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Multiband Satellite Image Clustering using K-means Optimization with Reinforcement Programming

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Abstract

Multispectral image delivers a great source of data for studying spatial and temporal changeability of the environmental factors. It consists of big data size that were difficult to be handled for segmentation. Commonly, K-Means clustering is considered to use because its ability to make segmentation for big data of the multispectral image. However has sensitivity of its first generated centroids. In this paper we propose a new approach to optimize K-Means clustering using Reinforcement Programming in order to make segmentation of multispectral image. We build a new mechanism for generating initial centroids by implementing exploration and exploitation knowledge from Reinforcement Programming. This optimization will lead a better result for K-means data cluster. We selected multispectral image from Landsat 7 in Medawai, Borneo, Indonesia, and apply 3 segmentation areas. We made series of experiments and compared the experimental results of K-means using Reinforcement Programming as optimizing initiate centroid and normal K-means without optimization process.

Keywords: Multispectral images, landsat, automatic clustering, K-means.

1. Introduction

Multispectral image delivers great source of data for studying temporal changeability of earth environment. It is used in a number of implementation such as environmental damage, nursing of land use, radiation level check, urban planning, growth directive, soil test and crop outcome increment [1]. One major area of multispectral image analysis is vegetation mapping classification. This area delivering information about forestation, deforestation or the changes of vegetation on earth. Multispectral image provide an information which could delivers a good coverage, mapping and classification about land cover features like vegetation, soil, water and forest information. Nowadays, Multispectral image analysis became a trend and replace the manual classification techniques for Mapping area in earth surface, which the manual classification techniques necessitates expensive and time-intensive field surveys [8]. Because of this trend, many researches and studies has been done on working in multispectral image classification. Classification result will shows identifiable or meaningful features of land cover area [9]. The result could be implied in a bunch of information kind, depends on how the information will serve. Regardless of all the advantages, Multispectral image classification is a difficult things to do, because of the complexity of landscapes captured and the large data size of images.

Multispectral images consist of multiband Landsat satellite image, it is composed from seven bands or layers, each band represent a different portion of electromagnetic spectrum. Thsi seven bands will be used as one dataset before processing in classification algorithm. Multispectral image classification project done by combining image processing and unsupervised classification methods or clustering. Multispectral classification algorithms have gained attention in the recent days, due to their good performance in showing desire information from Landsat images. Multispectral clustering result can be receive by grouping area in multispectral images by comparing and grouping the similarities between each area. Multispectral clustering will produce similar object and generate a new image of clustered image. Cluster algorithm will specify and identify new cluster of items with a high degree of similarity toward each item (internal homogeneity) and a not likely members of other clusters (external homogeneity).

However, Landsat images have a big data size and has colour feature that tend to be similar with the other bands, that were difficult to handle In other hand, K-Means discovered as one of most well-known methods for clustering, it is developed by Mac Queen in 1967. The simplicity of K-means made this algorithm could be implemented in various cases that has a big size data. K-means is a partition clustering method that separates data into k groups. This reason makes k-means method

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became very popular to be implemented because of its ability to cluster huge and large data size with quickly and efficiently. However, K-means algorithm still has lack in its flow, K-means very sensitive in first-generated centroid. Original K-means algorithm generate its first centroid randomly, when the value of random initial centroid has close distance with correct data, K-means will have high possibility to find out the optimal centroid. Otherwise, if the initial centroid was random incorrect value, K-Means will lead to incorrect clustering group results [11]. Because of initial starting points generated randomly, K-means does not always guarantee the optimal clustering result [12]. In some case K-means method will not reach global optimum, but only in local optimum value.

Several methods proposed cluster initialization for K-means to solve multispectral images. Modification of K-means, Coting K-means is discussed by James and Galen (1997) by expressed as a sum of (dis)contiguities at each pixel for easy compute, using fixed k cluster.

In this paper, we propose a new approach, combining Reinforcement Programming to optimizing K-means first initial centroid.

