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Performance of Unsupervised Change Detection Method Based on PSO and K-means Clustering for SAR Images

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***Abstract*—This paper presents unsupervised change detection method to produce more accurate change map from imbalanced SAR images for the same land cover. This method is based on PSO algorithm for image segmentation to layers which classify by Gabor Wavelet filter and then K-means clustering to generate new change map. Tests are confirming the effectiveness and efficiency by comparison obtained results with the results of the other methods. Integration of PSO with Gabor filter and k-means will providing more and more accuracy to detect a least changing in objects and terrain of SAR image, as well as reduce the processing time.**

***Keywords*—Change detection, k-means clustering, multitemporal satellite images, PSO, Gabor wavelet filter, remote sensing**

I. Introduction

A PROCESS of analyzing pair images captured over the same land cover at different times to detect and identify significant changes is called "Change Detection Process" [1]. This process may be categorized according to data processing into: supervised and unsupervised change detection. The first type includes a classification which requires a land truth dataset to obtain a suitable training set for the classifiers learning process. This performs detection process through a direct comparison between the two multitemporal images without incorporating any additional data [2]. While the second type deals with two digitized images as input and detect locations where the differences between the pair images can be identified [3]. No conceivable antenna size can provide, for example, a range space of about 1000 km and at least 100 meters resolution, if considered that the resolution provided by the antenna size. For this purpose, a so-called synthetic aperture radar (SAR) is used [4]. By means of coherent processing of the reflected signal, high resolution is achieved with a relatively small antenna size. SAR images are attracting a lot of attention, for example, in terrain observation or in military aviation mainly for reconnaissance and navigation purposes. SAR allow obtaining objects and terrain detailed images with a quality better than optical systems in any weather conditions and at any time [5,6]. After filtrating SAR images from noise, in particular speckle noise, accuracy of change map generated under unsupervised change detection conditions is an important task. Detection of a least changing in the real time SAR images to achieve more and more accuracy in object detection process to observe terrain is a real challenge. This challenge needs to develop an effective change detection technique or method which can deals with the imbalanced SAR image processing. To solve this task, this paper presents an effective unsupervised change detection method for SAR images using Particle Swarm Optimization (PSO), Gabor wavelets filter and k-mean clustering. Integration of PSO with Gabor wavelet filter for segmenting images into layers to extract features and then employing K-mean algorithm to implement change map are providing a quite development and reduce the processing time. Production of the difference image (DI) from two imbalanced SAR datasets for the same land area and set this DI to the parallel PSO segmentation is not enough for classification features. Therefore, the Gabor filter will play a pivot role to support this process. Consider two multitemporal images segmented by PSO, then the Gabor wavelets is applied to select pixels which have values less than '1' or more than '0' (i.e. changed or unchanged pixels). Consequently, a new image patches centered at interested pixels are produced and classified by K-mean clustering to produce a new change map. However, the other sections of this paper are organized as: the previous works, the proposed procedure, results and analysis, and Finally, conclusions.

II. The Precious Works

Several works include unsupervised change detection methods were suggested to solve the task of change map accuracy. Among these works, for example, the author of [7] use principal component analysis (PCA) filters to exploit from each pixel the representative neighborhood features. This method can produce the change map with min. noise and time. The author utilizes the Gabor wavelets filter with fuzzy C-means algorithm (FCM) for choosing pixels and implement new image patches for PCANet model to train. Another change detection method for SAR datasets is proposed in [1] and depending on neighborhood-based ratio (NR) with extreme learning machine (ELM). The author applies NR operator to obtain some pixels interested, which have high probability to be change. ELM is used to train a model according to new image patches generated to classify SAR images. The final change map production is

