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Data-Driven Sign Language Video Generation

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Why is sign language generation a challenge?

- Sign languages are an integral part of the lives of the Deaf and Hard of Hearing.
- Translating spoken languages to sign languages is difficult as sign languages use multiple channels to convey meaning.
- Sign languages are not limited to hands and their shape, but also: facial expression, body pose, hand position, mouthings.
- However sign languages can be transcribed to gloss form (each gloss is the closest word representation of a given sign).

e.g. What is the weather today?

TODAY WEATHER WHAT

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Our approach

We propose using this very simplified version to generate **information-rich, life-like sign language** content using advancements in machine learning.

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Literature review

Traditionally avatars are used to generate synthetic sign language content which rely on manually annotated, and/or motion capture data, making their scalability questionable.

Recently, Stoll et al.[1a&b] introduced an approach that uses a sequence-to-sequence model to translate spoken language text to gloss. Whilst scalable, there are two main issues with this work:

1. The lookup-table restricts this approach in terms of co-articulation between signs, and expressiveness.
2. The GAN in this work is only capable of low-resolution output.

[1a] Stoll, S., Camgoz, N.C., Hadfield, S., Bowden, R., Text2Sign: Towards Sign Language Production Using Neural Machine Translation and Generative Adversarial Networks. Int J Comput Vis 128, 891–908 (2020).

[1b] Stoll, S., Camgoz, N.C., Hadfield, S., Bowden, R., Sign Language Production using Neural Machine Translation and Generative Adversarial Networks, In Proceedings of the British Conference on Machine Vision (BMVC), BMVA Press, 2018.

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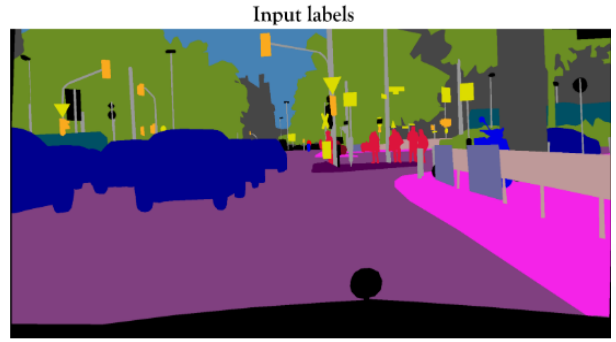
Literature review

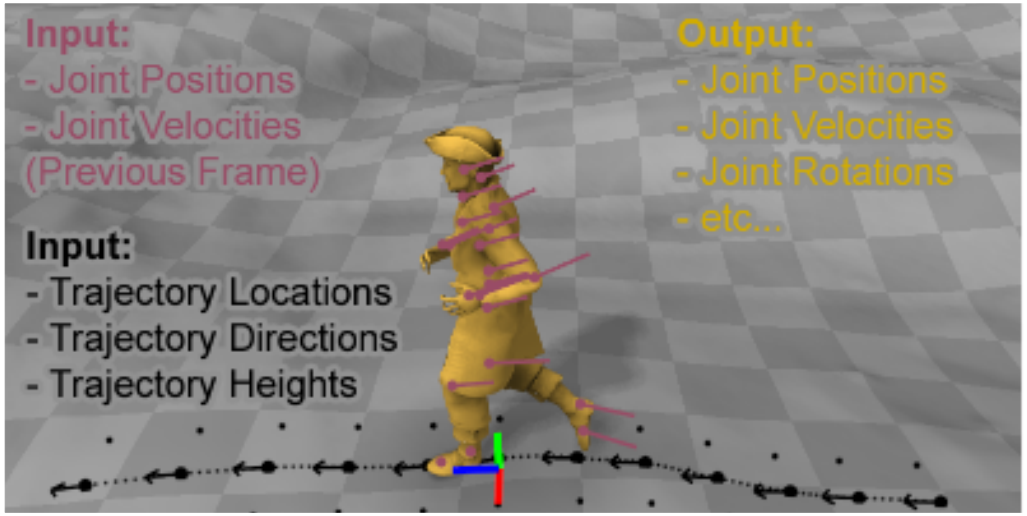
We base our solution on advancements in **Motion Graphs**, a popular concept in **Computer Graphics** and **image-to-image translation**, improving those points significantly.

