# Investigation of Fusion Image Enhancement Methods for Satellite Image

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## ABSTRACT

Satellite images are used in various applications. Satellite images acquired are generally blurry and noisy. Thus enhancement of images is a needed process. It is a strong research topic in Image processing. Main motive behind enhancement is to get an image more effective than the original image for different remote sensing applications. Various choices of techniques are available for improving quality of satellite images. Here, enhancement by machine learning methods for image fusion acts a prominent role. It efficiently combines image content and then enhances information present in each datasets. This article provides overviews of the existing fusion enhancement techniques. Till now various techniques have been proposed for enhancing digital images. Some of them can be used for enhancing satellite images. It was found that fusion-based enhancement performs better than non-fusion based enhancement techniques. This review paper will give a survey of various fusion-based enhancement techniques. Based on application best methods among various techniques have been discussed.

**Keywords:** Fusion Enhancement, Satellite Images, Remote Sensing, Image fusion, Image Processing

## 1. INTRODUCTION

Over some years, satellite remote sensing data has played an important role in different applications such as in areas like agriculture, geology, biodiversity, local planning, education and warfare etc. Firstly images are captured by different imaging cameras onboard and after going through radiometric and geometric correction, still images are not good for ground use. Thus they need to be enhanced, so images are passed through different processing methods.

Enhancement of Satellite image makes visual description and realizing imagery are easier. By using digital imagery we can change digital pixel values of an image.

Image enhancement is a process in which improvement of satellite image quality is done without having knowledge about the cause of degradation. Hyper spectral imaging is analogous to other spectral imaging, it collects and processes information across the spectrum. Main objective of hyper spectral imaging is to get spectrums of each pixel of image. Then, objective to finding objects, materials and deciding processes can be achieved.

There are generally three kinds of spectral imagers. Spatial Scanner which takes images over time are Push-broom and the Whisk-broom. Band sequential scanners do spectral scanning and imaged an area at various wavelengths. In snapshot hyper spectral imaging, image at an instant is generated using staring array. Satellite imaging is a difficult task for researchers. In remote sensing hyperspectral Image enhancement is an important part. Due to mixed pixel in Hyperspectral image, their classification is very difficult. It can be refined by enhancing the hyperspectral image and separating classes. Now to develop and then applying enhancement techniques to these remotely sensed images, complete information of present problems and ideas about how these hyper-spectral images are captured is needed. Classifying pure pixel from mixed one enhancement of hyper spectral images is very important task. But, still separation of classes from hyper spectral image is hard process as it has mixed pixels, high dimension and low spatial resolution. This paper reviews the most prominent working enhancement algorithms.

## 2. REMOTE SENSING

In remote sensing, physical properties of an area are captured without being there. It helps users to visualize and analyze objects and features on the surface. It traces and monitors physical features of a large portion on ground. Basically it analyzes emitted and reflected radiation from the ground or oceanic surfaces. Special cameras collect remotely sensed images such as cameras on satellites, airplanes, ships etc. Satellite Camera can image large areas on the ground and also can image temperature drifts in ocean. Similarly, Sonar systems on ships can create images of the ocean floor. Uses of remotely sensed images are tracking clouds, watching volcano erupting and dust storms, tracking growth of city, changes in forest over a period, discovering and mapping rugged topography of ocean floor, forest fires etc.

## 3. ELECTROMAGNETIC SPECTRUM

The electromagnetic spectrum ranges from short wavelengths (like X-rays) to long wavelengths (like radio waves). Some sensors can see beyond human vision. Engineers have design sensors to capture beyond visible spectrum (390-700 nm) wavelengths in the atmospheric window. Vegetation is more sensitive to near-infrared. Hence NDVI is used for classifying vegetation.

Spectral region is classified based on its frequency (v) or wavelength. For Passive Sensors, two types of imagery are Multispectral imagery and Hyperspectral Imagery. Hyperspectral images have hundreds of narrow bands, while multispectral images consist of 3-10 wider bands. For example, Landsat-8 generates 11 different images for each scene. Hyperspectral imagery has much narrower bands (10-20 nm). For example, Hyperion, which is part of the EO-1 satellite produces 220 spectral bands (0.4-2.5 um).

