

Land Cover Classification Using Interval Type-2 Fuzzy Clustering for Multi-spectral Satellite Imagery

Long Thanh Ngo and Dzung Dinh Nguyen
Department of Information Systems
Le Quy Don Technical University, Hanoi, Vietnam
Email: ngotlong@gmail.com, dinhdung1082@gmail.com

Abstract—Land cover classification have been developed for specially surveillance of change of land and generating update information. The paper introduces an approach to classification of land cover from multi-spectral satellite imagery using interval type-2 c-means clustering. Two channels (Near Infrared - NIR and Visible Red - NR) are used to generate NDVI image of study area. Then IT2-FCM is used to classify NDVI into six sub-classes presenting for six types of land cover. The method is implemented for two study areas in comparing with ISODATA algorithm and FCM.

Index Terms—Type-2 fuzzy sets, type-2 fuzzy c-means clustering, land cover classification.

I. INTRODUCTION

Technology of remote sensing has been developed in the last three decades with many applications, specially for surveillance of change of land cover and for generating up-to-date land cover information. Such images are captured by multi-spectral scanners (such as Landsat TM), that acquire data at several distinct spectral bands producing multi-spectral images. Many approaches are used to analysis such data involving statistical modeling, artificial neural networks, fuzzy classifier or Dempster and Shafer's evidence theory. Recently, an approach is great deal with using fuzzy classifier or fuzzy clustering in classification of land cover in multi-spectral satellite imagery, have been investigated by various researchers.

Type-2 fuzzy logics with the capability of handing the uncertainty are widely applied in many fields [1], [2], [4], [5], [6], especially pattern recognition[3]. Clustering algorithms have developed for applications of pattern recognition in different approaches. The family of k-mean clustering algorithms has archived positive results with refinements such as identifying the number of clusters [9]. Type-2 fuzzy c-mean clustering [7], [8] is an extension of fuzzy c-mean algorithm with identifying FOU of fuzzifiers with the advantages of handling uncertainty. Lucas et al [20] proposed a general type-2 fuzzy classifier using rule-based classifier for land cover classification in thematic mapper representing the land cover of a real plain cultivated area.

Studies related on classification of land cover in satellite imagery using soft approaches have been investigated, recently. Chen et al [12] developed method of enhancing satellite imagery using fuzzy-based contrast before classification of land cover. W.Su et al [13] proposed method of object oriented information extraction for land cover classification of SPOT5

imagery, involves two steps: image segmentation and classification. Han et al [19] proposed an approach using neuro-fuzzy method derived from a generic model of a three-layer fuzzy perceptron with most accurate in comparing with maximum likelihood and neural network. Many other approaches based fuzzy logic also proposed in various manner such as using reformed fuzzy c-means clustering from colour satellite imagery [10], genetic fuzzy rule-based classification system designed under the iterative rule learning approach[14].

The paper deals with an approach to land cover classification for multi-spectral satellite imagery using interval type-2 fuzzy c-means clustering. Because of technology of electromagnetic remote sensing, there are many ambiguous pixels in satellite imagery, i.e. a pixel may belongs to forest area or water area at flooded forest. Type-2 fuzzy c-means clustering is suitable for handling uncertainty from ambiguous pixels of satellite imagery. The classification of land cover involves two steps: the first is to generate NDVI image from near-infrared channel (NIR) and visible red channel (VR). The second is classification of NDVI image into classes using interval type-2 fuzzy c-means clustering (IT2-FCM). Experimental results are shown in comparing with ISODATA method and fuzzy c-means clustering.

The paper is organized as follows: II presents an overview on type-2 fuzzy sets, IT2-FCM; III proposes land cover classification based on IT2-FCM; IV presents experimental results of study area in comparing with other methods; V is conclusion and future works.

II. PRELIMINARIES

A. Type-2 Fuzzy Sets

A type-2 fuzzy set in X is \tilde{A} , and the membership grade of $x \in X$ in \tilde{A} 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 the domain of $\mu_{\tilde{A}}(x, u)$ are called primary memberships of x in \tilde{A} and the memberships of the 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.,

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

or

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

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

At each value of x , say $x = x'$, the 2-D plane whose axes are u and $\mu_{\tilde{A}}(x', u)$ is called a *vertical slice* of $\mu_{\tilde{A}}(x, u)$. A *secondary membership function* is a vertical slice of $\mu_{\tilde{A}}(x, u)$. It is $\mu_{\tilde{A}}(x = x', u)$ for $x \in X$ and $\forall u \in J_{x'} \subseteq [0, 1]$, i.e.

$$\mu_{\tilde{A}}(x = x', u) \equiv \mu_{\tilde{A}}(x') = \int_{u \in J_{x'}} f_{x'}(u) / u, J_{x'} \subseteq [0, 1] \quad (3)$$

in which $0 \leq f_{x'}(u) \leq 1$.

