A Study of Evaluation of the Feature from Cooccurrence Matrix and Appropriate Applicable Resolution

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Abstract

Since the advent of high resolution satellite image, possibilities of applying various human interpretation mechanism to these images have increased. Also many studies about these possibilities in many fields such as computer vision, pattern recognition, artificial intellegence and remote sensing have been done. In this field of these studies, texture is defined as a kind of quantity related to spatial distribution of brightness and tone and also plays an important role for interpretation of images. Especially, methods of obtaining texture by statistical model have been studied intensively. Among these methods, texture measurement method based on cooccurrence matrix is highly estimated because it is easy to calculate texture features compared with other methods. In addition, these results in high classification accuracy when this is applied to satellite images and aerial photos. But in the existing studies using cooccurrence matrix, features have been chosen arbitrarily without considering feature variation. And not enough studies have been implemented for appropriate resolution selection in which cooccurrence matrix can extract texture.

Therefore, this study reviews the concept of cooccurrence matrix as a texture measurement method, evaluates usefulness of several features obtained from cooccurrence matrix, and proposes appropriate resolution by investigating variance trend of several features.

1. Introduction

Today, many classification techniques use a pixel value of an individual pixel and among these techniques, MLC is popularly used. Since the advent of high resolution satellite image, possibilities of applying various human interpretation mechanism to these images have increased. Also many studies about these possibilities in many fields such as computer vision, pattern recognition, AI, and remote sensing have been performed. In photogrammery, elements of interpretation are defined as shape, size, pattern, tone, texture, shadows, site, and association[1)], and in computer vision, are defined as spectral, texture, and contexture[2)]. Texture contains information about the spatial distribution of tonal variations within a band, and plays an important role for interpretation of images. Two broad classes of techniques to describe texture are methods involving structure model and statistical model[4)]. Especially, method based on statistical model has been mostly studied. Among this method, texture measurement method based on cooccurrence matrix is highly estimated because it is easy to calculate texture features compared with other methods. In addition, these results in high classification accuracy when this is applied to satellite images and aerial photos[3)]. But in the existing studies using cooccurrence matrix, features have been chosen arbitrarily without considering feature variation. And not enough studies have been implemented for appropriate resolution selection in which cooccurrence matrix can extract texture.

Therefore, this study reviews the concept of cooccurrence matrix as a texture measurement method, evaluates usefulness of several features obtained from cooccurrence matrix, and proposes appropriate resolution by investigating variance trend of several features.

2. Cooccurence matrix

Cooccurence matrix describes spatial distribution of pixel values. Then, several texture features can be calculated from cooccurence matrix.

Suppose that the image to be analyzed has N_x pixel in the horizontal direction and N_y in the vertical direction. Suppose that gray tone appearing in each pixel is quantized to N_g levels. Let $L_x=\{1,2,\ldots,N_x\}$ be the horizontal spatial domain, $L_y=\{1,2,\ldots,N_y\}$ be the vertical spatial domain, and $G=\{1,2,\cdots,N_g\}$ be the set of quantized gray tones. The set $L_y \times L_x$ is the set of pixels of the image ordered by their row-column designation. The image can be represented as a function which assigns some gray tone in G to each resolution cell or pair of coordinates in $L_y \times L_x$; I: $L_y \times L_x \rightarrow$G.

Then a single cooccurence matrix is made through the image. Cooccurence matrix has $N_g \times N_g$ dimension and each element shows frequency P_{ij} with which two neighboring pixels separated by distance d occur on the image, one with gray tone i and the other with gray tone j. The angular relationship between the neighboring pixels is illustrated in Fig.1.

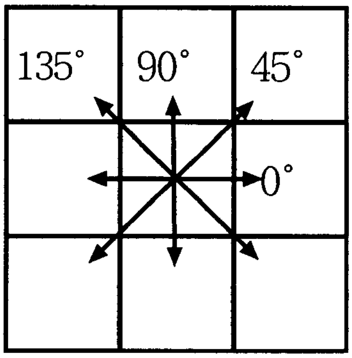


Fig. 1. angular relationship

Then, P_{ij} is calculated by eq. 1.

$$
\begin{aligned}
P(i,j,d,0^\circ) &= \#\{((k,l),(m,n)) \in (L_y,L_x) \\
&\quad \times (L_y,L_x) \mid k-m=0, |l-n|=d, \\
&\quad I(k,l)=i, I(m,n)=j\} \\
P(i,j,d,45^\circ) &= \#\{((k,l),(m,n)) \in (L_y,L_x) \\
&\quad \times (L_y,L_x) \mid (k-m=d, l-n=-d) \\
&\quad \text{or } (k-m=-d, l-n=d), \\
&\quad I(k,l)=i, I(m,n)=j\} \\
P(i,j,d,90^\circ) &= \#\{((k,l),(m,n)) \in (L_y,L_x) \\
&\quad \times (L_y,L_x) \mid |k-m|=d, \\
&\quad l-n=0, I(k,l)=i, I(m,n)=j\} \\
P(i,j,d,135^\circ) &= \#\{((k,l),(m,n)) \in (L_y,L_x) \\
&\quad \times (L_y,L_x) \mid (k-m=d, l-n=d) \text{ or} \\
&\quad (k-m=-d, l-n=-d), \\
&\quad I(k,l)=i, I(m,n)=j\}
\end{aligned}
\qquad \text{(eq. 1.)}
$$

where # denotes the number of elements in the set.

