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4 Benchmarking of Data Fusion Algorithms in Support of Earth Observation Based
5 Antarctic Wildlife Monitoring
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Abstract

Remote sensing is a rapidly developing tool for mapping the abundance and distribution of Antarctic wildlife. While both panchromatic and multispectral imagery have been used in this context, image fusion techniques have received little attention. We tasked seven widely-used fusion algorithms: Ehlers fusion, hyperspherical color space fusion, high-pass fusion, principal component analysis (PCA) fusion, University of New Brunswick fusion, and wavelet-PCA fusion to resolution enhance a series of single-date QuickBird-2 and Worldview-2 image scenes comprising penguin guano, seals, and vegetation. Fused images were assessed for spectral and spatial fidelity using a variety of quantitative quality indicators and visual inspection methods. Our visual evaluation elected the high-pass fusion algorithm and the University of New Brunswick fusion algorithm as best for manual wildlife detection while the quantitative assessment suggested the Gram-Schmidt fusion algorithm and the University of New Brunswick fusion algorithm as best for automated classification. The hyperspherical color space fusion algorithm exhibited mediocre results in terms of spectral and spatial fidelities. The PCA fusion algorithm showed spatial superiority at the expense of spectral inconsistencies. The Ehlers fusion algorithm and the wavelet-PCA algorithm showed the weakest performances. As remote sensing becomes a more routine method of surveying Antarctic wildlife, these benchmarks will provide guidance for image fusion and pave the way for more standardized products for specific types of wildlife surveys.

Keywords: penguins, seals, guano, data fusion, VHSR imagery

1. Introduction

1.1 Remote sensing for Antarctic wildlife

Since its discovery, the Antarctic has been plagued by data scarcity, as geological and biological surveys have been largely confined to easily-accessed coastal regions, or to the areas surrounding permanent Antarctic stations capable of providing logistical support to survey operations. However, the Antarctic is quickly becoming a model system for the use of remote sensing for the physical and biological sciences because the costs of field access are high, the landscape is simple (e.g., rock, snow, ice, water) and free of woody vegetation, and polar orbiting satellites provide extensive regular coverage of the region. Increased access to sub-meter commercial satellite imagery, which rivals aerial imagery in terms of spatial resolution, has sparked a number of developments in geology, glaciology, geography, oceanography, and biology. Very high spatial resolution (VHSR) satellite sensors like IKONOS, QuickBird, GeoEye, Pléiades, Worldview-2, and Worldview-3 provide very high resolution multi-spectral imagery that can capture the detail needed for an array of applications, e.g. individual houses on a city street, individual animals standing on the ground, or individual tree canopies within a forest stand (Ardila et al., 2012; Kurtz et al., 2012; Lynch et al., 2012; Beguet et al., 2014; Huang et al., 2014; Karlson et al., 2014). Due to shorter revisit times of these sensors, it is also possible to acquire near real-time imagery over the area of interest (Kim et al., 2011).

While remote sensing has a long and fruitful history of use mapping environmental layers such as land cover type, which can be used as an indirect measure of biodiversity, the use of remote sensing imagery to directly survey animals (either individual animals, or groups of animals) is, with a few notable exceptions (Schwaller et al., 1983; Schwaller et al., 1989), a much more recent phenomenon (Barber-Meyer et al., 2007, Fretwell and Trathan, 2009; LaRue et al., 2011, Lynch et al., 2012). Recent satellite-supported surveys of wildlife in the Antarctic have included penguins (*Pygoscelis* spp. and Emperor Penguin, *Aptenodytes forsteri*; Barber-Meyer et al., 2007; Fretwell and Trathan, 2009; Fretwell et al., 2012; Lynch et al., 2012; Schwaller et al., 2013; LaRue et al., 2014; Lynch and LaRue, 2014; Fretwell et

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4 al., 2015), seals (Weddell seal, *Leptonychotes weddellii*, LaRue et al., 2011; Ainley et al. 2015; elephant
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6 seal, *Mirounga leonina*, McMahon et al., 2014), and whales (Abileah, 2002; southern right whale,
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8 *Eubalaena australis*; Fretwell et al., 2014).
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10
11 VHSR satellite sensors typically record image data in a low resolution multispectral (MS) mode and
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13 high resolution panchromatic (PAN) mode. High spatial resolution is needed to accurately describe
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15 feature shapes and textural patterns, while high spectral resolution is needed to classify detailed land-use
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17 and land-cover types (Wald, 2000; Rachin et al., 2003; Ehlers et al., 2010; Myint et al., 2011; Yuhendra et
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19 al., 2012). Fusing PAN and MS images with complementary characteristics can provide a better
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21 representation of the observed area (Wald, 2000; Ranchin et al., 2003). In this respect, data fusion serves
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23 as an integral step in the processing of remotely sensed imagery for ecological applications. This is
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25 particularly true in surveys of wildlife, where classification hinges on both spectral and spatial
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27 information.
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31 The increasing availability of VHSR imagery has resulted in the need for more sophisticated image
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33 processing techniques (Gamba, 2014; Pohl and van Genderen, 2014; Xu et al., 2014; Zhan, 2014). Over
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35 the years, many image fusion methods have been developed and tested (Hallada and Cox, 1983; De
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37 Bethune et al., 1998; Zhan, 2002; Ehlers et al., 2010). A fusion algorithm that preserves the spectral
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39 properties of the MS data and the spatial properties of the PAN data would be ideal, but there is always a
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41 compromise between these two elements (Civco et al., 2009). The choice of fusion algorithm depends on
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43 the application domain because the reflectance varies with different environmental features. Data fusion
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45 algorithms introduce spectral and spatial distortions to the resulting fused product that depend on the
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47 scene content; therefore, a careful selection of fusion method is required. For example, a fusion algorithm
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49 designed to address high-frequency edge information in urban landscapes might not produce satisfactory
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51 results when applied to a relatively homogenous agricultural or forested landscape (Witharana et al.,
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53 2013b). In this respect, it is challenging to transfer the knowledge on the performances of fusion
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55 algorithms that have been tested in one application domain to another application domain. There is a
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57 plethora of literature on fusion-quality assessments addressing general context (Vijayaraj et al., 2006;
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Karathanassi et al., 2007; Ling et al., 2007; Ling et al., 2008; Nikolakopoulos, 2008; Ehlers et al., 2010) and focusing on specific remote sensing applications (Ashraf et al., 2012, Yang et al., 2012; Witharana et al., 2013a; Witharana et al., 2013b), but nothing that would address the needs of Antarctic biology.

