Anbar Journal Of Engineering Science©Vol (year) first page – last page

University of Anbar

Anbar Journal Of Engineering Science©

journal homepage: http:// http://www.uoanbar.edu.iq/Evaluate/

IHS Image Fusion Based On Gray Wolf Optimizer (GWO)

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PAPER INFO

Paper history:
Received 08/05/2022
Received in revised form 05/06/2022
Accepted 08/06/2022

Keywords:
Spectral Distortion, Gray Wolf Optimizer, Image Fusion, Panchromatic, IHS

ABSTRACT

Satellites may provide data with various spectral and spatial resolutions. The spatial resolution of panchromatic (PAN) images is higher, but the spectral resolution of multispectral (MS) images is greater. There is Satellite sensors limitation for capturing an image with high spatial and spectral resolution. Whereas many remote sensing, as well as GIS applications, need high spatial and spectral resolution. Image fusion merges images of different spectral and spatial resolutions based on certain algorithm and can be used for overcoming the sensors limitation and play an important role in extraction of information. But the standard image fusion approaches lose spatial information or distort spectral characteristics. Optimizations of fusion rules can be used for overcome and degrade the distortions as the core of the fusion is image fusion rules. In this paper the Gray Wolf Optimizer (GWO) is used for finding the optimal injection gain as the most distortions in image fusion caused by extraction and injection of spatial detail. Both qualitative and quantitative metrics were utilized to evaluate the quality of the merged image.

Keywords: Spectral Distortion, Gray Wolf Optimizer, Image Fusion, Panchromatic, IHS.

1. Introduction

Remote sensing applications have improved significantly in recent decades in a variety of fields of research, including land-cover classification (Mirzapour and Ghassemian, 2015) and change detection (St-Charles et al., 2014). The electromagnetic bandwidth of the spectral signatures acquired by the sensor is referred to as spectral resolution in remote sensing images, while spatial resolution is the actual area of the ground recorded by one pixel. A high spectral resolution is essential for land cover identification, and a high spatial resolution is particularly important for accurately describing the forms and structures of objects in images. (Leung et al., 2013). In order to meet the needs in varies fields of applications, obtaining of satellite images with high spectral and spatial resolutions is very important. Collecting energy over a larger instantaneous field of view (IFOV) reduces spatial resolution, while collecting it over a larger bandwidth reduces its spectral resolution.

Earth observation satellites, for instance, may gather two types of data at the same time in order to maintain a specified Signal-to-Noise Ratio (SNR) rate, panchromatic (PAN), and multispectral (MS) images (Patel and Anand, 2019). In general, a PAN image has a higher spatial resolution than the MS image, but the MS image has a higher spectral resolution than the PAN image. Because of this trade-off between MS and PAN image resolutions, it may be challenging to maintain both spectral and spatial resolution in a single image. Nowadays, Pan and MS images can be obtained in bundle by several commercial optical satellites such as IKONOS, Orb View, Landsat 8, SPOT, Quick Bird, and WorldView-2 (Alparone et al., 2015).

Pan-sharpening, which is the fusing of a low-spatial-resolution MS picture with a high-spatial-resolution Pan image to generate an MS image with the same spatial resolution as the Pan image, can be utilized to meet the requirements for images with high spatial and spectral resolutions in applications. Pan-sharpening products have been found to have a high potential for improving classification accuracy and visual interpretation (Leung et al., 2013).

The number of algorithms has increased over the years, and it has become a challenge to organize and present the various possibilities of fusing remote sensing images. In particular, it has become extremely difficult to identify the various algorithms since they often appear under different names. This is due to the fact that many fusion algorithms have been implemented in commercial software. Different software providers chose different names to supply the same thing. Another difficulty in listing available algorithms occurs in the identification of who really originated the approach because over the years published research on the development of new algorithms has not been cited from the originator.

The majority of pansharpening processes may be broken down into two steps: spatial detail extraction and spatial detail injection. The spatial detail extraction stage is responsible for extracting meaningful spatial information from the high-resolution Pan image, and the spatial detail injection step is responsible for determining how the retrieved spatial details may be injected into the upsampled MS image.

