# Quantitative Analysis of Hand Locations in both Sign Language and Non-linguistic Gesture Videos

**Niels Martínez-Guevara***, **Arturo Curiel**†
*Universidad Autonoma de Coahuila, †Independent
*Centro de Investigación en Matemáticas Aplicadas. Unidad Saltillo. Saltillo, Coahuila, 25280, México.
niels.martinez@uadec.edu.mx, me@arturocuriel.com

**Abstract**

This paper explores whether measurable quantitative linguistic relationships are readily apparent in the use of space of three different Sign Languages (SLs): British Sign Language (BSL), Dutch Sign Language (NGT) and Mexican Sign Language (LSM). To this end, three SL datasets were collected; one for each of the languages of interest. Informative video frames were extracted from the collected datasets, which in turn were automatically processed to detect hand locations. The obtained information was analyzed through statistical methods, and compared against a dataset of non-linguistic gestural communication: the latter, in an effort to observe whether space-use differs between linguistic and non-linguistic gestures. The results show that meaningful gestures—regardless of whether they are deemed linguistic or not—seem to induce a spatial hierarchy around the gesturer, disproportionately favoring certain areas during articulation. SLs in particular seem to exert pressure on those areas to become more efficient, as signers appear to concentrate hand activity over more cohesive regions than non-signers. In addition, these results point towards an indirect relationship between culturally-recognized gestures and their surrounding SLs, showing that there is still work to be done on the exploration of iconicity and its effects on gestural communication.

**Keywords:** Zipf's law, signing space, non-linguistic gestures

## 1. Introduction

Quantitative linguistics is the sub-field of linguistics that studies language through empirical mathematical methods (Best et al., 2017), most of which arise from statistics (Johnson, 2008). Previous work on quantitative linguistics has shown that spoken and written languages fulfill statistical laws that can be asserted as language universals; notably Zipf's law of abbreviation (Bentz and Ferrer-i Cancho, 2016; Linders and Louwerse, 2023) (which states that there is a negative relationship between word length and frequency) and Menzerath-Altmann's law (Eroglu, 2013; Milička, 2014) (which states that larger linguistic structures have shorter constituents and vice versa). Research in the field has also delved into the study of animal communication systems (Ferrer-i Cancho and McCowan, 2009; Heesen et al., 2019; Clink et al., 2020; Huang et al., 2020; Safryghin et al., 2022), and how their rudimentary encoding of meaning produces patterns reminiscent of both laws. However, quantitative linguistic laws have seldom been confirmed in more than a few Sign Languages (SLs) (Malaia et al., 2023); thus, even though SL research has emerged as a compelling area of study for the exploration of statistical linguistic universals, little work has been directed towards the study of quantitative relationships akin to the ones observed in spoken language.

This paper explores the existence of quantitative spatial relationships in three different SLs: British Sign Language (BSL), Dutch Sign Language (NGT) and Mexican Sign Language (LSM). To this end, four SL datasets were analyzed: three dictionaries and one continuous signing video. Relevant frames were extracted from each collection, which in turn were processed to automatically detect hand locations. Location points were then analyzed with statistical methods, in an effort to discover whether signers assign a strict hierarchy in the signing space consistent with previous observations in quantitative linguistics. The obtained measurements were compared against a dataset of non-linguistic gestural communication videos, so as to explore the differences between linguistic and non-linguistic gestures.

The results show that communicative gestures—whether they are SL or not—seem to induce a spatial hierarchy, disproportionally favoring certain space regions for articulation. SLs in particular seem to exert pressure on those areas to become more efficient, as signers appear to concentrate hand activity over more cohesive regions than non-signers.

The rest of this paper is organized as follows. Section 2 presents some of the existing work in quantitative linguistics for SLs. Section 3 presents the methodology, whereas Section 4 shows the obtained results. Finally, Sections 5 and 6 present the discussion and conclusions, respectively.



*Proceedings of the 11th Workshop on the Representation and Processing of Sign Languages*, pages 225–234

## 2. Related work

The volume of existing research in quantitative linguistics strongly implies that SLs must fulfill (at least) the same statistical patterns as spoken languages—even despite their highly iconic nature. However, few works have been directed towards their quantitative exploration.

Among these, Riedl and Sperling (1988) attempted to measure how American Sign Language (ASL) intelligibility is affected depending on changes on the visual signal. The authors filtered the videos of an ASL corpus of isolated signs into different spatiotemporal bands; afterwards, they measured how combining them or adding noise improved (or decreased) intelligibility with Deaf individuals. They found that they could divide isolated signing videos into four high intelligibility bands with enough visual information to discriminate between them; in essence, proving that the discrete nature of language is preserved in SLs regardless of modality.

More recently Stewart (2014) studied how role shifting, sign-type or information status (new vs. given) may affect the duration of ASL signs. The author found that duration (in milliseconds) can be used to distinguish between lexicalized signs and non-conventionalized forms (*i.e.* iconic), pointing towards an underlying meaning-length relationship akin to the law of abbreviation.

