

# How2Sign: A Large-scale Multimodal Dataset for Continuous American Sign Language

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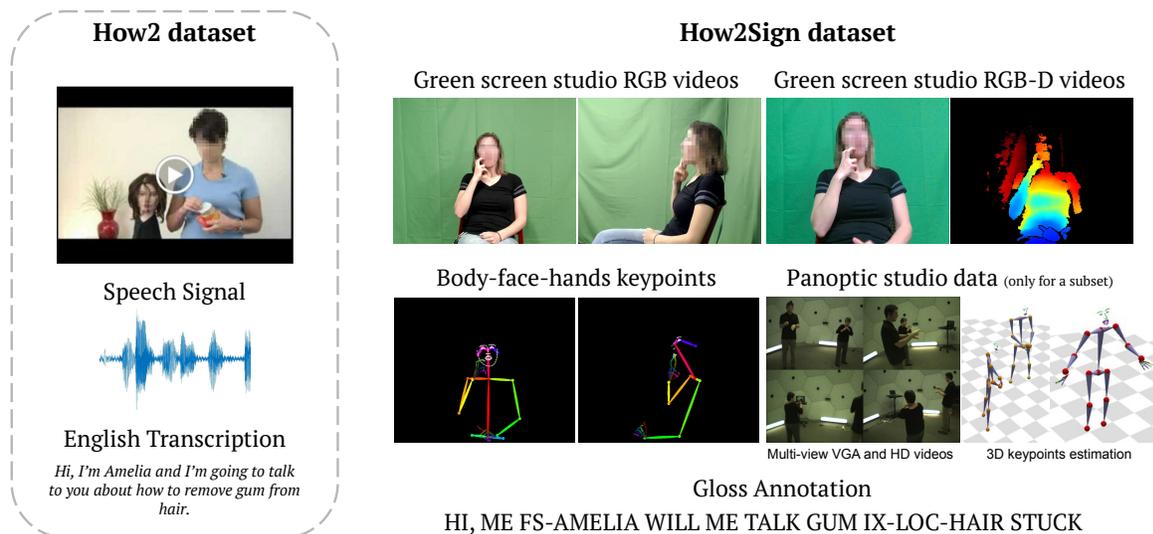


Figure 1: The **How2Sign** dataset consists of over 80 hours of multiview sign language videos and aligned modalities.

## Abstract

One of the factors that have hindered progress in the areas of sign language recognition, translation, and production is the absence of large annotated datasets. Towards this end, we introduce How2Sign, a multimodal and multiview continuous American Sign Language (ASL) dataset, consisting of a parallel corpus of more than 80 hours of sign language videos and a set of corresponding modalities including speech, English transcripts, and depth. A three-hour subset was further recorded in the Panoptic studio enabling detailed 3D pose estimation. To evaluate the potential of How2Sign for real-world impact, we conduct a study with ASL signers and show that synthesized videos using our dataset can indeed be understood. The study further gives insights on challenges that computer vision should address in order to make progress in this field.

Dataset website: <http://how2sign.github.io/>

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## 1. Introduction

Sign languages (SL) are the primary means of communication for an estimated 466 million deaf<sup>1</sup> or hard-of-hearing people worldwide [1]. Like any other natural language, sign languages are consistently evolving and have structure directed by a set of linguistic rules [3]. They differ from spoken languages and do not have standard written forms, e.g. American Sign Language (ASL) is not a sign form of English. Although sign languages are used by millions of people everyday to communicate, the vast majority of communications technologies nowadays are designed to support spoken or written language, but not sign languages. At the same time, most hearing people do not know a sign language; as a result, many communication barriers exist for deaf sign language users [6, 7, 14].

<sup>1</sup>We follow the recognized convention of using the upper-cased word Deaf which refers to the culture and describes members of the community of sign language users and the lower-cased word deaf describes the hearing status[37].

Promising recent works in sign language processing<sup>2</sup> [12, 30, 33, 41, 40, 19] have shown that modern computer vision and machine learning architectures can help break down these barriers for sign language users. Improving such models could make technologies that are primarily designed for non-sign language users, *e.g.* voice-activated services, text-based systems, spoken-media based content, *etc.*, more accessible to the Deaf community. Other possibilities include automatic transcription of signed content, which would help facilitating the communication between sign and non-sign language users, as well as real-time interpreting when human interpreters are not available, and many other educational tools and applications [6].