If diagonal elements in the matrix have high value, neighboring pixel values are alike, and it means coarse or smooth texture. On the contrary, if non-diagonal elements in the matrix have high value, there is much variance of pixel values, and the texture is fine. Fourteen texture features that can be calculated from cooccurence matrix are proposed by Robert M. Haralick, K. Shanmugam, and Its'Hak Dinstein[2]. Among the fourteen features, four features that are angular second moment, correlation, inverse difference moment, and entropy are mainly used to describe texture of images[2)5)6)], accordingly this study is bounded by these four features. These are calculated by eq. 2.

1) Angular Second Moment = $\sum_i \sum_j p(i,j)^2$

2) Correlation = $\dfrac{\sum_i \sum_j (ij)\,p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$

3) Inverse Difference Moment =

$$\sum_i \sum_j \frac{1}{1+(i-j)^2}\, p(i,j)$$

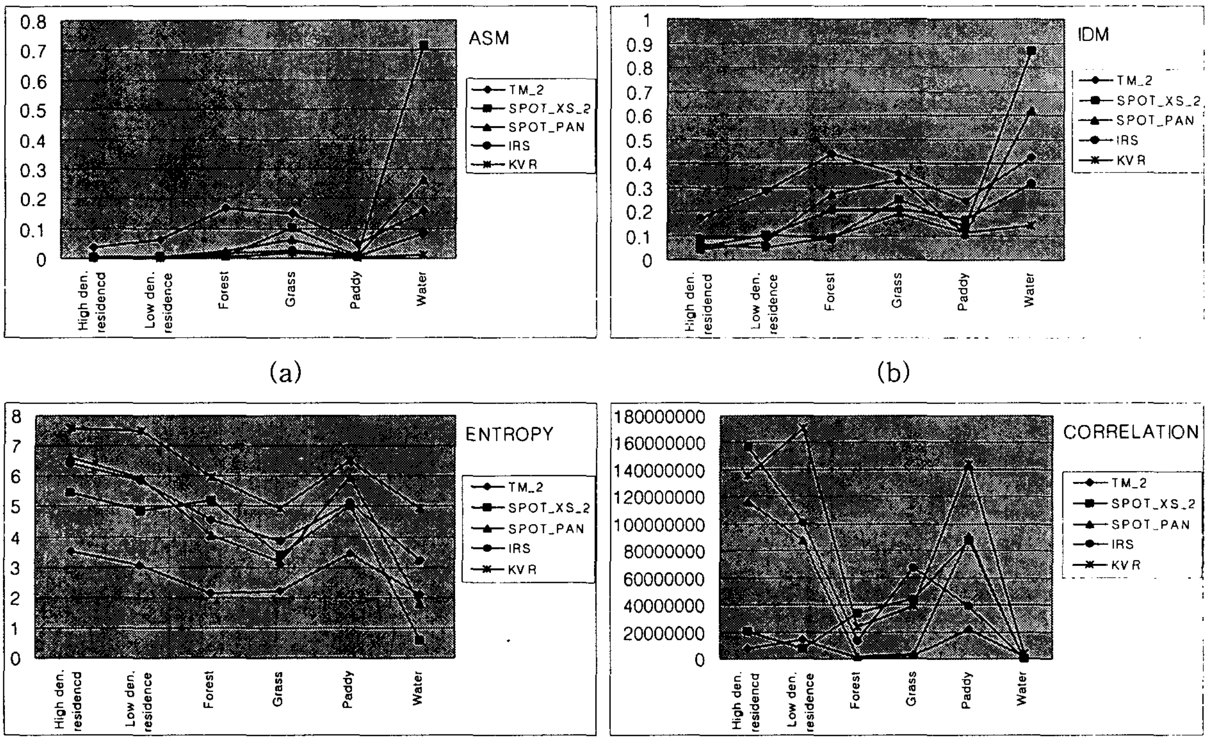
4) Entropy = $-\sum_i \sum_j p(i,j) \log(p(i,j))$

(eq. 2.)

where μ_x, μ_y, σ_x, and σ_y are the means and standard deviations of the marginal distributions associated with $P(i,j)/R$, R is a normalizing constant and the total sum of elements. If $p(i,j)$ equals zero, $p(i,j)$ is substituted for very small value to calculate entropy[2].

