Improving Ultrasound Tongue Image Reconstruction from Lip Images Using Self-supervised Learning and Attention Mechanism

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ABSTRACT
Speech production is a dynamic procedure, which involved multi human organs including the tongue, jaw and lips. Modeling the dynamics of the vocal tract deformation is a fundamental problem to understand the speech, which is the most common way for human daily communication. Researchers employ several sensory streams to describe the process simultaneously, which are incontrovertibly statistically related to other streams. In this paper, we address the following question: given an observable image sequences of lips, can we picture the corresponding tongue motion. We formulated this problem as the self-supervised learning problem, and employ the two stream convolutional network and long-short memory network for the learning task, with the attention mechanism. We evaluate the performance of the proposed method by leveraging the unlabeled lip videos to predict an upcoming ultrasound tongue image sequence. The results show that our model is able to generate images that close to the real ultrasound tongue images, and results in the matching between two imaging modalities.

1 INTRODUCTION
In the natural speech production process, researchers have employed a number of sensory streams to describe the highly variable movements of articulators simultaneously [39]. Accurately modeling the deformation of vocal tract not only can be helpful to the theoretical quest in speech-related researches but also can be helpful for lots of seen applications, such as pronunciation training [4], speech therapy and biosignal-based spoken communication [29] (including: Silent Speech Interfaces (SSI) [3]).

Since last several decades, different imaging techniques have been employed to analyze the speech production processing, such as X-ray, electromagnetic mid-sagittal articulography (EMA) [37], Magnetic Resonance Imaging (MRI) [24] and ultrasound [33]. X-ray imaging can provide good temporal resolution, however, the subjects are exposed to radiation and it is forbidden presently. As for the EMA, the data can provide motion information by measuring the motion trajectory of the tongue. Nevertheless, EMA is invasive, which makes it difficult for natural speech production recording. MRI system can capture tongue movement with good resolution, but requires summation of repetitions to get good spatial-temporal resolution [24]. Ultrasound is attractive, as it is non-invasive and relatively easy to conduct the experiments with good temporal and spatial resolution [33]. Moreover, ultrasound equipment is much relatively cheaper.

It is well known that different imaging modality contains the information which is directly related to the speech signals. These imaging modalities are incontrovertibly statistically related each other, such as recent studies suggest that one can picture the corresponding tongue motion from their voice and vice versa [26]. Here, we would like to ask a related question: given an observable image sequences of lips, can we predict the motion of the tongue [21]. The authors in [39] demonstrated that deep learning model[12, 20] can reconstruct the tongue’s motion from the lip images with satisfactory performance. However, there remains considerable room for improvement for the reconstruction task.

Inspired by the advancements in deep learning and cross-modal mapping[7], we explored self-supervised learning [13] to build the correspondence between these two modalities. In more detail, we explore a deep neural network architecture: two-stream Convolutional long short memory network for the task, in which the deep network is trained to predict tongue motions in ultrasound image sequences based on lip image sequence. Thus, the model can leverage the temporal alignment information between two modalities.
Moreover, to improve the performance further, the attention mechanism is explored. To demonstrate the effectiveness of proposed method, extensive experiments are conducted. The experimental results show that our model is able to generate images that close to the real ultrasound tongue images, and results in the matching between two imaging modalities.

The remaining of this paper is organized as follows: the related work is described in the next section. Section 3 presents the methodology and experimental results are given in Section 4. Conclusions and future perspectives appear in the last section.

2 RELATED WORK

The task defined in this paper can be uniquely positioned in the context of two research fields: speech production study and self-supervised learning.

2.1 Speech production study

Measuring vocal tract’s deformation directly is difficult since the vocal tract lies within the oral cavity and is inaccessible to most instruments [33]. Indirectly imaging method has served as a valuable tool for the studies in speech production. Previous attempts focus on extract features from the images [10, 15, 34, 35]. As aforementioned, these imaging modalities are incontrovertibly statistically related each other. In [21], the authors explored the use of deep neural networks to estimate the tongue’s motion from the face pictures. In this paper, we follow the task defined in [39] and we aim to picture tongue’s motion from the lip images, leveraging the ultrasound tongue imaging.

