Segmentation of Very High Resolution Remote Sensing Imagery of Urban Areas Using Particle Swarm Optimization Algorithm

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Abstract. As the improvement of the resolution of aerial and satellite remote sensed images, the semantic richness of the image increases which makes image analysis more difficult. Dense urban environment sensed by very high-resolution (VHR) optical sensors is even more challenging. Occlusions and shadows due to buildings and trees hide some objects of the scene. Fast and efficient segmentation of such noisy images (which is essential for their further analysis) has remained a challenging problem for years. It is difficult for traditional methods to deal with such noisy and large volume data. Clustering-based segmentation with swarm-based algorithms is emerging as an alternative to more conventional clustering methods, such as hierarchical clustering and k-means. In this paper, we introduce the use of Particle Swarm Optimization (PSO) clustering algorithm segmenting high resolution remote sensing images. Contrary to the localized searching of the K-means algorithm, the PSO clustering algorithm performs a globalized search in the entire solution space. We applied the PSO and K-means clustering algorithm on thirty images cropped from color aerial images. The results illustrate that PSO algorithm can generate more compact clustering results than the K-means algorithm.

Keywords: Swarm Intelligence, Particle Swarm Optimization (PSO), Remote Sensing, Aerial Images, and Clustering-Based Segmentation.

1 Introduction

With the rapid development of aerospace technologies and remote sensing sensor technologies, images of very high spatial resolution of the earth surface have been obtained more frequently and quickly than before (for example the recently launched satellites: GeoEye-1 and WorldView-2). Therefore, remote sensing images have significant applications in different areas such as urban planning, surveys and mapping, agricultural analysis, environmental monitoring and military intelligence, etc. Remote sensing image analysis, such as image segmentation, image classification and feature extraction, can be challenging because there are many uncertainties in remote sensing data and there is no definite mathematical model that truly captures the image data. Urban land cover information extraction is a hot topic within urban studies. Heterogeneous spectra of the VHR imagery caused by the inner complexity of dense urban

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areas and the occlusions and shadows caused by the variety of objects in urban area, for example buildings, roads, and trees - make it even more difficult and challenging, hindering exhaustive automatic or manual extraction.

In most cases, information needed for image analysis and understanding is not represented in pixels but in meaningful image objects and their mutual relations. Therefore, to partition images into sets of useful image objects is a fundamental procedure for successful image analysis or automatic image interpretation. In this sense, image segmentation is critical for subsequent image analysis and understanding. Image segmentation may be defined as the process of subdividing an image into meaningful non-overlapping regions [1]. Image segmentation can be viewed as a clustering problem, which aims to partition the image into clusters such that the pixels within a cluster are as homogenous as possible whereas the clusters among each other are as heterogeneous as possible with respect to a similarity measure. Clustering algorithms can be divided into four main classes: partitioning methods, hierarchical methods, density-based clustering and grid-based clustering. An extensive survey of clustering techniques is described in [2].

VHR Remote sensing image clustering-based segmentation is a complex task as images are noisy and of large size. It is difficult for traditional methods to deal with these images. This type of data has posed a formidable task for finding global optima in most of traditional clustering techniques. This motivates exploring the use of computational intelligence techniques. For many years now, several papers have highlighted the efficiency of approaches inspired from nature [3]. A variety of algorithms inspired from the biological examples by swarming, flocking and herding phenomena. These techniques incorporate swarming behaviours observed in flocks of birds, schools of fish, or swarms of bees, and even human social behaviour.

Swarm Intelligence (SI) is actually a complex multi-agents system, consisting of numerous simple individuals (e.g., ants, birds, etc.), which exhibit their swarm intelligence through cooperation and competition among the individuals. Although there is typically no centralized control dictating the behaviour of the individuals, the accumulation of local interactions in time often gives rise to a global pattern, SI mainly involves two approaches, i.e., Particle Swarm Optimization (PSO) and ant colony optimization (ACO). SI has currently succeeded in solving problems such as traveling salesman problems, data clustering, combination optimization, network routing, rule induction, and pattern recognition [4], However, using SI in remote sensing clustering is a fairly new research area and needs much more work. In [4] PSO was used as a clustering algorithm. The results show that despite k-means is known to be efficient at clustering large data sets, as its computational complexity only grows linearly with the number of data points [5], k-means may converge to solutions that are not optimal, hence PSO outperformed it as well as fuzzy *c*-means and other state-of-the-art clustering algorithms.

