Semi-supervised Method with Spatial Weights based Possibilistic Fuzzy c-Means Clustering for Land-cover Classification

Dinh-Sinh Mai*
Institute of Techniques for Special Engineering
Le Quy Don Technical University, Hanoi, Vietnam
maidinhsinh@gmail.com

Long Thanh Ngo
Institute of Simulation Technology
Le Quy Don Technical University, Hanoi, Vietnam
ngotlong@gmail.com

***Abstract*—In remote sensing image analysis, the accuracy of the results depends not only on the accuracy of the image acquisition process but also on the segmentation and classification accuracy of the image. The fuzzy classification technique works by dividing the pixels of the image into sets of fuzzy clusters by iteratively optimizing the objective function to update the cluster membership and center centroid. This technique overcomes the disadvantages of hard clustering; However, this method is quite sensitive to interference and extraneous elements. In this paper, we propose a novel semi-supervised clustering method with spatial weights (SPFCM-W) for multi-spectral remote sensing image land-cover classification by the extension of the possibilistic fuzzy c-means (PFCM) algorithm, in which spatial weights of the pixels and labeled data are used to increase the accuracy of clustering results when the data structure of input patterns is non-spherical and complex. Results obtained on two kinds of multi-spectral remote sensing images (Landsat-7 ETM+, Sentinel-2A) by comparing the proposed technique with some variations of the fuzzy clustering algorithm demonstrate the good efficiency and high accuracy of the proposed method.**

***Index Terms*—semi-supervised, spatial weights, multi-spectral, remote sensing image.**

I. Introduction

Clustering or cluster analysis is a division of data into groups of similar objects, it involves assigning pixels to clusters such that pixels in the same cluster are as similar as possible, while pixels belonging to different clusters are as dissimilar as possible. In the clustering technique, fuzzy clustering techniques have many advantages when processing data that overlap, the boundary between clusters is unclear. The most common fuzzy clustering algorithm is the fuzzy c-means algorithm (FCM) [1], with fuzzy memberships was used to determine a pattern belonging to a certain cluster and they measured by the degree of similarity between the pattern to cluster centroids. In fact, the process of clustering also affected by the structure and shape of the cluster, so this method does not describe all the characteristics of the data.

Among the variants of fuzzy clustering can mention that possibilistic c-means approach (PCM) [2]. By this approach, a possibilistic membership is used to determine the absolute degree of typicality of a pattern in clusters. However, the disadvantage of algorithms is that they do not handle well with noise data. To overcome this difficulty in making the algorithm stronger by inheriting the characteristics of PCM, some improvements are proposed such as semi-supervised method [3], fuzzy method [4]. However, the possibilistic approach exists certain disadvantages such as the selection of parameters and does not describe full of characteristic the data.

Therefore, Nikhil et al. [5] proposed a model called possibilistic fuzzy c-means (PFCM) model. The PFCM algorithm is a hybridization of PCM and FCM to take advantage of both methods, the FCM handles well with noise data, while the PCM handles well with overlapping and circular clusters.

The remote sensing image data allows for direct observation of the soil surface at repeated intervals, thus allowing mapping of using and monitoring of changes in land-cover. Recently, in remote sensing image analysis techniques, the semi-supervised clustering method received much attention of scientists [6], [7], [8], [9], [10], [11], [14]. This classification method has advantages of both unsupervised and supervised method of classification.

In addition, spatial constraints were considered in the clustering process to increase the accuracy of clustering results. Mai et al. [13], [15] proposed remote sensing image classification method by using spatial information for spectral fuzzy clustering algorithm. Another approach to spatial information in [12], uses the local spatial information between the pixel and its neighbors to calculate the degree of membership in the type-2 fuzzy clustering algorithm for classification and detecting changes on remote sensing imagery. and some other studies use spatial information such as, Liu et al. [16], Vargas et al. [17], Zhao et al. [18], Liu and Pham [19].

Some studies recently, for the problem remote sensing image classification based on fuzzy sets of type 2 have also been mentioned [20], [21]. However, the computation based on type 2 fuzzy set is quite complex and quiet slow. Therefore, this technique requires the calculation speed improvements significantly.

This paper introduces a novel semi-supervised possibilistic fuzzy c-means clustering method using spatial weights (SPFCM-W) for multi-spectral remote sensing image land-

*Corresponding author; +84988906223

978-1-5386-7983-8/18/$31.00 ©2018 IEEE

cover classification by the extension of the PFCM algorithm, in which spatial weights of the pixels and labeled data are used to increase the accuracy of clustering results when the data structure of input patterns is non-spherical and complex. The paper is organized as follows: Section II briefly introduces some backgrounds; Section III proposes the semi-supervised possibilistic fuzzy c-means clustering based on spatial weights; Section IV experimental results and section V conclusion and the next research direction.

