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UAV-BCD: A UAV BUILDING CHANGE DETECTION DATASET

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ABSTRACT

Remote sensing change detection (RSCD) holds significant prominence as a research topic within the realm of computer vision. However, previous RSCD datasets have been constructed based on satellite remote sensing images. Traditional satellite remote sensing images have problems such as insufficient resolution, difficult data acquisition, and complex processing processes, and there is a certain gap between data distribution and actual needs. UAVs not only have the advantages of flexibility and high-speed, but also can capture high-resolution images, which are especially suitable for high-precision RSCD in small areas. Therefore, this paper proposed a new UAV RSCD dataset — UAV Building Change Detection Dataset (UAV-BCD). The proposed dataset contains 2024 pairs of finely registered high-resolution images collected by UAVs and their corresponding pixel-level labels, which can provide a new benchmark for RSCD. We evaluate the effectiveness of UAV-BCD with the five state-of-art deep neural networks in RSCD.

***Index Terms*—** Remote sensing, change detection, computer vision, UAV, dataset.

1. INTRODUCTION

With the increasing growth of the world population and the rapid development of the global economy, human activities continue to facilitate the dynamic changes of land use cover and the update of change patterns. Under the background of global change, mastering the change information of ground objects is beneficial for human's cognition of practical problems and the prediction of future development. Using remote sensing technology to detect changes in ground objects is a research hotspot in earth science today. RSCD is to detect places of change from bittemporal or multitemporal remote sensing images acquired at the same geographic location. This task plays an increasingly important role in areas such as disaster assessment, environmental monitoring, land management, and urban transformation.

In recent years, advancements in satellite remote sensing technology and computer vision have enabled the extraction of change information from high-resolution remote sensing images, making it feasible. Most of the previous RSCD work was carried out on public RSCD datasets, such as LEVIR-CD dataset [1], WHU Building change detection dataset [2], and SYSU-CD dataset [3]. However, these datasets are all obtained based on satellite sensors, and the obtained satellite remote sensing images needed to be processed by professionals. The using conditions are often inconsistent with the actual situation, and there are problems such as low resolution, great influence by weather, and high processing difficulty.

The rapid development of UAVs technology has made UAV remote sensing gradually become a new type of remote sensing platform after traditional satellite remote sensing. UAVs have high maneuverability and flexibility, and the collected images are characterized by low influence of weather and high resolution. Therefore, in order to solve the problems existing in the current satellite RSCD datasets, we proposed a UAV Building Change Detection Dataset (UAV-BCD), which greatly complements existing change detection datasets in terms of image resolution and image size. Extensive experiments were performed to evaluate the effectiveness of UAV-BCD.

2. DATA DESCRIPTION

This section details the data collection and data preprocessing of UAV-BCD.

2.1. Data collection

In order to produce as many changes as possible in the acquired images, the shooting interval between the two phases of images should be as long as possible. Therefore, our shooting time interval was 1-2 years. In accordance with the data collection requirements, the UAVs used to collect images should have sufficient load and endurance, a high-resolution camera, and additional equipment for integrated auxiliary processing and flight control. In the case of meeting the above conditions and maximizing cost-effectiveness, we used the DJI Mavic2 professional drone of DJI to take visible remote sensing pictures during flight missions. The main parameters of the DJI Mavic2 camera are shown in Table I.

While the UAV equipment itself is important, it is especially critical to develop a suitable flight plan. Before

Table I: Parmameter of DJI Mavic2 camera

Item	Value
Camera type	CMOS (FC2403)
Angle of view	77°
Aperture	f/2.8 - f/11
Equivalent focal length	28MM
Image format	JPEG/RAW
Maximum image size	5472×3648
Detector pixel pitch	1.61797 µm

shooting images, the weather conditions should be paid more attention so as to avoid the environment of excessive wind and rain. In the case of hot weather, it is necessary to pay attention to the temperature of the drone itself. At the same time, it is necessary to ensure appropriate lighting and scene diversity. Set the appropriate camera parameters according to the weather conditions. In addition, it is essential to formulate a suitable flight route and save it to ensure that the two images are taken at the same location as possible. After the implementation of the above preparatory work, a large number of original data can be effectively collected within 1-2 years.

2.2 Data preprocessing

Since the collected images would be affected by factors such as actual scene lighting, camera angle of view, and wind speed during the shooting process, it is necessary to preprocess and register the collected data in order to reduce the interference of external factors of the images.

(1) Radiation correction: In order to eliminate the change of image pixel gray value due to the change of non-surface objects, it is necessary to perform radiation correction on images of different time phases, thereby reducing the radiation differences between images. We use the radiation correction method based on the invariant target, and selecte representative houses and roads as pseudo-invariant features to perform radiation correction on UAV images. Pseudo-invariant features refer to ground objects whose reflectivity basically does not change with the changes of external conditions.