2. Basic Theory

Multispectral image clustering is a process from Multiband satellite image and process to get the analysis of reflected, emitted, or back-scattered data satellite from an object or an area of interest in multiple bands of regions of the electromagnetic spectrum[4]. Subcategories of multispectral image are also consist of hyperspectral images, which use some of bands that were collected as source for analyzing and presenting new information from it. The main purpose of multispectral image clustering is to find the potential for classify the image using multispectral classification. This is a much faster method to analyses changes of area toward image analysis than manual survey method.

2.1 Satellite image segmentation and clustering

Multispectral image representing geographical data. It consist of a series of spectral-bands in interval data time with fixed discrete range (e.g., 0-255). Each pixel of spectral image shows information about earth couture and related to radiance and characteristics of the Earth's surface materials. However, we need to convert this satellite data as source information and process this data to become meaningful information. We do this by inferring thematic information from the interval pixel in spectral image data as illustrated in Figure 1.

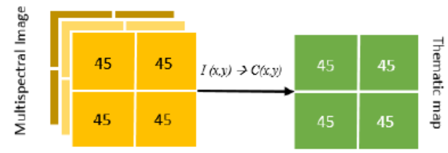

Figure 1. An illustration of the extracting process result from multi-spectral images to a thematic map.

Segmenting satellite images into differently regions is a complex problem. It is because the acknowledgment of texture types were exist in a satellite image, variances of textures, and what textures every region has [4]. In this paper we use Landsat Satellite images, which consist of seven spectral bands with a spatial resolution of 30 meters for Bands 1 to 5 and 7. Spatial resolution for Band 6 (thermal infrared) is 120 meters, but is resampled to 30-meter pixels. Approximate scene size is 170 km north-south by 183 km east-west (106 mi by 114 mi). As the experiment in this paper, we only use six spectral bands, it is because the image captured in band six could not give any information through its unclear data.

Table 1. Seven-spectral band

	Landsat	Wavelength (mm)	Resolution (m)
Thematic Mapper (TM)	Band 1	0.45-0.52	30
	Band 2	0.52-0.60	30
	Band 3	0.63-0.69	30
	Band 4	0.76-0.90	30
	Band 5	1.55-1.75	30
	Band 6	10.40-12.50	120* (30)
	Band 7	2.08-2.35	30

2.2 K-means for segmentation multispectral images

Unsupervised learning (also known as clustering) is a method for partitioning multispectral image data in map feature space and extracting land-cover information from multispectral images.

Classification result lead to representing the meaning information of each pixel to produce invaluable thematic data sets of information that can used in further GIS analysis. Unsupervised learning require less input information from the analyst compared to supervised classification because clustering does not require training data. This process consists in a series of numerical operations to search for the spectral properties of pixels. From this process, a map with m spectral classes is obtained. Using the map, the analyst tries to assign or transform the spectral classes into thematic information of interest (i.e. forest, agriculture, urban).

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The analyst has to understand the spectral characteristics of the terrain to be able to label clusters as a specific information class. There are hundreds of clustering algorithms. A common unsupervised segmentation approach - K-means clustering. K-means clustering is a simple unsupervised segmentation approach which works in the following manner:

1. Seeding (randomly) cluster mean vectors in feature space.
2. Allocates all pixels to one of the cluster mean vectors using Euclidean distance.
3. Updates the clusters mean vector on basis of the assigned pixels.
4. New cluster mean vectors used in second allocation, runs for N-iterations

Implementation of K-means in clustering multispectral images using six band, done by inserting data from each band and combine it into one dataset. This dataset will be sent for clustering process to identify k area. This system flow shown in Figure 2. It is also showing the recolor process after cluster member has been found.

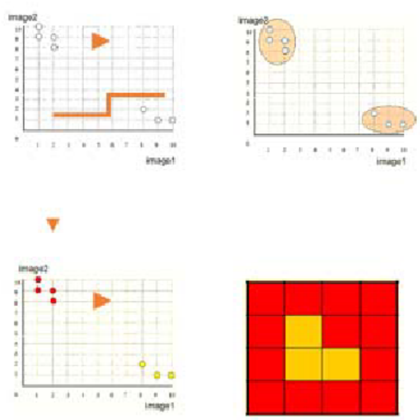

Figure 2. An illustration of K-means clustering and recoloring object

As the design of figure 2 shown Therefore, it try to make Distortion as minimum as possible. Therefore, the determining of initial cluster centroids for K-means is very important because it can determines the distortion and the precision of clustering results.

