THE UNIVERSITY OF CHICAGO

Language or Action?
Functional Distinctions Between Imagistic and Categorical Gesture in English and ASL

by

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ABSTRACT

This study reanalyzed motion capture data from 13 native American Sign Language (ASL) signers and 32 hearing English speakers, who were asked to physically imitate and then describe the trajectory of a three-dimensional version of the Müller-Lyer illusion (Brown et al., 2021). Building on the previous findings that all participants were less affected by the visual illusion when actually interacting with the object or gesturing/signing while describing it than when estimating the size of the object, this study examines specific kinematic features of their gesture, focusing on smoothness, accuracy, velocity, and rhythmicity using dynamic time warping and other quantitative methods. This analysis demonstrated that signers have smoother movements during gestures about trajectory than English speakers (but not during instrumental action), have faster hand movements overall, have greater general rhythmicity in their gestures (particularly in description taks), and are less accurate in their description of the object's trajectory than English speakers. These results suggest that there are subtle differences in the gestures produced by signers and speakers, which may indicate their engagement of different cognitive mechanisms while producing descriptive gestures. Specifically, this process seems to be more informed by action in speakers, but more by language in signers.

INTRODUCTION

The study of gesture, or “visible action as utterance” (Kendon, 2004), especially as it relates to and differs from the structure of sign language systems, has inspired many questions about the cognitive underpinnings of communicative expression. By evaluating differences between English speakers and ASL signers in their susceptibility to the Müller-Lyer illusion (in which the shape of line’s length is affected by the shape of the fins at its ends, see Figure 1) as a function of different gesture types, this project aims to bring greater clarity to the distinction between representation and action-based movement as it relates to the linguistic and gestural components of ASL and spoken English. Preliminary data analysis suggested that manual description of an object’s motion seems more informed by action in speakers, but more informed by language in signers, a finding that indicates there may be different cognitive mechanisms mediating this process. Although our understanding of sign language as it relates to and differs from spoken language and co-speech gesture has matured greatly in recent years, this detail-oriented, kinematic comparison of gesture and sign could reveal to what extent ASL signers are engaging in the same linguistic processes as speakers, and therefore lend insight into the cognitive and perceptual underpinnings of both categorical and imagistic uses of the manual modality.

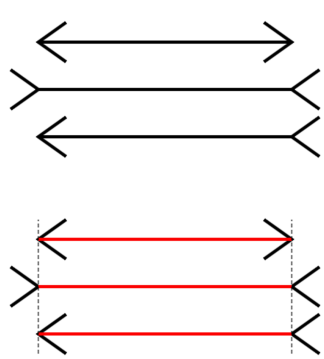


Fig. 1: The Müller-Lyer illusion (Foster, 1923).

This study builds on a previously published paper by Amanda Brown, Wim Pouw, Diane Brentari, and Susan Goldin-Meadow, titled “People Are Less Susceptible to Illusion When They Use Their Hands to Communicate Rather Than Estimate” (2021), and re-examines the same data set to draw additional conclusions about the differences between gestures with a description, action, and estimation function. This original paper found that for both hearing English speakers and deaf American Sign Language signers, susceptibility to a three-dimensional version of the Müller-Lyer illusion (see Figure 1) - was unaffected by attempting to estimate its length using their hands, but that participants were far less susceptible to the illusion when actually interacting with the object or gesturing/signing while describing it (Brown et al., 2021). The researchers concluded that both co-speech gesture and sign language are perceptually tied more to interacting with objects in our environment than to estimation tasks.

Notably, despite the fact that ASL has four pre-existing hand shapes that represent linguistic categories to describe length (Brentari, 1998) (see Appendix 1), which could plausibly be less affected by the visual illusion than the non-categorical co-speech gesture, Brown et al. (2021) found that this effect held for both speakers and signers. They therefore posited that “gesture may thus play the same role in sign and speech” in terms of object interaction/description, a conclusion that supports the field’s relative consensus that signers utilize both categorical signs (akin to spoken words) and imagistic gestures (resembling co-speech gesture) (Goldin-Meadow & Brentari, 2017). However, in contemporary gesture and language research, a lively debate still persists on the distinctions and similarities between these ‘gestures’ and ‘signs’, with some researchers arguing that (imagistic) gestures can be at least theoretically distinguished from (categorical) signs, while others maintain that the differences between these communicative modalities are exaggerated and largely a product of structuralist linguistics (Goldin-Meadow & Brentari, 2015; Kendon, 2008). Clearly, sign language demonstrates a formal linguistic structure, and yet shares obvious physical similarities with co-speech gesture.

Goldin-Meadow & Brentari (2015) emphasize that clarifying this distinction is crucial to furthering understanding of linguistic learning and cognition, and specifically call for novel technological approaches in this research. In contrast to the commonly used manual coding of video data, markerless motion-tracking technology allows for precise quantification of the kinematics of gestures by extracting specific kinematic features of the movement (Trujillo et al. 2019). In this sense, despite their similarities in susceptibility to optical illusion as a function of the gesture task, there are aspects of the original data from Brown et al. (2021) that demonstrate subtle differences in the motion of gestures by signers and speakers. This may indicate their engagement of distinct cognitive mechanisms while producing descriptive gestures and/or that this process is more informed by action in speakers, but more by language in signers. In a provocative case study, an aphasic signer demonstrated a clear dissociation between signing ability and gesture production (Marshall et al., 2010); a study comparing pointing gestures and pointing signs found that pointing is constrained differently when accompanying sign language and spoken language (Fenlon et al., 2019). These findings indicate that there are dissimilarities between speakers and signers that can benefit from precise quantification and analysis. In addition, we find that aphasics demonstrate greater variability in the standard coupling of gesture and speech, and that this variability is positively related to the severity of aphasia symptoms (Jenkins & Pouw, 2021).

Given notable differences in the smoothness and rhythmicity of their gestures, as well in the accuracy of the imitated motion in terms of velocity and trajectory, there remain certain inconsistencies in their usage of the manual modality, which this analysis aims to untangle and interpret.

PREDICTIONS

We can generate several predictions about the comparison between imagistic and categorical gestures in English speakers and ASL signers:

1. Signers are smoother during gestures about trajectory than English speakers, but not during instrumental action, since only during the description task do they employ the enhanced manual dexterity associated with their use of sign language,
2. Signers have faster hand movements overall than English speakers due to their greater experience with producing manual gestures,
3. Signers have greater general rhythmicity in their gestures than English speakers; this difference is most pronounced in description tasks for the same reasons noted above,
4. Signers are less accurate in their description of the object's trajectory than English speakers, since the categorical signs for describing a path have greater distinctions than the range of possible co-speech gestures.

These predictions all point to a differential function of imagistic and categorical gestures between native ASL signers and native English speakers, in that only signers demonstrate the hallmarks of linguistic processing in their descriptive gestures, but that the two groups are alike in the performance of action/instrumental gestures. This would indirectly provide evidence that different cognitive mechanisms underlie the use of the manual modality in speakers and signers.

