

Identification of Building Changes Using a Gray-Level Co-Occurrence Framework and Artificial Neural Systems

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Description

The recovery phase of a disaster management plan aims to restore the landscape to its pre-disaster state and reduce future vulnerability. Following a catastrophic earthquake, the progression of the recovery phase is determined by decision makers' classification of disaster-affected areas, which is generally divided into three types: collective resettlement area, original site recovery area and non-disaster area. The utility of geospatial data obtained through remote sensing technology has been widely demonstrated in recent years. Remote sensing has evolved into an extremely useful tool in gathering, processing and analysing geospatial data with the goal of extracting valuable information for proper decision making in various scientific fields by incorporating both spaceborne and airborne techniques.

Change detection is one of the many fields where remote sensing is used. Remote sensing data, with their unique characteristics such as high temporal frequency, digital format and the availability of several sensors with a variety of spatial and spectral resolutions, can be efficiently used to detect changes in a variety of applications such as land use management and planning, urban expansion and planning and disaster monitoring and management [1-3]. Because of its superior abilities in automatic feature learning and visual pattern recognition, machine learning now plays an important role in improving the efficiency of change detection and monitoring. Machine learning techniques, such as Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs), are widely used in change detection, particularly in cases where traditional change detection methods, such as post-classification comparison, are frequently problematic, such as in urban change detection. The application of ANNs is gaining popularity.

The use of ANNs has grown in popularity and they have been used for a variety of change detection applications such as vegetation change, land cover change and urban change. These studies suggest that, when compared to other techniques, the ANN method can improve the accuracy of change detection. Another method for detecting changes in remote sensing is to extract a large number of image features with the goal of improving the discriminative capability of image change information; texture is one of these features. Texture is one of an image's key structural characteristics, used to identify objects or regions of interest and it is also consistent with human visual characteristics [4,5]. Texture extraction is important because it serves as an input for more advanced processing and has a significant impact on extraction quality; thus, many studies on texture extraction from remote sensing data have been conducted.

Furthermore, texture-related research is still a hotspot for computer vision and image processing researchers and it is constantly evolving. There are various methods of texture analysis that involve both the colour and the arrangement of pixels in an image, i.e., GLCM (Gray-Level Co-occurrence Matrix), fractal model, Fourier and wavelet transformations. Furthermore, different classification schemes for these methods, such as statistical, model-based and geometrical/structural methods, have been developed. The GLCM method has proven to be one of the most useful and powerful texture analysis techniques because it is straightforwardly simple, easily executable and produces good results.

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Conflict of Interest

Authors declare no conflict of interest.

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