The utility of VHSR imagery in Antarctic wildlife detection is new and actively evolving owing to the availability of data and the ever increasing demand for ecological information. It is necessary to revisit best available remote sensing image processing tools, gauge their potential use, and understand the degree of transferability to support accurate and timely wildlife surveys. The study described below reports the first comprehensive work on pansharpening techniques in support of remote-sensing-based wildlife monitoring in Antarctica. The central objective of this research is to investigate how well different fusion algorithms perform when applied to single-sensor single-date VHSR images comprising key wildlife elements (penguin guano, seals, and vegetation); benchmarking these image fusion approaches will provide specific guidance for ongoing wildlife mapping efforts in Antarctica and general guidance for highly similar applications in other high latitude or alpine environments.

1.2 Image fusion and quality assessment

Pohl and van Genderen (1998) defined image fusion as a tool to combine multisource imagery using advanced image processing techniques that can be performed at three different processing levels (pixel, feature, and decision) depending on the stage at which the fusion takes place. Image fusion can occur in different ways such as inter-sensor, intra-sensor, single-date, and multi-date. Pansharpening, also called resolution merge (Gangkofner et al., 2008) is a pixel-level fusion technique used to increase the spatial resolution of the multispectral image while preserving the spectral information (Vijayaraj et al., 2006). Many studies report the problems and limitations associated with different fusion techniques (Chavez et al., 1991; Wald et al., 1997; Zhang, 2002). The most frequently encountered problem in fusion algorithms is that the fused image exhibits a notable deviation in visual appearance and spectral values from the original MS image (Ling et al., 2007; Kalpoma and Kudoh, 2007). Spectral distortions including spatial artifacts affect both manual and automated classifications because any error in the synthesis of the

spectral signatures at the highest spatial resolution incurs an error in the decision (Ranchin et al., 2003). Thus, it is necessary to evaluate the quality of fused images in terms of qualitative and quantitative indices. Qualitative comparison of the fused image and the original MS and PAN images for color preservation and spatial improvements is the most simple but effective way of benchmarking different fusion algorithms (Nikolakopoulos, 2008); on the other hand, visual inspection methods are also subjective and largely depend on the experience of the interpreter (Klonus and Ehlers, 2007; Ehlers et al., 2010).

A number of objective metrics have been proposed to quantify spectral and spatial distortions incurred during the fusion process. Li et al. (2010) document a comprehensive survey on spectral quality indices. The most widely used metrics for evaluating spectral fidelity are the two-dimensional correlation coefficient (CC), root mean squared error (RMSE), relative difference of means, relative variation, deviation index, and band discrepancy. Research by Vijayaraj et al. (2006), Karathanassi et al. (2007), and Yakhdani and Azizi (2010) used peak-signal-to-noise ratio (PSNR) and entropy as spectral quality metrics in addition to common indicators. Wald (2000) proposed the ERGAS metric, which aims to provide a quick but accurate measure of the overall quality of a fused product. Samadzadegan et al. (2012), Witharana et al. (2013b), and Liu et al. (2014) used the spectral angle mapper (SAM) to assess the overall spectral quality of fused images. The universal image quality index (Q-average) is a global metric that models any distortions as a combination of loss of correlation, luminance distortion, and contrast distortion (Wang and Bovik, 2002). Alparone et al. (2004) generalized the Q-average as the Q-4 index, which Alparone et al. (2007) applied to assess fusion quality along with SAM and ERGAS. Alparone et al. (2006) proposed a new index called QNR based on the findings of Wang and Bovik (2002) and Xydeas and Petrovic (2000). The correlation of the gradient information, a combined quantity to evaluate spectral consistency and information content, was developed by Weidner (2010) based on the findings of Wang and Bovik (2002) and Xydeas and Petrovic (2000). Wang et al. (2004) proposed another metric called mean structure similarity index (MSSIM), which is an enhanced version of the Q-average. Ling et al. (2007) and Ehlers et al. (2010) adopted the MSSIM to evaluate the spectral fidelity of fused images.

Compared to spectral quality indicators, only a few metrics are available to evaluate the spatial fidelity of fused images (Makarau et al., 2012). Ehlers et al. (2010), Gangkofner et al. (2008), Klonus and Ehlers (2007), and Yakhdani and Azizi (2010) used high-pass correlation and edge detection using filters like Canny, Sobel, and Perwitte. In contrast, Civco et al. (2009), Civco and Witharana (2012), and Witharana et al. (2013a) tested a new approach based on Fast Fourier Transform (FFT). Guo et al. (2010) used another metric called average gradient index that describes the changing features of image texture and detailed information to evaluate the spatial quality of fused images.

The remainder of this paper is structured as follows. Section 2 describes the study area, image data, fusion algorithms, and evaluation methods. Section 3 reports the spatial and spectral fidelity of fused products in terms of quantitative indices and visual inspections. Section 4 contains a discussion explaining the results based on the performances of fusion algorithms and proposes a suite of suggested methods for manual and automated ecological feature extraction in EO-based Antarctic monitoring studies. Finally, conclusions are drawn in Section 5.

2. Materials and methods

2.1 Study area and image data

In this study we used a set of cloud-free QuickBird-2 and Worldview-2 images comprising penguin (*Pygoscelis* spp.), seal, and shag (*Phalacrocorax* spp.) colonies previously surveyed on the ground by the Antarctic Site Inventory (ASI; Lynch et al. 2013) (Figure 1). Images were obtained during the austral summer during 2002-2014. Candidate scenes were radiometrically corrected, orthorectified, and spatially registered to WGS 84 datum and Stereographic South Pole projection. The QuickBird-2 sensor has a ground sampling distance (GSD) of 0.61 m for the PAN and 2.44 m for MS bands at nadir with 11-bit radiometric resolution. The Worldview-2 hyperspatial sensor records the PAN and the 8 MS bands with a GSD of 0.46 m and 1.84 m at nadir, respectively, with 11 bit radiometric resolution (Table 1).

< Figure 1 >

< Table 1 >

2.1 Methods

From the candidate image scenes, we extracted 50 non-overlapping subsets (each approximately $2 \text{ km} \times 2 \text{ km}$) for the detailed fusion evaluation. The selection of subsets was made based on three target classes: penguin guano, seals, and vegetation, which are those targets most fully developed for satellite-based Antarctic wildlife monitoring. We used seven data fusion algorithms (Table 2) commonly encountered in the literature and incorporated into commercial remote sensing image processing software packages (e.g., ERDAS Imagine 2014, ENVI 5.2, and PCI Geomatica 2014). The underlying principles of the candidate algorithms are briefly described below and we refer the reader to the literature listed in Table 2 for detailed information. All fusion techniques were performed at their default settings to preclude the effect of the parameter optimization process on individual algorithms and to ensure an unbiased quality assessment. Fusion results were assessed using a series of quality metrics along with detailed visual inspection procedures to benchmark the spectral and spatial fidelity of fused products compared to their original MS and PAN images.

