SNR Characterization in RapidEye Satellite Images

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SNR Characterization in RapidEye Satellite Images

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Abstract

This report outlines an entirely new method of automatically detecting homogeneous regions in images for the purpose of noise characterization. The method was developed with the support of BlackBridge AG in Berlin, Germany. The aim of the method was to characterize the signal-to-noise ratio as a function of radiance of the multi-spectral image sensors aboard the RapidEye satellite constellation. The method uses the random nature of noise in order to detect homogeneous image regions. The method works by dividing an image into multiple square tiles. Each tile is then corrupted with additive Poisson noise (Gaussian noise with zero mean and a standard deviation equal to the tile mean). The Pearson Correlation Coefficient between the corrupted tile and the original tile is then used as a homogeneity criterion. It was found that a Pearson Correlation Coefficient of less than 0.7 identifies homogeneous regions. When applied to RapidEye images, the method correctly identified homogeneous regions and allowed the characterization of the signal-to-noise ratio of the RapidEye image sensors across their dynamic range. Three case studies of Level 3A RapidEye image products are presented herein. These clearly demonstrate the high quality of RapidEye images as well as the effectiveness of the described method.
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1 Introduction

This report outlines a method for characterising the signal dependent signal-to-noise ratio (SNR) of the Jena-Optronik multi-spectral imager (MSI) payloads aboard the five satellites comprising the RapidEye (RE) constellation. The method resolves various difficulties faced by contemporary noise estimation algorithms in that it characterises the noise in the sensor across its dynamic range, requires no supervision once an appropriate threshold is set, and makes only a single, well-substantiated assumption about the noise effecting the image. The algorithm consists of an entirely new method whereby an image is divided into multiple smaller tiles. Each tile is then corrupted with Poisson noise. The Pearson correlation coefficient (PCC) between the corrupted tile and the original tile is then used to determine if the tile is homogeneous. The method was applied to multiple Level 3A RE image products to characterise the SNR as a function of radiance. The noise in the sensor was found to adhere to Poisson statistics, a well-known attribute of CCD based imaging sensors. RE images were found to have a SNR that is consistently above that predicted by theory ranging from 50 at low radiance levels, to 250 at high radiance levels.

In Section 2, the MSI will be introduced with emphasis on CCD sensor itself. This will serve as a basis for the explanation of the anticipated noise sources and their relevant statistical properties which will also be included in Section 2. Both random and structured noise sources will be elaborated upon including photon counting noise, read-out noise, dark noise, impulse noise, periodic and aperiodic structured noise, and quantisation noise. Assumptions regarding the dominant noise sources and the definition of the SNR will be presented and justified. The statistical concepts necessary of the interpretation of the results will only be briefly covered in Section 2. Section 2 will also outline the difficulties previously encountered by noise estimation algorithms, and the requirements for the present algorithm will be listed.

In Section 3, the proposed method will be explained. This section will include a description of the requisite pre-processing steps. These include selection of image products conducive to the success of the algorithm, mitigation of structured noise, and the filtering of impulse noise. Following this, a detailed explanation of the algorithm itself will be given. Section 3 will also include pseudo-code for the proposed method.

In Section 4, the results obtained from the analysis of RE imagery will be presented. Two images products will be used to illustrate the quality of RE images, but also the functionality of the proposed method. It will be seen that the algorithm successfully locates homogeneous regions in various types of images. The SNR will be shown to follow a power law of the form $y = c_1x^{c_2}$. The results will show that RE image products are of excellent quality, that the calibration of the MSI is effective at mitigating structure noise, and will demonstrate the validity of all previous assumptions about the noise in the image products.

In Section 5, the merits and limitations of the proposed method will be discussed and recommendations will be made for further development.
2 Theory

2.1 RE Sensor & Image Product Descriptions

The RE constellation comprises five optical satellites. The constellation can be seen in Figure 2 prior to its launch on August 29, 2008. Each satellite is less than one cubic meter in size, and weighs roughly 150kg.[2] The imaging sensor aboard each satellite was manufactured by Jena-Optronik and consists of six linear arrays of twelve thousand CCD elements (Atmel AT71544) with a pixel pitch of 6.5 micrometres. Each array is read out synchronously by four outputs that differentiate between the left side of the sensor and the right, and between even and odd pixels on either side.[3] The six arrays are distributed into two line scanners placed at the focal plane.[3] The linear arrangement of the sensing elements provides one image dimension, and the motion of the satellite perpendicular to the axis of the array provides the second. This is known as a push-broom configuration. Of the six arrays, only five are used to provide the distinct spectral bands. The five spectral bands are: blue (440nm to 510nm), green (520nm to 590nm), red (630nm to 685nm), red-edge (690nm to 730nm), and near-infrared (760nm to 850nm). The five spectral bands are illustrated in Figure 1.

![Figure 1: Spectral bands of the RE constellation.](image)

The CCD elements are read-out and converted to digital numbers using a 12-bit analog-to-digital converter (ADC). However, the full 12-bit dynamic range is rarely used. Of the 4096 digital number (DN) dynamic range, the highest DN recorded never exceeded 3000.

