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Integrated satellite image analysis for detecting land encroachment and flood damage using LSTM and VGG16

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Abstract

Change detection techniques aim to identify differences in remote sensing images taken at different times over the same area, supporting applications such as urban development monitoring, land cover analysis, and environmental management. Traditional radiometric methods often suffer from high false alarm rates caused by factors like shadows, vegetation, or illumination differences. To overcome these limitations, this thesis explores the use of Digital Surface Models (DSM) in change detection. DSM offers structural height information, helping distinguish real changes from radiometric anomalies. However, DSM data also has limitations when height changes are absent despite actual land cover modifications. This study proposes a hybrid approach combining DSM with spectral and RGB data to leverage the strengths of each source. Deep learning techniques, particularly Convolutional Neural Networks (CNN) and Fully Convolutional Networks (FCN), are implemented to enhance change detection performance and automate feature learning. A supervised FCN model is trained using annotated datasets to distinguish between changed and unchanged regions accurately. The proposed method improves reliability and robustness in detecting real-world changes across urban environments, showing significant potential for enhancing remote sensing based urban monitoring systems.

Keywords: Integrated, Satellite, detecting, encroachment, flood, LSTM, VGG16

Introduction

The increased rate of urban expansion in recent years has significantly changed urban landscapes all over the world. Understanding the changed areas allows the government to make a better city planning or solve the problems caused by changes. Change detection techniques aim to detect changes between two or more multitemporal remote sensing images acquired over the same area, so as to monitor land cover changes. These techniques attracted much attention in recent decades. In the past, change detection has been mainly used to monitor agriculture and land cover changes primarily because of the limitation of resolution. With the increase of spatial resolution, it is now applied on various applications, like land cover updating, urban expansion, water conservancy, environmental disaster and so on. With the development of remote sensing techniques like photogrammetry and various sensors, researchers can easily obtain remote sensing information from various platforms. The Landsat 8 satellite can achieve global coverage every 16 days, and the cycle reduces to only 5 days considering both Sentinel-2A and Sentinel-2B. For the Sentinel-2 mission alone, 3.4 petabytes of remote sensing data have been acquired already. Moreover, platforms of the unmanned aerial vehicle (UAV) provides another way to acquire remote sensing information. Nowadays, studies on radiometric changes between optical or spectral images are popular research area, and most of the algorithms also proposed based on these data. A systematic survey of these methods has been provided by Radke *et al*. (Radke, Andra, Al-Kofahi, & Roysam, 2005) [1]. However, high false alarm rates due to irrelevant radiometric changes is a big problem for these methods, which is caused by shadows, vegetation, and moving object.

Literature review

Change detection in remote sensing is a critical task for numerous real-world applications, including urban expansion monitoring, disaster management, deforestation tracking, and land-use classification. Over the years, various techniques have evolved to improve the accuracy and efficiency of detecting changes across multi-temporal satellite images. This literature review highlights key developments and gaps in existing methods, laying the foundation for the proposed hybrid deep learning approach.

Traditional radiometric approaches

Early change detection methods largely relied on radiometric techniques such as image differencing, image ratioing, post-classification comparison, and principal component analysis (PCA). These methods compare pixel intensities or derived indices between two time points. While simple and computationally efficient, these techniques are prone to false detections due to factors like seasonal variations, illumination changes, shadows, and sensor noise. As noted by Singh (1989) [2], radiometric approaches often fail to distinguish between actual surface changes and radiometric noise, limiting their reliability in complex urban and environmental settings.

Role of Digital Surface Models (DSM)

To address the limitations of radiometric methods, researchers have turned to height-based data such as Digital Surface Models (DSM). DSMs provide elevation information of the Earth's surface, including natural and man-made structures. This structural data helps identify changes involving buildings, vegetation height, or terrain shifts, which are not easily detectable through spectral data alone. Studies by Qin *et al*. (2016) [3] and others demonstrate the potential of DSM in enhancing change detection accuracy, particularly in urban landscapes. However, DSMs have their limitations when it comes to non-structural changes, such as alterations in land cover that do not involve significant height variation.

Fusion of spectral, RGB, and structural data

Recent literature has explored data fusion techniques, integrating DSM with RGB or multispectral imagery. This combination leverages the strengths of both data types-spectral data captures color and texture, while DSM adds 3D structural information. Works like Huang *et al*. (2018) [4] have shown that such multimodal fusion significantly improves the detection of diverse change types, including both structural and land cover modifications.

