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# Unsupervised Change Detection using Thin Cloud-Contaminated Landsat Images

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***Abstract*—In this paper, a novel unsupervised change detection method is proposed to automatically detect changes between two cloud-contaminated Landsat images. To achieve this, firstly, a photometric invariants technique with Stationary Wavelet Transform (SWT) are applied to input images to decrease the influence of cloud and noise artifacts in the change detection process. Then, mean shift image filtering is employed on the sub-band difference images, generated via image differencing technique, to smooth the images. Next, multiple binary change detection masks are obtained by partitioning the pixels in each of the smoothed sub-band difference images into two clusters using Fuzzy c-means (FCM). Finally, the binary masks are fused using Markov Random Field (MRF) to generate the final solution. Experiments on both semi-simulated and real data sets show the effectiveness and robustness of the proposed change detection method in noisy and cloud-contaminated Landsat images.**

***Keywords*—change detection, Landsat images, wavelet, mean-shift, fuzzy c-means.**

## I. Introduction

In remote sensing context, automatic change detection is the computerised process of identifying differences between images acquired on the same geographical area, but at different times [1], [2]. It has been applied in many important remote sensing applications including environmental measurement, forestry management, regional mapping, urban monitoring, and widespread disaster measurement [3]. Amongst all the remote sensing techniques, Landsat imagery has been intensively employed in change detection problem as it has provided continuous land surface observations for more than three decades. However, due to high sensitivity of this remote sensing technique to noise and meteorology conditions, automatic and robust change detection from moderate resolution Landsat images remains challenging.

Change detection methods in Landsat images are mostly based on supervised and unsupervised techniques [4]. However, the later approach is mostly used in change detection problem as it does not depend on any prior labelling knowledge. The unsupervised change detection methods mainly consist of two stages: 1) difference image estimation and 2) difference image analysis. In the first step, a difference image is obtained by comparing images using a similarity metric method such as image subtraction [5], [6], Change Vector Analysis [7], [8], Correlation Coefficient (CC) [9], Erreur Relative Globale Adimensionnelle de Synthese (ERGAS) [10], and structure similarity index [11]. In the second step, the difference image is analysed to estimate the change detection map using thresholding methods (i.e. dynamic threshold method [6] and Otsu's threshold method [10]), clustering approaches (i.e. Expectation Maximisation (EM) [12], MRF [13], *k*-means [14], and FCM [15]), metaheuristic optimisation algorithms (i.e. genetic algorithm [5], particle swarm optimisation [16], and multi-objective evolutionary algorithm [11]) and many others [17]. In the existing threshold methods, the difference image is sharply divided by the selected threshold value into unchanged and changed sets. However, this process is usually inappropriate as many pixels can be misclassified in the binary change mask [18]. To solve this issue, many methods based on the clustering and metaheuristic optimisation have been proposed. Among all these methods, the FCM algorithm is the most popular method as: 1) it is robust to ambiguity and can retain much more information than hard clustering methods (e.g. k-means) and 2) it requires less computational time than metaheuristic optimisation-based change detection methods. However, one of the main drawbacks of the standard FCM clustering algorithm is that it is sensitivity to noise in images.

Most of the state-of-the-art change detection methods are performed in spatial-domain, hence they are sensitive to noise as they directly extract information from the input images. To solve this issue, different transform-domain change detection methods have been proposed such as Principle Component Analysis (PCA) [14], Dual-Tree Complex Wavelet Transform (DT-CWT) [19], and SWT [20]. Even though these methods have shown good performance against existence of noise in

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the difference image, they have a common problem which is that they are sensitive to atmospheric condition changes. In the existing change detection methods in Landsat images, the influence of cloud on change detection problem is neglected as they assume the input images are free from cloud. However, Landsat images can be captured with different thin cloud(s) fractions, which can easily cause the change detection methods generate erroneous information by mapping cloud as change.