II. BACKGROUND

In the PFCM algorithm, there are two types of membership functions, which are the fuzzy membership function in the FCM algorithm and the possibilistic membership function in the PCM algorithm. And so the objective function of the PFCM algorithm is constructed as follows:

$$J_{m,\eta}(U,T,V,X,\beta) = \sum_{i=1}^{c}\sum_{k=1}^{n}(\mu_{ik}^{m}+\tau_{ik}^{\eta})\|v_i - x_k\|^2 + \sum_{i=1}^{c}\beta_i\sum_{k=1}^{n}(1-\tau_{ik})^{\eta} \tag{1}$$

Subject to the constraints:

$$m > 1, \eta > 1; 0 \le \mu_{ik}, \tau_{ik} \le 1; \sum_{i=1}^{c}\mu_{ik} = 1; \sum_{k=1}^{n}\tau_{ik} = 1 \tag{2}$$

In which, n is the total number of patterns in a given data set, c is the number of clusters, X are data characteristics, V are the centers of the clusters, U is a fuzzy partition matrix, which contains the fuzzy membership degree; T is a typicality partition matrix, which contains the possibilistic membership degree, m and η are fuzzy parameters and possibilistic parameters. β_i are constants given by the user.

For clustering, the PFCM algorithm performs an iterative process for optimizing the objective function 1 with the constraints in 2, in each iteration the calculation is done on the formulas 3, 4 and 5. The goal of this process is to find the optimal clusters, the final result showing that the objective function $J_{m,\eta}$ has the smallest value.

$$v_i = \frac{\sum_{k=1}^{n}(\mu_{ik}^{m}+\tau_{ik}^{\eta})x_i}{\sum_{k=1}^{n}(\mu_{ik}^{m}+\tau_{ik}^{\eta})} \tag{3}$$

$$\mu_{ik} = 1/\sum_{j=1}^{c}\left(\frac{\|v_i - x_k\|}{\|v_j - x_k\|}\right)^{2/(m-1)} \tag{4}$$

$$\tau_{ik} = 1/\left(1 + (\frac{1}{\beta_i}\|v_i - x_k\|)^{1/(\eta-1)}\right) \tag{5}$$

The PFCM algorithm consists of the following steps:

Algorithm 1: The PFCM algorithm

1. Initialization of parameters: number of clusters c, ϵ, m and η, fuzzy partition matrix U and typically partition matrix T with constraint in 2.

2. Update the center of the fuzzy clusters, $\mathrm{V} = \{\mathrm{v}_i\}$ for $i = 1, 2, , c$ by Eq. 3.

3. Update the fuzzy membership matrix U by Eq. 4.

4. Update the typically membership matrix T by Eq. 5.

5. If $Max(\left\|\mu_{ik}^{(t+1)} - \mu_{ik}^{(t)}\right\|) < \epsilon$ then stop; otherwise, go to step 2.

Next, defuzzification for PFCM is made as if $\mu_{ik} > \mu_{jk}$ for $j = 1, ..., c$ and $i \ne j$ then x_k is assigned to cluster i.

III. SEMI-SUPERVISED POSSIBILISTIC FUZZY C-MEANS CLUSTERING WITH SPATIAL WEIGHTS

A. Spatial weights

In data sources for studying the surface of the earth, remote sensing data has many advantages such as wide coverage, fast acquisition, and updating. Multi-spectral remote sensing image data is made up of pixels, where each pixel can contain different types of information, including its position in the image, color, etc. The position or coordinate of a pixel in an image is information related to the spatial relationship, which is important in high-level image processing. This can be explained by the fact that, processing algorithms are independent of pixel level, there are many algorithms, processors based on regions or uses information on the whole image.

To find the weights for pixels, this paper uses the SLIC algorithm [24] to generate super-pixels, with the grid interval $S = \sqrt{n/j}$ is used to roughly generate the approximately sized super-pixels with n is the total number of pixels, j is the number of super-pixel desired. Let $|SuperPixel_j|$ be the number of pixels of the j^{th} super-pixel and w_k is the weight of the pixels, for $k = 1, 2, ..., n$, if $\mathrm{P}ixel_k \in SuperPixel_j$ then $w_k = 1/|SuperPixel_j|$. Easily noticed, with large super-pixel then the weight of the smaller pixels.