2.2 Self-supervised Learning

Self-supervised learning[18, 23] aims to build the deep model which exploits implicit labels, and the labels are free available in the data themselves. There has been an increasing interest in the self-supervised learning framework within the speech production research community [1, 6, 30]. As we employ the temporal alignment information between the ultrasound tongue image and the lip images from stand industrial camera, our work belongs to the domain of self-supervised learning. Last two years, more attempts have been made to match the speaker identity between the face images and voice [25, 36, 40] or audio to gesture[11, 22] and audio to dance[8, 41]. However, very few attempts have been made to build the correspondence between the ultrasound images and the lip images.

3 METHODOLOGY

Our goal is to generate the ultrasound tongue image sequences, which corresponds to the duration of the lip image sequences during the natural speech production process. Central to our method is the observation that the natural synchronization between the ultrasound tongue images and lip images in unlabeled video, which can serve as a form of self-supervision for learning [9]. As shown in Figure 1, the architecture of our model is given, which comprised of an two-stream convolutional neural network [31] and Long short-term memory (LSTM) network [14], with attention mechanism [2]. In the following of this paper, we denote our method as TS-CNN-LSTM (two-stream CNN and LSTM). The two-stream convolutional neural network takes the aforementioned lip video clip and its optical flow as inputs and compact them into a latent vector representing the visual features, which can be used to reconstruct the ultrasound tongue image using the LSTM. The details of the components will be in given subsequently.

3.1 Two stream convolutional neural network

As suggested in [5], the instantaneous movements of the lips could be significantly disambiguated. Therefore, here we employ two streams deep model for the learning task, which including two input branches: a clip of N consecutive grayscale lip image frames, and (N – 1) consecutive dense optical flow fields. The optical flow fields can correspond to the motion in (u, v) directions for pixels of consecutive frames. Previous studies proven that optical flow can provide better performance of deep models when combined with raw input, and has even been successfully used as a stand-alone network input. Here, we crop the region of the mouth and resized the region to a fixed size of $H \times W$ (set as $96 \times 96$ in our experiments). Thus, the size of input for the first branch is $H \times W \times N$ (N is the number of frames, and we found that using $N = 7$ frames as input worked best). The dense optical flow is employed as the input for the second branch, which adds an additional input with the size of $H \times W \times (N - 1) \times 2$. Optical flow is positively influential in our experiments as well, which will be shown later.

3.2 Long short-term memory

To capture the temporal information from the sequence, our network architecture also contains the LSTM layer, which is one of the recurrent neural network (RNN)[27] models. The core part of LSTM is the memory unit $C_t$, which can be adjusted. Specifically, the input gate $i$ encodes the information $x_t$ input at the current moment and the hidden unit $h_{t-1}$ at the previous moment, and then recognizes the information that can change the memory unit. In addition, the forget gate $f$ can control whether to forget the information of the memory unit $c_{t-1}$ at the previous moment. Finally, the input gate $o$ adjusts how many proportions of memory unit information can pass and then generate hidden units $h_t$. Given a sequence input $x = \{x_1, x_2, \cdots, x_N\}$, LSTM can learn the relation between the input sequences (the lip image sequences), and the updated rules are shown in the following formula:

$$i_t = \sigma(W_{xi} \times x_t) + W_{hi} h_{t-1} + b_i \quad (1)$$

$$f_t = \sigma(W_{xf} \times x_t) + W_{hf} h_{t-1} + b_f \quad (2)$$

$$o_t = \sigma(W_{xo} \times x_t) + W_{ho} h_{t-1} + b_o \quad (3)$$

$$g_t = tanh(W_{xg} \times x_t) + W_{hg} h_{t-1} + b_g \quad (4)$$

$$c_t = f_t \times c_{t-1} + i_t \times g_t \quad (5)$$

$$h_t = o_t \times \text{tanh}(c_t) \quad (6)$$

where $x_t$ is a fixed-length input vector representation. $W_{ij}$ is the weight parameter representation that links different layers. LSTM is widely-used for sequential modeling.
3.3 Attention mechanism

