QUANTITATIVE SURVEY OF THE STATE OF THE ART IN SIGN LANGUAGE RECOGNITION

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ABSTRACT

This work presents a meta study covering around 300 published sign language recognition papers with over 400 experimental results. It includes most papers between the start of the field in 1983 and 2020. Additionally, it covers a fine-grained analysis on over 25 studies that have compared their recognition approaches on RWTH-PHOENIX-Weather 2014, the standard benchmark task of the field. Research in the domain of sign language recognition has progressed significantly in the last decade, reaching a point where the task attracts much more attention than ever before. This study compiles the state of the art in a concise way to help advance the field and reveal open questions. Moreover, all of this meta study’s source data is made public, easing future work with it and further expansion. The analyzed papers have been manually labeled with a set of categories. The data reveals many insights, such as, among others, shifts in the field from intrusive to non-intrusive capturing, from local to global features and the lack of non-manual parameters included in medium and larger vocabulary recognition systems. Surprisingly, RWTH-PHOENIX-Weather with a vocabulary of 1080 signs represents the only resource for large vocabulary continuous sign language recognition benchmarking world wide.

Keywords  Sign Language Recognition · Survey · Meta Study · State of the Art Analysis

1 Introduction

Since recently, automatic sign language recognition experiences significantly more attention by the community. The number of published studies, but also the quantity of available data sets is increasing. This work aims at providing an overview of the field following a quantitative meta-study approach. For that, the author covered the most relevant 300 published studies, since the earliest known work [Grimes, 1983]. The 300 analyzed recognition studies have been manually labeled based on their basic recognition characteristics such as modeled vocabulary size, the number of contributing signers, the tackled sign language and additional details, such as the quality of the employed data set (e.g. if it covers isolated or continuous sign language), the available input data type (e.g. if provides colors as well as depth information or specific measuring devices for tracking body parts) and the employed sign language modalities and features (e.g. which of the manual and non-manual sign language parameters have been explicitly modeled and which additional features are employed). Based on this data, extensive analysis is presented by creating graphics and tables that relate specific characteristics, visualize correlations, highlight short-comings and allow to create proven hypotheses. Beyond that, this work focuses on the RWTH-PHOENIX-Weather data set, which has evolved to currently be the standard benchmark data set of the sign language recognition field. We provide a detailed structured view comparing over 25 research studies that have evaluated their approaches on the RWTH-PHOENIX-Weather corpus. We track the employed neural architectures, the training style, the employed losses and the data augmentation of all covered studies.

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Figure 1: Showing the number of published recognition results between 1983 and 2020.

and present it in a unified table jointly with the achieved performance. The raw data of this work is made publicly available\(^2\). As such, this paper makes the following contributions:

- Extensive quantitative structured data covering a large part of the sign language recognition research is made publicly available.
- First sign language recognition meta study, providing quantitative insights and analysis of the state of the art.
- First overview and in-depth analysis of all published papers that have compared their proposed recognition systems on PHOENIX 2014, the standard benchmark of the field.

In the following, we will start in Section 2 to dive into the analysis and present the general development of the field, followed by looking into the available input data used for modeling in Section 2.1 and the chosen sign language modalities and features to be modeled in Section 2.2. In Section 2.4, we point out the differences of the research landscape before and after 2015. We compare the studies and investigate general sign language recognition trends as manifested on the RWTH-PHOENIX-Weather 2014 benchmark data set in Section 3. Finally, we conclude this paper with Section 4. The full data table can be found in the appendix.

2 Analysis of the State of the Art

Figure 1 shows the number of published isolated and continuous recognition results in blocks of five years up until 2020. We see that growth looks exponential for isolated studies, while being close to linear for continuous studies. This may reflect the difficulty of the continuous recognition scenario and also the scarcity of available training corpora. On average it seems that there are at least twice as many studies published using isolated sign language data.

However, Figure 2, which shows the number of isolated and continuous recognition results aggregated by vocabulary size, reveals that the vast majority of the isolated sign language recognition works model a very limited amount of signs only (i.e. below 50 signs). This is not the case when comparing continuous sign language recognition, where the overall studies more or less evenly spread across all sign vocabularies (with exception of 500-1000 signs due to lack of available corpora).

Table 1 provides a more detailed perspective on the same data: Here, the number of published results is shown per year and per vocabulary range. In the middle and lower parts of the table, we see this information for isolated and continuous results, respectively, while in the top part of the table it is provided jointly for both data qualities. As in Figure 1 and 2, we note that overall the number of studies increases over the years. However, we also see that this trend is true for the smallest and medium vocabulary (below 50 signs and between 200 and 1000 signs) only. The large vocabulary tasks (over 1000 signs) have been low until year 2015 and following. When looking at the continuous studies only (lower part of Table 1), we see that large vocabulary (> 1000 signs) and 50-200 vocabulary tasks have experienced a large gain in the number of published results since 2015. This can be explained with the community focusing on two benchmark corpora since then ([Koller et al., 2015] with a vocabulary of 1080 signs and [Huang et al., 2018b] with a vocabulary of 178).

\(^2\)https://github.com/oskoller/sign-language-state-of-the-art
Table 1: Shows the number of recognition results that were published in a specific range of years, modeling a specific vocabulary size. The top part of the table show all studies jointly, while the middle and the bottom part of the table show isolated and continuous studies, respectively. E.g. this table reads like: “After 2015, there were 43 results published tackling vocabularies larger than 1000 signs.”

| Vocabulary | > 2015 | 2010 – 2015 | 2005 – 2010 | 2000 – 2005 | 1995 – 2000 | 1990 – 1995 | < 1990 |
|------------|--------|-------------|-------------|-------------|-------------|-------------|--------|
| All Studies |        |             |             |             |             |             |        |
| > 1000     | 40     | 4           | 3           | 6           | 1           | 0           | 0      |
| 500 – 1000 | 13     | 13          | 1           | 0           | 0           | 0           | 0      |
| 200 – 500  | 25     | 15          | 7           | 2           | 3           | 1           | 0      |
| 50 – 200   | 51     | 22          | 27          | 10          | 6           | 1           | 0      |
| 0 – 50     | 50     | 35          | 40          | 12          | 12          | 5           | 2      |

| Vocabulary | > 2015 | 2010 – 2015 | 2005 – 2010 | 2000 – 2005 | 1995 – 2000 | 1990 – 1995 | < 1990 |
|------------|--------|-------------|-------------|-------------|-------------|-------------|--------|
| Isolated Studies |        |             |             |             |             |             |        |
| > 1000     | 6      | 2           | 2           | 3           | 1           | 0           | 0      |
| 500 – 1000 | 12     | 11          | 1           | 0           | 0           | 0           | 0      |
| 200 – 500  | 19     | 6           | 3           | 1           | 2           | 1           | 0      |
| 50 – 200   | 34     | 17          | 12          | 8           | 2           | 1           | 0      |
| 0 – 50     | 43     | 29          | 27          | 7           | 7           | 4           | 2      |

| Vocabulary | > 2015 | 2010 – 2015 | 2005 – 2010 | 2000 – 2005 | 1995 – 2000 | 1990 – 1995 | < 1990 |
|------------|--------|-------------|-------------|-------------|-------------|-------------|--------|
| Continuous Studies |        |             |             |             |             |             |        |
| > 1000     | 34     | 2           | 1           | 3           | 0           | 0           | 0      |
| 500 – 1000 | 1      | 2           | 0           | 0           | 0           | 0           | 0      |
| 200 – 500  | 6      | 9           | 4           | 1           | 1           | 0           | 0      |
| 50 – 200   | 17     | 5           | 15          | 2           | 4           | 0           | 0      |
| 0 – 50     | 7      | 6           | 13          | 5           | 5           | 1           | 0      |
Table 2: Shows the fraction in [%] of published sign language recognition results that make use of a specific input data type (e.g. ‘RGB’, ‘Depth’, etc.) relative to all published results that fall in the same modeled vocabulary range (top part of the table) and that have been published in a similar range of years (bottom part of the table). E.g. this table reads like: “86% of all results with a modeled vocabulary above 1000 signs employ RGB input data. 88% of all results published after 2015 also use depth as input data.”

| Vocabulary | RGB | Depth | Color Glove | Elect. Glove | Mocap |
|------------|-----|-------|-------------|--------------|-------|
| > 1000     | 85  | 4     | 0           | 17           | 13    |
| 500 – 1000 | 93  | 41    | 0           | 4            | 4     |
| 200 – 500  | 77  | 23    | 6           | 12           | 12    |
| 50 – 200   | 72  | 24    | 13          | 10           | 8     |
| 0 – 50     | 72  | 24    | 13          | 10           | 8     |

| Year       | RGB | Depth | Color Glove | Elect. Glove | Mocap |
|------------|-----|-------|-------------|--------------|-------|
| > 2015     | 87  | 22    | 3           | 4            | 6     |
| 2010 – 2015| 85  | 38    | 4           | 7            | 7     |
| 2005 – 2010| 72  | 1     | 18          | 10           | 6     |
| 2000 – 2005| 33  | 0     | 10          | 50           | 57    |
| 1995 – 2000| 36  | 0     | 18          | 41           | 23    |
| 1990 – 1995| 29  | 0     | 0           | 71           | 29    |
| < 1990     | 50  | 0     | 0           | 50           | 0     |

2.1 Type of Employed Input Data

Table 2 shows in the top part of the type of employed input data across different sizes of modeled vocabulary. The input data refers to the data that is consumed by the recognition algorithms to extract features from and perform computation. We can observe that RGB is the most popular type of input data both for small and larger scale vocabulary ranges. Colored gloves have only ever been applied to small and medium vocabulary tasks and did never get significant attention. The lower part of Table 2 shows the type of employed input data relative to all results published in the same range of years. We can see that RGB data attracts most attention since 2005. Depth as input modality became only popular after the release of the Kinect sensor in 2010. There was one work that employed depth data before [Fujimura and Xia Liu, 2006] which had access to early time-of-flight sensors. Colored gloves got some traction between 1995 and 2010, which looks like a transition phase from electronic measuring devices to pure vision based processing.

Table 3 displays the input data aggregated into the categories ‘non-intrusive’ and ‘intrusive’. Intrusiveness refers to the need to interfere with the recognition subject in order to perform body pose estimation and general feature extraction. As such, ‘RGB’ and ‘Depth’ are non-intrusive capturing methods, while ‘Color Glove’, ‘Electronic Glove’ and ‘Motion Capturing’ are intrusive techniques. As can be seen in Table 3 on the left, intrusives capturing methods can be encountered in about one quarter of all experiments with a vocabulary of up to 500 signs. They are more rare in larger vocabulary sizes, possibly due to the fact that those have mainly been researched after 2010 (compare Table 1). We clearly see a paradigm shift after 2005, when the formerly dominating intrusives capturing methods were less and less used and their prevalence decreased from around 70% to less than 30% with a tendency to further reduce over time.

Table 4 shows the number of recognition results per per sign language and employed type of input data. We note that experiments recognizing American sign language (ASL) are clearly dominated by RGB data. Chinese sign language (CSL) has most results using RGB-D (color with depth) data or just RGB data. Gloves make up a significant number of published results in both sign languages as well. German Sign Language (Deutsche Gebärdensprache) (DGS) and most other sign languages focus mainly on RGB based recognition.

2.2 Modeled Sign Language Parameters

In the previous section, we have looked at what kind of input data is being employed for sign language recognition studies. Now, we will investigate the sign language parameters and features that are extracted based on the input data. Therefore, we tagged which sign language parameters are covered by the modeled features. We distinguish manual parameters (i.e. hand shape, movement, location and orientation) and non-manual parameters (i.e. head, mouth, eyes, eye blink, eye brows and eye gaze). For non-manual parameters, it needs to be pointed out that we focused on studies that explicitly target sign language recognition and also include non-manuals. There are many works that focus on non-manual marker recognition for sign language, but these works typically do not model a sign language
Table 3: Shows the fraction in [%] of published sign language recognition results that make use of non-intrusives data input capturing methods (i.e. ‘RGB’ or ‘Depth’) and those that are intrusives (i.e. ‘Color Glove’, ‘Elect. Glove’ or ‘Mocap’) relative to all published results that fall in the same modeled vocabulary range (left table) and relative to a year range (right table). E.g. this table reads like: “84% of all published results with a modeled vocabulary larger than 1000 signs employ non-intrusives input data capturing methods.”

| Vocabulary | non-Intrusive | Intrusive |
|------------|---------------|-----------|
| > 1000     | 83            | 17        |
| 500 − 1000 | 93            | 7         |
| 200 − 500  | 77            | 23        |
| 50 − 200   | 73            | 27        |
| 0 − 50     | 74            | 26        |

| Year       | non-Intrusive | Intrusive |
|------------|---------------|-----------|
| > 2015     | 89            | 11        |
| 2010 − 2015| 87            | 13        |
| 2005 − 2010| 72            | 28        |
| 2000 − 2005| 30            | 70        |
| 1995 − 2000| 27            | 73        |
| 1990 − 1995| 29            | 71        |
| < 1990     | 50            | 50        |

Table 4: Shows the number of published recognition results per sign language and type of input data. The sign language abbreviations are mentioned in the appendix. The sign languages are ordered by result counts. This table reads like: “99 results were published for ASL that used RGB input data.”

| Input Data       | ASL   | CSL   | DGS   | BSL   | ArSL  | IndianSL | FlemishSL | LIS | ArgusSL | TaiwaneseSL | IrishSL | KSI | ItalianSL | MexicanSL | PersianSL | LSE | KurdishSL | ISL  |
|------------------|-------|-------|-------|-------|-------|-----------|-----------|-----|---------|-------------|---------|-----|-----------|------------|-----------|-----|-----------|-----|
| RGB              | 93    | 53    | 59    | 18    | 7     | 6        | 7         | 12  | 5       | 7           | 4       | 0   | 0         | 0          | 0         | 0   | 0         | 1   |
| Depth            | 14    | 38    | 1     | 4     | 1     | 2        | 4         | 0   | 0       | 4           | 2       | 0   | 1         | 5          | 0         | 0   | 0         | 0   |
| Color Glove      | 16    | 17    | 1     | 0     | 4     | 2        | 0         | 1   | 0       | 0           | 1       | 4   | 0         | 3          | 0         | 2   | 0         | 0   |
| Elect. Glove     | 14    | 15    | 0     | 0     | 4     | 3        | 4         | 0   | 0       | 0           | 0       | 1   | 0         | 2          | 0         | 0   | 1         | 0   |
| Mocap            |       |       |       |       |       |           |           |     |         |              |         |     |           |            |           |     |           |     |

Table 5 shows the employed sign language parameters and features relative to all results published using a similar sign vocabulary (top of the table) and relative to all results published during a similar time (lower part of the table).

