Semi-Supervised Fuzzy C-Means Clustering for Change Detection from Multispectral Satellite Image

Dinh Sinh Mai, Long Thanh Ngo
Department of Information Systems,
Le Quy Don Technical University, Hanoi, Vietnam
E-mail: maidinhsinh@gmail.com, ngotlong@gmail.com

***Abstract*—Data clustering has been applied in almost areas such as health, natural resource management, urban planning... especially, fuzzy clustering which the advantage with handling better for ambiguous data. This paper proposes a method of improving fuzzy c-means clustering algorithm by using the criteria to move the prototype of clusters to the expected centroids which are pre-determined on the basis of samples. The proposed algorithm is used for a model of change detection on multi-spectral satellite imagery at multiple temporals. The experiments are implemented on various data sets in comparison with other approaches.**

***Index Terms*—Fuzzy C-mean Clustering, Change Detection, Imagery Satellite Classification.**

I. Introduction

In satellite image segmentation, the problem is to solve which is a method to determine whether or not the considered pixel belongs to a certain cluster. Normally, method based on statistical parameters have been widely used because it is easy to implement and highly accurate. However, this method is often quite expensive, time consuming and only applicable on small areas. The algorithms like k-Means, Fuzzy C-Mean (FCM) exhibit the same strategy based on the Euclidean distance to determine the degree of similarity between the considered objects and cluster centroids. Normally, satellite imagery are affected by noise because of weather and errors associated with the photographic equipment. Therefore, these algorithms like k-Means, FCM are difficult to fully resolve problems related satellite images.

Fuzzy clustering has been widely applied in almost all scientific and technical fields, typically FCM algorithm [4], which is widely applied in many fields such as image processing [1], data mining... FCM algorithm is an iterative algorithm associated fuzzy membership values for the sample data, then update the centroids according values assigned with a fuzzy parameter. This values are as the weight values, they exhibit degree of influence of a data sample on the prototypes of clusters. However, this algorithm does not effectively perform when the size or density of each cluster is not similar. Moreover, this algorithm is also quite sensitive with noise or uncertainty.

On this issue, Moumita et al [10] proposed for semi-supervised change detection on satellite images. The algorithm uses a multiple classifier system in semi-supervised (learning) framework instead of a single weak classifier. Besides Yuan et al [12] focused on semi-supervised change detection method and proposed a new distance metric learning framework for change detection by abundant spectral information of hyper-spectral image in noisy condition. Moreover, Ying et al [13] proposed a novel semi-supervised SVM model using self-training approach to address the problem of remote sensing land cover classification.

A Boosted Genetic Fuzzy Classifier (BGFC) was proposed by Stavrakoudis [18] for land cover classification from multi-spectral images. The model comprises a set of fuzzy classification rules, which are generated in an iterative fashion, incrementally covering subspaces of the feature space, as directed by a boosting algorithm. To overcome the limitations of the FCM algorithm, an automatic histogram-based fuzzy C-means (AHFCM) algorithm was presented by Saman [19].

While, Stavrakoudis et al [5] proposed the use of a genetic fuzzy-rule-based classification system for land cover classification from hyper-spectral images. Moreover, to address the limitations of urban regional scale and the features of extraction of urban vegetation from high resolution satellite image based on object-oriented approach. Chengfan et al [6] presented a new approach to use segmentation of high-resolution remote sensing image and the fuzzy classification technique based on multi-thresholds method, and then forests, thin grassland, thick grassland were extracted accurately. The new object-based method performances were assessed using Kappa coefficients and overall accuracy. Beside, Huiyu Zhou et al [22] proposed segmentation method incorporates a mean field term within the standard fuzzy c-means objective function. Since mean shift can quickly and reliably find cluster centers, the entire strategy is capable of effectively detecting regions within an image.

Determination of scattered urban areas in a very heterogeneous environment can prove to be quite difficult using conventional classification techniques of remotely sensed images. On the other hand, fuzzy logic methods enable this difficulty to overcome by assigning one pixel to more than one class according to a membership grade, determined using a pre-defined function.

The paper deals with an a novel fuzzy clustering approach to the problem of change detection. Two issues are mentioned addressed in this paper: consisting of 1) propose the semi-supervising Fuzzy C-Means algorithm using spatial information, called SFCM, to drive the prototype of clusters to the expected centroids which are pre-defined from on a basis of samples 2) apply SFCM to problem of change detection of multi-temporal points from multi-spectral remote sensing imagery. Experimental results are implemented on various datasets of LandSat images at multi-temporal points in comparison with previous algorithms and survey data. The clustering results with validity indexes exhibit that the proposed algorithms have given the better quality of clusters and more accuracy in land cover classification and change detection.

The paper is organized as follows: section II is Background; Section III shows Semi-Supervised Fuzzy C-Means Clustering; Section IV introduces SFCM for land-cover change detection; Section V is conclusion and future works.

II. BACKGROUND

A. Type-2 Fuzzy Sets

A type-2 fuzzy set in X is denoted $\tilde{A}$, and its membership grade of $x \in X$ is $\mu_{\tilde{A}}(x,u), u \in J_x \subseteq [0,1]$, which is a type-1 fuzzy set in [0, 1]. The elements of domain of $\mu_{\tilde{A}}(x,u)$ are called primary memberships of x in $\tilde{A}$ and memberships of primary memberships in $\mu_{\tilde{A}}(x,u)$ are called secondary memberships of x in $\tilde{A}$.

