The Egyptian Journal of Remote Sensing and Space Sciences (2010) **13**, 1–10

National Authority for Remote Sensing and Space Sciences

The Egyptian Journal of Remote Sensing and Space Sciences

www.elsevier.com/locate/ejrs
www.sciencedirect.com

A proposed multi-scale approach with automatic scale selection for image change detection

Eid M. Emary *, Khaled M. El-Saied, Hoda M. Onsi

Information Technology Dept., Faculty of Computers and Information, Cairo University, Giza, Egypt

Received 16 April 2008; accepted 17 August 2008
Available online 20 October 2010

KEYWORDS
Change detection;
Multi-scale image analysis;
Optimal scale selection

Abstract In this paper a system for multi-scale change detection with automatic scale selection is proposed. The generation of the multi-scale data set is performed based on the fractal net evolution approach (FNEA). The set of scales used by FNEA are optimally selected from the scale domain ensuring that the selected levels present a good enough representation of the scale domain. A pattern search module is used to select good enough set of scales with the least redundancy. The change detection is performed on each scale individually. For each individual object in a specific scale change indicators are extracted for the pixels corresponding to this object in the base-scale images. After extracting the change indicators for each scale, the extracted indicators are thresholded to obtain a per-scale binary change map. To obtain the final change map, a scale-driven fusion of all the extracted change maps is performed. The fusion is based on detecting for each pixel the preferred scale to obtain its change information. The best scale for an object is the scale where the object area keeps static/almost static while moving from one scale to the next scale(s). The proposed system proves advantageous over other change detection systems.

1. Introduction

Change detection on complex landscape is a very difficult problem. The reason for this difficulty is that landscapes are complex systems composed of a large number of heterogeneous components that interact in a non-linear way and exhibit adaptive properties through space and time. In addition, complex systems exhibit characteristics of emergent properties, multi-scale hierarchical interactions, unexpected behavior and self organization, all of which produce characteristic patterns that appear to change depending on their scale of observation. So the rule of scale is critical for the analysis of change. Since there is no way of defining a priori the appropriate scales associated to specific patterns and there is a need to derive adequate rules for transferring information through

* Corresponding author.
E-mail address: eidemary@yahoo.com (E.M. Emary).

Peer review under responsibility of National Authority for Remote Sensing and Space Sciences.
doi:10.1016/j.ejrs.2010.07.001

Production and hosting by Elsevier

multiple scales, it is imperative to develop a multi-scale approach that allows dominant patterns to emerge at their characteristic scales of expression. Scale is a variable intrinsically linked to the entities under observation, and corresponds to one's window of perception. Thus every scale reveals information specific to its level of observation (Hall and Hay, 2003).

Analyzing data at multiple scales reveals the problem of *mis-registration* of the data and helps to decide the optimal analysis area for individual objects.

Many studies have made use of multi-scale analysis in literature (Carvalho et al., 2003, 2005; Desclée et al., 2006; Hall and Hay, 2003; Youjing and Hengtong, 2007) and (Duveillera et al., 2008).

Mainly, the process of multi-scale analysis can be divided into three modules (Fig. 1).

- Selecting the scaling levels.
- Generating a multi-scale data set.
- Analyzing the multi-scale data set.

The task of only selecting significant scales for processing a given image, having no prior information is frequently too inconsistent and subjective. The scale selection poses a problem in that a non-trained human operator is generally unable to obtain well enhanced images isolating specific structures. This may affect the results of any visual system which uses these images for processing and analysis . Objectivity and repeatability would be assured if scale selection could be automated. Multi-scale analysis captures information at a range of scales. Nevertheless, the problem is that without knowledge about the desired features, explicitly selecting significant scales is a difficult task.

Most of the methods for multi-scale analysis require generating and analyzing a very huge multi-scale data set. The generated data sets are always provided by uniformly quantizing the scaling variable (Blaschke et al., 2001), or manually selecting specific scaling level(s) (Blaschke, 2005); in case of Scale Space system and scale threshold in case of fractal net evolution approach (FNEA).

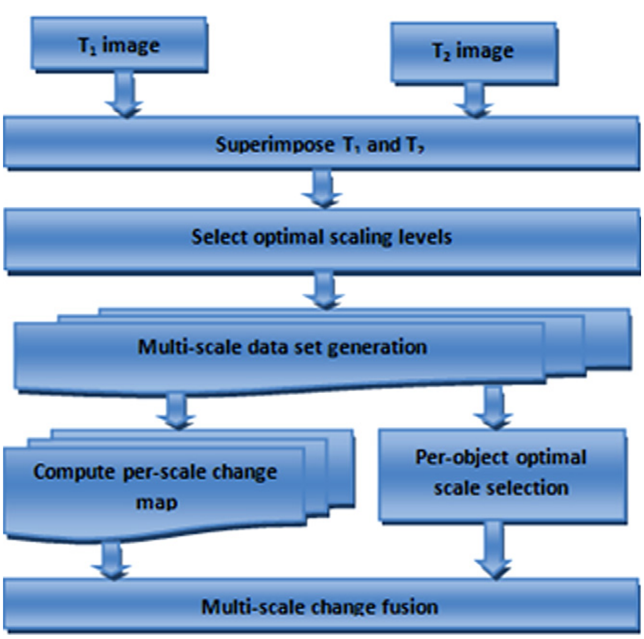

Figure 1 The proposed change detection system.