We note that hand shape is the most covered parameter, while location and movement are the next popular parameters across all vocabulary sizes below 1000 signs. Fullframe features followed by hand shapes are most frequently encountered in large vocabulary tasks beyond 1000 signs. The lower part of Table 5 confirms that since 2015 fullframe features have become the most frequently encountered feature (while being very close to hand shape features). Furthermore, it can be noticed that since 2015 hand shape are tackled by a much larger fraction of published results. It needs to be pointed out that while most studies that have been published after 2015 employ a cropped hand patch as input to their recognition systems, we tagged that with the hand shape parameter. However, using deep learning based feature extractors, such hand inputs may implicitly learn hand posture / orientation parameters. Similarly, global input features such as fullframe inputs may implicitly help to learn location and movement parameters and, to a lesser degree, all other parameters as well as the full image comprises all available information.

Table 6 aggregates hand location, movement, shape and orientation into manual parameters. Head, mouth, eyes, eye blink, eyebrows and eye gaze are referred to as non-manual parameters. Body joints, fullframe, depth and motion are all computed on the full image and hence we call them global features. We can see that with larger modeled vocabularies the trend goes from manual to global features (left side of Table 6), where the latter increase from 18% usage across all published results with vocabularies of up to 50 signs to 62% with large vocabularies above 1000 signs. The increase of global features may have two reasons:

1. The availability of body joints and full depth image features with the release of the Kinect in 2010.
2. The shift towards deep learning and trend to input fullframes instead of manual feature engineering.
Table 5: Shows the fraction in [%] of published sign language recognition results that make use of a specific sign language parameter (e.g. ‘Loc.’, ‘Mov.’, etc.) relative to all published results that fall in the same vocabulary range (top part of the table), or in the same range of years (lower part of the table). ‘Loc.’, ‘Mov.’, ‘Shape’ and ‘Orient.’ stand for hand location, movement, shape and orientation (manual parameters). ‘Joints’ refers to tracked body joint locations. ‘Fullframe’ and ‘Depth’ are the full RGB and depth image, respectively, while ‘Motion’ unites all types of motion estimation on the full image (often optical flow). E.g. this table reads like: “27% of all results with a modeled vocabulary above 1000 signs include the location modality.”

| Vocabulary Range | Loc. | Mov. | Shape | Orient. | Head | Mouth | Eyes | Blink | Brows | Gaze | Joints | Fullframe | Depth | Motion |
|------------------|------|------|-------|---------|------|-------|------|-------|-------|------|--------|-----------|-------|--------|
| > 1000           | 28   | 17   | 47    | 19      | 11   | 9     | 6    | 0     | 6     | 0    | 11     | 55        | 0     | 4      |
| 500 – 1000       | 46   | 58   | 58    | 4       | 0    | 0     | 0    | 0     | 0     | 0    | 42     | 21        | 0     | 4      |
| 200 – 500        | 44   | 35   | 73    | 17      | 21   | 8     | 2    | 0     | 2     | 0    | 25     | 27        | 0     | 4      |
| 50 – 200         | 56   | 52   | 56    | 17      | 7    | 2     | 1    | 0     | 0     | 0    | 14     | 23        | 0     | 1      |
| 0 – 50           | 55   | 52   | 66    | 17      | 6    | 3     | 2    | 0     | 2     | 0    | 12     | 8         | 1     | 1      |

| Year             | Loc. | Mov. | Shape | Orient. | Head | Mouth | Eyes | Blink | Brows | Gaze | Joints | Fullframe | Depth | Motion |
|------------------|------|------|-------|---------|------|-------|------|-------|-------|------|--------|-----------|-------|--------|
| > 2015           | 23   | 22   | 43    | 9       | 6    | 5     | 3    | 0     | 3     | 0    | 22     | 46        | 1     | 4      |
| 2010 – 2015      | 65   | 67   | 81    | 12      | 17   | 2     | 2    | 0     | 2     | 0    | 31     | 6         | 0     | 0      |
| 2005 – 2010      | 73   | 71   | 65    | 8       | 10   | 6     | 0    | 0     | 0     | 0    | 0      | 1         | 0     | 0      |
| 2000 – 2005      | 87   | 57   | 80    | 53      | 0    | 0     | 0    | 0     | 0     | 0    | 0      | 0         | 0     | 0      |
| 1995 – 2000      | 68   | 45   | 77    | 55      | 5    | 0     | 0    | 0     | 0     | 0    | 0      | 0         | 0     | 0      |
| 1990 – 1995      | 57   | 57   | 86    | 71      | 0    | 0     | 0    | 0     | 0     | 0    | 0      | 0         | 0     | 0      |
| < 1990           | 50   | 50   | 100   | 50      | 0    | 0     | 0    | 0     | 0     | 0    | 0      | 0         | 0     | 0      |

Both hypotheses can be confirmed by looking at the right side of Table 6. There, we see that global features started gaining traction just after 2010 (release of the Kinect) and also coincides with when deep learning for sign language took off in 2015.

While for the previous tables each sign language parameter has been looked at separately and tagged when present, Table 7 shows the frequency of combinations of features over different vocabularies. Hence, if a study models two types of parameters their combination will appear in this table. Inline with previous results, we see that fullframe features alone are by far the most popular on large vocabulary (> 1000 signs) tasks. They are followed by hand shape features and body joints. On very small vocabulary (< 50 signs) tasks, a preference on hand shape features can be noticed.

Table 8 shows the number of published results with employed parameters broken down per sign language. In the top part of the table all studies are reflected, while the lower part of the table only shows studies with a vocabulary of at least 200 signs. We see that while ASL has the most published results overall, non-manual parameters (e.g. head, mouth or eyes) are most frequently included in studies on DGS. It is also striking that despite the fact that CSL is the second most frequently researched sign language, there is only a single study that includes non-manual parameters like the face [Zhou et al., 2020a]. We also note that there are studies on smaller sign languages such as Kazakh-Russian sign language (K-RSL) that explicitly focus on non-manual parameters [Mukushev et al., 2020, Sabyrov et al., 2019]. Eyes and specifically eyebrows have only been tackled in few studies [Koller et al., 2016a, Koller et al., 2015, Koller et al., 2016b, Mukushev et al., 2020, Sabyrov et al., 2019, Yang and Lee, 2011, Zhang et al., 2016a], while, to the best of our knowledge, no single work has explicitly included eye gaze or eye blinks for sign language recognition. In the lower part of Table 8 studies are limited to have at least a vocabulary of 200 signs. Besides two British sign language (BSL) studies [Albanie et al., 2020, von Agris et al., 2008b], all others are works on DGS, covering the 450 sign language corpus SIGNUM [Oberdörfer et al., 2012, von Agris et al., 2008a] and the 1080 sign vocabulary corpus RWTH-PHOENIX-Weather [Forster et al., 2013a, Forster et al., 2013b, Koller et al., 2016a, Koller et al., 2015, Koller et al., 2016b, Zhou et al., 2020a]. [Zhou et al., 2020a] is the first work that uses the face in a deep learning based large vocabulary task.

2.3 Analysis by Sign Language

Table 9 and Table 10 show the number of published recognition results per sign language over time and per modeled vocabulary range, respectively. ASL has usually been the sign language with the most results published. However, we see in Table 10 that this is only true for vocabularies below 200 signs. On larger vocabularies CSL is leading and on vocabularies above 1000 signs DGS has significantly more research published. Table 10 further reveals that it is
Table 6: Shows the fraction in [%] of published sign language recognition results that employ manual, non-manual or global features relative to all published results that fall in the same vocabulary range (left side) or the same range of years (right side). Manual parameters refer to hand location, movement, shape and orientation. Non-manual parameters are head, mouth, eyes, eyeblink, eyebrow and eyegaze features. Global features refer to body joints, fullframe, depth and motion features. E.g. this table reads like: “46% of all results with a modeled vocabulary above 1000 signs include manual parameters.”

| Vocabulary | Manual | non-Manual | Global |
|------------|--------|------------|--------|
| > 1000     | 49     | 15         | 64     |
| 500 – 1000 | 67     | 0          | 62     |
| 200 – 500  | 77     | 0          | 62     |
| 50 – 200   | 74     | 7          | 35     |
| 0 – 50     | 90     | 7          | 20     |

Table 7: Shows the 26 most frequently used modality combinations and their relative frequency of use as. This is displayed as fraction in [%] of published sign language recognition results that make use of the specific combination of sign language parameters relative to all published results that fall in the same vocabulary range. ‘Loc.’, ‘Mov.’, ‘Shape’ and ‘Orient.’ stand for hand location, movement, shape and orientation (manual parameters). ‘Joints’ refers to tracked body joint locations. ‘Fullframe’ and ‘Depth’ are the full RGB and depth image, respectively, while ‘Motion’ unites all types of motion estimation on the full image (often optical flow). E.g. this table reads like: “39% of all results with a modeled vocabulary above 1000 signs rely fully on the fullframe modality, while 7% rely on the hand shape modality.”

| Modality Combination | Vocabulary |
|----------------------|------------|
|                      | > 1000 | 500 – 1000 | 200 – 500 | 50 – 200 | 0 – 50 |
| Fullframe            | 39     | 15         | 20        | 18       |
| Shape                | 7      | 0          | 9         | 5        |
| Loc.-Mov.-Shape      | 4      | 11         | 0         | 14       |
| Loc.-Mov.            | 0      | 4          | 0         | 9        |
| Loc.-Mov.-Shape-Orient.| 6   | 4          | 4         | 8        |
| Mov.-Shape           | 2      | 11         | 2         | 3        |
| Loc.-Shape           | 0      | 0          | 9         | 8        |
| Joints               | 6      | 11         | 8         | 5        |
| Loc.-Shape-Orient.   | 9      | 0          | 4         | 3        |
| Loc.-Mov.-Shape-Joints| 0 | 15         | 4         | 3        |
| Loc.-Shape-Joints    | 2      | 7          | 8         | 2        |
| Mov.                 | 0      | 4          | 2         | 3        |
| Loc.                 | 0      | 0          | 0         | 2        |
| Mov.-Shape-Orient.   | 0      | 0          | 2         | 3        |
| Shape-Orient.        | 0      | 0          | 4         | 0        |
| Mov.-Shape-Head-Fullframe | 0 | 0      | 9         | 0        |
| Loc.-Mov.-Shape-Head | 0      | 0          | 0         | 1        |
| Shape-Fullframe      | 4      | 0          | 0         | 1        |
| Shape-Head-Joints-Fullframe | 4 | 0      | 0         | 1        |
| Mov.-Shape-Joints    | 0      | 4          | 2         | 0        |
| Loc.-Shape-Head      | 0      | 0          | 4         | 0        |
| Loc.-Mov.-Shape-Head-Mouth-Eyes-Brows | 4 | 0 | 2 | 0 |
| Loc.-Mov.-Shape-Head-Mouth | 0 | 0 | 4 | 1 |
| Loc.-Mov.-Head       | 0      | 0          | 0         | 2        |
| Loc.-Joints          | 0      | 0          | 0         | 2        |
Table 8: Shows the number of published recognition results per sign language and employed sign language modality. The top part of the table shows all studies, while the lower part only shows studies with a vocabulary of at least 200 signs. The sign language abbreviations are mentioned in the appendix. This table reads like: “There are 62 results published that use the location modality in the recognition of ASL.”

