External Source Attribution and Adaptation while Viewing the Hand

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Overview

This document discusses figures and statistics for the Hand View project. The four main sections include data and analyses with regards to Learning Curves, Reach Aftereffects, Localization, and Contributions of proprioception and predictions to reach aftereffects.

Learning Curves

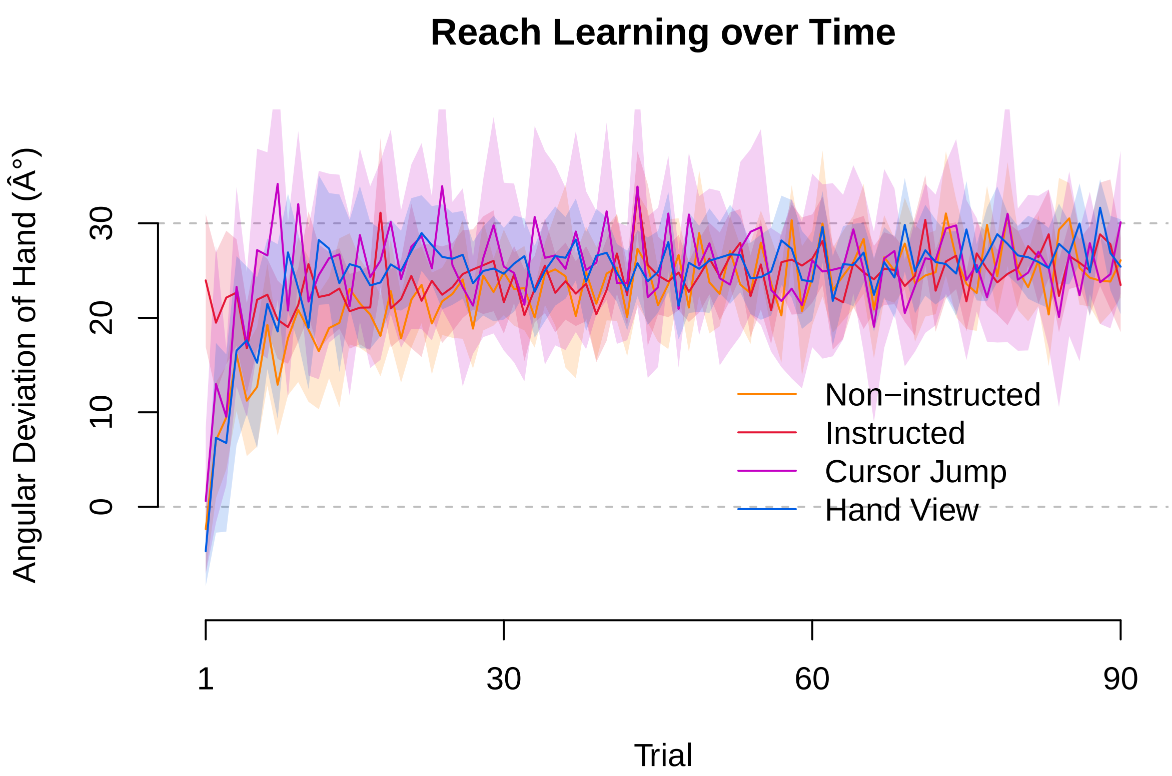
First, we aimed to determine the effects of manipulating the extent of attributing the source of errors externally, on reaching movements while experiencing a 30° CW rotation.

Training reaches in *Cursor Trials* for both aligned and rotated sessions were manually inspected for failing to perform the required reach, e.g. not reaching the target with a smooth and straight movement. Trials that were not useable for further analyses were removed. For the remaining trials, we calculated angular deviation of the hand at the point of maximum velocity. This is the angular difference between a line connecting the home position to the target and a line connecting the home position to the participant's hand position at the peak of their movement velocity. Thus, in order to fully compensate for the cursor-rotation, participants had to deviate their reaches in the 30° CCW direction. We then calculated the difference between angular deviations in the first 90 trials of the rotated session and individual biases in reaches during the last 30 out of the first 45 trials in the aligned session. This process was completed for every participant in each group.

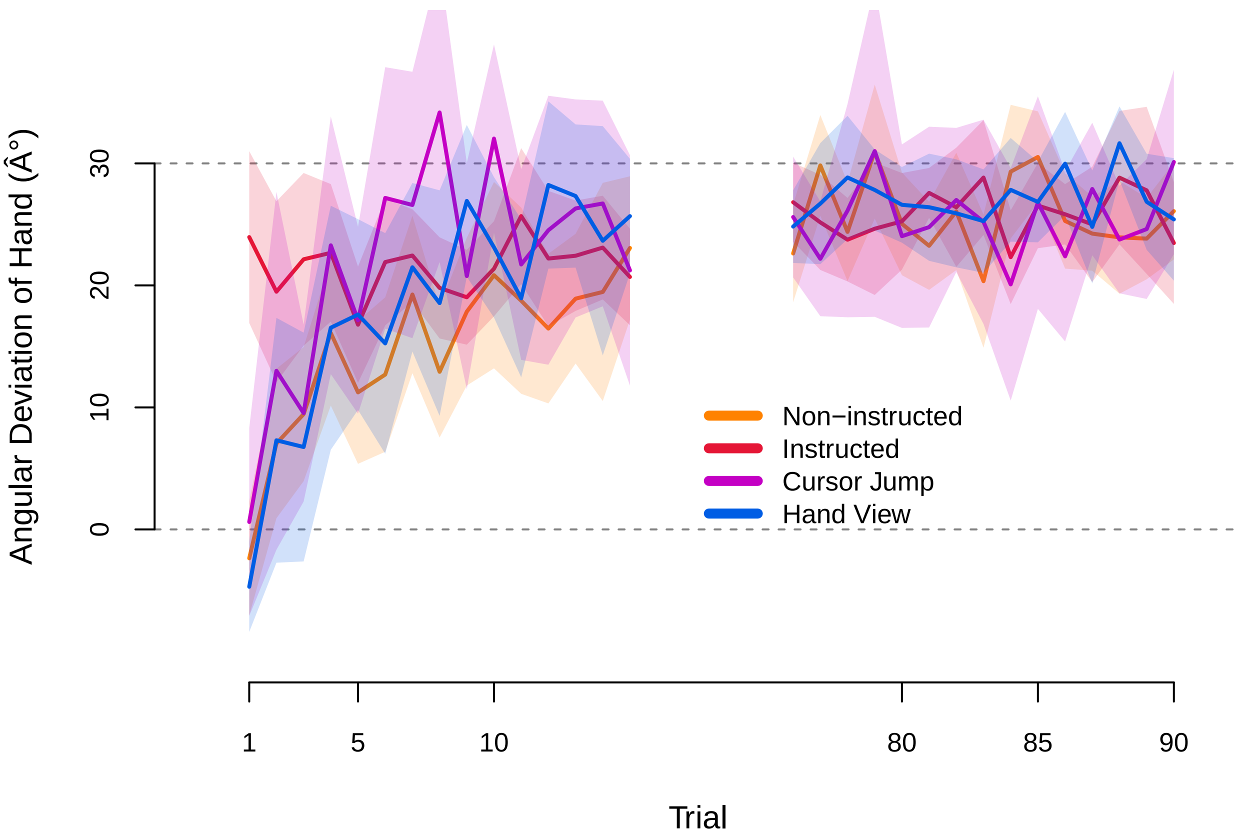
Show the data

Below is a plot of the angular deviation of the hand across the first 90 trials of the rotated session. Lines represent the mean angular deviation of each group in every trial, and corresponding shaded regions represent 95% Confidence Intervals. For a closer look, we also show the same data, but only for the first 15 and last 15 trials.

```
plotLearningCurvesOLD(target='inline')
```




```
plotBlockedLearningCurves(target='inline')
```

