package: foreach

Loading required package: doParallel

Loading required package: iterators

Loading required package: parallel

	2.5%	50%	97.5%
	43.20146	53.56108	65.83471

```
getPeakConfidenceInterval('exposure',part='all',CIs=c(.95))
```

EXPOSURE

removed 133 outliers, kept 96.6%

	2.5%	50%	97.5%
	49.23354	63.01827	78.86351

Although the two peaks are not different from each other, the 95% confidence interval for the classically trained group includes the 45 degree target (where the visual feedback was during training) but not the 75 degree target, whereas the 95% confidence interval for the exposure training group includes the 75 degree target (where the hand really was during training) but not the 45 degree target. Something might be going on – but the evidence is far from concrete.

To sum up:

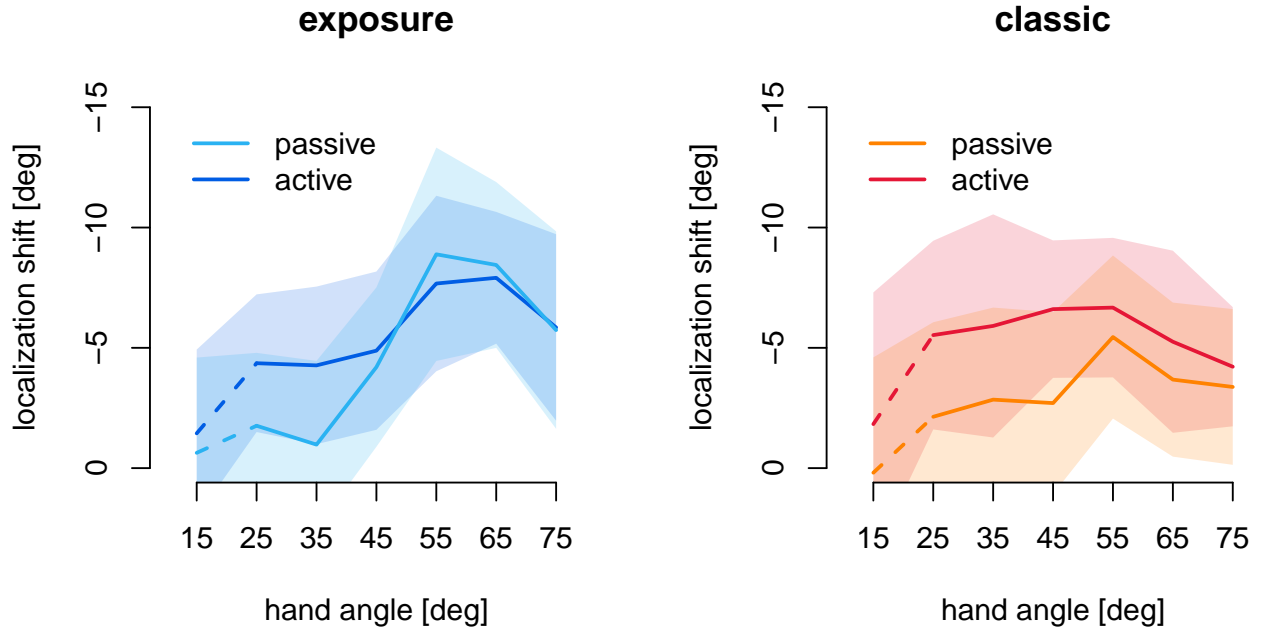
1. Rotated exposure training evokes substantial shifts in no-cursor reach direction across the workspace,
2. these changes persist over time, and
3. these changes are comparable to the ones we found after classic training.

3 Localization

Here is a plot, probably figure 3:

```
plotLocalization()
```

WARNING: Partial localization can not be returned for classic/online data.



That looks OK to me. It seems that just like after classic training, there is a change in localization responses following exposure training. There might still be a difference between active and passive localization after exposure training - contrary to our expectations - but it could be smaller than the difference after classic training. This will need to be tested.

