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Building and Tree Detection Using Multiscale Matched Filtering

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***Abstract*—In this study, an automated building and tree detection method is proposed using DSM data and true orthophoto image. A multiscale matched filtering is used on DSM data. Therefore, first watershed transform is applied. Then, Otsu's thresholding method is used as an adaptive threshold to segment each watershed region. Detected objects are masked with NDVI to separate buildings and trees. The proposed method is able to detect buildings and trees without entering any elevation threshold. We tested our method on ISPRS semantic labeling dataset and obtained promising results.

***Keywords*—Building detection, tree detection, matched filtering, multiscale, local maximum filtering, watershed segmentation.

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I. Introduction

IN this study, automated building and tree detection method is proposed on DSM and real orthophoto belonging to city(urban). The proposed method is expanded(enhanced) from our previous work, multiscale tree detection [10]. Similar works to the proposed method are based on only tree detection. We indicated that buildings additionally to trees can be detected using matched filter on height data. Our other work, building detection from height data in the literature is summarized [9]. Tree detection methods can be categorised in four group. These are local maximum filtering, image thresholding, scale analysis, and template matching. Peaks of trees reflect more light. Therefore, these peaks points seem as bright point in the 2 dimensional images. Reflection decreases from top to bottom on a tree. That means, bottom points seems darker in the images. Local maxima filtering is used to extract bright points namely peaks of trees [19], [18], [4], [13]. In image thresholding method, bright and dark points are tried to separate each other by thresholding two dimensional image. Common different thresholding methods are used in image processing [12], [17]. The spatial resolution of the image and the size of a tree is important for detection. If a pixel is smaller than the tree, looking at the image in different scales is required. Therefore, image is smoothed by using different scales to find local maxima. This method is also used to detect different sized trees [3], [14], [2], [1]. In template matching method, a simple tree template is used to detect trees in the image. In the literature, the first two methods are used extensively [5], [15].

The local maxima filtering method for tree detection is a fast method giving reasonably good results. It is also simple to implement. Therefore, it is used in practice most of the times. This method is used with watershed segmentation. Here, the image is first smoothed by a symmetric Gaussian filter. If the filter size is close to the tree size to be detected, then tree tops (as local maxima) can be detected via this operation. Local maxima can be used with watershed segmentation to extract the crude boundary of the tree at the same time. Here, the most important step is selecting the Gaussian filter size. If this size becomes smaller compared to the tree to be detected, there will be more than one local maxima on the tree. If this size is selected as larger compared to the tree to be detected, then there may be no local maxima extracted. Hence, the tree may be missed. Not detecting or falsely detected local maxima points will effect the watershed segmentation method in extracting the tree boundary. Therefore, if one filter size is used in a region with different sized trees, some trees will not be detected correctly. Moreover, some false tree detection result may also be obtained. This will effect the tree detection performance of the method.

In this study, first of all, DSM data belonging to urban areas are segmented to separate from each other using matched filtering. If the filter size is close to the object size, entire of the object may be inside the segment. If the filter size is smaller than the object size, an object may be separated to more than one segment. If the filter size is greater than the object size, there may be more than one object inside the segment. In all cases,for each obtained segment, local threshold value is obtained using Otsu's method.Therefore, local height variations are also eliminated in the image. Morphologic based approaches are generally used in order to detect object from DSM data. However, the convenient shape and size of the structural element should be selected according to region and object size [20], [7], [11], [6]. Opening and closing operations are applied on DSM data by increasing the structural element size in iterative morphologic based methods using DSM data. For each increasing structural element size, objects are detected by increasing threshold values. In the proposed method, different sized buildings and trees are simultaneously detected by using matched filter for only three filter size and Otsu thresholding method based on watershed segmentation.We tested our method on ISPRS semantic labeling dataset.Next, we will introduce the proposed methods. Afterwards, we will provide the visual results in the experiments section. Finally, we will summarize the method and the findings in the conclusions section.

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A. Method

The proposed method covers smoothing DSM, watershed segmentation, automated threshold selection, combining detections, separation of building and tree with NDVI mask. In summary, DSM data are firstly smoothed by using isotropic Gaussian filter. Watershed segmentation are applied on smoothed DSM. Automated thresholds which are calculated by using Otsu's method are used for each segment. All detections for each segment are combined. This procedure is reapplied by changing the size of Gauss function. As can be seen in Fig. 1, if the Gaussian filter size is selected small, there will be more than one local maximum on a large building or tree. As we increase the Gaussian filter size, then there will be no local maxima detection on small buildings or trees. This clearly indicates that, one filter size will not be suitable to detect all local maxima in such data.

