Research Article

Multitemporal Change Detection and Irregular Land Shape Area Measurement from Multispectral Sensor Images through BSO Algorithm

L. Ashok Kumar,1 M. R. Ebenezer Jebarani,1 V. Gokula Krishnan2 and Mohd Wazih Ahmad3

1School of Electrical and Electronics Engineering, Sathyabama Institute of Science and Technology, Chennai, Tamil Nadu, India
2Department of Computer Science and Engineering, RMK Engineering College, Kavaraipettai 601206, Thiruvallur, Tamil Nadu, India
3Adama Science and Technology University, Adama, Ethiopia

Correspondence should be addressed to L. Ashok Kumar; ashokkumarsathphd@gmail.com and Mohd Wazih Ahmad; wazih.ahmad@astu.edu.et

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1. Introduction

The earth surface comprises of manmade developments such as terrains, artificial water bodies, roads, and buildings. The manmade components refer as land cover. The land cover shape and size vary according to land use. Humans modify land cover according to their use by constructing road, building, and parks. The land cover modification has increased in recent times due to population, economic growth, and human needs. The extensive land cover modification affects existing ecosystem and influence climate at local and global levels. The climate changes and inadequate seasonal rainfall increase global temperature and water drought. The adverse effects to change in land use and land cover need continuous monitoring of land surface.

The land surface area monitors through satellite images such as sentinel-2, Landsat-8, planet scope, and Rapid eye. Satellite optical sensors capture the land cover image changes in land surface detected in temporal and spatial image. The land cover change in terms of vegetation, water body, and urban buildings is classified with time series satellite images of land cover. The land cover is classified
with the supervised and unsupervised classification algorithm. The supervised classification algorithm for land area measurement includes minimum distance, parallelepiped, and maximum likelihood. The unsupervised classification algorithms for land surface area measurement include K-means and Support Vector Machines (SVMs). The supervised algorithm classifies land cover based on land samples for land cover classification. The unsupervised classification performs land cover classification by assigning radiometric pixels values to land cover components. The conventional land classification algorithms fail to delineate land cover in satellite image due to mixed pixels.

The historical aerial data in aerial image improve by Rotated CorneR local binary pattern (R-CRLBP). R-CRLBP extracts features from challenging French territory aerial images, which comprises both urban and rural areas. In addition, R-CRLBP filters the images with Local Binary Pattern (LCoBP) for land cover assessment [1].

Land cover estimation is performed with entropy-based reliability measurement (EBRM). Initially, homogeneous segment of land is performed and then adaptive clustering is done. The adaptive clustering determines the anomaly features in land image. EBRM provides quantitative measurement of vector-based land cover estimation. Due to the lower complexity of the local-variation calculation, the EBRM technique can dramatically reduce processing time when compared with the Gaussian mixture model, allowing for real-time processing of high-resolution images as well as efficient analysis of large-scale image. Furthermore, the local variation-based approach is stable with larger input data dimensions, which is not always the case with an EBRM type algorithm. [2]. The homogeneous region in Landsat image is detected with the region growing method. The shortcomings of the snapshot model overcome through integration of time and spatial region growing. The segmentation method identifies spatial-temporal region in image with the Dynamic Time Wrapping algorithm [3]. The dynamic classifier system (DCS) classifies hyperspectral images. The image is classified based on context and information class characteristics of land cover. DCS overcomes human intervention in supervised image classification [4]. In PolSAR (polar metric synthetic aperture radar) image, a hybrid image segmentation-based algorithm detects land cover with minimal false rate. The method involves region-based image segmentation and followed by polar metric feature selection and binary image object classification [5].

