# Correspondence

## Analysis of IRS Imagery for Detecting Man-Made Objects With a Multivalued Recognition System

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*Abstract*—**The present work describes a method of analyzing Indian Remote Sensing (IRS) satellite imagery for detecting various man-made objects, namely, *roads, bridges, airports, seaports, city area* and *township/industrial areas*. A multivalued recognition system has initially been used to classify the image pixels into six land cover types by providing multiple choices of classes. In order to identify certain targets, some spatial knowledge about them and their inter-relationships have been incorporated on the clustered image using some heuristic rules. The use of multiple class choices makes the detection procedures effective.**

### I. Introduction

Analysis of remotely sensed images for detecting man-made objects has been a topic of research for the past two decades. Initially, various image processing techniques [1], [2], have been used in analyzing remotely sensed images. In order to identify certain targets, some knowledge about the targets and the scene is to be incorporated in the algorithm [3]. A good proportion of the existing literature in the field of remote sensing has addressed the problem of road detection (for example, see [4]). Some approaches [5], [6] can also be found in the literature which concern with detecting various man-made objects. IRS (Indian Remote Sensing satellite) images were also been considered by some researchers [7].

The theory of fuzzy sets provides suitable tools in analyzing complex systems and decision processes where pattern indeterminacy is due to inherent vagueness (fuzziness) rather than randomness. Since an image possesses some ambiguity within the pixels due to the possible multivalued levels of brightness, it is justified to apply the concept of fuzzy sets to an image processing problem [8], [9]. In a remotely sensed image, the regions (objects) are usually ill-defined (because of both grayness and spatial ambiguities). Moreover, the gray value assigned to a particular pixel of a remotely sensed image is the average reflectance of different types of ground covers present in the corresponding pixel area (36.25 m × 36.25 m for the IRS imagery). Therefore, a pixel may represent more than one class with a varying degree of likeliness. Thus, the approaches based on fuzzy set theory can be very effective in analyzing remote sensing images. Few attempts have been made in the remote sensing image analysis using fuzzy set theory. Interested readers may see [10].

Multivalued recognition systems based on the concept of fuzzy sets have been formulated recently by Pal and Mandal [11] and Mandal, Murthy and Pal [12]. These systems are capable of handling various imprecise inputs and in providing multiple class choices corresponding to any input. The recognition system [12] is initially used on an IRS image to provide multi-state decision in classifying (based on the spectral knowledge of the image) its pixels into six classes corresponding to six land cover types, namely, *pond water, turbid water, concrete structure, habitation, vegetation* and *open space*. The system provides the output either as *single choice* (possibility to belong only to one class) or *combined choice* (possibility to belong to more than one class with same preference) or *first-second choice* (possibility to belong to more than one class with different preferences) or *null choice* (possibility of not belonging to any of the classes) for the classification of any new pattern. The *green* and *infrared* band information are used for the classification. The fuzzy partitioned images, thus obtained, are then processed further for detecting various ill-defined man-made objects, namely, *roads, bridges, airports, seaports, city area*, and *township/industrial areas*. Multiple class choices of a pixel have been utilized in detecting some of these objects involving linear structures. In other words, the present work describes a real life application of the concept of multi-state decision for identifying various ill-defined objects from IRS imagery.

In order to identify certain targets, some spatial knowledge about them and their inter-relationships are incorporated on the clustered images. Various image processing techniques including thinning [14] and morphological operations [13] are used in our proposed algorithms. Some heuristic constraints are considered solely because of the resolution value which is 36.25 m × 36.25 m. The effectiveness of the algorithms is demonstrated on a scene corresponding to the city Bombay (India).

### II. Land Cover Types and Overall Strategy

#### A. Land Cover Types

The IRS (Indian Remote Sensing Satellite) image corresponding to a scene in India is considered in the present work. This scene primarily consists of the following six different land cover types namely

1) *Pond Water*: Contains pond water, fisheries etc.
2) *Turbid Water*: Contains sea water, river water etc. where the soil content is more.
3) *Concrete Structure*: Contains buildings, railways, roads, air strips etc. The signature of *sandbeds* in remote sensing images also belongs to this class.
4) *Habitation*: Basically consists of suburban and rural habitation i.e., concrete structures but comparatively less in density than the concrete structure class.
5) *Vegetation*: Essentially represents crop and forest areas.
6) *Open Space*: Contains basically the barren land. More specifically, a pixel with less greenery and less concrete structures falls into this class. The beaches come under this class.