METHODS

Study Design

The original research design of Brown et al. (2021) utilized motion-capture technology to record the hand movements of participants while interacting with sticks of different lengths (50mm, 70mm, 90mm, 110mm) placed on a piece of paper with drawn fins, which simulated the Müller-Lyer illusion (see Figure 1) in both the open fin or closed fin version. Including the control condition of a set of sticks without fins, the experiments comprised 12 distinct displays that were presented in pseudorandom order. The displays were repeated eight times for each task. At the outset, participants sat at a table and placed their right fist on a mark on the table, holding their thumb and forefinger extended and pressed together at the fingertips. In each condition, participants were shown video models of the task, then closed their eyes while each visual display was placed before them, and finally performed each of the three tasks. The order of action and estimation tasks was counterbalanced across trial days, while the description task was always assigned last. Since each participant completed all tasks twice, the final data set included 96 description trials, 168 action trials, and 72 estimation trials per participant. The primary measure in the original paper was maximum grip aperture, while this study focuses on more precise kinematic features of the participants' motions.

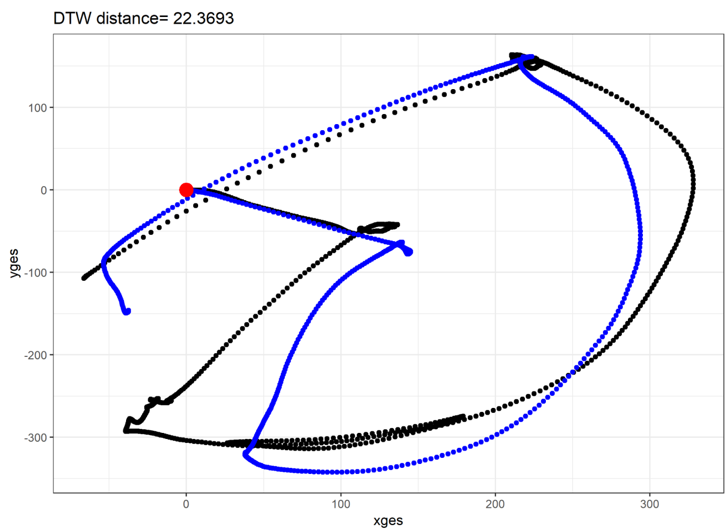


Fig. 2: Example of the original (blue) and imitated (black) trajectories and the dynamic time warp (dtw) distance score between the two.

In the action task, participants picked up the stick by holding it at both ends before replacing it on the table. In the estimation task, they estimated the length of the stick using the distance between their thumb and forefinger, while holding their hand/wrist in a natural position on the table perpendicular to the stimulus. After making the estimate, participants picked up the stick and then set it down again. In the description task, participants were shown a video of a hand performing a given trajectory while holding a 20mm white disk. They were then presented with a visual display, and asked to pick up the stick and imitate the trajectory. Subsequently, participants provided a detailed description of the path of motion (Brown et al., 2021). For all original study tasks, see Figure 2. This study focuses exclusively on the description task, differentiating between the imitation of the trajectory ("action") and the description thereof ("gesture") as its conditions.

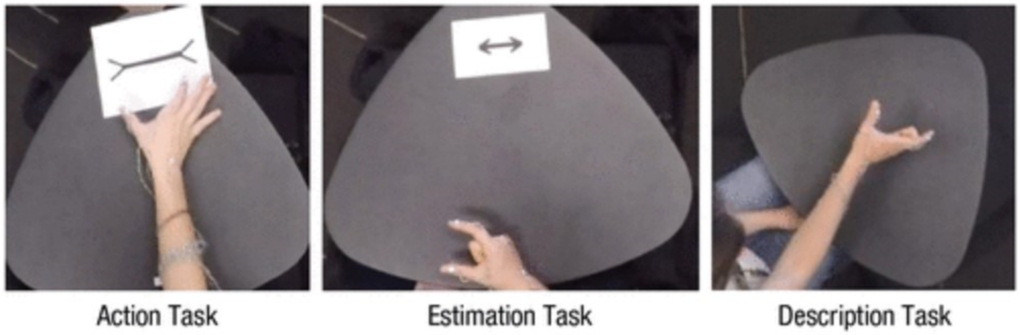


Fig. 3: Tasks given by Brown, Pouw, Brentari, & Goldin-Meadow, (2021).

Participants

Participants were forty-five right-handed adults (ages 19–68 years, 23 female/22 male), composed of 13 native ASL signers (all of whom were deaf and learned ASL before 6 years of age) and 32 native English speakers (Brown et al., 2021). English speakers were recruited from the University of Chicago's study participant pool, while ASL signers were recruited through email advertisements and at local deaf events (Brown et al., 2021). To compensate for the small sample size of deaf native ASL signers, multiple measurements were taken in each experimental condition, yielding 96 total observations of the description task. All participants had normal or corrected-to-normal vision (self-reported) and were confirmed to be right-handed using the Edinburgh Handedness Inventory (Oldfield, 1971; Brown et al., 2021).

Data Analysis

This study utilized a quantitative analysis of video and motion-capture data to assess individual components of the participants' movements. In examining video data akin to that used for this research, Wim Pouw and colleagues (2021) parsed the individual articulatory movements within silent gesture, which are commonly interpreted only in categorical (rather than specific kinematic) terms. This study thereby demonstrated that utilizing computer vision techniques to quantitatively analyze the kinematic structure of gesture can reveal additional linguistic aspects, such as may not have been captured in the original comparison of speakers and signers in Brown et al. (2021). Specifically, the present re-examination of the data focused on accuracy, smoothness, velocity, and rhythmicity of movement, using methodologies described by Wim Pouw of the Radboud University Nijmegen.

The accuracy of the movement in replicating the object's action, which is intrinsically tied to the velocity of the gesture itself (as relates to the velocity of the object), can be analyzed utilizing dynamic time warping (DTW), an algorithm which can assess the similarity of two time-dependent sequences after optimally aligning them (Müller, 2007; Mueen & Keogh, 2016; Pouw & Dixon, 2020). Videographic motion tracking systems have been proven to be a valid alternative to more expensive (device based) methods, specifically in the temporal estimation of kinematic peaks (Pouw & Dixon, 2020), and therefore the DTW analysis technique seems particularly well-suited to this data set. Following the procedure suggested by Pouw & Dixon (2019), the kinematic variable chosen was the absolute spatial trajectory, represented by 3D (x, y, z) motion variables. To simplify the comparison, the DTW analysis focused on the coordinates of the forefinger, which essentially 'led' the object's trajectory. After normalizing each observation for the length of the time series, the distance for each matched observation from maximal alignment was computed and summed to yield a measure of the dissimilarity between the two time series under examination. The R package *dtw* (Giorgino, 2009) was used for these relative distance DTW analyses.

Smoothness of gesture was assessed using a measure of intermittency (the opposite of smoothness) as described in regards to gesture segmentation by Pouw, Dingemanse, Motamedi, and Özyürek (2021). A dimensionless squared jerk measure (here, x'''), scaled to the maximum movement speed and duration, was computed using the formula presented by Hogan & Sternad (2009), and then used to compute the intermittency measure.

$$\int_{t2}^{t1} x'''(t)^2 dt * \frac{D^3}{max\left(v^2\right)}.$$

Fig. 4: Hogan & Sternad equation for intermittency.

Here, the jerk (x''', second derivative of speed) is squared, integrated over time, and multiplied by duration (D), itself cubed over the maximum squared velocity (v). This jerk measure is particularly helpful in that it computes changes of movement shape that differ from the smoothness baseline, including both changes in speed and breaks in motion (Hogan & Sternad, 2009). In this method, higher intermittency scores indicate less smooth movement.