In targeted land cover classification, land cover classes of interest such as agriculture, forestry, disaster management, habitat mapping are effectively classified. Targeted land cover classification (TLCC) has certain drawbacks and limitations, such as time complexity and economic cost. For effective targeted classification, the ground-truth samples are performed for class of interest and avoids the ground truth information. The targeted land cover in images is identified with respect to ground-truth reference. The targeted land cover classification (TLCC) technique combines unlabeled samples in image and targeted land cover samples and identifies targeted land cover. In addition, the land cover with no ground-truth reference is identified by Markov random field and Expectation Maximization algorithm [6]. The SAR image of tropical forest with cloud is classified with algorithms such as AdaBoost, Naive Bayes, random forest, multilayer perceptron, and support vector machine. The SAR image analyzes with respect to pixel and object and evaluates classifier performance in terms of processing speed and accuracy [7]. Instead of directly matching pixels in the image classes by their appearance, the matching is conducted through reference space where the descriptor of land surface class pixel is transformed to texture descriptors to similarity measures between the pixels of land surface pixels class and reference set is created for segmentation. The Reference Descriptor (RD) feature identifies similar intra-class data between sample dataset and reference dataset. RD generates super pixel by comparing feature of super pixel in image and super pixel of disjoint reference set. The reference set comprises super pixel obtained from different land cover types [8]. The spatial content in high-resolution multispectral (MS) image is extracted with the hierarchical segmentation classification system. Hierarchical segmentation tree selects appropriate scale to represent segmentation layer for modeling pixel in image and avoids region of interest under segmentation.

The SVM classifier classifies each pixel spatial information at different tree levels. The classifier extracts spatial context from image accurately [9]. The land cover type identifies trend component with phonological feature variability from time series of remote sensing images. The phonological features such as Length of Season (LOS), End of Season (EOS), Rate of Grow-up (ROG), and Amplitude of Season (AOS) are extracted from time series of remote sensed image by BFAST (Breaks For Additive Seasonal Trend) approach. The dynamic time warping and SVM with phonological features train and classify land cover [10]. The LiDAR high-resolution images provide better land cover classification compared with hyperspectral images. The geospatial data from multiple sources fuse with geographic object image analysis. The analysis involves preprocessing, object segmentation, and evaluation of mean, standard deviation, skewness, and kurtosis for evaluation and intensity calculation [11]. The multiscale segmentation with appropriate segmentation scale extracts feature from objects. The simple scale synthesis divides and groups image section with similar segmentation scale. The optimal segmentation of each image section provides suboptimal object scales similar to ground objects [12]. The land cover in SAR and optical fused image classifies by extracting texture and polar metric features from images. The normalization applies at different scales for land cover classification [13].

1.1. Problem Statement. In Google map, online measure distance feature is used for distance and area measurement as in Figure 1(a). The starting and ending point on an area lead to measurements error, and moving the points with slight variation in distance leads to error in measurement. The area measurement of irregular shapes and size of area leads to more error as shown in Figures 1(a) and 1(b).
From online area measurements in maps for curved path measurements especially in on-road areas measurement, error is about 5 to 50 m. Curved path measurements need clear boundary regions to fix the points. The more points in curved region lead to compound error in area measurement. Furthermore, area measurement error is more in the long-distances in the multiple earth surfaces areas such as roads, water body, and vegetation.

### 1.2. Contributions

The classification accuracy of traditional methods such as KNN, SVM, and PSO provide more error in area measurement. Hence, in this paper, the backtracking search optimization (BSO) algorithm is applied to delineate land covers in urban, semiurban, hill, and coastal region. The BSO iteratively classifies mixed pixels in image by producing new population of radiometric pixel values via selection, crossover, and mutation process. The mixed pixel classifies until global optimal solution satisfies for particular classification process.

(i) To obtain multitemporal change detection through accurate area measurement obtained through the BSO segmentation algorithm to exact enhanced boundary end point selections under different earth surfaces.

(ii) To obtain more accuracy in the measurement of area for on and off-road condition, implement through the single and multiple thresholding of pixels with more number of iterations in BSO algorithms, and improve enhancement and segmentation algorithm.

(iii) To validate area measurement of the proposed BSO algorithm, different areas such as hill, urban, road, and water body areas are measured form multiple-year period satellite images.

