Adversarial Training for Multi-Channel Sign Language Production

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Abstract

Sign Languages are rich multi-channel languages, requiring articulation of both manual (hands) and non-manual (face and body) features in a precise, intricate manner. Sign Language Production (SLP), the automatic translation from spoken to sign languages, must embody this full sign morphology to be truly understandable by the Deaf community. Previous work has mainly focused on manual feature production, with an under-articulated output caused by regression to the mean.

In this paper, we propose an Adversarial Multi-Channel approach to SLP. We frame sign production as a minimax game between a transformer-based Generator and a conditional Discriminator. Our adversarial discriminator evaluates the realism of sign production conditioned on the source text, pushing the generator towards a realistic and articulate output. Additionally, we fully encapsulate sign articulators with the inclusion of non-manual features, producing facial features and mouthing patterns.

We evaluate on the challenging RWTH-PHOENIX-Weather-2014T (PHOENIX14T) dataset, and report state-of-the-art SLP back-translation performance for manual production. We set new benchmarks for the production of multi-channel sign to underpin future research into realistic SLP.

1 Introduction

Sign languages, the principal communication of the Deaf community, are rich multi-channel languages. Communication is expressed through manual articulations of hand shape and motion, in combination with diverse non-manual features including mouth gestures, facial expressions and body pose [48]. The combination of manual and non-manual features is subtle and complicated, requiring a detailed articulation to fully express the desired meaning. Sign Language Production (SLP), the translation from spoken language input to sign language output, is therefore required to encompass the full sign morphology in order to generate an accurate and understandable production.

Although sign languages are inherently multi-channel languages, deep learning based SLP approaches have, to date, focused solely on the manual features of sign [42, 62, 63], producing only the hand and body articulators. Ignoring non-manual features discards the

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contextual and grammatical information that is required to fully understand the meaning of the produced sign [51]. Mouthing, in particular, is vital to the comprehension of most sign languages, differentiating signs that may otherwise be homophones. Previous SLP models have also been trained using a regression loss [42, 62], which results in an under-articulated production due to the problem of regression to the mean. Specifically, an average sign pose is generated, with non-expressive hand shape and body motion.

In this paper, we propose adversarial training for multi-channel SLP, implementing a discriminator model conditioned on the source spoken language sentence, and expanding production to non-manual features. We frame SLP as a minimax game between a progressive transformer Generator that produces a sequence of sign poses from input text, and a conditional Discriminator that evaluates and promotes the realism of sign production. Building on the increase in discriminative production, we expand SLP to include Non-Manual Features, producing the head motion and mouthing patterns alongside the hands and body for a more expressive output. An overview of our approach is shown in Figure 1.

We evaluate on the RWTH-PHOENIX-Weather-2014T (PHOENIX14T) dataset using a back translation evaluation, achieving state-of-the-art results for the production of manual features and setting new benchmarks for non-manual and multi-channel production. We provide qualitative examples, demonstrating the impact of adversarial training in increasing the articulation of sign production. The contributions of this paper can be summarised as:

- The first application of conditional adversarial training to SLP, to produce expressive and articulate sign pose sequences
- The first SLP model to fully encapsulate sign articulators through the production of non-manual features
- State-of-the-art SLP results on the PHOENIX14T dataset, with baselines for multi-channel sign production

The rest of this paper is organised as follows: We outline the previous work in SLP and adversarial training in Section 2, and the background on machine translation and transformer models in Section 3. We present our Adversarial Multi-Channel approach for SLP in Section 4, with quantitative and qualitative evaluation provided in Section 5. Finally, we conclude the paper in Section 6 by discussing our findings and future work.
2 Related Work

Sign Language Recognition & Translation The goal of vision-based sign language research is to develop systems capable of recognition, translation and production of sign languages [4]. Although studied for the last three decades [43, 49], previous work has mainly focused on Sign Language Recognition (SLR) [6, 26, 27]. These early works relied on manual features to understand sign, but as further linguistic aspects of sign were understood [38, 55], focus shifted to more than just the hands. Subsequent tackling of the modalities of face [24, 53], head pose [34] and mouthings [1, 25] have aided recognition performance.

Recently, Camgoz et al. introduced the first end-to-end Sign Language Translation (SLT) approach [7], learning a translation from sign videos to spoken language rather than just recognising the sequence of signs. SLT is more demanding than SLR due to sign language possessing different linguistic rules and grammatical syntax from spoken language [44]. Neural Machine Translation (NMT) networks are predominantly used in SLT [7, 23, 60], translating directly to spoken language or via gloss intermediary. Transformer based models are the state-of-the-art in SLT, jointly learning the recognition and translation tasks [8, 9].

