Seminar Nasional Aplikasi Teknologi Informasi 2006 (SNATI 2006) *ISSN: 1907-5022*
Yogyakarta, 17 Juni 2006

THE METHODOLOGY OF REMOTE SENSING IMAGE DATA SCALE SPACE FORMING

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ABSTRACT

Remote sensing image has information and reality of earth surface content. The principle aim of the producing n-classes object is information extraction. The need of users can be defined correspond to the information scale of object classes, the scale issue is their studying. It will be important as the scaling property has a characteristic hierarchy and link, from the class level of global scale to detail scale. The scaling is performed by using the Gaussian function, the scaling result with factor of more than 100 gives an homogenous image and also object class forms conserving image.

***Keywords**: remote sensing, image, Gaussian, kernel, space, scale.*

1. Introduction

The remote sensing satellites that map the earth surface of Indonesia, such as LANDSAT ETM, SPOT, MODIS, NOAA, IKONOS, Quick Bird, Orbview, Feun Yeun, etc. Have spectral, spatial and textural characteristic. All spectral, spatial and textural assembly can be located in such of space that emerges spectral, spatial and textural space terminalogy.

The treatment that can be done to a space is in its presentation corresponds to its scale. The presentation correlates to its content, therefore it will provide different information depth.

The above alinea being studied in this paper to develope the scaling methods in a remote sensing image data space. The importence of the scale space existence correlates to the increasing property of remote sensing data nowadays and future, for instant hyperspectral and ultra apectral. The scale space characteristic especially are class structure and connection. They all depend on their ability to explore and exploit the class labeling process.

The paper consist of 7 (seven) sections, that are introduction, filtering theory, methodology, data and processing results, analysis and synthesis, conclusion and the list of literatures.

2. Scale Space Theory

The scale space can be described as multiscale presentation of a convoluted signal by widening Gaussian kernel, the scale space categories into linear and unlinear. The linear scale space is identic to casuality, homogenity, and isotropy, in the contrary with unlinear scale space.

Acording to [1,2], the linear scale space can be constructed by attaching a *Lo* image into a image parameter *L(.,s)*, so that there is a such process look like diffusion with formula as diffusi

$$\partial_t L = \nabla^2 L. \qquad \text{..............................} \; (1)$$

With the original condition of *L(.,0)=L0*. In order to finish the scale space in a special “time” t, can be done by Gaussian convolution, as the following formula

$$L(\cdot, t) = L * G^{\sqrt{2t}} \qquad \text{........................} \; (2)$$

where

$$G^s(\mathbf{x}) = \frac{1}{(s\sqrt{2\pi})^D}\exp(-\frac{\|\mathbf{x}\|^2}{2s^2}). \qquad \text{..........} \; (3)$$

The scale is not the same as the spreading time, the substitution is $s = \sqrt{2t}.$

In relation with the computation, the mathematical derivation is replaced by Gaussian concept, the formula becomes:

$$\partial L \longrightarrow \partial^s L = \partial(L * G^s) = L * \partial G^s \qquad \text{......} \; (4)$$

The equation (4) state that one derivation is replaced by convolution of Gaussian cernel derivation. The calculation can be performed by the following formula:

$$(L * \partial G^s)(\mathbf{x}) = \int_\Omega L(\mathbf{x} - \mathbf{y})\partial G^s(\mathbf{y})d\mathbf{y} \qquad \text{......} \; (5)$$

L is not a function but it is a sample of object class, while ∂G^s kernel widening the spatial. The equation (5) can be explained as the following; that the limited amount of sample, while the Gaussian function has unlimited influence to the sample.

