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A Brief Survey of Building Extraction Techniques of Remote Sensing Images

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Abstract: **- This paper aims to provide a review of automatic building extraction techniques from remote sensing images. The building extraction technique is used for detecting and separating buildings from other land cover classes. In the past few years, researchers have proposed a number of building extraction methods. This paper commonly divides these methods into four main categories: template matching-based methods, knowledge-based methods, OBIA-based methods, and machine learning-based methods and provide a detailed survey of these methods. This paper also discusses the challenges and demerits of these methods to give a clear idea about these existing approaches. So this survey will be beneficial for the researchers to have a better understanding of this building extraction field.**

Keywords: - Remote Sensing, Building Detection, Extraction, Template, Machine Learning.

I. INTRODUCTION

Automatic extraction of objects such as buildings or roads from digital aerial imagery. In this paper, the term "extraction" is used for the detection of buildings. The discovery of buildings has many uses in the region, such as city planning, disaster management, flood assessment, disaster recovery, tax breaks, etc. It is very important for agents such as military land and others. The remote data detection tool has the following limitations. In urban areas, the picture can be highly complex in the scene or may be of a low and unhealthy color, or other objects may have similar light reflections such as a building. In addition, unbalanced roofing, tilting, and terrace can lead to a separation feature. Incorrect detection can be attributed to images of multiple buildings, where incorrect modeling can describe a link to a wire. Shadows also cause problems. The algorithm does not efficiently locate buildings in a region where the shadow of a building falls into another building or where only clogs appear to build a roof. In addition, there may be non-structured objects, such as roads and bridges, which cannot be deleted by height verification but may be misidentified as a building. Another disadvantage is that in some residential areas where the buildings are in dense streets and crowded, some isolated buildings can be found as a building.

The paper surveys the state-of-the-art automatic building detection techniques from aerial imagery. The survey is extensive, but it does not claim to be complete. This survey includes approaches for building detection from satellite images, which influence the extraction from aerial imagery. It only covers models and strategies. Specific algorithms or techniques derived from them are not reviewed, to limit the extent of the survey.

The rest of the paper is organized as follows. The second section provides a detailed literary study of the existing method used to build buildings from remote data. The exhaustive review template matching-based building detection methods, knowledge-based building detection methods, OBIA-based building detection methods, and machine learning-based building detection methods are described in the third section. The fourth section gives the conclusion of this work.

II. LITERATURE SURVEY

Attribution and distribution using high-quality satellite data (Cartosat-1, included with IRS-1C, LISS IV data) for automatic construction [6] were observed using two characteristics, such as placement Different application forms and subgroups of unknown objects. The merged images are filtered using several high filters such as Kirsch, Laplace, Prewitt, Sobel, and Canny to improve the size of the captured data remotely. Crop methods are used to separate data that need human intervention, and to draw boxes in the area of the image is separated. To be fully automated, they use the obscure landscape that creates shadow clouds. Additional warnings of Gibb power converter were accomplished using the enhanced search of bacteria. Separate and merge breaks are used, and segment images are filtered using different filters. To improve the solution of the image, network creation is complete. The ED Lines [8] integrated electronic device was created to accurately copy the construction line. A built-in network creation [5] was designed to provide improved image display power. A supervised classification technique took on [10] where the training parts for supervised A

Table 1. Detailed Summary for Building Detection Techniques Mentioned in Literature Survey

S.No	Authors	Year	Methods	Limitation
1	E Li, S Xu, W Meng, X Zhang [1]	2017	Support Vector Machine (SVM) classifier	Studying an intelligent method to evaluate the possibility of further enhancements to accuracy is the future work reported in the paper.
2	LI Jiménez, J Plaza, A Plaza [2]	2017	Morphological building index (MBI) and morphological shadow index (MSI)	Improved accuracy and calculation presentations of the proposed approach are the future jobs outlined in the paper.
3	X Huang, W Yuan, J Li, L Zhang [3]	2017	Advanced Morphological building index (MBI)	Exploring the nature of buildings is a challenge that is addressed in the text.
4	J Yuan [4]	2016	Polarization Orientation Angle (POA)	Improvements to the accuracy of building output have been published as outlined in the work.
5	N Shrivastava, PK Rai [5]	2016	Convolutional network formation	The paper said that achieving universal construction machinery to address different problems was a challenge.
6	C Collet, V Mazet [6]	2015	Spatial filers, and object-oriented fuzzy classification	All edges of the building are not extracted, but parallel to the original image of the city building
7	J Wang, X Yang, X Qin [7]	2015	MRF segmentation method	The discovery of shadows is a challenge that is addressed in the paper.
8	J Han, D [8]	2015	Segment detection	The report said that the completed extraction of buildings in large data sets was a challenge.
9	Zhang, G Cheng, L Guo [9]	2015	Deep Boltzmann Machine (DBM)	The report said that the combination of spatial and spectral information for accurate and robust findings was a challenge.
10	S Ghaffarian [10]	2014	Parallelepiped supervised classification.	Improving the accuracy of shadow finding output is challenging

