Spectral-spatial MODIS image analysis using swarm intelligence algorithms and region based segmentation for flood assessment

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Abstract. This paper discusses an approach for river mapping and flood evaluation based on multi-temporal time-series analysis of satellite images utilizing pixel spectral information for image clustering and region based segmentation for extracting water covered regions. MODIS satellite images are analyzed at two stages: before flood and during flood. Multi-temporal MODIS images are processed in two steps. In the first step, clustering algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are used to distinguish the water regions from the non-water based on spectral information. These algorithms are chosen since they are quite efficient in solving multi-modal optimization problems. These classified images are then segmented using spatial features of the water region to extract the river. From the results obtained, we evaluate the performance of the methods and conclude that incorporating region based image segmentation along with clustering algorithms provides accurate and reliable approach for the extraction of water covered region.

Keywords: MODIS image, Flood assessment, Genetic algorithm, Particle swarm optimization, Shape index, Density index.

1 Introduction

Over the past decades, many regions around the globe have witnessed many natural hazards, flood being the most destructive one. Flood accounts for nearly 1/3rd of the worldwide disaster damage [1]. There is also huge monetary loss involved in such natural calamity because of the unwary flood management system. Hence there is a need for efficient flood disaster management tool to

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endure the aftermath of flooding. Now a day, most prominent tool for evaluating the flood extent is satellite imagery because of its easy data acquisition and development of robust image processing techniques for gauging the flood map.

There has been lot of research during past decades towards the flood extent evaluation using optical imagery. One such optical image is MODIS which has attracted many researchers to work towards optical image based flood assessment because of their easy availability and cost-effectiveness. Islam *et.al* [1] presented a flood inundation mapping based on Normalized Difference Water Index (NDWI). Zhan *et.al* [2] proposed vegetative cover conversion algorithm for land cover analysis. Khan *et.al* [3] employed ISODATA algorithm for the classification of flooded and non-flooded regions using MODIS image.

However, there are several other algorithms which are more accurate compared to above conventional techniques. Genetic Algorithms (GA) are one such family of adaptive search methods and hence found its application in image segmentation in the past decades. Bosco [4] formulated image segmentation as global optimization problem used a genetic approach to solve. Particle Swarm Optimization (PSO) is one more technique which is also a population based. Many researchers have explored wide areas of applications of PSO [5, 6, 7]. PSO has been quite efficient in optimizing multi-modal problems. Nagesh *et.al* [5] presented multi-purpose reservoir system operation using PSO. Huang *et.al* [6] proposed flood disaster classification based on multi co-operative PSO. Also, Omran *et.al* [7] made use of PSO algorithm and spectral un-mixing for image classification. In their study, remote sensing data and MRI images were classified based on spectral features.

In this paper, we propose a flood extent evaluation method based on MODIS image using unsupervised techniques such as GA and PSO. In our study, the above two algorithms are used for clustering the image region into flooded and non-flooded regions based on spectral features. Time-series data for the automatic extraction of river regions (using before flood image) and for evaluating floods (using during flood image) is presented in this paper. Since GA and PSO are based on spectral features, sometimes it is unreliable for the reason that some of the non-water particles may be misclassified as water because of similar spectral information. Hence, flood inundation evaluation based on spatial features like Shape Index (SI) and Density Index (DI) is also considered. Spatial information of before flood and during flood images can be effectively analysed using the above parameters. These parameters were first proposed by Mingjun *et.al* [8] for road extraction using satellite image. Finally, the performance of these methods is evaluated by comparison with ground truth data.

2 Problem Formulation

The optimization problems often involve finding the optimal solution for a given problem. Normally clustering algorithms involve global optimization [7] and local optimization [9] to partition the given data set into n groups. In terms of image clustering, the data points within a group share similar spectral characteristics. Pixel values refer to each pattern in a group and image region corresponds to a cluster. The concept of fitness function is used for finding out the best solution.

