

LSGENSYS - An Integrated System for Pattern Recognition and Summarisation

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Abstract—This paper presents a new system developed in Java[®] for pattern recognition and pattern summarisation in multi-band (RGB) satellite images. The system design is described in some detail. Results of testing the system to analyse and summarise patterns in SPOT MS images and LANDSAT images are also discussed.

Keywords—Pattern recognition, image analysis, feature extraction, blackboard component, linguistic summary.

I. INTRODUCTION

IN this paper, a new system is presented, whose objectives are to extract patterns such as land, island, water body, island, and fire from multi-band satellite images and to summarise such patterns with the aid of linguistic summaries. The new system (C.T.R.F.'s LSGENSYS) can analyse, extract and describe patterns using unsupervised classification techniques, as well as with user interaction and intervention, thus providing some degree of supervised classification and description. The results in both cases are then compared.

Image analysis is a process of image data transformation leading to some actions, decisions or conclusions [1]. It provides the means to quantify image patterns. Some of the measurements that can be computed are area, perimeter, length, feret diameter, pattern width, co-ordinates of pattern centroid, grey level intensity etc.

A pattern recognition system [2], [3] extracts key information about patterns by grouping related pixels together. The quantitative analysis measures mentioned earlier could then form the feature vector which has sufficient discriminating information for identification of the pattern but disregards unwanted information that increases the dimensionality of the pattern recognition problem. Feature extraction is the process of extracting those attributes of a pattern/object that best describe the pattern/object quantitatively. In addition to features such as perimeter, area etc, derived features such as shape factor ($\text{perimeter}^2/\text{area}$) or moments could be used for the classification of the pattern. Shape factor is a dimensionless quantity, invariant to scale, rotation or translation which makes it a useful feature for identifying shapes such as circle, square, triangle, ellipse etc. Moments can be used to describe the properties of a pattern object in terms of its area, position and orientation.

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LSGENSYS (Linguistic Summary Generation System) is an integrated system that allows the user to analyse images, extract feature descriptors such as area, length, location etc of patterns and then use these descriptors to form linguistic summaries of these patterns. This system also provides an interactive environment, wherein, the user may suggest some possible linguistic summaries for the image patterns. The system would evaluate the fitness of these user-summaries. Alternately, the system could, without user intervention, generate some possible summaries and evaluate their fitness and suitability with respect to the image patterns. The system architecture is described in detail in Section II.

At this juncture, a comparison is made with some other existing software that perform similar functions. MATLAB [4] and ENVI [5] are some of the popular tools used in the educational environment. MATLAB's Image Processing Toolbox is a general-purpose toolbox with many tools to aid image processing. It does not fulfil the needs of image analysis per se. For example, there is no function to permit the calculation of length of curvilinear patterns such as rivers. ENVI also focuses more on image processing. Both these tools have extensive image processing capabilities. There are some limitations on the image formats that both MATLAB and ENVI support. There are other commercially available pattern recognition tools also, for instance, Definiens[®] eCognition [6] is based on object-oriented image analysis. Some rules for pattern classification are employed by the tool. Contextual information and data are used as input for this process. Definiens[®] Professional [7] works with panchromatic, multi/hyper-spectral imagery, infrared, and polarimetric SAR data from space-borne and air-borne imaging platforms. Partek [8] has developed a toolbox for pattern recognition that includes features such as cluster analysis, classification, variance analysis, predictive and diagnostic modelling etc in the scientific domain. PRTools [9] is a pattern recognition toolbox that includes algorithms for classification such as quadratic classifier and k-nearest neighbour classifier. The toolbox is aimed at classification, parameter estimation and state estimation. It includes routines for statistical pattern recognition such as data generation, training classifiers, density estimation, cluster analysis, evaluation and visualisation. SPRLIB/ANNLIB [10] are a library of functions (written in C) developed to support construction and simulation of pattern classifiers (k-nn, Fisher, Parzen etc). ANNLIB is a neural network simulation library that includes functions for creating, training and testing neural networks. Training algorithms include back-

propagation, conjugate gradient descent etc. It also has the capability to build Kohonen maps. DIPimage toolbox [11] is another toolbox used in conjunction with MATLAB to aid in image processing. Pattern Recognition Workbench [12] is another software that supports comprehensive pattern classification algorithms as well as estimation and modelling. Other commercially available pattern recognition software exist as well, but they are not specific to any particular domain. The software mentioned do not have any facility for automatic classification of patterns in remote-sensed images.