Definition 2.1: A $type-2\ fuzzy\ set$, denoted $\tilde{A}$, is characterized by a type-2 membership function $\mu_{\tilde{A}}(x,u)$ where $x \in X$ and $u \in J_x \subseteq [0,1]$, i. e. ,

$$\tilde{A} = \{((x,u), \mu_{\tilde{A}}(x,u)) | \forall x \in X, \forall u \in J_x \subseteq [0,1]\} \tag{1}$$

or

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} \mu_{\tilde{A}}(x,u))/(x,u), J_x \subseteq [0,1] \tag{2}$$

in which $0 \leq \mu_{\tilde{A}}(x,u) \leq 1$.

Type-2 fuzzy sets are called an interval type-2 fuzzy sets if the secondary membership function $f_{x'}(u) = 1\ \forall u \in J_x$ i. e. a type-2 fuzzy set are defined as follows:

Definition 2.2: An *interval type-2 fuzzy set* $\tilde{A}$ is characterized by an interval type-2 membership function $\mu_{\tilde{A}}(x,u) = 1$ where $x \in X$ and $u \in J_x \subseteq [0,1]$, i. e. ,

$$\tilde{A} = \{((x,u), 1) | \forall x \in X, \forall u \in J_x \subseteq [0,1]\} \tag{3}$$

Uncertainty of $\tilde{A}$, denoted FOU, is union of primary functions i. e. $FOU(\tilde{A}) = \bigcup_{x \in X} J_x$. Upper/lower bounds of membership function (UMF/LMF), denoted $\overline{\mu}_{\tilde{A}}(x)$ and $\underline{\mu}_{\tilde{A}}(x)$, of $\tilde{A}$ are two type-1 membership function and bounds of FOU.

B. Fuzzy C-Means Algorithm

In general, fuzzy memberships in fuzzy C-means algorithm is achieved by computing the relative distance among the patterns and cluster centroids. Hence, to define the primary membership for a pattern, we define the membership value are defined using value m. In (4), m is fuzzifier which represent different fuzzy degrees. The primary membership is defined for a pattern. The use of fuzzifier gives different objective functions to be minimized as follows:

$$\left\{ \quad J_m(U,v) = \sum_{k=1}^{N} \sum_{i=1}^{C} (u_{ik})^m d_{ik}^2 \right. \tag{4}$$

in which $d_{ik} = \parallel x_k - v_i \parallel$ is Euclidean distance between the pattern x_k and the centroid v_i, C is number of clusters and N is number of patterns. Degree of membership, u_{ik} is determined as follows:

$$u_{ik} = \frac{1}{\sum\limits_{j=1}^{C} \left(\frac{d_{ik}}{d_{jk}} \right)^{2/(m-1)}} \tag{5}$$

in which $i = \overline{1,C}$, $k = \overline{1,N}$.

Cluster centroids is computed in the same way of FCM as follows:

$$v_i = \frac{\sum_{k=1}^{N} (u_{ik})^m x_k}{\sum_{k=1}^{N} (u_{ik})^m} \tag{6}$$

in which $i = \overline{1,C}$.

Next, defuzzification for FCM is made as if $u_i(x_k) > u_j(x_k)$ for $j = 1,...,C$ and $i \neq j$ then x_k is assigned to cluster i.

III. SEMI-SUPERVISING FUZZY C-MEANS CLUSTERING FOR LAND-COVER CHANGE DETECTION

A. Semi-Supervising Fuzzy C-Means Clustering

Normally, fuzzy clustering algorithms will determine prototype of clusters depending on the structure of data samples i.e. each data sample could obtain a different prototype of clusters. In fact, a family of problems always obtain fixture prototype of clusters, for example the centroid of clusters in classification of remote sensing images because properties of clusters are not change for all data samples. Hence, fuzzy clustering algorithms could give incorrect result of clusters, especially large difference of cluster size.

Consider a problem of classification related to multi-spectral images with k bands partitions points into C clusters. Because of physical properties of electromagnetic spectrum when reflect from land cover surface, the centroid of clusters are fixture for all region of imagery. Provide that we take m centroids of clusters by averaging m regions in which the region i^{th} only involves points characterized for the cluster i. Call $V^* = [v_1^*, v_2^*, ..., v_c^*]$ is set of cluster centroids.

The idea of the approach is to use the pre-defined set of centroids V^* to adjust centroid of clusters to move closer V^* by extending the FCM, called Semi-supervising Fuzzy C-Means(SFCM).

Call $D_{v_i} = |v_i - v_i^*|$ is a measure of the difference between the computing clusters and sampling cluster.

Hence, we define a new objective function:

$$J_m(U,v) = \sum_{j=1}^{N} \sum_{i=1}^{C} (u_{ij})^m [R_{ij}^2 + D_{v_i}^2] \tag{7}$$

In which $\sum_{i=1}^{C} u_{ij} = 1$, N is the number of patterns, C is the number of clusters.

