LINGUISTIC DESCRIPTION OF PATTERNS FROM MINED IMAGES

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Abstract: The objective of this paper is to propose an approach to describe patterns in remote-sensed images utilising fuzzy logic. The general form of a linguistically quantified proposition is *"QY's are F"* where Q is a fuzzy linguistic quantifier, Y is a class of objects and F is a summary that applies to that class. The truth of such a proposition can be determined for each object characterised by a tuple in the database. Fuzzy descriptions of linguistic summaries help to evaluate the degree to which a summary describes an object or pattern in the image. A genetic algorithm technique is used to obtain optimal solutions that describe all the objects or patterns in the database. Image mining is used to extract unusual patterns from multi-dated satellite images of a geographic area.

1 INTRODUCTION

In the past, research has focussed on data mining or extracting implicit patterns in relational databases (Nair, 1994), (Nair, 2003), (Motro, 1994), (Yager, 1991), (Kacprzyk, Ziolkowski, 1986), but data mining in multimedia environment has met with limited success. This is mainly due to the fact that multimedia data is not as structured as relational data (Zaine et al., 1998). There is also the issue of diverse multimedia types such as images, sound, video etc. While one method of data mining may find success with one type of multimedia such as images, the same method may not be well-suited to many other types of multimedia due to varying structure and content. Some related work (Zaine et al., 1998) has met with success. In (Zaine et al., 1998), the objective is to mine internet-based image and video. The results generated could be a set of characteristic features based on a topic (keyword), a set of association rules which associate data items, a set of comparison characteristics that contrast different sets of data, or classification of data using keywords. Data mining techniques can be used in image mining (Thuraisingham, 2001) to classify, cluster or associate images. Image mining is an area with applications in many domains including space images and geological images.

This paper proposes an approach that utilises fuzzy logic to describe patterns in remote-sensed images. This method aims to extract some feature descriptors such as area, length etc., of objects in remote-sensed images and store them in a relational table. Data mining techniques that employ genetic algorithms are then used to develop the most suitable linguistic summary of each object/pattern stored in the table. Image mining is used to detect unusual patterns such as forest or field fires in SPOT Multispectral satellite images of the same geographic area on two different dates separated by a considerable time interval. The objective is to generate linguistic summaries of these and other natural patterns in remote-sensed images. The approach is to use fuzzy logic to match actual image feature descriptors with feature definitions and to evolve the best-suited linguistic summary of the image object/pattern using genetic algorithms. Genetic algorithms are parallel, mathematical search procedures inspired by Darwinian genetic theories of natural selection (Filho et al., 1994). These algorithms apply genetically-inspired operators such as selection, cross-over, and mutation to populations of potential solutions in an iterative manner, creating new populations while searching for an optimal

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solution to the problem at hand. Many points in the solution space are searched in parallel.

This paper is organised as follows. Section 2 describes the system architecture, section 3 describes the approach, section 4 discusses the implementation issues, and section 5 discusses the conclusions and future work.

2 SYSTEM ARCHITECTURE

The system architecture is shown in Figure 1. The data summariser is the key component of the system. The input image is analysed and feature descriptors extracted by the image analysis component. Feature descriptors are extracted using MATLAB (The Mathworks Inc, 1997) and ENVI (Research Systems Inc, 1997) which perform the functionality of the image analysis component. These descriptors are stored thereafter in a relational table in the database. The knowledge base uses geographic facts to define feature descriptors in a typical remote-sensed image. It interacts with a built-in library of linguistic labels. As new feature definitions are added into the knowledge base, corresponding linguistic labels are added in the built-in library. Likewise, in order to expand the built-in library, corresponding feature definitions based on geographic facts have to be added in the knowledge base. The built-in library also interacts with the summariser as it supplies the necessary labels to it. The summariser receives input from the database and the knowledge base. It performs a comparison between actual feature descriptors of the image stored in the database with the feature definitions stored in the knowledge base. The summariser then finds a valid optimal linguistic summary for the data by interaction with the engine (genetic algorithm). The linguistic summary would be optimal in the sense that the linguistic label would be the most suitable one to describe the object or pattern. The GA evolves the most suitable solution to the problem and passes it back to the summariser which translates this solution into its corresponding linguistic summary. Thus, this system is composed of two subsystems at this stage. The feature descriptor extraction using MATLAB and ENVI is a manual subsystem involving user interaction. After descriptors are extracted and stored in a relational table in the database, the automated subsystem consisting of summariser, knowledge base, library and engine evaluate the descriptors and compare them with feature definitions. An optimal linguistic summary of each object is then generated automatically.