| Modalities   | ASL | CSL | DGS | BSL | ASL | ISL | GSL | TSL | NCT | FlemishSL | LIS | Asslan | ArgentinianASL | TaiwaneseASL | PolishASL | LithuanianSL | KSL | IrishSL | IndosSL | MalayalamSL | K-RSL | DGS | TamilsSL | PersianSL | MexicanSL | LSE | KurdishSL |
|--------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----------|-----|---------|--------------|--------------|-----------|-------------|-----|---------|----------|------------|-------|-----|----------|-----------|-----------|-----|-----------|
| Location     | 62  | 38  | 16  | 12  | 12  | 8   | 3   | 9   | 7   | 3        | 0   | 3       | 3             | 2             | 2            | 4           | 1   | 3       | 2        | 2            | 0     | 0   | 0       | 0         | 1       | 0  | 0        |
| Movement     | 63  | 32  | 16  | 14  | 7   | 7   | 2   | 11  | 5   | 2        | 0   | 2       | 2             | 2             | 2            | 2           | 4   | 1       | 1        | 1            | 0     | 0   | 1       | 0         | 0       | 1  | 0        |
| Shape        | 68  | 49  | 34  | 15  | 8   | 7   | 5   | 10  | 7   | 2        | 0   | 2       | 5             | 4             | 3            | 3           | 3   | 1       | 3        | 2            | 3     | 2   | 0       | 1         | 1       | 1  | 1        |
| Orientation  | 18  | 19  | 1    | 4   | 3   | 2   | 1   | 0   | 2   | 0        | 2   | 2       | 4             | 1             | 0           | 1           | 0   | 2       | 0        | 0            | 0     | 0   | 0       | 0         | 0       | 0  | 1        |

All Studies

| Modality     | Head | Mouth | Eyes | Eyeblink | Eyebrows | Gaze |
|--------------|------|-------|------|----------|----------|------|
| Location     | 8    | 1     | 15   | 2        | 0        | 1    |
| Movement     | 2    | 0     | 8    | 1        | 0        | 0    |
| Shape        | 2    | 0     | 4    | 0        | 0        | 0    |
| Orientation  | 0    | 0     | 0    | 0        | 0        | 0    |

Bodyjoints

| Modality     | Head | Mouth | Eyes | Eyeblink | Eyebrows | Gaze |
|--------------|------|-------|------|----------|----------|------|
| Location     | 2    | 25    | 8    | 3        | 2        | 0    |
| Movement     | 2    | 20    | 10   | 1        | 0        | 1    |
| Shape        | 3    | 34    | 26   | 3        | 2        | 0    |
| Orientation  | 1    | 14    | 1    | 1        | 0        | 0    |

Studies with vocabulary > 200

| Modality     | Head | Mouth | Eyes | Eyeblink | Eyebrows | Gaze |
|--------------|------|-------|------|----------|----------|------|
| Location     | 0    | 0     | 14   | 2        | 0        | 1    |
| Movement     | 0    | 0     | 7    | 1        | 0        | 0    |
| Shape        | 0    | 0     | 4    | 0        | 0        | 0    |
| Orientation  | 0    | 0     | 4    | 0        | 0        | 0    |

Bodyjoints

| Modality     | Head | Mouth | Eyes | Eyeblink | Eyebrows | Gaze |
|--------------|------|-------|------|----------|----------|------|
| Location     | 6    | 14    | 3    | 1        | 0        | 0    |
| Movement     | 13   | 0     | 33   | 1        | 0        | 0    |
| Shape        | 0    | 0     | 0    | 0        | 0        | 0    |
| Orientation  | 0    | 1     | 3    | 0        | 0        | 0    |

RWTH-PHOENIX-Weather with a vocabulary of over 1000 signs that represents the only resource for large-scale continuous sign language world wide.

This can partly be explained by the public availability of sign language data sets, which represent after all still extremely low resource languages. However, there are corpora available for ASL that have larger vocabularies (e.g. ASLLRP [Neidle and Vogler, 2012]). It seems there is necessity for the corpora to be packaged for reproducible sign language recognition research. Fixed partitions into train, development and test and an easily accessible download method are required. Also, the licenses under which the corpora are provided may impact dissemination.

2.4 Change of Continuous Recognition Landscape After 2015

Figure 3 shows counts of published continuous sign language recognition experiments and modeled vocabularies before and after 2015. Prior 2015, there were 80 results published, while after 2015 66 results can be found. We note that prior 2015 most studies model different vocabulary sizes, while after 2015 there is a large peak of close to 30 published results at a 1080 vocabulary and a smaller peak at a vocabulary size of 178.
Table 9: Shows the number of published recognition results per sign language and year. The sign language abbreviations are mentioned in the appendix. This table reads like: “There are 50 results published after 2015 that use ASL.”

| Year     | ASL | CSL | BSL | Auslan | IndianSL | GSL | TSL | FlamSL | LIS | Auslan | ArgentSL | IsraeliSL | PolishSL | LithuanianSL | IrishSL | IndoSL | CzSL | MalaySL | K-RSL | DGS | TamisSL | PersianSL | MexicanSL | LSE | KurishSL |
|----------|-----|-----|-----|--------|----------|-----|-----|--------|-----|--------|----------|-----------|----------|------------|---------|--------|-----|---------|------|-----|---------|-----------|-----------|-----|----------|
| > 2015   | 46  | 35  | 40  |        |          | 2   | 4   | 1     | 9   | 2      | 4        | 4         | 5        | 1         | 1       | 5        | 0     | 1      | 0    | 1      | 3    | 1    | 2      | 2         | 1         | 1   | 1       |
| 2010−2015| 21  | 21  | 17  |        |          | 2   | 7   | 1     | 2   | 10     | 0        | 2         | 0        | 0         | 2       | 2        | 1     | 0      | 0    | 0      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
| 2005−2010| 30  | 4   | 41  |        |          | 6   | 2   | 0     | 1   | 5      | 2        | 2         | 0        | 0         | 0       | 1        | 1     | 3      | 0    | 2      | 2    | 0    | 0      | 0         | 0         | 0   | 0       |
| 2000−2005| 11  | 0   | 25  |        |          | 3   | 0   | 1     | 0   | 2      | 0        | 0         | 0        | 0         | 0       | 1        | 1     | 2      | 2    | 0    | 0      | 0         | 0         | 0   | 0       |
| 1995−2000| 5   | 2   | 1   |        |          | 0   | 0   | 4     | 0   | 0      | 2        | 0         | 3        | 0         | 0       | 0        | 0     | 2      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
| 1990−1995| 5   | 0   | 0   |        |          | 0   | 0   | 0     | 0   | 1      | 1        | 0         | 1        | 0         | 0       | 0        | 0     | 0      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
| < 1990   | 1   | 0   | 0   |        |          | 0   | 0   | 1     | 0   | 0      | 0        | 0         | 0        | 0         | 0       | 0        | 1     | 0      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |

Table 10: Shows the number of published recognition results per sign language and modeled vocabulary. The sign language abbreviations are mentioned in the appendix. This table reads like: “There are 6 recognition results of ASL published.”

| Vocabulary | ASL | CSL | BSL | Auslan | IndianSL | GSL | TSL | FlamSL | LIS | Auslan | ArgentSL | IsraeliSL | PolishSL | LithuanianSL | IrishSL | IndoSL | CzSL | MalaySL | K-RSL | DGS | TamisSL | PersianSL | MexicanSL | LSE | KurishSL |
|------------|-----|-----|-----|--------|----------|-----|-----|--------|-----|--------|----------|-----------|----------|------------|---------|--------|-----|---------|------|-----|---------|-----------|-----------|-----|----------|
| > 1000     | 4   | 11  | 36  |        |          | 2   | 0   | 0     | 0   | 0      | 1        | 0         | 0         | 0         | 0       | 0        | 0     | 0      | 0    | 0      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
| 500−1000   | 7   | 10  | 2   |        |          | 0   | 0   | 1     | 5   | 2      | 0        | 0         | 0         | 0         | 0       | 0        | 0     | 0      | 0    | 0      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
| 200−500    | 8   | 17  | 16  |        |          | 3   | 2   | 0     | 2   | 2      | 0        | 1         | 0         | 0         | 0       | 0        | 0     | 0      | 0    | 0      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
| 50−200     | 43  | 20  | 3   |        |          | 8   | 7   | 4     | 3   | 4      | 1        | 4         | 4         | 2         | 4       | 2        | 2     | 1      | 1    | 1      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
| 0−50       | 57  | 14  | 7   |        |          | 7   | 8   | 7     | 5   | 1      | 6        | 4         | 3         | 3         | 1       | 3        | 3     | 4      | 2    | 3      | 2    | 2    | 0      | 1         | 1         | 1   | 1       |
| > 1000     | 4   | 7   | 0   |        |          | 2   | 0   | 0     | 0   | 1      | 0        | 0         | 0         | 0         | 0       | 0        | 0     | 0      | 0    | 0      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
| 500−1000   | 7   | 9   | 0   |        |          | 0   | 0   | 0     | 1   | 5      | 2        | 0         | 0         | 0         | 0       | 0        | 0     | 0      | 0    | 0      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
| 200−500    | 8   | 16  | 0   |        |          | 1   | 2   | 0     | 2   | 1      | 1        | 0         | 0         | 0         | 0       | 0        | 0     | 0      | 0    | 0      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
| 50−200     | 24  | 7   | 1   |        |          | 8   | 2   | 3     | 3   | 4      | 1        | 4         | 4         | 2         | 4       | 2        | 1     | 0      | 1    | 0      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
| 0−50       | 34  | 11  | 7   |        |          | 6   | 8   | 3     | 5   | 1      | 3        | 5         | 3         | 2        | 1       | 3        | 2     | 3      | 2    | 2    | 0    | 1      | 1         | 1       | 1   | 1       |
| > 1000     | 0   | 4   | 36  |        |          | 0   | 0   | 0     | 0   | 0      | 0        | 0         | 0         | 0         | 0       | 0        | 0     | 0      | 0    | 0      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
| 500−1000   | 0   | 1   | 2   |        |          | 0   | 0   | 0     | 0   | 1      | 0        | 0         | 0         | 0         | 0       | 0        | 0     | 0      | 0    | 0      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
| 200−500    | 0   | 1   | 16  |        |          | 2   | 0   | 0     | 1   | 0      | 0        | 0         | 0         | 0         | 0       | 0        | 0     | 0      | 0    | 0      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
| 50−200     | 19  | 13  | 2   |        |          | 5   | 1   | 0     | 0   | 0      | 0        | 0         | 0         | 0         | 0       | 0        | 0     | 0      | 0    | 0      | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
| 0−50       | 23  | 3   | 0   |        |          | 1   | 0   | 2     | 2   | 0      | 1        | 1         | 1         | 0        | 0       | 0        | 0     | 0      | 0    | 0    | 0    | 0      | 0         | 0         | 0   | 0       |
Since 2015, the sign language recognition community is focusing more on benchmark data sets, which explains these characteristics. RWTH-PHOENIX-Weather 2014 [Koller et al., 2015] has a vocabulary of 1080 and the CSL corpus [Huang et al., 2018b] covers 178 signs. In the following section, we will provide a deep analysis of the research studies that compared their work on the PHOENIX corpus.

![Published Results](image)

Figure 3: Showing the number of published continuous sign language recognition results per modeled vocabulary (prior to 2015 on the top and 2015-2020 on the bottom plot). This allows to see that after 2015 researcher have started to focus on few benchmark data sets.

## 3 Analysis of PHOENIX 2014 Benchmark Papers

Table 11 and Table 12 present, to the best of our knowledge, all known results on the RWTH-PHOENIX-Weather 2014 continuous sign language recognition benchmark that have been published as of June 2020. Table 11 provides information on the employed features, the chosen neural architecture and the achieved results, while Table 12 shows what kind of data augmentation was used, if iterative training was employed and what training losses were part of the optimization. Iterative training refers to an expectation maximization (EM) like training procedure where a trained model is used to create pseudo labels on the training data which will then be used to train a part or the full recognition network. Inspired by EM training refers to a Gaussian mixture model (GMM) hidden Markov model (HMM) systems, this way of training was first proposed in [Koller et al., 2016a]. It was then adopted by many teams as can be seen in Table 12. Besides [Cheng et al., 2020], all best performing approaches on PHOENIX with a word error rates (WERs) below 27.0% make use of iterative training procedures. In many works it is described to help overcome vanishing gradients issues when training deep convolutional neural network (CNN) architectures that are succeeded by bi-directional long short-term memory (BLSTM) layers [Zhou et al., 2020a, Papastratis et al., 2020, Cui et al., 2019].

The employed losses are very diverse, as can be seen in Table 12. However, most networks that achieve below 30.0% WER are trained with cross-entropy (CE) loss and also use connectionist temporal classification (CTC) loss. Additionally, a variety of different loss terms are reported ranging from Kullback-Leibler (KL) divergence, over squared error to smooth-L1 loss and others.

Table 11 shows that [Cui et al., 2017] first suggested the use of 2D convolutions followed by 1D convolutions on PHOENIX. Later, [Tran et al., 2018] did a detailed analysis for action recognition. All best performing approaches on PHOENIX with WERs below 25.0% employ 2D+1D convolutions [Cheng et al., 2020, Cui et al., 2019, Papastratis et al., 2020, Zhou et al., 2020a].

While the early works on PHOENIX all relied on tracked and cropped hand shape features [Koller et al., 2017] first proposed to train the CNNs directly on the fullframe input image. This trend continues and all recent studies rely on this feature (e.g. [Adaloglou et al., 2020, Cheng et al., 2020, Papastratis et al., 2020, Zhou et al., 2020b, Zhou et al., 2020a]).
In terms of data augmentation, the most popular choice seems to be random cropping, followed by temporal scaling (re-sampling or random frame drop) as can be seen in Table 12. However, many papers do not specify any augmentation methods leaving the reader without a clear understanding of what happens. While augmentation certainly has significant impact on the results, no study has yet analyzed the effect of the various augmentation options.

