Aggregation Pheromone Density Based Change Detection in Remotely Sensed Images

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Ants, bees and other social insects deposit pheromone (a type of chemical) in order to communicate between the members of their community. Pheromone that causes clumping or clustering behavior in a species and brings individuals into a closer proximity is called aggregation pheromone. This article presents a novel method for change detection in remotely sensed images considering the aggregation behavior of ants. Change detection is viewed as a segmentation problem where changed and unchanged regions are segmented out via clustering. At each location of data point, representing a pixel, an ant is placed; and the ants are allowed to move in the search space to find out the points with higher pheromone density. The movement of an ant is governed by the amount of pheromone deposited at different points of the search space. More the deposited pheromone, more is the aggregation of ants. This leads to the formation of homogenous groups of data. Evaluation on two multitemporal remote sensing images establishes the effectiveness of the proposed algorithm over an existing thresholding algorithm.

Keywords: Change detection; Remote sensing; Aggregation pheromone system

1. Introduction

Automatic detection of landcover transitions in multitemporal remotely sensed images is of widespread interest due to a large number of real world applications ranging from forestry and agricultural surveys to urban studies and natural disaster management.[1-3] In many real world applications of change detection, the objective is to map only one (or, few) landcover transition(s) of interest like agricultural land to urban area, forest to burned area, forest to agricultural land *etc.* Land-cover change detection using multi-temporal remote-sensing images is a challenging task due to lack of a-priori information about the shape of changed areas, absence of a reference background, differences in light conditions, atmospheric conditions, sensor calibration, ground moisture at the two image acquisition dates, alignment of multi-temporal images (registration) *etc.*[4,5] These factors restrict the use of most classical multitemporal image-analysis techniques to few remote-sensing change analysis problems. There are several techniques available in the literature [6-11] where Neural Networks, Markov Random Field (MRF) and Support Vector Machines (SVM) are used for detecting changes in remotely sensed images. In this article change detection is viewed as a segmentation problem, where changed and unchanged regions are segmented using clustering. Clustering is performed considering the aggregation behavior found in ants and ant like agents.

Numerous clustering algorithms have been developed inspired by the ability of ants to cluster their corpses into "cemeteries" in an effort to clean up their nests.[12] Besides nest cleaning, many functions of aggregation behavior have been observed in ants and ant like agents.[13,14] These include foraging-site marking and mating, finding shelter and defense. For example, after finding safe shelter, cockroaches produce a specific pheromone with their excrement, which attracts other members of their species.[14] Tsutsui and Ghosh[15] used aggregation pheromone systems for continuous function optimization where aggregation pheromone density is defined by a density function in the search space. Inspired by the aforementioned aggregation behavior found in ants and other similar agents, attempts are already made for solving clustering[16] and image segmentation[17] problems. In this article this metaphor is used to detect changes in remote sensing images.

2. Aggregation Pheromone Density based Change Detection

As mentioned in the introduction, aggregation pheromone brings individuals into closer proximity. This group formation nature of aggregation pheromone is being used as the basic idea of the proposed technique. Here each ant represents one data/pixel of an image. The ants move with the aim to create homogenous groups of data. The amount of movement of an ant towards a point is governed by the intensity of aggregation pheromone deposited by all other ants at that point. This gradual movement of ants in due course of time will result in formation of groups or clusters. The proposed technique has two parts. In the first part, clusters are formed based on ants' property of depositing aggregation pheromone. The number of clusters thus formed might be more than the desired number. So, to obtain the desired number of clusters, in the second part agglomerative *average linkage*[18] clustering algorithm is applied on these already formed clusters.

2.1. *Formation of Clusters*

While performing segmentation for a given image, we group similar pixels together to form a set of coherent image regions. Similarity of the pixels can be measured based on intensity, color, texture and consistency of location of different pixels. Individual features or combination of them can be used to represent the pixel of an image. For each pixel, we associate a feature vector $\mathbf{x}$. Clustering is then performed on all the pixels to group them into segments.

