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Multitemporal SAR images for monitoring cultivation systems using case-based reasoning

X. Li[a,*], A.G. Yeh[b]

[a] School of Geography and Planning, Sun Yat-sen University, 135 West Xingang RD, 510275, Guangzhou, Guangdong, China
[b] Centre of Urban Planning and Environmental Management, the University of Hong Kong, Pokfulam Road, Hong Kong SAR, PR China

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Abstract

This paper demonstrates that multitemporal satellite SAR images are most suitable for monitoring the rapid changes of cultivation systems in a subtropical region. A new method is proposed by applying case-based reasoning (CBR) techniques to the classification of SAR images. Stratified sampling is carried out to collect the cases so that the variations of backscatters within a class can be appropriately captured. The use of discrete cases can conveniently represent the internal changes of a class under complicated situations, such as spatial changes in soil conditions and terrain features. These spatial variations are difficult to represent by using rules or mathematical equations. The proposed method has better classification performance than supervised classification methods in the study area. The case library is reusable for time-independent classification when the SAR images are acquired at the same time of the crop growth cycles for different years. The proposed method has been tested in the Pearl River Delta in South China.

Keywords: Knowledge-based systems; Case-based reasoning; Land use changes; Classification; Radar remote sensing

1. Introduction

The drastic changes of global landscape were witnessed in the last a few decades because of rapid urbanization process in the world. Land use changes have been accelerated in many rapid-growing countries. There are growing concerns about the impacts of land use changes because they have been blamed for a series of environmental problems such as global warming, flooding, soil erosion, pollution, and food shortage. The information of land use and land use changes has been used as the key input to many environmental models in estimating the impacts of global changes (Sellers et al., 1995). These models are important for estimating and predicting the consequences of specific human behaviors and land use policies.

Remote sensing has been widely used to obtain land use information (Li & Yeh, 1998). However, conventional optical remote sensing cannot acquire good-quality images when the weather is cloudy. In tropical and subtropical regions, it is very difficult to obtain the commonly used satellite images, such as TM and SPOT images during the seasons of crop growth. Usually, only 1–2 dates of these images are available within a year because of cloudy weather. Most of these images can only be acquired during autumn or winter seasons. This is very unsatisfactory for monitoring agricultural activities, mapping fast urban expansion and agricultural land loss, and detecting illegal land development in fast-developing areas.

Orbital SAR is a fast-developing technique that can overcome some of the limitations in conventional remote sensing. SAR technologies allow the same resolution to be possible from aircrafts and satellites. This means that much detailed ground information can be regularly observed using orbital SARs. In recent years, some operational orbital radar systems have been available for regular collection of remote sensing data. These orbital systems include ERS-1, 2 (C band, VV polarization at 23°) and JERS-1 (L band, HH-polarized at 35°). The most recent operational orbital radar system is the Canadian Radarsat which consists of C band SAR with HH polarization. The system has a variety of modes for various resolutions and swath widths.

Satellite SAR is able to obtain the information about the ground at 'real' time. This can permit the monitoring of rapid land use changes and urban development, and thus

* Tel.: +86-20-87670156.
E-mail address: lixia@graduate.hku.hk (X. Li).

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provide very useful information for land use planning and management. For example, JERS-1 SAR images from various years were used to analyze land use changes (Angelis et al., 2002). Textural information was derived from SAR images to assist the classification of land use types (Kurosu et al., 1999).

However, the existing orbital SARs have only one single band, such as C band of ERS-2 and C band of Radarsat. Although useful, when taken alone, each of these orbital SARs will encounter limitations for land cover classification because of signal saturation at high levels of biomass and ambiguities between various land cover types (Dobson et al., 1995, 1996). Many efforts have been dedicated to improve the classification accuracy for SAR images. One possible solution is to increase the temporal information as compensation. It is easy to acquire multitemporal satellite SAR images that can cover the whole growth circle of crop systems.

There is also a need to develop the methodology for classifying SAR images. Numerous studies have been carried out to classify land use types and detect land use changes from remote sensing (Carpenter et al., 1997; Huang & Jensen, 1997; Li & Yeh, 1998; Richards & Jia, 1999). There are experiments on developing knowledge-based systems (KBS) that use rules to classify radar imagery. SAR images seem to be most suitable for the experiment of using KBS. Studies indicate that orbital SARs can obtain quite stable sensors' signals. For example, the time variance in the ERS-1 SAR instrument is within $\pm$ 0.4 dB (Attema, 1992; Dobson et al., 1995). This benefits a number of investigations with repeatable experiments. In particular, the stability of SAR signals has presented a unique opportunity to the use of KBS for classification. However, a problem with the KBS classification is that the backscatter of SAR is affected by soil moisture. The same or similar conditions of soil moisture are important for successful implementation of KBS methods for classification.

The rule-based techniques have limitations in implementation because the identification and definition of rules are usually tedious, user-unfriendly, and time-consuming. This study proposes a new method for classifying remote sensing imagery based on the CBR techniques. CBR, which is a different type of knowledge-based systems (KBS), uses pervious cases to solve a new problem. It is considered that much of human reasoning is case based rather than rule based (Schank & Cleary, 1995). People often recall previous experiences when they face a new problem. Although CBR has a great appeal to many fields (e.g., engineering, medicine, and business), it has not been applied to the classification of remote sensing data because it is a new technique.