Finally, it needs to be pointed out that all of the works that compared their performance on PHOENIX were based on whole sign units during inference. Only two works made use of subunits, i.e. to additionally guide the alignment process [Koller et al., 2019] or in a pretraining stage [Borg and Camilleri, 2020].

Table 11: The table covers (to the best of our knowledge) all published sign language recognition works until mid 2020 that report results on the RWTH-Phoenix Weather 2014 [Koller et al., 2015] task. The works are ordered by year and by WER. It allows to compare the type of employed features (manual, non-manual and fullframe features), the employed neural architectures and the achieved WER on the development and test partition of the corpus.

| Reference                  | Group          | Short Title                  | Manuals | Non-M. | Fullframe | Neural Architecture | WER  |
|----------------------------|----------------|------------------------------|---------|--------|-----------|--------------------|------|
| [Koller et al., 2015]      | RWTH           | CSLR                         | x x x   | x x x  |           |                    | 55.0 |
| [Koller et al., 2016a]     | RWTH/Surrey    | Align Hannosys               | x x x   | x x x  | 2d        |                    | 49.6 |
| [Koller et al., 2016b]     | RWTH/Surrey    | 1 Million Hands              | x x x   | x x x  | 2d        |                    | 47.1 |
| [Koller et al., 2016c]     | RWTH/Surrey    | Deep Sign                    | x       | 2d     |           |                    | 38.3 |
| [Campgoz et al., 2017]     | Surrey/RWTH    | SubUNets                     | x       | 2d     | x         |                    | 40.8 |
| [Cui et al., 2017]         | Tsinghua       | Staged Optimization          | x       | 2d-d   | x         |                    | 39.4 |
| [Koller et al., 2017]      | RWTH           | Re-Align                     | x       | 2d     | x         |                    | 27.1 |
| [Huang et al., 2018b]      | USTC/Here      | Without Segmentation         | x       | 3d     | x         |                    | 38.3 |
| [Wang et al., 2018]        | Hefei Tech/USTC| Temporal Fusion              | x       | 3d-1-d | x         |                    | 37.9 |
| [Pu et al., 2018]          | USTC           | Dilated Convolutions         | x       | 3d-2-d | x         |                    | 38.0 |
| [Koller et al., 2018]      | RWTH/Surrey    | Hybrid CNN-HMMs              | x       | 2d     | x         |                    | 31.6 |
| [Pei et al., 2019]         | Hefei Tech     | Pseudo Supervised Learning   | x       | 3d     | x         |                    | 40.9 |
| [Song et al., 2019]        | Hefei Tech     | Parallel Temp. Encoder       | x       | 3d-2-d | x         |                    | 38.1 |
| [Zhang et al., 2019]       | USTC           | Reinforcement Learning       | x       | 3d     | x         |                    | 38.0 |
| [Cui et al., 2019]         | Tsinghua       | Iterative Training           | x       | 2d-1-d | x         |                    | 37.9 |
| [Pu et al., 2019]          | USTC           | Iterative Alignment Network  | x       | 3d     | x         |                    | 37.1 |
| [Guo et al., 2019]         | Hefei Tech/Huawei| Dense Temporal Conv.       | x       | 3d-1-d | x         |                    | 35.9 |
| [Yang et al., 2019]        | Tencent/HKUST  | SF-Net                       | x       | 3d-2-d | x         |                    | 35.6 |
| [Zhou et al., 2019]        | USTC           | Pseudo Label Decoding        | x       | 3d-1-d | x         |                    | 35.6 |
| [Cui et al., 2019]         | Tsinghua       | Iterative Training           | x       | 2d-1-d | x         |                    | 31.7 |
| [Koller et al., 2019]      | RWTH/Surrey    | Multi-Stream CNN-HMMs        | x x     | 2d     | x         |                    | 26.0 |
| [Cui et al., 2019]         | Tsinghua       | Iterative Training           | x       | 2d-1-d | x         |                    | 23.8 |
| [Cui et al., 2019]         | Tsinghua       | Iterative Training           | x x     | 2d-1-d | x         |                    | 23.1 |
| [Zhou et al., 2020b]       | HKBU/HKU/BJTU/Nvidia| Fully-Inception Networks   | x       | 2d-1   | x         |                    | 31.7 |
| [Adaloglou et al., 2020]   | CERTH/Patras   | Comprehensive Study          | x       | 2d-1-d | x         |                    | 28.9 |
| [Borg and Camilleri, 2020] | Malta          | Phonological Subunits        | x x     | x      | x         |                    | -    |
| [Cheng et al., 2020]       | HKUST/Tencent/Kwai| Fully Conv Networks       | x       | 2d-1-d | x         |                    | 24.6 |
| [Papastratis et al., 2020] | CERTH          | Cross-Modal Alignment       | x       | 2d-1-d | x         |                    | 23.9 |
| [Zhou et al., 2020b]       | USTC           | ST Multi-Cue Network         | x x     | 2d-1-d | x         |                    | 21.1 |
Table 12: The table covers (to the best of our knowledge) all published sign language recognition works until mid 2020 that reported results on the RWTH-Phoenix Weather 2014 [Koller et al., 2015] task. The works are ordered by year and by WER. It allows to compare the type of employed data augmentation and the employed loss. Additionally, it can be seen if a paper performed an iterative training and the achieved performance in WER.

| Reference | Group/Short Title | Data Augmentation | Employed Loss | WER |
|-----------|------------------|-------------------|---------------|-----|
| [Koller et al., 2015] | RWTH CSLR | Crop Framedrop Temporal Scaling Spatial Scaling Noise Flip Brightness Hue Saturation Not Specified | CE | 2 |
| [Koller et al., 2016a] | RWTH/Surrey Align Hamnosys | x x x | CTC | 49.6 48.2 |
| [Koller et al., 2016b] | RWTH/Surrey 1 Million Hands | x x x | KL-Divergence | 47.1 45.1 |
| [Koller et al., 2016c] | RWTH/Surrey Deep Sign | x x x | Squared Error | 38.3 38.8 |
| [Camgoz et al., 2017] | Surrey/RWTH SubUNets | x x | Reinforce | 40.8 40.7 |
| [Cui et al., 2017] | Tsinghua Staged Optimization | x x x | Other | 39.4 38.7 |
| [Koller et al., 2017] | RWTH Re-Align | x x x | | 27.1 26.8 |
| [Huang et al., 2018b] | USTC/Here Without Segmentation | x x | | - 38.3 |
| [Wang et al., 2018] | Hefei Tech/USTC Temporal Fusion | x x | | 37.9 37.8 |
| [Pu et al., 2018] | USTC Dilated Convolutions | x x x | | 38.0 37.3 |
| [Koller et al., 2018] | RWTH/Surrey Hybrid CNN-HMMs | x x x | | 31.6 32.5 |
| [Pei et al., 2019] | Hefei Tech Pseudo Supervised Learning | x x | | 40.9 40.6 |
| [Song et al., 2019] | Hefei Tech Parallel Temp Encoder | x x | | 38.1 38.3 |
| [Zhang et al., 2019] | USTC Reinforcement Learning | x x | | 38.0 38.3 |
| [Cui et al., 2019] | Tsinghua Iterative Training | x x x x | | 37.9 37.6 |
| [Pu et al., 2019] | USTC Iterative Alignment Network | x x x | | 37.1 36.7 |
| [Guo et al., 2019] | Hefei Tech/Huawei Dense Temporal Conv. | x x | | 35.9 36.5 |
| [Yang et al., 2019] | Tencent/HKUST SF-Net | x x | | 35.6 34.9 |
| [Zhou et al., 2019] | USTC Pseudo Label Decoding | x x x x | | 35.6 34.5 |
| [Cui et al., 2019] | Tsinghua Iterative Training | x x x x | | 31.7 31.5 |
| [Koller et al., 2019] | RWTH/Surrey Multi-Stream CNN-HMMs | x x x | | 26.0 26.0 |
| [Cui et al., 2019] | Tsinghua Iterative Training | x x x x | | 23.8 24.4 |
| [Cui et al., 2019] | Tsinghua Iterative Training | x x x x | | 23.1 22.9 |
| [Zhou et al., 2020b] | HKBU/HKU/BJTU/Nvidia Fully-Inception Networks | x x | | 31.7 31.3 |
| [Adaloglou et al., 2020] | CERTH/Patras Comprehensive Study | x x x | | 28.9 29.1 |
| [Borg and Camilleri, 2020] | Malta Phonological Subunits | x x | | - 28.1 |
| [Cheung et al., 2020] | HKUST/Tencent/Kwai Fully Conv Networks | x x | | 24.6 24.6 |
| [Papastratis et al., 2020] | CERTH Cross-Modal Alignment | x x x x x x x | | 23.9 24.0 |
| [Zhou et al., 2020a] | USTC ST Multi-Cue Network | x x x x | | 21.1 20.7 |

4 Conclusion and Outlook

In this paper we shared, to the best of our knowledge, the most extensive quantitative study on the field of sign language recognition covering analysis of over 300 publications from 1983 till 2020. All analyzed studies have been manually tagged with a number of categories. This source data is shared in the supplemental materials of this work. Among others, we present following findings in this meta study:
While many more studies are published on isolated than on continuous sign language recognition, the majority only covers small vocabulary tasks.

After 2005 there was a paradigm shift in the community abandoning intrusive capturing methods and embracing non-intrusive methods.

Deep learning led the community towards the predominant use of global feature representations that are based on fullframe inputs. Those are particularly more common for larger vocabulary tasks.

Non-manual parameters are still very rare in sign language recognition systems, despite their known importance for sign languages [Pfau and Quer, 2010]. No sign recognition work has included eye gaze or blinks yet. Despite being the second most frequently researched sign language, research studies for CSL have hardly incorporated non-manual parameters. DGS is currently the only sign language where non-manuals have been successfully incorporated considering tasks with a vocabulary of at least 200 signs.

RWTH-PHOENIX-Weather with a vocabulary of 1080 signs represents the only resource for large vocabulary continuous sign language world wide.

Moreover, we also presented the first meta analysis covering all known works that compared themselves on the RWTH-PHOENIX-Weather benchmark data set. Besides many details, we note that the best performing systems typically adopt an iterative training style to overcome vanishing gradients in deep CNN architectures followed by BLSTMs. We also find that 2D convolutions followed by 1D convolutions on fullframe inputs can be encountered in most state-of-the-art systems. Surprisingly, we see that in many studies data augmentation is not carefully described and also an ablation study that details the effect of various augmentation methods is left for coming research.

We hope that in the future more works will include and be led by Deaf researchers, which seems the only viable way to continue on this accelerated path the field is currently on. More efforts are needed to create real-life large vocabulary continuous sign language tasks that should be made publicly accessible with well defined train, development and test partitions.

Acronyms

- ArgentSL  Argentinian sign language.
- ArSL  Arabic sign language.
- ASL  American sign language.
- Auslan  Australian sign language.
- BLSTM  bi-directional long short-term memory.
- BSL  British sign language.
- CE  cross-entropy.
- CNN  convolutional neural network.
- CSL  Chinese sign language.
- CTC  connectionist temporal classification.
- CzSL  Czech sign language.
- DGS  German Sign Language (Deutsche Gebärdensprache).
- DSGS  Swiss German sign language / Deutschschweizerische Gebärdensprache.
- EM  expectation maximization.
- FlemishSL  Flemish sign language.
- GMM  Gaussian mixture model.
- GSL  Greek sign language.
- HKSL  Hong Kong sign language.
HMM hidden Markov model.

IndianSL Indian sign language.
IndoSL Indonesian sign language.
IrishSL Irish sign language.
ISL Irish Sign Language.

JSL Japanese sign language.

KL Kullback-Leibler.
K-RSL Kazakh-Russian sign language.
KSL Korean sign language.
KurdishSL Kurdish sign language.

Libras Brazilian sign language / Lingua Brasileira de sinais.
LIS Italian sign language / Lingua Italiana dei segni.
LSE Spanish sign language / Lengua de signos española.

MalaySL Malaysian sign language.
MexicanSL Mexican sign language.

NGT Dutch sign language / Nederlandse Gebaren Taal.

PersianSL Persian sign language.
PolishSL Polish sign language.

RussianSL Russian sign language.

TaiwanSL Taiwanese sign language.
TamisSL Tamil sign language.
TSL Turkish sign language.

WER word error rate.

**Glossary**

**Continuous** Specifies the nature of sign language data sets that encompass long phrases or full sentences as opposed to single, isolated signs.

**Intrusive** Specifies the capturing of sign language data sets that requires the signer to wear specific measuring devices such as gloves or trackers.

**Isolated** Specifies the nature of sign language data sets that only encompass single signs as opposed to long phrases or full sentences.

**Non-Intrusive** Specifies the capturing of sign language data sets that does not require the signer to wear specific measuring devices such as gloves or trackers.

**Parameter** Each sign consists of a set of parameters. We distinguish manual and non-manual parameters. Hand shape, orientation, location and movement are the four manual parameter, while non-manual parameters include head and body posture, facial expression, eye gaze and mouth patterns.

