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Utility of multiple choices in detecting ill-defined roadlike structures

Deba Prasad Mandal, C.A. Murthy and Sankar K. Pal
Machine Intelligence Unit, Indian Statistical Institute, Calcutta 700 035, India

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Abstract: A multivalued recognition system has been formulated recently by Mandal, Murthy and Pal which is capable of handling various imprecise inputs and in providing multiple choices of classes corresponding to any input. In the present work, we have demonstrated an application of the recognition system for detecting the ill-defined roadlike structures from an Indian Remote Sensing (IRS) satellite image. The concept of multiple choiees of the recognition system is found to be very effective in the detection procedure. The results are found to be quite satisfactory when the scenes of Calcutta and Bombay were considered as input.

Keywords: Remote sensing; fuzzy sets; management of uncertainty; pattern recognition; image processing.

1. Introduction

Multivalued recognition systems [10] based on the concept of fuzzy sets have recently been formulated by Pal and Mandal [18] and Mandal, Murthy and Pal [11]. These systems are capable of handling various imprecise inputs and in providing multiple class choices corresponding to any input. In the present article, we have demonstrated the utility of the multiple choices (as provided by the recognition system [11]) in detecting the ill-defined (fuzzy) roadlike structures from Indian Remote Sensing (IRS) satellite imagery.

There are many approaches found in the literature which addressed the problem of detecting roadlike structures from remote sensing imagery. Fischer et al. [5] have presented a method where locally evaluated evidence of road presence from multiple sources is combined. Bajcy and Tavakoli [1] used a world model of roads for detecting road and roadlike features from ERST-1 satellite data using only the green band image. Groch [6] has proposed a semi-automatic method of following line shaped objects in aerial images. Mckeown and Pane [14] have addressed the problem of alignment and connection of linear feature fragments in aerial imagery. Bezdek et al. [2] described a parallel line detector (PLO) algorithm which compares the contrast of neighboring pixels and checks for uniformity along the tracking direction, to detect a roadlike structure from radar images. Zhu and Yeh [28] have proposed a method for road network detection where low level image processing techniques are used to detect linear segments. In order to predict missing links between broken segments, they used the facts about the road network and perceptual continuity. Vasudevan et al. [21] have developed an intermediate processing stage that addresses tasks of partitioning and connecting road-like fragments. Parui et al. [19] have proposed a method to extract the linear features from IRS images based on only infrared band image.

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

Correspondence to: Dr. S.K. Pal, Machine Intelligence Unit, Indian Statistical Institute, 203 Barrackpore Trunk Road, Calcutta 700035, India.

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image is the average reflectance of different types of ground covers present in the corresponding pixel area (36.25 m $\times$ 36.25 m for the IRS imagery). Therefore, a pixel may represent more than one class with a varying degree of belongingness. Thus, the approaches based on fuzzy set theory [3, 17, 24] can be very effective in analyzing remote sensing images.

Attempts [4, 7, 9, 22, 26] have been made in the literature to analyze the remotely sensed imagery using fuzzy set theory. The existing approaches are unable to extract the majority of information dormant within the data and the accuracy levels of image classification are quite often unsatisfactory [23]. To improve the analysis, it was suggested that studies are required on resolutions of sensor systems, physical principles of remote sensing and image processing algorithms [8].

In the present work, the multivalued recognition system [11] has initially been applied on an IRS image to classify (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 green and infrared band information are used for the classification. The concrete structure pixels of the clustered images are then processed for detecting the roadlike structures present in the scene. The proposed algorithm is implemented on some IRS images where the pixel resolution is 36.25 m $\times$ 36.25 m. Some heuristic constraints for the detection of roadlike structures are considered solely because of the resolution value. For example, the maximum width of the roadlike structures is restricted here to three pixels for their detection. To demonstrate the effectiveness of the algorithm, two of such images are considered. These two images correspond to the scenes of two cities in India, namely Calcutta and Bombay. The results are found to be quite satisfactory.

In Section 2, a brief description of the multivalued recognition system [11] is provided. Section 3 deals with the method of detecting the roadlike structures from IRS imagery. The results are demonstrated in Section 4. Section 5 contains the conclusions and discussion.

2. Multivalued recognition system [11]

The multivalued recognition system developed by Mandal, Murthy and Pal is described here in brief. The system has the capability of handling various input patterns and it provides multiple class choices as the output decisiou. For describing the system, let us consider an M class ($C_1, C_2, \ldots, C_j, \ldots, C_M$) and N feature ($F_1, F_2, \ldots, F_i, \ldots, F_N$) problem. The block diagram of the recognition system is shown in Figure 1. It consists of two parts, namely *Learning* aud *Fuzzy Processor*. The learning sectiou basically decomposes the entire feature space into some *space sub-domains* aud finds a relational matrix. The Fuzzy Processor uses the relational matrix in the modified compositional rule of infereuce [25] to

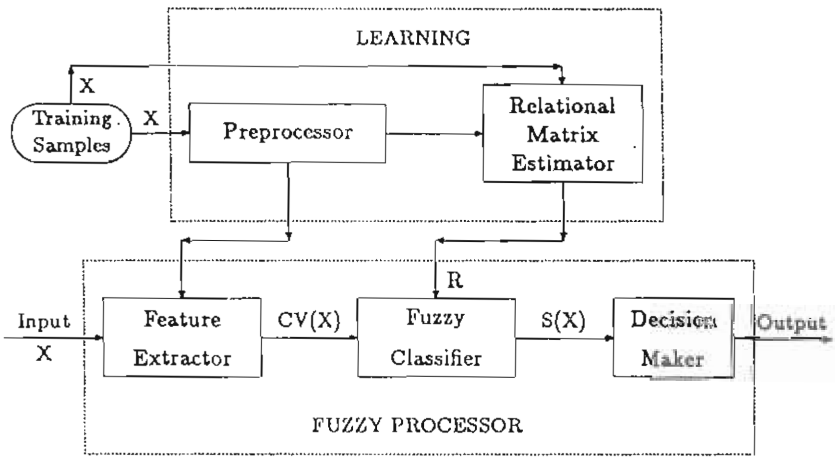

Fig. 1. Block diagram of the multivalued recognition system [11].

decide about the class or classes in which a pattern X may belong. The operations of various blocks in Figure 1 are discussed below.