In the remotely sensed data, the gray value that is assigned to a particular pixel is the average reflectance of different types of ground covers present in the corresponding pixel area (36.25 m × 36.25 m for IRS imagery). If a pixel contains the area corresponding to a big building and some open space, it is more likely to fall into the class "habitation" than "concrete structure". Considering the concept of *second* and *combined choices* of the aforementioned recognition system [12] on output decisions, the information about the building can be obtained.

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It is to be observed that the same region may fall in different classes in different seasons. As for example, "A cultivated land, which is a vegetation area, becomes open space after harvestation", "A river bed during summer falls under the class open space when it is dried up".

### B. Overall Strategy

The multivalued recognition system [12], as mentioned in Section I, is initially applied on an IRS image to classify its pixels into the aforesaid six classes. The overall strategy to discriminate hierarchically *roads, bridges, airports, islands, sandbeds, beaches, seaports, city area, township/industrial areas* is described here. The meaning of the targets considered here is stated below.

- *Water*: The pure and turbid water pixels constitute the water bodies in a scene.
- *Land*: The remaining pixels (i.e., not belonging to water bodies) are primarily categorized as the land.
- *Island*: A land portion surrounded completely by water bodies.
- *Sandbed*: The land portions (which belong to concrete structure) adjacent to the water bodies (sea, river etc.). Note that if all the pixels in an *island* are concrete structures, then the *island* is referred to as a *sandbed*.
- *Beach*: An open space region adjacent to water bodies and/or *sandbeds*.
- *Road*: The *roads* are the strips of varied width or single dotted curves, locally approximated by straight lines or parabolas, although globally they are arbitrary curves of concrete structure pixels. The railway tracks also come under *roads* here.
- *Bridge*: The only *bridges* considered here are the *bridges* on the water bodies. If a narrow concrete structure region lies in between two disjoint water bodies (i.e., the segment subdivides a water body into two distinct parts) and is connected with a *road* then the region is referred to as a *bridge*. If the segment is not attached with any road, then the region is categorized as a *sandbed*.
- *Airport*: An *airport* should possess a runway. A runway is a discrete narrow linear concrete structure region with a moderate length.
- *Seaport*: A sea is a vast homogeneous region of (turbid) water. A *seaport* is a concrete structure region adjacent to water bodies and it should be connected with the *city* by *roads* and/or it belongs to the *city area*. For landing of ships, either the edge adjacent to water bodies should be linear [Seaports with linear edge] or the concrete structure regions should be protruded on the water bodies [Seaports protruded on water bodies].
- *City Area and Township/Industrial Areas*: The *city area* is the largest densed concrete structure region connected with many *roads*. The other densed concrete structure regions with moderate sizes represent *township/industrial areas*. By filling up all intermediate nonconcrete structure pixels with concrete structure pixels, the *city area* and *township/industrial areas* are detected. In case there are major townships on the opposite sides of a river connected with *bridge(s)*, those townships are considered as a single entity and the intermediate water bodies are taken as the part of the township. As there exist many buildings as well as many *roads* in a *city area*, it is extremely difficult to differentiate them inside the *city area*.

Corresponding to any scene, there are four available IRS band images, namely, *blue, green, red,* and *infrared*. It has been observed that the *green* and *infrared* band images are more sensitive than other band images to discriminate various land cover types [3]. Thus, the data corresponding to these two band images are considered here as the features. Initially fifty pixels corresponding to each of the aforesaid six landuse classes are chosen as the training samples. The system classifies all the pixels of the scene into six classes based on these training samples.

Initially, all the disjoint water bodies are identified through their boundary pixels. The *island, sandbed,* and *beach* areas are then identified. The *sandbed* pixels are now eliminated from the concrete structure pixel set for the detection of other attributes, namely, *roads, bridges, airport, seaports, city area,* and *township/industrial areas* in the following stages.

Analyzing the concrete structure pixels of the clustered image, the *roadlike structures* (which include *roads, airport runways, and bridges*) are extracted. The disjoint linear segments of roadlike structures are categorized as the *airport runways* and the remaining pixels of the roadlike structure are assumed to represent the *roads* of the scene. Some road segments which lie between two different water bodies are identified to represent the *bridges*.

