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Research Article

Remote Sensing Imagine Change Detection Using Semi-Supervised Neural Networks

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Abstract: By comparing and contrasting photographs of the same location taken at various periods using remote sensing technology, we may determine whether or not there have been any changes to the land cover there. Identifying shifts in a timely manner will facilitate the identification of natural disasters and climate change, the evaluation of damage, and the rehabilitation of affected areas. Both supervised and unsupervised methods have been utilised historically for change detection. In practise, specialists can only gather a small number of tagged patterns to use in solving the change detection issue. In this case, supervised techniques are ineffective, and if unsupervised methods are employed instead, some scarce but useful labels are wasted. In this dissertation, we offer a novel methodology to enhance change detection in the face of data scarcity by combining a small number of labelled patterns with a large number of unlabeled ones. In this study, many neural network architectures are employed to develop active and semi-supervised learning change detection methods. For better change detection when only a small number of labelled patterns are available, we redesign two unsupervised learning based neural networks, a modified self-organizing feature map and a Hopfield type neural network, in a semi-supervised framework.

Keywords: Neural Networks, Semi-Supervised, Active Learning Frameworks, Hopfield type

Introduction

Multi-temporal image analysis is known as change detection [1-4]. In a nutshell, this method identifies the areas that have changed between two snapshots of the same panorama taken at separate times. In the modern day, change detection is widely used in many fields, including remote sensing [1, 2, 5-9], video image processing [10-17], and medical judgement [18, 19]. This Paper focuses on methods for identifying shifts in remotely sensed imagery. Here, change detection is employed to determine the temporal shifts in a land-cover by comparing photos captured by remote sensing instruments at various intervals of time [1]. Changes in this field may result from a variety of factors, including but not limited to natural disasters, urban expansion, deforestation, and climatic shifts. The topography of Earth is in constant motion. Time slowly reshapes every part of Earth, including the ice, wind, form of land, continents, and seas. Even after natural disasters like earthquakes, volcanoes, and storms, the planet's surface undergoes a dramatic change. Early detection of natural disasters and climate change, damage assessment, and rehabilitation are all simplified by the ability to identify changes in a timely way. Multi-temporal remotely sensed pictures are useful for observing these shifts, and automated methods for identifying shifts are needed to lessen the burden on humans. Change detection, from the perspective of pattern recognition and machine learning, is analogous to an image segmentation issue [12–16] in which two groups of pixels are created, one for the altered category and the other for the unchanged one. Both supervised (through classification) and unsupervised (by clustering) methods have been utilised historically for change detection. In a supervised method, it is required to have access to extra data, such as ground truth. Ground-truth generation is labor-intensive and resource-intensive. In contrast, more data isn't necessary when using an unsupervised method. As labelled patterns become scarce, it seems that unsupervised methods must be used for change detection. It's possible for a human expert to classify a subset of change detection patterns. It's possible that if there aren't enough of these labelled patterns, we won't have enough data to use in creating supervised techniques. Knowledge of labelled patterns, albeit limited in quantity, may be wasted in such a situation if an unsupervised technique is pursued.

In this paper, two types of ANNs are used to deal with the inadequate labelled information: semi-supervised learning [5, 6] and active learning [7]. Both methods of learning tackle the same issue from different perspectives. Active learning, like semi-supervised learning, gets its start with certain labelled patterns. Semi-supervised learning then iteratively includes the'most confident' unlabeled patterns in the training process, while active learning repeatedly collects some of the'most confusing' patterns from the collection of unidentified patterns employing the well-defined query selection function, and the collected patterns are labelled by a supervisor. The current work serves a dual purpose: first, to improve the effectiveness of change identification on multi-spectral and multi-temporal remotely sensed images, by employing novel algorithms developed using ANNs in semi-supervised and active learning mode so that ANNs can utilise a few labelled patterns along with plenty unlabeled patterns during learning.

Analysis of Remotely Sensed Images

To acquire physical data about an object from a distance without making direct contact is the procedure known as remote sensing [5-8]. Remote sensing has several uses in earth observation, including climate change forecasting, monitoring land use, protecting forest ecosystems, overseeing agricultural expansion, and many more. In the 1940s, U.S. Navy scientist Evelyn Pruitt used the phrase "Remote Sensing" to describe her work. In terms of earth observations, 1972 was the most pivotal year in the history of remote sensing. Landsat 1, the first satellite to orbit the Earth specifically to monitor its surface, was launched in 1972. In remote sensing, sensors installed on an aircraft platform measure the amount of energy radiated from Earth's surface. The resulting computer images are based on these measurements. Using electromagnetic radiation emitted or reflected from these objects, sensor data is mostly used to observe water, bare soil, and plants. In turn, this information is useful for landscape analysis. The wavelength utilised to acquire the image during sensing is perhaps the most crucial aspect of a remote sensing image. The spatial distribution of reflected solar energy in the ultraviolet, visible, and near-to-middle infrared spectral ranges is the primary data point for remotely sensed images. The spatial distribution of the energy emitted by the earth itself in the thermal infrared wavelength range has also been measured. Spectral behaviour can be used as a proxy for colour identification, even if the actual wavelength range lies beyond the visible spectrum.