In this paper, a novel frequency-domain unsupervised change detection method is proposed using the SWT and mean-shift based FCM algorithm to solve the change detection problem in cloud-contaminated Landsat images with noise artifacts. The method firstly uses a photometric invariants technique to convert RGB satellite images into the Hue-Saturation-Value (HSV) colour space. This is opposed to the most of the existing methods as they only use the gray/colour value constancy assumption, such techniques are not robust enough to withstand the typical atmospheric artifacts occurred during Landsat acquisitions. Note that, only hue channel of Landsat images are used as they are invariant under both shadow and shading (i.e. illumination intensity changes) as well as highlights and specularities. Second, the SWT is applied to the hue channel of the images to generate Low-Low (LL), Low-High (LH), High-Low (HL), and High-High (HH) sub-band images. This preprocessing strategy aims at making the proposed method robust to existence of noise and cloud(s) in the input images and preserving detailed information. Third, the FCM [21] with the mean shift algorithm is used to improve the efficiency of traditional FCM. The main reason of using the mean shift clustering method is that this method decreases the intensity variations in the image while preserving edges. This makes the classical FCM robust to noise and/or atmospheric artifacts and improves its computational time. In this step, four different binary images are obtained so that, a fusion approach based on MRF [22] is used to merge binary masks.

## II. Proposed Change Detection Method

This section consists of two parts, the first part discusses about the preprocessing steps that are used to decrease the influence of cloud and noise artifacts in change detection process and the difference image estimation. The second part provides solutions for analysing difference images and generating final binary change mask. The block diagram of the proposed method is shown in Fig. 1. The main objective of this work is to estimate high accurate change detection mask even when the multispectral Landsat images are captured with different thin cloud fraction(s) or/and corrupted by noise.

### A. Preprocessing

Let $X_1^n$ and $X_2^n$ be two Landsat images with size of $h \times w$ pixels, where $h$ and $w$ are height and width of images, respectively. In this paper, the natural color band combination (RGB color space) is used so that the images consist of three spectral bands ($n$). These images are acquired on the same geographical area but at two different time instances.

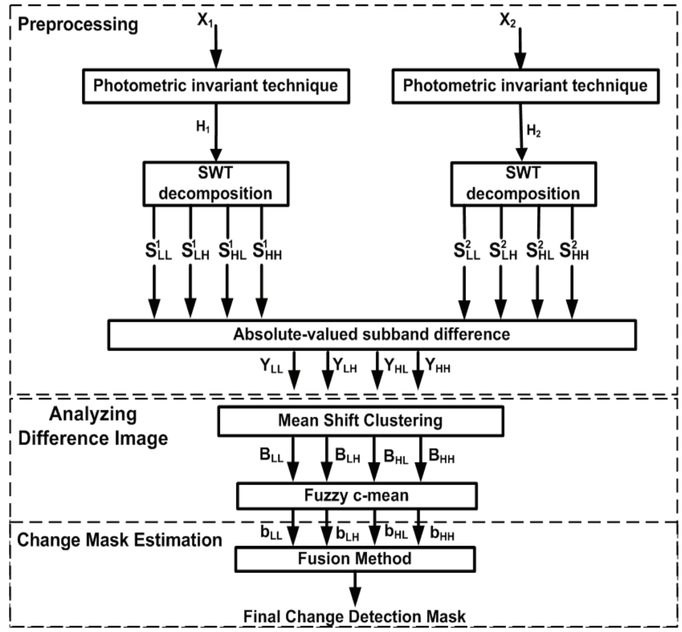



Fig. 1. Block diagram of the proposed method.

Furthermore, they have been registered with respect to each other [23].

The proposed change detection method is composed of three preprocessing steps: 1) color space transformation, 2) generation of sub-band images using the SWT, and 3) image comparison to compute the difference image.

*1) Colour Space Transformation:* Many photometric invariants techniques including normalised RGB, HSI, HSV, $r\phi\theta$, and derivatives of the logarithmized colour channels have been proposed in literature [24]. Among all the photometric invariants techniques, the HSV colour transform shows its robustness to shadow, shading, and specular edges in images [24]. In the HSV, the hue channel describes the pure colour of the image, the saturation channel describes how strong color is, and the value channel determines the image brightness. Among these three channels, only the hue, $h$, is shadow-shading-specular invariant. Hence, in this paper, the hue channel ($H$) is only used and formulated as follows:

$$H_i = \begin{cases} \frac{X_i^2 - X_i^3}{max(X_i^1,X_i^2,X_i^3) - min(X_i^1,X_i^2,X_i^3)} \times 60^\circ & X_i^1 \geq X_i^2, X_i^3 \\ 2 + \frac{X_i^3 - X_i^1}{max(X_i^1,X_i^2,X_i^3) - min(X_i^1,X_i^2,X_i^3)} \times 60^\circ & X_i^2 \geq X_i^1, X_i^3 \\ 4 + \frac{X_i^1 - X_i^2}{max(X_i^1,X_i^2,X_i^3) - min(X_i^1,X_i^2,X_i^3)} \times 60^\circ & X_i^3 \geq X_i^1, X_i^2 \end{cases} \quad (1)$$

where $i = \{1, 2\}$ denotes the corresponding Landsat image.

