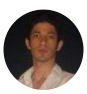
Unsupervised Satellite Change Detection Using Particle Swarm Optimisation in Spherical Coordinates

Conference Paper · November 2015

3 authors:


Amir Yavariabdi
Karatay Univeristy


Huseyin Kusetogullari


Ali Bulent Usakli
KTO Karatay University, Konya, Turkey

Unsupervised Satellite Change Detection Using Particle Swarm Optimisation in Spherical Coordinates

Amir Yavariabdi[1], Huseyin Kusetogullari[2], and Ali Bulent Usakli[1]

[1] Department of Mechatronics Engineering, KTO Karatay University, Konya, Turkey
amir.yavariabdi@karatay.edu.tr & abulent.usakli@karatay.edu.tr
[2] Department of Computer Science and Engineering, Blekinge Institute of Technology, Karlskrona, Sweden
huseyinkusetogullari@gmail.com

Abstract. This paper proposes a new unsupervised satellite change detection method, which is invariant to shadow and shading effects. To achieve this, firstly, the RGB satellite images are transformed into spherical colour space to remove illumination artifacts. Then, a new unsupervised change detection is used. The resultant optimal binary change mask is obtained by minimisation a mean square error based cost function using Binary Particle Swarm Optimisation (BPSO). The proposed method is compared with three other satellite change detection methods and the results demonstrate that our method provides a significant improvement of obtaining the changed and unchanged regions on the difference image. The total errors show that our method at least 39.62% better than the best compared method and are utmost 176.18% better than the worst one.

Keywords: Remote sensing, change detection, spherical coordinate system, optimisation, binary particle swarm optimisation.

1 Introduction

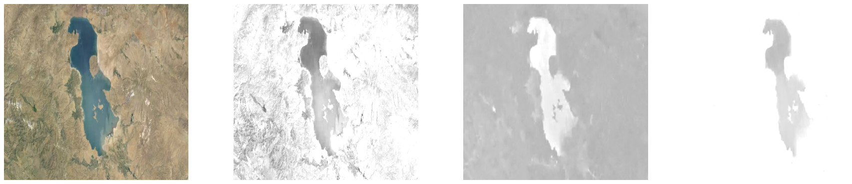
In the last decade, there has been tremendous escalation in the development of change detection techniques for the analysis of multitemporal Landsat satellite images [1]. This escalation stems from the fact that there are many important remote sensing applications in which change detection can be applied, such as environmental measurement (e.g. deforestation, land degradation and desertification), forestry management, regional mapping, urban monitoring, and widespread disaster measurement (e.g. forest burned area, landslide and flooding).

In remote sensing context, change detection can be defined as the process of identifying differences between corresponding objects or phenomenon by analysing two aligned remote sensing images which are captured at different times [2]. Such an analysis aims at detecting and identifying land cover changes that can be done manually via visual inspection or automatically by change detection methods. Manually labelling and identifying changes is a cumbersome task and it is prone to errors and highly subjective depending on the expertise of the inspector. Therefore, many methods have been proposed to automatically find changes through the satellite images and some of these are presented in comprehensive review articles such as those by Singh [2], Lu et al. [3] and in the textbook by Jensen [4]. Generally, change detection methods can be classified into supervised and unsupervised approaches.

The supervised approach is based on classification methods, which needs a training set with multitemporal ground truth to learn patterns which can be used to identify changes. Although this approach exhibits some advantages over the unsupervised one, the generation of ground truth information is usually a tedious, difficult and expensive task. Consequently, the use of unsupervised change-detection approach is vital in many applications in which ground truth does not exist [2, 5].