Similarly, Börstell et al. (2016) analyzed the relationship between sign duration and frequency in Swedish Sign Language (STS). The authors showed that high-frequency signs in their corpus had shorter durations than low-frequency signs. Also, they showed that signs that act as function words had shorter durations than content signs, once again pointing towards an underlying length-meaning relationship.

Caselli et al. (2017) presented a lexical database of 1000 ASL signs containing information including frequency (as estimated by users), duration, iconicity rating, grammatical class and the signs' phonological properties. Having these measurements enabled the authors to calculate statistical relationships between them; notably, in contrast to previous works, they also took into account sub-lexical features. Their results show that:

- shorter signs were more frequent;
- less iconic signs were more frequent; and,
- the frequencies of individual phonological properties (including location) tended to approximate a power-law distribution.

Bosworth et al. (2019) also analyzed sub-lexical characteristics of ASL, measuring spatiotemporal properties such as: hand location, hand eccentricity in the visual space, hand motion speed and total traveled distance of the dominant hand. As their predecessors, they also calculated sign duration. The authors found that signers produce *asymmetries* in the visual field (concentrating movement around certain areas). In that regard, their results show that the statistical laws underlying SLs may not only express themselves temporally, but also spatially.

Fenlon et al. (2019) analyzed the difference between linguistic and non-linguistic gestures in SL. The authors compared how pointing signs (with grammatical function) in BSL differed from the pointing gestures produced by non-signing American English speakers. To this end they annotated features such as hand-shape, number of hands, duration and body-contact of the observed pointing instances (in both corpora). Their results show that there is an evolutionary pressure consistent with Zipf's law of abbreviation that makes pointing signs both systematically shorter than pointing gestures, and more stable shape-wise upon production. The authors emphasize that this reduction is expressed along several formational parameters (not only duration) and that it may be related to the high frequency of pointing signs in BSL.

A similar observation was made by Flaherty et al. (2023), regarding the signing space. The authors compared the signing of young and old Nicaraguan Sign Language (ISN) signers using motion tracking technology. Their comparison was based on measuring the size of the 3D space that the signers actually used during production, as well as the average body-wrist distance. The results show that younger signers tended to use less space that older signers, pointing towards a reduction of the signing space consistent with an underlying linguistic optimization model.

## 3. Methodology

The experiments consisted in automatically extracting hand locations from both SL and non-SL gestural videos, so as to explore their respective spatial characteristics. To this end four publicly available SL resources were collected, as well as a non-SL communication dataset.

### 3.1. Datasets

For SL communication three dictionaries were chosen:

- BSL (Waters, 2003) with 280 signs;
- NGT (Els van der Kooij, 2003) with 250 signs; and,

- LSM (Alvarez Hidalgo et al., 2009) with 300 signs.

Dictionaries were preferred over continuous signing videos so as to remain fully comparable with the non-SL videos. However, to account for potential changes due to the grammatical use of space, a continuous signing dataset was compiled:

- LSM (continuous) (López-Obrador, 2023), extracted from a publicly available government conference.

Regarding non-SL gestural communication, a video dataset of pantomimes, emblems[1] and meaningless gestures was chosen (Lingnau, 2018), containing the following video distribution (Agostini et al., 2019):

- Emblems (103 videos);
- Pantomimes (90 videos); and,
- Meaningless (77 videos).

Notably, the gestures represented in the dataset were rated on how meaningful they were deemed by American and Italian raters; with Pantomimes showing a higher consensus on their apparent meaning than Emblems. These differences between them may be important for comparison against SL signs, as it means that some gestures may share an iconic “root” with some signs (particularly Pantomimes). Moreover, lower consensus on the meaning of Emblems might also point towards cultural differences that may affect the creation of meaningful communication symbols—which, in turn, could potentially have a measurable effect on SLs.

From this dataset, only Emblems and Pantomimes were analyzed; the ambiguous nature of the Meaningless videos made them difficult to interpret when compared against signing videos. Thus, in the end, a total of six collections were considered: three SL dictionaries, one continuous signing video and two non-SL video datasets.

### 3.2. Frame extraction

For this study only a subset of informative video frames were considered from each dataset. Mainly, in an effort to avoid over-representation of space regions across collections, which could be biased by frame rate differences or changes in signing speed. This strategy also served to reduce the computational overhead of the analysis.

Thus, all relevant video frames were automatically extracted from each of the six aforementioned collections. The extraction process followed the algorithm proposed by Martinez-Guevara et al. (2023), based on finding stable *fixed postures*: video frames with minimal change with respect to a context window, as given by the Structural Similarity Index (SSIM) (Wang et al., 2004). The authors showed that the extracted frames are relevant in the sense that they contain enough information for native signers to still understand the utterance if presented with those frames alone; *i.e.* they contain enough information to preserve the message.

