Seeing Who Is Signing and With Which Hand

Carl Börstell
Department of Linguistic, Literary and Aesthetic Studies, University of Bergen
Bergen, Norway
carl.borstell@uib.no

Abstract

This study is a computer vision analysis of 4.5 hours of video data from 40 signers in the Swedish Sign Language Corpus, aiming to evaluate the reliability of classifying 1) who the main signer is at any given time during dyadic conversation, and 2) the dominant hand (i.e., handedness) of each signer. First, the distance moved by the hands of each signer is used to compare the manual activity between a) the two signers to determine whose hands are more active, and b) the hands of each signer to determine which hand is more likely to be dominant. Second, the height of the hands is used to compare their prominence in signing space between a) the two signers to determine whose hands are more prominent, and b) the hands of each signer to determine which hand is more likely to be dominant. The results show that while both distance and height approaches can reliably classify – individually or combined – the main signer in any segment of a conversation, the height approach is better at determining the overall handedness (right- or left-dominant) of signers. For the handedness classification, the optimal method turns out to be a two-step approach, first classifying the main signer per segment, then using only signer-relevant segments to classify handedness.

Keywords: sign language, handedness, corpus, conversation, computer vision

1. Introduction

Signed language is produced through simultaneous movements of manual and non-manual articulators, of which the two hands are generally seen as the main articulators of the lexical items (i.e., the signs). While the two hands are symmetrical articulators, most signers display some handedness-preference, generally signing with either right or left hand as their more dominant hand (Papadatou-Pastou and Sáfár, 2016). The dominant hand is the one used for most one-handed signs, and is the more active hand in unbalanced two-handed signs, for which the other (non-dominant) hand acts as a place of articulation (Sandler, 1993; van der Hulst, 1996; Crasborn, 2011). However, in natural discourse, the dominant hand can switch, a concept known as *dominance reversal*. Dominance reversal can happen for multiple reasons, ranging from articulatory ease to discourse and information structure (Crasborn and Sáfár, 2016). For instance, a hand may retain a fragment of a previous sign or establish a referential anchor (known as *buoys*) to structure discourse (Liddell, 2003; Liddell et al., 2007; Nilsson, 2007; Kimmelman et al., 2016), which can also lead to dominance reversal (Crasborn and Sáfár, 2016). While a signer's hand dominance is often assumed to be the same as their general handedness (right- or left-handed), this is not always the case, and some signers may be referred to as *mixed-handed*, exhibiting a high degree of ambidexterity in their signing (see Papadatou-Pastou and Sáfár, 2016).

Just as one of a signer's two hands may be more dominant at a given point during signing, one signer may be more dominant during some stretch of signed conversation. Turn-taking practices have been studied in several sign languages to date, and concern the switching of the "main signer" in a conversation – i.e., a transfer of who holds the floor – which may involve more or less overlap between participants' signing (Baker, 1977; Van Herreweghe, 2002; Groeber and Pochon-Berger, 2014; de Vos et al., 2015; Manrique and Enfield, 2015; Ferrara, 2022). Conversational feedback (backchanneling) may lead to overlap in signing, whether by manual or non-manual means, without necessarily involving a switch of main signer (Mesch, 2016; Bauer et al., 2024; Börstell, 2024; Lutzenberger et al., 2024). Using a computer vision analysis of Swedish Sign Language (STS) conversational video data, Börstell (2024) demonstrated that manual backchanneling – more specifically *continuers*, signals that encourage the conversational partner to proceed – are articulated lower in signing space and with less movement relative to other signs. Börstell (2024) argued that these properties may decrease visual prominence, signaling that the signing is not an attempt to claim the floor.

Börstell's (2024) study on continuer backchannels involved computer vision to analyze some phonetic properties of backchannels. The use of computer vision for processing sign language data directly from videos has proven useful for analyzing phonetic and spatial properties of both manual (Östling et al., 2018; Börstell and Lepic, 2020) and non-manual articulation (Kimmelman et al., 2020; Bauer et al., 2024; Kuznetsova and Kimmelman, 2024; Sargano et al., 2024). However, while signer handedness has been estimated on the basis of distance or velocity of hand movements as a pre-

Proceedings of the 12th Workshop on the Representation and Processing of Sign Languages, pages 42–50
16 May 2026.

processing step for further analysis (e.g., Östling et al., 2018; Fragkiadakis et al., 2020; Fragkiadakis and van der Putten, 2021; Akamine et al., 2026), it is rarely evaluated in its own right. An exception to this is Börstell (2023), who used computer vision estimates of manual movement distances to predict signers' dominant hand from individual dictionary sign videos, compared to their known handedness in the lexical database metadata as ground truth. Börstell (2023) reports around 80% accuracy overall, although there were large discrepancies between one-handed signs, which the method predicted with high accuracy, and balanced two-handed signs, in which both hands move in a similar/symmetrical fashion, hence were much more difficult to classify in terms of handedness.

