DEVELOPMENT OF SUMMARIES OF CERTAIN PATTERNS IN MULTI-BAND SATELLITE IMAGES

Hema Nair
C.T.R.F., 813, 7th Main, 1st Cross, HAL 2nd Stage, Bangalore 560008, India

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Abstract: This paper describes a system that is designed and implemented for interpretation of some patterns in multi-band (RGB) satellite images. Patterns such as land, island, water body, river, fire, urban area settlements in remote-sensed images are extracted and summarised in linguistic terms using fuzzy sets. Some elements of supervised classification are introduced to assist in the development of linguistic summaries. A few LANDSAT images are analysed by the system and the resulting summaries of the image patterns are explained.

1 INTRODUCTION

Data mining is a term applied to the set of techniques and processes that analyse raw data to discover implicit patterns which are useful for decision-making. Pattern recognition can be considered as a form of data mining because both concentrate on the extraction of information or relationships from data (Kennedy et al., 1997). Knowledge discovery and data mining systems employ methods and techniques from the field of pattern recognition, as well as related topics in database systems, machine learning, artificial intelligence, statistics, and expert systems, where the unifying goal is to extract knowledge from large volumes of data (Friedman, Kandel, 1999). Several pattern classification techniques have been proposed in literature. These include neural nets, genetic algorithms (GA), Bayesian methods, statistical methods, decision tables, decision trees etc. A multimedia database system (Thuraisingham, 2001) is an example of a heterogeneous database system because it manages heterogeneous data types such as audio, images, video etc. Such data is typically unstructured in format. Although many techniques for representing, storing, indexing and retrieving multimedia data have been proposed, the area of multimedia mining has seen few results (Zaine et al., 1998a), (Zaine et al., 1998b). This is mainly due to the fact that multimedia data is not as structured as relational data (Zaine et al., 1998b). There is also the issue of diverse multimedia types such as images, sound, video etc. A particular data mining technique may be successful with one type of multimedia such as images, but the same technique may not be well suited to many other types of multimedia due to varying structure and content. In (Zaine et al., 1998a), (Zaine et al., 1998b), 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. From another perspective, (Barnard et al., 2003a), (Barnard et al., 2003b) describe the approach involved in matching images to text. Their work describes models used for automatic image annotation, browsing support and auto-illustration of blocks of text. Such models are focussed on prediction of words (from an available pool) that match with specific image regions. This is a form of labelling and requires assistance from training data and manually annotated images.

A system that classifies and interprets patterns such as land, island, water body, river, fire, urban area settlements in satellite images is described in this paper. It utilises fuzzy logic to describe these patterns (Nair, 2003), (Nair, Chai, 2004), (Nair, 2004), (Nair, Chai, 2005). Some feature descriptors such as area, length, shape ratio etc., of such patterns are extracted and stored in a relational database. Data mining techniques that employ clustering and

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genetic algorithms are then used to develop the most suitable linguistic summary of each pattern/object stored in the database. 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 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 (Nair, Chai, 2005) is that presently the user has the choice of suggesting concepts such 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 (Kacprzyk, Yager, 2001). 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. 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 4) 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.

This research focuses on analysing multi-band (RGB) satellite images. The following set of rules is developed to perform pattern classification in multi-band satellite 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) above, 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.
5. A new rule is proposed for the classification and identification of urban area settlements in an image. At this stage, only simple, geometrically regular settlements can be identified. The grey level intensity (indicated as white colour for settlements) and shape are used as attributes to aid the identification and classification process. Settlements are identified by sharp edges and corners. Shape ratio can be used to verify the preciseness of the shape. This classification will have a percentage of accuracy associated with it.

3 APPROACH

Area, length, location (X, Y pixel co-ordinates of centroid of pattern in image), Additional Information or Pattern Id, grey level intensity, and shape ratio are the attributes of the patterns/objects that are used to develop their linguistic summaries. Area, length, location, grey level intensity, shape ratio 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.