Table 1 shows the quantity of fixed postures extracted from each collection. Note that fixed postures were obtained from at most 90 random signs per dataset, so as to remain consistent with the number of gestures available in the Pantomimes dataset.

| **Dataset** | No. of Fixed Postures | No. of Gestures or Signs |
|---|---|---|
| BSL | 137 | 44 |
| NGT | 136 | 44 |
| LSM | 272 | 86 |
| LSM (continuous) | 280 | ≈90 |
| Emblems | 133 | 90 |
| Pantomimes | 148 | 90 |

Table 1: Number of fixed postures (frames) extracted from each dataset.

As implied by Table 1, during the extraction process some signs had to be discarded due to issues arising from the extraction script: namely, with the oldest datasets (BSL and NGT) the algorithm had trouble distinguishing between similar frames. In part, because of image noise. The same happened with four out of the 90 LSM signs; however, it was far less common as the LSM videos were of decidedly better quality than the others (higher resolution and less noise). For the continuous LSM collection, frame extraction was artificially capped to 280 frames, assuming it would correspond to approximately 90 signs (following the values obtained from the dictionary videos).

The idea of the extraction is roughly based on the phonetic/phonological models proposed by Liddell and Johnson (1989); Johnson and Liddell (2011). Fixed postures would approximate *Holds* in the original phonological model, or *postural segments* in the phonetic framework.

### 3.3. Hand location extraction

For the analysis, the extracted fixed postures were labeled with OpenPose (Simon et al., 2017; Cao et al., 2019): a body location detection toolkit capable of detecting the 2D positions of up to 135 keypoints. Figure 1 shows the toolkit’s output on a

[1] Gestures with a culturally agreed-upon meaning.

single frame.

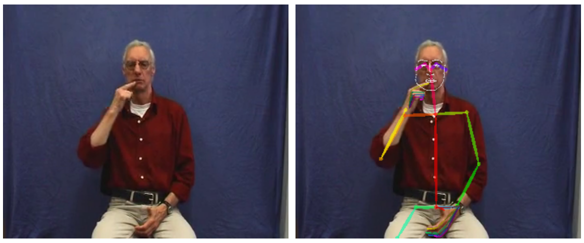


Figure 1: Keypoint posture detection with OpenPose.

For each fixed posture, only two points of interest were considered: the left and right hand locations, which were assumed to be indicative of place of articulation. In that regard, both keypoints would be able to show the entire extent of the signing space; notably, enabling the study of regions with out-sized importance for communication—those concentrating the most activity across multiple fixed postures. Figure 2 shows a scatter plot with all the points extracted from the continuous LSM dataset.

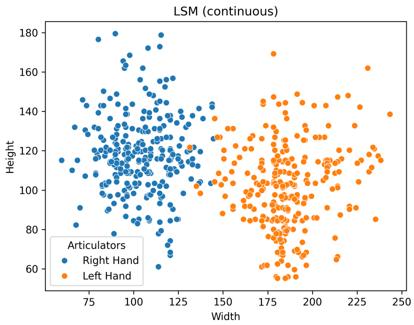



Figure 2: Points extracted from the continuous LSM dataset.

The obtained points were normalized prior to their analysis using the following formulae:

$$\hat{x}_i^k = \frac{x_i^k}{W_i} \tag{1}$$

$$\hat{y}_i^k = \frac{y_i^k}{H_i} \tag{2}$$

where:

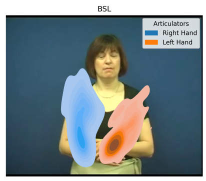
- $(x_i^k, y_i^k)$ denotes the $k$-th point in collection $i$, in pixels.
- $H_i$ is the pixel height of the videos contained in collection $i$.
- $W_i$ is the pixel width of the videos contained in collection $i$.

The resulting $(\hat{x}_i^k, \hat{y}_i^k)$ normalized points were defined in the interval $[0, 1]$, regardless of the source. This enabled the direct comparison of space regions between datasets, using both classical Euclidean metrics and clustering evaluation scores.

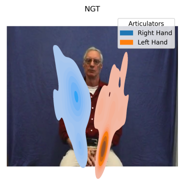
Note that the normalization procedure didn't consider intrinsic features such as body size of the signer or proximity to the camera. However this shouldn't pose problems for the analysis, save for the comparison of point dispersion across datasets through standard deviation. The results are shown in Section 4.1.

### 3.4. Location density analysis

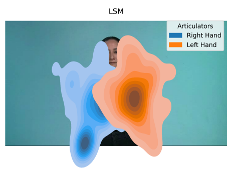
The normalized point clouds induced by the previously described procedure enabled the approximation of a location Probability Density Function (PDF) for each dataset, showing where activity tended to concentrate across relevant frames. The approximation was performed through Kernel Density Estimation (KDE) (Sheather, 2004), using the Python implementation included with the Scikit-learn library (Pedregosa et al., 2011). Scott's rule was used to determine the optimal bandwidth. A visual depiction of the obtained densities can be observed in Figure 3.