According to representation based on embedded fuzzy sets, a type-2 fuzzy sets [1] is union of its type-2 embedded sets, i.e

$$\tilde{A} = \sum_{j=1}^n \tilde{A}_e^j \quad (4)$$

where $n \equiv \prod_{i=1}^N M_i$ and \tilde{A}_e^j denoted the j^{th} type-2 embedded set for \tilde{A} , i.e.,

$$\tilde{A}_e^j \equiv \left\{ (u_i^j, f_{x_i}(u_i^j)), i = 1, 2, \dots, N \right\} \quad (5)$$

where $u_i^j \in \{u_{ik}, k = 1, \dots, M_i\}$.

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. an interval 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.,

$$\tilde{A} = \{((x, u), 1) | \forall x \in X, \forall u \in J_x \subseteq [0, 1]\} \quad (6)$$

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 $\bar{\mu}_{\tilde{A}}(x)$ and $\underline{\mu}_{\tilde{A}}(x)$, of \tilde{A} are two type-1 membership functions and bounds of FOU.

B. Interval Type-2 Fuzzy Clustering

IT2FCM is extension of FCM clustering by using two fuzziness parameters m_1, m_2 to make FOU, corresponding to upper and lower values of fuzzy clustering. The use of fuzzifiers gives different objective functions to be minimized as follows:

$$\begin{cases} J_{m_1}(U, v) = \sum_{k=1}^N \sum_{i=1}^C (u_{ik})^{m_1} d_{ik}^2 \\ J_{m_2}(U, v) = \sum_{k=1}^N \sum_{i=1}^C (u_{ik})^{m_2} d_{ik}^2 \end{cases} \quad (7)$$

in which $d_{ik} = \|x_k - v_i\|$ is Euclidean distance between the pattern x_k and the centroid v_i , C is number of clusters and

N is number of patterns. Upper/lower degrees of membership, \bar{u}_{ik} and \underline{u}_{ik} are determined as follows:

$$\bar{u}_{ik} = \begin{cases} \frac{1}{\sum_{j=1}^C \left(\frac{d_{ijk}}{d_{jk}}\right)^{2/(m_1-1)}} & \text{if } \frac{1}{\sum_{j=1}^C \left(\frac{d_{ijk}}{d_{jk}}\right)} < \frac{1}{C} \\ \frac{1}{\sum_{j=1}^C \left(\frac{d_{ijk}}{d_{jk}}\right)^{2/(m_2-1)}} & \text{otherwise} \end{cases} \quad (8)$$

$$\underline{u}_{ik} = \begin{cases} \frac{1}{\sum_{j=1}^C \left(\frac{d_{ijk}}{d_{jk}}\right)^{2/(m_1-1)}} & \text{if } \frac{1}{\sum_{j=1}^C \left(\frac{d_{ijk}}{d_{jk}}\right)} \geq \frac{1}{C} \\ \frac{1}{\sum_{j=1}^C \left(\frac{d_{ijk}}{d_{jk}}\right)^{2/(m_2-1)}} & \text{otherwise} \end{cases} \quad (9)$$

in which $i = 1, \dots, C, k = 1, \dots, N$.

Because each pattern has membership interval as the upper \bar{u} and the lower \underline{u} , each centroid of cluster is represented by the interval between v^L and v^R . Cluster centroids are computed in the same way of FCM as follows:

$$v_i = \frac{\sum_{k=1}^N (u_{ik})^m x_k}{\sum_{k=1}^N (u_{ik})^m} \quad (10)$$

in which $i = 1, \dots, C$ (detail in [7]).