A particle $\boldsymbol{x}$ is defined by its cluster centers as $x_i = \{m_{i1}, m_{i2}..... m_{ij}......m_{iN}\}$, where N is the number of clusters, m_{ij} refers to j^{th} cluster centre of i^{th} particle. For each particle x_i, fitness function is described as follows [7],

$$f(x_i, Z_i) = w_1 d_{\max}(Z_i, x_i) + w_2(z_{\max} - d_{\min}(x_i)) \tag{1}$$

where Z_i is a matrix comprising the assignment of the pixels to clusters of i^{th} particle. Z_{max} is 2^s-1 for an s-bit image, w_1 and w_2 are the inertia factors set by the user. Also,

$$d_{\max}(x_i, Z_i) = \max\{\textstyle\sum_{\forall z_p \in C_{i,j}} d(Z_{p,m_{i,j}}) / |C_{i,j}|\} \tag{2}$$

describes the maximum Euclidean distance of particles to their associated clusters. Here, $C_{i,j}$ is nothing but j^{th} cluster of i^{th} particle.

$$d_{\min}(x_i) = \min_{\forall j_1, j_2, j_1 \neq j_2} \{d(m_{ij_1}, m_{ij_2})\} \tag{3}$$

where d is the minimum average Euclidean distance between any pair of clusters.

However, the problem associated with image clustering algorithms based on spectral features is that sometimes it leads to misinterpretation of image segments because of spectral similarities. Hence, some of the researchers have adopted region based segmentation to extract geometrical features. To extract spatial features of roads or river networks, Shape Index (SI) and Density Index (DI) are used [8, 10].

$$SI = \frac{P}{4\sqrt{A}} \tag{4}$$

where P is the perimeter of the image object and A is an area of the segmented region (or total number of pixels in the segmented image object).

$$DI = \frac{\sqrt{N}}{1 + \sqrt{\mathrm{var}(X) + \mathrm{var}(Y)}} \tag{5}$$

where N is the number of pixels inside the region, $Var(X)$ is the variance of X co-ordinates of all the pixels in the region and $Var(Y)$ is the variance of Y co-ordinates of all the pixels in the region. $\sqrt{\mathrm{var}(X) + \mathrm{var}(Y)}$ gives the value of approximate radius of the image object. Suitable thresholds of SI and DI are employed to classify the regions into water and non-water region.

2.1. Illustrative Example

Though there are several clustering algorithms which help in solving multi-modal optimization problems, in case of flood mapping, some of the non-water regions are also classified as water region due to similar spectral features. Hence, adopting SI and DI would effectively distinguish between water and non-water region.

Here, we present an illustrative example taking a sample portion of before flood MODIS image shown in fig. 1 (a) which is classified as river and non-river regions using a clustering algorithm (fig. 1 (b)). Fig. 1(c) shows the improvement over a spectrally clustered image using spatial information (SI and DI). The extracted river is shown in fig. 1(d). The following matrix is a 12x10 image portion with grayscale intensities.

Pixel-co ordinates	49	50	51	52	53	54	55	56	57	58	59	60
345	179	169	112	76	135	154	163	157	144	141	143	143
345	196	215	110	74	145	159	139	127	133	138	138	132
346	233	209	107	88	150	168	142	126	124	119	113	108
347	241	185	93	99	149	172	147	127	126	111	103	103
348	209	166	89	117	152	166	156	142	134	118	111	113
349	195	165	99	147	174	165	160	151	144	132	126	123
350	208	54	101	164	195	175	156	138	143	138	129	120
351	196	119	110	165	185	180	158	141	139	143	130	118
352	161	88	132	168	160	175	168	169	156	163	148	134
353	125	108	143	176	162	149	149	150	149	153	149	148

A clustering algorithm is applied on an image using the fitness function according to eqn (1). Regions clustered as river are represented by 1 and non-river regions are represented by 2. Consequentially, clustered matrix of above image matrix as follows:

