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High-Resolution SAR Image Reconstruction Using Deep Unfolding for Disaster Monitoring

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ABSTRACT

This study proposes a deep unfolding approach for high-resolution SAR (Synthetic Aperture Radar) image reconstruction, aiming to improve image quality in disaster monitoring applications. SAR images often suffer from deterioration and resolution degradation due to atmospheric conditions and signal interference, which can reduce the accuracy of disaster analysis. The proposed deep unfolding technique combines the advantages of conventional optimization methods with the capabilities of deep learning to learn better and more accurate image representations. The approach consists of iterative unfolding that adapts data-driven learning with an optimization model to address noise, distortion, and resolution deficiencies in SAR images. The developed deep unfolding model is trained using SAR data from various disaster events, such as floods, earthquakes, and tsunamis, to learn distinctive patterns and structures in SAR images. Experimental results show that this approach successfully improves image quality with significant noise reduction and up to 30% resolution increase compared to conventional reconstruction techniques. Evaluation using the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) metrics demonstrated substantial improvements in the quality of recovered imagery, enabling more effective and accurate disaster monitoring. With the ability to recover lost details in SAR imagery, this deep unfolding approach opens up opportunities for broader applications in satellite imagery-based disaster monitoring and emergency response.

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INTRODUCTION

Synthetic Aperture Radar (SAR) imagery has become an essential tool in disaster monitoring due to its ability to produce high-resolution images of the Earth's surface even under adverse weather conditions or low light. SAR is widely used in various applications such as monitoring floods, earthquakes, tsunamis, and other natural disasters, thanks to its ability to provide a clear picture of the condition of the affected area without being affected by clouds or inclement weather. However, while SAR offers many advantages, the quality of the resulting imagery is often affected by several factors, including noise, atmospheric distortion, and geometric changes during the scanning process. This results in image degradation that can hinder the ability to accurately analyze and detect objects or surface changes.

Reconstructing high-quality SAR images is a significant challenge, especially when dealing with distorted or low-resolution images. Various conventional techniques, such as filtering and spectral filtering, have been used to reduce noise and improve image resolution. However, these techniques are often ineffective in addressing the more complex and diverse distortions present in SAR images, especially when the image quality is low due to interference or data acquisition errors.

A new approach combining optimization methods with deep learning has begun to gain attention as a potential solution to this problem. Deep unfolding, a combination of conventional optimization approaches and deep learning models, has proven effective in a number of image processing applications. In this approach, deep learning models are studied to leverage data learning and model-based optimization to iteratively improve image quality, while preserving important structural details. Although deep learning has been used in many imaging applications, its application in high-resolution SAR image reconstruction remains rarely explored.

This research aims to develop a deep unfolding approach for high-resolution SAR image reconstruction by addressing the problems of noise, distortion, and image degradation that often occur in SAR images. We propose a method that combines gradient descent-based optimization techniques with deep learning capabilities of deep neural networks to improve SAR image quality, increase resolution, and reduce noise. By using SAR image datasets from various disaster events, such as floods, earthquakes, and tsunamis, we hope to produce images with better resolution, which in turn will improve the accuracy of disaster monitoring.

The main objective of this research is to explore the potential of deep unfolding in improving the quality of SAR imagery and contribute to the development of a more effective and efficient satellite-based disaster monitoring system. By improving the quality of SAR imagery, this approach is expected to accelerate the response to natural disasters and provide more accurate information for disaster mitigation.

METHODS

In this study, the Synthetic Aperture Radar (SAR) image dataset used was obtained from several natural disasters, such as floods, earthquakes, and tsunamis, recorded using SAR satellites such as Sentinel-1 and RADARSAT. The images obtained from these satellites have varying resolutions, but are often degraded due to noise, interference artifacts, and geometric changes during data acquisition. Before being used in model training, the degraded SAR image data was first processed through several preprocessing stages. The first process is radiometric calibration, which aims to eliminate differences in signal intensity due to sensor variability and atmospheric conditions during image acquisition. Next, the SAR images were processed with filtering techniques to reduce speckle noise that is common in SAR images, using methods such as the Wiener filter or median filter that reduce noise while preserving image detail. After filtering, the image data was divided into 64x64 pixel patches that were used for deep learning model training.

To improve the quality of SAR images, this study proposes the use of a deep unfolding approach, which combines model-based optimization methods with deep learning. In the initial stage, we use an optimization approach to model SAR image reconstruction as a noise reduction and resolution enhancement problem. Next, a deep learning model based on Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) is used to process the degraded SAR images, with the aim of improving image quality through detail recovery and noise reduction. This deep unfolding model consists of several convolutional layers to learn local features in the image, followed by a deconvolution layer tasked with increasing image resolution and recovering lost texture details.

Model training was performed using a categorical cross-entropy loss function that measures the difference between the restored image and the reference ground truth image. The Adam optimizer was used to train the model with a customized learning rate, and the training process was stopped early if there was no significant improvement in image quality to avoid overfitting. After the model was completed, its performance was evaluated using the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) as the main metrics for assessing the quality of the restored image. Furthermore, the model was tested on various types of natural disasters to determine its ability to improve the quality of degraded images under different conditions.

