End-to-End Lip Synchronisation

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\textbf{Abstract}

The goal of this work is to synchronise audio and video of a talking face using deep neural network models. Existing works have trained networks on proxy tasks such as cross-modal similarity learning, projecting audio and video frames into a joint embedding space\cite{10,11,12}. There are a number of works that have utilized the joint embedding vectors to tackle various tasks. The goal of this work is to synchronise audio and video of a talking face using deep neural network models. Existing works have trained networks on proxy tasks such as cross-modal similarity learning, projecting audio and video frames into a joint embedding space. There are a number of works that have utilized the joint embedding vectors to tackle various tasks.

\textbf{Index Terms}: Audio-to-video synchronisation, pattern recognition.

\textbf{1. Introduction}

Audio-to-video synchronisation is one of the crucial characteristics that any video clip should have. An off-sync video is not only unnatural to the human eye, but also causes errors in audio-visual speech enhancement\cite{2,3} and in making datasets for speaker recognition\cite{4} and lip reading\cite{5}. However, in several stages of recording and broadcasting, a video can go out of synchronisation. During recording, the delay between the audio and the video stream can cause the video to go out of sync. Also, when a video stream is transmitted, loss or corruption of frames can occur during both wired and wireless communication, causing synchronisation errors.

Cross-modal learning has received increasing attention recently, using two or more data modalities such as text, image, audio and video\cite{6,7,8,9}. It effectively represents not only an instance of a modality, but also the complex correlation between instances of multiple modalities, projecting them into a joint embedding space\cite{10,11,12}. There are a number of works that have utilized the joint embedding vectors to tackle various tasks.

Speech enhancement\cite{2,13}, source localization\cite{14,15}, active speaker detection\cite{16,17,18}, lip reading\cite{19,20,21} and action recognition\cite{22,23} are examples of audio-video tasks; and video captioning\cite{24,25} and video-text retrieval\cite{26,27} are video-text modality tasks.

In this paper, we propose a method based on the joint embeddings to tackle the AV synchronisation problem. More specifically, we predict the time offset between audio and video streams by using the similarities between the embeddings of the two streams.

A previous work of particular relevance to this paper is\cite{28}, which introduced a two stream architecture called SyncNet to handle the AV sync task. SyncNet is trained to maximize the similarities between features of the audio and the video segments that come from the same point in time, while minimizing the similarities for segments that come from different points in time. In\cite{29,30}, cross-modal embeddings are learnt by using the multi-way matching objective that optimises the relative similarities between multiple audio features and one video feature. Both use the trained network to project audio and video inputs into the joint embedding space, and use the sliding window approach to correct the AV sync error. By sliding the window of fixed length, the similarities of every embedding pair are calculated, and the sync offset is determined from the embedding indices where the similarity is maximised.\cite{31} addresses the problem of synchronising lip motion in re-dubbed or animated videos, where dynamic time warping is needed to compute the offset at frame-level. While this is an interesting problem in its own right, we do not consider this case.

In this paper, we propose a new approach to determine AV time offset, by focusing on the fact that the offset is consistent in a recorded video. We assume that this consistency can be represented as a linear pattern in the similarity matrix, calculated from continuous audio and video features. The matrix consists of similarities between all audio-video embedding pairs extracted from the two-stream CNN feature extractor. Based on this assumption, we formulate AV synchronisation task as a pattern classification problem where the offset value can be predicted directly. Pattern matching approach integrates the information over multiple time steps, learning to ignore the non-discriminative time steps such as when mouth is occluded or phonemes are repeated. The method can be trained in an end-to-end manner jointly with feature extractors. We demonstrate the proposed classification-based approach outperforms all existing method in lip synchronisation.

The remainder of this paper is organized as follows. Section 2 describes the cross-modal training framework including the proposed approach. The experimental settings and system specifications are presented in Section 3 with the results. The paper is concluded in Section 4.

\textbf{2. Cross-modal learning framework}

In this section, we introduce the baseline system and propose a novel framework for directly predicting the temporal offset between audio and video streams. Typically, a process of AV synchronisation is as follows: (1) a network configuration is defined to handle audio and video streams (2) the network is trained to learn audio-visual representations in a joint embedding space (3) audio-visual offset is established using the output of the trained network. Each stage of the pipeline is described in the following subsections.
The network specifications are identical to SyncNet [28] except for a small change in the input dimensions. Figure 1 shows the layer configuration for both audio and video streams. The input to the network are audio and video streams of a synchronised talking face video. 0.2 seconds of the clip are digested to the each stream of the feature extractor at each timestep.

