BAYESIAN CLASSIFICATION FOR RICE PADDY INTERPRETATION

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ABSTRACT

In this paper, we present a case study of interpreting paddy distributions of three counties on Northern Taiwan during two crop seasons on year 2000 using multitemporal imageries together with cadastre GIS by Bayesian posteriori probability classifier. In order to integrating Bayesian conditional probability, priori probabilities of paddy's attributes were estimated from photogrammettric interpretation results provided by the Food Bureau, and the spectrum reflectance from different growth stages was used. Due to the spatial heterogenous of paddy's distribution, classifier parameters were established individually on each map-quadrangle. Temporal change of NDVI from different growth stages pass through rice's life cycle has been measured and we find two-stage images make significant improvement on classification results. Results of the study help us to evaluate the accuracy of the classifier. Imagery classification results were compared with aerial photo's interpreting results for assessing accuracy. Overall accuracy of first crop of Tao-yuan, Hsin-chu, and Miao-li were 89.93%, 92.83%, 95.33% respectively. Bayesien classifier has advantages including easy-to-adjusted and easy-to-computed rules and comparative stable results when limited SPOT satellite imageries available. Bayesin method also provides results with probability that help the operator to assess the places having least confidence. These advantages allow us to suggest Bayesian method be used in paddy-area investigation in Taiwan.

1. INTRODUCTION

Taiwan Food Bureau has adopted aerial photography to investigating rice paddy area over 20 years. Although photogrammetric interpretation is a labor-intensive work, the accurate result provides government a reference of rice inventory and made policy refinement for food stabilization. When Taiwan becomes member of World Trade Organization (WTO) and toward import rice from abroad that causes reducing of rice crop area. There is a need for a more efficient method to reduce labor and data costs for rice paddy interpretation. Using remotely sensed images is a highly expected alternative.

Remote sensing technology has been successfully applied in plant identification. However, cropland interpreting is often mixed with other vegetation background. To cope with the mis-classification problem, meltitemporal imageries over the same scene were used to extract temporal change information by which rice paddies show greater different change to natural background. Frequently cloud cover on Taiwan may causes other problem on data acquisition, ground station in Taiwan receives every SPOT images passing Taiwan that provides one or two qualified images per month (Tseng and Chen, 2002). Other problem blocked on the road is the small and trifles paddies and diverse crop pattern in Taiwan, which requires high-resolution images for cropland interpreting. Combining remote sensing and cadastral data (Lau, 2000) that excluded out-of-paddy data increases the classification performance.

When the temporal and spatial problems were solved, implementation of using remotely sensed images still needs a better tool to analyze the full potential of remotely sensed data. Rice paddy mapping is a general interest topic in remote sensing society. Many researches present valuable methods and acceptable results but seldom of them were applied to actual operation. It may be caused by 1).Classifier needs training data every time, traditional supervised classifiers requite training site to establish credible signature pattern. But usually only a limited number of training sites available for each temporal data set. 2). Well-trained interpreter were needed to perform a complicate classification procedure.

Comparing with other classifier, Bayesian classification method is simple and effectiveness. First, it is simple and easy-to-calculate. The classification rules are easy to extent from calibrated data set to other data set, and it is worthy when update previous rule when new data sets area available. Second, it is easy to combine multitemporal data sets by using join probability, the discriminating power of multitemporal images can be maximized. To evaluate performance of the classifier, following is an experiment of using Bayesian decision classifier to interpreting rice paddy of large area through mulittemporal images.

2. BAYESIAN CLASSIFICATION

Bayesian classifier falls into the category of "soft classification" that defines class by probability-to-feature (PTF) rather than distance-to-feature (DTF). DTF method decides class of a pixel (or object) by the shortest distance from pixel to class centroid in the feature domain, and PDF method decides the class of a pixel by which class has the highest possibility. Bayes' decision theory is a fundamental statistical approach to the problem of classification (Duda and Hart, 1973). This approach is based on the assumption that the decision problem is posed in probabilistic terms, and that all of the relevant probability values are known. The aim of the decision is to assign an object to a class. This classification is only carried out by means of measurements taken over the objects.