In this study, I evaluate whether classification of main signer and hand dominance can be done accurately from conversational video data using computer vision. The research questions are:

- Using a computer vision analysis of Swedish Sign Language (STS) dyadic, conversational corpus video data, is it possible to determine
    1. ...who the main signer is at a given time?
    2. ...which hand is a signer's dominant one?

2. Methodology

2.1. Data

For the goals of this study, 40 dyadic, conversational texts were sampled from the Swedish Sign Language (STS) Corpus (see Öqvist et al., 2020). The dataset used here consists of 80 MPEG video files (Mesch et al., 2012), each showing the (slightly angled) frontal view of each signer in the dyad, as well as the accompanying EAF annotation files (Mesch et al., 2014), all retrieved from *The Language Archive*.[1] The texts range from about 30 seconds to 8 minutes in duration (about 3.5 minutes on average), comprising over 2 hours and 15 minutes of conversation, or about 10% of the STS Corpus. The texts were selected with two main goals in mind: first, they should all involve both signers engaging in signing; second, they should cover as many signers as possible and involve different text types. From these criteria, two specific tasks were selected: a) the *presentation* texts in which each signer provides a short self-introduction to their addressee; b) the *elicited narratives* in which the signers retell short comic strips. Thus, each text should have at least one switch of main signer, and the texts include both free and narrative-type conversation. There was comparative data available for 40 out of the 42 signers in the STS Corpus (across 20 pairs of signers) for these texts, and these were all selected to maximize signer diversity. Table 1 shows the sampled signers and texts, using the labels found in the corpus itself, with each row representing a single pair of signers and their associated texts.

[1] https://archive.mpi.nl/tla/

Signer		Text type	
S1	S2	Presentation	Elicited narrative
S003	S004	SSLC01_020	SSLC02_028
S005	S006	SSLC01_040	SSLC02_049
S007	S008	SSLC01_060	SSLC02_070
S009	S010	SSLC01_080	SSLC02_089
S011	S012	SSLC01_100	SSLC02_117
S013	S014	SSLC01_120	SSLC02_132
S015	S016	SSLC01_140	SSLC02_149
S017	S018	SSLC01_160	SSLC02_169
S019	S020	SSLC01_180	SSLC02_190
S021	S022	SSLC01_200	SSLC02_214
S023	S024	SSLC01_220	SSLC02_229
S025	S026	SSLC01_240	SSLC02_250
S027	S028	SSLC01_260	SSLC02_275
S029	S030	SSLC01_280	SSLC02_295
S031	S032	SSLC01_300	SSLC02_310
S033	S034	SSLC01_320	SSLC02_333
S035	S036	SSLC01_340	SSLC02_352
S037	S038	SSLC01_360	SSLC02_372
S039	S040	SSLC01_380	SSLC02_394
S041	S042	SSLC01_400	SSLC02_411

Table 1: The sampled texts by signer pair and text type with the STS Corpus signer and file labels.

2.2. Analysis

In total, 80 video files (40 signers $\times$ two texts), about 4.5 hours in total duration, were analyzed using the MediaPipe pose estimation model (Lugaresi et al., 2019). This model outputs coordinates of 33 landmarks of the body, shown in Figure 1. The coordinates used for this study are the so-called *world landmarks*, which reconstruct the landmark coordinates in three-dimensional space, using the middle of the person (around the hips) as the origin to which all other landmarks are positioned (see Figure 1). For the purposes of this study, the movement of the hands in space was the relevant measure, and thus the landmarks for the wrist of each hand (Figure 1) are used for measuring manual activity. The reason for using the wrist rather than finger landmarks is that the wrists tend to be more visible and thereby have higher reliability for pose estimation of the hands compared to the fingers.[2]

[2] In the current dataset, the visibility of the wrists ($M = .95; SD = .11$) is indeed higher than that of the index fingers ($M = .91; SD = .13$).

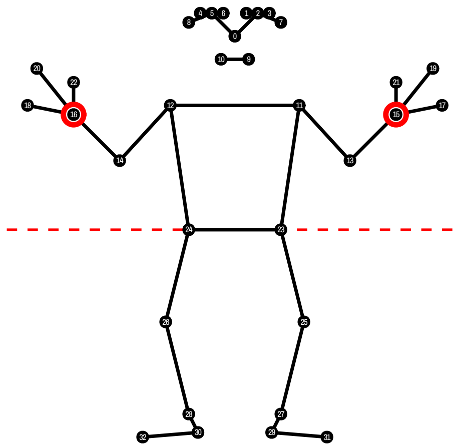

Figure 1: The 33 landmarks in the MediaPipe pose estimation model. The red circles mark the wrist landmarks, used for calculating both distance and height. The dashed red line indicates the vertical origin of the pose estimation model coordinates.