A graphical tool in Java[®] [13], [14], [15] to perform image analysis and feature extraction has been developed and employed in this research. The image analysis component is user-friendly with many features and menu options that allow the user to interact with an image that is loaded, and extract or calculate necessary information such as quantitative analysis measures and also automatically classify patterns, to be used in later components of a typical pattern recognition system [16], [17], [18], [19], [20], [21]. In [16], the author described the initial design of such a system which uses a few trapezoidal fuzzy sets in its knowledge base in order to quantify typical feature definitions derived from geographic facts such as area of largest continent, length of longest river etc. In [17], the system was further expanded to include some triangular fuzzy sets in the knowledge base. In [18], the knowledge base was expanded to include both trapezoidal and triangular fuzzy sets (29 sets) to extract and describe natural patterns such as river, island, land, water body etc in satellite images. The system also incorporated classification rules at this stage for automatic classification of the natural patterns. In [19], the system was integrated as a whole to include an image analysis tool, which was then in its initial stage of design and development. In [20], the image analysis tool was presented and discussed in detail. In [21], the system architecture was modified to add some elements of supervised classification and summarisation. These modifications were discussed only theoretically in [21]. In this paper, the said modifications have been developed, implemented and tested on SPOT MS and LANDSAT images.

This paper is organised as follows. Section II explains the architecture and design of the system. Section III explains the methodology and approach. Section IV presents results of testing the system for image analysis, pattern recognition and summarisation on LANDSAT and SPOT MS satellite images. Section V presents the conclusions and future work.

II. SYSTEM ARCHITECTURE

The system architecture is shown in Fig. 1. The input image is analysed and some feature descriptors extracted. These descriptors are stored thereafter in a relational table in the database. The blackboard holds the current state in the process of developing summaries. The key difference with [19] is that presently the user has the choice of suggesting concepts such

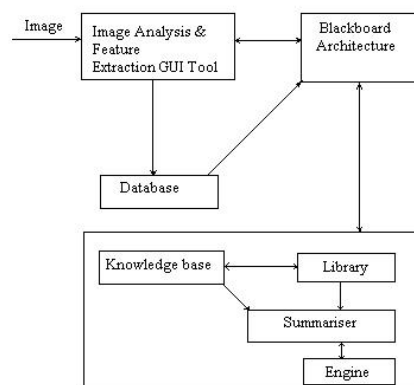


Fig. 1 System architecture

as descriptions of area, length, location of patterns etc. Also, human interaction could be of assistance when complicated summaries that involve a combination of attributes need to be developed [22]. It would be possible for the user to assign importance to each of the attributes. The knowledge base uses geographic facts to define feature descriptors using fuzzy sets [23]. It interacts with a built-in library of linguistic labels, which also interacts with the summariser as it supplies the necessary labels to it. The summariser receives input from these components and performs a comparison between actual feature descriptors of the image patterns stored in the database, the concepts suggested by the user, and the feature definitions stored in the knowledge base. After this comparison, the summariser uses the linguistic labels supplied by the library to formulate some possible summaries for each pattern/object in the database. These summaries are stored in the blackboard. From among these summaries, the most suitable one describing each pattern is selected by interaction with the engine (genetic algorithm). As the GA evolves through several generations, it generates better summaries (indicated by higher fitness, as defined in Section IV) which are then stored and indicated on the blackboard. Thus, the system has been improved and enhanced to include some elements of supervised classification and summarisation.

The blackboard architecture component in Fig. 1 is a new addition to the earlier system. The idea behind the blackboard architecture is a collection of independent programs that work cooperatively on a common data structure [24], [25]. The independent modules are the knowledge sources. The blackboard is the shared data structure through which the knowledge sources communicate with each other. The third component of the blackboard architecture is the control system which determines the order in which the knowledge sources operate on the entries on the blackboard. The implementation of this blackboard architecture is discussed in Section IV.

This system focuses on analysing multi-band (RGB) satellite images. The following set of rules has been developed to perform pattern classification in such images.

1. If a pattern/object is to be classified as an island, it

should have a water envelope surrounding it such that it has a uniform band ratio at at least eight points on this envelope (corresponding to directions E, W, N, S, NE, NW, SE, SW). Also grey level values on the envelope could be lower than the grey level values on the object.

2. If an object does not have an envelope in all directions as described in rule (1), then it is classified as land.
3. If an object is to be classified as water body (expanse of water, river), it is necessary that it should have a uniform band ratio.
4. Fire is classified as a separate pattern. It is identified by applying colour density slicing to the image and by viewing the histogram of the affected area. The histogram would show a majority of pixels at lower intensity for the burnt scar area near the fire.

The image analysis tool can analyse images in standard formats such as tif, jpg, bmp, gif, png and generate the recorded feature descriptors in delimited ASCII text format.

III. APPROACH

Area, length, location (X, Y pixel co-ordinates of centroid of pattern in image), Additional Information or Pattern Id, and grey level intensity are the attributes of the patterns/objects that are used to develop their linguistic summaries. Area, length, location, and grey level intensity are calculated/extracted automatically by the GUI tool. Additional information contains the pattern's id, which is obtained by using the classification rules described in the earlier section. The linguistic summary of patterns/objects is evaluated as follows.

$$\text{If } Y = y_1, y_2, \dots, y_p \quad (1)$$

then

$$\text{truth}(y_i \text{ is } F) = \mu_F(y_i); i=1, 2, \dots, p, \quad (2)$$

where $\mu_F(y_i)$ is the degree of membership of y_i in the fuzzy set F and $0 \leq \mu_F(y_i) \leq 1$. The linguistic proposition y_i is F could be instantiated as for example, *River is long*. Thus referring to equations (1) and (2), y_i could be *island* or *area of land* or *expanse of water* or *river*. For each object y_i , the degree of membership of its feature descriptor such as area or length in corresponding fuzzy sets is calculated. An example of a typical linguistic summary for island generated by the system in this paper would be:

A considerably large island at the top in the image

In order to generate such summaries, it is necessary to formulate fuzzy sets that quantify area/length attributes of the object/pattern. Some of the triangular fuzzy sets formulated for area are *large*, *fairly large*, *moderately large*, *considerably large*, and *small* and some fuzzy sets for length are *long*, *relatively long*, *fairly long*, *considerably long* and *short*.

Trapezoidal fuzzy sets have also been formulated for area and length. The linguistic description is calculated as follows:

$$T_j = m_{1j} \wedge m_{2j} \wedge \dots \wedge m_{nj}, \quad (3)$$

where m_{ij} is the matching degree [26] of the i th attribute in the j th tuple. $m_{ij} \in [0, 1]$ is a measure of degree of membership of the i th attribute value in a fuzzy set denoted by a fuzzy label. The logical AND (\wedge) of matching degrees is calculated as the minimum of the matching degrees [26].

$$T = \sum_{j=1}^k T_j \quad \forall m_{ij} \neq 0, \quad (4)$$

T in equation (4) is a numeric value that represents the truth of a possible set of summaries of the k objects in the database. The next section discusses how the GA evolves the most suitable linguistic summary for all the objects by maximising T.

IV. IMPLEMENTATION ISSUES

This section explains the implementation of the system, including the genetic algorithm approach and then discusses the results from applying this approach to analysing images.

A. GA Approach

A genetic algorithm emulates biological evolutionary theories as it attempts to solve optimisation problems [27], [28], [29]. Each binary chromosome string in a population represents a possible linguistic summary for a pattern. Selection, crossover and mutation operators in the GA [27] manipulate this population of strings such that as the GA evolves through several generations, only those strings with highest fitness survive. The evaluation or fitness function for the linguistic summaries or descriptions of all objects in the table is

$$f = \max(T), \quad (5)$$

where T is evaluated as shown in the previous section and f is the maximum fitness value of a particular set of linguistic summaries that has evolved over several generations of the GA.

B. Results and Discussion

As in [19], image objects/patterns are classified at the highest level into land, water or fire. Land is further classified into island and other land. Water is further classified into river and other water body. The fuzzy sets that quantify area or length are defined based on geographic facts such as:

- Largest continent is Asia with area of 44579000 km^2
- Largest freshwater lake is Lake Superior with area of 82103 km^2
- Smallest continent is Australia/Oceania with area of 7687000 km^2 .
- Longest river is the Nile with length 6669 km

A total of 29 fuzzy sets have been formulated in this research. Only some of the triangular fuzzy sets formulated are shown here due to space limitation. The fuzzy sets for *large expanse of water*, *considerably large expanse of water* and *small expanse of water* are formulated as shown in equations (6), (7), and (8).

$$\begin{aligned} \mu_{\text{large expanse of water}}(x) &= 1, \text{ for } 82103 \leq x \\ &= x/2203 - 36.27, \text{ for } 79900 \leq x \leq 82103 \\ &= 0, x < 79900 \end{aligned} \quad (6)$$

$$\begin{aligned} \mu_{\text{considerably large expanse of water}}(x) &= 1 - (55068.66 - x)/27034.33, \text{ for } 28034.33 \leq x \leq 55068.66 \\ &= 1 - (x - 55068.66)/27034.33, \text{ for } 55068.66 \leq x \leq 82103 \\ &= 0, x < 28034.33 \\ &= 0, x > 82103 \end{aligned} \quad (7)$$

$$\begin{aligned} \mu_{\text{small expanse of water}}(x) &= 1, 0 \leq x \leq 600 \\ &= -x/400 + 2.5, \text{ for } 600 \leq x \leq 1000 \\ &= 0 \text{ otherwise} \end{aligned} \quad (8)$$

An example SPOT Multispectral satellite image to be analysed is shown in Fig. 2. K-means clustering [30] is used in order to cluster the pixels in the image. Table I shows a small sample data set of feature descriptors calculated/collected from the patterns in the image using the image analysis tool. The R band grey level at centroid location of pattern is shown in the table, as this band shows all patterns clearly. Area of each pattern is in sq km. Length is in km. Pattern id attribute denotes numbers as follows: 0= River, 1=Water Body, 2=Island, 3=Land, 4=Fire. Location is indicated by X, Y pixel co-ordinates of centroid of pattern/object. The additional information or pattern id attribute of each object in Table I is calculated using the classification rules in Section II, which hold for multi-band (RGB) images. For land, island, and water body (expanse of water), area is the most significant parameter in calculations and therefore their length is ignored. A river's length is its most significant parameter in calculations and therefore its area is ignored. In order to extract other patterns such as different types of vegetation, supervised classification which uses observational ground data is required.

From Fig. 2, it is noted that four patterns/objects have been extracted and identified. The area and length of these patterns are calculated by the tool, as displayed in a table in Fig. 3.

The user may choose, at this stage, to interact with the system and suggest some possible summaries. The system can evaluate the fitness of the user-summaries and inform the user if they are most suitable to describe the image patterns in the table. In order to start the user interaction process, the user clicks the user icon on the second horizontal menu bar in the snapshot displayed in Fig. 4. As a result, a pop-up window then requests the user to select whether to use trapezoidal fuzzy sets or to use triangular fuzzy sets to form the linguistic

summaries. In this case, the user has selected triangular fuzzy sets to be used in the knowledge base in Fig. 1. The system then displays triangular fuzzy set definitions (lower-left window in Fig. 4) in order to guide the user to select the appropriate fuzzy set for area or for length of different patterns such as land, island, water body, river etc. With the aid of these fuzzy set definitions, the user then constructs some possible pattern summaries as shown in Window 1. The summaries are:

- A small expanse of water at the lower left.
- A short river at the centre.
- A small area of land at the right.
- A small area of land at the top left.

The fitness value (1.0) of these possible summaries is calculated and displayed in Window 1. Thereafter, the user may verify the correctness of these summaries and their suitability with respect to the image patterns by running the GA Inference Engine.

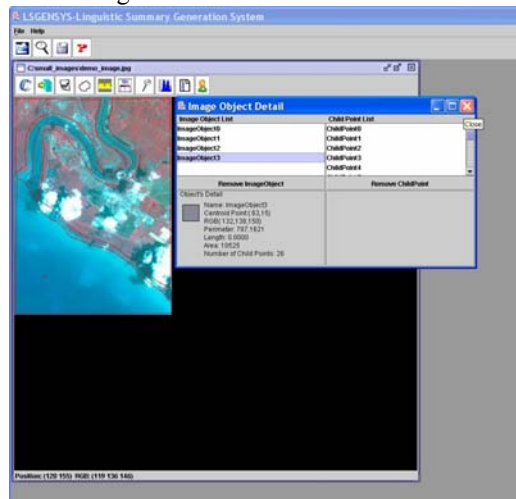


Fig. 2 The image analysis tool of the system as it extracts area and length of patterns in a SPOT MS image. Approximate scale of image 1: 0.0003764 sq km

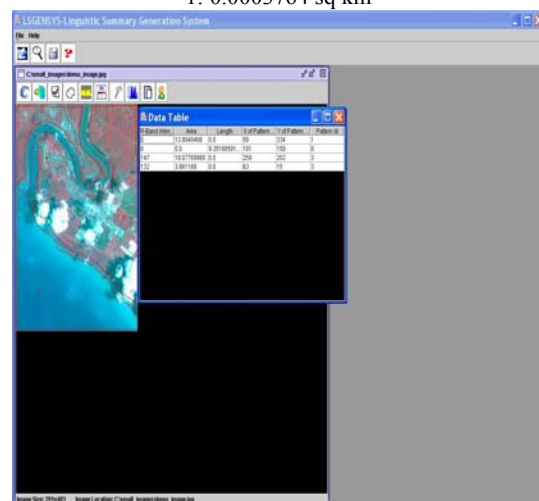


Fig. 3 The area and length of patterns calculated and displayed in a table by the tool