We assume that there is a priori probability $P(\omega_1)$ that an agricultural parcel is a paddy, and probability $P(\omega_2)$ is not a paddy. These priori probabilities reflect our priori knowledge of how likely a paddy to be before to estimate any feature of the parcel. Without additional information, we make the decision about the attribute of the parcel can be made by comparing $P(\omega_1)$ and $P(\omega_2)$. However, the sate - the state-conditional probability density function for an agricultural field given the state of nature can be defined by leaf reflectance or Normalized Difference Vegetation Index (NDVI or VI). If NDVI values from paddy-parcel and non-paddy-parcel define the state-conditional probability density function $P(w_1|VI)$ and $P(w_2|VI)$, and one agricultural field can be classified as :

if $(P(w_1|VI) > P(w_2|VI))$ then attribute = paddy else attribute = non-paddy (1)

If we know both the priori probabilities $P(w_i)$ and conditional probabilities $P(w_i|VI)$, and the NDVI values can be estimated from multitemporal images, Bayes' rule provides the state-conditional probability:

$$P(w_i|VI) = \frac{P(VI|w_i) * P(w_i)}{P(VI)} \quad (2)$$

Where $P(VI)$ is the priori probability of VI which can be expressed by total probability theorem, equation 2 can be written as:

$$P(w_i|VI) = \frac{P(VI|w_i) * P(w_i)}{\sum_j \left[P(VI|w_j) * P(w_j)\right]} \quad (3)$$

Where $P(w_i|VI)$ is the posterior probability of ω_i of a given NDVI = VI, ω_1 is paddy and ω_2 is non-paddy. $P(w_i)$ is the priori probability of w_i. It can be estimated by counting the number of paddy and number of total agricultural field. $P(VI|w_i)$ is the posterior probability of VI, it can be estimated by combining the tableting imagery-derived NDVI and historical paddy information.

If we put equation (3) into inequality (1) and eliminating the denominator, the decision equation can be expressed as:

if $(P(VI|w_1) * P(w_1) > P(VI|w_2) * P(w_2))$ then attribute=paddy,else attribute=non-paddy (4)

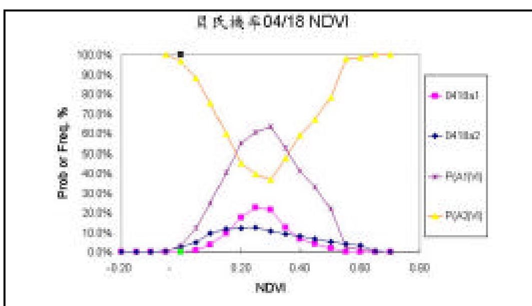
When meltitemporal data of NDVI were used, we put all these probabilities together to obtain the global probability, and fellow the assumption of class conditional independence of the NDVI valuse to reduce the computation complexity of calculating of all ***P(VI|w***$_i$***)***

$$P(\omega_i \mid VI1, VI2, \ldots VIn) = \frac{\prod_{k=1}^{n} P(VI_k \mid w_i) * P(w_i)}{\sum_j \left[\prod_{k=1}^{n} P(VI_k \mid w_j) * P(w_j) \right]} \qquad (5)$$

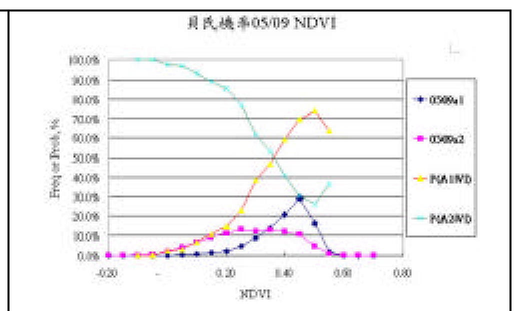
3. DATA ANALYSIS

Bayesian classifier was tested in a small site occupied a size of two map-quadrangle located on Maioli county, and then implemented in large area of three counties in North Taiwan, namely Taioyuan, Hsinchu, and Maioli, to evaluated the operation procedure and classification accuracy. Because there are two growing seasons in Taiwan, two series of SPOT images acquired year 2000 were collected. Results from aerial-photo interpretation and cadastral information were adopted for calculating probabilities and assessing accuracy.