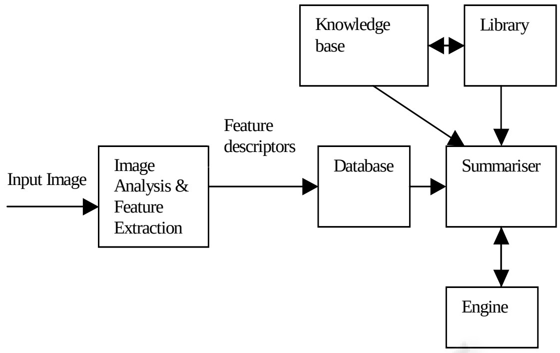

Figure 1: System Architecture

3 APPROACH

The following assumptions are made regarding the data model. R is a relational table defined as:

$$R(A_1,A_2,...,A_i,...,A_n)$$

$A_1,A_2,...A_n$ are the attributes in the table R (i.e. the columns of the relational table).

$t_1,t_2,...,t_k$ are the tuples or records or entries in the table R (i.e. the rows of the relational table).

A fuzzy set is the most natural representation of a linguistic variable. A linguistic variable is one whose value is not a number but a word or a sentence in a natural language (Mendel, 2001). In order to generate linguistic summaries of objects, some fuzzy sets are defined that represent our notion of what the object description or summary should look like.

The general form of a linguistically quantified proposition is *"QY's are F"* where Q is a fuzzy linguistic quantifier, Y is a class of objects and F is a summary that applies to that class. F is defined as a fuzzy set in Y. Q represents a linguistic quantifier that groups objects in the class Y. An object/pattern in the image is characterised by a single tuple in our database, therefore, we can ignore Q in this analysis.

An example of such a linguistically quantified proposition in the domain of remote-sensed images would be as follows:

Island is moderately large.

In the above example, Y is *Island* and F is *moderately large*. In terms of linguistics, this description is equivalent to:

Moderately large island.

The objects/patterns considered are river, expanse of water(other water body which is not river), land and island. The attributes of the objects that are used to develop their linguistic summaries are :

1. Area
2. Length
3. Location in image
4. Addition information

Area, length and location (X, Y co-ordinates in image) are extracted by user interaction using the image analysis component in Figure 1. For river, the most significant feature descriptor that is extracted is its length. For land, island and expanse of water, the most significant feature descriptor extracted is area.

If
$Y = y_1, y_2, \ldots y_p$ (1)
then
$truth(y_i \text{ is } F) = \mu_F(y_i) : i = 1,2,\ldots,p,$ (2)

where $\mu_F(y_i)$ is the degree of membership of y_i in the fuzzy set F and $0 \le \mu_F(y_i) \le 1$. The higher the degree of membership, the higher the truth value of the linguistic proposition. In our case, referring to equations (1) and (2), y_i could be *island* or *area of land* or *expanse of water* or *river*. *Area of land* represents land other than island, *expanse of water* represents any water body that is not a 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. Fuzzy sets for area are *large, considerably large, moderately large, fairly large* and *small* and fuzzy sets for length are *long, considerably long, relatively long, fairly long* and *short*.
The linguistic description is calculated as follows:
$T_j = m_{1j} \wedge m_{2j} \wedge m_{3j} \ldots \wedge m_{nj}$ (3)
where m_{ij} is the matching degree (Kacprzyk, Ziolkowski, 1986) of the *ith* attribute in the *jth* tuple. $m_{ij} \in [0,1]$ is a measure of degree of membership of the *ith* attribute value in a fuzzy set denoted by a fuzzy label. Referring to equation (3), T_j thus evaluates the truth value for each object y_i, as it matches the feature descriptors of that object with fuzzy set definitions by calculating the matching degrees and combining them together using logical AND operator. The logical AND ($\wedge$) of matching degrees is calculated as the minimum of the matching degrees (Kacprzyk, Ziolkowski, 1986).

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

Equation (4) means that the conjunction of only those matching degrees that are non-zero is calculated in order to evaluate T_j. This aids in computational efficiency. All such T_j's are added up to evaluate T. T is a numeric value that represents the truth of the overall summary of the objects in the database.

4 IMPLEMENTATION ISSUES

This section explains the genetic algorithm approach and then discusses the results from applying this approach to mining images.