In this work a method for selecting significant scales for multi-scale analysis is proposed. The method employs pattern search (Abramson et al., 2004) for selecting a set of scales for analysis where the selected scales ensure good enough representation of the scale domain.

Wavelet Transform is one of the most common transformations for generating a multiresolution representation of a signal (Carvalho et al., 2003, 2005; Marcos et al., 2006; Youjing and Hengtong, 2007) and (Daryaei, 2003), but adhoc methods are used to select suitable scale(s) for change analysis. Of the scale selection criteria are avoiding lower scales because of misregistration errors and noise, and avoiding very high levels because of the lake of information they represent (Carvalho et al., 2003), the reduction of search space (Carvalho et al., 2005). A per-pixel scale selection method is based on whether the pixel under consideration is on a border or in a smooth area (Marcos et al., 2006).

Growing Window; (windows with growing sizes), is used to reflect different analysis scales and the results of the per-window analysis are fused either using principal component analysis or maximum operator (Inglada and Mercier, 2006, 2007).

Gaussian Mixture Model is fitted to the input data and split sequentially until a satisfactory fitting resolution is achieved to generate a hierarchical data set. The used scale is chosen to speedup the processing time and to keep enough detail (Wilson and Calway, 2004).

Scale Space (SS) is a method used to generate multi-scale representation of a signal. SS makes use of a set of Gaussian masks with different standard deviations, which are convolved with the original signal to make specific resolution. The result of SS is a set of signals diffused with different Gaussian masks each representing specific resolution. Always analysis scales are selected by trial and error (Hay et al., 2003).

Multi-scale Object Specific Analysis (MOSA) is a multi-scale approach that automatically defines unique spatial measures specific to individual image-objects composing a scene. These specific measures are used in a weighting function to automatically upscale an image to coarser resolution (Hall and Hay, 2003; Hay et al., 2003).

Recently, a new system for multi-scale data-set generation, FNEA is implemented in commercial software (eCognition) (Hay et al., 2003). This approach extracts objects of interest at the scale of interest, segmenting images by operating on the relationships between linked objects. FNEA is a region-based approach that involves generating a hierarchical segmentation at various scales. The segmentation is based on an optimization function which involves three parameters, namely the spectral, the compactness and the scale parameters. Depending on the scale parameter, different segmentation levels can be produced, each characterized by its own mean object size (Hay et al., 2003). Most of the work making use of FNEA for multi-scale analysis selects the appropriate scale for each phenomenon manually based on experience, or by trial and error (Bitelli et al., 2004; Blaschke et al., 2004; Hay et al., 2003).

In this paper a framework for multi-scale image change detection is proposed. The proposed system utilizes the FNEA to generate the multi-scale data set. The proposed system performs individual scale change detection and automatically determines the preferred scale to analyze each pixel.

Delineating information extracted from all the scales to generate the overall change map is a difficult problem. Most of the existing systems manually select a specific-scaling level to work on (Blaschke, 2005). The maximum operator is also commonly used where maximum is applied on the change indicators resultant at each scale to form a single matrix containing change indicators to be thresholded. In the PCA fusion method all change indicators at each scale are superimposed to form a set of vectors. Each vector represents a pixel's change indicators at all scales. The resulted vectors are passed to PCA module to be transformed into a new domain where the first component in each vector represents its final (fused) change indicator to be thresholded.

In this paper, a scale-driven method is proposed to fuse information from all the scales. The scale-driven method determines for each individual object the preferred scale to model it.

Figure 2 Sample T_1 image.

2. Data and study area

The proposed system has been applied on three bands of IKONOS image set covering a region in new Cairo, Egypt. The region is covered on two dates; T_1, T_2 which are in 2000 and 2005 respectively; sample regions are outlined in Figs. 2 and 3, the spatial resolution of the images is 1 m.

3. The proposed methodology

The multi-scale change detection system consists of the following six phases; (Fig. 1).

1. *Superimposing the two-date images:* to capture different objects in T_1 or T_2 or both.
2. *Informative scales selection:* targets at selecting a set of scales that best represent the scale domain.
3. *Multi-scale data-set generation:* which is the generation of different versions of the superimposed image each represents different segmentation level or resolution.
4. *Individual scale change detection:* handles each level independently where change indicators are extracted for the objects in the target level and the change map for this level also is obtained by thresholding the resulted change indicators.

Figure 3 T_2 image for the same area in Fig. 2.

Figure 4 The superimposed image.

5. *Optimal scale detection:* where an object's preferred scale is obtained based on the change of the object's extent through scales.
6. *Scale-based change fusion:* where change information from all scales is fused to make the final change map.