2.1. Learning

The learning section has two blocks, namely *preprocessing* and *relational matrix estimator*. The *space sub-domains* in the feature space are obtained in the preprocessing block and the block relational matrix estimator finds a relational matrix R.

Initially depending on the geometric structure [12] and the relative positions of the pattern classes in the feature space, the training sample set of each pattern class (say, C_j) is decomposed into a few sample groups (say, m_j). That is, the training sample sets of all the M pattern classes are decomposed into $\sum_{j=1}^{M} m_j$ ($=\hat{M}$, say) groups. Accordingly, each individual featnre axis (say, F_i) is divided into a number (say, n_i) of sub-domains (referred to as feature sub-domains) to highlight the sample groups. Each of the feature sub-domains is extended to incorporate the portions (of the pattern classes) possibly uncovered by the training samples. Thus the whole feature space is decomposed into some, say $\hat{N}$ ($=\prod_{i=1}^{N} n_i$) overlapping space sub-domains.

The feature sub-domains are then characterized by the piecewise linear triangular functions of the form $T(x, \alpha, \beta_l, \beta_u, \Gamma_l, \Gamma_u)$ in which α is the central part where the membership value is 1.0; β_l and β_u are the lower and upper most ambiguous (cross-over) points where the membership values are 0.5; Γ_l and Γ_u are the lower and upper end points beyond which the membership values are zero. Such a piecewise linear triangnlar function is graphically shown in Figure 2.

The relational matrix, R, denotes the compatibility of the pattern classes corresponding to the space sub-domains. The order of R is $\hat{N} \times M$. The matrix R is estimated from the training samples in the relational matrix estimator block. Let r_{hj} denote the (h, j)th element of R, i.e., the element corresponding to the hth space sub-domain and jth pattern class. The value of r_{hj} is decided as

$$r_{hj} = \begin{cases} 0 & \text{if the } h\text{th space sub-domain does not highlight the } j\text{th pattern class?} \\ 1 & \text{if the } h\text{th space sub-domain highlights only the } j\text{th pattern class;} \\ (0.8)^{NS_h/(NG_h NC_j^h)} & \text{if the } h\text{th space sub-domain highlights the } j\text{th pattern class along with some other classes.} \end{cases} \quad (1)$$

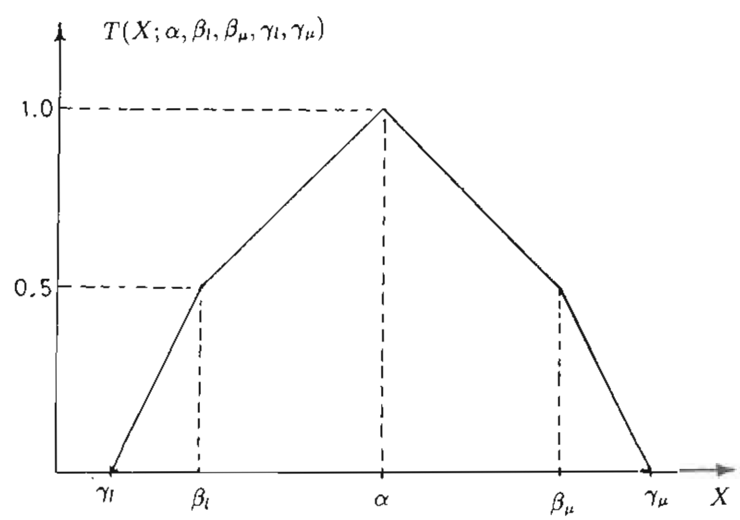

Fig. 2. Piecewise linear triangular function [11].

Here NG_h is the number of training sample groups highlighted by the space sub-domain h; NC_j^h is the number of training samples from the jth class (C_j) in the hth space sub-domain and NS_h is the total number of training samples in the hth space sub-domain i.e., $NS_h = \sum_{j=1}^{M} NC_j^h$. If $NG_h = 0$ then $r_{hj} = 0$ for all $j = 1, 2, \ldots, M$. If $NG_h = 1$ and hth space sub-domain highlights the class C_j then $r_{hj} = 1$ and $r_{hk} = 0$ for $k \neq j$. Otherwise, i.e., if $NG_h > 1$, then the space sub-domain h is overlapping according to the training sample groups. The factor $NS_h/(NG_h NC_j^h)$ is used as a density factor for the jth pattern class in the hth (overlapping) space sub-domain.

So the block relational matrix estimator finds the relational matrix R which is utilized in the fuzzy classifier block to provide the final output of the recognition system.

2.2. Fuzzy processor

This section consists of three parts, namely *feature extractor*, *fuzzy classifier* and *decision maker*. It uses the relational matrix in the modified compositional rule of inference [11] to decide about the class or classes in which a pattern X may belong.

The feature extractor block determines the membership values (degree of belonging) of an unknown pattern X ($= [F_1, F_2, \ldots, F_N]$) to the space sub-domains. Initially, each individual feature information is considered separately to find the membership values (f) of X to the corresponding feature sub-domains.

For an unknown pattern of X, a *characteristic vector* $CV(X)$ is then defined as

$$CV(X) = (cv_1(X), cv_2(X), \ldots, cv_{\hat{N}}(X)) \tag{2}$$

where the hth element $cv_h(X)$ denotes the degree of its belonging to the hth space sub-domain. Let the hth ($h = 1, 2, \ldots, \hat{N}$) space sub-domain be consisting of the feature sub-domains $g_1^h, g_2^h, \ldots, g_i^h, \ldots, g_N^h$. Suppose $f_{g_u^h}(X)$ represents the membership of X to belong in the g_u^hth feature sub-domain. Then the hth element of $CV(X)$, i.e., the membership value of X corresponding to hth space sub-domain, is defined [11] as

$$cv_h(X) = \begin{cases} \dfrac{1}{N} \sum_1^N f_{g_i^h}(X) & \text{if } f_{g_i^h}(X) > 0 \text{ for all } i = 1, 2, \ldots, N, \\ 0 & \text{otherwise,} \end{cases} \qquad h = 1, 2, \ldots, \hat{N}. \tag{3}$$

So the block feature extractor determines a characteristic vector with $\hat{N}$ elements (for $\hat{N}$ space sub-domains) corresponding to each input pattern X.