*2) Stationary Wavelet Transform:* In the change detection problem, the main issue is to accurately classify pixels on the high frequencies and ignore noise artifacts on input images. In this paper, the SWT is used to reduce the undesired affects on images such as noise. Moreover, the main reason of using the SWT rather than Discrete Wavelet Transform (DWT) is to minimize information loss due to the downsampling in the DWT. Here, one level SWT is employed to decompose the input image into four different sub-band images ($S^i_{LL}$, $S^i_{HL}$, $S^i_{LH}$, and $S^i_{HH}$).

*3) Image Comparison:* After generating the sub-band images, four difference images $Y_j$ are obtained as follows:

$$Y_j = \left| S_j^2 - S_j^1 \right| \quad (2)$$

where $j = \{LL, LH, HL, HH\}$. The intensities of the difference image $Y_j$ are normalized into $[0, 1]$.

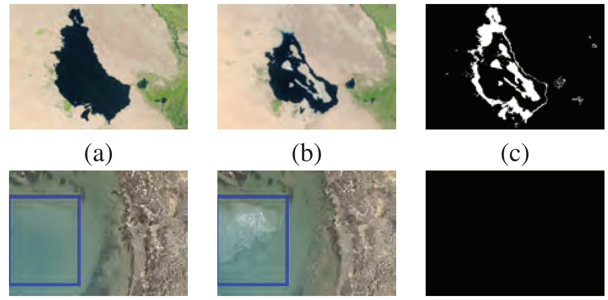
### B. Postprocessing: Mean Shift Clustering with Fuzzy C-Means

In most of the state-of-the-art change detection methods, the raw difference image(s) is directly used in the process of analysing difference image. Consequently, the clustering methods including $k$-means [14] and FCM [25] can lead to low correct detection rates as pixels from disconnected regions of the difference image(s) are grouped together if their feature space overlap. To solve this, the mean shift clustering, which is an edge-preserving smoothing technique, is used. In this manner, the noise is removed and meaningful edges preserved.

The mean shift algorithm is a density-based nonparametric clustering method which is well known for its flexibility and effectiveness in vision problems. The mean shift algorithm requires only one parameter to tune which is window size (bandwidth). In this algorithm, data points (difference image intensities) iteratively shift to the closest stationary point along the density gradient. Consequently, this approach can significantly reduce the intensity variations while preserving high frequencies. For $\ell_1 \times \ell_2$ sample pixels $Y_j(x, y)$, $y = 1, \cdots, \ell_1$ and $x = 1, \cdots, \ell_2$, the mean shift vector can be obtained as follows:

$$M_\hbar(c_j) = \underbrace{\frac{\sum_{y=1}^{\ell_1} \sum_{x=1}^{\ell_2} Y_j(x, y) G\left(\frac{c_j - Y_j(x,y)}{\hbar}\right)}{\sum_{y=1}^{\ell_1} \sum_{x=1}^{\ell_2} G\left(\frac{c_j - Y_j(x,y)}{\hbar}\right)}}_{m(c_j)} - c_j \quad (3)$$

where $c_j$ is the centre of the kernel for each sub-band and starts at an arbitrary value, $m(c_j)$ is the densities estimation of sample pixels in the neighbourhood of $c_j$, $\ell_1$ and $\ell_2$ are the height and width of the kernel, respectively, $\hbar > 0$ is the bandwidth parameter, and $G(r) = \exp\left(-\frac{1}{2}r\right)$ indicates Gaussian kernel function. Note that, the weighted function $G(r)$ tunes the effect of each intensity value inside the parzen window based on its distance from $c_j$. Note that the gradient ascent technique is used to optimize the equation 3. In this manner, at each iteration $c_j$ is updated until $\|M_\hbar(c_j)\| < \epsilon$, where $\epsilon$ is a convergence threshold. In this paper, $\epsilon$ is $10^{-5}$. Note that the stationary points obtained via gradient ascent, represent the modes of the density functions. All the data points associated with the same stationary point belong to the same cluster. In this paper, the mean shift approach has been applied to the four sub-band difference images separately and thus, four smoothed images are obtained. The next stage of the proposed approach is to partition each smoothed sub-band difference image into two clusters using the FCM [21]. In order to obtain the final binary mask, it is necessary to fuse all the change masks. To achieve this, Chen et al. [22] propose a fusion approach based on the MRF to merge two binary masks and in this work, the MRF model is adapted to fuse the four binary masks.