**Vocabulary** The set of unique signs (or words) that occur in a dataset. Typically, statistical recognition systems are limited to recognize a specific set of words: the vocabulary.
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Supplemental Material

Table S1: The table covers most published works up until early 2020 in the field of sign language recognition that report results on a sign language recognition task or introduce a related corpus. Each work is presented with a number of key properties. ‘Vocabulary’ refers to the unique signs in a data set. ‘Signer’ represents the joint number of signers in training and test sets. ‘Isolated’ and ‘Continuous’ refer to the nature of recorded sign language. ‘Input Data’ specifies the employed capturing method for the input (‘RGB’ are colored images, ‘Depth’ is depth information, ‘Colored’ or ‘Electronic Gloves’ represent intrusive gloves that ease the extraction of hand related features, ‘Mocap’ means motion capture to accurately track the body parts). The three columns ‘Manuals’, ‘Non-Manuals’ and ‘Fullframe’ characterize the employed features used for modeling. ‘Benchmark Dataset’ specifies if the employed dataset is a known benchmark dataset, providing comparable tasks.

| Reference | Year | Vocabulary | Signer | Isolated | Continuous | Input Data | Manuals | Non-Manuals | Fullframe | Benchmark Dataset | Language |
|-----------|------|------------|--------|----------|------------|------------|---------|-------------|-----------|------------------|----------|
| Grimes, 1983 | 1983 | 26 | x | x | x | x | x | x | x | ASL |
| Tamura and Kawasaki, 1988 | 1988 | 10 | x | x | x | x | x | x | x | JSL |
| Murakami and Taguchi, 1991 | 1991 | 10 | 1 | x | x | x | x | x | x | JSL |
| Charayaphan and Marble, 1992 | 1992 | 31 | 1 | x | x | x | x | x | x | ASL |
| Fels and Hinton, 1993 | 1993 | 203 | x | x | x | x | x | x | x | ASL |
| Kadous and Taylor, 1995 | 1995 | 95 | 5 | x | x | x | x | x | x | Auslan |
| Liang and Ouhyoung, 1995 | 1995 | 26 | x | x | x | x | x | x | x | ASL |
| Waldron and Kim, 1995 | 1995 | 14 | x | x | x | x | x | x | x | ASL |
| Starner and Pentland, 1995 | 1995 | 40 | x | x | x | x | x | x | x | ASL |
| Ouhyoung and Liang, 1996 | 1996 | 71 | x | x | x | x | x | x | x | TaiwanSL |
| Kim et al., 1996 | 1996 | 25 | x | x | x | x | x | x | x | KSL |
| Kadous, 1996 | 1996 | 95 | 5 | x | x | x | x | x | x | Auslan |
| Vamplew and Adams, 1996 | 1996 | 52 | 7 | x | x | x | x | x | x | Auslan |
| Assan and Grobel, 1997 | 1997 | 26 | 1 | x | x | x | x | x | x | NGT |
| Assan and Grobel, 1997 | 1997 | 262 | 2 | x | x | x | x | x | x | NGT |
| Matsuo et al., 1997 | 1997 | 38 | 1 | x | x | x | x | x | x | JSL |
| Lee et al., 1997 | 1997 | 131 | x | x | x | x | x | x | x | KSL |
| Vogler and Metaxas, 1997 | 1997 | 53 | x | x | x | x | x | x | x | ASL |
| Kobayashi and Haruyama, 1997 | 1997 | 6 | 20 | x | x | x | x | x | x | JSL |
| Huang and Huang, 1998 | 1998 | 15 | x | x | x | x | x | x | x | TaiwanSL |
| Liang and Ouhyoung, 1998 | 1998 | 250 | x | x | x | x | x | x | x | TaiwanSL |
| Starner et al., 1998 | 1998 | 40 | x | x | x | x | x | x | x | ASL |
| Vogler and Metaxas, 1999a | 1999 | 22 | x | x | x | x | x | x | x | ASL |
| Vogler and Metaxas, 1999b | 1999 | 22 | x | x | x | x | x | x | x | ASL |
| Bauer et al., 1999 | 1999 | 100 | 1 | x | x | x | x | x | x | DGS |
| Imagawa et al., 2000 | 2000 | 33 | 6 | x | x | x | x | x | x | JSL |
| Ma et al., 2000 | 2000 | 5177 | x | x | x | x | x | x | x | CSL |
| Wang and Gao, 2000 | 2000 | 274 | 1 | x | x | x | x | x | x | CSL |

Continued on next page
| Reference                        | Year | Vocabulary | Signer | Isolated | Continuous | Input Data | Manuals | Non-Manuals | Fullframe | Benchmark | Dataset | Language |
|---------------------------------|------|------------|--------|----------|------------|------------|---------|-------------|-----------|-----------|---------|----------|
| [Holden and Owens, 2000]        | 2000 | 22         | 1      | x         | x          | x          | x       |             |           |           |         | Auslan   |
| [Cui and Weng, 2000]            | 2000 | 28         | x      | x         |             | x          | x       |             |           |           |         | ASL      |
| [Sagawa and Takeuchi, 2000]     | 2000 | 17         | x      | x         |             |             | x       |             |           |           |         | JSL      |
| [Su et al., 2001]               | 2001 | 90         | 2      | x         |             | x          | x       |             |           |           |         | TaiwanSL |
| [Wang et al., 2001]             | 2001 | 5100       | 1      | x         | x           | x          | x       |             |           |           |         | CSL      |
| [Wu and Gao, 2001]              | 2001 | 30         | x      | x         |             |             | x       |             |           |           |         | CSL      |
| [Fang et al., 2001a]            | 2001 | 208        | 7      | x         |             | x          | x       |             | x          |           |         | CSL      |
| [Fang et al., 2001b]            | 2001 | 208        | 7      | x         |             |             | x       |             | x          |           |         | CSL      |
| [Vogler and Metaxas, 2001]      | 2001 | 22         | x      | x         |             |             |         |             |             |           |         | ASL      |
| [Bauer and Kraiss, 2002a]       | 2002 | 12         | x      | x         |             |             |         |             |             |           |         | CSL      |
| [Tanibata et al., 2002]         | 2002 | 65         | 1      | x         |             |             | x       |             |             |           |         | JSL      |
| [Deng and Tsui, 2002]           | 2002 | 192        | 2      | x         |             | x          | x       |             |             |           |         | ASL      |
| [Bauer and Kraiss, 2002b]       | 2002 | 100        | 1      | x         |             | x          | x       |             |             |           |         | CSL      |
| [Yang et al., 2002]             | 2002 | 50         | 1      | x         |             |             | x       |             |             |           |         | CSL      |
| [Yuan et al., 2002]             | 2002 | 40         | x      | x         |             |             | x       |             |             |           |         | ASL      |
| [Wang et al., 2002]             | 2002 | 5119       | 1      | x         | x           |             | x       |             | x          |           |         | CSL      |
| [Wang et al., 2002]             | 2002 | 5119       | 1      | x         |             |             | x       |             | x          |           |         | CSL      |
| [Brashear et al., 2003]         | 2003 | 5          | 1      | x         |             | x          | x       |             |             |           |         | ASL      |
| [Gao et al., 2004b]             | 2004 | 5113       | 6      | x         |             |             | x       |             |             |           |         | CSL      |
| [Windridge and Bowden, 2004]    | 2004 | 115        | 1      | x         |             |             | x       |             |             |           |         | BSL      |
| [Kadir et al., 2004]            | 2004 | 164        | 1      | x         |             |             | x       |             |             |           |         | BSL      |
| [Hernandez-Regollar et al., 2004]| 2004 | 176        | 17     | x         |             |             | x       |             |             |           |         | ASL      |
| [Bowden et al., 2004]           | 2004 | 43         | 1      | x         |             |             | x       |             |             |           |         | BSL      |
| [Vogler and Metaxas, 2004]      | 2004 | 43         | 1      | x         |             |             | x       |             |             |           |         | ASL      |
| [McGuire et al., 2004]          | 2004 | 141        | 1      | x         |             |             | x       |             |             |           |         | ASL      |
| [Gao et al., 2004a]             | 2004 | 5113       | 6      | x         |             |             | x       |             |             |           |         | CSL      |
| [Gao et al., 2004a]             | 2004 | 5113       | 6      | x         |             |             | x       |             |             |           |         | CSL      |
| [Nayak et al., 2005]            | 2005 | 18         | 1      | x         |             |             | x       |             |             |           |         | ASL      |
| [Zahedi et al., 2005a]          | 2005 | 10         | 3      | x         |             |             | x       |             |             |           |         | ASL      |
| [Oz and Leu, 2005]              | 2005 | 60         | 6      | x         |             |             | x       |             |             |           |         | ASL      |
| [Zahedi et al., 2005b]          | 2005 | 50         | 3      | x         |             |             | x       |             |             |           |         | ASL      |
| [Kapuscinski and Wysocki, 2005] | 2005 | 101        | 2      | x         |             |             | x       |             |             |           |         | PolishSL |
| [Zahedi et al., 2006]           | 2006 | 103        | 3      | x         |             |             | x       |             | x          |           |         | BU-104   |
| [Rybch, 2006]                   | 2006 | 103        | 3      | x         |             |             | x       |             | x          |           |         | BU-104   |
| [Wang et al., 2006a]            | 2006 | 2435       | 1      | x         |             |             | x       |             | x          |           |         | CSL      |
| [Farhadi and Forsyth, 2006]     | 2006 | 21         | x      | x         |             |             | x       |             | x          |           |         | ASL      |
| [Brashear et al., 2006]         | 2006 | 22         | 5      | x         |             |             | x       |             | x          |           |         | ASL      |
| [von Agris et al., 2006]        | 2006 | 153        | 4      | x         |             |             | x       |             |             |           |         | BSL      |
| [Fujimura and Xia Liu, 2006]    | 2006 | 100        | x      | x         |             |             | x       |             |             |           |         | JSL      |
| [Wang et al., 2006b]            | 2006 | 26         | x      | x         |             |             | x       |             |             |           |         | ASL      |
| [Fang et al., 2007]             | 2007 | 5113       | 2      | x         |             |             | x       |             |             |           |         | CSL      |
| [Zahedi, 2007]                  | 2007 | 102        | 3      | x         |             |             | x       |             |             |           |         | BU-104   |
| [Zahedi, 2007]                  | 2007 | 10         | 2      | x         |             |             | x       |             |             |           |         | ASL      |

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Table S1 – continued from previous page

| Reference | Year | Vocabulary | Signer | Isolated | Continuous | Input Data | Manuals | Non-Manuals | Fullframe | Benchmark | Dataset | Language |
|-----------|------|------------|--------|----------|------------|------------|---------|-------------|-----------|-----------|---------|----------|
| [Zahedi, 2007] | 2007 | 50 | 3 | x | x | x x x | x | BU-50 | | ASL |
| [Stein et al., 2007] | 2007 | 103 | 3 | x | x | | x | BU-104 | | ASL |
| [von Agris and Kraiss, 2007] | 2007 | 450 | 5 | x | x | | | | Signum | DGS |
| [Dreuw et al., 2007] | 2007 | 103 | 3 | x | x | | | | | ASL |
| [Mohandes et al., 2007] | 2007 | 300 | 1 | x | x | | | | | ArSL |
| [Infantino et al., 2007] | 2007 | 40 | x | x | x | | | | | LIS |
| [Infantino et al., 2007] | 2007 | 40 | x | x | x | | | | | LIS |
| [Shanableh et al., 2007] | 2007 | 23 | 3 | x | x | | | | | ArSL |
| [Cooper and Bowden, 2007b] | 2007 | 5 | 9 | x | x | | | | | BSL |
| [Wang et al., 2007] | 2007 | 100 | 1 | x | x | | | | | CSL |
| [Cooper and Bowden, 2007a] | 2007 | 164 | 1 | x | x | | | | | BSL |
| [Yang et al., 2007] | 2007 | 39 | | x | | | | | | ASL |
| [von Agris et al., 2008b] | 2008 | 152 | x | x | x | x x x | | BU-104 | | DGS |
| [Forster, 2008] | 2008 | 103 | 3 | x | x | | | | | ASL |
| [von Agris et al., 2008a] | 2008 | 450 | 25 | x | x | x x x | | | | Signum |
| [Maebatake et al., 2008] | 2008 | 183 | 4 | x | x | | | | | JSL |
| [Paulraj et al., 2008] | 2008 | 32 | x | x | x | | | | | MalaySL |
| [Kim et al., 2008] | 2008 | 7 | 8 | x | x | x | | | | DGS |
| [Marraqa and Abu-Zaiteer, 2008] | 2008 | 30 | 2 | x | x | x | | | | ArSL |
| [Aran and Akarun, 2008] | 2008 | 19 | 8 | x | x | x x x | x | | | TSL |
| [Trmal et al., 2008] | 2008 | 25 | 20 | x | x | x | | | | CzSL |
| [Lichtenauer et al., 2008] | 2008 | 120 | 75 | x | x | | | | | NGT |
| [Derpanis et al., 2008] | 2008 | 148 | 3 | x | x | | | | | ASL |
| [Zahedi et al., 2008] | 2008 | 102 | 3 | x | x | x x x | | | | ASL |
| [Athitos et al., 2008] | 2008 | 108 | 2 | x | x | x | | | | ASL |
| [Dreuw and Ney, 2008] | 2008 | 104 | 3 | x | x | x | | | | ASL |
| [Dreuw, 2008] | 2008 | 103 | 3 | x | x | x x x | | | | ASL |
| [Kelly et al., 2009b] | 2009 | 8 | 1 | x | x | x | | | | IrishSL |
| [Kelly et al., 2009a] | 2009 | 8 | 1 | x | x | x | | | | IrishSL |
| [Yin et al., 2009] | 2009 | 141 | 1 | x | x | x x | | | | ASL |
| [Theodorakis et al., 2009] | 2009 | 93 | 1 | x | x | x | | | | GSL |
| [Lichtenauer et al., 2009] | 2009 | 120 | 75 | x | x | x | | | | NGT |
| [Hrůz et al., 2009] | 2009 | 50 | 1 | x | x | x x x | | | | CzSL |
| [Ding and Martinez, 2009] | 2009 | 38 | 10 | x | x | x x x | | | | ASL |
| [Dreuw et al., 2009] | 2009 | 103 | 3 | x | x | x x x | | | | ASL |
| [Dias et al., 2009] | 2009 | 15 | 4 | x | x | | | | | Libras |
| [Buehler et al., 2009] | 2009 | 210 | 3 | x | x | x x x | | | | BSL |
| [Liwicki and Everingham, 2009] | 2009 | 100 | x | x | x | | | | | BSL |
| [Yang et al., 2009] | 2009 | 48 | 1 | x | x | x x x | | | | ASL |
| [Cooper and Bowden, 2009] | 2009 | 23 | 1 | x | x | x | | | | BSL |
| [Han et al., 2009] | 2009 | 10 | 1 | x | x | x | | | | IrishSL |
| [Han et al., 2009] | 2009 | 20 | 1 | x | x | x | | | | BSL |