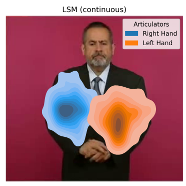

(a) BSL



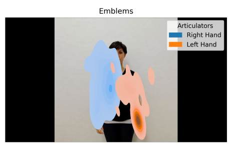

(b) NGT



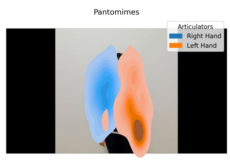

(c) LSM




(d) LSM (continuous)




(e) Emblems




(f) Pantomimes

Figure 3: Location density maps for the six analyzed datasets.

In the Figure, darker densities imply higher activity: this is, there is a stronger probability of a hand being active in said region, for any given fixed posture. Regions with no color overlap denote zero (or nearly zero) probability of including a hand.

The obtained PDFs were sampled and compared against other probability distributions in two distinct cases:

- To determine their goodness-of-fit against a power law distribution, so as to show whether locations are *Zipfian* in nature.
- To compare whether the use of space changes between SL and non-SL gestures.

The comparisons were performed by way of the Kolmogorov-Smirnov test. The results are shown in Section 4.2.

## 4. Results

In order to determine whether the use of space changes depending on the type of dataset, two kinds of measurements were taken from the extracted data:

- **Dispersion and separation measures:** to observe if there is a measurable *cohesion* regarding the spatial distribution of the hands across multiple signs (*i.e.* if the signing space tends to "shrink").
- **Hypothesis testing:** to confirm whether there is a hierarchical relationship between space regions, as given by location densities (*i.e.* if signers will disproportionately "prefer" some regions above others).

### 4.1. Dispersion and separation measures

Dispersion was measured in terms of the Euclidean distance between the normalized points described in Section 3.3. For each dataset, the pairwise distances between all the extracted points were calculated. Table 2 shows both the mean distance and the obtained standard deviation for each of the six collections.

| **Dataset** | RIGHT | | LEFT | |
|---|---|---|---|---|
| | $\mu$ | $\sigma$ | $\mu$ | $\sigma$ |
| BSL | 0.155 | 0.095 | 0.109 | 0.085 |
| NGT | 0.187 | 0.135 | 0.156 | 0.174 |
| LSM | 0.231 | 0.155 | 0.206 | 0.134 |
| LSM (cont.) | 0.118 | 0.063 | 0.131 | 0.071 |
| Emblems | 0.161 | 0.108 | 0.098 | 0.124 |
| Pantomimes | 0.175 | 0.110 | 0.196 | 0.155 |

Table 2: Mean ($\mu$) Euclidean distances and their standard deviation ($\sigma$) for all datasets.

Note that the measurements in Table 2 are separated by hand: as hands are able to act with relative independence with respect to one another, it is expected that they'd have their own preferred regions of activity. Thus, any measurable pressure or spatial hierarchy should be independently observable in at least one of the hands.

Separation between the hands' regions was measured by way of two intrinsic clustering evaluation metrics: the Silhouette Coefficient (Rousseeuw, 1987) and the SDbw validity index (Halkidi and Vazirgiannis, 2001).

The Silhouette Coefficient measures the difference between the average intra-cluster distance (*i.e.* calculated between the points in the group) and the average inter-cluster distance (*i.e.* calculated between the points outside the group). It is defined on the interval $[-1, 1]$, where -1 denotes poor cluster separation and 1 denotes perfect cluster separation.

The SDbw validity index measures the difference between the average intra-cluster distance and the average inter-cluster point density (*i.e.* the distance between the cluster centroids). The resulting value is higher than zero, with **lower** values denoting better cluster separation. Table 3 shows the calculated scores for each dataset.

| **Dataset** | SILHOUETTE | SDBW |
|---|---|---|
| BSL | 0.481 | 0.717 |
| NGT | 0.473 | 0.741 |
| LSM | 0.271 | 0.855 |
| LSM (cont.) | 0.580 | 0.569 |
| Emblems | 0.512 | 0.670 |
| Pantomimes | 0.285 | 1.352 |

Table 3: Silhouette coefficient and SDbw validity index for all point clouds.

Together, these results show how cohesive the use of space is in the tested datasets. However, they don't show whether there might be a spatial hierarchy between specific regions, as indicated by hand activity. For the latter, measurements over location probability densities (rather than individual points) had to be considered, as presented in the next section.

### 4.2. Hypothesis testing

For these experiments, the estimated PDFs described in Section 3.4 were sampled and compared against a power law distribution. The comparison was performed by way of a two-sided Kolmogorov-Smirnov test, using the Scipy library (Virtanen et al., 2020). The results are shown in Table 4.