B. Semi-supervised method

Let c be the number of clusters, calculation c centroids, $v_1^*, v_2^*, ..., v_c^*$ from the labeled pixel dataset and $V^* = [v_1^*, v_2^*, ..., v_c^*]$ is the set of approximate cluster centroids:

$$v_i^* = \sum_{s=1}^{m_i} P_{is}/m_i \tag{6}$$

Where P_{is} is the s^{th} pixel labeled on the i cluster, m_i is the number of pixels labeled on the i cluster, $s = 1, ..., m_i; i = 1, .., c$. The approximation membership function is calculated based on a set of approximate centroid V^* by FCM algorithm:

$$\mu_{ik}^* = 1/\sum_{z=1}^{c}\left(\frac{x_k - v_i^*}{x_k - v_z^*}\right)^{\frac{2}{m-1}} \tag{7}$$

The objective function $J_{m,\eta}$ of the PFCM algorithm is changed as follows:

$$J_{m,\eta}(U,T,V,X,\beta) = \sum_{i=1}^{c}\sum_{k=1}^{n}(\|\mu_{ik} - \mu_{ik}^*\|^m + \tau_{ik}^{\eta})(w_k d_{ik}^2 + \|v_i - v_i^*\|^2) + \sum_{i=1}^{c}\beta_i\sum_{k=1}^{n}(1-\tau_{ik})^{\eta} \tag{8}$$

In which, $\|v_i - v_i^*\|$ is the distance between the calculated centroid and the expected centroid and $\|\mu_{ik} - \mu_{ik}^*\|$ is the distance between the calculated fuzzy membership and the expected fuzzy membership. The purpose of the addition of these distances in the objective function $J_{m,\eta}$ to help them do not fall into local convergence and the centroid of clusters is faster convergence. The Lagrange function for finding the minimum value for the objective function $J_{m,\eta}$ is constructed as follows:

$$J_{m,\eta}(U,...,X,\lambda,\beta) = \sum_{i=1}^{c}\sum_{k=1}^{n}(\|\mu_{ik} - \mu_{ik}^*\|^m + \tau_{ik}^\eta)(w_k d_{ik}^2 + \|v_i - v_i^*\|^2) + \sum_{k=1}^{n}\lambda_k\sum_{i=1}^{c}(1-\mu_{ik}) + \sum_{i=1}^{c}\beta_i\sum_{k=1}^{n}(1-\tau_{ik})^\eta \tag{9}$$

With $0 < \lambda_k, \beta_i < 1$ are user defined constants. Based on the Lagrange method, by taking derivative of $J_{m,\eta}(U,T,V,X,\lambda,\beta)$ over μ_{ik}, τ_{ik}, v_i and assuming the result zero.

$$\frac{\partial J_{m,\eta}(U,T,V,X,\lambda,\beta)}{\partial \mu_{ik}} = 0 \tag{10}$$

$$\frac{\partial J_{m,\eta}(U,T,V,X,\lambda,\beta)}{\partial \tau_{ik}} = 0 \tag{11}$$

$$\frac{\partial J_{m,\eta}(U,T,V,X,\lambda,\beta)}{\partial v_i} = 0 \tag{12}$$

Subject to $0 < \sum_{k=1}^{n}\mu_{ik} < n$; $0 \le \mu_{ik} \le 1$; $\sum_{i=1}^{c}\mu_{ik} = 1$; $0 < \sum_{i=1}^{c}\tau_{ik} < c$; $0 \le \tau_{ik} \le 1$; $\sum_{k=1}^{n}\tau_{ik} = 1$; $1 \le k \le n$; $1 \le i \le c$.

We will obtain the value of the membership functions μ_{ik} and τ_{ik}, cluster centroid v_i as following, if $\mu_{ik} > \mu_{ik}^*$ then:

$$\mu_{ik} = \mu_{ik}^* + (1 - \sum_{j=1}^{c}\mu_{jk}^*)\frac{(w_k d_{ik}^2 + \|v_i - v_i^*\|^2)^{1/(1-m)}}{\sum_{j=1}^{c}(w_k d_{jk}^2 + \|v_j - v_j^*\|^2)^{1/(1-m)}} \tag{13}$$

if $\mu_{ik} < \mu_{ik}^*$ then:

$$\mu_{ik} = \mu_{ik}^* - (1 - \sum_{j=1}^{c}\mu_{jk}^*)\frac{(w_k d_{ik}^2 + \|v_i - v_i^*\|^2)^{1/(1-m)}}{\sum_{j=1}^{c}(w_k d_{jk}^2 + \|v_j - v_j^*\|^2)^{1/(1-m)}} \tag{14}$$

$$\tau_{ik} = 1/\left(1 + \left(w_k {d_{ik}}^2 + \|v_i - v_i^*\|^2\right)^{1/(\eta-1)}\right) \tag{15}$$

$$v_i = \frac{\sum_{k=1}^{n}(\|\mu_{ik} - \mu_{ik}^*\|^m + \tau_{ik}^\eta)(x_k + v_i^*)}{\sum_{k=1}^{n}(\|\mu_{ik} - \mu_{ik}^*\|^m + \tau_{ik}^\eta)} \tag{16}$$

Algorithm 2: The SPFCM-W algorithm

Input: Multi-spectral remote sensing image data, the number of clusters c and $m, \eta > 1$, stop condition ϵ, grid size S.

Output: The fuzzy membership matrix $U = \{\mu_{ik}\}$.