Using the DTW methodology as described above (Pouw & Dixon, 2019), the 3D peak velocity was computed with the R package *dtw* (Giorgino, 2009). The distances for each matched observation in terms of velocity were summed and then used to compute the DTW distance measure.

To assess rhythmicity of the gesture, a submovement measurement was first computed using a peak-finding function to identify and count the maxima in a given movement speed time series (Trujillo, Vaitonyte, Simanova, and Özyürek, 2019; Pouw et al., 2021). Using this submovement measure, the rhythm tempo was then computed using the average interval between each submovement. Given that this measure is shown to be highly correlated with intermittency (Pouw et al., 2021), the temporal variability of the movements was subsequently computed using the standard deviation of the temporal interval between submovements. Here, temporal variability is given by a higher score on this measure, while a lower score indicates a more isochronous rhythm of the gesture (Pouw et al., 2021).

Statistical Analysis

Measures were compared using R Studio (RStudio 2022.02.1+461 "Prairie Trillium" Release for Windows) with the *lme4* package (Bates et al., 2014). With the outcome variables of accuracy, smoothness, velocity, and rhythmicity of movements (as defined above), the averages and standard deviations were calculated for both the ASL and English samples as a function of the gesture or description conditions (and vice versa) and assessed for statistical significance using t-scores and degrees of freedom to compute the p-value. A two-factor ANOVA test was also performed to test the two-way interaction between task condition and language and yield effect sizes, and Tukey Fence and Shapiro-Wilk tests were performed to assess validity of these results. Since only in the instrumental action version of the original study's 'description' task (what this paper terms the 'action condition') were subjects encouraged to recreate the object's trajectory as accurately as possible, 'accuracy' was only assessed within this task condition. Where applicable, these tests were supplemented by the Levene Test and the Kruskal Wallis non-parametric analysis.

RESULTS

Velocity

In line with the original hypothesis, the signers gestured faster overall than the English speakers (had higher peak velocities, denoted as "vpeak"), and while both groups were slightly faster in the gesture than in the action condition, the inter-group difference was also more pronounced in this task. Across the two groups, the difference in velocity between the action and gesture conditions were very significant, with faster speeds overall in the descriptive gesture task (mean(vpeak_action) = 103.96 cm/s (SD = 42.68) and mean(vpeak_gesture) = 125.93 cm/s (SD = 58.81). The difference between these means = -21.94 with a standard error (SE) of 1.26. A one-tailed t-test with a confidence interval (CI) of 95% yielded a t-score of -1.96 (DF = 4372), so the difference between the peak velocity of the action and gesture tasks across language groups was statistically significant at $p < 0.05$, with a p-value of 0.025 (Figure 5). Across tasks, there was also a significant difference between the ASL signers ("ASL") and English speakers ("ENG") in the peak velocity of their manual movements: mean(vpeak_ASL) = 107.17 (SD = 46.68), mean(vpeak_ENG) = 117.81 (SD = 54.26), difference between means = -10.643 (SE = 1.581). Given a one-tailed t-score of 1.961 (CI = 95%, DF = 4372), this difference in velocity between language groups was statistically significant at $p < 0.05$, with a p-value of 0.025 (Figure 5).

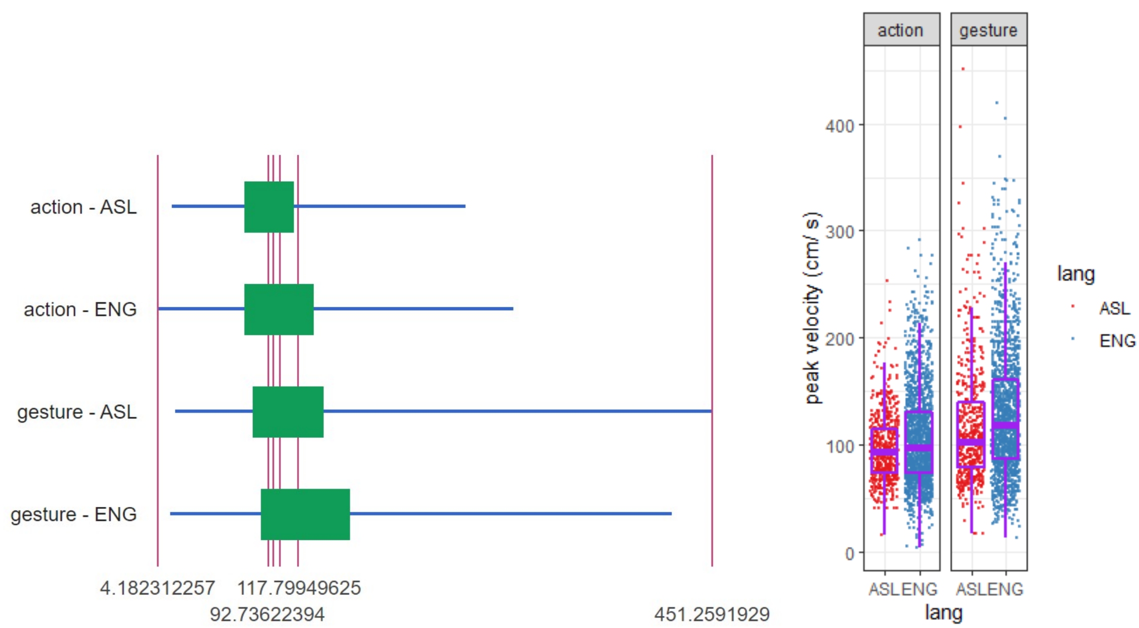


Fig. 5: Comparison of motion capture data of ASL signers and English speakers between the object interaction (action) and trajectory description (gesture) conditions of the description task in terms of peak velocity.

Most relevant for this analysis is the two-way interaction of language and task condition to assess whether the ASL signers and English speakers differ in the velocity of their gestures as a function of whether they are engaging in an instrumental action task or linguistically describing a trajectory. A two-factor ANOVA with fixed factors of language and condition was used to assess this possible two-way interaction. As indicated above, the null hypothesis could be rejected for the influence of condition, with a small effect size ($\eta 2$) of 0.044. Similarly, the null hypothesis for the effect of language on velocity could also be rejected, but with only a very small effect size of 0.0084. However, the p-value for the interaction of language and condition in peak velocity was 0.4706, meaning there is a 47.06% chance that any two-way interaction occurred by chance (Figure 6). Therefore the null assumption cannot be rejected and the differences are not statistically significant for the condition x language interaction for vpeak. The effect size is also extremely small ($\eta 2 = 0.00012$). Thus the only significant results are an overall higher velocity in the gesture condition and an overall higher velocity among the ASL signers.

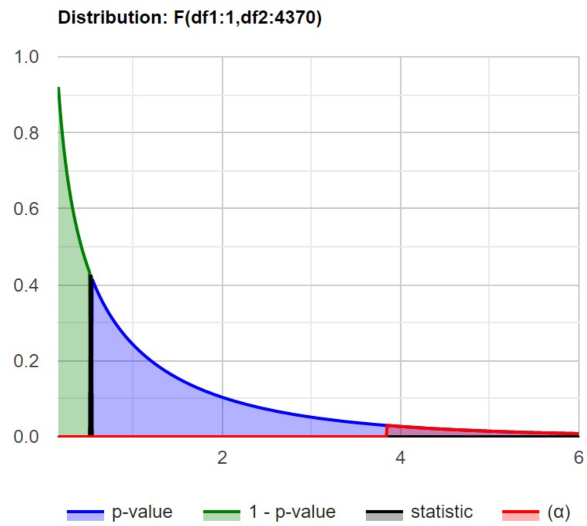


Fig. 6: Distribution of two-factor interaction between task condition and language (null hypothesis not rejected).