1

2



3



- Zhang, H., Starke, S., Komura, T., Saito, J.: Mode-adaptive neu- ral networks for quadruped motion control. ACM Trans. Graph. 37(4), 145:1–145:11 (2018).[1]
- Wang, T.C., Liu, M.Y., Zhu, J.Y., Tao, A., Kautz, J., Catanzaro, B.: High-resolution image synthesis and semantic manipulation with conditional gans. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (2018) [2]
- Holden,D.,Komura,T.,Saito,J.: Phase-functioned neural networks for character control. ACM Trans. Graph. 36(4), 42:1–42:13 (2017). [3]

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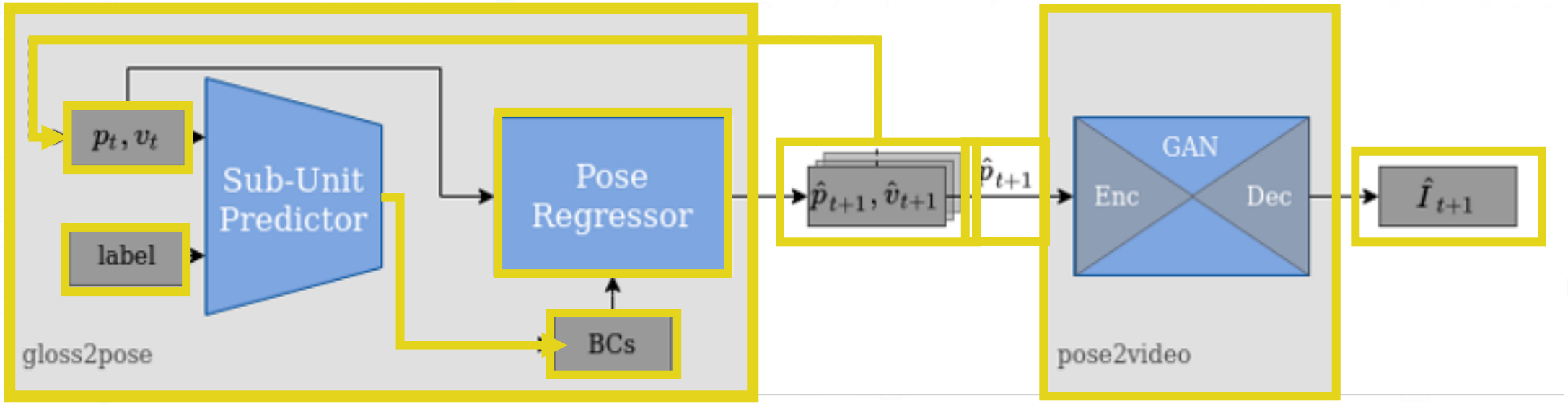
Methodology

Our approach to generating sign language video from glosses works in two stages. First glosses are translated into a human pose sequence by our gloss2pose network. The acquired poses are then used to condition a generative network called pose2video.



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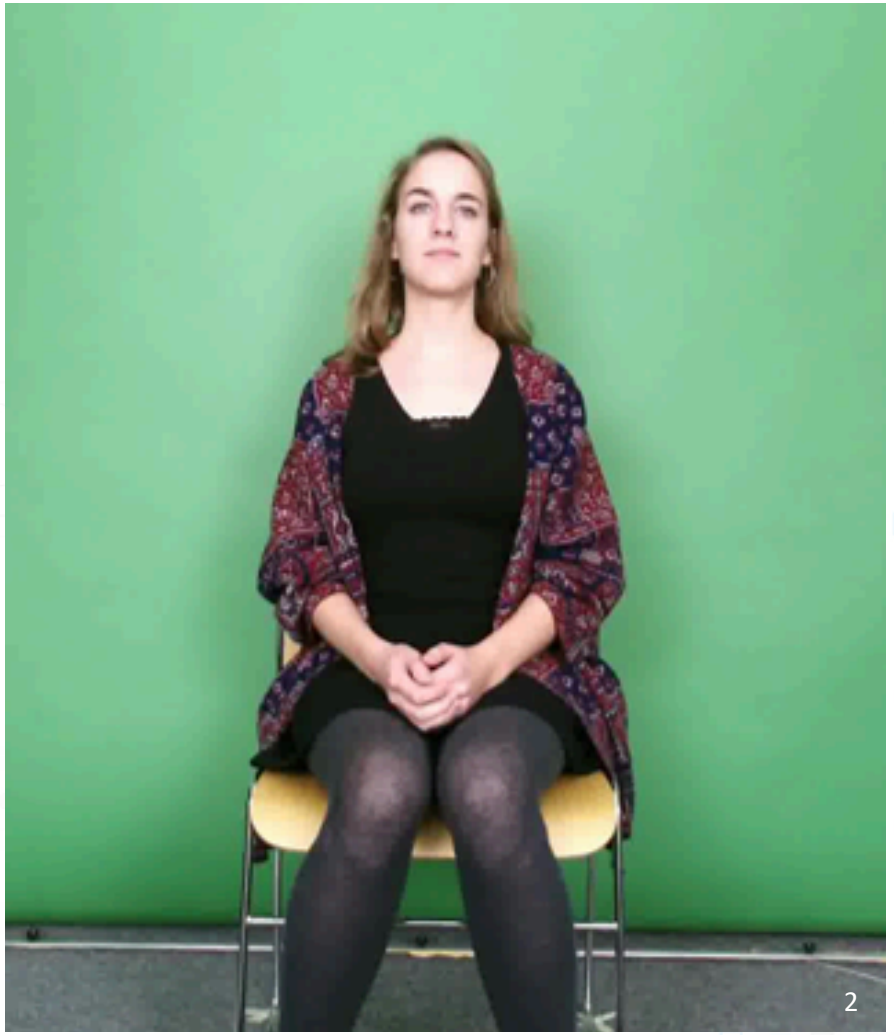
Experiments & Results – Dataset