The two objectives of this study were to evaluate whether a computer vision analysis of sign language conversations can identify 1) who the main signer is at a given time in a conversation (i.e., the current *main signer*), and 2) which hand each signer uses as their overall dominant one (i.e., the *handedness* of each signer). The two approaches to attempt such classifications use *distance moved* by the hands and their *height* in signing space.

For the first approach, the distance moved by the hands was calculated as the Euclidean distance between each wrist position across sequential frames.[3] Thus, when the coordinates of one wrist in a frame are measured as (p_1, p_2, p_3) and in following frame as (q_1, q_2, q_3), the distance moved between those two frames can be calculated as:

$$d(p,q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + (p_3 - q_3)^2}$$

Distance was calculated across frames per text, signer and wrist and then summarized across the two hands per frame and signer, since the signer's handedness is unknown for this task and we do not know which movements are actual signing (rather than grooming/adjusting), nor which signs are one- vs. two-handed (cf. Börstell, 2023).

For the second approach, the height of the hands was calculated as the maximum and mean height, across the two wrists of each signer.[4]

[3] Approximately .01% of MediaPipe pose estimation frames had a (mostly single-frame) gap compared to video frames. Due to the low frame-drop rate, gaps were disregarded and frames were treated as consecutive.

[4] The *y* coordinates were inverted in the height calculations, as MediaPipe outputs *y* coordinates that are vertically inverted as per standard image processing.

In both approaches, texts were cut into 5-second segments, resulting in many individual data points per text. The 5-second duration was chosen somewhat arbitrarily, but estimated as a unit that should span multiple signs but preferably not multiple turns (see Börstell et al., 2024; Börstell, 2024). In the classification of main signer, distance is taken as the *total* across frames per segment and signer, while height is taken as the *maximum* and *mean* per segment and signer. Each segment is then assigned a main signer for each method: distance, maximum height and mean height, respectively. Each method allowed for ties (i.e., no *main* signer), although no such cases were ultimately observed. In the classification of handedness, distance and height are kept separate for each hand, and the two hands are compared within each signer and segment. For each segment, signers are assigned a dominant hand for each method – distance, maximum height and mean height – allowing for ties, although no such cases were observed. Signers are ultimately classified based on the majority of left-/right-predicted segments, defaulting to right-handed in cases of equal prediction counts.

For the classification of main signer, the ground truth was based on the number of sign glosses produced by each signer for each text segment, labeling the signer with more signs as the main signer of that segment. Segments in which both signers had the same number of sign glosses (<1% of all segments) were removed from further analysis. For the classification of signer handedness, the ground truth was given as the handedness label found in the metadata files of the STS Corpus, which use the labels *right-*, *left-* and *mixed-handed*. However, three signers' handedness were corrected before applying the labels as ground truth. First, signers S003 and S004 have erroneously had their handedness swapped, which is obvious from observing the video data as well as seeing that the annotation file gloss tiers have the reverse hand dominance compared to the metadata. That is, the annotation tiers are correctly assigned, but the metadata files have incorrect handedness labels for this pair of signers. Second, signer S037 is the only one labeled as *mixed-handed*, but has been assigned a right-handed status in the annotation files, in which the dominant hand tier is the right hand. According to Mesch and Wallin (2015, 109), dominant hand tiers in the STS Corpus files were determined based on the perceived dominant hand by annotators, which in undecided cases defaulted to the right hand.

MediaPipe was run in Python v3.10.5. Data analysis was done with R v4.5.3 (R Core Team, 2026) and `tidyverse` v2.0.0 (Wickham et al., 2019), `tidysigns` v.0.2.2 (Börstell, 2025), `scales` v1.4.0 (Wickham et al., 2025), `gt` v1.3.0 (Iannone et al., 2026) and `here` v1.0.2 (Müller, 2025).

3. Results

3.1. Classifying Main Signer

The first objective of this study was to classify the main signer for each 5-second segment, using the annotated sign glosses as the ground truth for evaluation. Table 2 shows the accuracy of the approaches: distance vs. (max/mean) height.

	Classification	
Method	correct	incorrect
distance	1,573 (95.3%)	78 (4.7%)
height (max)	1,567 (94.9%)	84 (5.1%)
height (mean)	1,535 (93.0%)	116 (7.0%)
combined	1,600 (96.9%)	51 (3.1%)

Table 2: Accuracy of main signer classification for each method by number of segments correctly vs. incorrectly labeled (percentages in brackets).

