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Modernizing the multi-temporal multispectral remotely sensed image change detection for global maxima through binary particle swarm optimization

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ABSTRACT

Change detection is the amount of changes that can guide to more concrete understandings into essential method concerning land cover, land usage and ecological variations. This paper deals with an intelligent methodology to optimize the solution out of the solution space that improves the efficiency of the change detection process. To support the theme, an integrated semi-supervised method is designed with a focus on image fusion, semi supervised clustering and binary swarm based optimization. A new approach of handling fusion using sparse coding is referred to expand the amount of information. Using the extracted information, change detection process is carried out by a constrained clustering technique to provide a solution reflecting the level of changes occurred in the region of investigation. To improve the accuracy by proposing a global optimum solution, still the result is refined through binary swarm based optimization process and hence the results are accelerated towards the increased level of accuracy followed by which the change map is reconstructed to show case changes prominently. To determine the accurateness of the proposed methodology quantitative and qualitative analysis has been done with different datasets. The proposed method has been evaluated with existing techniques such as k-means, AKM, FCM, ECKM and ASCC to show the efficiency and proved to be the preeminent change detection methodology compared to the state-of-art methods.

1. Introduction

Change detection is a process of detecting the changes in the state of an object or phenomenon by observing it at different times (Singh, 1989; Bottomley, 1998). The changes in an image may be due to shape, movement, occurrence or desertion of an object. Especially, in the remotely sensed images, it is helpful in map apprising, land use analysis, monitoring shifting cultivation, urban planning, deforestation assessment, disaster monitoring, thermal analysis of day & night, tracking urban and economic growth. The complexity involved in the applications leaves great challenges in the change detection. Especially when dealing with environmental and urban changes, the issues are very difficult to address. Irrespective of all difficulties, one of the popularly adapted technologies to address the issue is remote sensed image processing composed of enhancement, image comparison and image analysis. Many dynamic attempts had been carried out towards the change detection of remotely sensed images. Most of the approaches fall under the category of supervised or unsupervised methods that use multi-temporal datasets to qualitatively analyse the temporal effects and measure the changes. The methodology is adopted either fully or partially on the sub processes such as enhancement, fusion, spatial difference identification, post classification and change map formulation. The general objectives of change detection in remote sensing include recognizing the environmental locality and type of changes, measuring the changes, and calculating the accurateness of change detection. Ultimately, the main mission of change detection is to identify and recognize the changes in multi-temporal multispectral Landsat images of the same geographic area acquired at different timings.

Several evolutionary computing based optimization techniques are used to optimize the solution out of solution space. One of the most widely used techniques is the particle swarm optimization. Particle swarm optimization (PSO) is a computational method that

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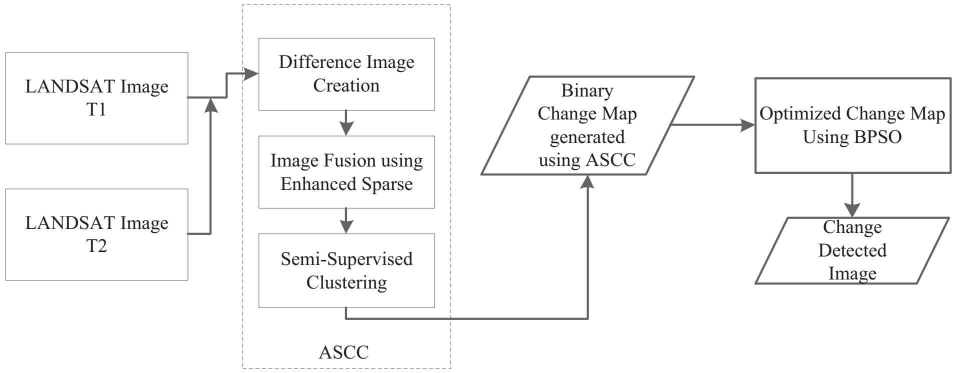

Fig. 1. Overall block diagram of Change Detection Process.

enhances a problem by iteratively trying to develop an optimal solution with regard to a given degree of quality. It is a global optimization method to provide a best solution when dealing with problems which can be represented as a point or surface in an n-dimensional space. It is an effective and popular optimization method to explore the optimal solution in the search space problems. Keeping this scope, an efficient method and a cost function to optimize the change detection process accurately is envisioned. Thus, working with change detection of remote sensed images, where a huge number of iterations are required to find the final change detection mask or optimal result is alleviated with the introduction of this efficient methodology.

The organisation of this paper is as follows. Section 2 presents some of the related works and the gaps identified. Section 3 gives an outline of the methodology adapted and describes the proposed system in detail. In Section 4, description about dataset, experimental results and discussion are described. Performance evaluation of results for change detection are analysed in Section 5. Finally, Section "References" draws the conclusions of this work.

