Dependence of Image Information Content on Gray-Scale Resolution

Ram M. Narayanan*, T.S. Sankaravadivelu*, and Stephen E. Reichenbach†

*Department of Electrical Engineering and Center for Electro-Optics
University of Nebraska, Lincoln, NE 68588-0511, USA
T: 402.472.5141 F: 402.472.4732 EMail: rnarayanan@unl.edu
†Department of Computer Science and Engineering
University of Nebraska, Lincoln, NE 68588-0115, U.S.A.
T: 402.472.2401 F: 402.472.7767 EMail: reich@ser.unl.edu

Abstract—Remote sensing images acquired in various spectral bands are used to estimate certain geophysical parameters or detect the presence or extent of geophysical phenomena. In a majority of cases, the raw image acquired by the sensor is processed using various operations such as filtering, compression, enhancement, etc. In performing these operations, the analyst is attempting to maximize the information content in the image to fulfill the end objective. The information content in a remote sensing image for a specific application is greatly dependent on the gray-scale resolution of the image. One of the measures to quantify information content is classification accuracy. Our research reveals that the loss in information is exponential with respect to the number of gray levels. The model is seen to be applicable for Landsat TM and SIR-C images. Using our mathematical model for the information content of images as a function of gray-scale resolution, one can specify an "optimal" gray-scale resolution for an image.

INTRODUCTION

The number of gray levels needed to properly digitise an image for visual quality depends upon the characteristics of the human eye. It has been determined that the eye can typically resolve between 40-60 gray levels without succumbing to false contour detection [1]. In general remote sensing applications, 256 gray levels (or 8-bits) are used to represent an image. However, if only 16 levels (or 4-bits) are adequate without sacrificing quality, two images can be be stored in place of one, thereby doubling the storage capacity. Thus, an understanding of the effects of gray-scale resolution on image quality and interpretability is important from the standpoint of resource allocation, and is the subject of our research presented in this paper.

The following model for information content I_m was developed.

$$I_m = exp\left\{-k\left(\frac{L-l}{l-2}\right)^n\right\} \tag{1}$$

In Eq.(1), L is the number of gray-levels in the original image or its gray-scale resolution, while l is the gray-scale resolution of the degraded image. Thus, $0 \leq l \leq L$. Also k and n are best-fit sensor specific constants.

While developing the above model, we assumed that a bi-level ($l = 2$) image does not convey any information about the textural features of the scene. Our formulation is intuitively appealing, since for $l = L$, $I_m = 1$, i.e., all the information is preserved, while for $l = 2$, $I_m = 0$, which indicates that the degraded image does not furnish any information about the textural aspects of the scene.

PROCEDURE FOR ANALYSIS OF DATA

Both TM and SIR-C imagery were analyzed. The method of analysis and consisted of the following steps. (1) Choose the bands in the original image to be used for generating the classified image, (2) Perform an unsupervised classification of the chosen bands of the original image, by using the K-means approach for number of classes ($N_c = 5, 10, 15$), (3) Obtain the "ground-truth" image using classification of the original bands, with a pixel size (R) equal to 1, for each value of N_c, (4) Degrade the gray-scale resolution for $l = \{128, 64, 32, 16, 8, 4, 2\}$ for each band and reclassify the image, (5) Compare the degraded image with the "ground-truth" image to obtain the information content I, (6) Plot I obtained versus $bits/pixel$ ranging from 1 to 8, (7) Determine the best-fit constants k and n, (8) Substitute the values of k and n in the model to generate a plot of I_m versus $bits/pixel$ for values of l ranging from 0 to 255, and (9) Compare the plots from steps (6) and (7) to determine the accuracy of the model.

The same procedure from step (2) was repeated for spatially degraded original bands at other values of spatial resolution, i.e., for $R = 5, 11$. Spatial degradation was performed using an appropriate equally weighted local mean filter [2].

The original bands had a gray-scale range of $L = 256$. Gray-scale degraded images with $l = \{128, 64, 32, 16, 8, 4, 2\}$ were generated by performing an integer division of the value of each pixel in the image by powers of 2 corresponding to the seven values of l, followed by rescaling to an $l = 256$. The rescaling process is effected by the use of the following formula:

$$S = \left(\frac{P - P_{min}}{P_{max} - P_{min}}\right) 255 \tag{2}$$

In Eq.(2), S is the value of the pixel after gray-scale degradation and rescaling, and P is the pixel value before the rescaling process and after integer division. P_{max} and P_{min} are the largest and smallest pixel values present in the image after integer division. Since we performed a contrast-stretch operation on the images before analysis, its minimum and maximum gray levels were always 0 and 255 respectively. Thus, in our case, $P_{min} = 0$ and $P_{max} = l - 1$. Pixel values are rounded to the largest integer multiple of $(\frac{256}{l})$ smaller than itself.

Since we are investigating the interpretability of classified remote sensing images, we need to compare the ground-truth image with the classified degraded image to ascertain the latter's information content. A loss in information would occur whenever a pixel in the classified degraded image is misclassified in comparison to the same pixel in the ground-truth image. Hence *classification accuracy* would be a good measure of information content, I.