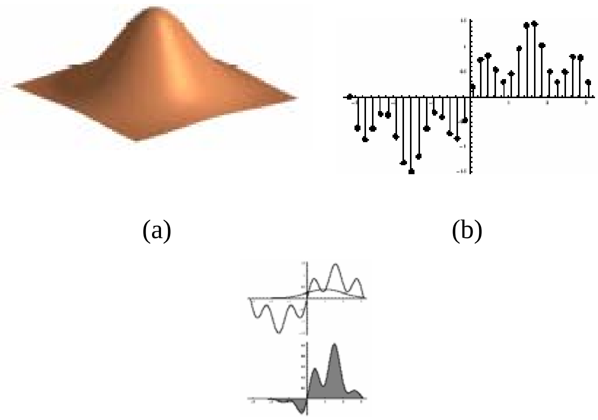
The equation (5) can be presented as convolution form, with formula as follows:

$$(L * W)(\mathbf{x}) = \int_{\Omega} L(\mathbf{x}-\mathbf{y})W(\mathbf{y})d\mathbf{y} \quad \ldots\ldots \quad (6)$$

If it is presented as convolution sum, the formula is following:

$$(\mathsf{L} \star \mathsf{W})(\mathbf{k}) = \sum_{\mathbf{l}\in\Omega} \mathsf{L}(\mathbf{k}-\mathbf{l})\mathsf{W}(\mathbf{l}) \quad \ldots\ldots\ldots \quad (7)$$

The following, the visualization of Gaussian function graph, sample funstion and convolution function.



(a) (b) (c)

Figure 1. (a) Visualization of Gaussian Function; (b) Visualization of Sample Function; (c) Visualization of Convolution Function

In order to convolate a small scale of sample function of Ln, it can be formulate as follows.

$$L^n(x,y) = \frac{1}{n!}x^n \quad \ldots\ldots\ldots\ldots\ldots \quad (7)$$

The equation (7), the n derivation is

$$\partial_{x^n} L^n = 1 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (8)$$

3. The Scaling Methodology

According to [3], the simplification of scaling *(s)* in the scale space is performed by interpolation *(I)*, application *(G)*, and sampling *(S)*, the formula is the following:

$$s = I*G*S \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (9)$$

If the sample image is **B**=$\{b_1 \ldots b_p\}$, then the L function become

$$\mathsf{L}(\mathbf{k}) = \mathcal{S}_B(L)(\mathbf{k}) = L(\mathbf{Bk}) \quad \ldots\ldots\ldots\ldots\ldots \quad (10)$$

To interpolate B, can be used the interpolation methods bellow:

$$\mathcal{I}_{B,\phi}(\mathsf{L})(x) = \sum_k \phi(x - Bk)\mathsf{L}(k) \quad \ldots\ldots\ldots\ldots\ldots \quad (11)$$

The convolution of L in interpolation approach, results

$$\begin{aligned}(\mathcal{I}_{B,\phi}\mathsf{L} * W)(x) &= \int_{\mathbb{R}^D}\left(\sum_k \phi(x-y-Bk)\mathsf{L}(k)\right)W(y)dy \\ &= \sum_k \mathsf{L}(k)\int_{\mathbb{R}^D}\phi(x-y-Bk)W(y)dy \\ &= \sum_k \mathsf{L}(k)\,(\phi * W)\,(x-Bk) \quad \ldots\ldots \quad (12)\end{aligned}$$

The equation (11), can be explained that the convolution integral count for the the sample image sum convolution approach and kernel sample. The accuracy depends on the interpolation accuracy.

Briefly the derivation methodology of the Gaussian scale space is:

$$f_\sigma(x,y) = g_\sigma(x,y) * f(x,y) \quad \ldots\ldots\ldots \quad (12)$$

$$\frac{\partial f_\sigma}{\partial x} = \frac{\partial g_\sigma}{\partial x} * f \quad \ldots\ldots\ldots\ldots\ldots \quad (13)$$

4. Data and Processing

This research uses multispectral data, by using Landsat ETM (Enhanced Thematic Mapper) sensor, Figure 2 shows around Soekarno Hatta Airport areal. The specification of used data in the research can be seen in Table 1. The image size is 488 x 329 x 3 = 160.552 byte, snd its resolution is 15 m. This data is acquired in 1 Juni 2001. The geographical characteristic of the image is using Universal Transform Marcator (UTM) projection, with datum WGS 48 S and the geographic location of data is (LL: 6°7'52.20"S, 106°42'2.85"E) or (834652.50E,9287167.50S).