In this study, the method is applied to the classification of SAR images, but it is also valid for the classification of other sources of remote sensing data. The experiment will be carried out in a fast-growing area in the Pearl River Delta, South China, as compared to our previous studies that use optical remote sensing (Li & Yeh, 1998). The subtropical region is frequently affected by cloudy weather. Usually, only 1–2 dates of optical satellite images (e.g., Landsat TM and SPOT images) are available in autumn or winter seasons each year. These limited images can hardly be used to monitor agricultural activities such as the growth conditions of crops and the changes of cultivation systems. Some other studies have been carried out by using SAR images to monitor and estimate rice production in this region (Shao et al., 2001). However, this study is different because of using a new approach for classifying SAR images.

2. Case-based reasoning for classifying SAR data

Many existing classification methods require training inputs and application-sensitive parameters. Users must have a good understanding of the area under study so that they can select appropriate training sites, algorithms and thresholds. This assumption can lead to a significant discrepancy in the classification of the same study area between different users because users' knowledge and preferences have introduced uncertainties to the classification.

Knowledge-based systems (KBS) are considered as a good alternative to traditional classification methods with better performance. There is a need to develop such systems to facilitate the interpretation of remote sensing data in a more objective and efficient way. Supervised classification is a commonly used method, but it strongly depends upon users' skills and training procedures and often involves time-consuming analysis. KBS are useful when concrete knowledge about the application domain is available. It is expected that KBS can automatically classify remote sensing images without operator's intervention (Newkirk & Wang, 1990; Pierce et al., 1994). This is achieved through a sequence of processes which are bounded by rules. Numerous studies using expert systems or knowledge-based systems have been reported in remote sensing applications (Kartikeyan et al., 1995; Murai & Omatu, 1997; Huang & Jensen, 1997). For example, Huang and Jensen (1997) built a knowledge-based system to perform a wetland classification of Par Pond on the Savannah River Site, SC using SPOT multispectral imagery and GIS data. Stefanov et al. (2001) used logical decision rules with various data sets to assign class values to each pixel.

Rule-based techniques, a common type of KBS, have been widely tested for the classification of radar images and produced satisfactory results in many applications (Dobson et al., 1996). Pierce et al. (1998) find that the same rules developed in previous studies can be applied to other studies for a time-independent classification of land cover on radar images. An example of the rules for land cover classifier using SAR images is described as follows (Pierce et al., 1998):

IF L-hv>0.91 × L-hh-33 dB	THEN tall vegetation
ELSE C-hv> – 20 dB	THEN shortveg
ELSEIF C-hv ≤ – 20 dB and L-hv < – 20 dB	THEN surface
ELSE	THEN shortveg

The rule-based techniques assume that knowledge should be well bounded and can be clearly expressed. However, there are difficulties in providing rules because most applications involve complicated elements and relations. The constructing of rule bases is very time-consuming because a large set of rules is usually required. For example, McAvoy and Krakowski (1989) defined approximately 100 rules to classify ice floes into different 'age' categories from SAR images. Applying pieces of knowledge to a class with arbitrary or abstract rules is usually difficult to understand. The problems become worse as there are usually only incomplete and inconsistent knowledge.

Furthermore, the signature of a class may not be stable because there are spatial variations of spectral properties. Different soil and roughness conditions can affect the backscatter properties of radar images (Wang et al., 1986). It is unreasonable to use the same set of rules to identify a land use type in the whole region. For example, the same type of crop may have different backscatter properties under different soil conditions and terrain features. The variations in environmental settings may be very complex in real-world situations. How to define dynamic rules that can adapt to these spatial variations of backscatter properties within a class becomes extremely difficult. It is also not easy for users to comprehend and use such types of systems because of the complexity.

Case-based reasoning (CBR) has more appealing features than the traditional rule-based approaches under such situations. It is developed to overcome the problems of rule-based systems. However, it still has the advantages inherited from KBS, such as artificial intelligence, reduction of repetitive tasks, and highly automated capability. Studies have also shown that the CBR method can even provide a much better accuracy of classification than traditional statistical methods (Watson, 1997). CBR can be traced back to the work of Roger Schank and his students at Yale University in the early 1980s.

Cases are the basic units in a CBR system. A case is a contextualized piece of knowledge representing an experience that can help a reasoner to achieve his goals (Kolodner, 1993). The fast development of CBR is attributed to its capabilities of resolving some of the problems in knowledge acquisition and maintenance in rule-based KBS. It doesn't require users to elicit rules from training data and thus save much of the time in reasoning process. In a case library, each case is represented by a description of the problem, plus a solution and/or the outcome. The knowledge for solving a problem is not recorded, but is implicit among the cases. Similar cases will be matched and retrieved from the case library to solve a current problem. The retrieved cases are used to suggest a possible solution which can be reused and tested, or even adapted to a current problem. This can allow users to formulate solutions quickly, and save much of the time that is necessary to derive those answers from scratch. CBR can also allow users to find the solutions in domains that are not completely understood by them (Watson, 1997). Moreover, CBR can well handle the domains where problems have many exceptions to rules (Holt & Benwell, 1999).

In this study, the philosophy of CBR is applied to the classification of remote sensing data. The data of each pixel are treated as the attributes of a case. The method can get rid of some restrictions in conventional classification techniques. It can allow the use of both numeric and nonnumeric data. Data are not compulsorily required to be in a normal distribution.