(iv) To obtain accurate area measurement in curved path, BSO algorithm is proposed. The BSO algorithm enhances and segments the curvature boundary of different land surfaces such as road, hills, and waterbody.

The paper is organized as follows. Section 2 explains the methodology of BSO in land area measurement. Section 3 explains backtracking search optimization (BSO) algorithm for land surface segmentation and area measurement, and finally Section 4 discusses and concludes about the efficiency of the BSO algorithm.

### 2. Methodology

The land cover change in a locality over the year is identified by shape and spectral characteristics of land features from satellite images. The shape and land features extractions are never accurate due to irregular shape and size of area. The
traditional segmentation algorithm of land image provides false positives and classifies land cover with minimal accuracy. The land cover classifies with different segmentation algorithms such as threshold segmentation, SVM, and K nearest neighborhood (KNN). The threshold-based segmentation algorithm includes noisy pixels in land image classification. The noisy pixel occurs in image since segmentation is performed with pixel intensity values. The noisy pixels in image classification are eliminated with multithresholding algorithm. The multithresholding
algorithm classifies images with Root Mean Square (RMS) values. However, the multithresholding never extracts the edges and boundary of land areas in Landsat and sentinel images. The LANDSAT and sentinel images are classified with pattern recognition methods.

The land cover classifier algorithm is classified as parametric and nonparametric classifier. Parametric classifier algorithms such as Markov process and probability algorithms classify the land cover with pixel values obtained by normal distribution probability theories. The
nonparametric method classifier such as artificial neural network (ANN), Decision tree, and Support Vector Machine (SVM) classifies the land cover with deterministic theories. The classifier algorithm further classifies as supervised and unsupervised classification algorithm. The supervised classification algorithm requires data training. The supervised classification trains by sample pixels from land cover image as input. The unsupervised classifier classifies land components with interpreter. The interpreter assigns class to different land components present in image depending on pixel spectral values. The traditional methods provide inaccurate land cover classification for complex land cover with mixed pixels and nonspectral land cover region. Hence, the backtracking search optimization (BSO) algorithm is applied, and it classifies land surface of low resolution (LANDSAT) and high-resolution (Sentinel) satellite images. The BSO classifies land surface successively and classifies mixed pixels in the image. The performance of the BSO algorithm is compared with particle swarm optimization for land cover classification. Figure 2 shows overview of area measurement methods.

The PSO algorithm works based on social behavior of birds. The synchronized bird flocking with sudden changes in movement, regrouping, and flying in a particular direction is influenced in the PSO algorithm. In land cover classification, PSO algorithms apply to group similar land covers. The similar land cover in image is identified as particles. Initially, the particles distribute randomly over the image solution space. The particles group until the global optimal solution is reached. The particle group with random change in particle coordinates, speed in successive approximation, and find personal best fit are represented by (1) and (2):

\[ v_{ij}^{k+1} = v_{ij}^k + cr_1 f (p_{ij}^k - x_{ij}^k) + cr_2 f (p_{gj}^k - x_{ij}^k), \] 

\[ x_{ij}^{k+1} = x_{ij}^k + v_{ij}^{k+1}, \]

i = 1, 2, 3, . . . N where “N” is the swarm size. j = 1, 2, 3, . . . D where “D” is the problem dimension. k = 1, 2, 3, . . . I where I represents iteration number. \( x_{ij}^k \) represents particle position, dimension, and current iteration. \( v_{ij}^k \) represents velocity of particle with respect to its coordinates.

The “c” represents particle acceleration; \( p_{ij}^k \) and \( p_{gj}^k \) are personal best fit and neighbor best fit of particular particle in solution space. The particle keeps track of the coordinates and personal best fit of adjacent particles. All particles work under same principle to reach global optimal solution. The particles move towards global best solution by evaluating fitness function for each coordinate to group land with similar aesthetics. The PSO terminates when global fit solution is reached or number of iterations has completed. The PSO further classifies as Discrete Particle Swarm Optimization (DPSO) and Fractional Order Darwinian Particle Swarm Optimization (FODPSO).

