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Supervised Classification Using Training Parameters and Prior Probability Generated from VITD

- The Case of QuickBird Multispectral Imagery

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Abstract : In order to classify an satellite imagery into geospatial features of interest, the supervised classification needs to be trained to distinguish these features through training sampling. However, even though an imagery is classified, different results of classification could be generated according to operator's experience and expertise in training process. Users who practically exploit an classification result to their applications need the research accomplishment for the consistent result as well as the accuracy improvement. The experiment includes the classification results for training process used VITD polygons as a prior probability and training parameter, instead of manual sampling. As results, classification accuracy using VITD polygons as prior probabilities shows the highest results in several methods. The training using unsupervised classification with VITD have produced similar classification results as manual training and/or with prior probability.

Key Words : supervised classification, training sampling, VITD, prior probability, unsupervised classification.

1. Introduction

Supervised classification of satellite imagery in statistical methods needs the training process to extract the pixels to be used for defining means and covariances by multispectral bands, also determines the discriminant functions within feature classes in multi-dimension (Schowengerdt, 1997). Sampling design of training assumes the specific distribution of population and it focuses on the prediction of the mean, the variables, and the reliability through sampling process (Rosenfield, 1982). If a certain spatial feature of interest could be separated completely from others, operators can extract the training area with homogeneous pixels of a specific feature. But, in most cases, it is not easy to find a imagery which includes clear separate features. To make the condition of training area clean, operator

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would need auxiliary data such as existing topographic maps, thematic maps etc. Therefore, the training process is intensive labor and costs a lot for searching and validating optimal training regions, and it also has an effect largely on the accuracy of classification. The better spatial and spectral resolution the satellite imageries have, the more sensitive the training result affect the accuracy of classification. As training is a kind of optimization before classification, there are mainly two issues in research area of training. One is the determination of representatives of trained samples and the other is automatization of training process (Hixon *et al*, 1980; Eo *et al*, 1999).

There are many useful auxiliary data such as VITD (Vector Interim Terrain Data), CADRG (Compressed Arc Digitized Raster Graphics) and these data are for military application of remote sensing. VITD is the vector data of small scale and has six layers of geospatial attribute such as Obstacle, Slope/Surface configuration, Soil/Surface configuration, Suface Drainage, Transportation, and Vegetation (Lee *et al*, 2004). Using rasterized VITD as a prior probability and training area for MLC (Maximum Likelihood Classification), this paper describes the experiment results and analyzes the usefulness of VITD in training process.

2. Experimental Site and Data

For this study, a 2.8m spatial resolution/4 multispectral bands QuickBird image is used and it was obtained on 11 August 2004. The area of imagery is Yeoncheon-County and the north area of Kyunggi-Do. Test site covers 11 × 10km, and holds diverse landcover categories such as forest, water, built-up, paddy, bare land, and field. For processing of geometric correction, 9 control points and RPC (Rational Polynomial Coefficient) with which imagery vendor provided as input parameters of sensor modeling. Also, Socetset S/W was used for generating an ortho-imagery (BAE systems, 2006). Contours with 10m interval were manually made by digital stereo-plotting using SPOT5 imageries, and then interpolated to 5m DEM (Digital Elevation Model). As control points for SPOT5 sensor modeling, U.S. army's records of control points were used in case of access denied area, and the results of GPS surveying in case of field trip. Sensor modeling of QuickBird used the control points which had been extracted from SPOT5 ortho-imagery because the generation of QuickBird ortho-imagery used DEM which is made from SPOT5 as described above. The

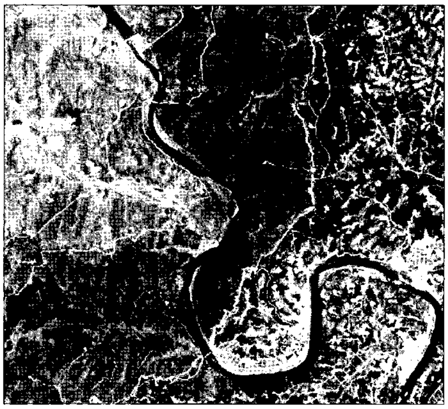

Fig. 1. QuickBird imagery in test site.