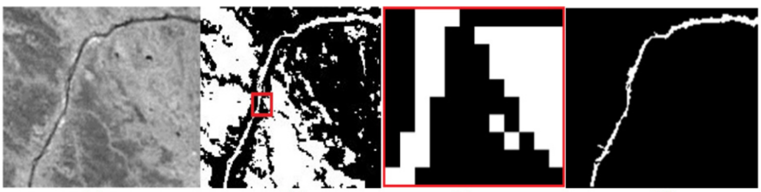
Pixel-co ordinates	49	50	51	52	53	54	55	56	57	58	59	60
345	2	2	1	1	1	2	2	2	2	2	2	2
345	2	2	1	1	2	2	1	1	1	1	1	1
346	2	2	1	1	2	2	2	1	1	1	1	1
347	2	2	1	1	2	2	2	1	1	1	1	1
348	2	2	1	1	2	2	2	2	1	1	1	1
349	2	2	1	2	2	2	2	2	2	1	1	1
350	2	2	1	2	2	2	2	1	2	1	1	1
351	2	1	1	2	2	2	2	2	1	2	1	1
352	2	1	1	2	2	2	2	2	2	2	2	1
353	1	1	2	2	2	2	2	2	2	2	2	2

From the above image matrix, we can see that some portion is marked in red, which is misclassified as river region. To avoid the discrepancies due to similar spectral features, SI and DI as mentioned in eqn (4 and 5) are applied on clustered image. SI and DI being spatial parameters resolve the issue with spectral inconsistency. The resulting image matrix is as follows,

Pixel-co ordinates	49	50	51	52	53	54	55	56	57	58	59	60
345	2	2	1	1	1	2	2	2	2	2	2	2
345	2	2	1	1	2	2	2	2	2	2	2	2
346	2	2	1	1	2	2	2	2	2	2	2	2
347	2	2	1	1	2	2	2	2	2	2	2	2
348	2	2	1	1	2	2	2	2	2	2	2	2
349	2	2	1	2	2	2	2	2	2	2	2	2
350	2	2	1	2	2	2	2	2	2	2	2	2
351	2	1	1	2	2	2	2	2	2	2	2	2
352	2	1	1	2	2	2	2	2	2	2	2	2
353	1	1	2	2	2	2	2	2	2	2	2	2

SI and DI are chosen as spatial parameters for image segmentation because of their contrasting property in identifying a river. From the above clustered image matrix and final result image matrix, we can see that some of the non-water region pixels are also classified as water pixels because of similar spectral information.

From the above two matrices, we can see that in clustered image matrix, there are 31 misclassified water region pixels out of which, 19 pixels constitute for the perimeter. SI is calculated using the eqn (4) and it turned out to be 0.8531. Upon computing DI using eqn (5), we get DI as 1.5384. However, if we look at the region which is properly classified as water region; it has area of 19 pixels and also perimeter of 19 pixels. Hence, SI of this region is 1.0897 and DI equal to 1.0131. From the above illustration, it is evident that river regions have higher SI because of the longer perimeter and less area. Similarly, DI is lesser for river regions because of large distance coverage. Thus, suitable ratio (SI/DI) is set as threshold for classifying river and non-river regions.



(a) (b) (c) (d)

Fig. 1 (a) Original MODIS image (b) Clustered Image (c) Subset employed for the spatial analysis of flood extraction & (d) River extracted using region based segmentation.

