Annals of the University of Craiova, Mathematics and Computer Science Series
Volume 42(1), 2015, Pages 175–185
ISSN: 1223-6934

A fusion of remote sensing images segmentation based on Markov random fields and fuzzy c-means models

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Abstract. Remote sensing images segmentation is a challenging task in analysis process of terrestrial applications. In this paper, we propose a combination of two segmentation methods of remote sensing images. The first based on MRF (Markov Random Fields) method which takes into account the neighboring labels of the pixels and the second is computed with a Fuzzy C-means technique to improve the likelihood criterion. After, a fusion by Dempster Shafer theory is performed on results from the two images segmentation techniques. The contribution of this work is to improve the belongingness of pixels in order to extract more useful information in terrestrial applications of remote sensing images. The whole algorithm is evaluated on a real remote sensing image and experimental results show that the developed approach has more performance than previously discussed methods in term of accuracy and quality of segmentation.

Key words and phrases. Markov Random Fields, ICM, Fuzzy C-means, Theory of evidence, Dempster-Shafer, Remote sensing image.

1. Introduction

Image segmentation is the process of partitioning an image into homogenous regions using its attributes such as pixel intensity, spectral values or textural properties. This step is a primordial task in image analysis and pattern recognition especially in remote sensing images.

Remote sensing imagery needs to be converted into tangible information which can be utilized in conjunction with other data sets [1]. This kind of images has been significantly increased in recent years. The obtained images provide a lot of details about surface, which are useful for mapping, environmental monitoring, resource investigation, disaster management, and military intelligence [2].

In this context, Alistair and al.[3] give a review on studies that have applied remote sensing imagery to characterize vegetation vulnerability in both retrospective and prospective modes , in natural terrestrial ecosystems including temperate forests, tropical forests, boreal forests, semi-arid lands, coastal areas, and the arctic. Abkar and al. [4] describe a likelihood-based segmentation and classification method for remotely sensed images. It is based on optimization of a utility function that can be described as a cost-weighted likelihood for a collection of objects and their parameters. In their paper, Zhijian and al. [5] propose a Dynamic Statistical Region Merging to improve segmentation accuracy and the correctness of remote sensing images.

In addition, Remote Sensing Image is more seriously disturbed by luminance, noise and so on [6]. Thus, any single segmentation method can barely produce satisfying results in finding urban regions, roads, vegetation and water areas.

This paper has been presented at Congrès MOCASIM, Marrakech, 19-22 November 2014.

In this paper, a combination of two segmentation methods of remote sensing images is proposed. The first based on MRF (Markov Random Fields) method which takes into account the neighboring labels of the pixel and the second is computed with a fuzzy c-means technique to improve the likelihood criterion. Then, a fusion by Dempster Shafer theory of evidence is performed to reduce the uncertainty in segmentation results. This method is robust than combination techniques discussed in literature in term of improving accuracy and quality of segmentation. Experimental results on a real image demonstrate the robustness of this algorithm in terrestrial applications of remote sensing.

The organization of this paper is as follows: Section 2 introduces the segmentation and fusion techniques used in this study. Section 3 presents an overview and scheme of the proposed method. Experimental results and discussion are given in Section 4. Finally, Section 5 draws the conclusions of this work.

2. Preliminaries

2.1. Markov Random Fields model. Markov Random Fields MRF model has been used for image segmentation and classification last decades [7]. It is a spatio-contextual model based segmentation scheme that partitions an image into different clusters with the constraint of Gibbs distribution as prior gray level. Each pixel in Remote Sensing image Y is assumed as a site s denoted by Ys, s belongs to S, where S represents the set of sites and its cardinal $card(S) = M * N$. Y represents a random field and y is a realization of it.