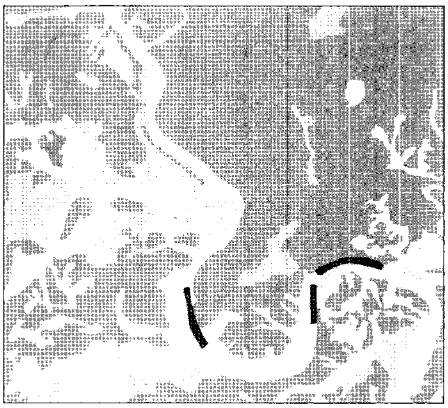

Fig. 2. VITD (forest, water, built-up, paddy, bare land, and field) in test site.

result of QuickBird modeling showed that errors were calculated at 1.5m, 0.3m in x, y direction, respectively.

Interpolation of raw imagery is necessary to calculate the pixel value to be inserted to the processed imagery during generation of ortho-imagery (Schowengerdt, 1983), the nearest neighborhood method was used to preserve pixel values of raw imagery. The ortho-imagery has been made in 0.7m of spatial resolution, and supported geotiff format. VITD is used as a prior probability and training area for this study and it was rasterized in geotiff format using ESRI ArcView GIS and Erdas Imagine. As the rasterized VITD had the same grid interval with QuickBird ortho-imagery, rasterized VITD was able to be compared pixel-to-pixel with ortho-imagery. Fig. 3 and 4 show that test site in VITD was extracted using "Clip one theme based on another" function of ArcView GIS.

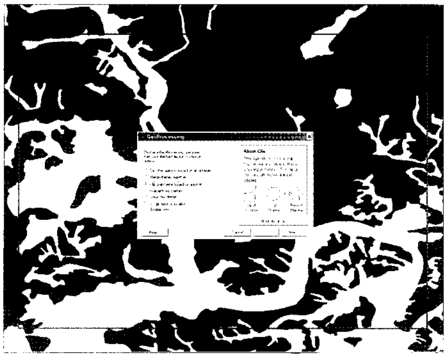

Fig. 3. Clipping Process of Forest Layer in VITD.

Fig. 4. Clipping Result of Forest Layer in VITD.

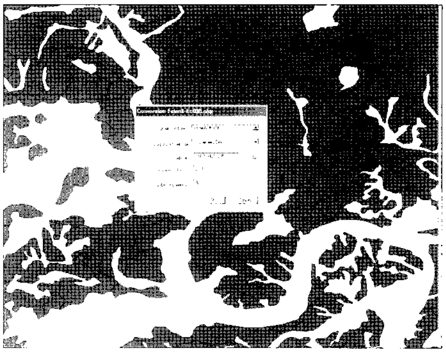

Fig. 5. GRID Process of Forest Layer in VITD.

Fig. 6. GRID Result of Forest Layer in VITD.

A shape format of the clipped VITD was converted into GRID format, which the input value of cell size for the grid process turned out 0.0000342102052 deg and it is considered same interval with ortho-imagery. In case of forest, 24(deciduous), 25(coniferous), 50(mixed) are input in the attribute field of feature, other features' value range 1~10 to discriminating for each other features.

Using Erdas Imagine, GRID file could be transformed into raster file of img format and reprojected from geographic coordinates to UTM coordinates based on WGS84 ellipsoid.

3. Experiment and Analysis

Table 1 shows 10 features of VITD for this study (DMA, 1989). Author analyzed the imagery visually then grouped into several features. Therefore, EC030

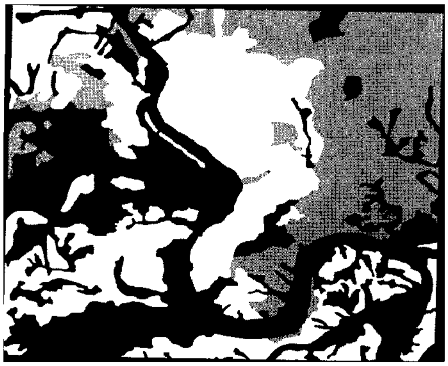

Fig. 7. Rasterized VITD (Forest).

Fig. 8. VITD Rasterized VITD (forest, grass, water, built-up, crop).

and EA040 are considered as forest class, EB020 and EB010 as grass class, AL020 as builtUp, EA010 and BH135 as Crop. Also, water class binds BH140, SA010 and BH090.