The Tukey Fence test for detecting outliers demonstrated that the residuals do not contain outliers (k=1.5). The Shapiro-Wilk Test for normality showed that the velocity data does not follow a normal distribution (α=0.05), but the two-way ANOVA test is robust to this moderate violation of the normality assumption.

Smoothness

As predicted, the ASL signers demonstrated greater smoothness in their gestures (lower intermittency scores) than the English speakers during the “gesture” trajectory description task, but were indistinguishable from this group during the action task. Both language groups were more smooth in the action task than in the gesture/description task (lower intermittency), with the following average values for log-transformed smoothness: mean(smoothness_action) = 5.697 (SD = 0.583), mean(smoothness_gesture) = 6.673 (SD =1.141), and difference between means = -0.975 (SE = 0.027). With a confidence interval of 95%, these values yielded a t-score of 1.961

(DF = 4372), which demonstrates statistical significance of the greater smoothness in the action task at a level of $p < 0.05$ ($p = 0.025$) (Figure 7). The ASL signers also had smoother gestures than the English speakers overall, with mean(smoothness_ASL) = 5.505 (SD = 0.611), mean(smoothness_ENG) = 6.436 (SD = 1.038), and difference between means = -0.931 (SE = 0.0256). Here, the t-score is 1.961 for a CI of 95% (DF = 4372). Therefore, the intermittency scores among the ASL signers are lower at a statistical significance of $p = 0.025$ (Figure 7).

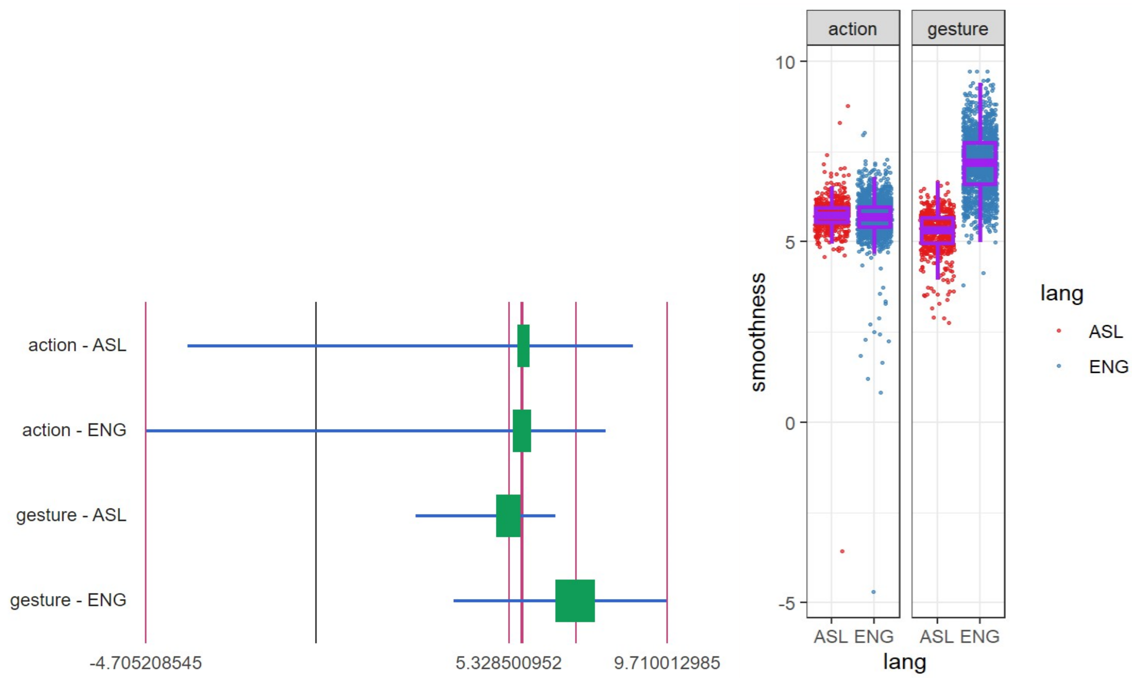


Fig. 7: Comparison of motion capture data of ASL signers and English speakers between the object interaction (action) and trajectory description (gesture) conditions of the description task in terms of smoothness (lower score indicates greater smoothness). All values were log transformed for clearer comparison.

The two-factor ANOVA test supported the above effects of condition and language on the smoothness of gesture, as well as demonstrated a robust two-way interaction between these factors. For the condition factor, the null hypothesis could be definitively rejected, and ANOVA yielded a large effect size of the task type on smoothness (η2 = 0.34), wherein the total sample showed less intermittency during the action task than the description task. Therefore the gesture type accounts for the largest proportion (about 34%) of the variance observed in the smoothness/intermittency measure. Similarly, the native language of participants also had a large effect on smoothness (η2 = 0.27), with ASL signers scoring more highly on smoothness than English speakers. In addition, the ANOVA revealed a strong two-way interaction between language type and condition, with a large effect size of η2 = 0.29. As can be seen in the averages plot in Figure 8, the smoothness of the ASL signers and English speakers is virtually indistinguishable within the action task, but in the gesture condition the signers demonstrate notably higher smoothness/lower intermittency scores. Therefore we see a large direct effect of gesture type (action = smoother), a large direct effect of language (ASL = smoother), and a large interactive effect of the two. In this latter case, not only are the English speakers significantly less smooth during the description than the action task, but the ASL signers are comparatively *more* smooth than in the action condition.

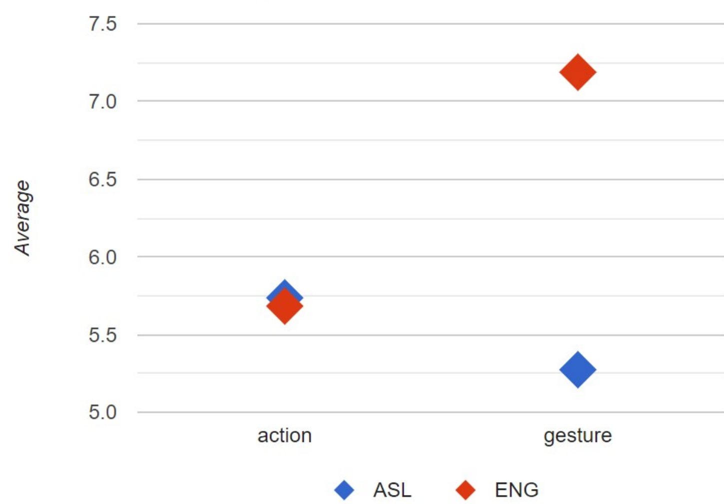


Fig. 8: Average (log-transformed) smoothness values by task condition and language. Lower scores indicate greater smoothness/less intermittency.

The Tukey Fence test confirmed that there were no outliers ($k=1.5$), and while the Shapiro-Wilk Test showed that the data residuals did not follow a normal distribution ($\alpha=0.05$), the ANOVA is robust to this moderate assumption violation.