However, training such models requires large amounts of data. The availability of public large-scale datasets suitable for machine learning is very limited, especially when it comes to *continuous sign language* datasets, *i.e.*, where the data needs to be segmented and annotated at the sentence level. Currently, there is no ASL dataset large enough to be used with recent deep learning approaches.

In order to instigate the advance in the area of research that involves sign language processing, in this paper we introduce the *How2Sign* dataset. *How2Sign* is a large-scale collection of multimodal and multiview sign language videos in American Sign Language (ASL) for over 2500 instructional videos selected from the existing *How2* dataset [27]. Figure 1 shows samples of the data contained in the dataset. Working in close collaboration with native ASL signers and professional interpreters, we collected more than *80 hours* of multi-view and multimodal (recorded with multiple RGB and a depth sensor) ASL videos, and corresponding gloss annotations [22]. In addition, a three-hour subset was further recorded at the Panoptic studio [17], a geodesic dome setup equipped with hundreds of cameras and sensors, which enables detailed 3D reconstruction and pose estimation. This subset paves the way for vision systems to understand the 3D geometry of sign language.

Our contributions can be summarized as follows: a) We present *How2Sign*, a large-scale multimodal and multiview continuous American Sign Language dataset that consists of more than *80 hours of American Sign Language videos*, with sentence-level alignment for more than 35k sentences. It features a vocabulary of 16k English words that represent more than two thousand instructional videos from a broad range of categories; b) Our dataset comes with a rich set of annotations including gloss, category labels, as well automatically extracted 2D keypoints for more than 6M frames. What is more, a subset of the dataset was re-recorded in the Panoptic studio with more than 500 cameras that enabled high quality 3D keypoints estimation for around 3 hours of

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<sup>2</sup>For brevity, we follow [6] and use the term *sign language processing* to refer to the set of sign language recognition, translation and production tasks.

videos; c) We conduct a study with ASL signers that showed that videos generated using our dataset can be understood to a certain extent, and at the same time gave insights on challenges that the research community can address in this field.

## 2. Background and Related Work

In this section we discuss some of the challenges that comes with sign languages that can be interesting to the computer vision community, as well as an overview of the current publicly available sign language datasets.

### 2.1. Sign Language

Sign languages are visual languages that use two types of features to convey information: *manual* that includes handshape, palm orientation, movement and location and; *non-manual markers* that are movement of the head (nod/shake/tilt), mouth (mouthing), eyebrows, cheeks, facial grammar (or facial expressions) and eye gaze [32]. All these features need to be taken into account while recognizing, translating or generating signs in order to capture the complete meaning of the sign. This makes sign language processing a challenging set of tasks for computer vision.

When it comes to continuous sign language, a simple concatenation of isolated signs is not enough to correctly recognize, translate or generate a complete sentence and neglects the underlying rich grammatical and linguistic structures of sign language that differ from spoken language. Besides the fact that the alignment between sign and spoken language sequences are usually unknown and non monotonic [12], the transitions between signs must also be taken into account. Usually, the beginning of a sign is modified depending on the previous sign, and the end of the same sign is modified depending on the following sign making them visually different in the isolated and continuous scenarios [3]. This phenomenon is called “co-articulation” and brings an extra challenge for tasks with continuous sign language [2].

### 2.2. Sign Language datasets

One of the most important factors that has hindered the progress of sign language processing research is the absence of large scale annotated datasets [6]. Many existing sign language datasets contain isolated signs [10, 4, 18, 21, 23, 34]. Such data may be important for certain scenarios (*e.g.*, creating a dictionary, or as a resource for those who are learning a sign language), but most real-world use cases of sign language processing involve natural conversational with complete sentences (*i.e. continuous sign language*).

A number of continuous sign language datasets have been collected over the years mainly for linguistic purposes. *SIGNUM* [35] and the *BSL Corpus* [31] were recorded in

Name	Language	Vocab.	Duration (h)	Signers	Modalities					
					Multiview	Transcription	Gloss	Pose	Depth	Speech
Video-Based CSL [16]	CSL	178	100	50	✗	✓	✗	✓	✓	✗
SIGNUM [35]	DGS	450	55	25	✗	✓	✓	✗	✗	✗
RWTH-Phoenix-2014T [12]	DGS	3k	11	9	✗	✓	✓	✗	✗	✗
Public DGS Corpus [15]	DGS	–	50	327	✓	✓	✓	✓	✗	✗
BSL Corpus [31]	BSL	5k	–	249	✗	✓	✓	✗	✗	✗
Boston104 [39]	ASL	104	8.7 (min)	3	✗	✓	✓	✗	✗	✗
NCSLGR [24]	ASL	1.8k	5.3	4	✓	✓	✓	✗	✗	✗
<b>How2Sign (ours)</b>	ASL	16k	79	11	✓	✓	✓	✓	✓	✓