- **We use the SMILE Sign Language Assessment Dataset for training and testing** which consists of 42 signers performing 105 signs in isolated form in Swiss-German Sign Language (DSGS).

- **We extract 2D human pose estimations from the video data**, using OpenPose for the upper body, face and hands.



- Z. Cao, G. Hidalgo Martinez, T. Simon, S. Wei and Y. A. Sheikh, "OpenPose: Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields," in IEEE Transactions on Pattern Analysis and Machine Intelligence.[1]
- SMILE Sign Language Data Set, in 11th edition of the Language Resources and EvaluationConference (LREC),2018, S. Ebling, N. C. Camgz, P. Boyes Braem, K. Tissi, S. Sidler-Miserez, S.Stoll, S. Hadfield, T. Haug, R. Bowden, S. Tornay, M. Razavi, M. Magimai-Doss.[2]

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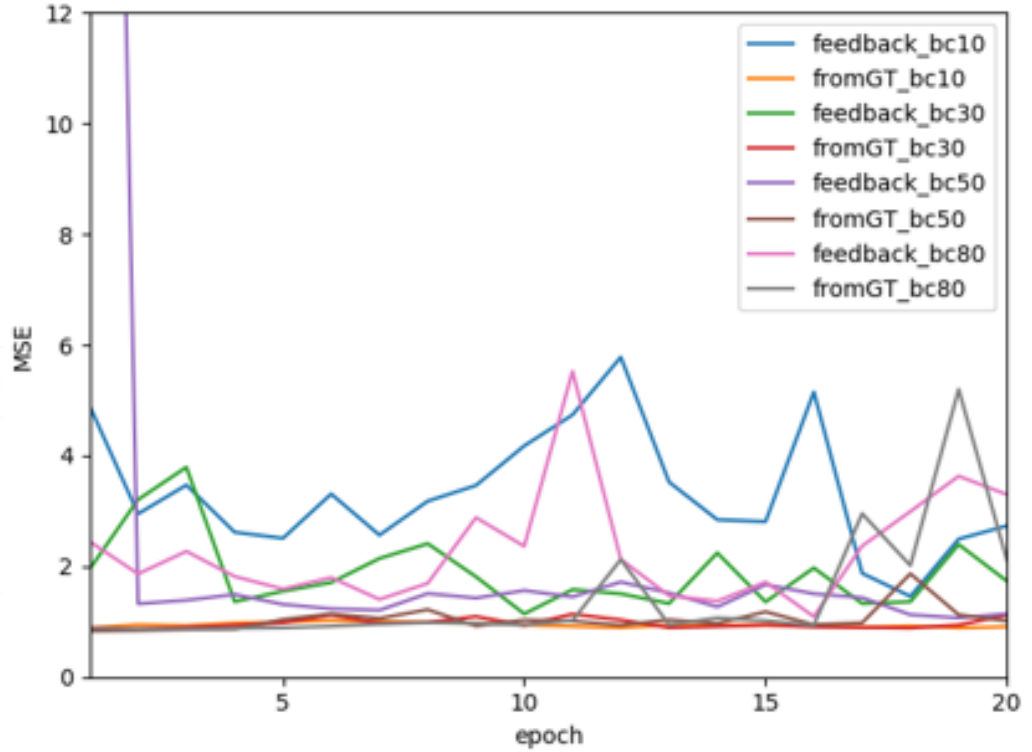
Experiments & Results – Gloss2Pose