3.1. Superimposing the two-date images

The pair of images is superimposed to form a single image containing six bands; three bands from T_1 and three bands from T_2. The superimposing of the two images is performed to capture individual objects in either T_1 or T_2, or both (Fig. 4).

3.2. Informative scales selection

The proposed method for selecting significant scales for multi-scale analysis can be considered as an optimization problem. The optimization targets at selecting a set of scales or scale thresholds $\{L_1, L_2, \ldots, L_K\}$ that maximizes the amount of information obtained by this scale domain representation. The search method is limited by the number of scales that have to be set by the user to satisfy his storage and processing time limits.

Pattern search (PS) method (Abramson et al., 2004) is used for selecting the appropriate set of scale thresholds. The PS module aims at maximizing the amount of *average mutual information* between successive scales. The average mutual information index (AMI) (Rosin, 2315); as indicated in Eq. (1), quantifies the similarity between two data sets based on the degree that one set of values predicts the other.

$$\mathrm{AMI} = \sum_{i=0}^{M} \sum_{j=0}^{N} P(b_i, a_j) \log \frac{P(b_i|a_j)}{P(b_i)} \tag{1}$$

where a_j is the pixel label in scale A and b_i is pixel label in scale B, $P(b_i)$ is the proportion of pixels in scale B having a value b_i, and A, B are two successive selected scales, N is the number of different labels in scale image A and M is the number of different labels in scale image B.

The overall optimization function aims at maximizing the AMI measure over all the scale thresholds; $[L_1, L_2, \ldots, L_{K-1}, L_K]$. The objective function is to minimize $\mathrm{AMI}_{\mathrm{tot}}$; indicated in Eq. (2)

$$\mathrm{AMI}_{\mathrm{tot}} = -(\mathrm{AMI}_{(1.2)} + \mathrm{AMI}_{(2.3)} + \cdots + \mathrm{AMI}_{(K-1,K)}) \tag{2}$$

where $\mathrm{AMI}_{(i,j)}$ is the average mutual information between image at scale L_i, and image at scale L_j, K is the required number of scales.

The PS module is initialized with a set of K equally spaced scale thresholds that are readjusted iteratively by the PS module to minimize the target objective function (Fig. 5).

3.3. Multi-scale data-set generation

This phase aims at generating a multi-scale data set from the superimposed 6-band image. The superimposed 6-band image was fed into the eCognition software specifying the following parameters w_{sp}, w_{cp}, and K different values for h_{sc} each represent different scales. In the ideal case all possible scales have to be considered, h_{sc} from 0 to infinity. h_{sc} are the set of informative scales obtained in the previous stage. Each scale image is obtained by merging objects in the previous scale while not violating the h_{sc} value at this scale.

The spectral parameter (w_{sp}), trading spectral homogeneity versus object shape, is included in order to obtain spectrally homogenous objects while irregular or branched objects are avoided.

The compactness parameter (w_{cp}), trading compactness versus smoothness, adjusts the object shape between compact objects and smooth boundaries.

FNEA starts with a single pixel and a pairwise comparison of its neighbors with the aim of minimizing the resulting summed heterogeneity. The system uses successive merging of objects based on the least heterogeneity; see Eq. (3), between merged objects until the overall heterogeneity violates a specific scale threshold.

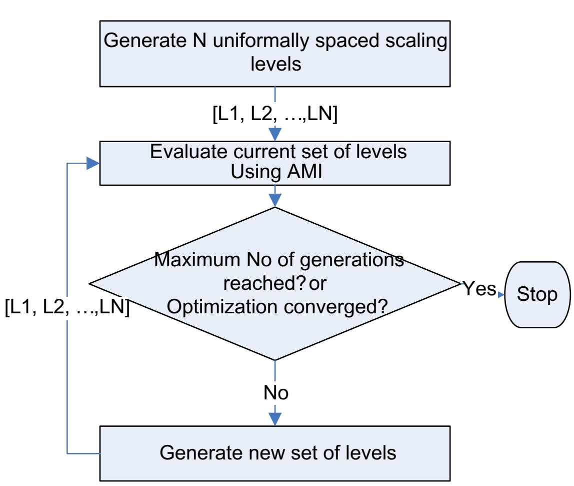

Figure 5 Informative scale selection algorithm.

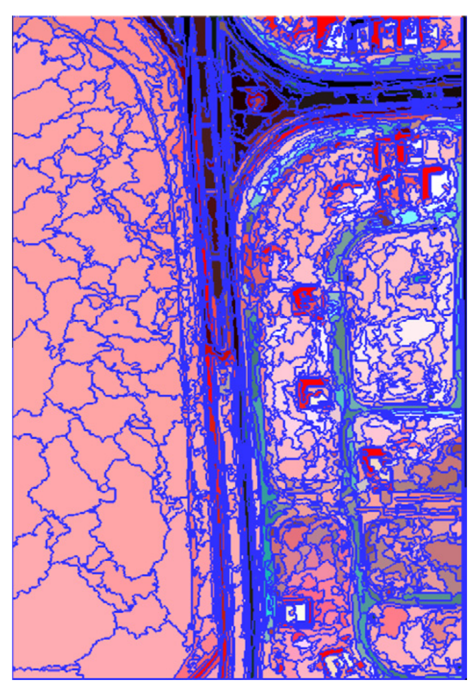

Figure 6 Sample image at one scale.