Several image products are generated from the raw images acquired by the RE spacecraft. Level 1B products are the least processed and only have radiometric correction tables (RCT) applied to them as well as having all five bands coregistered. These images are roughly 11,700 pixels wide, corresponding to the overlapping area of all five bands, and the number of rows is only limited by the onboard memory which can accommodate 1,500 km (over 230,00 pixel rows) of image data per orbit. These images are radiometrically correct. The images from each band are then flattened through the application of geometric corrections, alligned to within two pixels using ground control points, and trimmed to eliminate the portions of the images from each band which do not overlap. The result is then orthorectified (aligned so that the image is presented North-up) and tiled into 25 km by 25 km tiles. These are known as Level 3A products. Level 3B products are orthorectified, full swath-width products. Although the results presented later will only include Level 3A products, the algorithm is capable of analyzing all levels of image products.
2.2 Noise Affecting CCD Sensors

In this section, the types of noise relevant to the RE MSI will be discussed. The sources, characteristics, methods of estimation, and mitigation techniques for each type of noise will be elaborated upon. Although the scope of this work is limited to accurately estimating the random noise in RE image products, structured noise will also be discussed here for two reasons. The first and most important reason is that the method presented benefits when structured noise is adequately treated as a pre-processing step in order to accurately estimate the random noise. The second reason being that a basic understanding of the nature of noise is necessary for predicting and evaluating the results of the developed algorithm.

Noise can be defined as the component of a measured signal which deviates from the actual quantity being measured. Although noise is undesirable, it is also unavoidable in practical systems. Therefore, the only approach to dealing with noise is to identify its source and characterise its nature in order to mitigate its effect on the image. To this end, random noise is often characterised in statistical terms. This is because the amplitude of the noise corrupting a signal at a given time is a random variable. Relevant concepts include the probability density function which expresses the probability that the noise will have a given amplitude at a point in time; the expected value or mean value which is a measure of the average amplitude the noise will have; and the variance which is a measure of the range of amplitudes the noise will

Figure 2: The RE constellation
take. Fundamental mathematical descriptions of various statistical distributions can
be found in [5] and [1]. The standard deviation of the noise is often used as a gauge of
its severity; the greater the standard deviation of the noise, the less certain one can be
of the actual value of the underlying signal. The quality of a signal is often expressed
as the SNR. This is a unitless quantity which can have many definitions. We there-
fore define it here has the ratio of the mean amplitude of the signal and the standard
deviation of the noise.

The noise found in the MSI can be classified into two types: random noise and
structured noise. The photon shot noise, read-out noise, dark noise, and impulse noise
which occur in the MSI are random noises. The structured noises which exist in the
sensor include both periodic and aperiodic structured noise.

2.2.1 Random Noise
Photon shot noise (also known as photon counting noise or Poisson noise) is caused
by the random arrival times of photons at the sensor.[3][1] The name of photon shot
noise comes from the fact that most imagers are photon counters.[1] Such devices
operate on the photoelectric effect whereby electrons are released by semi-conducting
materials as a result of excitation by light. These electrons are temporarily stored in
what are known as potential wells until they are transferred, amplified and quantised.
Photon shot noise is best characterised by Poisson statistics but is often approximated
as Gaussian under bright illumination conditions. This approximation does not hold
in cases of weak signals. Photon shot noise has previously been found to be positively
correlated to signal strength and can be estimated as the square-root of the signal
strength.[3] This approximation arises from the statistical properties of the Poisson
distribution.[1] Poisson noise is unavaoidable an can only be accepted and mitigated.

Read-out noise in the MSI is due to the fact that the charge accumulated in the
CCD elements must be transferred and amplified prior to being converted to digital
numbers. The read-out noise typically increases as the read-out rate is increased.[3]
However, the read-out rate for the MSI is fixed and consequently so is the noise. Read-
out noise can be reduced by selecting sensors which combine the sensing, amplifica-
tion, and analog-to-digital conversion on the same chip. RE images have been known
to display read-out noise in the blue band. It appears as a “fish-bone” pattern.

Dark noise arises from the random thermal motion of electrons in the sensor. It is
often referred to as thermal noise.[1] Dark noise can be approximated as the square-
root of the dark current. The dark current itself can be off-set through calibration, but
not dark noise. Dark noise is known to be positively correlated with both temperature
and integration time. As the integration time for the MSI is relatively fixed, only
the temperature of the sensor is expected to cause variations in the SNR. Indeed, the
sensor will be coldest upon leaving an eclipse period and will gradually warm up as
the satellite is exposed to sunlight.

Impulse noise is most commonly known as salt and pepper noise. Salt and pepper
noise manifests itself as individual pixels with extremely high values or extremely low
values. On a greyscale image, these pixels appear as either white or black. Hence the
name. The most common source of salt and pepper noise is transmission of the image
data over a noisy digital link. Malfunctioning detectors can also be a source of salt and
pepper noise.[1] The extreme values of salt and pepper noise result from the flipping
of the most significant bits, and dead or saturated pixels. Such a scenario is very rele-
vant to satellite images which are transmitted to ground stations by radio. In the case of the RE constellation, the images are transmitted to the ground segment using the X-band frequency range. Salt and pepper noise can be addressed by the use of either error detection and correcting codes during transmission, or by median filtering the affected images. Due to the sheer volume of data generated by the RE constellation (the constellation can capture five million square kilometres per day[2]), error detection and correction is limited during the transmission of the images. This maximizes the amount data transmitted during a given downlink period. Instead, images are subjected to a quality control process. Salt and pepper noise is easily detected because the detectors never reach saturation under nominal conditions, and consistently malfunctioning pixels are identified as they are discovered. The extreme values are then eliminated by median filtering or interpolation. Currently, RE imagery is not subject to this type of noise.

Another type of noise that will only be briefly discussed is quantisation noise. This type of noise arises when a continuous signal is quantised, or expressed as discrete values. It can also occur when a signal’s resolution is reduced.[1] In the case of electronic sensors, the quantisation noise is inversely proportional to the number of bits provided by the ADC. More specifically, the SNR increases by 6 dB for each additional bit in the ADC.[1] As previously discussed, the MSI includes a 12-bit ADC, but the digital numbers are reduced to an 11-bit resolution for transmission. Nonetheless, this resolution results in a quantisation noise which is negligible relative to the other sources of noise.

