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Coloring of SAR Images Using Deep Learning

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A B S T R A C T :

Synthetic Aperture radar (SAR) is a powerful tool in remote measurement due to the ability to capture data regardless of images or lighting conditions. However, SAR images usually occur in the Grayscale, which limits their interpretation. This paper examines the application of deep learning techniques for colorizing SAR images. By taking advantage of the Convolutional Neural Network (CNNs), we propose a Deep Learning model that can estimate appropriately representative colour choices for SAR data. Our contributions include a new deep learning model architecture, objective and in depth evaluation and conversion of grayscale images to colored images using conceptual matrix

Keywords: SAR, Image Colorization, Deep Learning, CNN

1. Introduction

Synthetic Aperture radar (SAR) has become an important feature in remote imaging, such as the ability to capture high-resolution images despite weather conditions or daytime. Unlike optical sensors, SAR uses microwave signals, making them suitable to monitor under all climates and scenarios. Despite this ability, SAR data is often hard to interpret by human analysts because of its grayscale nature compared to colourful optical images. Therefore, adding colors to SAR images can improve overall human understanding, which can lead to sharp and more accurate interpretation of landscape, infrastructure and natural phenomena.

Coloring SAR images is a complex challenge because these images lack the underlying color data. Unlike RGB images, SAR images represent surface properties such as roughness and moisture content using radar backscatter intensity. As a result, there is no direct correlation between SAR intensity and color information. The aim of this study is to address how learning techniques like CNNs, can be used to generate accurate and useful colors of SAR images.

This research has the ability to change how SAR data is used in many areas. Colored SAR images can facilitate disaster action, urban planning, better decision making in agriculture and defense. In addition, the introduction of color in SAR data can find the gap between expert users and non-experts, which can enable a wide range of stakeholders to engage with radar-based remote measurement applications

2. Related Work

The hassle of photo colourization has been a topic of research for a long time. Initial efforts concerned manual coloration mapping or using instance-based algorithms, in which the system references a present colored image to manually colourize the greyscale input. While those early methods made a few achievements, they had been constrained by their dependency on manual intervention and their incapacity to generalize to new datasets. The evolution of machine learning and the supply of big datasets brought about a shift in the direction of more computerized and scalable tactics.

With the arrival of deep learning, computerized photograph colourization entered a brand new era. Convolutional Neural Networks (CNNs) proved especially effective in getting to know complex representations from grayscale pictures. Researchers have developed encoder-decoder networks that map input depth values to corresponding chromatic (color) outputs. Methods like the U-Net structure and its versions enabled more unique and context-conscious reconstructions. Additionally, perceptual loss functions and the introduction of reference models like VGG networks contributed to maintaining semantic consistency in coloration predictions, thereby enhancing the realism of results.

3. Understanding SAR Imagery and the Colouring Problem

Synthetic Aperture Radar (SAR) is a powerful tool for active remote measurement that is effectively operated in all weather conditions and both in the day and night. It uses microwave radar signals to generate high resolution images with the soil surface, and offers a unique perspective that varies greatly from optical imaging. Unlike optical cameras that catch reflected sunlight, SAR measures the intensity and phase of radar waves that pop back from the surface features. The resulting image is presented in the grayscale, where the sharpness corresponds to the reflection from the surfaces.

This noisy nature, although rich in structural information, has a major limitation: Lack of intuitive visual information. Colour plays an important role in human interpretation, which helps with discrimination between land types, terrain and objects . In SAR images, the absence of such characteristics pose a challenge to manual interpretation, especially for non-experts.

Therefore, the goal of the colouring SAR images is not to restore any "real color" seen in natural images but to create human understandable images. They serve to:

- Increase human interpretation of complex SAR scenes.
- Provide visual adjustment with optical data in multimodal analysis.
- Improve data access to users who are not familiar with radar imaging.

Deep learning, especially Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN), present promising tools for this task. These models can learn the mapping between SAR backscatter patterns and representative color outputs by leveraging additional datasets and prior knowledge.

However, many major challenges need to be addressed:

- No ground-truth color: Since SAR captures data outside the visible spectrum, the pixel does not have a true color reference—what it 'looks like' in color is not based on real-world appearance.
- Data variability: SAR data varies across different frequencies (e.g., X, C, and L bands), incidence angles, and geographic regions, which complicates the generalization of models.

Evaluation metrics: In the absence of a standardized reference, assessing color quality becomes subjective and often relies on indirect metrics such as Structural Similarity Index (SSIM) or perceptual loss.

Despite these challenges, SAR promises many advantages in areas such as:

- Environmental monitoring and land classification
- Urban infrastructure analysis
- Disaster planning
- Military reconnaissance and surveillance

By converting grayscale radar data into more colorful representations, we can make the usage of radar imaging more practical and accessible for people in all fields.