Throughout the manuscript I may cite references of the form [1], [2] or [3]. The numbers are based on the order you place them in the bibliography, not the order they appear in the text. The references should be in alphabetical order.

3. Our Proposed Idea

In this paper, a new approach to determine initial centroids for K-means is proposed, using Reinforcement Programming. The approach modified Reinforcement Learning algorithm to optimize K-means initiated centroid. Reinforcement Programming (RP) algorithm is the algorithm using basic concept of reinforcement learning. So in its implement, Reinforcement programming has the same behaviour of Reinforcement Learning, by involving a balance between exploration of uncharted territory and exploitation of current knowledge to find solution. The solution determined by as much reward as possible in process learning. Reward and punishment are a value given by environment from the agent step.

In RP, this policy is learned through trial-and-error interactions of the agent with its environment: on each interaction step the agent senses the current states of the environment, chooses an action to perform, executes this action, altering the states of the environment, and receives a scalar reinforcement signal r (a reward or penalty).

The benefits of Reinforcement Programming are to bring a benefit in optimization case using an intelligent learning approach based on Reinforcement Learning. With involving the characteristics of Reinforcement Learning, Reinforcement Programming provides an experience-based learning to achieve the global optimum.

3.1. Main Variables of Reinforcement Programming

Reinforcement Programming is mainly based on the Reinforcement Learning. A number of slight modifications of Reinforcement Programming can be formulated where:

- β : is a variable value to give impact to step that the agent will take.
- μ : a variable that will set a step value to the last step.

The goal of the agent in a RP problem is to learn an optimal solution by set $action \leftarrow d_p \,.\, step_p$ that action is accumulated from previous step with direction of step that will be taken. The current States will be assign in variable $newS \leftarrow$ .New states will be accumulated by cuttent new states and action $newS_p \leftarrow newS_p + action$ ($newS_p$ must be in $[minval_p..maxval_p]$). And assign variable step with rule :

$$newS_p \leftarrow S_p + action \quad (1)$$

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The RL technique is well-known uses a strategy to learn an optimal via learning of the action values. It iteratively approximates new States. In RP the condition of using exploitation or exploration are decided by random

$$step_p \leftarrow step_p - \mu \, . \, r_p \, . \, step_p \qquad (2)$$

p are probability to take action whether to exploit or explore a finite state. To balance exploitation and exploration p can be set in 0.5. Variable on reinforcement Programming structure is given in figure 2.

State is the first position of agent to start solving problem. State can be initiate as assigned value or random number, depends of cases that will handled by agent. Variable reward is an array to save reward of each state that has been declared. To change the action direction of agent we need to declare direction variable. In first position direction can be assign with positive number to increase the direction in positive grid line. Action value is an array to save the calculation of action that has been taken by agent. Variable above are formulating to have compatible with optimization cases. Modification of different heuristic case will change the condition of variable state and direction.

3.2. System Architecture

System architecture given in figure 3, explain the flow of Reinforcement Programming while find the best solution from optimization problem. The basic Reinforcement Programming algorithm starts with an initialization phase, where

i. Assign data item and set into variable dataset
ii. Set modelling state value calculation(depend on optimization cases)
iii. Set probability for exploration rate. Use 0.5 to get a balanced action for exploration and exploitation.
iv. Assign the value of new state in state.
v. The agents process state evaluation to whether receive reward or punishment for current action.

This is done using an index that stores the positions of all ‘free’ data items on the grid. The process is as followed by figure 3.