4.1 GA Approach

A genetic algorithm emulates biological evolutionary theories as it attempts to solve optimisation problems. The GA comprises of a set of individual elements (the population) and a set of biologically inspired operators such as selection, cross-over and mutation. According to evolutionary theories, only the most suited elements in a population are likely to survive and generate offspring, thus transmitting their biological heredity to new generations. In computing terms, a genetic algorithm maps a problem onto a set of binary strings (the population); each string representing a potential solution. Using selection, cross-over and mutation operators, the GA then manipulates the most promising strings (denoted by their high fitness value from the evaluation function), as it searches for the best solution to the problem (Filho et al., 1994), (Smith et al., 1994), (Goodman, 1996).
Given n attributes, each having m possible fuzzy labels, it is possible to generate m^n+1 descriptions. The GA searches for a optimal solution among these descriptions. Each of these summaries is represented by a uniquely coded chromosome string (a string of 0's and 1's). The population of such strings is manipulated and evaluated by the GA and the most suitable linguistic summary that fits each object is generated. The evaluation function for the linguistic summary or description is
$f = max(T),$ (5)
where T in equation (5) is evaluated as shown in the previous section and f is the maximum fitness value of a particular linguistic summary or description that has evolved over several generations of the GA.

4.2 Results

In general, image objects are classified at the highest level into land and water. Land is further classified into island and other land. Water is further classified into river (characterised by its length) and other water body (characterised by area). Fire is considered as a separate pattern identified by its bluish white smoke plume. Some of the fuzzy sets being considered are :

1. For Island or land: *Large, Considerably large, Moderately large, Fairly large* and *Small* based on degree of membership of area of the land in the respective fuzzy sets.

2. For Other Water Body: *Large, Considerably large, Moderately large, Fairly large* and *Small* based on degree of membership of area of the water body in the respective fuzzy sets.
3. For River: *Long, Considerably long, Relatively long, Fairly long* and *Short* based on degree of membership of length of the river in the respective fuzzy sets.

These fuzzy sets 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
- Shortest river is the Roe with length 0.037 km

The fuzzy set for *large expanse of water* is defined in equation (6) referring to Figure 2(a), where x_1= 79900 km^2, x_2 = 82103 km^2.

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

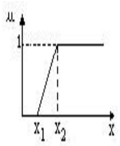

Figure 2(a):Fuzzy Set for Large

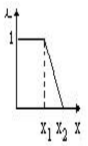

Figure 2(b): Fuzzy Set for Small or Short

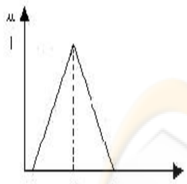

Figure 3: Fuzzy Sets for Considerably large or Moderately large or Fairly large

The fuzzy set for *fairly large expanse of water* is defined in equation (7) referring to Figure 3, where x_1= 100 km^2, x_2 = 1000 km^2, x_3 = 28034.33 km^2.

$$\mu_{fairly\ large\ expanse\ of\ water}(x)$$
$$=1-(1000-x)/900,\ for\ 100\leq x\leq 1000$$
$$=1-(x-1000)/27034.33,\ for\ 1000<x\leq 28034.33$$
$$=0,\ x< 100$$
$$=0,\ x> 28034.33 \quad (7)$$

The fuzzy set for *small expanse of water* is defined in equation (8) referring to Figure 2(b).

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

The set for *small area of land* is defined in equation (9) referring to Figure 2(b).

$$\mu_{small\ area\ of\ land}(x) = 1,\ 0<x\leq 7687000$$
$$=-x/313000 + 25.56,\ for\ 7687000<x\leq 8000000$$
$$= 0\ \text{otherwise} \quad (9)$$

The fuzzy set for *short river* is defined in equation (10) referring to Figure 2(b)

$$\mu_{short\ river}(x) = 1,\ 0<x\leq 50$$
$$=-0.1x + 6,\ for\ 50<x\leq 60$$
$$= 0\ \text{otherwise} \quad (10)$$