After obtaining v_i^R, v_i^L , type-reduction is applied to get centroid of clusters as follows:

$$v_i = (v_i^R + v_i^L) / 2 \quad (11)$$

For membership grades:

$$u_i(x_k) = (u_i^R(x_k) + u_i^L(x_k)) / 2, j = 1, \dots, C \quad (12)$$

in which

$$u_i^L = \sum_{l=1}^M u_{il} / M, u_{il} = \begin{cases} \bar{u}_i(x_k) & \text{if } x_{il} \text{ uses } \bar{u}_i(x_k) \text{ for } v_i^L \\ \underline{u}_i(x_k) & \text{otherwise} \end{cases} \quad (13)$$

$$u_i^R = \sum_{l=1}^M u_{il} / M, u_{il} = \begin{cases} \bar{u}_i(x_k) & \text{if } x_{il} \text{ uses } \bar{u}_i(x_k) \text{ for } v_i^R \\ \underline{u}_i(x_k) & \text{otherwise} \end{cases} \quad (14)$$

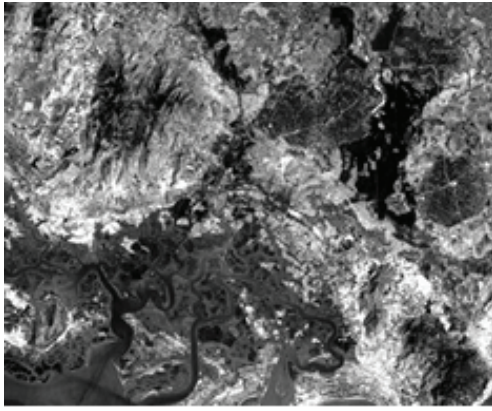
Next, defuzzification is made as if $u_i(x_k) > u_j(x_k)$ for $j = 1, \dots, C$ and $i \neq j$ then x_k is assigned to cluster i .

III. LAND COVER CLASSIFICATION

A. Data Study

Data study for land cover classification is implemented over two areas involving Ba Ria area and Hanoi area (Vietnam) in Fig. (1), are described as follows:

- 1) Ba Ria Area locates in Southern of Vietnam ($10^{\circ}34'27.97''N, 107^{\circ}5'3.68''E$ to $10^{\circ}24'31.36''N, 107^{\circ}17'9.40''E$) with area is 405.4752 km^2 . This area



a)



Fig. 1. Study data: a) Ba Ria Area; b) Hanoi Area

is covered by 6 types of land covers such as water, rocks or bare soil, sparse tree, planted forests, perennial tree crops and jungles. Main feature is the rate of types be regularly distributed over the area and high rate of vegetables.

- 2) Hanoi Area locates in Northern of Vietnam with area 38.5843 km^2 , is high building density of urban area and low rate of vegetable; especially there are a large river, a large lake; there are many small ponds. These features may result in wrong classification of land cover using NDVI image.

B. Methodology

The proposed method is to use IT2-FCM clustering into NDVI image made from channels of Landsat TM. The pre-processing step is performed to compute NDVI image from NIR channel and VR channel i.e. each pixel of NDVI is computed corresponding pixel of Landsat TM. NDVI image may be directly used to class using hard clustering, but in fact each pixel contains ambiguous information, for example, rate of 30% is soil, rate of 25% is forest and rate of 45% is water. In this case, the pixel is assigned as water cover, but its rate of 55% is no water. So methodology of fuzzy clustering is more

suitable than hard clustering. Fuzzy clustering, especially IT2-FCM, is used to handle the uncertainty that appear from input data of image and handle the ambiguously.

The diagram of land cover classification involves steps described in Fig. 2. The diagram is described as follows:

- 1) *Step 0*: Input data involves two channels NIR and VR of Landsat TM.

- 2) *Step 1*: Convert to NDVI image from input data according to the formula (16).

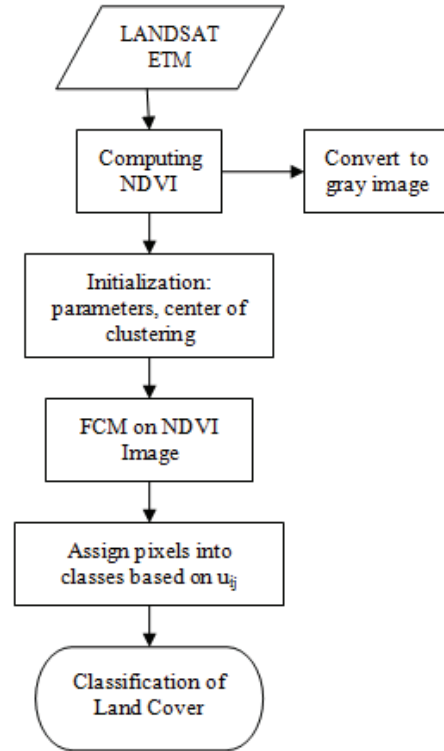


Fig. 2. Diagram of land cover classification

- 3) *Step 2*: Initialization parameters, cluster centroids.