First step, RP processing case based function by modelling state and state value calculation. Then agent will begin state exploration in finite environment of problem, the actions that can be taken by agent is determined by exploration rate. If a random number is bigger than exploration rate than the agent will choose solution randomly in finite area. But if the random numbers are smaller than exploration rate than agent will consider taking an action based on reward. After take an action agent updates the current state and calculates current state value. A value from current state will label as reward or punishment, and determining the next direction of exploration. If agent receives punishment, then the agent will change its direction for the next exploration step. This process will be iterates in some value that already assign as number of learning time for agent of RP.

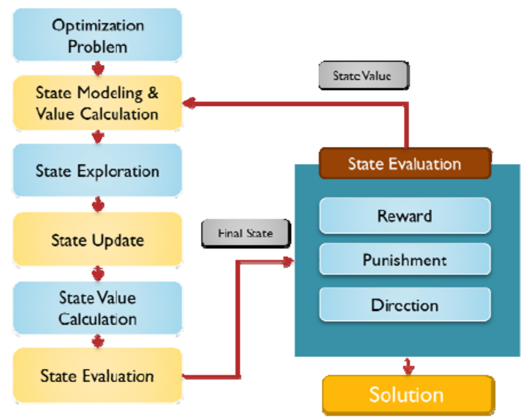

Figure 3. Step of Reinforcement Programming

An extension of this algorithm is algorithm is presented where the parameter is an adaptively updated during the execution of the algorithm. This algorithm is given in Figure 4. Reinforcement Learning needs to initialize dataset to identify problem environment. Agent will place randomly or assigned value depends on handled cases. After calculate state value, agent will determine action between exploration and exploitation. Then execute action and calculating new state value to determine reward based on state current value.

Reward of new state in the environment is computed through the following Equation (3) and (4)

$$r_p \leftarrow r_p + \beta \, . \, (1\text{-}r_p) \qquad (3)$$

The equation above show the formula for increasing reward value.

$$r_p \leftarrow r_p - \beta \, . \, (1\text{-}r_p) \qquad (4)$$

And in case to give punishment, Reinforcement Programming used formula above to decrease reward value. Where β is a constant to set a value of reward with scalar 0.1 until 1. The more scalar that will be used it will impact the increase or decrease value of reward.

The output of Reinforcement Programming algorithm is a solution of given problem.

