Reviews On Papers Related To:

Image Inpainting Using Context Encoders

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

**Course Code :** 18EC61

**11) “Context-Aware Image Inpainting with Learned Semantic Priors”**

SPL, a context-aware picture inpainting model that makes use of semantic priors for improved restoration of missing regions, is introduced in this study. SPL promotes understanding of complicated scenarios by extracting high-level knowledge from pretext tasks and capturing global contextual links. The model is split into two stages: first, low-level image characteristics are extracted, then high-level semantic priors are learned, and finally, local features and semantic priors are adaptively integrated into a single generator. This method enhances global structural inference as well as local texture consistency. On common image inpainting datasets, SPL provides state-of-the-art performance without the need for extra human annotations. Overall, SPL considerably improves the development of plausible and realistic image contents by fusing semantic comprehension and local feature consistency to address the difficulties of complicated image inpainting.

**Link:** [Click Here](https://arxiv.org/abs/2106.07220)

**12) “Light-weight pixel context encoders for image inpainting”**

Pixel Content Encoders (PCE), a simple picture inpainting model that creates content for sizable missing sections in images, are introduced in this study. In order to preserve fine-grained spatial information, PCE uses dilated convolutions. On benchmark datasets of natural photos and paintings, PCE performs at the cutting edge. Without modifying the architecture, the concept can also be applied to image extrapolation. PCE greatly reduces the number of trainable parameters compared to earlier convolutional neural network (CNN)-based inpainting algorithms. PCE provides plausible content that is consistent with the context by encoding the context around the missing region. On a variety of inpainting tasks, the model performs better than previous approaches and provides the possibility of image extrapolation. For efficient and effective picture creation and inpainting, PCE offers promise.

**Link:** [Click Here](https://arxiv.org/abs/1801.05585)

**13) “Diverse Image Inpainting with Bidirectional and Autoregressive Transformers”**

In this research, BAT-Fill, a novel method for picture inpainting, is introduced. It makes use of a bidirectional autoregressive transformer (BAT) to produce a variety of realistic contents for missing or damaged parts of an image. BAT-Fill uses masked language modelling (MLM) and autoregressive modelling to successfully represent bidirectional contextual information and improve image completion, in contrast to conventional CNN-based techniques that have trouble collecting global characteristics. The framework delivers better inpainting results by utilising BAT, which captures both spatial linkages and bidirectional dependencies. The two stages of BAT-Fill are texture synthesis using a CNN-based texture generator and structure recovery using BAT. According to experimental findings, BAT-Fill performs better than cutting-edge techniques for image inpainting in terms of both diversity and fidelity.

**Link:** [Click Here](https://dl.acm.org/doi/abs/10.1145/3474085.3475436)

**14) “A Review on Image Inpainting Techniques and Datasets”**

An in-depth analysis of picture inpainting methods and datasets is provided in this work. The techniques are divided into two groups: conventional techniques and Deep Learning (DL) techniques. Traditional methods, such as diffusion-based, patch-based, and convolution filter-based methods, struggle with vast regions and are unable to produce unique objects or semantically coherent outcomes. However, they are effective for tiny missing portions. DL methods, on the other hand, have demonstrated potential in creating innovative things, rebuilding intricate structures, and creating coherent visuals. Additionally, the research addresses the difficulties associated with inpainting arbitrary picture sizes, arbitrary masks, high-resolution textures, computational resources, and training time. Its conclusion lists the most popular datasets and evaluation metrics in the industry.

**Link:** [Click Here](https://ieeexplore.ieee.org/abstract/document/9265979)

**15) “EdgeConnect: Generative Image Inpainting with Adversarial Edge Learnin”**

In this paper, a two-stage adversarial model for picture inpainting called EdgeConnect is introduced. An edge generator creates edges in the missing areas of an image in the first step, and an image completion network fills in the blank areas using the hallucinated edges in the second stage. By concentrating on replicating minute features, the model solves the issue of the too smoothed and blurry outcomes frequently seen in existing image inpainting techniques. On datasets including CelebA, Places2, and Paris StreetView, the suggested method beats state-of-the-art methods in terms of both quantitative and qualitative evaluations. The model may be used for tasks like scene generation and object removal in image editing.