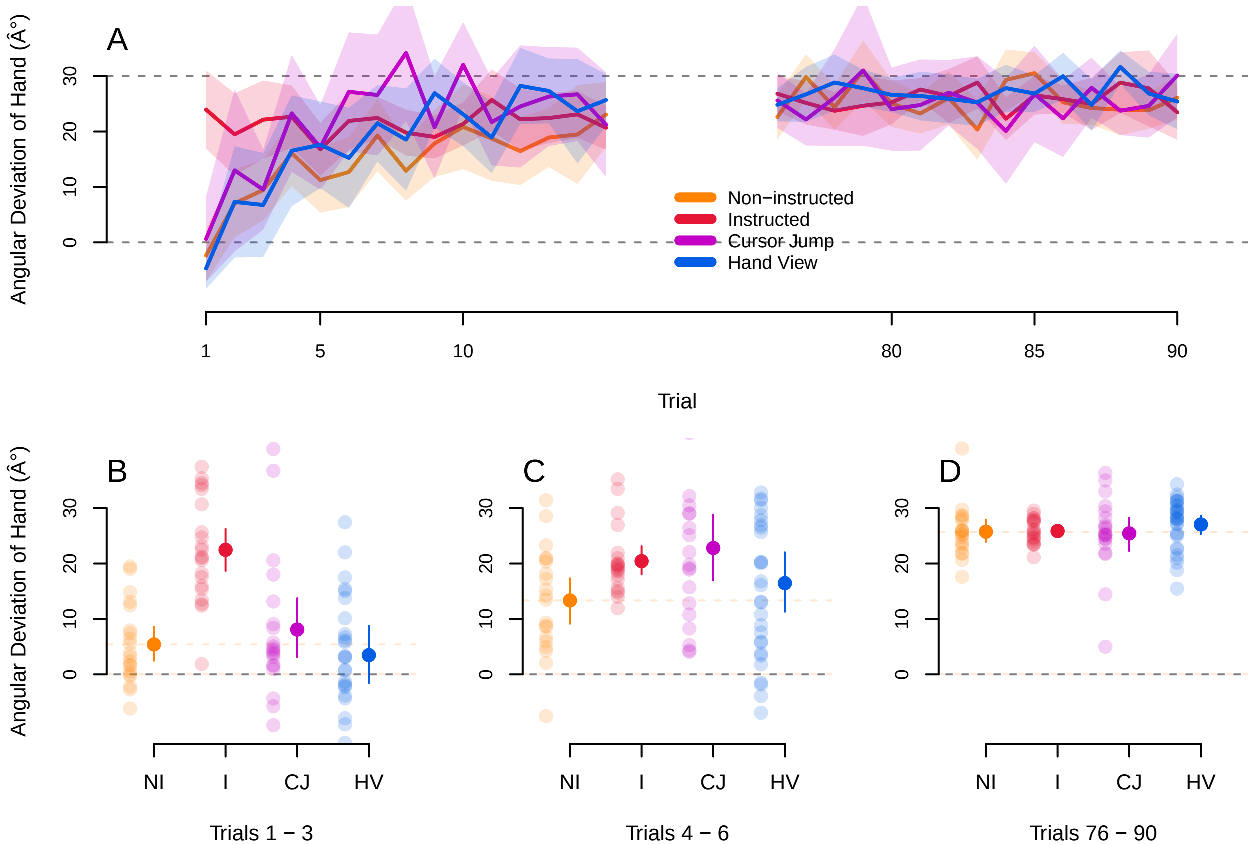


We see that, during training, the Instructed Group countered the rotation immediately, while the other groups took longer (within 15-20 trials) to compensate for the cursor-rotation. The Cursor Jump group's rate of learning seems to suggest that their rate of learning was much faster than the Non-instructed, control group (i.e. the slope of the learning curve is steep). Lastly, all groups performed similar reaching movements at the end of training.

ANOVAs

To analyze the effects of our manipulation on rates of learning, we blocked the rotated training data into three blocks of trial sets. The first block consisted of the first set of three trials, the second consisted of the next three trials, and the third consisted of the last 15 trials of rotated training. Below is a plot showing individual participant data for each group across these three blocks. Dot and error bars represent the mean and bootstrapped 95% confidence intervals. Shaded regions are density distributions of the bootstrapped means.

```
plotLearningCurves()
```



From the plot, we see that the distribution of the angular hand deviation across all participants are relatively normal and unimodal for all groups and blocks. Therefore, we proceeded to investigate how the four groups and their performance during adaptation training, compared with each other, for each of these three blocks. We performed a 3X4 mixed design ANOVA with block as a within-subject factor (blocks 1, 2, and 3) and group as a between-subject factor (Non-instructed, Instructed, Cursor Jump, Hand View). For this and the following tests, the alpha level was set to 0.05 and, when necessary, Greenhouse Geisser corrections were applied.

```
learningCurveANOVA()
```

```
## Warning: Data is unbalanced (unequal N per group). Make sure you specified a
## well-considered value for the type argument to ezANOVA().

## $ANOVA
##            Effect DFn DFd         F            p p<.05        ges
## 2       diffgroup   3  86  5.677939 1.350501e-03     * 0.09235814
## 3           block   2 172 78.410892 6.263779e-25     * 0.30716530
## 4 diffgroup:block   6 172  7.855695 1.733714e-07     * 0.11758332
##
## $`Mauchly's Test for Sphericity`
##            Effect         W         p p<.05
## 3           block 0.9813597 0.4494693
## 4 diffgroup:block 0.9813597 0.4494693
##
## $`Sphericity Corrections`
##            Effect       GGe        p[GG] p[GG]<.05      HFe        p[HF]
```

```
## 3           block 0.9817008 1.605131e-24         * 1.004419 6.263779e-25
## 4 diffgroup:block 0.9817008 2.189187e-07         * 1.004419 1.733714e-07
##   p[HF]<.05
## 3         *
## 4         *
```

We see that the main effects of group and block, and their interaction, were statistically significant. This suggests that the rate of learning of at least one group differed from the other groups and that this difference was dependent on the block of trials. Hence, it was appropriate to look at differences between groups in each block. Particularly, we only looked into the first 2 blocks, since it was observed from our plots that the groups did not differ in the last block.