In the fuzzy c-means algorithms, problem is how to initialize the centroid matrix V , because initialization of matrix V can cause affect on the number of steps and results of clustering. Hence, a method to generate the matrix V to make fuzzy c-means algorithms stable and efficient, called *initialization of centroid algorithm*, is shown to initialize centroid matrix V based on density of patterns. The centroid will be in the samples that the density surrounding the sample data are large. This step is quite large to affect the calculation process. The concept of statistical variance mathematical model is used to solve the problem of selecting a surrounding data points.

Algorithm 3.1: Initialization of centroid algorithm

Consider $X = (x_1 \dots x_N)$, $x \in R^M$

- 1) Compute the expected pattern $\bar{z}_i = \frac{1}{N} \sum_{j=1}^N x_{ji}$ and

$$\text{standard deviation } s_i = \sqrt{\frac{1}{N} \sum_{j=1}^N (x_{ji} - \bar{z}_i)^2}. \text{ with } i =$$

1, 2, ..., M.

Consider the surround of each data point is m-dimensional box with radius can be defined by the standard deviation is $r = \min_{1 < i < M} s_i$.

2) Compute density D_i of pattern x_i .

$$D_i = \sum_{j=1}^N T(r - \|x_j - x_i\|) \quad (15)$$

in which $u_{jl} = \begin{cases} 1 & \text{if } z \geq 0 \\ 0 & \text{otherwise} \end{cases}$

3) Find pattern x_i with $D_i = \max_{1 \leq j \leq N} D_j$

$V_u = V_u \cup x_i$

4) Compute $CS = \{x_j | r_i - \|x_i - x_j\| \geq 0\}$

$X = X \setminus CS$

5) If $X = \emptyset$ then go to Step 6 else back to Step 2.

6) Given a set of candidate points V_u .

If V_u is large then we can proceed with this algorithm to reduce the number of candidate clusters.

We can speed up calculations by dividing the input data set into subsets, then proceed to apply the algorithm for that subset, we have candidates set V_i . Then we proceed with the candidate set $\cup V_i = V$, then apply this algorithm to the set V . Depending on the particular problem that we can apply the following measures to reduce the number of candidate clusters such as the shape of the clusters that we can remove the candidates in a straight line, or by ellipses ...Finally, the centroid matrix V can be initialized by choosing the patterns in V_u according to the density of candidates.

4) *Step 3: Generate NDVI image and clustering using IT2FCM.*

Multi-channels satellite images are processed to classify on the basis of vegetation i.e NDVI image. Among the seven channels of multi-channels satellite images, using only two channels are NIR (Near-Infrared) and VR (Visible Red) corresponding to channel 3 and channel 4 in the order of 7 channels. These two channels are combined together to form an intermediate NDVI (Normalized Difference Vegetation Index) channel. NDVI is calculated as follows:

$$NDVI = (NIR - VR)/(NIR + VR) \quad (16)$$

The NDVI is not clear enough to identify the type of background cover, because the rules to describe background is semantic rules and there is some uncertainty in processing mechanism. It is considered that the density of green leaves is approximated to value of NDVI, but there are no rules to give the density level base on a NDVI value. Besides, the ground covering layers such as forestry, agriculture, milpa, bare land, water surface,... do not usually have clear boundaries in geographic space and boundaries are not accurate. Some of them are:

The ambiguity of attributes: In this case we can not assign a specific location for a single layer.

The ambiguity of space: Boundaries are drawn between the two regions in space are not positioned with 100% certainty.

For instance: a pixel may contain 30% of arable land, 25% forests and 45% water, it is confusing to assign this pixel into water representing layer because 55% of the pixel are not water. In these cases, applying the clear classification is inappropriate - because this method assigns pixels into water instructing layer - it should be replaced by fuzzy classification in which we can assign a pixel into many layers according to the changing rate.

Thus, IT2FCM will be performed on two channels in the seven channels of multi-channels satellite images, including three main steps:

1) Multi-channels satellite image preprocessing.

The NDVI is one of the greatest successes of many efforts to simplify and quickly identify areas where there is vegetational cover, and it remains the best-known index and is used to detect the green canopy living in multi-spectral remote sensing data. For the convenience in processing NDVI data, it is converted to image pixel values base on the formula (17).

$$\text{Pixel value} = (NDVI + 1) \times 127 \quad (17)$$

2) Perform IT2FCM on the intermediate channel, NDVI. This channel will be default classified into six classes representing six types of land cover:

- a) Rivers, ponds, lakes
- b) Rocks, bare soil;
- c) Fields, sparse tree;
- d) Planted forests, low woods;
- e) Perennial tree crops;
- f) Jungles.