The concrete structure pixels (excluding *sandbeds*) connected with the *roads* are now put back which is now reffered to as the *extended roadmap* image. This *extended roadmap* image is analyzed to find attributes like *seaports, city area,* and *township/industrial areas*. The morphological dilation and erosion operations [13] are found useful to decide about the possible locations of *city area* and *township/industrial areas*. *Some Remarks:* The descriptions of the methods for detecting man-made objects are provided in the subsequent sections. It is to be mentioned here that the characteristics of various man-made objects and the algorithms to detect those objects have been developed keeping in view the Indian environment and the resolution of IRS imagery. In many developing countries like India, the construction of man-made objects and their interconnections are not, in general, on the same scale nor of the same specifications as in the developed countries in many cases. For example, the *roads* do not always have significant width in order to be reflected in the corresponding satellite images. Thus, it is possible to get *township/industrial areas* not connected by any *road* which, in reality, should not be the case.

On the other hand, the pixels in the boundaries of homogeneous regions do not possess the exact match with a single land cover type and so such pixels sometimes reflect wrong land cover types in the corresponding satellite imagery. For example, the boundary pixels of various water bodies, in general, reflect concrete structures, which are not always found to be true. Because of such inconsistencies and the low pixel-resolution of IRS imagery, a few heuristic constraints have been used in our proposed methods. These heuristic rules along with the description of the detection procedures are mentioned in the subsequent sections.

### C. Determining Water Bodies

From the classified image (with *single* and *first choices* of the multivalued recognition system [12]), all possible boundary (edge) pixels of water bodies are initially marked. With the boundary water pixels, various distinct water bodies are then identified using a contour tracing method. To find this, the aforesaid image is scanned horizontally from left to right starting with the first row to search for a boundary water pixel. Starting with that pixel, all the connected boundary water pixels are traversed using octal codes. The neighboring pixels with respect to the current pixel are searched for other boundary water pixels (not already traversed). If only one traversable pixel is found, then that pixel is taken for next traversal. In case, multiple traversable pixels are found, the next movement is taken by choosing that direction which most closely matches that of the previous description of the path. The remaining traversable pixels are kept reserved. This enables one to use these pixels for counting the description of other contours connected to them.

The traversal procedure is continued until there is no nontraversed boundary pixel found in the eight neighbors of the current pixel. After that, a pixel is taken from the reserved set provided it is not already traversed, and the traversal procedure is similarly continued. It is terminated for a water body when there is no more nontraversed reserve pixel. In this way, the boundaries of all the distinct water bodies are identified. Different possible cases, as explained below, may arise out of different types of water boundaries.

- It is mentioned earlier that the pixels corresponding to the *sandbeds* belong to the class "concrete structure". The narrow concrete structure regions adjacent to the water pixels are categorized as *sandbeds*. The width of the *sandbeds* along the water bodies is, in general, not significant. The width of such *sandbeds* are restricted to three pixels for practical reasons.
- There may be a narrow concrete structure region between two distinct water bodies. In such cases, two possibilities may arise with such a concrete region. The region may represent a *bridge* and in that case, there should be a *road* passing through the *bridge*. The other possibility is that the region may represent a *sandbed* and in that case, the region will not be connected with any *road*. So, for the time being, such concrete structure regions are marked as the *candidate regions for bridges*. Final decision on these regions is taken in Section III after detecting the *roads*.
- Sometimes the boundaries may make either an open path or a closed path or a multiple closed path. In the case of a closed path, it may enclose a water body or a land portion and/or a concrete structure region. The enclosed land portions are identified as *islands* and the enclosed concrete structure regions are categorized as *sandbeds*.
- If an open space region with a moderate size (≥25 pixels) is found adjacent to a water body and/or *sandbeds*, it is identified as a *beach*.

The aforementioned observations are utilized in our experiment for detecting the *islands, sandbeds, beaches*, and the *candidate regions for bridges*.

## III. Roads, Bridges and Airports

The method of identifying the roadlike structures (i.e., *roads, bridges*, and the *airport runways* from concrete structure pixels is initially described here.

