Reviews On Papers Related To:

Image Inpainting Using Context Encoders

**Karthik Uday Jadhav**

**Instructor**’**s Name :** Dr. Anil Gavade.

**Course Title :** Image Processing and Computer Vision

**Course Code :** 18EC61

**01) “Generative Image Inpainting with Contextual Attention”**

Using a Context Encoder network for picture inpainting, which is described in the research, missing areas of an image are filled in based on the context of the pixels around them. Given that it was trained on such a large number of images, the network is known to produce outputs that are both realism- and aesthetically-pleasing. The authors compare their approach to other cutting-edge inpainting techniques and show that it outperforms them in terms of visual quality and accuracy. The method's limitations are also discussed, including difficulties in dealing with complex and changeable textures. In terms of picture inpainting, the Context Encoder network is a potential technique that might be used in fields like synthesis, restoration, and image modification.

Link: [Click Here](https://openaccess.thecvf.com/content_cvpr_2018/html/Yu_Generative_Image_Inpainting_CVPR_2018_paper.html)

**02) “High-Resolution Image Inpainting Using Multi-Scale Neural Patch Synthesis”**

With the goal to produce detailed findings on high-resolution photos, this research suggests a novel method for image completion that makes use of deep neural networks and patch synthesis. It is based on combined optimisation of image content and texture restrictions, matching and adapting patches with similar mid-layer feature correlations using a trained classification network. On the ImageNet and Paris Streetview datasets, the suggested method is assessed, and it obtained cutting-edge inpainting accuracy. The limits of current approaches are also discussed, along with how the suggested strategy gets around them.

Link: [Click Here](https://openaccess.thecvf.com/content_cvpr_2017/html/Yang_High-Resolution_Image_Inpainting_CVPR_2017_paper.html)

**03) “Context Encoders: Feature Learning by Inpainting”**

Context Encoders, an unsupervised visual feature learning approach based on context-based pixel prediction using a convolutional neural network, are introduced in this research. Using a common pixel-wise reconstruction loss and an adversarial loss, it creates missing portions of an image based on its surroundings. With regards to classification, detection, and segmentation tasks, the learnt features are useful for CNN pre-training. The system can also be applied to applications requiring semantic inpainting, and by including an adversarial loss, predictions become significantly more accurate. By fine-tuning the encoder for various image interpretation tasks, the learnt feature representation is verified.

Link: [Click Here](https://openaccess.thecvf.com/content_cvpr_2016/html/Pathak_Context_Encoders_Feature_CVPR_2016_paper.html)

**04) “Learning Pyramid-Context Encoder Network for High-Quality Image Inpainting”**

PEN-Net, short for Pyramid-context Encoder Network, is a deep learning model that has been presented for picture inpainting in this research report. The topic of inpainting missing areas of a damaged image with plausible material is introduced in the study, along with the shortcomings of the techniques currently used. By filling in the gaps at both the image-level and feature-level, the suggested PEN-Net is intended to guarantee both visual and semantic plausibility. An adversarial training loss, a multi-scale decoder, and a pyramid-context encoder are the three main parts of the PEN-Net architecture that are presented in this study. The experimental findings of the suggested PEN-Net are also discussed in the paper; these results demonstrate superior performance to that of existing techniques.

Link: [Click Here](https://openaccess.thecvf.com/content_CVPR_2019/html/Zeng_Learning_Pyramid-Context_Encoder_Network_for_High-Quality_Image_Inpainting_CVPR_2019_paper.html)

**05) “Semantic Image Inpainting with Perceptual and Contextual Losses”**

The research described here provides a picture inpainting method based on Deep Convolutional Generative Adversarial Networks (DCGAN). The method uses a loss function made up of perceptual loss and contextual loss to map a corrupted image to a smaller latent space, which is then used to predict the missing data. The technique is evaluated for two challenging inpainting tasks with random 80% corruption and huge blocky corruption on the CelebA and SVHN datasets. The results show that the system can accurately predict semantic information in the missing region and also offer pixel-level photorealism, which is nearly unattainable with some other methods.

Link: [Click Here](https://www.scinapse.io/papers/2479644247)

**06) “PEPSI : Fast Image Inpainting With Parallel Decoding Network”**

With the help of a single shared encoding network and a parallel decoding network, the new image inpainting technique PEPSI (short for  parallel extended-decoder path for semantic inpainting) lowers the number of convolution operations. A preliminary painting result is produced by the coarse route, using which the encoding network is trained to forecast characteristics for the contextual attention module (CAM). In addition to being more effective in terms of testing time and qualitative results, this strategy outperforms more traditional procedures. The limitations of earlier image inpainting techniques are actually overcome by PEPSI.

Link: [Click Here](https://openaccess.thecvf.com/content_CVPR_2019/html/Sagong_PEPSI__Fast_Image_Inpainting_With_Parallel_Decoding_Network_CVPR_2019_paper.html)

**07) “Image Inpainting With Learnable Bidirectional Attention Maps”**

The research suggests a novel method for image inpainting that makes use of learnable bidirectional attention maps. The lack of ability of earlier convolutional neural network (CNN)-based techniques to handle irregular holes or provide results with inconsistent colours and blurriness is addressed by this technique. To enable the decoder of U-Net to concentrate on filling in irregular holes rather than recreating both holes and known regions, the suggested method uses feature re-normalization and mask-updating in an end-to-end manner. It also provides learnable reverse attention maps. Based on experimental findings, the suggested method produces inpainting results that are crisper and more visually convincing than state-of-the-art procedures.