(2) Geometric correction: Usually, the relative positions of targets can often be misaligned due to various systematic or non-systematic factors like azimuth angle parameters, flight height, and terrain fluctuations, leading to pixel distortion and stretching relative to their actual positions. During the data collection process, the attitude information of the camera is recorded by the UAV itself in real time, including pitch, longitude, altitude, and latitude. We matched the captured images with their corresponding attitude information and performed height compensation and other operation to ensure that the output data was consistent with the actual geographic location of the captured scenes, completing geometric correction.

(3) Registration: Since traditional image registration algorithms only use the low-level features of images, they

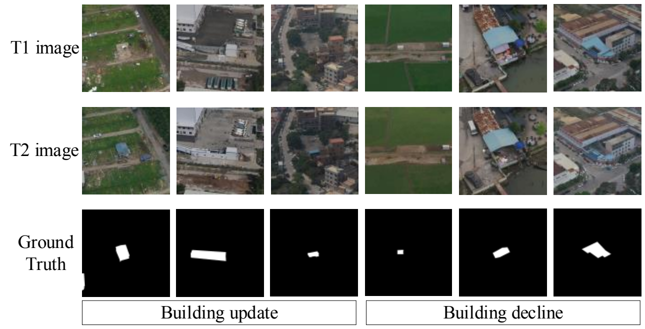

Fig. 1. Samples of UAV-BCD

cannot be applied to high-resolution images with complex background information collected by drones. Therefore, the registration algorithm we used is SuperRetina [4]. The algorithm is applied to eye retinal image registration, and the registration requirements of retinal images are extremely high. A large number of accurate annotations in images were required to achieve a good registration effect. Therefore, under the same labeling conditions as retinal images, this algorithm is also applicable to images collected by UAVs.

3. UAV-BCD DATASET

This section gives the details of UAV-BCD and its comparison with other RSCD datasets.

3.1 Details of UAV-BCD

UAV-BCD contains 2024 pairs of optical images collected by UAVs from prefecture-level cities in Guangdong Province and their corresponding pixel-level labels. The pixel size of each image is 768×768, the spatial resolution is 0.06m, and the shooting interval is one to two years, with an average of three changing objects per pair of images.

The annotation of UAV-BCD was performed by remote sensing experts with extensive expertise in interpreting remote sensing images and a comprehensive understanding of RSCD tasks. The entire dataset was manually annotated, which took approximately two months to complete.

Detecting changes in buildings is an important change detection task which plays an important role in many areas such as urban change analysis and illegal building detection. The prefecture-level cities in Guangdong Province have always been prosperous and populous metropolises in southern China. Due to rapid economic development, there are a fast renewal and increasing demolition for buildings. Therefore, our attention is directed towards changes related to buildings, which included both updates and decline of buildings. The scope of our new dataset encompassed a wide range of building types, such as villas, high-rise apartments, factories, and so on. Some samples we selected

Table II: Summary of UAV-BCV

Item	Value
Number of image pairs	2024
Image size	768×768
Image resolution	0.06m/pixel
Tiime span	1~2 years
Modality	RGB image

from UAV-BCD are shown in Figure 1. Table II is the summary of UAV-BCD.

3.2 Comparison with other RSCD datasets

Over the past few decades, there have been several attempts to develop open RSCD datasets. The details of UAV-BCD and six other existing commonly used RSCD datasets are shown in Table III. The SZTAKI Air Change Benchmark set [5] is the earliest and most widely used RSCD datasets in early works, which consists of 12 pairs of 952×640 optical aerial images with a spatial resolution of 1.5 m. The Onera Satellite Change Detection dataset (OSCD) [6] comprises 24 pairs of Sentinel-2 images, each with a size of 600×600 pixels and a spatial resolution of 10 m, captured between 2015 and 2018. In recent years, several datasets have been raised specifically to facilitate the development of RSCD, which are the most common and relevant RSCD types nowadays, including the WHU building change detection dataset (BCDD) [2], the seasonal-vary change detection dataset (CDD) [7], LEVIR-CD dataset [1], and SYSU-CD dataset [3].

Although greate progress has been made in addressing the problem of detecting changes between multi-temporal remote sensing images in RSCD with the development of datasets, there is still room for improvement in achieving large-scale and fine-grained RSCD. First, the spatial resolution of some datasets is still inadequate, which limits the precision of the information that can be obtained. Second, the existing datasets do not cover enough change types to meet the diverse needs of practical applications. Finally, the volume of some datasets is too small, which may result in poor performance and overfitting of models for data-driven deep learning-based methods. As show in Table III, UAV-BCD has the highest spatial resolution, which shows the great advantages of the images captured by UAVs. Furthermore, with the same size of image, the volume of UAV-BCD is the second only to SYSU-CD.