To find the roadlike structures, the concrete structure pixels except the *sandbeds* are considered as the patterns. The width of the *roads* as well as the *airport runways* has an upper bound which is considered here to be 108.75 m (three pixels) for practical reasons. So, all the pixels lying on concrete structure segments with width not more than three pixels are initially considered as the candidates for the roadlike structures. As the size of a pixel is quite big (36.25 m), all the portions of such actual roadlike structures may not be reflected as concrete structures and as a result, the candidate pixels may constitute some broken segments. The total procedure to find the roadlike structures consists of three parts—i) selecting the candidate pixels, ii) thinning the candidate patterns and iii) traversing the thinned patterns to make some obvious connections between various roadlike segments. Fig. 1(a) represents an input concrete structure patterns of dimension $80 \times 80$ and the results at various stages of the above mentioned operations are shown in Fig. 1(b)–(i).

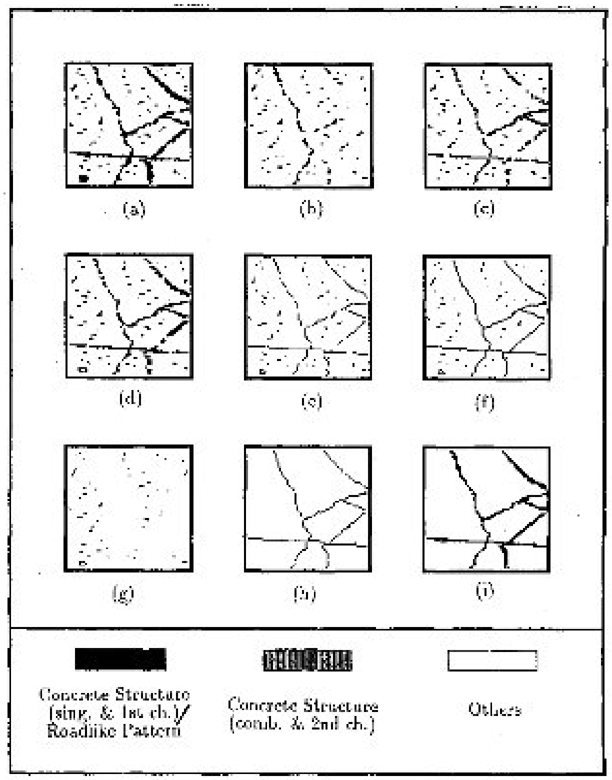


Fig. 1. Illustrating the method for finding roadlike patterns starting with the concrete structure patterns.

i) *Selection of the Candidate Pixels:* To find the candidate pixel set for the roadlike structures, the image is initially scanned horizontally from left to right starting with the first row and the concrete structure runs of maximum three pixels are marked [Fig. 1(b)] as the *candidate pixels*. Similarly, vertical scan and diagonal scans (in both directions) are made to identify all the elongated patterns and some junction points of the roadlike structures [Fig. 1(c)]. The complete candidate pixel set for roadlike structures is shown in Fig. 1(d) corresponding to the concrete structure patterns in Fig. 1(a).

ii) *Thinning:* The parallel thinning algorithm proposed by Zhang and Suen [14] is applied here for thinning the patterns. Using the algorithm, the *candidate roadlike patterns* are thinned. The resultant thinned patterns provide some broken segments [Fig. 1(e)]. Note that the thinning algorithm may remove some pixels belonging to the actual skeleton of *roads*. The traversal algorithm considers the pixels removed during the thinning process as a separate group to overcome this problem to some extent.

iii) *Traversal and joining:* The roadlike structures consist of the *roads* and the *airport runways*. In India, the *roads* (or some of its portions) are some times very narrow. In some places, the *roads* are surrounded by big trees. Because of such unavoidable circumstances, some pixels on the real *roads* may not be reflected as concrete structures and will make the roadlike segments discontinuous. The information about many of such ambiguous/distorted segments can be obtained from the *second* and *combined choices* provided by the multivalued classifier [12]. When there is a big building adjacent to a *road*, the corresponding *road* portion in the image will look wider with the concrete structure pixels. Therefore, the pixels on that *road* portion may not come under the candidate pixel set; thereby resulting in a discontinuation in the roadlike structures [Fig. 1(d)]. Again, some of the candidate pixels belonging actually to the *roads/airport runways* may be removed during thinning process [Fig. 1(e)].