2.1. Audio stream

The input to the audio stream is 40-dimensional mel-spectrogram extracted from the 16kHz audio signal. As a result, the input dimension is $224 \times 224 \times 40$ seconds at 25 fps). The dimension of the input is therefore $3 \times 3 \times 224 \times 224$.

The architecture of the audio stream is based on VGG-M [32] that is originally designed for the image, but the filter sizes are modified to accommodate smaller input dimensions of the mel-spectrogram.

2.1.2. Video stream

For the video stream, the input is the RGB frames extracted from cropped talking face videos. The frames are extracted from the video at 25 fps, and then resized into $224 \times 224$. The network ingests 5 frames at a time (corresponding to 0.2 seconds at 25 fps). The dimension of the input is therefore $224 \times 224 \times 3 \times 5 (H \times W \times C \times T)$. As with the audio stream, the architecture is based on the VGG-M [32] network, except that a 3D filter instead of the 2D one at the first layer to capture the temporal information through the stacked frames.

2.2. Learning cross-modal embeddings

The goal here is to train audio and visual representations in a joint embedding space, such that matching audio-video pairs lies close together in the embedding space, while non-matching pairs lie far apart. To achieve this goal, SyncNet uses the contrastive loss from Siamese networks [31] to train the feature extractor. The loss function maximises or minimises the similarity between one audio and one visual feature.

2.2.1. Audio stream

The architecture of the feature extractor is shown in Figure 1. The layer configuration consists of convolutional layers (Conv) with kernel sizes of $3 \times 3$ and $5 \times 5$, followed by pooling layers (Pool) with kernel sizes of $3 \times 3$.

2.2.2. Video stream

The layer configuration for the video stream is similar to the audio stream, except that a 3D filter instead of the 2D one at the first layer to accommodate the 3D nature of the video data.

2.3. Computing the audio-visual offset

Baseline. To find out the time offset from AV stream, [28] and [29] use the sliding window approach shown in Figure 2. In a fixed-length length window, the distances between a visual feature and all audio features contained in a window are calculated. However, it is not efficient to determine the time offset within a single window due to the limited information. For example, there can be a moment when the speaker covers his/her mouth or stops talking, in which case the video cannot provide discriminative information, considering that AV synchronisation is computed based on the phonetic information. Therefore, the distances are computed several times by sliding the window and then averaged to obtain more accurate results. The audio and the video streams are considered synchronised when the feature distances between them are minimised. More details on the sliding window approach can be found in [29].

Proposed approach. In this section, we propose a novel method to determine the temporal offset between the co-occurring data streams. The proposed method is motivated from the fact that the AV time offset of a video clip is constant within a short clip, which can be represented by a linear pattern in a similarity matrix. We calculate the cosine similarity matrix of size $M \times M$, where $M$ is the number of audio and video features. The element at $(i,j)$ is the cosine similarity between the $i$-th audio feature and the $j$-th visual feature.

The elements at the point where the audio and the video features are synchronised have the relatively large value compared to others in the matrix. Since the AV sync error is assumed to be constant in a video clip, the points with the larger similarities...
should represent a linear pattern in the matrix. Based on this assumption, we treat the similarity matrix as an image, and use it as an input to a pattern classifier to predict the temporal offset. We expect that the classifier extracts the pattern in the matrix, and maps the pattern to a class representing the offset value.

Figure 3(a) shows the process of generating the similarity matrix, and Figure 3(b) shows examples of the patterns for various offset values on similarity matrices. If AV are synchronised, the linear pattern can be found along the diagonal of the distance matrix (middle). If the video stream leads the audio, the pattern is located parallel to, but below the diagonal (left), and in the opposite case, it is located above the diagonal (right). Therefore, we hypothesise that it is possible to predict the offset value by formulating the problem as one of pattern recognition. In our experiments, we search for the offset over $[-5, +5]$ frame range. This makes it a 11-way classification including zero offset. A negative offset denotes the video stream leads the audio stream, and zero offset represents perfect synchronisation.

We propose two strategies to determine the AV offset based on the pattern recognition approach: (1) the similarity matrices are pre-extracted and the offset is determined as a classification task, (2) the feature extractor and the offset classifier are trained end-to-end with full supervision. We refer to the former as SyncNet-cls, and the latter as SyncNet-e2e. By training a classifier with a large amount of data, SyncNet-cls can learn to deal with non-regular patterns that are difficult to detect using the heuristic in the baseline method. In addition, SyncNet-e2e optimizes the entire network for further improvement in performance. Figure 4 shows an overview of the proposed approach compared to the existing approaches.