A *class similarity vector* $S(X)$ is then defined as

$$S(X) = (s_1(X), s_2(X), \ldots, s_M(X)) \tag{4}$$

where the jth element $s_j(X)$ denotes the degree of similarity of a pattern X to the jth class. The $s_j(X)$ is determined as

$$s_j(X) = \begin{cases} \underset{h=1,2,\ldots,\hat{N}}{\mathrm{Max}} \{\tfrac{1}{2}(cv_h(X) + r_{hj})\} & \text{if } cv_h(X) > 0 \text{ and } r_{hj} > 0, \\ 0 & \text{otherwise,} \end{cases} \qquad j = 1, 2, \ldots, M, \tag{5}$$

where $cv_h(X)$ is the hth element of $CV(X)$; r_{hj} is the (h, j)th entry of R and $\hat{N}$ is the number of space sub-domains. Therefore, the block fuzzy classifier finds a class similarly vector $S(X)$ corresponding to an unknown input X.

The similarity vector $S(X)$ is then analyzed in the decision maker block. The system provides output in one of the following four forms:

(i) *Single Choice:* If the entry in $S(X)$ corresponding to only one class is positive then the said class is considered as the output with single choice.

(ii) *Combined Choice:* If the entries in $S(X)$ corresponding to more than one class are positive and if they are nearly the same (difference $\leqslant 0.05$) then the said classes are considered as output with combined choice.

(iii) *First-second Choice:* If the entries in $S(X)$ corresponding to at least two classes are positive and the said entries do not satisfy the criteria for combined choice then the first-second choice is considered. The highest two entries in $S(X)$ are taken as the first and second choices respectively.

(iv) *Null choice:* If all the entries in $S(X)$ are zero then the system refuses to assign the unknown sample to any class, i.e., null choice is given.

In order to give the final decision in linguistic form regarding the class or classes to which the unknown input pattern X may belong, the confidence factor (CF), as defined in [11], is calculated and accordingly the final output decision in linguistic form is provided.

The effectiveness of the system had been adequately demonstrated on some artifically generated pattern sets and also on a speech recognition problem [11]. Its theoretical performance has also been derived [13].

In remotely sensed imaginery, the regions are usually ill-defined (becanse of both grayness and spatial ambignities) and a pixel may consist of more than one land cover type. Therefore, the aforementioned recognition system providing multivalued output decision should be very appropriate (as compared to the conventional crisp or hard decision) in analyziug remote sensing imagery. In the present work the recognition algorithm is initially used to classify an IRS image into six classes. The clnstered images are further processed for detecting roadlike structures present in the scene. The aforesaid concepts of second and combined choices, as will be shown in the next section, are very effective in discriminating the roadlike structures. In the next section, we describe the proposed methodology for detecting the roadlike structures from IRS images alongwith the description of various land cover types present in the scene.

3. Roadlike structures

3.1. Land cover types

The IRS (Indian Remote Sensing) satellite images corresponding to scenes of Calcutta and Bombay are considered in the present work. These scenes primarily consists of six different land cover types, namely pond water, turbid water, concrete strncture, habitation, vegetation and space. The constituents of the six classes are furnished below:

(i) *Pond water:* This class contains pond water, fisheries etc.

(ii) *Turbid water:* This class contains sea water, river water etc. where the soil content is more.

(iii) *Concrete structure:* This class contains buildings, railway tracks, roads, airport runways etc. The signature of sandbeds in remote sensing images also belong to this class.

(iv) *Habitation:* This class basically consists of suburban and rural habitation, i.e., concrete structures but comparatively less in density than the previous class (concrete structure).

(v) *Vegetation:* This class essentially represents crop and forest areas.

(vi) *Open space:* This class contains basically the barren land. More specifically, a pixed with less greenery and less concrete structures falls into 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 $\times$ 36.25 m for IRS imagery). If a pixel has a big building and some open space, it is more likely to fall into the class habitation than concrete strncture. Considering the concept of second and combined choices on output decisions, the information about the building can be obtained.

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, after harvestation becomes open space', 'a river bed during summer when it is dried up falls under the class open space', 'some land portions during flood fall under water body'.

Corresponding to any scene, there are four available IRS images, namely blue, green, red and infrared. It has beeu observed that the green and infrared hand images are more sensitive than other band images to discriminate various land cover types [20]. 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 classes are chosen as the training samples. These training samples provide the spectral knowledge about the classes and the scene to the recognition system. Therefore, the system classifies all the pixels of the sceue into six classes.

It is already mentioned earlier than 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 and all such sandbed pixels are found.

8-directional Code: To find the roadlike structures, the traversal algorithm used for connecting various roadlike segments involve 8-directional chain code [Figure 3] to keep track of the direction. The pixels $P_1, P_2, \ldots, P_8$ in Figure 3 are the eight direct neighbors with respect to the pixel P_0 so that the direction of the pixel P_i with respect to P_0 is coded as i ($i = 1, 2, \ldots, 8$).

3.2. Detection of roadlike structures

To find roadlike structures, concrete structure pixels except sandbeds are considered as the patterns. The roadlike structures basically consist of the roads and the airport runways. 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 *candidates for the roadlike structures.* As the size of a pixel is quite high (36.25 m for IRS imagery), 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. In order to identify the roadlike segments in a better extent, a traversal through the candidate pixels is required. Before traversing, one also needs to thin the candidate roadlike patterns so that a unique traversal can be made through them. The total procedure to find the roadlike structures

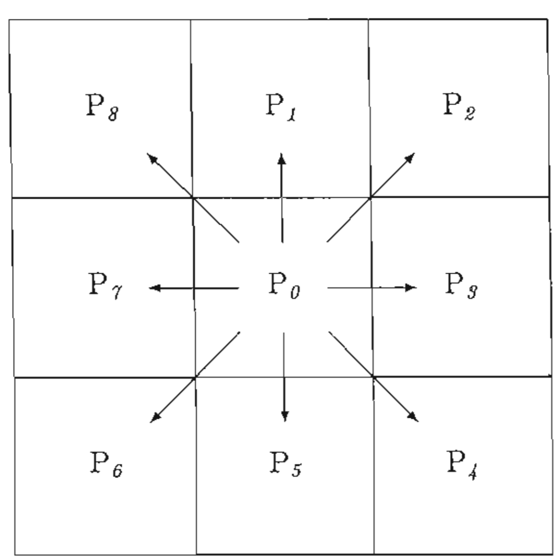

Fig. 3. 8-directional codes.