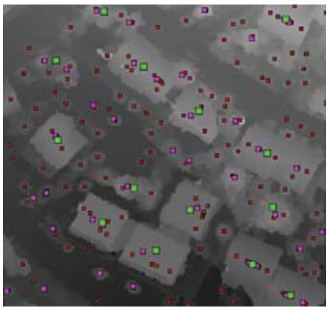


Fig. 1 Local maxima obtained using different sized Gaussian filters. The largest filter scale: Green, The middle filter scale: Magenta, The smallest filter scale: Red

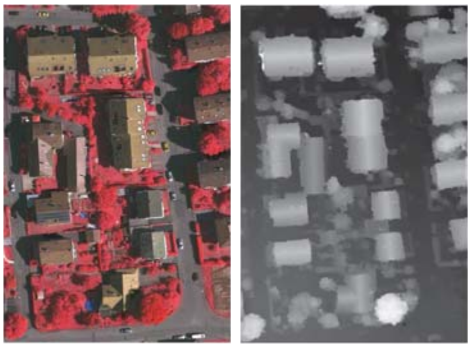
Detection results for each size of Gauss function are (combined). Resultant detections are processed by using NDVI mask obtained from real orthophotos to separate buildings and trees. Steps of the proposed method will be described on data set in the following subsections.

B. Smoothing with Matched Filter

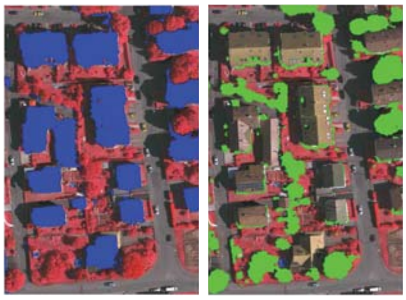
DSM data are smoothed with adaptive filter in the first step. The proposed method will be described on images indicated in Figs. 2(a) and 2(b). Color channels in real orthophotos are changed to NIR (near infrared), R (red) and G (green). That means, we do not use blue channel. Therefore, trees and vegetation seem like reddish. We extract NDVI (Normalized Difference Vegetation Index) using NIR and R channels [16]. Stereo based DSM data belonging to the same region is indicated in Fig. 2(b). Spatial resolution of images is 9 cm. DSM data smoothed with Gaussian function is represented in Fig. 3(a). If objects are matched with Gauss filter, in other words filter size and object size are similar, local maximum points appears at the object centers. Thus, it is possible to apply watershed segmentation on smoothed images.

C. Watershed Segmentation

We use watershed segmentation on smoothed DSM image. The result of watershed segmentation which is applied to filter output in Fig. 3(a) is shown Fig. 3(b). As can be seen, there are one or more objects depend on filter and object size in all segments. In contrast, objects can be separated more than one segment especially buildings.

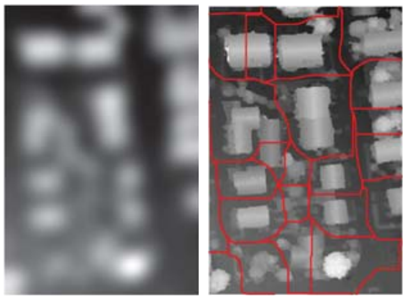


(a) Real orthophoto (b) DSM



(c) Final detections for building detection (blue) (d) Final detections for tree detection (green)

Fig. 2 Data set for method description and final results



(a) Smoothed DSM data (b) Watershed segmentation result

Fig. 3 Red lines represent the boundary of segments

D. Automated Thresholding

Objects and ground surface in segments have to be thresholded according to their heights for each watershed segment. For this purpose, We find automated threshold using Otsu's method in all segments [8]. For three different segments, automated height thresholds found by Otsu's method and their results are indicated in Fig. 4.

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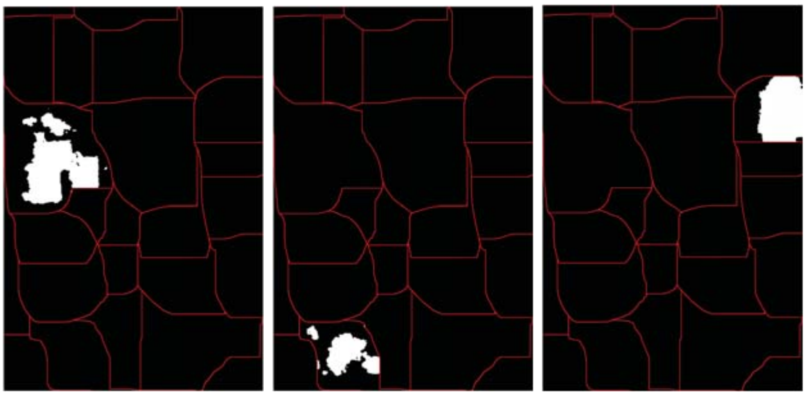
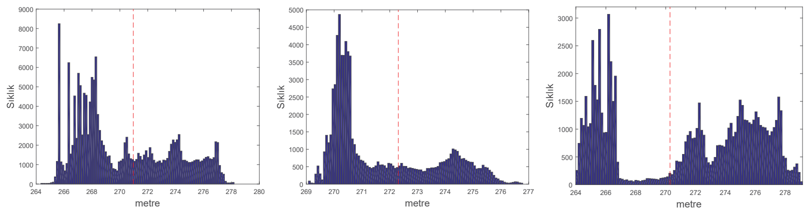