Table 1 shows the layer configuration of SyncNet-cls that consists of four convolution layers. The $(3 \times 3)$ kernel of the first convolution layer captures the local pattern, and the second kernel captures the global pattern in the similarity matrix. The second layer’s kernel size, $(N \times N)$ is same as the input tensor. All convolution layers have BatchNorm and ReLU, except for the last layer. Note that no strides or max-pooling layers are used, since location invariance would be an adverse characteristics of the network for this task, unlike in image recognition. Softmax is used as the last activation function, and cross-entropy loss is used to train the network. For SyncNet-e2e, we train the feature extractor and the SyncNet-cls at the same time, using the same cross-entropy loss.

In addition to the above, we provide another ablation to demonstrate the effectiveness of our method. We compute the average values of the lines parallel to the diagonal in the similarity matrix, and find the line that has the largest average value representing the highest correspondence between the streams. This is done for the diagonal line, and those adjacent to it in the $[-5, +5]$ frame range. This method benefits from the use of similarity matrix and avoids the adverse effect of padding in the baseline sliding window approach, but does not learn to deal with irregular patterns unlike the trainable methods. We name this method Diag-avg in the subsequent tables.

3. Experiments

We evaluate the performances of baseline, Diag-avg, SyncNet-cls and SyncNet-e2e methods. We then analyze and discuss the performance improvement given by each of our proposed approaches. All the networks in our experiments are implemented using PyTorch [35] and evaluated in NAVER Smart Machine Learning (NSML) environment [36].
3.1. Setting

3.1.1. Dataset

Pre-train sets of Lip Reading Sentences 2 (LRS2) [27] and Lip Reading Sentences 3 (LRS3) [38] are used for training and testing. LRS2 has 96,318 clips in the pre-train set and consists of videos sourced from the BBC television. LRS3 has 118,516 clips which are sourced from TED and TEDx videos. Both sets are used for training, however 7,100 videos from the LRS2 dataset is reserved for testing.

All videos in the dataset are perfectly synchronised, therefore we introduce a random artificial offset of $[-5, +5]$ both during training and test.

3.1.2. Evaluation protocol

We measure 2 types of accuracies – with ±1 frame tolerance or without. For the accuracy with tolerance, a prediction regarded as correct when it falls within ±1 range [29, 30] of the ground truth. We repeat the evaluation 10 times and report the average value and standard deviation to mitigate the effect of random offset during evaluation.

3.2. Result

3.2.1. Performance evaluation

Table 2 shows the accuracy for different numbers of input RGB frames. The baseline shows the lowest performance in all cases, and the difference is particularly large for shorter clips. Diag-avg shows the significant improvement over the baseline. SyncNet-cls predicts the time offset better than both non-trainable methods, because of its robustness to the noisy patterns that result from less representative features or non-informative video segments. SyncNet-e2e consistently shows the highest performance across all number of the input frames, and the best accuracy without tolerance is 79.26% with 20 input images. The end-to-end method shows superior performance to SyncNet-cls since the whole network is trained specifically for the task, hence the feature extractor is able to provide optimal features for the classifier to predict the offset.

Table 2 (bottom) shows the accuracy with one frame tolerance for all methods. The overall pattern is similar to the case without tolerance. The baseline shows the lowest accuracy, and SyncNet-e2e achieves the highest performance across all scenarios. The best model predicts the offset of 95.18% of videos to with one frame tolerance, using only 0.8 second streams.

3.2.2. Analysis and discussion

We calculate the relative error reduction (RER) [39] between the baseline and the proposed methods. Across all experiments, the proposed methods show significant improvement over the baseline, with the highest relative gain of 39.59% for 11 frames in the experiments without tolerance. The RER is more significant with tolerance than without, and the biggest error reduction rate is 50.22% for 11 frame input. Note that the relative performance gain is smaller when the input length is longer – this is because the baseline method can already predict most of the examples correctly, while many of the incorrectly classified segments contain no discriminative information.