In general, spatial details are retrieved by subtracting the Pan image from its low-pass approximation. Pansharpening methods are roughly classified into two types based on how the low-pass approximation of the Pan picture is calculated (Wang et al., 2005): the linear combination approximation (LCA) methods and the spatial filter approximation (SFA) methods. The LCA methods compute the low-pass approximation by a weighted average of the MS bands. Some popular methods of this class are the Brovey transform (Hallada and Cox, 1983) and the component substitution (CS)-based methods including principal component analysis (Chavez et al., 1991) and intensity–hue–saturation (IHS) (Tu et al., 2001, Leung et al., 2013).

IHS technique converts a color image from RGB space to the IHS color space and the “I” band is replaced by the panchromatic image, in general, the stronger the correlation between the Pan image and the replacement component, the less spectral distortion will generate, Before the substitution, histogram matching of Pan to the chosen component is conducted. The procedure is finished by reversing the data to its original MS space via the inverse transformation (Alparone et al., 2015). Because of their ease of computation, great spatial resolution, and efficiency, IHS-based algorithms are often employed. The fused image results in high spatial resolution and low spectral resolution (Rahmani et al., 2010).

A new formalization of the IHS approach was presented to overcome the method's spectral distortion (Tu et al., 2001) and it was then investigated by other following publications (Tu et al., 2004, Rahmani et al., 2010) . It was demonstrated that the fusion process may be produced via a proper injection method instead of the actual application of the forward and backward transformations under the hypothesis of a linear transformation and the replacement of just a single nonnegative component.

One of the major flaws in image fusion approaches is the lack of a reliable metric for evaluating fusion outputs. Several attempts have been undertaken to objectively represent the human perception system. Due to the lack of a High Resolution MS (HRMS) image, two generic methods are proposed to address this issue. The fusion framework is conducted in downscaled versions of the input data in the first method, and the original MS data is used as the reference image. The fusion process, on the other hand, is carried out in the full-scale scenario in the second method, and the no reference quality metrics are used to evaluate the fusion outcomes (Patel and Anand, 2019).

To improve the performance of the different image fusion approaches, many approaches of the metaheuristics were applied to image fusion (Gharbia and Hassanien). In the area of optimization, solving an optimization problem typically means finding optimal values for the decision variables to maximize or minimize a set of objective functions (Nadimi-Shahraki et al., 2021).

This research proposes a novel framework for the pansharpening issue, which is classified as IHS-based. The goal of this technique is to identify a suitable objection function for estimating the appropriate injection gain of spectral bands in an LRMS image. We choose the Gray Wolf Optimizer as optimization algorithm as it requires less variable changing and less iteration numbers for finding the optimal value and the Relative Dimensionless Global Error (ERGAS) measure as objective function for this purpose because it can better depict the nonlinear link between the detail maps of CS-based techniques.

2. Mathematical Background

The previously described LCA approach produces a fused image with high geometrical quality of spatial information, but with potential spectral problems. However, if the spectral combination of bands is optimized for spectral quality of pansharpened products, the result of fusion will be more adaptive than standard methods.

The main difference between IHS and BT is how spatial features are weighted before injection, not how they are derived from the Pan image. Regardless of how spatial features are collected, their injection into the interpolated MS bands may be balanced by appropriate gains, which may be different for each band and perhaps space-varying, i.e. a different gain for each pixel (Alparone et al., 2015).

A general formulation of the IHS fusion scheme is given by

$\acute{M}_k = M_k + g_k (P - I)$ ……….. (2.1)

In which: $\acute{M}_k$ is multispectral image after pansharpening.

M_k is orginal multispectral image.

k indicates the k^{th} band, g = [g1,. . . gk, . . . , gK] is the vector of the injection gains.

While, I is defined as:

$I = 1/3(B+R+G)$ ……….. (2.2)

Where: R,G,B are RGB bands.

The injection gain for BT is as follow: