QUALITY MEASURES ON MULTISPECTRAL IMAGES

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In this paper the Quality measures of Multispectral images are analysed by using Textual features. An experimental result of textual features on different tasks in multispectral images vise TM, SAR is measured. Six different statistical moments based on common descriptors of the features are measured and based on those statistical moments, Quality measures are analyzed.

Keywords: Quality Measures, Statistical Moments, Textual Features.

1. INTRODUCTION

A Multispectral image is a collection of several monochrome images of the same scene, each of these taken with different sensors. Each image is referred to as a band. A well multispectral is a RGB color image, consisting of red, green and blue image each of these taken with a sensor sensitive to different wavelengths. In image processing, multi spectral images are most commonly used for remote sensing applications. Satellites generally takes several images from frequency bands in the visual and non visual range. For example Landsat 5 produces 7 band images with the wavelength of the bands being between 450 and 1250 nw. All the single band image processing operators can also be applied to multispectral images by processing each band separately. For example, a multispectral image can be edge detected by finding the edges in each band and then O ring the three edge images together. However we could obtain more reliable edges, if we associate a pixel with an edge based on its properties in all three bands and not only one. To fully exploit the additional information which is contained in the multiple bands we should consider the images as are multispectral image rather than a set of monochrome grey level images. For an image with 10 bands, we can then describe the brightness of each pixel as a point in a k-dimensional space represented by a vector of lengths. Spatial techniques are existed to process multispectral images. For example, to classify a pixel as belonging to one particular region, its intensities in the different bands are said to form a feature vector describing its location in the k-dimensional feature space. The simplest way to define is to choose a upper and lower threshold for each band, thus producing a k-dimensional “hyper-cube” in the feature space. Only if the feature vector of a pixel points to a location with this cube is the pixel based classification as belonging to this class. Armitage [1997] have analyzed the user need in image achieves. Dalta et al. [2005] describes content based image retrieval approaches and trends of the new age. Deselares et al. [2007] describes the image retrieval and annotation using maximum entropy. Felgus et al. [2003] have used the learning technique for object class recognition. Jain et al. [2004] describes the fast image retrieval using local features. Keysere et al. [2007] have developed the deformation model for image recognition. In this paper we gave experimental results of variety of features for content based image retrieval on different tasks in multispectral images vise TM, SAT. Six different statistical moments based on common descriptors of the features are analyzed.

2. STUDY AREA AND CHARACTERISTICS

The Landsat5 satellite has on board sensor called the Thematic Mapper (TM). The TM sensor records the surface reflectance of electromagnetic (EM)
radiation from the seen in seven discrete bands. EM radiation refers loosely to light waves and other energy such as x-rays or monochromable. Essentially the satellite sees reflected sunlight in portions of the spectrum including visible light and three bands beyond visible light. The following figure illustrates where EM spectrum in TM sensor can be used. The rectangle shows the band width recorded within that region of the spectrum.

![Figure 1: Use of EM Spectrum in TM Sensor](image)

Many TM Images utilizes a combination of bands 1, 2 and 3 represented as blue, green and red to visualize the data. Synthetic Aperture Radar (SAR) an active microwave illumence, producing high resolution imaging of the earths surface in all weather. What is the meaning of color in a SAR image? Of course all SAR image color is false color, Most SAR images are monochrome. However multiple images of the same scene taken at different times may be super imposed, to generate false colour multi temporal images. The shuttle SAR’s image are the nearest to ‘natural colour’ in the sense that they are viewing three different wavelengths, which can be mapped to RGB for be pseudo – naturalistic display purpose. In single band and single polarized synthetic aperture radar (SAR) images, the information is limited to intensity and texture only and it is very difficult to interpret such SAR images without any a priori information. A single band, single polarized SAR image is classified into water, urban and vegetation areas. SAR can acquire images even at night or in rain, which makes it useful for obtaining images of areas with heavy rainfall such as the Amazon or South-east Asia. L-band SAR (wavelength ~23cm) is more suitable for forest monitoring than C- and X-band SAR since L-band SAR doesn’t affect the fine structure on the ground and can readily distinguish forested and deforested areas.