Rhythmicity

In terms of rhythmicity (calculated as the standard deviation of tempo, where a lower score indicates a more isochronous pattern and therefore greater rhythmicity), both groups demonstrated more variability in their gestures (lower rhythmicity) in the gesture task than in the action task. For clarity, the scores reported will be designated as time variability (or "variability") and therefore represent the inverse of rhythmicity. Across language groups, the mean(variability_action) = 0.752 (SD = 0.632), mean(variability_gesture) = 1.249 (1.086), and the difference between means = -0.496 (SE = 0.027). Using a one-tailed t-test, the t-score was calculated as 1.961, with CI = 95% and DF = 4372. Therefore these results are significantly different at $p < 0.05$ ($p = 0.025$), and there is greater rhythmicity overall in the action task (Figure 7). The ASL signers were also much more rhythmic in their gestures overall than the English speakers, with lower temporal variability: mean(variability_ASL) = 0.405 (SD = 0.218), mean(variability_ENG) = 1.255 (SD = 0.998), difference between means = -0.85 (SE = 0.019). This yields a t-score of 1.961 (DF = 4372, CI = 95%), which demonstrates that the signers are more rhythmic across conditions with statistical significance at a level of $p < 0.05$ ($p = 0.025$) (Figure 7).

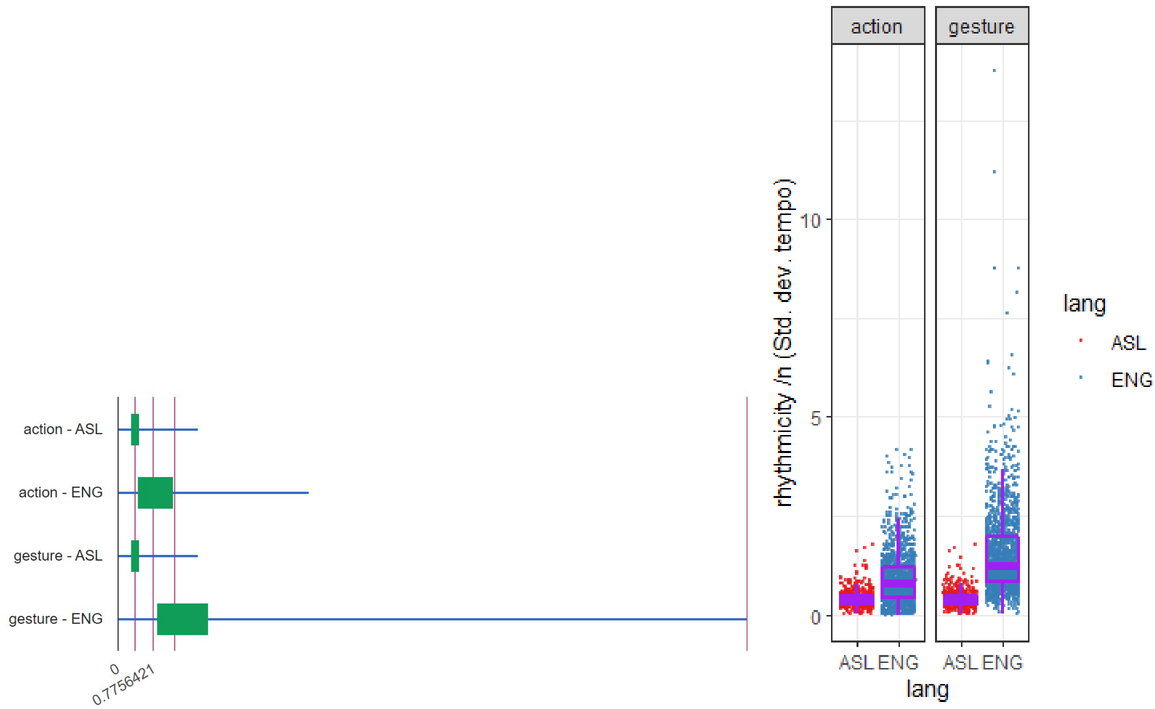


Fig. 7: Comparison of motion capture data of ASL signers and English speakers between the object interaction (action) and trajectory description (gesture) conditions of the description task in terms of rhythmicity (lower score indicates greater rhythmicity).

In terms of the interaction between task condition and native language, a two-factor ANOVA test confirmed the above results, and also demonstrated a two-way effect of language and task on the gestures' rhythmicity. For the distinction between gesture and action conditions, the null hypothesis could be rejected with a medium effect size of $\eta 2 = 0.086$. The type of task therefore had a moderate effect on the rhythmicity of the produced gesture at a high level of significance. Similarly, the null hypothesis could also be confidently rejected for the effect of language type on rhythmicity with a large effect size of $\eta 2 = 0.18$. The native language (ASL or English) of the participants therefore changed the amount of variability in their gestures quite dramatically. Unlike velocity, the ANOVA did detect a small two-way interaction between task condition and language on the measure of rhythmicity. The null hypothesis could be definitely rejected, with a small effect size of $\eta2 = 0.021$. Thus, the rhythmicity of gesture was significantly affected by the type of task (greater rhythmicity in instrumental action gestures), moderately affected by the language type (greater rhythmicity among ASL signers), and slightly affected by their interaction. As seen in the averages in Figure 8, the ASL signers were relatively consistent across task conditions, while the English speakers demonstrated much greater temporal variability/less rhythmicity during the gesture task compared to the instrumental action task.

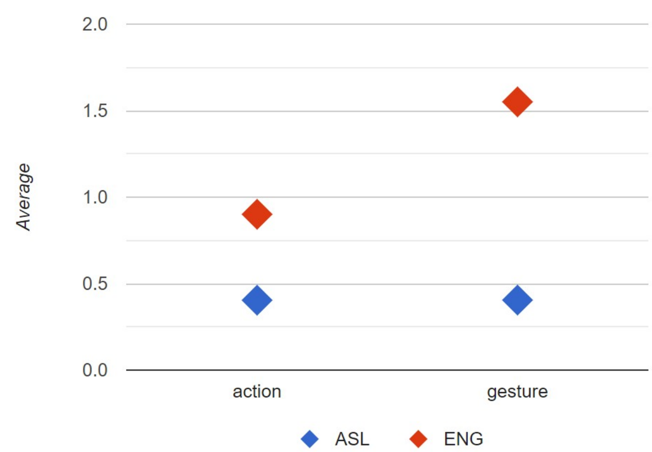


Fig. 8: Average rhythmicity values by language and condition.

The Tukey Fence test confirmed that the residuals contained no outliers (k=1.5). The Shapiro-Wilk test showed that the residuals do not follow a normal distribution ($\alpha=0.05$), but the ANOVA test is robust for this type of moderate violation.

Accuracy

Within the action condition, in which subjects attempted to imitate the trajectory they were presented with, dynamic time warping revealed notable differences between the ASL signers and the English speakers in terms of their accuracy in recreating the object's path. Since the DTW method quantifies the distance between the original trajectory and that produced by the participants, a higher score indicates lower accuracy. For clarity, this dynamic time warping score will therefore be reported as 'inaccuracy'. As predicted, the signers were less accurate than the English speakers, with mean(inaccuracy_ASL) = 63.73 (SD = 76.41), mean(inaccuracy_ENG) = 43.56 (SD = 45.50), and the difference between these means = -20.17 (SE = 2.37) . This yields a t-score of 1.962 (CI = 95%, DF = 4372), so this difference is statistically significant at $p < 0.05$ ($p = 0.025$) (Figure 9).