3.1 Is there a localization shift after exposure training?

We first want to see if there is any overall effect of aligned versus rotated training in the exposure group, with movement type and hand angle as fixed effects, and participant as random effect.

```
exposureLocalization(remove15=TRUE)
```

LME with session, target and movement type as fixed effects, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: taperror_deg

	Chisq	Df	Pr(>Chisq)	
(Intercept)	33.7267	1	6.342e-09	***
rotated_b	134.0547	1	< 2.2e-16	***
passive_b	0.0684	1	0.7937402	
handangle_deg	17.0418	5	0.0044212	**
rotated_b:passive_b	0.7516	1	0.3859600	
rotated_b:handangle_deg	22.0972	5	0.0005018	***
passive_b:handangle_deg	7.9422	5	0.1594518	
rotated_b:passive_b:handangle_deg	2.9420	5	0.7089216	

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

Whether or not the feedback was rotated makes a difference according to two terms in the model. In other words: exposure training caused localization responses to shift (systematically), as we could already guess by looking at the figure.

This means we can look at the difference between responses after rotated and after aligned feedback: the training induced shift in localization.

3.2 Effects of movement type and hand angle in exposure localization

Let's first see if there is a difference between active and passive localization after exposure training.

```
exposureLocalizationShift(remove15=TRUE)
```

LME with hand angle and movement type as fixed effects, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: taperror_deg

	Chisq	Df	Pr(>Chisq)
(Intercept)	24.7154	1	6.645e-07 ***
passive_b	1.1669	1	0.2800
handangle_deg	34.1984	5	2.174e-06 ***
passive_b:handangle_deg	4.5246	5	0.4766

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

There is no difference between passive and active localization after exposure training, even with double the number of trials as in classic delayed.

3.3 Comparing localization after exposure and classic training

Let's see what we get in a model with all data (localization differences between rotated and aligned though) from both groups:

```
groupLocalization(model='full',remove15=TRUE)
```

WARNING: Partial localization can not be returned for classic/online data.

LME with group, hand angle and movement type as fixed effects, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: taperror_deg

	Chisq	Df	Pr(>Chisq)
(Intercept)	36.5513	1	1.487e-09 ***
group	0.3139	1	0.575287
passive_b	9.6127	1	0.001932 **
handangle_deg	29.7910	5	1.621e-05 ***
group:passive_b	2.2619	1	0.132595
group:handangle_deg	12.4669	5	0.028921 *
passive_b:handangle_deg	6.4458	5	0.265228
group:passive_b:handangle_deg	1.2769	5	0.937294

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

In the exposure group there is no effect of movement type, but we see one here. This could be because the effect of movement type is much larger in the classic group. This would predict an interaction between group and movement type, but this is not even a trend ($p=.133$).

What if we don't care about hand angle:

```
groupLocalization(model='movementtype',remove15=TRUE)
```

WARNING: Partial localization can not be returned for classic/online data.

LME with group and movement type as fixed effects and participant and hand angle as random effects:

Analysis of Deviance Table (Type III tests)

Response: taperror_deg

	Chisq	Df	Pr(>Chisq)
(Intercept)	37.0374	1	1.159e-09 ***
group	0.3342	1	0.5632198
passive_b	10.9954	1	0.0009134 ***
group:passive_b	2.7848	1	0.0951644 .

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

Now there is a trend towards significance for the interaction between training group and movement type. That is closer to what we would expect.

Let's see if the classic group shows an effect of movement type (with the current preprocessing procedures):

```
classicLocalizationShift(remove15=TRUE)
```

WARNING: Partial localization can not be returned for classic/online data.

LME with hand angle and movement type as fixed effects, and participant as random effect:

Analysis of Deviance Table (Type III tests)

Response: taperror_deg

	Chisq	Df	Pr(>Chisq)
(Intercept)	13.6221	1	0.0002235 ***
passive_b	11.6351	1	0.0006472 ***
handangle_deg	5.4091	5	0.3680163
passive_b:handangle_deg	3.0120	5	0.6981338

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

So there is a fairly strong effect of movement type in the classic group. Together with the absence of an effect of movement type in the exposure group and a trend of an interaction between group and movement type, this might indicate a sub-threshold effect of movement type in the exposure group in the same direction as the effect of movement type in the classic group.

Also note the absence of an effect of hand angle in the classic group here – potentially because we excluded the 15 degree target.

To sum up our findings on localization:

1. Rotated exposure training leads to changes in localization responses.
2. In the exposure group, there is no effect of movement type: localization responses with and without efference copies are indistinguishable.
3. In the classic group, there is an effect of movement type: localization responses informed by efference copies are shifted more than those with only proprioception (as found before).
4. This predicts an interaction between movement type and group, but that is only a trend, suggesting that either the difference in the classic group is not so large, or that there is a small, sub-threshold difference in the exposure group.
5. The shift in localization is different across the workspace in the exposure group. I.e., there is a generalization *curve*.
6. This effect is not present in the classic group, so that generalization can be said to be flat; there is no *curve*. **NOTE:** When we do include the 15 degree target, there is an effect of hand angle though.