Table 1. Wavelength Spektral of LANDSAT ETM

No	*Band Width (nm)*	*Mid Wavelength (μm)*
1	5,7	445,7
2	5,8	503,0
3	5,8	532,9
4	5,8	571,3
5	4,9	602,4
6	5,8	651,6
7	5,8	674,3
8	5,9	710,5

This location is selected because of it has unique object classes and relatively stable; such as building, ponds, grass pattern, aspal roads and trees. The conservated of forms, texture and the greeness give opportunity in observation and research of the administration border. The research location is Soekarno Hatta airport, Tangerang region, Province Banten that can be seen in the Figure 2. All calculation and other processing was conducted by using PC and Matlab 7.2.

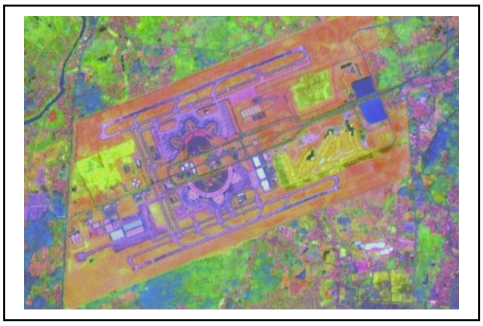


Figure 2. Landsat ETM Image

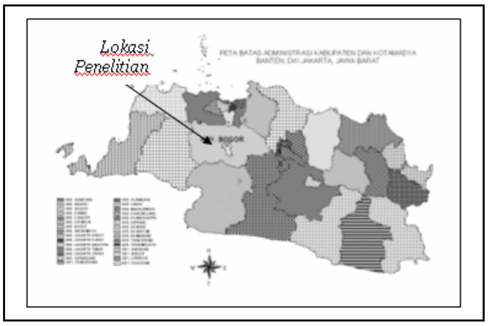


Figure 3. Researach Location

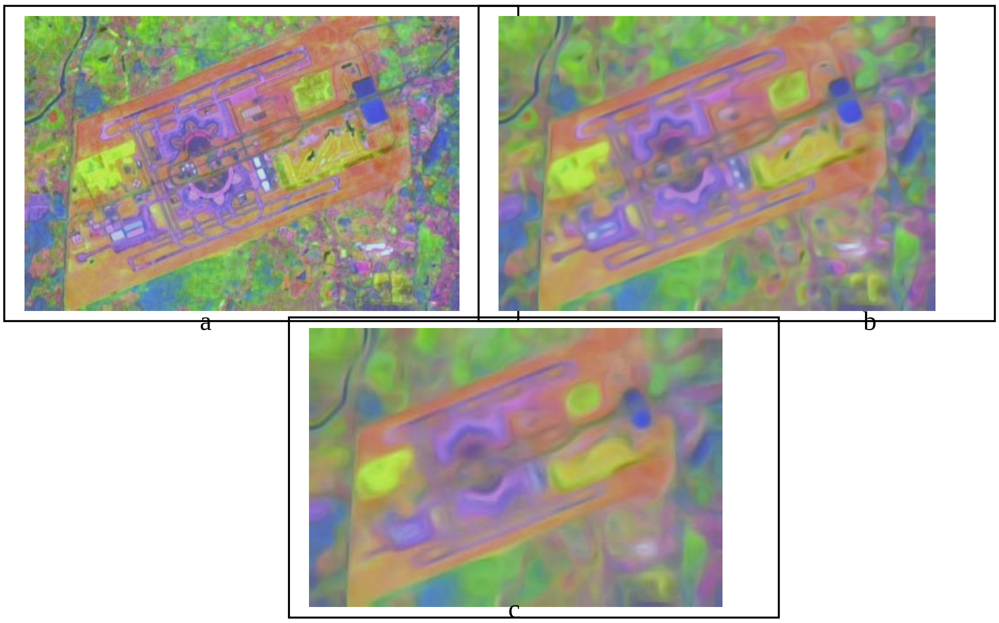


Figure 4. (a) Scaling of factor 5; (b) Scaling of factor 100; (c) Scaling of factor 500