The first step is to establish the case library which is the fundamental core of a CBR. The library can be built by collecting data from remote sensing, land use maps and field investigation. The attributes (features) of an input case (pixel) may include backscatters and ancillary GIS data. The information of texture and contexture can also be used as the inputs.

Fig. 1 shows the details of using CBR to classify remote sensing data. Each case contains two parts—the description of the problem (e.g., the brightness of remote sensing imagery or other ancillary data) and the solution to the problem (e.g., classified land use types). A case can be represented as follows:

$$x = (x_1, x_2, \ldots, x_N; C_k) \quad (1)$$

where x_n is the nth feature related to backscatters or textural properties of a case (pixel), and C_k is the land use type of the case.

Given a set of features, the land use type of a case can be inferred by using the CBR method. Usually, land use types are represented by the rigid Boolean method—whether it belongs to a land use type or not. The Boolean method can be used if a new case can perfectly match an existing case in the case library. However, it is very difficult to identify two cases with exactly the same attributes. Therefore, a fuzzy membership is more suitable for the matching process of the CBR method.

Fuzzy sets have the potentials in dealing with environmental data more accurately. Heuvelink and Burrough (1993) indicate that many environmental problems cannot be realistically modeled using the rigid Boolean classification rules. It is found that the Boolean method is unsatisfactory with poor results. They demonstrate that continuous classification with fuzzy sets has advantages because it is less sensitive to the errors in data. The use of

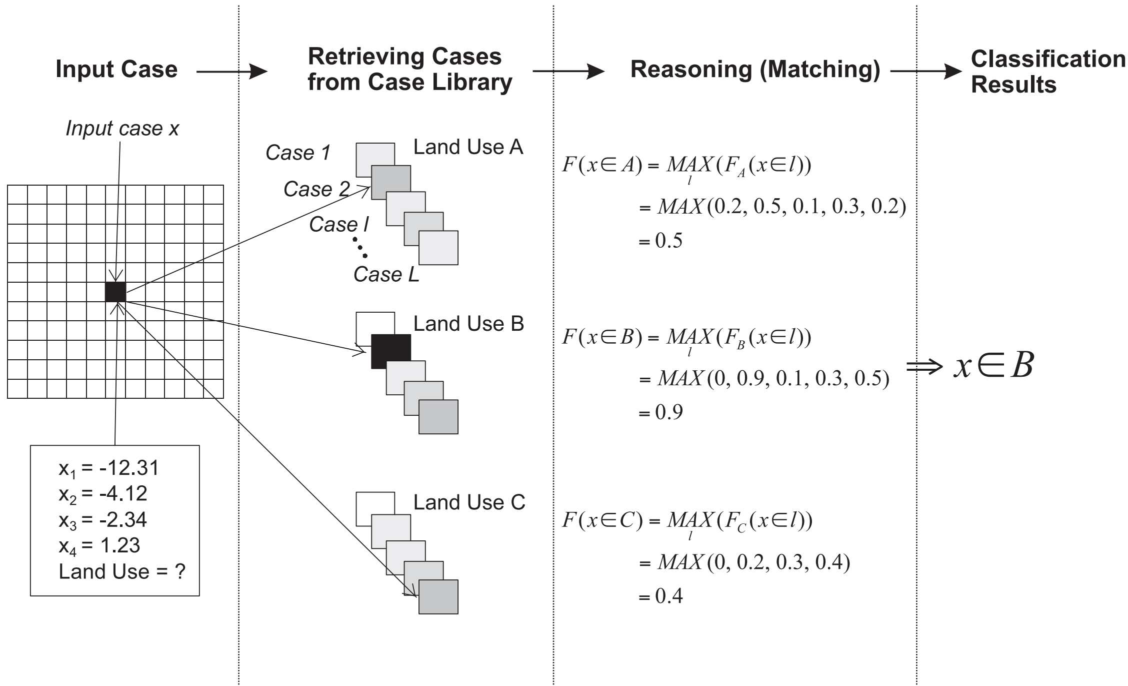

Fig. 1. The classification of SAR imagery using the CBR method.

fuzzy sets can also greatly reduce the error propagation in general modeling.

By incorporating fuzzy sets to represent the land use type of a case, Eq. (1) can be revised as follows:

$$x = (x_1, x_2, \ldots, x_N; F(x\in C_1), F(x\in C_2), \ldots, F(x\in C_l), \ldots, F(x\in C_L)) \tag{2}$$

where $F(x\in C_l)$ is the fuzzy membership that x belongs to land use type C_l.

The reasoning process of classification is based on the similarity between the input case and the existing cases in the case library. The construction of case library is essential to the successful implementation of the CBR method. The case library can be built by using land use maps and field investigation data.

It seems that the method is similar to the training procedure of supervised classification. However, there are some major differences between them. Supervised classification has a number of restrictions and limitations. It assumes that a group of training pixels can be identified for each class. There are uncertainties in the selection of training sites because of the influences from users' knowledge and preferences. Homogeneous regions are usually required to define training data for a class. Signatures, which represent the characteristics of classes, should be created from statistical analysis. The signature of each class should be stable in the whole region for the classification. These assumptions may not be true in many situations. The method has limitation when there are obvious spectral variations within a class in the whole region because of the spatial changes in environmental settings. Moreover, the signatures from supervised classification are not intended for reusing in the next classification.