< Table 2 >

Ehlers fusion algorithm

The Ehlers (EH) fusion algorithm is based on an intensity-hue-saturation (IHS) transform coupled with adaptive filtering in the Fourier domain (Klonus and Ehlers, 2007). The main design goal of the EH algorithm is to enhance the spatial resolution of the MS image without adding new grey level information to its spectral components. The EH algorithm entails a twofold workflow: 1) separation of spectral and spatial information and 2) manipulation of spatial information content in a way that allows an adaptive enhancement of the images. The MS image is subjected to an IHS transform for an optimal separation of spectral information. A Fast Fourier Transform (FFT) is then applied to the intensity component and the PAN image, which facilitates an adaptive filter design in the frequency domain. A low-pass and a high-pass filter are used to filter intensity spectrums and high-frequency information from PAN, respectively.

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4 Finally, an inverse FFT is tasked to transform the images to the spatial domain with complementary
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6 frequency information from the MS and PAN images and the new intensity component is inversely
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8 transformed combining the original hue and saturation components of the MS image (Ehlers et al. 2010).
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10 11 12 13 *Gram-Schmidt fusion algorithm* 14

15 The Gram-Schmidt (GS) method is a component substitution method (Nikolakopoulos, 2008), which
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17 is, in principle, analogous to the principal component analysis fusion technique. The GS technique
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19 transforms a set of vectors into a new set of orthogonal and linear independent vectors (Ehlers et al.
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21 2010). First, the low spatial resolution MS spectral bands are averaged to simulate a low resolution PAN
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23 band. Next, the GS orthogonalization transformation is performed for the simulated PAN band and the
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25 MS band, where the simulated PAN band applied as the first band. The original high frequency PAN
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27 band is then swapped with the first GS component. Finally, an inverse GS transform is applied to form a
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29 resolution-enhanced MS image (Laben et al. 2000).
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35 *Hyperspherical color space fusion algorithm* 36

37 The hyperspherical color space (HCS) fusion technique, which taxonomically falls into the
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39 ‘component substitution’ class of fusion methods, is specifically designed for enhancing WorldView-2 8-
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41 band images, though it is capable of pansharpening any MS data containing 3 or more bands (Padwick et
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43 al. 2010; ERDAS, 2014). The main task involved in the HCS methods is the transformation (forward and
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45 reverse) of data from native color space to hyperspherical color space. An image with N input bands
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47 yields a single intensity component and N-1 angles on the hypersphere. Thus, within the hyperspherical
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49 color space, the single intensity component can be scaled without distorting the color. In the first pass,
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51 mean and standard deviation of the square of the PAN image and the intensity component of the MS
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53 image are computed. Then a forward transformation is applied to the intensity component from the native
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55 color space to the hyperspherical color space. Pansharpened intensity is obtained by matching the signals
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57 from the square of PAN and the intensity component. Next the matched intensity is swapped with the
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original intensity component of the MS image and a reverse transformation is performed from the hyperspherical color space to the native color space.

High-pass filter fusion algorithm

The High-pass filter (HPF) method is a spatial domain fusion technique. The image synthesis process involves a convolution using a high-pass filter on the high resolution data and then combining the filtered frequencies with the lower resolution MS data (Gangkofner et al. 2008). The algorithm has three key steps. First, the HP filtering is applied to the PAN image to extract the structural detail. Then, the HP-filtered image is combined with each of the MS bands using a standard deviation-based injection model. Finally, a linear histogram matching is tasked to adapt the standard deviation and mean of the synthesized image bands to those of the corresponding original MS Image.

Principal component analysis fusion algorithm

Principal Component Analysis (PCA) is a statistical method that transforms a multivariate dataset of correlated variables into a dataset of uncorrelated linear combinations of the original variables. In terms of its relationship to other data fusion methods, PCA methods fall into the component substitution class. First, the MS image is converted into a new set of uncorrelated components and the first PC is extracted assuming that it contains only the overall scene luminance (Karaksanthi et al. 2007). Next the PAN image is histogram matched to the first PC and then substituted with the selected component. Finally, an inverse PC transform projects the fused dataset back to the original MS feature space (Ehlers et al. 2010).

University of New Brunswick fusion algorithm

The University of New Brunswick (UNB) technique is a statistic based fusion method (Zhang 2002, Zhang, 2004). UNB fusion adapts a least squares approach to approximate the grey value relationship between the original MS, PAN, and fused images to achieve an optimal color representation that aims to address two fundamental drawbacks inherent to image fusion algorithms: 1) color distortion and 2)

operator /dataset dependency. As the first step, a histogram standardization is applied to the original MS and PAN images. The MS bands in the spectral range of the PAN image are then selected and a regression analysis is performed using a least squares algorithm, the results of which are used as weights for the synthesis of multispectral bands into a single image. Finally, the resolution-enhanced image is created by multiplying each standardized MS with the standardized PAN image and dividing by the synthesized image.

Wavelet transform fusion algorithm

The Wavelet transform (WV) technique, a spatial domain fusion method, extracts the high-frequency detail coefficients from the high spatial resolution PAN image and combines it with the spectral information obtained from the MS image using a combination model (Vijayaraj et al. 2006; Ehlers et al. 2010). First, three new PAN images are produced based on the histogram of the MS image. Next, each synthesized PAN image is decomposed into a low-resolution approximation image and wavelet coefficients (detail images) comprising spatial information. Next the decomposed low-resolution PAN images are then substituted with the original MS image bands. Finally, a reverse wavelet transform is applied to each of the three sets containing the local spatial details and one of the MS bands to inject high-resolution spatial details from the PAN image to the low-resolution MS image.

2.1.1 Quantitative evaluation

Objective quality assessments can be either direct or indirect. Whereas the former gauges the quality of the fused imagery itself, the latter assesses the quality of products extracted from the fused imagery. We chose the direct approach, which entailed eleven spectral and four spatial metrics, each calculated independently for each subset and separately for each band (except for ERGAS and SAM). Use of eleven spectral and three spatial metrics, totaling 14 objective quality indicators in our evaluation procedure, might be questionable because these metrics might be redundant and correlated (Pradhan et al. 2006; Gangkofner et al. 2008; Li et al., 2010; Jawak and Luis 2013; Witharana et al., 2013). Previous

researchers used different combinations of quality indicators to rank fusion algorithms (Vijayaraj et al., 2006; Karathanassi et al., 2007; Ehlers et al., 2010; Kim et al., 2011; Witharana et al., 2013), however these studies found no consistent suite of quality metrics that worked for all ground targets. We employ a full complement of objective quality indicators to reexamine their stability and redundancy, and to investigate the dependency of the ranking of fusion algorithms on quality metrics. These metrics' mathematical and statistical bases are summarized in Table 3. The fusion-evaluation workflow tasked in this study is depicted in Figure 2.