When minimize the objective function, method of Lagrange is used to find the solution by function:

$$L(u_{ij}, \lambda_j) = \sum_{j=1}^{N} \sum_{i=1}^{C} (u_{ij})^m [R_{ij}^2 + D_{v_i}^2] + \sum_{j=1}^{N} \lambda_j (1 - \sum_{i=1}^{C} u_{ij}) \tag{8}$$

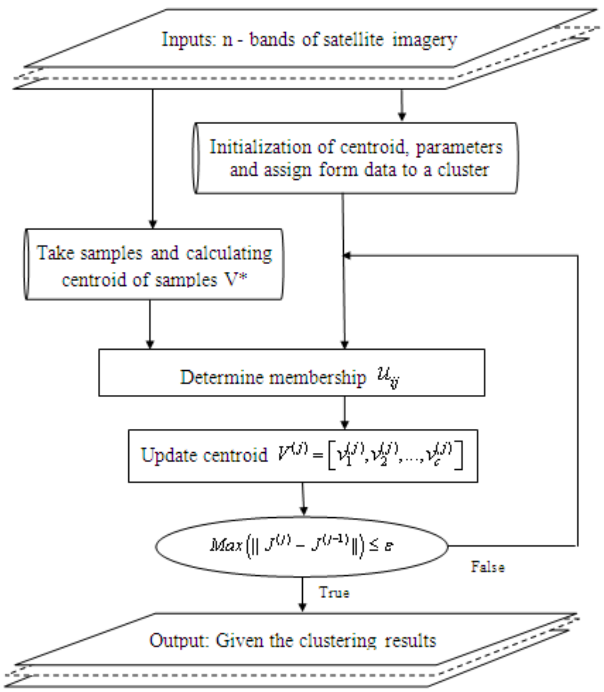


Fig. 1. Diagram of Semi-supervising fuzzy classification

Set to $D_{ij} = R_{ij}^2 + D_{v_i}^2$ and calculate the first derivative, we have:

$$\begin{cases} \frac{dL}{du_{ij}} = m.u_{ij}^{m-1}.D_{ij} - \lambda_j = 0 \\ \frac{dL}{d\lambda_j} = 1 - \sum_{i=1}^{C} u_{ij} = 0 \end{cases} \tag{9}$$

$$\begin{cases} \lambda_j = \frac{m}{\sum_{i=1}^{C} [\frac{1}{D_{ij}}]^{1/(m-1)}} \\ u_{ij} = [\frac{1}{D_{ij} \sum_{i=1}^{C} [\frac{1}{D_{ij}}]^{1/(m-1)}}]^{1/(m-1)} \end{cases} \tag{10}$$

Hence, we have a membership matrix as follows:

$$u_{ik} = \left(\frac{1}{D_{ij} \sum_{j=1}^{C} (1/D_{ij})^{\frac{1}{m-1}}}\right)^{\frac{1}{m-1}} \tag{11}$$

The primary membership u_{ik} is for a pattern with fuzzifier m, update the centroid $V^j = [v_1^j, v_2^j, ..., v_c^j]$.

Algorithm 1: The SFCM algorithm detailed

Step 1: Take C samples

1.1 Take C samples from multi-spectral satellite images are characterized for C clusters.

1.2. Calculating centroid $V^* = [v_i^*], v_i^* \in R^n$ of samples by averaging of points in each sample.

Step 2: Initialization

2.1 Choose fuzzifier m, $(1 < m)$, error e.

2.2 Initialization centroid $V = [v_i], v_i \in R^n$.

Step 3: Compute the membership matrix U and update centroid V:

3.1. Compute the membership matrix U_{ik} by formulas 11.

3.3. Update centroids $V^j = [v_1^j, v_2^j, ..., v_c^j]$ by using the algorithm of finding v^L and v^R and formula (6).

Step 4: Verify if the termination condition is satisfied:

If $Max(|J^{(j+1)} - J^{(j)}|) < \varepsilon$, go to step 4, otherwise go to step 2.

Step 5: Report results clustering.

The objective function resolved by the method of Lagrange is to find the formula of distance between the centroid to pixels (D_{ij}). So SFCM algorithm complexity as well as FCM algorithms is $O(n^2CR)$.

B. Land cover change detection

Multi-spectral image are one of types which acquired from remote sensing (RS) radiometers. By dividing the spectrum into many bands, multi-spectral is the opposite of panchromatic, which only records the total intensity of radiation falling on each pixel. Usually, satellites have three or more radiometers. Each one acquires one digital image (in remote sensing, called a 'scene') in a small band of visible spectra, ranging from $0.0004mm$ to $0.0007mm$, called red-green-blue (RGB) region, and going to infrared wavelengths of $0.0007mm$ to $0.001mm$ or more, classified as near infrared (NIR), middle infrared (MIR) and far infrared (FIR or thermal). In the case of $Landsat^{TM}$ image, seven scenes combine into a seven-bands multi-spectral image.