A random field $X = (X_1, ..., X_{card(S)})$ is a Markov field associated to the neighborhood system V if and only if:

$$P(X = x) > 0 \tag{1}$$

$$P(x_i/x_j, j \in S - \{i\}) = P(x_i/x_j, j \in V_i) \tag{2}$$

The theorem of Hammersly-Clifford [8] demonstrates that the random field X is a Markov field on S with respect to a neighborhood system V if and only if its distribution $P(X = x)$ is a Gibbs distribution defined by:

$$P(X = x) = \frac{1}{Z}.e^{-U(x)} \tag{3}$$

where $P(X = x)$ is called the a-priori probability, Z is the partition function or the sum of the numerator over all possible labeling and $U(.)$ is the energy function desfined as follows:

$$U(x) = \sum_{t=1}^{Card(S)} \sum_{r \in V_t} \theta_r..J(x_t, x_r)] \tag{4}$$

$J(a, b) = -1$ if $a = b$, 0 if $a \neq b$, and θ_1, θ_2,... are the clique parameters (in our context we use the Ising model with $\theta_1 = \theta_2 = ... = \beta$).

The image segmentation is the estimation of the label process X from the pixel realization Y. Several approaches use the estimation using the a-posteriori probability $P(X/Y)$ which is a Gibbs distribution given by :

$$P(X = x/Y = y) = \frac{1}{Z_y}.e^{-U(x/y)} \tag{5}$$

where Zy is the normalization constant and $U(x/y)$ is the energy function. We can use the energy function proposed by Dubes and al. in [9] :

$$U(x/y) = \sum_{t=1}^{Card(S)} [(\frac{1}{2}.ln(\sigma_{xt}^2)) + \frac{(y_t - \mu_{xt})^2}{2\sigma_{xt}^2} + \sum_{r \in V_t} \theta_r.J(x_t, x_r)] \quad (6)$$

The segmentation problem can be stated as the problem of observing vector y and estimating the labels in the perfect image. The Maximum A Posteriori (MAP) estimate is the vector $\hat{x}$ which maximizes $P(X = x/Y = y)$ with respect to x.

To approach the image segmentation problem within the MAP-MRF framework, a classical solution named the Iterated Conditional Modes (ICM)[10]. Despite being computationally efficient, the ICM algorithm has an evident drawback of locally convergences. It was presented by Besag study described in [8] as an alternative to MAP estimation.

The ICM algorithm can be presented as follows [8]:

(1) Initialization of x.
(2) For i=1 to M*N do:
Update the value of x_i Which maximizes the probability $P(x_i/x_j, j \in V_i)$.
(3) Repeat the steps 2 a number of iterations.

The ICM is a perfectly deterministic algorithm that depends strongly on the initialization phase.

2.2. Fuzzy c-means model. Fuzzy c-means (FCM) clustering algorithm is a classical clustering algorithm for image segmentation [11]. Its advantage is that it can retain more information in the image because of introducing the fuzziness for the belongingness of each image pixel. Let $X = \{x_1, x_2, .., x_n\} \subset R^s$ denote a dataset with n data points. The standard FCM algorithm is an iterative algorithm of clustering technique that aims to partitioning X into c clusters. The objective function of FCM is defined as follows:

$$J_m = \sum_{k=1}^{c} \sum_{i=1}^{n} U_{ki}^m ||x_i - v_k||^2 \quad (7)$$

with $\sum_{k=1}^{c} U_{ki} = 1, U_{ki} \in [0, 1], 0 \leq \sum_{i=1}^{n} U_{ki} \leq n$

Where the operator $||x_i - v_k||$ denotes the Euclidean norm between x_i and v_k (the center of class k) where the parameter m ($m > 1$) is the membership function weighting exponent that determines the amount of fuzziness of the resulting partition [6]. In our study we take $m = 2$.

2.3. Dempster shafer theory of evidence. It is difficult to avoid uncertainty when attempting to make models of the real world. Uncertainty is inherent to natural phenomena, and it is impossible to create a perfect representation of reality [12].

To represent and handle uncertainties in available information, Dempster-Shafer's theory offers a powerful tool as it helps to overcome the limitations of classical methods [13]. That means that in the Dempster-Shafer's theory of evidence , the knowledge about the problem induces a basic belief assignment modeled by a distribution of evidence mass m on the subsets A of the classes set [14].