Fig. 5 shows a snapshot of the GA Inference Engine as it runs (in the top left window) and evolves the most suitable summaries with higher fitness, over several generations. The summaries generated by the engine are captured in a text file as displayed in the top right window of Fig. 5.

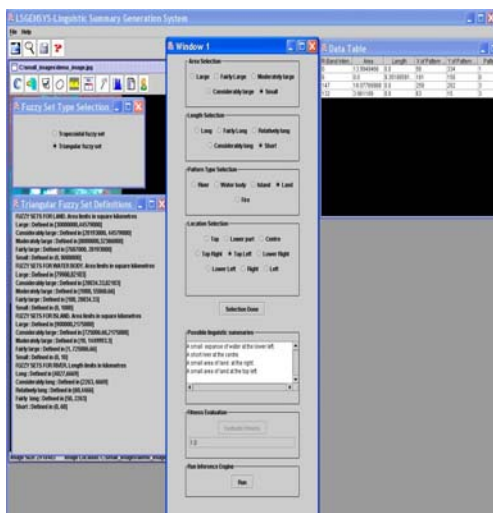


TABLE I
 DATA CALCULATED FROM THE IMAGE PATTERNS IN FIG. 2

R-band grey level	Approx Area sq km	Approx Length km	X	Y	Id
6	-	9.35	181	150	0
147	18.08	-	259	202	3
132	3.96	-	63	15	3
0	13.99	-	58	334	1

No: of bits in a chromosome string of the population = 10
 Generations per cycle = 27
 Population size = 200 strings
 Probability of cross-over = 0.535
 Probability of mutation = 0.001

After 216 generations, the linguistic summaries generated for the data in Table I are:

- A short river at the centre
- A small area of land at the right
- A small area of land at the top left
- A small expanse of water at the lower left

Fig. 4 The user icon on the second horizontal menu bar is clicked in order to start the user interaction process

The user may also chose to bypass the summary construction process, and directly invoke the inference engine (by pressing the Run button in Fig. 5) to construct and generate the most suitable summaries. This would resemble unsupervised classification and description.

Thus, the possible summaries formulated by the user compare well with the summaries generated by the inference engine.

Fig. 6 and Fig. 7 show the same procedure as applied to a LANDSAT image. The image consists of a section of two land areas separated by a water body. Table II shows the data calculated from the image patterns. In Fig. 6, the system evaluates and displays the fitness of the summaries suggested and formulated by the user. The summaries are:

- A fairly large expanse of water at the centre.
- A small area of land at the top in the image.
- A small area of land in the lower part of the image.

In this case, the fitness value calculated is 0.789, which is considered by the system to be too low. Therefore, the system rejects the summaries and the user re-formulates some possible summaries as shown in Fig. 7. The fitness of this set of summaries is higher at 0.88, and the system accepts this possible set of user summaries. The summaries are:

- A moderately large expanse of water at the centre.
- A small area of land at the top in the image.
- A small area of land in the lower part of the image.

The GA Inference Engine is invoked by the user to verify and validate the suitability of the above possible set of summaries. The resulting summaries from the inference engine are enumerated below.

The GA is run with following input parameter set. These parameter values are set after several trial runs.

No: of bits in a chromosome string of the population = 10
 Generations per cycle = 27
 Population size = 200 strings

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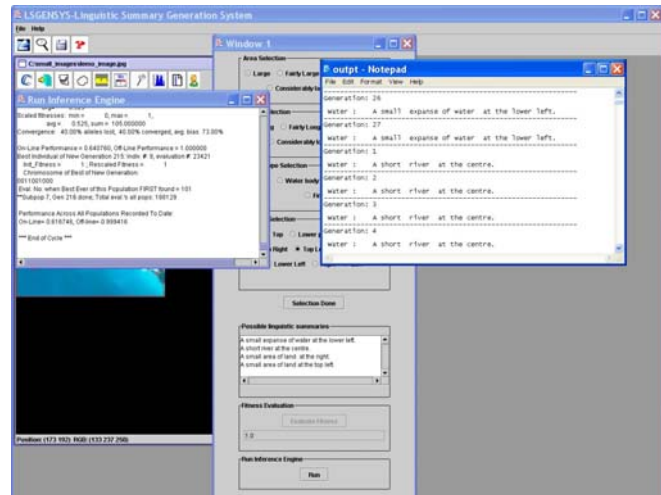


