Urban Man-made Object Extraction using the Distribution of the Gradient Directions

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Abstract - Automatic extraction of man-made objects from remotely sensed data is an important and challenging task. A method is proposed for edge extraction from objects by analyzing the patterns of the distribution of the gradient directions. Once the gradient of a given image is obtained, its magnitude is used to find edges and its direction is used in the process of extracting objects. The pattern of the gradient direction distribution of each edge segment is then studied. Objects with straight edges like buildings can be detected using their specific patterns. The method is applied to airborne LiDAR data to extract building edges. By using this method, building edges can be extracted with improved accuracy.

Keywords: gradient direction, distribution, pattern, edge extraction, LiDAR image

1. INTRODUCTION

Automatic detection of man-made objects such as buildings are important for urban land use mapping, urban Geographic Information System (GIS) updating, natural hazard studies, urban climate modeling, and so on. In the recent decade, LiDAR data (NOAA) have been widely used in 3D building modeling, where building edge extraction plays a significant role in the process. LiDAR data provide highly accurate georeferenced elevation points such that objects with height are clearly shown in the image. LiDAR images are usually of super high resolutions and a lot of conventional noises are not found in the images. However, building edge extraction from LiDAR images of urban areas is still not easy. For example, edges caused by trees with similar heights of buildings are not easy eliminated, and building edges in a LiDAR image are usually coarse so the detected edges tend to be zigzagged, which are not smoothly straight.

In this paper, we use a wavelet transformation based gradient operator to detect edges and then use information of the gradient directions of each edge segment to extract linear object edges such as building edges. Gradient operators usually contain smoothing processing and this makes it reasonable to consider a bigger neighborhood of a pixel when computing partial derivatives on it. Since each pixel in the neighborhood determines a direction, a bigger neighborhood gives more gradient directions such that a more accurate distribution of the gradient directions can be obtained. For a pixel, a 5 by 5 window is used to calculate 16 directions. In this window, 16 pixels that is one pixel away from the center are used to determine 16 directions, and this makes the analysis of the pattern of the distribution of directions more accurate, compared with that only 8 directions are used within a 3 by 3 window.

The distribution of the gradient directions of the edges of an object with linear boundaries shows specific patterns. Characteristics of the patterns are studied in the paper and are used to extract linear edges. We propose a way to determine the probability of whether a single edge segment is a straight linear edge.

The method to extract linear edges of objects such as buildings is briefly described as follows: Use a wavelet transformation based gradient operator to detect the edges of the given image. Then the edges are decomposed into disconnected segments. And then the pattern of the distribution of the gradient directions of each segment is studied and a probability is computed. Finally, a size threshold and a probability threshold are used to filter out the noises and non-linear edges. This method is applied on LiDAR images to extract building edges. These edge segments generally have bigger sizes and higher probabilities so they can be effectively extracted.

2. EDGE DETECTION WITH GRADIENT OPERATOR

2.1 Gradient operator with smoothing processing

Gradient operators are classic methods used in edge detection. Usually, a gradient operator consists of a pair or more masks to compute the partial derivatives of a given image, which are used to find the gradient of the image. Edges have big magnitude of the gradient in an image so they can be easily detected by a gradient operator. Extracting edges of specific kinds must delete a large amount of irrelevant edge segments and noises from the edge image produced by the gradient operator.

To attenuate noises in an image, a typical gradient operator carries smoothing processing, such as the smoothing processing embedded in the classical Prewitt operator and Sobel operator, and the explicit smoothing processing as the first step in Canny's operator (Chen). When computing a partial derivative at a pixel, the difference between the intensities of two neighbor pixels locating on both sides of the pixel along a specific direction is used. When a partial derivative mask is of small

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size, which causes slight smoothing effect, the neighboring pixels that are adjacent to the center pixel are used in the computation of difference.

However, it is very often in edge detection using a gradient operator that bigger sizes of neighborhoods are used, so the smoothing processing of the operator greatly attenuates the difference between the intensities of pixels that are very close to each other. This means the eight-pixel neighborhood of a pixel is no longer adequate to be used to find the partial derivatives. In high resolution images, objects of interest are usually big in size and pixels farther away from the edge pixels are less affected by the smoothing processing. Therefore, at an edge pixel, it is more reasonable to use the difference between intensities of two pixels on different side that are a little farther apart to determine its partial derivative. Of course, they cannot be too far away. For a pixel, the 5 by 5 window is a good choice in the computation of its partial derivatives. This results in that 16 directions can be considered in the gradient calculation.