Recent studies suggested that: the performance of deep learning can be heavily decreased when the entire input features is squashed to a fixed length vector. Attention mechanism can be used to alleviate this issue, which is proposed in [2], which is a brain-like information processing mechanism based on human visual characteristics research. It can dynamically assign different weights to lip video based on the output of the TS-CNN-LSTM network at different times. We implement the attention mechanism as an additional sigmoid layer with one node output, and the propose is force the LSTM network to focus more on the frame in which the lip’s motion events occur. The predicted attention factor \( F_{\text{att}}(t) \) at the \( t_{\text{th}} \) clips indicates the importance of each fusion feature for the final ultrasound tongue image reconstruction task:

\[
F_{\text{att}}(t) = \sigma(W_{\text{att}} Y_t + b_{\text{att}}),
\]

(7)

here \( Y_t \) is the output features for the LSTM network, at the \( t_{\text{th}} \) video clips. \( \sigma \) is the sigmoid function. \( W_{\text{att}} \) and \( b_{\text{att}} \) denote the weights and bias of the attention mechanism. Then, the importance of each fusion feature is multiplied with the LSTM network’s outputs to ensure the pipeline more deterministic:

\[
Y_{\text{LSTM}}(t) = F_{\text{att}}(t) Y_{\text{LSTM}}(t),
\]

(8)

where \( Y_{\text{LSTM}}(t) \) denotes the result generated from the hidden layers of the LSTM. The weighted feature for final ultrasound tongue image reconstruction is denoted by \( Y'_{\text{LSTM}}(t) \).

During this process, the importance of some certain frames will be highlighted and the reconstruction performance will be improved.

4 EXPERIMENTS RESULTS

4.1 Dataset and implementation details

Following [39], the 2010 Silent Speech Challenge (SSC) data is used for our experiments [17]. In this dataset, the ultrasound tongue images and lip videos are synchronously recorded at a speed of 60 frames per second. We randomly selected 100,000 sequence pairs from the dataset and 60% of the data were used in training, 20% are used for validation and the remaining 20% were used for the evaluation. We implemented the network using the Keras library 1 built on top of TensorFlow 2. Before each activation layer, we perform the Batch Normalization process[16]. Dropout[32] is used to prevent overfitting, and the dropout rate is set as 0.25 after convolutional layers and 0.5 after fully connected ones. The Leaky ReLU[38] activation function is used as the non-linear activation function in all layers but the last two. We use Adam optimizer[19] with an initial learning rate of \( 10^{-4} \). The batch size is set as 32 and stop training is conducted when the validation loss stops decreasing (around 50 epochs). We trained network using the back-propagation with mean squared error (MSE) loss. The ConvLSTM architecture proposed in [39] is used for the quantitatively comparison.

4.2 Performance evaluation

4.2.1 Subjective evaluation. Figure 2 is given to visualize the reconstructed frames, in which both the predicted ultrasound tongue image sequences and the real ones are given. As shown in the figure, our results are promising enough to indicate that reconstructing ultrasound tongue images is a feasible task, leveraging the lip image sequence as the input. The predicted contains the realistic tongue shapes. To further evaluate the reconstruction performance

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1 https://keras.io/
2 https://www.tensorflow.org/
between different approaches, we randomly chose 40 generated frames from the test set of the speaker. 12 subjects (4 females, 8 males; 18–21 years old; the author is not included) are asked to score the similarity between the generated ones and the original. The range of the similarity score is 1-5 (higher is better). The Table 1 shows the average similarity scores for the tested approaches. The higher score means the better performance. In general, the proposed method can provided preferred performance, compared to the ConvLSTM network.