2. Related work

Remote sensing is the process of collecting information using sensors which are not in physical contact with surfaces and phenomenon of interest, which provides details about earth surfaces and phenomenon. Remote sensing includes the choice of sensors, the reaction, recording and processing of signal data and finally the analysis of the subsequent data. The varieties of remote sensing methods existing are such as aerial photography, multispectral, active and passive microwave. The information content of a single image is limited by the spatial and spectral resolution of the imaging system. In spite of all the difficulties, the remote sensed images are analysed frequently for a variety of applications ranging from Land cover classification, Change Detection, Water Quality Monitoring, Measurement of sea surface temperature, Snow survey, Monitoring of Atmospheric Constituents to Geological Interpretation (Lal and Anouncia, 2015b). Among these applications, with the advent of the high spatial resolution satellite images, the change detection using multispectral multi-temporal Landsat images has been an important field of research. Nielsen (2007) proposed a multivariate alteration detection (MAD) method for

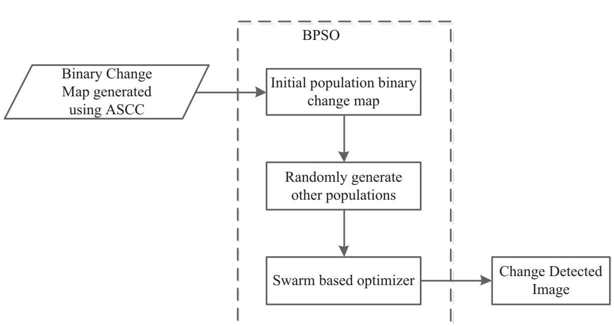

Fig. 2. Optimization of Change Map using BPSO.

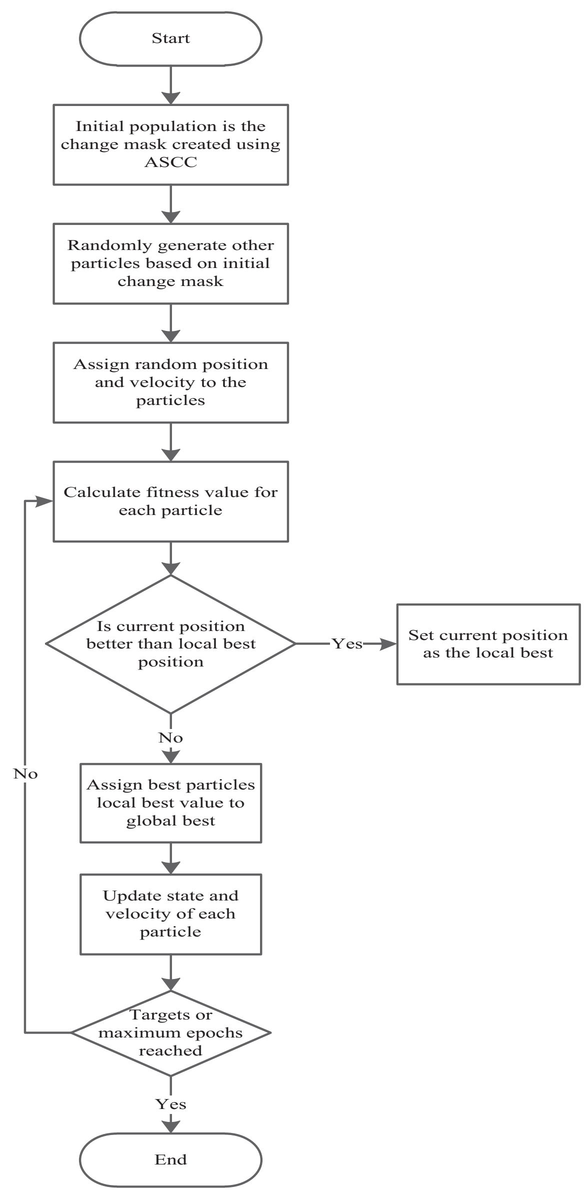

Fig. 3. Flow Diagram for Binary PSO.

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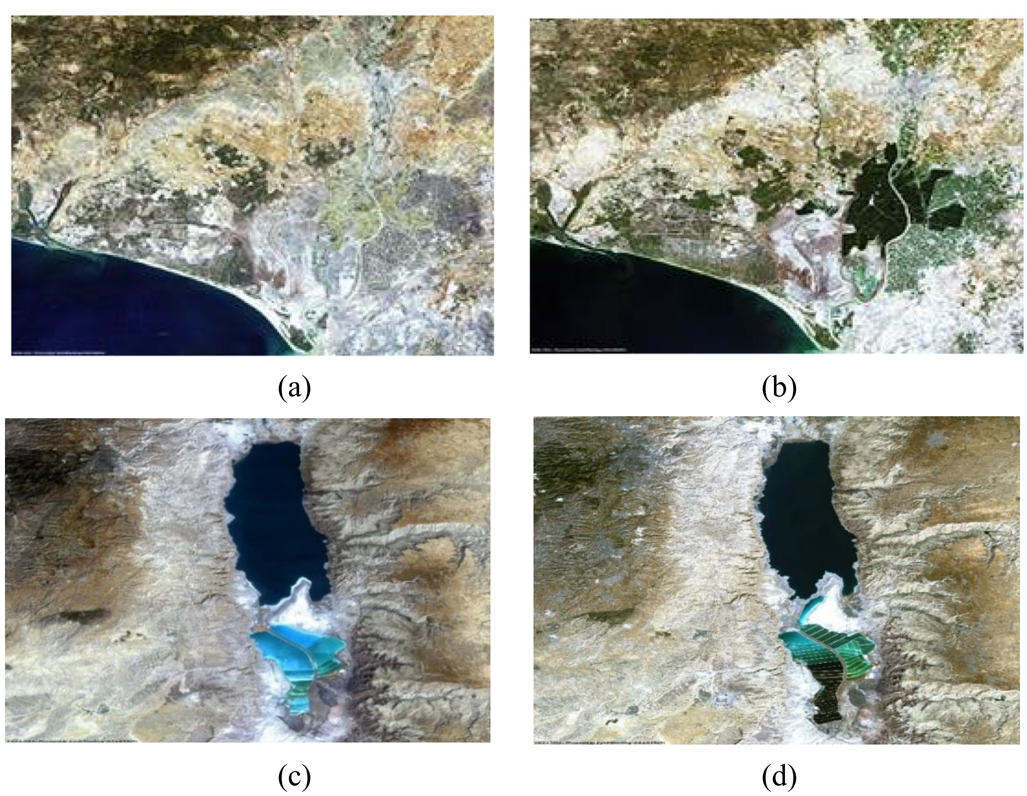
change detection in multi-temporal remote sensing images. Xian et al., (2009) used CVA for change detection with other techniques such as MAD to normalize and classified the changes using tree methods. Wu et al., (2017a) has concentrated on post classification using Iterative slow feature analysis and Bayesian soft fusion to obtain reliable and accurate change detection maps. Wu et al., (2017b) has proposed a novel method using kernel new feature analysis and a post classification fusion is done to identify the transition type. In order to improve the dependability for extracting remotely sensed information, and enhance the efficiency of change detection, the process is carried out through common image processing tasks such as image enhancement followed by image comparison, region detection and analysis. In some cases, due to limited convergence towards accuracy, some of the optimization techniques also had been employed along with image processing mechanisms to provide effective result.