In the literature most of the conventional and SI clustering methods are tested on simple scenes, such as low scale grayscale images of rural or suburban sites, where objects of the sensed scenes are quite visible with less shade or occlusion artefacts than in inner cities. Encouraged by the success of PSO in such scenes, in this paper we aim at using the PSO potential in solving complex optimization problems, to handle dense VHR remote sensing images of dense urban areas, the result shows that

PSO algorithm is capable of segmenting such complex images and it outperforms k-means algorithm.

2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based evolutionary computation technique developed by [3]. PSO simulates the social behaviour of animals, i.e. birds in a flock or fish in a school. Members of such societies share common goals (e.g., finding food) that are realized by exploring its environment while interacting among them. The popularity of PSO is partially due to the simplicity of the algorithm, but mainly to its effectiveness for producing good results at a very low computational cost [6]. In PSO, each solution can be considered an individual particle in a given D-dimensional search space, which has its own position (x_{id}) and velocity (v_{id}). During movement, each particle adjusts its position by changing its velocity based on its own experience (memory) p_{id}, as well as the experience of its neighbouring particles, until an optimum position is reached by itself and its neighbour. All of the particles have fitness values based on the calculation of a fitness function. Particles are updated by following two parameters called p_{best} and g_{best} at each iteration. Each particle is associated with the best solution (fitness) the particle has achieved so far in the search space. This fitness value is stored, and represents the position called p_{best}. The value g_{best} is a global optimum value for the entire population. The two basic equations which govern the working of PSO are that of velocity vector and position vector given by:

$$v_{id}(t+1) = w\, v_{id}(t) + c_1 r_1(t)(p_{id}(t) - x_{id}(t)) + c_2 r_2(t)(p_{id}(t) - x_{id}(t)) \tag{1}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{2}$$

The first part of Eq (1) represents the inertia of the previous velocity, the second part is the cognition part and it tells us about the personal experience of the particle, the third part represents the cooperation among particles and is therefore named as the social component. Acceleration constants c_1, c_2 and inertia weight w are the predefined by the user and r_1, r_2 are uniformly generated random numbers in range of [0, 1].

2.1 PSO Clustering

A particle represents a K-cluster centroids. That is, each particle x_i is constructed as $x_i = (m_{i,1},\ldots m_{i,j},\ldots m_{i,d})$ where $m_{i,j}$ refers to the j-th cluster centroid vector of ith particle. Therefore, a swarm represents a number of candidate data clusterings. The quality of each particle is measured using an objective function [7]. There is a matrix representing the assignment of patterns to the cluster of particle i. Each element $z_{i,k,p}$ indicates if pattern z_p belongs to cluster c_k of particle i. The fitness function has an objective to simultaneously minimize the intra-distance between pixels and their cluster means and to maximize the inter-distance between any pair of clusters. The algorithm is composed of the following steps:

1. Initialize each particle to contain N_c randomly selected cluster centroids.
2. For $t = 1$ to t_{max} do

i. For each particle *i* do
ii. For each data vector z_p
   a. calculate the Euclidean distance $d(z_p, m_{ij})$ to all cluster centroids C_{ij}
   b. assign z_p to cluster C_{ij} such that distance
      $d(z_p, m_{ij}) = \min_{\forall c=1,\ldots Nc} \{ d(z_p, m_{ic}) \}$
   c. calculate the fitness function [7].
iii. Update the global best and local best positions
iv. Update the cluster centroids.

where t_{max} is the maximum number of iterations. The population-based search of the PSO algorithm reduces the effect that initial conditions have, as opposed to the K-means algorithm; the search starts from multiple positions in parallel. However, the K-means algorithm tends to converge faster (after less function evaluations) than the PSO, but usually with a less accurate clustering [4].