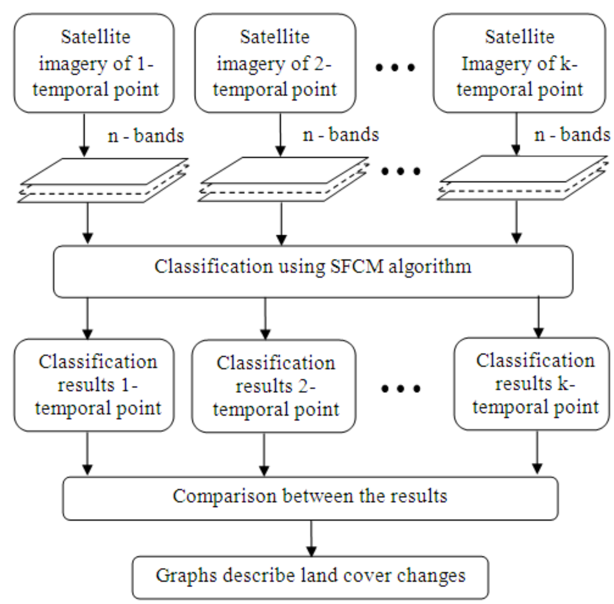


Fig. 2. Model for land-cover change detection

In Fig.2, this model is descriptive model for land cover classification of multi-spectral satellite images using fuzzy logic. The model shows that satellite imagery data of different periods have n bands. The classification results will be compared with each other and show a graph of changes in land cover.

IV. SFCM FOR LAND-COVER CHANGE DETECTION

In the experiments, authors have selected the problem of classification on multi-spectral satellite imagery to test the proposed algorithm. We used 4 bands 1, 2, 3 and 4 of $Landsat^{TM}$

images and NDVI image. The SFCM algorithm is applied to classify land cover from images of $Landsat^{TM}$. The detailed algorithm of SFCM for land cover change detection from multi-spectral satellite images consists of the following three main steps:

Algorithm 2: The SFCM algorithm:

Step 1: Multi-spectral satellite imagery multi-period pre-processing.

Step 2: Apply SFCM on the n-bands of images. These n-bands will be classified into six classes representing six types of land covers:

1) Class1: Rivers, ponds, lakes.
2) Class2: Rocks, bare soil.
3) Class3: Fields, grass.
4) Class4: Planted forests, low woods.
5) Class5: Perennial tree crops.
6) Class6: Jungles.

Step 3: Compute percentage of the identical region:

$$S_i = n_i/N \tag{12}$$

where S_i be area of ithregion, n_i be the number of points of the ithregion, N be the total samples of n-bands imagery.

Step 4: The classification results at multi-temporal will be summaried to evaluate the change of land cover.

A. Experiments 1

Study data is $Landsat-7^{TM}$ satellite images of Hanoi(HN), Vietnam (21^{o}24'26.976"N, 104^{o}41'21.67"E to 20^{o}32'14.285"N, 106^{o}37'18'.527"E) with area is 3161.304 km^2 at four temporal points (1995, 200, 2007, 2009).

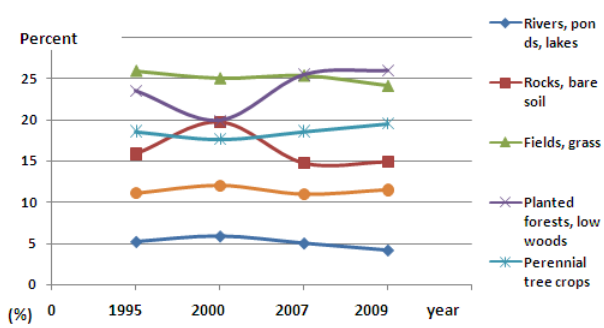


Fig. 4. Change detection of Hanoi region: a) 1995; b) 2000; c) 2007; d) 2009;

The results of experimental 1 are shown in Fig.3, in which (a), (b), (c) and (d) are land cover classification at temporal point of 1995, 2000, 2007 and 2009, respectively. Results of the proposed method are compared with the statistic data of the Hanoi Department of Natural Resources and Environment(DNREH). The Table I shows the results of the land cover classification(km^2) from multi-spectral satellite imagery compared with DNREH data of 1995, 2000, 2007 and 2009, respectively. The summarized data shows that the difference does not exceed 2.33%, the smallest difference is at the class 1 (below 0.17%), the remaining classes are under 2.33% at all temporal points. Fig.4 and Fig.5 are graphs comparing the

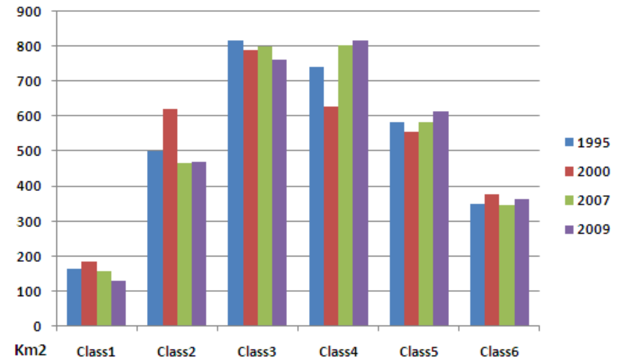


Fig. 5. Hanoi area classification result: a) 1995; b) 2000; c) 2007; d) 2009;

change in the area of 6 classes of the Hanoi area according to the 1995, 2000, 2007 and 2009, respectively. We can see no major changes in the area, the changes are less than 3% for all classes from 1995 to 2009.

