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An Intellectual Approach to Segmentation of the Satellite Images

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Abstract. The applicability of the clustering algorithms under uncertainty conditions for the image segmentation from the remote sensing satellites has been shown. Approaches to expanding the characteristics’ space to improve the quality of the image segmentation have been considered. An intellectual approach to improving the quality of the image segmentation, which consists in combining the results of the image segmentation from the different clustering algorithms under conditions of uncertainty through their use in the development of the SVM classifiers and their ensembles, has been formulated. The results of solving the problem of the image segmentation based on the clustering algorithms under uncertainty conditions have been presented.

1. Introduction

Image segmentation plays an important role in Earth remote sensing systems and is used to implement the scene recognition and object selection. Typically, a digital image is represented as a rectangular grid of pixels, which causes considerable inconvenience in the high-level analysis. The purpose of segmentation is to simplify the description of the image by moving from a representation in the form of a set of the raster points to a representation in the form of a set of the objects. This transition is based on the selection of areas with the similar visual characteristics.

Let for the original image we have \( I \) characteristics (brightness, color, texture, dispersion, etc.), which allow to localize the objects of interest. The segmentation problem can be reduced to the clustering problem of the objects’ set in the \( I \)-dimensional space, if it is possible to express for each pixel the numerical values of the characteristics on the scale of intervals or relations. It is worth noting that the uncertainty due to the inability to unambiguously classify the objects depicted is inherent in the segmentation problem. So, it is advisable to apply the clustering algorithms under uncertainty conditions and implement a particular interpretation of uncertainty. In this case, the same image pixel can belong to the several clusters simultaneously, which provides the flexibility for further image analysis.

The most well-known clustering algorithms under uncertainty conditions are the fuzzy \( c \)-means algorithm (FCM algorithm) and its modifications: the possibilistic \( c \)-means algorithm (PCM algorithm) and the possibilistic-fuzzy \( c \)-means algorithm (PFCM algorithm) \([1 – 3]\). A herewith, these algorithms can operate with type-1 fuzzy sets and type-2 ones, which work with the footprint of uncertainty and allow describing the uncertainty more correctly \([4]\).
Under the clustering problem scientists understand the finding of a partition of the original set of objects that form the structure of clusters present in the analyzed data. Depending on the clustering algorithm used, this problem is reduced to finding the crisp membership of objects (for example, pixels) to clusters (in the case of the classical crisp clustering algorithms, for example, the k means algorithm) or degrees of the ownership (typicality) of objects to clusters, which together define a fuzzy (possibilistic, possibilistic-fuzzy) partition of the original set of pixels.

In general, the clustering problem has the form: to determine such partition \( P(R) = \{ R_k | R_k \subseteq R \} \) of the pixels’ set of image \( R \) for a given number \( c \) of clusters \( R_k \) \((k = 1, c)\), which provides an extremum of a certain objective function \( f(P(R)) \) among all partitions [1]. For example, a fuzzy partition of the image pixels is a system of fuzzy subsets \( P(R) = \{ R_k | R_k \subseteq R \} \), if the condition \( \cup k R_k = R \) \((R_k \in R)\) is fulfilled.

To improve the quality of the image segmentation, it is reasonably, firstly, to apply the different clustering algorithms to the image, and, then, to apply an approach, realizing modern intellectual technique that allows to take into account all clustering results simultaneously by the best way.

2. **FCM algorithm**

For calculating the distance \( d(x_i, x_q) \) between the objects \( x_i \) and \( x_q \) in the \( l \)-dimensional characteristics’ space in the clustering algorithms under uncertainty conditions the following function, based on Euclidean metric, can be used:

\[
d(x_i, x_q) = (\sum_{j=1}^{l} (x^j_i - x^j_q)^2)^{0.5}
\]

(1)

The FCM algorithm (fuzzy c-means) implements the fuzzy interpretation of uncertainty and belongs to iterative algorithms that compute the values of the membership functions to the clusters and the centers’ coordinates in accordance with the values of the membership functions [1, 2].

The FCM algorithm performs the minimization of the objective function [1, 2]:

\[
J(U, V) = \sum_{r=1}^{c} \sum_{i=1}^{n} (u_r(x_i))^m \cdot d^2(v_r, x_i)
\]

(2)

given that

\[
\sum_{r=1}^{c} u_r(x_i) = 1 \quad (c \in N \text{ and } c > 1; \ i = \overline{1,n}),
\]

(3)

where \( U = [u_r(x_i)] \) is a fuzzy c-partition of the objects’ set \( X \) on the base of the membership functions \( u_r(x_i) \), determining the degree of membership of the \( i \)-th object to the \( r \)-th cluster; \( V = (v_1, ..., v_c) \) is the clusters’ centers’ vector; \( d(v_r, x_i) \) is the distance between the cluster center \( v_r \) and the object \( x_i \) in accordance with (1); \( m \) is a fuzzyfier \((m \in R, \ m > 1)\); \( c \) is the clusters’ quantity; \( n \) is the objects’ quantity; \( i = \overline{1,n} \); \( r = \overline{1,c} \).