2.1.1 Visual inspection

Four remote sensing experts, two interpreters with domain-specific (Antarctic wildlife monitoring; HJL and MAL) manual image-interpretation skills and another two with general land use/cover mapping expertise, were tasked to inspect the color preservation and spatial improvement of fused images with respect to their parent MS and PAN images. For each sensor, we chose eight test sites for each target class, totaling 22 zoomed-in views. We selected false-color composites (bands green, red, and near infrared [NIR] for QuickBird images and bands green, red, and near infra red1 [NIR1] for Worldview-2 images) for visual inspections because this band combination is widely used for many remote sensing applications (Ehlers et al., 2010; Witharana et al., 2013; Witharana et al., 2014). False-color composites along with their original images were inspected by all the experts to identify spectral distortions (e.g., brightness reversions, saturation, a complete change of spectral characteristics, unnatural/artificial colors) and spatial improvement in general context. When benchmarking pansharpening quality, the domain-specific experts specifically focused on spectral and spatial clarity (e.g. counting of seals at the individual level and delineation of penguin guano based on color and texture) of wildlife elements in fused images.

< Table 3 >

< Figure 2 >

3. Results

3.1 Visual analysis

Figures 3-5 and Figures 6-8 depict six representative test scenes acquired by QuickBird and Worldview-2 sensors, respectively. The experts were asked to report the best two and the worst two fusion algorithms for each target class. Rank ordering of all algorithms would have been ideal; however, in reality, ranking of seven fusion algorithms (i.e., best to worst) based on their performances is a difficult task even for an expert photointerpreter because, while the human brain easily discriminates among extreme variations (i.e., the best and worst fused images), it fails to distinguish subtle variations among images with similar spectral and spatial properties.

Table 4 reports the subjective rating of pansharpening quality from the viewpoints of domain-specific wildlife detection (Analysts 1 and 2) and general land cover mapping (Analysts 3 and 4). With only one exception (Analyst 2's rating on guano), all experts elected the HPF and UNB fusion algorithms best for all three target classes and the EHL and WVL algorithms as the worst. Inspecting representative scenes of QuickBird (Figure 3) and Worldview-2 (Figure 6) scenes containing penguin guano, we see that the HPF fusion algorithm has clearly improved the spatial resolution of the MS image while improving edge information and injecting texture features, which are innate to penguin colonies, from the PAN image. The resulting high contrast images show some spectral degradation, however, the spatial improvement compensates for losses in color fidelity. The HPF product is more visually efficient than its main contender (the UNB fusion algorithm) since it expediently signals rich visual cues to the observer to spot the presence of guano and delineate its spatial extent. The EHL and WVL algorithms have preserved the spectral character of the original MS images at the expense of spatial improvement. No edge improvement can be seen in EHL and WVL products. The GSM and PCA fusion algorithms exhibited mediocre visual quality. In the case of seal haul outs, the HPF fusion algorithm provides valuable visual cues to detect individual seals on the beach (Figure 7); however, it has introduced spatial artifacts to the fused scene comprising seals on pack ice (Figure 4). The HPF algorithm has over-emphasized the surface

undulations, which ultimately lead to dark pseudo blobs that are visually analogous to seals and thus problematic for seal census. Of the seven algorithms, the WVL fusion method shows the worst spatial improvement with zero injection of high frequency information from the PAN image to the MS image, which precludes the individual detection of seals. Visual analysis of QuickBird (Figure 5) and Worldview-2 (Figure 8) scenes comprising vegetation reveal that the EHL fusion algorithm has produced distinct spatial artifacts while the PCA fusion algorithm has introduced serious color distortions (color reversion). Similar to previous cases, the HPF fusion algorithm exhibits significant edge enhancement with some spectral degradation. The GSM and UNB algorithms show mediocre visual quality while mitigating both spectral and spatial distortions. Figure 9 shows a set of zoomed-in Canny-edge filtered images of the original WV-2 images and fused products. The WVL, EHL, and HCS fusion methods show weak performances in injecting high frequency information from the PAN image to the MS image. Noticeably, the WVL's filtered image shows fuzzy and poorly improved edges when compared to its parent images. In general, the edge information embedded to the filtered images of the GSM, UNB, and HPF methods exhibit a promising agreement with the structural information encoded to their parent images.

< Table 4 >

< Figures 3, 5, 6, 7, 8, and 9 >

3.2 Quantitative assessment

We corroborated visual assessment with eleven spectral metrics and four spatial metrics. Figures 10-12 and Figures 13-15 depict the summary plots constructed based on the objective metrics for the fused images of QuickBird and Worldview-2, respectively.

When analyzing the quality plots of the QuickBird scenes with penguin guano (Figure 10), the basic spectral metric - correlation coefficient (CC) - reports the best scores for the WVL, EHL, and HCS fusion algorithms indicating discernible band-wise agreement between fused and original MS images. While the GSM, PCA, and UNB methods reported comparable results, the HPF method emerged as the worst with respect to the CC. The plots of root-mean-squared-error (RMSE), spectral discrepancy (SD), and

divination index (DI) reported high scores for EHL, HPF, and PCA fusion algorithms indicating degraded spectral fidelity. The plots of relative distance to mean (RDM) and the relative distance to standard deviation (RDS) clearly manifest the underlying histogram shift in the EHL and PCA fused products. With respect to the peak signal-to-noise ratio (PSNR) and entropy difference, the WVL and the HPF methods had the least and greatest radiometric distortions, respectively. The EHL fusion algorithm showed low structural similarity measure (SSIM) scores with high variability. The low SSIM indicates the loss of illumination, radiometric alteration, and contrast distortion between the fused and the original MS images. The WVL and the HCS fusion methods yielded the best results and were comparable to each other. Also, the GSM and the UNB methods yielded superior SSIM scores compared to EHL, HPF, and PCA fusion methods. According to the two global measures (ERGAS and SAM), the EHL and the PCA fusion methods had the worst spectral quality preservation character, while GSM, HCS, and UNB methods yielded superior results and were comparable each other. From the viewpoint of spatial fidelity, all four spatial indices have disqualified the WVL fusion algorithm. The best results for the Canny edge correspondence (Canny edge) were found for the PCA, UNB, and GSM fusion methods. A similar trend was observed for the Sobel edge correlation (Sobel-CC), the high-pass correlation coefficient (HP-CC), and the PAN correlation coefficient (PAN-CC). With respect to the Canny edge, the HCS method outperformed the HPF method; however, the opposite was observed for Sobel-CC. The HPF method clearly outperformed the WVL method with respect to two edge detectors (Canny and Sobel); however, HP-CC and PAN-CC metrics indicate the inferior spatial edge enhancement of the HPF method compared to the WVL fusion algorithm.

Figure 13 entails the quality plots of the Worldview-2 scenes with penguin guano. In general, spectral plots are comparable with those of QuickBird scenes (Figure 9). The EHL fusion, the HCS fusion, and WVL fusion methods showed the highest band-wise correlation with the original MS images while the HPF showed the worst CC results. Despite the high CC values, the EHL method yielded the worst results for per-pixel deviation (RMSE), band-wise deviation (SD, DI), histogram shift (RDM, RDS), radiometric fidelity (PSNR, entropy), structural distortion (SSIM), and global indices (ERGAS, SAM). In most cases

the PCA fusion algorithm yielded results comparable to the EHL method. The GSM, HCS, and UNB methods reported the highest spectral fidelity with respect to most of the spectral indices. Based on all the spatial metrics, the GSM, PCA, and UNB fusion algorithms surpass the others. Except the PAN-CC, the other three spatial metrics manifest the WVL method's deficient spatial improvement character.