The fusion process does not start from one single frame of discernment [15], as it was described in previous works, but does start from first defining two independent frames of discernment associated with the two images to be fused, and then combining them for forming a new frame of discernment.

Dempster Shafer uses belief rather than probability, inherently increasing the flexibility. The measure of belief allows vague states to exist whereas Bayesian probability grants weight to both a single event and its compliment[16]. There are three functions related to Dempster-Shafer's Theory of evidence, the Basic Probability Assignment function (bpa), the Belief function (Bel), and the Plausibility function (Pl).

In the context of theory of evidence belief mass or simply mass refers to Basic Probability Assignment function (bpa), defined as:

$$m_i : 2^{\Omega} \longrightarrow [0,1] \tag{8}$$

$$m_i(\phi) = 0 \tag{9}$$

$$\sum_{A \subseteq \Omega} m_i(A) = 1 \tag{10}$$

Credibility (Belief Function) is the amount of information that is entirely contained in the subset considered. It contains all the knowledge crediting the veracity of this subset:

$$Cr(A) = \sum_{B \subset A} m(B) \tag{11}$$

The plausibility of a subset A is the amount of information does not discrediting A, that is to say, all the information contained in the subsets with intersection with A:

$$Pl(A) = \sum_{B \cap A \neq \phi} m(B) \tag{12}$$

It is important to note that $m(A)$ measures the belief that is committed exactly to A and makes no specific claims to any particular subsets of A as detailed in [14]. Information about specific subsets of A would be represented by another bpa, $m(B)$ such that $B \subset A$.
In this context, Image fusion is a method of combining the data contained in images to bring out more useful information. Various fusion techniques are available including morphological pyramid, HIS transform, multiresolution analysis associated to wavelet [17] and dempster-shafer theory of evidence.
To combine information convoyed by sources, each information source S_i has a set of mass $mi()$ that characterize this source information [18]; As an example, combination of two sets of masses $m1()$ and $m2()$ results in a unique set of mass noted $m()$ with $m() = m1() + m2()$.

The theory of evidence provides appropriate tools. The Dempster fusion operator, also called orthogonal sum, verifies the properties of commutative and associative. The mass resulting from the combination of N information sources S_j is denoted $m\oplus$ such as :

$$m_{\oplus} = m_1 \oplus m_2 \tag{13}$$

$$m_{\oplus}(A) = \frac{1}{1-K}.m_{\cap}(A) \tag{14}$$

$$m_{\cap}(A) = \sum_{B \cap C = A} m_1(B).m_2(C) \tag{15}$$

with K represents the conflict coefficient between the two sources of information defined as follows:

$$K = \sum_{B \cap C = \phi} m_1(B).m_2(C) \tag{16}$$

After reminding the basic concepts to the development of our method, the following section details the fusion algorithm for image segmentation proposed in this paper.

3. Our proposed method

In order to reduce the uncertainty of pixel belongingness in image segmentation process, a fusion under Dempster Shafer theory of evidence is proposed. In fact, from the same image (input image), two frames are generated by using two different image segmentation models: the first based on Markov Random Fields and the second is performed by Fuzzy c-means technique, and then combining them to form a new frame (output image).

The estimation of the mass function is a very difficult problem, which did not fit.