Table 1: **Summary of publicly available continuous sign language datasets.** To the best of our knowledge, How2Sign is the largest publicly available Sign Language dataset across languages in terms of vocabulary, as well as the largest American Sign Language (ASL) dataset in terms of video duration. We also see that How2Sign is the dataset with the most parallel modalities. A detailed explanation of each modality can be found in the subsection 3.2

controlled environments with a single RGB camera. Recent works in neural machine translation [8] and production [30, 28] have adopted *RWTH-Phoenix-2014T* [12], a dataset of German Sign Language (DGS) on the specific domain of weather forecast from a TV broadcast that features 9 signers. The *Public DGS Corpus* [15] and the *Video-Based CSL (Chinese Sign Language)*[16] provide much larger video collections enriched with the body keypoint of the signers. In the case of *Public DGS Corpus*, these are 2D poses estimated with OpenPose [9] and from different view points, while *Video-Based CSL* provides 3D joints and depth information thanks to the recordings with a Kinect camera. If we focus on American Sign Language (ASL), *RWTH-BOSTON-104* [39] only contains 8.7 minutes of grayscale video, while *NCSLGR* [24] is larger but an order of magnitude smaller than How2Sign. In terms of annotation, all datasets but *Video-Based CSL* provide gloss annotations, that is, a text-based transcription of the signs that can serve as a proxy in translation tasks.

Table 1 presents an overview of publicly available continuous sign language datasets ordered by vocabulary size<sup>3</sup>. An important factor for the lack of large-scale datasets is that the collection and annotation of continuous sign language data is a laborious and expensive task. It requires linguistic experts working together with a native speaker, e.g. a Deaf person. *RWTH-Phoenix-2014T* [12] is one of the few datasets that are publicly available and has been used for training deep neural networks. A recent re-alignment in the annotations also allows studying sign language translation. However, their videos cover just 11 hours of data from weather broadcasts, and are restricted to one domain.

In summary, the current publicly available datasets are constrained by one or more of the following: (i) limited vocabulary size, (ii) short video or total duration and (iii)

limited domain. The How2Sign dataset provides a considerably larger vocabulary than the existing ones, and it does so in the continuous sign language setting for a broader domain of discourse. It also is the first sign language dataset that contains speech thanks to its alignment with the existing How2 dataset [27].

### 3. The How2Sign dataset

The How2Sign dataset consists of a parallel corpus of speech and transcriptions of instructional videos and their corresponding American Sign Language (ASL) translation videos and annotations. A total of *80 hours* of multiview American Sign Language videos were collected, as well as gloss annotations [22] and a coarse video categorization.

**Source language.** The instructional videos translated into ASL come from the existing *How2 dataset* [27], a publicly available multimodal dataset for vision, speech and natural language understanding, with utterance-level time alignments between the speech and the ground-truth English transcription. Following the same splits from the *How2-300h* dataset, we selected a 60-hour subset from the training set and the complete validation and test sets to be recorded.

#### 3.1. Sign language video recordings

**Signers.** In total, 11 people appear in the sign language videos of the How2Sign dataset; we refer to them as *signers*. Of the 11 signers, 5 self-identified as hearing, 4 as Deaf and 2 as hard-of-hearing. The signers that were hearing were either professional ASL interpreters (4) or ASL fluent.