A value of $I = 1$ indicates that the classified degraded image is identical in interpretability to the ground-truth image, while $I = 0$ indicates that the classified degraded image has no interpretability value for the scene that it represents. We also define the Maximum Achievable Information, I_{max}, as that value of I at 8 $bits/pixel$ for each combination of N_c and R.

SITE DESCRIPTION

The chosen scene, shown in Figure 1, lies along the central California coast about half way between San Francisco and Los Angeles, in the county of San Luis Obispo. (All figures are gray-scale reproductions of color images.) This sub-scene was extracted from Landsat 5 Thematic Mapper scene 5026-31810 (Path 043; Row 035) acquired on November 19, 1984 with center latitude and longitude as $35°21'N$ and $120°49'W$ respectively. Each pixel has a size of 30 m, and the entire image is about 16 km (10 miles) in length. The largest town in the image is Morro Bay, located about 21 km NW of the city of San Luis Obispo. The coastal Highway 1 extends inland to the east in this scene. The second major road, California Highway 41, is visible as it passes through a valley between hills en-route to Atascadero 27.5 km to the NE. Cayucos is a small residential town along the coast just north of Morro Bay. Near the bottom of the image is the town of Los Osos. Morro Rock, a great erosional monolith made of granite that reaches a height of 175 m above the Pacific is also visible. Dense forestation extends from the higher elevations into the lowlands along the streams.

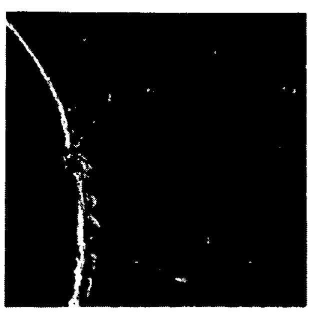

Fig. 1. The color composite images using TM bands 2, 3 and 4, of Morro Bay, California.

INFORMATION ANALYSIS & MODEL EFFICIENCY

Six TM bands (Bands 1-5 and 7) were used to obtain the K-means classified images for the eight different values of l. For each value of l, I was calculated following which the best-fit values of k and n were obtained. Then, an equally weighted local mean filter was used to spatially degrade the original image to obtain images with $R = 5$ and $R = 11$, after which the same procedure was repeated.

Figures 2 and 3 illustrate the visual effects of degrading the gray-scale resolution. It can be easily deduced that the classified images for values of $l = \{256, 128, 64, 32\}$ shown in Figure 2 are practically indistinguishable from one another. Similarly, the images with $l = \{16, 8\}$ from Figure 3 are equally indistinguishable from the ground-truth image, i.e the classified image with $l = 256$. However, the images with l values lower than 8 are clearly different, and show increasing misclassification in comparison to the ground-truth image. This implies that the interpretability (information content) of the image with $l = 8$ is same as the interpretability of the ground-truth image. Hence, we may as well use the image with $l = 8$ instead of the ground-truth with $l = 256$ for characterizing the scene, and in the process save 5 $bits/pixel$. To check whether this observation was mathematically consistent, the plots between the calculated information content, I, and $bits/pixel$, $log_2 l$, were studied.

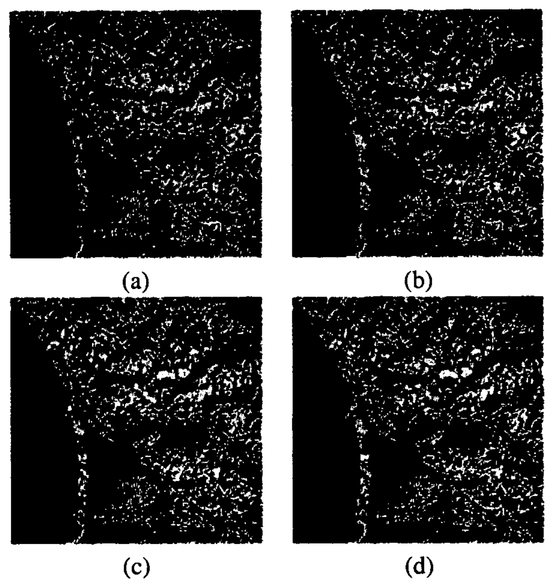

Fig. 2. Classified Morro Bay TM images with $R = 1$, $N_c = 5$, and (a) $l = 256$, (b) $l = 128$, (c) $l = 64$, (d) $l = 32$.