The unsupervised methods directly compare multitemporal images or process the difference image using pattern recognition techniques. In this approach, there is no need for a training set. In the literature of unsupervised change detection approach, changes are mostly detected from multitemporal greyscale images. Many algorithms have been developed for dealing with this problem, such as image difference [2], k-means [8], normalised cut clustering [9], Fuzzy c-means [7], Principle Component Analysis (PCA) [6], Markov Random Field (MRF) [11], and sequential-based methods [10]. Most of the existing unsupervised change detection methods have three main problems. First, they use one spectral band to obtain the difference image. This is a disadvantage as converting RGB images to greyscale images may affect discrimination between changed and unchanged regions of the difference image. Second, the effect of illumination variations, which is highly influential in discriminating between changed and unchanged pixels, has been discarded from the unsupervised change detection methods. However, in the field of change detection for remote sensing applications it is often necessary to cope with the phenomenon of illumination changes as it causes significant changes most of the times so that pixels may incorrectly be selected as changed by an algorithm. Thus, using greyscale images and discarding illumination changes may cause to obtain high miss or false alarm rates. Hence, it is important to design a multispectral cost function which is robust to illumination changes in order to improve the change detection performance in terms of accuracy rate. Third, as the size of images involved in remote sensing tends to be quite large, the complexity of comparing and analysing them for finding changes increases and needs more time. Therefore, the sequential-based change detection methods (e.g. change detection based on Genetic Algorithm (GA) [10]) need a large number of iterations to find the final change detection mask or optimum result. Accordingly, it is necessary to apply an optimisation method to minimise the change detection cost function efficiently.

In this paper, we propose a new photometric invariants unsupervised satellite change detection method, which is robust to illumination changes. To achieve



(a) RGB Image (b) r Channel (c) θ Channel (d) ϕ Channel

Fig. 1. RGB colour image transformed into $r\phi\theta$ colour space.

this, the RGB colour space transformed into $r\phi\theta$ colour space via spherical transformation of RGB coordinates. Then, a cost function based on image difference is defined and optimised by using BPSO algorithm. Note that in our method, instead of calculating perceived colour difference of images, our method calculates the difference of ϕ and θ channels. The reason that these two channels are only selected from spherical coordinates is because they are invariants with respect to shadow and shading. The cost function is used to find the weak and strong changes by updating the population in BPSO, iteratively. To improve the convergence rate of the proposed method, we use an initial binary change detection mask which is obtained by a change detection method in the population.

The rest of the paper is organised as follows. In section 2, the proposed method is presented. Qualitative results and the performance of the proposed method are discussed in Section 3. In the last section, the paper is concluded.

2 Proposed Method

Let us consider two registered RGB Landsat images, $x_1^{(n)}$ and $x_2^{(n)}$ (n=1,2,3 denotes spectral bands), which are acquired on the same geographical region, but at two different times. Here, the main goal is to obtain a binary change mask m, based on the difference image $d^{(n)}$.

The proposed method consists of two main steps. First, a preprocessing strategy is used to design photometric invariants for colour sequences. This step makes our algorithm robust to shadow and shading (i.e. illumination intensity changes). Second, a mean square error based cost function is proposed and optimised using BPSO algorithm to generate optimal binary change mask.

2.1 Spherical Coordinate System

Generally, since the Landsat images are captured at different date and time, there is illumination difference between them. Therefore, it is important to embed a photometric invariants technique into our change detection method to robust the performance of the method under illumination changes. To achieve this, the RGB colour space transformed into $r\phi\theta$ colour space, using a well-known photometric invariants technique called spherical transformation. This transformation is given by:

$$\begin{cases} r_i = \sqrt{\left(x_i^{(1)}\right)^2 + \left(x_i^{(2)}\right)^2 + \left(x_i^{(3)}\right)^2} \\ \theta_i = \arctan\left(\frac{x_i^{(2)}}{x_i^{(1)}}\right) \\ \phi_i = \arccos\left(\frac{x_i^{(3)}}{\sqrt{\left(x_i^{(1)}\right)^2 + \left(x_i^{(2)}\right)^2 + \left(x_i^{(3)}\right)^2}}\right) \end{cases} \tag{1}$$

where $i = 1, 2$ denotes Landsat images in both RGB and spherical colour spaces, r is the radial component in spherical coordinate system and θ and ϕ are the phase angle components. Note that both angles are invariant with respect to shadow and shading whereas the colour magnitude is not robust to illumination changes [12]. Therefore, in our method, ϕ and θ channels will be used to calculate the difference of images. Fig. 1 shows an example of the spherical transformation.