**Recording pipeline.** The signer would first watch the video with the transcript as subtitles in order to become familiar with the overall content; this enables them to perform a richer translation. ASL translation videos were then recorded, while the signer was watching the video with subtitles, and at a slightly slower-than-normal (0.75) speed. For each hour of video recorded, the preparation, recording and

<sup>3</sup>An extended overview of related datasets can be found at: [https://how2sign.github.io/related\\_datasets.html](https://how2sign.github.io/related_datasets.html)

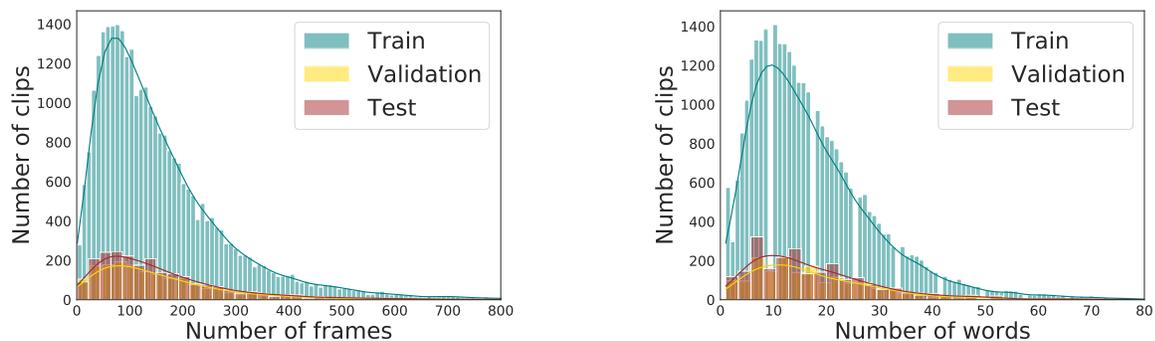


Figure 2: Distribution of the number of frames (left) and words (right) over sentence-level clips.

video review took approximately 3 hours on average.

All recordings were performed in a supervised setting in two different locations: at the *Green Screen studio* and at the *Panoptic studio*, both presented below. We recorded the complete 80 hours of the dataset in the green screen studio. We then chose a small subset of videos (approx. 3 hours) from the validation and test splits and recorded them again in the Panoptic studio. After recording, we trimmed all sign language videos and divided them in *sentence-level clips*, each annotated with a corresponding English transcript, and the modalities presented in Section 3.2.

**Green screen studio.** The *Green Screen studio* was equipped with a depth and a high definition (HD) camera placed in a frontal view of the participant, and another HD camera placed at a lateral view. All three cameras recorded videos at 1280x720 resolution, at 30 fps. Samples of data recorded in this studio are shown in the top row of Figure 1.

**Panoptic studio.** The *Panoptic studio* [17] is a system equipped with 480 VGA cameras, 30 HD cameras and 10 RGB-D sensors, all synchronized. All cameras are mounted over the surface of a geodesic dome<sup>4</sup>, providing redundancy for weak perceptual processes (such as pose detection) and robustness to occlusion. In addition to the multiview VGA and HD videos, the recording system can further estimate high quality 3D keypoints of the interpreters, also included in How2Sign. Samples of data recorded in this studio are shown on the bottom-right of Figure 1.

### 3.2. Dataset Modalities

The modalities enumerated in the columns of Table 1 are detailed in this section. Apart from the English translations and speech modalities that were already available from the How2 [27] dataset, all other modalities were either collected or automatically extracted. To the best of our knowledge, How2Sign is the largest publicly available sign

<sup>4</sup><http://www.cs.cmu.edu/~hanbyulj/panoptic-studio/>

language dataset across languages in terms of vocabulary, as well as an order of magnitude larger than any other ASL dataset in terms of video duration. We see that How2Sign is also the dataset with the most parallel modalities, enabling multimodal learning.

**Multiview.** All 80 hours of sign language videos were recorded from multiple angles. This allows the signs to be visible from multiple points of view, reducing occlusion and ambiguity, especially in the hands. Specifically, the sign language videos recorded in the Green Screen studio contain two different points of view, while the Panoptic studio recordings consist of recordings of more than 500 cameras allowing for a high quality estimation of 3D keypoints [17].

**Transcriptions.** The English translation modality originates from the subtitles track of How2 original videos. The transcriptions were provided by the uploader of the instructional video in form of text, that was loosely synced with the video’s speech track. As subtitles are not necessarily fully aligned with the speech, transcriptions were time-aligned at the sentence-level as part of the How2 dataset [27].

**Gloss** is used in linguistics to transcribe signs using spoken language words. It is generally written in capital letters and indicates what individual parts of each sign mean, including annotations that account for facial and body grammar. An example of gloss annotation is shown on the bottom right of Figure 1. It is important to note that gloss is not a true translation, it instead provides the appropriate spoken language morphemes that express the meaning of the signs in spoken language [20, 22]. Glosses do not indicate special hand-shape, hand movement/orientation, nor information that would allow the reader to determine how the sign is made, or what its exact meaning in a given context. They also do not indicate grammatical uses of facial expressions (for example, raising the eyebrows is used in yes/no questions). Gloss is the form of text that is closest to sign language and it has been used by a number of approaches as an intermediate representation for sign language processing [12, 30, 28, 40, 19].

