

A REMOTE SENSING APPLICATION OF A FUZZY CLASSIFIER

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A multivalued (fuzzy) recognition system was formulated by Mandal *et. al.* which is capable of handling various imprecise inputs and provides multiple class choices to any input. In the present article, an application of the recognition system for detecting road-like structures from Indian Remote Sensing satellite (IRS) imagery has been described. The concept of multiple choices of the recognition system is found to be quite useful here. The results are seen to agree well with the geographical maps when various image frames were considered as input.

Keywords: Remote Sensing; Fuzzy Sets; Management of Uncertainty.

1. Introduction

The theory of fuzzy sets¹ provides suitable tools in analyzing complex systems and decision processes where pattern indeterminacy is due to inherent vagueness (fuzziness) rather than randomness. 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. 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.

Multivalued recognition systems² based on the concept of fuzzy sets have been formulated recently by Mandal, Murthy and Pal³ and Pal and Mandal.⁴ These systems are capable of handling various imprecise inputs and in providing multiple class choices corresponding to any input. The present article describes an application the recognition system³ in detecting roadlike structures from Indian Remote Sensing satellite (IRS) imagery.

There are many approaches⁵⁻⁸ found in the literature which addressed the problem of detecting roadlike structures from remote sensing imagery. Attempts^{9,10} 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.¹¹

In the present work, the recognition system³ has initially been applied on an IRS image to classify (based on the spectral knowledge of the image) its pixels into six classes, 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 effectiveness of the algorithm has been demonstrated on an IRS image frame corresponding to the city Calcutta.

In Sec. 2, a brief description of the recognition system³ is provided. Section 3 deals with the proposed method of detecting the *roadlike structures* from IRS imagery. Experimental results and conclusions are furnished in Sec. 4. ♠

2. Multivalued Recognition System³

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 decision. For describing the system, let us consider an M class and N feature problem. The block diagram of the recognition system³ is shown in Fig. 1. It consists of two parts, namely, *Learning* and *Fuzzy Processor*. Learning section basically decomposes the entire feature space into some *space sub-domains* and finds a relational matrix. The Fuzzy Processor uses the relational matrix in the modified compositional rule of inference¹² to decide about the class or classes in which a pattern X may belong.

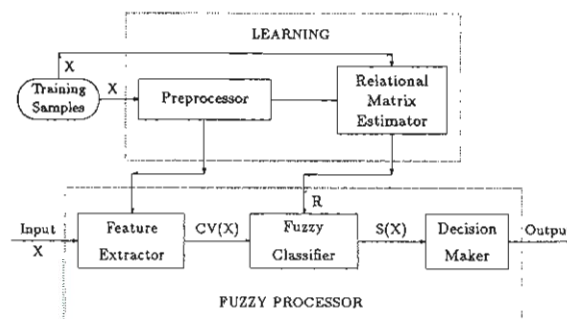


Fig. 1. Block diagram of the recognition system.³

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 structure¹⁰ and the relative positions of the pattern classes in the feature space, the training sample set of each pattern class is decomposed into a few sample groups. Accordingly, each individual feature axis is divided into a number of sub-domains (referred to as *feature sub-domains*) to highlight the sample groups. Each of the *feature sub-domains* is extended to an extent (using triangular membership functions³) 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}) overlapping *space sub-domains*.

The relational matrix, R , denotes the compatibility of the pattern classes corresponding to the *space sub-domains*. The order of R is $\hat{N} \times M$ and it is estimated from the training samples in the relational matrix estimator block. The relational matrix R is utilized in the fuzzy classifier block to find the final output of the recognition system.

The fuzzy processor section consists of three parts, namely, *feature extractor*, *fuzzy classifier* and *decision maker*. It uses the relational matrix in the modified compositional rule of inference¹² to decide about the class or classes in which a pattern X may belong.