To overcome these problems, a new traversal (road finding) algorithm (different from that used in Section II) through the thinned candidate patterns is adopted here. During traversal, it always looks forward for the obvious joining between various roadlike segments. One of the inherent properties of the traversal procedure is that the tracing of roadlike structures proceeds more or less in the same direction. So to keep track of the direction, the usual 8-directional code is used during the traversal. After analyzing the potentialities of the pixels to be in the roadlike segments, conceptually, five different potential groups are assumed which are coded as **A**: (The pixels present after thinning), **B**: (pixels removed during thinning), **C**: (pixels already traversed), **D**: (concrete structure pixels decided either by the *single* or *first* or *second* or *combined choices* of the multivalued recognition system [12]), **E**: (pixels not belonging to the aforementioned categories). Obviously the pixels in group **A** have the highest potentiality than the pixels in other groups to be in the roadlike segments.

First of all, the longest thinned segment is chosen and the traversal begins with the middle most pixel of that segment. To find the next pixel to be traversed, the pixels in the eight neighboring positions of the starting pixel are analyzed. One of the neighboring pixels with potential category **A** is taken for the traversal and the directional code of the pixel with respect to the starting pixel is noted. Other neighboring pixels having the potential code **A** are marked as reserved for the future traversal and the directional codes of the pixels with respect to the starting pixel are also noted.

Now, at any point of time, there may be many possible choices for the next traversal depending on the potential categories of the neighboring pixels and the current traversal direction. Twelve such situations are considered in our experiment and are shown in Fig. 2. These situations are arranged in an order so that if one fails, then the next is considered for choosing the next traversal pixel. (One may always think of some more situations but we restrict ourselves with these twelve cases.) The current traversal directions are shown here by thick lines, the next traversal directions are shown by thin lines, and the intermediate movements are shown by dotted lines. The solid circles inside a box, dotted box and solid line box represent the pixels in current, intermediate and final traversal positions respectively. Note that the situations in (5) and (8)–(12) of Fig. 2 are considered for the possible extension (i.e., looking forward to join the present segment with other segments) of the existing roadlike segments, and these situations are considered only when the number of pixels in the current traversing segment becomes greater than or equal to five.

When none of the aforementioned twelve cases is satisfied, the current traversing pixel is considered as one of the *end points* for the present segment. The *end points* are utilized later in this section to verify the linearity criterion for the *airport runways*.

Now a nontraversed and reserved pixel is taken and the traversing of the segment is continued assuming its directional code as the current traversing direction. When all the reserved pixels are exhausted (i.e., traversed), the traversing is stopped for the present segment. The same procedure is repeated for other isolated segments in the scene.

(iv) *Use of Multiple Choices:* As our recognition system [12] provides multiple choices, the information about all the classes present in a particular pixel can be obtained. For completing the task of identifying roadlike structures, the use of multiple choices is directly realized. Out of the twelve movements considered [Fig. 2] for traversing the roadlike patterns, the movements in (5), (8)–(12) are governed by the *second* and *combined choices*. Note that after using *second* and *combined choices* in traversing the segments in Fig. 1(e), we have more complete information as in Fig. 1(f).

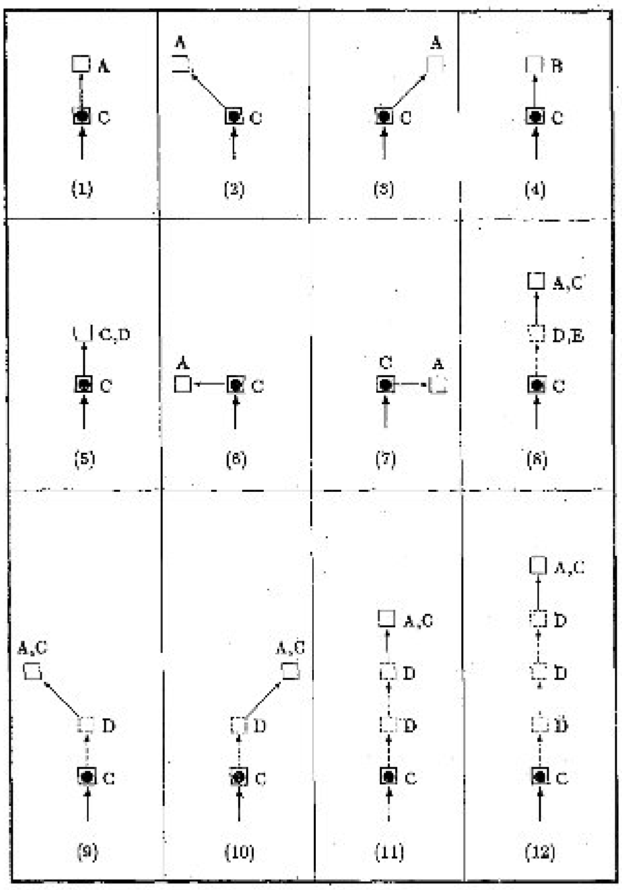


Fig. 2. Various movements considered for connecting/traversing roadlike structures.