<table>
<thead>
<tr>
<th>Band No.</th>
<th>Spectral Range (in Microns)</th>
<th>EM Region</th>
<th>Generalized Application Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.45 - 0.52</td>
<td>Visible Blue</td>
<td>Coastal water mapping, differentiation of vegetation from soils</td>
</tr>
<tr>
<td>2</td>
<td>0.52 - 0.60</td>
<td>Visible Green</td>
<td>Assessment of vegetation vigor</td>
</tr>
<tr>
<td>3</td>
<td>0.63 - 0.69</td>
<td>Visible Red</td>
<td>Chlorophyll absorption for vegetation differentiation</td>
</tr>
<tr>
<td>4</td>
<td>0.76 - 0.90</td>
<td>Near Infrared</td>
<td>Biomass surveys and delineation of water bodies</td>
</tr>
<tr>
<td>5</td>
<td>1.55 - 1.75</td>
<td>Middle Infrared</td>
<td>Vegetation and soil moisture measurements; differentiation between snow and cloud</td>
</tr>
<tr>
<td>6</td>
<td>10.40-12.50</td>
<td>Thermal Infrared</td>
<td>Thermal mapping, soil moisture studies and plant heat stress measurement</td>
</tr>
<tr>
<td>7</td>
<td>2.08 - 2.35</td>
<td>Middle Infrared</td>
<td>Hydrothermal mapping</td>
</tr>
<tr>
<td>8</td>
<td>0.52-0.90</td>
<td>Green, Visible Red, Near Infrared</td>
<td>Large area mapping, urban change studies</td>
</tr>
</tbody>
</table>

### Table 2

**General Characteristics of SAR Image**

<table>
<thead>
<tr>
<th>Band</th>
<th>Wavelength</th>
<th>Generalized Application Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single polarized (L,C,X-bands)</td>
<td>23cm</td>
<td>water, urban and vegetation areas.</td>
</tr>
</tbody>
</table>

### 3. METHODOLOGY

The purpose of the study is to find the degree to which a quality measure can discriminate the coding artifacts and translate it into a meaningful
score, to establish how various quality measures are related to each other and to show the degree to which measures respond dissimilarly to coding and sensor artifacts. As the outcome of these investigations we intend to extract a subset of measures that satisfies the image quality measure.

- To measure the statistical moments on TM, SAR Multispectral images.
- To assess the quality of these images by using texture statistics.
- To extract the subset of these measures as quality measures.

4. MODEL

To measure the quality of the image, the texture based statistical and spectral measures are used. Statistical approach is for texture analysis of image on statistical properties of the intensity histogram. One class of such measures is based on statistical moments.

The expression for the $n$th moment about the mean is given by

$$
\mu_n = \sum_{i=0}^{L-1} (Z_i - m)^n P(Z_i)
$$

where $Z_i$ is a random variable indicating intensity

$P(z)$ is the histogram of the intensity levels in a region.

$L$ is no. of possible intensity levels and

$$
m = \sum_{i=0}^{L-1} Z_i P(Z_i) \text{ is the mean average intensity.}
$$

In MATLAB for finding statistical moments the M-function is ‘statxture’.

\[ T = \text{statxture (f, scale)} \]

Where $f$ is an input image (or subimage) $t$ is a six element row vector whose components are the descriptors viz Mean, Standard deviation, Smoothness, Skewness, Uniformity or Energy and Entropy.

**Mean**

A measure of average intensity, which was calculated by using the formulae

$$
m = \sum_{i=0}^{L-1} Z_i P(Z_i)
$$

**Standard Deviation**

A measure of average contrast of given image by using the formulae

$$
\sigma = \sqrt{\mu_2(z)} = \sqrt{\sigma^2}
$$

Where $\sigma^2$ is the variance.

**Smoothness**

A measure of relative smoothness of the intensity in a image, which is calculated by using

$$
R = 1 - 1/(1 + \sigma^3)
$$

$R$ is 0 for constant intensity

1 for large excursions in the values of its intensity levels.

The variance should be normalized to the range $[0, 1]$ by dividing it by $(L - 1)^2$

**Third Moment**

It measures the skewness of the histogram, which was calculated by

$$
\mu_3 = \sum_{i=0}^{L-1} (Z_i - m)^3 P(Z_i)
$$

This is 0 for symmetric histograms, Positive for histogram skewed to right (about the mean), Negative for histograms skewed to left.

Values of these measures are used to normalize the variance values of these measures are brought into comparable range with all other five measures.

**Uniformity**

To measure the uniformity of the given image by using the given formulae

$$
U = \sum_{i=0}^{L-1} P(Z_i)^2
$$

This measure is maximum when all gray levels are equal (uniform) and decreases from there.