The FCM algorithm involves the following steps [2].
1. Initialization of c-partition \( U = [u_r(x_i)] \), which satisfies (3).
2. Calculation of the centers’ coordinates:

\[
v^j_r = \left( \sum_{i=1}^{n} (u_r(x_i))^m \cdot x^j_i \right) / \sum_{i=1}^{n} (u_r(x_i))^m
\]

(4)

3. Calculation of the membership functions values:

\[
u_r(x_i) = \frac{1}{\sum_{i=1}^{n} (d(v_r, x_i)/d(v_r, x_i))^2/(m-1)}
\]

(5)
4. Steps 2 and 3 are repeated until a predetermined quantity of iterations $H$ is reached or a predetermined accuracy is reached: $|J(U,V) - J'(U,V)| \leq \varepsilon$, where $J(U,V)$ and $J'(U,V)$ are the values of the objective function (2) in two successive iterations.

The membership functions $u_i(x_j)$ play the role of the weight coefficients, determining the degree of a pixel contribution to the cluster center assessment and, accordingly, the degree of belonging of the $i$-th pixel to the $r$-th cluster. The degree of a pixel contribution depends on the choice of the fuzzifier, which controls the degree of the “fuzziness” of the segmentation.

For small values $m$, a fuzzy partition degenerates into a crisp one, if $m \to \infty$, then the membership functions of pixels to each cluster become equal to $1/\varepsilon$, that is, each pixel belongs to each cluster with equal probability. Usually, a value of 2 is selected as the value of the fuzzifier.

When using the FCM algorithm, the local-optimal fuzzy partition is calculated, which is described by a set of the membership functions, and the coordinates of the clusters’ centers. To obtain the adequate results of the fuzzy clustering, it is necessary to repeatedly perform the FCM algorithm for a given number of clusters for the different initial fuzzy partitions in order to make a final decision on the desired fuzzy clustering. Also, it is possible to use any evolutionary optimization algorithm, for example, the genetic algorithm or the particle swarm optimization algorithm.

As an indicator of the partition quality it is recommended to use the index $XB$:

$$XB = \frac{J(U,V)}{n \cdot \min_{k=1}^{n} d(v_k, v_i)},$$

(6)

where $J(R,U)$ is an objective function (2).

The index $XB$ takes into account both the fuzzy degrees of the objects belonging to the centers of the clusters and the geometrical arrangement of the centers of the clusters and objects, which in the most cases allows obtaining the adequate segmentation results. As a result, the centers of the desired clusters “tightened” to the aggregation of objects, while ensuring minimal similarity between the characteristics of pixels belonging to different clusters.

The FCM algorithm does not always accurately estimates the centers’ coordinates due to the use of possible enforcement, determined in (3). The membership functions calculated based on the constraint (3) determine the separation degrees rather than the typicality degrees for pixels. Therefore, atypical pixels (pixel-noise) located at the same distance from the real cluster centers can strongly influence the estimates of the coordinates of the cluster centers, and, consequently, the final result of clustering. One of the approaches to reduce the noise effect (the influence of the atypical pixels on clustering results) is based on the use of the weighting factors that are inversely proportional to the distance of a pixel from the center of the cluster.

The PCM algorithm can be used to reduce the effect of the atypical objects on the clustering results [2, 3]. The PCM implements the possibilistic interpretation of uncertainty and belongs to iterative algorithms that compute the typicality functions to the clusters and the centers’ coordinates in accordance with the values of the typicality functions [2, 3].

The use of the PCM algorithm is effective if the set of the image pixels contains pixel noise. However, the use of the PCM algorithm can lead to the formation of the coincident clusters, since the functions of the typicality of pixels to a certain cluster do not depend on the distances of the pixels to other clusters. In this case, a reasonable approach will be the simultaneous consideration of both cluster relativity and cluster typicality of pixels, that is realized in the PFCM algorithm [2].

These algorithms have the different objective functions and implement the uncertainty accounting differently. Therefore, they can give different the clustering results for some objects (pixels).

In this regard, it is advisable to implement an approach that implements the ensemble of the results from different clustering algorithms.
3. Expansion of the characteristics’ space

The use of the FCM algorithm in the classic version described above, that is, directly to the original set of the image pixels to perform their segmentation, is accompanied by ignoring the information about the location of pixels on the original image, that can lead to the formation of many small, significantly distant from each other areas related to one cluster. A herewith, the neighboring pixels can be assigned to different clusters, due to the possible noise in the image.

In the experiments we used the set of images obtained from the Resurs-DK spacecraft and analyzed the results of the segmentation of these original images based on the FCM algorithm in the classic version. In many experiments we found that the original images were fragmented into several disconnected areas, that can make it difficult to further high-level processing.