3) Identify the percentage of the area:

$$S_i = \frac{n_i}{N} \quad (18)$$

S_i : Square of i^{th} region.







n_i : Number of points in i^{th} region.

N : Total points of NDVI Channel

IV. RESULTS

Test Data from LANDSAT-7 imagery includes two above mentioned areas.

In Fig. (3) and (5), colors of classes are denoted as follows:

-  Class 1. Rivers, ponds, lakes.
-  Class 2. Rocks, bare soil.
-  Class 3. Fields, sparse tree.
-  Class 4. Planted forests, low woods.
-  Class 5. Perennial tree crops.
-  Class 6. Jungles.

The experimental results are shown in Fig. 3 and 5 in which a) for NIR channel, b) for VR channel, c) for NDVI image generating from NIR and VR channels, d), e), f) for result image of classification of ISODATA, FCM and IT2FCM algorithm, respectively. Tables I and II are detail results of classification into six types of land cover involving number of pixels, percentage of class on over study data and area of regions. Fig. 4 and 6 are the comparing results between

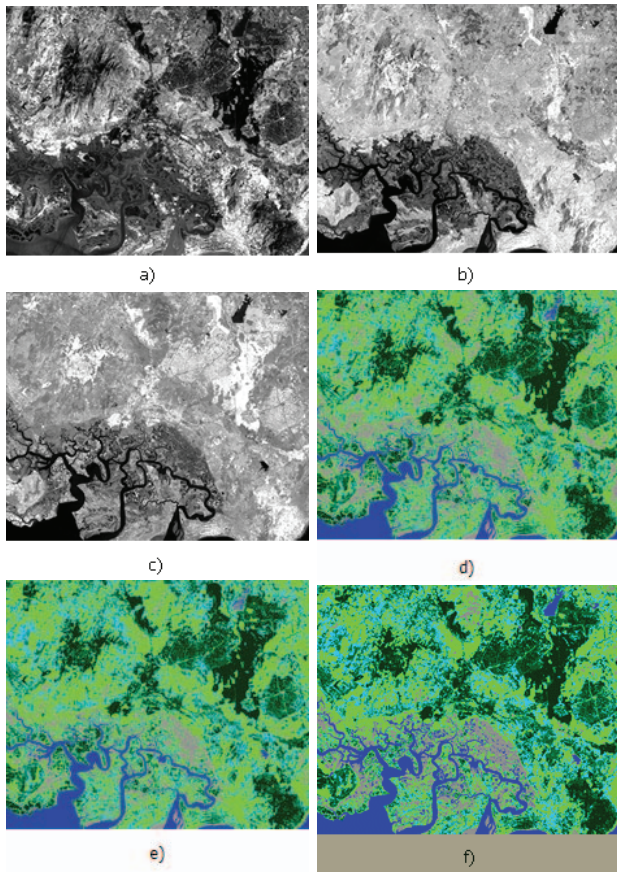


Fig. 3. Study data 1: Result of land cover classification. a) NIR channel image; b) VR channel image; c) NDVI image; d) ISODATA classification; e) FCM classification; f) IT2FCM classification

TABLE I

STUDY DATA 1: RESULT OF LAND COVER CLASSIFICATION USING IT2FCM

Class	N. of pixels	Percentage(%)	Square(hec.)
1	42 924	8.599	3486.502
2	62 968	12.614	5114.576
3	131 849	26.412	10709.435
4	116 264	23.290	9443.543
5	88 058	17.640	7152.511
6	57 137	11.446	4640.953