classification was chosen by without human intervention and determining a buffer zone on every building and Standard deviation thresholding was applied to the Parallelepiped classification method to increase the accuracy. The new WSL recognition method in fiber optics [9], where training materials require a binary label, indicate whether the image contains the target. In the distribution of buildings, the dividers were trained to determine the line sections that corresponded to the edges of the building, studying the relationship between low image quality and building size. Despite the inconsistencies between the linear part obtained and the construction edge, it has been found that there is a linear relationship between the number of buildings and the linear number of those constructions. Based on this

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observation, they estimate the number of buildings in the picture. Since the purpose of Saliency as a new feature [1] has been used to determine whether there is a roof in any part obtained from the previous step. The basic idea of using the privilege information is that the roof is likely to attract the attention of the surrounding objects. Hyperspectral datasets [2] are used to create extractions using Morphological building index (MBI) and morphological shadow index (MSI). They also use the Advanced Building Index Index (MBI) [3]. The detection of earthquake damage in buildings [4] in urban areas was measured using data from Post Sale PolSAR. The brief survey of these methods in shown in Table 1.

III. CATEGORIZATION OF METHODS FOR BUILDING DETECTION

In the last decades, a large number of methods have been developed for building detection from aerial and satellite images. We can generally divide them into four main categories: template matching-based methods, knowledge-based methods, OBIA-based methods, and machine learning-based methods. These four categories are not necessarily independent and sometimes the same method exists with different categories.

A. Template Matching-Based Building Detection

Template matching-based methods are one category of the simplest and earliest approaches for building detection. There are two main steps in template matching-based

Table 2. Categorization of Building Detection Techniques - Detailed Survey

S.No	Template	Authors & Publication	Strengths	Limitations
1	Rigid template	Lefèvre et al., 2007; Stankov and He, 2013, 2014	Simple and easy to implement	Scale and rotation dependent; Sensitive to shape and viewpoint change.
2	Deformable template	Ahmadi et al., 2010; Karantzalos and Paragios, 2009; Sirmaçek and Ünsalan, 2009	More powerful and flexible than rigid shape matching in dealing with shape deformations and intra-class variations	Need more prior information and parameters of the geometrical shape for template designing; Computationally expensive
3	Knowledge-based object detection methods.	Akçay and Aksoy, 2010; Haala and Brenner, 1999; Hofmann et al., 2002; Huertas and Nevatia, 1988; Irvin and McKeown, 1989; Lin and Nevatia, 1998; Liow and Pavlidis, 1990; McGlone and Shufelt, 1994; Ok, 2013; Ok et al., 2013; Peng and Liu, 2005; Shufelt, 1996; Stilla et al., 1997; Weidner and Förstner, 1995	Detection can be performed through a coarse-to-fine hierarchical structure	How to define the prior knowledge and detection rules is subjective; Too loose rules will cause false positives and vice versa
4	OBIA-based object detection methods	Bontemps et al., 2008; Chen and Hay, 2012; Contreras et al., 2016; Dissanska et al.,2009; Doxani et al., 2012,2008; Hussain et al., 2013;Im et al., 2008; Nebiker et al.,2014; Walter, 2004	The flexible incorporation of shape, texture, geometry, and contextual semantic features, as well as GIS-like functionality and expert knowledge, makes OBIA context-aware and multi-user capable	Generic solutions to the full automation of segmentation process are still missing; The expert knowledge of how to define the classification rules are still subjective
5	Machine learning-based object detection	Ari and Aksoy, 2014; Lei et al., 2012; Li et al., 2015a; Senaras et al.,	The object model (detector) can be automatically established	Need a lot of training samples of objects and non-objects to learn classifiers; Detection

S.No	Template	Authors & Publication	Strengths	Limitations
	methods	2013; Wegner et al., 2011a, 2011b	via machine learning technique; Detection system is scalable and compatible; Have high detection accuracy	accuracy depends on the training samples