3 Methodology

In this section, we present a flood detection and mapping in two stages: At spectral level, image clustering is done by Genetic Algorithm (GA) and Particle Swarm Optimization(PSO) and at spatial level, Shape Index (SI) and Density Index (DI) are used to classify flooded and non-flooded regions. Our proposed methodology is depicted in fig. 2

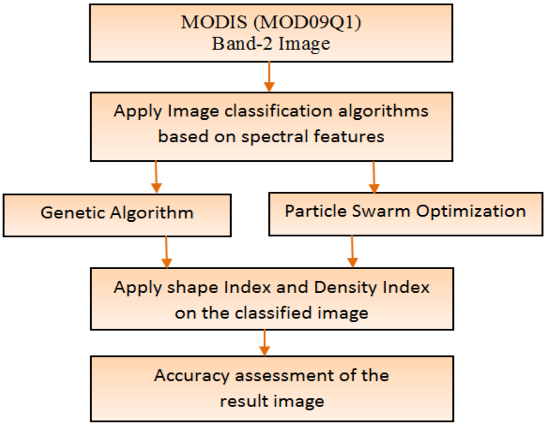


Fig. 2 Flow chart of proposed methodology

3.1 Genetic algorithm

Genetic Algorithms is a population based stochastic search and optimization techniques with inherent parallelism. For clustering, the cluster centers are encoded in the form of strings (called chromosomes). A collection of such strings is called a population. Initially, a random population of different points is created within the search space. The fitness value for each chromosome of the population is evaluated. These chromosomes are then subjected to genetic operators – reproduction, crossover and mutation to yield a better population for a fixed number of generations. The chromosomes converged to the least fitness value is the solution to the given problem.

3.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is also a population based method, inspired by the social behaviour of bird flocks. It was first developed by Kennedy *et.al* [11]. It was then proposed by Omran *et.al*. [7] for image segmentation. Their results show that PSO outperformed K-means, Fuzzy C-means and other clustering algorithms.

Similar to the bird flock in search of its nutrition, each particle flies through the search space to find out the best solution with a velocity adjusted dynamically. There are two types of solutions are associated with each particle, one is personal best and the other is global best. Personal best is the best solution that each particle visited so far in the search space. Global best is the overall best solution found by the swarm of particles. Each particle is evaluated based on the fitness function as mentioned earlier in section 2. The main characteristics associated with each particle in the swarm are current position of the particle, current velocity of the particle and personal best position of the particle. For each iteration, particle tries to find the most optimal solution (personal best) with the dynamic adjustment of velocity. Fitness function evaluates the personal best position [7]. Global best solution takes into account all the personal best solutions [11] and it is the best solution of the entire swarm.

4 Results and discussions

In this section, we present the results obtained from image clustering done by genetic algorithm and particle swarm optimization. Accuracy assessment of the above two methods is done in terms of root mean square error (RMSE) [10] for before flood image and Receiver operating characteristics (ROC) [12] for evaluating the result of during flood image. Also, the above algorithms are compared with the two of the existing conventional unsupervised techniques.

4.1 Study area and data description

Region surrounding Krishna river near Manthralaya, Andhra Pradesh is taken as study area which is located between 16^0 38’ 00”N-$77^0$09’00”W and 15^0 26’ 00’’S-78^0 26’ 00’’E. The dataset obtained from MODIS (MOD09Q1) Terra surface reflectance 8-Day L3 Global 250m^2 satellite images are used for this purpose. This dataset comprises of 2 bands. Band 1 (visible red region) lies between 620-670 mm and Band 2 (Near Infra-Red region) is centred between 841-876 mm. Band1 is more sensitive for the detection of land/cloud boundaries and NIR band is more efficient in detecting water region since water has significant low reflectance in NIR region [13].

4.2 Genetic Algorithm

All the images used for validation are clustered by GA. The pixels comprising this cluster are eventually clustered as water and those not present in the cluster are clustered as non-water. In GA, each generation has 20 chromosomes and the maximum number of generations allowed to find the best solution to the problem is 30.

The crossover operator tries to optimize the solution globally while the mutation operator searches locally. So we use the variable rates of crossover and mutation to aid swift optimization. The chromosome with best fitness value is used to cluster the image. The clustering result of the Krishna River before flood i.e. March 2009 by the GA technique is shown in Fig. 3(b). During flood classification result is depicted in fig. 4(b). As it can be seen from the results of clustering, many non-water segments have also been clustered as water because of their spectral resemblance with water. These non-water features are further removed by region based segmentation.