Generally the clustering approaches only locate the important changes between two multispectral images and have deficiency of adaptableness and flexibility to attain feeble changes. Therefore, computational methods are required to find optimum outcome by obtaining both feeble and robust changes on the difference image. To attain an optimal outcome, Celik (2010) proposed unsupervised change detection on the difference image by an optimization approach using Genetic Algorithm (GA). This method is based on a fitness function which minimizes according to the difference image. GA was designed to create elements of binary change images which are iteratively progressed to the final change detection mask. This method successfully produced the change detection result on the difference image without a previous conventions. Particle Swarm Optimization (PSO) is another effective computational based optimization method for searching the optimal solution in the search space problems. A swarm based unsupervised change detection for remotely sensed images are proposed by Dai et al. (2010). In order to optimize the change detection problem efficiently and accurately an effective optimization method has to be applied. PSO performs optimization based on a swarm of particles. Swarm based optimization has been widely used in different problems such as image enhancement (Braik et al., 2007), face and iris recognition (Ramadan and Abdel Kader, 2009), feature extraction (Xue et al., 2012), image coding (Kusetogullari, 2015) and remote sensed image classification (Soliman et al., 2012). Change detection with less noise using PSO has been proposed by Sagnika et al. (2015). The method has produced better accuracy with minimal noise. A Parallel Binary Particle Swarm Optimization (PBPSO) unsupervised approach for change detection in multi-temporal multispectral images has been proposed by Kusetogullari et al. (2015). The approach provides better convergence and detection performance through parallel processing. Change detection using particle swarm optimization in spherical coordinates has been proposed by Yavariabdi et al. (2017) which provides less error than the existing methods. Thus an optimization process is attempted to reach the global optima using Binary Particle Swarm Optimization (BPSO).

Based on the evaluations of the existing systems the change map formulated as a resultant of change map detection process has been less evaluated to provide the optimum solution. It was also identified that the search over the spatial data of remote sensed images for change detection is tedious and time consuming as it is difficult to interpret and label change information. In order to overcome these issues an intelligent methodology to c which improves the efficiency of the change detection process.

3. Methodology

An intelligent methodology is designed with a focus on image fusion, semi supervised clustering and binary swarm based optimization to improve the efficiency of the change detection process. The overall block diagram of the change detection process adapted is shown in Fig. 1. The process starts with a pre-processing followed by



(a) (b)

(c) (d)

Fig. 4. (a) Landsat 5 image recorded on 12 October 1984 of Huelva, Spain. (b) Landsat 8 image recorded on 12 August 2014 of Huelva, Spain. (c) Landsat 5 Image Acquired on October 24, 1984 of Dead Sea, Israel. (d) Landsat 8 Image Acquired on October 27, 2014 of Dead Sea, Israel.

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integrated sparse and semi-supervised technique known as ASCC (Lal and Margret Anouncia, 2017) for finding the change detection mask. In order to obtain a global optimum solution an intelligent methodology has been adapted with binary particle swarm optimization to further optimize the change detection mask.

A new approach of handling fusion using sparse coding is devised to expand the amount of information (Lal and Anouncia, 2016). Using the extracted information, change detection process is carried out by a constrained clustering technique to provide a solution reflecting the level of changes occurred in the region of investigation. Thus, the analysis towards the suitability of region detection methods pushed to a decision of choosing ASCC as a better methodology to perform change detection in the multi-temporal multispectral images. However, the solution obtained through these clustering is the minimization of the objective function, so that it is clear that it would reach only local maxima. In case of change detection in remote sensed images, this may not provide the required accuracy as the minor changes in the region may not be revealed. Hence, it is required to optimize the solution so that all the possible changes are reflected in the change map to make change detection effective. One of the feasible approaches to carry such process is applying the binary change map obtained as result of region detection for optimization so that the global maximum is achieved. Thus the process demands to use evolutionary approaches that lead to fulfil the objective of reaching global maxima. The popular methods that converges solution to global maxima is PSO.

3.1. Particle swarm optimization

PSO is a computational optimization technique which performs based on the association and shrewdness of swarms. It involves a number of agents (particles) that create a swarm, moving around in the search space, looking for the global best solution. In this case, each particle can communicate to each of the other particle and thereby a fully connected network is formulated. Of course, each particle is attracted to the best particle out of entire swarm. Hence, this kind of approach is well suited for discrete optimization. One of the areas where the discrete optimization takes a prime role in the remotely sensed images is the change detection process. Especially, in the case of detecting changes happened in a region between time stamps T1 and T2, it is required to determine the changes happened in the whole area in terms of discrete regions if present. Hence, an appropriate method is needed to find such changes which may be considered to be the global best with respect to that region of interest. Since the change map formulated is in the binary format, the process is carried out using binary particle swarm optimization. The optimization of the change map obtained using binary particle swarm optimization is shown in Fig. 2.