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following the results of ELM model and pre-classification. While in paper [8], the author develops change detection algorithm depend on the hybrid genetic FCM to classify image features. Harris and Shift operators are used to perform registration with two images of the same region at different time. The logarithmic method is used to produce the initial DI. To reduce the difference image dimension, PCA algorithm is employed. The proposed method in [6] follows a coarse-to-fine procedure to select distinctive and salient regions from the difference image while the otherwise non-salient regions are neglected. In the coarse-to-fine regions, classification stage, random multi-graphs are used as the classification model and noisy unchanged regions incurred by the speckle noise are suppressed. Article [9] suggests method with Deep Cascade Network (DCNet) and called a deep learning-based method to solve the exploding gradient problem. A fusion mechanism is used to alleviate this problem after combining the outputs of different hierarchical layers. Moreover, to solve the feature redundancy problem, a simple yet effective channel weighting-based model is formed. By comparison with the deep learning model, the proposed method in [10] achieves precision more than some another change detection methods. Due to fewer parameters, the multi-scale gcForest is easy to be trained and tests using four types of datasets are confirm the method efficiency. In the paper [11], the author suggests a framework of an unsupervised change detection hypergraph-based SAR image. This work includes a novel hypergraph designed by depending upon the coupling neighborhood. Via modelling, DI generated can be formulated as a hypergraph matching problem. The DDI generation method proposed in [5] can effectively minimize speckle noise and enhance features. A parallel FCM clustering developed method was used to increase the gap between the change and unchanged classes. This provide excellent clustering performance under imbalanced data by providing highly reliable pseudo-label training samples. Over-sampling and under-sampling were employed to mitigate the imbalance effects on PCANet.

In this work, dealing with the edges of the visible objects is a major difference for detection. Therefore, PSO was used to divide the image, which represents the difference between two SAR images, into several layers. The purpose of this operation is to increase accuracy of detection for the changed pixels. Next step is using Gabor wavelets filter to classify these detected pixels which are undefined and uncleared. The classified results are submitting to K-mean clustering to set the values “1” & “0” to the changed and unchanged pixels. The two main steps are illustrating the proposed procedure:

1) Preprocessing: log-ratio image will generated through using log-ratio operator to produce DI. Then, PSO and Gabor wavelets are employed to select pixels which have unknown status to be changed or unchanged (i.e. intermediate between “0” and “1”).

2) Changed and Unchanged Pixels Classification: Results obtained from preprocessing step will be set to K-mean algorithm for classifying into two clusters for generating change map at the end.

III. THE PROPOSED PROCEDURE

Consider two multitemporal SAR datasets Z_1 and Z_2 are registered for the same land cover at different time and filtered from the multiplicative noise. The purpose of change detection is to produce a change map, which has the difference occurred between both images when the time is different. SAR image can be viewed as a binary classification process. In this case, a binary image will produce in which set zero to the unchanged pixels while 1 is set to the change pixels. The binary image generated is also called a change map and contains all changes occurred between both images. Figure 1. show the overall proposed detection method to generate a change map by integrating PSO, Gabor wavelet and k-mean clustering.