4 Correlation

In this section we look at how recalibrated proprioception (hand localization) correlates with reach aftereffects.

I'm not sure if we should use the initial reach aftereffects here, or the four later blocks. Unfortunately, it does matter for the results, but I don't want to choose with hindsight.

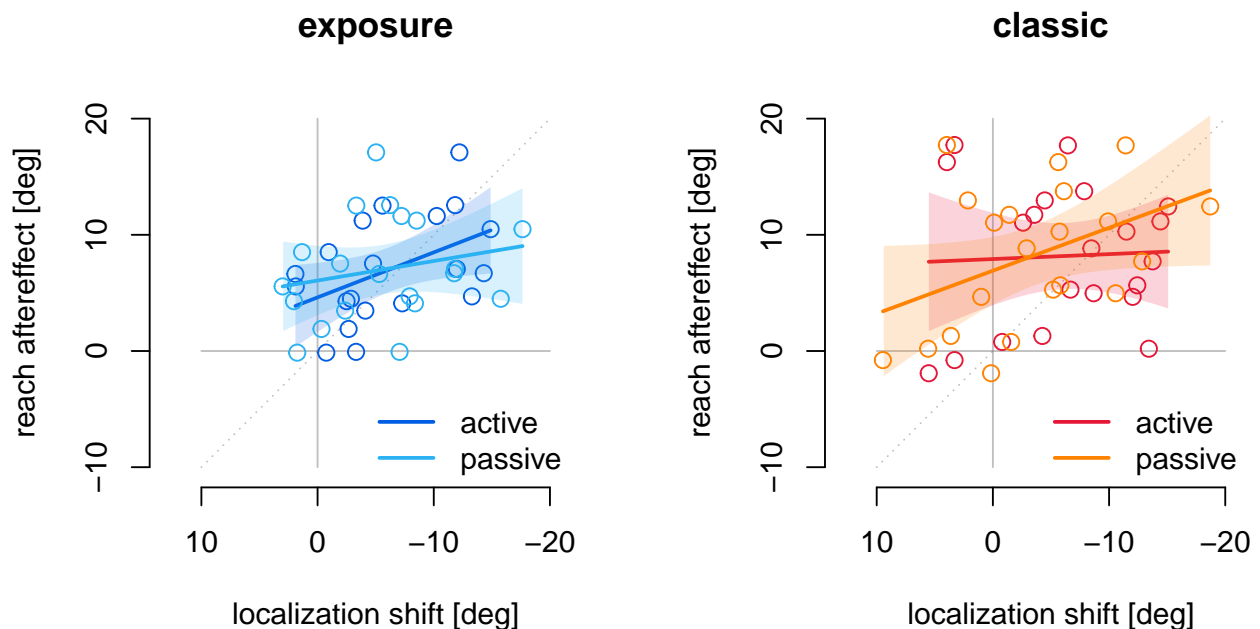
This plot shows regression lines with localization shifts as predictor of reach aftereffects:

```
correlations <- correlateNoCursorsLocalization()
```

removed 133 outliers, kept 96.6%

WARNING: Partial localization can not be returned for classic/online data.

removed 131 outliers, kept 96.7%



It looks like for exposure, active localization is the better predictor of reach aftereffects, whereas in classic it is passive localization. But are any of them real? The function also returns the correlation tests and linear

regressions for all four datasets.