2.2 Illumination-Invariant Change Detection Method

In the second step of the proposed method, the difference image must be generated. Let $d^{(n)}$ be the difference image with two spectral bands. When detecting changes in optical images, the common way of comparing a pair of spectral images is to generate a difference image by applying a pixel-by-pixel subtraction. However, when Landsat satellite images are considered, this technique is error prone, as it is not robust to illumination changes. Therefore, in our method, instead of calculating perceived colour difference of images, the proposed method estimates the difference of ϕ and θ channels, due to aforementioned features. This can be found by the following formula:

$$\begin{cases} d^{(1)}(x, y) = |\phi_2(x, y) - \phi_1(x, y)| \\ d^{(2)}(x, y) = |\theta_2(x, y) - \theta_1(x, y)| \end{cases} \tag{2}$$

where $x = 1, \cdots, W$ and $y = 1, \cdots, H$, H and W are height and width of the Landsat images. The the difference image $d^{(n)}$ is then normalised into $[0, 1]$.

After estimating $d^{(n)}$, the changed map m must be obtained. The change map is a binary image with $2^{(H\times W)^n}$ possibilities. Each of these possible binary images has a corresponding cost function which is estimated from $d^{(n)}$ and one of them is the optimum change map. Due to the large number of possible combinations, it is impossible to examine all the combinations to find the optimum result, then an optimisation strategy must be used to solve this problem. In this work, we use BPSO algorithm [13] to obtain the optimum change mask.

2.2.1 Binary Particle Swarm Optimisation

The BPSO is a population-based optimisation method that seeks multiple solutions and it optimises the problem based on a swarm of particles. Generally, each particle consists of a position, which is a candidate solution, and a velocity in a search space. The position and velocity of each particle are updated iteratively until the cost function is minimised. The BPSO algorithm must initialise with a population of random solutions and seeks optimum solution by updating iterations. During the optimisation procedure, each particle is moved toward the best problem particle which is estimated by any member of the entire swarm. Note that particles should be initialised with respect to the problem. Generally, the initial solutions in a population are randomly generated and they are iteratively updated based on the generation features of the algorithm. However, this makes the algorithm inefficient and impractical as it increases the number of iterations to overcome local minima in the optimisation process [14]. Therefore, this initialisation strategy is not a proper approach to resolve our large search space problem. To tackle this problem, in the proposed method, an initial binary change detection mask is created by PCA-based change detection method [6] and used as one of the initial particle in the population. This improves the convergence rate and reduces the cost efficiently. Moreover, in the proposed method, each particle's location is represented by a fix length array with the length of $H \times W \times n$, and each array element is assigned with a real number. Thus, we are creating a two dimensional mask including zeros and ones to estimate the final change detection mask.

2.2.2 Cost Function

To solve an optimisation problem using the BPSO algorithm, it is necessary to evaluate the quality of the potential solutions. To achieve this, a cost function must be used to assess the candidates solutions by estimating their cost values. Notably, the fitness values may also be used in a process of natural selection to generate next population. In other words, the strong and weak particles can be evaluated according to the cost values and the new population is created based on them. In our problem, the main idea of using the cost function is to cluster the unchanged and changed pixels between two different Landsat images. So that, the optimal binary change mask can be estimated by the following formula:

$$C_{\wp}^{k} = \sum_{n=1}^{2} P_0^{(n)} + P_1^{(n)} \tag{3}$$

where

$$P_0^{(n)} = \frac{N_0^{(n)}}{H \times W} \sum_{y=1}^{H} \sum_{x=1}^{W} \left(\delta_{A_0}(x,y)(d^{(n)}(x,y)) - \frac{1}{N_0^{(n)}} \sum_{y=1}^{H} \sum_{x=1}^{W} \delta_{A_0}(x,y)(d^{(n)}(x,y)) \right)^2 \tag{4}$$

$$P_1^{(n)} = \frac{N_1^{(n)}}{H \times W} \sum_{y=1}^{H} \sum_{x=1}^{W} \left(\delta_{A_1}(x,y)(d^{(n)}(x,y)) - \frac{1}{N_1^{(n)}} \sum_{y=1}^{H} \sum_{x=1}^{W} \delta_{A_1}(x,y)(d^{(n)}(x,y)) \right)^2 \tag{5}$$

where $C_{\wp}^{k}$ denotes the cost function of particle $\wp$ at iteration number k, P_0 and P_1^n are the estimated cost functions based on unchanged and changed pixels (A_0 and A_1) at n^{th} spectral band, respectively, and $N_0^{(n)}$ and $N_1^{(n)}$ are the number of changed and unchanged pixels on the change detection mask, respectively.