**Entropy**

To measure the randomness of the given image, by using

$$
E = -\sum_{i=0}^{L-1} P(Z_i) \log_2 P(Z_i)
$$

5. EXPERIMENTAL RESULTS

The TM image data sets used to analyze are given below
The SAR image data set used to analyze are given below:

<table>
<thead>
<tr>
<th>Image Name</th>
<th>Size</th>
<th>Mean</th>
<th>Standard</th>
<th>Smooth</th>
<th>Skewness</th>
<th>Uniformity</th>
<th>Entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>TM1-R</td>
<td>532 × 485</td>
<td>141.9674</td>
<td>62.1521</td>
<td>0.0561</td>
<td>1.0403</td>
<td>0.0205</td>
<td>7.1584</td>
</tr>
<tr>
<td>TM1-G</td>
<td>532 × 485</td>
<td>142.5441</td>
<td>66.2988</td>
<td>0.0633</td>
<td>0.8481</td>
<td>0.0201</td>
<td>7.3034</td>
</tr>
<tr>
<td>TM1-B</td>
<td>532 × 485</td>
<td>143.6488</td>
<td>61.8391</td>
<td>0.0555</td>
<td>1.0825</td>
<td>0.0206</td>
<td>7.1748</td>
</tr>
<tr>
<td>TM2-R</td>
<td>532 × 485</td>
<td>154.4441</td>
<td>52.8306</td>
<td>0.0412</td>
<td>0.7816</td>
<td>0.0214</td>
<td>6.9095</td>
</tr>
<tr>
<td>TM2-G</td>
<td>532 × 485</td>
<td>156.5038</td>
<td>50.8879</td>
<td>0.0383</td>
<td>0.4643</td>
<td>0.0234</td>
<td>6.6933</td>
</tr>
<tr>
<td>TM2-B</td>
<td>532 × 485</td>
<td>175.4124</td>
<td>43.0692</td>
<td>0.0277</td>
<td>0.1572</td>
<td>0.0234</td>
<td>6.6413</td>
</tr>
<tr>
<td>SAR1</td>
<td>196 × 174</td>
<td>147.3698</td>
<td>46.4413</td>
<td>0.0321</td>
<td>-0.4756</td>
<td>0.0072</td>
<td>7.4552</td>
</tr>
<tr>
<td>SAR2</td>
<td>94 × 85</td>
<td>69.2533</td>
<td>34.6798</td>
<td>0.0182</td>
<td>0.1806</td>
<td>0.0088</td>
<td>7.0386</td>
</tr>
<tr>
<td>SAR3</td>
<td>94 × 90</td>
<td>77.3779</td>
<td>49.8615</td>
<td>0.0368</td>
<td>2.2673</td>
<td>0.0071</td>
<td>7.4158</td>
</tr>
</tbody>
</table>

When a TM, SAR images were given as input, the statistical moments were produced. These images were collected from various locations. For TM images all texture measures are varied from one color band to the other. By analyzing these statistical values the quality measures of TM images are noise less, more uniform, average intensity, contrast and entropy values are high. For SAR images the textual measures are same for all R, G, B color images. By analyzing these textual measures the quality measures of SAR images are average intensity and high entropy means the values of the pixels are more random. The uniformity and smoothness are very least while comparing with TM images.

**Quality Measures of TM&SAR Images**

To measure the quality of image, the statistical moments on texture are analyzed for given images. These Quality measures are shown in table.

### Table 4

<table>
<thead>
<tr>
<th>Type of Image</th>
<th>Quality Measures</th>
</tr>
</thead>
<tbody>
<tr>
<td>TM</td>
<td>H A H A H</td>
</tr>
<tr>
<td>SAR</td>
<td>H A L L H</td>
</tr>
</tbody>
</table>

A-Average, H-High, L-Least

By analyzing these quality measures the TM images are noiseless and high uniform images. This is one of good characteristic for experimental evaluations.

### 6. CONCLUSIONS

In this work we have presented collectively a comprehensive set of image quality measures and categorized them using statistical moments of six categories based on texture of images. In this work the image data has collected form SAR, TM Landsat Satellites. Comparatively TM images are...
more suitable for all types of analysis because of its high quality and less noise. The uniformity also
more for these images. SAR images panchromatic images means there is no color bands and images
are non uniform. SAR images are less smooth and noisy characteristics are identified while measu-
ring texture features.

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