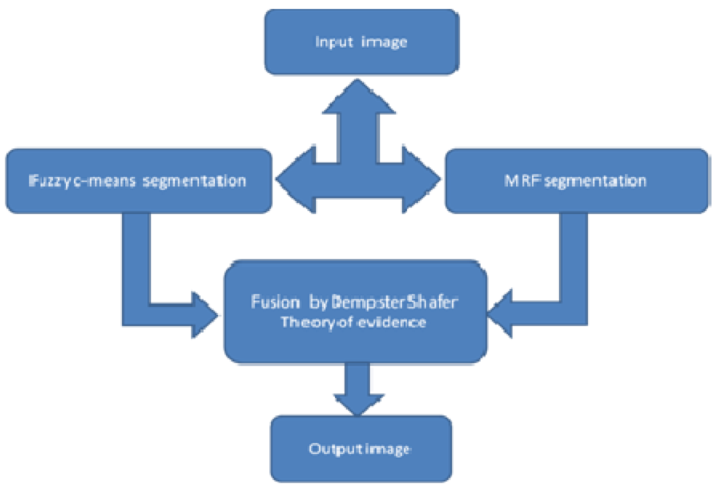

FIGURE 1. Workflow of the proposed algorithm.

This estimate can be directly expressed, or through transfer models. In this work, we use the model proposed by [19] to estimate the mass functions, defined as a transfer model as follows:

$$m[x](A_i) = P_{aii}.p(x/A_i) \tag{17}$$

$$m[x](A_i A_j) = P_{aij}.p(x/A_i) + P_{aji}.p(x/A_j) \tag{18}$$

With P_{aij} represent the accuracy. It indicates the percentage of pixels of a reference class assigned to the same class in the classification. It is calculated as follows:

$$P_{aij} = \frac{X_{ij}}{X_{i+}} \tag{19}$$

X_{ij} represents the elements of the confusion matrix, X_{i+} is the total sum of rows elements, N is the total number of matrix pixels and M is the number of classes.

$$X_{i+} = \sum_{j}^{M} X_{ij}$$

and

$$N = \sum_{i,j}^{M} X_{ij}$$

and $p(x/A_i)$ represents the conditional probability that can be modeled by a Gaussian probability for each class A_i as:

$$p(x/A_i) = \frac{1}{\sigma_i\sqrt{2\pi}}.exp^{\frac{-(x-\mu_i)^2}{2\sigma_i^2}} \tag{20}$$

Note that the transfer model used satisfies the condition $\sum m() = 1$.

The proposed algorithm is detailed following the steps below:

(1) A first image segmentation is performed using MRF method (ICM algorithm).
(2) A second independent Image segmentation is performed by fuzzy method (c-means fuzzy algorithm). The result of step 1 is considered as a source of information S_1 and the result of step 2 as an independent source of information S_2.
(3) For each source j and for each pixel x, do:
    - The computation of the average vector of each class and the covariance matrix.
    - The computation of the conditional probability using the exponential distribution of the Gaussian.
    - The estimation of mass functions from the functions of probabilities by the model transfer Described in earlier.
(4) The computation of multitemporal conflict.
(5) The computation of the combined mass of each focal element Ai by applying the orthogonal Dempster rule.
(6) The computation plausibility from the combined masses.
(7) Decision making using the maximum of plausibility.

The different steps of this proposed algorithm are implemented for a real remote sensing image and results are detailed in the next section.

4. Experimental results

To demonstrate the efficiency of the proposed algorithm, we have performed it on a large greyscale remote sensing image of Rabat region (Morocco) shown on Figure 2a. To normalize segmentation results, a manuel segmentation is so applied to the original image and considered as the reference segmentation (see Figure 2b).

After, we consider two independent sources S1 and S2 such that:

- S1: Source of information resulting from the segmentation of the original image using a Markovian method (ICM algorithm);
- S1: Source of information resulting from the segmentation of the original image by the fuzzy logic method (fuzzy c-means algorithm);

The study of the original image histogram reveals that there are three significant classes. The execution of the steps 1 and 2 of the proposed algorithm gives the results illustrated on Figures 3 and 4.

Consider the frame of discernment $\Omega = \{C_1, C_2, C_3\}$ such that each C_i is a membership class of image pixels for classification of vegetation and water areas from the given image.

- C_1: represents the heavy vegetation area;

- C_2: represents the low vegetation area or buildings;
- C_3: represents the water area.

Figure 3 and Figure 4 show the segmentation results divided into separate classes of the original image by using respectively the ICM and FCM methods. Figure 5a and 5b show respectively the reconstitutions of classes previously segmented from S1 and S2.