Quantitative quality metric plots for the fused QuickBird and Worldview-2 image scenes with seals are shown in Figures 11 and 14, respectively. When analyzing the spectral quality plots of pansharped QuickBird products, the HPF fusion algorithm exhibited noticeably low CC compared to its contenders. The EHL fusion and the PCA fusion methods seemed to be the worst algorithms with respect to spectral distortions measured by RSME, SD, and DI. The histogram-based metrics (RDM and RDS) also reported high values for the EHL and PCA algorithms. Based on the PSNR, the PCA fusion method yielded the worst results while the HCS, GSM, and WVL fusion methods showed a high degree of radiometric fidelity. In terms of retaining image structure, the WVL method reported the best results while HPF method exhibited the worst results for the SSIM metric. Generally, the GSM, HCS, and UNB methods yielded high values for SSIM, proving their ability to conserve the image structure during synthesis. From the view point of global spectral metrics, the PCA and the HPF methods yielded the worst results for the ERGAS and SAM metrics, respectively. Despite the weak spectral performances, the PCA fusion method reported the best results for all spatial quality indicators. Across all dimensions, the WVL fusion method produced the weakest spatial improvement. In terms of Canny edge correspondence and Sobel edge correlation, the HPF fusion method showed performances comparable to GSM and UNB fusion methods. However, the HPF method yielded inferior results with respect to HP-CC and PAN-CC.

The quality plots based on Worldview-2 scenes (Figure 14) summarize the image synthesis capabilities of candidate fusion methods. With respect to the CC, the WVL, the HCS, and the EHL fusion methods reported the highest spectral congruency between fused and original MS images. However, the EHL method yielded the worst performances (along with PCA fusion method) for RMSE, SD, RDM, and for two global metrics. The HCS algorithm reported stable performances for most of the spectral metrics. It showed low pixel- and band-wise deviation, a high degree of radiometric fidelity, structural

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4 congruency, and minimal distortion to the shape of the histograms. In many instances, the HPF algorithm
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6 emerged as the third worst performing algorithm. From a spatial fidelity perspective, the WVL fusion
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8 algorithm exhibited the worst edge enhancement. The two edge-based metrics and the HP-CC have
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10 clearly indicated the WVL method's inability to inject spatial structure during synthesis. The GSM, PCA,
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12 and UNB methods seemed to be the best performing algorithms. Despite the marked spectral
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14 performances, the HCS algorithm showed mediocre results (comparable to the HPF fusion method) for
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16 the spatial metrics.
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20 Objective results for the vegetation dominant QuickBird and Worldview-2 image scenes are shown in
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22 Figure 12 and 15, respectively. For both sensors, the EH- and PCA-pansharpened images reported the
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24 least spectral congruency compared to their contenders. Their radiometric and structural distortions are
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26 also apparent when analyzing boxplots of SSIM and PSNR (Figure 12). For the most of the spectral
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28 indices derived from QuickBird scenes, the HCS algorithm reported highly satisfactory results. Generally,
29
30 the GSM and UNB fusion methods have equally conserved the spectral properties during the fusion
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32 process. In terms of spatial fidelity, the WVL and PCA algorithms rank as the worst while the GSM,
33
34 HCS, HPF, and UNB methods produced satisfactory results for the two edge detectors. In the case of
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36 Worldview-2 images, the GSM, HCS, UNB, and WVL methods showed equal performances for the most
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38 of the per-pixel and band-wise deviation spectral indices. In the case of ERGAS, the HPF fusion exhibited
39
40 the best results while the EHL and PCA methods reported the worst. Similar to previous cases, the WVL
41
42 algorithm further proved its systematic failure in injecting high frequency information to the MS image.
43
44 The EHL and HPF methods showed a relatively weak Canny edge correspondence. Despite the degraded
45
46 spectral fidelity, the PCA fusion method showed promising results (comparable with GSM and UNB) for
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48 the spatial metrics.
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54 < Figures 9,10,11,12,13 and 14 >
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57 58 **4. Discussion** 59 60 61 62 63 64 65

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4 Ideally, the fusion process should synthesize the MS image that would have been observed if the
5 multispectral sensor had the spatial resolution of the panchromatic sensor. Data fusion algorithms deviate
6 from this ideal and introduce a variety of spectral and spatial distortions to the modeled image during
7 synthesis. Fusion artifacts may affect subsequent image processing steps like image segmentation, manual
8 image analysis, semi-/fully-automated classification, and other data mining methods. Scene dependency
9 of fusion algorithms impedes the transferability of the knowledge on their performances across
10 application domains (Witharana et al., 2013b). Thus, a comprehensive quantitative evaluation in
11 conjunction with domain expert-led visual gauging of fusion algorithm is necessary to identify those
12 techniques that are optimal with respect to the practical implementation.
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15 Here we report the first detailed study on the performances of data fusion algorithms in support of
16 VHSR-based Antarctic wildlife mapping. We tasked seven widely-used fusion algorithms to pansharpen a
17 series of single-date image scenes acquired by QuickBird-2 and Worldview-2 sensors. We chose penguin
18 guano, seals, and vegetation as target features; of those, the first two have been used in multi-scale EO-
19 driven mapping efforts (Lynch and LaRue, 2014; LaRue, 2014). These early efforts have used either
20 expert visual analysis or expert-derived training datasets because automated classification and
21 segmentation of Antarctic scenes is in its infancy.
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24 From the viewpoints of both subjective and objective evaluations, no single algorithm was able to
25 produce superior results by simultaneously preserving spectral and spatial properties of the original MS
26 and PAN images. Generally speaking, for all target classes, four experts with two different foci (target-
27 specific inspection and general inspection) rated the HPF and UNB methods as the best fusion algorithms
28 and the EHL and WVL methods as the worst two fusion algorithms. Our quantitative assessment supports
29 the visual rating of the EHL and WVL fusion algorithms as being the worst.
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32 In the objective quality budget, across sensors and target features, the WVL method exhibited
33 superior results at the expense of spatial fidelity. On the other hand, despite the degraded spectral
34 congruency, the EHL and PCA fusion methods yielded better results for spatial metrics. These
35 observations emphasize the necessity of a combined approach (i.e., spectral and spatial fidelity) for
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4 interpreting fusion results because the best color preservation of an algorithm can be observed even if no
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6 pansharpening is performed; on the other hand, a fusion algorithm can achieve the best spatial
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8 improvement while producing results with the worst color preservation. The EHL algorithm, which was
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10 demonstrated by several studies to be successful (Klonus and Ehlers, 2007; Ling et al., 2007; Ehlers et al.,
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12 2010; Ehlers and Klonus, 2014) and was designed specifically for preserving the color information,
13
14 exhibited poor performances in our study. The overall performance of the PCA fusion algorithm was not
15
16 consistent: in some instances, it incurred serious color reversions (Figure 5), findings that are in
17
18 agreement with Witharana et al. (2013b). Despite the spectral superiority, the WVl-sharpened products'
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20 spatial fidelity is seriously distorted due to the systematic noise resulting from the shift variance property
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22 of the wavelet transform and the filtering procedure. In most cases, both spectral and spatially, the HPF
23
24 fusion algorithm has been able to surpass the EHL, WVl, and PCA fusion methods. The GSM and UNB
25
26 fusion methods were able to produce the best quality results by mitigating spatial and spectral artifacts.
27
28 The validity of the CC is questionable as it elects the EHL as one of the best-performing algorithm, while
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30 all the other indicators disqualify the EHL's spectral fidelity. This reflects the ambiguous nature of quality
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32 measures (Makarau et al., 2012) and the necessity of taking a multidimensional assessment.
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38 Padwick et al. (2010) proposed the HCS fusion algorithm with the key design goal of effectively
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40 handling the increased spectral information content produced by the Worldview-2 hyperspatial sensor
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42 during image synthesis. The HCS-pansharpened images exhibited a marked spectral, radiometric, and
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44 structural consistency; however, the spatial consistency was inferior to the GSM and UNB algorithms. A
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46 number of studies, such as Zhang (2002), Karathanassi et al. (2007), Yuhendra (2012), Jawak and Luis
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48 (2013), and Witharana et al. (2013b) report the success of the GSM and UNB fusion methods. The UNB
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50 method serves as the proprietary fusion algorithm for the DigitalGlobe® image products (Zhang 2014).
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52 The Polar Geospatial Center (PGC, www.pgc.umn.edu) at the University of Minnesota, which is the key
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54 organization engaged in VHSR imagery support for Arctic and Antarctic research, adapts the UNB
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56 method as the core pansharpening technique. By design, this algorithm aims to address color distortions
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and operator- and data-dependency through least-squares adjustment and standardized automated fusion process.