UAV-BCD dataset greatly complements the existing RSCD datasets, relieving the limitations of image resolution and dataset size, which makes up for the shortcomings of existing RSCD datasets, and establishes a new benchmark for RSCD.

4. EXPERIMENT

This section gives the experiment details and experiment results and analysis.

Table III: Comparison between different RSCD datasets

Dataset	Number of image pairs	Image size (pixels)	Resolution (m/pixel)
SZTAKI	12	952×640	4.5
OSCD	24	600×600	10
BCDD	1	32207×15354	0.2
CDD	16000	256×256	0.03-1
LEVIR-CD	637	1024×1024	0.3
SYSU-CD	20000	256×256	0.5
UAV-BCD	2024	768×768	0.06

4.1 Experiment details

To verify the effectiveness of UAV-BCD, we randomly partitioned the dataset into training, validation, and test sets, adhering to an 8:1:1 ratio respectively, following the division method of LEVIR-CD. We chose five state-of-the-art deep learning-based methods in RSCD for evaluation, including FC-Siam-Conc [8], FC-Siam-Diff [8], STA-Net [1], BIT [9], and Snunet [10]. We compared UAV-BCD with the two most commonly used public RSCD datasets, LEVIR-CD and BCCD.

We conducted experiments based on the PyTorch framework, and used GeForce RTX 2080ti to speed up model training. During the training process, all training parameters except batch size were the default parameters of the code they released. Due to the limitation of memory size, the batch sizes of some models were adjusted to be smaller.

Four standard evaluation metrics are utilized to assess the effectiveness of these methods, including precision, recall, iou, and F1 score. The precision measures the false positive rate of the model, while recall reflects the false negative rate. The F1 score, which considers both precision and recall, provides a comprehensive measure of model performance. Iou quantifies the degree of overlap between the change class on the detection map and the ground truth, making it a crucial metric for evaluating model accuracy.

4.2 Experiment results and analysis

We use LEVIR-CD, SYSU-CD and UAV-BCD to conduct experiments, and the the experimental results are shown in Table IV. We can draw some conclusions according to Table IV:

(1) In these three datasets, the model with the lowest F1 score is FC-Siam-Conc or FC-Siam-Diff, and the model with the highest F1 score is BIT. Moreover, other indicators of the model with the highest F1 score are much higher than those with the lowest F1 score in the three datasets, which shows the huge performance gap between them.

(2) The F1 score in UAV-BCD is obviously much lower than that in the other two datasets, which also reflects

Table IV: Experiment results on three datasets

Dataset	Models	Precision	Recall	F1	IoU
LEVIR	FC-Siam-Conc	0.8548	0.8711	0.8629	0.7589
	FC-Siam-Diff	0.8719	0.8522	0.8719	0.7729
	STA-Net	0.9503	0.8243	0.8828	0.7903
	Snunet	0.9105	0.8893	0.8998	0.8179
	BIT	0.9221	0.8897	0.9056	0.8275
BCDD	FC-Siam-Conc	0.8861	0.8557	0.8706	0.7709
	FC-Siam-Diff	0.9048	0.8514	0.8773	0.7814
	STA-Net	0.8923	0.8866	0.8895	0.8009
	Snunet	0.9255	0.8858	0.9052	0.8269
	BIT	0.9610	0.9089	0.9342	0.8766
UAV-BCD	FC-Siam-Conc	0.7369	0.2784	0.4001	0.2500
	FC-Siam-Diff	0.7428	0.1637	0.2683	0.1549
	STA-Net	0.5626	0.4250	0.4842	0.3194
	Snunet	0.5516	0.4353	0.4866	0.3215
	BIT	0.7115	0.4160	0.5251	0.3560

that the images taken by UAVs are high-resolution images. They contain not only rich semantic information, but also more complex contextual information. It is necessary to continuously improve the performance of the model to accurately learn knowledge from the complex background environment. This also shows that UAV-BCD face certain challenges and can promote the development of RSCD in the future.

5. CONCLUSION

We proposed a new UAV-based building change detection dataset for RSCD, consisting of 2024 pairs of UAV-captured images and their corresponding pixel-level labels. We evaluated this dataset using five state-of-the-art deep learning-based methods in current RSCD. The experimental results show that UAV-BCD has certain accuracy and potential but also faces challenges, which offers an opportunity to evaluate and enhance RSCD methods. We hope that UAV-BCD could facilitate deeper research on RSCD in the future.

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