

# CS 381V Visual Recognition Final Project Proposal

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## Abstract

*In this project, we plan to explore the benefits of providing semantic segmentation data to an image super-resolution (SR) system.*

## 1. Introduction

Image super-resolution is a compelling area of computer vision. Being able to convert low resolution photos and video to higher resolution counterparts is an important problem as hardware continues to improve. With higher resolution displays and cameras more available today than ever before, it would be nice if we could convert old media to the same resolution standards as current photos and video. Naive methods of upsampling using bicubic interpolation introduce many artifacts and produce visually displeasing images. With the increase in popularity of deep networks sparked by work from Krizhevsky et al. [8], it appears that some variant of a deep network could provide good results for this task. We also plan to combine semantic segmentation with state-of-the-art SR techniques to provide for better results.

## 2. Related Work

Prior work involving image synthesis with deep networks involves one of two techniques: using a more conventional CNN for upsampling [6] [12] [7] or using a generative adversarial network (GAN) [4]. Typically, the CNN approaches attempt to minimize the per-pixel loss between the upsampled output image and the original unmodified image. The error metric frequently used is peak signal-to-noise ratio (PSNR). However, when this is applied directly on the pixel space, this often encourages the network to make soft changes in the upsampled image rather than generate the high-frequency changes often found in real images. GAN based approaches like in [9] attempt to overcome this by using an adversarial network. Though they get lower PSNR values, the images often look more realistic, which suggests that some other metric should be used to get better results.

In [2], Chen and Koltun experiment with using semantic segmentation from the Cityscapes dataset [3] to perform photorealistic image synthesis. However, to our knowledge, there have been no papers published that attempt to merge together this explicit semantic data with a SR technique for better results. We believe that this will provide for better results than what is currently achievable with the published methods.

## 3. Technical Plan

## 4. Experimental Plan

We will build upon the open-source implementation of [9] which uses TensorFlow 1.2.

## 5. Sources of Data

Image SR techniques are self-supervised in that explicit annotation of data is unneeded. Given an image, a training pair can easily be generated by using the downsampled image as the input to the SR network and the original image as the ground truth. However, in order to integrate semantic segmentation knowledge, we need to obtain the semantic layout for each image. There are two ways that we plan on going about this. The first is to use datasets that already include the segmentation such as the Cityscapes [3] dataset. The other approach is to use existing segmentation networks like in [10] to generate the segmentation before the down-sized image is fed into our SR network. We plan to compare the results of the two to see if the more accurate human annotated segmentations are required to get good results from our technique, or if a fully-automated SR approach can be achieved.

To compare our results against those obtained from other papers, we plan on using standard evaluation datasets that are used in [9]. These include Set5 [1], Set14 [13], and BSD100 which is the a subset of BSD300 [11]

## 6. Partner Plan

For the programming portion of the project, we plan to pair-program and divide equally the implementation work.

For experiments, we will individually drive each one while working together as needed, with each person driving an equal number of experiments. The report will be written collaboratively. The person with more expertise on a given section will lead writing for that section.

## 7. Speculation of Results

Current state-of-the-art semantic segmentation methods already involve CNNs. One may argue that a CNN based approach for SR would automatically learn information regarding segmentation if it is useful for providing better results. However, this argument does not take into account the difficulty of learning such information. A parallel argument was made for residual networks in [5] with regards to learning identity mappings. However, the authors found that it was often difficult for networks to learn such mappings. We predict that adding the semantic segmentation data explicitly to the network will allow it to make more intelligent decisions along object boundaries. We expect this will help provide more crisp edges. Because of the success with using semantic masks at various resolutions in [2], we expect that our results will be better at high upsampling factors.

## References

- [1] M. Bevilacqua, A. Roumy, C. Guillemot, and M. Alberi-Morel. Low-complexity single-image super-resolution based on nonnegative neighbor embedding. In *British Machine Vision Conference, BMVC 2012, Surrey, UK, September 3-7, 2012*, pages 1–10, 2012.
- [2] Q. Chen and V. Koltun. Photographic image synthesis with cascaded refinement networks. *CoRR*, abs/1707.09405, 2017.
- [3] M. Cordts, M. Omran, S. Ramos, T. Rehfeld, M. Enzweiler, R. Benenson, U. Franke, S. Roth, and B. Schiele. The cityscapes dataset for semantic urban scene understanding. *CoRR*, abs/1604.01685, 2016.
- [4] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. Generative adversarial nets. In Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 27*, pages 2672–2680. Curran Associates, Inc., 2014.
- [5] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. *CoRR*, abs/1512.03385, 2015.
- [6] J. Johnson, A. Alahi, and F. Li. Perceptual losses for real-time style transfer and super-resolution. *CoRR*, abs/1603.08155, 2016.
- [7] J. Kim, J. K. Lee, and K. M. Lee. Deeply-recursive convolutional network for image super-resolution. *CoRR*, abs/1511.04491, 2015.
- [8] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 25*, pages 1097–1105. Curran Associates, Inc., 2012.
- [9] C. Ledig, L. Theis, F. Huszar, J. Caballero, A. P. Aitken, A. Tejani, J. Totz, Z. Wang, and W. Shi. Photo-realistic single image super-resolution using a generative adversarial network. *CoRR*, abs/1609.04802, 2016.
- [10] J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. *CoRR*, abs/1411.4038, 2014.
- [11] D. Martin, C. Fowlkes, D. Tal, and J. Malik. A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. In *in Proc. 8th Intl Conf. Computer Vision*, pages 416–423, 2001.
- [12] W. Shi, J. Caballero, F. Huszar, J. Totz, A. P. Aitken, R. Bishop, D. Rueckert, and Z. Wang. Real-time single image and video super-resolution using an efficient sub-pixel convolutional neural network. *CoRR*, abs/1609.05158, 2016.
- [13] R. Zeyde, M. Elad, and M. Protter. *On Single Image Scale-Up Using Sparse-Representations*, pages 711–730. Springer Berlin Heidelberg, Berlin, Heidelberg, 2012.