Sign Language Production Previous work into SLP has focused on avatar-based [3, 21, 32, 65] or Statistical Machine Translation (SMT) [19, 28] methods, requiring expensive motion capture or post-processing, with output limited to pre-recorded phrases. Non-manual features have been included in avatar production, such as mouthings [56] and head positions [13], but are often viewed as “stiff and emotionless” with an “absence of mouth patterns” [22].

More recently, there have been approaches to automatic SLP via deep learning [58, 62]. However, these works focus on the production of isolated signs of a set length and order without realistic transitions, resulting in robotic and non-realistic animations that are poorly received by the Deaf [3]. Stoll et al. [45, 46] use Generative Adversarial Networks (GANs) to generate a sign language video of a human signer, as opposed to a skeleton pose. Even though the output video is visually pleasing, the approach still relies on the concatenation of isolated signs, which disregards the grammatical syntax of sign.

The closest work to this paper is that of Saunders et al. [42], who use a progressive transformer architecture to produce continuous 3D sign pose sequences, utilising a counter decoding to predict sequence length and drive generation. However, the use of regression-based training, even with multiple data augmentation techniques, suffers from the known problem of regression to the mean, resulting in an under-expressed sign production.

All previous deep learning based SLP works produce only manual features, ignoring the important non-manuals. The expansion to non-manual features is challenging due to the requirement of temporal coherence with manual features and the intricacies of facial movement. We expand production to non-manual features via the use of adversarial training to synchronise manual features and produce natural, expressive sign.

Adversarial Training Since being introduced by Goodfellow et al. [16], GANs have been used extensively to generate images of increasing realism, pairing a generator and discriminator model in an adversarial training setup. GANs have produced impressive results when applied to image generation [17, 39, 64] and, more recently, video generation tasks [50, 54]. Conditional GANs [51] extend GANs to a dependent setting, enabling generation conditioned on specific external data inputs.

1Glosses are a written representation of sign language, and defined as minimal lexical items.
There has been recent progress in using GANs for natural language tasks [31, 61, 63]. Specific to NMT, Wu et al. designed Adversarial-NMT [57], complimenting the original NMT model with a Convolutional Neural Network (CNN) based adversary, and Yang et al. [59] proposed a GAN setup with translation conditioned on the input sequence.

Specific to human pose generation, adversarial discriminators have been used for the production of realistic pose videos [5, 11, 40]. Ginosar et al. show that the task of generating skeleton motion suffers from regression to the mean, and adding an adversarial discriminator can improve the realism of gesture production [14]. Lee et al. utilise a conditioned discriminator to produce smooth and diverse human dancing motion from music [30].

3 Background

In this section, we provide a brief background on NMT sequence-to-sequence models, focusing on the recent transformer networks and their application to SLP. The goal of machine translation is to learn the conditional probability $P(Y|X)$ of generating a target sequence $Y = (y_1, ..., y_U)$ of $U$ tokens, given a source sequence $X = (x_1, ..., x_T)$ with $T$ tokens.

Recurrent Neural Networks (RNNs) were first introduced for sequence-to-sequence tasks, mapping between sequences of different lengths using an iterative hidden state computation [18]. The encoder-decoder architecture was later developed, encoding the source sentence into a “context” vector used to decode the target sequence [12, 47]. However, this context introduced an information bottleneck and long term dependency issues. Attention mechanisms overcame this by expanding the context to a soft-search over the entire source sequence, conditioning each target prediction with a learnt weighting of the encoded tokens [2, 33].

Building on attention mechanisms, Vaswani et al. introduced the transformer network, a feed-forward model that replaces recurrent modules with self-attention and positional encoding [52]. Within each encoder and decoder stack, Multi-Headed Attention (MHA) layers perform multiple projections of self-attention, learning complementary representations of each sequence. The decoder utilises a further MHA sub-layer to combine these representations, learning the mapping between source and target sequences in an auto-regressive manner.