![Image of reconstructed ultrasound tongue images using ConvLSTM and TS-CNN-LSTM (with attention).](image)

**Figure 2:** This figure illustrates the reconstructed ultrasound tongue images using ConvLSTM and TS-CNN-LSTM (with attention).

| Method                      | Similarity score |
|-----------------------------|------------------|
| ConvLSTM[39]                | 2.67 ± 0.56      |
| TS-CNN-LSTM (w/o attention) | 2.84 ± 0.49      |
| TS-CNN-LSTM (Ours)          | **3.01 ± 0.33**  |

**Table 1:** The similarity score for the user study from 12 subjects. Our results are given by averaging the scores for different approaches. Higher score means better performance.

4.2.2 **Objective evaluation.** Except for the subjective evaluation, we also conduct quantitative evaluation of the learning model. To measure the naturalness of the reconstructed ultrasound images, three metrics were chosen. The first two metrics, structural similarity index (SSIM) and complex wavelet structural similarity index (CW-SSIM) [28] are calculated over each frame from the original image sequences and the predicted ones. For the third metric, we used the mean sum of distances (MSD) to compare the contour manually extracted from the real ultrasound tongue image and the reconstructed ones. Table 2 presents the results. According to these objective experiments, all measures have shown the advantage of proposed TS-CNN-LSTM method, instead of ConvLSTM. Moreover, attention mechanism consistently improves the prediction performance.

| Method                      | AT | SSIM ↑ | CW-SSIM ↑ | MSD ↓ |
|-----------------------------|----|--------|-----------|-------|
| ConvLSTM[39]                |    | 0.697  | 0.719     | 5.263 |
| ConvLSTM[39]                | ✓  | 0.699  | 0.728     | 5.234 |
| TS-CNN-LSTM                 |    | 0.711  | 0.761     | 5.056 |
| TS-CNN-LSTM (Ours)          | ✓  | **0.728** | **0.765** | **4.953** |

**Table 2:** Quantitative comparison between different experiments settings. Higher SSIM, CW-SSIM and lower MSD means better performance. In the table, attention mechanism is denoted as “AT”.

4.3 **Ablation study**

We conducted a few ablation studies to understand the key components in our model. We compare our full model with (i) a model using only raw lip image sequences; (ii) a model with no attention mechanism; (iii) a model using raw data and optical flow as the input, but without attention mechanism. Table 3 shows the results of this analysis. Our analysis shows that adding optical flow provide most of the information needed for reconstructing speech, while the attention mechanism give slightly better results.

| Input                      | SSIM | CW-SSIM |
|----------------------------|------|---------|
| Raw Images (with TS-CNN-LSTM) | 0.683 | 0.706 |
| Ours (w/o OF)              | 0.691 | 0.712  |
| Ours (w/o AT)              | 0.711 | 0.761  |
| Ours                       | **0.728** | **0.765** |

**Table 3:** Results of ablation analysis. Adding optical flow can provide most of the information needed, and attention mechanism gives slightly better results. In the table, optical flow and attention mechanism are denoted as “OF” and “AT”, respectively.

5 **CONCLUSION**

We aim to reconstruct the tongue image from the simultaneously recorded lip motion using the TS-CNN-LSTM network, and the proposed method is seen to achieve better reconstruction results through subjective and objective evaluation compared to ConvLSTM architecture. As aforementioned, our method might be useful for speech production studies, articulatory motion synthesis and for pronunciation training. It is worthwhile to notice that our method is speaker-dependent, and a new model needs to be fine-tuned for each new speaker. Achieving speaker-independent ultrasound tongue image reconstruction is a non-trivial task, and will be explored in our future work.
REFERENCES

[1] Hassan Akbari, Himani Arora, Liangliang Cao, and Nima Mesgarani. 2018. Lip2audspec: Speech reconstruction from silent lip movements video. In 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2516–2520.