- Most stable performance was achieved with 50 blending coefficients.
- Our subunit-predictor can dissect sign motions into sub-motions.
- We next compare the MSE of our best performing network against the lookup table approach of Stoll et al.
- Our network outperforms the SotA by a factor of 18.



	LUT (Stoll et al)	G2p (ours)
MSE	19.2886	**1.0673**

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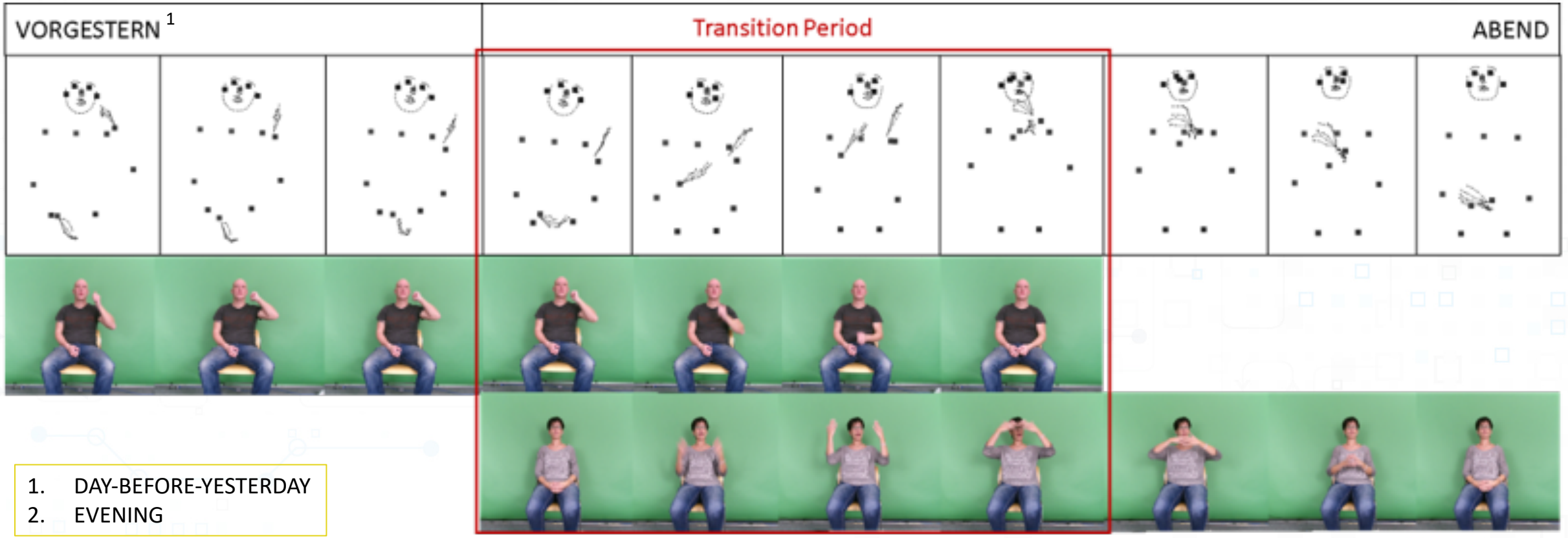
Experiments & Results – Gloss2Pose