**Link:** [Click Here](https://arxiv.org/abs/1901.00212)

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

To address the problems of fuzzy textures and deformed structures in current deep learning-based systems, this study addresses the topic of picture inpainting. To preserve the contextual structure and enhance predictions of missing sections, the authors suggest a novel method that includes a Coherent Semantic Attention (CSA) layer. Rough estimation and refinement, both carried out using neural networks inside the U-Net architecture, are the two processes that make up the task. The refining step's encoder contains an embedded CSA layer. To stabilise training and improve details, consistency loss, and a feature patch discriminator are also introduced. The suggested method outperforms current state-of-the-art methodologies, as shown by experimental findings on the CelebA, Places2, and Paris StreetView datasets, which result in high-quality inpainting results.

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

**17) “Chest X-ray Inpainting with Deep Generative Models ”**

This study investigates the use of chest X-rays in the medical imaging field to use deep learning-based inpainting models. The authors look into three cutting-edge models: the contextual attention model, semantic image inpainting, and context encoders. The models learn to estimate the centre region of each patch after being trained on a sizable dataset of healthy X-rays. On both normal and healthy radiographs, the models' performance is assessed using visual inspection and PSNR values. Results show that the models can produce incredibly lifelike painted regions and have the ability to improve and discover anomalies. Additionally, observer research demonstrates how challenging it is for human experts to find inpainted areas. The study makes a strong case for the viability and potential of realistic inpainting in medical images using generative models.

**Link:** [Click Here](https://arxiv.org/abs/1809.01471)

**18) “Free-Form Image Inpainting with Gated Convolution”**

A generative picture inpainting system for completing images using free-form masks and direction is presented in this study. The system makes use of gated convolutions, which provide a learnable dynamic feature selection method for each channel at each spatial position and alleviate the shortcomings of vanilla convolutions. Furthermore, the SN-PatchGAN patch-based GAN loss is shown, which employs a spectral-normalized discriminator on dense picture patches. The suggested system performs better than earlier approaches in producing results for inpainting that are of higher quality and more adaptable. Users can edit faces in pictures, delete watermarks, change image layouts, and eliminate irritating objects. On benchmark datasets, the system performs at the cutting edge and offers user-guided inpainting.

**Link:** [Click Here](https://openaccess.thecvf.com/content_ICCV_2019/html/Yu_Free-Form_Image_Inpainting_With_Gated_Convolution_ICCV_2019_paper.html)

**19) “Shift-Net: Image Inpainting via Deep Feature Rearrangement”**

In order to fill in blank areas of images with precise structures and minutely detailed textures, this article offers a novel CNN architecture dubbed Shift-Net. Shift-Net uses a unique shift-connection layer to reorder characteristics between the encoder and decoder, in contrast to conventional approaches that employ fully connected layers to forecast missing pieces. To enforce the similarity between the decoder feature and the ground-truth encoder feature of the missing sections, a guiding loss is added. According to experimental findings, Shift-Net performs better than other techniques at producing accurate and visually appealing inpainting results. The suggested method delivers cutting-edge performance by fusing the benefits of exemplar-based and CNN-based methodologies.

**Link:** [Click Here](https://openaccess.thecvf.com/content_ECCV_2018/html/Zhaoyi_Yan_Shift-Net_Image_Inpainting_ECCV_2018_paper.html)

**20) “A Context Encoder For Audio Inpainting”**

In this study, deep neural networks (DNNs) are investigated for audio inpainting, with an emphasis on gaps lasting tens of milliseconds or less. Using the context of the audio around the gap, the proposed DNN structure is trained on music and individual musical instruments independently. The DNN outperforms an LPC-based reference approach for music inpainting, proving its suitability for handling complicated audio inputs. A phase-reconstruction approach is utilised after the DNN reconstructs the magnitude coefficients using time-frequency (TF) coefficients taken from the audio stream. The study makes other suggestions for advancements, like investigating various audio aspects, deepening the network, and training specialised networks for particular musical instruments or genres.

**Link:** [Click Here](https://ieeexplore.ieee.org/abstract/document/8867915)

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