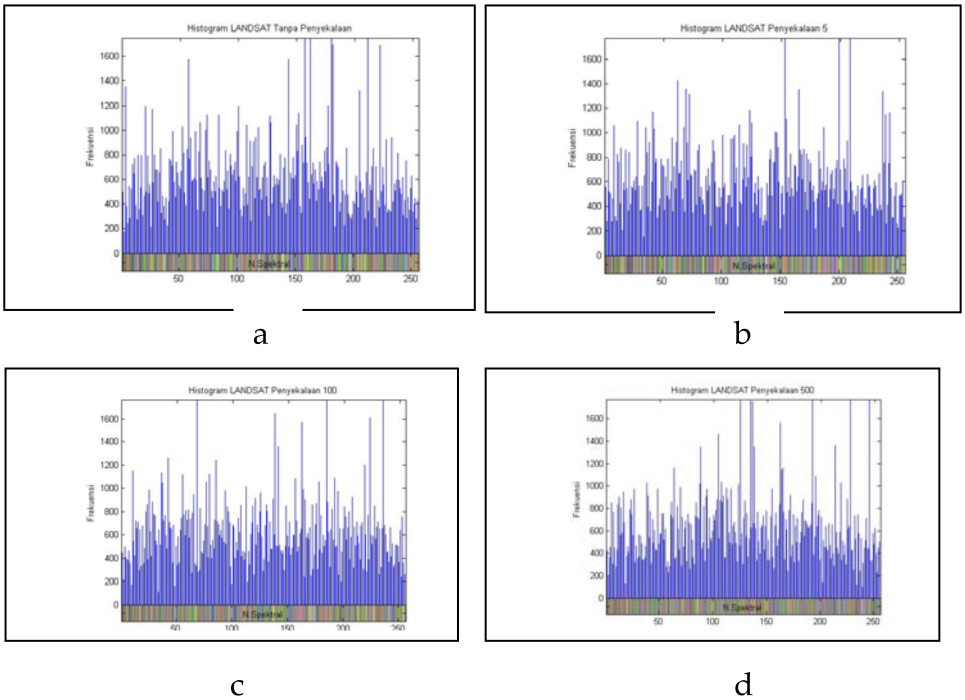


Figure 5. (a) Histogram of no scaling; (b) Histogram of scaling factor 5; (c) Histogram of scaling factor 100; (d) Histogram of scaling factor 500

5. Processing Result

5.1 Scaling Result

Figure 4.a explain that the result of scaling of factor 5 compare to the original image has almost the same feature classes. But the differences can be seen physically in figure 5.b. The quantitatively can be shown in the statistcal calculation result in figure 5.b.

Figure 4.b explain that scaling of 100 has a significant change of original image. There is some group of object classes with some medium homogenities. They can be seen from the object class feature forms, such as apron/ airport buildings, runway, pond near runway end, grass pattern around the runway and airport.

5.2 The Histogram of Scaling

Figure 4.c is the result of scaling of 500. It shows that the image has a high homogenity. It is easier to group the object classes. Therefore from the figure 4.a, 4.b and 4.c it is known that there is hierarchy of objec classes. Figure 4.c has less object classes than figure 4.b and less than figure 4.a. This fenomenon indicates that scale space can be used in processing remote sensing data.

5.3 Statistical Calculation

a. No Scaled Image

Band	Min	Max	Mean	Stdev
1	56	232	148.685566	33.394490
2	68	242	142.923607	28.597587
3	0	254	123.792298	37.897499

Covariance Matrix

Band	Band 1	Band 2	Band 3
1	1115.191967	176.021703	-58.594860
2	176.021703	817.822001	-410.886014
3	-58.594860	-410.886014	1436.220421

Correlation Matrix

Band	Band 1	Band 2	Band 3
1	1.000000	0.184316	-0.046299
2	0.184316	1.000000	-0.379124
3	-0.046299	-0.379124	1.000000

b. Scaled 5 Image

Band	Min	Max	Mean	Stdev
1	53	236	148.567218	32.155178
2	67	245	142.845919	27.538045
3	0	255	123.673701	36.239117

Covariance Matrix

Band	Band 1	Band 2	Band 3
1	1033.955445	151.960230	-74.046986
2	151.960230	758.343930	-418.403211
3	-74.046986	-418.403211	1313.273588