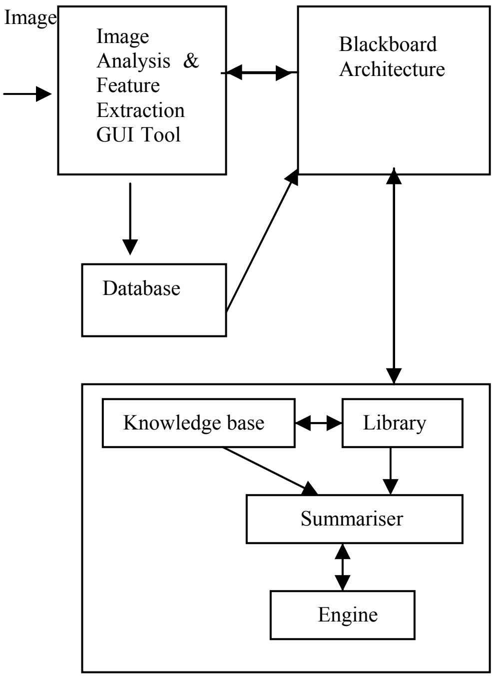

Figure 1: System architecture.

If $\quad Y = y_1, y_2, \ldots y_p \qquad (1)$

then

$truth(y_i isF) = \mu_F(y_i): i = 1,2,\ldots,p, \qquad (2)$

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 land generated by the system in this paper would be:

A moderately large area of land at the centre of 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 trapezoidal fuzzy sets formulated for area are *large, fairly large, moderately large,* and *small* and fuzzy sets for length are *long, relatively long, fairly long* and *short*. Triangular fuzzy sets have also been formulated for area and length. The linguistic description is calculated as follows:

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

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. The logical AND ($\wedge$) of matching degrees is calculated as the minimum of the matching degrees (Kacprzyk, Ziolkowski, 1986).

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

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.

4 IMPLEMENTATION ISSUES

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

4.1 GA Approach

The genetic algorithm emulates biological evolutionary theories as it attempts to solve optimisation problems (Filho et al., 1994), (Goodman, 1996), (Smith et al., 1994). Each binary chromosome string in a population represents a possible linguistic summary for a pattern. Such a population of strings is manipulated by selection, cross-over and mutation operators in the GA (Filho et al., 1994) 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

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

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.

4.2 Results and Discussion

In general, image objects/patterns are classified at the highest level into land, water or fire. Land is further classified into island and other land. Urban area settlement is a pattern that can be identified on land or island. Water is further classified into river and other water body. The fuzzy sets that quantify area or length are defined with reference to 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
- Largest island is Greenland with area 2175000 km^2

A total of 29 fuzzy sets have been formulated in this research. Formulation of these fuzzy sets is based on the universal geographic facts given earlier. Only some of the trapezoidal fuzzy sets and triangular fuzzy sets formulated are shown here due to space limitation. The trapezoidal fuzzy sets for *large expanse of water*, *fairly large expanse of water* and *small expanse of water* are formulated as shown in equations (6), (7), and (8). In (9), the triangular fuzzy set for *considerably large expanse of water* is shown.

$$\mu_{\text{largeexpanseofwater}}(x)=1, \textit{for } 82103\leq x$$
$$=x/2203 - 36.27, \textit{for } 79900\leq x\leq 82103$$
$$=0, x<79900 \quad (6)$$

$$\mu_{\text{fairlylargeexpanseofwater}}(x)=1, \textit{for } 100\leq x\leq 900$$
$$=1-(100-x)/91, \textit{for } 9\leq x\leq 100$$
$$=1-(x-900)/100, \textit{for } 900\leq x\leq 1000$$
$$=0, x<9$$
$$=0, x>1000 \quad (7)$$

$$\mu_{\text{small expanse of water}}(x) = 1,\ 0\leq x\leq 100$$
$$=-x/900 +1.11, \textit{for } 100\leq x\leq 1000$$
$$=0, \text{otherwise} \quad (8)$$

$$\mu_{\text{considerably large expanse of water}}(x)=1-(55068.66-x)/27034.33, \textit{for } 28034.33\leq x\leq 55068.66$$
$$=1-(x-55068.66)/27034.33, \textit{for } 55068.66\leq x\leq 82103$$
$$=0, x< 28034.33$$
$$=0, x> 82103 \quad (9)$$