Fig. 5 Snapshot of the GA Inference Engine as it runs and evolves the most suitable summaries that fit all the patterns extracted from the image

The GA is run with following input parameter set. These parameter values are set after several trial runs

Probability of cross-over = 0.535
 Probability of mutation = 0.001

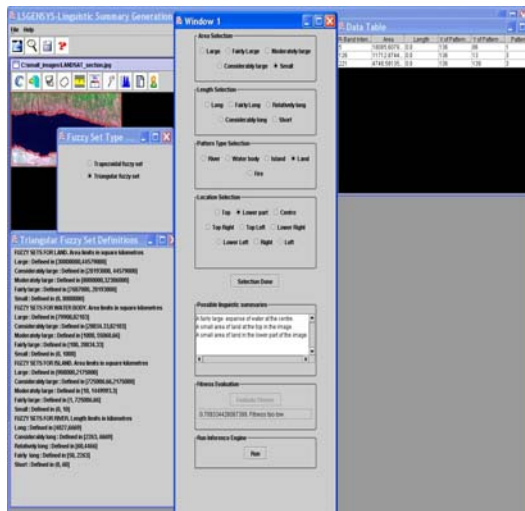


Fig. 6 A LANDSAT image is analysed by the system and some possible summaries formulated by the user. Approximate scale of image is 1: 0.952 sq km

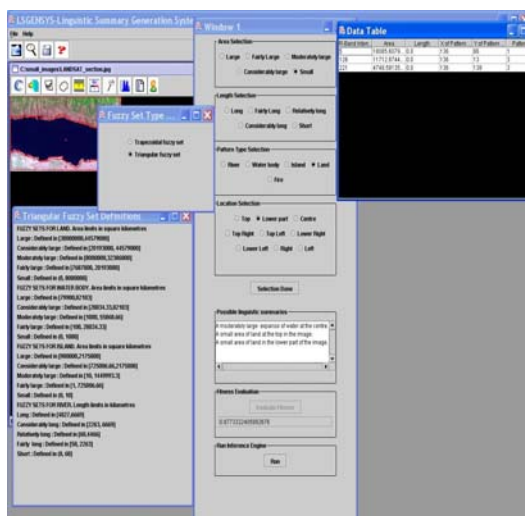


Fig. 7 For the image in Fig. 6, a different set of summaries as formulated by the user and fitness re-evaluated by the system

After 216 generations, the linguistic summaries generated for the data in Table II are:

- A small area of land in the lower part of the image.
- A small area of land at the top in the image.
- A moderately large expanse of water at the centre.

These summaries match the user-formulated summaries in Fig. 7.

The blackboard architecture component of the system has been implemented via the user interaction process. The sequence of windows such as Fuzzy Set Type selection

window, Fuzzy Set Definitions window, Window 1, Run Inference Engine Window, and the Outpt window are programs integral to the blackboard architecture component. The Data Table and possible set of user-formulated summaries in Window 1 are part of the blackboard data structure. Control in the blackboard architecture directs the order in which the programs are invoked depending on the user-formulated summaries stored in the blackboard.

TABLE II
 DATA CALCULATED FROM PATTERNS IN FIG. 6

R-band grey level	Approx Area sq km	X	Y	Id
5	18085.61	136	86	1
126	11712.87	136	13	3
221	4748.59	136	139	3

V. CONCLUSIONS AND FUTURE WORK

This paper has presented a new system developed in Java for image analysis and pattern recognition in multi-band satellite images. The system architecture and design have been described. The system has been tested successfully with a SPOT MS image and a LANDSAT image and the results have been presented and discussed. Some directions of future work include:

1. Adding the provision to upload ground data in order to help classify more patterns such as vegetation in satellite images using supervised classification techniques.
2. Adding enhancements to image analysis functions.
3. Adding a scripting feature that allows the user to program a sequence of image analysis instructions in a user-friendly language.
4. Adding more fuzzy sets and corresponding labels in the knowledge base and library respectively, to have a system that is richer and can generate a wider variety of linguistic summaries.
5. As a future application, it would be possible to construct an index for an image database using the linguistic summaries developed.
6. Expanding the system to test application domains other than remote-sensing.

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