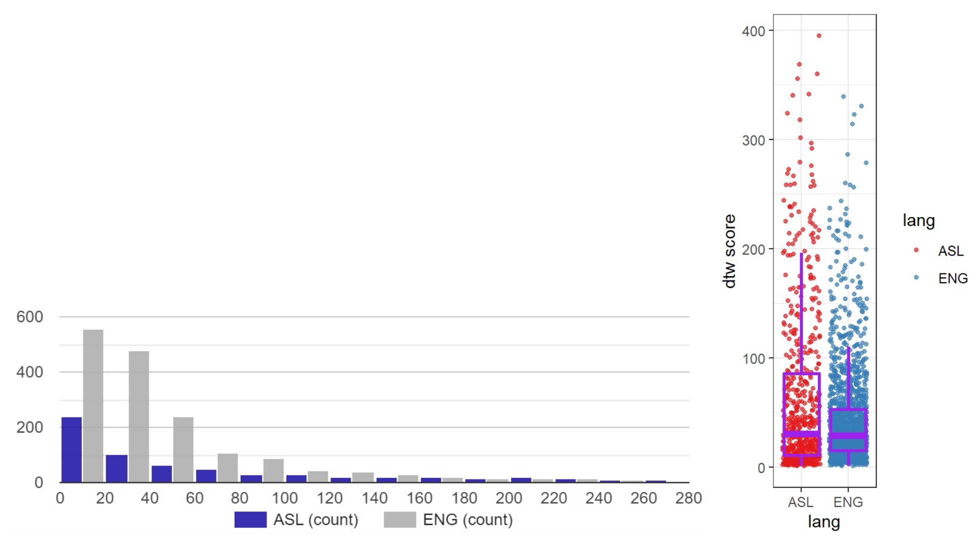


Fig. 9: Comparison of motion capture data of ASL signers and English speakers within the action condition of the description task in terms of accuracy to the original shown trajectory (higher dtw score indicates greater distance between the trajectories, and thus lower accuracy).

A one-way, right-tailed ANOVA test demonstrated that the null hypothesis could very confidently be rejected ($p < 0.001$), and therefore the difference between the average dtw/inaccuracy scores between the two groups is confirmed to be statistically significant.

However, the effect size is small ($f = 0.16$) and $\eta 2 = 0.025$, so the language group only explains 2.5% of the observed variance in the trajectory accuracy.

The Shapiro-Wilk Test (α=0.05) confirmed the assumption of normality. The Tukey HSD / Tukey Kramer Test also confirmed that the means of the two groups were significantly different (difference = 20.172, critical value = 5.25). However, Levene's Test to assess the equality of variances concluded that the population's variances are not equal at (p-value = 0.001), and that the groups' sizes are significantly different (ratio ENG:ASL = 2.71). Therefore the Kruskal-Wallis (non-parametric) ANOVA was applied, which checks the null assumption that when selecting a value from each of the groups, each of these groups will have an equal probability of containing the highest value. The Kruskal Wallis Test, which is more appropriate when comparing only two groups, was conducted with a significance level of $\alpha = 0.05$, DF = 1, and a rejection region of the Chi-Square Test of $R = \{\chi 2 : \chi 2 > 3.841\}$. The accuracy data yields an H statistic of 0.068, and since $\chi 2 = 0.068 \leq 3.841$, the null hypothesis cannot be rejected (p-value = 0.794) and we cannot conclude that there is a statistically significant difference in accuracy between the ASL and English groups. Rather, the boxplot in Figure 9 suggests that any observed difference is more likely due to greater upward variance in the ASL signers' dtw scores.

DISCUSSION

Velocity

While across the sample there was a higher velocity in the descriptive gesture task, signers also have slightly faster hand movements overall. The relation between speed and smoothness suggests this does not simply represent greater manual dexterity, and therefore velocity can be related to our language vs. gesture distinction. In a 2D modeling study of the spatiotemporal dynamic of sign language, the speed of signing fell within a very specific range (15.7-22.5 degrees/second) across the ‘sign’, ‘sentence’, and ‘narrative’ conditions (Schembri, Jones, & Burnham, 2005). This suggests that not only do signers have greater ‘practice’ producing manual gestures (speed of signing was correlated with number of years of ASL experience (Schembri, Jones, & Burnham, 2005)), but their signs as linguistic elements are produced on a particular time scale. By contrast, co-speech gesture aligns in a very specific way with the temporal dynamics of the speech, in that the peaks of intonation and the apexes of gestures are highly correlated in their relation to the prosodic structure (Esteve-Gibert & Prieto, 2013). It is relatively unsurprising, therefore, that gesture and sign should present slightly different temporal patterns, however the higher speed of ASL signers’ production of descriptive gestures (rather than signs) suggests that for signers these two types of motions share a process of production.

In addition, this data shows that signers perform better depending on the type of motion, i.e. if the trajectory of the object being described matches up with lexical categories for trajectory in ASL (Pouw, unpublished data). In this particular case, trajectories that dramatically and abruptly change direction are more akin to existing signs (constituting two separate lexical movements), and may therefore be performed more quickly and smoothly as compared to non-signers engaging in the same gestures. Because the accuracy of hand movement is important for effective communication in sign language, when the manual modality is routinely utilized for signing, other less stereotyped hand gestures are similarly ‘improved’ (i.e. produced with higher velocity).

Smoothness

In addition to robust main effects of condition and language (greater smoothness in the action task and among ASL signers, respectively), we find that the signers are significantly smoother than English speakers during gestures about trajectory, but not during instrumental action, suggesting that in sign language these represent separate types of manual movement roughly corresponding to language vs. gesture. Given that we see this difference from English speakers' gestures only within the domain of trajectory (a descriptive activity), the use of gesture during description may be more informed by language in signers than in speakers. For example, Ortega, Sumer, & Ozyurek (2014) described how children signing to adults, and parents signing to children, tended to use more action-based signs to describe an image, while adults signing to other adults used more perceptual signs that drew on perceptual features of the stimulus. In this case, language development is linked to a greater reliance on perceptual rather than action gestures, the result of which we see in our own video data.

Speakers also tend to gesture differently than they act (as quantified by i.e. smoothness), in that their gestures are sloppier (Pouw et al., 2021), and past research on the difference between these movements has suggested that gesture may "serve as a unique bridge between action and abstract thought", rather than simply mimicking action (Goldin-Meadow & Beilock, 2010). Potentially, the particular demands of sign production may result in greater gestural smoothness overall. In combination with our observations on signers' smoothness, this research suggests that the success conditions may be different for gestures and action due to the semiotic resources for gesture in signers vs. speakers. In addition, smoothness of sign is a reliable predictor of ASL fluency (Pearson's r correlation coefficient of 0.798) - and signers who are "choppy" are judged to be less fluent (Lupton, 1998); smoothness has also been found to increase as a particular sign language ages (Wilbur, 1990). The kinematic characteristic of smoothness therefore seems fundamentally associated with successful linguistic production in the manual modality.

