The quest for automated land cover change detection using satelite time series data

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Abstract

The paper shows that a Multi-layer Perceptron (MLP) operating on a sliding window of multi-spectral MODIS timeseries data is able to detect simulated change which was introduced by concatenating timeseries of two pixels belonging to two different land cover types. This approach requires training data and is thus supervised. An unsupervised change detection method is proposed based on a non-linear Extended Kalman Filter. The parameters were estimated to represent a triply (amplitude, frequency and phase) modulated cosine function and were separable. Change detection may thus be performed using a classifier operating on these parameters as a function of time.

I. Introduction

Automation of land cover change detection at regional or global scales using hyper-temporal, multi-spectral coarse resolution satellite data has been a highly desired, but often elusive goal of environmental remote sensing [1], [2]. Land cover change often indicate land use change with major socio-economic impacts, while the transformation of vegetation cover (e.g. deforestation, agricultural expansion, urbanisation) have significant impacts on hydrology, ecosystems and climate [3], [4]. Digital change detection encompasses the quantification of temporal phenomena from multi-date imagery that is most commonly acquired by satellite-based multi-spectral sensors [5]. For regional applications, these methods need to be sufficiently automated when processing exceptionally large volumes of data [6]. As global datasets become more accessible and computational resources become more affordable, such global or regional automated change detection systems should become more attainable.

Due to the complex, non-linear and non-parametric nature of land cover classification and change detection, machine learning methods are widely regarded as the most viable option for automated change detection [6], [7], [8]. This paper presents two different approaches towards achieving the goal of automated change detection. The first approach is based on a supervised multilayer perceptron (MLP), while the second is based on unsupervised Extended Kalman Filtering (EKF). Section 2 will present the key ideas behind the MLP, including the use of a sliding window [9], [10] and short term Fast Fourier Transform. Section 3 presents the ideas behind the application of the EKF, while section 4 presents some conclusions.

II. Change detection using a supervised MLP and a sliding window FFT

Information on examples of confirmed land cover change is often rare. Simulating land cover change helps us control the type and timing of land cover change in order to evaluate machine learning methods. Land cover change was simulated by concatenating the time series of pixels of class 1 to that of nearby pixels of class 2. A trained MLP may be applied to detect this change after training it to recognise time series derived from pixels in class 1 and class 2 in the *training set*. The training set is formed by selecting pixels known to belong to either class 1 or 2 for the entire period under study. The MLP is trained to recognise time series data from a short window sliding over time [9]. The features extracted from the data in the sliding window are the first 4 components of the FFT. These contains the essential features associated with changes in land cover over the short term. As time advances the window position is moved at a fixed increment, and the MLP is adaptively trained over time.

It will be shown how this process is able to accurately detect change in simulated (concatenated) time series. As a control set where timeseries belonging to different pixels but of the same class were concatenated the false detection probability was below 5 percent.

III. Unsupervised change detection based on the EKF

In spite of the good performance achieved using the supervised MLP, the requirement of having access to training data across an entire region is prohibitive. In order to formulate an unsupervised change detector, it is postulated that the time series data in each of 7 MODIS surface reflectance bands may be modelled as a cosine function where the amplitude A, instantaneous frequency ω and the phase ϕ are functions of time; i.e. the cosine function is triply modulated. A triply modulated cosine function is able to model the observed timeseries data accurately, but the estimation of the parameters A^k, ω^k, ϕ^k (k is the discrete time index) given the observed timeseries data is difficult, since the problem is non-linear. The nonlinear EKF was applied to this problem and it was found that the parameters over time and for a specific land cover type tend to be correlated, while they are not correlated with the parameters of a timeseries belonging to a different land cover type. Statistical examination suggests that the parameters of different land cover types are separable over time. The EKF may be adapted by introducing process and observation noise artificially, and it was found that typical values may be found for a region of interest that will maximise the separability of the parameters. Preliminary results indicate that separability achieved using the method outlined above is superior to traditional approaches where the FFT is computed of the data and the components are used to separate the data belonging to more than one class [11].

IV. Conclusions

This paper demonstrated that a MLP operating on a sliding window of MODIS time series data was able to detect change in an automated fashion after initial training. It appears as if the window length can be optimised to ensure it takes cognisance of short-term inter-annual climate variability. It was also shown that an EKF is able to estimate the parameters of a triply modulated cosine function, given the multidimensional timeseries, and that these parameters are separable for different types of land cover. The EKF may be adapted by introducing artificial noise into the process and/or measurement processes to increase separability.

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