In (Nair, Chai, 2005), SPOT Multi-spectral images were analysed and their resulting summaries discussed. A few LANDSAT images are analysed in this paper. An example LANDSAT satellite image to be analysed is shown in Figure 2. Table 1 shows the data collected from the image to perform k-means clustering (Mather, 1999) in order to cluster the pixels in the image. The feature vector used consists of X, Y, R, G, B values. Table 2 shows a small sample data set of feature descriptors calculated/collected from the patterns in the image using the graphical 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, 5=Urban area settlement. 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 2 is calculated automatically using the classification rules in Section 2, which hold for multi-band 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 more patterns such as different types of vegetation, observational ground data is required for training. Such data could not be afforded in this research.

The GA is run with following input parameter set. These parameter values are set after several trial runs.
Number of bits in a chromosome string of the population = 10
Generations per cycle = 15
Population size = 200 strings
Probability of cross-over = 0.53
Probability of mutation = 0.001

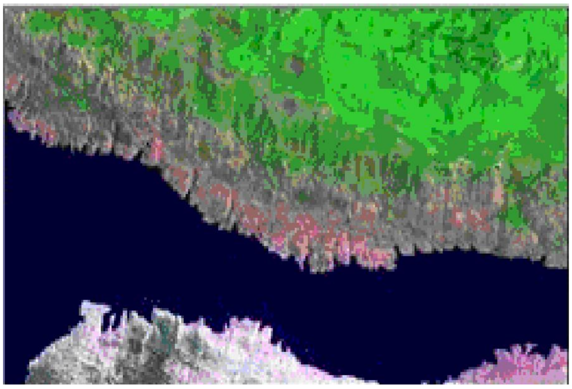

Figure 2: LANDSAT 7 ETM+ image of a section of Kvarneric islands, Croatia. Approximate scale 1:0.952 sq km.

With triangular fuzzy sets in the knowledge base, after 120 generations of the GA, the linguistic summaries generated for the data in Table 2 are:

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

Figure 3 shows another sample LANDSAT image, which is analysed by the system. The k-means clustering table is Table 3 and the data collected/calculated by the graphical tool is shown in Table 4. The corresponding output linguistic summaries from the system are also shown.

For the data in Table 4 corresponding to image in Figure 3, the GA is run with following input parameter set. These parameter values are set after several trial runs.
Number of bits in a chromosome string of the population = 9
Generations per cycle = 10
Population size = 200 strings
Probability of cross-over = 0.53
Probability of mutation = 0.001

Table 1: Data collected from image in Figure 2 for clustering. The header of the table denotes data from left to right as follows: X_{object}, Y_{object}, $X_{envelope}$, $Y_{envelope}$, R_{object}, G_{object}, B_{object}, $R_{envelope}$, $G_{envelope}$, $B_{envelope}$.

X_{object}	Y_{object}	$X_{envelop}$	$Y_{envelop}$	R_{object}	G_{object}	B_{object}	$R_{envelop}$	$G_{envelop}$	$B_{envelop}$
257	37	204	145	50	189	46	0	9	69
238	16	205	130	52	193	52	0	9	69
170	4	183	125	45	200	36	0	11	72
141	4	162	127	50	173	57	0	9	73
119	19	136	130	100	140	80	0	11	74
138	41	154	134	80	146	72	0	8	68
185	57	164	148	60	153	64	0	8	68
203	47	187	147	51	181	57	0	9	74
204	145	257	37	0	9	69	50	189	46
205	130	238	16	0	9	69	52	193	52
183	125	170	4	0	11	72	45	200	36
162	127	141	4	0	9	73	50	173	57
136	130	171	173	0	11	74	245	248	251
154	134	144	158	0	8	68	218	181	224
164	148	132	153	0	8	68	240	214	249
187	147	115	157	0	9	74	255	229	255
171	173	204	145	245	248	251	0	9	69
144	158	205	130	218	181	224	0	9	69
132	153	183	125	240	214	249	0	11	72
115	157	162	127	255	229	255	0	9	73
105	159	136	130	71	94	100	0	11	74
123	169	154	134	199	201	224	0	8	68
135	175	164	148	187	171	198	0	8	68
149	172	187	147	231	212	244	0	9	74