Rhythmicity

Both ASL signers and English speakers were significantly more rhythmic in their instrumental actions than in their descriptive gestures. In addition, signers demonstrated moderately greater rhythmicity in general, which is of particular interest in relation to the study of sign language development. Wilbur (1990) found that as a sign system ages, both rhythmicity and smoothness increase, a pattern not found in gesture and therefore seemingly indicative of a language-specific process. Since sign language production requires a complex coordination of motor output, it is unsurprising that ASL is rhythmically structured. In particular, the rhythm of ASL narratives relies largely on repeated signs, signs with primary stress, and phrase-final signs (Allen, Wilbur, & Schick, 1991). Early learners of sign have been shown to be more rhythmic in their sign than late learners, suggesting that native proficiency rather than experience with sign as such underpins the rhythm of sign production (Braem, 1999). In addition, ASL-naive subjects more often identified signs with secondary or weak stress as central to the sign language's rhythm, demonstrating that knowledge of ASL is crucial to an accurate sense of this pattern. Indeed, the slight interaction between language and task in our data suggests that specific linguistic backgrounds differentially impact distinct gesture types in a similar experience-dependent manner.

However, hand gestures have also been shown to oscillate in accordance with the quasi-rhythm of speech, even demonstrating a slightly faster timescale in its periodicity than sign language (4-5 Hz vs. 2-2.5 Hz) (Pouw et al., 2020). Indeed, we see certain prosodic features of spoken languages, such as phrase-final lengthening, also patterning the rhythm of ASL (Coulter, 1993). Thus, the difference in rhythmicity between ASL signers and English speakers is likely a function of the description task in particular rather than distinguishing gesture and sign as such. Our analysis of the precise kinematic periodic features of the different types of recorded gestures also revealed that the rhythmicity ratio between signers and speakers was lowest in the description tasks, supporting the proposition that description among signers draws upon linguistic rather than action-based input.

Accuracy

Finally, our analysis turns to accuracy of the movement in replicating the object's action, where we found slightly lower accuracy among the signers than the speakers in their imitation of the object's motion. This result supports the original hypothesis that categorization into specific handshapes reduces the accuracy of ASL signers. While research by Schembri, Jones, & Burnham (2005) found that native signers display greater accuracy in both movement and locative units, they also tend to encode movement and location of an object separately (unlike non-signing gesturers). They may therefore be overall less accurate in recreating the trajectory as a whole, which relies on integration of movement and location elements. This kind of categorical gesture production (which should have lower accuracy on this task as its consequence) further indicates that the instrumental action task is more linguistically informed in signers. However, since the effect size was quite small and further statistical analysis could not demonstrate significance, it is unclear whether the observed group difference is more than an artifact in the data.

There was also an overall decrease in accuracy over time (Pouw, data not shown). Previous research has demonstrated a reduction of complexity over time through the use of recurring gestures, as well as a reduction in the complexity of the movement itself (Pouw et al, 2021), both of which could be contributing to this effect. We see this same process in spoken dialogue, in which repeated references to the same referent use fewer, acoustically reduced words, as well as fewer gestures (Hoetjes et al., 2015). Thus it is unsurprising to find a similar decline in accuracy in both participant populations.

Notably, the models of Schmidt, Zelaznik, and Frank (1978), and Meyer, Smith, and Wright (1982) of speed-accuracy relationships in aimed hand movements state that as the speed of movement increases, its accuracy decreases proportionally. Here we see a similar increase in speed at the cost of accuracy among the signers. Since this group difference seems to be mostly a result of greater variance in accuracy among the signers, we can look to research such as that by Zelaznik, Schmidt, and Gielen (2013), which finds that the simple time-rescalable acceleration patter of the 'speed-accuracy trade-off' is complicated by processes involved in limb deceleration (a motor program that may be differentially implemented among signers). Despite our null result, further study of the association between sign/gesture production and physical and cognitive motor systems is warranted.

Our prediction expected less accuracy from the signers due to the lexical categorization of specific speeds, locations, and trajectories into existing ASL handshapes and the finding that sign language is more conventionalized and less flexible than co-speech gesture (Sweetser, 2008). While this hypothesis was not completely disconfirmed, the minimal group differences and the lack of such effects on estimations of object length in the original data set (Brown et al., 2021) do not allow us to draw such definitive conclusions.

General Discussion

Citing the way in which our gestures can sometimes communicate separately from our spoken words, Goldin-Meadow (2003) provides a compelling link between gesture production and cognition in a less-than-predictable manner. For example, in neural research, fMRI activation studies have shown that signers engage slightly different brain systems than those activated in nonsigners when viewing sign language and gesture. While both groups engage the middle/anterior superior temporal sulcus (STS) region of the right hemisphere - a region commonly associated with theory of mind, biological motion, faces, voices, and language (Beauchamp, 2015) - when viewing gesture and ASL signs, other brain activation patterns differ dramatically (Newman et al., 2015). While signers engaged the classical language centers in the left hemisphere in both conditions (although more strongly in response to signs), nonsigners only demonstrated activation in human movement areas (Newman et al., 2015). Native sign language proficiency therefore altered the use of certain neural networks, leading to a linguistic perception of not only sign, but of descriptive gestures in general.

Additionally, signers observing sign language elicits greater activation in movement processing regions of the posterior middle temporal gyri, while audio-visual speech elicits greater activation in hearing subjects in auditory processing regions in superior temporal cortices (MacSweeney et al., 2008). Bosworth, Wright, and Dobkins (2015) even suggest the “Enhanced Exposure Hypothesis”, which states that regular visual exposure to sign language may shape and modify low-level visual processing. In any case, these compelling (albeit subtle) cognitive differences between signers and nonsigners suggests that the observed kinematic differences in their gesture production may be underpinned by distinct neural mechanisms.

Similarly, these kinematic features may be determined by the precise context and purpose of the gesture itself, which may in turn be influenced by linguistic experiences. Indeed, Trujillo and colleagues (2020) found that not only does the intention to communicate modulate certain details of the gestures (i.e. velocity), but this modulatory process in turn increases semantic comprehension (primarily due to late identification) of gestures. A further influence on the structure of gestures lies in the adaptation and implementation of motor systems. Kimura (1993) suggests that through the gradual adaptive processes of evolution, human communication has become dependent on certain motor programming systems and specific musculature, which in turn is shaped by the pressures of communication (among others). While her research focuses on the manual communication of the great apes, Kimura's (1993) conclusions about the necessity of specialized motor systems (here, of the arm and hand) for communication also seems directly applicable to our observed kinematic differences between signers and speakers.

As argued by Goldin-Meadow and Brentari (2017), productive gesture research relies on a clear distinction between sign/speech and gesture, as well as the use of speech-plus-gesture as a comparison to sign. Much of the debate surrounding sign language's status as a language and the differentiation between sign and gesture has focused on theoretical models such as that proposed by Hockett (1960), rather than on the physical details of its production. An understanding of the ways in which kinematic features differ between 'gesture' and 'sign', as well as between natives of manual and vocal/auditory language systems, may therefore provide a much-needed quantitative basis for the further study of language learning, utilization, and production.

