SUGISAKA MASANORI

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Research Article

A Comparative Analysis of Serial and Parallel Models in the Morphological Component Analysis-Based Structure Pattern Extraction for Aerial Image Edge Detections

Wataru Oshiumi, Ankur Dixit, Hiroaki Wagatsuma
Kyushu Institute of Technology, 2-4 Hibikino, Wakamatsu, Kitakyushu, 808-0196, Japan

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ABSTRACT

A refinement process by human experts is still needed for areas/feature extractions of interest from aerial images in multiple map makers. The construction/road edge extraction is one of them which is highly important in the preprocessing stage for map-making, while it is difficult to isolate man-made structures from a natural landscape involving different size objects. In the present study, we focused on an actual procedure in the decomposition of the Morphological Component Analysis known as MCA to extract specific patterns as serial and parallel models. In our computer experiments, dictionaries of Curvelet and Local Discrete Cosine Transform known as LDCT were introduced for the MCA decomposition and then two models demonstrated a non-negligible difference in the feature extraction performance. This result may contribute to the extension of future possibilities of structural data analyses especially for buildings and roads from shapes in nature.

1. Introduction

In the map-making process from aerial photographs, a man-made structure extraction is unavoidable because of the isolation of roads and buildings from natural landscapes and recently accuracy levels in deep learning schemes were discussed [1][2][3]. Feature analyses of natural shapes including woods and forests is a difficult task in common in the image processing history.

As an alternative approach, an image processing with MCA is highlighted as an accurate feature extraction method by selecting an appropriate set of dictionaries [4], without pre-learning stages, which is necessary for machine learning and deep learning systems. The MCA-based denoising and decomposition of features was theoretically proposed and applied to image processing [5]; however, an actual implementation of this method is considerable for improvements of the accuracy level of features not only in the dictionary selection, but also serial and parallel models in the implementation model of MCA. In the present study, the MCA decomposition performance was verified in the case of aerial photographs. LDCT and Daubecheis basis known as Curvelet [6] were introduced for target dictionaries and then image sections of residential district with houses and apartments and natural landscapes were examined for the comparison of the feature extraction performance in MCA.

2. Methods

2.1. *Image decomposition using sparse modeling*

For the sake of simplification, two types of structural features were assumed in the process. Suppose that the original image is X and two structures are denoted as x_0 and x_1, they are described as vectors as Eq. (1) and Eq. (2), and it is supposed that the target information is obtained after decomposition in which x_0 is the background and x_1 is the structural information of the aerial photograph.

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

In the consideration of the original image X, Eq. (3) represents a possible decomposition of the original data as image X by using the linear combination of vectors as the general expression of the sum of x_0 and x_1, and it leads Eq. (4). Thus, x_k can be expressed by the relationship between the dictionary α_k and coefficient T_k.

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

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

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

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

Therefore, the original image X is represented by Eq. (3) and Eq. (4) in the sense of the relationship between the bases α_k and T_k.

By assuming that the original image X is composed for each feature based on an index called a dictionary, it is formulated in a form of optimization problems in image decomposition as described in Eq. (5).

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

In Eq. (5), the optimization problem with l_0 norm and l_1 norm is converted to Eq. (6) by using Lagrange's method of undetermined multipliers.

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

By using the scheme, we assumed that the image can be decomposed using dictionaries of LDCT, which is consist of sine waves, and Curvelet. In the case of LDCT transform, parameters of signal resolutions and time windows in the low frequency component can be modified. In the case of Curvelet, we also adjusted the number of layers for the optimization for the target image.

