A Structure Pattern Extraction by Using Morphological Component Analysis in the Aerial Image Edge Detection

Wataru Oshiumi[1]
[1]Kyushu Institute of Technology, 2-4 Hibikino, Wakamatsu-Ku, Kitakyushu, 808-0196, Japan

Ankur Dixit[1]
[1]Kyushu Institute of Technology, 2-4 Hibikino, Wakamatsu-Ku, Kitakyushu, 808-0196, Japan

Hiroaki Wagatsuma[1,2]
[1]Kyushu Institute of Technology, 2-4 Hibikino, Wakamatsu-Ku, Kitakyushu, 808-0196, Japan
[2]RIKEN CBS, Japan

E-mail: oshiumi.wataru745@mail.kyutech.jp, ankur.dixit003@gmail.com, waga@brain.kyutech.ac.jp

Abstract

Automated extraction of areas of interest from aerial images is a central issue for map makers. The road skeleton is one of the most frequent targets, and then the prefiltering of road structures is highly important; however, the isolation of man-made structures from a natural landscape is technically tricky because image parts to represent natural geographical features are not uniform patterns. In the present study, we focused on the function of the Morphological Component Analysis (MCA) method to extract structural patterns when dictionaries were appropriately given and demonstrated the effectiveness of edge detection if the prefiltering was done by using MCA. MCA decomposes the image into two patterns in our computer experiment with Curvelet transform and Local Discrete Cosine Transform (LDCT) dictionaries. This approach will explore extensive possibilities of structural data extraction from complex images as an automated method.

Keywords: Morphological Component Analysis, Edge detection, Curvelet transform, Local discrete transform

1. Introduction

The detection of man-made structures from aerial photographs, such as roads on the land surface, can be performed with a certain level of accuracy using deep learning [1][2][3]. On the other hand, detections of non-uniform structures, especially with natural patterns, including forests, are still challenging issues with respect to schemes using machine learning and deep learning.

As an alternative option, it is worthwhile to apply morphological component analysis (MCA) to tackle those issues[4], which has the advantage of extracting a target texture pattern by implementing an appropriate dictionary as a signal basis. The MCA method also considered the possibility of image denoising and decomposition when extracting specific patterns in the map image data [5]. In the sense of the decomposition of components that conform image or signal, target data can be separated from the original data. In the case of aerial photography, the same strategy can be applied to obtain the target structure. In the present study, we focused on the structural decomposition method of MCA and demonstrated the effectiveness of edge detection from the decomposed data.

Therefore, the decomposition performance will be a measure to evaluate the accuracy of MCA for the present purpose the effectiveness of edge detection can be discussed. In MCA, a dictionary selection is also an issue, while as a preliminary study, we focused on the function of local discrete cosine transform (LDCT) and curvelet transform (CURVE) [6]. This approach will explore extensive possibilities of structural data extraction from complex images as an automated method.

2. Methods

2.1. *Image decomposition in sparse modeling*

In the present paper, it is assumed that an image consists of two structures. If the original image is X and the two

structures are x_0 and x_1, we can express them from Eq. (1) and Eq. (2). Furthermore, the decomposition was performed with x_0 as the background and x_1 as the structure information of the aerial photograph.
Next, consider the original image X. After decomposing from Eq. (3), structures x_0 and x_1 can represent the original image X, and the coefficients corresponding to the dictionary α_k are denoted by T_k to represent x_k from Eq. (4).

$$\mathrm{X} = x_0 + x_1 \tag{1}$$

$$\mathrm{X} = \begin{bmatrix} x_0 \\ x_1 \end{bmatrix} \tag{2}$$

$$\mathrm{X} = \sum_{k=0}^{1} T_k \alpha_k \tag{3}$$

$$T_k \alpha_k = x_k \tag{4}$$

The basis α_k and the coefficients T_k are X using Eq. (3) and Eq. (4). Find the basis α_k and the corresponding coefficients T_k.
Since the original image X is represented sparsely using a dictionary, it can be defined as an optimization problem for image decomposition from Eq. (5).