As with the clustering experiments, hands were measured separately. Note that with a $p = 0.05$ significance level, the null-hypothesis (samples come from the same distribution) **cannot** be rejected for any case.

| KS Test | | | | |
|---|---|---|---|---|
| **Dataset** | Right Hand | | Left Hand | |
| | $D$ | $p$ | $D$ | $p$ |
| BSL | 0.106 | 0.19 | 0.062 | 0.81 |
| NGT | 0.113 | 0.14 | 0.058 | 0.86 |
| LSM | 0.064 | 0.78 | 0.095 | 0.30 |
| LSM (cont.) | 0.067 | 0.74 | 0.075 | 0.59 |
| Emblems | 0.111 | 0.15 | 0.054 | 0.91 |
| Pantomimes | 0.106 | 0.19 | 0.087 | 0.41 |

Table 4: Kolmogorov-Smirnov test results comparing location densities against a power law distribution.

To complement these results, Figure 4 shows six plots describing how a power law distribution fits the location density data. Only the values for the dominant hand are displayed.

In Figure 4, note that the following $\alpha$ parameters were estimated for the depicted power laws:

- BSL $\alpha$ = 2.81
- NGT $\alpha$ = 2.44
- LSM $\alpha$ = 2.81
- LSM (continuous) $\alpha$ = 2.53
- Emblems $\alpha$ = 2.02
- Pantomimes $\alpha$ = 1.97

Finally, Table 5 shows the comparison of location density distributions between SL and non-SL datasets. As before, the comparison was performed by way of a two-sided Kolmogorov-Smirnov test.

Note that $D$ denotes the maximum absolute difference between the two tested distributions: this is, a higher $D$ indicates that they are very different from one another, whereas a lower $D$ indicates that they are very similar. The results are discussed in the next section.

| KS Test | | |
|---|---|---|
| **Dataset** | Right Hands | |
| | $D$ | $p$ |
| Emb. - BSL | 0.279 | $3.79 \times 10^{-5}$ |
| Emb. - NGT | 0.323 | $9.50 \times 10^{-7}$ |
| Emb. - LSM | 0.705 | $1.76 \times 10^{-43}$ |
| Emb. - LSM (cont.) | 1.0 | $2.01 \times 10^{-111}$ |
| Pant. - BSL | 0.324 | $4.02 \times 10^{-7}$ |
| Pant. - NGT | 0.594 | $7.38 \times 10^{-24}$ |
| Pant. - LSM | 0.647 | $1.68 \times 10^{-38}$ |
| Pant. - LSM (cont.) | 1.0 | $1.61 \times 10^{-118}$ |
| Pant. - Emb. | 0.479 | $3.65 \times 10^{-15}$ |
| **Dataset** | Left Hands | |
| | $D$ | $p$ |
| Emb. - BSL | 0.698 | $3.95 \times 10^{-32}$ |
| Emb. - NGT | 0.812 | $4.98 \times 10^{-45}$ |
| Emb. - LSM | 0.838 | $2.77 \times 10^{-65}$ |
| Emb. - LSM (cont.) | 1.0 | $2.01 \times 10^{-111}$ |
| Pant. - BSL | 0.788 | $2.30 \times 10^{-44}$ |
| Pant. - NGT | 0.396 | $1.64 \times 10^{-10}$ |
| Pant. - LSM | 0.849 | $5.37 \times 10^{-72}$ |
| Pant. - LSM (cont.) | 1.0 | $1.61 \times 10^{-118}$ |
| Pant. - Emb. | 0.789 | $5.32 \times 10^{-44}$ |