The feature extractor block basically finds a *characteristic vector* $CV(X)$ corresponding to each input pattern X . The $CV(X)$ was defined as

$$CV(X) = (cv_1(X), cv_2(X), \dots, cv_{\hat{N}}(X)) \quad (1)$$

where the h th element $cv_h(X)$ denotes the membership value (degree of belonging) of X to the h th *space sub-domain*.

The fuzzy classifier block uses the modified compositional rule of inference¹² between the characteristic vector $CV(X)$ and the relational matrix R . As a result, a *class similarity vector* $S(X)$ is found as

$$S(X) = (s_1(X), s_2(X), \dots, s_M(X)) \quad (2)$$

where the j th element $s_j(X)$ denotes the degree of similarity of a pattern X to the j th pattern class.

The similarity vector $S(X)$ is then analyzed in the decision maker block. The system provides the final output either as *single choice* (possibility to belong only in one class) or *combined choice* (possibility to belong in more than one class with same preference) or *first-second choice* (possibility to belong in more than one class with different preferences) or *null choice* (possibility of not belonging to any of the classes).

The effectiveness of the system had been adequately demonstrated on some artificially generated pattern sets and also on a speech recognition problem.³ Its theoretical performance has also been derived.¹⁴ ♠

3. Detection of Roadlike Structures

The IRS image corresponding to scene of Calcutta is considered in the present work which primarily consists of six different classes. These six classes are *pond water*

(pond water, fisheries etc.), *turbid water* (sea water, river water etc.), *concrete structure* (buildings, railways, roads, air strips etc.), *habitation* (suburban and rural habitation), *vegetation* (crop and forest areas) and *open space* (barren land). 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. Considering the multiple choices of the recognition system,³ the information about all the classes can be obtained.

Corresponding to any scene, four IRS band images, namely, *blue*, *green*, *red* and *infrared* are available. Since the *green* and *infrared* images were found to be more sensitive than other band images to discriminate various land cover types,¹⁵ 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. Therefore, the system classifies all the pixels of the image into six classes.

To find the *roadlike structures*, the *concrete structure pixels are considered* as the patterns. The *roadlike structures* basically consist of the roads and the airport runways. The total procedure to find the roadlike structures can be visualized as having 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 Fig. 2 as an example. Fig. 2(a) represents an input (concrete structure patterns) image. The successive results are shown in Figs. 2(b)–(i).)

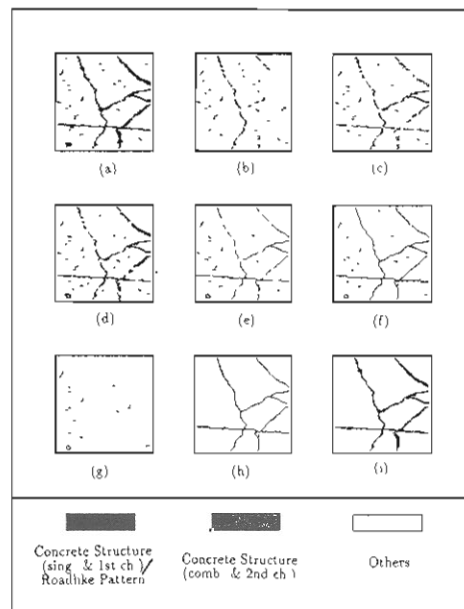


Fig. 2. Illustrating the method for finding roadlike patterns.

3.1 Finding the candidate pixels for roadlike patterns

For determining 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. 2(b)] as the candidate pixels. The image is then scanned vertically from top to bottom starting with the first column [Fig. 2(c)]. Finally, the image is scanned in both the diagonal directions. The complete candidate pixel set for roadlike structures is shown in Fig. 2(d) corresponding to the concrete structure patterns in Fig. 2(a). ♣

3.2 Thinning

The parallel thinning algorithm proposed by Zhang and Suen¹⁶ is applied here for thinning the patterns. The method consists of removing all the contour points of the pattern except those points that belong to the skeleton. Using the algorithm,¹⁶ the candidate roadlike patterns are thinned. The resultant thinned patterns provide some broken segments [Fig. 2(e)]. ♣

3.3 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.³ 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. 2(d)]. Again, some of the candidate pixels belonging actually to the roads may be removed during the thinning process [Fig. 2(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. 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** (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 system³ and **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 other neighboring pixels which having the potential code **A** are marked as reserved for the future traversal.