Based on these results, both approaches obtain a high degree of accuracy, with the distance method performing the best (95.3% correct classifications), slightly ahead of height, for which maximum height (94.9%) performs better than mean height (93%). The influence of text type appears insignificant, with the accuracy for the distance approach scoring equally well for both types, and the height approach scoring similarly across text types (max: presentation 95.1% and narrative 94.7%; mean: presentation 94.1% and narrative 91.6%).

Looking at some individual texts to gauge potential sources of error, it is clear that many incorrect classifications occur at turn-taking boundaries, such as in the example from text SSLC01_020, visualized in Figure 2. Determining who the main signer is around natural turn-taking points in a conversation will obviously be difficult, as there may be overlapping signing and slightly different classifications by different methods (e.g., a signer ending their turn may still be signing more signs, but with lowered manual articulators). However, other issues also exist, such as the text SSLC01_100, in which a signer is classified as main by the mean height method while having almost no manual activity, but having both arms crossed on the chest, giving a high average height despite not actively articulating with the hands. Another case can be seen in the text SSLC01_180, in which a signer is being incorrectly labeled as main by the distance method, due to several instances of self-grooming (e.g., face scratching) or occasional manual backchannels, thus creating sudden bursts of greater distances moved by the hands from a rest position on the lap.

If the methods fail in different contexts and for different reasons, a combined approach could be more accurate. Indeed, combining the three methods together and classifying main signer based on the majority label does increase the accuracy to 96.9%, higher than any individual method (see the bottom row of Table 2).

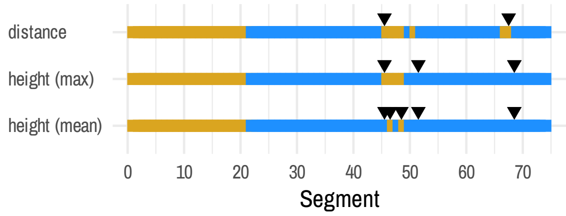

Figure 2: Classification of main signer by segment in one text (SSLC01_020). Segment colors show main signer predictions by method. Black triangles indicate segments with incorrect classification compared to gloss dominance as ground truth.

Since the 5-second segment duration was somewhat arbitrary, different segment lengths were compared in order to explore the effects of this parameter setting on the classification.[5] Figure 3 shows the main signer prediction accuracy across methods and the five different segment durations evaluated: 1, 2.5, 5, 7.5 and 10 seconds. As seen in Figure 3, the distance approach appears to increase in accuracy when using slightly longer segment durations, whereas the height approach may rather benefit from shorter durations. However, it turns out that the combined majority-rule approach across methods actually performs optimally with the initial 5-second segment setting, perhaps as the best trade-off across methods. Since it appears that the initial 5-second segment length performs well, it will be used throughout the analyses that follow.

3.2. Classifying Signer Handedness

The second objective of this study was to classify each signer by their overall handedness, whether they are mainly right- or left-dominant signers. Here, the ground truth is the classification in the STS Corpus metadata files, labeling each signer as either *right-handed* (n = 35), *left-handed* (n = 4) or *mixed-handed* (n = 1). Upon visual inspection of the videos and annotation files, it is clear that two signers in the same pair have had their classifications swapped (S003 and S004) and that the mixed-handed signer (S037) has been labeled right-handed in the STS Corpus annotation structure (see Section 2.2). Thus, the handedness labels used as ground truth include the corrected classification of S003 and S004, and classifying S037 as right-handed.

Since signs are annotated on separate tiers for each hand in the STS Corpus, we can use the

[5] I thank an anonymous reviewer for this suggestion.

Figure 3: Accuracy of main signer classification by method and segment length. Shapes and colors denote the method, with the combined approach using majority rule across the three methods.

distribution of sign gloss annotations across tiers as a frequency measure of handedness, labeling whichever hand has more sign gloss annotations as the dominant one for each signer. Using this measure across all sampled texts, the classification is 100% accurate, correctly predicting all 40 signers: 36 right-handed and 4 left-handed.

As for the computer vision approaches, signer handedness was classified based on the majority of 5-second segments in which one hand was deemed the more active in terms of a) distance moved, b) maximum height, and c) mean height. For each method, if ≥50% of segments were labeled *right*, the signer was classified as right-handed, otherwise left-handed. All three methods correctly classify the four left-handed signers as such, but incorrectly label a number of right-handed signers as left-handed: distance (15/36 incorrect); maximum height (8/36 incorrect); mean height (6/36 incorrect) – see classifications in Figure 4 and F-scores in Table 3. Thus, the height approach is overall better than the distance approach, and using mean height performs slightly better than using maximum height. Unlike the main signer classification, a combined approach classifying by majority rule across the three methods does not outperform the best individual approach (see the bottom row in Table 3).

