A framework for multi-sensor image segmentation using fuzzy collaborative clustering

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SUMMARY

The massive availability of remote sensing data and advances in data analytics have improved the capacity for mapping land cover and subsurface.

Specifically, in case of multi-sensor remote sensing images, the independent analysis of each image ignores the valuable complementary information available in other images. To address this problem, a framework of multi-sensor image analysis using fuzzy collaborative clustering is proposed. The proposed framework avoids the independent analysis of each image but combines the information available in one image with the complementary information given by the all other images for improved image understanding and segmentation.

Specifically, the clustering of pixels in each image is collaborated with the clustering results of other images to refine its results. The proposed framework can simultaneously process different heterogeneous images from various sensors. The proposed framework was evaluated and validated through an experiment in which two multi-sensor images, i.e., Landsat-5 TM and ENVISAT ASAR were used over the Beijing urban area and compared with the standard fuzzy c-means clustering. Experimental results show that the proposed framework outperforms the independent image segmentation analysis in detecting the urban growth of Beijing. This framework serves as a useful tool for various earth science applications.

Key words: image segmentation, fuzzy collaborative clustering, multi-sensor images, urban growth information extraction.

INTRODUCTION

Remote sensing is widely used for mapping large and remote areas providing an insight into their structural, geological and geo-morphological features to assist geoscientists in making successful business decisions (Saibi et al., 2018).

In recent years, the increase in number of satellite sensors made it possible to have multi-sensor images of the same area with very different characteristics. Often the multi-sensor images are characterised by diverse spectral, temporal and spatial resolutions. The independent analysis ignores the useful information available in other images lowering the accuracy and visual interpretation. In this context, we process several images simultaneously in the clustering phase. We address the problem of image segmentation by using an unsupervised approach to automatically build a segmentation. The proposed framework utilizes multi-sensor images simultaneously by combining the information from one image with the complementary information given by the all other images. Each image collaborates with other images and integrates the semantic information into the clustering algorithm to improve the accuracy and visual interpretation compared with the independent approach.

The standard change detection methods based on clustering deal with the remote sensing images independently discounting the valuable complementary information available in other images (Singh, 1989), (Lu et al., 2004) and (Bhagat, 2012). In the domain of multi-sensor image analysis, a lot of work was focused on the development of image fusion techniques. Pohl and Genderen (1998) described three types of image fusion: pixel, feature and decision level, based on the stage where fusion took place. In pixel level fusion scheme, the values given by several sources are merged to generate a fused image. Feature level fusion consists of two steps. The first step creates new features from different data sources that are merged and analysed in the second step. Decision level fusion deals with finding a single decision from all the decisions produced by the classifiers. Du et al. (2012) discussed the both decision and feature level fusion of difference images generated by various methods for temporal change detection over an urban area by using images from same sensor. Since each method for producing difference image has its own pros and cons, therefore, integrating their merits to recognize spectral changes produced better results from each individual method.

Unlike the standard methods of image fusion which are based on either the pixel, feature or decision level, the proposed framework communicates the clustering result of one image with the clustering results of the images from other sensors. The required communication links are established at the level of information granules (more specifically, fuzzy sets forming the partition matrices) rather than patterns that are directly available in the images as in the case of feature level fusion. The proposed framework captures the structure among all the images by exchanging information about local patterns in form of a partition matrix and is anticipated to improve the visualization and accuracy of the application area.

The rest of the paper is organized as follows. The next section describes the data and study area. Then proposed multi-sensor image segmentation framework and experimental results are presented. Finally, last section draws the conclusions.
STUDY AREA

The urban area of Beijing has expanded at a very high rate since late 1970s when the reform and opening policy was established. To analyse the urban growth, accurate and timely land-cover data produced from multi-sensor data sets are required. Two different sensor’s data were utilized for segmentation, from the Landsat-5 TM and ENVISAT ASAR sensors. The Landsat-5 TM image was acquired in July 2005 with 30 m spatial resolution. The ENVISAT ASAR data with 30 m spatial resolution was acquired in May 2005 with two polarizations HH and HV. This image was co-registered to the Landsat TM image with a RMSE less than 0.5 pixels. An image subset of 1860 × 1600 pixels selected for the analysis is shown in Figure 1. The largest land cover class in this subset is the built-up area represented by purple colour in the Landsat-5 TM image and with light grey colour in the ENVISAT ASAR image. The problem of measuring the urban growth can be regarded as a clustering problem with two clusters in which the built-up class needs to be delineated from the non-built-up class. Let the Landsat-5 TM and ENVISAT ASAR images be the target and the auxiliary image, respectively.