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. 3. 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.

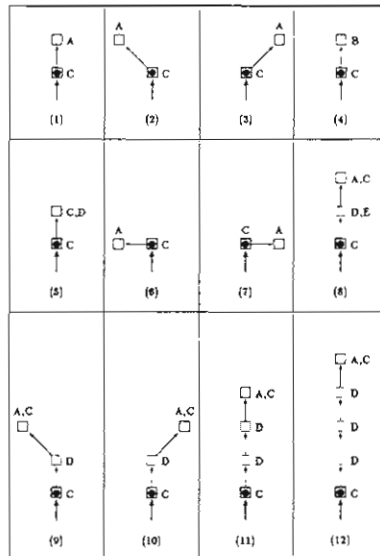


Fig. 3. Various movements considered for traversing/connecting roadlike patterns.

When none of the aforementioned twelve cases is satisfied, the traversing of the segment is continued with a non-traversed and reserved pixel. 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. •

Use of multiple choices: It has already been mentioned earlier that one pixel may represent more than one land cover type. As the recognition system³ provides multiple choices, the information about most of the classes present in a particular pixel can be obtained. Out of the twelve movements considered [Fig. 3] 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. 2(e), we have more complete information as in Fig. 2(f). ■

Removal of noisy segments: 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 roadlike patterns. The removal of the stray points as seen in Fig. 2(g) makes the resultant roadlike patterns [Fig. 2(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 represent the roadlike structures corresponding to an image frame. The final *roadlike structures* corresponding to the image in Fig. 2(a) is displayed in Fig. 2(i).

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. Experimental Results and Conclusions

The data used for the present work are acquired from Indian Remote Sensing satellite (IRS). 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. The considered data have the resolution of $36.25m \times 36.25m$.

To verify the effectiveness of the proposed methodologies, these have been implemented on some IRS image frames corresponding to various scenes in India. 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,¹⁵ these two band images have been used as the input images for the present work. The results were found to be quite satisfactory in all the cases.

We have considered here one of these IRS frames for demonstrating the results. This image frame represents one major city in India, namely, Calcutta and it was taken on 7th March, 1992. Figures 4(a) & (b) show the *green* and *infrared* band images of the city Calcutta. The classified image is shown in Fig. 5(a). As the recognition system is multivalued, a pixel may be classified into more than one class. In this clustered image, each of the pixels reflects only the class having maximum similarity value. This is done for the convenience of representation.