Pre-Processing Of Remotely Sensed Images

There is a chance that the images collected by the remote sensors contain inaccuracies. There are two primary categories of mistakes that might occur during the learning process. The terms "radiometric error" and "geometric error" are used to describe them. The former can be found in the brightness that was actually measured, whereas the latter can be found in geometry. When using a multi-date or multi-sensor framework, such as change detection, adjusting or correcting these mistakes becomes increasingly crucial. Images acquired on different dates or with different sensors may be susceptible to different kinds of mistakes in such application domains. To solve the problem of image comparability, error correction is essential. A short look at how radiometric and geometric corrections work

Land-cover Classification using Remotely Sensed Images

Identification of land-cover classes existent in a geographic area matching to a picture is an essential step for interpretation of remotely sensed images [7]. Poor lighting, insufficient spatial resolution of photographs, and the negative impact of environmental conditions during image collecting make this a challenging operation. Both supervised and unsupervised methods have been utilised for land-cover classification in the remote sensing community historically [7]. Artificial neural networks [9, 5], kernel-based methods [1, 2], support vector machines (SVMs) [3, 4], etc. are only a few examples of the many techniques available for supervised categorization in the scientific literature. In contrast to the unsupervised approach, which does not require labelled data, the success of supervised methods is highly dependent on the number and quality of labelled patterns. Collecting labelled data in remote sensing is not only tedious and time-consuming, but also expensive.

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As labelled data becomes scarce, the unsupervised approach [5] becomes more readily applicable in remote sensing research. In addition to these two common methods, the literature has been expanding its focus on semi-supervised and active learning methods. In remote sensing, these frameworks appear obligatory due to the limited availability of training samples from on-the-ground experts. If an unsupervised method is used in this situation, valuable labelled data may be lost. This dissertation focuses mostly on semi-supervised and active learning methods for change detection. In this article, we take a quick look into the semi-supervised and active learning framework for classifying remotely sensed photos. Classification of hyperspectral images is one area where semi-supervised methods have been put to use [4-7]. The vast number of spectral bands and relatively small number of training samples leads to the 'curse of dimensionality' [8] issue.

Remotely sensed pictures from the ERS2 SAR and Landsat TM sensors are beneficial for monitoring urban expansion and cloud screening when utilising a Laplacian SVM in a semi-supervised framework in a graph theoretical manner [9]. Additionally, hyperspectral crop detection, multi-spectral cloud screening, and multi-source urban surveillance all make use of semi-supervised one-class SVM [6]. In this scenario, the classifier is responsible for identifying which pixels belong to which class and discarding all others. The urban picture classification challenge was addressed by Tuia et al. [6] using semi-supervised SVM on very high resolution multi-spectral and hyperspectral images. Here, a base kernel and a likelihood kernel are used to train a support vector machine in a linear fashion. Only labelled instances can be used with the base kernel; to encode similarities between labelled and unlabeled examples, a probability kernel is used.

Literature Survey

Radke et al. (2005) covered everything from calculating significance to testing hypotheses in contemporary change detection techniques. Predictive model algorithms, shading model algorithms, and background modelling algorithms were also discussed.

Jia et al. (2006)] have combined data from two difference images using several wavelet kernels; the subtraction image and the ratio image. Research is conducted using these photos. The ratio image mutes out noise in the background, while the subtraction process pulls out the area of change. Each image's wavelet kernels are calculated at a number of different scales, and the correlation coefficients are used to determine the final scale. The two reliable-scale images with differences are then merged using their wavelet kernels.

Hussain et al. (2013) in addition to the brief explanation of the methods, offered a detailed classification of the many strategies and methodologies utilised for change detection. They classified the algorithms into two groups, one using pixels and the other using objects as its comparative basis for change detection. Methods based on analysing the variance in pixel intensities were employed to quantify the evolution. In contrast, object-based approaches 20 analyse items after they have been extracted from images.