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(1)  Procedure Reinforcement Programming
(2)    Initialize dataset on the toroid grid
(3)    Randomly place agent on toroid grid
(4)      For I = 1 to max_iteration
(5)      Calculate sv
(6)      R = random exploration number
(7)      If (r > exploration_rate)
(8)        Let agent randomly explore environment
(9)      Else
(10)       Let agent use its knowledge to determine the next
           action by the biggest reward value
(11)     End If
(12)     Execute action
(13)     Calculate new state value
(14)     Calculate new step position // see equitation (2)
(15)     If(newsv > sv)
(16)       Update array S
(17)       Increase and Update reward value  // see
           equitation (3)
(18)     Else if (newsv < sv )
(19)       Set punishment and update reward value //see
           equitation (4)
(20)       Change direction
(21)     Else
(22)       Let agent change direction to explore environment
(23)     End If
(24)   End for
(25) End Procedure
```

Figure 4. Reinforcement Programming Algorithm

4. Experimental

In order to analyse the accuracy of our proposed method, we apply Normal K-means and K-means using Reinforcement Programming in Multiband data images. The imagery data that we use are from Landsat imaginary, the study area that has been used in this paper is Medawai, Borneo (fig 5).

There are three classes consist of vegetation, water, and bare soil. In fig. 4.2 performs the results between our proposed methods with normal K-means which using random initialization. It is found that the clustering result from our proposed method can make better separated cluster than the random initialization K-means.

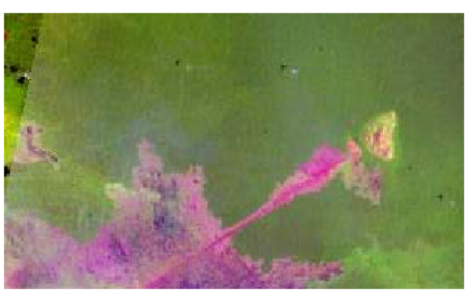

Figure 5. An experiment area: Medawai, Borneo, Indonesia.

The algorithm for cluster sources images can be shown as follows:

1. First, convert color space from RGB to LAB color.
2. Next, Initiate centroid from combination data band as source data.
3. Clustering images data using K-means
4. Get the vegetation data and combine with sequential data.

There are three classes over sources data that will be clustered. The important element to be used are vegetation area, it used for counting the main area of forest that exist on recent year. Fitness value of cluster calculated by variance number of a cluster. Smaller number of cluster variance will show the best cluster performance. This paper shows the optimum result from solving K-means using Reinforcement Programming for optimization.

4.1 Study area Example

The data sets used for comparison experiments consist of 6 band. The experiments are performed over a mathematically generated 2D datasets. This dataset will be proceed in K-menas to produce a clustered area. The data set samples are to be tested using K-Means using Reinforcement Programming and normal K-means. it will reduce the system accuracy in clustering the field of the study area.

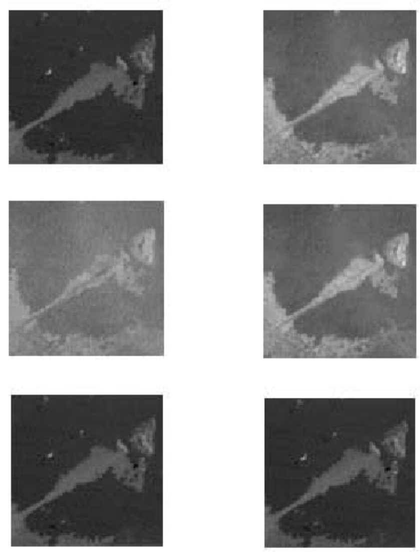

Figure 6. Six Band of Medawai, Borneo

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In this experimental, this six bands were used as one dataset. This six dataset are composed from band 1, band 2, band 3, band 4, band 5, and bang 7.

Band 6 could not be implied as resource data, it is because band 6 showing unclear captured data. So, if we include band 6 to system,

4.2 Experimental Comparison

The average error and average time taken by the K-means from two different algorithms will be proceed and compared, it is used to find the best algorithm for solving multispectral images. The two algorithm that will be compared are K-means using Reinforcement Programming and normal K-means. The following table in each algorithm will show the result and performance of each algorithm.

As for the experiment result, we ran total 40 times experiment. We ran 10 times for the 10 iteration experiment and produced weak stability, 10 times for 50, 100 and 150 iteration and produced high stability for solving problem.

Reinforcement Programming

The figure 7 values show Reinforcement Programming increase the accuracy and has more stability after reach greater number of iteration.

It is because reinforcement programming is gaining its experience in beginning of iteration, and after reach some number of iteration Reinforcement programming became clever and can reach better solution by its own knowledge And Reinforcement Programming shows good performance to solve minimization problem.

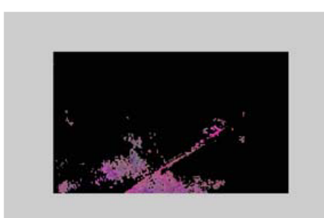

Figure 7. Bare soil distribution using K-means with RP