3.2. Binary particle swarm optimization

BPSO is a variant of PSO that is designed to handle discrete optimization problem. According to this method, each particle is assumed to be present in binary format. It differs from PSO in updating the particle using current velocity than by combining velocity and current position as in PSO. Due to this, it is always noted that the search space is based on the current velocity only. Hence position is not an issue, yet the method updates the velocity towards the pbest and gbest. Considering the accelerating concept, the change detection is approached.

Initially, a binary change detection mask is obtained by using the Adapted Sparse Constrained Clustering (ASCC) method (Lal and Margret Anouncia, 2017). The ASCC method would generate a change map with significant changes in the multi-temporal images. The post processing using the BPSO is expected to increase the convergence rate and minimizes the error in finding the final change detection mask. The method operates by considering the created initial solution for searching the optimal solution. The other populations are created randomly using the initial solution. Thus the particle is assumed to move towards the gbest and once the specified convergence is met, it is assumed that the gbest is achieved.

Thus, the change map formulated after applying BPSO will have changes projected prominently to result in improved visual effect on the change map.

The process followed is shown in Fig. 3.

The procedure adopted in the case of optimizing the solution space of c as follows:

Input: Initial particle is the binary change map formulated using ASCC
Output: Final Change detected image
  Choose binary change map formulated using ASCC as the initial population
  Generate other populations randomly
  Initialize the populations with random positions and velocities
  For each population
    Evaluate the fitness value for each population as,

$$F_i = \Big[(N_0 * \sum_{\forall (i,j) \in S_0} ADM(i,j) - mean(S_0))^2 + (N_1 * \sum_{\forall (i,j) \in S_1} ADM(i,j) - mean(S_1))^2 \Big] / (M * N)$$

    Fitness function = minimize (F_i)
    Compare the current position of the particle to the pbest position
    If
      Current position is better.
      Set current position → pbest
    Else continue with the old pbest.
    Choose the particle having best fitness value and set as gbest.
    Update the state 'sta' and velocity 'vel' of each particle as,

$$vel = v_i + a1 * rand1 * (pbest - s_i) + a2 * rand2 * (gbest - s_i)$$

$$sta = s_i + vel$$

    Check for stopping criteria
    If stopping criteria is achieved
    Stop
    Else
    Continue
  Until convergence

In the designed BPSO method N_0 and N_1 are the number of elements in the set S_0 and S_1 respectively. S_0 denotes the number of elements in the current mask representing 0 and S_1 denotes the number of elements in the current mask representing 1. The mean of sets S_1 and S_2 will be are represented in Eqs. (1) and (2) ,

$$mean(S_0) = \left(\frac{1}{N_0}\right) * \sum_{\forall (i,j) \in S_0} ADM(i,j) \quad (1)$$

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$$mean(S_1) = \left(\frac{1}{N_1}\right) * \sum_{\forall (i,j) \in S_1} ADM(i,j) \quad (2)$$

where, ADM is the difference image created using Absolute difference method. The updation of state and velocity is based on the random variables 'rand1', 'rand2' and learning factors 'a1' and 'a2' of local and global information.

4. Experimental results and analysis

4.1. Datasets

The developed framework is evaluated using two different data sets. Data Set 1 is the Original Landsat 5 image recorded on 12 October 1984 from Huelva, Spain and Original Landsat 8 image