Planned follow-up tests

We first display the means and 95% CI's for each group in each block. This table gives us an idea of which contrasts we want to test further. That is, if the mean of a group falls outside the confidence interval range of another group then the two groups must differ significantly from each other. For these contrasts, we use the Non-instructed group as a reference (since it is the control group) and compare all the other groups to it. We then compare all groups to the non-instructed group for blocks one and two, respectively. To control for multiplicity, we adjusted for p values using the Sidak method. Note that the Sidak method is the default used in R when an alternative test, such as Tukey, is inappropriate for a given dataset. The Tukey method would be appropriate if we were comparing each mean with every other mean, but comparing only a selection of means would require the Bonferroni or Sidak. The Sidak method offers the slight advantage of being a less conservative method than the Bonferroni. Another option would be to use the Dunnett method when comparing a group with a control group. Nevertheless, all of these are just for adjusting p values. Our results do not change, however, regardless of the method used in terms of which comparisons reached significance. Hence, we chose to stick with the default Sidak method.

```r
learningcurveComparisonMeans()
```

```
## Contrasts set to contr.sum for the following variables: diffgroup
```

```
##  diffgroup  block  lsmean   SE  df lower.CL upper.CL
##  30explicit first   22.29 2.17 227   18.009    26.56
##  30implicit first    5.22 2.21 229    0.863     9.58
##  cursorjump first    7.91 2.21 229    3.550    12.26
##  handview   first    3.29 1.93 213   -0.519     7.10
##  30explicit second  20.24 2.17 227   15.960    24.51
##  30implicit second  13.16 2.21 229    8.800    17.51
##  cursorjump second  22.62 2.21 229   18.264    26.98
##  handview   second  16.28 1.93 213   12.469    20.08
##  30explicit last    25.68 2.17 227   21.402    29.96
##  30implicit last    25.55 2.21 229   21.197    29.91
##  cursorjump last    25.25 2.21 229   20.894    29.61
##  handview   last    26.86 1.93 213   23.056    30.67
##
## Warning: EMMs are biased unless design is perfectly balanced
## Confidence level used: 0.95
```

```r
getComparisonEffSize(method='sidak')
```

```
## Contrasts set to contr.sum for the following variables: diffgroup
```

```
##  contrast                          estimate   SE  df t.ratio p.value
##  Block1: Instr vs. Non-instr          17.07 3.13 225  5.452  <.0001
##  Block1: Cursor Jump vs. Non-instr     2.69 3.17 225  0.848  0.9520
##  Block1: Hand View vs. Non-Instr      -1.93 2.91 225 -0.663  0.9858
##  Block2: Instr vs. Non-instr           7.08 3.13 225  2.262  0.1391
##  Block2: Cursor Jump vs. Non-instr     9.46 3.17 225  2.987  0.0186
##  Block2: Hand View vs. Non-instr       3.12 2.91 225  1.072  0.8665
##
## P value adjustment: sidak method for 6 tests
##                             contrast  etasquared
## 1       Block1: Instr vs. Non-instr 0.116688524
## 2 Block1: Cursor Jump vs. Non-instr 0.003187346
## 3   Block1: Hand View vs. Non-Instr 0.001950291
## 4       Block2: Instr vs. Non-instr 0.022231951
## 5 Block2: Cursor Jump vs. Non-instr 0.038147130
## 6   Block2: Hand View vs. Non-instr 0.005076500
```

In block one, when each group was compared to the Non-instructed group, only the Instructed group differed significantly. This suggests that only the instructed group had an initial advantage in learning to counter for the rotation of the cursor. In block two, however, only the cursor jump group significantly differed from the non-instructed group, suggesting that the cursor jump group learned to counter for the rotation of the cursor at a faster rate than the non-instructed group. The hand view group, however, did not differ significantly from the non-instructed group. Note that effect sizes are provided with eta-squared, which is interpreted as the percent of variance in angular deviation of the hand, accounted for by the difference between the given group and the control, Non-Instructed group.

To summarize, instruction on the nature of the perturbation and being given a strategy to counter it, creates an initial advantage in reducing hand direction error when reaching towards a target with a rotated cursor. However, our other manipulations, despite the error being more clearly external in nature, do not produce a similar initial advantage.

Reach aftereffects

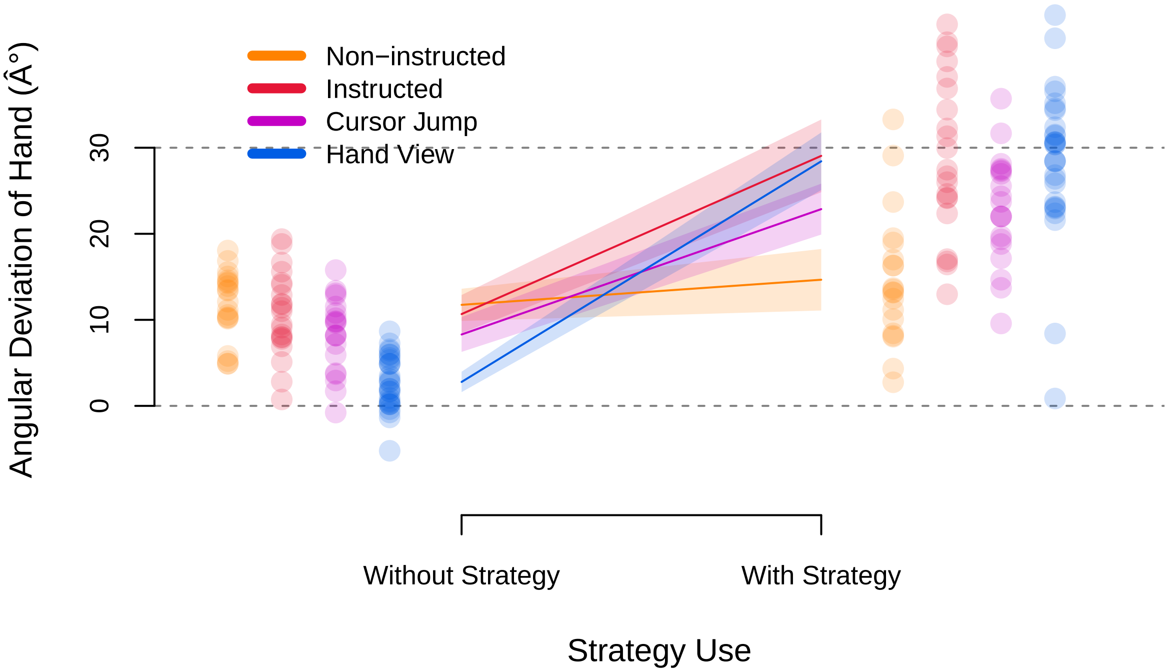
We then investigated how manipulating the extent of external error attribution affected participants' reaching movements when no cursor-feedback is presented.

Similar to the Learning Curves section, reaches in *No Cursor Trials* for both aligned and rotated sessions were manually inspected for failing to perform the required reach. Trials that were not useable for further analyses were removed. For the retained trials, we used the endpoint angle to calculate for the angular deviation of the hand. This is the angular difference between the point where the participant's hand movement ended and the target. We then subtracted mean angular deviations in the aligned session from those after training in the rotated session, in order to measure the effects of adaptation training during No Cursor reaches, i.e. reach aftereffects. We then implemented a process dissociation procedure (PDP) type of analysis. We calculated mean angular deviations per participant when either including any strategy they learned during adaptation training or excluding such a strategy. Thus, awareness of learning about the visuomotor rotation would be associated with a difference between exclusion and inclusion trials, while lack of awareness will have no such difference between the two types of trials.

Show the data

Below is a plot of the mean angular reach deviation of the hand for each group as a function of either excluding or including a strategy. Lines represent the mean angular deviation of each group, and corresponding shaded regions represent 95% Confidence Intervals.