Regardless of the inherent subjectivity of visual analysis, our contention is that the human perception employs the most integrated mechanisms that include spectral and spatial criteria for benchmarking fusion results. Although the objective metrics report noticeable disturbances to the spectral response, the experts have elected the HPF method as one of the best contenders for manual photo-interpretation. Visibility of important information and information saliency are main elements in the subjective quality assessment (Gracia et al., 2010). In our study, the HPF-pansharpened images provided the optimal visual grammar (*sensu* Aksoy 2010) to accurately identify the targets of interest. For example, the HPF method preserves the general spectral characteristics of penguin guano, improved the boundary (crispness) between the guano patch and the background substrate, and at the same time preserved the texture, which is distinct to guano and important for classification. In the case of seal haul-outs on the coast (Figure 4), the HPF-pansharpened products showed the highest visual detectability of seals compared to the other contenders. Conversely, the HPF method showed some spatial artifacts (pseudo visual cues of black blobs) for the seal haul-outs over the snow-covered areas (Figure 4). A closer analysis on the design goals of the HPF algorithm elucidates the cause of these artifacts. Of the three parameters of this algorithm (high-pass filter size, center value of filter kernel, and injection weight of the added high-pass filtered image), the injection weight depends on the global standard deviation of the MS image (Gangkofner et al., 2008). Thus, extreme brightness differences (e.g., snow or cloud) within images can elevate the overall standard deviation causing overly crisp localities. These scene-dependent artifacts can be mitigated by fine tuning the center value of the HP kernel and the injection weight.

5. Conclusion

Very high spatial resolution satellite remote sensing is being developed as an efficient alternative for traditional, intrusive, time-intensive, and expensive ground and aerial wildlife surveys in Antarctica

(Fretwell et al., 2012; LaRue et al., 2014; Lynch and LaRue, 2014). Data fusion serves as integral component of remote sensing mapping workflows and is systematically explored in this study. Our visual evaluation determined that the High-pass fusion algorithm and the University of New Brunswick fusion algorithms are optimal for manual feature extraction while the quantitative assessment suggested the Gram-Schmidt fusion algorithm and the University of New Brunswick fusion algorithm for automated classification. The PCA fusion algorithm showed spectral superiority at the expense of spectral inconsistencies. The Ehlers fusion algorithm and the Wavelet-PCA algorithm showed the weakest performances. Further research will be required to 1) explore the fine-tuning capability of the High-pass fusion algorithm, 2) employ an indirect quality assessment workflow to benchmark fusion algorithms, and 3) investigate the synergies of data fusion and the geographic-object based image analysis in the wildlife census applications.

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Figure 1. Maps of study area on the Antarctic Peninsula and South Georgia. Black triangles indicate the location of the candidate QuickBird-2 and Worldview-2 scenes.

Figure 2. A schematic of the fusion-evaluation workflow

Original PAN image

Original MS image

EHL fusion

GSM fusion

HCS fusion

HPF fusion

PCA fusion

UNB fusion

WVL-PCA fusion

Figure 3. A visually inspected site (acquired by QuickBird-2 sensor) for the panshaping quality of fused products comprising penguin guano. Original MS image and fused images are shown as false color (green, red, NIR2) composites. Imagery Copyright DigitalGlobe, Inc.

Figure 4. A visually inspected site (acquired by QuickBird-2 sensor) for the panshapening quality of fused products comprising seals. Original MS image and fused images are shown as false color (green, red, NIR2) composites. Imagery Copyright DigitalGlobe, Inc.

Original PAN image

Original MS image

EHL fusion

GSM fusion

HCS fusion

HPF fusion

PCA fusion

UNB fusion

WVL-PCA fusion

Figure 5. A visually inspected site (acquired by QuickBird-2 sensor) for the panshaping quality of fused products comprising vegetation. Original MS image and fused images are shown as false color (green, red, NIR2) composites. Imagery Copyright DigitalGlobe, Inc.

Original PAN image

Original MS image

EHL fusion

GSM fusion

HCS fusion

HPF fusion

PCA fusion

UNB fusion

WVL-PCA fusion

Figure 6. A visually inspected site (acquired by Worldview-2 sensor) for the panshaping quality of fused products comprising penguin guano. Original MS image and fused images are shown as false color (green, red, NIR2) composites. Imagery Copyright DigitalGlobe, Inc.

Original PAN image

Original MS image

EHL fusion

GSM fusion

HCS fusion

HPF fusion

PCA fusion

UNB fusion

WVL-PCA fusion

Figure 7. A visually inspected site (acquired by Worldview-2 sensor) for the panshaping quality of fused products comprising seals. Original MS image and fused images are shown as false color (green, red, NIR2) composites. Imagery Copyright DigitalGlobe, Inc.