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Table S1 – continued from previous page

| Reference                        | Year | Vocabulary | Signer | Isolated | Continuous | Input Data | Manuals | Non-Manuals | Fullframe | Benchmark | Language   |
|---------------------------------|------|------------|--------|----------|------------|------------|---------|-------------|-----------|-----------|------------|
| [Awad et al., 2009]             | 2009 | 20         | 1 x    | x        | x x x x    |            |         |             |           |           | BSL        |
| [Aran et al., 2009a]            | 2009 | 19         | 8 x    | x        | x x x x x  |            |         |             |           |           | TSL        |
| [Santemiz et al., 2009]         | 2009 | 40         | 1 x x  | x        | x x x x    |            |         |             |           |           | TSL        |
| [Aran et al., 2009b]            | 2009 | 19         | 8 x    | x        | x x x x x  |            |         |             |           |           | TSL        |
| [Oszust and Wysocki, 2010]      | 2010 | 10         | x x    | x        | x           |            |         |             |           |           | PolishSL   |
| [Paulraj et al., 2010]          | 2010 | 9          | x x x  |          |             |            |         |             |           |           | MalaySL    |
| [Toiba et al., 2010]            | 2010 | 28         | x x    |          |             |            |         |             |           |           | ArSL       |
| [Aran and Akarun, 2010]         | 2010 | 19         | 8 x    | x x x x  |            |            |         |             |           |           | TSL        |
| [Buehler et al., 2010]          | 2010 | 210        | 3 x    | x x x x  |            |            |         |             |           |           | BSL        |
| [Zafrulla et al., 2010]         | 2010 | 19         | 5 x x  | x x x x  |            |            |         |             |           |           | ASL        |
| [Kong and Ranganath, 2010]      | 2010 | 33         | 1 x x  |          | x x x x    |            |         |             |           |           | ASL        |
| [Cooper, 2010]                  | 2010 | 164        | 1 x x  | x x x x  |            |            |         |             |           |           | BSL        |
| [Cooper, 2010]                  | 2010 | 5          | 9 x x  |          |             |            |         |             |           |           | BSL        |
| [Cooper and Bowden, 2010]       | 2010 | 164        | 1 x x  |          |             |            |         |             |           |           | BSL        |
| [Assaleh et al., 2010]          | 2010 | 80         | 1 x x  |          |             |            |         |             |           |           | ArSL       |
| [Assaleh et al., 2010]          | 2010 | 23         | 3 x    |          |             |            |         |             |           |           | ArSL       |
| [Zhou et al., 2010]             | 2010 | 256        | 6 x    | x x x x  | x           |            |         |             |           |           | CSL        |
| [Wang et al., 2010]             | 2010 | 1113       | 2 x x  |          |             |            |         |             |           |           | ASL        |
| [Athitos et al., 2010]          | 2010 | 921        | 3 x    | x x       | x           |            |         |             |           |           | ASL        |
| [Theodorakis et al., 2010]      | 2010 | 20         | 1 x x  | x x x x  | x           |            |         |             |           |           | ASL        |
| [Yang et al., 2010]             | 2010 | 39         | 1 x x  |          |             |            |         |             |           |           | ASL        |
| [Yang et al., 2010]             | 2010 | 40         | 1 x x  |          |             |            |         |             |           |           | ASL        |
| [Yang et al., 2010]             | 2010 | 99         | 3 x x  |          |             |            |         |             |           |           | ASL        |
| [Pitsikalis et al., 2010]       | 2010 | 50         | 1 x x  |          |             |            |         |             |           |           | ASL        |
| [Kong, 2011]                    | 2011 | 107        | 8 x x  | x x x x x | x x x      |            |         |             |           |           | ASL        |
| [Yang and Lee, 2011]            | 2011 | 24         | 1 x x  | x x x x  | x x x x x  |            |         |             |           |           | ASL        |
| [Cooper et al., 2011]           | 2011 | 984        | 1 x x  | x x x x  | x           |            |         |             |           |           | GSL        |
| [Zafrulla et al., 2011]         | 2011 | 19         | 7 x x  | x x x x  |            |            |         |             |           |           | ASL        |
| [Sarkar et al., 2011]           | 2011 | 65         | x x x  | x x       |            |            |         |             |           |           | ASL        |
| [Sarkar et al., 2011]           | 2011 | 147        | 10 x   | x x x x  | x           |            |         |             |           |           | ASL        |
| [Mekala et al., 2011]           | 2011 | 26         | x x    | x         |            |            |         |             |           |           | ASL        |
| [Kosmidou et al., 2011]         | 2011 | 61         | 9 x    |          | x x x x x  |            |         |             |           |           | GSL        |
| [Kelly et al., 2011]            | 2011 | 8          | 2 x x  | x         |            |            |         |             |           |           | IrishSL    |
| [Uebersax et al., 2011]         | 2011 | 26         | 7 x x  |          | x x x x    |            |         |             |           |           | ASL        |
| [Rekha et al., 2011]            | 2011 | 10         | x x x  |          |             |            |         |             |           |           | ASL        |
| [Pugeault and Bowden, 2011]     | 2011 | 24         | 4 x x  | x x x x  |            |            |         |             |           |           | ASL        |
| [Barczak et al., 2011]          | 2011 | 36         | 5 x x  |          |             |            |         |             |           |           | ASL        |
| [Thangali et al., 2011]         | 2011 | 82         | 2 x x  |          |             |            |         |             |           |           | ASL        |
| [Zaki and Shaheen, 2011]        | 2011 | 30         | 3 x x  | x x x x  |            |            |         |             |           |           | ASL        |
| [Shanableh and Assaleh, 2011]   | 2011 | 23         | 3 x x  | x         |            |            |         |             |           |           | ArSL       |
| [Pitsikalis et al., 2011]       | 2011 | 961        | 1 x x  | x x x x  | x           |            |         |             |           |           | GSL        |
| [Ong et al., 2012]              | 2012 | 40         | 14 x x  | x x x x  | x           |            |         |             |           |           | DGS        |
| [Ong et al., 2012]              | 2012 | 982        | 1 x x x | x x x x   | x           |            |         |             |           |           | GSL        |
| [Cooper et al., 2012]           | 2012 | 164        | 1 x x  | x x x x  | x           |            |         |             |           |           | BSL        |
Quantitative Survey of the State of the Art in Sign Language Recognition

| Reference                        | Year | Vocabulary | Signer | Isolated | Continuous | Movements | Manual | Non-Manual | Fullframe | Benchmark | Dataset | Language  |
|----------------------------------|------|------------|--------|----------|------------|-----------|--------|------------|-----------|-----------|---------|-----------|
| Cooper et al., 2012              | 2012 | 20 6 x     | x x    | x x      | x x x      | x x x     | x      | x          | x         | GSL       |         |           |
| Cooper et al., 2012              | 2012 | 40 15 x    | x x    | x x      | x x x      | x         | x      | x          | x         | DGS       |         |           |
| Cooper et al., 2012              | 2012 | 984 1 x    | x x    | x x      | x x x      | x         | x      | x          | x         | GSL       |         |           |
| Forster et al., 2012             | 2012 | 266 1 x    |        |          |            |           | x      | x          | x         | DGS       |         |           |
| Forster et al., 2012             | 2012 | 911 7 x    |        |          |            |           | x      | x          | x         | DGS       |         |           |
| Oberdörfer et al., 2012          | 2012 | 455 1 x    | x x    |          | x x x      | x x x     | x      | x          | Signum    | DGS       |         |           |
| Oberdörfer et al., 2012          | 2012 | 455 25 x   | x x    |          | x x x      | x x x     | x      | x          | Signum    | DGS       |         |           |
| Gweth et al., 2012               | 2012 | 455 1 x    |        |          |            |           | x      | x          | Signum    | DGS       |         |           |
| Kishore and Kumar, 2012          | 2012 | 80 10 x    | x x    |          |            |           | x      | x          | x         | IndianSL  |         |           |
| Mohandes et al., 2012            | 2012 | 300 3 x    |        | x        | x x x      | x x x     | x      | x          | x         | AsSL      |         |           |
| Lang et al., 2012                | 2012 | 25 x x x   |        |          |            |           | x      | x          | x         | DGS       |         |           |
| Kindiroglu et al., 2012          | 2012 | 88 11 x    |        | x        |            |           | x      | x          | x         | CzSL      |         |           |
| Caridakis et al., 2012           | 2012 | 118 3 x    | x x    |          | x x x      | x x x     | x      | x          | GSL       |         |         |           |
| Dreuw, 2012                      | 2012 | 103 3 x    | x x    |          | x x x      | x x x     | x      | x          | ASL       |         |         |           |
| Fagianis et al., 2012            | 2012 | 147 10 x   |        |          |            |           | x      | x          | LIS       |         |         |           |
| Sun et al., 2013b                 | 2013 | 73 9 x x   | x x    |          | x x x      | x x x     | x      | x          | ASL       |         |         |           |
| Sun et al., 2013a                 | 2013 | 73 9 x x   | x x    |          | x x x      | x x x     | x      | x          | ASL       |         |         |           |
| Oszust and Wysocki, 2013b         | 2013 | 30 1 x x   | x x    | x x x    |            | x x x     | x      | x          | PolishSL  |         |         |           |
| Oszust and Wysocki, 2013a         | 2013 | 30 1 x x   | x x    | x x x    |            | x x x     | x      | x          | PolishSL  |         |         |           |
| Forster et al., 2013b             | 2013 | 266 1 x    | x x    |          | x x x      | x x x     | x      | x          | DGS       |         |         | RussianSL |
| Forster et al., 2013b             | 2013 | 455 1 x    | x x    |          | x x x      | x x x     | x      | x          | Signum    | DGS       |         |           |
| Forster et al., 2013b             | 2013 | 455 25 x   | x x    |          | x x x      | x x x     | x      | x          | Signum    | DGS       |         |           |
| Forster et al., 2013a             | 2013 | 266 1 x    | x x    |          | x x x      | x x x     | x      | x          | DGS       |         |         | RussianSL |
| Forster et al., 2013a             | 2013 | 455 1 x    | x x    |          | x x x      | x x x     | x      | x          | Signum    | DGS       |         |           |
| Mohandes and Deriche, 2013        | 2013 | 100 1 x    |        |          |            | x x x     | x      | x          | AsSL      |         |         |           |
| Chai et al., 2013                 | 2013 | 239 x x x  |        |          |            |           | x      | x          | CSL       |         |         |           |
| Agarwal and Thakur, 2013          | 2013 | 10 x x x   |        |          |            |           | x      | x          | CSL       |         |         |           |
| Mohandes, 2013                    | 2013 | 100 2 x    |        | x x      | x x x x    | x         | x      | x          | ArSL      |         |         |           |
| Kuznetsova et al., 2013           | 2013 | 24 3 x x   | x x    |          |           |           | x      | x          | CSL       |         |         |           |
| Elons et al., 2013                | 2013 | 50 x x x   |        |          |            |           | x      | x          | AsSL      |         |         |           |
| Yang and Lee, 2013                | 2013 | 24 x x     | x x    |          | x         |           | x      | x          | CSL       |         |         |           |
| Roussos et al., 2013              | 2013 | 100 2 x    | x x    |          | x x x     |           | x      | x          | GSL       |         |         |           |
| Han et al., 2013                  | 2013 | 20 2 x x   | x x    |          | x x x     |           | x      | x          | BSL       |         |         |           |
| Zhang et al., 2014                | 2014 | 34 3 x x   | x      |          |            |           | x      | x          | CSL       |         |         |           |
| Zhang et al., 2014                | 2014 | 34 5 x x x |        |          |            |           | x      | x          | CSL       |         |         |           |
| Ong et al., 2014                  | 2014 | 48 3 x x   |        |          |            |           | x      | x          | CSL       |         |         |           |
| Ong et al., 2014                  | 2014 | 40 14 x x   | x x    |          |            |           | x      | x          | DGS       |         |         |           |
| Ong et al., 2014                  | 2014 | 981 1 x    |        |          | x x x x    | x         | x      | x          | GSL       |         |         |           |
| Chai et al., 2014                 | 2014 | 2000 8 x   | x x    |          | x x        |           | x      | x          | Devisign-L | CSL      |         |           |
| Chai et al., 2014                 | 2014 | 36 8 x x   | x x    |          |            |           | x      | x          | Devisign-G | CSL      |         |           |
| Chai et al., 2014                 | 2014 | 500 8 x x  | x x    |          | x x        |           | x      | x          | Devisign-D | CSL      |         |           |
| Kong and Ranganath, 2014          | 2014 | 107 8 x    |        | x x x x   | x x x x    | x        | x      | x          | ASL       |         |         |           |

