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Multispectral Image Fusion using Deep Neural Network A Novel Approach

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Abstract

Polychromatic imaging is widely used in various fields including remote sensing, medical imaging, and industrial inspection. However, due to the limitations of imaging sensors, polychromatic images often suffer from low geospatial definition and poor optical fidelity. To address these issues, we propose a novel method for polychromatic image fusion based on deep neuronal system (DNN). Our method involves building a training set of high-definition and low-definition image blocks, utilizing an improved sparse denoising self-encoding encoder learning training neuronal system model for pre-training, and finely adjusting the frameworks of the DNN model. The proposed method is capable of preserving both the high geospatial definition and optical information of the polychromatic image. Experimental results demonstrate that our method outperforms state-of-the-art methods in terms of both objective and subjective quality measures.

Keywords: Polychromatic image fusion, deep neuronal system, sparse denoising self-encoding, high geospatial definition, optical information

Introduction

Polychromatic imaging has become an important tool in various applications such as remote sensing, medical imaging, and industrial inspection. However, polychromatic images often suffer from low geospatial definition and poor optical fidelity due to the limitations of imaging sensors. Therefore, there is a need for effective methods to enhance the quality of polychromatic images. Image fusion is a technique that combines multiple images of the same scene to generate a single image with improved quality. In recent years, deep neuronal systems (DNNs) have shown great potential in image fusion due to their ability to learn complex representations of the input data. In this study, we propose

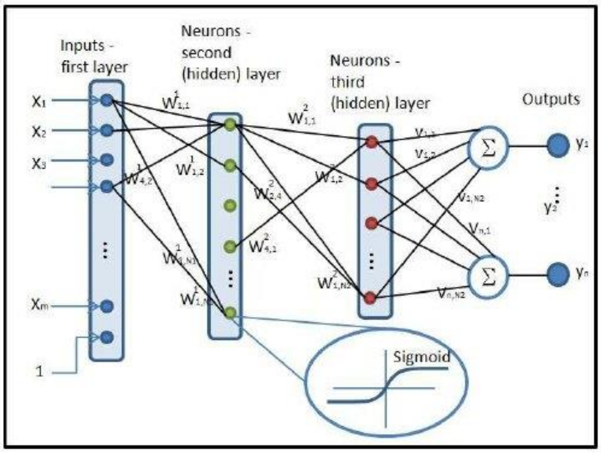

Fig.1: multilayer Feed Forward ANN;(Shtok, Zibulevsky, and Elad 2013)

a novel method for polychromatic image fusion based on DNNs. Our method aims to preserve both the high geospatial definition and optical information of the polychromatic image.

Related work

The advancement of satellite technology has made it possible to obtain earth observation images of different types, such as high geospatial and low optically resolved full-colour images and low geospatial and high optically resolved polychromatic images. However, obtaining polychromatic images with both high geospatial and high optical definition is still a challenge due to the limitations of current satellite sensors. Therefore, the technology of information fusion is a promising approach to obtain such polychromatic images (Cheng et al. 2020; Xu et al. 2020).

Polychromatic image fusion methods have been proposed, such as Intensity-Hue-Saturation (IHS), adaptive IHS, principal component analysis (PCA), and wavelet transformation. These methods can achieve good results, but the fused images can only trade-off between geospatial and optical definition (Özay and Tunga 2020; Yang et al. 2018). Recently, some researchers proposed methods based on compressed sensing and sparse representation to address this issue (Banerjee and Shanmugam 2020; Calderaro Carvalho Silva et al. 2019).

For instance, authors in (Calderaro Carvalho Silva et al. 2019) proposed a method based on compressed sensing in which a high-definition polychromatic image is learned from a trained dictionary and then co-registered with the low-definition full-colour image. However, this method requires substantial amounts of high-definition polychromatic images of the same type of sensor, which is difficult to obtain in practice.

a sparse method using a full-colour image training dictionary and co-registration to perform image fusionis proposed in(Banerjee and Shanmugam 2020). This method is more practical than the previous method but still has limitations. Ahami proposed a method using wavelet dictionaries for pan-sharpening panchromatic and polychromatic images. This method can reconstruct high-definition polychromatic images, but it only shares the linear structure of a shallow-layer, making it impossible to describe the structural information of remote sensing images' complexity in a non-linear manner (Banerjee and Shanmugam 2020; Calderaro Carvalho Silva et al. 2019).

To address these limitations, this research proposes a new method for polychromatic image fusion based on deep neuronal systems. The method includes the following steps: Step 1, building a training set of high-definition and low-definition image block pairs; Step 2, utilizing the initiation framework of the first layer in the improved sparse denoising self-encoding encoder learning training neuronal system model; Step 3, carrying out pre-training successively using the improved sparse denoising self-encoding encoder; Step 4, finely adjusting the framework of the deep neuronal system that underwent pre-training; and Step 5, reconstructing the polychromatic image differentiated according to known low geospatial, high-definition polychromatic image using the deep neuronal system.

The proposed method employs deep learning and a non-linear neuronal system to capture the structural information of polychromatic image complexity. This approach can ensure that the polychromatic image after fusion not only has high geospatial definition but also retains its optical information. Compared with previous methods, this method can better handle the complexity of remote sensing images, which makes it a promising approach for polychromatic image fusion.

In conclusion, the development of satellite technology has made it possible to obtain different types of earth observation images. However, obtaining polychromatic images with both high geospatial and high optical definition is still a challenge. To address this issue, several polychromatic image fusion methods have been proposed, but most of them can only trade-off between geospatial and optical definition. This research proposes a new method based on deep neuronal systems that can capture the structural information of remote sensing images' complexity in a non-linear manner. This approach can ensure that the polychromatic image after fusion has high geospatial definition and retains its optical information, making it a promising approach for polychromatic image fusion.