2.1. Study Area. The study area is Chennai urban and Tirupathi suburban province of INDIA for land cover classification. The study area of Chennai and Tirupathi with latitude and longitude is shown in Table 1. The selected land images comprise roads, building, vegetation, water body, lake, hills, and coastal. LANDSAT and sentinel image of study area are processed with the BSO and PSO algorithm for classification and comparative analysis. The study area LANDSAT and Sentinel images are obtained from https://earthexplorer.usgs.gov/ for the period of 2016 to 2019 for
land cover classification. Sentinel satellites acquire high-resolution image of land covers with 10- to 60-meter spatial resolution. The image resolution varies because of spectral band usage. The four spectral band and six spectral band provide 10-meter and 20-meter resolution images. Landsat-8 satellite consists of thermal infrared sensor and operational land imager. The sensors provide radiometric output of land cover with the reflected radiation and electromagnetic spectrum from earth surface.

Figure 3 shows urban Chennai region land cover classification with PSO algorithm. The PSO and DPSO perform well for high-resolution land cover classification. The DPSO shows discontinued roads and minimal vegetation present in land image and fails to classify vegetation boundary region and water body in Landsat and sentinel images. The vegetation boundary region in urban region in Landsat and sentinel image is never properly visible due to mixed pixel values in vegetation region. Similarly, the road which ranges from 50 to 60 feet identifies and road below 40 feet fails to detect with PSO and DPSO as shown in Figures 3(a) and 3(b).

Figure 4 shows low-resolution and high-resolution satellite image classification with PSO family. The PSO family never classifies land cover region accurately around vegetation region due to higher population of mixed pixels around vegetation and barren land components in Landsat and sentinel image. The water body and green land show distinct variation due to distinct pixel variations. Similarly, the hill region and coastal region show minimal land surface classification as in Figures 5 and 6. Figure 6 shows coastal region of kodiakadu in Tamilnadu, India. The PSO, DPSO, and FODPSO never segment the region such as beach face, land cover, fallow land, barren land, salt pan, saltwater body, and plantation. The high-resolution sentinel image shows more pixel classification around the coastal region due to pixel saturation by PSO family as in Figures 6(a) and 6(b). The pixel saturation and mixed pixels are classified more accurately with the backtracking search optimization (BSO) algorithm.

3. Backtracking Search Optimization (BSO) Algorithm for Land Surface Segmentation and Area Measurement

The backtracking search optimization algorithm determines global minimum and global maximum of radiometric pixel values in land cover image as described in the following:
Figure 9: Semiurban area land cover classification with BSO. (a) Sentinel suburban July 2017. (b) Sentinel suburban August 2019. (c) Landsat suburban July 2017. (d) Landsat suburban August 2019.

Figure 10: Hill region land covers classification with BSO. (a) Sentinel hill region July 2017. (b) Sentinel hill region July 2019. (c) Landsat Hill region July 2017. (d) Landsat hill region July 2019.
where $f(x)$ is the input image and $\epsilon$ ranges from values between (0.01 to 0.1). The different components in land image are randomly assigned with radiometric pixel values as follows:

$$P_{ij} = \text{rand} \times (\text{up}_j - \text{low}_j) + \text{low}_j. \quad (4)$$

The pixels of land image surface initially randomize for $i = 1, 2, 3, \ldots, N$ and $j = 1, 2, 3, \ldots, D$ where $N$ is the pixel intensity range and $D$ is the land surface boundary size.

The $\text{up}_j$ and $\text{low}_j$ are upper and lower bound of land surface and rand assign with random number between 0 and 1. The majority of land surface in image select and radiometric pixel values update according to (4).