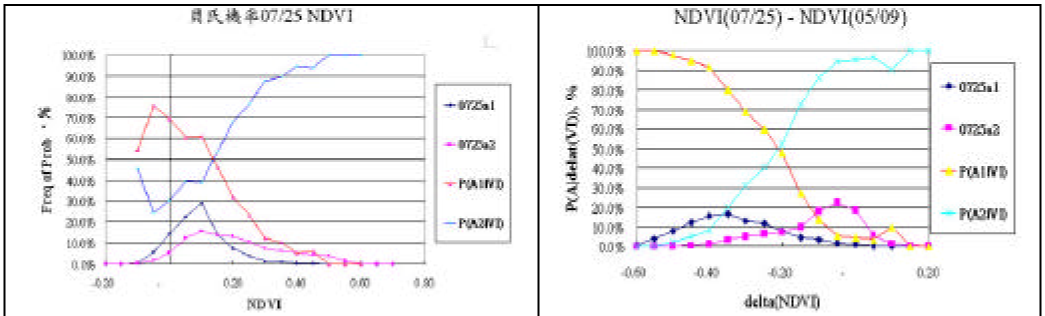
Priori probability P(ω) was directly counted by dividing the number that belong to each class (paddy or non-paddy) with total number of parcel. Conditional probability of ***P(VI|w)*** was estimated by counting the number of paddy (or non-paddy) that falls into same NDVI category (division 0.05 is used). Posterior probabilities to decide paddy ***P(w|VI)*** (or non-paddy) were calculated from equation 3. Figure 1 shows probabilities derived from three different date, and derived from the difference value of two dates (07/25 and 05/09). Probability to decide a paddy using April 18 (04/18) data has lower and upper bounds, and other two probabilities show the open-end. The same pattern of decision rule is shown on other manual-adjusted rule classifier.



(a) Bayesian probability using 04/18 NDVI



(b) Bayesian probability using 05/20's NDVI



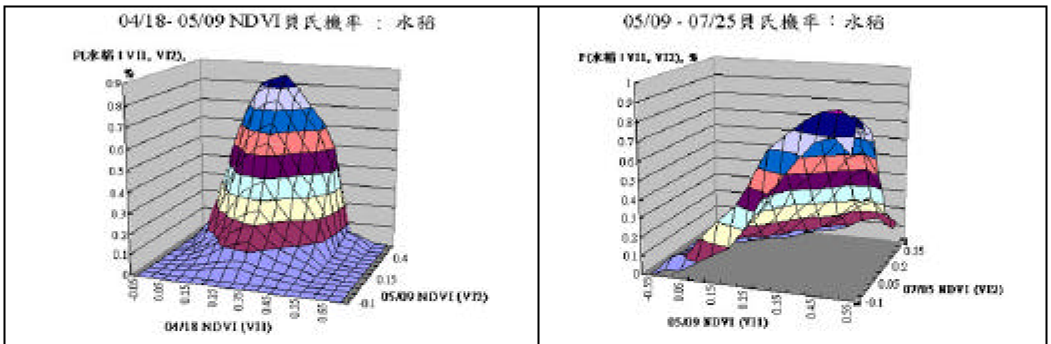
(c) Bayesian probability using 07/25's NDVI

(d) Bayesian probability using difference between 07/25 and 05/09's NDVI

Figure 1. priori and posterior probability estimated from NDVI in study area.

When multitemporal images were applied, two images acquired on May and July were used. A conditional probability table (CPT) is constructed by using a 0.05 increment of NDVI in both data sets. From the CPT different probabilities are established to estimate $P(w_i \mid VI_1, VI_2)$. Figure 2 shows probabilities density surfaces from data of CPT. The surface diagram gives an opportunity to watch the changing pattern of paddy related to two dates' NDVI values.

Since there are only two classes to be classified, 50% is used to decide either an agricultural field is paddy or non-paddy. Posterior probability used two dates' NDVI difference yields the best accuracy. The overall accuracy of classification is 96.27% and $\hat{k}$ index is 0.92. It is the highest accuracy comparing with other classifier in prior study.