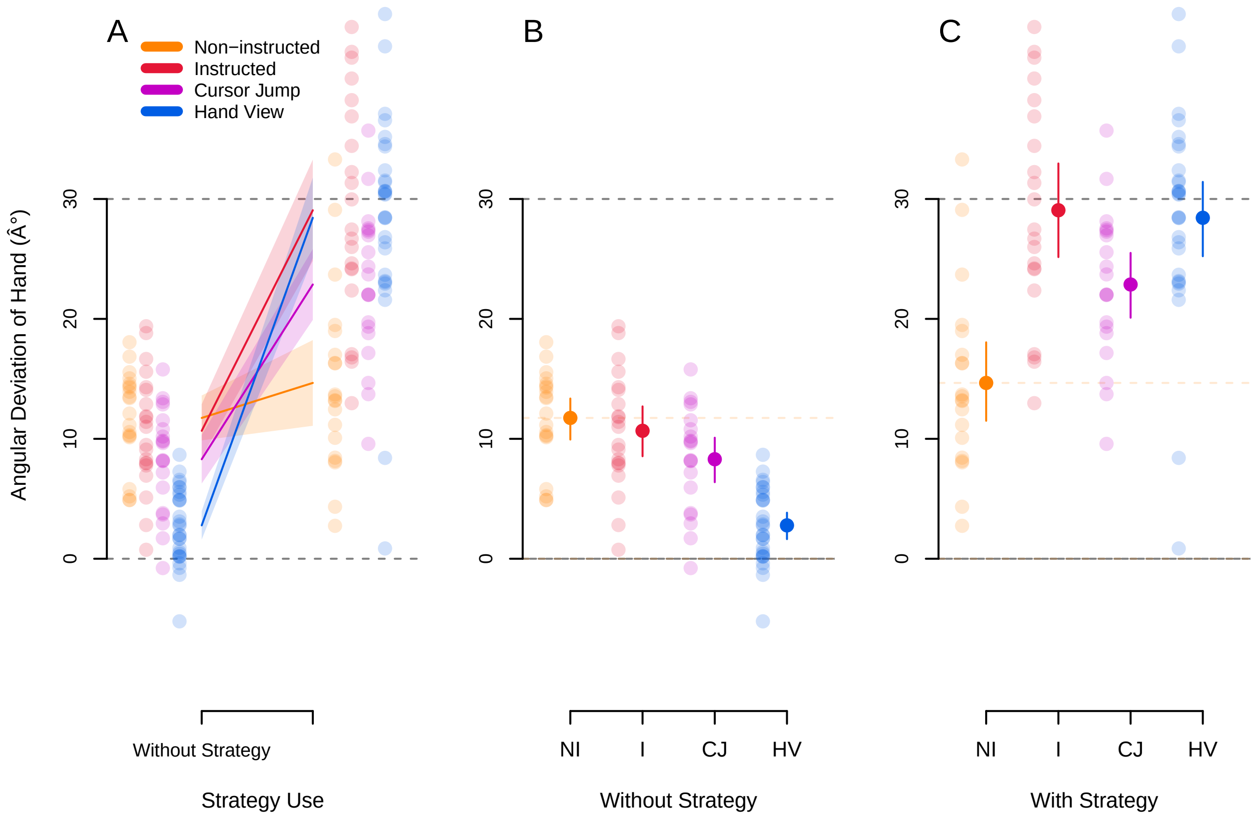
```r
plotGroupReachAfterEffects()
```



We see from the figure that when including or excluding the strategy learned to counter the rotation, only the non-instructed group could not switch their strategy on or off at will. This suggests unawareness of learning for this group. Importantly, all groups still showed angular deviations of their hand to some degree during exclusive trials. This suggests that despite awareness of learning of the visuomotor rotation, implicit reach aftereffects were still observed in all groups. Note, however, that implicit reach aftereffects were smaller for the Hand View group compared to the other groups.

Below is a plot showing individual data points for reach aftereffects and strategy use across all groups. The left panel is the same as the plot shown above. For the centre and right panels, dot and error bars represent the mean and bootstrapped 95% confidence intervals. Shaded regions are density distributions of the bootstrapped means.

```r
plotReachAfterEffects()
```



We see that distributions for all groups are approximately normal and unimodal. Thus, we proceeded with the statistical tests performed below.

Test for Reach Aftereffects

First, we tested whether or not adaptation led to reach aftereffects. To do this, we compared the rotated no cursor trials to the aligned no cursor trials. Particularly, we used rotated no cursor trials where participants did not make use of a strategy. We performed a 2X4 mixed design ANOVA with session (aligned or rotated) as a within-subject factor and group as a between-subject factor.

```
NoCANOVA()
```

```
## Warning: Data is unbalanced (unequal N per group). Make sure you specified a
## well-considered value for the type argument to ezANOVA().

## $ANOVA
##             Effect DFn DFd         F            p p<.05       ges
## 2        diffgroup   3  86  16.57615 1.386109e-08     * 0.2998184
## 3          session   1  86 373.02348 5.033611e-33     * 0.5295135
## 4 diffgroup:session   3  86  22.60505 6.977690e-11     * 0.1698537
```

We see that there were implicit reach aftereffects after adaptation due to the significant main effect of session. However, since the interaction between group and session was also significant, it is possible that the effect of session was modulated by groups (i.e. the effect of session occurs differently for at least one group). Thus, we performed planned follow-up tests comparing each group to itself between the two sessions.

```r
NoCursorComparisonMeans()
```

```
## Contrasts set to contr.sum for the following variables: diffgroup
```

```
##  diffgroup  session   lsmean    SE  df lower.CL upper.CL
##  30explicit aligned    1.196 0.897 141   -0.577    2.970
##  30implicit aligned    1.017 0.911 142   -0.785    2.819
##  cursorjump aligned   -0.670 0.911 142   -2.471    1.132
##  handview   aligned   -0.761 0.814 134   -2.370    0.848
##  30explicit exclusive 12.120 0.897 141   10.346   13.893
##  30implicit exclusive 13.234 0.911 142   11.433   15.036
##  cursorjump exclusive  7.893 0.911 142    6.092    9.695
##  handview   exclusive  2.411 0.814 134    0.802    4.020
##
## Warning: EMMs are biased unless design is perfectly balanced
## Confidence level used: 0.95
```

```r
getNoCurComparisonEffSize(method='sidak')
```

```
## Contrasts set to contr.sum for the following variables: diffgroup
```

```
##  contrast                           estimate    SE df t.ratio p.value
##  AL.Instr vs. ROT.Instr               -10.92 0.923 86 -11.830 <.0001
##  AL.Non-Instr vs. ROT.Non-Instr       -12.22 0.946 86 -12.912 <.0001
##  AL.Cursor Jump vs. ROT.Cursor Jump    -8.56 0.946 86  -9.050 <.0001
##  AL.Handview vs. ROT.Handview          -3.17 0.786 86  -4.037 0.0005
##
## P value adjustment: sidak method for 4 tests
##                              contrast etasquared
## 1             AL.Instr vs. ROT.Instr  0.6193710
## 2     AL.Non-Instr vs. ROT.Non-Instr  0.6596934
## 3 AL.Cursor Jump vs. ROT.Cursor Jump  0.4878008
## 4       AL.Handview vs. ROT.Handview  0.1592948
```

Planned follow-up tests show that the aligned and rotated sessions differed significantly for each group. Note that this test does not definitively tell us which of the groups differed from the others, in terms of differences between sessions. However, we see from our figure that it is the Hand View group which exhibited a lower angular deviation of the hand in exclusive trials compared to the other three groups. For the purpose of answering the question we are investigating in this subsection, it is sufficient that the follow-ups showed that sessions differed for each group. Note that effect sizes are provided with eta-squared, which is interpreted as the percent of variance in angular deviation of the hand, accounted for by the difference between the two sessions.

PDP-type analysis (Strategy Use)

After confirming that reach aftereffects were present in all groups, we tested whether our manipulation of the extent of external error attribution differed across groups, when either excluding or including a strategy to counter for the rotation. We performed a 2X4 mixed design ANOVA with strategy use as a within-subject factor (with or without strategy) and group as a between-subject factor.

```r
RAEANOVA()
```

```
## Warning: Data is unbalanced (unequal N per group). Make sure you specified a
## well-considered value for the type argument to ezANOVA().
```

```
## $ANOVA
##               Effect DFn DFd          F            p p<.05       ges
## 2          diffgroup   3  86   6.778685 3.710780e-04     * 0.1175839
## 3           strategy   1  86 285.492988 4.620492e-29     * 0.5916683
## 4 diffgroup:strategy   3  86  28.677647 6.018123e-13     * 0.3039368
```