Let us consider a data set of n patterns $(\mathbf{x_1}, \mathbf{x_2}, \mathbf{x_3}, ..., \mathbf{x_n})$ and a population of n-ants $(A_1, A_2, A_3, ..., A_n)$ where an ant A_i represents the data pattern $\mathbf{x_i}$. Each individual ant emits pheromone in its neighborhood. The intensity of pheromone emitted by an individual A at $\mathbf{x}$ decreases with its distance from it. Thus the pheromone intensity at a point closer to $\mathbf{x}$ is more than those at other points that are farther from it. To achieve this, the pheromone intensity emitted by A is assumed to follow a Gaussian distribution. The pheromone intensity deposited at $\mathbf{x}'$ by an ant A (located at $\mathbf{x}$) is given by

$$\triangle\tau'(A, \mathbf{x}') = \exp^{-\frac{d(\mathbf{x},\ \mathbf{x}')^2}{2\delta^2}}, \tag{1}$$

and the total aggregation pheromone density deposited by the entire population of n ants at $\mathbf{x}'$ is then given by

$$\triangle\tau(\mathbf{x}') = \sum_{i=1}^{n} \exp^{-\frac{d(\mathbf{x_i},\ \mathbf{x}')^2}{2\delta^2}}, \tag{2}$$

where, δ denotes the spread of Gaussian function. In the similar way, we can compute the total aggregation pheromone density $\triangle\tau(\mathbf{x})$ for any point $\mathbf{x}$.

Now, an ant A' which is initially at location $\mathbf{x}'$ moves to the new location $\mathbf{x}''$ (which is computed using Eq. 3) if the total aggregation pheromone density at $\mathbf{x}''$ is greater than that at $\mathbf{x}'$. The movement of an ant is governed by the amount of pheromone deposited at different points in the search space. It is defined as

$$\mathbf{x}'' = \mathbf{x}' + \eta . \frac{Next(A')}{n}, \tag{3}$$

where,

$$Next(A') = \sum_{i=1}^{n} (\mathbf{x_i} - \mathbf{x}') . \exp^{-\frac{d(\mathbf{x_i},\ \mathbf{x}')^2}{2\delta^2}}, \tag{4}$$

with η as a step size. This process of finding a new location continues until an ant finds a location where the total aggregation pheromone density is more than its neighboring points. Once the ant A_i finds out such a point $\mathbf{x}_i'$ with greater pheromone density, then that point is assumed to be a new potential cluster center, say $\mathbf{Z_j}$ ($j = 1, 2, ..., C$, C being number of clusters); and the data point with which the ant was associated earlier (*i.e.*, $\mathbf{x_i}$) is assigned to the cluster so formed with the center $\mathbf{Z_j}$. Also the data points that are within a distance of $\delta/2$ from $\mathbf{Z_j}$ are assigned to the newly formed cluster. On the other hand, if the distance between $\mathbf{x}_i'$ and the existing cluster center $\mathbf{Z_j}$ is less than $\delta/2$ and the ratio of their densities is greater than *threshold_density* (a predefined parameter), then the data point $\mathbf{x_i}$ is allocated to the already existing cluster centering at $\mathbf{Z_j}$. Higher value of density ratio represents that the two points are of nearly similar density and hence should belong to the same cluster. The proposed aggregation pheromone based clustering (APC) algorithm for formation of clusters is given below.

```
begin
Initialize σ, threshold_density, η and C = 0
for i = 1 : n do
if the data pattern xi is not already
assigned to any cluster
```

```
Compute Δτ(x_i) using Eq. 2
label 1: Compute new location x'_i using Eq. 3
Compute Δτ(x'_i)
if (Δτ(x'_i) > Δτ(x_i))
Update the location of ant A_i to x'_i and goto label 1
else continue
if (C == 0) //If no cluster exists
Consider x'_i as cluster center Z_1 and increase C by one
else
for j = 1 : C
if (min(Δτ(x'_i), Δτ(Z_j))/max(Δτ(x'_i), Δτ(Z_j)) > threshold_density and d(x'_i, Z_j) < δ/2)
Assign x'_i to Z_j
else
Assign x'_i as a new cluster center say, Z_{C+1} and increase C by one
Assign all the data points that are at a distance of δ/2 from x'_i to the newly formed cluster Z_{C+1}
end of else
end of for
end of else
end of if (if the data pattern x_i ...)
end of for
end
```

2.2. *Merging of Clusters*

In this stage, to obtain the desired number of clusters we apply *average linkage*[18] algorithm. The algorithm works by merging the two most similar clusters until the desired number of clusters are obtained.