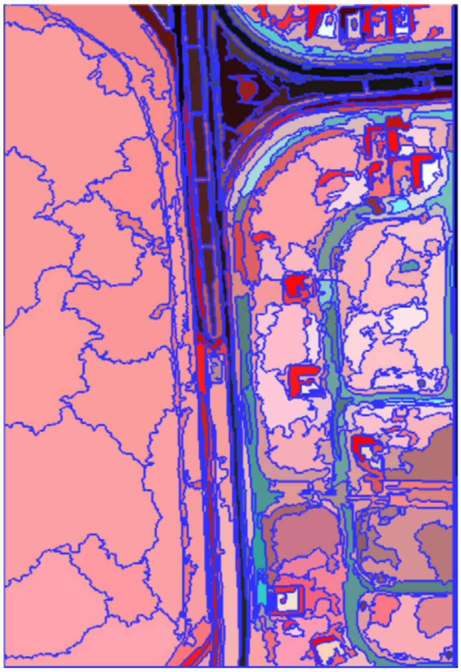

Figure 7 Sample image at coarser scale.

$$h = \sqrt{\sum_d (h_{1d} - h_{2d})^2} \quad (3)$$

where h_{id} is the set of features describing object i. A more detailed equation for heterogeneity is outlined in Eqs. (4) and (5).

$$h_{\text{total}} = w_{\text{sp}} h_{\text{sp}} + (1 - w_{\text{sp}}) h_{\text{sh}} \quad (4)$$

where w_{sp} is the spectral parameter, h_{sp} is the spectral heterogeneity and h_{sh} is the shape heterogeneity.

$$h_{\text{sh}} = w_{\text{cp}} h_{\text{cp}} - (1 - w_{\text{cp}}) h_{\text{smooth}} \quad (5)$$

where h_{sh} is the shape heterogeneity parameter and w_{cp} is the compactness parameter and h_{smooth} describes smoothness heterogeneity.

The result of this phase is a K different image each represents different scale segmentation. Figs. 6 and 7) outline samples of the resulted multi-scale data set.

3.4. Individual scale change detection

In this phase change indicators are extracted and thresholded at each scale image resulting in a change map for each scale.

3.4.1. Change indicators computation

In this phase change indicators are computed for each individual object in the target scale.

1. For each scale image indexed from [0 to $K - 1$]
   a. Find individual objects (segments) in this scale Figs. 6 and 7).
   b. For each object
   (1) Get its corresponding pixels form the base-scale images; (T_1 and T_2) Fig. 8.
   (2) Compute change indicator(s) for the whole object pixel set.
   (3) Goto next object.

2. Goto next scale

Change indicators are any indicators reflecting the amount of change between two segments, e.g. average image difference or ratio (Rebelo et al., 2004), texture difference (Coppin and Bauer, 1996) or PCA Eigen values (Radke et al., 2005).

The used change indicators are:

1. *Spectral difference* which is a three component vector representing the mean spectral difference over the three bands inside the object being considered.
2. *PCA maximum Eigen value* which is a single value vector where pixels inside the object being considered in T_1, and T_2 images are superimposed to form a set of vectors each being a $6 * 1$. The PCA transform is computed for these vectors and the maximum Eigen value is recorded.

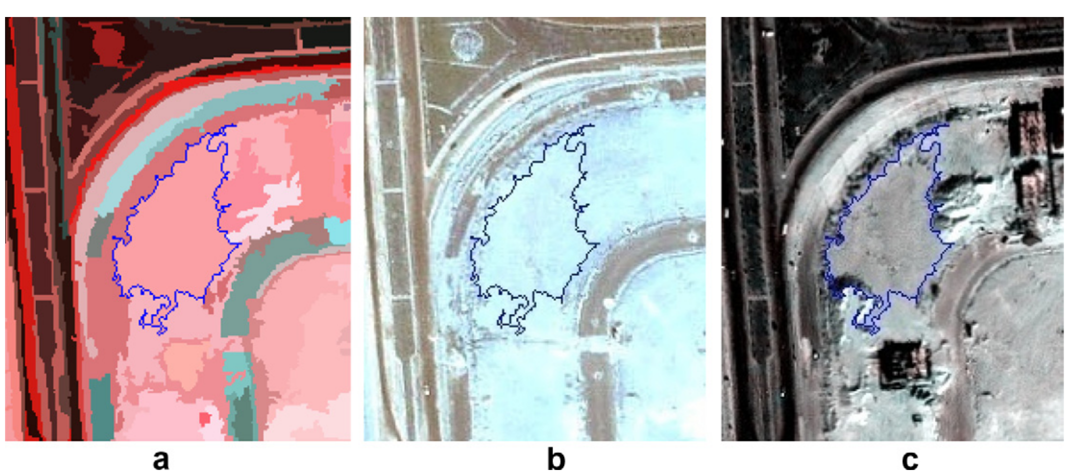

Figure 8 Sample object in one scale and the corresponding object at T_1 and T_2.