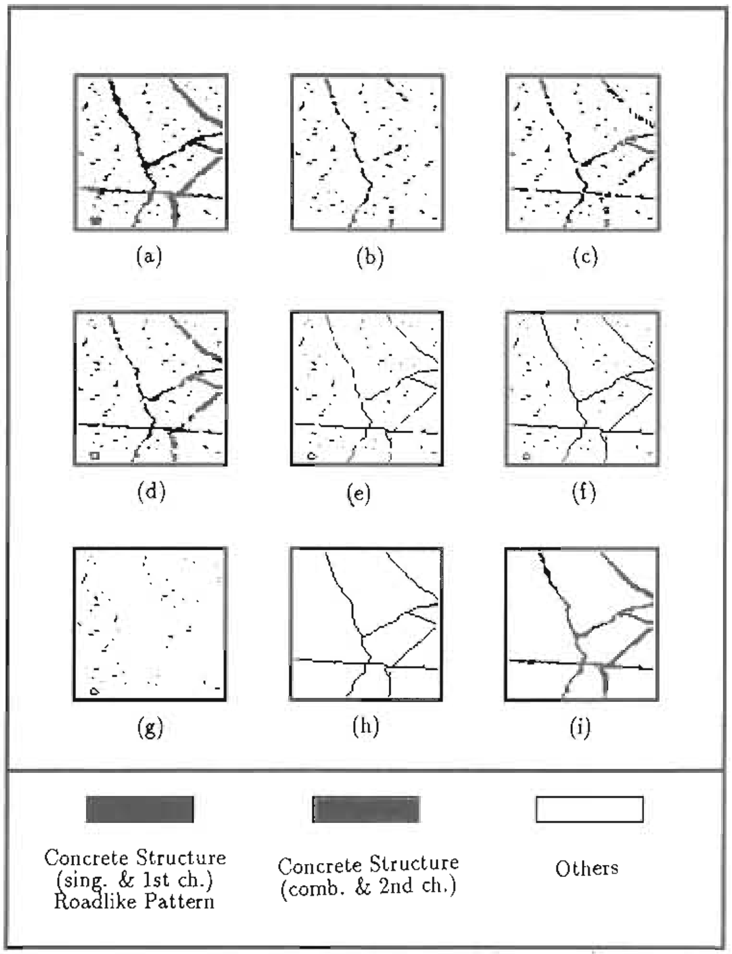

Fig. 4. Illustrating the method for finding roadlike patterns starting with the concrete structure patterns.

therefore 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. These are sequentially described below.

(For a better understanding of the total procedure for finding the roadlike structures, we have included Figure 4 as an example. Figure 4(a) represents an input (concrete structure patterns) image. The successive results are shown in Figures 4(b)–(i).)

A. Finding the candidate for roadlike patterns

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 as the *candidate pixels.* Note that this horizontal scan can identify only the vertically elongated patterns and some diagonally elongated patterns (Figure 4(b)]. The image is then scanned vertically from top to bottom starting with the first column in order to identify the horizontally elongated patterns along with some diagonally elongated patterns [Figure 4(c)]. The aforesaid scans may not still be able to identify all the diagonally elongated patterns and some junction points of the roadlike structures [Figure 4(c)]. For this purpose, the image is scanned in both the diagonal directions. The complete *candidate pixel for roadlike structures* is shown in Figure 4(d) corresponding to the concrete structure patterns in Figure 4(a).

B. Thinning

The parallel thinning algorithm proposed by Zhang and Suen [27] is applied here for thinning the patterns. In this procedure, the new value given to a point at the nth iteration depends on its own value as well as those of its eight direct neighbors [Figure 3] at the $(n-1)$th iteration. The method consists of removing all the contour points of the pattern except those points that belong to the skeleton. The algorithm has two subiterations as discussed below.

In the first subiteration, the contour point P_0 [Figure 3] is deleted (i.e., 0 is assigned) from the digital pattern if it satisfies the following conditions:

(a) $2 \leq B(P_0) \leq 6$,
(b) $A(P_0) = 1$,
(c) $P_2 \times P_4 \times P_6 = 0$,
(d) $P_2 \times P_4 \times P_8 = 0$,

where $A(P_0)$ is the number of 01 patterns in the ordered set $P_1, P_2, \ldots, P_8$ that are the eight neighbors of P_0 [Figure 3] and $B(P_0)$ is the number of non-zero neighbors of P_0, that is,

$$B(P_0) = P_1 + P_2 + \cdots + P_8.$$

In the second subiteration, only condition (c) and (d) are changed as follows:

(c′) $P_2 \times P_6 \times P_8 = 0$,
(d′) $P_4 \times P_6 \times P_8 = 0$,

and the rest remains the same.

The iterations continue until no more points can be removed.

For the purpose of thinning, all the candidate pixels of the image are assigned the value 1 and the remaining pixels are considered to be 0. So the image matrix consists of 1 or 0. Using the aforesaid thinning algorithm [27], the candidate roadlike patterns are thinned. The resultant thinned patterns provide some broken segments [Figure 4(e)].

C. Traversal and joining

The roadlike structures consist of roads and 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 [11] (described in Section 2). 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 [Figure 4(d)]. Again, some of the candidate pixels belonging actually to the roads/airport runways may be removed during the thinning process [Figure 4(e)].

To overcome these problems, a new traversal algorithm 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 8-directional code [Figure 3] is used during the traversal. After analyzing the potentialities of the pixels to be in the roadlike segments, conceptually, five different potential groups (coded by A–E) are assumed. These are

A: The pixels present in the thinned candidate patterns,
B: The pixels removed during thinning,
C: The pixels already traversed,
D: Other concrete structure pixels decided either by the single or first or second or combined choices of the multivalued recognition system [11],
E: The 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.

The thinned candidate roadlike patterns provide some broken segments. The middle most pixel of each of such disjoint roadlike segments is chosen as the starting pixel for traversing the corresponding segment. The intention behind this choosing is to allow the growth of the segments in all possible directions.