4.3 Particle Swarm Optimization

In case of PSO, each iteration has 20 particles and the maximum number of iterations allowed to find the best solution to the problem is 30. The best particle fitness value is used to cluster the image. The clustering result of the Krishna River before flood i.e. March 2009 by the PSO technique is shown in fig. 3(c), the clustering result of the Krishna River during flood i.e. September 2009 by the PSO technique is shown in fig. 4(c). Here also many non-water segments have also been clustered as water. These non-water features are further removed by region based segmentation.

4.4 Region based image segmentation

The failure of spectral based image clustering to extract water features is overcome by region based segmentation. For segmentation purpose, we use the geometrical features of the linear segments. As mentioned earlier, we use two indices- SI and DI with suitable thresholding to differentiate linear segments from non-linear segments.

For the image of Krishna river before the flood (March 2009), we use SI threshold of 2.0 and a DI threshold of 0.9 to extract the river course. The result of region based segmentation of the March 2009 image classified by GA is shown in fig. 3(d). Similarly, PSO classified image is segmented based on geometrical parameters whose result is shown in fig. 3(e). However, in the case of Krishna river system image during the flood i.e. September 2009, to extract flood, we use

SI threshold of 2.0 and DI threshold of 1.4. The reason behind this change in DI threshold value is that due to flood, the segment to be extracted is not perfectly linear anymore; instead it is spread on a larger area. Thus to accommodate the flooded parts, a relaxation in the DI threshold is provided. Thus, region based geometrical segmentation eventually extracts the linear features from images to a reliable extent. In case of before flood image of Krishna River 2009, the final segmented images as a result of clustering by GA are shown on a backdrop of the original image in fig. 3(f) and that of PSO is shown in fig. 3(g). In these images, river course is represented by white pixels.

Fig. 4(a) indicates the ground truth in which flooded cities are white discs and non-flooded ones have black centre. The cities flooded according to the clustering by GA and PSO are shown as white dots in the fig. 4(b) and fig. 4(c) respectively. The result images shown in fig. 4 (b) and fig. 4 (c) are evaluated in terms of true positive (TP), False positive (FP), True Negative (TN) and False negative (FN). These ROC parameters are TPA, TNR, FPR and ACC [12]. Result interpretation of cities picked by GA and PSO are presented in table 1. The ROC parameters are evaluated for accuracy assessment which is depicted in table 2.

Table 1.ROC parameters comparison for flooded cities shown in Figure 4

Terms	GA	PSO
True positive	10	11
False positive	1	1
True negative	15	15
False negative	2	1

Table 2. Evaluating features based on ROC parameters in Table 1.

Terms	GA	PSO
True positive Rate (Sensitivity)	0.83	0.92
True negative Rate (specificity)	0.94	0.94
False positive rate	0.06	0.06
Accuracy (ACC)	0.89	0.92

4.5 Comparison of unsupervised techniques

In the literature, the methods such as k-means [14] and Mean shift segmentation (MSS) [15] are widely used for image segmentation. In our study, we applied these methods to segment before flood (March 2009) image.

K-means is a parametric clustering method; here 2 clusters are generated for both classes (water and non-water) to cluster before flood image. After clustering, we have used a SI threshold value of 2.0 and a DI threshold value of 0.9 to segment the image. RMSE value for k-means to segment pre-flood image is 0.45.

One more method for image segmentation is Mean shift segmentation which is a popular non-parametric method based on kernel density estimation [15]. This method helps in identifying river network feature in the image. Initially, arbitrary point is chosen in the feature space and move towards the locally maximal density. It is an iterative procedure, where the modes of the density are the convergence points. It has been observed that RMSE value for MSS to segment before flood image is 0.26. In comparison with these two methods, RMSE value of GA is 0.18 and that of PSO is 0.15. From this result, we conclude that the approaches used in the paper are reliable techniques for linear segment extraction and thus can be successfully be used to map river courses and evaluate the flood extent in a river.