## 4. HYPER SPECTRAL IMAGE ENHANCEMENT

Over Past decades, various methods for the enhancement of hyper spectral images have been developed. Hyper spectral imagery can be depicted as an image cube or data cube where X-Y plane represent spatial information while Z-direction represent spectral information. Sensors can operate in two mode i.e. panchromatic mode or hyper spectral mode.

Panchromatic image have only one band which display black and white aerial digital photograph of captured ground. Thus, it displayed a grayscale image.

A panchromatic sensor doesn’t give spectral resolution i.e. color information but it provides high spatial resolution image. Hence, to get both spatial and spectral information from image fusion based enhancement techniques are used [1]. As, the panchromatic spectral range is different from hyper spectral image range, there is a need for a model which incorporate details while considering enhancement of spatial quality and keeping spectral quality same having fine edge features. Extracted details from the panchromatic image could result in the spectral distortions in images. So, the algorithm which must be designed to obtain high-resolution images is by fusing image bands having high entropy. It increases the spatial information.

Basically, the enhancement algorithm could be of two types non-fusion-based and fusion-based [1]. It is found that fusion based is best among them.

## 5. FUSION-BASED ENHANCEMENT METHODS REVIEW

In fusion-based enhancement technique, images with low spatial resolution are fused to generate high resolution images. Various methods have been suggested in the past. Some important methods are Component Substitution method, Multi resolution method, Optimization – based method and lastly, numerical and statistical-based approach [1].

### 5.1. Component substitution

Malpica, 2007 suggested Intensity-Hue Saturation (IHS) color transformation, is most widely used Component substitution (CS) approach [2]. Back to its origin, color, feature and spatial resolution enhancement are standard procedures for image analysis [3]. Using this technique color images in RGB color space get converted into HIS (Hyperspectral Image Saturation) color space. Here, auxiliary information is placed in place of the intensity band. This method has a weakness as it produces color distortion. However, algorithm is highly efficient. Color distortion is due creation of auxiliary information from different wavelengths of light, not the same as RGB image.

Thus to remove this distortion, Tu et al., 2004 proposed modification of this method as Fast Intensity-Hue Saturation (FIHS) [4]. In FIHS method bands are increased. Here four bands are used. Here Infrared component is extension to IHS method. It gives auxiliary information, which is taken from infrared and visible wavelength. These changes makes computed intensity to get better matched with extra information and finally give less color distortion of fused images. Some parameters are needed known as trade-off parameters to get the expected result for spatial improvement and spectral quality loss [4]. Users can fine tune these parameters.

Rahmani et al. 2010 proposed adaptive IHS method to resolve the spectral quality short comes [5]. Adjustment of Linear combinations of multi spectral bands' coefficients are operated using weights. These weights are implemented in the spatial detail by the edge injection process. These weights are very large which cause color changes. Due to color change, fused image have spectral distortion and reduction in sharpness.

Leung et al. 2014 provide an improvement on this algorithm [6]. In this improved AIHS, injection of a more adaptive weighting matrix is executed. In performance, this method is better than AIHS. Distortion occurs more on the edge of the high reflection area making overall spectral distortion higher.

Dehnavi et al. 2013 suggested a method which have Brovey Transform (BT), Generalized HIS and Smoothing Filter-based Intensity Modulation (SFIM) with only two parameters [7]. Method is used for controlling spatial and spectral information. But still this method suffers a drawback of large spatial information loss while keeping large spectral information.

A new fusion technique is suggested by Hubert et al. 2005 based on Principal Component Analysis. In this technique datasets are divided into sub-groups of bands [8]. Thus, it reduces the computational complexity. Based on dominant class PCA is implemented separately to every subgroup and matched filter to corresponding bands. Spectral signature of a class represents transfer function of this matched filter. As, Energy is randomly distributed, components of the output RGB image are taken as the main component for each sub-group.