Building detection framework. (1) Template generation: a template T for each to-be-detected building class should be firstly generated by handcrafting or learning from the training set. (2) Similarity measure: given a source image, the stored template T is used to match the image at each possible position to find the best matches, according to the minimum distortion or maximum correlation measures, while taking into account all allowable translations, rotation, and scale changes. The most popular similarity measures are the sum of absolute differences (SAD), the sum of squared differences (SSD), the normalized cross correlation (NCC), and the Euclidean distance (ED). According to the template type selected by a user, the template matching-based building detection approaches are generally categorized into two groups: rigid template matching and deformable template matching.

a) Rigid template matching

Early research in this area mainly concentrated on rigid template matching. Various rigid templates have been designed for detecting specific buildings with simple appearance and small variations such as buildings. The morphological hit-or-miss transform (HMT) is a powerful tool dedicated to template matching. Since its first definition for binary images [11], its recent extensions to grayscale images [12],[13]. [11] presented a method for building extraction in Quickbird images based on an adaptive binary HMT with varying sizes and shapes of the structuring element. In this method, a binary image was firstly generated from a gray-level panchromatic input image before building detection. To make use of the spectral information, the authors in [12],[13] generated grayscale images from the spectral bands and then applied the grayscale HMT to building detection, where [12] is a supervised method that requires a set of reference windows for each roof color present in the image while the method in [13] is unsupervised.

b) Deformable template matching

Deformable template matching is more powerful and flexible than rigid shape matching in dealing with shape deformations and intra-class variations because of its capability impose both geometrical constraints on the shape and to integrate local image evidence. There has been a substantial amount of studies on deformable template matching in recent years. These studies can be roughly divided into two classes: free-form deformable templates and parametric deformable templates. A brief summary of template matching-based building detection methods is given in Table 2.

B. Knowledge-based Building Detection

Knowledge-based building detection methods are another type of popular approaches for building detection in optical RSIs. An extensive collection of papers on the knowledge-based building detection has been published for buildings in [14-27]. This type of approach generally translates building detection problem into a hypothesis testing problem by establishing various knowledge and rules. The establishment of knowledge and rules is the most important step. Two kinds of widely used knowledge of target buildings are geometric knowledge and context knowledge.

a) Geometric Knowledge

The building geometric information is the most important and widely used knowledge of building detection, which encodes prior knowledge by taking parametric specific or generic shape models. Huertas and Nevatia [27] assumed that the buildings are rectangular or composed of rectangular components (e.g. ‘‘box,” ‘‘T,” ‘‘L,” and ‘‘E” shapes) and used a generic model of the shapes to detect buildings. Weidner and Förstner [26] developed an approach for extracting the 3D shape of buildings from high-resolution digital elevation models (DEMs) by establishing and using explicit geometric constraint knowledge in the form of parametric and prismatic building models. McGlone and Shufelt [20] proposed to include the target geometric and metric knowledge into the building extraction system for the generation of building hypotheses, and the generated hypotheses were finally verified with the shadow information.

b) Context Knowledge

The context knowledge is another crucial cue for knowledge-based-knowledge-based building detection and the most widely used context knowledge is the spatial constraints or relationships between buildings and background or the information regarding how the building interacts with its neighboring regions. As a representative example, shadow evidence has been considered to be one of the most important clues for building detection [17-27] exploited the relationship between man-made structures and their cast shadows to predict the locations and shape of buildings, and Liow and Pavlidis [19] used shadow information to complete the boundary grouping process. Ok, et al. (2013) employed the shadow evidence to automatically detect buildings with arbitrary shapes from monocular VHR images. In their work, the authors modeled the directional spatial relationship between buildings and their shadows by proposing a new fuzzy landscape generation approach. Besides, the shadow areas derived from monocular images were extensively used during the verification of the building hypotheses. For example, Lin and Nevatia [18] proposed an approach to detect buildings from oblique aerial images, in which the hypothesized rectangular buildings are verified with both shadow and wall pieces of evidence by following the basic assumption that the building shapes are rectilinear. Peng and Liu [23] developed a shadow-context model to extract buildings in dense urban aerial images by combining shadow information with context to verify building regions. A brief summary of knowledge-based building detection methods is given in Table 2.

C. OBIA-Based Building Detection

Recently, with the increasing availability and wide utilization of sub-meter imagery, building-based image analysis has become a new methodology or paradigm to classify or map VHR imagery into meaningful buildings. OBIA involves two steps: image segmentation and building classification. Firstly, imagery is first segmented into homogeneous regions (segments also called buildings) representing a relatively homogeneous group of pixels by selecting a desired scale, shape, and compactness criteria. And in a second step, a classification process applied to these buildings. Once the segments are generated, one can extract building features, such as spectral information as well as size, shape, texture, geometry, and contextual semantic features. These features are then selected and fed to a classifier for classification. A brief summary of OBIA-based building detection methods is given in Table 2.

