Image inpainting using deep generative models

Review 1]

In order to fill in significant empty sections in images by conditing on the data that is already accessible, the research suggests a novel method for semantic image inpainting. The suggested method is based on deep generative modelling and views semantic inpainting as a constrained picture production problem, in contrast to classical inpainting methods that use just local or non-local information to restore the image. The procedure reconstructs the image using the generator by looking for an encoding of the corrupted image that is most similar to the original in the latent space. The technique can be used to infer missing regions with any kind of structure and does not require masks for training. The study's experimental findings on three datasets show how well the suggested approach predicts information in large datasets.

Review 2]

The difficulties of picture inpainting are covered in the article along with the requirement for particular methods to solve them. The author classifies the works in the literature on digital inpainting into three groups: disocclusion, texture synthesis, and film restoration. The first group interpolates losses in films from consecutive frames using motion estimates and autoregressive models, while the second group employs frequency and spatial domain data to fill a specific region with a certain texture. Disocclusion algorithms, the third class, connect T-junctions at the same grey level with elastica minimising curves or combine the points of the isophotes that arrive at the boundary of the region to be inpainted with geodesic curves.

Although these methods served as inspiration for the author's work, the article points out that they have some drawbacks, such as the inapplicability of these methods to still images or to films in which the regions to be inpainted span a number of frames, the requirement that the user choose the texture to be copied into the region to be inpainted, or the restriction to images with simple topology. Some of these issues are resolved by the author's approach, which offers better outcomes for natural photos with complicated topology.

Review 3]

In this paper, we proposed a novel method for semantic inpainting. Compared to existing methods based on local image priors or patches, the proposed method learns the representation of training data, and can therefore predict meaningful content for corrupted images. Compared to CE, our method often obtains images with sharper edges which look much more realistic. Experimental results demonstrated its superior performance on challenging image inpainting examples.

4]

Clearly, the key idea of this paper is the contextual attention mechanism. The contextual attention layer is embedded in the second refinement network. Note the role of the first coarse reconstruction network is to have a rough estimation of the missing region. This estimation is used at the contextual attention layer. By matching the generated features inside the missing region and the features outside the missing region, we can know the contributions of all the features outside the missing region to each location inside the missing region. Note that the contextual attention layer is differentiable and fully-convolutional. With the proposed contextual attention, they achieve the state-of-the-art inpainting results.

Review 5]

This paper discusses a new method for semantic face inpainting based on deep generative models, which improves upon traditional image inpainting methods by achieving semantic face completion with better content continuity and structural consistency. The authors propose further directions for research, including developing a standard face model and corresponding representation loss function, incorporating symmetry features and corresponding loss functions, and addressing the challenge of high-resolution face inpainting through a synthesis approach. The authors also hope that more applications based on face image inpainting will be developed and applied in real life in the future.

Review 6]

The article presents a cropping artifact-repair cropping vector quantized variational autoencoder architecture for multi-shell diffusion weighted images. The technique is demonstrated to perform better in picture reconstruction than existing landmark models and produces FA maps with reduced FA values in regions previously affected by the cropping artefact, suggesting its potential to increase the power of group-level analysis. Future directions for this strategy include generalising the model to other MR imaging modalities and training the model with various levels of cropping to increase robustness.

Review 7]

This research suggests a novel approach to inpainting facial images that combines deep generative models with a search for related patches. To hasten convergence, the approach employs a deep generative model based on Pix2Pix and Laplace Loss. When calculating distance and looking for similar patches, various weights are applied to various areas surrounding the boundary. The theory underlying the proposed method is supported by experimental results, which show that it performs remarkably well when inpainting facial images. With this technique, a fresh concept for picture inpainting and other image processing tasks is offered.

Review 8]

The suggested context encoders are trained to produce images with context in mind. They succeed in performing at the cutting edge of semantic inpainting.

Other tasks like classification, detection, and semantic segmentation can benefit from the learned feature representations.

Review 9]

The method for estimating missing material in an image using the surrounding values is new and is suggested in the study. The suggested method may predict important contents not visible in corrupted images and, unlike previous techniques, it learns the distribution of training data. The recovered images have realistic-looking edges and higher performance on difficult image inpainting situations. However, the method is dependent on the generative model and training process and cannot resolve the ambiguity brought on by corruption. Through examples of failure, such as the incomplete representation of complex scenes, the method's limitations are made clear. For future work, the authors advise looking into more potent generative models.

Review 10]

Additional information on image inpainting is covered in the article, along with its connection to self-supervised learning and current methods for enhancing it. Similar to how embeddings are used in NLP to comprehend the semantic relationships between words, image inpainting models are capable of understanding images to some extent. This aspect of image inpainting can be used for later computer vision applications. The essay also discusses the concepts of contextual attention and approximation exact matching, two cutting-edge methods for enhancing image inpainting.

Reference

**1]** link]: <https://openaccess.thecvf.com/content_cvpr_2017/papers/Yeh_Semantic_Image_Inpainting_CVPR_2017_paper.pdf>

**2]** Link: <https://dl.acm.org/doi/abs/10.1145/344779.344972>

**3] Link:** [**https://arxiv.org/abs/1607.07539**](https://arxiv.org/abs/1607.07539)

**4]**

Link ;

<https://towardsdatascience.com/a-breakthrough-in-deep-image-inpainting-review-generative-image-inpainting-with-contextual-1099c195f3f0>

**5]**

Link : <https://www.atlantis-press.com/journals/ijcis/125920178/view#sec-s5>

**6]** Link : <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8123091/>

**7]** Link: <https://ieeexplore.ieee.org/abstract/document/8723111>

**8] Link:** [**https://medium.com/analytics-vidhya/introduction-to-generative-models-for-image-inpainting-and-review-context-encoders-13e48df30244**](https://medium.com/analytics-vidhya/introduction-to-generative-models-for-image-inpainting-and-review-context-encoders-13e48df30244)

**9] Link :** [**https://www.arxiv-vanity.com/papers/1607.07539/**](https://www.arxiv-vanity.com/papers/1607.07539/)

**10] Link :** [**https://wandb.ai/site/articles/introduction-to-image-inpainting-with-deep-learning**](https://wandb.ai/site/articles/introduction-to-image-inpainting-with-deep-learning)