Original PAN image

Original MS image

EHL fusion

GSM fusion

HCS fusion

HPF fusion

PCA fusion

UNB fusion

WVL-PCA fusion

Figure 8. A visually inspected site (acquired by Worldview-2 sensor) for the panshaping quality of fused products comprising vegetation. Original MS image and fused images are shown as false color (green, red, NIR2) composites. Imagery Copyright DigitalGlobe, Inc.

Original PAN image

Original MS image

Canny-edge PAN

Canny-edge MS

Canny-edge EHL

Canny-edge GSM

Canny-edge HCS

Canny-edge HPF

Canny-edge PCA

Canny-edge UNB

Canny-edge WVL

Figure 9. Zoomed-in views showing Canny-edge filtered images of the original WV-2 PAN and MS images and the fused products.

Figure 10. Spectral and spatial quality plots for the fused pansharpened QuickBird image scenes containing penguin guano. In each plot, the x and y axes depict the value of the quality metric and the candidate fusion algorithms, respectively.

Figure 11. Spectral and spatial quality plots for the fused pansharpened QuickBird image scenes containing seal haul-outs. In each plot, the x and y axes depict the value of the quality metric and the candidate fusion algorithms, respectively.

Figure 12. Spectral and spatial quality plots for the fused pansharpened QuickBird image scenes containing vegetation. In each plot, the x and y axes depict the value of the quality metric and the candidate fusion algorithms, respectively.

Figure 13. Spectral and spatial quality plots for the fused pansharpened Worldview-2 image scenes containing penguin guano. In each plot, the x and y axes depict the value of the quality metric and the candidate fusion algorithms, respectively.

Figure 14. Spectral and spatial quality plots for the fused pansharpened Worldview-2 image scenes containing seal haul-outs. In each plot, the x and y axes depict the value of the quality metric and the candidate fusion algorithms, respectively.

Figure 15. Spectral and spatial quality plots for the fused pansharpened Worldview-2 image scenes containing vegetation. In each plot, the x and y axes depict the value of the quality metric and the candidate fusion algorithms, respectively.

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Table 1. Basic specifications of QuickBird-2 and Worldview-2 sensors.

Sensor	Spectral band	Spectral range (nm)	Spatial resolution (m) (nadir)
Quickbird-2	Panchromatic	405-1053	0.61
	Blue	430-545	2.44
	Green	466-620	2.44
	Red	590-710	2.44
	NIR	715-918	2.44
Worldview-2	Panchromatic	450-800	0.46
	Coastal	400-450	1.85
	Blue	450-510	1.85
	Green	510-580	1.85
	Yellow	585-625	1.85
	Red	630-690	1.85
	Red edge	705-745	1.85
	NIR1	770-895	1.85
	NIR2	860-1040	1.85

Table 2. Candidate fusion methods, related literature, and implementation

Algorithm	Reference	Implementation
Ehlers fusion (EHL)	Ling et al., 2007; Ehlers et al., 2010; Yuhendra, 2012; Jawak and Luis, 2013; Witharana et al., 2013; Ehlers and Klonus, 2014	ERDAS Imagine
Gram-Schmidt fusion (GSM)	Laben et al. 2000; Aiazzi et al., 2007; Karathanassi et al., 2007; Klonus and Ehlers, 2007; Yuhendra, 2012; Jawak and Luis, 2013	ENVI
Hyperspherical color space (HCS)	Padwick et al., 2010	ERDAS Imagine
High-pass filter (HPF)	Chavez et al., 1991; Gangkofner et al., 2008; Yang et al., 2012; Yuhendra, 2012; Jawak and Luis, 2013; Witharana et al., 2013	ERDAS Imagine
Principal component analysis (PCA)	Chavez et al., 1991; Pohl and van Genderen, 1998; Kalpoma and Kudoh, 2007; Karathanassi et al., 2007; Ling et al., 2008; Yang et al., 2012; Witharana et al., 2013	ERDAS Imagine
University of New Brunswick (UNB)	Zhang, 2002; Zhang, 2004; Alparone et al., 2007; Karathanassi et al., 2007; Wong et al., 2011; Zhan and Jixian, 2014	PCI Geomatics
Wavelet Transform (WVL)	Vijayaraj et al., 2006; Karathanassi et al., 2007; Gangkofner et al., 2008; Yakhdani and Azizi, 2010; Yang et al., 2012; Yuhendra, 2012; Jawak and Luis, 2013	ERDAS Imagine

Table 3

Quality metric		Mathematical expression	Addressed issue/domain/expected value
Spectral	Correlation coefficient (CC)	$CC(B_k B_k^*) = \frac{\sum_{m=1}^M \sum_{n=1}^N (B_{k(m,n)} - \bar{B}_k)(B_{k(m,n)}^* - \bar{B}_k^*)}{\sqrt{\sum_{m=1}^M \sum_{n=1}^N (B_{k(m,n)} - \bar{B}_k)^2 \sum_{m=1}^M \sum_{n=1}^N (B_{k(m,n)}^* - \bar{B}_k^*)^2}}$	<ul style="list-style-type: none"> Quantifies the spectral correspondence between the original MS and fused images. domain [-1,1] As close to 1 as possible
	Root-mean-square-error (RMSE)	$RMSE(k) = \sqrt{\frac{\sum_{m=1}^M \sum_{n=1}^N (B_{k(m,n)} - B_{k(m,n)}^*)^2}{m \times n}}$ <p>Also defined as;</p> $RMSE(k) = \sqrt{bias_k^2 + \sigma_k^2}$ <p>where,</p> $\sigma_k = \sigma_{original(k)} - \sigma_{fused(k)} \cdot bias_k = mean_{original(k)} - mean_{fused}$	<ul style="list-style-type: none"> Measures the average amount of spectral distortion in each pixel domain [0,∞) Lower value
	Relative difference to mean (RDM)	$RDM = \frac{\bar{B}_k^* - \bar{B}_k}{\bar{B}_k}$	<ul style="list-style-type: none"> Measure the changes in the shape of the histogram of fused image compared to original MS image. domain (-∞, ∞) As close to 0 as possible
	Relative difference to standard deviation (RDS)	$RDS = \frac{\sigma_{B_k^*} - \sigma_{B_k}}{\sigma_{B_k}}$	<ul style="list-style-type: none"> Band-wise measure of the spectral quality of the fuse image domain [0,∞) As close to 0 as possible
	Spectral discrepancy (SD)	$SD = \frac{1}{(M \times N)} \sum_{m=1}^M \sum_{n=1}^N B_{k(m,n)}^* - B_{k(m,n)} $	<ul style="list-style-type: none"> Quantifies the normalized absolute difference of the fused image with the original MS image. domain [0,∞) As close to 0 as possible
	Deviation index (DI)	$DI = \frac{1}{(M \times N)} \sum_{m=1}^M \sum_{n=1}^N \frac{ B_{k(m,n)}^* - B_{k(m,n)} }{B_{k(m,n)}}$	<ul style="list-style-type: none"> Indicates the radiometric distortion of the fused image compared to the original MS image. The highest possible PSNR
	Peak signal-to-noise ratio (PSNR)	$PSNR = 20 \log_{10} \frac{Peak}{\sqrt{MSE}}$ <p>where,</p> $MSE = \frac{1}{I} \sum_{i=1}^I (B_{k,i}^* - B_{k,i})^2$ <p>Peak is the maximum possible pixel value (peak = 255, 2057, and 65535 for 8-bit, 11-bit, and 16-bit images, respectively). I is the number of non-null pixels.</p>	<ul style="list-style-type: none"> Measures the additional information (spectral and spatial) available in the fused image compared to the original MS image. The smallest possible entropy difference with the original MS image.
	Entropy	$E = \sum_{i=0}^R (-p_i \log_2(p_i))$ <p>Increase in information (entropy difference) = $E_{B_k} - E_{B_k^*}$</p>	