D. Machine Learning Based Building Detection

With the advance of machine learning techniques, especially the powerful feature representations and classifiers, many recent approaches regarded building detection as a classification problem and have achieved significant improvements. In this approach, building detection can be performed by learning a classifier that captures the variation in building appearances and views from a set of training data in a supervised or semi-supervised or weakly supervised framework. The input of the classifier is a set of regions with their corresponding feature representations and the output is their corresponding predicted labels, i.e., building or not. A brief summary of machine learning-based building detection methods is given in Table 2.

IV. CONCLUSION

In this paper, we have surveyed various methodologies for building extraction from the given input remote sensing images. We broadly categorized the methods into four groups, namely the template matching-based methods, knowledge-based methods, OBIA-based methods, and machine learning based methods, and exhaustively reviewed them respectively. Besides, we also discussed the strengths and limitation of these methods. This survey will be significantly beneficial for the researchers to get better understand this research field.

REFERENCES

1. E Li, S Xu, W Meng, X Zhang, Building extraction from remotely sensed images by integrating saliency cue, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 10, no. 3 (2017): 906- 919.
2. LI Jiménez, J Plaza, A Plaza, Efficient implementation of a morphological index for building/shadow extraction from remotely sensed images, the Journal of Supercomputing 73, no. 1 (2017): 482- 494.
3. W Yuan, J Li, L Zhang, A new building extraction postprocessing framework for high-spatial-resolution remote-sensing imagery X Huang, xIEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 10, no. 2 (2017): 654- 668..
4. W Zhai, H Shen, C Huang, W Pei, Building earthquake damage information extraction from a single post-earthquake image, Remote Sensing 8, no. 3 (2016): 171.
5. J Yuan, arXiv Automatic building extraction in aerial scenes using convolutional networks, International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 40, no. 3 (2014): 101.
6. N Shrivastava, PK Rai, Remote-sensing the urban area: Automatic building extraction based on multiresolution segmentation and classification,2015 - pdf.semantic cscholar.org.
7. TT Ngo, C Collet, V Mazet, Automatic rectangular building detection from VHR aerial imagery using shadow and image segmentation, IEEE Transactions