(a) Detections on segment-4 (b) Detections on segment-9 (c) Detections on segment-22



(d) Distribution of height values on segment-4 (e) Distribution of height values on segment-9 (f) Distribution of height values on segment-22

Fig. 4 Automated threshold value (red horizontal lines in d, e and f) obtained from Otsu thresholding method for three different segment and findings (a, b and c)

E. Merging Different Scale Results

All detections for each segment are combined. All of these processes are reapplied by changing the size of Gauss function in the first step and all results are merged.To separate buildings and trees each other, we use NDVI mask. This NDVI mask is obtained using NIR and R channels of orthophotos. NDVI is defined as $(NIR - Red)/(NIR + Red)$. The sum of results provided by three different sizes, NDVI, buildings masked with NDVI, trees masked with NDVI are represented in Fig. 5, respectively.

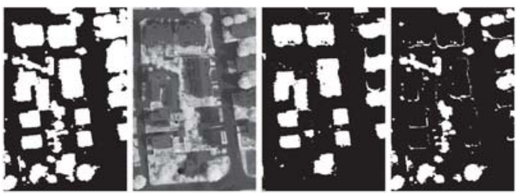


Fig. 5 From left to right final detection result, NDVI, buildings masked with NDVI, trees masked with NDVI

II. Experiments

ISPRS 2D Semantic Labeling Vaihingen dataset was used for the proposed method. This dataset is at http://www2.isprs.org/commissions/comm3/wg4/2d-sem-label-vaihingen.html. The resolutions of DSM and orthophotos are 9 cm in this dataset. Results belong to 4 ones of 33 data. Completeness $Cm = TP/(TP + FN)$, correctness $Cr = TP/(TP + FP)$ and $F1 = 2 * (Cr * Cm)/(Cr + Cm)$ are calculated for measurement of metric performances in pixels. These results are listed in Table I for buildings and in Table II for trees. Also, visual results are represented in Fig. 6.

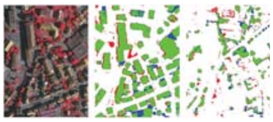
TABLE I:
Building Detection Performance

	Cr (%)	Cm (%)	F1 (%)
Vaihingen-1	87.19	87.75	87.47
Vaihingen-3	90.48	83.87	87.05
Vaihingen-5	91.76	91.96	91.86
Vaihingen-7	90.87	87.93	83.37
Average	90.08	87.88	87.44

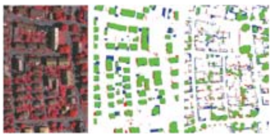
TABLE II:
Tree Detection Performance

	Cr (%)	Cm (%)	F1 (%)
Vaihingen-1	72.63	74.95	73.77
Vaihingen-3	76.04	65.63	70.45
Vaihingen-5	79.70	84.30	91.94
Vaihingen-7	90.41	71.06	79.57
Average	79.70	73.99	78.93

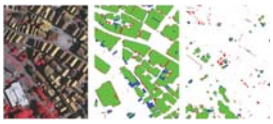
Gaussian filter sizes are taken as [50, 25, 10] in the experiments. NDVI mask is created from NDVI values of pixels in real orthophotos which is greater than 0.18. As can be seen, although there are different sized buildings and trees, buildings and trees can be detected using three scales without height threshold.



(a) Vaihingen-1



(b) Vaihingen-3



(c) Vaihingen-5

(d) Vaihingen-7

Fig. 6 Visual results for Vaihingen dataset. The first column is real ortofoto. The second column is building detection. The third column is tree detection. TP: Green, TN: White, FP: Red, FN: Blue

III. Conclusion

In this study, we proposed a method that uses matched filtering in multiscale to detect automatically building and tree from height data. The method implements detection step with matched filtering, watershed segmentation, and local Otsu threshold. The detections is masked with NDVI mask to separate buildings and trees. We tested the method on public dataset, ISPRS semantic labelling dataset, and we obtained successful results.

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