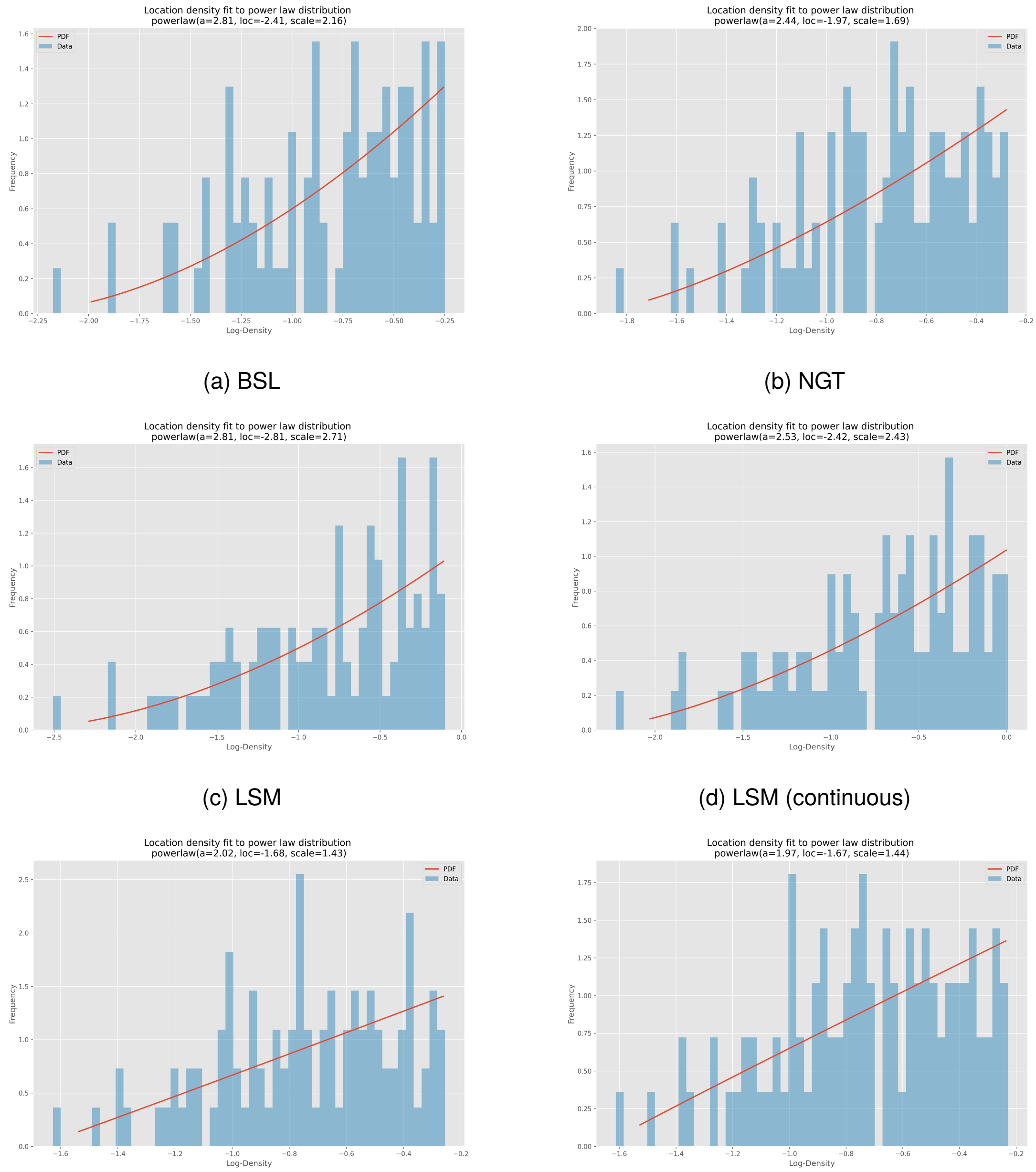
Table 5: Kolmogorov-Smirnov test results comparing the location density distributions between SL and non-SL datasets.

## 5. Discussion

In general, the results support the notion that conveying meaning puts pressure on the use of space during gestural communication, regardless of whether it is SL or not.

For instance, looking at the Euclidian distance statistics, it can be observed that both signers and non-signers tend to concentrate movement around certain regions: the results in Table 2 show that the average distance between locations (for all cases) tends to be below 20% of the available space, with a systematically lower-than-the-mean standard deviation pointing towards low dispersion. Regarding the dominant hand (the right hand in all collections), the continuous signing video was the one that covered the shortest distance. This was to be expected: lexicons are intended to show signs in a clear, systematic, manner, whereas continuous signing intends to convey a concrete message—implying that communication has to be more efficient, thus limiting the breadth of movement to its minimal expression. As such, it is not surprising that continuous signing had the lowest standard deviation of all collections. However, as implied before, this could also be an effect of camera positioning or the fact that the signer is aware of the space limitations he has—taking into account the fact that the continuous signing example comes from an interpretation task.

Similarly, the clustering results from Table 3 show that the continuous LSM dataset provided a stronger definition of hand regions, whereas pantomimes tended to be remarkably less stable than both SLs and emblems alike. A notable exception is the LSM lexicon, which shows a lower Silhouette score than pantomimes; however, when accounting for point density, its cluster definition became closer to the remaining lexicons rather than to pantomimes or emblems. Essentially, implying that there is a more systematic use of space in the former that is not well established in the latter. This can be partially seen in Figure 3 as well, where it can be observed that the use of space in the Pantomimes dataset tends to be less focused than in




(a) BSL

(b) NGT

(c) LSM

(d) LSM (continuous)

(e) Emblems

(f) Pantomimes

Figure 4: Dominant hand location log-density data fitted to a power law distribution.

the SL lexicons.

Regarding the location density results, Table 4 shows that not only do signers limit their movement to specific space regions, but they do so in a *Zipfian* manner: some regions are exponentially more active than others. The six collections showed tendency to this phenomenon, consistent with previous observations on the effects of meaning on natural communication systems. Nevertheless, when compared to SL datasets, pantomimes and emblems showed a marginally lower growth on their calculated power law distribution; this may indicate that a spatial hierarchy already exists in non-linguistic communication, but it is less strict than the one induced by SLs.

Finally, the direct comparison between SL and non-SL datasets shows that, even though the density distributions are decidedly different from one another, they are close enough to warrant further explanation—at least, with respect to BSL and NGT. For instance, Table 5 shows that space-use in the Emblems videos is surprisingly similar to BSL; this could be due to the fact that the former dataset was created considering cultural gestures in mind, which could very well be represented in BSL. Thus, there could be an underlying relationship not readily apparent between the two: they could share the same iconic DNA due to cultural proximity. Nonetheless, there is not enough information in the selected datasets to confirm the existence of such a relationship.