To assessing the performance of the algorithms on the experimental images we analyzed the results on the basis of several validity indexes. We considered the different validity indexes such as the Bezdeks partition coefcient (PC-I) [3], Classication Entropy index (CE-I) [2]. The values of these validity indexes are shown in the Table II.

Note that the validity indexes are proposed to evaluate the quality of clustering. The better algorithms have smaller values of CE-I and larger value of PC-I. The results in Table II show that the SFCM have better quality clustering than the other typical algorithm such as FCM, k-Means.

B. Experiments 2

Study data from $Landsat-7^{TM}$ satellite images of Bao-lam(BL), Lam Dong province, Vietnam (11^{o}18'29.13"N, 108^{o}18'10.57"E to 11^{o}58'29.63"N, 107^{o}01'44.93"E) with area is 1463,44 km^2 at four temporal points (1990, 2000, 2010 and 2014).

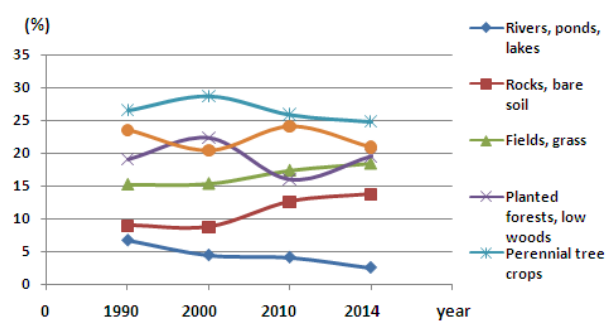
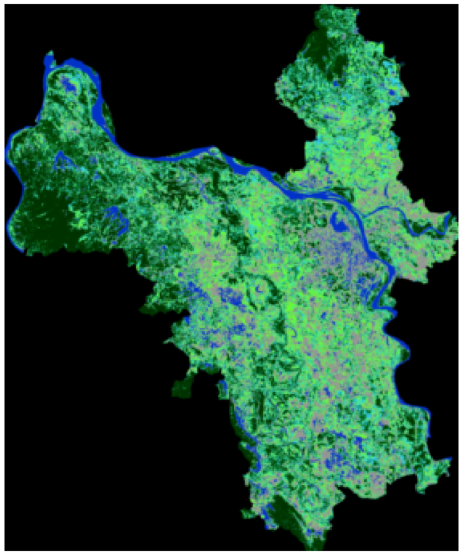
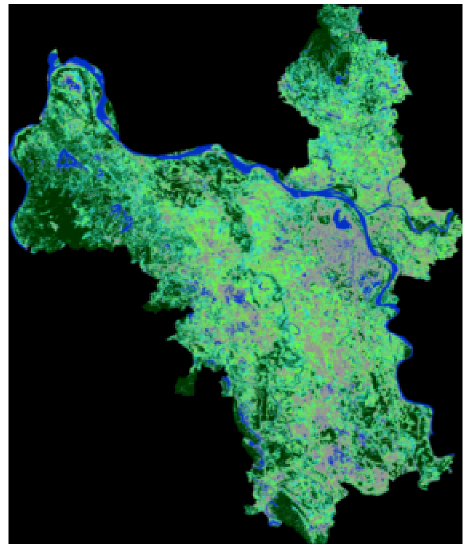


Fig. 7. Baolam area classification result: a) 1990; b) 2000; c) 2010; d) 2014;

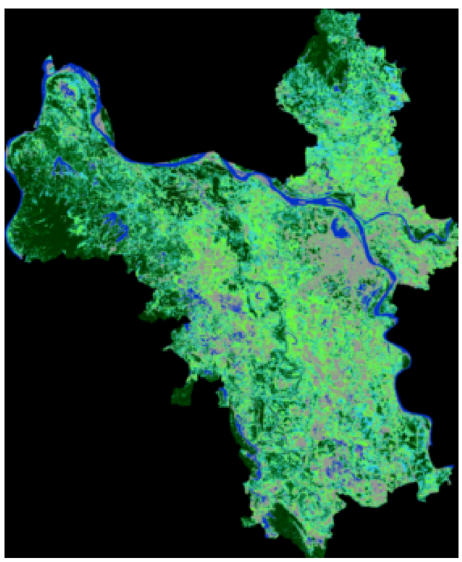
The results of experiment are shown in Fig.6, in which (a), (b), (c) and (d) are land cover classification at temporal point of 1990, 2000, 2010 and 2014, respectively. This is the time of the dry season in South Vietnam, satellite images less affected by clouds, fog. Results of the proposed method in Tab.III is compared with the statistic data of the Lam Dong Department



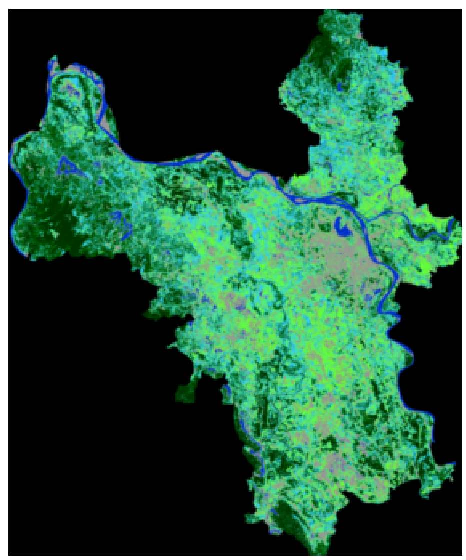
(a)