Figure 5 shows the proportional right hand preference for each signer as calculated across segments for each method. As Figure 5 illustrates, most signers are correctly classified, but seven right-handed signers are incorrectly classified as left-handed when basing the classification on majority rule. It is noteworthy that signer S037, the only

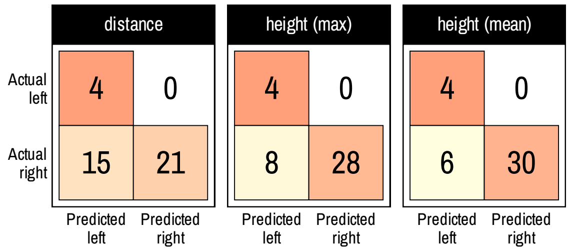

Figure 4: Predicted vs. actual handedness of signers (n = 40) by method.

	F-score	
Method	balanced	weighted
distance	0.54	0.70
height (max)	0.69	0.84
height (mean)	0.74	0.88
combined	0.71	0.86

Table 3: Performance of handedness classification by method as balanced and weighted F-scores.

mixed-handed signer according to the metadata, is classified as a left-handed signer, despite being annotated as right-handed in the STS Corpus.

Looking at some of the misclassified signers' sign gloss annotation frequencies, it becomes obvious that some (e.g., S021) are among the signers with the fewest annotations in the dataset sampled for this study. Since these computer vision methods are using the entire video files as data, it is likely that much of the recording will be of the signers as addressees, with their hands mostly at rest, apart from the occasional grooming or backchanneling (Mesch, 2016; Börstell, 2024). Thus, a two-step approach was attempted, in which the best-performing method for determining main signer (i.e., distance moved; see Section 3.1) is used to subset the analyzed segments to only those in which a signer is classified as the main signer – that is, segments in which they are likely actively signing – and these segments are subsequently used to classify the signers' handedness using the best-performing method for determining handedness (i.e., mean height). The classification in this two-step approach turns out to be 100% accurate, with all 40 signers being correctly classified according to their known handedness. The classification for each signer in this two-step approach is shown in Figure 6, for which we can also see that signer S037 – the one originally listed as *mixed-handed* in the metadata – is the one closest to the midpoint between right and left hand preference, whereas all other misclassified right-handed signers (see Figure 5) now show a clear right hand preference.

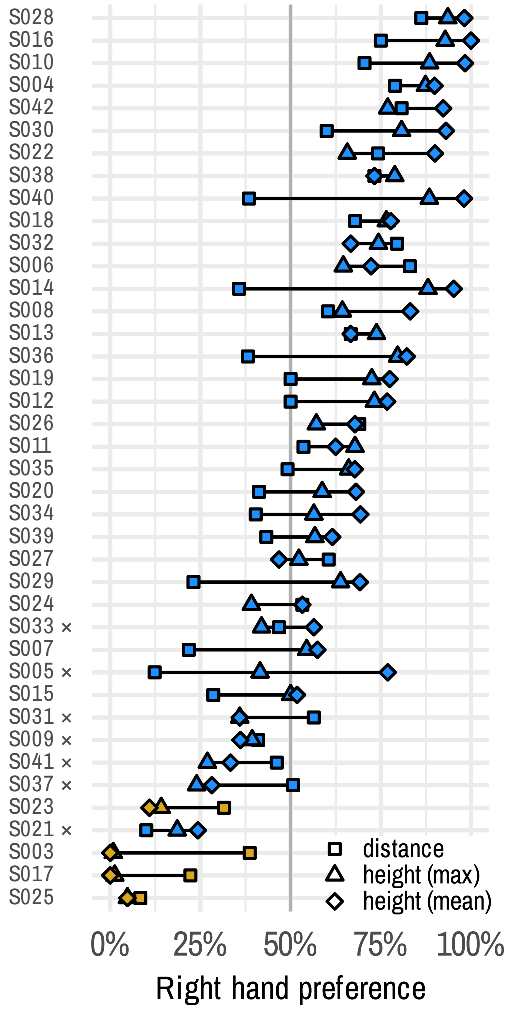

Figure 5: Handedness preference across signers according to the three methods: distance, height (max) and height (mean). Colors show true handedness (blue: right-handed; yellow: left-handed); shapes represent the method. Xs (×) mark signers classified incorrectly by majority rule.