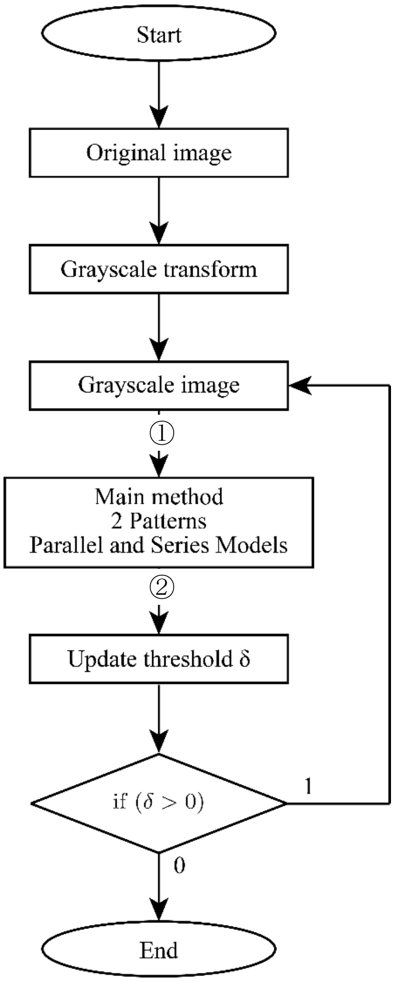
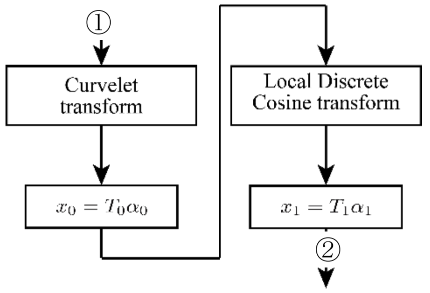
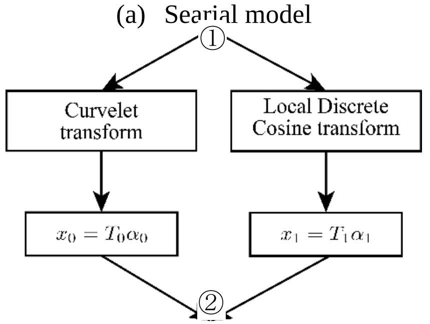


Fig.1. Flowchart of this method



(a) Searial model



(b) Parallel model

Fig.2. Flow diagram of parallel and serial models

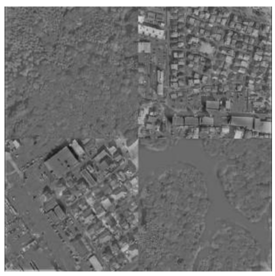
The flow diagram for the proposed image decomposition method was shown in Figure 1. In the flow diagram, a process was set to convert from color image to grayscale image in the beginning. The converted image is transmitted to MCA main process, which estimates appropriate coefficients mapping to individual dictionaries. The process is repetitively applied to residual components in the loop and then it is evaluated until the error is under the threshold value. It indicates that decomposed components exceed a satisfactory level to reproduce the original image, which is the goal of the system as performing decomposition with respect to the maintenance of sparsity in the representation. Interestingly, two different flows are considerable to realize the main process as shown in Figure 2. We call those the serial model (Figure 2(a)) and the parallel model (Figure 2(b)). In the validation of the effectiveness of two models, image sections of residential areas and natural landscapes were applied to the evaluation process.

2.2. *Evaluation method*

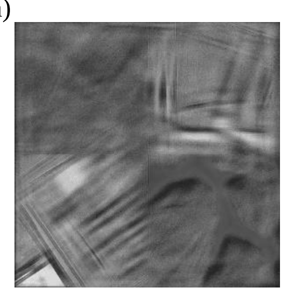
In the evaluation of the effectiveness, the function of edge detections was verified by using filtered images with a Canny filter, which is consistent with the result by Rong et al. (2014) [7]. The edge detection performance is a plausible measure because of contours on an image exhibiting brightness levels of adjacent pixels is apparently useful to be a basement of the map-making process. If it is difficult to capture the contours of images, such as forests and houses, it can be concluded that the MCA does not work for the purpose. Natural landscapes are dynamic and complex accompanied with a hierarchical substructure, it is difficult to prepare the standard, or templates for learning schemes in principle. In MCA, individual dictionaries have a capability of recursive decompositions in scales, which is consistent with Fourier transformation and wavelet transformation. Thus, an accurate extraction is expected from the contour generation in MCA.