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| Reference | Year | Vocabulary | Signer | Isolated | Continuous | Input Data | Manuals | Non-Manuals | Fullframe | Benchmark Dataset | Language |
|-----------|------|------------|--------|----------|------------|-----------|---------|------------|-----------|------------------|----------|
| [Forster et al., 2014] | 2014 | 1558 | 9 | x | x | DGS |
| [Forster et al., 2014] | 2014 | 911 | 7 | x | x | DGS |
| [Mohandes et al., 2014] | 2014 | 38 | 10 | x | x | x | ArSL |
| [Igari and Fukumura, 2014] | 2014 | 80 | 3 | x | x | x | JSL |
| [Theodorakis et al., 2014] | 2014 | 1046 | 2 | x | x | x | GSL |
| [Theodorakis et al., 2014] | 2014 | 94 | 1 | x | x | x | ASL |
| [Theodorakis et al., 2014] | 2014 | 97 | 2 | x | x | x | ASL |
| [Almeida et al., 2014] | 2014 | 34 | 1 | x | x | x | x | Libras |
| [Geng et al., 2014] | 2014 | 8 | 8 | x | x | x | CSL |
| [Huang et al., 2015] | 2015 | 25 | 9 | x | x | x | x | x | CSL |
| [Yin et al., 2015] | 2015 | 1000 | 7 | x | x | x | x | x | CSL |
| [Koller et al., 2015] | 2015 | 1080 | 9 | x | x | x | x x x | Phoenix14 | DGS |
| [Zhang et al., 2015] | 2015 | 30 | 5 | x | x | x | x | x | CSL |
| [Zhang et al., 2015] | 2015 | 30 | 5 | x | x | x | x | x | CSL |
| [Yin et al., 2015] | 2015 | 1000 | 7 | x | x | x | x | x | CSL |
| [Yin et al., 2015] | 2015 | 370 | 1 | x | x | x | x | x | CSL |
| [Wang et al., 2015] | 2015 | 1000 | 1 | x | x | x | x | x | CSL |
| [Wang et al., 2015] | 2015 | 1000 | 7 | x | x | x | x | x | CSL |
| [Neto et al., 2015] | 2015 | 18 | x | x | x | | | | Libras |
| [Chai et al., 2015] | 2015 | 1000 | 1 | x | x | x | x | x | CSL |
| [Chai et al., 2015] | 2015 | 1000 | 7 | x | x | x | x | x | CSL |
| [Nagendraswamy et al., 2015] | 2015 | 147 | 10 | x | x | | x x x | x | LIS |
| [Tubaiz et al., 2015] | 2015 | 80 | 1 | x | | x x x | x | | ArSL |
| [Cheng et al., 2015] | 2015 | 223 | 5 | x | | x | | x | CSL |
| [Zhou et al., 2015] | 2015 | 20 | 7 | x | | x | | x | CSL |
| [Koller et al., 2016a] | 2016 | 1080 | 9 | x | x | x | Phoenix14 | DGS |
| [Koller et al., 2016c] | 2016 | 455 | 1 | x | x | | Signum | DGS |
| [Koller et al., 2016a] | 2016 | 1080 | 9 | x | x | x | x x x | x | Phoenix14 | DGS |
| [Koller et al., 2016b] | 2016 | 1080 | 9 | x | x | x | x x x | x | Phoenix14 | DGS |
| [Koller et al., 2016b] | 2016 | 455 | 1 | x | x | | x x x | x | Signum | DGS |
| [Zheng and Liang, 2016] | 2016 | 36 | 8 | x | x | | x | | Devisign-G | CSL |
| [Yin et al., 2016] | 2016 | 1000 | 1 | x | x | x | x | | x | CSL |
| [Yin et al., 2016] | 2016 | 1000 | 7 | x | x | x | x | x | CSL |
| [Yin et al., 2016] | 2016 | 2000 | 8 | x | x | x | x | Devisign-L | CSL |
| [Zhang et al., 2016b] | 2016 | 100 | 1 | x | x | x | x | x | CSL |
| [Zhang et al., 2016b] | 2016 | 500 | 1 | x | x | x | x | x | CSL |
| [Zhang et al., 2016a] | 2016 | 99 | 5 | x | x | x | x x x | x | ASL |
| [Pigou et al., 2016a] | 2016 | 500 | 50 | x | x | x | x | x | CSL |
| [Liu et al., 2016] | 2016 | 500 | 50 | x | x | x | x | | CSL |
| [Liu et al., 2016] | 2016 | 100 | 50 | x | x | x | x | | CSL |
| [Lim et al., 2016] | 2016 | 50 | 3 | x | x | | | | BU-50 | ASL |
| [Nagendraswamy and Kumar, 2016] | 2016 | 26 | 4 | x | x | | x | | IndiSL |
| [Pigou et al., 2016] | 2016 | 10 | 53 | x | x | | x | | FlemishSL |
| [Pigou et al., 2016] | 2016 | 100 | 78 | x | x | | x | | NGT |
| [Camgöz et al., 2016] | 2016 | 33 | 6 | x | x | x | x | x | TSL |
Table S1 – continued from previous page

| Reference | Year | Vocabulary | Signer | Isolated | Continuous | Input Data | Manuals | Non-Manuals | Fullframe | Benchmark | Dataset | Language |
|-----------|------|------------|--------|----------|------------|------------|---------|-------------|-----------|-----------|---------|----------|
| [Yang et al., 2016] | 2016 | 21 | 2 | x | x | x | x | x | CSL |
| [Yang et al., 2016] | 2016 | 21 | 8 | x | x | x | x | x | CSL |
| [Ronchetti et al., 2016] | 2016 | 16 | 100 | 14 | x | x | x | x | LSA16 | ArgentSL |
| [Pu et al., 2016b] | 2016 | 110 | 5 | x | x | x | x | x | CSL |
| [Li et al., 2016] | 2016 | 510 | 5 | x | x | x | x | x | CSL |
| [Wang et al., 2016] | 2016 | 1000 | 1 | x | x | x | x | x | CSL |
| [Wang et al., 2016] | 2016 | 370 | 1 | x | x | x | x | x | CSL |
| [Camgoz et al., 2016] | 2016 | 855 | 10 | x | x | x | x | x | CSL |
| [Cui et al., 2017] | 2017 | 1080 | 9 | x | x | x | x | x | Philadelphia | DGS |
| [Camgoz et al., 2017] | 2017 | 1080 | 9 | x | x | x | x | x | Philadelphia | DGS |
| [Koller et al., 2017] | 2017 | 1080 | 9 | x | x | x | x | x | Philadelphia | DGS |
| [Koller et al., 2017] | 2017 | 455 | 1 | x | x | x | x | x | Signum | DGS |
| [Li et al., 2017] | 2017 | 80 | 10 | x | x | x | x | x | CSL |
| [Guo et al., 2017] | 2017 | 370 | 5 | x | x | x | x | x | CSL |
| [García-Bautista et al., 2017] | 2017 | 20 | 35 | x | x | x | x | x | MexicanSL |
| [Pigou et al., 2017] | 2017 | 10 | 53 | x | x | x | x | x | FlemishSL |
| [Pigou et al., 2017] | 2017 | 10 | 78 | x | x | x | x | x | FlemishSL |
| [Pigou et al., 2017] | 2017 | 100 | 53 | x | x | x | x | x | FlemishSL |
| [Pigou et al., 2017] | 2017 | 100 | 78 | x | x | x | x | x | FlemishSL |
| [Pigou et al., 2017] | 2017 | 20 | 53 | x | x | x | x | x | FlemishSL |
| [Hu et al., 2017] | 2017 | 20 | 78 | x | x | x | x | x | NGT |
| [Hu et al., 2017] | 2017 | 20 | 9 | x | x | x | x | x | ASL |
| [Quiroga et al., 2017] | 2017 | 24 | 5 | x | x | x | x | x | LSA16 | ArgentSL |
| [Thang et al., 2017] | 2017 | 45 | 6 | x | x | x | x | x | ASL |
| [Thang et al., 2017] | 2017 | 95 | 5 | x | x | x | x | x | ASL |
| [Pezzuoli et al., 2017] | 2017 | 40 | 1 | x | x | x | x | x | LIS |
| [O’Connor et al., 2017] | 2017 | 26 | x | x | x | x | x | x | ASL |
| [Ji et al., 2017] | 2017 | 6 | x | x | x | x | x | x | KSL |
| [Costa Filho et al., 2017] | 2017 | 61 | 10 | x | x | x | x | x | Libras |
| [Fang et al., 2017] | 2017 | 16 | 11 | x | x | x | x | x | ASL |
| [Fang et al., 2017] | 2017 | 56 | 11 | x | x | x | x | x | ASL |
| [Huang et al., 2018b] | 2018 | 1080 | 9 | x | x | x | x | x | Phoenix14 | DGS |
| [Huang et al., 2018b] | 2018 | 178 | 50 | x | x | x | x | x | CSL | CSL |
| [Pu et al., 2018] | 2018 | 1080 | 9 | x | x | x | x | x | Phoenix14 | DGS |
| [Pu et al., 2018] | 2018 | 178 | 50 | x | x | x | x | x | CSL | CSL |
| [Wang et al., 2018] | 2018 | 1080 | 9 | x | x | x | x | x | Phoenix14 | DGS |
| [Wang et al., 2018] | 2018 | 178 | 50 | x | x | x | x | x | CSL | CSL |
| [Koller et al., 2018] | 2018 | 1080 | 9 | x | x | x | x | x | Phoenix14 | DGS |
| [Koller et al., 2018] | 2018 | 455 | 1 | x | x | x | x | x | Signum | DGS |
| [Konstantinidis et al., 2018a] | 2018 | 50 | 1 | x | x | x | x | x | x | x | DGS |
| [Konstantinidis et al., 2018a] | 2018 | 64 | 10 | x | x | x | x | x | x | x | x | LSA64 | ArgentSL |