We see that the main effects of group and strategy, as well as their interaction were significant. This suggests that angular reach deviations from at least one group differed from the other groups, when either using or not using a strategy. Planned follow-up tests were necessary to determine which of the groups differed.

```r
RAEComparisonMeans()
```

```
## Contrasts set to contr.sum for the following variables: diffgroup
```

```
##  diffgroup  strategy  lsmean   SE  df lower.CL upper.CL
##  30explicit exclusive  10.67 1.40 170    7.905    13.43
##  30implicit exclusive  11.74 1.42 170    8.929    14.55
##  cursorjump exclusive   8.29 1.42 170    5.484    11.10
##  handview   exclusive   2.78 1.25 166    0.313     5.25
##  30explicit inclusive  29.06 1.40 170   26.296    31.82
##  30implicit inclusive  14.66 1.42 170   11.847    17.47
##  cursorjump inclusive  22.86 1.42 170   20.055    25.67
##  handview   inclusive  28.43 1.25 166   25.959    30.89
##
## Warning: EMMs are biased unless design is perfectly balanced
## Confidence level used: 0.95
```

```r
getRAEComparisonEffSize(method='sidak')
```

```
## Contrasts set to contr.sum for the following variables: diffgroup
```

```
##  contrast                             estimate   SE df t.ratio p.value
##  WO.Instr vs. WITH.Instr                -18.39 1.86 86  -9.877 <.0001
##  WO.Non-Instr vs. WITH.Non-Instr         -2.92 1.91 86  -1.529 0.4267
##  WO.Cursor Jump vs. WITH.Cursor Jump    -14.57 1.91 86  -7.637 <.0001
##  WO.Handview vs. WITH.Handview          -25.65 1.58 86 -16.185 <.0001
##
## P value adjustment: sidak method for 4 tests
##                               contrast etasquared
## 1              WO.Instr vs. WITH.Instr 0.53145073
## 2      WO.Non-Instr vs. WITH.Non-Instr 0.02647764
## 3 WO.Cursor Jump vs. WITH.Cursor Jump 0.40410183
## 4        WO.Handview vs. WITH.Handview 0.75284197
```

The tests confirmed our conclusions from the figure. All groups, except the non-instructed group, showed significantly different angular reach deviations when comparing reaches using a strategy to reaches when they are not using a strategy. This suggests unawareness of learning for the non-instructed group. Note that effect sizes are provided with eta-squared, which is interpreted as the percent of variance in angular deviation of the hand, accounted for by the difference between using and not using a strategy.

Localization

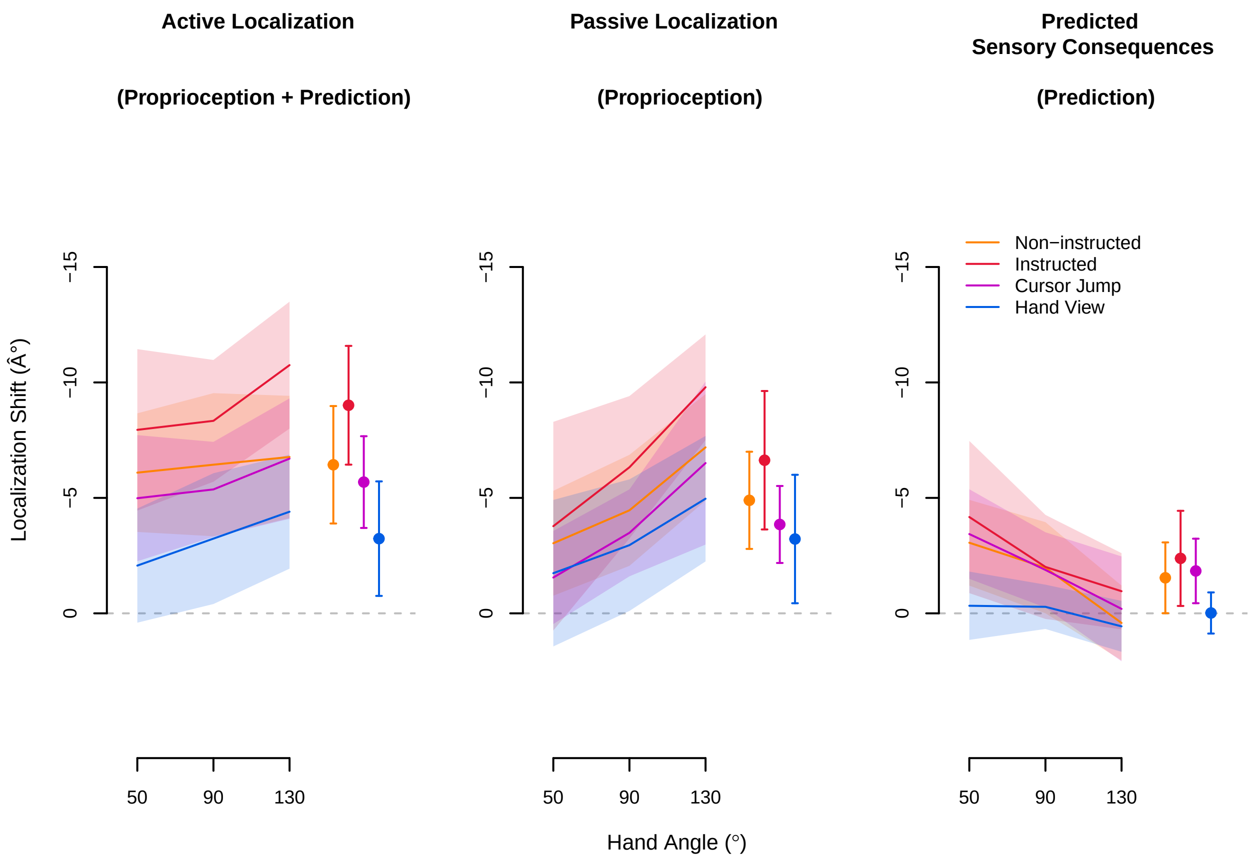
We also investigated how manipulating the extent of external error attribution affected participants' hand position estimates for both before and after adaptation training.

we analyzed estimates of hand position in *Active Localization* and *Passive Localization* trials, before and after rotation training. In obtaining hand position estimates, we calculated the angular difference between the point where the participant's unseen right hand movement ended and their perceived hand position, i.e. their touchscreen response using the left hand. For us to be able to calculate these angular difference measures appropriately, the touchscreen and monitor position must be coordinated. However, during our analyses of the data, we encountered inconsistencies with the location of the touchscreen responses relative to the arc location. This is because the touchscreen position is fixed, but the monitor can be moved to different positions. Thus, these inconsistencies showed that some of the responses were not centred on where the arc stimuli were expected to be displayed (12 cm from home position). Despite this, responses still fell within the shape of an arc, which allowed us to fix for this problem by implementing a circle fitting procedure that finds a circle of best fit for the responses. Moreover, this procedure also allowed us to account for any participant response biases. The procedure used a fitting algorithm that minimized mean squared errors (MSE), where errors were defined as the difference between the touchscreen response locations and the expected arc stimulus location. The MSE measures were then passed on to an optimizing function (optim in R), which minimized the error to return a best fitting home position, such that the responses were shifted to where we expected it to be (i.e. 12 cm from home position). In short, the circle fitting procedure ensured that any localization shifts we detected in our analyses were not due to technical issues or response biases. Furthermore, we conducted an outlier removal procedure for this fitted data, such that touchscreen responses beyond ±20° from the arc centre and angular errors beyond ±3 standard deviations from the mean angular error were removed. Lastly, as participants chose the points on the arc that they moved towards, their movements did not end on all possible points on the arc. To account for this, we used a kernel smoothing method (width = 15°) to interpolate changes in hand localization at specific interpoints (50°, 90°, and 130°). Note that these interpoints are the same points where the arc stimuli are centred on in polar coordinates. We then calculated for the mean of these interpolated values, at every interpoint, to estimate shifts in hand localization.