$\delta_{A_1}(x, y)$ is the Kronecker delta function whose value is 1 at $\forall(x, y) \in A_1$ and 0 otherwise whereas $\delta_{A_0}(x, y)$ is 1 at $\forall(x, y) \in A_0$ and 0 otherwise. In the optimisation problem, the purpose of the proposed method is to minimise the cost function (equation (3)) for finding the best change detection mask.

In equations (4) and (5), for both unchanged and changed pixels, the mean-squared Euclidean distance between the difference image values and the mean of the difference image values is calculated. Then, the sum of the mean-squared Euclidean distance of the unchanged and changed pixels is used in equation (3) to discriminant changed and unchanged pixels. Note that, the lower the mean-squared Euclidean distance, the more precise the discrimination is. Equation (3) must approach to zero when $C_{\wp}^{k}$ divides the difference image $d^{(n)}$ into changed and unchanged regions.

3 Experimental Results

We evaluate the proposed method against MRF-based [11], PCA-based [6], and GA-based [10] change detection methods. The MRF-based method depends on a smoothing parameter β that effects the change detection process. In this paper, β is set to be 1.7. In the PCA-based method, the parameters are chosen using minimising an error between the obtained change detection mask and the ground truth one. In the GA-based method, each population consists of 40 individuals with 0.6 crossover rate. Moreover, the mutation rate is set to be 0.04. In our method, the values of the population size, inertia weight, and acceleration coefficient are 40, 0.4, and 2, respectively.

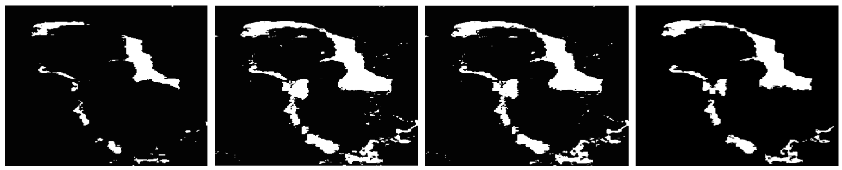
3.1 Data Sets

We evaluate the performance of the proposed method by using quantitative tests on real multitemporal multispectral data set. The data corresponds to the surface of the lake Urmia locating in Iran. The data set is taken from [15] and includes a set of images of size 980×540 pixels. The images show that the water surface of lake Urmia rises up in 1995 (Fig. 2 (b)) when compared to the 1992 (Fig. 2 (a)). These images are acquired by Landsat satellite with 1.7 terapixel snapshots of the Earth at 30-meter resolution. To evaluate changes in lake Urmia, a small area of size 550×350 pixels are selected from input images. The ground truth change detection mask for the lake area is shown in Fig. 2 (c).

3.2 Quantitative Error Measures

We calculate three different quantitative error measures to validate the results. For quantitative tests, the obtained binary change detection mask is compared with the ground truth mask. The first test is based on False Alarms (FA). This error measure can be defined as the number of actually unchanged pixels that were wrongly selected as changed pixels. The FA rate is manipulated in percentage as $P_{FA} = FA/N_1 \times 100$, where N_1 is the total number of unchanged pixels

(a) Landsat image I (b) Landsat image II (c) Ground truth



(d) MRF-based (e) PCA-based (f) GA-based (g) Proposed

Fig. 2. Change detection results. (a)-(b) show the lake Urmia input data acquired in 1992 and 1995. (c) shows the ground truth image. (d)-(g) show the results of various methods on the lake Urmia data set. The proposed method obtains the final change detection mask more accurately than the other methods.

Methods	P_{FA}	P_{MA}	P_{TE}
MRF-based	19.35	8.22	13.51
PCA-based	2.19	6.67	1.69
GA-based	1.37	1.50	1.27
Proposed	0.074	0.66	0.85

Table 1. Quantitative results obtaining from various methods.

counted in the ground truth mask. The second test is based on Miss Alarm (MA) which can be defined as the number of actually changed pixels that were mistakenly determined as unchanged pixels. The MA rate is estimated in percentage as $P_{MA} = MA/N_0 \times 100$, where N_0 is the total number of changed pixels counted in the ground truth mask. The last measure is Total Error (TE) which is the sum of the FA and MD. Therefore, the TE rate in percentage is calculated as $P_{TE} = (FA + MD) \, / \, (N_0 + N_1) \times 100$.