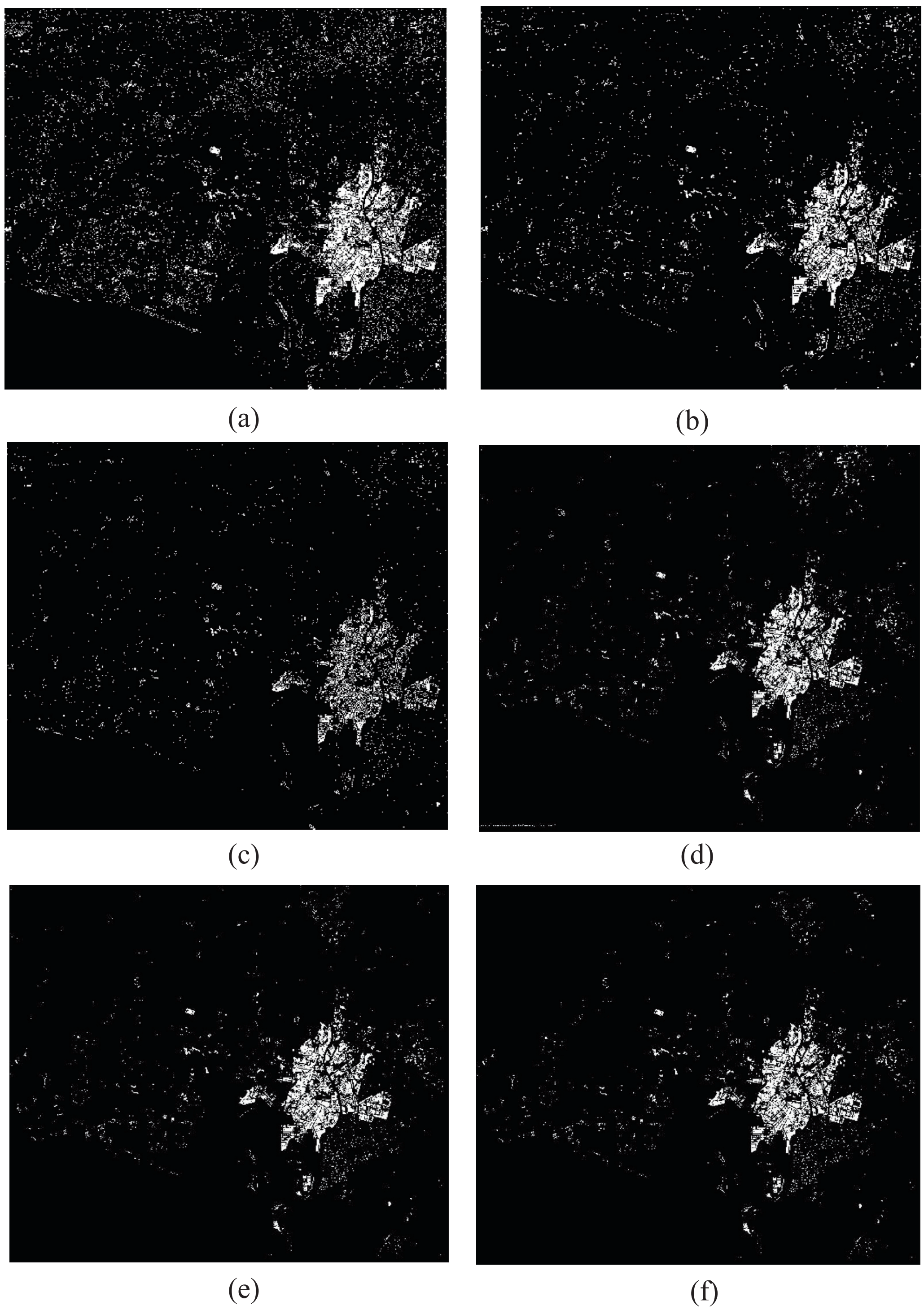

Fig. 5. Change detected via various methods with fusion for Huelva data set. (a) Change Detection using K-means. (b) Change Detection using AKM. (c) Change Detection using FCM. (d) Change Detection using ECKM. (e) Change Detection using ASCC. (f) Change detected using EASCC.

recorded on 12 August 2014 from Huelva, Spain of size 512 × 512. Data set 2 is Original Landsat 5 image acquired on October 24, 1984 form Dead Sea and Landsat 8 image acquired on October 27, 2014 from Dead Sea of size 512 × 512.

Having identified the two study areas, Two images of the study area 1 say Huelva, Spain acquired as Landsat 5 image recorded on 12 October 1984 and Landsat 8 image recorded on 12 August 2014 as shown in Fig. 4 (a) and (b) are considered. Two images of the study area 2 say Dead Sea acquired as Landsat 5 image acquired on October 24, 1984 and Landsat 8 image acquired on October 27, 2014 as shown in Fig. 4(c) and (d) are considered.

4.2. Results and discussions

The performance of the designed intelligent approach (EASCC) is qualitatively and quantitatively analysed. In order to assess the performance of the developed methodology, a comparative analysis is performed with k means, AKM, FCM, ECKM and ASCC.

The change detection maps obtained for Huelva and Dead Sea data set by k means, AKM, FCM, ECKM with sparse fusion, ASCC and EASCC are shown in Figs. 5 and 6. The visual effects obtained out of the designed intelligent methodology shows the clarity of changes in the images which is quite evident from the results that