2.2.2 Structured Noise

Structured noise can be periodic or aperiodic in nature. Periodic noise is often caused by electrical interference during the acquisition of the image. Although careful design and testing can eliminate the occurrence of this type of noise during manufacturing, it may appear occasionally after launch due to degradation or damage. In such a case, the only option is to filter the affected images. Various techniques for mitigating or completely eliminating periodic structured noise can be found in [5]. Aperiodic structured noise arises from the difference in sensitivity and dark current generation between the pixels in the array.[4][3] This is sometimes referred to as the photo response non-uniformity.[9] This results in visible striping or banding in the affected images. This can be corrected by approximating the response of each detector as linear and calculating appropriate gain and offset values. These correction factors are collectively known as RCT. The gain values correct for the difference in sensitivity between detectors while the offsets correct for the difference in dark current between detectors. Figure [3] shows a raw image received at the ground station affected by aperiodic structured noise and Figure [4] shows the same image after processing. The striping and banding is visibly reduced.

Historically, a statistical approach was used to calculate the RCT but newer approaches such as the side-slither manoeuvre are gaining wider use.[6] The side slither manoeuvre is specific to the push-broom configuration and involves yawing the spacecraft 90 degrees so that the linear arrays are aligned with the flight direction. As a result, each detector perceives the exact same point on the ground and their relative sensitivities can be established. The RCT are regularly re-evaluated applied to images.

From this point onwards, it will be assumed that all structured noise has been
adequately treated according to the methods described in [4] and [6]. That is, the random noises have the dominant effect on the image. Furthermore, it is assumed that impulse noise and quantisation noise are negligible relative to photon shot noise, thermal noise, and read-out noise.

Previously, CCD sensors like the MSI are typically said to operate in one of two regimes. The first regime is the low illumination regime. In this regime, dark noise and read-out noise are the dominant noise types.[1] The MSI is rarely operated in this regime. It is also worth noting that the MSI lacks both the CCD cooling capability to reduce the dark noise, and the shutter necessary for the calibration and mitigation of the dark noise and read-out noise. The second regime is the high illumination regime. In this regime photon shot noise, dark noise and read-out noise exist, but the photon shot noise dominates.[1] The MSI is almost exclusively operated in this regime. The orbit of the constellation was specifically chosen to be a sun synchronous orbit known as a noon-midnight orbit. This allows images to be taken near mid-day when the light from the sun is most intense and the shadows of objects on the ground are shortest. As a result of the dominance of the photon shot noise and the high illumination levels, the noise follows Poisson statistics but appears to have a Gaussian PDF.[1] Furthermore, the SNR in this regime increases with brightness level as a result of the statistical properties of the Poisson distribution and the definition of SNR being used.[1] With the advent of higher resolution ADC (12-bit), the two regimes are no longer distinguished but the nature of the noise is the same.

2.3 Relevant Statistical Principles

Noise is often characterised in statistical terms. Specifically, noise consists of random variations in a signal and we are defining the probability that the signal has a certain value at any point in time. Thus, noise is modelled using probability density functions (PDF). In the previous section, two important PDFs were mentioned: the Poisson distribution and the Gaussian distribution. These will be formally defined in this section, and their relevant characteristics will be discussed in the context of noise.

The Gaussian distribution is used to model thermal noise. The PDF, \( g(x) \), of a univariate Gaussian noise source with mean, \( \mu_g \), and standard deviation, \( \sigma_g \), is defined in Equation 1. The subscript “\( g \)” in Equations 1, 2, and 3 denotes the Gaussian distribution.

\[
g(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-\mu_g)^2}{2\sigma_g^2}}
\]

The mean of a sample set \( X \) is defined in Equation 2 where \( X_i \) is any given sample value and \( n \) is the number of samples being considered. Here \( n \) is used instead of \( n - 1 \) for accuracy because the method presented later will use sample sizes as small as 10 pixel by 10 pixels. This choice improves accuracy at small sample sizes but does not affect larger sample sizes.

\[
\mu_g(X) = \frac{1}{n} \sum_{i=1}^{n} X_i
\]

The standard deviation of the distribution \( \sigma \) is given in Equation 3.
The Gaussian distribution has many pleasant properties. Amongst these is its symmetry. This results in its mean, median, and mode all being equal. Therefore, there is no doubt to which measure of central tendency is the most accurate representation of the data. Furthermore, there is no dependence of the SNR on the measure of central tendency used.

Photon counting noise is governed by Poisson statistics. The Poisson PDF is defined in Equation 4 where \( k = 1, 2, 3, \ldots \)

\[
p(X) = \frac{e^{-\lambda} \lambda^k}{k!}
\]

As explained in [11] the Poisson parameter, \( \lambda \), can be shown to be equal to the expected value or mean of the distribution. It can also be shown that the variance is equal to \( \lambda \). This is a defining characteristic of the Poisson distribution.

\[
\mu_p(X) = \lambda
\]

\[
\sigma_p(X) = \sqrt{\lambda}
\]