The experiment includes four kinds of supervised training using VITD. MLC process itself was processed by Erdas Imagine. Using panchromatic imagery, the accuracy assessment of MLC was performed on 399 reference points which are taken visually with stratified random sampling. The mean and covariance by multispectral bands and classification accuracies were analyzed as below;

- Training only with visual interpretation
- VITD used as prior probability
- VITD used as training
- Training using clusters selected with VITD polygon

1) Training only with visual interpretation

With visually supervised training, Maximum Likelihood Classification was processed. Generally, several areas per feature are chosen to maintain the range of variability. Fig. 9 and 10 show the training areas and the result of MLC using Erdas Imagine.

The overall accuracy was 67.7%, Kappa statistics was 0.53. As shown in Table 2, it is expected that the overlap of discriminant function and the class separability have bad condition between Grass and Crop features. Also Built-up feature is 90% for producer's accuracy, but it is only 40% for user's accuracy. In case of Crop in error matrix, the number of pixels classified correctly is less than that of incorrect pixels. Even though training for Built-up

Table 1. VITD feature code and definition for this study

Feature Code	Definition
EC030	Woody-perennial plants, having a self-supporting main stem or trunk.
EA040	An area covered by systematic plantings of trees which yield fruits, nuts or other products.
EB020	Low-growing woody plants.
EB010	An area composed of uncultured plants which have little or no woody tissue.
EA010	An area that has been tilled for the planting of crops.
BH135	An area periodically covered with water used for growing rice.
BH090	An area periodically covered by flood water, excluding tidal waters.
BH140	A natural flowing watercourse.
AL020	An area containing a concentration of buildings and other structures.
SA010	An area containg any surface water that is flowing or free standing such as lakes, rivers, oceans, reservoirs, etc.

class was not simple because this is composed of various materials, the result of classification was satisfied relatively.

2) VITD used as prior probability

Prior probability does not affect the classification result when class separability is good, that is to say, spectral signatures between classes separate widely. But where the prior probabilities of the involved classes show significant differences under the condition of poor separability, the appropriate estimated prior probabilities move the boundaries of the classes to the correct direction. (Kim, 2008; Pedroni, 2003). For this experiment, the probabilities of forest, grass, water, builtup, and crop class are 0.616, 0.231, 0.045, 0.001, 0.108 for each, which means area ratios of classes are considered as prior probabilities. Other training parameters are same as the values described at 3.1.

Table 3 shows a little more improved classification result than section 3.1 described above. Even though the accuracies of forest and water, we estimated good separability with others not changed, other classes' results were improved. This means that features of grass, crop, builtup don't have good condition of separability. additional discussion will be described at section 3.5. Overall accuracy was 73.7%, Kappa statistics was 0.60.

3) VITD used as training

The rasterized VITD is used as training areas for MLC classification. As mentioned before, VITD has several layers which can be used as training references. Considering that VITD and imagery have different acquisition time, the operator selected the training VITD polygons manually to compare VITD with test imagery. Several polygons were selected for training sampling, Fig. 12 shows the result of selecting VITD polygons. Considering the variance of class distribution, operator couldn't select large polygons at upper-right area of imagery (see Fig. 8). Compared with classification result of visual training, the area of forest is much enlarged and the area of crop and grass are reduced. Especially, grass feature encroached on large portion of crop. There is a limitation for using VITD polygon directly as training sampling because the positional accuracy of VITD is based on scale of 1:50,000 and it has the temporal

Table 2. Error Matrix of MLC with Visual Interpretation Training

	forest	Grass	Water	Built-up	Crop
forest	93	24	0	0	0
Grass	7	127	0	1	15
Water	0	0	11	0	0
Built-up	3	10	2	19	13
Crop	2	53	0	1	20

Table 3. Error Matrix of MLC Result with VITD as Prior probability

	forest	Grass	Water	Built-up	Crop
forest	96	26	0	0	0
Grass	5	146	0	2	18
Water	0	0	11	0	0
Built-up	1	3	2	13	2
Crop	1	39	0	6	28

Table 4. The Error matrix of MLC result with VITD training

	forest	Grass	Water	Built-up	Crop
forest	96	109	0	0	6
Grass	6	93	0	4	34
Water	1	0	13	0	0
Built-up	0	6	0	11	7
Crop	0	6	0	6	1

Table 5. The Error matrix of MLC result - clusters selected with VITD polygon

	forest	Grass	Water	Built-up	Crop
forest	76	2	0	0	0
Grass	10	129	0	0	13
Water	0	0	13	0	0
Built-up	0	0	0	11	1
Crop	17	83	0	10	35

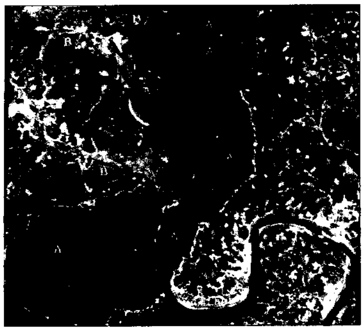

Fig. 9. Training with Visual Interpretation (A: Forest, B: Grass, C: Water, D: BuiltUp E: Crop).