3. *Texture difference* comprises the gray level cooccurrence matrix (GLCM) computed for the pixels inside the object under consideration. Three different texture measures are used; maximum, entropy, and homogeneity (Onsi et al., 2007).

3.4.2. Change indicators thresholding

After computing the change indicators for each scale image, a thresholding method must be applied to judge the change/no change pixels at each scale. Any thresholding method can be used to threshold the change indicator matrices in each scale. Examples of thresholding methods are the Gaussian mixture thresholding method (GMM) (Radke et al., 2005), or pattern search (PS) (Abramson et al., 2004). We made use of pattern search method with the optimization function mentioned in Eq. (6).

$$J = \frac{1}{2n}\sum_{j=1}^{2}\sum_{i=1}^{n}||x_i - C_j|| + ||C_1 - C_2|| \qquad (6)$$

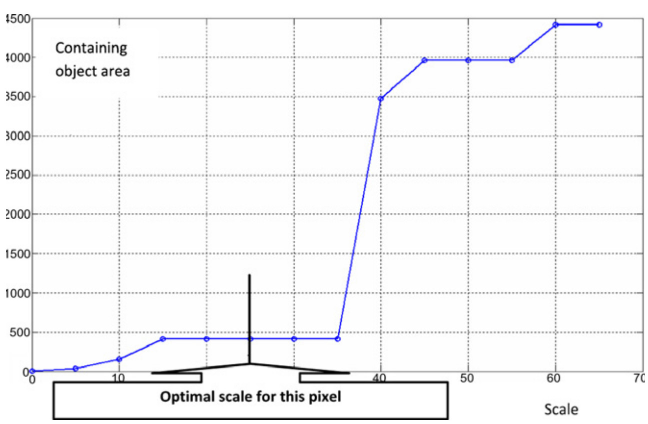

Figure 9 Optimal scale selection for sample pixel.

where $||x_i - C_j||$ is the Ecludian distance between a data point x_i and the cluster center C_j, $||C_1 - C_2||$ is the Ecludian distance between the resulted cluster centers and n is the set of points being clustered.

The optimization function is used such that it reflects the intercluster homogeneity and the intracluster heterogeneity.

3.5. Optimal scale detection

The input to this phase is the set of multi-scale 6-band superimposed images; K images, each image represents a scale. Each scale image $(i + 1)$ is obtained by merging objects in scale image (i) while not violating the scale threshold at $(i + 1)$. The output from this phase is a matrix with the same height and width of the original image and at each pixel position the appropriate scale index is recorded.

The rule used to detect the appropriate scale is that if an object is kept static regarding its area; or almost static, in a set of successive scales, then any of these scales can be chosen for the analysis of the pixels of this object. The motivation for this scale selection method is that an object will only keep static while increasing the scale threshold parameter when the object takes its stable form; the object cannot accept more pixels.

The detailed algorithm for detecting a suitable scale for each pixel is as follows:

1. For each scale i
   a. Get the image at scale index I; called $I_{(i)}$, and the image at scale index $(i + 1)$; called $I_{(i+1)}$.
   b. For each object in $I_{(i+1)}$, O_{i+1}^{j}
      (1) Find the corresponding object(s) in $I_{(i)}$ in the same spatial extent, $\{O_i^1, O_i^2, \ldots, O_i^N\}$, where N is the number of objects in scale i composing individual object O_{i+1}^{j}.
      (2) Find the object with the maximum area of these objects, maximum area of $\{O_i^1, O_i^2,, \ldots, O_i^N\}$, called A_i^{max}.

```
744444444444444444444444445555555553335555666666666666666666666666662555555.
744744444444444444444444445555555555555555666666666666666666666666622555555.
777744444444444444444444644444555557755555555666666666666666666666662255555.
777744444444444444466646444445577577777555555556666666666666622222662225555.
777777777747444666666464666657775777775555555555566666666662222222222255555.
333777777447444444666664666677775777777777777555555666666662222222222555555.
333377777777477222266666666667777777777777777775555556666662222222222555555.
333337773377777222266666666667777777773777777775555556662222222222255555555.
333337733777772222266666666667767777773777777777555556662222222224455555555.
333333337777222222266666666666667333333377777777755555566255522244555555555.
333333337722222222226666666666667333333333337733777755555555522444555555555.
333333337222662222226666666666666333333333333333333777755555555544444455555.
333333366666666662266666666666666333333333333333333377555555555444444555555.
333333333333333666666666666666666333333333333333333337775555554444444455.
333333333333333333666666666666663333333333333333333337775555554444444445.
333333333333333333366366666666663333333333333333333377777555544444444444.
333333333333333333333666666666633333333333333333333377777775555444444444.
333333333333333333333336666633333333333333333333333337777777755554444444.
333333333333333333333333366663333333333333333333333333777777777755554444·
333333333333333333333333336666666333333633333333343777777777777777555444·
333333333333333333333333333366663633666333333333444777777777777777755554·
333333333333333333333333332222666666666333333333444444777777777777777755555·
```

Figure 10 Part of the optimal scale matrix.