The nature of the Poisson distribution is such that for low values of \( \lambda \) the distribution is asymmetric and the mean, median, and mode of the distribution are quite different. As a result, the choice of the measure of central tendency for the calculation of the SNR will affect the accuracy of the result. However, at higher values of \( \lambda \), the Poisson distribution resembles a Gaussian distribution. This is a result of the Central Limit Theorem. It is for this reason that a distinction between two regimes of operation for CCD sensors was previously made. In fact, thermal noise is also governed by Poisson statistics, but in almost all practical cases it occurs in the regime where it can be very accurately modelled by Gaussian statistics. Thus, the Gaussian distribution can be used to model the Poisson distribution in limiting cases. It was previously asserted that the MSI operated exclusively in this particular regime, this statement will now be substantiated. Figure 5 depicts a lake in the Potosi region of Bolivia. This particular image tile provides an excellent homogeneous region with no structure from which to make noise estimations. Unfortunately, such bodies of water only provide a small range of brightness levels at the lower end of the dynamic range of the MSI. This range is generally below that of vegetation. Nonetheless, the image is representative of lower limit of operational brightness levels. Figure 6 shows the histograms for each of the five spectral bands of a sample homogeneous region extracted from the water region of the image containing 463,074 pixels. Table 1 shows the corresponding statistical properties.

There are several observations to make with regards to Table 1 and Figure 6. First, by observing the green, red, and near-infrared bands, it can be seen that the noise is indeed governed by Poisson statistics. This can be seen by the fact that the standard deviation of the pixel values of the homogeneous region is very close to the square-root of the mean. Therefore, it is reasonable to conclude that the photon shot noise does indeed dominate. This implies that all other noise sources are negligible. In
Table 1: Statistical properties of a homogeneous region containing 463,074 pixels

<table>
<thead>
<tr>
<th>Spectral Band</th>
<th>Pixel Mean</th>
<th>Pixel Standard Deviation</th>
<th>Predicted Standard Deviation</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blue</td>
<td>4176.82</td>
<td>136.98</td>
<td>64.63</td>
<td>52.82</td>
</tr>
<tr>
<td>Green</td>
<td>4756.44</td>
<td>77.66</td>
<td>68.97</td>
<td>11.19</td>
</tr>
<tr>
<td>Red</td>
<td>1991.58</td>
<td>50.28</td>
<td>44.63</td>
<td>11.24</td>
</tr>
<tr>
<td>Red-edge</td>
<td>1860.36</td>
<td>60.65</td>
<td>43.13</td>
<td>28.89</td>
</tr>
<tr>
<td>Near-infrared</td>
<td>1038.04</td>
<td>35.12</td>
<td>32.22</td>
<td>8.26</td>
</tr>
</tbody>
</table>

In particular, this means that the structured noise was adequately mitigated through calibration and the application of RCTs. The blue and red-edge bands do not appear to obey Poisson statistics. This is seen in the fact that the standard deviation of the pixel values is much greater than the square-root of the mean. In the case of the blue band, this is to be expected. In the blue spectral band, the scattering of light by the atmosphere is known to have a significant degrading effect. In the case of the red-edge band, it is uncertain what caused the degradation. Finally, it should be noted that the histograms resemble Gaussian PDFs. This confirms that the sensor is operating in the regime where the noise can be accurately modelled as Gaussian. This also upholds the chosen definition for the SNR as the mean, median and mode are identical and the Gaussian function is entirely defined by its mean and standard deviation. The SNR is explicitly defined in Equation (7)

$$SNR = \frac{\mu}{\sigma}$$

In summary, various noise sources affect the CCD sensors of the RE constellation including dark noise, read-out noise, quantisation noise, photon counting noise, impulse noise and structured noise. Structured noise, both periodic and aperiodic, and impulse noise are easily treated by the ground segment. Of the remaining noise sources, photon counting noise, read-out noise and dark noise are the most significant. Of these, photon counting noise and thermal noise both abide by Poisson statistics, but can be accurately modelled as Gaussian due to the high brightness levels in the typical operating regime of the MSI sensor. For the purposes of this work the mean was decided upon as the estimate for the signal strength, and the standard deviation was chosen to represent the variation due to noise. The ratio of the two will give the SNR within a given image. Finally, due to the statistical characteristic of the Poisson distribution whereby the standard deviation is equal to the square-root of the mean, the variance of the noise is expected to increase with increasing brightness. However, the SNR is also expected to increase as the brightness level increases.

2.4 Difficulties in Noise Estimation

As explained in [9] noise characterisation is a difficult task for various reasons. The most significant being the lack of appropriate calibration sites. Noise is best estimated from a homogeneous image region. That is, a region whose reflectance and illumination are constant in the ideal case. When this condition is met, it follows that any variations in brightness within the image are due exclusively to noise. Furthermore, large homogeneous regions are desirable because the noise is being characterised in statistical terms. From such homogenous areas, the mean of the region characterises the signal strength and the standard deviation characterises the noise.
In the case of the RE sensor, there are no calibration sites that span the full 77 kilometre swath-width of the sensor, and conducting several passes over a smaller target would preclude the different image acquisitions from having the same illumination and atmospheric conditions. This is problematic given that the dominant noise type has a variance that changes with brightness as previously discussed. The lack of adequate artificial calibration sites has led to the use of naturally occurring homogeneous regions such as snow fields and deserts.[9] This leads to the second greatest challenge in noise estimation: that of characterising noise over the entire dynamic range of the sensor. Although deserts and snowfields provide large, relatively homogeneous areas that vary only little with time, they only allow the characterisation of the noise at high albedos. This lies outside the normal operational albedo ranges for agriculture and forestry which are the main interest of the RE constellation for land cover usage analysis.[9] Homogeneous areas in the tepid regions are usually small and dispersed. This leads to the final challenge of noise characterisation: the manual identification of appropriate homogeneous areas within the satellite data. This is a daunting task because of the vast volume of satellite imagery being generated, the subjective nature of the human selection process, and the need to re-evaluate the noise of the sensors on a continuous basis due to the degradation of the sensor and periodic updates to the RCT. All the aforementioned have resulted in varied approaches to the estimation of noise yielding different levels of success. However, noise estimation as a whole remains an ongoing problem and its automation has progressed little.