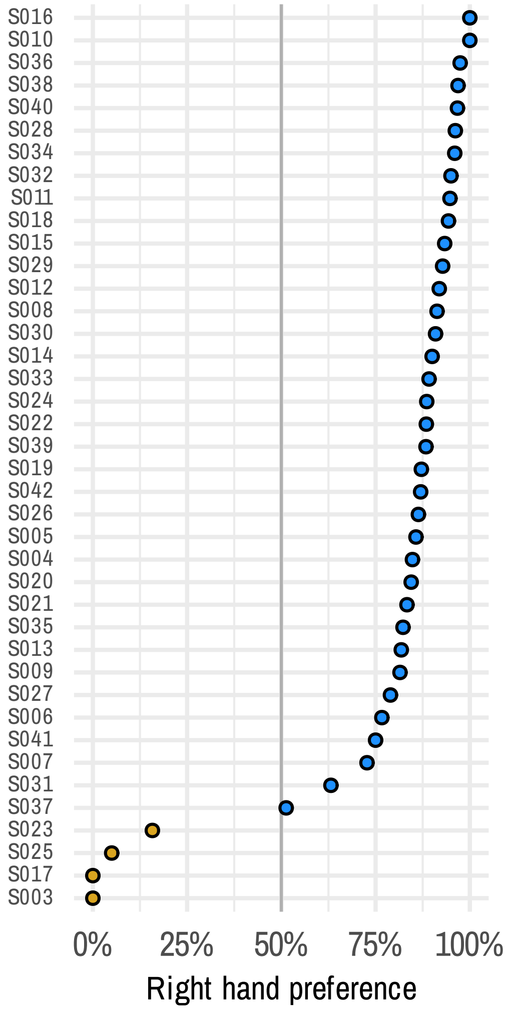

Figure 6: Handedness preference across signers according to the combined two-step approach in which active signing is determined by distance, and handedness is determined by mean height for active signing segments only. Colors show true handedness (blue: right-handed; yellow: left-handed).

4. Conclusions

This study set out to evaluate the applicability of computer vision in determining 1) the main signer at any given point in dyadic, conversational signing, and 2) the dominant hand (or, preferential handedness) of each signer in the dataset. While the sampled dataset is small, it constitutes quite a substantial portion of the entire STS Corpus (≈ 10%) and is different among computer vision analyses by looking at whole conversations rather than extracted clips or individual sign videos – e.g., Börstell (2023), who also addressed hand dominance, but in individual dictionary videos. Despite limited data, both tasks turned out to be quite reliably solved, whether through individual or combined approaches.

For the main signer classification, both distance moved by the hands and their height in space as measures could reliably identify the correct signer with high accuracy (≈ 95%). These approaches could thus be used as a first-pass analysis of not-yet-annotated sign language conversations, to get a sense of conversational turn-taking patterns. They could also be applied to already annotated sign language datasets and corpora, as a way to spot interactions or mismatches between manual annotations and phonetic/visual prominence, and analyze the connections between kinematics and grammatical and conversational structure.

For the signer handedness classification, it turned out that the distance and height approaches both struggled to accurately identify all signers according to their known handedness. Since the videos contain a lot of segments of manual inactivity, there is a lot of noise in the data, which may skew the metrics simply based on irrelevant features, such as the choice of manual rest position (e.g., on the lap vs. arms crossed). However, with the high accuracy of the main signer classification already established, a two-step approach could be devised, in which only active signing segments are identified by looking at the distance moved by the hands, followed by an analysis of mean hand height for these segments only. For this dataset, the accuracy of this two-step approach was 100%, correctly classifying all 40 signers according to their known hand dominance. Employing a handedness classification analysis could be used during the initial stages of building a dataset or corpus, automatically classifying handedness for signer metadata purposes without first having to commit to manual annotation work. Furthermore, even if sign gloss annotations have already been added to the data, or metadata about signers' self-reported handedness has been collected, an automated classification of hand dominance could contribute to a more gradient view of preferential handedness among signers, categorizing signers as more or less right-/left-dominant. Similarly, a hand dominance analysis could assist in locating relevant segments in conversations involving dominance reversal or interesting simultaneous use of the two hands.

5. Data Availability

Data and code for this study can be found at: https://osf.io/3da27

6. Acknowledgments

Funded by the European Union (ERC, NONMANUAL, project number 101039378). Views and opinions expressed are however those of the author only and do not necessarily reflect those of the European Union or the European Research Council. Neither the European Union nor the granting authority can be held responsible for them.

7. Bibliographical References

Sho Akamine, Mark Dingemanse, and Aslı Özyürek. 2026. Validating dynamic time warping as a measure of gesture form similarity.

Charlotte Baker. 1977. Regulators and turn-taking in American Sign Language discourse. In Lynn A. Friedman, editor, *On the other hand: New perspectives on American Sign Language*, pages 215–236. Academic Press, New York, NY.