Correlation Matrix

Band	Band 1	Band 2	Band 3
1	1.000000	0.171611	-0.063545
2	0.171611	1.000000	-0.419261
3	-0.063545	-0.419261	1.000000

c. Scaled 100 Image

Band	Min	Max	Mean	Stdev
1	64	211	147.786736	29.863402
2	77	237	142.216478	24.905842
3	28	241	123.493304	33.548966

Covariance Matrix

Band	Band 1	Band 2	Band 3
1	891.822797	87.543530	-124.462185
2	87.543530	620.300977	-460.612673
3	-124.462185	-460.612673	1125.533100

Correlation Matrix

Band	Band 1	Band 2	Band 3
1	1.000000	0.117702	-0.124228
2	0.117702	1.000000	-0.551259
3	-0.124228	-0.551259	1.000000

d. Scaled 500 Image

Band	Min	Max	Mean	Stdev
1	67	201	147.735681	27.672430
2	84	234	141.792217	22.583065
3	31	224	123.474718	30.864132

Covariance Matrix

Band	Band 1	Band 2	Band 3
1	765.763403	49.369511	-110.483973
2	49.369511	509.994808	-424.836920
3	-110.483973	-424.836920	952.594648

Correlation Matrix

Band	Band 1	Band 2	Band 3
1	1.000000	0.079000	-0.129359
2	0.079000	1.000000	-0.609516
3	-0.129359	-0.609516	1.000000

5.4 Synthesis and Analysis

Visually, there is a feature color changing, from divergence spreading color to convergence, indicated by the reduction of the various type object class number. The obviously can be seen in the un scaled image and scale of factor 500.

In realizing of an homogeneity of class, will easier to object classification, that is called scaling process. The pattern of the resulted scale of statistical result, obviously can be known in the covariance matrix and correlation matrix, histogram pattern of its statistic is also different. The indication points that scaling process has been run that result to object class.

6. Conclusion

The scaling gives a meaning of the execution of object class classification in remote sensing, therefore will give the estimation of class numbers. The Gaussian function can be utilized for the scaling of the remote sensing image. The result is quite significant in developing the remote sensing image scale.

References

[1] Lindeberg, T., *Scale-Space Theory in Computer Vision*, Kluwer Academic Publishers, The Netherlands, 1994.
[2] Rein van den Boomgaard, *Algorithms for Linear Scale-Space*, University of Amsterdam, January 2004
[3] Vasile Gui, *Kernel Density Estimation Techniques With Applications To Image Filtering And Segmentation*, Polytechnic University of Timisoara, 2005

Enclosure

```
function Ig=gaussian(I,uk,sg)
% I=input citra
% uk = ukuran kernel
% sg = simpangan gauusian

[Ny,Nx]=size(I);
huk=(uk-1)/2;  % ukuran kernel
if (Ny<uk)   % konvolusi 1 D
    x=(-huk:huk);
    filter=exp(-(x.^2)/(2*sg));  % gaussian
1D
    filter=filter/sum(sum(filter));  %
normalisasi
   % Perluasan
   x0=mean(I(:,1:huk)); xn=mean(I(:,Nx-
huk+1:Nx));
    eI=[x0*ones(Ny,uk) I xn*ones(Ny,uk)];
    Ig=conv(eI,filter);
    Ig=Ig(:,uk+huk+1:Nx+uk+huk);
else
   %% Konvolusi 2D
    x=ones(uk,1)*(-huk:huk); y=x';
    filter=exp(-(x.^2+y.^2)/(2*sg));  %
gauusian 2D
    filter=filter/sum(sum(filter));  %
normalisasi
   % Perluasan
   if (huk>1)
      xL=mean(I(:,1:huk)')';
xR=mean(I(:,Nx-huk+1:Nx)')';
   else
      xL=I(:,1); xR=I(:,Nx);
   end
   eI=[xL*ones(1,huk) I xR*ones(1,huk)];
   if (huk>1)
      xU=mean(eI(1:huk,:)); xD=mean(eI(Ny-
huk+1:Ny,:));
   else
    xU=eI(1,:); xD=eI(Ny,:);
   end
    eI=[ones(huk,1)*xU; eI;
ones(huk,1)*xD];
    Ig=conv2(eI,filter,'valid');
end
```