Gradient directions have not been fully exploited in edge extraction. In fact, information from the gradient directions of an image could be used to determine the characteristics of objects with specific geometric shapes. Sixteen gradient directions would provide a fine sample space to study the distribution of the directions. To use 16 directions in an application, the classical gradient operators such as the Prewitt operator and the Sobel operator with fixed size of 3 by 3 are inappropriate. Canny's operator would be a good choice since the Gaussian smoothing function can be scaled to use bigger masks (Canny). Specifically designed gradient operators would also work if the embedded smoothing processing is well designed. In this paper, we use a wavelet transformation based gradient operator to detect edges because of the flexibilities in choosing the smoothing functions and scaling.

2.2 Wavelet transformation based gradient operator

A wavelet function is derived from a smoothing function. A one dimensional smoothing function, denoted as $\theta(x)$, is defined as an even, differentiable, finitely supported function, which is decreasing on $x > 0$. It can be scaled to any level $s > 0$, producing a scaled smoothing function $\theta_s(x) = \theta(x/s)/s$. The derivative of a smoothing function $\theta(x)$ gives a wavelet function, denoted as $\phi(x)$, which can also be scaled to any level $s > 0$, yielding a scaled wavelet function. The scaled wavelet function is proportional to the derivative of the corresponding scaled smoothing function, which is

$$\phi_s(x) = \phi(x/s)/s = s\left(\theta_s(x)\right)'.$$

The wavelet transformation of a function $f(x)$ at scale level $s > 0$ is defined as the convolution

$$W_s f(x) = f * \phi_s(x).$$

An important property of the wavelet transformation of a function $f(x)$ is that it is proportional to the derivative of the smoothed function $(f * \theta_s)(x)$ obtained by smoothing the given function to the scale level *s* (Mallat and Zhong), which is

$$W_s f(x) = s(f * \theta_s)'(x).$$

When the process is generalized to the two dimensional situation, a gradient operator can be defined.

For the two dimensional smoothing function scaled to level *s*, $\Theta_s(x,y) = \theta_s(x)\theta_s(y)$, where $\theta_s(x) = \theta(x/s)/s$ is a scaled smoothing function, its two partial derivatives give two wavelet functions, also scaled to level *s*. The two dimensional wavelet transformation of a function $f(x,y)$ at scale level *s* is defined as a vector with two components,

$$s\left((f * \Theta_s)_x^{'}(x,y), (f * \Theta_s)_y^{'}(x,y)\right).$$

Similar to the one dimensional case, this vector is proportional to the gradient of the smoothed function that is obtained by smoothing the given function $f(x,y)$ to scale level *s*. When it is applied on an image function, it is equivalent to a gradient operator with embedded smoothing processing.

To design a wavelet transformation based gradient operator, one can start to design an appropriate smoothing function depending on the type of application. The operator can be flexibly scaled to an appropriate level so that 16 directions can be used. A pixel is detected as an edge pixel if the magnitude of the gradient at the position is a local maximum along the gradient direction at the same position. Since 16 directions are considered the edges are detected more accurately.

Another important use of gradient directions is to make pattern analysis of their distribution. Objects with specific geometric shapes have specific characteristics in the distributions of gradient directions. Objects with linear edges like buildings show clear patterns in the distributions, although they might be affected by irrelevant objects and noises, so the edges can be extracted if the patterns are not heavily affected.

3. DISTRIBUTION OF GRADIENT DIRECTION

3.1 Distribution of gradient directions and patterns of linear edges

For the 16 directions, each one is assigned a number between 0 and 15. When computing the gradient of a given image, the magnitude and the direction of the gradient at each pixel are saved for later analysis. After the edges are detected, we can study the histogram of the gradient directions of the edges to characterize the patterns of some specific edge types.

The distribution of the gradient directions of edges depends on the edge types and the region size covered. Usually, the distribution covering the whole image does not show useful information about the edges, because it is just a mixture of all the information about different types of edges, including edges of irrelevant objects and noises. Distributions of the gradient directions can be obtained over sub regions and edges can be extracted separately from the sub regions. Although a smaller size of region would sometimes show a clearer pattern in the distribution of gradient directions, irrelevant objects in the region still affect the distribution. Besides, the sizes of sub regions cannot be determined automatically. In this paper we use an edge segment oriented method to study the distribution of the gradient direction of each edge segment.

When the edges are obtained by the gradient operator, they are decomposed into disconnected segments. A threshold may be used to eliminate small irrelevant objects and noises. Each edge segment is then checked on the distribution of the gradient directions and if the pattern is of a kind for extraction then the edge segment is kept, otherwise it is removed.