2.5 Algorithm Requirements

The above discussion illustrates the need for an algorithm to automatically characterise noise. In more specific terms, an algorithm with the following characteristics was desired:

1. The algorithm should be able to detect homogeneous areas of various sizes and in different types of images in order to extract the local SNR.

2. The algorithm should be able to characterise the SNR across the dynamic range of the sensor from one or more images.

3. The algorithm should have a level of autonomy which represents an improvement over current manual methods and thereby allow noise characterisation more frequently.
Figure 3: Raw image showing striping and banding.
Figure 4: Image corrected for photo response non-uniformity.
Figure 5: Lake in the Potosi region of Bolivia.
Figure 6: Histograms of homogeneous water region in each spectral band.
3 Method

3.1 Image Selection

In order to obtain an accurate characterization of the SNR of the sensor throughout its dynamic range, appropriate images must be pre-selected. Single images with a broad dynamic range are desirable. Such images eliminate the inaccuracy and difficulty of pooling together data from multiple images taken under different atmospheric and lighting conditions in order to characterize the full dynamic range. This is achievable by selecting images such as desert agriculture facilities, or images containing deserts and bodies of water such as oceans. Moreover, the images should preferably contain farmland or forests as these are the primary targets of interest for the RE constellation. Finally, the images should contain large homogeneous regions in order to ensure statistical accuracy. Overall, the criteria for selecting tiles to be processed is similar to that for selecting calibration sites described in [11] except that areas containing vegetation, forests and bodies of water are desired in order to characterise the entire dynamic range of the sensor. The criteria are summarised as follows:

1. Relatively homogeneous surface
2. Relatively flat terrain
3. Distance to urban or industrial areas to avoid aerosols
4. Large dynamic range
5. Presence of agriculture or forests
6. No clouds or sandstorms

3.2 Algorithm Overview

In this section, we will first describe the algorithm as a whole in concise terms prior to elaborating on each of its steps.

The algorithm takes advantage of the random nature of noise. More specifically, it uses the fact that two samples of noise do not correlate with one-another. Indeed, the homogeneous regions which are of interest here are in fact merely noise. Therefore, homogeneous regions can be separated from regions containing features by evaluating how well they correlate with simulated noise. This is achieved here by dividing the image into multiple smaller, square tiles. Each tile is then corrupted with additive Poisson noise. Poisson noise is used because this is the type of noise which is expected to be dominant. Due to the operating regime of the MSI, the noise generated is in fact Gaussian noise with a standard deviation equal to the square-root of the tile mean. The noise is added to the tile resulting in a corrupted tile. The Pearson correlation coefficient (PCC) of the corrupted tile and the original tile is then calculated and compared to a threshold to determine if the original tile is homogeneous. This approach works because homogeneous tiles theoretically contain only Poisson noise whose variance is directly related to the mean. As a result, adding noise with a variance equal to the tile mean results in more noise, which is uncorrelated with the original tile. The variations in tiles containing features are dominated by the scene content. Adding Poisson noise
to such a tile has little effect because the variance of the tile is not related to its mean. Consequently, the corrupted tile is still well-correlated with the original tile. This is illustrated in Figure 7. Figure 7(a) shows a homogeneous 50x50 pixel tile extracted from an image of farmland, and Figure 7(b) shows the result of corrupting the tile with additive Poisson noise. The two tiles are essentially noise and have a correlation coefficient of 0.6915. Figure 7(c) shows a 300x300 pixel tile extracted from the same image of farmland and centered on the same pixel, and Figure 7(d) shows the result of corrupting the tile with additive Poisson noise. The variance in the pixel values due to the scene content far exceeds that of the additive Poisson noise resulting in little difference between the two images and a correlation coefficient of 0.9984.

Figure 7: Illustration of Algorithm Concept

The spatial and spectral correlation in hyperspectral images have been used in the past for the estimation of noise. In this method, the PCC was used as a criteria for homogeneity. The PCC, as defined in Equation 8, expresses how two variables vary
linearly with respect to one another. In Equation 8, \( X \) and \( Y \) denote the two variables considered, \( n \) denotes the number of elements in the set comprising the variable, and \( \mu_X \) and \( \mu_Y \) are the mean values for each variable. The PCC is a convenient gauge of how two variables are related because it gives a value between \(-1\) and 1.

\[
l_{8} = \frac{\sum_{i=1}^{n} (X_i - \mu_X)(Y_i - \mu_Y)}{\sqrt{\sum_{i=1}^{n} (X_i - \mu_X)^2 \sqrt{\sum_{i=1}^{n} (X_i - \mu_X)^2}}}
\]

\(-1 \leq r \leq 1\) (9)

A positive correlation coefficient indicates that the two variables increase and decrease together. A negative correlation coefficient indicates that as one variable increases, the second variable decreases. A correlation coefficient of 1 indicates perfect linear correlation. That is any variation in the first variable is perfectly reflected in the second variable. A correlation coefficient of \(-1\) indicates that any variation in the first variable results in the same but opposite variation in the second variable.