2.2 Clustering Validation Measures

These measures are usually used to evaluate to quantitatively evaluate the result of a clustering algorithm[8]. In the following, we briefly explain some quality measures of clustering techniques[7]:

- *Compactness*: samples in one cluster should be similar to each other and different from samples in other clusters. An example of this would be the within-cluster distance and can be calculated by:

$$\mathrm{F_c}(\mathrm{m_1},\ldots..\mathrm{m_k}) = \frac{1}{K}\sum_{k=1}^{K}\frac{1}{n_k}\sum_{j=1}^{n_k} d(m_k, y_{jk}) \tag{3}$$

where $d(\cdot)$ is the distance between cluster center, m_k, and y_{jk} which is sample j of cluster k. The objective is to minimize this measurement as possible.

- *Separation*: clusters should be well-separated from each other. It's also known as between-clusters distance. An example of this criterion is the Euclidean distance between clusters centroids. The objective is to maximize the separation between different clusters as possible. Separation is calculated using the following equation:

$$\mathrm{F_s}(\mathrm{m_1},\ldots..\mathrm{m_k}) = \frac{1}{K(K-1)}\sum_{j=1}^{K}\sum_{k=j+1}^{K} d(m_j, m_k) \tag{4}$$

- *Combined measure:* This measure is a linear combination of the compactness and separation measures [7]. Having the within-cluster and between-cluster distances defined, we can now construct the combined measure

$$F_{\text{combined}} = \omega_1 F_c - \omega_2 F_S \tag{5}$$

where ω_1 and ω_2 are weighting parameters such that $\omega_1 + \omega_2 = 1$.

- *Turi's validity index:* Turi, [9], proposed an index incorporating a multiplier function (to penalize the selection of a small number of clusters) to the ratio between intra-cluster and inter-cluster, the measure is defined as;

$$F_{Turi}(m_1,....,m_K) = (c \times N(2,1)+1) \times \frac{\text{int}\,ra}{\text{int}\,er} \tag{6}$$

where c is a user specified parameter and N(2,1) is a Gaussian distribution with mean 2 and standard deviation of 1. The *intra* term is the average of all the distances between each data point and its cluster centroid and it's used to measure the compactness of clusters as given is Eq. 3 while the inter term is the minimum distance between the cluster centers, this term used to measure the separation of the clusters and is given by:

$$\text{int}\,er = \min\{\|m_k - m_l\|\} \forall k = 1,..K-1, l = k+1,....K \tag{7}$$

The goal is to minimize the Turi's validity index as possible.

3 Experimental Results

The goal here is to compare the performance of the PSO clustering methods and k-means in segmenting VHR remote sensing imagery, and to investigate the PSO ability to segment land-use classes in dense urban areas.

3.1 Dataset

The study area is the city of Kitchener-Waterloo (K-W), Canada. The data was provided by the University Map Library at the University of Waterloo [10] as ortho-rectified aerial images taken in April 2006 at 12 cm spatial resolution by a digital color airborne camera with 8 bit radiometric resolution. We cropped a set of forty test images of size 666*372 from the original image. The cropped test images were chosen for high density urban parts which are highly corrupted by noise. Samples of the test image are shown in Figure. 1.

Fig. 1. Samples of test images that are corrupted by noise

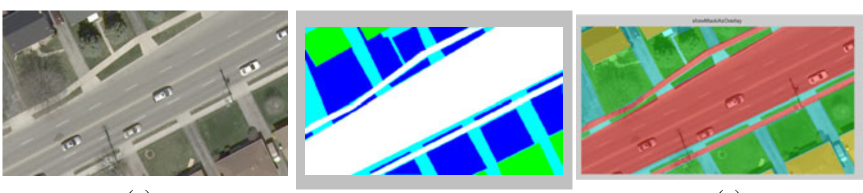
It is difficult to specify any desired number of clusters in the segmentations of remote sensing images, because the ground truth is always not available for the scenes covered by those images. The major objects of interests in urban planning are roads, buildings and green area such as parks. Test images were manually segmented into four land use types (roads, buildings, green area and other). Other represents pixilation which is either difficult to interpret or does not correspond to the objects of interests like building entrance with a very small parking area alongside the road, swimming pools and other small objects in the image. A sample test image is shown in Fig. 2 with its ground truth.

