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A BENCHMARK SURVEY ON HIGH-RESOLUTION REMOTE SENSING IMAGES LEARNING TECHNIQUES

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Abstract: Change detection using remote sensing images plays a significant role within the realm of analysis using remote sensors and has been widely employed in various areas like resource monitoring city planning and disaster assessments and more. In recent times it has sparked widespread curiosity due to the rapid growth in artificial intelligence (AI) technology. In addition, the use of change detection algorithms that are built on deep learning frameworks have enabled it to recognize more delicate modifications (such as changes to tiny buildings) using massive amounts of remote sensing and, in particular, HD (HR) records. Although there are numerous ways to detect changes, there isn't an exhaustive review of current developments regarding the most advanced deep learning methods for change detection. This is why the purpose in this article is to present an overview of the current deep learning-based algorithms for detecting changes which employ HR remote sensing imagery. The paper starts by explaining the framework used to detect changes and categorizes the techniques in terms of the architectures of deep networks that are used. Then, we discuss the most recent developments in the field of applying deep learning at different granularity structures to aid in change detection. The paper also provides an overview of HR data that are derived from various sensors, as well as information on change detection for possible use of researchers. In parallel, the most appropriate metrics of evaluation for this job are analysed. In the end, a summary of the issues in the detection of changes through HR remote sensing images that must be addressed to improve the performance of the model, is provided. We also suggest promising avenues for further research in this field.

Keywords: deep learning; change detection; high-resolution; remote sensing images.

1 INTRODUCTION:

The field of deep learning has seen rapid growth in recent years, and has achieved impressive results in a wide range of areas. Contrary to traditional algorithms, deep-learning-based methods typically use deep networks to obtain features from data in order to perform different tasks. Particularly, the use of deep learning to remote sensing is currently receiving a lot of attention, by the many successful applications within the field of computer vision [1]-[7]. Therefore, the rapid development of deep-learning applications for remote sensing increases the number as well as the variety of classification techniques that can be used to recognize various objects that are on earth's surface, like automobiles, aircrafts and homes [8, 9]. The focus of our research is to review the latest developments in remote sensing that allow aerial and satellite-based object detection. By doing this we aim to encourage future research in related fields by providing a broad overview of the detection of objects in overhead images to experienced and novice.

Change detection that is based on remote sensing (RS) technology is utilized to detect and distinguish the differences between ground objects by with the help of two or more images from the same geographical place [1]. The advancement of technology for remote sensing has drawn the attention of numerous researchers, and has been utilized to many areas including monitoring of disasters [2,3] surveying resources [4,5,6] along with urban development. The interpretation of information from visual images is approached in a variety of methods over time However, the basic idea is the same: looking at images with the intention of finding objects and assessing their importance. The issue of learning from visual information can be divided into image classification detection and localization of objects semantic segmentation, and instance segmentation as well as other. Semantic segmentation in images, is described by separating portions of images to ensure that every pixel of the group is related to the class of objects in the entire group. In this instance the object classes are related to roads and background. In a multi-class environment it is possible to classify the classes further divided into meadows, buildings parking spaces, etc. The remainder of this chapter discusses recent developments in the field of semantic segmentation issue, along with the literature on the subject used to analyse satellite or aerial imagery.

2 REVIEW ON OBJECT DETECTION IN COMPUTER VISION COMMUNITY

With the rise of a myriad types of deep-learning models particularly Convolutional Neural Networks (CNN) and their remarkable success in image classification (He and. 2016, ; Kievsky et al. (2012); Luan et al. (2018); Simonyan and Zisserman, 2015; Szegedy et al. (2015) Numerous deep learning-based object recognition frameworks have been suggested in the community of computer vision. So, we'll first present a comprehensive overview of the sources for the data sets as well as deep learning-based approaches to the purpose of object detection in natural images of scenes.

2.1 Deep Learning Based Object Detection Methods in Computer Vision Community

Recently, a variety of deep learning-based techniques for detecting objects have been suggested, which can greatly improve the efficiency of detection. In general, the deep learning techniques specifically designed for detection of objects can be separated into two streams on basis of whether or not they are producing region proposals. They are methods that are based on regions and regression-based techniques.

2.1.1 Region Proposal-based Methods

In the past few years, region proposal-based object detection methods have achieved great success in natural scene images (Dai et al., 2016; Girshick, 2015; Girshick et al., 2014; He et al., 2017; He et al., 2014; Lin et al., 2017b; Ren et al., 2017). These kinds of methods divide the process of object detection into two distinct stages. The first is focused on creating a sequence of proposed regions which may include objects. The second step is to categorize the candidate region suggestions gathered from the initial stage into background classes or object classes and then fine-tune the boundaries of bounding boxes.

The region-based CNN (R-CNN) suggested by Girshick and colleagues. (Girshick et al. 2014) is among the most well-known approaches to different region proposal-based techniques. This is the most representative effort to apply the CNN models to produce complex features for object detection, which has achieved an astonishing performance improvement when compared to all prior research, which is primarily constructed using deformable part models (DPM) (Felzenszwalb and colleagues. (2010).