Qu et al. 2018 suggested a method that fuses Panchromatic Image and Hyper spectral image. It is based on Structure Tensor. This fusion algorithm improves the spatial details of the hyper spectral image and the spatial information of panchromatic image using an image enhancement process. Images can be generated by an adaptive weight model. The Spatial detail from improved panchromatic image is extracted by structure tensor. To avoid any defects at boundaries, fused spatial information image is passed from a guided filter [55]. The Injection Matrix is created to overcome spectral and spatial distortion. By this method spatial details are generated and preservation of spectral information is achieved.

An Enhancement algorithm is proposed by Jayanth et al. 2018 which uses local weighted principal component analysis along with wavelet algorithm. This algorithm also preserves spectral information [9]. It provides good spatial quality and clarity.

Another image enhancement approach for low resolution satellite image is proposed by Parveen et al. 2018. By this algorithm, interpretation about images becomes simpler and the image gets visually clear [10].

Based on observation system and using multispectral and hyper spectral fusion models, Xie et al. in 2019 modeled an enhancement method. Here, training data is used for learning process of all parameters and then Spatial and spectral output operators are found. By this method, color and brightness of processed images is much similar to the low resolution hyper spectral image [11].

Component substitution-based methods make image intensity model and high-frequency injection model so that they can protect their spectral information. But it incurs sharpness reduction, more spatial information loss and increase in spectral distortion [1]. Some methods are only applicable to a specific sensor. Nevertheless, little commercially available fusion software gives suitable outputs when applied to all optical multispectral and panchromatic images. Also, these tools can increase the spectral quality; despite they only show visually important results.

### 5.2. Multi Resolution Method

Multi Resolution Approach (MRA) combines the radiometric information present in low-resolution image with the spatial information present in high-resolution image. This process helps in sharpening the low-resolution image. Various Multi-Resolution techniques are suggested due to an increase in algorithms and computational power present in commercial remote sensing software [1].

Nunez et al, 1999 shows MRA-based approaches based on local frequency content which decompose images into various channels [12].

Miao et al. 2006 proposed a multi resolution contour let transform method. Using contourlet decomposition; directional image pyramids of certain levels can be generated. Fusion of low frequency coefficients which are present at tip of image pyramids is processed using the average-based rule. For other levels, coefficients with higher energy in the local area of source image are selected by fusion rule. Here, the pyramid represents the multi-scale models used for original image. As level increases, coarser will be spatial resolution of the original image which is approximated [13].

Wavelet and Curvelet transforms are used among pyramid levels. The wavelet transform method applies substitution and addition approaches. Substitution approach selects and substitute multi spectral wavelet planes by the planes of the panchromatic images [1]. Also, multi spectral bands are added by the decomposed panchromatic planes.

Garzelli, et al. 2005 suggested a multi resolution approach based on fusion method. They show that high-pass information of an image can be designed from a panchromatic image. Wavelet transform approaches are of four types low-low, low-high, high-low and high-high. Using these decompositions, pyramids at several levels can be formed. The generated fused image is inversely transformed [14].

Amolins et al. 2007, show practically that exact derivation for scaling and wavelet transform function is not possible. So, we can describe it by coefficients. Using different fusion rules these coefficients are fused to generate the output image [15].

Aiazzi et al. 2002, explain that context-driven fusion processes give better results. In this process fused bands gets matched with narrow band multi spectral image. Resolution of these fused bands is same as the resolution of broadband image [16]. This Broadband image captures the single panchromatic band. Based on statistical congruence higher frequency coefficients are selected from the high-resolution image. Also, Gain equalization can be obtained by weighing it using a space-varying factor. Here, ringing artifacts i.e. Spurious signals are completely moderate.

Aiazzi et al. 2001 shows that, reconstruction of greatly damaged image with spectral signatures of small size is possible [17].

Pradhan et al. 2006 have suggested an extension to the discrete function known as multiresolution analysis. Number of decomposition levels which are required for merging images can be calculated. These images have definite resolution ratio. It was found that resolution ratio is directly proportional to decomposition levels and thus generates better output. But, as levels of decomposition increases computational complexity also increases [18].

Metwalli et al. 2014 proposed Contourlet Transform (CT). Here discontinuity points are searched and connected to form linear structures. Due to this it provides at each multi-resolution decomposed scale different countless directions. Working of the non-sub sampled CT depends upon a non- sub sampled pyramid. By this it produce better results [19].