In this sense, two types of the image section were used for the evaluation as a comparative analysis of whether it is containing only the forest or containing mainly building structures. The criterion was designed as the summation of the number of pixels in the decomposed image after the feature extraction.

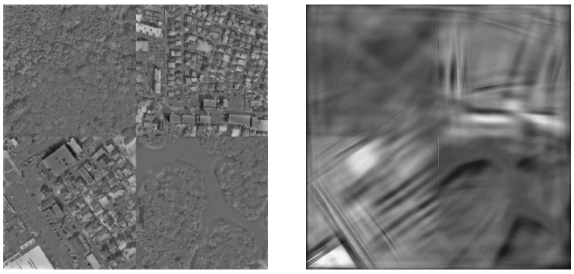
(a)



(b)



(c)



(d) (e)

Fig.3. Decomposition by MCA using two dictionaries from the model shown in Figure 2.
Original image (a), LDCT image by serial model (b), CURVE image by serial model (c), LDCT image by parallel model (d), CURVE image by parallel model (e).

3. Results and Discussion

3.1. *Decompose aerial image*

In computer experiments, four types of images were analyzed as shown in Figure 3(a), which contains forest1 (upper-left), forest2 (lower-right), structure1 (upper-right) and structure2 (lower-left).

Figure 3(a) demonstrated the conversion from the original image to a grayscale image. Figure 3(b) and Figure 3(c) showed decomposition results from the serial model. Figure 3(d) and Figure 3(e) showed decomposition results from parallel models. Those process were described in the previous section. The texture from the LDCT dictionary (LDCT component) and the texture from the Curvelet dictionary (Curvelet component) appear differently (Figure 3(b) and Figure 3(c)). It implies that it is able for MCA to discriminate forests and building structures by focusing on the LDCT component. Conversely, there is no significant appearance in the Curvelet component.

Figure 3(d) and Figure 3(e) showed decomposed images by the parallel model. As the result in Figure 3(d) and Figure 3(e), it is considerable that the LDCT image (d) represents the texture, and the Curvelet image (e) represents the background.

According to the result, the parallel mode finely extracted building structures rather than the serial model.

In this experiment, 16 as the window interval in the LDCT and 5 as the window interval in the Curvelet transform were used.

3.2. *Edge detection by using Canny filter*

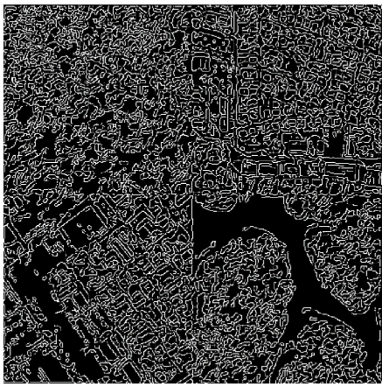
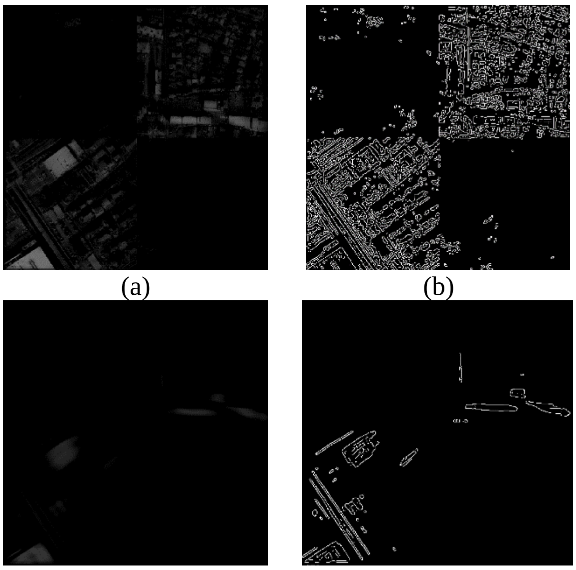


Fig.4. Edge detection in the original image

Figure 4 showed the edge detection from the original image without the MCA main process.