2.2. Regression-based Methods

This type of approach employs one-stage object detectors that are used for object instance prediction, thereby making it easier to detect objects as a regression problem. Comparatively to methods based on region proposals Regression-based methods are less complicated and efficient since they do not require to generate candidate region proposals as well as the subsequent features re-sampling stages. In Over Feat (sermonette., 2014) is the first object detector based on regression that is based on deep network using sliding-window technology. In the past, You Only at Once (YOLO) (Redmon and Farhadi. 2016, 2016; Redmon and Farhadi, 2017; Farhadi and Redmon,) the Single Shot multi-box detector (SSD) (Fu et al., 2017; Liu et al.. 2017, Liu and Liu. (2016)a) and Retina Net (Lin et al. 2017c) have improved the effectiveness of regression-based methods. YOLO (Redmon et al., 2016; Liu et al., 2017c). in 2016) is an example of a regression-based object detection method. It uses one CNN backbone to identify bounding boxes as well as probabilities of classes from all images within one assessment. It functions in the following manner. When an image is inputted it is then split in SxS grids. When the central point of an object is positioned within a grid it is the grid responsible for the identification of the object. Each grid cell will predict B bounding boxes, along and their scores of confidence as well as Probabilities of class C. YOLO can detect objects in real-time, by redefining it as a single-regression problem. But it is still struggling to pinpoint the location of objects, particularly small-sized ones.

2.3 Semi supervised learning methods

In 2006, Lorenzo Bruzzone et al. in their paper [8 in 2006in 2006] in 2006, proposed a semi-supervised method of classification that utilized both labelled and unlabelled sample to solve the problem of unsolved (also known as Hughes phenomenon) which is predominantly due to the limited size of the training sets, that can result in over - or under-fitting of algorithms utilized to learn. They utilized semi-supervised SVMs, also known as transudative SVMs(TSVMs)[15,16], an iterative algorithm that slowly look for a reliable separating hyperplane using transudative processes that include both unlabelled and labelled samples in the training phase. The proposed TSVM classifier could combine the advantages of semi-supervised methods with kernel-based methods.

In general, region-based techniques for detecting objects have higher accuracy than regression-based methods, although regression-based algorithms offer advantages in terms of speed (Lin and. 2017c). It is widely acknowledged that the CNN framework plays a significant role in the object detection task. CNN architectures function as the network backbones utilized in various frameworks for object detection.

3. REVIEW ON OBJECT DETECTION IN EARTH OBSERVATION COMMUNITY

In recent several years, many techniques for detecting objects have been investigated to find diverse geospatial objects in the community of earth observation. Cheng and colleagues (Cheng and Han 2016) offer a thorough review in 2016 of the methods to detect objects in optical remote sensing photos. However, the research by (Cheng and Han (Cheng and Han, 2016) is not a comprehensive review of the various

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deep learning-based techniques for detecting objects. Contrary to previous surveys, our focus is on examining the literature on datasets and deep-learning based techniques for object detection within the community of earth observation.

3.1 Object Detection Datasets of Optical Remote Sensing Images

In the past few years, a variety of research teams have released their public earth observation datasets to aid in the detection of objects (see Table 1.). The datasets will be discussed in the following manner.

Table 1 : Publicly available object detection datasets in earth observation community.

Datasets	# Categories	# Images	# Instances	Image width	Annotation way	Year
TAS	1	30	1319	792	horizontal bounding box	2008
SZTAKI-INRIA	1	9	665	~800	oriented bounding box	2012
NWPU VHR-10	10	800	3775	~1000	horizontal bounding box	2014
VEDAI	9	1210	3640	1024	oriented bounding box	2015
UCAS-AOD	2	910	6029	1280	horizontal bounding box	2015
DLR 3K Vehicle	2	20	14235	5616	oriented bounding box	2015
HRSC2016	1	1070	2976	~1000	oriented bounding box	2016
RSOD	4	976	6950	~1000	horizontal bounding box	2017
DOTA	15	2806	188282	800-4000	oriented bounding box	2017
DIOR (ours)	20	23463	192472	800	horizontal bounding box	2018

3.2 Deep Learning Based Object Detection Methods in Earth Observation Community

Based on the immense popularity of deep learning-based object detection techniques in the computer vision, a lot of research has been conducted recently to the detection of objects in the optical images of remote sensing. Contrary to the detection of objects within natural scene mazes most studies utilize region proposal-based methods for detecting objects with multiple classes within the community of earth observations. Therefore, we no longer differentiate the two methods, region proposal-based or regression-based techniques in earth observation. We will mainly discuss several examples of the methods.

While the methods mentioned above have shown good results within the earth observation community however, they

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can be slow because they rely on the human-designed generation of object proposals methods that consume the majority of the processing time of an object-detection system. Furthermore the quality of the regions proposed based on the hand-engineered low-level characteristics is not sufficient, which is causing a decline in the performance of object detection.

4. CONLUSION

In this paper, we present a comprehensive review of change detection based on deep learning using high-spatial-resolution images, which covers the most popular feature extraction deep neural networks and the construction mechanisms. Furthermore the granularity of the algorithms for change detection in relation to what is detected is examined and allows us to select the most appropriate technique, regardless of the specific applications they are used for the methods for detecting changes discussed in this paper demonstrate that deep-learning techniques have significantly contributed to the advancement of change detection techniques and have made huge advances. But, there remain numerous challenges to changing detection due to the diverse requirements and the sheer complexity of data. Additionally, multisource data fusion and multiscale issues that arise from remote sensor data are aspects that should be considered when using remote sensing. It is worthwhile to mention the possibility of being able to solve various kinds of challenges with different ground targets. For instance the displacement of high-rise structures is among the most significant problems in images taken from various perspectives [16], while heterogeneous appearance [19] is an issue that is of great importance. So, a number of ideas to research future directions for the detection of changes using remotely sensed data is advised to focus on these problems. The first is that producing a huge quantity of sample labels for the purpose of detecting changes is essential for training a large model with sufficient generalization capabilities to handle different complicated sceneries. Second, in order to handle the difficulties of change detection, domain knowledge (the spatial-temporal-spectral characteristics of remote sensing images,

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geographic information, and other geoscience-related knowledge) must be integrated into the learning framework to enhance the reliability of the method. Thirdly, the learning process using smaller samples can be useful in the design of algorithms when data from a vast number of samples that have been labelled are not available and difficult.

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