Figure 2a. Original image.

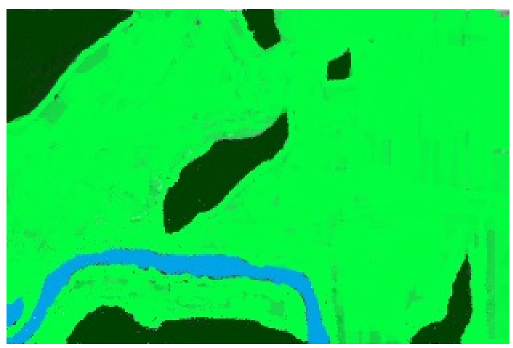

Figure 2b. Manuel segmentation (Reference segmentation).

After computing the confusion matrix of the two sources (Tables 1 & 2), we estimate the mass functions using the model described above (Table 3).
In order to evaluate the quality of segmentation we adopt the correct classification rate (CCR)that represent the percentage of pixels affected to their correct classes. Based on the confusion matrix illustrated by tables 1 and 2 we can calculate this criterion for the two sources(CCR(S1)=90.32% and CCR(S2)= 96.56%). Since the values of CCR(S1) and CCR(S2)are above than 90%, we can consider that both segmentations using ICM of FCM have good results. However, S1 has a bad delimitation of the class C2 and S2 has an important confusion between classes C1 and C2.
The aim of the proposed method is to eliminate those imperfections so to have a good segmentation that gives the maximum possibility of identifying classes and distinguishing between them in a remote sensing image.
To do so, we calculate the conflict coefficient (step 4 of the proposed algorithm) from mass values on Table 3. This coefficient varies between 0.145 and 0.965 and has a mean value equal to 0.589.
The decision making process relative to the combination under Dempster-Shafer's Theory of evidence of the proposed images (from sources S1 and S2) gives the result shown on Figure 6 (steps 5, 6 and 7). By evaluating the segmentation quality for this fusion image we find that CCR= 98.76% that means a quality improvement

of segmentation results and justify the performance of the proposed method and its adequacy to the remote sensing images.

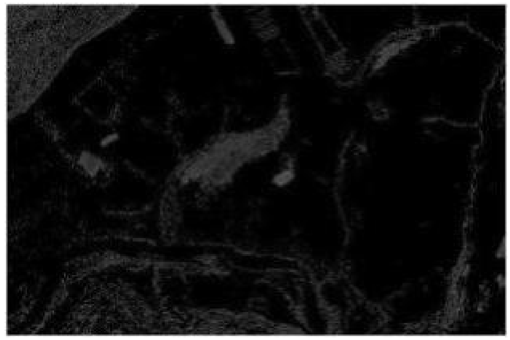

FIGURE 3a. Class C_1 using MRF segmentation of the original image.

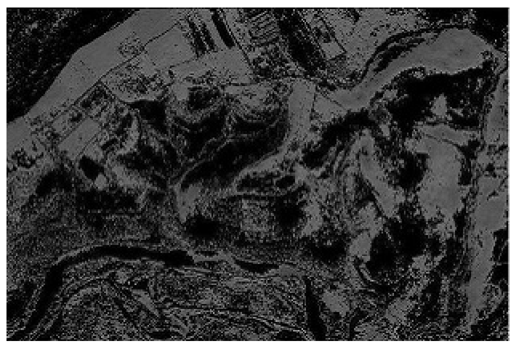

FIGURE 3b. Class C_2 using MRF segmentation of the original image.

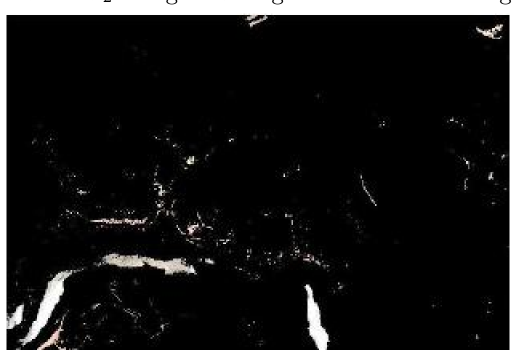

FIGURE 3c. Class C_3 using MRF segmentation of the original image.