**Pose information.** Human pose information, *e.g.* body, hand and face keypoints were extracted for all the recorded sign language videos in the full resolution – 1280 x 720 pixels. For the Green Screen studio data, the 2-dimensional (2D) pose information was automatically extracted using OpenPose [9]. In total, each pose consists of 25 body keypoints, 70 facial keypoints and 21 keypoints for each hand. We provide pose information for both frontal and side view of the Green Screen studio data. A sample of the pose information extracted can be seen on the bottom row in the left side of Figure 1. For the Panoptic studio data, we provide high quality 3-dimensional (3D) pose information estimated by the Panoptic studio internal software [17] that can be used as ground-truth for a number of 3D vision tasks.

**Depth data.** For the Green Screen studio data, the sign language videos were also recorded using a Depth sensor (Creative BlasterX Senz3D) from the frontal viewpoint. The sensor has high precision facial and gesture recognition algorithms embedded and is able to focus on the hands and face, the most important human parts for sign language.

**Speech.** The speech track comes from the instructional videos as part of the How2 dataset [27].

### 3.3. Collected Annotations

Beyond the video recordings and automatically extracted pose information, we further collected a number of manual annotations for the sign language videos.

**Gloss and sentence boundaries.** We collected gloss annotations by employing ASL linguists. The annotations were collected using ELAN [13], an annotation software for audio and video recordings, specifically enhanced for sign language annotations. Information in ELAN is represented in tiers which are time-aligned to the video files, giving us the start and end boundaries of each sentence and producing what we call the sentence boundaries. The gloss annotation took in average one hour per 90 seconds of video.

**Video Categories.** Although the How2 dataset provides automatically extracted “topics” for all videos using Latent Dirichlet Allocation [5], we found that the automatic annotations were in general very noisy and not properly characterizing the selected videos. In order to better categorize the videos, we manually selected 10 categories<sup>5</sup> from the instructional website Wikihow<sup>6</sup> and manually classified each How2Sign video in a single category. The distribution of videos across the ten categories can be seen in Figure 3.

### 3.4. Dataset statistics

In Table 2 we show detailed statistics of the How2Sign dataset. A total of 2,456 videos from the How2 [27] were

<sup>5</sup>The categories are: Personal Care and Style, Games, Arts and Entertainment, Hobbies and Crafts, Cars and Other, Vehicles, Sports and Fitness, Education and Communication, Food and Drinks, Home and Garden and Pets and Animals.

<sup>6</sup><https://www.wikihow.com/Special:CategoryListing>

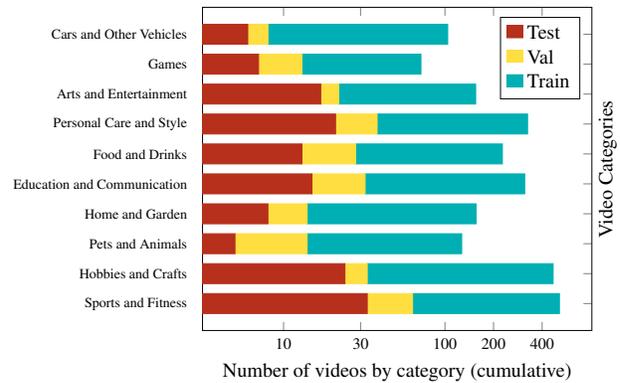


Figure 3: Cumulative number of videos per category.

used to record the sign language videos. Some of the videos were recorded more than once by a different signer in the Green screen studio – 21 videos from the training set, 17 videos from the validation set and 35 videos from the test set. All the recorded Videos were split into sentence-level clips. Each clip has on average 162 frames (5.4 seconds) and 17 words. The distribution of frames (right) and words (left) over all the clips for the 3 splits of the dataset can be seen in Figure 2. The collected corpus covers *more than 35k sentences* with an English vocabulary of more than 16k words. Where approximately, 20% of it is finger spelled. The videos were recorded by 11 different signers distributed across the splits. The test set contains 26 duplicated videos that were recorded by a signer that is not present in the training set; this subset of 26 videos can be used for measuring *generalization across different signers*. In total, 9 signers participated in the Green Screen studio recordings, and 6 signers in the Panoptic studio recordings. The bottom section of Table 2 refers to the automatically extracted human pose annotations.