(v) *Removal of Noisy Segments:* The segments with insignificant lengths (<20 pixels) among the detected roadlike patterns are discarded. The removal of the stray points as seen in Fig. 1(g) makes the resultant roadlike patterns [Fig. 1(h)] further prominent. The residual segments represent the skeleton version of the roadlike patterns. To complete the roadlike patterns, we now put back all the concrete structure pixels lying in the eight neighboring positions corresponding to the pixels on the previously obtained narrow roadlike patterns. This resultant image [Fig. 1(i)] represents the roadlike structures. These roadlike structures basically contain *roads* and the *airport runways*. Note that the *bridges* are included in the *roads*.

### A. Finding Airports, Roads, and Bridges

An *airport* should possess a runway and a runway is a discrete narrow linear concrete structure region with a moderate length. The minimum length of a runway is set to 30 pixels for practical reason. Again, it is observed that the end points of the runways are open in the sense that the ends of the airport runways should not be connected with any other concrete structure regions. In a digital image, the concept of linearity is used loosely to tackle the loss of information solely because of digitization. Moreover, as the pixel size of satellite images is big, an approximate linearity criterion is proposed below. It has been used to check the linearity for *airport runways* and also for *seaports*.

*Linearity Criterion:* The linearity criterion to identify the existence of a linear roadlike pattern between any two points (pixels), say

$P(x_p, y_p)$ and $Q(x_q, y_q)$ is defined here. A window of parallelogram shape is assumed here and all the roadlike pattern pixels in the window are taken to find an approximate linearity. Let $m$ denote the inclination of the line between $P$ and $Q$ i.e.,

$$m = \tan^{-1}\left(\frac{y_q - y_p}{x_q - x_p}\right). \quad (1)$$

Define

$$\hat{m} = \frac{\pi}{4}\,\mathrm{Int}\left(\frac{m}{\frac{\pi}{4}}\right) \quad (2)$$

where Int denotes integer operator and from all the angles multiple of $\pi/4$, $\hat{m}$ takes the angle which is nearest to $m$.

Find

$$m_1 = \hat{m} + \frac{\pi}{2} \quad \text{and} \quad m_2 = \hat{m} - \frac{\pi}{2} \quad (3)$$

so that among all the angles multiple of $\pi/4$, $m_1$ and $m_2$ take the nearest angles corresponding to the inclinations of the two lines drawn perpendicular to the line between $P$ and $Q$.

Let $d_1$ and $d_2$ be the directional codes corresponding to the inclinations $m_1$ and $m_2$ respectively. Now from the eight neighboring pixels of $P$, the two pixels in the directions $d_1$ and $d_2$ are chosen as $p_1$ and $p_2$ respectively. Similarly from the eight neighboring pixels of $Q$, the two pixels in the directions $d_1$ and $d_2$ are chosen as $q_1$ and $q_2$ respectively. A parallelogram is formed with $p_1$, $p_2$, $q_1$ and $q_2$ as the four corner points, and all the roadlike pattern pixels lying on or within this window are marked. In case a traversal can be made from $P$ to $Q$ through the connected marked pattern pixels, the pattern segment in between $P$ and $Q$ is considered as linear.

*Airports:* Note that the roadlike patterns are the collection of few disjoint concrete structure segments. Recall that at the time of traversing each of these segments, some pixels were marked as the *end points* i.e., the segments could not be extended beyond those points.

Each set of *end points*, corresponding to different isolated curve segments, is considered separately to check the linearity for existence of the *airport runways*. For the *end point* pairs lying at least 30 pixels apart and satisfying the said linearity criterion, the intermediate roadlike segment is classified as the *airport runways*. After the *runways* are detected, the other concrete structure regions in its vicinity may be assumed to represent the terminal buildings, car parking areas etc. for the airports.

*Roads:* After the detection of *airport runways*, the remaining roadlike patterns are assumed to represent the *roads* (roadmap) of a scene. Note that *bridges* are included in the *roads*.