Progressive Transformer Model

Sign languages are inherently continuous, encompassing fluid motions of hand shape, body pose and facial expressions. As SLP represents sign with continuous joint positions [45, 62], classic symbolic NMT architectures, such as transformers, cannot be applied directly without modification. To tackle this, Saunders et al. proposed a progressive transformer architecture [42], an alternative formulation of transformer decoding for continuous sequences. The model employs a counter decoding mechanism that drives generation and enables a prediction of the sequence end, alleviating the need for the classic end of sequence token found in symbolic NMT. Multiple MHA sub-layers are applied over both the source, $x_{1:T}$, and target, $y_{1:U}$, sequences separately, with a final MHA layer used to learn the translation mapping between them. This can be formalised as:

$$[\hat{y}_{u+1}, \hat{c}_{u+1}] = \text{ProgressiveTransformer}(y_u \mid y_{1:u-1}, x_{1:T})$$

where $\hat{y}_{u+1}$ and $\hat{c}_{u+1}$ are the produced joint positions and counter value respectively, given the source sentence, $x_{1:T}$, and previously predicted target poses, $y_{1:u-1}$. The model can be trained end-to-end using a regression loss of Mean Squared Error (MSE) between the ground
truth, $y_i^*$, and produced, $\hat{y}_i$, sign pose sequences:

$$L_{\text{Reg}} = \frac{1}{U} \sum_{i=1}^{U} (y_i^* - \hat{y}_i)^2$$ (2)

In this paper, we build upon the progressive transformer architecture, employing a conditional adversarial discriminator that supplements the regression loss with an adversarial loss. This mitigates the effect of regression to the mean and prediction drift found in the original architecture. To further improve sign comprehension, we also include production of the non-manual sign features of facial expressions and mouthings.

## 4 Adversarial Training for Multi-Channel SLP

In this section, we introduce our Adversarial Training scheme for Multi-Channel SLP, learning to distinguish between real and fake sign pose sequences to ensure the production of realistic and expressive multi-modal sign language. Our objective is to learn a conditional probability $P(Y|X)$ of generating a target sign pose sequence $Y = (y_1, ..., y_U)$ of $U$ time steps, given a source spoken language sentence $X = (x_1, ..., x_T)$ with $T$ words.

Realistic sign consists of subtle and precise movements of both manuals and non-manuals. However, SLP models often suffer from regression to the mean resulting in under-articulated output, producing average hand shapes due to the high variability of joint positions. To address the under-articulation of sign production, we propose an adversarial training mechanism for SLP. We utilise the previously described progressive transformer architecture (Section 3) as a Generator, $G$, to produce sign pose sequences from input text. To ensure realistic and expressive sign production, we introduce a conditional adversarial Discriminator, $D$, which learns to differentiate real and generated sign pose conditioned on the input spoken language. These models are co-trained in an adversarial manner, with mutually improved performance. The adversarial training scheme for SLP can thus be formalised as a minimax game, with $G$ aiming to minimise the following equation, whilst $D$ maximises it:

$$\min_G \max_D L_{\text{GAN}}(G, D) = \mathbb{E}[\log D(Y^* | X)] + \mathbb{E}[\log(1 - D(G(X) | X))]$$ (3)

where $Y^* = y_{1:U}$ is the ground truth sign pose sequence, $G(X)$ equates to the produced sign pose sequence, $\hat{Y} = \hat{y}_{1:U}$, and $X$ is the source spoken language.

In addition to the adversarial training, we incorporate Non-Manual Feature production to create a more realistic signer output. Non-manual features are essential in the understanding of sign language, providing grammatical syntax, context and emphasis. In this paper, we model the facial landmarks of the signer, expanding sign pose sequences, $Y$, to include head nods, mouthings and eyebrow motion. The facial landmarks of a signer can be represented as coordinates, similar to the manuals, enabling a direct regression.

### 4.1 Generator

Our Generator, $G$, learns to produce sign pose sequences given a source spoken language sequence, integrating the progressive transformer into a GAN framework. Contrary to the standard GAN implementation, we require sequence generation to be conditioned on a specific source input. Therefore, we remove the traditional noise input, and generate a sign pose sequence conditioned on the source sequence, taking inspiration from conditional GANs.
We propose training $G$ using a combination of loss functions, namely regression loss, $L_{\text{Reg}}$ (Equation 2), and adversarial loss, $L_{\text{GAN}}^G$ (Equation 3), with the total loss function as:

$$L^G = \lambda_{\text{Reg}} L_{\text{Reg}}(G) + \lambda_{\text{GAN}} L_{\text{GAN}}^G(G, D)$$

(4)

where $L_{\text{GAN}}^G$ is the latter component of Equation 3 and $\lambda_{\text{Reg}}$, $\lambda_{\text{GAN}}$ determines the importance of each loss function during training. The regression loss provides specific details about how to produce the given input, whereas the adversarial loss ensures a realistic signer motion. These losses work in tandem to create both an accurate and expressive sign production.