First of all, the longest thinned segment is chosen and the transversal begins with the starting 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 which have 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 Figure 5. These situations are arranged in

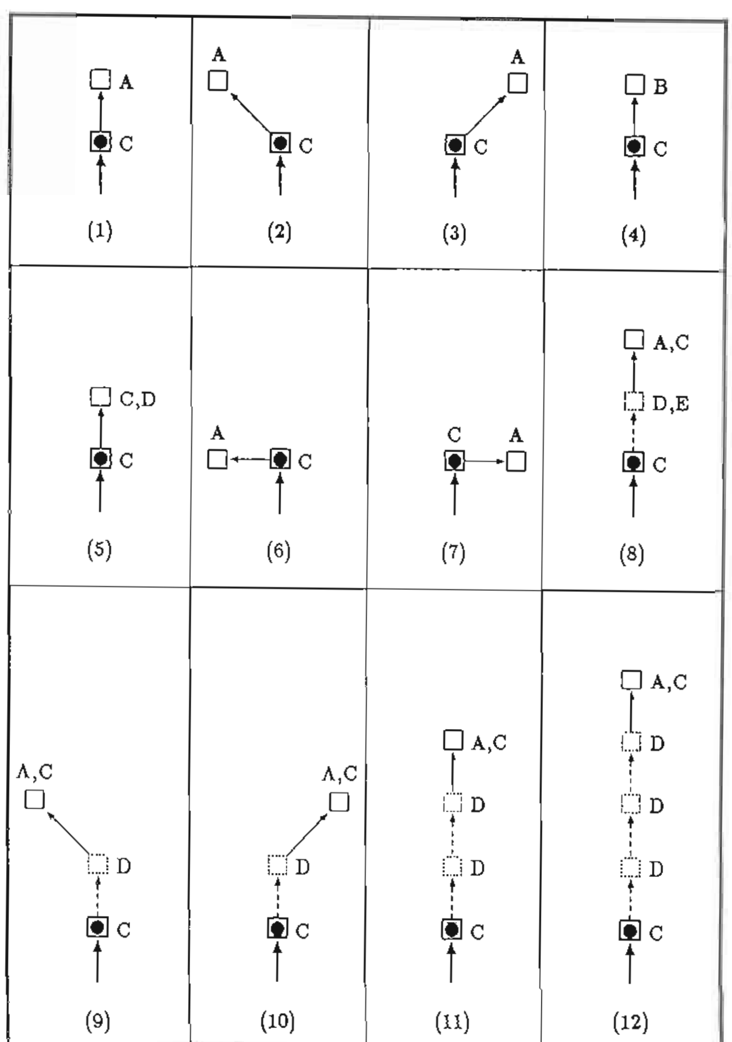

Fig. 5. Various movements considered for connecting/traversing roadlike structures.

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 restricted 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 Figure 5 are considered for the possible extension (i.e., looking forward to join the present segment with other segmeuts) of the existing roadlike segments, and these situations are considered in case the pixel-count of the current traversing segment is at least five.

When none of the aforementioned twelve cases is satisfied, a non-traversed 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) and none of the considered twelve situations [Figure 5] is satisfied, the traversing is stopped for the present segment. The same procedure is repeated for other isolated segments iu the scene.

Use of multiple choices: It has already been mentioned earlier that one pixel in an IRS image may represent more than one land cover type. As our recognition system [11] provides multiple choices, the information about all the classes present in a particular pixel can be obtained. In the aforesaid traversal algorithm for linking various roadlike structures, the use of multiple choices is directly realized. Out of the twelve movements considered [Figure 5] 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 Figure 4(e), we have more complete information as in Figure 4(f).

The aforementioned traversal procedure results in detecting the roadlike patterns which may also include some spurious wingles and some isolated noisy segments. These segments with insignificant lengths (<20 pixels) are discarded from the detected road-like patterns. The removal of the stray points as seen in Figure 4(g) makes the resultant roadlike patterns [Figure 4(b)] further prominent. Note that the residual segments represent the skeleton version of the roadlike patterns. To complete the task of identifying 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 represent the roadlike structures corresponding to an image frame. The final roadlike structures corresponding to the image in Figure 4(a) is displayed in Figure 4(i).

It is to be mentioned here that the minimnm width of the roadlike structures that can be detected by the proposed algorithm is decided by the pixel resolution of the image. In the present case, it is 36.25 m (i.e., one pixel). The maximum width of the roadlike structures has been considered here to be three pixels i.e., 108.75 m.

In this section, we have furnished our proposed algorithm to find roadlike structures from IRS imagery. The effectiveness of the algorithm is demonstrated in the next section.

4. Implementation and results

Data sets: The data used for the present work are acquired from Indian Remote Sensing (IRS) satellite. The IRS data is obtained through satellite IRS-1A which has been launched from a cosmodrome at Baikanaur, in the republic of Kazhakstan in the USSR in March, 1988. This is a circular sun-synchronous satellite, rotating around the earth at the rate of 14 orbits per day, at an altitude of 904 km and a repetition cycle of 22 days [29]. This satellite is equipped with two different sensors: LISS-I and LISS-II. LISS-I has a resolution of 72.5 m × 72.5 m while LISS-II has a resolution of 36.25 m × 36.25 m. Data used in the present work was obtained from the LISS-II sensor. LISS-II has a focal length of 324.4 m with the spectral range between 0.45 μm–0.86 μm (micrometer). The radiometric resolution is 128. The whole spectral range has been decomposed into 4 bands, namely blue (0.45 μm–0.52 μm), green (0.52 μm–0.59 μm), red (0.62 μm–0.68 μm), and infrared (0.77 μm–0.86 μm) [29].

To verify the effectiveness of the proposed methodologies, these have been implemented on some