| # RGB frames | 11 | 13 | 15 | 20 |
|--------------|----|----|----|----|
| Mean acc. w/o tolerance ± std (RER) | | | | |
| Baseline | 76.73 ± 0.34 | 83.85 ± 0.40 | 88.05 ± 0.26 | 93.34 ± 0.23 |
| Diag-avg | 83.05 ± 0.35 | 88.38 ± 0.25 | 90.88 ± 0.20 | 94.35 ± 0.08 |
| SyncNet-cls | 86.52 ± 0.19 | 90.49 ± 0.24 | 92.10 ± 0.19 | 95.18 ± 0.18 |
| SyncNet-e2e | 88.42 ± 0.29 | 90.79 ± 0.15 | 92.60 ± 0.19 | 95.18 ± 0.14 |

4. Conclusions

In this paper, we have proposed the new approach to synchronise audio and video in a talking face. Previous works extract the audio and visual features using the trained feature extractor, and then determine the time offset between the two streams by using the sliding window approach. However, there are many challenging cases that are difficult to handle using the heuristic in the previous works. To this end, we propose a novel approach that trains the network to directly find the time offset between the two streams. We evaluate the performances of baseline, Diag-avg, SyncNet-cls, and SyncNet-e2e, using LRS2 and LRS3 lip-reading datasets, measuring the accuracy with and without ±1 frame tolerance. Proposed methods outperform the baseline by a large margin, across a range of experiments. Our best model shows the highest accuracy 95.18%, only given a short input of 0.8 seconds.

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6. References

[1] ITU, “Bt.1359 : Relative timing of sound and vision for broadcasting,” International Telecommunication Union, ITU, 1998.

[2] A. Ephrat, I. Mosseri, O. Lang, T. Dekel, K. Wilson, A. Hassidim, W. T. Freeman, and M. Rubinstein, “Looking to listen at the cocktail party: A speaker-independent audio-visual model for speech separation,” arXiv preprint arXiv:1804.03619, 2018.

[3] T. Afouras, J. S. Chung, and A. Zisserman, “The conversation: Deep audio-visual speech enhancement,” in INTERSPEECH, 2018.

[4] A. Nagrani, S. Albanie, and A. Zisserman, “VoxCeleb: a large-scale speaker identification dataset,” in INTERSPEECH, 2017.

[5] J. S. Chung and A. Zisserman, “Lip reading in the wild,” in Proceedings of the Asian Conference on Computer Vision, 2016.

[6] B. Korbar, D. Tran, and L. Torresani, “Cooperative learning of audio and video models from self-supervised synchronization,” in Advances in Neural Information Processing Systems, 2018, pp. 7763–7774.

[7] A. Owens and A. A. Efros, “Audio-visual scene analysis with self-supervised multisensory features,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018.

[8] C. Kim, H. V. Shin, T.-H. Oh, A. Kasper, M. Elgharib, and W. Matusik, “On learning associations of faces and voices,” arXiv preprint arXiv:1805.05553, 2018.

[9] S. Morishima, S. Ogata, K. Murai, and S. Nakamura, “Audio-visual speech translation with automatic lip syncronization and face tracking based on 3-d head model,” in Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing, vol. 2. IEEE, 2002, pp. II–2117.

[10] A. Nagrani, S. Albanie, and A. Zisserman, “Learnable pins: Cross-modal embeddings for person identity,” in Proceedings of the European Conference on Computer Vision, 2018.

[11] A. Nagrani, J. S. Chung, S. Albanie, and A. Zisserman, “Disentangled speech embeddings using cross-modal self-supervision,” in Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing, 2020.

[12] A. Nagrani, S. Albanie, and A. Zisserman, “Seeing voices and hearing faces: Cross-modal biometric matching,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 8427–8436.

[13] T. Afouras, J. S. Chung, and A. Zisserman, “My lips are concealed: Audio-visual speech enhancement through obstructions,” in Interspeech, 2019, pp. 4295–4299.

[14] R. Arandjelovic and A. Zisserman, “Objects that sound,” in Proceedings of the European Conference on Computer Vision, 2018, pp. 435–451.

[15] A. Senocak, T.-H. Oh, J. Kim, M.-H. Yang, and I. So Kweon, “Learning to localize sound source in visual scenes,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 4358–4366.

[16] P. Chakravarty and T. Tuytelaars, “Cross-modal supervision for learning active speaker detection in video,” in Proceedings of the European Conference on Computer Vision. Springer, 2016, pp. 285–301.

[17] P. Chakravarty, J. Zegers, T. Tuytelaars, and H. Van hamme, “Active speaker detection with audio-visual co-training,” in Proceedings of the ACM Multimedia Conference, 2016, pp. 312–316.

[18] A. Garg, V. Pavlovic, and J. M. Rohg, “Audio-visual speaker detection using dynamic bayesian networks,” in Proceedings Fourth IEEE International Conference on Automatic Face and Gesture Recognition. IEEE, 2000, pp. 384–390.