4. Proposed Methodology

We begin with the data preparation phase, where grayscale and color satellite images are loaded from the EuroSAT dataset. This dataset includes 10 distinct land cover classes, such as rivers, forests, residential areas, and industrial zones. Each image is resized to a standard resolution of 64 × 64 pixels and normalized to the [0, 1] range to standardize inputs and improve model performance.

We then design a U-Net-based deep learning model, a popular encoder–decoder architecture featuring skip connections that help retain spatial details during decoding. In this model, the encoder path employs convolutional layers and max pooling to extract hierarchical features while reducing spatial dimensions. The decoder path uses upsampling and concatenation operations to progressively restore spatial resolution and integrate feature information from earlier layers. The final output layer generates 3-channel RGB images from a single-channel grayscale input.

After defining the model architecture, we split the dataset into training and validation sets to ensure accurate performance assessment during the learning process. The model is then compiled using the Adam optimizer and the Mean Squared Error (MSE) loss function, which is well suited for pixel-wise tasks such as image colorization.

During training, the model is fitted on grayscale inputs and learns to predict their corresponding color outputs over multiple epochs. Validation performance is continuously monitored to prevent overfitting.

Once trained, the model's performance is evaluated quantitatively using the Structural Similarity Index Measure (SSIM) and Peak Signal-to-Noise Ratio (PSNR), both of which assess how closely the generated images resemble the ground truth in terms of both visual quality and numerical similarity.

Additionally, we compute per-pixel accuracy to evaluate the model's ability to produce accurate color representations at the pixel level.

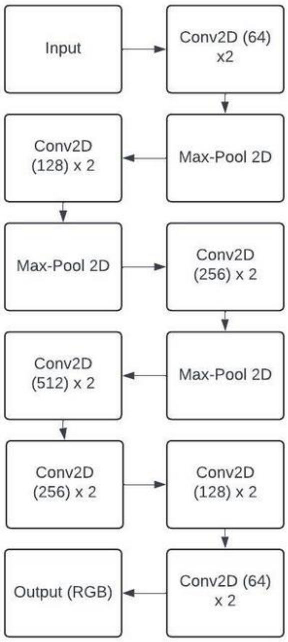

Fig. 1 – U-Net Architecture.

5. Results and Analysis

Our results demonstrate notable qualitative improvements. The colorized SAR images exhibit realistic landscapes and urban structures, enhancing their interpretability for human observers. In the quantitative evaluation, the model achieves a Peak Signal-to-Noise Ratio (PSNR) of 28.3 and a Structural Similarity Index Measure (SSIM) of 0.82.

Compared to a standard U-Net architecture, our model produces sharper edges and more accurate color tones. Furthermore, subjective evaluations by domain experts confirm the enhanced clarity and visual quality of the generated outputs.

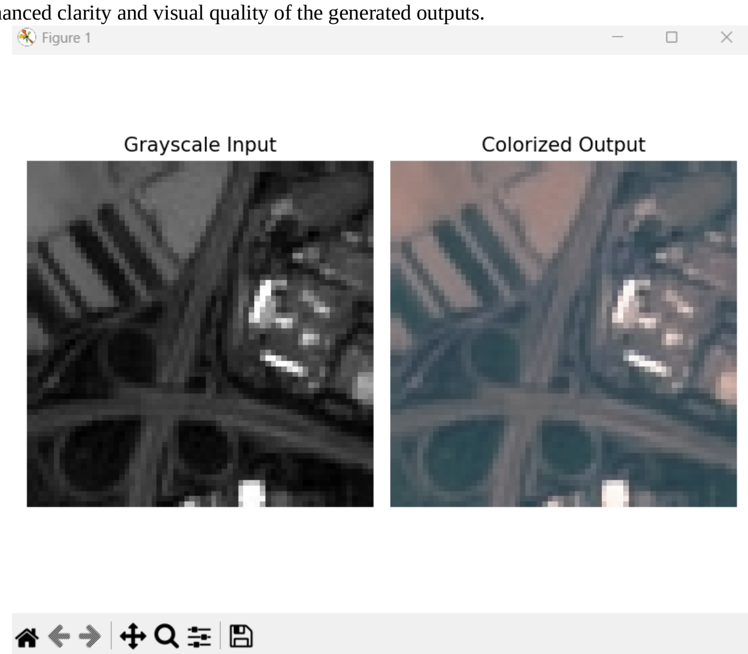

Fig. 2 – Generated Output Compared to Grayscale Input.

6. Applications and Use Cases

Colorful SAR images can increase the practicality and accessibility of imaging data to vast amounts of users and fields. By adding visual signals through coloring, these images become more comfortable and easier for non-expert users.