The purple colour of figure 7 shows soil distribution in Medawai, Borneo, Indonesia. The experiment has been done in 10 times nd shows the high number of accuracy by using variance as the clustering measurement. In other hand, this experiment also compared to another algorithm for clustering, the others are clustering without optimization. It will use random centroid value. The result result of this experiment can be seen in figure 4.4.

Figure 8. Bare soil distribution using normal K-means

The purple colour of figure 7 and figure 8 shows soil distribution in Medawai, Borneo, Indonesia. The accurate result of soil clustering can be shown using K-means with Reinforcement Programming as optimization of K-means, in first initiated centroid. Figure 9 shows complete reshaping images using k-means with RP as optimization centroid. The accurate soil area also shown in solid colour to highlighting the soil area that will be main point for this clustering methods result.

It is representing that K-means using Reinforcement Programming has a good performing rather than normal k-means.

Figure 9. Reshaping image after clustered by K-means with RP

In other hand, we also compared the result with normal K-means. The result of normal K-means in Figure 10 shows value of normal K-means was not as good as Reinforcement Programming optimization

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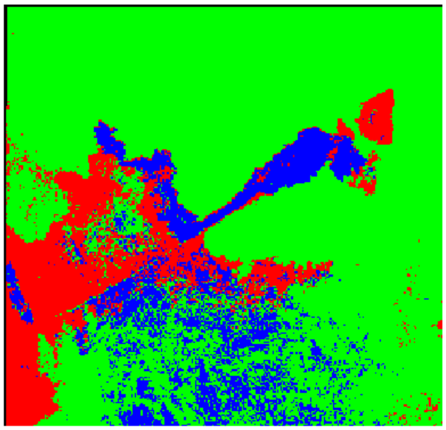
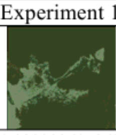
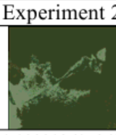
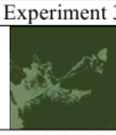
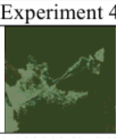
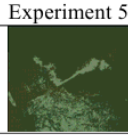
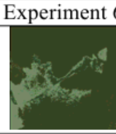
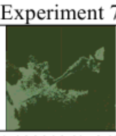
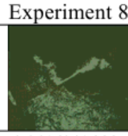


. **Figure 4.6.** Reshaping image after clustered by normal K-means

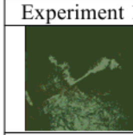
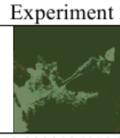
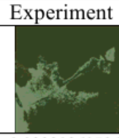
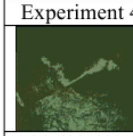
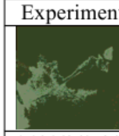
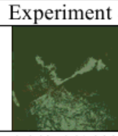
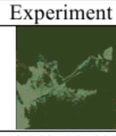
As for experiment, we did 10 times of experiment for Clustering multispectral images using Reinfocement Programming and shown in table 2, it is also repesent a value of overall cluster variance in each experiment.

Table 2. Experimental Result of K-means using Reinforcement Programming with overall cluster variance

Experiment 1	Experiment 2	Experiment 3
		
0.023202607862	0.023202607862	0.023202607862
Experiment 4	Experiment 5	Experiment 6
		
0.023202607862	0.04160416667	0.023202607862
Experiment 7	Experiment 8	Experiment 9
		
0.023202607862	0.04160416667	0.04160416667

As for experiment, we did 10 times of experiment for Clustering multispectral images using normal K-means and shown in table 3, it is also represent a value of overall cluster variance in each experiment.

Table 3. Experimental Result of normal K-means with overall cluster variance

Experiment 1	Experiment 2	Experiment 3
		
0.08160416667	0.023202607862	0.023202607862
Experiment 4	Experiment 5	Experiment 6
		
0.06160416667	0.06160416667	0.023202607862
Experiment 7	Experiment 8	Experiment 9
		
0.02462607862	0.04350416667	0.04350416667

Images on table 2 and table 3 shows recreate images for area medawai, borneo, Indonesia. The acurate result of soil clustering can be shown using K-means with Reinforcement Programming as optimization of K-means, in first initiated centroid. For validation of clustering result of each experiment we use variance of all cluster and show in table 4.

Table 4. Performance of normal K-Means and K-means using Reinforcement Programming

Parameter	Normal K-means	K-means using RP
Execution Time (min)	14	11
Average Variance	2.42026078×10^2	4.44906082×10^2
Average Iteration for fixed centroid	3	8

5. Contribution and Conclusion

Reinforcement Programming has capability of convergence and behaviour to solving k-means problem by using exploration and exploitation. Finally, when comparing the experimental result as for Clustering Result, K-means using Reinforcement Programming shows a good performance compared to normal K-means.

Although multispectral images can be segmented by using normal k-means, it is shown instability result. It's because of, normal k-means using random initiate centroid, that may causes empty cluster. So the use of Reinforcement Programming can produce a stable solution, and high precision. This lead people to get an optimum solution of K-means for solving multispectral images.

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