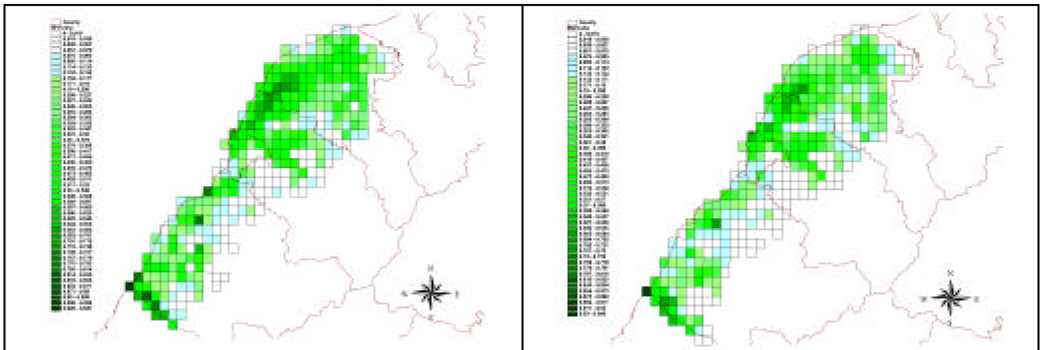


(a) 04/18 and 05/09s' NDVI

(b)05/09 and 07/25s' NDVI

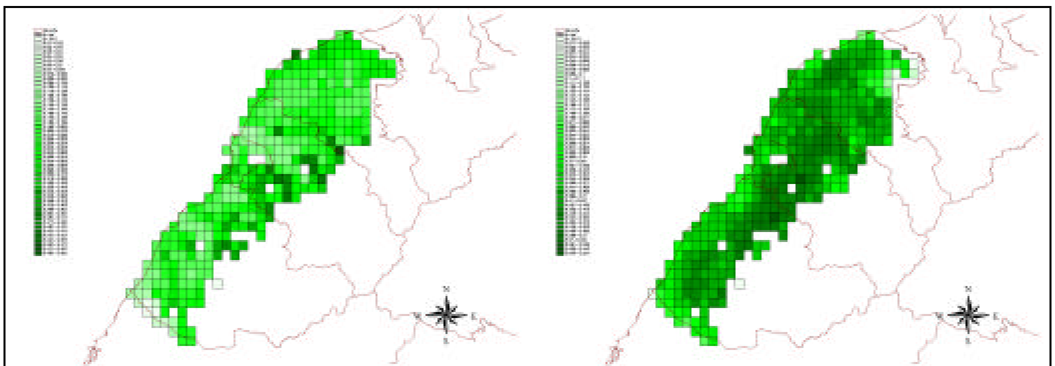
Figure 2. Posterior probability surface $P(w_i \mid VI_1, VI_2)$ estimated from two-date NDVIs.

Extending the classification procedure from test site to larger region, one may consider how to estimate the divers probabilities of different area. The three counties cover total 330 1/5,000-scale map-quadrangles and show a high diversity of framing pattern. Figure 3 shows the priori probabilities of paddy ($P(w_1)$) of each quadrangle that ranged from 0.02 to 0.98. Also, figure 4 shows the change pattern of the mean value of NDVI (second crop season) of rice paddy, $P(VI|w_1)$.



a. First crop season b. Second crop season

Figure 4 Prior probabilities of paddy ***P(w₁)*** of Northern Taiwan estimated from year 2000.



a. July 25, 2000 b. Sep 20, 2000

Figure 5 Mean values of NDVI calculated from rice paddy of second crop season, 2000.

The geographic diversity caused by the different weathers and growing schedules made it unrealistic to decide paddy by a single posterior probability ***P(w₁| VI)***. Comparing with other dividing methods, we find that the most effective way is calculating posterior probability of each map-quadrangle. Table 1 presents classification results in three counties. Compared with a manual-adjusted rule classifier, Bayesian classifier shows better result.

Table 1 Comparison of accuracys from Bayesian and fixed threshold rule classifiers

Classifier / County	Bayesian		Manual-adjusted rule	
	overall accuracy	Kappa $\hat{k}$	overall accuracy	Kappa $\hat{k}$
Taoyuan	89.93%	0.742	80.00%	0.651
Hsinchu	92.83%	0.801	91.66%	0.777
Maioli	95.33%	0.838	93.99%	0.793

4. DISCUSSION AND CONCLUSION

From the above test one can find that the Bayesian decision method presents a high accuracy with a simple computation procedure. This version of Bayesian classifier may be the most commonly used, because of its easy implementation and good results obtained in most cases. We had tried other classifiers in previous study, such as fuzzy classifier and manual-adjusted rule, most of them need a long time to refine parameter of rule-base. Bayesian classifier needs only a straight calculation of priori and posterior probabilities from data sets without try-and-error procedure. This characteristic makes Bayesian classifier can easy be applied to large region.

However, the Bayesian Classification techniques may loss accuracy because of the assumption of conditional independence. We have found that using NDVIs from different date images is necessary to produce better accuracy. The product of probabilities assigned by the two images actually come from same paddy and same crop. The assumption of independence may not be true at all. Using the difference of NDVI rather than combining two NDVI may be a better way to avoid the independence assumption. For the preparation of daily operation, we still need to work out a sensitivity analysis of the priori probability to find its influence to the final results, and the confidence intervals of the posterior probability.

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