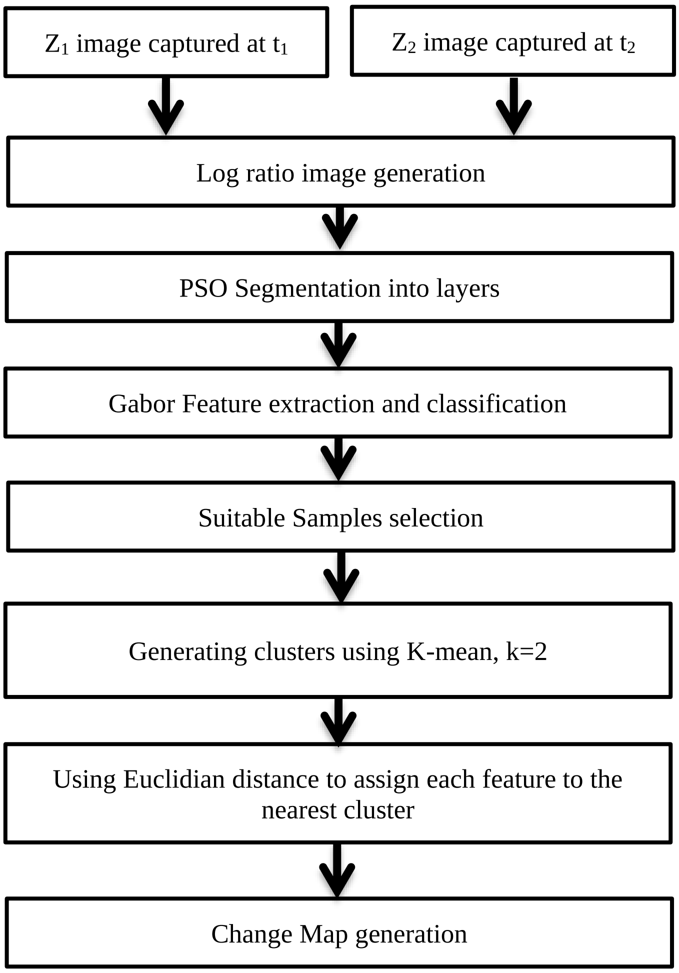

Fig.1. Scheme of the overall proposed procedure

A. *Producing of Difference Image (DI)*

According to the figure 1., difference image (DI) is produced from Z_1 & Z_2 and represents as the first step. DI can be define differently related to the input images type. In case of optical images, DI is defined as absolute-value difference of intensity as following:

$$Z_d=|\log(Z_2/Z_1)|,$$

where Z_d is the difference image resulted, which is consist of black and white color. Using log ratio will support alignment of edges and make distortion and deformation at minimum level as possible. However, the DI will set to PSO algorithm for segmenting into layers.

B. *PSO Segmentation*

In particle swarm optimization (PSO) method, the elements are particles in the parameter space of the optimization problem.

These particles have a confident position with a velocity vector in this multidimensional space at each moment of time (i.e. at each iteration). For each position, a corresponding value of the objective function was estimated. According to certain rules, the particle will change its position and velocity in the search space. In fact, PSO algorithm was formed from the socio-psychological behavioral model of population (N) with several variations and conditions. For example, in the canonical PSO method proposed in 1995 by Kennedy, Eberhart [12,13], information about the best particle among the "neighbors" of given particles is taken into account. Moreover, information about this particle at that iteration, when the best value of the objective function corresponded to this particle, is also taken into account. This process will be executed to determine the next position of a particle at each iteration [12,14]. Here the new velocity and posteriorly new position of a particle will be calculated according to its present velocity. However, the initial velocity $v_i = (v_{i1}, v_{i2}, v_{i3}, \dots, v_{id})$ is considered and initial position $x_i = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{id})$ in d-dimensional space. For the instant $(t+1)$:

$$v_i(t+1) = w_i(t)v_i(t) + c_1 r_1\big(p_{best}(t) - x_i(t)\big) + c_2 r_2\big(g_{best}(t) - x_i(t)\big),$$

$$x_i(t+1) = x_i(t) + v_i(t+1),$$

where $w -$ the inertia weight value (fixed); c_1 , c_2 are the learning parameters which have fixed values; $1 > r_1 , r_2 > 0$ are the random numbers; p_{best} , g_{best} are the personal best & global best of each particle [13,14]. After setting DI, the PSO algorithm is work as the follows:

Start PSO algorithm

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- Initializing of N;
- Set thresholds and iteration number;
- Set individual particles weight, social particles weight, inertial factor;
- Create N particle;
- Initialization values of the position & velocity for each particle;
- Select personal best & global best particles;
- Update status {
    - Position & velocity of each particle;
    - Inertia weight w of each particle;
    - Personal best & global best of each particle;
    - Return the membership value of the global best particle;

  }
- Assign the cluster according to the membership value of global best particle;
- Return center and membership values of the best particle;
- Segment the image;