(b)



(c)



(d)

Fig. 3. Change detection of Hanoi region: a) 1995; b) 2000; c) 2007; d) 2009;

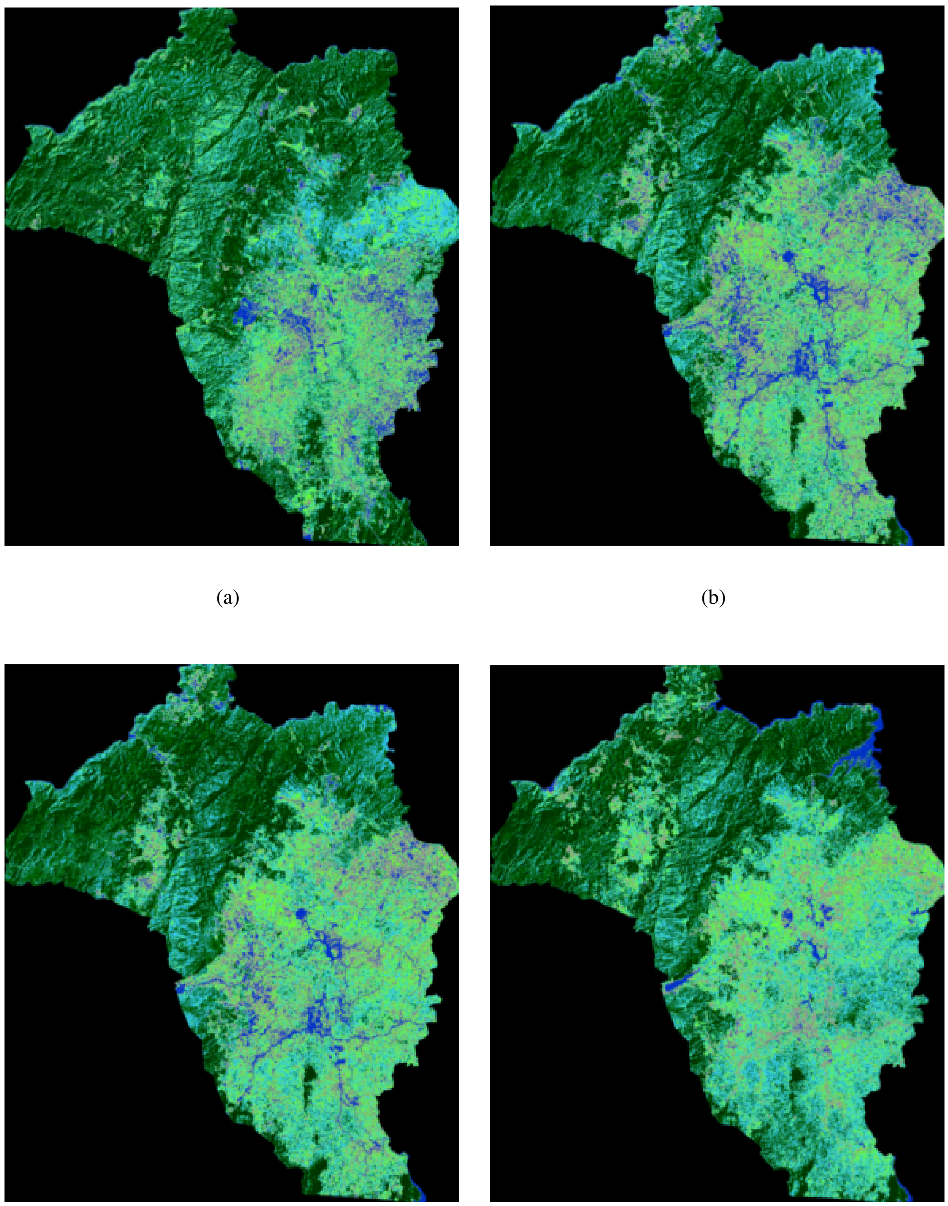
TABLE I

RESULTS OF LAND COVER CLASSIFICATION HANOI AREA (km^2)

Class	1995			2000			2007			2009		
	HN	DNREH	%	HN	DNREH	%	HN	DNREH	%	HN	DNREH	%
Class1	163.918	159.843	**0.13**	184.493	189.863	**0.17**	158.066	161.872	**0.12**	131.822	128.237	**0.11**
Class2	501.307	527.042	**0.81**	622.562	598.022	**0.78**	466.773	485.0312	**0.58**	471.211	494.596	**0.74**
Class3	818.964	745.274	**2.33**	790.804	731.176	**1.89**	801.171	761.176	**1.27**	761.781	743.787	**0.57**
Class4	741.667	801.577	**1.90**	628.627	692.475	**2.02**	802.995	748.475	**1.72**	818.933	878.326	**1.88**
Class5	585.119	608.604	**0.74**	556.739	596.843	**1.27**	585.029	632.843	**1.51**	614.372	573.861	**1.28**
Class6	350.870	318.964	**0.99**	378.079	352.925	**0.81**	347.270	371.925	**0.78**	363.186	342.497	**0.65**