3.2 Experiment Setup

In the applications of VHR remote sensing images in urban studies, road extraction is the most basic and important task. To extract it, the number of clusters is defined empirically to be four clusters. It was chosen by minimize the error between the clustered image and the ground truth images. Although four to seven spectral clusters work well for most of the test images, four clusters have been selected as it gives the best average accuracy for the entire set of the test images.

For each clustering method there are some free parameters need to be tuned in order to assess the best average performance provided by each one of them over the whole set of the test images. K-means doesn't require any parameter tuning. In the PSO clustering algorithm, we carried out different trials with different values for the number of particle, the value was set to 60 particles for all images which is higher then the recommended number, 20 to 30 particles, giving in [11] as the image data is large data set. Increasing the particle number in the algorithm can increase the chance for finding the optimal solution however the algorithm require more time to converge, the inertia weight ***w*** is initially set as 1.2 and is reduced by 1% at each generation to ensure good convergence . The acceleration coefficient constants c_1 and c_2 are set as 1.49. These values are chosen based on the results shown in [11].

Throughout this paper, we use f-measure as a quality assessment measure for the mapping between classes (ground truth) and clusters returned using four cluster validity indices. We compare the average performance of PSO clustering and K-means methods. We look at the average over 40 multiple runs for each method and consider the standard deviation. The average execution time of the 40 runs are also compared.



(a) (b) (c)

Fig. 2. Sample of the images and its ground truth: (a) original image, (b) ground truth and (c) ground truth overlaying the original image (right)

3.3 Results

We compare the average performance of PSO and K-means clustering methods focusing on dense urban areas in VHR aerial images. The original image pixel's RGB values are used as spectral feature. The average is taken over 40 for each method. The standard deviation of the error is around 0.1 and 0.2 for all methods. Table 1 shows the results over the 40 test set images using an Intel core 2 Duo T5550 @ 1.83 GHz Processors with 2 MB cache and 3 GB RAM. The table shows the clustering accuracy and the different error measures mentioned in sec 2.2. The result shows the potential of the PSO clustering of aerial images starting from the three RGB bands only. In the experiment we could achieve an average rate of 83% of extracting road areas even in the noisy images of the residential areas.

Table 1. Comparison of clustering accuracies and errors for k-means, PSO clustering methods using different clustering objective functions for road extraction from the aerial images test set

Roads	Clustering Accuracy ↑	*Compactness* ↓	*Separation* ↑	*Combination* ↓	*Turi's index* ↓
PSO-Separation	0.837± 0.081	63.628± 6.703	104.029± 11.487	37.655± 4.422	1.169± 0.203
PSO-Compactness	0.811± 0.078	12.232± 2.456	48.9729± 8.7828	3.166± 0.459	3.050± 1.019
PSO-Combined	0.853± 0.076	21.413± 3.897	87.576± 5.869	3.003± 1.116	2.7883± 0.769
PSO- Trui	0.826± 0.073	32.419± 3.098	55.836± 5.848	8.919± 1.234	1.830± 0.202
K-means	0.754 ± 0.074	6.0837± 0.1474	39.525± 1.022	-0.756± 0.716	0.611± 0.231

4 Conclusion

In this research, which has been motivated by the superiority of PSO over the traditional clustering algorithms in segmenting remote sensing imagery of rural and suburban areas, we tackled the use of PSO in segmenting more complex scenes as VHR remote sensing data in urban areas. The results show that we can extract geographic objects such as roads with 83% accuracy using primitive features as the RGB intensity values of the image pixels.

The next step in this research is to investigate the effect of adding texture and shape descriptors to differentiate between objects with similar spectral signatures such as roads and parking lots.

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