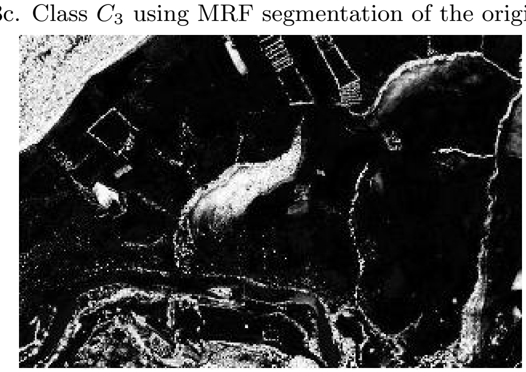

FIGURE 4a. Class C_1 using Fuzzy c-means segmentation of the original image.

FIGURE 4b. Class C_2 using Fuzzy c-means segmentation of the original image.

FIGURE 4c. Class C_3 using Fuzzy c-means segmentation of the original image.

FIGURE 5a. Representation of image segmentation using ICM method (S1).

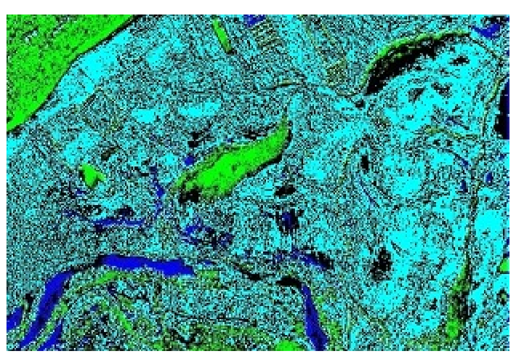

FIGURE 5b. Representation of image segmentation by FCM method (S2).

ICM	reference image		
	C1	C2	C3
C1	275	143	22
C2	82	8326	65
C3	73	93	228

Table 1. Confusion matrix of S1 relative to the reference segmentation.

FCM	reference image		
	C1	C2	C3
C1	585	81	0
C2	286	114	45
C3	0	77	202

Table 2. Confusion matrix of S2 relative to the reference segmentation.

Focal element	Mass values range			
	S1		S2	
	Min value	Max value	Min value	Max value
{C1}	0.322	0.625	0.445	0.878
{C2}	0.330	0.983	0.109	0.256
{C3}	0.2	0.579	0.228	0.724
{C1,C2}	0.162	0.325	0.239	0.643
{C1,C3}	0.042	0.209	0	0
{C2,C3}	0.044	0.212	0.113	0.276

Table 3. Calculation of min and max mass values using the proposed model.

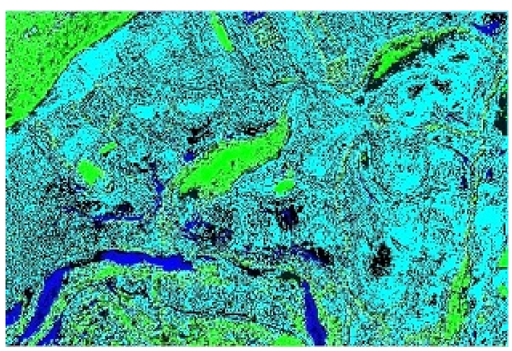

Figure 6. Image fusion using Dempster-Shafer's theory of evidence (the proposed algorithm).

5. Conclusion

In this paper, we have proposed a new method of remote sensing image segmentation. It is based on a Dempster-Shafer's fusion technique of two slightly different images. Those images are generated by applying separately an MRF method and a Fuzzy c-means model to segment the same initial remote sensing image. The evaluation of this algorithm shows that results are robust in sense that accuracy and quality were improved. The future work will be an application of this method on multispectral images and its implementation in a programmable hardware circuit to reduce the processing time.

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