Step 1. Initialization: ϵ, S, m, η, max loop, $V = \{v_i\}$.

Step 2. Run the SLIC algorithm to generate super-pixels and calculate the spatial weight of super-pixels w_k.

Step 3. Calculates the approximate center centroids and approximate fuzzy membership function by formula 6 and 7.

Step 4. Use Eq. 13 or 14 to update the fuzzy membership U.

Step 5. Use Eq. 15 to update the typically membership T.

Step 6. Use Eq. 16 to update the fuzzy cluster center V.

Step 7. If $Max(\left\|J_{m,\eta}^{(t+1)} - J_{m,\eta}^{(t)}\right\|)$ is less than a certain threshold (ϵ), then stop; otherwise, go to step 4.

Next, defuzzification for SPFCM-W is made as if $\mu_{ik} > \mu_{jk}$ for $j = 1, ..., c$ and $i \neq j$ then x_k is assigned to cluster i.

It is easy to see that, when $w_k = 1$, SPFCM-W algorithm becomes the semi-supervised possibilistic fuzzy c-means clustering algorithm (SPFCM) and if $\mu_{ik}^* = 0$, $v_i^* = 0$, SPFCM-W algorithm becomes the possibilistic fuzzy c-means clustering algorithm with weights (PFCM-W).

IV. Experiment

Tested on algorithms PFCM, SFCM [11], SPFCM, PFCM-W and SPFCM-W, the algorithms are executed for a maximum of 100 iterations, $\epsilon = 10^{-5}$, grid size $S = 5$, with $m = 2, \eta = 2$ are selected according [5]. Multi-spectral remote sensing imagery is Landsat and Spot satellite imagery. The remote sensing image data are clustered to 6 classes as follows: Class 1: Rivers, ponds, lakes ; Class 2: Rocks, bare soil ; Class 3: Fields, grass ; Class 4: Planted forests, low woods ; Class 5: Perennial tree crops ; Class6: Jungles . For an image with k bands, each pixel will be characterized by k components on k gray bands. Multi-spectral remote sensing image data can be described as a set $X = [x_1, x_2, ..., x_n]$, with $x_i = (b_{i1}, b_{i2}, ..., b_{ik})$.

To evaluate the effectiveness of algorithms, some validity indexes are used to measure the goodness of the clusters such as Bezdeks partition coefficient index (PC-I), Dunns separation index (D-I), Separation index (S-I) and Classification Entropy index (CE-I), Xie-Beni (XB-I) index. Note that the algorithm producing better results with the smaller values of D-I, XB-I, S-I, CE-I and the larger value of PC-I (see in [22], [23]).

On the other hand, from the data that has been labeled, comparisons with the classification result and give the correct classification rate, misclassification rate on the labeled data. The performance of the classification result was evaluated with the True Positive Rate (TPR) and False Positive Rate (FPR) which are defined by the following equations:

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{17}$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{TN} + \mathrm{FP}} \tag{18}$$

According to the above formula, TP is the number of correctly classified pixels, FN is the number of incorrectly misclassified pixels, FP is the number of incorrectly classified pixels and TN is the number of correctly misclassified pixels.

A. Experiment 1

The study dataset from Landsat 7 ETM+ multi-spectral images on 30 September 2009 is region center of Hanoi, Vietnam $(105^0 38' 38.8289" E, 21^0 07' 5.3254" N$ and $105^0 58' 53.5268" E, 20^0 58' 14.9711" N)$ in Fig. 1, with 6 image bands was obtained by 6 spectral bands including blue band, green band, red band, near infrared band, mid-infrared band, and thermal infrared band, these bands are selected because they contain a lot of information about land-cover. The size of each image band is $512x512$, therefore so the total number of pixels is 262,144 pixels. The number of pixels is labeled as 18,271 pixels, distributed equally to the land-cover classes.