Show the data

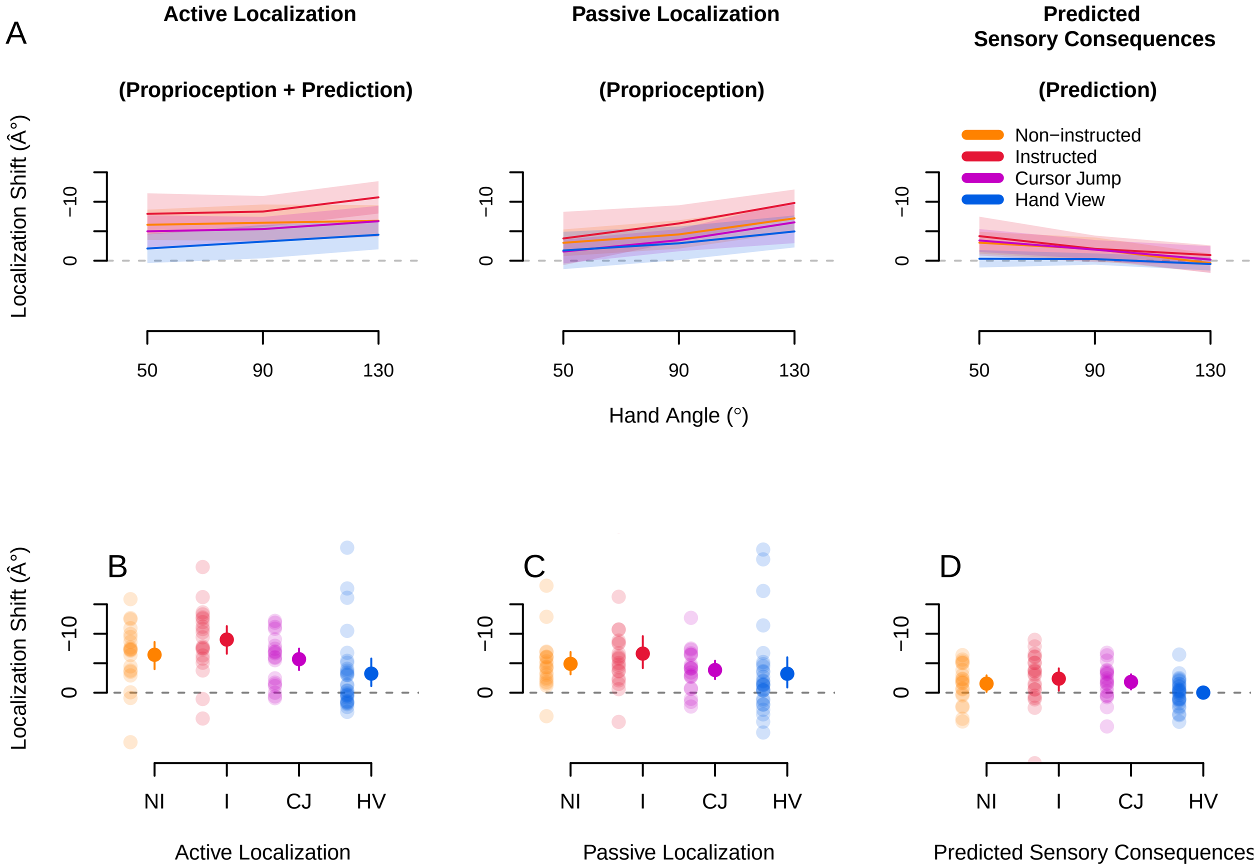
Below is a plot of the mean angular shift in hand localization for each group as a function of the three interpoints (50°, 90°, and 130°). Panel 1 shows shifts in hand localization when both proprioceptive information and efference-based predictions are available to the participant. Panel 2 shows shifts in hand localization when only proprioceptive information is available. Panel 3 shows shifts in hand localization when efference-based predictions are isolated (i.e., shifts in Active minus shifts in Passive Localization). Lines represent the mean angular shift in localization for each group, and corresponding shaded regions represent 95% Confidence Intervals. The right hand side of each panel shows the mean localization shifts and corresponding 95% Confidence Intervals for each group, regardless of Hand Angle.

```
plotLocalizationShift(target='inline')
```



We see from the figure that all groups showed a shift in hand localization, and that these shifts were larger when both efference-based predicitions and proprioceptive information were available to the participants (i.e., *Active Localization*). In comparing Panels 2 and 3, we see that majority of the shifts in active localization was accounted for by proprioceptive information, as the shifts in predicted sensory consequences were near 0. However, the lack of differences across groups seems to suggest that our manipulation of external error attribution did not affect both proprioceptive recalibration and updating of predicted sensory consequences. Before any statistical tests, however, we first checked for the shape of distributions of individual data points across groups. Below is a plot showing individual data points for shifts in localization according to groups and movement type. For the lower half, dot and error bars represent the mean and bootstrapped 95% confidence intervals. Shaded regions are density distributions of the bootstrapped means.

```
plotLocalizations()
```



We see that distributions for all groups are approximately normal and unimodal. Thus, we proceeded with the statistical tests performed below.

Localization shifts after rotated training

First, we wanted to test whether localization estimates did shift after training with the rotated cursor. We ran a 2X2X4 mixed design ANOVA with session (*rotated_b* in data; aligned and rotated) and movement type (*passive_b* in data; active and passive) as within-subjects factors and group (instructed, non-instructed, cursor jump, and hand view) as a between-subject factor.

```
localizationANOVA(test='omnibus')
```

```
## Warning: Data is unbalanced (unequal N per group). Make sure you specified a
## well-considered value for the type argument to ezANOVA().
```

```
## $ANOVA
##                        Effect DFn DFd          F            p p<.05          ges
## 2                       group   3  86 10.2140223 8.027644e-06     * 0.1948349585
## 3                   rotated_b   1  86 82.9722888 2.952983e-14     * 0.1998968369
## 5                   passive_b   1  86  0.2248202 6.365931e-01       0.0001014685
## 4             group:rotated_b   3  86  2.8949588 3.981800e-02     * 0.0254846797
## 6             group:passive_b   3  86  0.2332192 8.730026e-01       0.0003157102
## 7         rotated_b:passive_b   1  86 16.8023316 9.368043e-05     * 0.0044892506
## 8 group:rotated_b:passive_b   3  86  2.4249975 7.114493e-02       0.0019486945
```

To answer the question for this sub-section, we see that rotated_b had a significant main effect, which suggests that estimates of localization after rotated training differed from localization estimates before training. We also see other effects which we will investigate further.

Effect of external attribution and movement type on localization shifts

Since localization estimates shifted after rotated training, we tested whether these shifts were affected by our different groups (i.e. our manipulation of the extent of external error attribution) and by the movement type executed (i.e. active or passive). We ran a 2X4 mixed design ANOVA with movement type (*passive_b*) as a within-subject factor and groups as a between-subject factor.

```r
localizationANOVA(test = 'shifts')
```

```
## Warning: Data is unbalanced (unequal N per group). Make sure you specified a
## well-considered value for the type argument to ezANOVA().
```

```
## $ANOVA
##            Effect DFn DFd         F            p p<.05         ges
## 2           group   3  86  2.894959 3.981800e-02     * 0.084854522
## 3       passive_b   1  86 16.802332 9.368043e-05     * 0.015737408
## 4 group:passive_b   3  86  2.424998 7.114493e-02       0.006875259
```

We see that there is a main effect of group and movement type, but no significant interaction. This suggests that the effects of movement type on shifts in hand position estimates were not modulated by group, and vice-versa. Our main research question aimed to see changes in estimates of hand location due to proprioceptive recalibration and updating of predicted sensory consequences, which we investigated next.

Proprioceptive Recalibration

As previously stated, during active localization, participants have access to both information on proprioception and predicted sensory consequences. On the other hand, during passive localization, participants only have access to proprioceptive information. We are interested in testing the effect of manipulating the extent of external error attribution (group) on both proprioceptive recalibration and updates in predicted sensory consequences.