### 4.2 Discriminator

We present a conditional adversarial Discriminator, $D$, used to differentiate generated sign sequences, $\hat{Y}$, and ground-truth sign sequences, $Y^*$, conditioned on the source spoken language sequence, $X$. The aim of $D$ is to measure the realism of sign production, prompting $G$ towards an expressive and articulate output. In parallel, conditioning on the source sequence allows $D$ to concurrently measure the translation accuracy of source-target sequence pair, $(X, Y)$. Figure 2 shows an overview of the discriminator architecture.

For each pair of source-target sequences, $(X, Y)$, of either generated or real sign pose, the aim of the discriminator is to produce a single scalar, $d_p \in (0, 1)$, representing the probability that the sign pose sequence originates from the data, $Y^*$:

$$d_p = P(Y = Y^* \mid X, Y) \in (0, 1)$$

(5)

Due to the variable frame lengths of the sign sequences, we apply padding to transform them to a fixed length, $U_{\text{max}}$, the maximum frame length of target sequences found in the data:

$$Y_{\text{pad}} = [Y_{1:U}, \emptyset_{U:U_{\text{max}}}]$$

(6)

where $Y_{\text{pad}}$ is the sign pose sequence padded with zero vectors, $\emptyset$, enabling convolutions upon the now fixed size tensor. In order to condition the discriminator on the source spoken language, we first embed the source tokens via a linear embedding layer. Again dealing with variable sequence lengths, these embeddings are also padded to a fixed length $T_{\text{max}}$, the maximum source sequence length:

$$X_{\text{pad}} = [W^X \cdot X_{1:T} + b^X, \emptyset_{T:T_{\text{max}}}]$$

(7)
where $W^X$ and $b^X$ are the weight and bias of the source embedding respectively and $\emptyset$ is zero padding. As shown in the centre of Figure 2, the source representation is then concatenated with the padded sign pose sequence, to create the conditioned features, $H$:

$$H = [Y_{pad}, X_{pad}]$$  

To determine the realism of the sign pose sequence, the discriminator extracts meaningful representations through multiple 1D CNN layers. These convolutional filters are passed over the sign pose at the sequence level, analysing the local context to determine the temporal continuity of the signing motion. This is more effective than a frame level discriminator at determining realism, as a mean hand shape is a valid pose for a single frame, but not consistently over a large temporal window. Leaky ReLU activation is applied after each layer, promoting healthy gradients during training. A final feed-forward linear layer and sigmoid activation projects the combined features down to the single scalar, $d_p$, representing the probability that the sign pose sequence is real.

We train the discriminator by maximising the likelihood of producing $d_p = 1$ for real sign sequences and $d_p = 0$ for generated sequences. This objective can be formalised as maximising Equation 3, resulting in the loss function $L^D = L^D_{GAN}(G, D)$.

## 5 Experiments

In this section, we report quantitative and qualitative experimental results. Dataset and evaluation details are provided, with an evaluation of our adversarial SLP model to follow.

### 5.1 Implementation Details

**Dataset:** We evaluate our approach on the publicly available PHOENIX14T dataset introduced by Camgoz et al. The corpus provides 8257 German sentences and sign gloss translations alongside parallel sign pose videos of a combined 835,356 frames. We train our adversarial model to generate sign pose sequences of skeleton joint positions. Manual features of each video are extracted in 2D using OpenPose, and lifted to 3D using the skeletal model estimation improvements presented in. For non-manual features, we represent facial landmarks as 2D coordinates, again extracted using OpenPose. The face coordinates are scaled to a consistent size and then centered around the nose joint. Each frame is then represented by the normalised joints of the signer, as $x$, $y$ and $z$ coordinates.

**Implementation setup:** We setup our adversarial training with a progressive transformer generator built with 2 layers, 4 heads and a 512 embedding size. Our discriminator consists of 3 1D convolution layers, each with a feature size of 64 and a filter size of 10. We jointly train $G$ and $D$ by providing batches of source spoken language and target sign pose sequences, updating the model weights simultaneously with their respective loss functions $L^G$ and $L^D$. Experimentally, we find the best generator loss weights to be $\lambda_{Reg} = 100$ and $\lambda_{GAN} = 0.001$.