Table 1. Images, classes, and number of sub-images in this study

Image size(300m×300m)		Class and number of sub-images					
Image	Resolution	High den. residence	Paddy	Forest	Water	Low den. residence	Grass
Landsat TM band 2	28	10	14	12	12	12	6
SPOT XS band 2	20	10	12	11	8	11	6
SPOT PAN	10	9	11	10	9	12	6
IRS	5.8	9	9	9	9	8	10
KVR-1000	2	9	13	10	10	10	11



(a) (b) (c) (d)

Fig. 2. the variance of features for classes and variance of resolution
(a)ASM (b)IDM (c)ENTROPY (d)CORRELATION

3. Data

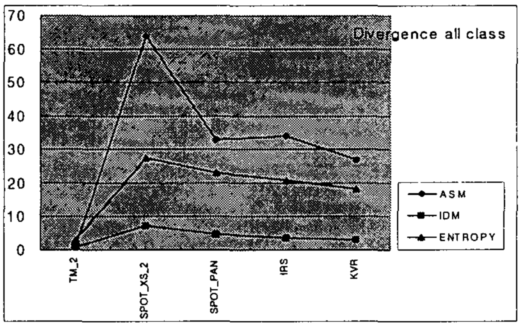
Images, classes, and the number of sub-images in this study are described in table 1, and the study area covers the south of Seoul and Anyang. Since the size of sub-images should be large enough to contain the largest area of the class, the size of sub-images retains 300×300m throughout all sub-images. Accordingly, the size of sub-images is 10×10 pixel in Landsat TM band 2, 15×15 pixel in SPOT XS band 2, 30×30 pixel in SPOT PAN, 50×50 pixel in IRS, and 150×150 pixel in KVR-1000. But a somewhat small size of sub-image is obliged to be selected for paddy and grass, because there is no large site that can contain 300×300m area such a paddy and grass. Since cooccurence matrix is affected by angular relationship, average features are calculated for four angular relationship. The distance of neighboring pixel is set at one pixel in our study, and the color depth of sub-images is 256 color.

4. Result

Fig. 2. shows the variance of features for resolution and class. ASM is defined as the feature that represents homogeneity[2], therefore ASM is smaller as resolution power increases. As resolution power increases, image becomes more detail, accordingly homogeneity of image decreases and ASM decreases. As regards IDM, the variance is similar to the variance of ASM. So IDM is also

related with homogeneity, but absolute value and the variance are larger than those of ASM. On the contrary, entropy represents heterogeneity, and entropy is larger as resolution power increases. Entropy is highly evaluated because variance is consistence according with the variance of resolution. At last, correlation sensitively responds to the number of bright neighboring pixel in case of large color depth. In addition, the variance of correlation is irregular for variance of resolution, so correlation is irrelevant for texture feature.

To measure separability, the average divergence is calculated for each resolution and three features, and excluding correlation. The total number of combination of classes is fifteen, ${}_6C_2$, and Fig. 3. shows the average divergence.



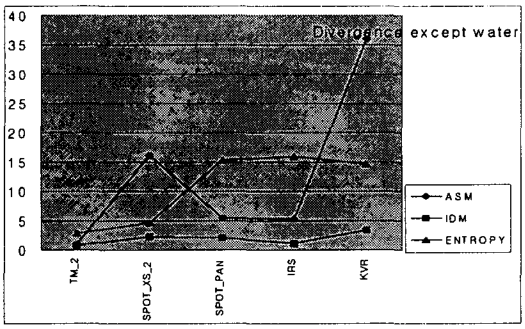


Fig. 3. The average divergence for resolution and the feature(a)(b)

Divergence is the maximum value at SPOT XS band 2 and decreases as resolution power increases. But this is caused by large divergence between high density residence and water[Fig. 3(a)]. To reduce the influence of these, the divergence between high density residence and water is excluded in calculating the average divergence[Fig. 3(b)]. The average divergence of IDM is low and shows small variance for the variance of the resolution, and the variance of the average divergence of ASM is irregular. The average divergence of entropy shows small increment, and then shows rapid increment starting with SPOT PAN, and remains constant.

5. Conclusion

Among the four features selected in our study, ASM, IDM, and Entropy showed consistent variance for class, and IDM showed low average divergence, so ASM and Entropy was highly evaluated as texture features.

There was no distinct trend of variance of ASM for resolution. It seems that the texture is determined by various factors such as land-use, the size of class and sub-image as well as resolution. The variance of entropy for resolution showed different aspect starting with SPOT PAN, it was hard to analyze variance of texture because of arbitrary selection of band. However when entropy is used in classification at image hasing resolution power over 10m, it is expected that the result will be better and uniform.

Further research would be required to develop classification techniques using texture, and to integrate texture features of multi-channel.

6. References

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