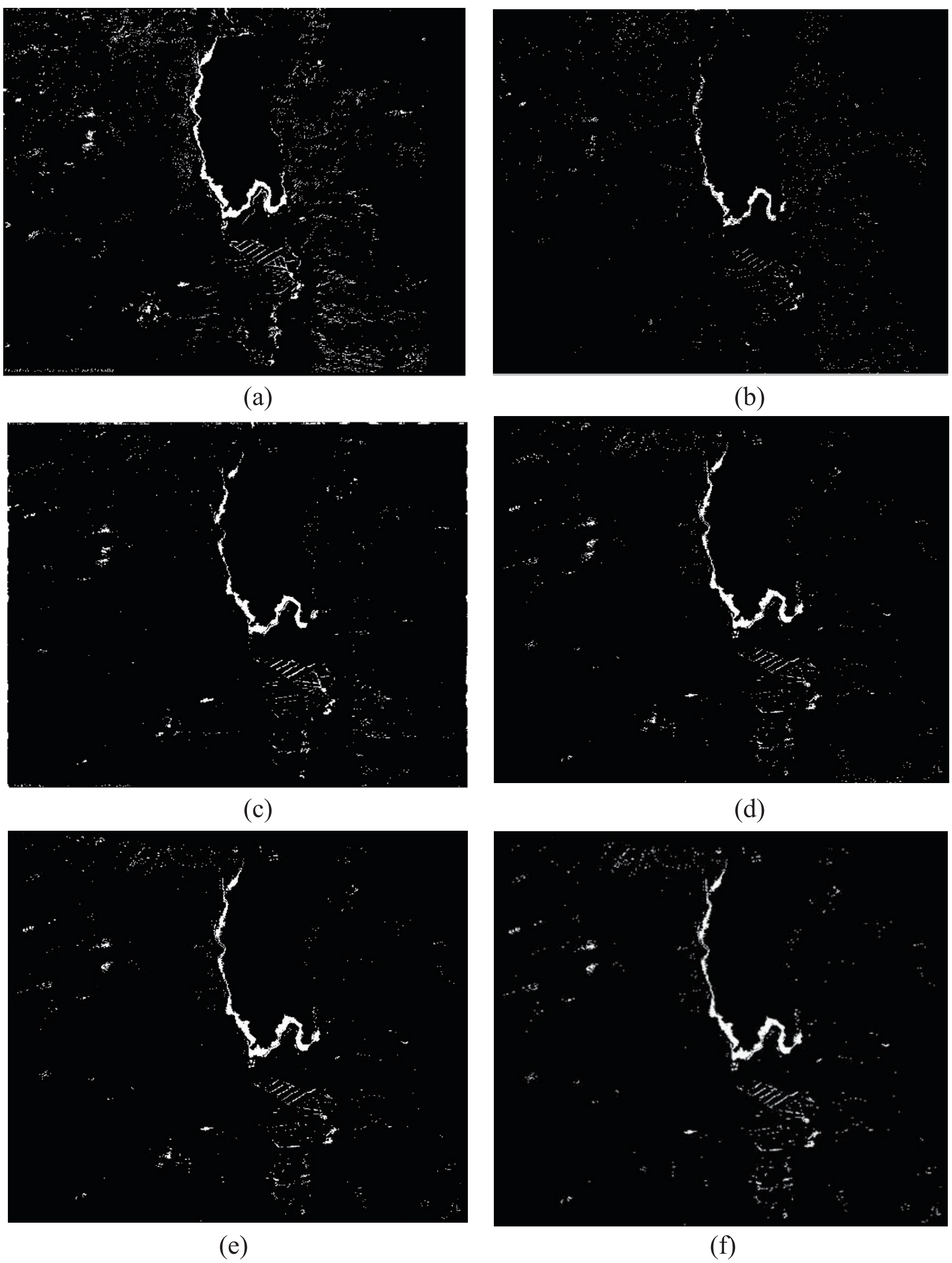

Fig. 6. Change detected via various methods with fusion for Dead Sea data set. (a) Change detected using k means. (b) Change detected using AKM. (c) Change detected using FCM. (d) Change detected using ECKM. (e) Change detected using ASCC. (f) Change detected using EASCC.

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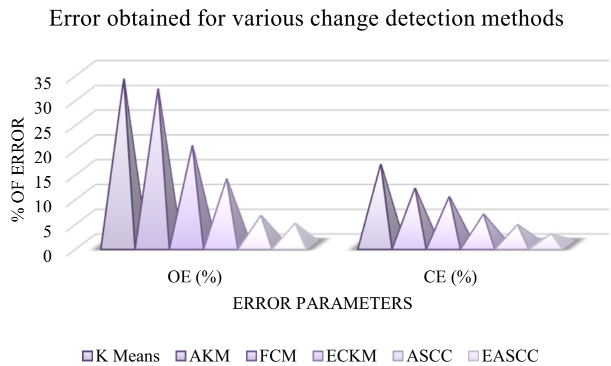

Fig. 7. Percentage of error obtained using various change detection techniques for Huelva Dataset.

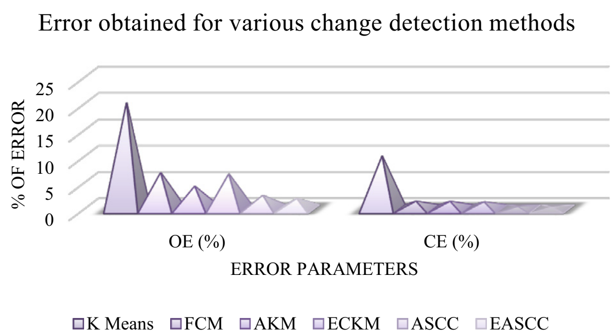

Fig. 8. Percentage of error obtained using various change detection techniques for Dead Sea Dataset.

the designed method outperformed than the other methods (see Figs. 7 and 8).

For the quantitative assessment of the proposed technique, the following metrics have been used for each change map with respect to the reference map (Rosenfield and Fitzpatrick-Lins, 1986).

T_p – the number of altered pixels recognised correctly.
T_n – the number of pixels correctly recognised as unaltered.
F_n – the number of altered pixels incorrectly recognised as unaltered pixels.
F_p – the number of unaltered pixels recognised as altered pixels.

The quantities given above are evaluated by a confusion matrix and various metrics can be obtained using the above derived quantities to assess the performance of an algorithm. In this paper, the following metrics are adopted:

1. Overall Error (OE)

Overall error deals with the probability that a altered pixel incorrectly recognised as unaltered pixels.

$$OE = \frac{Fn}{Fn + Tp} \tag{3}$$

2. Commission Error (CE)

Commission error deals with the probability that an unaltered pixel incorrectly recognised as altered pixels.

$$CE = \frac{Fp}{Tn + Fp} \tag{4}$$

3. Percentage Correct Classification (PCC)

It identifies the overall accuracy of the proposed method by means of detecting the altered pixels as altered and unaltered pixels as unaltered.

$$PCC = \frac{(Tp + Tn)}{(Tp + Tn + Fp + Fn)} \tag{5}$$

4. Recall

Recall is referred to the fraction of altered pixels recognised as unaltered.

$$Recall = \frac{Tp}{Tp + Fn} \tag{6}$$

From the Tables 1, 2, and Figs. 9 and 10 it's very clear that designed approach EASCC has obtained the PCC of 99.63% for Dead Sea Dataset and PCC of 97.65 for Huelva Dataset which is higher than existing methods such as k means, AKM (Lal et al., 2015),

Table 1
Result of Various Parameters Used for Quantitative Comparison with existing methods for Huelva Dataset.