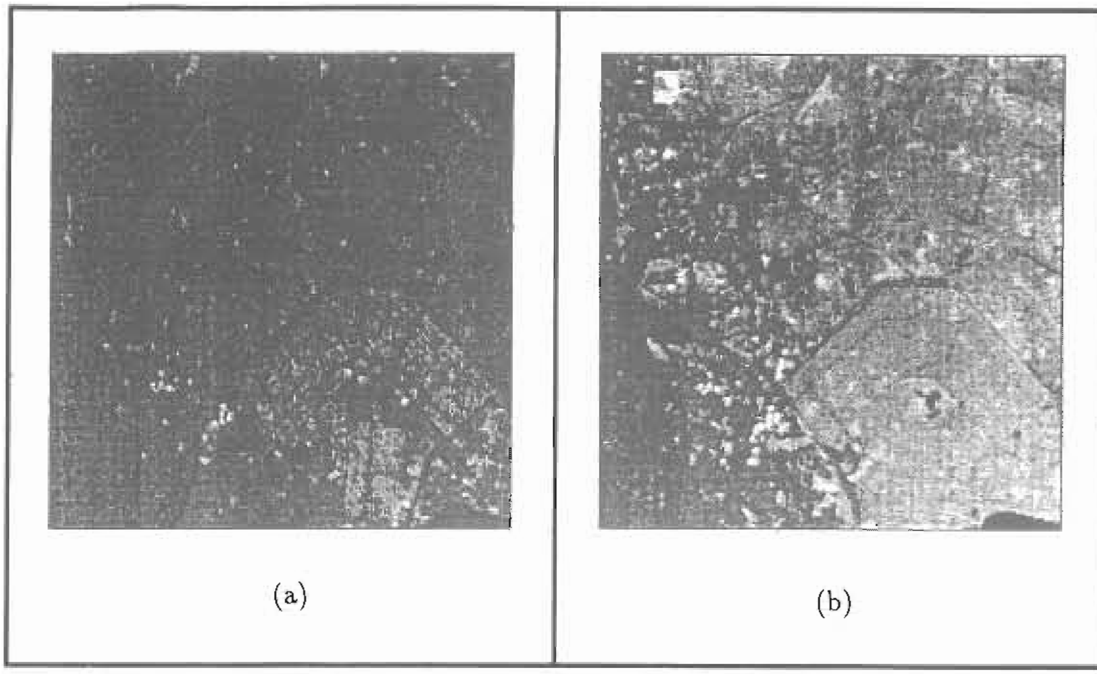

Fig. 6. IRS Calcutta (a) Band-2 (green) and (b) Band-4 (infrared) images.

IRS image frames corresponding to various scenes in India. The results were found to be quite satisfactory in all the cases. We have considered here two of these IRS frames for demonstrating the results. These two frames represent two major cities in India, namely Bombay and Calcutta. The image frames of Bombay and Calcutta were taken on 15th February 1992 and 7th March 1992 respectively. Both the image frames consist of 200 rows and 200 columns. For every scene, we have images corresponding to four spectral bands, namely blue, green, red and infrared. Since the green and infrared images were found to be more sensitive than other band images to discriminate various land cover types [20], these two band images have been used as the input images for the present work. The green and infrared images of Calcutta are shown in Figures 6(a)(b) respectively. Figures 7(a)(b) show the green and infrared band images of the city Bombay respectively.

The multivalued recognition system [11], described in Section 2, has initially been implemented on each of the IRS image frames to classify its pixels into six classes, namely pond water, turbid water, concrete structure, habitation, vegetation and open space. The classified Calcutta and Bombay images are shown in Figures 8(a)(b) respectively. As the recognition system is multivalued, a pixel may be classified into more than one class. In these clustered images, Figures 8(a)(b), each of the pixels reflects only the class having maximum similarity value. This is shown for the convenience of representation.

To visualize the concept of multivalued classification, the concrete structure pixels in single, first, second and combined choices are displayed in Figures 9(a)(b) corresponding to Calcutta and Bombay scenes respectively. It is to be mentioned here that the concrete structure pixels provide useful information for detecting the roadlike structures.

The clustered images are processed further for detecting the roadlike structures present in corresponding scenes. The detected roadlike structures in the Calcutta and Bombay frames are shown in Figures 10(a)(b). In order to provide a better idea of locations (or better reference) of various detected objects, the water bodies are always shown in all the output image frames. The gray value used to indicate various objects are appended with the corresponding output image frames. We have visually checked the detected roadlike structures (general structures and locations) with the corresponding geographical maps. The results are found to reflect well the roadmaps.

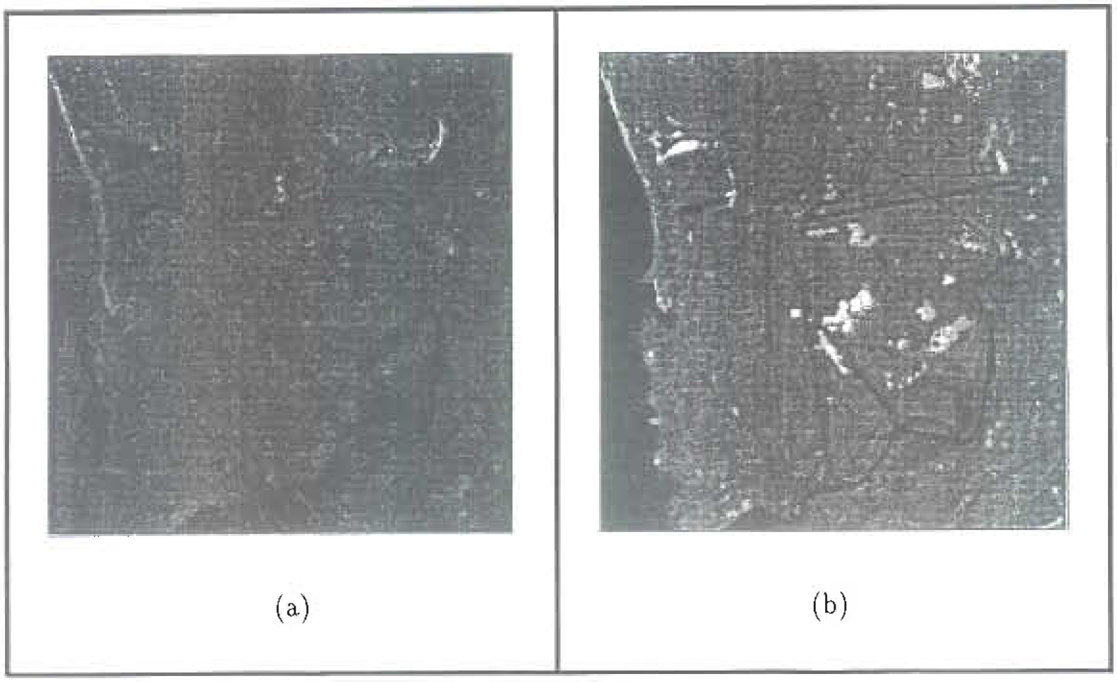

Fig. 7. IRS Bombay (a) Band-2 (green) and (b) Band-4 (infrared) images.