Anastasia Bauer, Anna Kuder, Marc Schulder, and Job Schepens. 2024. Phonetic differences between affirmative and feedback head nods in German Sign Language (DGS): A pose estimation study. *PLOS ONE*, 19(5):e0304040.

Carl Börstell. 2023. Extracting sign language articulation from videos with MediaPipe. In *Proceedings of the 24th Nordic Conference on Computational Linguistics (NoDaLiDa)*, NEALT Proceedings Series, No. 52, pages 169–178, Tórshavn, Faroe Islands. University of Tartu Library.

Carl Börstell. 2024. Finding continuers in Swedish Sign Language. *Linguistics Vanguard*, 10(1):537–548.

Carl Börstell. 2025. *tidysigns: Sign language corpus data in a tidy format*. R package version 0.2.2.

Carl Börstell and Ryan Lepic. 2020. Spatial metaphors in antonym pairs across sign languages. *Sign Language & Linguistics*, 23(1–2):112–141.

Carl Börstell, Adam Schembri, and Onno Crasborn. 2024. Sign duration and signing rate in British Sign Language, Dutch Sign Language and Swedish Sign Language. *Glossa Psycholinguistics*, 3(1).

Onno Crasborn. 2011. The other hand in sign language phonology. In Marc van Oostendorp, Colin J. Ewen, Elizabeth Hume, and Keren Rice, editors, *The Blackwell companion to phonology*, pages 223–240. Wiley, Malden, MA & Oxford.

Onno Crasborn and Anna Sáfár. 2016. An annotation scheme to investigate the form and function of hand dominance in the Corpus NGT. In Roland Pfau, Markus Steinbach, and Annika Herrmann, editors, *A matter of complexity*, pages 231–251. De Gruyter Mouton & Ishara Press, Boston, MA/Berlin & Preston.

Connie de Vos, Francisco Torreira, and Stephen C. Levinson. 2015. Turn-timing in signed conversations: coordinating stroke-to-stroke turn boundaries. *Frontiers in Psychology*, 6.

Lindsay Ferrara. 2022. Indexing turn-beginnings in Norwegian Sign Language conversation. *Gesture*, 21(1):1–27.

Manolis Fragkiadakis, Victoria Nyst, and Peter van der Putten. 2020. Signing as input for a dictionary query: Matching signs based on joint positions of the dominant hand. In *Proceedings of the LREC2020 9th Workshop on the Representation and Processing of Sign Languages: Sign Language Resources in the Service of the Language Community, Technological Challenges and Application Perspectives*, pages 69–74, Marseille, France. European Language Resources Association (ELRA).

Manolis Fragkiadakis and Peter van der Putten. 2021. Sign and search: Sign search functionality for sign language lexica. In *Proceedings of the 1st International Workshop on Automatic Translation for Signed and Spoken Languages (AT4SSL)*, pages 23–32, Virtual. Association for Machine Translation in the Americas.

Simone Groeber and Evelyne Pochon-Berger. 2014. Turns and turn-taking in sign language interaction: A study of turn-final holds. *Journal of Pragmatics*, 65:121–136.

Richard Iannone, Joe Cheng, Barret Schloerke, Shannon Haughton, Ellis Hughes, Alexandra Lauer, Romain François, JooYoung Seo, Ken Brevoort, and Olivier Roy. 2026. *gt: Easily create presentation-ready display tables*. R package version 1.3.0.

Vadim Kimmelman, Alfarabi Imashev, Medet Mukushev, and Anara Sandygulova. 2020. Eyebrow position in grammatical and emotional expressions in Kazakh-Russian Sign Language: A quantitative study. *PLOS ONE*, 15(6):e0233731.

Vadim Kimmelman, Anna Sáfár, and Onno Crasborn. 2016. Towards a classification of weak hand holds. *Open Linguistics*, 2(1).

Anna Kuznetsova and Vadim Kimmelman. 2024. Testing MediaPipe Holistic for linguistic analysis of nonmanual markers in sign languages. ArXiv:2403.10367v2.

Scott K. Liddell. 2003. *Grammar, gesture, and meaning in American Sign Language*. Cambridge University Press, Cambridge.

Scott K. Liddell, Marit Vogt-Svendsen, and Brita Bergman. 2007. A crosslinguistic comparison of buoys. Evidence from American, Norwegian, and Swedish Sign Language. In Myriam Vermeerbergen, Lorraine Leeson, and Onno Crasborn, editors, *Simultaneity in signed languages: Form and function*, volume 281 of *Current issues in linguistic theory*, pages 187–215. John Benjamins, Amsterdam/Philadelphia, PA.

