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COMPARISION OF IMAGE DATA FUSION TECHNIQUES USING ENTROPY AND INI

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ABSTRACT

The information content of a single image is mainly limited by the spatial and spectral resolution of the imaging system. Current imaging systems somehow offer a trade-off between high spatial and high spectral resolution - no single system offers both of these characteristics. For example, a high spatial resolution system such as IKONOS, can supply 1m spatial resolution images but the spectral information is limited to a single panchromatic (0.45µm – 0.90µm) band. The sensor also supplies 4 multi-spectral (blue, green, red and near infra-red) bands, i.e. with high spectral resolution, but with low spatial resolution of 4 meters. However, the image processing methods can overcome this limitation. In order to obtain the both characteristics in a single image, that is high spatial and high spectral resolution, a technique - image fusion can be employed. Work in this field has marked a satisfactory outcome in last few years but it has not defined or estimated the quality of information improvement quantitatively.

This paper presents the assessment of image fusion by measuring the quantity of enhanced information in fused images. Two measuring methods – Entropy and Image Noise Index were employed. Entropy can measure the information content of images but it has a limitation. It cannot distinguish between information and noise. A solution to this limitation is discussed and a new method is proposed – the Image Noise Index (INI) using entropy. This method was applied on three commonly used image fusion techniques - intensity-hue-saturation (IHS), principal component analysis (PCA) and high pass filter (HPF). The INI showed definite results distinguishing between noise and information. It also compares the fusion techniques and indicates which technique gives better results.

1. INTRODUTION

Image fusion is a useful technique for merging similar-sensor and multi-sensor images to enhance the image information. The purpose of multi-sensor fusion is to synthesize different pieces of image data coming from different sensors into a single data set. Other terms such as the enhancement of the spatial resolution of multi-spectral image or to sharpen the multi-spectral image or to merge different information from different sensors are used to describe multi-sensor fusion. Multi-sensor fusion is more convenient and economical than designing an advanced sensor with both resolution characteristics.

Previous works (Carper et al., 1990; Chavez et al., 1991 and Munechika et al., 1993) have recognized that multi-sensor fusion can achieve the child image with more information than either parent image. Their assessment was based on visual and graphical inspection and they have not defined or estimated the quality and degree of information improvement quantitatively. Recently, Pohl and Van Genderen (1998) have reviewed this topic in detail. They emphasized future works on methods to estimate and assess the quality of fused imagery.

Entropy is a measure of information and its concept has been employed in many scientific fields. It has been applied in image processing methods as a measure of information but has not been used to assess the effects of information change in fused images. The reason is that entropy sees information as a frequency of change in the digital numbers in images. It cannot distinguish between information belonging to the scene and noise. A new method using entropy is developed in this study - Image Noise Index (INI) to assess the effects of information change in fused images.

Initially, this paper describes entropy as a quantitative measure of information content of an image and INI to assess the information change. SPOT panchromatic and multi-spectral SPOT XS image data are then fused by the IHS (Intensity-Hue-Saturation), PCA (Principal Component Analysis) and HPF (High Pass Filter) fusion approaches and used as examples to explain the use of entropy and the INI. Finally, the benefits of the INI and its limitations in fusion assessment are discussed.

2. ENTROPY and INI

Entropy is not a new concept to measure the information content of image. Previously, Price (1984) had used entropy to estimate the information content of LANDSAT-4 images. Ghali and Daemi (1996) also employed the concept to define the information content of binary image and Sun et al. (1997) introduced entropy as a measure to directly conclude the performance of image fusion. Although it is not a new measure in image analysis, the confused meaning and misleading conclusion are made sometimes. To clearly place the application of entropy in this study of fusion, what follows is a review of entropy - in the contexts of communication information and image information, and then using entropy the method of INI is explained to distinguish between noise and information in fused images.