During the Data fusion contest, effective image fusion approaches have been proposed by Alparone et al. 2006. Methods are Laplacian - based, Context-based decision approach and the other one is Proportional Additive Wavelet. Context-based decision algorithms works well than CS-based approaches [20].

But, there are some shortcomings of MRA-based fusion algorithms studied by Aiazzi et al. 2006 such as spatial turbulence due to presence of aliasing effects and compared to CS based algorithms these methods does not have relevant spatial enhancement with more blurred textures [21].

Mallat et al. 1989 suggested MRA-based approaches provide prominent tools to merge images such as wavelets and pyramids [22].

But, Yocky et al. 1996 explained that injection of high pass details in an image can cause aliasing effects, spatial distortions, texture and contours blurring [23].

Aiazzi et al. 2002, González et al. 2004 explained that these disadvantages gets surfaced due to wrong registration among Multispecturm data and Panchromatic data and more focused if MRA is shift-variant while going through detail injection [16],[24].

Wenyan, Z et al. 2018 suggested an enhancement model which is based on equal weight. It improves the precision of change detection having lesser clearance in visuals [25]. Approaches based on Numerical and statistical methods are suggested to overcome these problems. This gives better results.

### 5.3. Numerical and statistical-based method

Mathematical combination of different images is the simplest and oldest method for remote sensing. It includes addition, subtraction, division and multiplication methods.

Ashraf et al. 2013 analyzed a subtractive resolution approach. They analyze same results by merging known calculated band weights and influence of user in subtractive resolution [26].

BT is a classical approach. This method applies addition and subtraction using spectral modeling to achieve normalization of the input band. But it produces distorted color.

Vrabel et al. 2000 gave an improvement of BT known as color normalized spectral sharpening. This method is an adaptive approach to upgrades fused images' spectral quality. Here, the input bands are clustered in the spectral segments [27].

Chibani et al. 2007 presents a modified BT for multispectral image which is based on its local modulation. Modulation is the ratio of the latest intensity components and starting intensity components [28].

Ballester et al. 2006 proposed the variational model which using filtering and sub sampling interpret the behavior between high-resolution panchromatic image and low- resolution multispectral image. It speculates that a panchromatic image is composed of a multispectral image and its geometry [29].

Duran et al. 2013 expand this algorithm. Process refers local relationships of adjacent pixels with denoising effect [30].

Statistical approach algorithm which is used for commercialization purposes is Fuze Go. It is known as Pan-Sharpening algorithm, and among gray values of input bands it uses least square method.

Xu et al 2014 shows that statistical methods are used for computing the resultant values [31].

Zhang et al. 2014 show that to obtain the best match using fully automated method, input images have to be taken individually. It even allows new users to accomplish good results [32].

To enhance satellite images, a fuzzy statistics-based algorithm has been proposed by Devika et al. 2018. This method gives accurate and efficient fuzzy clustering [33]. Thus, some algorithms are needed which uses combination calculation with results to enhance the contrast.

### 5.4. Optimization-based Method

Optimization is a technique which maximizes or minimizes a real function while selecting inputs from a valid set for deducing the function's solution. For solving these problems with converged finite solution iterative approach is used [1].

For fusion of multi exposure optical images, Raman et al. 2007 proposed an optimization-based method. Set of images are fused to get dynamic range of resultant image enhanced. Nevertheless, Cost function of a output image has a smoothness factor generating a smoothing solution [34].

Kotwal et al. 2010 proposed a fast strategy using redundancy elimination for fusion of hyper spectral images. In this algorithm, set of mutually correlated image bands are chosen and keeping maximum information in the data. Since only a small portion of the whole data is fused, this technique is much faster in computation [35]. Again Kotwal et al. 2012 proposed a new algorithm for hyper-spectral image bands based on visualization. But in this method, intrinsic contrast value in the geological input data is less and thus can't be visualized [36].

Qifal Wang et al. 2011 formulated an enhancement method for fusion of multispectral and panchromatic image. This algorithm results in a high spatial resolution multispectral image which is highly similar to true referenced high resolution multispectral image [37].