Adaptive Ensemble of Extreme Learning Machines (AEELM)

The steps taken to develop the AEELM are graphically represented in Figure 1. First, features were extracted from the images, then datasets were made, then ELMs were made, trained, tested, and their configurations saved, then an ensemble of the trained ELMs was made and adapted, then step 5 was used to detect changes, and finally step 6 was used to make a change map. Several procedures are outlined in this section.

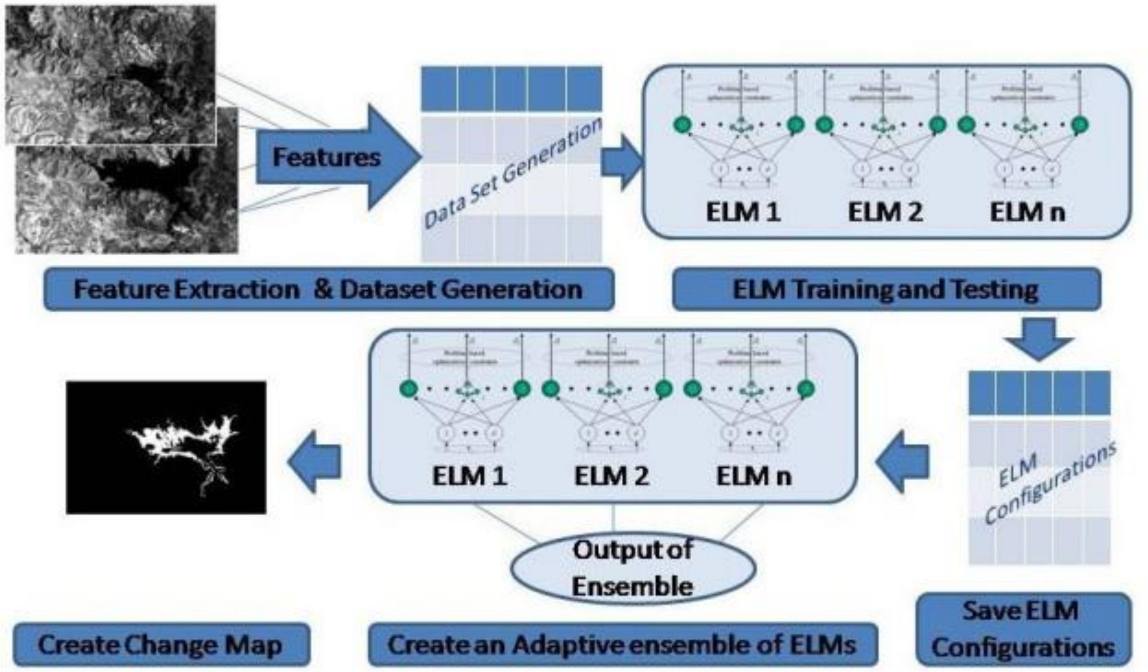

Figure 1. The proposed method

Training and Testing of the individual ELMs

The development and validation of individual ELMs is necessary for this algorithm. To establish the structure of the ELMs, a random number between 700 and 1400 hidden neurons was assigned to each ELM. The training set required 2100 input vectors, hence a value between 130 and 165 was chosen. Since sigmoidal activation is specified for all real values, is bounded, and differentiable, it was chosen as the activation for ELMs. And it solves categorization difficulties effectively. A unique training and testing dataset was produced for each ELM. From the 15000 total pixels in the dataset file, we randomly selected a training dataset of 2100 to use for instruction. The dataset was produced at random since doing so would increase the diversity of the ELMs and allow us to build an ensemble that could handle a wide variety of data. If each ELM used the same dataset, the resulting patterns would be identical. The categorization variety of the ensemble wouldn't improve if numerous ELMs shared the same pattern structure, because each ELM would yield the identical results. Therefore, the variety of the ensemble was improved by randomly generating the input dataset for each ELM. This was done so as to give each ELM a unique pattern structure.