(a) (b) (c)
(d) (e) (f)

Fig. 2. Data sets: (a) and (d) Landsat image $X_1$; (b) and (e) Landsat Image $X_2$; (c) and (f) ground truth change masks.

(a) (b) (c)

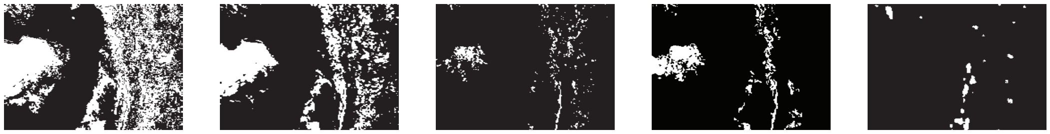
Fig. 3. Synthetic Data sets: (a)-(b) synthetic images that depict the $X_1$ image with various thin clouds; (c) synthetic image (a) with Gaussian noise.

## III. Experimental Results

To assess the proposed method, we apply our change detection method on three semi-synthetic images and two real medium resolution Landsat data sets. In the real-world experiments, the first data set shows the water surface of the lake Milh in 1995 and 2003 (Fig. 2 (a)-(b)) and the second data set illustrates the north east area of the Caspian sea in 2009 and 2012 (Fig. 2 (d)-(e)). Note that, in the second data set, an specific region (blue rectangle) is selected for quantitative measurement. Fig. 2 (c) and (f) show the ground truth change masks for the Lake Milh data set and the region of interest in caspian sea data set, respectively. The ground truth masks are obtained by manually labeling.

To generate the synthetic data sets various shapes and levels of thin cloud(s) are artificially added in the Fig. 2 (a). The synthetic data sets are shown in Fig. 3 (a-c). Moreover, to evaluate the robustness of the proposed method against existence of noise, the last synthetic image (Fig. 3 (c)) is corrupted by Gaussian noise with a mean of zero and 0.02 standard deviation.

The proposed change detection method is compared with DT-CWT-based [19], PCA-$k$ means-based [14], ERGAS-based [10], and PSO-GA-based [9] change detection methods. Note that the first compared method is in the frequency domain and the rest of them are in the spatial domain. In addition, in the DT-CWT-based and the PCA-$k$ means-based change detection methods, the input images must be in grayscale space whereas in the other methods, the input images must be in RGB color space. The DT-CWT-based and the ERGAS-based change detection algorithms, are parameter-free methods. In the PSO-GA and the PCA-$k$ means methods, the parameters which are



(a) DTCWT (b) PCA-*k*-means (c) ERGAS (d) PSO-GA (e) Proposed

Fig. 4. Change detection results for the Fig. 2 (d)-(e).

(a) DTCWT (b) PCA-*k*-means (c) ERGAS (d) PSO-GA (e) Proposed

Fig. 5. Change detection results for the Fig. 2 (b)- Fig. 3 (a).

TABLE I
QUANTITATIVE RESULTS FOR REAL DATA SETS.

| | Fig. 2 (a)-Fig. 2 (b) | | | Fig. 2 (d)-Fig. 2 (e) |
|---|---|---|---|---|
| Method | $P_{FA}$ | $P_{MA}$ | $P_{TE}$ | $P_{FA}$ |
| DT-CWT-based | 7.85 | 4.42 | 5.92 | 82.51 |
| PCA-k means | 6.42 | 5.96 | 5.45 | 68.33 |
| ERGAS-based | 9.38 | 18.83 | 16.48 | 12.46 |
| PSO-GA-based | 4.36 | 2.94 | 3.91 | 34.26 |
| Proposed Method | 4.83 | 3.05 | 4.20 | 0.00 |

TABLE II
QUANTITATIVE RESULTS FOR SYNTHETIC DATA SETS.