4.1 Pearons Correlations

As one possibility, we can look at the correlations. Not just the p-values, but there are confidence intervals for Pearson's ρ , which allow to directly see if one correlation is stronger/weaker than another:

```
for (name in names(correlations)) {  
  cat(name)  
  print(correlations[[name]][['cortest']])  
}
```

EXPOSURE ACTIVE

Pearson's product-moment correlation

```
data: X and Y  
t = -2.2276, df = 18, p-value = 0.03891  
alternative hypothesis: true correlation is not equal to 0  
95 percent confidence interval:  
-0.75257193 -0.02813027  
sample estimates:  
cor  
-0.4648643
```

EXPOSURE PASSIVE

Pearson's product-moment correlation

```
data: X and Y  
t = -0.94288, df = 18, p-value = 0.3582  
alternative hypothesis: true correlation is not equal to 0  
95 percent confidence interval:  
-0.6017021 0.2495297  
sample estimates:  
cor  
-0.2169468
```

CLASSIC ACTIVE

Pearson's product-moment correlation

```
data: X and Y  
t = -0.19776, df = 19, p-value = 0.8453  
alternative hypothesis: true correlation is not equal to 0  
95 percent confidence interval:  
-0.4678551 0.3940750  
sample estimates:  
cor  
-0.04532181
```

CLASSIC PASSIVE

Pearson's product-moment correlation

```
data: X and Y
t = -1.9954, df = 19, p-value = 0.06054
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.71877161 0.01883464
sample estimates:
      cor
-0.4162364
```

4.2 Linear regression models

And those linear regression models?

[code/results hidden] They get the same p-value, so that seems fine.

4.3 Multiple regression models

We've decided to use all the no-cursor blocks for these regression and correlations, so perhaps we shouldn't include the one below where I only use the initial block. The idea behind using only the initial block is that that initial block matches the time the localization is done – relative to the last training.

Here I do step-wise multiple regression, allowing active and passive localization shift as predictor of reach aftereffects. If I do this on all the no-cursor block data, the models converge on using the active localization for the exposure group, and passive localization for the classic group.

If we look at only the initial no-cursor block, the story changes. It uses both active and passive to predict reach aftereffects for the exposure group, but converges on using only an intercept term for the classic group. This might mean that in the classic group there is no relationship between reach aftereffects and localization, or this might mean that in the exposure group we have sufficient amount of measurements to detect the relationship, as we have twice the number of localization trials. One way to rule this out is to use only the first half of the localization data from the exposure group.

Here is what the step-wise multiple regressions look like with all available data:

```
multipleRegressionLocalization(group='exposure',NCpart='initial')
```

removed 133 outliers, kept 96.6%

EXPOSURE

Start: AIC=50.6

RAE ~ active + passive

	Df	Sum of Sq	RSS	AIC
<none>			185.98	50.598
- passive	1	21.904	207.88	50.825
- active	1	133.743	319.72	59.435

Call:

```
lm(formula = RAE ~ active + passive, data = df)
```

Residuals:

Min	1Q	Median	3Q	Max
-4.8706	-2.9307	-0.3416	2.2677	5.7854

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	4.2822	1.1639	3.679	0.00186 **
active	-0.6354	0.1817	-3.496	0.00277 **
passive	0.2391	0.1690	1.415	0.17513

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

Residual standard error: 3.308 on 17 degrees of freedom

Multiple R-squared: 0.4394, Adjusted R-squared: 0.3735

F-statistic: 6.662 on 2 and 17 DF, p-value: 0.007303

No terms are dropped as the adjusted R squared of the full model is low, but reasonable. *Note that the coefficient for the passive localization is positive.*

For classic training, it looks like this:

```
multipleRegressionLocalization(group='classic',NCpart='initial')
```

WARNING: Partial localization can not be returned for classic/online data.

removed 131 outliers, kept 96.7%

CLASSIC

Start: AIC=89.64

RAE ~ active + passive

	Df	Sum of Sq	RSS	AIC
- active	1	21.735	1148.7	88.039
- passive	1	104.499	1231.4	89.500
<none>			1126.9	89.637

Step: AIC=88.04

RAE ~ passive

	Df	Sum of Sq	RSS	AIC
- passive	1	83.839	1232.5	87.518
<none>			1148.7	88.039

Step: AIC=87.52

RAE ~ 1

Call:

```
lm(formula = RAE ~ 1, data = df)
```

Residuals:

Min	1Q	Median	3Q	Max
-14.6228	-4.8518	0.2389	7.1252	11.8479

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	9.265	1.713	5.409	2.71e-05 ***