$$\{\alpha_0, \alpha_1\} = \arg min_{\{\alpha_0,\alpha_1\}} \|\alpha_0\|_0 + \|\alpha_1\|_0$$
$$\text{Subject to:}\, \mathrm{X} = \mathrm{T}_0\alpha_0 + \mathrm{T}_1\alpha_1 \tag{5}$$

By relaxing the l_0 norm to the l_1 norm and using the Lagrange undetermined multiplier method, an approximation can be made to Eq. (6).

$$\{\alpha_0, \alpha_1\} = \arg min_{\{\alpha_0,\alpha_1\}} \|\alpha_0\|_1 + \|\alpha_1\|_1$$
$$+\lambda\|X - \mathrm{T}_0\alpha_0 - \mathrm{T}_1\alpha_1\|_2^2 \tag{6}$$

This paper used LDCT and curvelet transform dictionaries to decompose the images. In the LDCT transform, the window interval size and the truncation percentage of the low-frequency component represented by each interval were changed. The number of layers was considered and investigated in the curvelet transform.

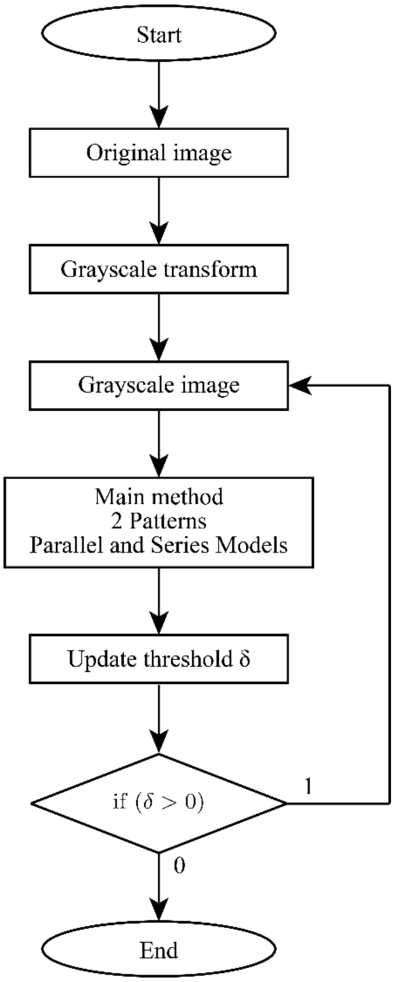
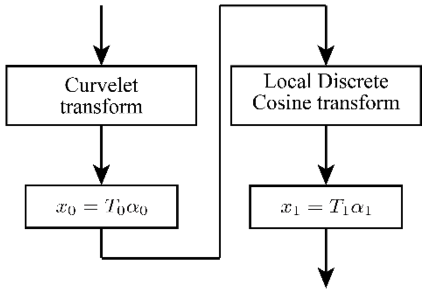
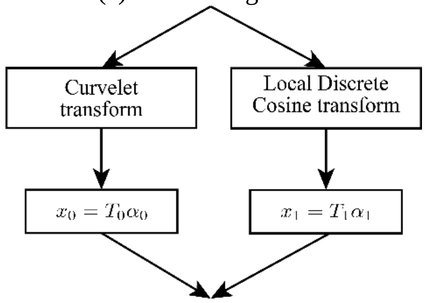


Fig.1. General flowchart of the system



(a) Searial algorithm



(b) parallel algorithm

Fig.2. Flowchart of the system

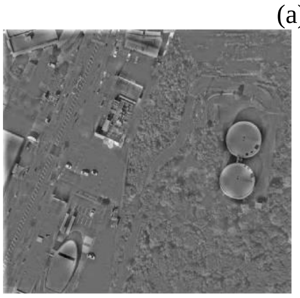
In the first place, a flow diagram of the decomposition process is shown (Figure 1). As shown in the flow diagram, the method first performs a grayscale transformation on the color image. In the second place, each dictionary is used to obtain the coefficients, and the coefficients are repeatedly compared using a threshold value δ to perform decomposition while maintaining sparsity. In addition, the decomposition method was divided into a serial algorithm (Figure 2(a)) and a parallel algorithm (Figure 2(b)). The detection results were compared to verify the effectiveness of each method.