| | Fig. 2(b)-Fig. 3(a) | | | Fig. 2(b)-Fig. 3(b) | | | Fig. 2(b)-Fig. 3(c) | | |
|---|---|---|---|---|---|---|---|---|---|
| Method | $P_{FA}$ | $P_{MA}$ | $P_{TE}$ | $P_{FA}$ | $P_{MA}$ | $P_{TE}$ | $P_{FA}$ | $P_{MA}$ | $P_{TE}$ |
| DT-CWT-based | 32.27 | 10.88 | 15.02 | 31.05 | 9.65 | 15.02 | 32.75 | 11.01 | 15.14 |
| PCA-k means | 28.66 | 7.93 | 12.45 | 25.37 | 6.55 | 10.40 | 28.79 | 7.93 | 12.48 |
| ERGAS-based | 4.43 | 21.31 | 8.53 | 5.67 | 15.14 | 6.64 | 4.49 | 21.32 | 8.61 |
| PSO-GA-based | 16.21 | 4.57 | 8.25 | 12.22 | 4.70 | 5.86 | 16.27 | 4.68 | 8.34 |
| Proposed Method | **4.29** | **3.86** | **4.06** | **5.44** | **3.98** | **4.61** | **4.31** | **3.86** | **4.07** |

given in [9] and [14] are used. In the proposed method, the bandwidth ($\hbar$) is the only parameter that must be tuned and here it is empirically chosen as $1.5$. In addition, for quantitative comparison purposes, three different error measurements such as False Alarm rate ($P_{FA}$), Missed Detection rate ($P_{MA}$), and Total Error ($P_{TE}$) [14] are used. Note that only $P_{FA}$ is used for the second real Landsat data set as there is no changed pixels in the region of interest.

Figs. 4 and 5 illustrate the qualitative results of the change detection methods using Fig. 2 (d)-(e) and Fig. 2 (b)- Fig. 3(a), respectively. According to the qualitative results, it is clear that the DT-CWT-based method provides the least accurate results and it is very sensitive to existence of thin cloud in the images. The PCA-*k* means-based method shows better performance, but it still wrongly detects cloud areas mostly as changed regions. The PSO-GA-based method shows less sensitivity to thin cloud as it uses CC similarity metric which is less sensitive to intensity variations. The ERGAS-based method detects the dense thin clouds as changed areas (see Fig. 4 (c)) and removes image features under the light thin cloud areas (see Fig. 4-5 (c)). In contrast to all these methods, the proposed strategy provides promising results and the results show the robustness of the proposed method to the existence of thin cloud in images and removes the influence of this artifact effectively.

The quantitative results for the real and the semi-synthetic data sets, which are shown in Fig. 2 and Fig. 3, are tabulated in Table I and II, respectively. For the first real data set, the quantitative results show that the PSO-GA-based method provides the best and slightly better results than the proposed method as it uses optimisation strategy, but at the cost of computational time. On the other hand, the proposed method gives the better accuracy results than the other change detection methods. However, when the complexity increases in the input images (e.g. Fig. 2 (d)-(e) and Fig. 3), the proposed method gives the most accurate results as the noise and thin cloud have influence on performances of the other methods. For instance, using Fig. 2 (b)- Fig. 3 (a) shows that the proposed method obtains the lowest $P_{FA}$, $P_{MA}$ and $P_{TE}$ with $4.29\%$, $3.86\%$ and $4.06\%$, respectively. The DT-CWT based method provides the poorest performance with $32.27\%$, $10.88\%$ and $15.02\%$ for the $P_{FA}$, $P_{MA}$ and $P_{TE}$, respectively.

There are several reasons that the other methods fail to resolve the change detection problem between two images efficiently: 1) The methods use the gray/colour value constancy assumption, which makes them to not be robust to the atmospheric artifacts. 2) The PSO-GA, PCA-*k* means and ERGAS based methods are applied into the spatial domain which decreases the accuracy of detection near boundaries. 3) The DT-CWT based method uses simple union fusion based approach and neglects the low sub-band coefficients which result in increasing the incorrect detection rate. On the other hand, the proposed method uses different pre-processing and post-processing strategies than the other methods which improve the performance and provide the greatest accurate change detection results. In addition, by comparing the results, we can conclude that the proposed method provides the best results as using the hue channel of Landsat images with the SWT make the proposed method strongly robust to existence of artifacts. Moreover, the mean shift algorithm does not permit the FCM algorithm to group together the pixels from disconnected regions of the difference image.

## IV. CONCLUSION

In this paper, an unsupervised change detection method is proposed to automatically detect changes between two cloud-contaminated Landsat images. The proposed method is compared with different change detection methods over real and semi-synthetic data sets and the results show that the proposed method is robust to the Gaussian noise and thin cloud. This is due to the use of the photometric invariants technique with the SWT along with the mean shift FCM.

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