In the end, the obtained results seem to show the existence of a spatial hierarchy linked to the act of conveying meaning. However, the scale of the performed experiments was too limited: only one signer-gesturer was present in each of the six collections. Furthermore, differences between digital media (*e.g.* image size, frame-rate, etc); the kind of dataset; noise introduced by OpenPose; or the accidental extraction of non-relevant frames may be acting as sources of bias that are difficult to interpret within the chosen framework of analysis. Ideally, an homogeneous parallel corpus would be better suited to explore the existence of quantitative linguistic laws. Thus, further experiments are required—on a larger scale—to confirm the presented results.

## 6. Conclusions

The quantitative exploration of SLs constitutes one additional step towards improving our understanding of the diversity of human language. The present study contributes to these efforts by showing that gestural communication seems to induce a measurable spatial hierarchy, that follows a probability distribution related to Zipf's law. Moreover the obtained results show that, contrary to non-linguistic gestures, SLs tend to systematize the use of space to optimize information exchange. Nonetheless, future research is needed to confirm these observations in larger, homogeneous corpora. Additionally, some results indicate that it may be worth it to explore the connection between culturally-recognized gestures and their surrounding SLs, as the articulation of the latter may be disproportionally influenced by the former. In that regard, understanding how both processes connect may also shed light on how iconicity influences SL morphology, leading to sign formation.

## 7. References

Beatrice Agostini, Liuba Papeo, Cristina-Ioana Galusca, and Angelika Lingnau. 2019. A norming study of high-quality video clips of pantomimes, emblems, and meaningless gestures. *Behavior Research Methods*, 51(6):2817–2826.

Christian Bentz and Ramon Ferrer-i Cancho. 2016. Zipf's law of abbreviation as a language universal. Leiden, The Netherlands.

K.H. Best, O. Rottmann, and RAM-Verlag. 2017. *Quantitative Linguistics, an Invitation*. Studies in quantitative linguistics. RAM-Verlag.

Rain G. Bosworth, Charles E. Wright, and Karen R. Dobkins. 2019. Analysis of the visual spatiotemporal properties of American Sign Language. *Vision Research*, 164:34–43.

Carl Börstell, Thomas Hörberg, and Robert Östling. 2016. Distribution and duration of signs and parts of speech in Swedish Sign Language. *Sign Language & Linguistics*, 19(2):143–196.

Z. Cao, G. Hidalgo Martinez, T. Simon, S. Wei, and Y. A. Sheikh. 2019. Openpose: Realtime multi-person 2d pose estimation using part affinity fields. *IEEE Transactions on Pattern Analysis and Machine Intelligence*.

Naomi K. Caselli, Zed Sevcikova Sehyr, Ariel M. Cohen-Goldberg, and Karen Emmorey. 2017. ASL-LEX: A lexical database of American Sign Language. *Behavior Research Methods*, 49(2):784–801.

Dena J. Clink, Abdul Hamid Ahmad, and Holger Klinck. 2020. Brevity is not a universal in animal communication: evidence for compression depends on the unit of analysis in small ape vocalizations. *Royal Society Open Science*, 7(4):200151. Publisher: Royal Society.

Sertac Eroglu. 2013. Menzerath–Altmann law for distinct word distribution analysis in a large text. *Physica A: Statistical Mechanics and its Applications*, 392(12):2775–2780.

Jordan Fenlon, Kensy Cooperrider, Jon Keane, Diane Brentari, and Susan Goldin-Meadow. 2019. Comparing sign language and gesture: Insights from pointing. *Glossa*, 4(1).

Ramon Ferrer-i Cancho and Brenda McCowan. 2009. A Law of Word Meaning in Dolphin Whistle Types. *Entropy*, 11(4):688–701.

Molly Flaherty, Asha Sato, and Simon Kirby. 2023. Documenting a Reduction in Signing Space in Nicaraguan Sign Language Using Depth and Motion Capture. *Cognitive Science*, 47(4):e13277.

M. Halkidi and M. Vazirgiannis. 2001. Clustering validity assessment: finding the optimal partitioning of a data set. In *Proceedings 2001 IEEE International Conference on Data Mining*, pages 187–194.

Raphaela Heesen, Catherine Hobaiter, Ramon Ferrer-i Cancho, and Stuart Semple. 2019. Linguistic laws in chimpanzee gestural communication. *Proceedings of the Royal Society B: Biological Sciences*, 286(1896):20182900. Publisher: Royal Society.

Mingpan Huang, Haigang Ma, Changyong Ma, Paul A. Garber, and Pengfei Fan. 2020. Male gibbon loud morning calls conform to Zipf's law of brevity and Menzerath's law: insights into the origin of human language. *Animal Behaviour*, 160:145–155.

Keith Johnson. 2008. *Quantitative Methods In Linguistics*. John Wiley & Sons. Google-Books-ID: M5uGEAAAQBAJ.