*Bridges:* It may be recalled here that some narrow concrete structure regions lying between two different water bodies were marked earlier as the *candidate regions for bridges*. For *bridges*, these regions should belong to the *roads*. The candidate regions belonging to the *roads* are confirmed as the *bridges*. The remaining candidate regions (not belonging to the *roads*) are categorized as the *sandbeds*.

## IV. Seaports, City Area and Township/Industrial Areas

The roadlike structures were obtained in the previous section. In order to identify the *seaports* and *city area*, the concrete structure pixels connected with the *roads* are put back and the resultant image is referred to here as *extended roadmap*. The *township/industrial areas* are detected from the original concrete structure patterns.

### A. Seaports

As mentioned in Section II, there exist two types of seaports. The methodology for detecting them is given here.

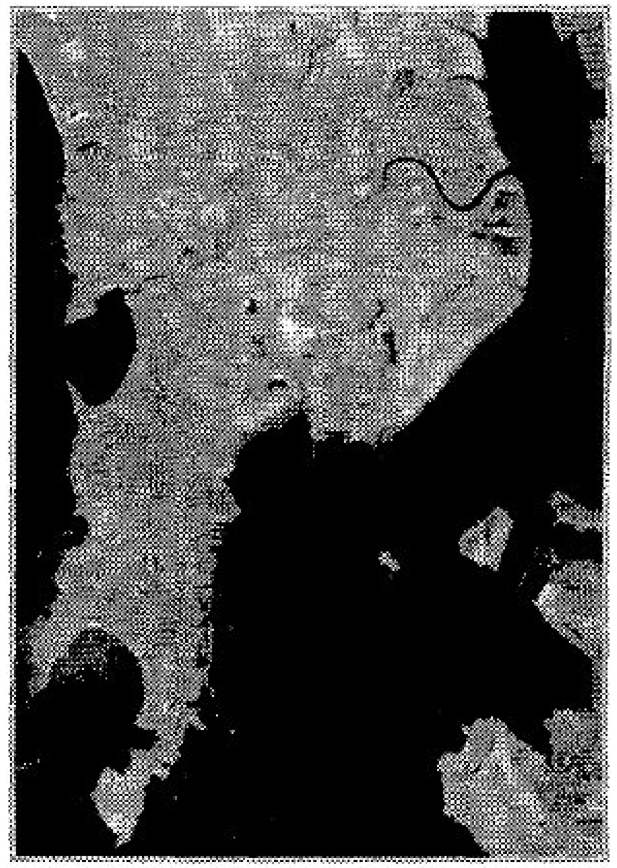

Fig. 3. IRS Bombay band-4 (infrared) image.

*Seaports with Linear Edge:* To find them, all the concrete structure pixels adjacent to the water bodies in the *extended roadmap* are initially marked. For this purpose, the *extended roadmap* image is first scanned horizontally and then vertically. With the connected marked pixels, some disjoint segments are visualized. The segments with insignificant length (<20 pixels) are assumed to be incapable of representing the seaports in this category, and therefore the pixels on such segments are discarded from the marked pixel set. All the distinct segments with the remaining marked pixels are considered one after another to find the linear portions, if there is any, of significant length (≥20 pixels). The linearity criterion [Section III] is used in a successive manner on various segments with the marked pixels. Thus, some concrete structure pixels belonging to the *extended roadmap* are identified and these provide the linear edges of the *seaports*. To obtain the other possible portions of the *seaports*, the obtained edges are extended with the connected concrete structure pixels to some extent (maximum 5 pixels) in all the directions.

*Seaports Protruded on the Water Bodies:* The edge of a *seaport* in this category on the water bodies makes a zig zag pattern. To find such *seaports*, the regions with concrete structure pixels having maximum 10 pixel width are initially found. For this, the *extended roadmap* image is scanned horizontally from left to right starting with the first row. The concrete structure pixel runs (with maximum 10 pixels) followed and proceeded by the water bodies are obtained and the first and the last pixels of such runs are marked. The *extended roadmap* image is also scanned vertically


Fig. 4. Sandbeds, islands, and beaches.