An example pair of SPOT Multispectral images to be analysed is shown in Figure 4 and Figure 5. Figure 6 shows a binary thresholded image for Figure 4. The geographic co-ordinates of the image are approximately 3º17'U-3º48'U latitude and 100º58'T-101º38'T longitude referring to the topographic map. The scale of the image is approximately 1: 0.0003764. This means that 1 pixel square represents 0.0003764 km^2**.** Figure 7 shows the histogram of the image without fire at the location where the fire is later detected. Figure 8 shows histogram of the image with fire at the location of fire. Comparing the histograms in Figures 7 and 8, it can be seen that most of the pixels are of lower intensity near the burnt scar next to the bluish white smoke plume in the image (Figure 5). Tables 1 and 2 show small sample data sets of feature descriptors extracted from some of the objects in the images(Figures 4 and 5 respectively). Area is in km^2 and length in *km.* Additional information attribute denotes numbers as follows : 0 = River, 1 = Other Water Body, 3 = Other Land, 4 = Fire. Location indicates X,Y co-ordinates of centroid of object. X,Y = 0 indicates the remaining part of image as location. The grey level values are from the R-Band as this band shows all the patterns clearly. River is characterised by length(its most significant dimension), its area is considered negligible in the calculations when compared to its length, and therefore its area is set to 0. Likewise, for other objects where area is considered as the most significant parameter in calculations, their length is ignored and set to 0. The degree of membership in the fuzzy sets for area and length given in Table 1 and Table 2 are calculated.

The location attribute is given a linguistic value such as centre, left, top left etc., using the following calculation. *Centre-span* is a variable defined in order to denote a circular distance around the X, Y co-ordinates of the centre of an image. The value of centre-span may vary from image to image as it is subjective. It is a number that is obtained by measuring the distance around the centre of the image, which can be used to denote an area that still represents the centre of the overall image. This value is evaluated by user-interaction with the image. All objects, whose centroids (Buckles et al., 1996) lie within the range of centre-span from the centre of the image, are still located at the centre of the image. If the difference between X, Y co-ordinates of the centroid of the object and the centre of the image is greater than centre-span, then the object is located at lower right (diagonally from image centre). If the reverse is true, then the object is located at top left (diagonally from image centre). If the difference between X co-ordinate of the object and the X co-ordinate of image centre is greater than centre-span and the difference between Y co-ordinate of image centre and the Y co-ordinate of centroid of the object is greater than centre-span, then object is located at the top right of the image. Similar calculations are used to evaluate the locations lower left, right, left, top and bottom of image. An X, Y co-ordinate of 0, 0 evaluates the location as *remainder of image.*

It is to be noted that patterns such as urban area settlements are ignored as trivial in this analysis.

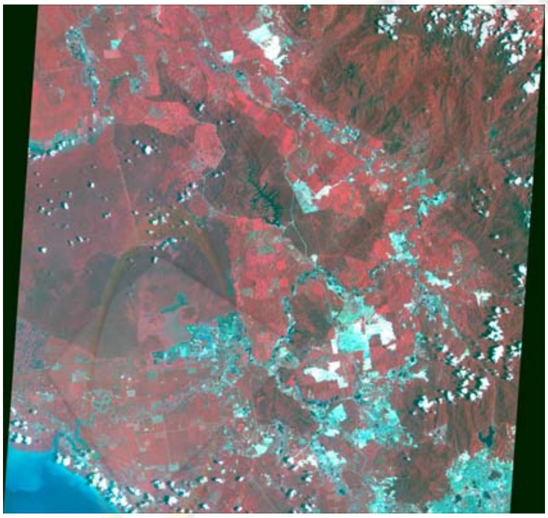

Figure 4: Image of area in peninsular Malaysia on March 6, 1998

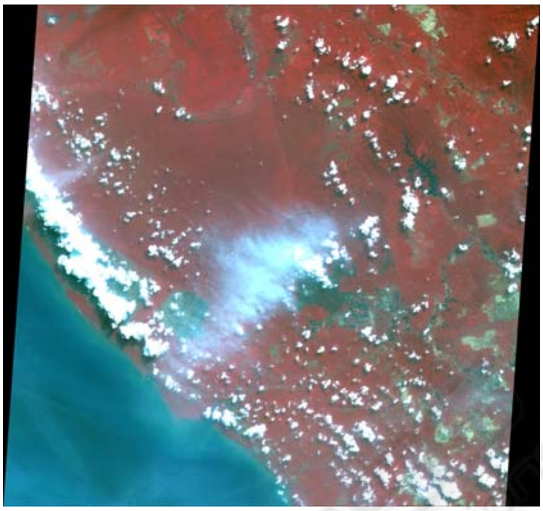

Figure 5: Image of area in peninsular Malaysia on July 10, 2001, showing fire on the left.

Figure 6: Binary image corresponding to Figure 4.

Table 1: Feature descriptors of some patterns from Figure 4

Grey level value (R Band)	Approximate Area	Location in image		Additional information
		X	Y	
150	3300.84	1606	1457	3
0	2.2275	2856	2566	1
0	6.683	1546	1132	1
0	68.54	0	0	1

The main concerns are natural patterns such as water bodies, land, and also extracting patterns that signal natural calamities such as fires.