Gram Schmidt algorithm is proposed by Xu et al. 2015. This method uses weighted summation of RGB bands and near-infrared multispectral bands to generate a simulated low resolution panchromatic image. Introduction of strange artifacts and unobvious color distortion with blurred outputs in all band are obtained while evaluating spatial and spectral information. This method takes more time in creating output images as transformation is rigorous in computation [38].

Based on unmixing non-negative matrix factorization, Wang et al. 2013 suggested a projected gradient algorithm. High spectral and high spatial resolution fused images are generated by this approach. This method preserve maximum color information of image with improved the spatial resolution [39].

Hashimoto et al. 2011 formulated a multispectral image enhancement algorithm for visualization. Using this method spectral feature and color from specified spectral bands can be extracted for independent visualization. Thus, specific feature of image gets enhanced in specific band and color [40].

For image enhancement Kaplan 2018 designed a weighted intensity color saturated transform model. Weighting function in this method has large information of input image bands. Here, one may get best visual and quantitative comparisons results, as weighting function are used for generating the intensity component [41].

Some researcher gives algorithm for vegetation. Ben Abbes et al. 2018 compared three kinds of satellite images by applying a time series decomposition algorithm. This method detects vegetation change on the ground [42].

A very good automated recognition algorithm is proposed by Mozgovoy et al. 2018. This algorithm can recognize in satellite images various territories, vegetation and water bodies. This method performs better in large area map updating, and thus economically good and free from human error [43].

Li et al. 2019 suggested an enhancement method for large scale underwater images which are degraded. This method computes effective quality evaluation metrics for non-reference underwater image [44].

Yadav et al. 2018 uses Otsu's method to give an enhancement algorithm for road identification and extraction. This technique performs detection, extraction and then enhancement of the road network present in high-resolution satellite images [45].

Some enhancement methods are also designed for medical hyper spectral images. One of them is for Injuries in corneal epithelium suggested by Md Noor et al. 2017. By this algorithm data interpretation into relevant clinically information improves and thus helps in early and faster diagnostics [46].

Gunlu 2014 suggested an enhancement algorithm by using pan-sharpened IKONOS satellite image for the knowing stand parameters. Estimation of these stand parameters are carried out by multiple stepwise regression analysis which results in high correct measurements, higher cost and time [47].

Rajathurai A et al. 2018 suggested a KNN matting algorithm. It generates best extracted visualized multilayer output in closed-form by considering available methods. This algorithm has less complex computation [48].

Based on Machine learning, Gewali et al. 2018 modeled an algorithm for hyper spectral image analysis. Here, extrinsic and intrinsic variations which are generated by unrelated factors are ignored and only relevant information from intrinsic variation is extracted [49].

Guo et al. 2018 suggested a convolution neural network based algorithm. This algorithm fuses panchromatic band and short wave infrared bands. This algorithm results in effective enhanced spatial information by segregating the basic design in three layers [50].

Maselli et al. 2016 suggested an innovative algorithm for enhancing spatial features that generates series of NDVI image. Based on end members, statistical method is operated on plenty of images that enhance the spatial information [51].

Tiede 2017 designed an implementation of architecture and prototypical of a well-formed querying system for big image bases. By this algorithm, vision of photographic images is improved [52].

Gavankar et al. 2018 modeled an automatic process for building footprint extracted from high-resolution images. It uses mathematical morphology. It ejects false-detected buildings and selects buildings from different sizes and shapes [53].

Lal et al. 2016 formulated sparse representation fusion algorithm useful for multi temporal images. It is also an enhancement method which is based on dictionary. Patches from images are kept in a local adaptive dictionary. Spectral information, color, errors and visual quality are preserved in this algorithm [54].

## 6. CONCLUSION

This paper reviews Satellite image enhancement algorithms based on fusion method. Other than satellite image some other images enhancement methods are also discussed. It is found that to obtain improved spatial information with less complex computation fusion based enhancement is best suited. It offers low spatial resolution, contrast and sharpness with high spectral distortion. Methods based on neural networks and machine learning is found good among different fusion based enhancement. Hence it gives good accuracy and visualization.

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