Mining Rules for Satellite Imagery Using Evolutionary Classification Tree

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Abstract -

Classification Tree (CT) can establish explicit classification rules of Satellite Imagery (SI). However, the accuracy of explicit classification rules are poor. Back-Propagation Networks (BPN) and Support Vector Machine (SVM) both can establish a highly accurate model to predict the classification of SI but cannot generate the explicit rules. This study proposes a novel mining rule method named Evolutionary Classification Tree (ECT) which is composed of Particle Bee Algorithm (PBA) and Classification Tree (CT) that automatically produce self-organized rules to predict the classification of SI. In ECT, CT plays the architecture to represent explicit rules and PBA plays the optimization mechanism to optimize CT to fit the experimental data. 600 experimental data sets were used to compare accuracy and complexity of four model building techniques, CT, BPN, SVM and ECT. The results showed that ECT can produce rules which are more accurate than CT and SVM but less accurate than BPN models. However, BPN is black box models while ECT can produce explicit rules which is an important advantage to mining the explicit rules and knowledge in practical applications.

Keywords -

Satellite Imagery (SI), Back-Propagation Networks (BPN), Support Vector Machine (SVM), Evolutionary Classification Tree (ECT), Particle Bee Algorithm (PBA).

1 Introduction

Due to vigorous economic development, the change of land usage severely causes the destruction of natural environment and land resources. Thus, how to effectively manage land resources to achieve the purpose of sustainable usage is an important topic. Satellite Imagery (SI) was a record and testing information technology which explores through a sensor to indirect survey with objects [1-3]. Since 1972, the United States launched land satellite to reflect object by the sensor receiving surface of solar electromagnetic radiation. All the raw data was sent back to the earth in the form of numeric data and provide detection of environmental resources information for researcher. SI mining has the characteristic for real time survey to covered extensive area. It has become an effective survey tools to build environmental resource database.

The mining steps of SI are: (1) the satellite scans surface spectral reflectance intensity from the sensor's spectrum to obtain the image data. (2) the staffs investigate on site to obtain the surface classifies information. (3) establish the relationship between the surface spectral reflectance intensity data and the surface classifies information with appropriate statistical methods. (4) the established relationship can be directly applying on other surface only based on its surface spectral reflectance intensity data to determine its surface classification. Thus, the staffs do not need to do investigation on site and can save considerable manpower and funding. In other hand, with a quick grasp of the ability of a region-wide data, it can be applied to land use, agriculture and forestry planning, environmental monitoring, disaster assessment, scientific research and other purposes. However, different surface classifications of spectral reactions on SI mining are extremely similar, so that to distinguish surface classification will be confusing. Therefore, how to solve SI classification problems through artificial intelligence (AI) mining technique is the purpose of this study.

In the past few years, (1) artificial neural networks (ANN) have been done a lot in science field. There were also much literature [4-7] proposed complex nonlinear models with highly accuracy for predicting material behavior. But these “black box” models are unable to generate explicit formulas or rules which can explain the essence of the models. Besides, there are a lot of research have been used in SI classification area such as (2) the nearest neighbor classifier (NNC) [8] and (3) inductive decision tree (IDT) [9]. However, those methods mostly focus on accuracy (accurately predict the performance of classification model) but ignore the understand ability of classification model.

In recent years, some researchers have employed genetic operation tree (GOT) that comprise genetic algorithms (GA) and operation tree (OT) in order to build material model that can accurately predict material behaviors and explain the substance of material models [10-12]. Operation tree is a tree structure that expresses a mathematical formula. Optimizing the operation tree can produce a self-organized regression formula. In general, the accuracy of GOT generated model are lower than those produced by neural networks, but more accurate than those produced by RA [10-12].

The strength of GA lies in its ability to locate the global optimum using random yet directed searching operators. Therefore, the GA is less likely to restrict the search to a local search [13]. Thus, GA was risk finding a suboptimal solution. Another main disadvantage of GA is the excessively long run-time that is needed to deliver satisfactory results for large instances of complex design problems.

A hybrid swarm algorithm, the particle bee algorithm (PBA) was proposed to instead GA that imitates a particular intelligent behavior of bird and honey bee swarms and integrates their advantages [14, 15]. PBA improves BA neighborhood search using PSO search [14, 15] and can solve discrete optimization problem, representing one paradigm of evolution computation. It is based on natural evolution and derived from the ideas of the survival of the fittest and successful applied to many case studies [14, 15]. PBA has some advantages, such as global optimization, local optimization, exploration process, exploitation process, flexibility, and parallelism [14-15].

Besides, due to previously studies [10-12], the researchers applied GOT only on producing self-organized regression formula. There still have classification and clustering problems have to mining. Thus, this study focus on propose a novel self-organized classification tree idea namely evolutionally classification tree (ECT) that optimize the tree rules structure by PBA.

A large number of 600 experimental [16] datasets were used to compare accuracy and complexity of the five model building techniques (CT, BPN, SVM and ECT) and evaluate whether ECT can produce simpler and understand ability but accurate classification trees to mining satellite imagery rules.

2 Particle Bee Algorithm (PBA)

Particle bee algorithm (PBA) was proposed by Cheng and Lien [14, 15]. It has been successful applied to many case studies [14, 15]. In PBA, the particle bee colony contains four groups, namely (1) number of scout bees (n), (2) number of elite sites selected out of n visited sites (e), (3) number of best sites out of n visited sites (b), and (4) number of bees recruited for the other visited sites (r). The first half of the bee colony consists of elite bees, and the second half includes the best and random bees. The particle bee colony contains two parameters, i.e., number of iteration for elite bees by PSO (*Peitr*) and number of iteration for best bees by PSO (*Pbitr*). PBA flowchart is shown in **Figure 1**.

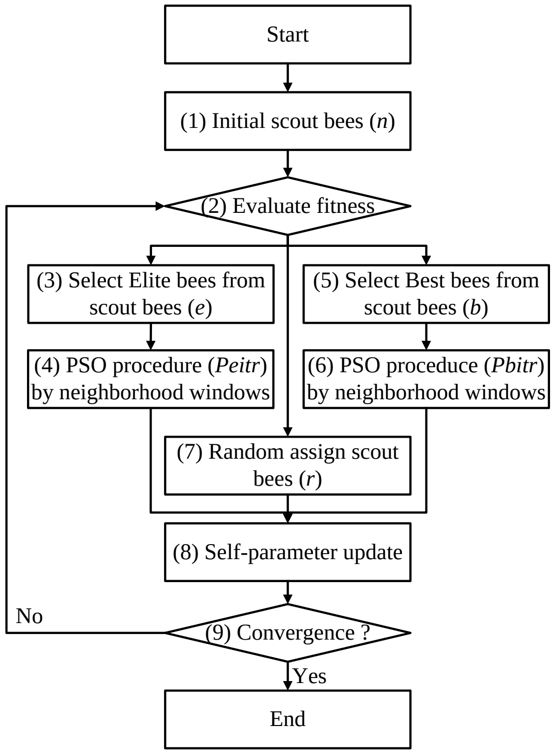


Figure 1. Particle bee algorithm flowchart

Step (1) Initialize scout bees

PBA starts with n scout bees being randomly placed with respective positions and velocities in the search space.

Step (2) Evaluate fitness

Start the loop and evaluate scout bee fitness.

Step (3) Select elite sites (e) from scout bees

Elite sites are selected for each elite bee, whose total number is equal to half the number of scout bees.

Step (4) Elite bees initiate the PSO procedure by *Peitr* iteration for neighborhood-windows (NW)

In this step, new particle bees from elite and best bees are produced using **Eq. (1)**. Elite and best bee velocity update are performed as indicated in **Eq. (2)**. This study further proposes a neighborhood-windows (NW) technique to improve PSO searching efficiency as show in **Eq. (3)**. Thus, after $x_{id}(t+1)$ is substituted into **Eq. (1)** and **Eq. (2),** the NW ensures PSO searching within the designated $x_{id\min}$ and $x_{id\max}$. In other word, if the sum of $x_{id}(t+1)$ exceeds $x_{id\min}$ or $x_{id\max}$ then $x_{id}(t+1)$ is limited to $x_{id\min}$ or $x_{id\max}$.

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (1)$$

where x_i is i_{th} x and i = 1 to n; v_i is i_{th} v; d is dimension in x_i or v and d = 1 to D; t is iteration; $x_{id}(t)$ is d_{th} dimension in i_{th} x and in t iteration; $v_{id}(t+1)$ is d_{th} dimension in i_{th} v and in t+1 iteration; $x_{id}(t+1)$ is d_{th} dimension in i_{th} x and in t+1 iteration; n is number of particles.

$$\begin{aligned} v_{id}(t+1) &= w \times v_{id}(t) + c_1 \times Rand \times [P_{id}(t) \\ &- x_{id}(t)] + c_2 \times Rand \times [G_d(t) - x_{id}(t)] \end{aligned} \quad (2)$$

where v_{id}(t) is d_{th} dimension in i_{th} v and in t iteration; w is inertia weight and controls the magnitude of the old velocity $v_{id}(t)$ in the calculation of the new velocity; P_{id} $(t)$is d_{th} dimension in i_{th} local best particle and in t iteration; $G_d(t)$ is d_{th} dimension global best particle in t iteration; c_1 and c_2 determine the significance of P_{id}(t) and G_d(t); *Rand* is a uniformly distributed real random number within the range 0 to 1.

$$x_{id\min} \le x_{id}(t+1) \le x_{id\max} \quad (3)$$

where x_i is i_{th} x and i = 1 to n; d is dimension in x_i and d = 1 to D; t is iteration; $x_{id}(t+1)$ is d_{th} dimension in i_{th} x and in t+1 iteration; n is number of particles.

Step (5) Select best sites (b) from scout bees

Best sites are selected for each best bee, the total number of which equals one-quarter of the number of scout bees.

Step (6) Best bees start the PSO procedure using the NW *Pbitr* iteration

In this step, new particle bees from elite and best bees are produced using **Eq. (1)**. Elite and best bee velocity updates are acquired using **Eq. (2)**. The NW technique improves PSO search efficiency, as show in **Eq. (3)**.

Step (7) Recruit random bees (r) for other visited sites

The random bees in the population are assigned randomly around the search space scouting for new potential solutions. The total number of random bees is one-quarter of the number of scout bees.

Step (8) Self-parameter-updating (SPU) for elite, best and random bees

Furthermore, in order to prevent being trapped into a local optimum in high dimensional problems, this study proposes a solution, i.e., the self-parameter-updating (SPU) technique, the idea for which came from Karaboga **[17]**. **Eq. (4)** shows the SPU equation.

$$x_{id(\text{new})} = x_{id(\text{cur})} + 2\times(Rand-0.5)\times(x_{id(\text{cur})} - x_{jk}) \quad (4)$$

$$j = \text{int}\,(Rand \times n) + 1 \quad (5)$$

$$k = \text{int}\,(Rand \times d) + 1 \quad (6)$$

where x_i is i_{th} x and i = 1 to n; d is dimension in x_i and d = 1 to D; x_{id}(cur) is d_{th} dimension in i_{th} x and in current solution; x_{id}(new) is d_{th} dimension in i_{th} x and in new solution; *Rand* is a uniformly distributed real random number within the range 0 to 1; j is the index of the solution chosen randomly from the colony as shows in **Eq. (5)**, k is the index of the dimension chosen randomly from the dimension as shows in **Eq. (6)**; n is number of scout bees.

In step (8), after elite, best and random bees have been distributed based on finesse, finesses are checked to determine whether they are to be abandoned or memorized using **Eq. (4)**. Therefore, if finesses of elite, best or random bees are both improved using **Eq. (4)** and improved over previous finesses, the new finesses are memorized. In step (3) through step (8), this differential recruitment is a key operation of the PBA.

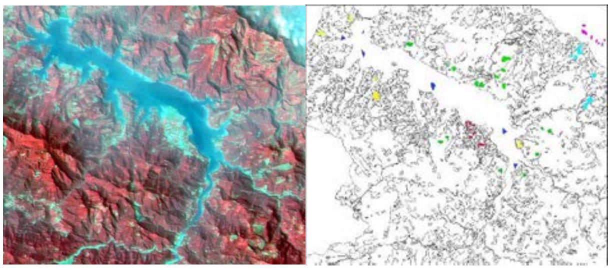
Step (9) Convergence?

In this step, only the bee with the highest fitness will be selected to form the next bee population. These steps are repeated until the stop criterion is met and bees are selected to be abandoned or memorized.

3 Mining Rules of Satellite Imagery

3.1 Experimental data

There are three features in the satellite imagery dataset include angular second moment (ASM), contrast (CON) and entropy (ENT). The three features both survey by four sources (twelve variables) include raw light, green light, infrared and red light. Thus, there are totally twelve input variables in the satellite imagery dataset. The outputs of the dataset are six different types of images include water, betel palm, building, cloud, orchard and wood. This study collected 600 experimental satellite imagery data, 200 data were randomly selected as the training set, and the remaining 400 data as the testing set **[16]**. All the variables were normalized into 0 to 1 by **Eq. (7)**. The training set was employed to build the classification rules model and the testing set was employed to evaluate model generalizations. **Table 1** and **Figure 2** present some descriptive statistics of the satellite imagery dataset.



Notice: the blue sign is water, the light blue sign is betel palm, the red sign is building, the pink sign is cloud, the yellow sign is orchard and the green sign is wood

Figure 2. A satellite imagery dataset sample

Table 1 Variables of satellite imagery

Variables	Range	Unit	Types	
Green light raw survey source (G_SOURCE)	35~ 159	Pixel	Continuous	Inputs
Green light on second-order differential angular survey momentum (G_ASM)	21~ 100			
Green light on contrast survey source (G_CON)	0~ 352			
Green light on entropy survey source (G_ENT)	0~ 69			
Infrared raw survey source (I_SOURCE)	15~ 135			
Infrared on second-order differential angular survey momentum (I_ASM)	21~ 100			
Infrared on contrast survey source (I_CON)	0~ 469			
Infrared on entropy survey source (I_ENT)	0~ 69			
Red light raw survey source (R_SOURCE)	25~ 171			
Red light on second-order differential angular survey momentum (R_ASM)	21~ 100			
Red light on contrast survey source (R_CON)	0~ 465			
Red light on entropy survey source (R_ENT)	0~ 69			
Water	0, 1	N/A	Binary	Outputs
Betel palm	0, 1			
Building	0, 1			
Cloud	0, 1			
Orchard	0, 1			
Wood	0, 1			

$$X_{new} = \frac{X_{old} - X_{\min}}{X_{\max} - X_{\min}}(D_{\max} - D_{\min}) + D_{\min} \quad (7)$$

Where X_{old} is the X value before normalization; X_{max} is the maximum value of X value before normalization; X_{min} is the minimum value of X value before normalization; D_{max} is the maximum X value after normalization. This study setting D_{max} is 1; D_{min} is the minimum X value after normalization. This study setting D_{min} is 0; X_{new} is the X value after normalization.

3.2 Rules and encoding of operation tree

This study adopted classification tree to express classification rules and employed particle bee algorithm (PBA) to optimize the tree to produce self-organized rules. In this study, a five-layered classification tree was adopted, as shown in **Figure 3**. In **Figure 3**, variables X_1 to X_{31} were external tree branch and variables K_1 to K_{15} were internal tree branch. The external and internal tree branch encoding variables and constants are listed in **Table 2** and **Table 3**, respectively. The encoding rule was designed to adhere to the following rules:

- The first to fourth layers of internal tree branch (X_1 to X_{15}) must be variables. The encode must be between integer 1 to 12 (see Table 3).
- The first to fourth layers of external tree branch (K_1 to K_{15}) must be variables or constants. The encode must be between integer 13 to 25 (see **Table 3**). When the gene encoding is 25, it represents a constant K, and a constant between 0 to 1.
- Between each layer, on the left of internal and external tree branch is smaller mathematical operator, on the right of internal and external tree branch is bigger or equal mathematical operators.

The fifth layer of internal tree branch (Y_1 to Y_{15}) is determined by the classification result. For an example, if Y_1 classification includes 20 water datasets, 1 wood dataset and 2 cloud datasets. The Y_1 classification will be assigned for water classification.

Table 2 Encode of internal tree branch

	X_1~X_{15}											
Encode	1	2	3	4	5	6	7	8	9	10	11	12
Variables	G_SOU	G_ASM	G_CON	G_ENT	I_SOU	I_ASM	I_CON	I_ENT	R_SOU	R_ASM	R_CON	R_ENT

Table 3 Encode of external tree branch

	K_1~K_{15}												
Encode	13	14	15	16	17	18	19	20	21	22	23	24	25
Variables	G_SOU	G_ASM	G_CON	G_ENT	I_SOU	I_ASM	I_CON	I_ENT	R_SOU	R_ASM	R_CON	R_ENT	***I***

3.3 Fitness function and PBA parameters

The correct rate (CR) was used to evaluate the models accuracy. Therefore, this study focus on producing an accurate model to predict satellite imagery classification, the CR was adopted as the evaluation function (fitness function) of solutions. This study adopted PBA to optimize the classification tree to fit the data set to produce the self-organized classification rules. There are some parameters may affect the performance of PBA. Reference **[14, 15]** suggested the parameters following as **Table 4**. In this study, these parameters were determined according to maximizing the CR on the training set.

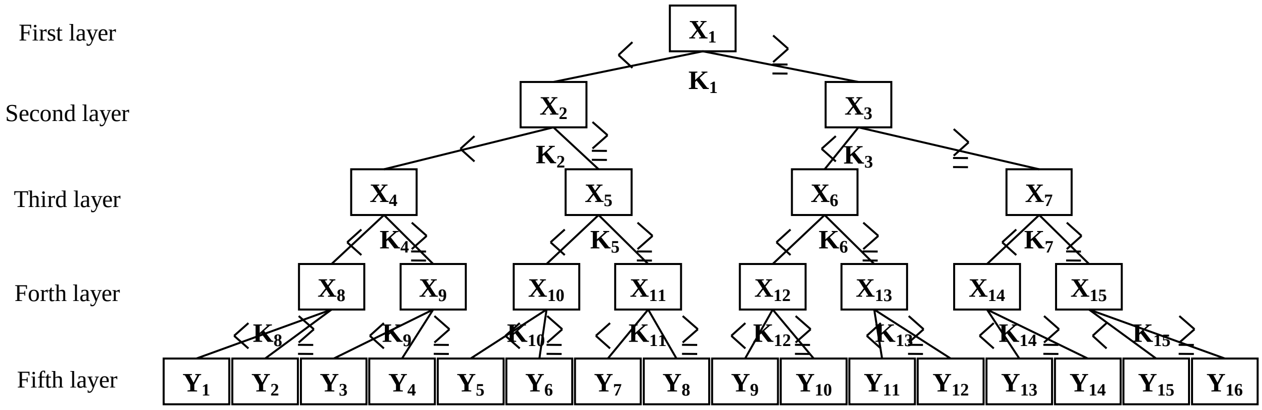


Figure 3. Five layers of evolutionary classification tree

Table 4 Parameter values used in the experiments

PBA parameters setting	
n	50
e	n/2
b	n/4
r	n/4
w	0.9~0.7
v	*X*min/10~*X*max/10
Peitr	15
Pbitr	9

where *n* is population size (colony size); *w* is inertia weight; *v* is limit of velocity; *e* is elite bee number; *b* is best bee number; *r* is random bee number; *Peitr* is PSO iteration of elite bees; *Pbitr* is PSO iteration of best bees.

4 Results

4.1 Evolutionary Classification Tree (ECT)

This study adopted particle bee algorithm (PBA) to optimize the operation evolutionary classification tree (ECT) to produce the self-organized classification rules. **Figure 4** is the result of satellite imagery classification by ECT. The mining classification rules are as follow. The correct rate of training set and testing set as shown in **Table 5** and **Table 6**. Thus, ECT not only can produce the satellite imagery classification but also can self-organized the classification rules.

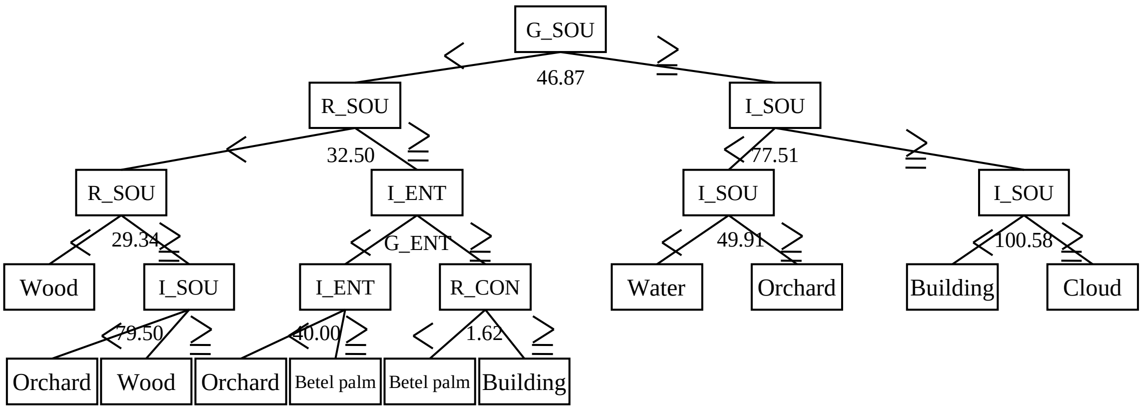


Figure 4. Five layers of satellite imagery evolutionary classification tree

ECT mined 11 classifies rules as the followed:

RULE (1): IF G_SOU >= 46.87 AND I_SOU >= 100.58 THEN Cloud

RULE (2): IF G_SOU >= 46.87 AND I_SOU >= 77.51 AND I_SOU < 100.58 THEN Building

RULE (3): IF G_SOU >= 46.87 AND I_SOU < 77.51 AND I_SOU >= 49.91 THEN Orchard

RULE (4): IF G_SOU >= 46.87 AND I_SOU < 77.51 AND I_SOU < 49.91 THEN Water

RULE (5): IF G_SOU < 46.87 AND R_SOU >= 32.50 AND I_ENT >= G_ENT AND R_CON >= 1.62 THEN Building

RULE (6): IF G_SOU < 46.87 AND R_SOU >= 32.50 AND I_ENT >= G_ENT AND R_CON < 1.62 THEN Betel palm

RULE (7): IF G_SOU < 46.87 AND R_SOU >= 32.50 AND I_ENT < G_ENT AND I_ENT >= 40.00 THEN Betel palm

RULE (8): IF G_SOU < 46.87 AND R_SOU >= 32.50 AND I_ENT < G_ENT AND I_ENT <40.00 THEN Orchard

RULE (9): IF G_SOU < 46.87 AND R_SOU < 32.50 AND R_SOU >= 29.34 AND I_SOU >= 79.50 THEN Wood

RULE (10): IF G_SOU < 46.87 AND R_SOU < 32.50 AND R_SOU >= 29.34 AND I_SOU <79.50 THEN Orchard

RULE (11): IF G_SOU < 46.87 AND R_SOU < 32.50 AND R_SOU < 29.34 THEN Wood

Table 5 Training set of CR for ECT

Training set		Actual classifies					
		Water	Betel palm	Building	Cloud	Orchard	Wood
Predict classifies	Water	32	0	0	0	0	0
	Betel palm	0	17	3	0	0	6
	Building	0	9	32	1	5	3
	Cloud	0	0	0	32	1	0
	Orchard	0	4	0	0	26	3
	Wood	0	4	0	0	2	20
Correct rate		100.00%	50.00%	91.43%	96.97%	76.47%	62.50%

Table 6 Testing set of CR for ECT

Testing set		Actual classifies					
		Water	Betel palm	Building	Cloud	Orchard	Wood
Predict classifies	Water	68	0	0	0	0	0
	Betel palm	0	26	7	0	5	17
	Building	0	15	51	5	13	2
	Cloud	0	1	3	62	0	2
	Orchard	0	11	4	0	40	10
	Wood	0	13	0	0	8	37
Correct rate		100.00%	39.39%	78.46%	92.54%	60.61%	54.41%

4.2 Classification Tree (CT)

This study adopted classification tree to self-organize the classification rules and to fit the data set of satellite imagery. The CR of training data and testing data of these models are presented in **Table 7** and **Table 8**.

Table 7 Training set of CR for CT

Training set		Actual classifies					
		Water	Betel palm	Building	Cloud	Orchard	Wood
Predict classifies	Water	31	0	0	0	0	0
	Betel palm	0	20	5	0	4	8
	Building	0	7	30	1	2	1
	Cloud	0	0	0	32	1	0
	Orchard	1	3	0	0	25	3
	Wood	0	4	0	0	2	20
Correct rate		96.88%	58.82%	85.71%	96.97%	73.53%	62.50%

Table 8 Testing set of CR for CT

Testing set		Actual classifies					
		Water	Betel palm	Building	Cloud	Orchard	Wood
Predict classifies	Water	68	0	0	0	0	0
	Betel palm	0	38	24	0	15	18
	Building	0	4	31	5	4	1
	Cloud	0	1	3	62	0	2
	Orchard	0	10	7	0	39	10
	Wood	0	13	0	0	8	37
Correct rate		100.00%	57.58%	47.69%	92.54%	59.09%	54.41%

4.3 Back-propagation Networks (BPN)

This study adopted back-propagation neural networks (BPN) **[16]** to fit the data set of satellite imagery. In this study, network parameters such as number of hidden neurons, learning rate, momentum factor, and number of learning cycles were determined according to maximizing the CR on the testing dataset. The best network structure is the network with one hidden layer containing six hidden units; and the optimum learning parameters are 1.0 for learning parameters and 0.5 for momentum factor. The CR of training data and testing data of these models are presented in **Table 9** and **Table 10**.

4.4 Support Vector Machine (SVM)

This study adopted nu-SVM to fit the data set of satellite imagery. In this study, Leave-One-Out (LOO) is the searching method for searching best value of nu and gamma according to maximizing the CR on the testing dataset. The best nu-SVM structure is the structure with nu=0.48 and gamma=0.0625. The CR of training data and testing data of these models are presented in **Table 11** and **Table 12**.

Table 9 Training set of CR for BPN

Training set		Actual classifies					
		Water	Betel palm	Building	Cloud	Orchard	Wood
Predict classifies	Water	32	0	0	0	0	0
	Betel palm	0	23	4	2	0	2
	Building	0	2	29	1	3	1
	Cloud	0	0	0	30	0	0
	Orchard	0	6	2	0	25	3
	Wood	0	3	0	0	6	26
Correct rate		100.00%	67.65%	82.86%	90.91%	73.53%	81.25%

Table 10 Testing set of CR for BPN

Testing set		Actual classifies					
		Water	Water	Water	Water	Water	Water
Predict classifies	Water	68	0	0	0	0	0
	Betel palm	0	29	15	2	5	6
	Building	0	10	37	3	2	2
	Cloud	0	1	2	62	0	0
	Orchard	0	19	10	0	46	10
	Wood	0	7	1	0	13	50
Correct rate		100.00%	43.94%	56.92%	92.54%	69.70%	73.53%

Table 11 Training set of CR for SVM

Training set		Actual classifies					
		Water	Betel palm	Building	Cloud	Orchard	Wood
Predict classifies	Water	32	0	0	0	1	0
	Betel palm	0	29	3	0	0	1
	Building	0	2	32	5	1	0
	Cloud	0	0	0	28	0	0
	Orchard	0	2	0	0	28	5
	Wood	0	1	0	0	4	26
Correct rate		100.00%	85.29%	91.43%	84.85%	82.35%	81.25%