The CBR method has much more flexibility in representing the spectral or backscatter variations within a class because of using discrete cases. In CBR method, a class is represented by a group of cases. Each case is unique with distinct spectral properties. Within the same class, a case may be quite different from others. This flexibility of cases can let the classification adapt to complex real-world situations. For example, the backscatter of the same type of crops may have spatial variations corresponding to the changes in geomorphologic features, irrigation conditions, and cultivation systems. It is much better and convenient to use discrete cases to reflect such variations. Moreover, the CBR method can easily allow nonnumerical data, such as soil types, terrain features, and land use, to be included in the classification process.

The classification in CBR is based on similarity assessment. There are many ways to calculate the similarity between two cases in CBR. One method is based on the most popular k-Nearest Neighbor (k-NN) algorithm (Dasarathy, 1991). The similarity between an input case (x) and an existing case (l) in the case library is calculated using the following equation:

$$\mathrm{SIM}(l,x) = \exp\left(-\sqrt{\sum_{k=1}^{N}\left(\mathrm{SA}_{kl}\frac{l_k - x_k}{\mathrm{ED}_k}\right)^2}\right) \tag{3}$$

where SA_{kl} is the salience of kth feature of case l in the case library. l_k is the value of kth feature of case l. x_k is the value of kth feature of input case x. ED_k is a standard deviation of kth feature value of all cases in the case-base. The standard deviation is used to normalize the feature value so that the features of equal salience have equal weight in the similarity function.

The land use type of an input case (pixel) can be determined when the most similar case in the case library is found according to the similarity assessment. The classification can be seen as primarily a matching process. In the case library, the cases are divided into different groups according to their land use types for easy matching. The cases of the same land use types are arranged in the same group (Fig. 1).

The next step is to calculate the fuzzy membership between an input case and a case in the case library. Because the value of SIM(l,x) falls within the range from 0 to 1, it can be used to represent the fuzzy membership value. When two cases are most similar, they should have the largest membership value of 1.

For land use type C_ξ, the fuzzy membership between the input case x and case l in the case library is calculated by:

$$F_{C_\xi}(x \in l) = \mathrm{SIM}_{C_\xi}(l, x) = \exp\left(-\sqrt{\sum_{k=1}^{N}\left(\mathrm{SA}_{kl}\frac{l_k - x_k}{\mathrm{ED}_k}\right)^2}\right) \tag{4}$$

A number of retrieved cases are usually available for each type of land use. Therefore, an input pixel may have different values of the fuzzy membership for the same type of land use. The maximum function can be used to obtain the final fuzzy membership from these different values for land use type C_ξ. The fuzzy membership that input case x belongs to land use type C_ξ is calculated by:

$$F(x \in C_\xi) = \underset{l}{\mathrm{MAX}}(F_{C_\xi}(x \in l)) \tag{5}$$

For different types of land use, an input pixel may have different values of the membership function. A pixel should be classified to the type of land use which has the largest value of the membership function. Finally, the land use type for an input case is determined according to the following inference:

$$F(x \in C_k) = \underset{C_\eta}{\mathrm{MAX}}(F(x \in C_\eta)) \Rightarrow x \in C_k \tag{6}$$

3. Test site and data

3.1. Study area

The study area covers most of Panyu, which is in the central part of the Pearl River Delta, South China (Fig. 2). Panyu used to be an agricultural county, but it was merged by Guangzhou, the largest city in s South China in 2000. The total land area is 1314 km^2, the population is 926,542, and the population growth rate is 1.7% in 2000. It is a densely populated area.

The topography is rather flat, although there are some occasional small hills. It is situated in the subtropical region

Fig. 2. The location of the study area.

with the latitude between 22°26′ and 23°05′, and the longitude between 113°14′ and 113°42′. The average temperature is 21.8 °C. The climate is very suitable for agricultural production, especially for growing rice paddy.

Radar backscatters are affected by soil moisture. The reuse of rule bases or case libraries for the next classification should require similar soil moisture conditions. In this study region, it is possible to acquire the images of similar soil moisture conditions according to local weather patterns. In most situations, it is expected that there are similar soil moisture conditions for the same seasons for different years.

Before economic reform, the region was dominated by agricultural activities which mainly consist of rice paddy production under the planned economy. However, diversified agricultural activities have been witnessed since the adoption of market economy in 1978. A significant part of the rice paddy fields has been converted into other types of land use, such as growing sugar cane and banana for better income. Land use changes are unprecedented in the Pearl River Delta because of fast economic development. The GDP growth rate of Panyu was 11.2% in 2000. The monitoring of land use changes can provide useful information for land use planning and management in the region.

3.2. Data

Radarsat fine-mode (F1) was selected for better resolution because the sizes of agricultural land in the region are small. A finer resolution is important for identifying the detailed land use information. The images have the resolution of 8.3×8.4 m and the swath width of 50 km on the ground. The average incidence angle is within the range of 37–41°. One scene of Radarsat SAR images can cover most of Panyu. The land use changes in two successive years, 2000 and 2001, were detected from the SAR images. For each year, a temporal series of three SAR images was acquired to cover the whole growth circle of the crop system. The dates for the SAR images are listed in Table 1. The Landsat TM image dated on 4 January 2000 was also used to obtain the terrain features in the region. Clustering was applied to this image by using five bands, TM2, TM3, TM4, TM5 and TM7.