CONCLUSION

The quantitative analysis of the kinematic features of the motion capture data from Brown et al. (2021) revealed several notable differences between the production of manual actions and descriptive gestures between native ASL signers and English speakers. Signers' gestures had a very slightly higher peak velocity overall than the English speakers, and both groups were slightly faster in the gesture than in the action condition. Both language groups were significantly more smooth in the action task and the ASL signers were notably more smooth overall. There was also a significant interaction between language and condition, in that the smoothness of the ASL signers and English speakers is virtually indistinguishable within the action task, but in the gesture condition the signers demonstrate notably higher smoothness. Both groups demonstrated moderately more rhythmicity in the action task, and the ASL signers were significantly more rhythmic in their gestures than the English speakers. There was also an interaction between these factors; the ASL signers were relatively consistent across task conditions, while the English speakers demonstrated much greater temporal variability/less rhythmicity during the gesture task compared to the instrumental action task. The English speakers were also very slightly more accurate in their imitation of the object's trajectory than the ASL signers, but further statistical analysis could not demonstrate significance.

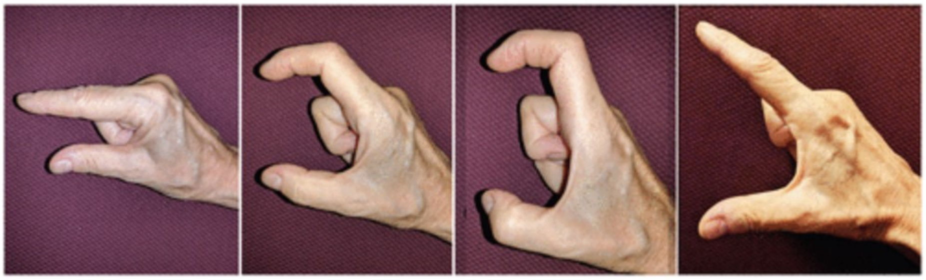
Taken together, these results indicate that the gestures generated by signers seem more akin to language than those produced by the English speakers, and may therefore be more informed by linguistic processes than by instrumental action systems. It remains to be seen to what extent these differences correspond to parallel differences in neural activation, but prior research comparing signers and speakers suggests this may prove a fruitful avenue for further research.

In addition, this research demonstrates the practical application of motion capture data and of the quantitative analysis methods of motion as put forward by Wim Pouw, J. P. Trujillo, and others. Not only did this methodology generate an informative overview of the kinematic structure of specific manual outputs, but the analysis was sufficiently detailed so as to allow comparison between groups. Indeed, while these two groups appeared alike in the results published in Brown et al. (2021) - both were less susceptible to the Müller-Lyer illusion (see Figure 1) when gesturing while describing the object's trajectory than in directly estimating its length - focusing on just one task condition revealed crucial distinctions between the way in which they produce and employ gesture. Many opportunities for further investigation lie in the analysis of different kinematic features other than those discussed here (smoothness, rhythmicity, velocity, accuracy), which may further clarify the way in which ASL signs can be contrasted with co-sign and co-speech gestures and with action motions. The results could also be strengthened by a larger sample size, especially of the ASL signers - as well as by testing various demographic factors such as handedness, age of hearing loss, age at ASL acquisition, bilingual status, etc., which is beyond the scope of this project. The extent to which low-level features of the movement and sensation systems differ between experienced signers and speakers will also clarify the extent to which these kinematic differences actually indicate cognitive mechanisms. This project also revealed certain differences between speakers and signers that did not differ by task condition, which could reveal fundamental contrasts in the production of all types of manual gestures as informed by native linguistic modality.

Overall, this re-analysis of an existing kinematic data set yielded compelling differences between the manual gestures of ASL signers and English speakers, which suggest that descriptive tasks may be more informed by language in signers and by instrumental action in speakers. These findings demonstrate that even within the realms of goal-directed manual motion and co-language gestures, there are distinguishable differences between these two groups that may indicate differential cognitive processes. The particular cognitive and motor demands of communicating in sign could serve to remodel these exact processes in a way that manifests in greater smoothness, rhythmicity, speed, and accuracy of gesture overall, with a particularly strong effect observed in tasks that require descriptive gestures rather than instrumental action.

APPENDIX

1. ASL handshapes for describing length:



Source: Brown et al., 2021

2. R Code=for computing velocity:

```
#FUNCTION for computing 2D and 3D speed (and apply butterworth filter)
velocity.it <- function(x, y, z, dimension, t)
{
  x <- as.numeric(x)
  y <- as.numeric(y)
  t <- as.numeric(t)
  z <- as.numeric(z)
  if(dimension == "3D") #important section for 3d analysis (check for 3d ("if"))
  {
    xyz <- cbind.data.frame(x,y,z,t)
    colnames(xyz) <- cbind("x", "y", "z", "t")
    #euclidean distance calc 3D: ((x1-xn) (y1-yn) (z1-zn))^2
    xyzdiff <- as.data.frame(apply( xyz , 2 , diff ))
    xyzdiff$v <- sqrt(rowSums(xyzdiff[,1:3]^2))
    xyzdiff$v <- xyzdiff$v/xyzdiff$t*1000
    velocity <- c(0, xyzdiff$v)
  }
  if(dimension == "2D") #important section for 3d analysis (check for 2d ("if"))
  {
    xy <- cbind.data.frame(x,y,t)
    colnames(xy) <- cbind("x", "y", "t")
    #euclidean distance calc 2D: ((x1-xn) (y1-yn)^2
    xydiff <- as.data.frame(apply( xy , 2 , diff ))
    xydiff$v <- sqrt(rowSums(xydiff[,1:2]^2))
    xydiff$v <- xydiff$v/xydiff$t*1000
    velocity <- c(0, xydiff$v)
  }
  velocity <<-  kz(velocity, 2, 3) #apply kolmogorov-zolai guassian-type filter
}
```

3. R Code for computing smoothness:

```
#dimensionless smoothness measure
library(kza)
smooth.get <- function(velocity) #Hogan & Sternad formula
{
  if(!all(velocity ==0))
  {
    velocity <- as.vector(scale(velocity))
    acceleration <- kz(diff(velocity), 5, 5)
    jerk         <- kz(diff(acceleration), 5, 5)
    integrated_squared_jerk <- sum(jerk^2)
    max_squaredvelocity <- max(velocity^2)
    D3 <- (length(velocity))^3 ##scale per second 33Hz
    jerk_dimensionless <-  integrated_squared_jerk*(D3/max_squaredvelocity)
    smoothness <- jerk_dimensionless
  }
  if(all(velocity ==0)) #if all zero, this
  {
    smoothness <- NA
  }p
  return(smoothness)
}
```

4. R Code for computing rhythmicity:

```
#rhythm
peakg       <- findpeaks(velocityg, minpeakheight = 15)
tempog     <- mean(abs(diff(time_g[peakg[,2]]))/1000, na.rm = TRUE) #compute interval in time between peaks
rhythmg     <- sd(abs(diff(time_g[peakg[,2]]))/1000, na.rm = TRUE) #compute rhythmicity
peaka       <- findpeaks(velocitya, minpeakheight = 15)
tempoa     <- mean(abs(diff(time_a[peakg[,2]]))/1000, na.rm = TRUE) #compute interval in time between peaks
rhythma     <- sd(abs(diff(time_a[peakg[,2]]))/1000, na.rm = TRUE) #compute rhythmicity
```

5. R Code for computing dynamic time warping/distance between trajectories:

```
#DTW analyses_allignment gesture and action
dtwR <- dtw(ges, mov)
allignment_g_a <- dtwR$normalizedDistance
```

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