on Geoscience and Remote Sensing 53, no. 6 (2015): 3325-3337.
8. J Wang, X Yang, X Qin, X Ye, An efficient approach for automatic rectangular building extraction from very high-resolution optical satellite imagery, ISPRS Journal of Photogrammetry and Remote Sensing 63, no. 3 (2008): 365-381.
9. J Han, D Zhang, G Cheng, L Guo, Object detection in optical remote sensing images based on weakly supervised learning and high-level feature learning, 2015 IEEE International Conference on, pp. 1483-1487.
10. [5] S Ghaffarian, Automatic building detection based on supervised classification using high-resolution Google Earth images, International Conference on Advances in Geographic Information Systems, pp. 271-280. ACM, 2014
11. Lefèvre, S., Weber, J., Sheeren, D., 2007. Automatic building extraction in VHR images using advanced morphological operators. In: Proc. Urban Remote Sens. Joint Event, pp. 1–5.
12. Stankov, K., He, D.-C., 2013. Building detection in very high spatial resolution multispectral images using the hit-or-miss transform. IEEE Geosci. Remote Sens. Lett. 10, 86–90.
13. Stankov, K., He, D.-C., 2014. Detection of buildings in multispectral very high spatial resolution images using the percentage occupancy hit-or-miss transform. IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens. 7, 4069–4080.
14. Akçay, H.G., Aksoy, S., 2010. Building detection using directional spatial constraints. In: Proc. IEEE Int. Geosci. Remote Sens. Sympos., pp. 1932–1935.
15. Haala, N., Brenner, C., 1999. Extraction of buildings and trees in urban environments. ISPRS J. Photogramm. Remote Sens. 54, 130–137.
16. Hofmann, A.D., Maas, H.-G., Streilein, A., 2002. Knowledge-based building detection based on laser scanner data and topographic map information. Int. Arch. Photogramm. Remote Sens. Spat. Inform. Sci. 34, 169–174.
17. Irvin, R.B., McKeown, D.M., 1989. Methods for exploiting the relationship between buildings and their shadows in aerial imagery. IEEE Trans. Syst., Man, Cybern. 19, 1564–1575.
18. Lin, C., Nevatia, R., 1998. Building detection and description from a single intensity image. Comput. Vis. Image Understand. 72, 101–121.
19. Liow, Y.-T., Pavlidis, T., 1990. Use of shadows for extracting buildings in aerial images. Comput. Vis. Graph. Image Process. 49, 242–277.
20. McGlone, J.C., Shufelt, J., 1994. Projective and object space geometry for monocular building extraction. In: Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., pp. 54–61.
21. Ok, A.O., 2013. Automated detection of buildings from single VHR multispectral images using shadow information and graph cuts. ISPRS J. Photogramm. Remote Sens. 86, 21–40.
22. Ok, A.O., Senaras, C., Yuksel, B., 2013. Automated detection of arbitrarily shaped buildings in complex environments from monocular VHR optical satellite imagery. IEEE Trans. Geosci. Remote Sens. 51, 1701–1717.
23. Peng, J., Liu, Y., 2005. Model and context-driven building extraction in dense urban aerial images. Int. J. Remote Sens. 26, 1289–1307.
24. Shufelt, J.A., 1996. Exploiting photogrammetric methods for building extraction in aerial images. Int. Arch. Photogramm. Remote Sens. 31, B6.
25. Stilla, U., Geibel, R., Jurkiewicz, K., 1997. Building reconstruction using different views and context knowledge. Int. Arch. Photogramm. Remote Sens. 32, 129– 136.
26. Weidner, U., Förstner, W., 1995. Towards automatic building extraction from high resolution digital elevation models. ISPRS J. Photogramm. Remote Sens. 50, 38– 49
27. Huertas, A., Nevatia, R., 1988. Detecting buildings in aerial images. Comput. Vis. Graph. Image Process. 41, 131–152.
28. Bontemps, S., Bogaert, P., Titeux, N., Defourny, P., 2008. An object-based change detection method accounting for temporal dependences in time series with medium to coarse spatial resolution. Remote Sens. Environ. 112, 3181–3191.
29. Chen, G., Hay, G.J., 2012. Object-based change detection. Int. J. Remote Sens. 33, 4434–4457.
30. Contreras, D., Blaschke, T., Tiede, D., Jilge, M., 2016. Monitoring recovery after earthquakes through the integration of remote sensing, GIS, and ground observations: the case of L'Aquila (Italy). Cartogr. Geogr. Inform. Sci. 43, 115– 133.
31. Dissanska, M., Bernier, M., Payette, S., 2009. Object-based classification of very high-resolution panchromatic images for evaluating recent change in the structure of patterned peatland. Can. J. Remote Sens. 35, 189–215.
32. Doxani, G., Siachalou, S., Tsakiri-Strati, M., 2008. An object-oriented approach to urban land cover change detection. Int. Arch. Photogramm. Remote Sens. Spat. Inform. Sci. 37, 1655–1660.
33. Hussain, M., Chen, D., Cheng, A., Wei, H., Stanley, D., 2013. Change detection from remotely sensed images: from pixel-based to object-based approaches. ISPRS J. Photogramm. Remote Sens.

80, 91–106.
34. Im, J., Jensen, J.R., Tullis, J.A., 2008. Object-based change detection using correlation image analysis and image segmentation. Int. J. Remote Sens. 29, 399–423.
35. Nebiker, S., Lack, N., Deuber, M., 2014. Building change detection from historical aerial photographs using dense image matching and object-based image analysis. Remote Sens. 6, 8310–8336.
36. Walter, V., 2004. Object-based classification of remote sensing data for change detection. ISPRS J. Photogramm. Remote Sens. 58, 225–238.
37. Ari, C., Aksoy, S., 2014. Detection of compound structures using a Gaussian mixture model with spectral and spatial constraints. IEEE Trans. Geosci. Remote Sens. 52, 6627–6638.
38. Lei, Z., Fang, T., Huo, H., Li, D., 2012. Rotation-invariant object detection of remotely sensed images based on texton forest and Hough voting. IEEE Trans. Geosci. Remote Sens. 50, 1206–1217.
39. Li, E., Femiani, J., Xu, S., Zhang, X., Wonka, P., 2015a. Robust rooftop extraction from visible band images using higher order CRF. IEEE Trans. Geosci. Remote Sens. 53, 4483–4495.
40. Senaras, C., Ozay, M., Yarman Vural, F.T., 2013. Building detection with decision fusion. IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens. 6, 1295–1304.
41. Wegner, J.D., Hänsch, R., Thiele, A., Soergel, U., 2011a. Building detection from one orthophoto and high-resolution I nSAR data using conditional random fields. IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens. 4, 83–91.
42. Wegner, J.D., Soergel, U., Rosenhahn, B., 2011b. Segment-based building detection with conditional random fields. In: Proc. Joint Urb. Remote Sens. Event, pp. 205– 208

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