### 3.5. Privacy, Bias and Ethical Considerations

In this section we discuss some metadata that we consider important for understanding the biases and generalization of the systems trained on our data.

**Privacy.** Since facial expressions are a crucial component for generating and/or translating Sign Language, it was not possible to avoid recordings that include the signer’s face. To that end, all the research steps followed procedures approved by the Carnegie Mellon University Institutional Review Board including a Social & Behavioral Research training done by the first and second authors, and a consent form provided by the participants agreeing on being recorded and making their data publicly available for research purposes. It is important to note that this puts at risk the authenticity of the linguistic data collected, as signers may monitor their production more carefully than usual.

**Audiological status and language variety.** The majority

	Green screen studio				Panoptic studio			
	train	val	test	Total	val	test	Total	
How2 [27] videos	2,192	115	149	2,456	48	76	124	
Sign language Videos	2,213	132	184	2,529	48	76	124	
Sign language video Duration (h)	69.62	3.91	5.59	79.12	1.14	1.82	2.96	
Number of frames (per view)	6.3M	362,319	521,219	7.2M	123,120	196,560	319,680	
Number of clips	31,128	1,741	2,322	35,191	642	940	1,582	
Camera views per SL video	3 HD + 1 RGB-D				480 VGA + 30 HD + 10 RGB-D			
Sentences	31,128	1,741	2,322	35,191	642	940	1,582	
Vocabulary size	15,686	3,218	3,670		1807	2360	3260	
Out-of-vocabulary	–	413	510					
Number of signers	8	5	6	9	3	5	6	
Signers not in train set	–	0	1		2	2		
		<u>2D keypoints</u>				<u>3D keypoints</u>		
Body pose		25				25		
Facial landmarks		70		137		70		
Hand pose (two hands)		21 + 21				21 + 21		

Table 2: Statistics of the **How2Sign** dataset. Some of the videos were recorded more than once by a different signer in the Green screen studio (see second row vs. first row). ASL videos recorded were split into sentence-level *clips*. Each clip has on average 162 frames (5.4 seconds) and 17 words.

of the participants identified American Sign Language and contact signing (Pidgin Sign English - PSE) as the main language used during the recordings. It is noteworthy that differences in audiological status are correlated with different language use. The Deaf were likely to identify ASL as the main language used in the recording process. In contrast, the hearing were likely to identify a mix of contact signing and ASL as the main language use in the recording process. More information about PSE and ASL can be found in [26].

**Geographic.** All participants were born and raised in the United States of America, and learned American Sign Language as their primary or second language at school time.

**Signer variety.** Our dataset was recorded by signers with different body proportions. Six of them were self-identified male and five self-identified female. The dataset was collected across 65 days during 6 months which gives a variety of clothing and accessories used by the participants.

**Data bias.** Our data does not contain large diversity in race/ethnicity, skin tone, background scenery, lighting conditions and camera quality.

#### 4. Evaluating the potential of How2Sign for sign language tasks

The communication barrier between sign and non-sign language users may be reduced in the coming years thanks to the recent advances in neural machine translation and computer vision. Recent works are making steps towards sign language production [30, 33, 41, 40, 29] by automatically generating detailed human pose keypoints from spoken language, and translation [19], *i.e.*, using keypoints as

input to generate text.

While keypoints can carry detailed human pose information and can be an alternative for reducing the computational bottleneck that is introduced when working with the actual video frames, no studies have been made so far on whether they are indeed useful when it comes to understanding sign language by its users. In this section we present a study where we try to understand *if and how well sign language users understand automatically generated sign language videos* that use keypoints from How2Sign as sign language representation. We run this study with four ASL speakers and record their understanding of the generated videos in terms of the category, translation into American English, and a final subjective rating about how understandable the videos were.