Not every object shows a clear pattern in the distribution of gradient directions and different kinds of objects may show similar patterns. However, objects with linear edges have specific patterns and they can be characterized in the distributions. This is very helpful in edge extraction for objects with linear edges such as road network and buildings.

An object with linear edges usually has a few outstanding bars in its histogram of gradient directions. The main edges of a building consist of a few linear edges and their gradient directions are perpendicular to their real geometric directions. The relations among the linear edges are reflected in their gradient directions. Buildings with corners of ninety degrees show a pattern in the histogram that long bars contributed by the gradient of the linear edges are apart away with a distance of 4. Unfortunately, the following things affect the patterns of linear objects: some irrelevant edges attach to the edges of linear objects; except the main linear edges, the objects have some other edges that are not linear; the detected linear edges are not smoothly straight that are zigzag in details. On the other hand, irregular edge segments may show similar patterns in the distribution of gradient directions to that of linear objects. Some measure on a distribution of the gradient directions of an edge should be introduced to give the probably of that the edge segment is linear.

3.2 Probabilities of linear objects

We introduce a crossbar to measure how the main gradient directions are outstanding over other directions. For convenience we first normalize the histogram of the gradient directions of an edge segment such that the highest bar has value 100. A crossbar is the least value, denoted by c, such that the number of bars in the histogram that are not lower than the value is not more than a predefined number n. The predefined number n in our experiment is 8 when 16 directions are used. Based on the application, n could be selected as a smaller number. Generally, the crossbar tells there are n bars in the histogram such that they are higher than c. The less the value of c, the more outstanding the higher bars are over the remaining lower bars. In a clear pattern of linear objects, the crossbar is apparently low.

In a normalized histogram, a bar represents a main gradient direction if it is above the crossbar and it is the longest bar among those of near directions. We consider no more than four main gradient directions for the edges of a building in general. To find a main gradient direction, one just needs to compare a bar with its neighbors in a histogram to see whether it is a local maximum. It is not difficult to find up to four local maxima, whose values are no less than the remaining values, and the indexes of the gradient directions they correspond to.

With the number of main gradient directions, the heights of their bars in the normalized histogram compared with the crossbar value, and the distances the main gradient directions apart away from the adjacent main gradient directions, a value can be assigned to indicate the probability of whether the edge segment is from a linear object. The probability is experimental, but the following two aspects are essentially significant, which should be combined in the consideration.

1. The lower the crossbar, the higher the probability. A low crossbar indicates that a few main gradient directions are outstanding in the normalized histogram. These main gradient directions could represent linear edges.
2. If the main gradient directions are sparsely scattered, then the probability is high. This is because objects such as buildings have linear edges in quite different directions. If some main gradient directions are near together, the probability is reduced.

Here are some experimental results. If there is only one main gradient direction, the probability is basically determined by the crossbar; and if the probability is high, the edge segment could be a side of a linear object. If there are two main gradient directions and their bars in the histogram is apart away with a distance of 4, and if the crossbar is low at the same time, then the edge segment could be two adjacent, perpendicular sides of some object. Similarly, if there are three or four main gradient directions sparsely scattered in the histogram and the crossbar is low at the same time, it is highly probably that the edge segment belongs to an object with linear sides.

There are some other considerations when determine the probability. For example, the choice of the number n in the definition of the crossbar affects the probability. Also, if the size of an edge segment is too small, the lack of enough samples makes the probability inaccurate. In fact, tiny segments should be eliminated directly from the edge image.

4. AN EXPERIMENTAL EXAMPLE

We apply the proposed method to extract building edges in a LiDAR image of an urban area, where vegetation is a main obstacle to the extraction. See Figure 1.

A wavelet transformation base gradient is used to detect the edges of the image. An edge pixel is determined if the magnitude of the gradient on the position is a local maximum along its gradient direction. Sixteen directions are taken into consideration. Figure 2 shows the detected edges.

The edges are then decomposed into disconnected segments. Small segments are eliminated with a threshold and then each remaining segment is checked on its distribution of the gradient directions. The probability of whether the segment is a linear edge, which is a side segment of a building, is determined by a properly selected crossbar and how the main gradient directions in the distribution are scattered. A threshold is selected to eliminate the edge segments with low probabilities. The extracted building edges are shown in Figure 3, with a small amount of irrelevant edge segments caused by trees included.

To illustrate the effectiveness of the method, lower vegetation areas are purposely not masked out beforehand and all the edge pixel intensities are set to zero.