METHODS

It is well known that combining different sources of information may improve the accuracy of remote sensing image analysis. Based on this rationale, we define the problem as follows. Given a finite number of multi-sensor images with pixels defined in the same or different feature space, develop a scheme based on cluster structure across all the multi-sensor images to finally produce a single segmented image.

In order to tackle the above stated problem, we used the fuzzy collaborative clustering method proposed by Pedrycz (2002) and Pedrycz and Rai (2008) for several subsets of patterns across databases. We adapted this method for simultaneous processing of multi-sensor images.

Let consider, we have P images from different sensors for the same study area, and the number of pixels in each image is the same and equal to n. Each image is segmented into c clusters to produce the respective prototypes and partition matrices. Let θ[ii] and U[ii] represent the ith prototype and partition matrix, respectively, produced by the clustering performed over the ii-image. The dimensionality of the pixels, represented by θ[ii], is equal to number of bands and could be different in each image. The standard Fuzzy C-means (FCM) algorithm is used to generate initial clusters. FCM attempts to find soft partitioning of the given image by minimizing the following objective function.

\[ J[ii] = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ii}^{2}[ii] d_{j}^{2}[ii], \quad ii = 1, 2, ..., P \]  

where, \( J[ii] \) is the objective function to be minimized for ii-image, \( U = u_{k}(x) \) a \( c \times n \) partition matrix, \( d_{j}^{2}[ii] \) is the dissimilarity between \( x \) and \( \theta_{k}, \theta = [\theta_{1}, \theta_{2}, ..., \theta_{c}] \), for \( ii = 1, 2, ..., P \). \( \theta \) is a parameterized representative (centroid) of the \( j^{th} \) cluster.

The collaboration between the images is established through a matrix of interaction \( a_{ii, jj} \), whose elements describe the intensity of interaction. The reformulated objective function incorporating the collaboration among all images is given by Equation 2.

\[ J[ii] = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ii}^{2}[ii] d_{j}^{2}[ii] \]

\[ + \sum_{j=1}^{p} \sum_{k=1}^{n} a_{ii, jj} \left( \sum_{i=1}^{c} u_{ii}^{2}[ii] - u_{ii}^{2}[jj] \right)^{2} d_{j}^{2}[ii], \quad ii = 1, 2, ..., P \]

(2)

The first term in the above expression is the standard FCM objective function (Equation 1) and the second term is responsible for incorporating the clustering results of other images.

The objective function is optimized by using the well-known Lagrange technique and leads to the following new objective function \( Q[ii] \) for each data point \( (j = 1, 2, 3, ..., n) \), namely

\[ Q[ii] = \sum_{i=1}^{c} u_{ii}^{2}[ii] d_{j}^{2}[ii] \]

\[ + \sum_{j=1}^{p} \sum_{k=1}^{n} a_{ii, jj} \left( \sum_{i=1}^{c} u_{ii}^{2}[ii] - u_{ii}^{2}[jj] \right)^{2} d_{j}^{2}[ii] \]

\[ - \lambda \left( \sum_{i=1}^{c} u_{ii}^{2}[ii] - 1 \right) \]  

(3)

In Equation 3, \( \lambda \) denotes a Lagrange multiplier. Optimization of \( Q[ii] \) yields the prototypes \( \theta[ii], \theta[ii,...,\theta[ii] \) and partition matrix \( U[ii] \) as follows

\[ \theta_{ii}[ii] = \frac{\sum_{j=1}^{c} u_{ii}[ii] x_{j} + \frac{p}{\sum_{j=1}^{p} a_{ii, jj}} \sum_{j=1}^{p} a_{ii, jj} \left( \sum_{i=1}^{c} u_{ii}^{2}[ii] - u_{ii}^{2}[jj] \right)^{2} x_{j}}{1 + \frac{\sum_{j=1}^{p} a_{ii, jj}}{\sum_{j=1}^{p} a_{ii, jj}}}, \]

(4)

\[ s = 1, 2, ..., c, \quad t = 1, 2, ..., n[ii], \quad ii = 1, 2, ..., P \]

\[ u_{ii}[ii] = \frac{1}{1 + \frac{\sum_{j=1}^{p} a_{ii, jj}}{\sum_{j=1}^{p} a_{ii, jj}}}, \]