##### 4.1. Synthesizing sign language videos

We experiment with two ways of generating sign language videos: 1) skeleton visualizations and 2) Generative Adversarial Network generated (GAN-generated) videos. **Skeleton visualizations.** Given a set of estimated keypoints, one can visualize them as a wired skeleton connecting the modeled joints (see the middle row of Figure 4). **GAN-generated videos.** Another option would be to go one step further and use generative models to synthesize videos on top of predicted keypoints. To generate the animated video of a signer given a set of keypoints, we use the motion transfer and synthesis approach called Everybody Dance Now (EDN) [11]. This model is based on Pix2PixHD [36], but is further enhanced with a learned model of temporal coherence for better video and motion

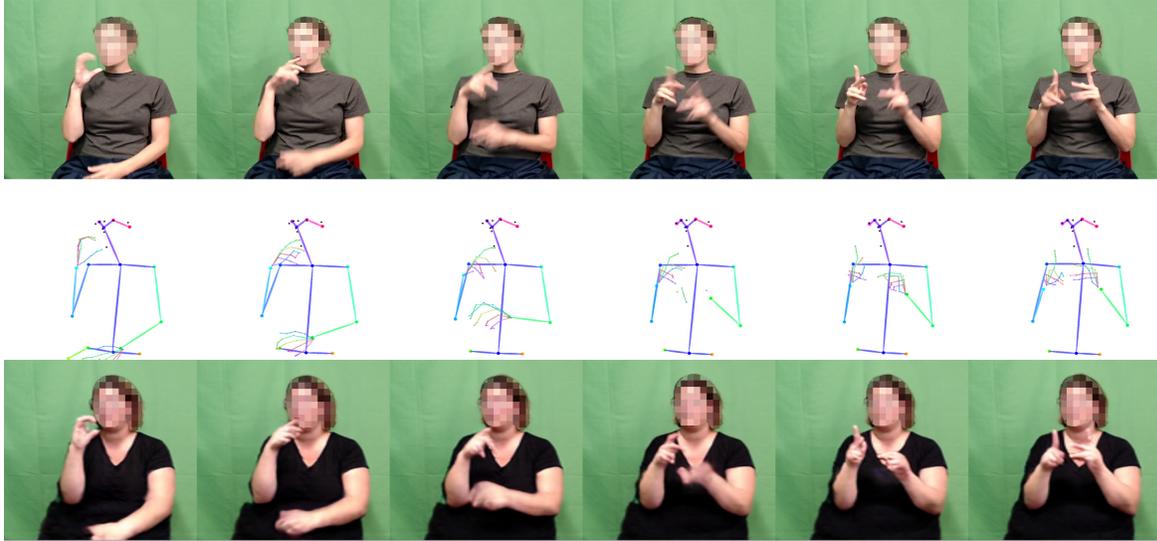


Figure 4: Sample of generated SL videos. Source video (top row) was used to automatically extract 2D keypoints (middle row) and generate frames of a video with a different identity (bottom row).

synthesis between adjacent frames by predicting two consecutive frames, as well as a separate module for high resolution face generation. It is worth noting that this approach models facial landmarks separately, something highly desirable in our case because they are one of the critical features for sign language understanding. The EDN model was trained on a subset of the How2Sign dataset that contains videos from *two* participants. Specifically, keypoints extracted from videos of the first signer (top row in Figure 4) were used to learn the model that generates realistic videos of the second signer (bottom row)<sup>7</sup>. The subset used consists of 28 hours of the training split.

#### 4.1.1 Quantitative evaluation of the GAN-generated sign language videos.

An approximate but automatic way of measuring the visual quality of the generated videos is by comparing the keypoints that can be reliably detected by OpenPose in the source and generated videos. We focus only on the 125 upper body keypoints which are visible in the How2Sign videos, and discard those from the legs. We use two metrics: a) the Percentage of Detected Keypoints (PDK), which corresponds to the fraction of keypoints from the source frame which were detected in the synthesized frame, and b) the Percentage of Correct Keypoints (PCK) [38], which labels each detected keypoint as “correct” if the distance to the keypoint in the original image is less than 20% of the torso diameter in all keypoints and 10% of the torso diameter for the hands.

<sup>7</sup>A sample of a generated video can be seen at: <https://youtu.be/wOxWUyXX6Ys>

OP confidence scores	PDK			PCK		
	0	0.2	0.5	0	0.2	0.5
All keypoints	0.99	0.88	0.87	0.90	0.94	0.96
Hands	0.99	0.38	0.17	0.08	0.11	0.12

Table 3: Percentage of Detected Keypoints (PDK) and Percentage of Correct Keypoints (PCK) for all keypoints and just for the hands, when thresholding at different detection confidence scores of OpenPose (OP).