}

C. *Gabor wavelet filter*

The number of changed pixels is often much less than unchanged pixels in SAR image [15]. High accuracy to classify and extract the image features is an important task here, but PSO method have not enough clustering effect in case of imbalanced data [12]. The image obtained from PSO stage (segmented image) needs more accurate method to limit pixels which have a quite probabilities to be classified into changed or unchanged classes correctly. Therefore, Gabor wavelets filter is suitable to use here. Gabor wavelet algorithm is commonly used in content-based image retrieval for texture local feature extraction and classification in various applications [15,16]. This algorithm is originally developed for modelling the receptive fields of simple cells in the visual cortex. Gabor wavelet advantages are also employed in many image analysis applications, for example, in face recognition and facial expression classification [17]. In Gabor wavelet transform, an image is convolved with a bank of Gabor filters and with different scales and directions [15,17]. Therefore, in this work, the role of Gabor wavelet is convolving DI obtained from PSO stage with a set of Gabor kernels. To produce a built-in representation, the Gabor wavelets (kernels, filters) can be defined as follows [15]:

$$G(Z) = \frac{||K_{u,v}||^2}{(sigma)^2}\, e^{\left(\frac{\left(-\left\|K_{u,v}\right\|^2 . Z^2\right)}{2(sigma)^2}\right)} \times (e^{(i\ .\ Ku,v\ .\ Z)} - e^{\left(-\frac{(sigma)^2}{2}\right)})$$

where u, v are the direction and scale of the Gabor kernels $Z = (M.N)^T$; ||.|| denotes the Euclidean norm; sigma is the Gaussian envelope along image axes (rows and columns); the wave vector is:

$$K = K\,e \quad K_{u.v} = K_v\, e^{j\varphi u} \quad . \quad K_v = \frac{K_{max}}{f^v} \quad . \quad \varphi_u = u\frac{\pi}{5}$$

where K_{max} represents the max. frequency; f represents the spacing factor between kernels in the frequency domain; φ_u represents the direction selectivity of Gabor filter; the value of v determines the wave length of the Gabor filter, while the scale of the sample can be controlled by transforming v; the value of u represents the direction of the Gabor filters [15]. The values assigned and applied in this paper are defined as follows: sigma $= 3 \cdot 8\pi$, $K_{max} = 2\pi$, $f = \sqrt{2}$, $u \in \{1.2.3.4.5\}. v = \{0.1.2.3\}$. The compact Gabor feature vector z for each pixel in DI is represents as $z = [z_0, z_1, \dots, z_{V-1}]$. However, the Gabor features $Z = [z_1, \dots, z_{MN}]^T$ are extracted from DI and $(M \times N)$ N are image dimensions.

D. *Classification Using K-mean algorithm*

In the k-means algorithm, each object is hard-coded to only one cluster and the shape of the clusters is not configurable. There are two main steps in the k-mean algorithm. First step is selection k different cluster centers and usually just random points in the dataset. Then, the second step is moving on to main loop, which also has two stages. The first stage is to choose which of the clusters each point from X belongs to. In this case, each example is taken and choosing the cluster whose center is closest. Important note that the centers are selected randomly at the beginning. The second stage is to recalculate each cluster center based on the set of points assigned to it. To do this, all relevant examples are taken and calculating their average value until the algorithm converges. That is, until the change in the distribution of points across clusters or in the coordinates of cluster centers stops. As a rule, this happens very quickly - in the region of 5 to 15 cycle passes. This is very different from gradient descent in deep learning, where thousands of iterations can go through before convergence occurs [18,19]. In this work, next stage is to cluster the feature vector space results from Gabor filter into two clusters, i.e. k = 2 (change=1 and unchanged=0). Let v_{w_u} and v_{w_c} be clusters mean feature vector for classes w_u and w_c, respectively, then these clusters are labeled with w_u and w_c. The labeled pixels are used to calculate two average values over DI. If the changed value is existed in a specific area limited, then this value is probably as a higher value of DI pixel in that area than the value of pixels in the same areas where there is no change. According to this statement, the cluster which have lower average pixels values in DI is assigned as w_u class, while the other cluster is assigned as w_c class. A binary change map $CM = \{cm(i.j)|1 \le i \le H. 1 \le j \le W\}$ can be obtained using v_{wc} and v_{wu}, where "1" refers to the corresponding pixel location belonged to w_c class which has a change, while "0" refers to pixel location belonged to w_u class no changes. This process can be observed as unsupervised thresholding:

$$cm(i.j) = \begin{cases} 1. & ||v(i.j) - v_{w_c}||_2 \le ||v(i.j) - v_{w_u}||_2 \\ 0. & otherwise \end{cases}$$

where $||.||_2$ is Euclidean distance. In this work, K-mean clustering will be represented as the following steps:

Start K-mean algorithm

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- The vector space is initially partitioned into K=2 clusters.
- The observations are randomly assigned to the clusters.
- Calculate Euclidean distance from the observation to the cluster centroid for each vector.
- If the vector is closest to its own cluster, then leave it else select another cluster.
- The steps repeated until no observations are moved from one cluster to another. In this case, the clusters are stable and each vector is assigned to a cluster which results in the lowest possible distance to the cluster centroid.

}

IV. Results and Analysis

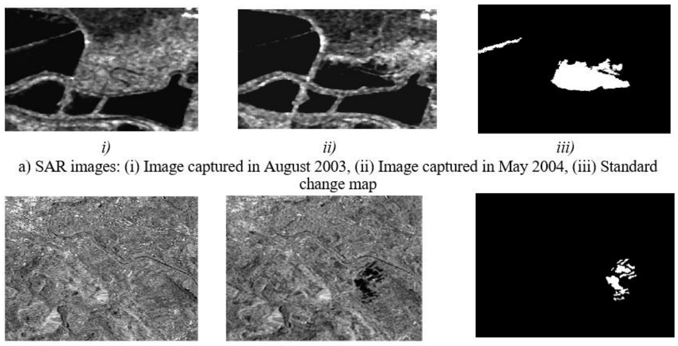
In this section, an evaluation of the proposed procedure by using two real SAR datasets is performed. Furthermore, a comparison of the obtained results with the other change detection techniques to illustrate efficiency and effectiveness is also present.

A. Dataset Description and Experimental Settings

Two SAR images with different characteristics attained by an ERS-2 SAR sensor are used to test method. These images are the city of San Francisco with (256 × 256) image size and the city of Bern before and after flood with (400 × 400) image size [20,21]. The variety of presented dataset with different size will be important to illustrate efficiency and effectiveness of the method. From the figure 2.a, the first image for San Francisco was captured in August 2003 while the second image was captured in May 2004 for the same terrain. The standard change map resulted from the present method is the third image shown. In the same vein, from the figure 2.b, the first image for Bern was captured before the flood in April 1999 and the second image was captured after the flood in May 1999. Also, the standard change map resulted from the present method is the third image shown.

In fact, the process of generating change map in this paper will be aided by simulation (i.e. applying the proposed method to obtain change map closely to the standard). The following indicators are employed to evaluate the proposed method:

a) False positives (FP) refer to the unchanged pixels number, which have false detected;
b) False negatives (FN) refers the real changed pixels number, which are detected as unchanged;
c) True negatives (TN) indicates the unchanged pixels, which are correctly detected;
d) True positives (TP) indicates the changed pixels, which are correctly detected;
e) Percentage correct classification (PCC);
f) Kappa coefficient (KC).



i) *ii)* *iii)*

a) SAR images: (i) Image captured in August 2003, (ii) Image captured in May 2004, (iii) Standard change map

i) ii) iii)

b) SAR images before and after flood: (i) April 1999, (ii) May 1999, (iii) Standard change map

Fig. 2. Bitemporal SAR images relating to the dataset of:
a) San Francisco, b) Bern