3. Experimental Results

3.1. *Description of Data Set*

Two real multitemporal images namely Mexico and lake Mulargia have been used for experimental purpose. Mexico image is acquired on 18^{th} April 2000 and 20^{th} May 2002 by Thematic Mapper Plus (TM+) sensor of Landsat-7 satellite. From the entire available Landsat scene, a section of 512x512 pixels has been selected as test site. Significant portion of the vegetation in the aforesaid area between the two dates was destroyed by wildfire. Figs. 1(a) and 1(b) show the channel 4 of the April and May images, respectively. Experts generated the reference map [Fig. 1(c)] by visual analysis of the images with the help of available ground truth concerning the location of wildfire. The reference map is required to assess the change detection errors.

Image of lake Mulargia of Sardinia Island is acquired by Thematic Mapper Plus (TM+) sensor of Landsat-5 satellite on September 1995 and July 1996. Between the two acquisition dates the water level in the lake was increased. Fig. 2 shows a section of 412x300 pixels of channel 4 of September and July image along with the reference map.

3.2. *Results*

From given multitemporal images we compute difference image by taking the absolute difference of the two co-registered images of different dates. The difference images corresponding to Mexico and lake Mulargia are shown in Figs. 1(d) and 2(d), respectively. Feature vector corresponding to each pixel of the difference image is generated by considering its gray value and the average gray value of neighboring pixels (second order). The algorithm, described in Section 2, is then applied on this difference image to obtain the corresponding change detection map [Figs. 3(a) and 4(a)]. Values of η and *threshold_density* are kept to 1 and 0.9, respectively and different values of δ in the range [0, 1] are considered. We determine a stable range of δ for which clusters were compact. Results are shown for a δ value taken from this range. The results obtained by the proposed *APC* algorithm are compared with those obtained by ground truth based optimal Manual Trial and Error Thresholding (MTET) technique and are depicted in Table 1.

Table 1. Missed alarms, false alarms and total alarms resulting from the proposed APC algorithm and MTET.

Images used	Technique used	Missed alarms	False alarms	Total alarms
Mexico	APC(δ=0.23)	2654	760	3414
	MTET	2404	2187	4591
Lake	APC(δ=0.57)	1000	599	1599
	MTET	1015	875	1890

It is seen from the table that missed alarms (changed pixels classified as unchanged) obtained by

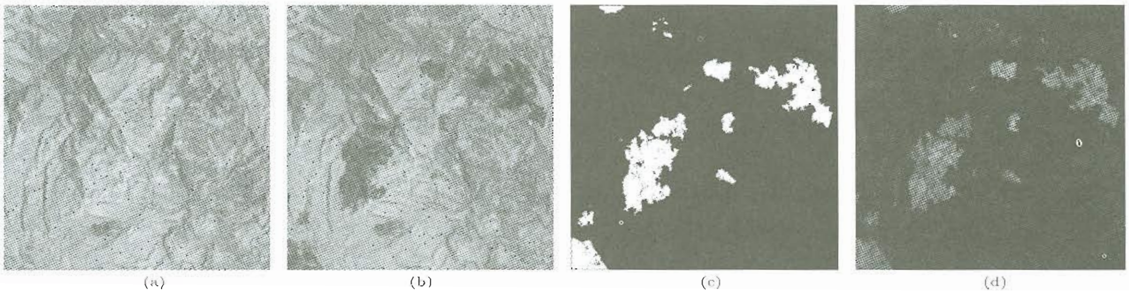

Fig. 1. Mexico image (a) Acquired on April 2000 (b) Acquired on May 2002 (c) Reference map (d) Difference image.