[19] Y. M. Assael, B. Shillingford, S. Whiteson, and N. de Freitas, “Lipnet: Sentence-level lipreading,” arXiv:1611.01599, 2016.

[20] T. Afouras, J. S. Chung, A. Senior, O. Vinyals, and A. Zisserman, “Deep audio-visual speech recognition,” IEEE Transactions on Pattern Analysis and Machine Intelligence, 2019.

[21] T. Afouras, J. S. Chung, and A. Zisserman, “Astr is all you need: cross-modal distillation for lip reading,” arXiv preprint arXiv:1911.12747, 2019.

[22] M. A. Arabac, F. Özkan, E. Surer, P. Jančović, and A. Temizel, “Multi-modal egocentric activity recognition using audio-visual features,” arXiv preprint arXiv:1807.00612, 2018.

[23] R. Gao, T.-H. Oh, K. Grauman, and L. Torresani, “Listen to look: Action recognition by previewing audio,” arXiv preprint arXiv:1912.04487, 2019.

[24] Z. Wu, T. Yao, Y. Fu, and Y.-G. Jiang, “Deep learning for video classification and captioning,” in Frontiers of multimedia research, 2017, pp. 3–29.

[25] Q. Jin and J. Liang, “Video description generation using audio and visual cues,” in Proceedings of the ACM Multimedia Conference, 2016, pp. 239–242.

[26] J. Siciv and A. Zisserman, “Video google: A text retrieval approach to object matching in videos,” in Proceedings of the International Conference on Computer Vision, 2003, p. 1470.

[27] N. C. Mithun, J. Li, F. Metze, and A. K. Roy-Chowdhury, “Learning joint embedding with multimodal cues for cross-modal video-text retrieval,” in Proceedings of the ACM Multimedia Conference, 2018, pp. 19–27.

[28] J. S. Chung and A. Zisserman, “Out of time: automated lip sync in the wild,” in Workshop on Multi-view Lip-reading, ACCV, 2016.

[29] S.-W. Chung, J. S. Chung, and H.-G. Kang, “Perfect match: Improved cross-modal embeddings for audio-visual synchronisation,” in Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing. IEEE, 2019, pp. 3965–3969.

[30] ——, “Perfect match: Self-supervised embeddings for cross-modal retrieval,” IEEE Journal of Selected Topics in Signal Processing, 2020.

[31] T. Halperin, A. Ephrat, and S. Peleg, “Dynamic temporal alignment of speech to lips,” in Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing. IEEE, 2019, pp. 3980–3984.

[32] K. Chatfield, K. Simonyan, A. Vedaldi, and A. Zisserman, “Return of the devil in the details: Delving deep into convolutional nets,” in Proceedings of the British Machine Vision Conference, 2014.

[33] S. Chopra, R. Hadsell, and Y. LeCun, “Learning a similarity metric discriminatively, with application to face verification,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, vol. 1. IEEE, 2005, pp. 539–546.

[34] S.-W. Chung, H. G. Kang, and J. S. Chung, “Seeing voices and hearing faces: learning discriminative embeddings using cross-modal self-supervision,” arXiv preprint arXiv:2004.14326, 2020.

[35] A. Paszke, S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, T. Killeen, Z. Lin, N. Gimelshein, L. Antiga, A. Desmaison, A. Kopf, E. Yang, Z. DeVito, M. Raison, A. Tejani, S. Chilamkurthy, B. Steiner, L. Fang, J. Bai, and S. Chintala, “Pytorch: An imperative style, high-performance deep learning library,” in Advances in Neural Information Processing Systems, 2019, pp. 8024–8035.

[36] N. Sung, M. Kim, H. Jo, Y. Yang, J. Kim, L. Lausen, Y. Kim, G. Lee, D. Kwak, J.-W. Ha et al., “Nsml: A machine learning platform that enables you to focus on your models,” arXiv preprint arXiv:1712.05902, 2017.

[37] J. S. Chung, A. Senior, O. Vinyals, and A. Zisserman, “Lip reading sentences in the wild,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2017, pp. 3444–3453.

[38] T. Afouras, J. S. Chung, and A. Zisserman, “Lrs3-ted: a large-scale dataset for visual speech recognition,” arXiv preprint arXiv:1809.00496, 2018.

[39] G. H. Golub and C. F. Van Loan, Matrix Computations, 3rd ed. The Johns Hopkins University Press, 1996.