It indicates that an appropriate process to tune a target structure is truly necessary before the edge detection, otherwise every tiny structure will be detected even in the natural landscape. In this case, the edge detector responds to those features, no matter what the image includes natural landscapes or buildings.



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

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

By using the MCA main process, the decomposed image by the serial model clearly exhibits a significant difference in cases of forest1 (upper-left), forest2 (lower-right), structure1 (upper-right) and structure2 (lower-left) as shown in Figure 5(a) and Figure 5(b). The decomposed image (texture) was subtracted from the original image. The result clearly demonstrated the target function.

In the parallel model as shown in Figure 5(c) and Figure 5(d), there are some effects to extract features to represent buildings, however the result was unclear in comparison with the result of the serial model (Figure 5(d)).

3.3. *Sum of pixel values*

For the numerical validation of the effectiveness of two models, pixel counting in results of forest1-2 and structure1-2 was introduced. It counts pixels in each region of Figure 5(a) and Figure 5(c).

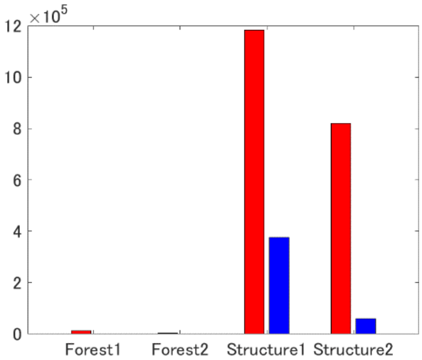


Fig.6. Sum of pixel values in serial (red) and parallel (blue) models

Figure 6 showed the result of the numerical evaluation. The red bar represents the total amount of pixels in the serial model, and the blue bar represents the total amount of pixels in the parallel model. As is shown in Figure 6, a significant difference was shown in the comparison between serial and parallel models.

In the overall evaluation, the serial model is an appropriate model for the present purpose.

4. Conclusion

We focused on the structural pattern extraction performance by using MCA and evaluated in the comparison between serial and parallel models. In the analysis, the set of dictionaries was fixed, and therefore it still has a possibility to find the best set of dictionaries, which may exceed the performance of the present study. On the other hand, this result demonstrated a capability of MCA with a wide range of applications especially for an automated extraction of structural data from images even in complex structures. In the further analysis, other field data is expected to verify in the same scheme. In addition, the parameter adjustment is also a topic to tune for the maximization of the accuracy of feature extractions in the image.

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Authors Introduction

Mr. Wataru Oshiumi

In 2022, he received his Bachelor’s degree, the Faculty of Engineering, Kyushu Institute of Technology (Kyutech) in Japan. He is studying advanced signal processing theories in the Master course, Kyushu Institute of Technology, Japan.

Mr. Ankur Dixit

In 2014, he received his Master's degree from National Institute of Technology (NIT) (Electronics & Communication Engineering), Kurukshetra, Haryana, India. He had worked to be an assistant professor in the Mangalayatan University in 2014-2017. He enrolled at the PhD course in Kyushu Institute of Technology (Kyutech), Japan from 2017 and he has made efforts for receiving the PhD degree.

Dr. Hiroaki Wagatsuma

In 1997, He received his M.S. In 2005, the Ph.D. degree was awarded from Tokyo Denki University, Japan. From 2009, he has employed in Kyushu Institute of Technology (Kyutech). He is currently Professor, Graduate School of Life Science and Systems Engineering (LSSE), Kyutech. His research was originally started from non-linear dynamics and then extended robotics. He has a membership of IEEE.