Link: [Click Here](https://openaccess.thecvf.com/content_ICCV_2019/html/Xie_Image_Inpainting_With_Learnable_Bidirectional_Attention_Maps_ICCV_2019_paper.html)

**08) “EdgeConnect: Structure Guided Image Inpainting using Edge Prediction”**

The work is divided into structure prediction and image completion in the paper's two-stage model for image inpainting. The missing region's structure is generated in the first stage in the form of edge maps, which are then employed as a guide for the second stage's image completion. The method is modelled after sketch art, where the lines are drawn first and the colours are added subsequently. On a number of publicly accessible datasets, the suggested model outperforms state-of-the-art methods and is applicable to scene generation and object removal. The discussion of upcoming research and the significance of edge information in image inpainting finishes the paper.

Link: [Click Here](https://openaccess.thecvf.com/content_ICCVW_2019/html/AIM/Nazeri_EdgeConnect_Structure_Guided_Image_Inpainting_using_Edge_Prediction_ICCVW_2019_paper.html)

**09) “Semantic Image Inpainting With Deep Generative Models”**

In this research, a novel method for creating missing content in semantic images is proposed. This method conditions on the data that is now accessible. Using context and previous losses, it searches the latent image manifold for the corrupted image's nearest encoding before passing the results via a generative model to determine what is missing from the image. The suggested approach can manage arbitrarily structured missing regions during inference and anticipate information in huge missing regions with pixel-level photorealism. On three datasets with various kinds of missing regions, it has been demonstrated to be effective.

Link: [Click Here](https://openaccess.thecvf.com/content_cvpr_2017/html/Yeh_Semantic_Image_Inpainting_CVPR_2017_paper.html)

**10) “Coherent Semantic Attention for Image Inpainting”**

In this research, a deep learning-based method for picture inpainting is presented. It makes use of a CSA layer to replace any damaged or missing portions of an image while maintaining its overall semantic structure and producing realistic texture details. The suggested technique makes use of a neural network with a U-Net architecture, as well as a consistency loss and feature patch discriminator to stabilise the network training process and enhance the details. When compared to current state-of-the-art methodologies, experimental findings on the CelebA, Places2, and Paris StreetView datasets show that the suggested approach can be improved and yet produce results that are of greater quality. While preserving the local pixel continuity and global semantic consistency, it can handle both centering and irregular gaps in the image.

Link: [Click Here](https://openaccess.thecvf.com/content_ICCV_2019/html/Liu_Coherent_Semantic_Attention_for_Image_Inpainting_ICCV_2019_paper.html)

**References:**

01) Yu, Jiahui, Zhe Lin, Jimei Yang, Xiaohui Shen, Xin Lu, and Thomas S. Huang. "Generative image inpainting with contextual attention." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 5505-5514. 2018.

02) Yang, Chao, Xin Lu, Zhe Lin, Eli Shechtman, Oliver Wang, and Hao Li. "High-resolution image inpainting using multi-scale neural patch synthesis." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 6721-6729. 2017.

03) Pathak, Deepak, Philipp Krahenbuhl, Jeff Donahue, Trevor Darrell, and Alexei A. Efros. "Context encoders: Feature learning by inpainting." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 2536-2544. 2016.

04) Zeng, Yanhong, Jianlong Fu, Hongyang Chao, and Baining Guo. "Learning pyramid-context encoder network for high-quality image inpainting." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 1486-1494. 2019.

05) Yeh, Raymond, Chen Chen, Teck Yian Lim, Mark Hasegawa-Johnson, and Minh N. Do. "Semantic image inpainting with perceptual and contextual losses." arXiv preprint arXiv:1607.07539 2, no. 3 (2016).

06) Sagong, Min-cheol, Yong-goo Shin, Seung-wook Kim, Seung Park, and Sung-jea Ko. "Pepsi: Fast image inpainting with parallel decoding network." In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pp. 11360-11368. 2019.

07) Xie, Chaohao, Shaohui Liu, Chao Li, Ming-Ming Cheng, Wangmeng Zuo, Xiao Liu, Shilei Wen, and Errui Ding. "Image inpainting with learnable bidirectional attention maps." In Proceedings of the IEEE/CVF international conference on computer vision, pp. 8858-8867. 2019.

08) Nazeri, Kamyar, Eric Ng, Tony Joseph, Faisal Qureshi, and Mehran Ebrahimi. "Edgeconnect: Structure guided image inpainting using edge prediction." In Proceedings of the IEEE/CVF international conference on computer vision workshops, pp. 0-0. 2019.

09) Yeh, Raymond A., Chen Chen, Teck Yian Lim, Alexander G. Schwing, Mark Hasegawa-Johnson, and Minh N. Do. "Semantic image inpainting with deep generative models." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 5485-5493. 2017.

10) Liu, Hongyu, Bin Jiang, Yi Xiao, and Chao Yang. "Coherent semantic attention for image inpainting." In Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 4170-4179. 2019.