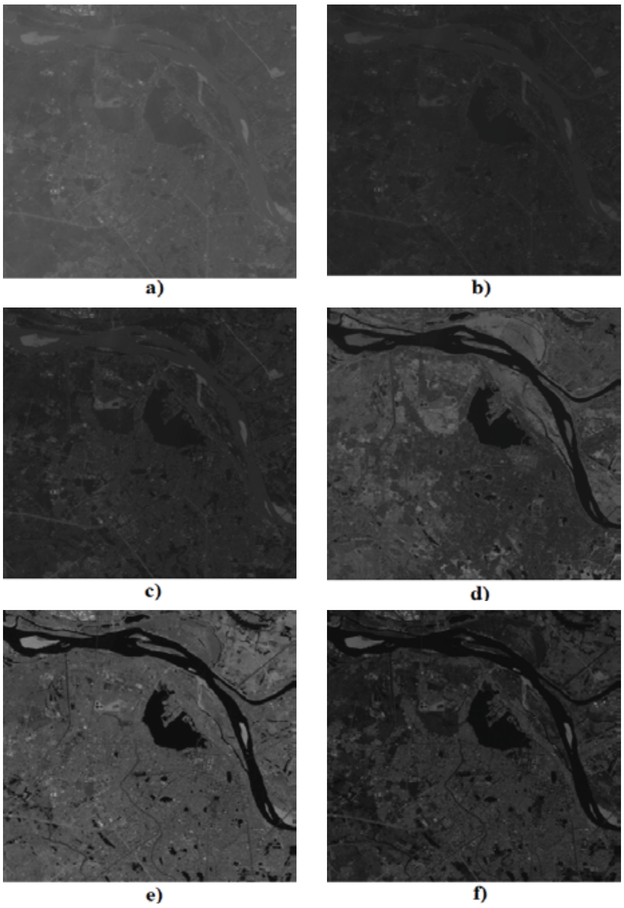

Fig. 1. Hanoi area dataset with 6 spectral bands: a) blue band, b) green band, c) red band, d) near infrared band, e) mid-infrared band and f) thermal infrared band

The result is shown in Fig. 2 in which (a) is color image, (b), (c), (d), (e) and (f) are the classification results of PFCM, SFCM, SPFCM, PFCM-W and SPFCM-W algorithms, respectively. The results show that SPFCM-W algorithm noise reduction quite good, while the PFCM algorithm is much the most noise.

The results summarized in Table I show that SPFCM-W algorithm produces better quality clustering than those obtained when running other algorithms such as PFCM, SFCM, SPFCM, PFCM-W. Visibly, the indexes obtained from SPFCM-W are significantly better than those for the PFCM, SFCM, SPFCM, PFCM-W. Following is the SPFCM algorithm for better results of PFCM, SFCM, PFCM-W algorithms in most cases.

Table II shows the proposed algorithm for higher accuracy

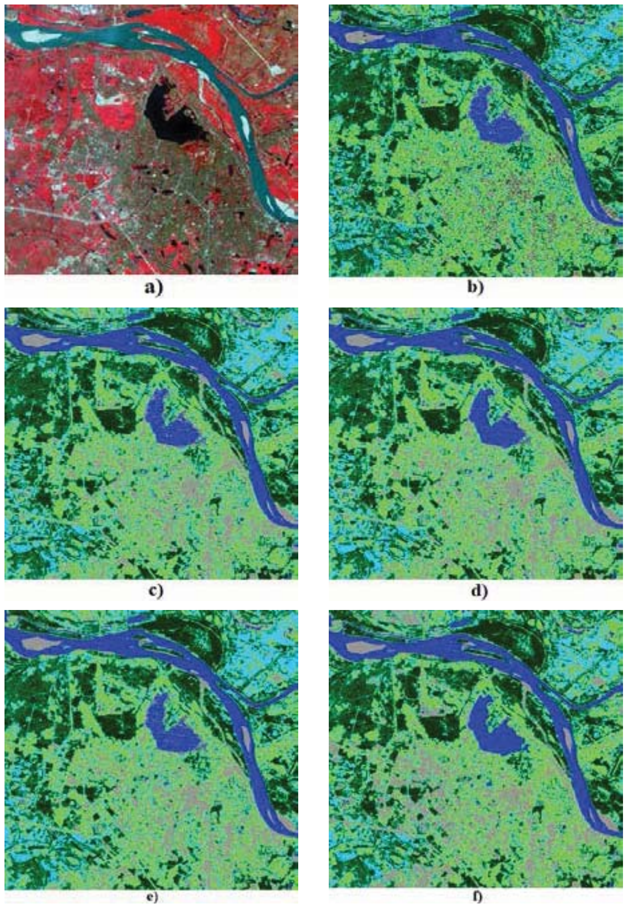

Fig. 2. Hanoi area land-cover classification result: a)Color image; b)PFCM; c) SFCM; d) SPFCM; e) PFCM-W; f) SPFCM-W

TABLE I
VALIDY INDICES OBTAINED FOR HANOI AREA

Index Algorithm	Validy indices				
	XB-I	*PC-I*	*CE-I*	*D-I*	*S-I*
PFCM	0.17523	0.68726	0.56228	0.76258	11.38724
SFCM	0.16782	0.81784	0.38793	0.48723	8.96342
SPFCM	**0.15971**	0.82878	0.39721	0.38707	6.86293
PFCM-W	0.16182	0.81986	0.39752	0.41986	6.69827
SPFCM-W	0.16073	**0.83082**	**0.35763**	**0.27387**	**5.99187**

TABLE II
TPR AND FPR FOR HANOI AREA

Methods	PFCM	SFCM	SPFCM	PFCM-W	SPFCM-W
TPR	89.73%	92.84%	95.32%	94.06%	**96.94%**
FPR	3.81%	3.15%	1.69%	2.14%	**1.38%**

with TPR value of 96.94% and FPR value of only 1.38%. While with the PFCM, SFCM, SPFCM and PFCM-W algorithms, the TPR values are respectively 89.73%, 92.84%, 95.32%, 94.06% and the corresponding FPR values are 3.81%, 3.15%, 1,69%, 2,14%.