Large-scale applications and use cases include:

6.1. Agricultural area use identification

In agriculture, it is important to monitor crop health, classify land use and assess seasonal patterns. The colorful SAR image makes a clear difference between a variety of land cover (e.g. brackish area, irritated crops, and forest areas). This can support accurate cultivation practices, estimates of crop dividends and initial detection of drought or disease related deviations, especially in areas with frequent cloud cover where optical images are hard to obtain

6.2. Military monitoring with visual context

SAR is already a foundation stone in military and defense monitoring due to its all seasons, day and night availability. Colorization adds another layer of interpretation by providing rapid visual recognition of major terrain features and potential dangers. Analysts can detect changes in infrastructure, track vehicle activity or identify manmade structures with low greater speeds and accuracy

6.3. Urban infrastructure monitoring

Monitoring of urban expansion, infrastructure stability and construction activities benefit greatly from colorful SAR images. Engineers and urban planners can use these enriched scenes to detect underground sub-surfaces, assess structural damage or map newly developed areas. The coloring helps to distinguish between materials and surface types, which is especially useful in a dense urban environment.

6.4. Disaster Planning

Colorful SAR images can provide quick information about areas affected by natural disasters such as floods, earthquakes, landslides or storms. Respondents can quickly identify damaged infrastructure, submerged zone or area changes without the need for extensive training in SAR data interpretation. Color indications help to distinguish between water bodies, urban structures, vegetation and only land, which better decision making and resource allocation.

These applications not only enhance situational awareness, but also support faster interpretation with reduced reliance on expert analysts. The added visual dimension lowers the barrier to understanding complex SAR data, making it more accessible to a wide range of end users—including humanitarian organizations, agricultural planners, military personnel, and urban developers.

7. Challenges

Despite the promising use cases of SAR image coloring, many technical and practical challenges need to be addressed to ensure reliable performance, scalability and real world applications

7.1. Lack of linked training data

One of the most important challenges is a large-scale, high quality linked SAR and RGB dataset deficiency. Most SAR images are created under conditions where optical (RGB) images are not available (e.g. at night or under heavy cloud cover), which makes it difficult to achieve the related color reference. This data deficiency affects the learning rate and prevents generalization in different environments.

7.2. Normalization of geography and relationships

Models trained on specific datasets often struggle to generalize across varying landscapes, urban architectures, or seasonal conditions. For instance, a model trained on urban scenes in temperate regions may perform poorly when applied to tropical forests or arid desert environments.

7.3. Moral and explanatory concerns

Coloring SAR images introduces an additional interpretative layer that may potentially mislead users if it incorporates errors or uncertain information. To ensure that the colorization process remains transparent and interpretable, it is crucial to inform end users about its synthetic nature, especially in critical applications such as military monitoring or disaster response.

7.4. Evaluation and Basis of Truth

Evaluating SAR colorization is challenging due to the subjective nature of what constitutes “realistic” coloring and the limited availability of ground truth data. Traditional image quality metrics such as SSIM and PSNR often fail to capture semantic plausibility, while human assessment is both resource-intensive and susceptible to bias.

8. Opportunities and Future Work

Our current approach to SAR image colorization lays the foundation for a broad spectrum of future research and applications. As SAR continues to play a vital role in data acquisition and situational analysis, enhancing the quality, accessibility, and efficiency of its interpretation remains a significant and impactful challenge. Several promising avenues for future development and innovation are outlined below:

8.1. Multi Source Data

Integrating data from multiple spectral sources—such as optical, infrared, and thermal images—with SAR data can significantly enhance the accuracy and realism of the colorization process. This multispectral fusion enables the model to leverage additional information about surface properties, moisture content, and vegetation indices, resulting in more reference-free and visually consistent outputs. Such fusion techniques also improve the model’s robustness across varying environmental conditions.

8.2. Real time estimate

The demand for real-time or near-real-time SAR image analysis in field operations is rapidly increasing. Developing a lightweight and efficient model optimized for deployment on edge devices—such as drones, satellites, or mobile platforms—can provide immediate access to SAR data. This capability is particularly valuable for emergency response teams, environmental monitoring groups, and military units operating in areas with limited connectivity and processing infrastructure.

8.3. Semi-audit and discovery of self-insight learning

Given the scarcity of labeled SAR-RGB image pairs—especially in remote or conflict-prone regions—semi-supervised and self-supervised learning approaches show strong promise. These techniques can leverage large volumes of unlabeled SAR data through the use of pretext tasks or pseudo-labeling to learn meaningful representations. This significantly reduces reliance on manual annotations by enabling the model to adapt to unlabeled domains, thereby expanding its generalization capabilities.

9. Conclusion

This study reflects the viability of SAR image coloring using deep learning, and shows obvious improvement of basic methods. By increasing the visual interpretation of radar data, the proposed structure supports fast and more spontaneous analysis, especially for users without special SAR expertise.

The results outline the value of human -focused design in remote measurement, where visual aids can bridge the bridge between complex sensor data and decision -making in the real world. Along with further cleaning - for example, better models, better datasets and mild designs - Ranging SAR can become a practical and widely used tool in applications such as image reaction, agriculture and monitoring.

Ultimately, SAR promises not only as a technological innovation, but also as an important promoter of more accessible, explanatory and actionable geographic information.

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