1. DAY-BEFORE-YESTERDAY
2. EVENING

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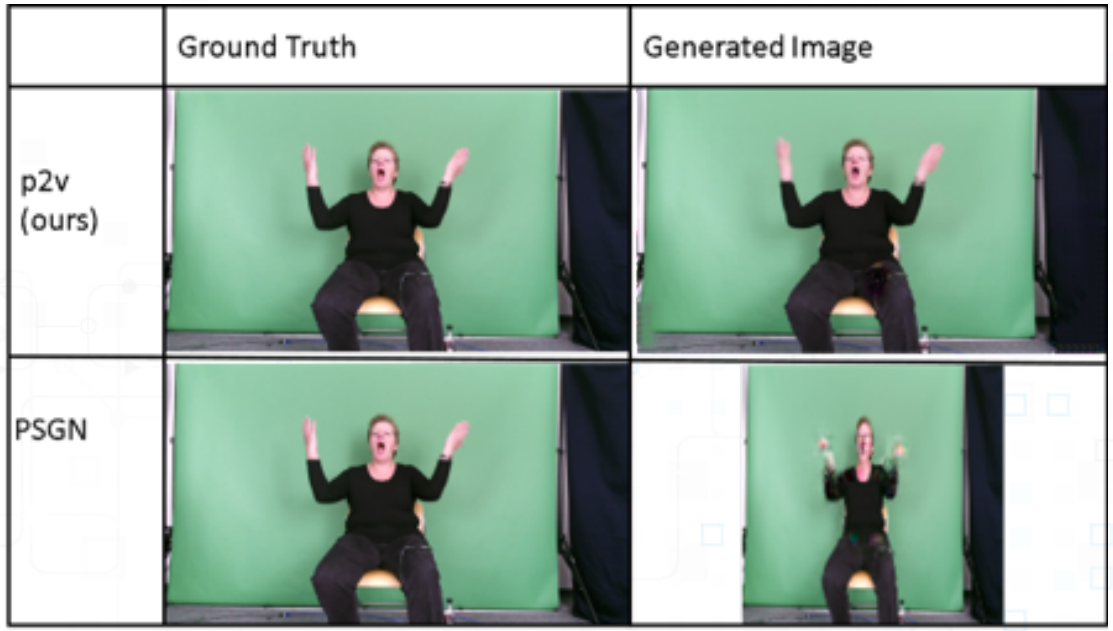
Experiments & Results – Pose2Video

- We evaluate the performance of pose2video against the Pose-Conditioned Sign Generation Network (PSGN) by Stoll et al.
- We evaluate the image generation using SSIM, PSNR and MSE.
- PSGN scores marginally higher for SSIM.
- In contrast pose2video beats PSGN by a large margin for both PSNR and MSE.



	PSGN (Stoll et al)	P2v (ours)
SSIM	**0.9434**	0.9428
PSNR	24.7248	**29.0181**
MSE	226.2474	**86.0553**

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Experiments & Results – Synthetic Sign Video Generation from Gloss

We devise two metrics to evaluate the quality of generated sign language videos:

1. A confidence score that assesses the level of detail and human characteristics of the generated videos.
2. A distance measure that assesses how closely generated sign videos resemble the ground truth videos for that gloss.

We refer to the paper for details on both metrics.

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Experiments & Results – Synthetic Sign Video Generation from Gloss

- For our first metric we assess confidences on specific body parts, such as the hands and the face, for both our approach and Stoll et al.

- For our second experiment we analyse the behaviour of keypoints over time.

- We report the mean distance between clusters of signs and synthetic samples.

	C_{pose}	C_{face}	C_{handl}	C_{handr}	C_{total}
Stoll et al. [34]	0.499	0.000	0.026	0.025	0.138
SignSynth	**0.791**	**0.766**	**0.120**	**0.266**	**0.485**

	SignSynth			Stoll et al. [34]			Reference		
Clusters	ABEND	ABER	ERZ	ABEND	ABER	ERZ	ABEND	ABER	ERZ
ABEND	**12.51**	14.49	16.17	19.82	**16.36**	19.29	**12.28**	14.61	14.69
ABER	15.58	**14.72**	17.02	18.13	**16.29**	19.35	14.86	**13.34**	15.43
ERZ	15.51	**15.32**	15.93	20.68	**17.04**	19.78	14.70	15.03	**13.54**

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Experiments & Results – Synthetic Sign Video Generation from Gloss

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Conclusions

1. We presented a **novel approach** to Sign Language Production that only requires **minimal user input**.
2. We produce sign language video with a **natural variance** in speed, expressiveness, distinctive hand shape, and **non-manuals**.
3. We smoothly and **automatically transition** between glosses, without manually enforcing co-articulation.
4. We **surpass the SotA** for pose and video generation, as well as generating videos from gloss.
5. We developed **two new metrics** to assess the quality of sign language videos.

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Future work

In the future, we want to:

1. Extend our approach to 3D data
2. Address complete spoken language to sign language translation
3. Undertake a user study with members of the Deaf community.

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Data-Driven Sign Language Video Generation

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For any questions

Live session on the 28th of August
8.00 – 10.00 UTC+1

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