The pixel values updated with pixel thresholding and old pixel ($\text{old}_p$) values are obtained by (4). The old radiometric pixel values reshuffle randomly up to $x$ iterations determined by mutation process as follows:

$$\text{Mutation} = P + F \cdot x \cdot (\text{old}_p - P). \quad (5)$$

The new population of radiometric values is generated for crossover operation. The crossover operation produces final radiometric pixel values for different land components in LANSAT and sentinel images. The radiometric values are obtained from crossover by assigning binary matrix values for component as 0 or 1. The binary values of component are set by the genetic algorithm. The above steps are followed by assigning mutation values where initial binary values in image are updated with new values. The values are updated according to different components in land image and their boundary region with respect to global minimum and maximum values. The selection, crossover, and mutation are repeated iteratively until global optimum solution is attained. In the second iteration process, the radiometric pixel values are updated to form new population of pixel for land components until new optimal global solution is reached. The flow diagram of the BSO algorithm is shown in Figure 7.

The low-resolution and high-resolution land components in urban land image are classified with the BSO algorithm as shown in Figure 8. The BSO algorithm shows change in road, building, and vegetation in high-resolution satellite images, unlike PSO algorithm, which failed to show

Figure 11: Coastal land cover classification with BSO. (a) Sentinel Coastal March 2016. (b) Sentinel coastal March 2019. (c) Landsat coastal March 2016. (d) Landsat coastal July 2019.
buildings, vegetation, and barren land in urban land image. Total study area considered was 27 km$^2$. The vegetation area was less than 1 km$^2$, and barren land was 1.6 km$^2$, which includes school, university ground, and car parking area. The algorithm distinguishes road breadth from 26 feet as shown in Figures 8(a) and 8(b), unlike PSO, DPSO, and FODPSO algorithms. The BSO delineates water logging in urban area due to extreme rainfall during July 2016 as shown in Figure 8(c). Similarly, the suburban region shows change in land, water body, and vegetation as in Figure 9. The AVADI Lake shows distinct change in pixel variation by delineating 451.34 m$^2$ land cover on 321588.37 m$^2$ lakes (as per AVADI municipality records). Furthermore, land mound with cross section of $10 \times 10$ meter was constructed on lake for fishing after year 2018 as in Figure 9(b). The BSO delineates land mound from high-resolution satellite image and never delineates land mound from low-resolution satellite images as in Figures 9(c) and 9(d).

The hill region and coastal area land classification with BSO is shown in Figures 10 and 11, respectively. The algorithm delineates hill pits, vegetation, water body, and barren land as shown in Figures 10(a) and 10(b). The delineation of land cover is performed well for high-resolution satellite images due to pixel thresholding at successive iterations during BSO mutation process in the BSO algorithm. Similarly, BSO classifies coastal area, which comprises saltpan, saltwater, plantation, fallow land, and barren land as shown in Figures 11(a)–11(d). The shoreline inundation and saltpan data were acquired from different sources such as Geological survey of INDIA, IFSAR, and ALOS PALSAR. The saltpan and saltwater in coastal area are classified by successive pixel value thresholding during mutation process of the BSO algorithm. The water body along coastal region has increased by 48% from March 2016 to March 2019 due to water inflow from ocean as in Figures 11(a) and 11(b).

The BSO classifies land cover and land surface better compared with particle swarm optimization. The ground-truth verification for BSO land cover estimation is 97% more accurate compared with PSO land cover classification. The comparative analysis of land use, land cover, and change in land cover changes is shown in Tables 2 and 3.