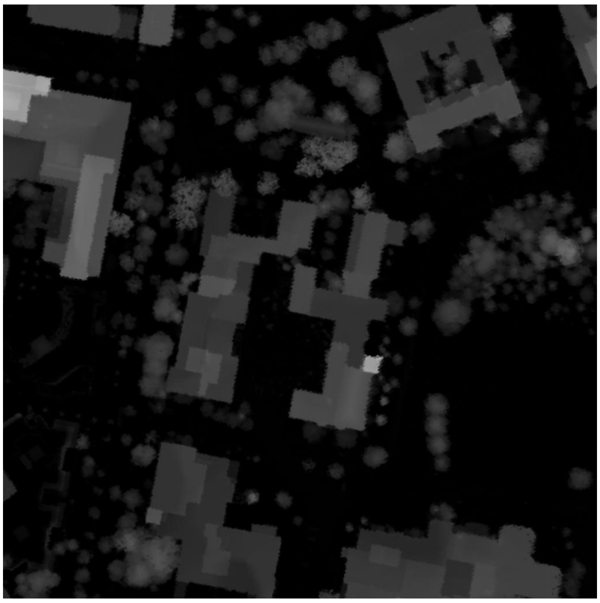

Figure 1. A LiDAR image of an urban area.

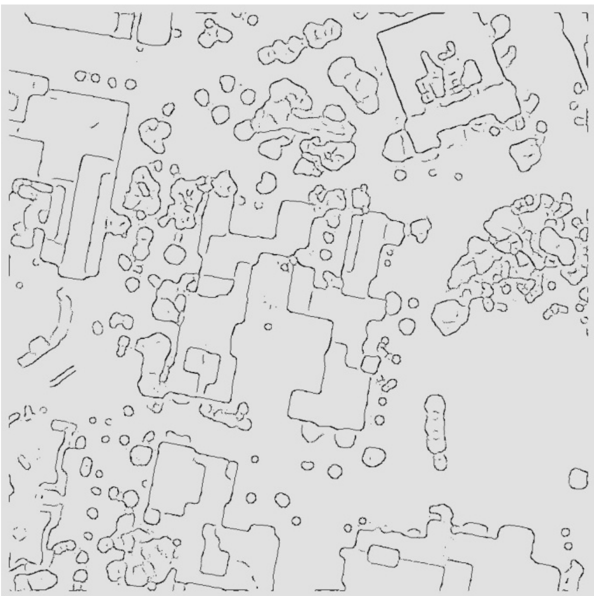

Figure 2. Edges detected with a wavelet transformation based gradient operator.

5. CONCLUSION

In this paper a method to extract straight linear edges is proposed and applied on building edge extraction from a LiDAR image of an urban area. A wavelet transformation based gradient is used to detect the edges, during which heavy smoothing process is performed. Sixteen directions are considered and the distribution of the gradient directions of each edge segment is checked to look for some characteristics of linear edges. A probability is assigned to each edge segment to indicate how possible it is a linear edge. The probability is based on the study of the patterns of the distribution of the gradient directions. When the parameters in the method are properly selected, it is effective on linear edge extraction from the LiDAR image with high resolutions.

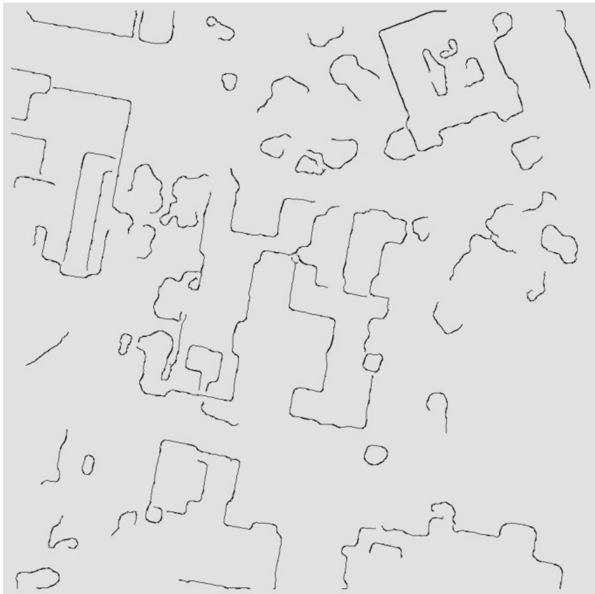

Figure 3. Linear edges of buildings extracted from the edge image of Figure 2.

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