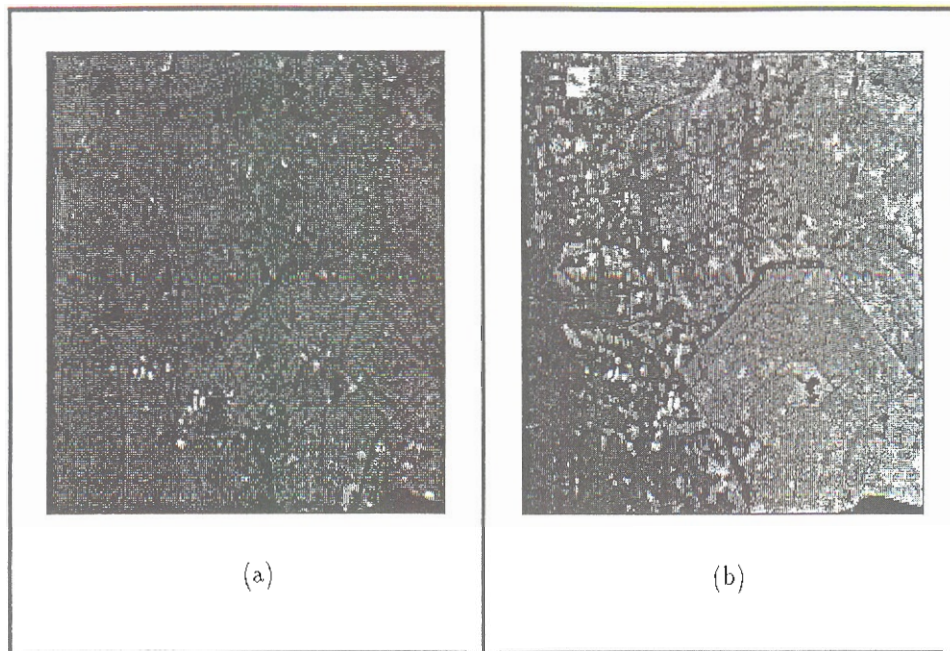


Fig. 4. IRS (a) green and (b) infrared band images corresponding to Calcutta.

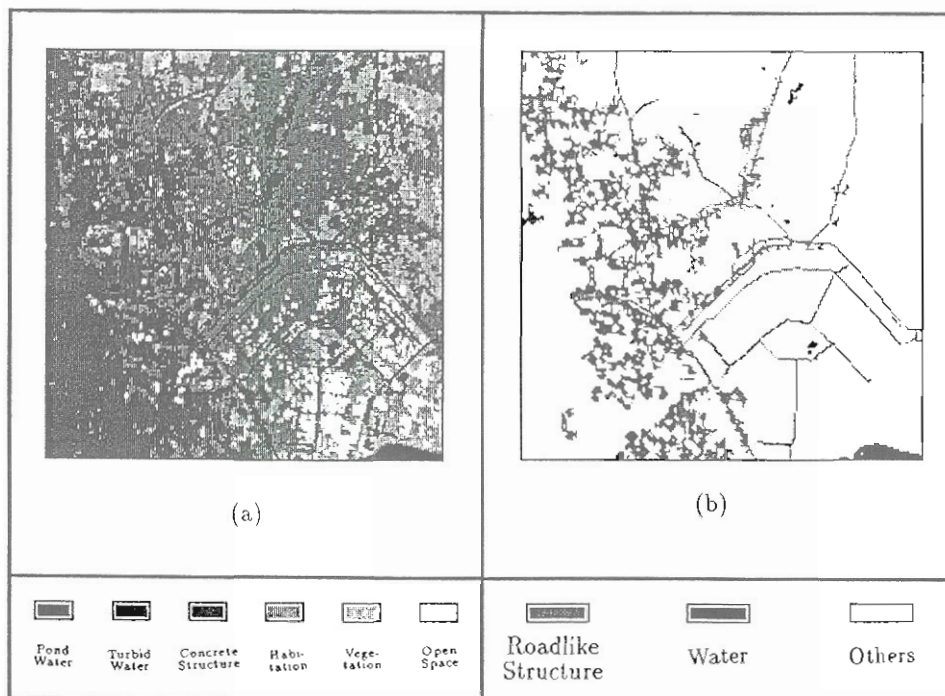


Fig. 5. (a) classified image and (b) roadlike structures corresponding to Fig. 4.

The clustered images are processed further for detecting the *roadlike structures*. The detected *roadlike structures* present in considered image frame are shown in Fig. 5(b). In order to provide better idea of locations (or better reference) of various detected objects, the water bodies are also shown in Fig. 5(b). The gray value used to indicate various objects are appended with the corresponding output image frames. The detected *roadlike structures* are found to agree well with the corresponding geographical map.

The major credit for the exact detections of the *roadlike structures* is due to the recognition system³ providing multiple choices for making decision. 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 *roadlike structures* from IRS images.

To implement the proposed algorithms on other satellite imageries, like LANDSAT, SPOT, Thematic Mapper (TM) etc., the heuristic rules adopted for the IRS image are only 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 etc. ♠

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