Camillo Lugaresi, Jiuqiang Tang, Hadon Nash, Chris McClanahan, Esha Uboweja, Michael Hays, Fan Zhang, Chuo-Ling Chang, Ming Yong, Juhyun Lee, Wan-Teh Chang, Wei Hua, Manfred Georg, and Matthias Grundmann. 2019. MediaPipe: A framework for perceiving and processing reality. In *Third Workshop on Computer Vision for AR/VR at IEEE Computer Vision and Pattern Recognition (CVPR) 2019*.

Hannah Lutzenberger, Lierin De Wael, Rehana Omardeen, and Mark Dingemanse. 2024. Interactional infrastructure across modalities: A comparison of repair initiators and continuers in British Sign Language and British English. *Sign Language Studies*, 24(3):548–581.

Elizabeth Manrique and N.J. Enfield. 2015. Suspending the next turn as a form of repair initiation: evidence from Argentine Sign Language. *Frontiers in Psychology*, 6:1326.

Johanna Mesch. 2016. Manual backchannel responses in signers' conversations in Swedish Sign Language. *Language & Communication*, 50:22–41.

Johanna Mesch and Lars Wallin. 2015. Gloss annotations in the Swedish Sign Language Corpus. *International Journal of Corpus Linguistics*, 20(1):103–121.

Kirill Müller. 2025. *here: A simpler way to find your files*. R package version 1.0.2.

Anna-Lena Nilsson. 2007. The non-dominant hand in a Swedish Sign Language discourse. In Myriam Vermeerbergen, Lorraine Leeson, and Onno Crasborn, editors, *Simultanteity in signed languages: Form and function*, volume 281 of *Current issues in linguistic theory*, pages 163–185. John Benjamins, Amsterdam/Philadelphia, PA.

Zrajm Öqvist, Nikolaus Riemer Kankkonen, and Johanna Mesch. 2020. STS-korpus: A sign language web corpus tool for teaching and public use. In *Proceedings of the LREC2020 9th Workshop on the Representation and Processing of Sign Languages: Sign Language Resources in the Service of the Language Community, Technological Challenges and Application Perspectives*, pages 177–180, Marseille, France. European Language Resources Association (ELRA).

Robert Östling, Carl Börstell, and Servane Courtaux. 2018. Visual iconicity across sign languages: Large-scale automated video analysis of iconic articulators and locations. *Frontiers in Psychology*, 9:725.

Marietta Papadatou-Pastou and Anna Sáfár. 2016. Handedness prevalence in the deaf: Meta-analyses. *Neuroscience & Biobehavioral Reviews*, 60:98–114.

R Core Team. 2026. *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria.

Wendy Sandler. 1993. Hand in hand: The roles of the nondominant hand in sign language phonology. *The Linguistic Review*, 10(4):337–390.

Allah Bux Sargano, Sébastien Vandenitte, Tommi Jantunen, and Vadim Kimmelman. 2024. Evaluation of head pose estimation algorithms for sign language analysis. In *2024 International Conference on IT and Industrial Technologies (ICIT)*, pages 1–6, Chiniot, Pakistan. IEEE.

Harry van der Hulst. 1996. On the other hand. *Lingua*, 98:121–143.

Mieke Van Herreweghe. 2002. Turn-taking mechanisms and active participation in meetings with Deaf and hearing participants in Flanders. In Ceil Lucas, editor, *Turn-taking, fingerspelling and contact in signed languages*, volume 8 of *Sociolinguistics in deaf communities series*, pages 73–103. Gallaudet University Press.

Hadley Wickham, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, Alex Hayes, Lionel Henry, Jim Hester, Max Kuhn, Thomas Lin Pedersen, Evan Miller, Stephan Milton Bache, Kirill Müller, Jeroen Ooms, David Robinson, Dana Paige Seidel, Vitalie Spinu, Kohske Takahashi, Davis Vaughan, Claus Wilke, Kara Woo, and Hiroaki Yutani. 2019. Welcome to the Tidyverse. *Journal of Open Source Software*, 4(43):1686.

Hadley Wickham, Thomas Lin Pedersen, and Dana Seidel. 2025. *scales: Scale functions for visualization*. R package version 1.4.0.

8. Language Resource References

Johanna Mesch, Maya Rohdell, and Lars Wallin. 2014. *Annotated files for the Swedish Sign Language Corpus. Version 2.* Sign Language Section, Department of Linguistics, Stockholm University.

Johanna Mesch, Lars Wallin, Anna-Lena Nilsson, and Brita Bergman. 2012. *Dataset. Swedish Sign Language Corpus project 2009–2011 (version 1)*. Sign Language Section, Department of Linguistics, Stockholm University.