TABLE II
THE VARIOUS VALIDITY INDEXS ON THE LANDSAT-7 IMAGERY OF HANOI AREA

Validity Index	1995			2000			2007			2009		
	k-Means	FCM	SFCM	k-Means	FCM	SFCM	k-Means	FCM	SFCM	k-Means	FCM	SFCM
CE-I	0.7818	0.1425	**0.1313**	0.7932	0.4325	**0.1527**	0.6958	0.3831	**0.1261**	0.7145	0.4278	**0.1135**
PC-I	0.6921	0.8854	**0.8912**	0.6756	0.9012	**0.9378**	0.71213	0.8754	**0.9158**	0.7965	0.8876	**0.9674**



(a) (b)

(c) (d)

Fig. 6. Baolam area classification result: a) 1990; b) 2000; c) 2010; d) 2014;

TABLE III

RESULTS OF LAND COVER CLASSIFICATION BAOLAM REGION (km^2)

Class	1990			2000			2010			2014		
	BL	DNREL	%	BL	DNREL	%	BL	DNREL	%	BL	DNREL	%
Class1	97,658	98,635	**0,07**	64,527	66,889	**0.16**	59,591	56,593	**0.20**	36,569	35,705	**0.06**
Class2	131,403	147,494	**1,10**	128,053	137,131	**0.62**	184,417	207,337	**1,57**	200,796	202,459	**0,11**
Class3	223,200	231,323	**0,56**	225,233	252,203	**1.84**	254,955	228,733	**1,79**	270,597	286,606	**1,09**
Class4	279,001	295,144	**1,10**	326,822	300,476	**1.81**	234,175	259,364	**1.72**	286,265	308,554	**1,52**
Class5	387,720	362,301	**1,74**	419,301	403,341	**1,09**	378,152	369,251	**0,61**	362,746	360,050	**0,18**
Class6	344,435	328,511	**1,09**	299,507	303,400	**0,27**	352,154	342,159	**0,68**	306,471	270,069	**2,49**

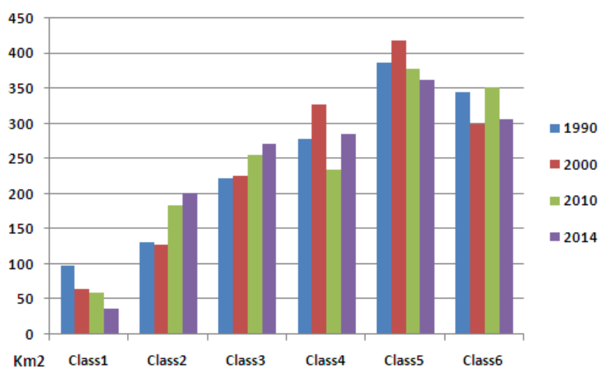


Fig. 8. Baolam area classification result: a) 1990; b) 2000; c) 2010; d) 2014;

of Natural Resources and Environment(DNREL). The Tab.III shows the results of land cover classification(km^2) from multi-spectral satellite images of Baolam in comparison with data of DNREL. The summaried data show that the difference does not exceed 2.49%, the smallest difference is at class 1 (approximately 0.20%), the remaining classes are under 2.49%. Fig.7 and Fig.8 are graphs comparing the change in the area of 6 classes of the Hanoi area according to the 1990, 2000, 2010 and 2014, respectively. The two layers 1 and 2 have a major change in the area with more than 5%, this is a result of urbanization here. The rest of the classes did not change significantly with less than 3%.

The values of these validity indexes are shown in the Table IV. The results in Table IV show that the SFCM have better quality clustering than the other typical algorithm such as FCM, k-Means.

In summary, experiment from two study data can be pointed out that the boundary of water and soil classes are usually quite clearly, while the vegetation classes are often confused in which both grasses and trees. With satellite image resolution of $30m$x$30m$, the differences of classification results can acceptable in assessment of land cover on a large area quickly, reduce costs compared to other ways of change detection. This result not only makes predictions about the land cover fluctuations but also supports planning urban, natural resources management and so on.

V. CONCLUSION

This paper presents a semi-supervised fuzzy logic algorithm based on FCM algorithm; using the set of pre-determined centroids to a just new centroids to move closer to the expected centroids. The results show that the proposed algorithm have improved the quality of clusters for a problem class of land cover change detection. The experiments were carried out based on the $Landsat-7^{TM}$ satellite images with two experiments of land cover change detection. Besides, the proposed approach can be applied to other types of satellite images.

The next goal is to implement further research on on the $Landsat-8^{TM}$ and hyper-spectral satellite imagery for environmental classification, assessment of land surface temperature changes; speed-up the proposed methods based on GPU platforms.

ACKNOWLEDGMENT

This paper is sponsored by Vietnam's National Foundation for Science and Technology Development (NAFOSTED).