By combining optimization techniques with deep learning, this deep unfolding approach successfully improves SAR image quality with significant noise reduction and up to 30% resolution improvement compared to conventional image reconstruction methods. Experimental results show that this approach is effective in improving the quality of degraded SAR images, which is crucial for disaster monitoring applications, such as flood, tsunami, and earthquake monitoring. By improving SAR image quality, this model opens up opportunities for wider use in satellite imagery-based disaster monitoring.

RESULTS AND DISCUSSION

Experimental results show that the proposed deep unfolding model for high-resolution SAR image reconstruction is capable of improving the quality of images degraded by noise and distortion. The model was tested on a SAR image dataset covering various natural disaster events, such as floods, earthquakes, and tsunamis. Evaluation was conducted by comparing the images restored by the model with ground truth images, which are high quality and free from interference. Evaluation results using the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) metrics showed a significant improvement in the quality of the restored images compared to conventional image reconstruction techniques.

Deep Unfolding Model Performance

The deep unfolding model successfully improves the PSNR of recovered images by up to 30% compared to standard image reconstruction methods, such as Wiener-based filtering and median filtering. The SSIM value also shows a consistent improvement, with the average SSIM value reaching 0.92 for recovered images, while the SSIM value for images processed using conventional methods is only around 0.81. This improvement indicates that the deep unfolding model is able to better recover the structural and textural details of images, which is very important for disaster monitoring that requires high resolution.

Comparison with Conventional Image Reconstruction Techniques
To assess the superiority of the deep unfolding model, we compared its results with two commonly used conventional SAR image reconstruction techniques: Wiener filtering and median filtering. While both methods are effective at reducing noise, they often fail to restore image detail lost due to geometric distortion or other signal disturbances. The comparison shows that while both conventional methods successfully reduce noise, they fail to restore image resolution and texture to the same extent as the deep unfolding model. The resulting images from the conventional method tend to be blurry and unclear, while the images restored using deep unfolding are sharper and clearer, with better detail in areas affected by disturbances.

Evaluation of Various Types of Disorders
The model was also tested on various types of disturbances found in SAR imagery resulting from natural disasters. For floods, the deep unfolding model successfully recovered lost surface detail and reduced noise from irregular water reflections. For earthquakes, the model was able to correct geometric distortions caused by ground shifts, allowing for more accurate monitoring of structural damage. For tsunamis, the model demonstrated excellent ability to recover sea level changes caused by tsunami waves, which were previously difficult to process using conventional methods. Each type of disaster exhibits different characteristics in SAR imagery, and the deep unfolding model effectively handles these disturbances, providing a clearer and more accurate picture of the affected area.

Processing Speed and Real-Time Implementation
One of the key advantages of the deep unfolding approach is its ability to refine SAR imagery with relatively fast processing times, making it suitable for real-time applications in disaster monitoring. This model successfully processes 256x256 pixel images in 1.5 seconds per image, enabling real-time disaster monitoring with sharper, higher-quality images. This processing time is significantly faster than some conventional image reconstruction methods, which require longer time to restore high-quality images. This speed makes the deep unfolding model very useful for disaster monitoring applications that require rapid response in identifying damage and disaster impacts.

Model Interpretability with Saliency Maps
Saliency maps are used to improve our understanding of how models make decisions when restoring SAR imagery. Saliency maps allow us to identify key areas of the image that are more influential in the reconstruction process. For example, for tsunami imagery, saliency maps show that the model pays more attention to areas with significant sea level changes, such as tsunami waves that alter coastal morphology. Conversely, for flood imagery, saliency maps focus more on areas with elevation changes and water reflectance that cause blurring of the land surface. This provides better insight into the model's reconstruction process and reveals how the model responds to specific image perturbations.

Discussion of Implications for Disaster Monitoring

The results obtained from this experiment demonstrate that deep unfolding can be used for SAR image reconstruction by increasing resolution and reducing noise in a more efficient manner compared to conventional techniques. The improved quality of the recovered images allows for more accurate and efficient disaster monitoring, which is essential for damage analysis and disaster response planning. By combining deep learning and model-based optimization techniques, this approach not only improves image quality but also provides a real-time solution that can be used in emergency applications. While the results are very positive, several challenges remain, such as handling very high-resolution SAR data and image processing under extreme conditions. Further research can focus on developing systems that can handle very high-resolution imagery and more complex data acquisition conditions, as well as implementing real-time processing in real-world environments.

CONCLUSION

Overall, this study demonstrates that a deep unfolding model for SAR image reconstruction can improve image quality with significant noise reduction and substantial resolution enhancement. Experimental results and evaluations on various types of natural disaster disturbances indicate that this model can provide clearer SAR images, which is very useful for disaster monitoring applications. With this approach, we hope to make a significant contribution to the development of more efficient and responsive satellite imagery-based disaster monitoring systems.

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