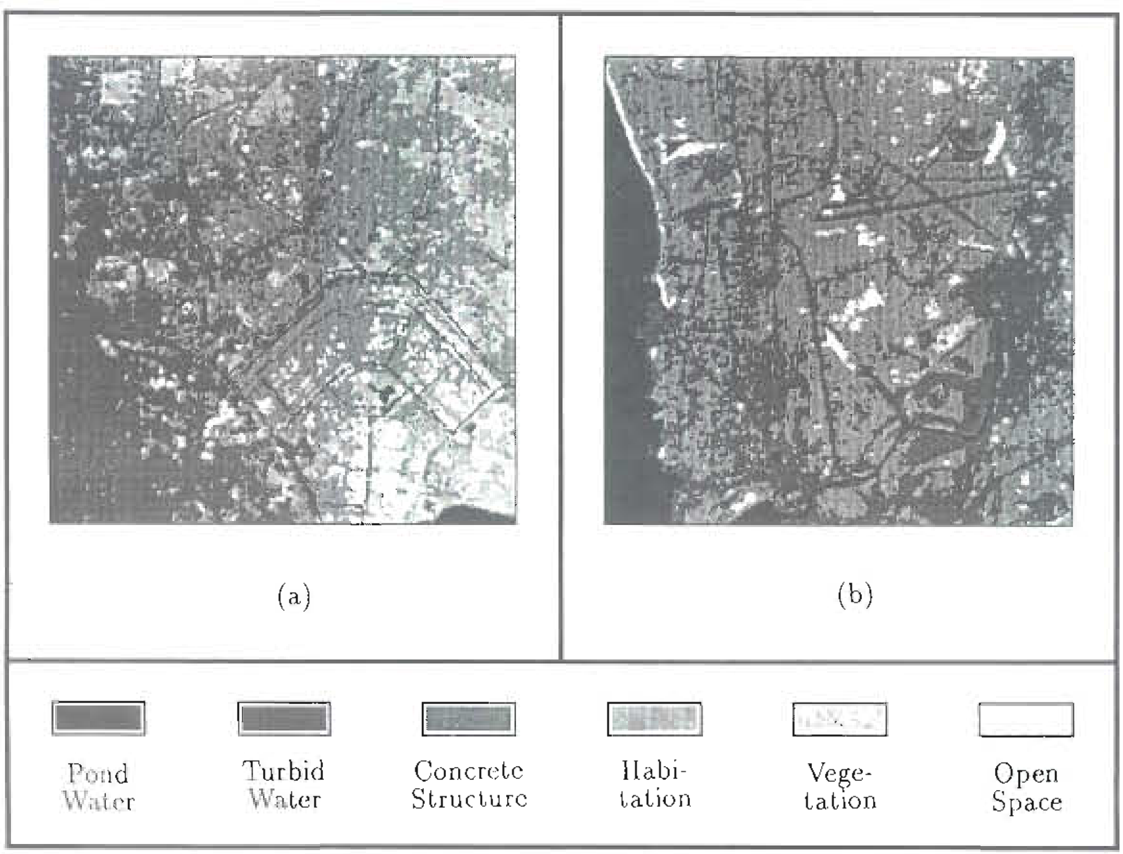

Fig. 8. IRS (a) Calcutta and (b) Bombay classified (clustered) images.

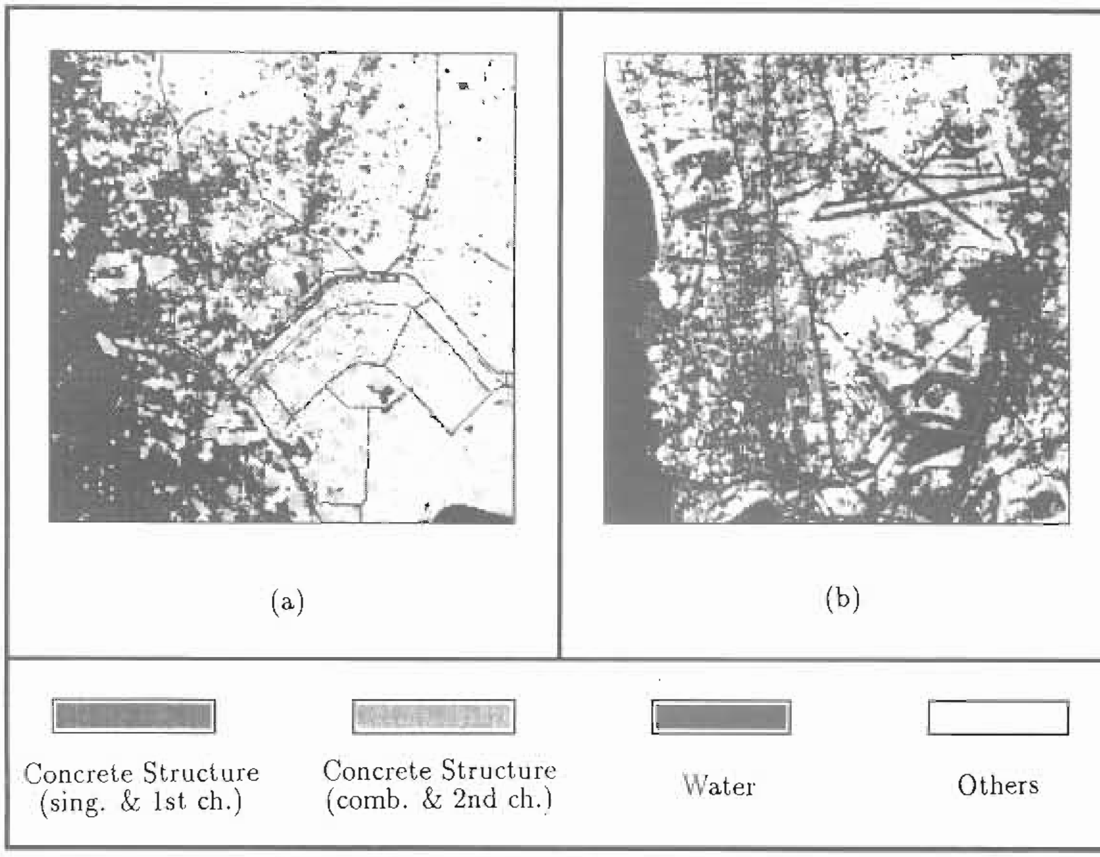

Fig. 9. Concrete structures with multiple choices in IRS (a) Calcutta and (b) Bombay images.

