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Uncertainty Handling in Remote Sensing Data Analysis for Defence Application

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ABSTRACT

Describes a way of handling uncertainty in IRS imagery by utilising a multivalued recognition system. Roads and bridges can be detected effectively by using the multiple class choices provided by the multivalued recognition system.

INTRODUCTION

This paper describes a method of handling uncertainty in remotely-sensed imagery for detecting various man-made objects with the help of Fuzzy sets. The theory of Fuzzy sets[1] provides suitable tools in analysing 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[2]. 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 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 analysing remote sensing images.

Multivalued recognition system[3] based on the concept of Fuzzy sets has been formulated recently by Mandal[4], *et al.* This system is capable of handling various imprecise inputs and in providing multiple class choices corresponding to any input. The recognition system[4] is initially used on an IRS image to provide multistate 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 green and infrared band information are used for the classification[5]. The Fuzzy partitioned images, thus obtained, are then processed further for detecting various ill-defined man-made objects, namely roads, bridges and airports. Multiple class choices of a pixel have been utilised in detecting these objects.

2. MULTIVALUED RECOGNITION SYSTEM

The multivalued recognition system developed by Mandal, *et al*[6], is described here in brief. The system has the capability of handling various input patterns and provides multiple class choices as the output decision. For describing the system, consider an M class and N feature problem. The block diagram of the recognition system 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 subdomains and finds a relational matrix. The Fuzzy processor uses the relational matrix in the modified compositional rule of inference to decide about the class or classes to which a pattern X may belong.

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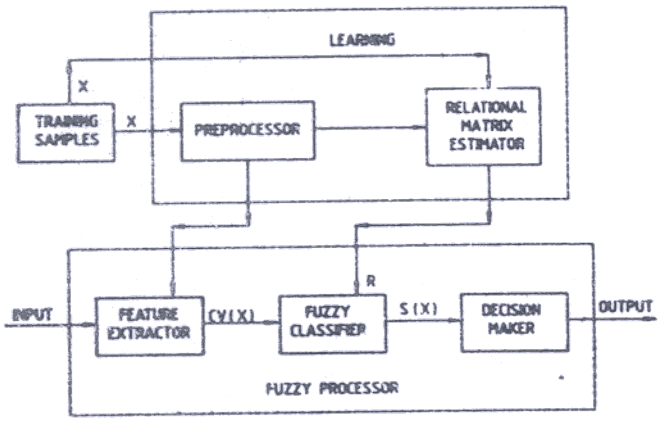

Figure 1. Block diagram of the multivalued recognition system.

2.1 Learning

The learning section has two blocks, namely preprocessing and relational matrix estimator. The space subdomains 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[7] 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 subdomains (referred to as feature subdomains) to highlight the sample groups. Each of the feature subdomains is extended to an extent (using triangular membership function) 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 subdomains.

The relational matrix R, denotes the compatibility of the pattern classes corresponding to the space subdomains. 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 utilised in the Fuzzy classifier block to find 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[4] to decide about the class or classes to 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

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

where the h^{th} element $cv_h(X)$ denotes the membership value (degree of belonging) of X to the h^{th} space subdomain.

The Fuzzy classifier block uses the modified compositional rule of inference[7] between the characteristic vector $CV(X)$ and the relational matrix R. As a result, a class similarity vector $S(X)$ is found as

$$S(X) = (s_1(X), s_2(X), \ldots, s_M(X)) \qquad (2)$$

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 analysed in the decision maker block. The system provides the final 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).

The effectiveness of the system had been adequately demonstrated on some artificially generated pattern sets and also on a speech recognition problem[4]. Its theoretical performance has also been derived[6].

In remotely-sensed imagery, the regions are usually ill-defined (because of both grayness and spatial ambiguities) 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 analysing remote sensing imagery.

3. RESULTS

The scene corresponding to Bombay has been considered for implementation of the above system. The ground resolution of the considered image[5] is 36.25 m × 36.25 m. The green band and the infrared band images have been used for analysing the scene. Different types of land cover have been taken and they are described below:

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

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

(c) *Concrete Structure*: This class contains buildings, railways, roads, air strips, etc. The signature of sand beds in remote sensing images also belong to this class.

(d) *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).

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

(f) *Open Space*: This class 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 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, for example, (i) a cultivated land, which is a vegetation area, becomes open space after harvestation, (ii) a river bed during summer falls under the class open space when it is dried up, and (iii) some land portions during flood fall under water body.

We have taken 50 representative samples from each class and used the above multivalued systems[4] to obtain the choices for each pixel. The infrared image of Bombay is provided in Fig. 2. The classified image is shown in Fig. 3, where each pixel reflects the class

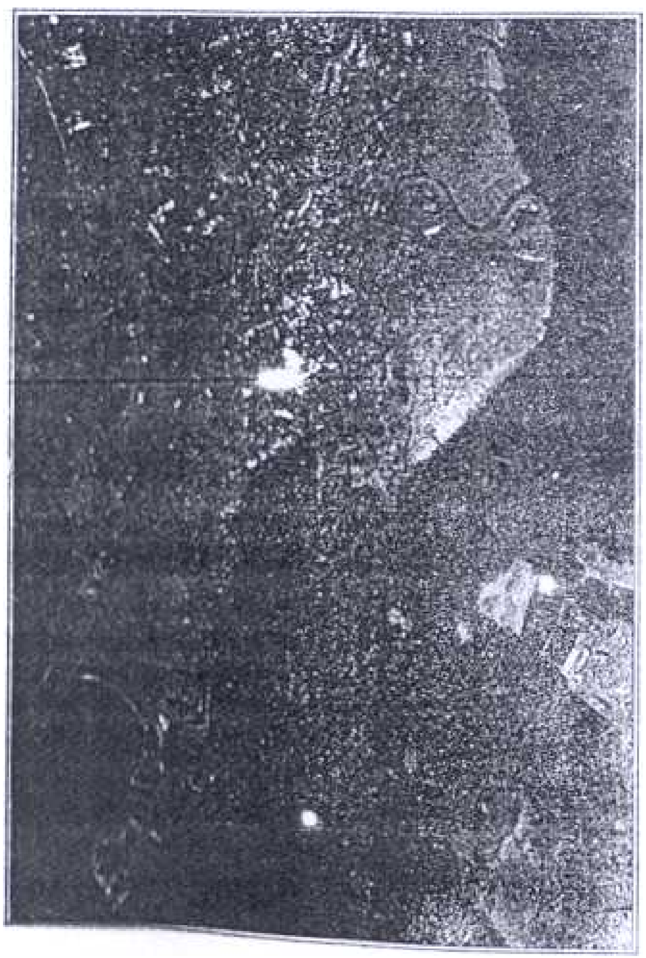

Figure 2. IRS Bombay band-4 (infrared) image.

Figure 3. Bombay classified (clustered) image.

Figure 4. Bombay image-roads, airports and bridges.

having maximum similarity value. Traversal, thinning and morphological operations are applied on the classified images. Second and combined choices are adequately incorporated in the above operations to obtain the roads, bridges, etc (Fig. 4). The results are found to agree well with the geographical maps.

The number of classes is assumed here to be six. In case the image frame consists of other classes, like deserts, hilly areas, snowy regions, etc., one needs only to include some training samples of these classes.

A detailed description of the methodology stated above can be found elsewhere[8].

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