Table 12 Testing set of CR for SVM

Testing set		Actual classifies					
		Water	Betel palm	Building	Cloud	Orchard	Wood
Predict classifies	Water	68	0	0	0	0	0
	Betel palm	0	28	8	0	7	10
	Building	0	7	41	7	8	2
	Cloud	0	0	0	60	9	0
	Orchard	0	12	10	0	40	13
	Wood	0	19	6	0	11	43
Correct rate		100.00%	42.42%	63.08%	89.55%	60.61%	63.24%

The model accuracy and understand ability comparison between those four methods are shown in **Table 13** to **Table 15** and **Figure 5**. Highest model accuracy (correct rate) means model has the better forecasting ability. Model understand ability means model can produce the rules for understanding and explaining by user. The result of **Table 13** to **Table 15** and **Figure 5** as following:

- Model accuracy: ECT produces the satellite imagery classification model which model accuracy only lower than BPN but better than CT and SVM
- Model understand ability: ECT and CT can produce the self-organized explicit classification rules but BPN and SVM cannot.

Thus, ECT not only can produce accurate satellite imagery classification model but also can self-organized the classification rules.

Table 13 Methods comparison for training set

Classify Method		Water	Betel palm	Building	Cloud	Orchard	Wood	Average
CT	Correct rate	96.88%	58.82%	85.71%	96.97%	73.53%	62.50%	68.80%
BPN		100.00%	67.65%	82.86%	90.91%	73.53%	81.25%	73.00%
SVM		100.00%	85.29%	91.43%	84.85%	82.35%	81.25%	70.00%
ECT		100.00%	50.00%	91.43%	96.97%	76.47%	62.50%	71.50%

Table 14 Methods comparison for testing set

Classify Method		Water	Betel palm	Building	Cloud	Orchard	Wood	Average
CT	Correct rate	100.00%	57.58%	47.69%	92.54%	59.09%	54.41%	79.00%
BPN		100.00%	43.94%	56.92%	92.54%	69.70%	73.53%	82.50%
SVM		100.00%	42.42%	63.08%	89.55%	60.61%	63.24%	87.50%
ECT		100.00%	39.39%	78.46%	92.54%	60.61%	54.41%	81.00%

Table 15 Methods comparison for model accuracy and understand ability

Method	Correct Rate (%)		Accuracy	Understand ability
	Training Set	Testing Set		
CT	79.00%	68.80%	Worst	Yes
BPN	82.50%	73.00%	Good	No
SVM	87.50%	70.00%	Fair	No
ECT	81.00%	71.50%	Good	Yes

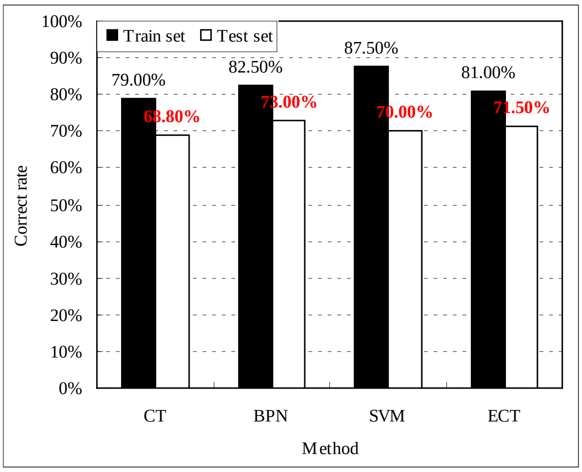


Figure 5. Methods comparison for model accuracy

5 Conclusion

The results showed that ECT can produce explicit rules which are more accurate than CT and SVM but less accurate than BPN model. However, BPN is black box models, while ECT can produce explicit rules which are an important advantage to mining the explicit rules and knowledge in practical applications.

If the user requirement is understandable satellite image classification models and rules, then ECT is an method which can produce accurate self- organized classification models and rules; If the user understand ability for satellite image classification model is not very important, then BPN is a more accurate and rapid method which can establish satellite image classification model.

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