The division of the image into multiple segments is borrowed from an image segmentation technique known as split and merge. The algorithm starts by determining the image dimensions. It then truncates the image so that the number of rows in the image is an integer multiple of the number of columns. It then calculates all the integer factors of the column dimension. These factors are subsequently used to divide the image into a number of smaller square tiles. In order to ensure statistical accuracy, tiles smaller than 10x10 pixels are eliminated. Similarly, tiles bigger than 100x100 pixels are not processed in order to save time. Each tile is then corrupted with additive Poisson noise. Due to the operating regime of the MSI, this is approximated by using additive Gaussian noise whose standard deviation is equal to the square-root of the mean digital number of the tile.

\[
\mu_j = \frac{\sum_{i=1}^{n} X_i}{n}
\]

(10)

\[
\sigma_j = \sqrt{\frac{\sum_{i=1}^{n} (X_i - \mu_X)^2}{n}}
\]

(11)

The SNR for each region is then calculated according to Equation 12.

\[
SNR = \frac{\mu_j}{\sigma_j}
\]

(12)

### 3.3 Detailed Pseudo-code

1. Load image and determine image dimensions.

2. Truncate the row dimension so that it is an integer multiple of the column dimension.

3. Calculate the integer factors of the column dimension.

4. Eliminate factors which result in a tile dimension below 10x10 pixels or above 100x100 pixels.
5. For each of the remaining factors:
   • Divide the image into square tiles.
   • Corrupt each tile with Poisson noise.
   • Calculate the PCC between the original tile and the corrupted tile.
   • If the correlation coefficient is below the specified threshold, calculate the mean, standard deviation and SNR of the tile.

6. Calculate a simple least-squares regression of the accumulated data.
4 Results

In this section, the results of the analysis of various RE Level 3A image products will be presented. These will serve both to demonstrate the effectiveness of the algorithm and to establish that RE images are of excellent quality.

4.1 Farmland

Figure 8 depicts a large agricultural facility in the United States. Such areas are of primary interest for the RE constellation for land cover usage and crop health monitoring. The image was acquired by RE-1 on August 19, 2013.

![Image of Farmland](image.png)

Figure 8: Farmland in the United States.

Figures 10 to 14 show the results produced by the algorithm. In these plots, each black dot represents a homogeneous region between 10x10 pixels and 100x100 pixels in size. The dashed lines represent a simple least squares regression fitted to the data after a logarithmic coordinate transform was applied to make the relationship between SNR and mean DN linear. The solid line represents the theoretical SNR as a function of mean DN calculated as the square-root of the mean. The trendlines fitted to the data follow Equation 13. The parameters $c_1$ and $c_2$ for each spectral band are summarized in Table 2. It should be noted that the plots are normalized for the bandwidth of each spectral band. The shape of the resulting trendline and the corresponding fit parameters clearly shows that the SNR is dependent on the square-root of the mean of the radiance as expected for Poisson noise. This demonstrates that the
photon shot noise is indeed the dominant noise source. This implies that all other noise sources are negligible in comparison and that the structured noise is properly mitigated through calibration. The trendline also illustrates that the SNR is on average greater than that expected. The exception being the blue spectral band which is the result of absorption and scattering by the atmosphere. The above average SNR is a result of the re-sampling of the image from a 6.5 meter ground sampling distance to a 5.0 meter ground sampling distance which is in effect a form of interpolation. Thus, noise is reduced as a side effect.

$$y = c_1 x^{c_2} \quad (13)$$

Table 2: SNR versus radiance linear regression parameters for an image of farmland

<table>
<thead>
<tr>
<th>Spectral Band</th>
<th>$c_1$</th>
<th>$c_2$</th>
<th>Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blue</td>
<td>0.5066</td>
<td>0.5435</td>
<td>0.80</td>
</tr>
<tr>
<td>Green</td>
<td>0.8597</td>
<td>0.5298</td>
<td>0.65</td>
</tr>
<tr>
<td>Red</td>
<td>1.0722</td>
<td>0.5183</td>
<td>0.60</td>
</tr>
<tr>
<td>Red-edge</td>
<td>0.8731</td>
<td>0.5278</td>
<td>0.65</td>
</tr>
<tr>
<td>Near-infrared</td>
<td>2.4927</td>
<td>0.4363</td>
<td>0.55</td>
</tr>
</tbody>
</table>

Figure 9 shows a region extracted from the blue band of Figure 8. The black squares in Figure 9 are regions identified as homogeneous by the algorithm. It can be seen that the algorithm correctly identifies homogeneous regions and avoids strong features. Of greater interest is the fact that the algorithm avoids the read-out noise patterns clearly visible spanning diagonally from the lower left to upper right. This is because the algorithm interprets these as legitimate image structure and recognizes them as non-homogeneous as a result of the chosen measure of homogeneity.
Figure 9: Homogeneous regions identified in the blue band of Figure 8.
Figure 10: SNR versus mean DN for an image of farmland in the blue band.
Figure 11: SNR versus mean DN for an image of farmland in the green band.
Figure 12: SNR versus mean DN for an image of farmland in the red band.
Figure 13: SNR versus mean DN for an image of farmland in the red-edge band.
Figure 14: SNR versus mean DN for an image of farmland in the near-infrared band.
4.2 Desert Agriculture

Figure 15 depicts an agricultural facility surrounded by desert. This type of image is of particular interest because it contains a very broad range of radiance levels in a single image. This allows the SNR for a large portion of the sensor’s dynamic range to be measured at once. This avoids complications inherent to pooling together data from multiple images which may not necessarily have comparable illumination or atmospheric conditions. This particular image was taken above Southern California by RE-5 on April 12, 2014.