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| Reference                          | Year | Vocabulary | Signer | Isolated | Continuous | Input Data | Manuals | Non-Manuals | Fullframe | Benchmark | Dataset | Language  |
|-----------------------------------|------|------------|--------|----------|------------|------------|---------|-------------|-----------|-----------|---------|-----------|
| [Konstantinidis et al., 2018b]    | 2018 | 64         | 10     | x         | x          | x          | x       | x           | x         | LSA64     | ArgentSL |
| [Kishore et al., 2018]            | 2018 | 500        | 5      | x         | x          | x          | x       | x           | x         | IndianSL  | ArgentSL |
| [Kumar et al., 2018c]             | 2018 | 30         | 10     | x         | x          | x          | x       | x           | x         | CSL       | ArgentSL |
| [Huang et al., 2018a]             | 2018 | 500        | 50     | x         | x          | x          | x       | x           | x         | CSL       | ArgentSL |
| [Liu et al., 2018]                | 2018 | 227        | x      | x         | x          | x          | x       | x           | x         | HKSL      | ArgentSL |
| [Rao and Kishore, 2018]           | 2018 | 18         | 10     | x         | x          | x          | x       | x           | x         | IndianSL  | ArgentSL |
| [Kumar et al., 2018b]             | 2018 | 200        | 10     | x         | x          | x          | x       | x           | x         | CSL       | ArgentSL |
| [Kumar et al., 2018a]             | 2018 | 500        | 10     | x         | x          | x          | x       | x           | x         | CSL       | ArgentSL |
| [Camgoz et al., 2018]             | 2018 | 1066       | 9      | x         | x          | x          | x       | x           | x         | Phoenix14T | ArgentSL |
| [Ebling et al., 2018]             | 2018 | 100        | 30     | x         | x          | x          | x       | x           | x         | DGS       | ArgentSL |
| [Huang et al., 2018c]             | 2018 | 310        | x      | x         | x          | x          | x       | x           | x         | CSL       | ArgentSL |
| [Guo et al., 2018]                | 2018 | 178        | 50     | x         | x          | x          | x       | x           | x         | CSL       | ArgentSL |
| [Gunawan et al., 2018]            | 2018 | 10         | 10     | x         | x          | x          | x       | x           | x         | LSA64     | ArgentSL |
| [Yugopuspito et al., 2018]        | 2018 | 23         | x      | x         | x          | x          | x       | x           | x         | CSL       | ArgentSL |
| [Gruber et al., 2018]             | 2018 | 18         | 10     | x         | x          | x          | x       | x           | x         | CSL       | ArgentSL |
| [Kumar et al., 2018d]             | 2018 | 51         | x      | x         | x          | x          | x       | x           | x         | CSL       | ArgentSL |
| [Rao et al., 2018]                | 2018 | 200        | 10     | x         | x          | x          | x       | x           | x         | IndianSL  | ArgentSL |
| [Shenoy et al., 2018]             | 2018 | 12         | x      | x         | x          | x          | x       | x           | x         | IndianSL  | ArgentSL |
| [Rakowski and Wandzik, 2018]      | 2018 | 24         | 5      | x         | x          | x          | x       | x           | x         | ASL       | ArgentSL |
| [Mathur and Sharma, 2018]         | 2018 | 32         | x      | x         | x          | x          | x       | x           | x         | ASL       | ArgentSL |
| [Lee and Lee, 2018]               | 2018 | 28         | x      | x         | x          | x          | x       | x           | x         | ASL       | ArgentSL |
| [Hashim and Alizadeh, 2018]       | 2018 | 12         | x      | x         | x          | x          | x       | x           | x         | ASL       | ArgentSL |
| [Handhika et al., 2018]           | 2018 | 25         | 2      | x         | x          | x          | x       | x           | x         | IndoSL    | ArgentSL |
| [Ariesta et al., 2018]            | 2018 | 30         | 10     | x         | x          | x          | x       | x           | x         | IndoSL    | ArgentSL |
| [Zadghorban and Nahvi, 2018]      | 2018 | 46         | 3      | x         | x          | x          | x       | x           | x         | PersianSL | ArgentSL |
| [Ye et al., 2018]                 | 2018 | 27         | 14     | x         | x          | x          | x       | x           | x         | ASL       | ArgentSL |
| [Xie et al., 2018]                | 2018 | 24         | 5      | x         | x          | x          | x       | x           | x         | ASL       | ArgentSL |
| [Ma et al., 2018]                 | 2018 | 276        | 5      | x         | x          | x          | x       | x           | x         | ASL       | ArgentSL |
| [Song et al., 2019]               | 2019 | 1080       | 9      | x         | x          | x          | x       | x           | x         | Phoenix14 | DGS     |
| [Pu et al., 2019]                 | 2019 | 1080       | 9      | x         | x          | x          | x       | x           | x         | Phoenix14 | DGS     |
| [Pu et al., 2019]                 | 2019 | 178        | 50     | x         | x          | x          | x       | x           | x         | CSL       | DGS     |
| [Liao et al., 2019]               | 2019 | 500        | 8      | x         | x          | x          | x       | x           | x         | Devisign-D | CSL     |
| [Guo et al., 2019]                | 2019 | 1080       | 9      | x         | x          | x          | x       | x           | x         | Phoenix14 | DGS     |
| [Guo et al., 2019]                | 2019 | 178        | 50     | x         | x          | x          | x       | x           | x         | CSL       | DGS     |
| [Pei et al., 2019]                | 2019 | 1080       | 9      | x         | x          | x          | x       | x           | x         | Phoenix14 | DGS     |
| [Cui et al., 2019]                | 2019 | 1080       | 9      | x         | x          | x          | x       | x           | x         | Phoenix14 | DGS     |
| [Cui et al., 2019]                | 2019 | 1080       | 9      | x         | x          | x          | x       | x           | x         | Phoenix14 | DGS     |
| [Cui et al., 2019]                | 2019 | 1080       | 9      | x         | x          | x          | x       | x           | x         | Phoenix14 | DGS     |
| [Cui et al., 2019]                | 2019 | 1080       | 9      | x         | x          | x          | x       | x           | x         | Phoenix14 | DGS     |
| [Cui et al., 2019]                | 2019 | 455        | 1      | x         | x          | x          | x       | x           | x         | Signum    | DGS     |
| [Zhou et al., 2019]               | 2019 | 1080       | 9      | x         | x          | x          | x       | x           | x         | Phoenix14 | DGS     |
| [Zhou et al., 2019]               | 2019 | 178        | 50     | x         | x          | x          | x       | x           | x         | CSL       | DGS     |
| [Zhang et al., 2019]              | 2019 | 1080       | 9      | x         | x          | x          | x       | x           | x         | Phoenix14 | DGS     |
| [Yang et al., 2019]               | 2019 | 1080       | 9      | x         | x          | x          | x       | x           | x         | Phoenix14 | DGS     |
| [Yang et al., 2019]               | 2019 | 178        | 50     | x         | x          | x          | x       | x           | x         | CSL       | DGS     |

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| Reference | Year | Vocabulary | Signer | Isolated | Continuous | Manual | Non-Manuals | Fullframe | Benchmark | Dataset | Language |
|-----------|------|------------|--------|----------|------------|--------|-------------|-----------|-----------|---------|----------|
| [Koller et al., 2019] | 2019 | 1066 | 9 | x | x | x | x | x | Phoenix14T | DGS |
| [Koller et al., 2019] | 2019 | 1080 | 9 | x | x | x | x | x | Phoenix14 | DGS |
| [Bilge et al., 2019] | 2019 | 50 | 1 | x | x | x | x | x | ASL |
| [Bilge et al., 2019] | 2019 | 50 | 1 | x | x | x | x | x | ASL |
| [Bilge et al., 2019] | 2019 | 50 | 1 | x | x | x | x | x | ASL |
| [Vaezi Joze and Koller, 2019] | 2019 | 100 189 | x | x | x | x | x | x | MS-ASL | ASL |
| [Vaezi Joze and Koller, 2019] | 2019 | 100 189 | x | x | x | x | x | x | MS-ASL | ASL |
| [Vaezi Joze and Koller, 2019] | 2019 | 1000 222 | x | x | x | x | x | x | MS-ASL | ASL |
| [Vaezi Joze and Koller, 2019] | 2019 | 1000 222 | x | x | x | x | x | x | MS-ASL | ASL |
| [Vaezi Joze and Koller, 2019] | 2019 | 200 196 | x | x | x | x | x | x | MS-ASL | ASL |
| [Vaezi Joze and Koller, 2019] | 2019 | 200 196 | x | x | x | x | x | x | MS-ASL | ASL |
| [Vaezi Joze and Koller, 2019] | 2019 | 500 222 | x | x | x | x | x | x | MS-ASL | ASL |
| [Vaezi Joze and Koller, 2019] | 2019 | 500 222 | x | x | x | x | x | x | MS-ASL | ASL |
| [Vaezi Joze and Koller, 2019] | 2019 | 200 | 196 | x | x | x | x | x | MS-ASL | ASL |
| [Vaezi Joze and Koller, 2019] | 2019 | 50 | 1 | x | x | x | x | x | MS-ASL | ASL |
| [Sabyrov et al., 2019] | 2019 | 20 | 3 | x | x | x | x | x | x | K-RSL |
| [Kindroglu et al., 2019] | 2019 | 174 | 4 | x | x | x | x | x | x | TSL |
| [Wang et al., 2019] | 2019 | 138 | 70 | x | x | x | x | x | x | CSL |
| [Kumar et al., 2019] | 2019 | 700 | 10 | x | x | x | x | x | x | IndianSL |
| [Wei et al., 2019] | 2019 | 178 | 50 | x | x | x | x | x | x | CSL |
| [Tornay et al., 2019] | 2019 | 94 | 30 | x | x | x | x | x | x | DGS |
| [Farag and Brock, 2019] | 2019 | 12 | x | x | x | x | x | x | x | JSL |
| [Paudyal et al., 2019] | 2019 | 25 | 100 | x | x | x | x | x | x | ASL |
| [Jose and Julian, 2019] | 2019 | 31 | x | x | x | x | x | x | x | TamisSL |
| [Latif et al., 2019] | 2019 | 32 | 40 | x | x | x | x | x | x | ArSL |
| [Avola et al., 2019] | 2019 | 30 | 20 | x | x | x | x | x | x | ASL |
| [Mittal et al., 2019] | 2019 | 35 | x | x | x | x | x | x | x | ISL |
| [Hassan et al., 2019] | 2019 | 80 | 1 | x | x | x | x | x | x | ArSL |
| [Hassan et al., 2019] | 2019 | 80 | 1 | x | x | x | x | x | x | ArSL |
| [Hassan et al., 2019] | 2019 | 80 | 2 | x | x | x | x | x | x | ArSL |
| [Borg and Camilleri, 2020] | 2020 | 1080 | 9 | x | x | x | x | x | Phoenix14 | DGS |
| [Albanie et al., 2020] | 2020 | 1000 | 222 | x | x | x | x | x | MS-ASL | ASL |
| [Albanie et al., 2020] | 2020 | 1064 | 40 | x | x | x | x | x | BSL |
| [Albanie et al., 2020] | 2020 | 1064 | 40 | x | x | x | x | x | BSL |
| [Albanie et al., 2020] | 2020 | 2000 | 119 | x | x | x | x | x | WSASL | ASL |
| [Adaloglou et al., 2020] | 2020 | 1080 | 9 | x | x | x | x | x | Phoenix14 | DGS |
| [Adaloglou et al., 2020] | 2020 | 178 | 50 | x | x | x | x | x | CSL |
| [Adaloglou et al., 2020] | 2020 | 310 | 7 | x | x | x | x | x | GSL |
| [Adaloglou et al., 2020] | 2020 | 310 | 7 | x | x | x | x | x | GSL |
| [Papastas et al., 2020] | 2020 | 1066 | 9 | x | x | x | x | x | Phoenix14 | DGS |
| [Papastas et al., 2020] | 2020 | 1080 | 9 | x | x | x | x | x | Phoenix14 | DGS |
| [Papastas et al., 2020] | 2020 | 178 | 50 | x | x | x | x | x | CSL |
| [Zhou et al., 2020] | 2020 | 1080 | 9 | x | x | x | x | x | Phoenix14 | DGS |
| [Cheng et al., 2020] | 2020 | 1066 | 9 | x | x | x | x | x | Phoenix14 | DGS |

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| Reference               | Year | Vocabulary | Signer | Isolated | Continuous | Input Data | Manuals | Non-Manuals | Fullframe | Benchmark | Dataset | Language |
|-------------------------|------|------------|--------|----------|------------|------------|---------|-------------|-----------|-----------|---------|----------|
| [Cheng et al., 2020]    | 2020 | 1080       | 9      | x         | x          | x          | x       |             |           | Phoenix14 | DGS     |
| [Cheng et al., 2020]    | 2020 | 178        | 50     | x         | x          |             | x       |             |           | CSL       | CSL     |
| [Zhou et al., 2020a]    | 2020 | 1066       | 9      | x         | x          | x          | x       | x           | x         | Phoenix14T | DGS     |
| [Zhou et al., 2020a]    | 2020 | 1080       | 9      | x         | x          | x          | x       | x           | x         | Phoenix14 | DGS     |
| [Zhou et al., 2020a]    | 2020 | 178        | 50     | x         | x          | x          |           | x           | x         | CSL       | CSL     |
| [Mukushev et al., 2020] | 2020 | 20         | 5      | x         | x          |             | x       | x           | x         |           | K-RSL   |
| [Vasudevan et al., 2020]| 2020 | 19         | 58     | x         |             |             | x       |             |           | LSE       |         |
| [De Coster et al., 2020]| 2020 | 100        | 67     | x         |             |             | x       |             |           | FlemishSL |         |
| [De Coster et al., 2020]| 2020 | 100        | 67     | x         |             |             | x       |             |           | FlemishSL |         |
| [Camgoz et al., 2020]   | 2020 | 1066       | 9      | x         |             |             |           | x           |           | Phoenix14T | DGS     |
| [Tamer and Saraçlar, 2020]| 2020 | 1066      | 9      | x         |             |             | x       |             |           | Phoenix14T | DGS     |
| [Li et al., 2020a]      | 2020 | 100        | 97     | x         |             |             | x       |             |           | WSASL     | ASL     |
| [Li et al., 2020a]      | 2020 | 100        | 97     | x         |             |             | x       |             |           | WSASL     | ASL     |
| [Li et al., 2020a]      | 2020 | 1000       | 116    | x         |             | x          | x       |             |           | WSASL     | ASL     |
| [Li et al., 2020a]      | 2020 | 1000       | 116    | x         |             |             | x       |             |           | WSASL     | ASL     |
| [Li et al., 2020a]      | 2020 | 2000       | 119    | x         |             | x          | x       |             |           | WSASL     | ASL     |
| [Li et al., 2020a]      | 2020 | 2000       | 119    | x         |             | x          | x       |             |           | WSASL     | ASL     |
| [Li et al., 2020a]      | 2020 | 300        | 109    | x         |             |             | x       |             |           | WSASL     | ASL     |
| [Li et al., 2020a]      | 2020 | 300        | 109    | x         |             |             | x       |             |           | WSASL     | ASL     |
| [Li et al., 2020b]      | 2020 | 100        | 189    | x         |             |             | x       |             |           | MS-ASL    | ASL     |
| [Li et al., 2020b]      | 2020 | 100        | 97     | x         |             |             | x       |             |           | WSASL     | ASL     |
| [Li et al., 2020b]      | 2020 | 200        | 196    | x         |             |             | x       |             |           | MS-ASL    | ASL     |
| [Li et al., 2020b]      | 2020 | 300        | 109    | x         |             |             | x       |             |           | WSASL     | ASL     |
| [Özdemir et al., 2020]  | 2020 | 744        | 6      | x         | x           |             |           |             |           |           | TSL     |
| [Izutov, 2020]          | 2020 | 100        | 189    | x         |             |             | x       |             |           | MS-ASL    | ASL     |
| [Izutov, 2020]          | 2020 | 1000       | 222    | x         |             |             | x       |             |           | MS-ASL    | ASL     |
| [Izutov, 2020]          | 2020 | 200        | 196    | x         |             |             | x       |             |           | MS-ASL    | ASL     |
| [Izutov, 2020]          | 2020 | 500        | 222    | x         |             |             | x       |             |           | MS-ASL    | ASL     |