First, we run a one way ANOVA to test for the effect of group on passive localization changes (proprioceptive recalibration).

```r
localizationANOVA(test='passive')
```

```
## Warning: Data is unbalanced (unequal N per group). Make sure you specified a
## well-considered value for the type argument to ezANOVA().
```

```
## Coefficient covariances computed by hccm()
```

```
## $ANOVA
##   Effect DFn DFd       F         p p<.05       ges
## 2  group   3  86 1.48161 0.2252412       0.0491441
##
## $`Levene's Test for Homogeneity of Variance`
##   DFn DFd      SSn      SSd         F         p p<.05
## 1   3  86 63.46828 1844.304 0.9865097 0.4030917
```

We see that there are no significant differences across the groups. This suggests that passive localization changes were not affected by our manipulation of error attribution. *NOTE: (In the instance that we might be interested in testing for the effect of group on active localization changes, the function can also run the one way ANOVA on active localization changes. I do not show it here, but in that test, there is a significant difference between groups).*

Next, we wanted to test whether each group showed any recalibration in proprioception. We ran t-tests that compared each group's magnitude of shifts in passive localization estimates against 0. These were one-tailed t-tests, where the null hypothesis was that the mean is greater than or equal to 0; the alternative hypothesis was that the mean is less than 0. Hence confidence intervals are all from minus infinity. Note that we do not need to control for multiplicity here, as each group is independently compared to zero (i.e., these are not pairwise comparisons).

```
pasLocTtests()
```

```
## Hand View group proprioceptive recalibration compared to 0:
##
##  One Sample t-test
##
## data:  subdf$prop_recal
## t = -2.3715, df = 28, p-value = 0.01242
## alternative hypothesis: true mean is less than 0
## 95 percent confidence interval:
##        -Inf -0.9099481
## sample estimates:
## mean of x
## -3.219151
##
## Effect Size - Cohen d:
## [1] 0.4403703
## Instructed group proprioceptive recalibration compared to 0:
##
##  One Sample t-test
##
## data:  subdf$prop_recal
## t = -4.6143, df = 20, p-value = 8.383e-05
## alternative hypothesis: true mean is less than 0
## 95 percent confidence interval:
##       -Inf -4.152556
## sample estimates:
## mean of x
## -6.631075
##
## Effect Size - Cohen d:
## [1] 1.006932
## Non-Instructed group proprioceptive recalibration compared to 0:
##
##  One Sample t-test
##
## data:  subdf$prop_recal
## t = -4.8691, df = 19, p-value = 5.329e-05
## alternative hypothesis: true mean is less than 0
## 95 percent confidence interval:
##       -Inf -3.156566
```

```
## sample estimates:
## mean of x
## -4.894859
##
## Effect Size - Cohen d:
## [1] 1.088756
## Cursor Jump group proprioceptive recalibration compared to 0:
##
##  One Sample t-test
##
## data:  subdf$prop_recal
## t = -4.8321, df = 19, p-value = 5.79e-05
## alternative hypothesis: true mean is less than 0
## 95 percent confidence interval:
##       -Inf -2.471709
## sample estimates:
## mean of x
## -3.849077
##
## Effect Size - Cohen d:
## [1] 1.080488
```

From the tests, we see that all groups differed significantly from 0, suggesting that all groups showed changes in proprioceptive estimates. Note that effect sizes are provided with Cohen's d, which is in standard deviation units. Thus, it indicates how many standard deviations the mean shift for a group is different from zero. Here, all Cohen's d values are relatively similar, except for the Hand View group.

Predicted Sensory Consequences

Next, we ran a one way ANOVA to test for the effect of group on changes in predicted sensory consequences. For this ANOVA, we obtained changes in predicted sensory consequences by subtracting the shifts in passive localization from active localization.

```r
predictedConsequencesANOVA()
```

```
## Warning: Data is unbalanced (unequal N per group). Make sure you specified a
## well-considered value for the type argument to ezANOVA().
```

```
## Coefficient covariances computed by hccm()
```

```
## $ANOVA
##   Effect DFn DFd        F          p p<.05       ges
## 2  group   3  86 2.424998 0.07114493       0.0779951
##
## $`Levene's Test for Homogeneity of Variance`
##   DFn DFd      SSn      SSd       F         p p<.05
## 1   3  86 26.89084 421.4135 1.82925 0.1478659
```

There were no significant differences across the groups, suggesting that changes in predicted sensory consequences were not affected by our manipulation of error attribution.

However, from the plot we generated above, it seems that only the Hand View group is at the 0-degree mark for changes in predicted sensory consequences. Thus, we tested whether each group showed any predicted sensory consequences at all, especially for the Hand View group. We ran t-tests that compared each group's magnitude of changes in predicted sensory consequences against 0.

```r
predConsTtests()
```

```
## Hand View group predicted sensory consequences compared to 0:
##
##  One Sample t-test
##
## data:  subdf$pred_update
## t = -0.036821, df = 28, p-value = 0.4854
## alternative hypothesis: true mean is less than 0
## 95 percent confidence interval:
##       -Inf 0.7239956
## sample estimates:
##  mean of x
## -0.0160175
##
## Effect Size - Cohen d:
## [1] 0.006837449
## Instructed group predicted sensory consequences compared to 0:
##
##  One Sample t-test
##
## data:  subdf$pred_update
## t = -2.4107, df = 20, p-value = 0.01283
## alternative hypothesis: true mean is less than 0
## 95 percent confidence interval:
##        -Inf -0.6773985
## sample estimates:
## mean of x
## -2.380476
##
## Effect Size - Cohen d:
## [1] 0.5260632
## Non-Instructed group predicted sensory consequences compared to 0:
##
##  One Sample t-test
##
## data:  subdf$pred_update
## t = -2.1013, df = 19, p-value = 0.02459
## alternative hypothesis: true mean is less than 0
## 95 percent confidence interval:
##        -Inf -0.2726259
## sample estimates:
## mean of x
## -1.539263
##
## Effect Size - Cohen d:
## [1] 0.469866
## Cursor Jump group predicted sensory consequences compared to 0:
##
##  One Sample t-test
##
```

```
## data:  subdf$pred_update
## t = -2.7513, df = 19, p-value = 0.00635
## alternative hypothesis: true mean is less than 0
## 95 percent confidence interval:
##        -Inf -0.6820571
## sample estimates:
## mean of x
## -1.835863
##
## Effect Size - Cohen d:
## [1] 0.6152064
```

From the tests, we see that only the Hand View group did not significantly differ from 0, suggesting that the Hand View group did not show any updates in predicted sensory consequences. Note that effect sizes are provided with Cohen's d, which is in standard deviation units. Thus, it indicates how many standard deviations the mean shift for a group is different from zero. Here, only the Hand View group has a very small effect size.