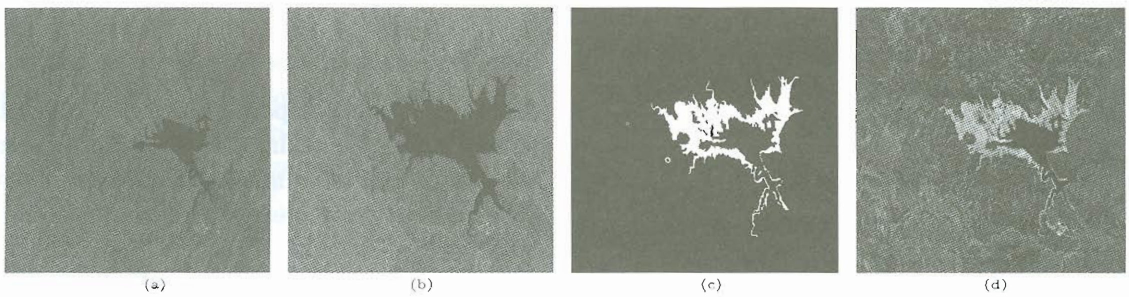

Fig. 2. Lake Mulargia image (a) Acquired on September 1995 (b) Acquired on July 1996 (c) Reference map (d) Difference image.

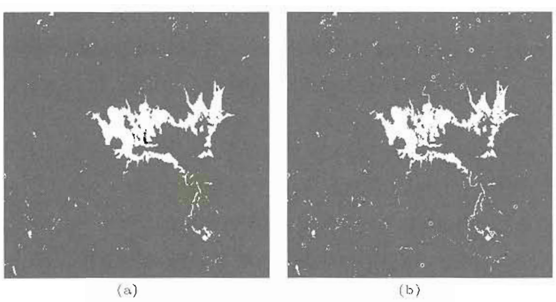

Fig. 4. Change detection map for lake Mulargia image by (a) APC algorithm (b) MTET.

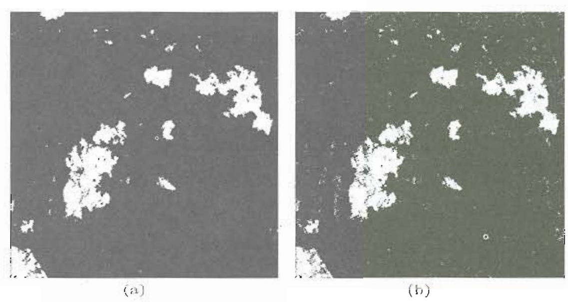

Fig. 3. Change detection map for Mexico image by (a) APC algorithm (b) MTET.

APC and MTET are comparable but false alarms (unchanged pixels classified as changed) obtained by APC are significantly less than those obtained using MTET. In terms of overall error, APC performs better than MTET. Figs. 3 and 4 show the change detection map obtained by both the techniques for Mexico and lake Mulargia image, respectively. Comparison of these change detection maps justifies the capability of the proposed APC algorithm for exploiting spatial contextual information to extract the changed regions properly. It is worth mentioning that MTET requires ground truth information to find out the optimal threshold whereas APC is completely unsupervised in nature.

4. Conclusions

In this paper we have proposed a new algorithm for change detection based on aggregation pheromone density, which is inspired by the ants' property to accumulate around points having higher pheromone density. To evaluate the performance of the proposed algorithm experiments were carried out with two multitemporal remote sensing images. Qualitative and quantitative evaluation of the experimental results establishes the superiority of the proposed APC algorithm over existing MTET. The proposed algorithm needs fewer parameters while producing better results. Moreover unlike MTET it does not require any ground truth information.

Acknowledgments

Authors would like to acknowledge the Department of Science and Technology, Government of India and University of Trento, Italy, the sponsors of the India-Trento Program on Advanced Research (ITPAR), under which a project titled **"Advanced Techniques for Remote Sensing Image Processing"** is being carried out at the Department of Computer Science and Engineering, Jadavpur University, Kolkata. Authors would also like to acknowledge Prof. Lorenzo Bruzzone, Italian collaborator of this project, for providing the images.

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