Table 3: SNR versus radiance linear regression parameters for an image of desert agriculture

<table>
<thead>
<tr>
<th>Spectral Band</th>
<th>$c_1$</th>
<th>$c_2$</th>
<th>Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blue</td>
<td>0.5637</td>
<td>0.5292</td>
<td>0.80</td>
</tr>
<tr>
<td>Green</td>
<td>0.8925</td>
<td>0.5131</td>
<td>0.70</td>
</tr>
<tr>
<td>Red</td>
<td>0.7355</td>
<td>0.5360</td>
<td>0.70</td>
</tr>
<tr>
<td>Red-edge</td>
<td>0.8957</td>
<td>0.5115</td>
<td>0.70</td>
</tr>
<tr>
<td>Near-infrared</td>
<td>0.9969</td>
<td>0.5042</td>
<td>0.70</td>
</tr>
</tbody>
</table>

Figure 16 shows a region extracted from the red band of Figure 15. Once again, the algorithm properly identifies the homogeneous crop regions and avoids the textured
sand regions. Figures 17 to 21 show that the SNR for Figure 15 is much closer to the theoretical value than that of Figure 8. This is due to the fact that higher thresholds were used in the former case than in the latter as can be seen in Table 3 and Table 2, respectively. A lower threshold corresponds to a more strict homogeneity criteria and yields fewer data points. Nonetheless, many points in Figures 18 to 21 far exceed the theoretical value and these are more representative of the sensors capabilities. The lower points are representative of the threshold which is subjectively set by the operator, as well as any adverse atmospheric or illumination conditions.

Figure 16: Homogeneous regions identified in the red band of Figure 15
Figure 17: SNR versus mean DN for an image of desert agriculture in the blue band.
Figure 18: SNR versus mean DN for an image of desert agriculture in the green band.
Figure 19: SNR versus mean DN for an image of desert agriculture in the red band.
Figure 20: SNR versus mean DN for an image of desert agriculture in the red-edge band.
Figure 21: SNR versus mean DN for an image of desert agriculture in the near-infrared band.
4.3 California Coastline

The previous image products represented the intermediate and the high radiance cases. The image product displayed in Figure 22 depicts farmland along the coast of Southern California and is representative of the low and intermediate radiance ranges. This particular image is of interest because in this case, the blue band has an SNR versus radiance curve comparable to that of the other four bands as can be seen in Figure 24. It is possible that the relatively weak reflectance of the land in the blue band for the previous two cases resulted in a poorer SNR. Whereas the strong reflectance of the water in the blue band for this case provides a stronger signal. The scattering due to the atmosphere is the same and the resulting noise is the same, but the signal is stronger than over land. The corresponding SNR versus radiance curves are shown in Figures 24 to 28. The fit parameters for the trendlines are summarized in Table 4. At this point it is evident that in all cases, the $c_2$ parameter is relatively constant around 0.5, and that the $c_1$ parameter is the most indicative of the quality of the image. A $c_1$ parameter greater than unity indicates an image quality above that predicted by theory, while a value less than unity indicates the image has a poorer quality than the ideal case. Figure 23 depicts homogeneous regions detected in the red-edge band.

![Figure 22: Farmland along the coast of Southern California.](image-url)
Table 4: SNR versus radiance linear regression parameters for an image of the Californian coast

<table>
<thead>
<tr>
<th>Spectral Band</th>
<th>$c_1$</th>
<th>$c_2$</th>
<th>Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blue</td>
<td>0.7955</td>
<td>0.5228</td>
<td>0.70</td>
</tr>
<tr>
<td>Green</td>
<td>0.9630</td>
<td>0.5031</td>
<td>0.70</td>
</tr>
<tr>
<td>Red</td>
<td>0.8406</td>
<td>0.5241</td>
<td>0.70</td>
</tr>
<tr>
<td>Red-edge</td>
<td>1.1237</td>
<td>0.4948</td>
<td>0.70</td>
</tr>
<tr>
<td>Near-infrared</td>
<td>0.9963</td>
<td>0.5142</td>
<td>0.70</td>
</tr>
</tbody>
</table>

Figure 23: Homogeneous regions identified in the red-edge band of Figure 22
Figure 24: SNR versus mean DN for an image of the Californian coast in the blue band.
Figure 25: SNR versus mean DN for an image of the Californian coast in the green band.
Figure 26: SNR versus mean DN for an image of the Californian coast in the red band.
Figure 27: SNR versus mean DN for an image of the Californian coast in the red-edge band.
Figure 28: SNR versus mean DN for an image of the Californian coast in the near-infrared band.
The results presented above clearly demonstrate that the algorithm can successfully detect homogeneous regions in diverse images depicting bodies of water, agriculture, and desert. These results also show that RE image products are of excellent quality in that they consistently display a SNR above the predicted figure for a signal degraded with Poisson noise. The $c_2$ parameter of the least-squares linear regression is relatively constant around 0.5, which is characteristic of Poisson noise, and the $c_1$ parameter is the most indicative of the quality of the image. In general, a $c_1$ parameter greater than unity indicates an image quality above that predicted by theory, while a value less than unity indicates the image has a poor quality. The resampling process involved in producing Level 3A products results in these products having a quality superior to that predicted by theory. The dominant noise source was confirmed to be the photon shot noise as seen by the shape of the SNR versus radiance curve. This noise source is typical of CCD sensors and is unavoidable. These results also imply that the structured noise in the sensor is properly mitigated through calibration and that all other noise sources are negligible.
5 Discussion & Conclusion

In this section, various aspects of the proposed algorithm and the interpretation of its results will be discussed.

