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

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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 $\alpha_k$ are denoted by $T_k$ to represent $x_k$ from Eq. (4).

\[
X = x_0 + x_1 \quad (1)
\]

\[
X = \begin{bmatrix} x_0 \\ x_1 \end{bmatrix} \quad (2)
\]

\[
X = \sum_{k=0}^{1} T_k \alpha_k \quad (3)
\]

\[
T_k \alpha_k = x_k \quad (4)
\]

The basis $\alpha_k$ and the coefficients $T_k$ are $X$ using Eq. (3) and Eq. (4). Find the basis $\alpha_k$ 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).

\[
\{\alpha_0, \alpha_1\} = \text{arg min}_{\{\alpha_0, \alpha_1\}} \|\alpha_0\|_0 + \|\alpha_1\|_0 \\
\text{Subject to: } X = T_0 \alpha_0 + T_1 \alpha_1 \quad (5)
\]

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).

\[
\{\alpha_0, \alpha_1\} = \text{arg min}_{\{\alpha_0, \alpha_1\}} \|\alpha_0\|_1 + \|\alpha_1\|_1 \\
+ \lambda \|X - T_0 \alpha_0 - T_1 \alpha_1\|_2^2 \quad (6)
\]

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.

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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 $\delta$ 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.

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


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