2.2. *Edge detection*

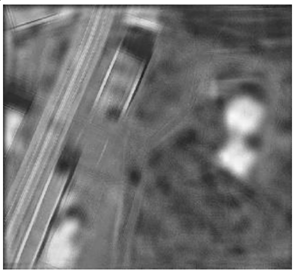
In the computer experiment, the result will be evaluated after the edge detection by filter processing using the Canny filter due to the clarification of how much the target

structure can be extracted accurately [7]. The edge detection is characterized by comparing the luminance values between adjacent or nearby pixels to detect the outline of a structure. In this sense, it is important to detect the outline of complex structures such as forests, leaves, and other small components of the structure, making it difficult to detect the forest itself. Therefore, detecting a specific structure in multiple areas, such as forests, is not a simple problem for pattern matching scheme and learning scheme with teacher patterns. In the proposed system, fine and coarse components are decomposed, and the outline of only the structure is extracted by subtracting the fine components, which are tuned for the forest in the image.

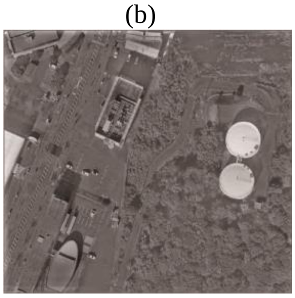
(a)



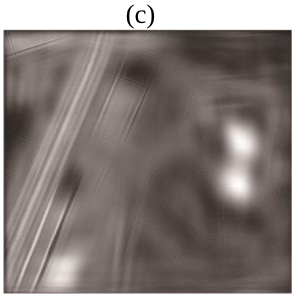
(b)



(c)



(d)



(e)

Fig.3. Decomposed results by MCA with two dictionaries in algorithms as shown in Figure 2. Original image (a), LDCT image in the serial algorithm (b), CURVE image in the serial algorithm (c), LDCT image in the parallel algorithm (d), CURVE image in the parallel algorithm (e).

3. Results and Discussion

3.1. *Decompose aerial image*

The original image was converted to grayscale in Figure 3(a). The decomposition results are shown in Figure 3(b) and Figure 3(c) for a serial algorithm and in Figure 3(d) and Figure 3(e) for a parallel algorithm. The decomposition of texture and background was performed using the method shown in Method 2. The LDCT image (b) is the texture, and the Curvelet image (c) is the background (Figure 3(b) and Figure 3(c)). In this case, it can be seen that structures and the superficial structure of the forest are extracted in the LDCT image. On the contrary, no such features can be seen in the Curvelet component.

Figure 3(d) and Figure 3(e) show images decomposed by the parallel algorithm. As in Figure 3(d) and Figure 3(e), the LDCT image (d) is the texture, and the curvelet image (e) is the background.

It can be seen that the parallel algorithm extracts more structure from the texture than the serial algorithm.

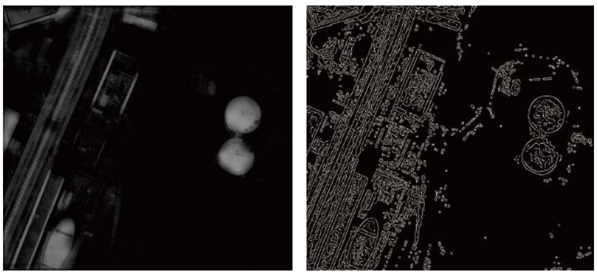
This method also used "16" for the window interval used in the LDCT and 5 for the curvelet transform.

3.2. *Edge detection by using Canny filter*

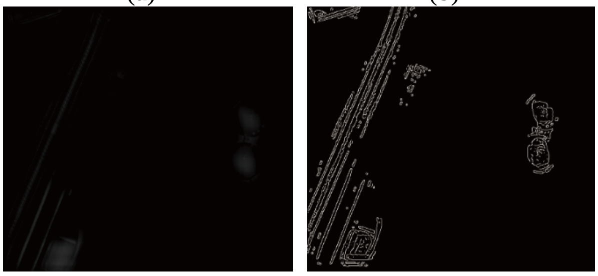
Fig.4. Edge detection from the original image (without MCA)

Figure 4 shows edge detection from the current image.