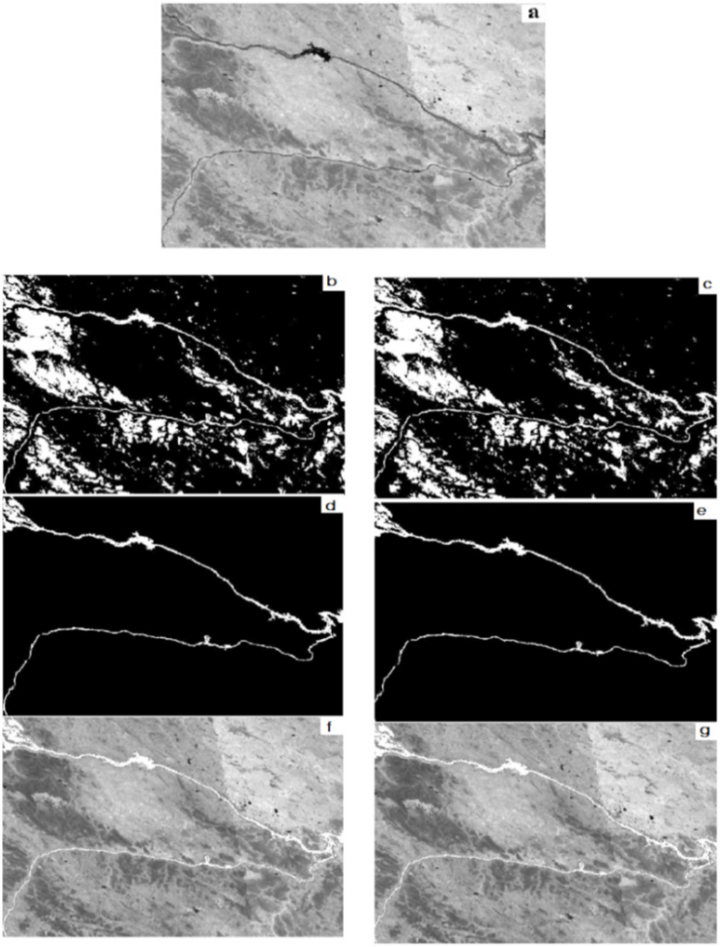


Fig. 3(a) Original MODIS image (before flood) (b) Image clustering using GA (c) Image clustering using PSO (d) Segmented image of GA clustered image (e) Segmented image of PSO clustered image (f) GA based river extraction overlaid on original image and (g) PSO based river extraction overlaid on original image

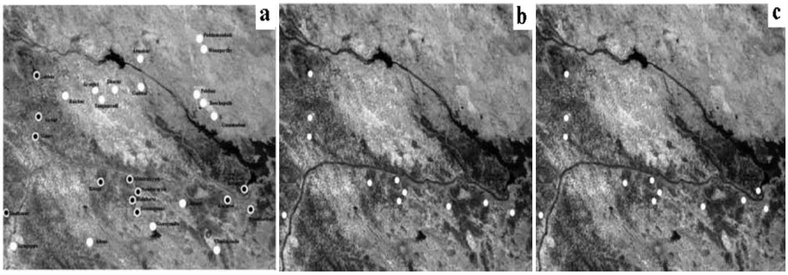


Fig. 4(a) MODIS during flood image with ground truth information – flooded (white discs) and non-flooded cities (black discs at the centre) (b) Segmented image using GA (White pts. are flooded cities) (c) Segmented image using PSO (White pts. are flooded cities)

5 Conclusions

The task of river mapping and flood extraction is accomplished successfully by the procedure of pixel based spectral information for clustering and shape information for region based segmentation as discussed above. In the clustering stage of extracting water and non-water groups, the GA and PSO are used. Results of clustering using spectral information are improved through region growing image segmentation based on geometrical features using similarity criteria resulting in effective water-covered regions.

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