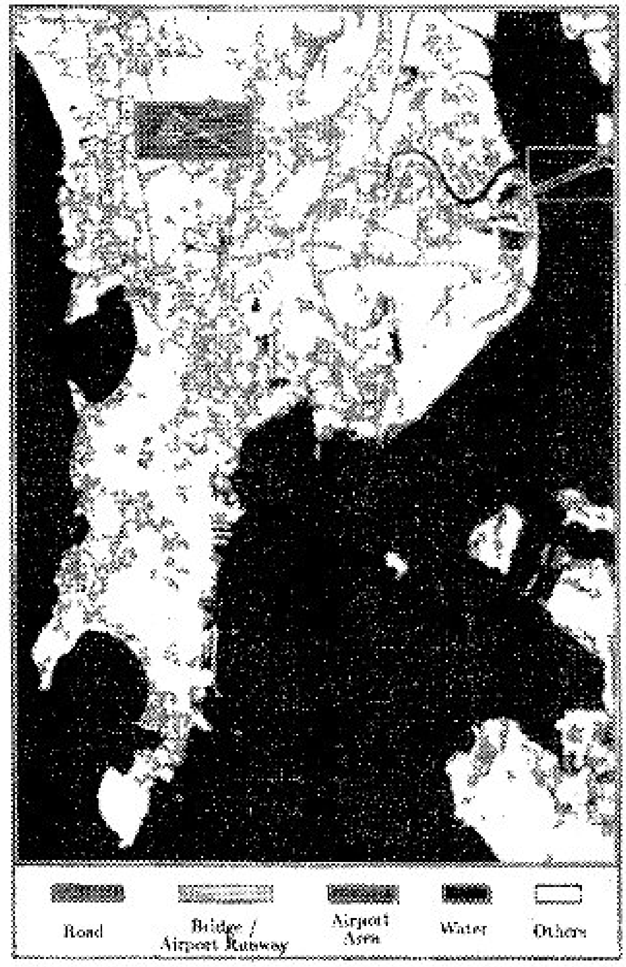


Fig. 5. Roads, airports, and bridges.

and in both the diagonal direction for the same purpose. So, some concrete structure pixels are marked which represent the boundary of some concrete structure regions protruded on the water bodies. The opposite sides of the protruded regions (adjacent to the water bodies) are, in general, parallel to some extent for a *seaport*. So to check this property of the protruded *seaports*, some more or less linear segments are visualized with the connected and marked pixels. The segments with insignificant sizes ($\leq 5$ pixels) are discarded. The inclinations of each of the segments with the marked concrete structure pixels are computed. Two segments lying on the opposite sides of the protruded regions are found, and if the difference of their inclinations is within $\pi/4$, the region is said to represent a protruded *seaport*.

*City Area and Township/Industrial Areas:* The largest compact concrete structure region with a significant size ($25 \times 25$) present in the scene is referred to as the *city area*. Other dense concrete structure regions with the minimum size $9 \times 9$ are assumed to represent either *townships* or *industrial areas*. The morphological dilation and erosion operations [13] are found to be very effective to find these target areas. In the present experiment, the dilation and erosion operations have been combined in a number of ways to detect the *city area* and the *township/industrial areas*. The same structuring element is considered throughout this paper which is of size $5 \times 5$, all with the concrete structure pixels and origin at the centre i.e., in the position $(3, 3)$.

The *city area* is obtained from the *extended roadmap* image. The dilation operation is initially applied thrice on the *extended roadmap* image. Then three morphological erosion operations are applied with the same structuring element. Then the erosion operation has been applied five times. After that, five dilation operations bring back the residual regions to their previous boundaries.

After the aforesaid processing, the largest compact region available in the image is considered to represent the *city area*. The other remaining compact regions may be viewed as various *township/industrial areas*. The rules for obtaining the *township/industrial areas* can be similarly formulated.

## V. Implementation, Results, and Discussion

The data used for the present work is acquired from the Indian Remote Sensing Satellite (IRS). We have used *green* and *infrared* band images and the spatial resolution of a pixel is approximately 36.25 m × 36.25 m [15]. We have implemented the proposed methodologies on various IRS image frames corresponding to various scenes in India. For brevity, we are presenting here the results corresponding to the image frame representing the city Bombay [Fig. 3]. The *sandbeds, islands* and *beaches* obtained are shown in Fig. 4. The *airports, roads* and *bridges* as identified from Bombay image are shown in Fig. 5. The *airport areas* and the *bridges* are distinctly marked (enclosed with dark and white boundaries) in the