5.1 Selection of Thresholds

As seen in Section 4, the selection of the threshold can have a significant impact on the results. At this point, it is necessary to recall that the threshold in question is the PCC between an image tile (a segment of the larger image) and the same image tile after it has been corrupted by Poisson noise (additive Gaussian noise with a standard deviation equal to the square-root of the mean of the original tile). A threshold of 0.7 will give results that are very close to the predicted SNR for a constant signal corrupted by Poisson noise. This threshold was determined through experimentation by having the algorithm run while displaying each tile, the corresponding corrupted tile, and the PCC between the two images. It was then observed that homogeneous tiles (in the eyes of a human being) always had a correlation coefficient below 0.7. Selecting a higher threshold results in a less strict homogeneity criteria, and yields more data points but a lower overall SNR. This is often, but not always, necessary in the blue band. Selecting a lower threshold results in a more stringent homogeneity criteria, fewer data points, and a higher overall SNR. A minimum number of data points are necessary in order to accurately characterize the SNR versus radiance curve. To achieve results that are the most representative of the actual image quality, the thresholds must be adjusted iteratively. It should also be kept in mind that a low overall SNR may not be representative of the sensor’s performance. Indeed, the image may not contain homogeneous regions, or there may be adverse atmospheric conditions (dust or sand storms, aerosols or other pollutants). Overall, if an image does not yield satisfactory results when analysed with a threshold below 0.7, it is not a good for SNR characterisation.

5.2 Image Selection Criteria

The selection of the image to be analyzed also has an effect on the measured image quality. The most basic criteria is that the image should have visible homogeneous areas. Images containing crops, deserts, lakes, glaciers and the like are all good options. The next criteria is the range of radiance levels encompassed by the image. A broad range of radiance levels allows for a more complete and accurate characterization of the SNR as a function of radiance. Images such as deserts bordered by ocean, desert agriculture, or glaciers bordered by ocean are all examples of scenes which possess large ranges of radiance levels. Such images eliminate the need to pool together data from multiple images. The latter should be avoided as the different images may not have comparable illumination and atmospheric conditions. This would degrade the accuracy of the results. It is of particular importance to constrain the low and high radiance levels as these have the greatest influence on the shape of the regression. Finally, the image should be controlled for favorable atmospheric conditions. The images should not contain clouds, sand storms, haze or similar conditions. Such control measures are already implemented by all satellite image providers.
5.3 Interpretation of the Results

Figures 10 to 14, Figures 17 to 21, and Figures 24 tp 28 clearly show that Poisson noise is the dominant noise source in RE images as can be seen by the shape of the regression curves. This is further upheld by the $c_2$ coefficient of the least squares regression in Tables 2 to 4 which are very close to 0.5. This is to be expected of CCD sensors. This confirms the previous assumption that all other noise sources were negligible in comparison. It also speaks to the quality of the calibration of the sensor which effectively mitigates structured noise. The $c_1$ is the most descriptive of the image quality. A value greater than unity indicates an image whose quality is greater than theory. Conversely, a value below unity indicates either an image of poor quality, a bad sensor calibration, or an image which does not have homogeneous regions. It is also apparent that there is considerable spread in the SNR for a given radiance. At times, the upper and lower limit differ by a factor of two. Which leaves the question: which points are most accurate? Figures 9, 16, and 23 verify that the regions identified are indeed homogeneous within the limits of human perception. However, the higher data points are indeed the most representative of the sensors’ capability rather than scene content or atmospheric effects. In this respect, the least-squares regression’s sensitivity to outliers serves to raise the curve towards these higher values.

5.4 Merits & Limitations of the Proposed Algorithm

The algorithm described here has many merits over current methods for estimating noise in images. Foremost, once the adequate threshold is set, the algorithm requires no supervision. Thus, it can be easily adapted to process large data archives, or process images as they are produced. Moreover, the method is relatively simple and makes use of well-established functions which reduces computational time relative to more elaborate and complex methods. In addition to this, the method functions on a single image while other methods rely on the correlation between spectral bands. Furthermore, the algorithm makes a single assumption (that the dominant noise source follows Poisson statistics) which is well-justified and applicable to almost all imaging technologies. Also, the method shows a certain immunity to structured noise which it perceives as image structure and avoids.

Nonetheless there are various limitations to the algorithm. The most notable is the dependency of the segmentation on the integer factors of the number of columns. This limits the size of the tiles to a given subset of dimensions. As a result, certain image dimensions will yield a better segmentation than others. In the case of prime numbers, the segmentation will not work. Despite this, this method is preferred over a moving window approach which is much more time-consuming. Similarly, the number of rows is truncated to an integer multiple of the number of columns. This is done so that only a single set of factors needs to be calculated but results in a loss of data. Another limitation is the degradation of accuracy as the tile dimensions decrease. As previously explained, large truly homogeneous areas rarely occur in nature (especially in the temperate climates and forested areas). Therefore, segmenting the image into smaller tiles is necessary in order to detect smaller regions. However, as the tile size decreases, the accuracy of the statistical quantisation of the noise degrades. Finally, impulse noise must be adequately mitigated prior to this method being used as a single extreme value pixel will offset the mean of a tile, which in turn effects the standard
deviation of the noise used to corrupt the tile. This could result in misidentified regions.

5.5 Proposed Future Work

In its current state, the proposed method was designed to work in two dimensions. This was done in order for the same algorithm to work on all levels of RE image products, as well as external image products. An interesting progression would be to adapt the product to the one-dimensional case. This would allow it to be applied to each column of Level 1B products to assess the SNR versus radiance curve of each individual detector. Although this is only a minor adaptation, time constraints did not allow its implementation.
References