Let Nc and Nu refers to the number of truly changed and unchanged pixels respectively for the standard change map [1,6]. The ratio (Nc/Nu) is used to measure the imbalance level between the changed and unchanged classes. While the overall errors (OE) may be computed by: OE = FN + FP to indicate the number of pixels for all detected errors. Moreover, PCC refers to the ratio of correctly classified pixels for all pixels and expressed as:

$$PCC = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

The KC is considered as an essential criterion, which is used for consistency check and calculated as following:

$$KC = PCC - \frac{[(TP + FP)(TP + FN)] + [(FN + TN)(FP + TN)]}{TP + TN + FN(1 + FN)}$$

The comparison between obtained results with the results of previous methods is illustrated in the table I. This comparison is based on the five indicators (FN, FP, OE, PCC, KC), while the methods are: PCA-kmeans [20], NR_ELM [1], Gabor_PCA Net [7],CWNN [21], DP_PCANet [5] for San Francisco dataset and PCA-k[2], ITDI-GC [22], FLICM [23], MRFFCM [24] and HCDF [10] for Bern data set. From the table I, PCC and KC values obtained from the presented method are 99.18% and 0.9481, respectively, which are slightly higher than 99.08% and 0.9296 of DP_PCANet, 98.90% and 0.9164 of Gabor PCANet, 98.94% and 0.9231 of CWNN methods. Analysis results show that the change map obtained from the proposed method is completely identical to the Ground truth map and improving accuracy is clearly obtained. Also, for the Bern dataset, PCC and KC values obtained are confirm efficiency and effectiveness of the proposed method as explained in table I too.

TABLE I
THE COMPARISON BETWEEN OBTAINED RESULTS WITH THE RESULTS OF PREVIOUS METHODS

SAR Image	Method	FN	FP	OE	PCC	KC
San Francisco	PCA-k means	218	13496	13714	0.7907	0.3170
	NR_ELM	10	10137	10147	0.8452	0.4161
	Gabor_PCA Net	409	311	720	0.9890	0.9164
	CWNN	150	545	695	0.9894	0.9231
	DP_PCANet	382	221	603	0.9908	0.9296
	Proposed method	**379**	**219**	**598**	**0.9918**	**0.9481**
Bern	PCA-k	122	251	373	0.9959	0.8450
	ITDI-GC	145	154	299	0.9967	0.8705
	FLICM	289	34	323	0.9964	0.8410
	MRFFCM	47	364	401	0.9955	0.8413
	HCDF	98	193	291	0.9968	0.8771
	Proposed method	**90**	**180**	**270**	**0.9973**	**0.9177**

Figures 3. & 4. illustrates the differences between the change maps obtained from the previous method and the change map resulted from the present method. These differences confirm that the present method, which have extremely strong detection performance, is significantly better than other methods and resulted map is produced with high accuracy in details.

B. *Analysis of level in PSO*

Level selection (LS) in PSO is an effective parameter to provide change detection results and will help to extract good Gabor features. In this paper, LS value is selected and tested from 2 to 20 or more. Figure 5. show that LS value is selected from 2 to 21 and a better result appears when LS=17 and more to indicate the relationship with PCC. With k=2, the method requires LS value large enough for feature extraction and noise sensitive. Also, when LS $\geq$ 5, the results are approximately good for extracting features, while if LS $\geq$ 17, the best method performance is achieved for both datasets.

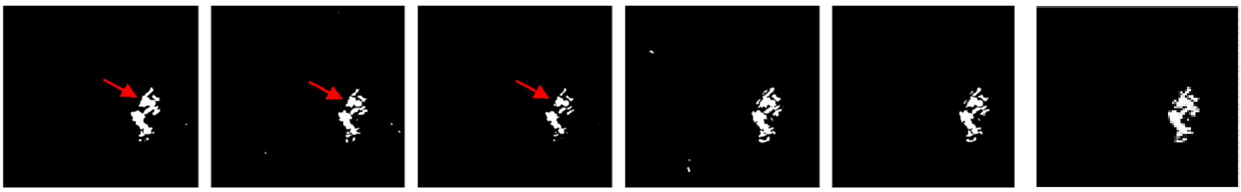
C. *Analysis of execution time*

The San Francisco dataset

(a) PCA k-means (b) NR ELM (c) Gabor PCANet (d) CWNN (e) DP PCANet (f) Proposed method