2.1 Entropy in an information context

Claude Shannon was the first person to introduce entropy in the quantification of information. Shannon (1948) employed the probabilistic concept in modeling message communication. He believed that a particular message is one element from a set of all possible messages. If the number of messages in this set is finite, this number or any monotonic function of this number can be regarded as a measure of the information when one message is chosen from the set, all choices being equally likely. Based upon this assumption, information can be modeled as a probabilistic process. If a receiver is designed for collecting all possible messages, it is essential to know the probability of each message occurring. To isolate one message (k) from all possible messages in a set, the occurrence of this random event k is the probability $P(k)$ of the message. The self-information of k is the quantity $I(k)$. It means that the amount of self-information of k is inverse to the probability of k. If the event k always occurs, $P(k)$=1, no (new) information can be transferred. The logarithmic measurement is only performed for mathematical convenience. In a discrete or continuous source of information, self-information for each k_i element in a set of messages can be given as:

$$I(k_i) = \log \frac{1}{P(k_i)} = -\log P(k_i) \qquad (1)$$

If there are large number, C, of elements in a set of messages, by the Law of Large Numbers, the expected number of k_i will be $CP(k_i)$ times. So, the average self-information in that set of messages with C outputs can be written as:

$$I(k) = -CP(k_1)\log P(k_1) - CP(k_2)\log P(k_2) - \dots - CP(k_n)\log P(k_n) \qquad (2)$$

The sum of the self-information of all the elements is the value for that set, H, which is the average information per source output.

$$H = -C\sum_{i=1}^{n} P(k_i)\log P(k_i) \qquad (3)$$

The value (H) increases with increase in the number of elements and thus more information is associated with the source. Besides, if the probability of each element is the same, the entropy is maximized and the source provides the greatest possible average information per element. In fact, to certain extent, Shannon's entropy (equation 3) is the same as thermodynamic entropy (see equation 4).

$$\begin{gathered} S = -k\sum_{i} p_i \ln p_i \\ k = 1.38 \times 10^{-23}\, J/K \end{gathered} \qquad (4)$$

Although their principles and generalizations are different, Shannon's value H is still named entropy. But in the computation, there are some arrangements. Constant C is the Boltzmann constant in thermodynamic entropy. However, to measure the information content, this constant is set to unity. And the logarithm's base is determined by the choice of unit for the information. For the digital manipulation a base of 2 is appropriate, and yields the unit of bit. Furthermore, to linearize the result, the natural logarithm of probability is used. Finally, Shannon's entropy is defined as:

$$H = -\sum_{i=1}^{n} P(k_i)\ln_2 P(k_i) \qquad (5)$$

2.2 Entropy in the Image Context

To quantify the information of an image (the digital numbers of the pixels) is similar to quantify the information of communication. According to Shannon's assumption, one element of a large number of messages from an information source is just as likely as another, so the digital number of one pixel in an image is just as likely as another pixel. In any one image the number of pixels can be very large. In such cases, to quantify the information content of an image one can just satisfy the Shannon's assumption. Hence, it is reasonable to use Shannon's entropy in image analysis. By applying Shannon's entropy in evaluating the information content of an image, the formula is modified as:

$$H = -\sum_{i=1}^{G} d(i) \ln_2 \{d(i)\} \tag{6}$$

Where G is the number of grey level of the image's histogram ranging for a typical 8-bit image ranges between 0 to 255 and $d(i)$ is the normalized frequency of occurrence of each grey level. To sum up the self-information of each grey level from the image, the average information content is estimated in the units of bit per pixel.

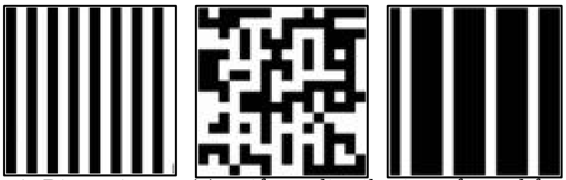

Figure 1: Binary image (a) uniform distribution of equal frequency, (b) random distribution, and (c) unequal frequency.