[2] Dzmitry Bahdanau, Kyung Hyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In 3rd International Conference on Learning Representations, ICLR 2015.

[3] Christian Kroos, Rikke L Bundgaard-Nielsen, Catherine T Best, and Mark Plumbley. 2017. Using deep neural networks to estimate tongue movements from speech face motion. Proceedings of AVSP 2017.

[4] Shaojin Ding, Christopher Liberatore, Sinem Sonaat, Ivana Lučić, Alif Silpachai, Guanlong Zhan, Evgeny Chukhaze-Hudailainen, John Levis, and Ricardo Gutierrez-Osuna. 2019. Golden speaker builder–An interactive tool for pronunciation training. Speech Communication 115 (2019), 51–66.

[5] Ariel Ephrat, Tavi Halperin, and Shmuel Peleg. 2017. Improved speech recognition from silent video. In Proceedings of the IEEE International Conference on Computer Vision Workshops. 455–462.

[6] Joao P Ferreira, Thiago M Coutinho, Thiago L Gomes, José F Neto, Rafael Azevedo, Fangxiang Feng, Xiaojie Wang, and Ruifan Li. 2014. Cross-modal retrieval with deep convolutional neural networks. In Proceedings of the 19th ACM International Conference on Multimedia. 7–16.

[7] Dzmitry Bahdanau, Kyung Hyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In 3rd International Conference on Learning Representations, ICLR 2015.

[8] Christian Kroos, Rikke L Bundgaard-Nielsen, Catherine T Best, and Mark Plumbley. 2017. Using deep neural networks to estimate tongue movements from speech face motion. Proceedings of AVSP 2017.

[9] Michael Wand, Tanja Schultz, and Jürgen Schmidhuber. 2012. Domain-Adversarial Training for Session Independent EMG-based Speech Recognition. In INTERSPEECH 2012.

[10] Karen Simonyan and Andrew Zisserman. 2014. Two-stream convolutional networks for action recognition in videos. In Proceedings of the 27th International Conference on Neural Information Processing Systems-Volume 1. 1–8.

[11] Simon Stone and Peter Birkholz. 2020. Cross-speaker silent-speech command word recognition using electro-optical stomatography. In ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 6789–7053.

[12] Karen Simonyan and Andrew Zisserman. 2014. Two-stream convolutional networks for action recognition in videos. In Proceedings of the 27th International Conference on Neural Information Processing Systems-Volume 1. 1–8.

[13] Michael Wand, Tanja Schultz, and Jürgen Schmidhuber. 2012. Domain-Adversarial Training for Session Independent EMG-based Speech Recognition. In INTERSPEECH 2012.

[14] Aciel Eshky, Manuel Sam Ribeiro, Korin Richmond, and Steve Renals. 2019. Synchronous audio and ultrasound by learning cross-modal embeddings. (2019).

[15] Fangxiang Feng, Xiaojie Wang, and Ruifan Li. 2014. Cross-modal retrieval with deep convolutional neural networks. In Proceedings of the 19th ACM International Conference on Multimedia. 7–16.

[16] Aciel Eshky, Manuel Sam Ribeiro, Korin Richmond, and Steve Renals. 2019. Synchronous audio and ultrasound by learning cross-modal embeddings. (2019).

[17] Christian Kroos, Rikke L Bundgaard-Nielsen, Catherine T Best, and Mark Plumbley. 2017. Using deep neural networks to estimate tongue movements from speech face motion. Proceedings of AVSP 2017.

[18] Christian Kroos, Rikke L Bundgaard-Nielsen, Catherine T Best, and Mark Plumbley. 2017. Using deep neural networks to estimate tongue movements from speech face motion. Proceedings of AVSP 2017.