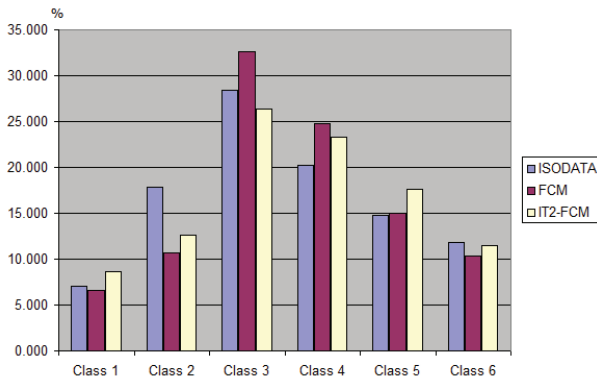


Fig. 4. Study data 1: Comparisons between ISODATA, FCM and IT2FCM

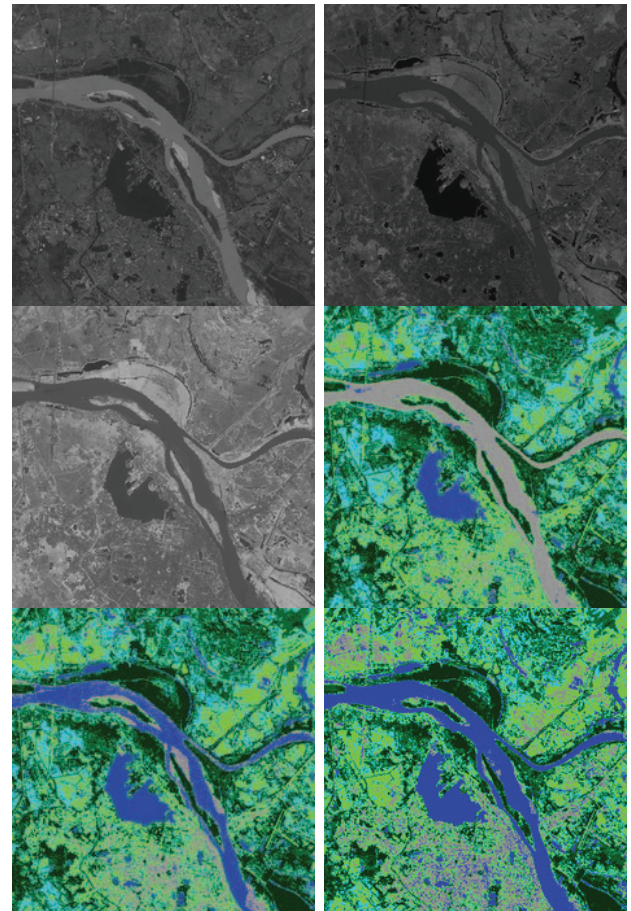


Fig. 5. Study data 2: Result of land cover classification. a) NIR channel image; b) VR channel image; c) NDVI image; d) ISODATA classification; e) FCM classification; f) IT2FCM classification

TABLE II

STUDY DATA 2: RESULT OF LAND COVER CLASSIFICATION USING IT2FCM

Class	Number of pixels	Percentage	Square(hectare)
1	38 885	15.554	3158.434
2	47 183	18.873	3832.399
3	48 411	19.364	3932.102
4	40 582	16.233	3296.314
5	43 883	17.553	3564.356
6	31 056	12.422	2522.442

ISODATA, FCM and IT2FCM on each class (in percentage %).

The significant difference between the algorithms in determining the area of regions, the largest difference between the algorithms up to 7%. Compare these experimental results with the result of The Vietnamese Center of Remote Sensing Technology with ISODATA algorithm, the largest difference is 11% and FCM algorithm is 8%. Meanwhile, IT2FCM algorithm does not exceed 5% difference.

Fig. 3 and 5 show that IT2FCM classifier gives clusters better. Low accuracy of classification for class 1 may see in Fig. 3 d) (ISODATA) and e) (FCM), especially in river region (center of image).

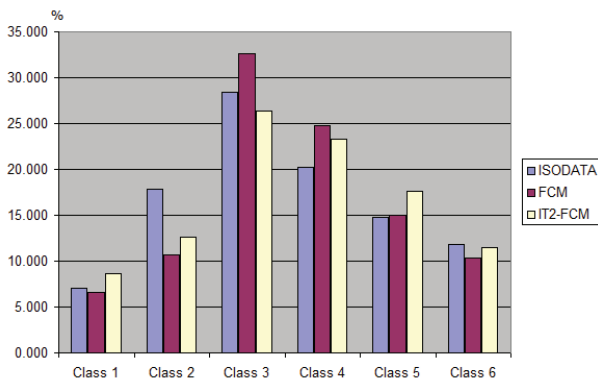


Fig. 6. Study data 2: Comparisons between ISODATA, FCM and IT2FCM

V. CONCLUSIONS

An approach to classification of land cover for multi-spectral satellite imagery using IT2FCM is presented in comparing with previous methods. IT2FCM may handle some source of uncertainty from ambiguous pixels on overlapping area of land covers, so the proposed method result in accurate classification of study data. IT2FCM is used to classify NDVI image that is generated from NIR and VR channels of multi-spectral satellite imagery.

The next goal is to implement further research on hyper-spectral satellite imagery for land cover classification; speed-up the proposed methods based on GPU.

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