The land use maps for 2000 were used to assist the construction of the case library. These maps were obtained from the Land Department of Panyu. They were made by interpreting air photographs and field checking. There are seven broad land use classes in these maps, such as agricultural land, orchards, forest, built-up areas, transport, water, and unused lands. Agricultural land is composed of a number of subclasses such as rice paddy, banana, sugar cane, and fishpond. Usually, land use maps are not updated each year in China. Therefore, the land use maps for 2001 are unavailable for the direct verification of the classification of 2001 images.

Field investigations were arranged during the same periods of acquiring these SAR images. The task of the field investigation was mainly to record the land use types in the field. It is especially important to collect the field data in 2001 because the land use maps for 2001 are unavailable. In this situation, field investigation was carried out in the locations where land use changes were detected from the classification of SAR images. Three GPS receivers were used to record the positions of these ground-collected data.

Table 1
The dates of SAR images for the study area

Year	Dates	Orbit
2000	18 April	Ascending
	29 June	Ascending
	6 August	Ascending
2001	30 April	Ascending
	22 June	Ascending
	11 August	Ascending

4. The monitoring of cultivation systems using satellite SAR images

4.1. SAR image processing

There is a need to convert the original digital number (DN) of the SAR images into the backscatter coefficient. In many quantitative analyses, the backscatter coefficient can represent the original signal amplitudes more accurately and thus provide more plausible results than the original digital number.

It is important to remove noise on the SAR images because they are affected by a kind of noise called speckle. The Frost adaptive filter (Frost et al., 1982) was used to preserve edges while significantly reducing the noise in homogenous regions. A 3×3 filter was applied for the smoothing. Most of the noise was removed after the filtering using the Frost algorithm.

These temporal SAR images were rectified to one another so that they could be overlaid perfectly. First, the 18 April 2000 SAR image was registered to the survey maps by using control points. After the geometric correction, the coordinates of the image were transformed into the Chinese Coordinate System (C80) from the map. Then, all of the rest images were rectified to this image by using control points. Around 50 control points were selected on each image to carry out the polynomial transformation. The criterion for selecting these control points is based on easy identification such as using the intersections of roads and the corners of fishpond. These control points were evenly distributed over the whole region to ensure accurate registration. DEM was not used for the rectification because the topography is rather even in the delta.

Textural features have been frequently used to improve the classification of SAR images (Baghdadi et al., 2002). The information can be derived from remote sensing based on a variety of methods, such as concurrence, variance and entropy. In this study, a textural feature was also used as one of the attributes for a case. The operator of variance (2nd order) in the ERDAS software was used to create the textural image. The operator computed the standard deviation using a moving window. The textural feature was derived from the 18 April 2000 SAR image. It is found that the incorporation of this textural feature can effectively discriminate fishponds from other water bodies. It is because fishponds usually have the textural feature of periodic alignment. The experiments show that the best results can be obtained if the textural feature is derived by using an 11×11 window to calculate the variance. The textural feature is also useful for achieving better detection of urban features.

4.2. Construction of case library

Eight types of land use were identified in the region including banana, sugar cane, grass, rice paddy, lotus, fishpond, water, and built-up areas. A reason to choose them is that they are the major types of land use in the region. Their separability in multitemporal SAR images is also another reason. Most of these land use types are related to agricultural activities which should be discerned for monitoring the cultivation system.

The backscatter of SAR images reflects crop growth conditions and moisture content of the field. Each type of land use, especially crops, is characterized with unique temporal backscatter behavior which has been confirmed by many studies (Rosenqvist, 1999; Tso & Mather, 1999). For example, rice paddy fields have unique backscatter curves over the growth circle. In the planting stage of rice paddy, the water surfaces in inundated fields result in very low backscatter values, from -14 to -18 dB. The backscatter values increase and reach -5 to -7 dB in the reproduction stage. The rice paddy fields are inundated again for next planting after harvesting. The unique backscatter behavior can allow rice paddy fields to be discerned easily from other crops. Rice paddy fields can be accurately detected according to the unique backscatter behavior in the growth circle. The use of temporal images is important for the identification of crops or other land use types from SAR data.

The case library was built using land use maps from year 2000. A total of 900 cases were collected and stored in the case library for the CBR classification and validation. Each case contains five features—the backscatters of the three SAR images (18 April 2000, 29 June 2000, and 16 August 2000), the textural information and the associated land use types.

It is important to collect the cases over different terrain features to include the possible backscatter variations within each land use type. This can allow different backscatter behavior to be captured by the cases. Stratified random sampling (Congalton, 1991) was employed to ensure that the cases of a class were properly allocated over different terrain features. This method is to use discrete cases to represent the backscatter variations instead of using complex mathematical equations.

The stratified sampling was arranged according to the terrain features to capture environmental variations as much as possible. The terrain classes were obtained by applying a clustering algorithm to the satellite TM image in 2000. The clustering provided the basis for the stratified random sampling that decides the coordinates of cases. As the result, the collected cases should be the most suitable representatives to various land use types and can be used as the backscatter signature for the classification. The cases do not include the total set of previously classified pixels, but only use some of them based on the sampling techniques for the matching.