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

Residual standard error: 7.85 on 20 degrees of freedom

The step-wise multiple regression algorithm thinks an intercept-only model is best. Now is this because localization after classic training has little to no information on reach aftereffects, or is this because we have double the data in the exposure group? We can test this partially by throwing away the second half of the data for the exposure group:

```
# THIS FAILS NOW... maybe because some participants don't have data in the first half?
multipleRegressionLocalization(group='exposure', NCpart='initial', LRpart='first')
```

removed these participants:

```
[1] "BP_2101"
```

removed 133 outliers, kept 96.6%

EXPOSURE

Start: AIC=53.88

RAE ~ active + passive

	Df	Sum of Sq	RSS	AIC
- passive	1	5.127	241.26	52.288
<none>			236.14	53.880
- active	1	59.717	295.85	56.163

Step: AIC=52.29

RAE ~ active

	Df	Sum of Sq	RSS	AIC
<none>			241.26	52.288
- active	1	54.614	295.88	54.165

Call:

```
lm(formula = RAE ~ active, data = df)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-6.6639	-2.3343	-0.4208	3.0299	7.4546

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5.5103	1.2107	4.551	0.000283 ***
active	-0.2342	0.1194	-1.962	0.066386 .

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

Residual standard error: 3.767 on 17 degrees of freedom

Multiple R-squared: 0.1846, Adjusted R-squared: 0.1366

F-statistic: 3.848 on 1 and 17 DF, p-value: 0.06639

Now the passive localization shifts are thrown out by the algorithm and the active localization shifts don't contribute much either. This means that perhaps previous papers didn't find any relationships between recalibrated proprioception and reach aftereffects because not enough data was collected to overcome the

noisiness of the measurements?

It also makes me wonder if reach aftereffects in classic can be better predicted by the online localization responses:

```
multipleRegressionLocalization(group='online',NCpart='initial')
```

WARNING: Partial localization can not be returned for classic/online data.

removed 131 outliers, kept 96.7%

ONLINE

Start: AIC=89.69

RAE ~ active + passive

	Df	Sum of Sq	RSS	AIC
- active	1	0.161	1129.8	87.691
- passive	1	88.818	1218.4	89.277
<none>			1129.6	89.688

Step: AIC=87.69

RAE ~ passive

	Df	Sum of Sq	RSS	AIC
- passive	1	102.72	1232.5	87.518
<none>			1129.8	87.691

Step: AIC=87.52

RAE ~ 1

Call:

```
lm(formula = RAE ~ 1, data = df)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-14.6228	-4.8518	0.2389	7.1252	11.8479

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	9.265	1.713	5.409	2.71e-05 ***






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

Residual standard error: 7.85 on 20 degrees of freedom

But no.

5 Conclusions

What can we conclude? Here is an initial list of what we might conclude.

1.  Exposure training leads to robust reach aftereffects that are similar to those after classic training, although they seem to have a more pronounced generalization curve. This means that evoking proprioceptive recalibration with visual-proprioceptive discrepancies leads to motor changes. In other words: proprioception informs movement plans.
2. Exposure training leads to shifts in localization, that are not very different between active and passive localization. Since both active and passive movements access recalibrated proprioception, while active localization also accesses updated predictions, this indicates that hand localization is makes very good use of proprioception.
 1.  Additionally, since predictions should not be updated in exposure training, but active localization might be evoking a slightly larger shift, this indicates a non-Bayesian process of combining predictions and perceptions in this case.
 2. After classic training (2016 paper) there was an effect of movement type, which indicates that with a training regime that allows updates of predicted sensory consequences, these updates do indeed also affect hand localization.
 3.  Within the workspace however, there is no interaction between movement type and training group. Perhaps there is a small update of predicted proprioceptive consequences, that we can't parcel out. A more computational approach would be needed to see if this can explain the pattern of results here.
3.  Calibrated proprioception can reliably predict reach aftereffects, but only after **exposure** training and for *active localization*. This means that recalibrated proprioception indeed leads to motor changes.
 1. There is also a trend towards significance for *passive localization* to predict reach aftereffects after **classic training**. Perhaps active localization is more similar to no-cursor reaches after exposure training, as both of these can only use recalibrated proprioception as well as updated predictions of proprioceptive consequences.  This does not explain the trend towards significance for predicting classic reach aftereffects with passive localization. However, a step-wise multiple regression favours an intercept model for classic reach aftereffects, and a model that mostly relies on active localization for exposure reach aftereffects. So perhaps not too much should be read into the trend towards significance in the correlation. On the other hand, the exposure group had twice as much data, so that the estimated recalibration would be more reliable within each participant. Perhaps with higher quality estimates of proprioceptive recalibration those would be able to predict part of the reach aftereffects even after classic training.