(3) Compute the ratio: $R = A_i^{\max}/\text{area}\ (O_{i+1}^j)$.
(4) Record the value R for all pixels representing object O_{i+1}^j in the matrix $S_{(i)}$.

c. $S_{(i)}$ contains the ratio information for each object between scale i and scale $i + 1$. Append $S_{(i)}$ to the 3D matrix S_{total} on the third dimension.

2. Goto next scale ($i + 1$).
3. For the 3D matrix S_{total}
   a. For each pixel (i,j) find the position of the maximum value in the third dimension; the scale dimension. The maximum value corresponds to minimum change in object area.
   b. Record this scale index as the best scale to analyze this pixel.
   c. If the maximum exists in a non-successive set of periods, select the longest period.
   d. If the maximum exists in a set of successive scales, select the scale in the middle. Selecting any of the scales representing the maximum will give same result as there is no change in the object's area but to idealize lets take the intermediate scale Fig. 9.

Part of the resulted best scale matrix is displayed in Fig. 10, it is noted from the figure that the best scale for pixels in nearby areas is always the same which indicates that the pixels belonging to the same object have the same manner through all scales.

3.6. Fusion of the multi-scale change maps

In this phase the resulted binary change maps at all the K used scales and the best scale matrix are fed to make a single overall change map.

To get the final change map the optimal scales matrix is checked at every pixel position (i,j) and change information for this pixel is recorded from the change map at its recorded best scale.

4. Results

The proposed multi-scale change detection system has been applied on the study area, where the T_1 and T_2 images are already coregistered and radiometrically adjusted. Also shadows are removed from the images before applying the proposed system as outlined in Onsi et al. (2007). The shadow removal method makes use of the dark spectral response of the shadow and their correlation to their original objects.

The proposed scale-driven change fusion method is compared to the PCA scale-based fusion method and the maximum operator scale-based fusion method proposed in Inglada and Mercier (2007). The used scale set in each method are both uniform scale set which is the most common method in literature for multi-scale systems and the proposed scale selection method.

Forty different test sets are used to evaluate the changed parts, each set contains 200 changed test points and 200 unchanged points distributed randomly over the reference change map. The total number of test points is 16,000 points covering the whole scene.

The statistical significance of the proposed method is asserted using the well-known t-test at a significance level 0.05, over the whole test sets (Walpole and Myers, 1993).

Fig. 4 outlines the superimposed images where interesting objects in T_1 and T_2 emerge.

Figs. 6 and 7 show all objects outlined at two of the used scales. It is noted that each individual object in Fig. 7 is composed of one or more objects in Fig. 6, also most of the new objects have larger spatial extent.

In Fig. 10 part of the optimal scale matrix is displayed where each pixel's preferred scale index is displayed. It is noted from the matrix that the best scale for pixels in nearby areas is always the same which indicates that the pixels belonging to the same object have the same manner through all scales. Also phenomena with a large spatial extent are represented in higher scales especially if it contains more details. On the contrary, phenomena with a small spatial extent are represented in lower scales.

Fig. 11 and Table 1 outline the resulted change map of the base-scale change detection. Base-scale change detection means applying the change indicators and the thresholding over the original images without any scaling. It is clear that false change alarms are apparent and missed changes also exist. It is apparent that the change objects have distorted outlines besides having distortion inside the object itself.

Figs. 12 and 13 outline fusion of multi-scale change maps using the max operator. It is apparent that the least missing change occurs but false alarms are clear. The increase in the amount of true positives and the amount of false positives

Figure 11 Base-scale change map.

Table 1 Base-scale evaluation.

	Change	No change	P value
Change	0.96	0.04	0.99
NoChange	0.25	0.75	
Accuracy	84%		

Figure 12 Uniform scale quantization with max operator fusion.

Figure 13 Non-uniform scale quantization with max operator fusion.

Table 2 Max fusion with uniform scales evaluation.

	Change	No change	*P* value
Change	0.95	0.05	0.99
No change	0.19	0.81	
Accuracy	87%		

Table 3 Max fusion with proposed scale selection.

	Change	No change	*P* value
Change	0.95	0.05	0.99
No change	0.17	0.83	
Accuracy	88%		

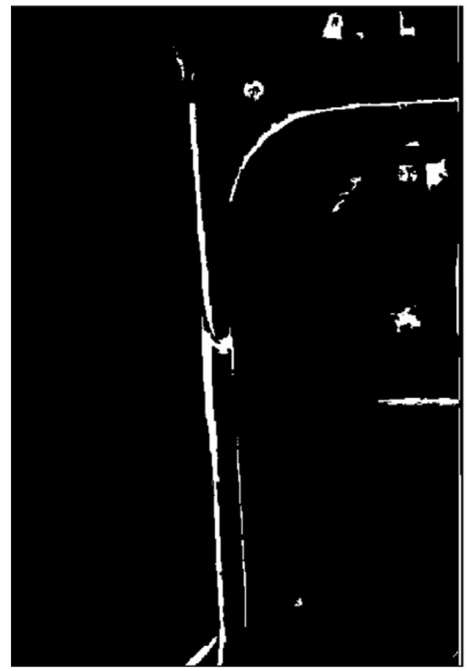

Figure 14 Uniform scale quantization with PCA fusion.