To evaluate the use of entropy in image analysis, the simple binary image (Figure. 1a) was tested. Two grey levels 0 and 255 were equally distributed in the image of size 16x16 pixels. From equation (6), entropy (H) was computed as 1 bit/pixel. The value implied that 1 bit information content was contained in each pixel of this image. If any one pixel in this image was extracted, only 1 bit information in either grey level 0 or 255 could be interpreted. Hence, the value indicated the average information content in the image. Moreover, even in a larger sized binary image (such as 32 x 32), the entropy was also 1 bit/pixel. Although the image sizes were different, any one pixel in these two images could only present 1 bit information. Other than the image size, distribution of grey levels has no effect on the entropy value of an image. For instance to compute the entropy of binary image (Figure. 1b) where the grey levels were of random distribution, the value still yielded 1 bit/pixel. Although the distribution of grey levels could be in various forms, the equal frequency of grey levels still generated the same amount of information content in the image. For another binary image (Figure. 1c) with unequal frequency of grey levels, only 25% of image was grey level 255 and the other 75% was 0. The entropy of this image was 0.81bit/pixel. As the frequency of grey level of 255 was decreased, a pixel in this image had a higher probability to present grey level 0 than 255. Any one pixel in an image was more likely to be grey level 0. Less amount of information content was presented, and a decrease in entropy implied a decrease in information content. As a consequence, the entropy or average information content of the image is not affected by the image size or the pattern of grey levels but by the frequency of each grey level.

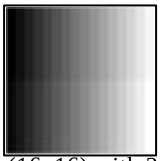

Figure2: An image (16x16) with 256 grey levels.

For an example to evaluate an 8-bit image, levels 0 to 255 were distributed over the image with each level occurring once (Figure 2). This 16x16 pixel image produced entropy (H) of 8 bits/pixel. Each and every pixel had a different grey level and so was carrying different information than any other pixel. With 256 pixels and 256 grey levels the amount of information in the image was a maximum. This 8-bit image example shows that entropy was governed with the number of grey levels and their frequencies. From these examples, it can be seen that entropy can directly reflect the average information content of an image. The maximum value of entropy was produced when each grey level of the whole range had the same frequency.

From a child image of multi-sensor fusion, if its entropy is higher than the parent images it may be deduced that the child image contains more information than either of the parent images. But it is not clear if that 'more information' is in the form of noise or useful information.

2.3 Image Noise Index

In the context of image fusion, entropy is used to estimate the change in quantity of information between the parent and child images. The value can reflect either wanted information or noise (unwanted information). In simple terms noise can be defined as a random or repetitive event that obscures or interferes with the desired information. To measure the amount of the unwanted information, an index based on entropy difference is proposed and is explained below.

A fused image may be restored to its original condition (parent) image through the reverse process used to create it and an entropy value of this restored original image can be estimated. In the reverse process the original spatial resolution value of the multi-spectral image is substituted to bring the fused image to its original condition. If the forward and reverse fusion processes are perfect then the entropy of the initial and final images should be identical. If this is not the case then the fusion process must be adding noise at either or both stages. It is understood that the purpose of image fusion is to preserve the spectral characteristics in fused images while enhancing its spatial resolution, but existing image fusion techniques cannot totally preserve the spectral properties (Liu, 2000). The result is a distortion and is the main cause of noise in fused images. It is reasonable to say that the greater the spectral distortion caused by a fusion process, the greater will be the noise content of the child image. Knowing the three entropy values of the original (x), fused (y) and restored (z) images, it is easy to estimate the noise content in fused images. The difference between the original and fused images, i.e. $(y-x)>0$, is the quantity of increased information content which might be useful information or noise, or both. If the fused image is restored to the original image through the reverse process, imported information is extracted out and the difference between the entropy of original and restored images, i.e. $|x-z|$, is the unwanted information or noise. To know the amount of added useful information (*Signal*) the two differences can be used as:

$$Signal = (y-x) - (|x-z|) \tag{7}$$

Using equation (7) it is easy to calculate the Image Noise Index (INI), which is the Signal-to-Noise ratio, as shown in the following equation.

$$INI = \frac{y-x}{|x-z|} - 1 \tag{8}$$

The INI can be used as the index to create a clear picture of the improvement or deterioration of the fused image. A positive index indicates an improvement of information and a negative one indicates a deterioration of information for the fused image.

3. EXPERIMENTAL RESULTS

3.1 Test Data

To evaluate entropy in the assessment of the change of information of fused images, two types of SPOT data were used. SPOT satellite platform has a HRV (High Resolution Visible) sensor with two modes of operation (panchromatic and multispectral) each with differing resolution. SPOT PAN (panchromatic) image is sensitive to the 0.51 to 0.73 µm wavelengths with 10m resolution and SPOT XS (multispectral) image is sensitive to green (0.50 to 0.59 µm), red (0.61 to 0.68 µm) and near infrared (0.79 to 0.89 µm) spectral bands with 20m resolution. For the purposes of analysis each of these SPOT XS spectral bands were considered as separated images XS1, XS2 and XS3. In this study, it was an advantage to use the SPOT image to minimize the optical, geometric and instrumental variances due to the highly correlated imaging conditions.