B. Experiment 2

The second experiment is selected in Tam Dao area, Vinh Phuc province (the north of Hanoi capital) on 20 September 2017. Remote sensing data used in the classification is Sentinel-2A multi-spectral satellite image in Fig. 3 with 4 image bands was obtained by 4 spectral bands including blue, green, red and near infrared. The number of pixels is labeled as 27,572 pixels, distributed equally to the land-cover classes.

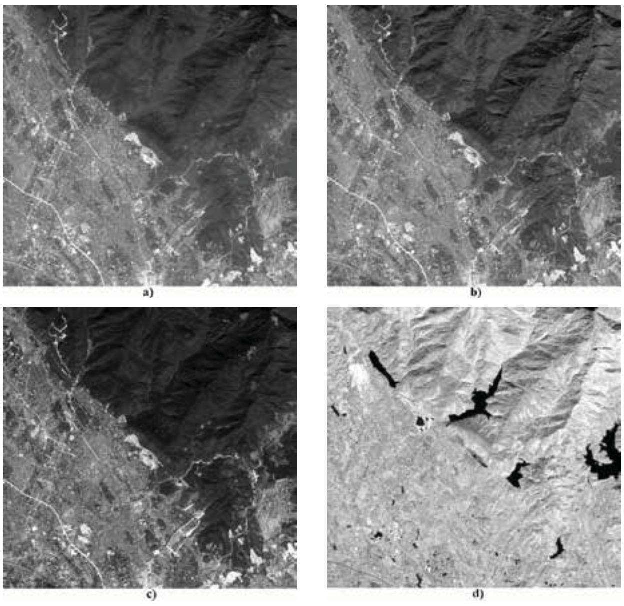

Fig. 3. Tam Dao area dataset with 4 spectral bands: a) blue band; b) green band; c) red band; d) near infrared band

TABLE III
VALIDY INDICES OBTAINED FOR TAM DAO AREA

Index	Validy indices				
Algorithm	*XB-I*	*PC-I*	*CE-I*	*D-I*	*S-I*
PFCM	0.52865	0.49851	0.42786	0.39634	5.48768
SFCM	0.43897	0.69865	0.31675	0.32699	4.98032
SPFCM	0.35982	0.71985	0.19845	0.28756	3.78952
PFCM-W	0.36813	0.63718	0.21875	0.22098	4.19865
SPFCM-W	**0.25872**	**0.76593**	**0.16872**	**0.20986**	**2.93874**

TABLE IV
TPR AND FPR FOR TAM DAO AREA

Methods	PFCM	SFCM	SPFCM	PFCM-W	SPFCM-W
TPR	93.03%	95.71%	96.89%	96.12%	**97.07%**
FPR	2.37%	2.04%	1.58%	1.79%	**1.13%**

Fig. 4 shows classification results, in which (a) is color image, (b), (c), (d), (e) and (f) are the classification results of PFCM, SFCM, SPFCM, PFCM-W and SPFCM-W algorithms, respectively. Table III shows that SPFCM-W algorithm giving the result better clustering than other algorithms such as PFCM, SFCM, SPFCM, and PFCM-W.

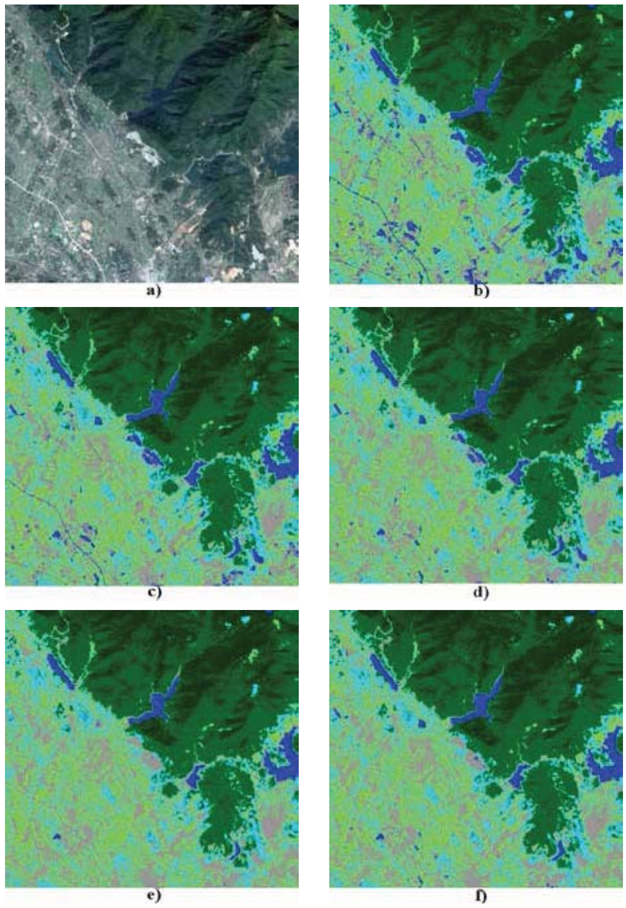

Fig. 4. Tam Dao area land-cover classification result: a)Color image; b)PFCM; c) SFCM; d) SPFCM; e) PFCM-W; f) SPFCM-W