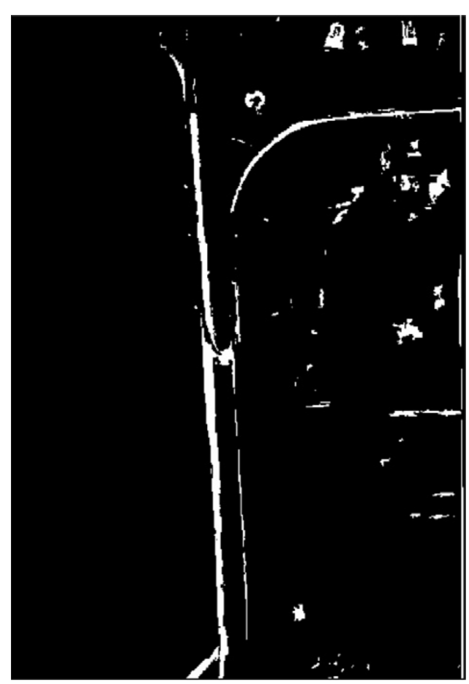

Figure 15 Non-uniform scale quantization with PCA fusion.

Table 4 PCA scale fusion with uniform scale selection.

	Change	No change	*P* value
Change	0.81	0.19	0.99
No change	0.13	0.87	
Accuracy		85%	

Table 5 PCA fusion with proposed scale selection

	Change	No change	*P* value
Change	0.89	0.11	0.98
No change	0.12	0.88	
Accuracy		89%	

can be noted from the error matrix in Tables 2 and 3). Although the application of multi-scaling enhances the result, the fusion is still suffering from the amount of false change alarms as the max operator always tends towards the change. Also, one can note that working over non-uniformly selected scales as proposed enhances the resulted change map.

Figs. 14 and 15 outline the use of the well-known PCA fusion method for fusing the same set of scales. It can be noted that PCA fusion achieves the least amount of change alarms

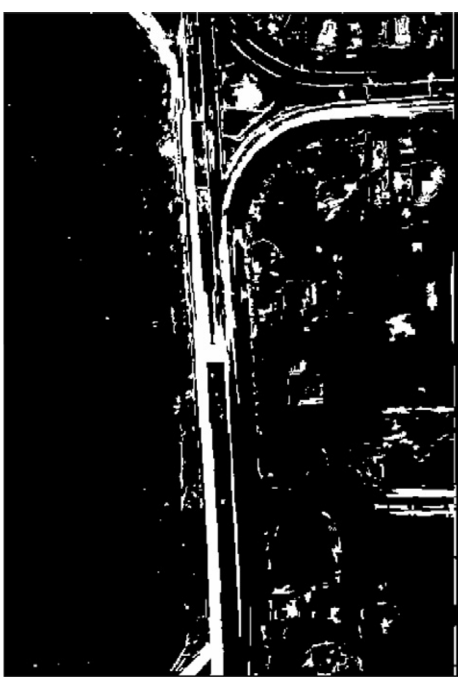

Figure 16 The proposed system change map.

Table 6 Overall proposed system evaluation.

	Change	No change	*P* value
Change	0.96	0.04	0.99
No change	0.13	0.87	
Accuracy		91%	

but a lot of misses occur. The main drawback of the PCA is that, it is regression-based tending towards the majority of pixels; if most of the image pixels are changed a lot of false change alarms will occur and if not a lot of missed changes will occur. One can remark the amount of missed change from the error matrices outlined in Tables 4 and 5. It is noted that using the proposed scale selection method also enhances the result of using the PCA fusion method (see Fig. 16).

Fig. 16 outlines the use of the proposed system for detecting changes. It is clear that the amount of false change alarms is minimized; better than in the max fusion method, and the amount of missed changes also minimized; better than in the PCA method. Most of the objects take their form without gaps or distortion on boundaries. Objects are modeled in their preferable scale so that the least distortion on the objects is achieved. The advance in the overall accuracy in the proposed method can be noted from Table 6. The advance in the accuracy by using the proposed scale selection method can be remarked. The proposed scaling levels selection method adds more scaling levels in the parts of the scale domain where phenomena change quickly from one scale to the other so that it can capture all the information in this part of the scale domain.

5. Conclusion

After applying the proposed system on the test site, the following conclusions can be derived.

The application of multi scaling enhances the results of change detection and allows for easy browsing based on image objects rather than pixels.

The study of an individual object is performed in the object's preferred scale so that noise is rejected and the least false change alarm is achieved.

The detected change objects keep their true shapes without any distortion on their boundaries or inside the objects that may result from noise or image sampling.

The scale-driven fusion method resolves the problem of delineating individual objects in their preferable scales and proves advance over the PCA and max fusion methods.