The spectral information content of SPOT PAN image is not sufficient for thematic classification and the spatial information of SPOT XS is inadequate for higher spatial analysis. Hence, multi-sensor fusion of these two images is a valid operation. To minimize temporal inconsistency, two sub-scenes where chosen as close as possible with the multi-spectral sub-scene obtained on 91/12/21 and panchromatic sub-scene obtained on 92/01/31. The scenes covered the area of Hong Kong and different features (such as harbour infrastructure, transportation network, building blocks and vegetated cover) are evident in the images (see figure 3). These objects were significant to provide spatial references for the evaluation of fused and original images.

The same dimensions of image data were set for convenience in the fusion process and post-processing analysis. Before fusing the images, they were registered to the local (Hong Kong) coordinate system with an RMS accuracy of sub-pixel. After the correction, the lower spatial resolution (SPOT XS) image was registered to the higher spatial resolution (SPOT PAN) image that was used as the control for the geometric registration. This "geometric locking" was applied to fix the orientation of two images. This process was necessary to maintain accurate spatial relationship in the fusion.

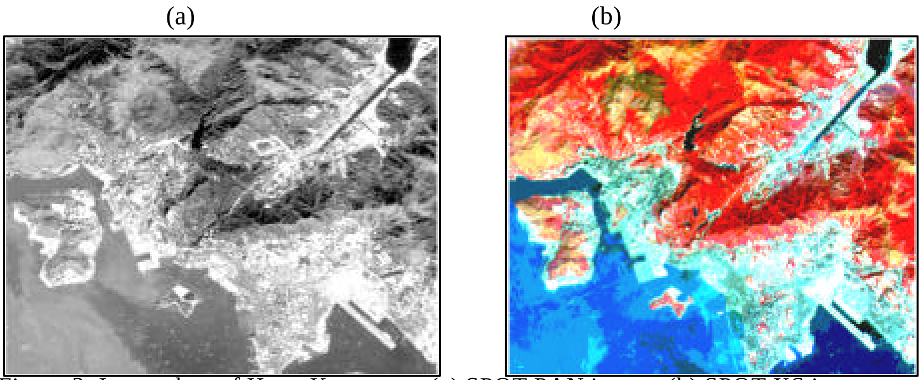

Figure 3: Image data of Hong Kong area: (a) SPOT PAN image; (b) SPOT XS image.

3.2 Multisensor Fusion Processing

After the geo-locking, the three commonly used fusion approaches - Intensity-Hue-Saturation (IHS), Principal Component Analysis (PCA) and High Pass Filtering (HPF) were used to create the fused images. For the fusion process the SPOT PAN image was used as the substituted component into the SPOT XS image during the IHS and PCA approaches. In the HPF approach, a high pass differential filter was applied to the SPOT PAN image and the information was inserted into the three channels of the SPOT XS image to improve its spatial resolution. The fused images are shown in figure 4.

All operations were carried out on a Digital Ultimate workstation model 533AU2 using PCI ImageWorks and Xpace version 6.01. These three fused images and the two original images were used in the evaluation task.