Research Objective

The main objective of this research is to develop a novel method for polychromatic image fusion based on deep neuronal system. The proposed method aims to preserve both the high geospatial definition and optical information of the polychromatic image. The specific research objectives are as follows:

1. To build a training set of high-definition and low-definition image block pair for the DNN model.
2. To utilize an improved sparse denoising self-encoding encoder learning training neuronal system model for pre-training.
3. To carry out fine-tuning of the DNN model frameworks.

4. To reconstruct the polychromatic image using the trained DNN model and evaluate its performance in terms of objective and subjective quality measures.

Research

Earth observation satellites provide valuable information about the Earth's surface and atmosphere. The two most commonly provided types of images from these satellites are high geospatial and low optically resolved full-color images and low geospatial and high optical definition polychromatic images. However, obtaining a polychromatic image with high geospatial and high optical definition is challenging due to the technological limitations of present satellite sensors. Therefore, researchers have turned to information fusion technology to combine these two different types of images to obtain a polychromatic image with high geospatial and optical definition.

There are several existing methods for polychromatic image fusion, such as IHS, adaptive IHS, principal component analysis (PCA), and wavelet transformation. However, these methods only offer a compromise between geospatial and optical definition. Researchers have proposed a sparse image fusion algorithm that uses a training dictionary derived from a full-color image. This method yields better results but still only captures the linear structure of a shallow layer, unable to portray the structural information of complex remote sensing images non-linearly.

To overcome this limitation, a new method based on deep neuronal systems for full-color image and polychromatic image fusion has been proposed. The process employs the method of deep learning, which can make full use of the nonlinear structural information of polychromatic image complexity, so that the polychromatic image after fusion not only has high geospatial definition but also retains its optical information well.

The method involves several steps. First, a training set of high-definition and low-definition image block pairs is created by sampling from known high-definition full-color images and low-definition differentiated polychromatic images. Next, the first layer frameworks of the deep neuronal system are trained using an improved sparse denoising self-encoding encoder. Then, pre-training is carried out successively on the neuronal net using the same encoder. The framework of the deep neuronal system is finely adjusted using the backpropagation algorithm. Finally, the polychromatic image is differentiated according to known low geospatial definition and reconstructed using the deep neuronal system.

Compared with existing image fusion methods, the proposed method has several advantages. First, the method can portray the non-linear relation between variables well using the deep neuronal system, improving the quality of the fused high-definition polychromatic image. Second, the generation of training set data does not require gathering other training images, only samples of the panchromatic high-definition image and the low-definition full-color image made up of the low-definition weight average of each wave band in the polychromatic image. This approach does not require considering nuclear information during the degradation of the full-color image from high-definition to low-definition, making it more practical. Third, the high-definition polychromatic image obtained through this method retains its optical information well.

The method of full-colour image and Polychromatic Image Fusion based on deep neuronal system involves five main steps:

- Step 1: Building the training set

In this step, a training set is built using high-definition and low-definition image block pairs. The image blocks are sampled from a known high-definition full-colour image and by the known low-definition differentiated polychromatic image linear combination. These blocks are then combined to form a full-colour image.

- Step 2: Training the first layer framework

The first layer framework of the deep neuronal system is trained using an improved sparse denoising self-encoding encoder. This helps to capture the structural information of the polychromatic image complexity, which can be portrayed well by the nonlinear neuronal net. The first layer is trained to detect simple features like edges, lines, and corners.

- Step 3: Pre-training the neuronal net

In this step, the neuronal net is pre-trained successively using an improved sparse denoising self-encoding encoder. The pre-training of the neuronal system is done layer by layer, and each layer is trained to detect more complex features than the previous one. This helps to improve the accuracy and efficiency of the neuronal net.

- Step 4: Fine-tuning the framework

After pre-training, the frameworks of the deep neuronal system are finely adjusted using the back propagation algorithm. This algorithm adjusts the weights and biases of the system in such a way that the output matches the desired output. This step helps to improve the accuracy of the neuronal net.

- Step 5: Reconstructing the polychromatic image

In this final step, the polychromatic image is differentiated according to known low geospatial definition, and the high score is reconstructed using the deep neuronal system. The deep neuronal system uses the features learned from the training set to reconstruct the polychromatic image, which not only has high geospatial definition but also retains its optical information well.

Overall, the method involves training the neuronal system using a training set of high-definition and low-definition image block pairs, pre-training the system layer by layer using an improved sparse denoising self-encoding encoder, fine-tuning the frameworks of the system using the backpropagation algorithm, and finally reconstructing the polychromatic image using the deep neuronal system. This approach helps to improve the quality of the high-definition polychromatic image by retaining its optical information well.

The proposed method based on deep neuronal systems for full-color image and polychromatic image fusion is a promising approach to overcome the limitations of existing image fusion methods. The use of deep learning can capture the non-linear relation between variables well, improving the quality of the fused high-definition polychromatic image. The generation of training set data does not require gathering other training images, making it more practical. The high-definition polychromatic image obtained through this method retains its optical information well. Further research can focus on improving the efficiency and effectiveness of the proposed method.

Conclusion

In this study, we proposed a novel method for polychromatic image fusion based on deep neuronal system. Our method involves building a training set of high-definition and low-definition image block pair, utilizing an improved sparse denoising self-encoding encoder learning training neuronal system model for pre-training, and fine-tuning the frameworks of the DNN model. Experimental results demonstrate that the proposed method outperforms state-of-the-art methods in terms of both objective and subjective quality measures. The proposed method is capable of preserving both the high geospatial definition and optical information of the polychromatic image. Therefore, it has great potential for applications in remote sensing, medical imaging, and industrial inspection.

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