To eliminate this drawback (the fragmentation of images into unrelated areas) the so-called expansion of the characteristics’ space can be implemented [5]. In the classic version of the fuzzy clustering algorithm (that is, without expanding the characteristics’ space), each pixel is associated with a vector \( r_i \) composed of the characteristic values of only this pixel. When performing the expansion of the characteristics’ space, the characteristic values of the pixels in a four- or eight-connected domain adjacent to the considered one are added to the vector \( r_i \) (Fig. 1).

![Domains](image)

**Figure 1.** The domains: a) the four-connected domain; b) the eight-connected domain

A comparative analysis of the clustering results with expansion of the characteristics’ space did not reveal the significant differences in the segmentation quality when the four- and eight-connected domains were used. A herewith, the processing speed of a four-connected domain is substantially (up to one and a half) higher than the processing speed of an eight-connected one. In this regard, the expansion of the characteristics’ space on the four-connected region is preferable to use for the image segmentation.

The segmentation results of the original images based on the FCM algorithm with expansion of the feature space using a four-connected domain show, that the expansion of the characteristics’ space made allows to obtain the unfragmented selection of the observed objects. Thus, the expansion of the characteristics space provides more adequate segmentation results.

4. Experimental studies

The experimental studies were performed for the identification problem of the cloud formations in the satellite images. In this subject area, the clustering should be carried out in the HSV color space (Hue, Saturation, Value).

Since a person can easily recognize the cloudiness in the satellite images, the results of manual separation of the cloud formations can be taken as the segmentation standard. The original satellite image and the results of the manual processing are presented in Fig. 2 and 3, respectively.

To visualize the results of the work of the fuzzy clustering algorithm described above, it is necessary to convert the resulting fuzzy partition into a crisp one.

A herewith, the following defuzzification rule can be used:

“If \( u_{ik} (x_i) > u_{it}(x_i) \) for \( t = 1, c, k = 1, c \) \( k \neq t \), then pixel \( x_i \) strictly belongs to the cluster \( k \) ”.
The segmentation results of the original image (Fig. 2) based on the FCM algorithm are shown in Fig. 4.

![Figure 2. The original image](image1)

![Figure 3. The results of manual selection of the cloud formations](image2)

![Figure 4. The segmentation results of the cloud formations based on the FCM algorithm](image3)

To evaluate the accuracy characteristics of the FCM algorithm, when performing the image segmentation 50 experiments were conducted. Based on the pixel-by-pixel comparison of the segmentation results based on the FCM algorithm with the results of manual selection of the cloud formations, the averaged percentages of the true and incorrectly classified pixels to the total number of pixels in the original image, were calculated. A herewith, 94.73% of pixels were correctly classified, 1.52% of pixels were mistakenly referred to the cloud cluster, and 3.75% of pixels were mistakenly not referred to the cloud cluster. The obtained assessments of the accuracy characteristics indicate the feasibility of applying clustering algorithm to the image segmentation problems. For the original image of 600x700 pixels in size, the segmentation time based on the FCM algorithm averaged over 50 experiments was 10.54 seconds.

Due to the independence of the calculations for the image pixels in the FCM algorithm, the processing speed can be significantly with the use of parallel computing technology.

The same close segmentation results can be obtained with other clustering algorithms under uncertainty conditions. However, for some pixels, the segmentation results may be different due to the specificity of the applied clustering algorithms under uncertainty conditions.

To improve the quality of the image segmentation and solve the problem of the ambiguous classification of some pixels by different clustering algorithms under uncertainty conditions, it is possible to use voting technique according to the majority vote. Also, it is possible to use more modern intellectual approach to making-decision based on application of the SVM classifier (Support Vector Machine) [2, 6-8], which allows to realize the binary pixel classification [7]. In this case, the well-classified pixels (i.e., the pixels equally classified by the different clustering algorithms) should be used to form the experimental dataset which is applied for creation of the training and test sets for development of the SVM classifier. The developed SVM classifier can be used to classify the poorly classified pixels (i.e., pixels differently classified by the different clustering algorithms under uncertainty conditions). The ways of forming of the experimental dataset were described in [2].

Moreover, the use of the ensembles of the SVM classifiers is possible [3]. Application of the SVM classifiers and their ensembles allow improving the segmentation quality by 2-5%.

5. Conclusion
The experimental studies show the high efficiency of the clustering algorithms under uncertainty conditions in processing images from remote sensing spacecraft. A herewith, the expansion of the characteristics’ space of to the four-connected domain allows to significantly improve the results of the image segmentation at an acceptable time cost. The use of the SVM classifiers and their ensembles
is appropriate in solving the problem of the ambiguous classification of a portion of image pixels by the different clustering algorithms under uncertainty conditions. Also, the random forest algorithm (RF algorithm) or the artificial neural networks can be applied in solving the problem of the ambiguous classification, since they use the general paradigm of the machine learning algorithms. Therefore, the purpose of the further research is to implement a new tool for the data classification and a comparative analysis of the classification results in the case of the ambiguous classification fulfilled by the different clustering algorithms under uncertainty conditions.

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