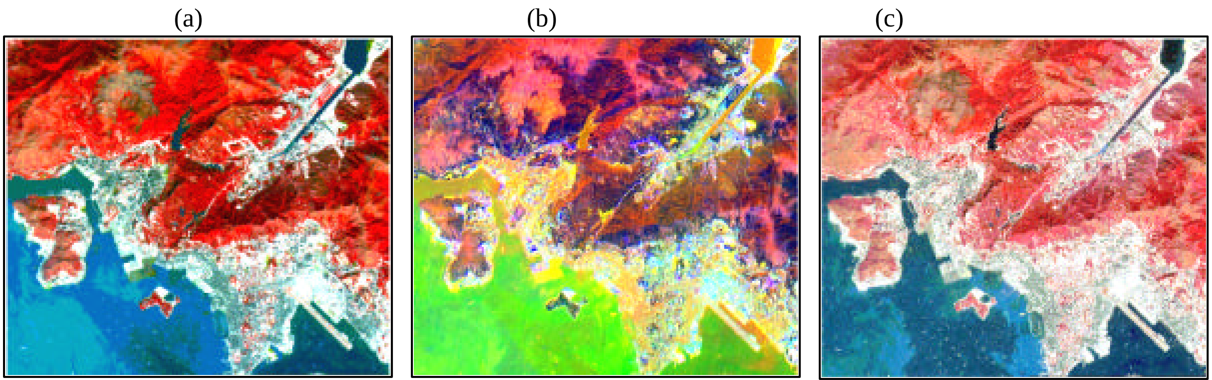

Figure 4: Fusion results of SPOT XS and SPOT PAN images: (a) IHS-fused image; (b) PCA-fused image; (c) HPF-fused image.

3.3 Results and Discussion

The entropy values (x) of the parent images SPOT PAN and multispectral XS (XS 1, XS 2 and XS 3) were found 5.09, 4.92, 5.01 and 5.72 bits/pixel respectively, using equation (6). The entropy values of fused (y) and restored (z) multi-spectral images are shown in table 1. Using these three entropies, the INI of each fused image was calculated.

Table 1. Entropy and INI values of fusion of SPOT XS and SPOT PAN images

Image Channel	Entropy of Fused Image	Entropy of Restored Image	Enhanced Image content	Noise	Signal	INI
IHS 1	5.60	4.88	0.68	0.04	0.64	16.00
IHS 2	5.65	5.01	0.64	0.00	0.64	∞
IHS 3	5.85	5.72	0.13	0.00	0.13	∞
PCA 1	6.32	7.35	1.40	2.43	-1.03	-0.42
PCA 2	7.16	7.51	2.15	2.50	-0.35	-0.14
PCA 3	7.27	7.30	1.55	1.58	-0.03	-0.02
HPF 1	5.81	4.92	0.89	0.00	0.89	∞
HPF 2	5.84	5.02	0.83	0.01	0.82	82.00
HPF 3	6.51	5.72	0.79	0.00	0.79	∞

The average entropy values of the IHS-, PCA- and HPF-fused images are 5.77, 6.92 and 6.05 bits per pixel respectively. The average of three channels of the multispectral image (XS) is 5.22 bits/pixel. According to the computation results, the increased entropy indicates the enhancement of information content through the IHS, PCA and HPF approaches, and PCA provided the greatest improvement. But it is not clear from these results whether the enhancement of information contains more useful information or noise. To solve this problem, the Image Noise Index algorithm developed in this research work was applied to calculate the INI values, which are shown in table 1.

The IHS and HPF fused images produced high INI values indicating increased information with almost no noise (unwanted information) added. For the PCA images, although the fused image contained highest entropy value (see table 1), the deterioration was rather higher. The negative value obtained from the PCA fusion indicates that this fusion was not increasing the information content but deteriorating the image through the addition of noise. This is also supported by the visual inspection of figures 4. It can be seen from this figure that a maximum distortion of spectral information is in PCA fused image (figure 4b), more than the IHS and HPF fused images.

The proposed index in this study provided a channel to compare the quantity of information with the use of entropy of the original, fused and restored images. The value of index proved that if INI >0, the increase in information is an improvement. Otherwise, the increased information is a deterioration of the fused image. It can be deduced from these results that entropy alone cannot provide the quality assessment of fused images, unless the proposed approach of Image Noise Index is used. This method is a useful tool in assessing the quality of fusion techniques.

4. CONCLUSION

The Image Noise Index (INI) method has shown satisfactory results, demonstrating that the HPF and IHS fusion techniques showed improvement in the image information and PCA deterioration. This approach seems reliable for low and medium size spatial resolution images. However, further investigation is needed for high resolution spatial images where the perspective distortion will play a significant role in accumulating errors in the data fusion results. The method was tested with limited data sets. Further testing is necessary for different types of images from different platforms to extend its range and performance.

A very important goal achieved by INI in this study was to evaluate the performance of multi-sensor fusion. This tool has an ability to assess the quality of fusion quantitatively and make remarks on image enhancement. This approach is more economic than designing a new sensor with both resolution characteristics, that is sensor with high spatial and high spectral resolution.

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