During testing, we drop $D$ and use the trained $G$ to produce sign pose sequences given an input text. All parts of our network are trained with Xavier initialisation and Adam optimization, with a learning rate of $10^{-3}$. Our code is based on Kreutzer et al.’s NMT toolkit, JoeyNMT, and implemented using PyTorch.
5.2 Adversarial Training

We start with evaluation of our proposed adversarial training regime, initially producing only manual features to isolate the effect of the adversarial loss. We first conduct experiments on the Gloss2Pose (G2P) task, evaluating the production capabilities of our network. As shown in Table 1, our adversarial training regime improves performance over Saunders et al., a model trained solely with a regression loss \[42\]. This shows that the inclusion of a discriminator model increases the comprehension of sign production. We believe this is due to the discriminator pushing the generator towards a more expressive and articulate production, in order to deceive the adversary. This, in turn, increases the sign content contained in the generated sequence, leading to a more understandable output.

We next experiment with conditioning the discriminator on the source input, to provide discrimination upon both the raw translation and the realism of sign production. As shown, the additional conditioning on the source input improves performance even further. We believe this is due to the generator now requiring a more accurate translation to fool the discriminator, improving the mapping between source input and sign pose.

Our next experiment evaluates the performance of our adversarial training approach for the Text2Pose (T2P) task. Table 2 demonstrates that our adversarial model again achieves state-of-the-art results, further showcasing the effect of adversarial training. As the discriminator is conditioned upon the source text, the generator is prompted to accomplish both the accurate translation and realistic production tasks simultaneously.

5.3 Multi-Channel Sign Production

Our final experiment evaluates the production of non-manual features, either independently (Non-M), or in combination with manual features (M + Non-M). We first produce sign using a sole regression loss and subsequently add the proposed adversarial loss, with G2P...
results shown in Table 3. The sole production of non-manual features contains less signing information than manuals, shown by the relatively low BLEU-4 score of 7.39. This is because facial features complement the manual communication of the hands, providing contextual syntax to emphasise meaning as opposed to independently delivering content.

However, the combination of manual and non-manual feature production significantly increases performance to the highest BLEU-4 score of 13.16. Even the regression model improves performance compared to the manual production alone, highlighting the isolated effect. We believe the multi-channel sign production allows the communication of complementary information, with non-manuals providing further context to increase comprehension. This results in an articulate sign production, moving the field of SLP closer towards a more understandable output. The addition of adversarial training further improves the performance of both non-manual and manual feature production, indicating the ability of our approach to capture the full content of the sign and its morphology.

### 5.4 Qualitative Experiments

Figure 3 shows example frames of multi-channel sign pose sequences produced by our proposed adversarial training approach, compared against Saunders et al. [42]. The examples show an increase in articulation and realism, with a highlight on the importance of non-manual production. Specific to non-manual features, we find a close correspondence to the ground truth video alongside accurate mouthings and head movements.

Figure 4 shows the isolated effect of adversarial training compared to a pure regression approach. Viewed alongside ground truth frames, the produced sign pose demonstrates accurate manual and non-manual production. We find that the addition of adversarial training produces sequences of increased articulation, with a smoother production. Hand shapes can
be seen to be more expressive and meaningful, an important result for sign comprehension and understandable SLP. Further examples are available in the supplementary materials.

6 Conclusion

Sign languages are visual multi-channel languages and the principal form of communication of the Deaf. Sign Language Production (SLP) requires the production of the full sign morphology in an articulate manner in order to be understood by the Deaf community. Previous deep learning based SLP work has generated only manual features, in an under-expressed production due to the problem of regression to the mean.

In this paper, we proposed an adversarial multi-channel approach for SLP. Framing SLP as a minimax game, we presented a conditional adversarial discriminator that measures the realism of generated sign sequences and pushes the generator towards an articulate production. We also introduced non-manual feature production to fully encapsulate the sign language articulators. We evaluated on the PHOENIX14T dataset, showcasing the effectiveness of our adversarial approach by reporting state-of-the-art results for manual production and setting baselines for non-manuals.

As future work, we would like to further increase the realism of sign production by generating photo-realistic human signers, using GAN image-to-image translation models [11, 17, 64] to expand from the skeleton representation. Furthermore, user studies in collaboration with the Deaf are required to evaluate the reception of the produced sign pose sequences.

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