3.3 Results

The quantitative and visual results of various methods on the lake Urmia data set, shown in Fig. 2 (a) and (b), are given in Table 1 and shown in Fig. 2, respectively. The visual results show that fewer isolated pixels can be found in the final change map obtained by proposed method compared with those of the other methods. Moreover, it is obvious that the binary change detection masks obtained by using the MRF-based method [11] is not precise. The reason is that the difference image is modelled using the Gaussian function which leads to inaccurate difference image modelling. On the other hand, PCA-based method [6], GA-based method [10], and the proposed method provide much more precise results; this can be due to that discrimination between unchanged and changed regions is attained using the difference image itself without including extra assumption. Our method obtains the least overall error of 0.85%, while the other methods provide 13.51%, 1.69%, and 1.27%, respectively. This is due to the fact that the proposed method is invariant to illumination changes, so that it has very few isolated pixels.

4 Conclusion

In this paper, we present a BPSO-based unsupervised change detection method to find changed and unchanged pixels between multitemporal and multi-spectral satellite images. Our algorithm consists of two main steps. Firstly, a preprocessing method is applied to the input satellite images to make the proposed method invariants to illumination artifacts. In the second step, the difference image is generated and then the change detection map is obtained by dividing the difference image into the unchanged and changed pixels by using the BPSO. The results on the given real-world data set show that our method remarkably reduce the error comparing to the other compared change detection methods.

References

1. G. Jianyaa , S. Haiganga , M. Guoruia, and Z. Qiming: A Review of Multi-Temporal Remote Sensing Data Change Detection Algorithms. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences **37**, 757–762, 2008.
2. A. Singh: Digital Change Detection Techniques using Remotely-sensed Data. International Journal of Remote Sensing **10**, 989–1003, 1989.
3. D. Lu, P. Mausel, E. Brondzio, and E. Moran: Change Detection Techniques. International Journal of Remote Sensing **25**, 2365–2407, 2004.
4. J. R. Jensen: Introductory Digital Image Processing—A Remote Sensing Perspective. 3rd edition, Upper Saddle River: Pearson Prentice Hall.
5. M. Roy, S. Das, and S. Ghosh: Semi-supervised Hopfield-Type Neural Network for Change Detection in Remotely Sensed Images. International Conference on Recent Advances in Information Technology, 2012.
6. T. Celik: Unsupervised Change Detection in Satellite Images Using Principal Component Analysis and K-means Clustering. IEEE Geoscience and Remote Sensing Letters **6**, 772–776, 2009.
7. P. Deer and P. Eklund: Values for the Fuzzy C-means Classifier in Change Detection for Remote Sensing. International Conference of Information Processing and Management of Uncertainty, 187–194, 2002.
8. Y. Zheng, X. Zhang, B. Hou, and G. Liu: Using Combined Difference Image and k-Means Clustering for SAR Image Change Detection. IEEE Geoscience and Remote Sensing Letters **11**, 691–695, 2014.
9. X. Zhang, Z. Li, B. Hou, and L. Jiao: Spectral Clustering Based Unsupervised Change Detection in SAR Images. In Proc. IEEE IGARSS, 712–715, 2011.

10. T. Celik: Change Detection in Satellite Images Using a Genetic Algorithm Approach. IEEE Geoscience and Remote Sensing Letters **7**, 386–390, 2010.
11. L. Bruzzone and D.F. Prieto: Automatic Analysis of the Difference Image for Unsupervised Change Detection. IEEE Transactions on Geoscience and Remote Sensing **38**, 1171–1182, 2000.
12. J. Van De Weijer, T. Gevers: Robust Optical Flow from Photometric Invariants. IEEE International Conference on Image Processing, 1835–1838, 2004.
13. J. Kennedy and R. Eberhart: Particle Swarm Optimization. In Proc. IEEE International Conference on Neural Networks, 1942–1948, 1995.
14. H. Kusetogullari, A. Yavariabdi, and T. Celik: Unsupervised Change Detection in Multi-temporal Multi-spectral Satellite Images using Parallel Particle Swarm Optimization. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (JSTARS), 2015.
15. Retrieved on August 2014 from the World Wide Web: http://earthengine.google.org/#intro/LakeUrmia