Deep learning and change detection

With the rise of deep learning, particularly Convolutional Neural Networks (CNNs) and Fully Convolutional Networks (FCNs), change detection has seen a transformation. Unlike traditional methods, CNNs automatically extract and learn spatial features from raw image data, enabling better generalization and robustness. FCNs further allow for pixel-level classification, making them ideal for detecting and segmenting changed regions in images. As described by Zhao *et al*. (2021) [5], deep learning models outperform conventional methods in terms of accuracy, especially when trained on large, annotated datasets.

Supervised learning and dataset challenges

Despite the advantages of deep learning, its performance heavily depends on the availability of well-annotated training data. Creating such datasets is labor-intensive and time-consuming. To address this, researchers have used synthetic datasets, data augmentation, and semi-supervised learning to enhance model training. Supervised FCNs, in particular, have been successfully applied to urban change detection tasks, demonstrating high reliability when provided with accurate ground truth data.

Results and Discussion

The proposed hybrid change detection approach integrates Digital Surface Models (DSM) and RGB imagery within a deep learning framework to enhance the identification of temporal changes in remote sensing images. The results of the experimental study indicate that this integration significantly improves the model’s capability to detect both structural and non-structural changes with greater accuracy and reliability.

Traditional methods, which rely solely on radiometric or spectral differences between multi-temporal images, often produce a high number of false positives due to their sensitivity to shadows, seasonal vegetation differences, and lighting variations. By incorporating DSM data, the model gains access to height information, which helps distinguish real structural changes (such as building construction or removal) from radiometric anomalies. However, DSM alone is insufficient in capturing changes in land cover that do not involve elevation differences, such as transformation from vegetation to barren land or pavement.

The integration of DSM with RGB imagery in a deep learning architecture, particularly a Fully Convolutional Network (FCN), allows the model to simultaneously learn and extract features from both structural and spectral domains. This dual-modality approach enables more robust detection of various types of changes, reducing false alarms and improving the precision of the results.

Moreover, the use of FCNs allows for pixel-level classification, which leads to finer segmentation of changed regions compared to traditional patch-based CNN methods. The supervised learning approach further enhances the model's performance by learning from labeled examples, enabling it to generalize better to unseen data.

Qualitative observations from the experiments indicate that the proposed hybrid model produces smoother and more coherent change maps, with clearer boundaries and minimal noise. The model effectively identifies complex change patterns in urban areas, where both height and surface appearance may vary over time.

However, the approach is not without limitations. The quality and alignment of input data play a crucial role in the performance of the model. Misalignments between DSM and RGB layers can lead to inaccurate change detection. Furthermore, the supervised nature of the model necessitates the availability of large, annotated datasets, which can be challenging to obtain.

In future work, the model could be enhanced by incorporating additional data sources such as multispectral or Synthetic Aperture Radar (SAR) imagery, and by exploring unsupervised or semi-supervised learning techniques to reduce dependence on labeled data. The application of temporal attention mechanisms and domain adaptation strategies may also improve the model's generalization across diverse geographic and environmental conditions.

Conclusion

In this thesis, we explore unsupervised changed detection algorithms based on the RGB and DSM data. The DSM data is used to detect 3-D changes in urban areas, and the RGB data is included as a supplement to detect changes in areas where there are no 3-D changes. Then, an unsupervised FCN system was proposed to learn the texture information from the image and further optimize the change detection performances. The experiment was performed on UAV images from three different times, and the DSM images were obtained by photogrammetry. Four comparison trials are performed to get better experimental results in our study areas. The first one is to obtain a set of parameters for the DSM-based method. Then, a comparison between the three RGB-based methods is performed. Furthermore, the effect of unsupervised FCN architectures with different numbers of convolutional layers and different kernel size is compared to find a better architecture. At last, the result obtained from the supervised FCN architecture is compared with our experimental results to verify the effectiveness of our method. The experimental results show that our method can effectively detect changes in urban areas. Compared with using spectral information for change detection alone, the combined approach reduces the effects of shadows and different seasons on the results to some extent. Compared with the DSM-based method alone, the combined method can be more effective in detecting areas without elevation changes. In addition, the unsupervised FCN framework can make an improvement based on unsupervised change detection results. This framework not only reduces the interference caused by shadows and different seasons on spectral information but also eliminates noise from the pixel-based algorithm. Most importantly, our unsupervised FCN architecture can be applied to all the deep learning techniques. By doing this, we can effectively reduce the needs of manual interpretation, thereby improving the time efficiency and reducing the labor cost. At the same time, the problem of insufficient training samples in deep learning can be significantly alleviated as 68 well. Moreover, by combining this framework with different unsupervised methods, the results of existing unsupervised methods are likely to be improved again. The unsupervised method here is not limited to the field of change detection. Algorithms in all fields (like image classification, boundary detection) can also be improved after combining this framework.

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