From Table II and Table IV, the TPR values obtained by running SPFCM-W on two datasets are about 97%, while the FPR value was less than 1.4%, this value indicates that the accuracy of the results in the two tests is best with the proposed algorithm.

Fig.5 and Fig.6 compare results between PFCM, SFCM, SPFCM, PFCM-W and SPFCM-W algorithms and data of the Vietnamese Center of Remote Sensing Technology (VCRST) which is considered as the survey data on each class (in percentage %). The significant difference between the algorithms PFCM, SFCM, SPFCM, PFCM-W and SPFCM-W in determining the area of regions. Compare these experimental results with the result of VCRST, with the result of PFCM algorithm, the largest difference is about 10%, SFCM algorithm is about 8%, PFCM-W algorithm is about 6% and SPFCM algorithm is about 5%. Meanwhile, the result of SPFCM-W algorithm does not exceed 5% difference.

From the above observations, it can be seen that the method proposed (SPFCM-W) in the paper gives better results than

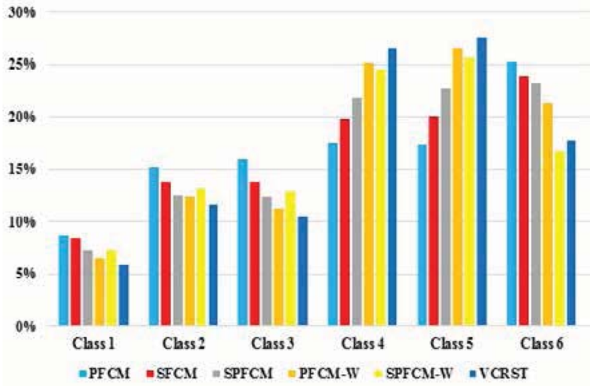

Fig. 5. Hanoi area: Comparative chart of classification results (%) of PFCM, SFCM, SPFCM, PFCM-W, SPFCM-W and VCRST.

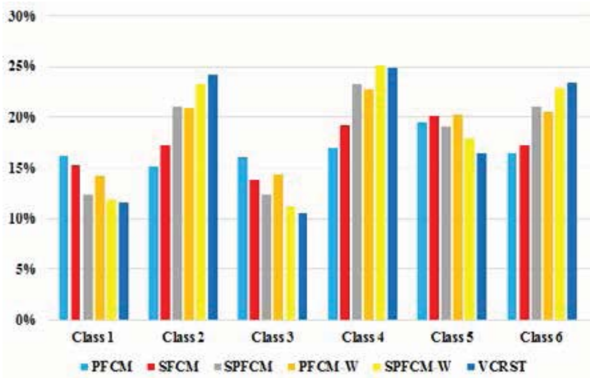

Fig. 6. Tam Dao area: Comparative chart of classification results (%) of PFCM, SFCM, SPFCM, PFCM-W, SPFCM-W and VCRST.

other methods (PFCM, SFCM, SPFCM, PFCM-W) in most cases. Therefore, we can find that that adding supplementary information as spatial weights combined with semi-supervised method can improve the clustering results.

V. CONCLUSSIONS

This paper presents an advanced possibilistic fuzzy c-means clustering method based on the semi-supervised method and spatial weights (SPFCM-W), which can reduce the noise and increase the accuracy of clustering results. In addition, the proposed spatial weighting method is beneficial for managing uncertainties. Experiments performed with multi-spectral remote sensing image datasets indicate that the proposed method provides better results than results obtained with other existing classification methods.

Some future studies may focus on using optimization methods to optimize the selection of parameters for the algorithm and accelerated computing based on high-performance computing.

Acknowledgements: This research is funded by Vietnam National Foundation for Science and Technology Development (NAFOSTED) under grant number 102.05-2016.09.