In this paper, we focus on the texture after decomposition and remove the forest area from the viewpoint of edge detection. Normally, forest areas in aerial photographs are composed of a sequence of detailed information on trees, so edge detection detects the edges of trees and leaves, making it difficult to obtain an outline of the area.



(a) (b)



(c) (d)

Fig.5. Edge detection results after MCA. Subtraction of LDCT image from the original (a) and its edge detection (b) in the serial algorithm, and Subtraction of LDCT image from the original (c) and its edge detection(d) in the parallel algorithm.

A decomposed image by MCA is used. Focusing on the decomposed image with the serial algorithm shown in Figure 5(a) and Figure 5(b), it can be seen that the decomposed image (texture) is subtracted from the original image, and edge detection is performed from Figure 5(b) to capture the outline of the structure without acquiring detailed information such as forests.

On the other hand, focusing on the decomposed image in the parallel algorithm shown in Figure 5(c) and Figure 5(d), the difference of the decomposed image (texture) is obtained from the original image, and edge detection is performed from Figure 5(d), which does not extract forest information but fails to detect other edges as well. In other words, it is necessary to determine the value and decomposition method of these features according to various situations.

4. Conclusion

This paper describes the possibility of removing the target objects by using dictionaries appropriately and focusing on the structural pattern extraction function. We believe this method has broad potential as an automated method for structural data extraction from complex images and can be applied to other fields.

Acknowledgements

This work was supported in part by JSPS KAKENHI (16H01616, 17H06383), Project on Regional Revitalization Through Advanced Robotics (Kyushu Institute of Technology/Kitakyushu city, Japan) and the New Energy and Industrial Technology Development Organization (NEDO).

References

1. S. Saito, Y. Aoki, "Building and road detection from large aerial imagery", Proceedings of SPIE, The International Society for Optical Engineering, February 2015.
2. M. Negri, P. Gamba, G. Lisini, Florence Tupin, "Junction-Aware Extraction and Regularization of Urban Road Networks in High-Resolution SAR Images", EEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 44, NO. 10, OCTOBER 2006.
3. G. Koutaki, K. Uchimura, S. Wakisaka, "Road Extraction from Aerial Imagery based on Crossing Detection", IPSJ SIG Technical Report.
4. M. Elad, J.-L. Starck, P. Querre, D.L. Donoho, "Simultaneous cartoon and texture image inpainting using morphological component analysis (MCA)", Applied and Computational Harmonic Analysis,Volume 19, Issue 3, November 2005, Page 340-358.
5. J.-L. Starck, Y. Moudden, J. Bobin, M. Elad, D.L. Donoho, "Morphological Component Analysis", Proceedings of SPIE – The International Society for Optical Engineering, August 2005.
6. E. Candes, L. Demanet, D. Donoho and L. Ying, "Fast Discrete Curvelet Transforms", July 2005, revised March 2006.
7. W. Rong, Z. Li, W. Zhang and L. Sun, "An Improved Canny Edge Detection Algorithm", Proceedings of 2014 IEEE, International Conference on Mechatronics and Automation, August 3 - 6, Tianjin, China.

Authors Introduction

Mr. Wataru Oshiumi

He received his Bachelor's degree in Engineering in 2022 from the Faculty of Engineering, Kyushu Institute of Technology in Japan. He is currently a Master's student at Kyushu Institute of Technology, Japan.

Mr. Ankur Dixit

He received his Master's degree in Electronics & Communication Engineering in 2014 from National Institute of Technology (NIT), Kurukshetra, Haryana, India. He worked in the Mangalayatan University as an assistant professor in 2014-2017. He enrolled at the PhD course in Kyushu Institute of Technology, Japan from 2017 and he is receiving the PhD supervision.

Dr. Hiroaki Wagatsuma

He received his M.S., and Ph.D. degrees from Tokyo Denki University, Japan, in 1997 and 2005, respectively. In 2009, he joined Kyushu Institute of Technology, where he is currently a Professor of the Department of Human Intelli- gence Systems. His research interests include non- linear dynamics and robotics. He is a member of IEEE.