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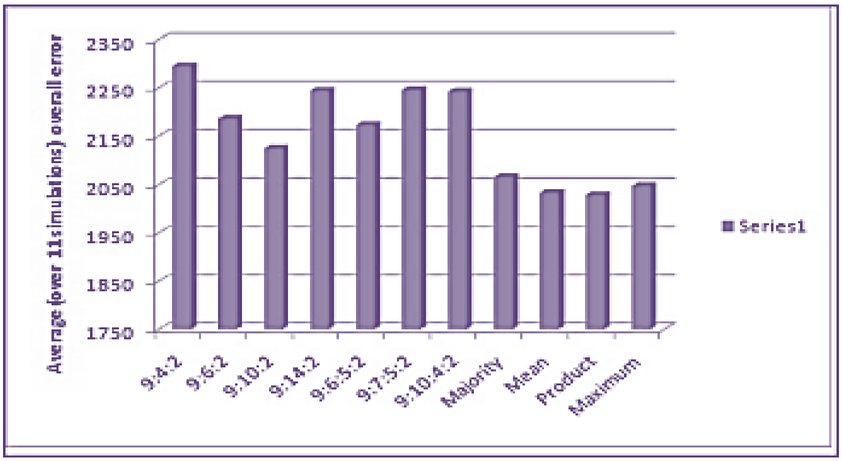
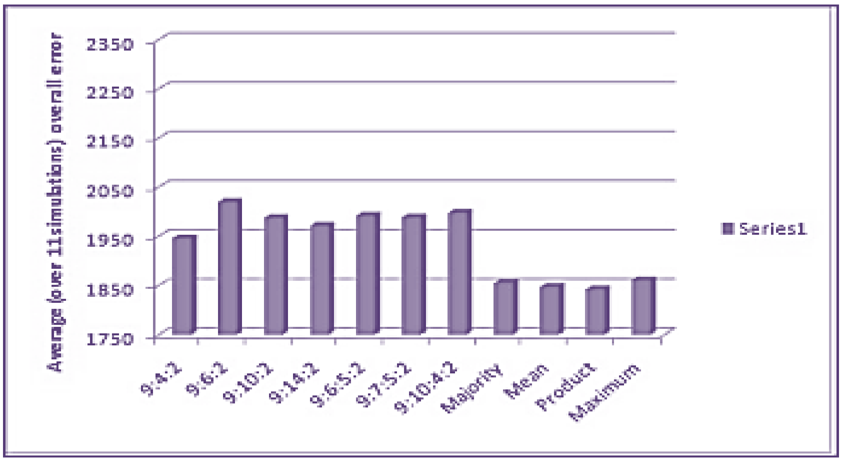


(a)



(b)

Figure 2: Bar charts showing the average overall error with different architectures of MLP for Kaggle dataset using: (a) 5% training patterns and (b) 10% training patterns

Result and Analysis using Semi-supervised MCS

As was previously indicated, the employment of an ensemble classifier in a semi-supervised context has also been the subject of experimentation. The proposed semi-supervised approach's performance is evaluated in comparison to that of other supervised methods, including those based on the MLP [10], the EBF [11,12,13], the fuzzy k-NN [14], and a semi-supervised MLP method [15]. Taking into account six performance measurement indices and the average execution time, eleven simulations are run for each of the five different percentages of training patterns (0.1, 0.2, 0.3, 0.5, and 1 percent). In this case, we don't only take into account two models; rather, we use an ensemble of three. Our experimental results are consistent with common sense explanations for this phenomenon. When combining the results of multiple models, it can be difficult to reach a consensus if the models arrive at opposite conclusions about the appropriate class label for a given pixel. This is why an odd number of classifiers is typically used in ensemble systems. Adding more (various) classifiers in an ensemble architecture makes the final judgement more robust and error-free but also more complicated. From a practical standpoint, it could make more sense to cap the total number of instances. In this study, we took into account three models: MLP, EBF, and fuzzy k-NN. In such cases, it is best to start with a base classifier that provides a nuanced answer for each pattern in both classes (modified and unmodified).

Conclusion

The entire planet is subject to the effects of geographical change. The use of satellite imagery to track Earth's evolution is essential. Updating aerial photos is a time-consuming and costly procedure that is currently done by hand. We presented a neural network-based method for detecting changes in satellite images as a solution to this issue. The current approach takes longer and is less precise. Our suggested approach employs a convolutional neural network strategy to address these limitations. Because of its superior performance in One-way propagation, this neural network was chosen for this application. It quickly and accurately calculates the outcome. Instead of employing a single multilayer perceptron (MLP), a group of MLPs with different designs are employed, and the results are fused using a combiner to assign class labels to the unlabeled patterns; this method is known as a multiple classifier system (MCS) and is proposed for use in change detection. The accuracy of the change detection process utilising an MLP relies heavily on choosing one of these factors as well as the optimal design, which is a downside of MLPs due to their reliance on free parameters. To reduce the potential for error while employing a single MLP, an ensemble of MLPs is employed. Based on the findings, the suggested ensemble technique significantly improves the stability of the MLP-based change detection system.

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