(5)

\[ s = 1, 2, ..., c, \quad t = 1, 2, ..., n[ii], \quad ii = 1, 2, ..., P \]
The fuzzy collaborative clustering framework for multi-sensor image segmentation consists of two phases. Firstly, independently generates same number of clusters in each image by using the standard FCM. Secondly, communicates the clustering results through the preliminary calculated prototypes (Equation 4) and partition matrices (Equation 5), and simultaneously proceeds optimization of all the partition matrices. Figure 2 presents the schematic illustration of the fuzzy collaborative clustering framework for a two multi-sensor image segmentation problem.

![Figure 2](image.jpg)

Figure 2. Schematic illustration of fuzzy collaborative clustering for two images (P = 2) from different sensors. The images are co-registered before clustering and then collaborative to integrate the information for final image segmentation and accuracy assessment.

RESULTS AND DISCUSSION

The proposed framework based on fuzzy collaborative clustering method (Pedrycz, 2002) was evaluated and validated through an experiment in which two multi-sensor images (P = 2) over the Beijing urban area were used. The goal is to utilize these two heterogeneous sources of information by fuzzy collaborative clustering to segment the target image into two clusters: built-up and non-built-up, and to show that the auxiliary image improves the segmentation of the target image. Figure 3a represents the segmentation of the target image (Landsat-5 TM) with no collaboration by using the standard FCM algorithm. A visual comparison with the original Landsat-5 TM image (Figure 1a) reveals that the standard FCM was not able to correctly identify quite a large area as the built-up class in the middle of the image indicated by purple colour. When the auxiliary information (ENVISAT ASAR image) is incorporated with interaction intensity of (L2), the outcome is improved significantly as shown in Figure 3(b). Collaboration with the auxiliary image helped to increase the segmentation accuracy of the built-up area especially in the middle of image.

The visual interpretation is confirmed quantitatively by the accuracy estimates for the built-up and non-built-up classes (Table 1). These estimates were calculated using the ground truth information about the two classes available for validation of the clustering results within a subset of the study area. There is a significant improvement in the overall accuracy (OA) and the Kappa coefficient (K) in case of collaboration as compared to the standard FCM with no collaboration (Table 1). The OA and K shows 9% and 24% improvement respectively over the standard FCM. Furthermore, the proposed fuzzy collaborative clustering framework was able to significantly reduce missed alarms (MA) by 8% and false alarms (FA) by 15% compared to the standard FCM approach.

CONCLUSIONS

An image segmentation framework based on fuzzy collaborative clustering for multi-sensor image segmentation is proposed to improve the image visualization and segmentation accuracy. The framework was applied to multi-sensor images covering the Beijing urban area and quantitatively compared with the standard FCM. Taking the advantage of the complementary information available in the auxiliary image, segmentation results of the target image were improved in terms of accuracy and visualization. The experimental results demonstrated the advantage of the collaborative clustering over the independent clustering approach due to utilizing the complementary information from multiple sensors. The proposed framework can be used for any number of multi-sensor images (P > 2). The framework has a potential to improve remote sensing applications for mineral, water and hydrocarbon exploration, geo-structural mapping, natural hazard analysis and geo-morphology enhancement.

REFERENCES


Figure 1. Location of study area (a) Target image (Landsat-5 TM 7, 4 and 2 bands as R, G and B) (b) Auxiliary image (ENVISAT ASAR-HH polarization).

Figure 3. Target image (Landsat-5 TM) segmentation with (a) no collaboration and (b) collaboration with auxiliary (ENVISAT ASAR) image.

Table 1. Accuracy assessment of standard FCM (no collaboration) and proposed framework based on fuzzy collaborative clustering.

<table>
<thead>
<tr>
<th>Target Image (Landsat-5 TM) Segmentation for Urban Built-up</th>
<th>OA (%)</th>
<th>K</th>
<th>MA (%)</th>
<th>FA (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No collaboration</td>
<td>75.89</td>
<td>0.5179</td>
<td>21.57</td>
<td>26.22</td>
</tr>
<tr>
<td>Collaboration with auxiliary (ENVISAT ASAR) image</td>
<td>87.59</td>
<td>0.7518</td>
<td>13.04</td>
<td>11.76</td>
</tr>
</tbody>
</table>