Fig. 3 shows the temporal backscatters of the major land use types in the Pearl River Delta. The backscatters were calculated from the 18 April 2000, 29 June 2000 and 16 August 2000 RADARSAT images. The associated land use

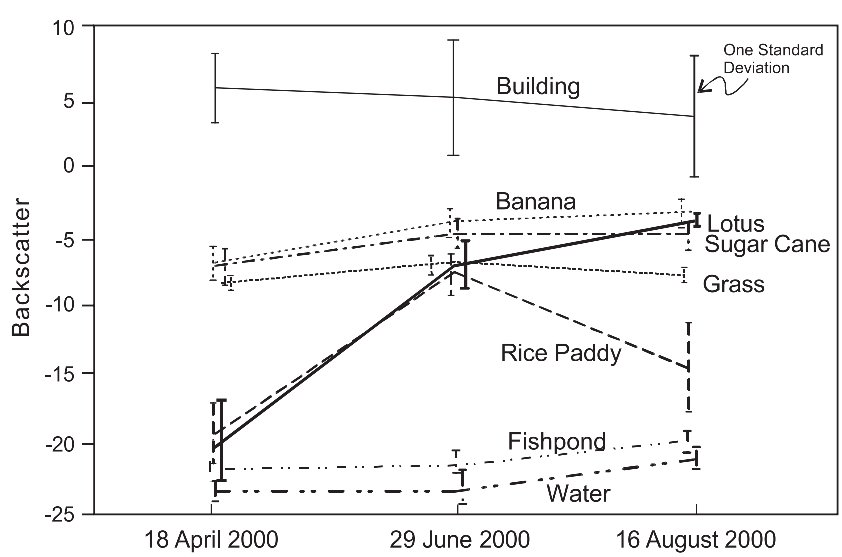

Fig. 3. Temporal backscatter behavior of the typical land use types in the Pearl River Delta.

types were confirmed from land use maps. The signatures for land use types were created by using the 450 cases in the case library. One standard deviation was also shown at each data point for these land use types. It is obvious that most of these land use types can be separated from each other based on the backscatters.

It is not easy to separate banana from sugar cane according to the mean values and standard deviations. It is because the statistics will 'average' the characteristics of these cases and thus reduce the separability. It cannot reflect the internal backscatter variations within each land use class. Soil moisture and terrain features all contribute to the internal variations. In reality, the class membership function is quite complex. The Gaussian membership function assumed by maximum likelihood has drawbacks in representing discrete cases. The use of discrete cases can solve this problem and produce higher classification accuracy than the traditional methods.

5. Monitoring of cultivation systems

The backscatters of the three SAR images and the textural information were used as the main attributes for the CBR classification. The salience (SA_{kl}) of each feature in Eq. (3) was assigned with the same value of 1 because no preference was given to any of them. Land use was classified according to the similarity between the input case and the cases in the case library using these attributes.

The 900 cases in the library were equally divided into two groups—one for classification and the other for validation. The first group of 450 cases in the case library was used for the classification of the 2000 SAR image. Fig. 4A is the land use classification of Panyu by applying the CBR method to the temporal Radarsat images in 2000.

The accuracy of the classification was examined by using the remaining 450 cases in the case library. The confusion matrix is shown in Table 2. The overall classification accuracy is 0.85 and the Kappa coefficient is 0.83. Much higher accuracy can be found for the detection of rice paddy. The accuracy is as high as 0.92 for rice paddy detection alone. This indicates that rice paddy can be more accurately detected according to its temporal backscatter behavior. Temporal SAR images provide a unique opportunity for mapping agricultural land use types, which are difficult to obtain for optical remote sensing in tropical and subtropical regions.

