論 文 の 内 容 の 要 旨

論文題目

Deep Learning for Planetary Exploration:

Improving image analysis capabilities under limited data resources

(深層学習の惑星探査への応用：データリソース制限下での画像解析能力の向上)

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Today, more than 25 space probes are actively exploring different planets and celestial bodies across the universe. Several others have either finished their mission or are planned to begin their journey. These spacecraft and planetary rovers carry several instruments and cameras onboard, which can capture a huge amount of planetary data. However, the inter-planetary communication capacity through Deep Space Network is limited by the law of physics. Therefore, it is not always possible to send the entire planetary data, back to Earth for further analysis. This can create problems such as a missed scientific opportunity during planetary exploration. On the other hand, even if the acquired data is sent back to Earth, it is sometimes corrupted or have missing pixels because of data unavailability caused due to the technical limitation of the onboard instrument operation timing and satellite orbiter control.

There is a need for systems that can overcome these problems (i) by analyzing data onboard and returning much smaller sized meta-data to Earth, to reduce the chances of missed scientific opportunity and improve the productivity of the mission, (ii) by predicting the "no-data" region of corrupted images to efficiently analyze the returned data to Earth, even if it is partially corrupted. In this dissertation, we propose machine learning (ML) algorithms to improve the planetary image analysis capabilities for future explorations under limited data constraints. These include image-text retrieval algorithm (Chapter 2) to enhance the onboard autonomy of future space missions and inpainting algorithms (Chapter 3 and 4) that can predict the missing regions on Mars or Lunar orbital images to enhance the data availability for downstream tasks such as classification of interesting morphological features. Overall, this dissertation shows how different machine learning algorithms can benefit future space missions by improving image analysis capabilities under various constraints.

Chapter 1: In the first chapter, we describe the background knowledge related to ML (particularly deep learning) techniques that are employed in this dissertation and the challenges associated with applying ML techniques for space applications. We further motivate the reader by describing the purpose of the research works presented in this dissertation.

Chapter 2: This chapter deals with solving the problem of limited inter-planetary communication opportunities through deep space network. As the number of acquired images continues to grow exponentially with each ongoing mission, it becomes increasingly difficult to return all the data to Earth because of limited bandwidth between Earth and other planets and planetary bodies. In this chapter, we propose an image-text retrieval algorithm to enhance the onboard analysis capabilities of the orbiting or roving spacecraft by detecting objects in the observed image and sending only much smaller-sized metadata to Earth that describes the image. The proposed image-text retrieval algorithm is also helpful to retrieve images of interest (images with desired geologic and/or non-geologic features) from a large database based on query text. We use the Mars surface images captured by the navigation camera of NASA's Mars Science Laboratory (MSL) Curiosity rover for experimental purposes and demonstrate that our method can accurately detect objects on the Mars surface images. Our experimental results also verify that our method can successfully retrieve images of interest, based on textual queries with superior performance compared to the state-of-the-art approaches. This study required labeling of Mars images (drawing bounding box around object/region of interest and creating captions for the image) for developing a new ML method for planetary image retrieval based on text/captions.

Chapter 3: This chapter solves the problem of restoring missing data in the acquired images collected by sophisticated imaging devices onboard the orbiting spacecraft. Although these images enable scientists to discover and visualize the unknown, they often suffer from the 'no-data' region because the data could not be acquired by the onboard instrument due to the limitation in operation time of the instrument and satellite orbiter control. This greatly reduces the usability of the captured data for scientific purposes. To alleviate this problem, in this chapter, we propose a machine learning-based "no-data" region prediction algorithm. Specifically, we leverage a deep convolutional neural network (CNN) based image inpainting algorithm to predict such unphotographed pixels in a context-aware fashion using adversarial learning on planetary images. The benefit of using our proposed method is to augment features in the unphotographed regions leading to better downstream tasks such as interesting landmark classification. We use the Moon and Mars orbital images captured by the JAXA's Kaguya mission and NASA's Mars Reconnaissance Orbiter (MRO) for experimental purposes and demonstrate that our method can fill in the unphotographed regions on the Moon and Mars images with good visual and perceptual quality as measured by improved PSNR and SSIM scores. Additionally, our image inpainting algorithm helps in improved feature learning for CNN-based landmark classification as evidenced by an improved F1-score of 0.88 compared to 0.83 on the original Mars dataset. Our main contributions in this chapter can be summarized as follows:

1. We introduce an adversarial learning-based image inpainting framework for planetary images (Moon, and Mars) that learns a non-linear end-to-end mapping from corrupted to clean images.
2. To enable better inpainting we extract various modes of histogram distribution in the input images by unsupervised clustering. We train mode-specific GAN models which are expert models for inpainting images belonging to that cluster of the histogram mode. The simulated and real experimental results show that our proposed approach can restore images with a significant improvement in terms of visual quality and evaluation metrics, thereby outperforming previous inpainting methods.
3. We show that our proposed inpainting method helps in augmenting features of interesting but masked/incomplete landmarks which in turn leads to better generalization. Our experimental results also validate this concept by boosting the classification accuracy of the morphological features on Mars images. By using diverse planetary datasets of Moon and Mars, we show that our approach is applicable to various planetary images.

Chapter 4: Chapter 4 extends the ideology of image inpainting (as presented in Chapter 3) by incorporating a frequency domain component that enables the network to use both frequency and spatial information to predict the missing region of an image. We present a novel image inpainting technique using frequency domain information. Prior works on image inpainting predict the missing pixels by training neural networks using only the spatial domain information. However, these methods still struggle to reconstruct high-frequency details for complex cases, leading to boundary artifacts, distorted patterns, and blurry textures. To alleviate these problems, we investigate if it is possible to obtain better performance by training the networks using frequency domain information (Discrete Fourier Transform) along with the spatial domain information. To this end, we propose a frequency-based deconvolution module that enables the network to learn the global context while selectively reconstructing the high-frequency components. We evaluate our proposed method on the Mars dataset and show that our method using both frequency and spatial domain information outperforms current state-of-the-art image inpainting techniques both qualitatively and quantitatively. We perform additional experiments on the standard datasets namely CelebA, Paris Streetview (PSV), and DTD texture dataset as well to check the validity of our proposed algorithm. Here also, our method could outperform state-of-the-art image inpainting techniques. Our main contributions in this chapter can be summarized as follows:

1. We introduce a new frequency domain-based image inpainting framework that learns the high-frequency component of the masked region by using the global context of the image. We find that the network learns to preserve image information in a better way when it is trained in the frequency domain. Therefore, adding the frequency domain and spatial domain information certainly improves the inpainting performance compared to the conventional spatial domain image inpainting algorithms. To enable better inpainting, we train the network using both frequency-domain and spatial domain information which leads to a better consistency of inpainted results in terms of the local and global context.
2. We validate our method on Mars dataset and show that our method achieves better inpainting results in terms of visual quality and evaluation metrics outperforming the state-of-the-art results.
3. We perform additional experiments on other benchmark datasets including CelebA, PSV, and DTD datasets. Experimental results demonstrate that our proposed algorithm can outperform state-of-the-art inpainting results both qualitatively and quantitatively for standard datasets as well. To the best of our knowledge, this is the first work that explores the benefits of using frequency domain information for image inpainting on both planetary images and standard datasets.
4. Furthermore, we show that our proposed frequency-based image inpainting algorithm also works well for standard datasets which look fundamentally very different from planetary images. This show the generalization ability of the proposed algorithm.

Chapter 5: In the final chapter, we summarize the work presented in Chapters 2-4, present some ideas for future research directions such as image compression, introducing interpretability in ML proposed for space science to increase the willingness of scientists to adopt ML algorithms for future space missions, etc. Finally, we suggest some initiatives such as making planetary datasets publicly available for research purposes, which we believe, if practiced, can bolster long-term interdisciplinary research of ML and planetary science.