	<p>where, p_i is the probability of existence for digital value i. R is the radiometric resolution of an image ($R = 255, 2057$, and 65535 for 8-bit, 11-bit, and 16-bit images, respectively).</p>	
Mean structural similarity index (SSIM)	$MSSIM(B_k B_k^*) = \frac{1}{W} \sum_j SSIM(x_j, y_j)$ $SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$ <p>where, x_i and y_j are the images contents of the original and the fused image at local window j; and W is the number of local windows of the image. μ is the mean intensity, σ is the standard deviation, C_1 and C_2 are constants.</p>	<ul style="list-style-type: none"> Reveals the spectral and structural similarity between the fused and original MS image by luminance, contrast, and structure and applying to a moving window. domain $[0,1]$ As close to 0 as possible
Spectral angle mapper (SAM)	$SAM(B, B^*) = \arccos \left[\frac{\sum_{k=1}^K B_k B_k^*}{\sqrt{\sum_{k=1}^K B_k^2} \sqrt{\sum_{k=1}^K B_k^{*2}}} \right]$ <p>where, K is the number of bands</p>	<ul style="list-style-type: none"> Pixel-wise comparison of fused image and original MS image. The value 0 indicates low resemblance while 1 indicates a high resemblance. domain $[0,1]$ As close to 0 as possible
Relative dimensionless global error in synthesis (ERGAS)	$ERGAS = 100 \frac{h}{l} \sqrt{\frac{1}{K} \sum_{k=1}^K \left(\frac{RMSE(k)}{\mu(k)} \right)^2}$ <p>where, h/l is the ratio between the pixel sizes of PAN and MS images, $RMSE(k)$ and $\mu(k)$ are the root mean squared error and mean of the k^{th} band, respectively. K is the total number of bands.</p>	<ul style="list-style-type: none"> A global indicator that calculates the amount of spectral distortion. domain $[0, \infty)$ Lower value (< 3)
Canny edge correspondence (Canny Edge CC)	$CEC = \left[\frac{\sum_{r=1}^R \sum_{c=1}^C (\hat{A}_{(r,c)} \times \hat{B}_{k(r,c)}^{**})}{\sum_{r=1}^R \sum_{c=1}^C \hat{A}_{(r,c)}} \right] \times 100$ <p>where, $\hat{A}, \hat{B}$ are the binary-edge images of the original PAN and degraded fused images.</p>	<ul style="list-style-type: none"> A band-wise comparison of edges detected in the original PAN and the fused image. CES measured in percent. domain $[0,100]\%$ as close to 100 as possible
High-pass(HP) correlation coefficient (HP-CC)	$CC(A B_k^{**}) = \frac{\sum_{r=1}^R \sum_{c=1}^C (A_{(r,c)} - \bar{A})(B_{k(r,c)}^{**} - \bar{B}_k^{**})}{\sqrt{\sum_{r=1}^R \sum_{c=1}^C (A_{(r,c)} - \bar{A})^2} \sqrt{\sum_{r=1}^R \sum_{c=1}^C (B_{k(r,c)}^{**} - \bar{B}_k^{**})^2}}$	<ul style="list-style-type: none"> Quantifies the correlation between the HP filtered bands of fused image and the HP-filtered PAN image. domain $[-1,1]$ as close to 1 as possible
Sobel edge correlation (Sobel Edge CC)	$CC(SA SB_k^{**}) = \frac{\sum_{r=1}^R \sum_{c=1}^C (SA_{(r,c)} - \bar{SA})(SB_{k(r,c)}^{**} - \bar{SB}_k^{**})}{\sqrt{\sum_{r=1}^R \sum_{c=1}^C (SA_{(r,c)} - \bar{SA})^2} \sqrt{\sum_{r=1}^R \sum_{c=1}^C (SB_{k(r,c)}^{**} - \bar{SB}_k^{**})^2}}$ <p>where, SA and SB_k^{**} are the Sobel-filtered images of original PAN and fused images, respectively</p>	<ul style="list-style-type: none"> Quantifies the correlation between the Sobel filtered bands of fused image and the Sobel-filtered PAN image. domain $[-1,1]$ as close to 1 as possible

	PAN correlation (PAN-CC)	$CC(A B_k^{**}) = \frac{\sum_{r=1}^R \sum_{c=1}^C (A_{(r,c)} - \bar{A})(B_{k(r,c)}^{**} - \bar{B}_k^{**})}{\sqrt{\sum_{r=1}^R \sum_{c=1}^C (A_{(r,c)} - \bar{A})^2 \sum_{r=1}^R \sum_{c=1}^C (B_{k(r,c)}^{**} - \bar{B}_k^{**})^2}}$	<ul style="list-style-type: none"> • Quantifies the correlation between the PAN image and the fused MS image. • domain [-1,1] • as close to 1 as possible
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A - original PAN image; B_k - k^{th} band of the original MS image with the resolution of A ; B_k^{**} - k^{th} band of fused image after degradation to the resolution of B_k ; M, R and N, C are the number of rows and columns of B_k and A , respectively.

Table. 4

Expert focus	Target features	Fusion quality			
		Best		Worst	
Target-specific inspection	Guano Seals Vegetation	Analyst 1	Analyst 2	Analyst 1	Analyst 2
		HPF,UNB	GSM,UNB	EHL,WVL	EHL,WVL
		HPF,UNB	HPF,UNB	EHL,WVL	EHL,WVL
		HPF,UNB	HPF,UNB	EHL,WVL	EHL,WVL
General inspection	Guano Seals Vegetation	Analyst 3	Analyst 4	Analyst 3	Analyst 4
		HPF,UNB	HPF,UNB	EHL,WVL	EHL,WVL
		HPF,UNB	HPF,UNB	EHL,WVL	EHL,WVL
		HPF,UNB	HPF,UNB	EHL,WVL	EHL,WVL

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