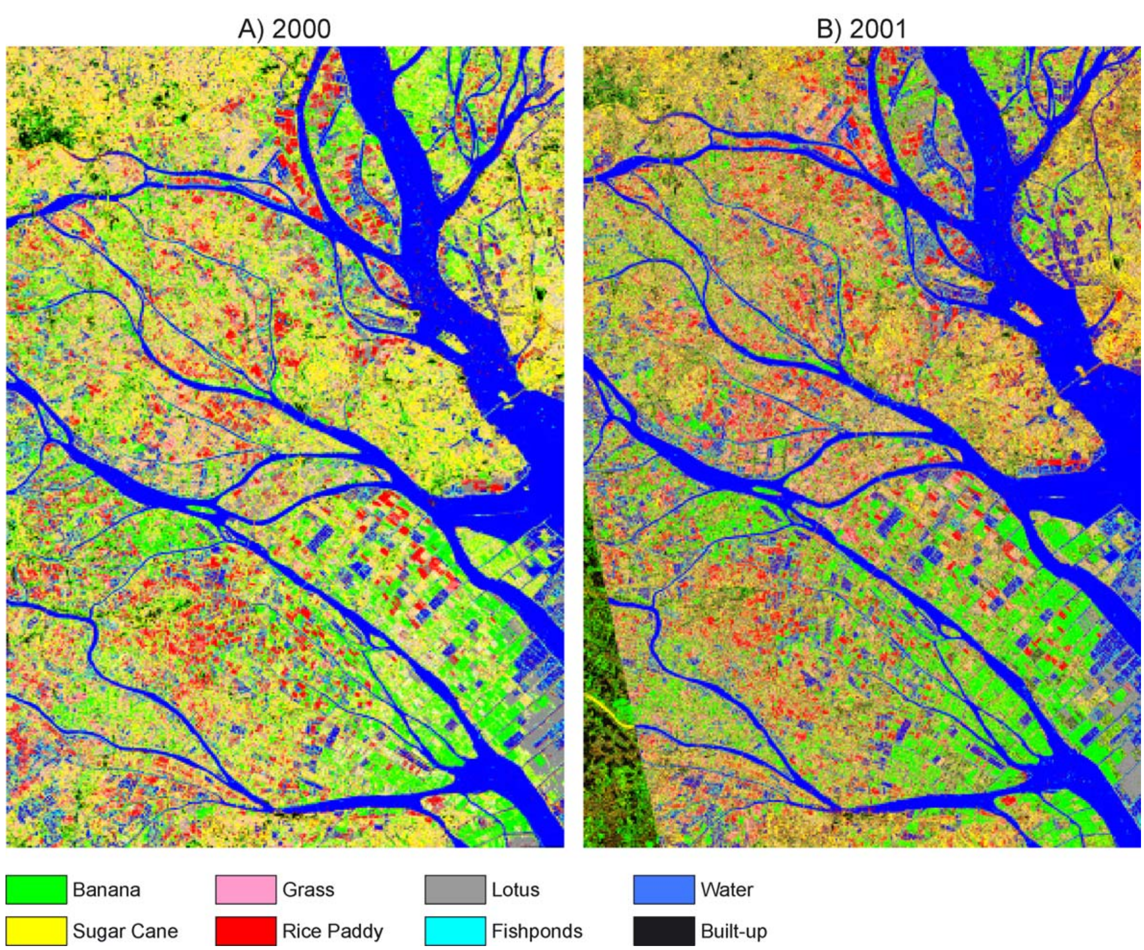

Fig. 4. Monitoring the changes in the cultivation system in the Pearl River Delta from multitemporal satellite SAR images using the CBR method.

Table 2
Confusion matrix of the CBR classification

		Reference								Total	Producer's accuracy
		Ba.	Su.	Gr.	Ri.	Lo.	Fi.	Wa.	Bu.		
Classified	Ba.	52	11	3	0	0	0	0	0	66	0.79
	Su.	6	58	6	0	0	0	0	4	74	0.78
	Gr.	6	6	87	0	0	0	0	9	108	0.81
	Ri.	0	0	0	35	2	0	0	0	37	0.95
	Lo.	0	0	0	3	21	0	0	0	24	0.88
	Fi.	0	0	0	0	0	24	3	0	27	0.89
	Wa.	0	0	0	0	3	5	58	0	66	0.88
	Bu.	0	0	0	0	0	0	0	48	48	1.00
Total		64	75	96	38	26	29	61	61	450	0.87
User's accuracy		0.81	0.77	0.91	0.92	0.81	0.83	0.95	0.79	0.85	

Banana (Ba.), Sugar cane (Su.), Grass (Gr.), Rice paddy (Ri.), Lotus (Lo.), Fishpond (Fi.), Water (Wa.), Built-up (Bu.).
Overall accuracy = 0.85, Kappa coefficient = 0.83.

A comparison was made by using a standard classification method, the supervised maximum likelihood classifier, for the classification of the same SAR images. The same 450 cases were used as the training data for the classification. According to the same accuracy assessment, the result is very unsatisfactory with a much lower accuracy of classification (Table 3). The overall accuracy is 0.75 and the kappa coefficient is 0.71. This indicates that the accuracy of the supervised classification method is significantly lower than that of the CBR method. The poorer classification from the supervised method may be caused by the obvious spatial variations of environmental settings (e.g., roughness and soil types). The agricultural field is usually small and the mixture of agricultural activities is common in this region. The variations have caused the difficulties in creating backscatter signatures for standard classification methods. It was not easy to define proper training sites for extracting signatures because of the complexity of environmental settings. The statistics based on means and standard deviations will generate 'average' effects, which cannot help to separate land use classes. However, the discrete cases in the CBR method should be most suitable for representing these complexities and help to obtain much better classification performance.

One of the advantages for CBR methods is that case libraries are reusable for time-independent classification. However, the SAR images in different years must be acquired in similar times of the crop growth cycles. In this study, the same case library developed for the classification of the 2000 SAR images was reused for the classification of the 2001 SAR images. It is expected that same case library is still valid because the 2001 SAR images cover almost the same crop growth circle. This can save much the time in the classification. Fig. 4B is the classification of land use types by applying the same case library to the 2001 SAR images.

The accuracy for classifying the 2001 SAR images was examined based on two steps. First, the changes in the land use types were identified by overlaying the 2000 and 2001 classified SAR images. Because these updated land use types were not stored in the validation group of the case library, field work using GPS was carried out to obtain the information for the validation. The remaining unchanged land use types were still verified by using the validation group of the case library. One hundred fifty changed pixels were visited, and 300 unchanged pixels were retrieved from the case library for the accuracy assessment. The overall classification accuracy is 0.83 according to this method. The experiment indicates that the case library can be used for

Table 3
Confusion matrix of the supervised maximum likelihood classification

		Reference								Total	Producer's accuracy
		Ba.	Su.	Gr.	Ri.	Lo.	Fi.	Wa.	Bu.		
Classified	Ba.	42	10	3	3	0	0	0	0	58	0.72
	Su.	9	52	18	0	0	6	0	12	97	0.54
	Gr.	6	10	84	0	0	0	0	9	109	0.77
	Ri.	0	0	0	27	3	0	0	0	30	0.90
	Lo.	0	0	0	6	18	0	0	0	24	0.75
	Fi.	0	0	0	0	0	10	7	0	17	0.59
	Wa.	0	0	0	0	4	6	63	0	89	0.71
	Bu.	0	0	0	0	0	0	0	42	42	1.00
Total		57	72	105	36	25	22	70	63	450	0.75
User's accuracy		0.74	0.72	0.80	0.75	0.72	0.45	0.90	0.67	0.72	

Banana (Ba.), Sugar cane (Su.), Grass (Gr.), Rice paddy (Ri.), Lotus (Lo.), Fishpond (Fi.), Water (Wa.), Built-up (Bu.).
Overall accuracy = 0.75, Kappa coefficient = 0.71.