Using the proposed informative scale selection method enhances the performance of the multi-scale system as it presents a better scale domain representation rather than the uniform quantization of the scale domain. The used scale selection method ensures repeatability and objectivity of the system.

References

Abramson, M., Audet, C., Dennis, J., 2004. Generalized pattern searches with derivative information. Mathematical Programming Journal 100 (1), 3–25.

Bitelli, G., Camassi, R., Gusella, L., Mognol, A., 2004. Image change detection on urban area: the earthquake case. In: XXth ISPRS Congress, Istanbul, Turkey.

Blaschke, T., 2005. A framework for change detection based on image objects. In: Erasmi, S., Cuffa, B., Kappas, M. (Eds.), Göttinger Geographische Abhandlungen, vol. 113. Göttingen, pp. 1–9.

Blaschke, T., Conradi, M., Lang, S., 2001. Multi-scale image analysis for ecological monitoring of heterogeneous, small structured landscapes. In: Proceedings of SPIE, Toulouse, pp. 35–44.

Blaschke, T., Cyffka, B., Erasmi, S., Kappas, M., 2004. Towards a framework for change detection based on image objects. Göttinger geographische abhandlungen 113, 1–9.

Carvalho, L., Clevers, J., Jong, S., Skidmore, A 2003. A new procedure for forestry database updating with GIS and remote sensing, Cerne, Lavras 9(2), 164–177.

Carvalho, L., Clevers, J., Jong, S., Skidmore, A., 2005. Forestry database updating based on remote sensing change detection, Anais XII simpósio Brasileiro de sensoriamento remoto proceeding. pp. 465–472.

Coppin, P., Bauer, M., 1996. Change detection in forest ecosystems with remote sensing digital imagery. Remote Sensing Reviews 13, 207–234.

Daryaei, J., 2003. Digital change detection using multi-scale wavelet transformation and neural network. The International Institute for Aerospace Survey and Earth Sciences (ITC), The Netherlands, Enschede.

Desclée, B., Bogaert, P., Defourny, P., 2006. Forest change detection by statistical object-based method. Remote Sensing of Environment 102 (1–2), 1–11.

Duveillera, G., Defournya, P., Descléea, B., Mayauxb, P., 2008. Deforestation in Central Africa: estimates at regional, national and landscape levels by advanced processing of systematically-distributed Landsat extracts. Remote Sensing of Environment 112 (5), 1969–1981.

Hall, O., Hay, G., 2003. A multiscale object-specific approach to digital change detection. International Journal of Applied Earth Observation and Geoinformation 4 (4), 311–327.

Hay, G., Blaschke, T., Mareceau, D., Bouchard, A., 2003. A comparison of three image-object methods for the multi-scale analysis of landscape structure. ISPRS Journal for Photogrammetry and Remote Sensing (57), 327–345.

Inglada, J., Mercier, G., 2006. The multiscale change profile: a statistical similarity measure for change detection in multitemporal SAR images. In: IEEE International Conference on Geoscience and Remote Sensing Symposium IGARSS, pp. 212–215.

Inglada, J., Mercier, G., 2007. A new statistical similarity measure for change detection in multitemporal SAR images and its extension to multiscale change analysis. IEEE Transactions on Geoscience and Remote Sensing 45 (5), 1432–1445.

Marcos, J., Romero, R., Carrasco, D., Moreno, V., Valero, J., Lafitte, M. 2006. Implementation of new SAR change detection methods: superresolution SAR change detector. Available from: <earth.esa.int/rtd/Events/ESA-EUSC_2006/Oral/Ar15_Marcos.pdf>.

Onsi, H., Mostafa, K., Emary, E. 2007. Integration of different features for enhancing image change detection. In: Proceedings Annual Conference for Statistics, Computer Science and Operations Research, Cairo, Egypt.

Radke, R., Andra, S., Al-Kofahi, O., Roysam, B., 2005. Image change detection algorithms: a systematic survey. IEEE Transactions on Image Processing 14 (3), 294–307.

Rebelo, L., Lewis, P., Roy, D.P., 2004. A temporal-BRDF model-based approach to change detection. In: Geoscience and Remote Sensing Symposium IGARSS'04, Proceedings, IEEE international, vol. 3, pp. 2103–2106.

Rosin, P., 1994. Parcel based change detection. In: European Symposium on Satellite Remote Sensing, Rome, Italy, SPIE, vol. 2315, pp. 289–298.

Walpole, R., Myers, R., 1993. Probability and Statistics for Engineering and Statistics. Macmillan publishing company, Oxford (Chapter 10).

Wilson, R., Calway, A., 2004. Multiresolution Gaussian mixture models for visual motion estimation. Proceedings of the IEEE International Conference on Image Processing 2, 921–924.

Youjing, Z., Hengtong, R., 2007. Identification scales for urban vegetation classification using high spatial resolution satellite data. In: Geoscience and Remote Sensing Symposium, IGARSS 2007, IEEE International, Barcelona, Spain, pp. 1472–1475.