Contributions of Proprioception and Predicted Sensory Consequences on Reach Aftereffects

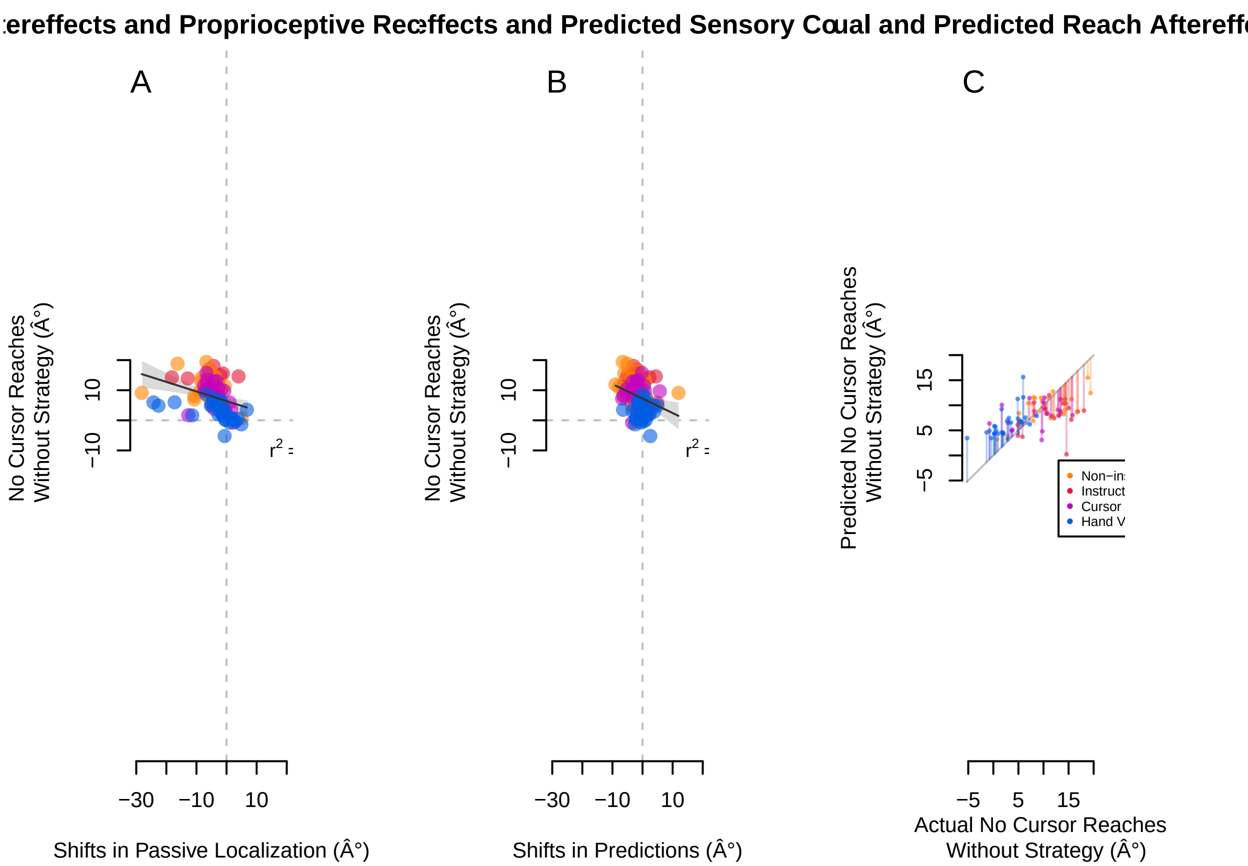
According to Modchalingam et al. (2019), afferent and efferent-based changes in hand localization are independent processes, and they suggested that afferent-based changes (proprioceptive recalibration) partly predicts implicit motor changes (reach aftereffects). Here, we test whether both afferent and efferent-based changes predict/contribute to implicit motor changes.

To visualize the data, we plot the relationship of proprioception and aftereffects, as well as predictions and aftereffects, individually. Note that we did perform a Pearson product moment correlation test for these two and found a significant relationship for both, but we only include it as analyses extra to the manuscript (i.e., the main test is the multiple regression below). For the extra analyses, refer to the other R Markdown document, AnalysesSupp.

```r
plotPropPredRelationships()
```

```
##
## Call:
## lm(formula = reachdev ~ prop_recal)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.8236  -4.0634  -0.2784   3.7385  10.8567
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  6.39900    0.67956   9.416  5.7e-15 ***
## prop_recal  -0.31817    0.09128  -3.486 0.000768 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.118 on 88 degrees of freedom
## Multiple R-squared:  0.1213, Adjusted R-squared:  0.1113
## F-statistic: 12.15 on 1 and 88 DF,  p-value: 0.000768
```

```
##
## Call:
## lm(formula = reachdev ~ pred_update)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -11.191  -3.720  -0.292   4.271   9.495
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   7.2109     0.5896  12.231  < 2e-16 ***
## pred_update  -0.4797     0.1635  -2.933  0.00427 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.211 on 88 degrees of freedom
## Multiple R-squared:  0.08907,    Adjusted R-squared:  0.07872
## F-statistic: 8.605 on 1 and 88 DF,  p-value: 0.004274
```



From the left and centre panels of the plot, we see that there is a relationship between predictions and aftereffects, as well as proprioception and aftereffects. For these plots and the regression below, we pooled data from all individuals across all groups together. One criticism could be that we are only detecting a relationship because of a group effect that is leading to a spurious correlation. However, even after taking into account the group effect, these predictors are still statistically significant. (See AnalysesSupp for these tests).

We then performed a multiple regression, where measures of aftereffects was the dependent variable, and both proprioceptive recalibration and predicted sensory consequences were the predictors.

```
getPropPredGLM()
```

```
##
## Call:
## glm(formula = RAE ~ pred_update + prop_recal)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -9.6900  -3.2806  -0.7717   3.6503  14.3770
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.98443    0.68624   7.263 1.51e-10 ***
## pred_update -0.69371    0.15109  -4.591 1.47e-05 ***
## prop_recal  -0.42979    0.08588  -5.005 2.89e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 21.32409)
##
##     Null deviance: 2622.9  on 89  degrees of freedom
## Residual deviance: 1855.2  on 87  degrees of freedom
## AIC: 535.74
##
## Number of Fisher Scoring iterations: 2
##
## The deltaR-square values: the change in the R-square
##       observed when a single term is removed.
## Same as the square of the 'semi-partial correlation coefficient'
##             deltaRsquare
## pred_update    0.1713831
## prop_recal     0.2036238
##     Variables      VIF
## 1  prop_recal 1.087117
## 2 pred_update 1.087117
```

We found that both changes in proprioception (Beta = -0.69, $p < .001$) and predictions (Beta = -0.43, $p < .001$) were significant predictors of reach aftereffects. As a measure of effect size, we can use the squared semi-partial correlation coefficient (sr-squared). This means that 17% of the variance in reach aftereffects is accounted for by updates in predictions, after partialling out proprioceptive changes. On the other hand, 20% of the variance in reach aftereffects is accounted for by proprioceptive changes, after partialling out updates in predictions.

Importantly, we note that changes in proprioception are independent from predicted sensory consequences due to how we have measured them. Recall that proprioceptive recalibration was measured from Passive localization, while predictions were calculated as a difference of Active and Passive Localization. This process ensures predictions do not have any shared variance with proprioceptive recalibration. Furthermore, predictions and proprioceptive changes are not collinear with each other (vif = 1.09 is considered low; see AnalysesSupp for extra analyses).

Next, we calculated the predicted reach aftereffects from our model and compared these with the actual/observed reach aftereffects from our experiment (right panel in the plot above).To calculate the predicted reach aftereffects, we refer to values from our model. The equation is:

$$\text{predicted RAE} = \text{Intercept} + \text{Prediction\_Coeff}(\text{actual\_prediction}) + \text{Proprioception\_Coeff}(\text{actual\_proprioception})$$

If the model predicted reach aftereffects perfectly, then points would fall along the diagonal of the plot. We see that the predictions overshoot the data on the lower end, but undershoot the data on the higher end. These could possibly be due to noise, or it could mean that the model is incomplete. It is very likely that another predictor needs to be included in the model, but the current study did not look further into this.

We note that these results do not definitively show that changes in proprioception and predictions are what cause aftereffects. That is, we cannot establish causation from this multiple regression. If we considered the correlations of each predictor with aftereffects (r-squared values from left and centre panels of plot), these values are still small in magnitude. It is possible that the significant relationships we found were due to an alternative variable or a common source (e.g. factors such as participant motivation). Therefore, although our results suggest that both proprioception and predictions partly contribute to aftereffects, these should be interpreted with caution.