### Table 2: Land cover classification spatial extent.

<table>
<thead>
<tr>
<th>Land use land cover</th>
<th>SVM Ref [14]</th>
<th>KNN Ref [15]</th>
<th>PSO classification (%)</th>
<th>DPSO classification (%)</th>
<th>FODPSO classification (%)</th>
<th>BSO classification (%)</th>
<th>Difference in classification between PSO family and BSO (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Road</td>
<td>9</td>
<td>8</td>
<td>12</td>
<td>14</td>
<td>3</td>
<td>25</td>
<td>11–22</td>
</tr>
<tr>
<td>Building</td>
<td>4</td>
<td>3</td>
<td>5</td>
<td>4</td>
<td>&lt;1</td>
<td>30</td>
<td>26–29</td>
</tr>
<tr>
<td>Vegetation</td>
<td>12</td>
<td>9</td>
<td>28</td>
<td>29</td>
<td>12</td>
<td>44</td>
<td>15–32</td>
</tr>
<tr>
<td>Waterbody</td>
<td>13</td>
<td>10</td>
<td>30</td>
<td>21</td>
<td>22</td>
<td>40</td>
<td>19–20</td>
</tr>
<tr>
<td>Barren vegetation</td>
<td>14</td>
<td>9</td>
<td>14</td>
<td>12</td>
<td>5</td>
<td>13–15</td>
<td>1–2</td>
</tr>
<tr>
<td>Bare land</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>15</td>
<td>13</td>
<td>18</td>
<td>5–15</td>
</tr>
<tr>
<td>Coastal</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>25</td>
<td>22–24</td>
</tr>
<tr>
<td>Hill</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>&lt;1</td>
<td>5</td>
<td>30</td>
<td>25–29</td>
</tr>
</tbody>
</table>

### Table 3: Land cover change between July 2016 and Jan 2019.

<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Area (sq km)</td>
<td>Area (%)</td>
<td>Area (sq km)</td>
</tr>
<tr>
<td>Building</td>
<td>0.24</td>
<td>74%</td>
<td>0.19</td>
</tr>
<tr>
<td>Vegetation</td>
<td>3.21</td>
<td>71%</td>
<td>2.79</td>
</tr>
<tr>
<td>Water body</td>
<td>8.21</td>
<td>63%</td>
<td>7.98</td>
</tr>
<tr>
<td>Barren vegetation</td>
<td>7.02</td>
<td>69%</td>
<td>5.92</td>
</tr>
<tr>
<td>Bare land</td>
<td>5.14</td>
<td>70%</td>
<td>4.71</td>
</tr>
<tr>
<td>Coastal</td>
<td>7.82</td>
<td>67%</td>
<td>6.32</td>
</tr>
<tr>
<td>Hill</td>
<td>3.12</td>
<td>68%</td>
<td>2.51</td>
</tr>
</tbody>
</table>

4. Conclusion

The online area measurement from Google maps is inaccurate in land area measurement due to the different surface areas, curvatures, and sample point problems. Moreover, targeted land cover classification and land-cover classes of interest needs more ground-truth samples to reduce complexity and economic cost. The proposed BSO algorithm never needs the samples to classify the class of interest. Furthermore, the BSO algorithm is compared with SVM and KNN algorithms. The accurate area measurement is obtained through the backtracking search optimization-based automated single and multithresholding pixels from different iterations on the land surface. The backtracking search optimization (BSO) algorithm for area measurement is implemented through pixel intensity change with respect to spatial and temporal changes. Form the experimentation results, accurate land area measurement such as urban, semiurban, hill, and coastal region from LANSAT and SENTINEL images for period 2016 to 2019 shows better accuracy for BSO algorithm-based area measurement than the online area measurement form Google maps, and then...
starting and end points can be fixed for high accuracy in land surface area measurement. The BSO algorithm performs better for land use and land cover classification of low-resolution and high-resolution images. The BSO successfully delineated land use and land covers with 97% more accuracy in land area measurement from different regions such as urban, semiurban, hill, and coastal region compared with PSO, DPSO, and FODPSO algorithms. The delineation accuracy improves by threshold in pixel values after successive iterations of BSO mutation process. The BSO shows land use in urban area increased by 12% in urban, 28% in suburban, less than 5% in coastal, and less than 1% in hill region. The land use change verified with ground-truth verification shows 97% accuracy. Furthermore, the BSO algorithm can be combined with deep learning algorithms for more accuracy and to reduce the ground-truth verification cost [14, 15].

Data Availability

The data shall be made available on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References