Method	T_p (Pixels)	T_n (Pixels)	F_p (Pixels)	F_n (Pixels)	OE (%)	CE (%)	PCC (%)	Recall
K Means	4390	214,543	41,992	2228	33.67	16.37	83.2	0.66
AKM	4590	226,843	29,592	2128	31.68	11.54	87.95	0.68
FCM	5395	231,223	25,175	1360	20.13	9.82	89.92	0.8
ECKM	6058	240,100	16,054	941	13.44	6.27	93.54	0.87
ASCC	7998	244,100	10,545	510	5.99	4.14	95.8	0.94
EASCC	8250	248,725	5805	373	4.33	2.28	97.65	0.96

Table 2
Result of Various Parameters Used for Quantitative Comparison with existing methods for Dead Sea Dataset.

Method	T_p (Pixels)	T_n (Pixels)	F_p (Pixels)	F_n (Pixels)	OE (%)	CE (%)	PCC (%)	Recall
K Means	2390	232,730	26,413	611	20.36	10.19	89.69	0.8
FCM	2791	255,204	3939	210	7	1.52	98.42	0.93
AKM	2869	255,265	3878	132	4.4	1.5	98.47	0.96
ECKM	3740	254,512	3622	270	6.73	1.4	98.52	0.93
ASCC	3689	257,095	1260	100	2.64	0.49	99.48	0.97
EASCC	3840	257,324	900	80	2.04	0.35	99.63	0.98

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FCM, ECKM (Lal and Anouncia, 2015a) and ASCC (Lal and Margret Anouncia, 2017). An analysis has been carried out in terms of OE and CE. It was observed that the lesser the value of OE and CE, the better is the technique. The overall error (OE) 4.33% for dataset1 and 2.04% for dataset 2 obtained in the designed intelligent approach EASCC indicates that changed pixels have been almost identified accurately with less misclassification errors. The CE obtained by the designed approach is also lesser than the existing techniques. The Recall measures obtained by EASCC is 0.96 and 0.98 which is more than k means, AKM, FCM, ECKM and ASCC (see Fig. 11).

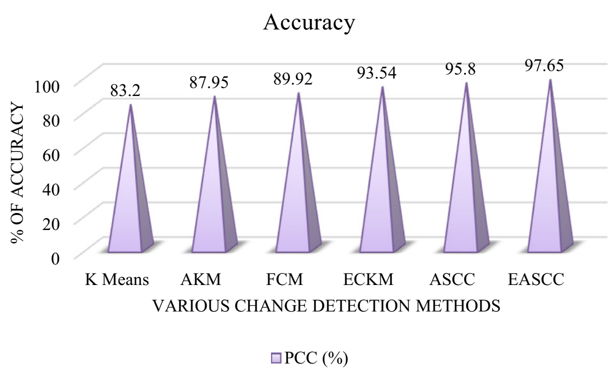

Fig. 9. Accuracy obtained using various change detection techniques for Huelva Dataset.

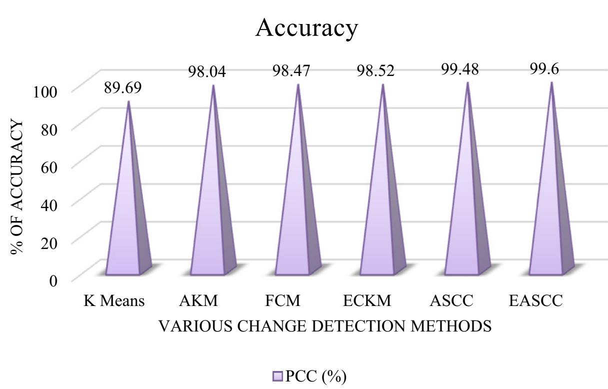

Fig. 10. Accuracy obtained using various change detection techniques for Dead Sea Dataset.

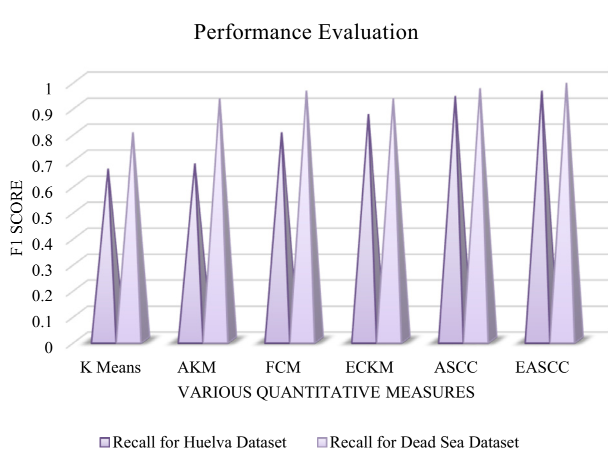

Fig. 11. Recall value of various change detection techniques for Huelva Dataset and Dead Sea Dataset.

From the overall analysis it is felt that while solving the change detection problem, incorporating fusion of the images with semi-supervised clustering the output is improved compared to the existing ones. Further in order to attain global maxima output optimization is carried out to produce more accurate results for change detection. The existing techniques require either the assumption of distributions of clusters and are very time consuming (k means, AKM, FCM, ECKM and ASCC). On the other hand the designed approach concentrates more on the changed areas to further predict the changes in the near future years.