Table 4
The changes for each land use category in 2000–2001 from the CBR method (in ha)

Land use categories	2000	2001	Increase by (%)
Banana	14,008	15,532	10.9
Sugar cane	32,566	38,301	17.6
Grass	23,859	19,282	− 19.2
Rice paddy	13,968	10,615	− 24.0
Lotus	6403	8414	31.4
Fishpond	5395	5885	9.1
Water	36,963	34,949	− 5.4
Built-up	3075	3260	6.0

time-independent classification of land use types from SAR images.

The monitoring of the changes in the cultivation system is convenient by the overlay of the two classified SAR images. Table 4 is the changes of each land use category in 2000–2001. The analysis indicates that agricultural land is rapidly declining. The study area witnessed a drop of 24.0% of the rice paddy field and an increase of 6.0% of the urban areas in the period of 2000–2001. However, the areas for growing banana and sugar cane increased by 10.9% and 17.6%, respectively, at the same period. The area for fishpond also rose by 9.1%. It is because banana, sugar cane and fishpond can produce much higher income than rice paddy production. Local farmers are not interested in rice paddy production. Thus, significant land use changes have taken place in the crop system. Multitemporal SAR images provide an opportunity for monitoring the internal restructuring of agricultural activities in the study area.

The rapid decrease of agricultural land can be easily confirmed by field investigation. In the Pearl River Delta, rice paddy used to be the dominant crop before economic reform, but now it is very difficult to find a piece of rice paddy fields in many places in the delta. According to the statistical yearbooks of Guangdong, the cropland decreased by 24.3% for the whole Pearl River Delta in 1990–2000.

6. Conclusion

The classification of remote sensing data can provide valuable land use information for land use planning and management. It can also provide important inputs to many environmental models for estimating the impacts of land use changes. However, conventional optical remote sensing has limitations for monitoring the cultivation systems in tropical and subtropical regions because of frequent cloud covers. This study demonstrates that multitemporal SAR images are able to monitor the rapid changes in the cultivation system in the Pearl River Delta, South China.

Classification is a common task of image processing in remote sensing applications. Numerous methods, such as contextual classifiers and rule-based systems, have been developed to improve the classification accuracy. There are increasing studies on using KBS to classify SAR imagery because SAR imagery can provide stable spectral properties. This study explores the possibility of using case-based reasoning (CBR) techniques to simplify the classification procedures of KBS.

Although rule-based systems have a number of advantages for remote sensing classification, they have limitations in dealing with complex situations. A large set of rules is usually required to cope with the complex situations. The jobs to define these rules are quite time-consuming because complicated and changing environmental settings can make the formation of rules very difficult. It is a bottleneck to acquire knowledge and define concrete rules. There are uncertainties on how to determine rule structures and parameter values such as thresholds.

This study indicates that the CBR method is very promising for the classification of SAR imagery. The method can avoid some of the problems, such as knowledge elicitation bottlenecks, in building KBS. Fuzzy sets have also been incorporated in the model to represent the matching of land use types more precisely. For a new case, it is unlikely to retrieve exactly the same case based on the similarity assessment. Fuzzy sets can reduce the uncertainties effectively in case matching. Fuzzy membership functions are used to deal with the vagueness of state (e.g., land use types). They can represent gradual class boundaries and overcome the limitations of the rigid Boolean model.

The experiment indicates that the CBR method works better than traditional methods such as the maximum likelihood classifier. Traditional classification usually assumes that a specific type of land use should maintain a stable spectral signature over the whole study area. It is not true for a large region in which the changes of terrain features (soil moisture and roughness) may lead to the variations in the spectral signature for this land use type. The variations may be very complicated under real-world situations.

It is very difficult to find out the relationships between the spectral properties and environmental background. For example, the maximum likelihood method assumes that the class membership function is Gaussian. Rule-based systems also need to define the threshold values and the boundary of changes. All these assumptions may not be true in reality. The use of discrete cases can conveniently solve this problem. The dynamic spectral variations of a class can be captured by properly allocating cases over various terrain features with a stratified sampling technique.

The case library in the CBR method is reusable for time-independent classification. Experiments indicate that satisfactory results can be generated by using the same case library for classifying SAR images in different years. The classification results from the CBR method are found to be largely consistent with actual land use patterns as obtained from land use maps and field investigation. However, the reusability of case library requires that the SAR images in different years should be acquired during the same time of the crop growth cycles. Moreover, the soil moisture should be stable for the same time in different years. These assumptions are also required for any other KBS methods.

The region has witnessed an astonishing rate of land use conversion. The cultivation system is undergoing rapid changes due to the introduction of market economy. The traditional rice paddy production is under threat because it is being replaced by other agricultural activities for higher income. Rice paddy fields may probably disappear in the delta in the near future if the governments do not intervene such changes soon. Local governments should implement measures of promoting sustainable land development in the region. The loss of rice paddy fields will have significant ecological consequences and other environmental impacts. Further studies can be carried out to assess the impacts of land use changes in the region.

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