In Table 3 we present these metrics for different minimum confidence thresholds of the OpenPose (OP keypoint detectors). We report results for all keypoints, as well as when restricting the evaluation only on the hand keypoints. We see that although the repeatability of keypoints is high in general, the model fails to predict reliable keypoints for the hands. This limitation is especially relevant in sign language processing.

#### 4.2. Can ASL signers understand generated sign language videos?

We evaluate the degree of understanding for both skeleton visualizations and the GAN-generated videos by showing 3-minute-long videos to four ASL signers. Two of them watched the skeletons visualizations, while the other two watched the GAN-generated videos. During the evaluation, each subject was asked to: a) classify six videos between the ten video categories (see subsection 3.2 for more information about the dataset categories); b) answer the question “How well could you understand the video?” on the five-level scale ((1) Bad, (2) Poor, (3) Fair, (4) Good, (5) Excel-

	Acc.	MOS	BLEU-1	BLEU-2	BLEU-3	BLEU-4
Skeleton	83.3 %	2.50	10.90	3.02	1.87	1.25
GAN-generated	<b>91.6 %</b>	<b>2.58</b>	<b>12.38</b>	<b>6.71</b>	<b>3.32</b>	<b>1.89</b>

Table 4: Comparison between generated skeletons and GAN videos in terms of classification (Accuracy), mean opinion score (MOS) and translation (BLEU) [25].

GT	<b>I'm not going to use a lot, I'm going to use very very little.</b>
Skeleton	That is not too much don't use much, use a little bit
EDN	Don't use a lot, use a little dont use lot use little bit
GT	<b>I'm going to dice a little bit of peppers here.</b>
Skeleton	cooking chop yellow peppers
EDN	cook with a little pepper chop it little bit and sprinkle

Table 5: Ground-truth (GT) and collected translations for two clips of the ‘‘Food and Drink’’ category. All subjects were able to correctly classify the category.

lent); and c) watch two clips from the previously seen video and translate them into American English. Results averaged over all subjects are presented in Table 4. We report accuracy for the classification task, the Mean Opinion Score (MOS) for the five-scale question answers and BLEU [25] scores for the American English translations. Qualitative results are shown in Table 5.

Results show a preference towards the generated videos rather than the skeleton ones, as the former result in higher scores across all metrics. In terms of general understanding of the topic, the subjects were able to mostly classify the videos correctly with both types of visualizations.

When it comes to finer grained understanding measured via the English translations, however, we can see from both Table 4 and Table 5 that neither skeletons nor GAN-generated videos are sufficient to convey important information needed from ASL signers to completely understand the sign language sentences. We hypothesize that current human pose estimation methods such as [9] are still not mature enough when it comes to estimate fast movements of the hands. We observed that due to the nature of sign language and the fast movements of the signers’ hands, OpenPose lacks precision in those cases which can make the visualizations incomplete, harming the understanding of some important parts of sign language.

**How can computer vision do better?** Our results show that the EDN model used as an out-of-the-box approach is not enough for sign language video generation. Specifically, we show that the model struggles with generating the hands and detailed facial expressions, which play a central role in sign language understanding. We argue that human pose es-

timation plays an important key in this aspect and needs to be more robust to blurry images, especially in the hands and to fast movements in order to be suitable to sign language research. We also argue that it is worth pursuing generative models that focus on generating hand details, particularly on the movements of the fingers, as well as clear facial expressions on full-body synthesis.

## 5. Conclusion

In this paper, we present the How2Sign dataset, a *large-scale multimodal and multiview dataset of American Sign Language*. With more than 80 hours of sign language videos and their corresponding speech signal, English transcripts and annotations, How2Sign has the potential to impact a wide range of sign language understanding tasks, such as sign language recognition, translation and production, as well as wider multimodal and computer vision tasks like 3D human pose estimation. How2Sign extends the How2 [27] dataset, an existing multimodal dataset with a new sign language modality, and therefore enables connecting with research performed in the vision, speech and language communities. In addition to that, we further conducted a study in which sign language videos generated from the automatically extracted annotations of our dataset were presented to ASL signers. To our knowledge, this is the first study how well keypoint-based synthetic videos, a commonly used representation of sign language production and translation, can be understood by sign language users. Our study indicates that current video synthesis methods allow the understanding to a certain extent *i.e.*, the classification of the video category, but lack in fidelity to allow for a fine-grained understanding of the complete sign language sentence.

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