

RSGAN: RECURRENT STACKED GENERATIVE ADVERSARIAL NETWORK FOR CONDITIONAL VIDEO GENERATION

INTRODUCTION

Generating video frames based on a pre-condition is a challenging problem and requires understanding of per frame contents and visual dynamics and their relevacies to the pre-condition. In this project, we propose a novel Recurrent Stacked Generative Adversarial Network (RSGAN) based model to generate video frames based on a given pre-condition. In our knowledge, this is the first work to address the problem of conditional video generation using adversarial network. We can address the problem of generating videos based on pre-conditions such as,

- 1. action classes
- 2. fMRI signals
- 3. sentence descriptions



OUR APPROACH



- connected by a Fully Convolutional LSTM Network.











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OBJECTIVE FUNCTION

Conditioned on Gaussian latent variables c_0 , Stage-I RSGAN trains discriminator D_0 and generator G_0 by alternatively maximizing \mathcal{L}_{D_0} and minimizing \mathcal{L}_{G_0} . **Stage-I RSGAN:**

 $\mathcal{L}_{D_{o}} = \mathbb{E}_{(I_{o},t)\sim p_{data}}[log D_{0}(I_{0},\varphi_{t})] + \mathbb{E}_{z\sim p_{z},t\sim p_{data}}[log(1-D_{0}(G_{0}(z,c_{0}),\varphi_{t}))]$ $\mathcal{L}_{G_0} = \mathbb{E}_{z \sim p_z, t \sim p_{data}} [log(1 - D_0(G_0(z, c_0), \varphi_t))] + \lambda D_{KL}(\mathcal{N}(\mu_0(\varphi_t), \sum_0(\varphi_t)) || \mathcal{N}(0, I))$

Conditioned on the low resulation sample s_0 and Gaussian latent variables c, discriminator D and generator G in Stage-II RSGAN is trained by alternatively maximizing \mathcal{L}_D and minimizing \mathcal{L}_G . **Stage-II RSGAN:**

 $\mathcal{L}_{D} = \mathbb{E}_{(I,t) \sim p_{data}} [log D(I,\varphi_{t})] + \mathbb{E}_{s_{o} \sim pG_{o},t \sim p_{data}} [log(1 - D(G(s_{o},c),\varphi_{t}))]$ $\mathcal{L}_{G} = \mathbb{E}_{s_{o} \sim pG_{o},t \sim p_{data}} [log(1 - D(G(s_{o},c),\varphi_{t}))] + \lambda D_{KL}(\mathcal{N}(\mu(\varphi_{t}),\sum(\varphi_{t}))||\mathcal{N}(0,I))$

RESULT

Ground truth (1st row) and the **partial result on Convolutional**

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Video action: Point finger at the other person

• Right now, we are trying to generate video with simple details. That's why we are using NTU RGB+D Action Recognition Dataset (skeletal data).

FUTURE RESEARCH

• Generate video with complex details and multiple moving objects. • Use fMRI dataset of human brain, to generate video.

REFERENCES

[1] H. Zhang, T. Xu, H. Li, S. Zhang, X. Huang, X. Wang, and D. Metaxas. StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks. *arXiv preprint arXiv:1612.03242*, 2016.

[2] S. Valipour, M. Siam, M. Jagersand, and N. Ray. Recurrent Fully Convolutional Networks for Video Segmentation. *arXiv preprint arXiv:1611.09904*, 2016.

[3] O. Mogren. C-RNN-GAN: Continuous recurrent neural networks with adversarial training. arXiv preprint arXiv:1611.09904, 2016.

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Video action: Slapping other person

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