Table 2: Data calculated and collected from image in Figure 2.

R-band grey level	Approximate Area in sq km	X	Y	Pattern id
45	28624.29	174	95	3
0	11528.145	158	135	1
188	8093.116	155	184	3

With trapezoidal fuzzy sets in the knowledge base, after 80 generations of the GA, the linguistic summaries generated are:

- A fairly large island at the top left
- A fairly large island at the right
- A moderately large expanse of water in the remainder of image

The summaries produced by this system have been verified to be correct using topographic maps of the areas in the images. In general, as the graphical tool is a user-interactive tool, it is limited by the accuracy of the user's point and click action.

Figure 3: LANDSAT 7 ETM+ image of a part of Kvarneric islands, Croatia. Approximate scale 1: 0.952 sq km.

Table 3: Data collected from image in Figure 3 for clustering. The header of the table denotes data from left to right as follows: X_{object}, Y_{object}, $X_{envelope}$, $Y_{envelope}$, R_{object}, G_{object}, B_{object}, $R_{envelope}$, $G_{envelope}$, $B_{envelope}$.

X_{object}	Y_{object}	$X_{envelope}$	$Y_{envelope}$	R_{object}	G_{object}	B_{object}	$R_{envelope}$	$G_{envelope}$	$B_{envelope}$
95	49	248	41	6	2	61	5	1	62
86	36	232	9	2	2	56	2	1	59
82	33	125	1	2	4	61	3	2	60
73	41	52	1	6	5	65	6	4	67
68	42	15	10	5	2	69	4	3	59
65	42	16	47	5	3	68	2	1	58
72	60	55	59	13	8	72	13	8	72
101	56	119	71	3	3	57	2	1	59
52	23	82	27	90	95	125	4	3	60
47	21	71	5	41	50	81	1	1	58
39	19	41	5	15	20	60	8	8	70
33	19	13	10	67	74	103	5	1	60
28	20	8	23	117	125	144	1	1	57
26	26	15	45	87	117	89	2	1	58
33	29	40	71	86	122	96	11	9	74
43	29	67	65	72	116	80	13	8	74
200	46	249	44	128	132	118	6	3	60
202	39	234	12	147	143	170	2	1	59
174	40	130	1	161	157	182	2	1	59
155	41	99	8	7	3	53	2	1	59
137	46	77	41	58	104	75	7	6	66
152	45	95	58	81	93	91	3	2	60
164	45	133	77	83	87	98	2	1	59
178	44	187	70	92	92	90	4	2	61

Table 4: Data calculated and collected from image in Figure 3.

R-band grey level	Approximate Area in sq km	X	Y	Pattern Id
86	447.71	41	27	2
113	2225.22	158	48	2
10	11073.696	128	40	1

5 CONCLUSIONS AND FUTURE WORK

This paper has presented a system for interpretation of multi-band remote-sensed images by extracting and classifying some patterns such as land, island, water body, river, fire and describing these patterns using linguistic summaries. A new rule has been proposed for the identification of urban area settlements. A genetic algorithm technique has been employed to evolve the most suitable linguistic summary that describes each object/pattern in the database. 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 interesting and unusual patterns that emerge over time. In this paper, only two images have been analysed by the system. More images with patterns such as urban area settlements will be available for analysis and summarisation in future. Some directions for future work include:

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

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