The major credit for the detection of the roadlike structures to a satisfactory level is due to the recognition system [11] providing multiple choices for making decision. It is to be mentioned here that some experiments [15, 16, 19] have already been carried out on the Calcutta image frame. The results obtained by the present work are found to be significantly improved over these earlier ones. The classification accuracy of the recognition system are not only found to be better, but also its ability of providing multiple choices in making decisions is found to be very effective in detecting the roadlike structures from IRS images.

5. Conclusions and discussion

The present work demonstrates the usefulness of multiple choices in detecting the roadlike structures from IRS imagery. The multivalued recognition system [11] as formulated recently by Mandal, Murthy and Pal has been found to be capable of handling uncertainties by providing multiple class choices for the ill-defined man-made objects in the scenes. The recognition system has been applied on an IRS image frame to classify its pixels into one of the six land cover types, namely pond water, turbit water, concrete structure, habitation, vegetation and open space. The green and infrared band images are only used for the pixel classification.

It is to be mentioned here that the characteristics of the roadlike structures and the proposed algorithm to detect them have been developed keeping in view the Indian environment and the pixel resolution of IRS images which is 36.25 m $\times$ 36.25 m. The roadlike structures are, in general, neither on

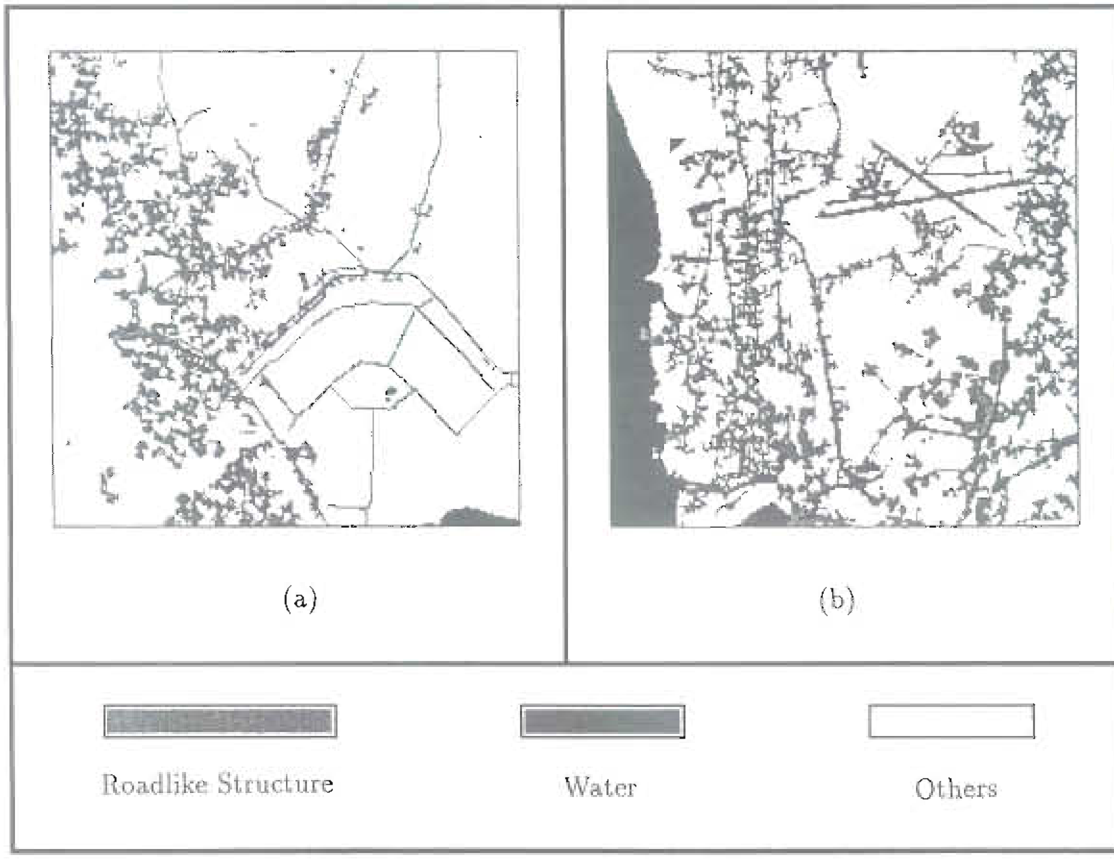

Fig. 10. Roadlike structures in IRS (a) Calcutta and (b) Bombay images.

the same scale nor of the same specifications as in the developed countries. For example, the roads do not always have the significant width in order to be reflected in the corresponding satellite images. Again, many road segments (specially in the city/township areas) are found to be surrounded by big buildings and it is quite difficult to detect such road segments from remotely sensed imagery. In the IRS image, the gray value that is assigned to a particular pixel is the average reflectance of different types of ground covers present in the corresponding $36.25\,m \times 36.25\,m$ area. If a pixel consists of water and vegetation, it is more likely to fall into the class concrete structure than the classes water and vegetation. Because of such inconsistencies (ambiguities) and the pixel resolution of IRS imagery, we could not use some of the usual constraints about the roadlike structures to detect them. Many times, we used heuristics for their detection. Although, the heuristic rules may sometime seem redundant, they are helpful in obtaining the targets to a reasonable extent.

The concept of multiple choices of the recognition system is found here to be very effective. Because of the low pixel resolution of the remotely sensed images, many portions of the roads were not classified as concrete structures. In order to identify them, a traversal algorithm through the detected road pixels has been developed where some of the movements are governed by only the combined and second choices of the multivalued recognition system. The results are found to agree well with the geographical maps when the scenes of Calcutta and Bombay were considered as input. It is to be mentioned here that the fuzzy c means algorithm is an unsupervised classification technique, and it has been applied previously to remotely sensed data [4] for segmenting images in various regions based on pixel classification. The proposed method is a supervised one which classifies the pixels into a number of known classes based on labeled samples. For detecting roadlike structures (using multiple choices), we need to have a supervised technique not only for efficient classification, but also for enabling one to use multi-class choices for its linking. However, the concept of post processing of the membership is also applicable for fuzzy c means algorithm.

To implement the proposed algorithms on other satellite imagery, like LAND-SAT, SPOT, Thermatic Mapper (TM) etc., the heuristic rules adopted for the IRS image are to be modified according to their pixel resolutions. The present investigation can find several real life uses such as township planning, estimating the damage caused by the natural disasters like floods, estimating the depleting forest area *etc.*

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