The objective of this paper is to describe patterns/objects such as river, land, island, expanse of water etc quantitatively in terms of measures such as area or length. The additional information attribute is added in the tables by visual inspection of the images. Thus, the current work is not concerned with identifying these patterns automatically. Pre-segmented images have been used for this purpose. Future work (Section 5) will focus on this aspect of identification.

The linguistic summaries are generated with reference to the scale of land and water defined in the geographic facts from which the fuzzy sets are developed, even though the area of land in the images may appear to be large compared to the expanse of water.

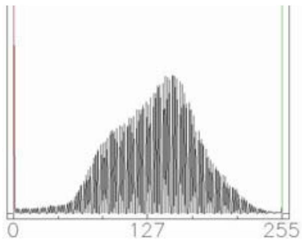

Figure 7: Histogram of Figure 4 near the location where fire is later detected.

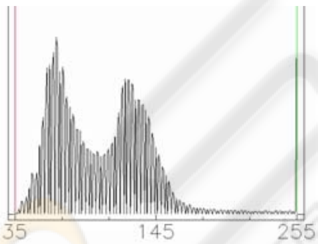

Figure 8 : Histogram of Figure 5 at the location of burnt scar near the fire.

The GA is run with following input parameter set. These parameter values are set after several trial runs. With other values, the GA produces the summary of only one or two object/patterns in the table:

1. Number of bits in a chromosome string of the population = 10
2. Generations per cycle = 26
3. Population size = 200 strings
4. Probability of cross-over = 0.53
5. Probability of mutation = 0.001

After 208 generations, the linguistic summaries generated from the image in Figure 4(no fire) are :

- A small area of land at the centre.
- A small expanse of water at the lower right
- A small expanse of water at the centre.
- A small expanse of water in the remaining part of the image.

The GA input parameters are varied to obtain the linguistic summaries of patterns of the image in Figure 5(with fire). The parameters used are:

1. Number of bits in a chromosome string of the population = 10
2. Generations per cycle = 10
3. Population size = 200 strings
4. Probability of cross-over = 0.53
5. Probability of mutation = 0.001

After 80 generations, the linguistic summaries generated from the image in Figure 5 are :

- Bluish white smoke indicating fire at the left
- A small expanse of water in the remaining part of the image
- A small expanse of water at the top right
- A small area of land at the centre

Table 2: Feature descriptors of some patterns from Figure 5

Grey level Value (R Band)	Approximate Area	Approximate Length	Location in image		Additional information
			X	Y	
150	2874.38	0	1899	1150	3
166	0	0	1550	1587	4
65	0	47.5	355	237	0
27	6.683	0	2506	976	1
64	509.31	0	0	0	1

After 88 generations and generations per cycle set to 11, the following summaries are generated:

- Bluish white smoke indicating fire at the left
- A short river at the top left
- A small expanse of water in the remaining part of the image.

In each case it is worth noting that there is at least one new pattern that has been extracted and described. Thus comparing the results of the GA after mining the images of the same geographic area without fire and with fire taken on two dates separated by a period of more than three years, it can be seen that that the GA can correctly describe an unusual pattern such as the fire indicated in the image in Figure 5. Referring to the corresponding topographic map, it is possible to conclude that this fire could be the result of burning in a paddy field or a nearby primary forest.

Thus, with two attributes such as length and area, each having five possible fuzzy labels, it is possible to generate 5^2+1 descriptions. The GA has searched for an optimal solution among these descriptions within a very short time.

5 CONCLUSIONS AND FUTURE WORK

This paper has presented a new approach to describing patterns in images using linguistic summaries that use fuzzy labels. A genetic algorithm technique has been employed to evolve the most suitable linguistic summary that describes each object/pattern in the database. Image mining is used to extract unusual patterns such as fire in the same geographic area from images collected over two different dates. This method can be extended to an array of images of the same geographic area, taken over a period of several years, to describe many other interesting and unusual patterns that emerge over time.

Some directions for future work include:

1. Development and implementation of clustering algorithms in order to evaluate automatically the additional information attribute in the tables. Currently pre-segmented images are used.
2. Development of a user friendly tool with graphical interface to ease the task of extracting and calculating feature descriptors such as area, length, gray level intensity, colour etc., stored in the tables. Currently, both MATLAB and ENVI are required in order to populate the tables. Each has its own limitations.

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