5. Conclusion

In this paper, an intelligent change detection approach EASCC combining ASCC and BPSO for multi-temporal remote sensing images has been designed. The method aimed in detecting changes in remote sensed multispectral, multi temporal images. Though the results appear to be acceptable, as the followed methods tend to converge at local minima the solution obtained would result in local optimum. Hence, to further seek good response in terms of global optimum, a binary PSO is applied. The optimization of solution achieved using BPSO resulted in a notable improvement with high recall and good precision rate. The increase in the precision rate of the designed process helped in drifting the visual quality of the detected change and thereby the change is highlighted prominently. The designed EASCC approach provided better results in terms of accuracy and effectiveness.

Investigations are carried out on multi-temporal and multi-spectral datasets to authorise the effectiveness of the designed intelligent approach. The methodology is demonstrated and evaluated using the measures recall, OE, CE and PCC. The comparison of outcome with other existing methods showed a notable enhancement on the designed methods. In future, more images can be used for change detection study to further promptly figure out the changes and ca also focus on the spectral characteristics of the image and the category of scene used for the change detection process.

References

Bottomley, B.R., 1998. Mapping rural land use & land cover change in carroll county, Arkansas utilizing multi-temporal Landsat Thematic Mapper satellite imagery Diss. University of Arkansas, Arkansas..

Braik, M., Sheta, A.F., Ayesh, A., 2007. Image enhancement using particle swarm optimization. In: World Congress on Engineering, pp. 978–988. No. 1.

Celik, T., 2010. Change detection in satellite images using a genetic algorithm approach. IEEE Trans. Geosci. Remote Sens. Lett. 7 (2), 386–390.

Dai, Q., Liu, J., Liu, S., 2010. Remote sensing image change detection based on swarm intelligent algorithm. In: International Conference on Multimedia Technology (ICMT), pp. 1–3, China.

Kusetogullari, H., 2015. Dynamic multiple description wavelet based image coding using enhanced particle swarm optimization. IEEE J. Sel. Top. Signal Process. 9 (1), 125–138.

Kusetogullari, H., Yavariabdi, A., Celik, T., 2015. Unsupervised change detection in multitemporal multispectral satellite images using parallel particle swarm optimization. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 8 (5), 2151–2164.

Lal, A.M., Anouncia, S.M., 2015a. Semi-supervised change detection approach combining sparse fusion and constrained k means for multi-temporal remote sensing images. The Egypt. J. Remote Sens. Space Sci. 18 (2), 279–288. https://doi.org/10.1016/j.ejrs.2015.10.002.

Lal, A.M., Anouncia, S.M., 2015b. Detection of boundaries by fusing the topographic sheets and multi-spectral images for geographic landscapes. Int. J. Ecol. Dev. 30 (3), 11–25.

Lal, A.M., Anouncia, S.M., 2016. Enhanced Dictionary based sparse representation fusion for multi-temporal remote sensing images. Europ. J. Remote Sens. 49 (1), 317–336. https://doi.org/10.5721/EuJRS20164918.

Lal, Anisha M., Margret Anouncia, S., Gopalakrishnan, M., 2015. Multispectral image change revealing using translation invariant wavelet transform fusion and adaptive K-means clustering. Int. J. Appl. Environ. Sci. 10 (2), 681–693.

Lal, Anisha M., Margret Anouncia, S., 2017. Adapted sparse fusion with constrained clustering for semisupervised change detection in remotely sensed images. J. Appl. Remote Sens. 11, (1). https://doi.org/10.1117/1.JRS.11.016013 016013.

Nielsen, A.A., 2007. The regularized iteratively reweighted MAD method for change detection in multi-and hyperspectral data. IEEE Trans. Image Process. 16 (2), 463–478.

Ramadan, R.M., Abdel Kader, R.F., 2009. Face recognition using particle swarm optimization-based selected features. Int. J. Signal Process. Image Process. Pattern Recogn. 2 (2), 51–65.

Rosenfield, G.H., Fitzpatrick-Lins, K., 1986. A coefficient of agreement as a measure of thematic classification accuracy. Photogramm. Eng. Remote Sens. 52 (2), 223–227.

Sagnika, S., Bilgaiyan, S., Mishra, B.S.P., 2015. Image change detection using particle swarm optimization. Intell. Comput. Commun. Devices, 795–803.

Singh, A., 1989. Review article digital change detection techniques using remotely-sensed data. Int. J. Remote Sens. 10 (6), 989–1003.

Soliman, O.S., Mahmoud, A.S., Hassan, S.M., 2012. Remote sensing satellite images classification using support vector machine and particle swarm optimization. In: IEEE International Conference on Innovations in Bio-Inspired Computing and Applications (IBICA), pp. 280–285. India.

Wu, C., Du, B., Cui, X., Zhang, L., 2017a. A post-classification change detection method based on iterative slow feature analysis and Bayesian soft fusion. Remote Sens. Environ. 199, 241–255.

Wu, C., Zhang, L., Du, B., 2017b. Kernel slow feature analysis for scene change detection. IEEE Trans. Geosci. Remote Sens. 55 (4), 2367–2384.

Xian, G., Homer, C., Fry, J., 2009. Updating the 2001 national land cover database land cover classification to 2006 by using Landsat imagery change detection methods. Remote Sens. Environ. 113 (6), 1133–1147.

Xue, B., Zhang, M., Browne, W.N., 2012. Multi-objective particle swarm optimisation (PSO) for feature selection. In: Proc. of the ACM Annual Conference on Genetic and Evolutionary Computation, pp. 81–88. Italy.

Yavariabdi, A., Kusetogullari, H., Usakli, A.B., 2017. Unsupervised satellite change detection using particle swarm optimisation in spherical coordinates. Int. J. Sci. Res. Inf. Syst. Eng. (IJSRISE) 1 (2).