REFERENCES

[1] J.C. Bezdek, R. Ehrlich, W. Full. FCM: the fuzzy c-means clustering algorithm Comput. Geosci. 10 (23), pp.191 - 203, 1984.
[2] R. Krishnapuram and J. Keller, A possibilistic approach to clustering, IEEE Trans. Fuzzy Syst., vol. 1, pp.98-110, 1993.
[3] L. Liu, X.J Wu. Semi-Supervised Possibilistic Fuzzy c-Means Clustering Algorithm on Maximized Central Distance, the 2nd International Conference on Computer Science and Electronics Engineering, pp.1366-1370, 2013.
[4] J.S Zhang and Y.W. Leung, Improved Possibilistic C-Means Clustering Algorithms, IEEE Trans on Fuzzy Systems, vol.12(2), pp.209-217, 2004.
[5] R.P Nikhil, P. Kuhu, J.M. Keller, and J.C. Bezdek. A Possibilistic Fuzzy c-Means Clustering Algorithm, IEEE Transactions on Fuzzy Systems, Vol. 13, No. 4, pp.517-530, 2005.
[6] Y. Endo, Y. Hamasuna, M. Yamashiro, and S. Miyamoto, On semisupervised fuzzy c-means clustering, IEEE International Conference on Fuzzy Systems, pp.1119-1124, 2009.
[7] W. Pedrycz, Algorithms of fuzzy clustering with partial supervision. Pattern Recognition Letters 3(1), pp.13-20, 1985.
[8] A. Bensaid, L.O. Hall, J.C. Bezdek, Laurence P. Clarke: Partially supervised clustering for image segmentation. Pattern Recognition 29(5), pp.859-871, 1996.
[9] N. Grira, M. Crucianu, N. Boujemaa. Active semi-supervised fuzzy clustering. Pattern Recognition 41(5), pp.1834-1844, 2008.
[10] V. Antoine, N. Labroche, V.V Vu. Evidential seed-based semi-supervised clustering. SCIS-ISIS, pp.706-711, 2014.
[11] S.D Mai, L.T Ngo. Semi-Supervised Fuzzy C-Means Clustering for Change Detection from Multi-spectral Satellite Image, IEEE International Conference on Fuzzy Systems, pp.1-8, 2015.
[12] S.D Mai, L.T Ngo. Interval Type-2 Fuzzy C-Means Clustering with Spatial Information for Land-Cover Classification, ACIIDS 2015, Springer LNAI 9011, pp.387-39, 2015.
[13] S.D Mai, L.T Ngo. H.L Trinh, Satellite Image Classification based Spatial-Spectral Fuzzy Clustering Algorithm. ACIIDS 2018, Springer LNAI 10752, pp.505 - 518, 2018.
[14] S.D Mai, L.T Ngo. Multiple Kernel Approach to Semi-Supervised Fuzzy Clustering Algorithm for Land-Cover Classification, Engineering Applications of Artificial Intelligence, Vol. 68, pp.205-213, 2018.
[15] S.D Mai, L.T Ngo, H.L Trinh. Spatial-spectral fuzzy k-Means clustering for remote sensing image segmentation, Vietnam Journal of Science and Technology, 56 (2), pp.257-272, 2018.
[16] H. Liu, F. Zhao, L. Jiao. Fuzzy spectral clustering with robust spatial information for image segmentation. Appl Soft Comput. pp.3636-3647, 2012.
[17] D.M. Vargas, F.J.G. Funes, A.J.R. Silva. A fuzzy clustering algorithm with spatial robust estimation constraint for noisy color image segmentation. Pattern Recognit. Lett. 34, pp.400 - 413, 2013.
[18] F. Zhao, L. Jiao, H. Liu. Kernel generalized fuzzy C-means clustering with spatial information for image segmentation. Digit. Signal Process. 23, 184 - 199, 2013.
[19] J. Liu, T.D Pham. A spatially constrained fuzzy hyper-prototype clustering algorithm. Pattern Recognit. 45, pp.1759 - 1771, 2012.
[20] L.T Ngo, D.S Mai and W. Pedrycz, Semi-supervising Interval Type-2 Fuzzy C-Means clustering with spatial information for multi-spectral satellite image classification and change detection, Computers & Geosciences, Vol.83, pp.1-16, 2015.
[21] L.T Ngo, D.S Mai, M.U Nguyen, GPU-based Acceleration of Interval Type-2 Fuzzy C-Means Clustering for Satellite Imagery Land-Cover Classication, 12th IEEE International Conference on Intelligent Systems Design and Applications, pp.992-997, 2012.
[22] W. Wang, Y. Zhang. On fuzzy cluster validity indices, Fuzzy Sets and Systems, Vol. 158, pp.2095-2117, 2007.
[23] U. Maulik, S. Bandyopadhyay, Performance Evaluation of Some Clustering Algorithms and Validity Indices, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 24, No. 12, pp.1650-1654, 2002.
[24] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, S. Susstrunk, Slic super-pixels compared to state-of-the-art super-pixel methods, Pattern Analysis and Machine Intelligence, IEEE Transactions on 34 (11), pp.2274-2282, 2012.
[25] D. Graves, W. Pedrycz, Kernel-based fuzzy clustering and fuzzy clustering: A comparative experimental study, Fuzzy Sets and Systems, vol. 161, pp.522-543, 2010.