Facial Image Generation from Speech Input using GAN

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Task and motivation

Task statement and definitions:

- Explore the usage of spoken descriptions directly as input for the task of image generation using GAN.

Motivation:

- Many world languages do not possess written form and are purely based on speech.
- Speech-to-image S2IGAN model in [5] is performed on the CUB and Oxford-102 datasets comparable to results achieved by state-of-the-art T2IGAN models. We plan to implement a similar model and test it on a Multi-Modal-CelebA-HQ Dataset [6].

Related work:

- S2IGAN model [5]

Goals

Our goals are as follows:

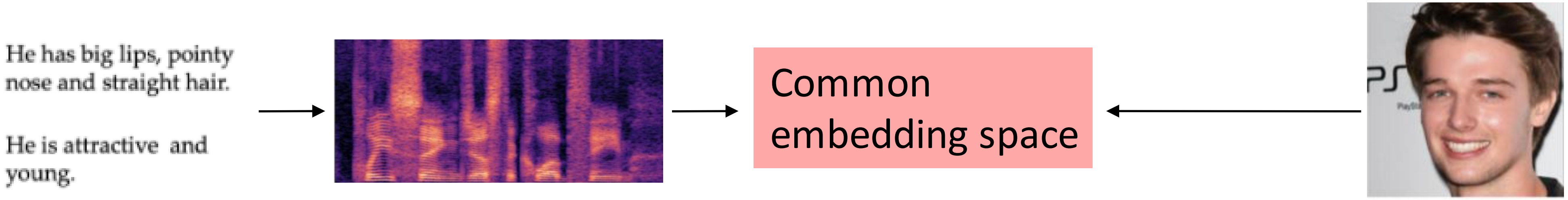
- Implement the S2IGAN model [5] using Multi-Modal-CelebA-HQ Dataset [6].
- Compare the results between text-to-image generation [6] and speech-to-image generation[5].

We aim to complete the following task by mid-term:

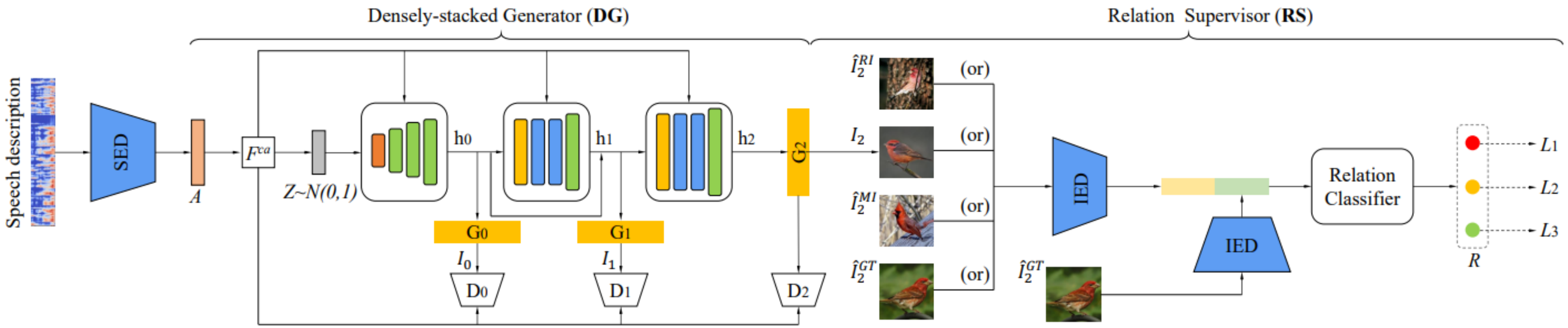
- Data preprocessing of speech and image pairs.
- Setup baselines: implement the generator and the classifier, prepare the model to run on toy sample.

Methods

- Pre-processing the dataset to have image-audio caption pairs.



- Implement a GAN architecture following the model used in [5].



- Train our model and evaluate it by generating images from the audio descriptions.
- (optional) Incorporate/experiment with other types of GAN architecture.

Dataset

- Dataset: Multi-Modal-CelebA-HQ [6]
  - 30,000 facial images paired with text descriptions (may use 1/3 - ½ of dataset)
  - Text will be translated to audio spectrogram via Tacotron2 TTS model [3].
- Rationale:
  - Benchmark evaluation with ready-to-use and processing friendly format
  - Model has not been tested on facial images
- Sample: [6]

Text Description
This woman has brown hair and wears lipstick. She is young and attractive

Evaluation

- Subjective Approach:
    - Qualitatively compare generated images with ground truth images
    - Compare generated images with those generated by benchmark T2IGAN models (e.g. imaged generated from TediGAN reported in [6])
- Objective Approach:
    - Fréchet Inception Distance (FID) [1]
        - Metric specifically developed to assess the quality of images from GAN generator
        - Compare distribution of the generated images with that of the real images
    - Inception Score (IS) [7]
        - Measure quality and diversity of the generated images
        - Only rely on the distribution of the generated images
    - May simplify and report only the FID

References

[1] Martin Heusel et al. “GANs Trained by a TwoTime-Scale Update Rule Converge to a LocalNash Equilibrium”. In:arXiv:1706.08500 [cs, stat](Jan. 2018). arXiv:1706.08500 [cs, stat].

[2] Maria-Elena Nilsback and Andrew Zisserman.“Automated flower classification over a large number of classes”. In:2008 Sixth Indian Conferenceon Computer Vision, Graphics & Image Processing. IEEE. 2008, pp. 722–729.

[3] Jonathan Shen et al. “Natural tts synthesis byconditioning wavenet on mel spectrogram predictions”. In:2018 IEEE International Confer-ence on Acoustics, Speech and Signal Processing(ICASSP). IEEE. 2018, pp. 4779–4783.

[4] Catherine Wah et al. “The caltech-ucsd birds-200-2011 dataset”. In: (2011).

[5] Xinsheng Wang et al. “S2IGAN: Speech-to-ImageGeneration via Adversarial Learning”. In:Proc.Interspeech 2020. 2020, pp. 2292–2296.doi:10.21437 / Interspeech . 2020 - 1759.url:http ://dx.doi.org/10.21437/Interspeech.2020-1759

[6] Weihao Xia et al. “TediGAN: Text-Guided Di-verse Face Image Generation and Manipulation”.In:IEEE Conference on Computer Vision andPattern Recognition (CVPR). 2021.

[7] Han Zhang et al. “StackGAN: Text to Photo-realistic Image Synthesis with Stacked GenerativeAdversarial Networks”. In:ICCV. 2017.