REFERENCES

[1] Despotovic, I., Goossens, B. ; Vansteenkiste, E. ; Philips, W. An improved fuzzy clustering approach for image segmentation, 17th IEEE International Conference on Image Processing (ICIP), 249-252, 2010.
[2] W. Wang,Y. Zhang, On fuzzy cluster validity indices, Fuzzy Sets and Systems, Vol. 158, 2095-2117, 2010.
[3] Bezdek, J., Pal, N.: Some new indexes of cluster validity, IEEE Transactions on Systems, Man and Cybernetics 28(3), 301-315, 1998.
[4] J. C.Bezdek, R. Ehrlich, W. Full, FCM: The Fuzzy C-Means clustering algorithm. Computers and Geosciences Vol.10, No.2-3, 191-203, 1984.
[5] Stavrakoudis, D. G., Galidaki, G. N., Gitas, I. Z., and Theocharis, J. B.: Enhancing the Interpretability of Genetic Fuzzy Classiers in Land Cover Classication from Hyperspectral Satellite Imagery. IEEE World Congress on Computational Intelligence, WCCI 2010, 1277-1284.
[6] L. Chengfan, Y. Jingyuan, J. Zhao. Extraction of urban vegetation from high resolution remote sensing image. 2010 IEEE International Conference on Computer Design and Applications (ICCDA), Vol. 4, p403-406, 2010.
[7] J. Liu, T. D. Pham, A spatially constrained fuzzy hyper-prototype clustering algorithm, Pattern Recognition 45, 1759-1771, 2012.
[8] A. Ghosh, N. S. Mishra, S. Ghosh. Fuzzy clustering algorithms for unsupervised change detection in remote sensing images, Information Sciences, vol. 181, pp. 699-715, 2011.
[9] M. Roy, S. Ghosh, A. Ghosh. A novel approach for change detection of remotely sensed images using semi-supervised multiple classifier system, Information Sciences, vol. 269, 35-47, 2014.
[10] Peter F. Fisher. Remote sensing of land cover classes as type 2 fuzzy sets, Remote Sensing of Environment 114, 309-321, 2010.
[11] Yuan Yuan, Haobo Lv, Xiaoqiang Lu. Semi-supervised change detection method for multi-temporal hyperspectral images, Neurocomputing 148, 363-375, 2015.
[12] Y. Liu, B. Zhang, L. Wang, N. Wang. A self-trained semisupervised SVM approach to the remote sensing land cover classification, Computers and Geosciences 59, 98-107, 2013.
[13] N. S. Mishraa, S. Ghoshb, A. Ghosh. A self-trained semisupervised SVM approach to the remote sensing land cover classification, Applied Soft Computing 12, 2683-2692, 2012.

TABLE IV
THE VARIOUS VALIDITY INDEXS ON THE LANDSAT-7 IMAGERY OF BAO LAM AREA

Validity Index	1990			2000			2010			2014		
	k-Means	FCM	SFCM	k-Means	FCM	SFCM	k-Means	FCM	SFCM	k-Means	FCM	SFCM
CE-I	0.6518	0.2821	**0.1163**	0.6951	0.3245	**0.1361**	0.7319	0.3889	**0.1216**	0.7314	0.4083	**0.1188**
PC-I	0.8273	0.8986	**0.9342**	0.7257	0.9451	**0.9474**	0.76213	0.8754	**0.9532**	0.7312	0.9256	**0.9591**

[14] F. Zhao, L. Jiao, H. Liu, X. Gao. A novel fuzzy clustering algorithm with non local adaptive spatial constraint for image segmentation, Signal Processing 91, 988-999, 2011.

[15] D. M. Vargas, F. J. Gallegos-Funes, Alberto J. Rosales-Silva. A fuzzy clustering algorithm with spatial robust estimation constraint for noisy color image segmentation, Pattern Recognition Letters 34, 400-413, 2013.

[16] Amjad Ali, C.A.J.M. de Bie, A.K. Skidmore, R.G. Scarrott, Amina Hamada, V. Venus. Mapping land cover gradients through analysis of hyper-temporal NDVI imagery, International Journal of Applied Earth Observation and Geoinformation 23, 301-312, 2013.

[17] D.G. Stavrakoudis, J.B. Theocharis, G.C. Zalidis. A Boosted Genetic Fuzzy Classifier for land cover classification of remote sensing imagery, ISPRS Journal of Photogrammetry and Remote Sensing 66, 529-544, 2011.

[18] S. Ghaffarian, S. Ghaffarian. Automatic histogram-based fuzzy C-means clustering for remote sensing imagery, ISPRS Journal of Photogrammetry and Remote Sensing 97, 46-57, 2014.

[19] B. U. Shankar, S. K. Meher, A. Ghosh. Wavelet-fuzzy hybridization: Feature-extraction and land-cover classification of remote sensing images, Applied Soft Computing 11, 2999-3011, 2011.

[20] H. Liu, F. Zhao, L. Jiao. Fuzzy spectral clustering with robust spatial information for image segmentation, Applied Soft Computing 12, 3636-3647, 2012.

[21] S. Ghosha, M. Roy, A. Ghosh. Semi-supervised change detection using modified self-organizing feature map neural network, Applied Soft Computing 15, 1 20, 2014.

[22] H. Zhou, G. Schaefer, A. H. Sadka and M. E. Celebi, Anisotropic Mean Shift Based Fuzzy C-Means Segmentation of Dermoscopy Images, IEEE Journal of Selected Topics in Signal Processing, Vol.3(1), 26-34, 2009.