Robert E Johnson and Scott K Liddell. 2011. A segmental framework for representing signs phonetically. *Sign Language Studies*, 11(3):408–463.

Scott K Liddell and Robert E Johnson. 1989. American sign language: The phonological base. *Sign language studies*, 64(1):195–277.

Guido M. Linders and Max M. Louwerse. 2023. Zipf's law revisited: Spoken dialog, linguistic units, parameters, and the principle of least effort. *Psychonomic Bulletin & Review*, 30(1):77–101.

Evie A. Malaia, Joshua D. Borneman, Emre Kurtoglu, Sevgi Z. Gurbuz, Darrin Griffin, Chris Crawford, and Ali C. Gurbuz. 2023. Complexity in sign languages. *Linguistics Vanguard*, 9(s1):121–131. Publisher: De Gruyter Mouton.

Niels Martinez-Guevara, Jose-Rafael Rojano-Caceres, and Arturo Curiel. 2023. Unsupervised extraction of phonetic units in sign language videos for natural language processing. *Universal Access in the Information Society*, 22(4):1143–1151.

Jiří Milička. 2014. Menzerath's Law: The Whole is Greater than the Sum of its Parts. *Journal of Quantitative Linguistics*, 21(2):85–99. Publisher: Routledge _eprint: https://doi.org/10.1080/09296174.2014.882187.

Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. 2011. Scikit-learn: Machine learning in python. *Journal of machine learning research*, 12(Oct):2825–2830.

Thomas R. Riedl and George Sperling. 1988. Spatial-frequency bands in complex visual stimuli: American Sign Language. *JOSA A*, 5(4):606–616. Publisher: Optica Publishing Group.

Peter J. Rousseeuw. 1987. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics*, 20:53–65.

Alexandra Safryghin, Catharine Cross, Brittany Fallon, Raphaela Heesen, Ramon Ferrer-i Cancho, and Catherine Hobaiter. 2022. Variable expression of linguistic laws in ape gesture: a case study from chimpanzee sexual solicitation. *Royal Society Open Science*, 9(11):220849. Publisher: Royal Society.

Simon J. Sheather. 2004. Density estimation. *Statistical Science*, 19(4):588–597.

Tomas Simon, Hanbyul Joo, Iain Matthews, and Yaser Sheikh. 2017. Hand keypoint detection in single images using multiview bootstrapping. In *CVPR*.

Jesse Stewart. 2014. A quantitative analysis of sign lengthening in American Sign Language. *Sign Language & Linguistics*, 17(1):82–101. Publisher: John Benjamins.

Pauli Virtanen, Ralf Gommers, Travis E. Oliphant, Matt Haberland, Tyler Reddy, David Cournapeau, Evgeni Burovski, Pearu Peterson, Warren Weckesser, Jonathan Bright, Stéfan J. van der Walt, Matthew Brett, Joshua Wilson, K. Jarrod Millman, Nikolay Mayorov, Andrew R. J. Nelson, Eric Jones, Robert Kern, Eric Larson, C J Carey, İlhan Polat, Yu Feng, Eric W. Moore, Jake VanderPlas, Denis Laxalde, Josef Perktold, Robert Cimrman, Ian Henriksen, E. A. Quintero, Charles R. Harris, Anne M. Archibald, Antônio H. Ribeiro, Fabian Pedregosa, Paul van Mulbregt, and SciPy 1.0 Contributors. 2020. SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. *Nature Methods*, 17:261–272.

Zhou Wang, A.C. Bovik, H.R. Sheikh, and E.P. Simoncelli. 2004. Image quality assessment: from error visibility to structural similarity. *IEEE Transactions on Image Processing*, 13(4):600–612.


## 8. Language Resource References


Alvarez Hidalgo, A. and Acosta Arrellano, A. and Moctezuma Contreras, C. and Sanabria Ramos, E. and Maya Ortega, E. and Alvárez Hidalgo, G. and Márquez Vaca, M. and Sanabria Ramos, M. and Romero Rojas, N. 2009. *Dielseme 2 Diccionario de Lengua de Señas Mexicana*. Secretaría de Educación Pública. http://campusdee.ddns.net/publicacionesdee.aspx.

Els van der Kooij, Annika Nonhebel & Wim Emmerik. 2003. *ECHO NGT lexicon, Male signer*. "ECHO", The Language Archive.

PID https://hdl.handle.net/1839/00-0000-0000-0008-1763-3.

Lingnau, Angelika. 2018. *Pantomimes, emblems, and meaningless gestures*. Royal Holloway, University of London. PID https://doi.org/10.17637/rh.c.4219988.

López-Obrador, Andres-Manuel. 2023. *#ConferenciaPresidente | Jueves 19 de octubre de 2023.* Presidencia de la República. https://www.youtube.com/watch?v=kU4VYK_RoRg.

Dafydd Waters. 2003. *BSL Lexicon CN*. "ECHO", The Language Archive. PID https://hdl.handle.net/1839/00-0000-0000-0008-1768-5.