Figure 4 shows the plots for the three pixel sizes, for Morro Bay, when the K-Means classifier was used with 5, 10 and 15 classes for site A. On studying the plots of I for $R = 1$, it can be seen that for number of classes, N_c, equal to 5 the measured information content of the image is greater than 0.9 for $bits/pixel$ of 3 and higher. For $bits/pixel$ less than 3, there is a sudden drop in the value of I. This supports our observations made from Figures 2 and 3, which show visual image degradation for l values less than 8, corresponding to 3 $bits/pixel$. Thus we can define the gray-scale resolution (in $bits/pixel$), at $I = 0.9$, $R = 1$ and N_c equal to the probable number of classes present in the scene, as the *optimal gray-scale* resolution. Since this particular TM imagery has an optimal gray-scale resolution of 3 $bits/pixel$, we can save 5 $bits/pixel$ on

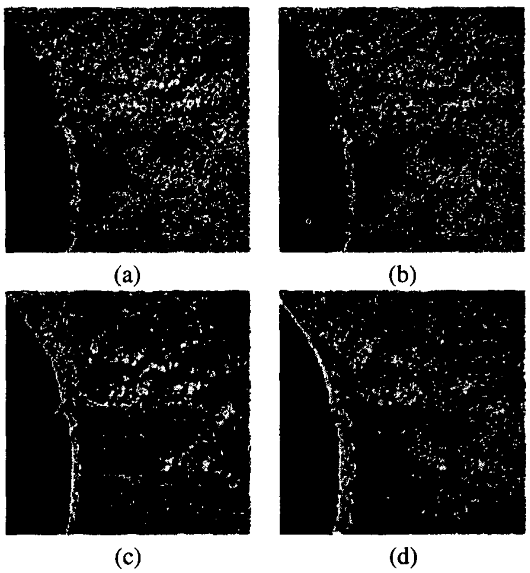

Fig. 3. Classified Morro Bay TM image with $R = 1$, $N_c = 5$, and (a) $l = 16$, (b) $l = 8$, (c) $l = 4$, (d) $l = 2$.

storage or transmission of this imagery, even without applying any kind of compression.

As the number of classes increase, we can notice that the rate of fall of information also increases. This results from the creation of subclasses within the existing classes which increases the probability of misclassification of a pixel. We also note that I_{max} reduces as spatial resolution is degraded.

Table 1 shows the values of k and n obtained for the three cases of R and N_c, for TM imagery. We infer that for a constant R, k increases with an increase in N_c, whereas, n decreases in almost all the cases. If we keep N_c a constant, it is evident that k once again increases with increasing values of R, while n mostly decreases. Our simulation experiments revealed that although the rate of information loss and I_{max} are functions of both k and n, the parameter k has much greater influence on I_{max} than n. However, the parameter n has a greater influence on the rate of information loss than k.

TABLE 1

k AND n VALUES FOR $R = \{1, 5, 11\}$ AND $N_c = \{5, 10, 15\}$ FOR TM IMAGERY

		Morro Bay	
R	N_c	k	n
1	5	0.0032	0.8743
	10	0.0247	0.6191
	15	0.1443	0.3938
5	5	0.4229	0.0310
	10	0.7087	0.0217
	15	0.9287	0.0103
11	5	0.5730	0.0188
	10	0.9008	0.0202
	15	1.2203	0.0152

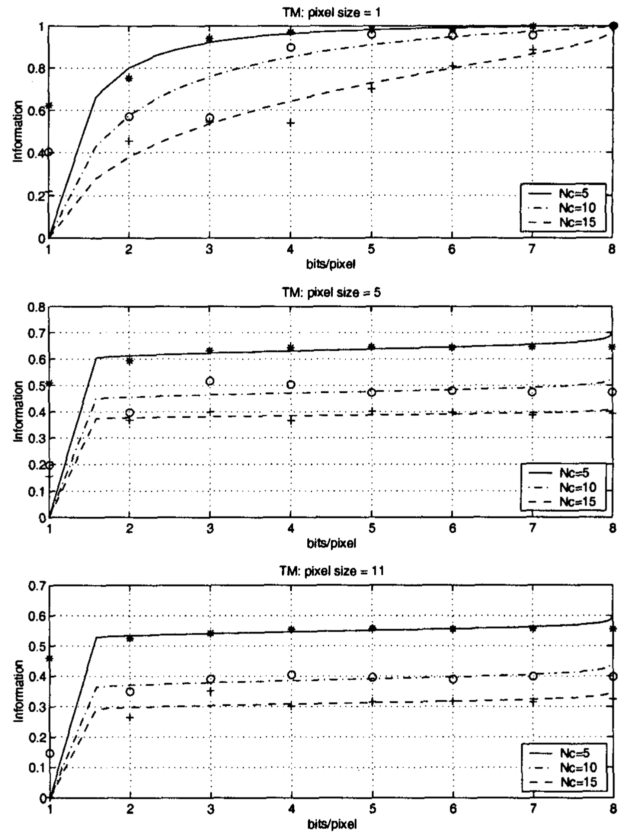

Fig. 4. Graphs of the Morro Bay images for $R = \{1, 5, 11\}$ and $N_c = \{5, 10, 15\}$ are shown. The measured information, I, is shown as points at different values of l, while the modeled information, I_m, is shown as a line.

CONCLUSIONS

This paper presents the effects of gray-scale resolution on the information content of remote sensing imagery. Our formulation relates information content to accuracy of pixel classification. Our study of real imagery indicates that the information content of TM imagery, which have N_c (number of classes) equal to the number of distinctly recognizable classes in the scene, is comparable between 3 and 8 *bits/pixel*, and also lies over 0.9. This property implies that a great deal (at least 4 *bits/pixel*) of memory overhead can be reduced even before applying any compression on the data set.

ACKNOWLEGMENTS

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