Fig. 3. The resulted change map of San Francisco dataset compared with the others

The Bern flood dataset



(a) PCA-K. (b) ITDI-GC (c) FLICM (d) MRFFCM (e) HCDF (f) Proposed method

Fig. 4. The resulted change map of Bern flood dataset compared with the others

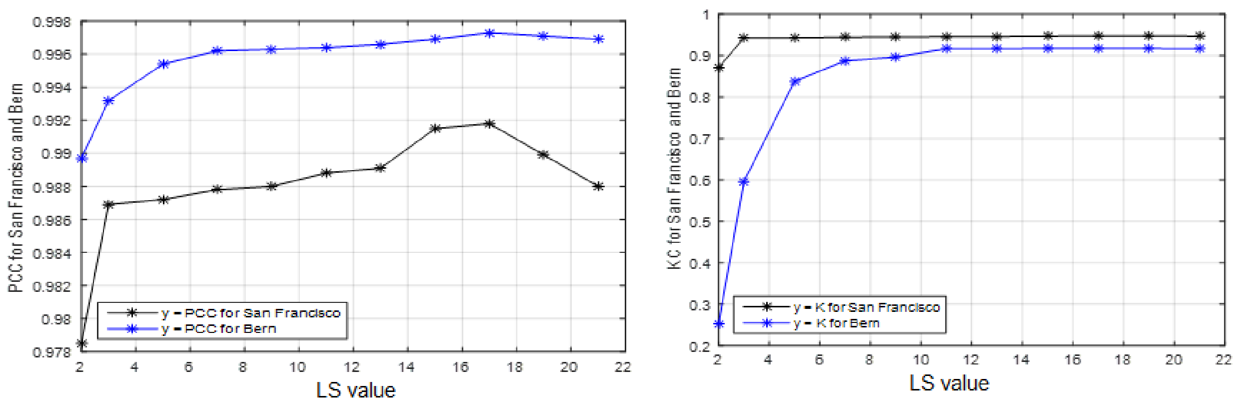


Fig. 5. Level selection in PSO for extracting features

Another important factor presents in this work is the processing time. The previous works are not touched on the time taken by the program code to complete results. The reason is that the most works are depending on using neural networks or long program steps, which consumes a very long time in order to complete the work with high accuracy. The present method consumes a very short time with high accuracy compared to previous works time as shown in table II for San Francisco. The software is implemented with instructions as minimum as others and used direct and effective functions found in the MATLAB programming language. For Bern flood dataset, the execution time is estimated about 28 second and this time is less than the time estimated in other methods.

TABLE II
THE PROCESSING TIME ESTIMATED

SAR dataset	Method	Time estimated (sec)
San Francisco	PCA k-means	551.812198
	NR_ELM	2100.321
	Gabor_PCA Net	2431.13
	CWNN	3981.23
	DP_PCANet	1542.89
	Proposed method	**25.557147**

CONCLUSION

This paper contains results of using PSO algorithm with Gabor filter and k-means clustering for processing SAR datasets to generate change map with more accuracy of terrain detection. Appling these algorithms for simulating the produced map will reduce the processing time and provide effectiveness to deals with the SAR images under unsupervised change detection conditions. By the comparison with the other previous methods, the present method is confirming the efficiency, robustness and effectiveness. Furthermore, the proposed method is simple in computations and detecting the objects and terrain with least change as possible. Otherwise, the method is suitable for real-time applications with a short time processing. The results prove success and sensitivity of the proposed method for change detection in optical and SAR images. Development and improvement of the method for the navigation purposes are the next works for the team.

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