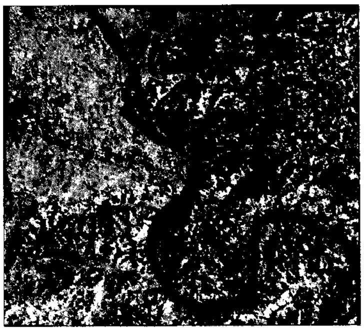

Fig. 10. MLC Result of Training with Visual Interpretation.

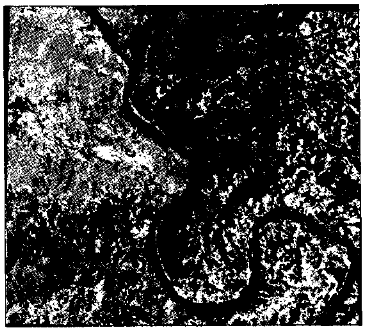

Fig. 11. MLC Result with VITD as Prior probability.

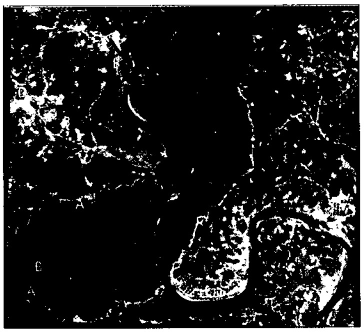

Fig. 12. Selected VITD area for training (A: Forest, B: Grass, C: Water, D: BuiltUp E: Crop).

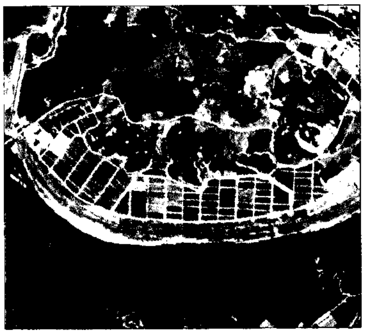

Fig. 13. Boundary difference of crop class between VITD and imagery.

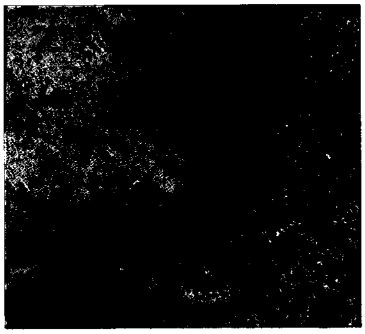

Fig. 14. MLC result with VITD training.

(a) (b) (c)

Fig. 15. Example of Selected crop clusters for training (a) selecting clusters (b) overlap clusters with VITD (c) the results of selecting clusters.

Fig. 16. The MLC Classification result using Unsupervised result+VITD as a training

difference from imagery acquisition. Fig. 13 shows the boundary difference of crop class between VITD and imagery. The overall accuracy was 53.6%, Kappa statistics was 0.31.

4) Training using clusters selected with VITD polygon

The classification result needs neither training data nor information about prior probability, but unsupervised classification may not match feature categories the researcher wants to acquire, (Kim, 2008). However, it may be useful for delineating homogeneous areas for potential supervised training polygons (Schowengerdt, 1983). The analyst can lead the better classification if the advantages in supervised and unsupervised training methods are combined. This experiment is that unsupervised classification is computed at the imagery, then compared with the rasterized VITD, if a certain pixels of group with classification result can be determined through the area ratio of features in VITD. Fig. 15 shows the example of crop cluster for training. Clustering options includes 10 classes, 0.95 of convergence threshold, and these is no skip factor. After the clusters of a certain feature were confirmed on imagery and VITD (Fig. 15 (a), (b)), then the operator manually selected clusters for training.

Fig. 16 shows the MLC result. As a result, the area of crop was overestimated, which means the area of forest and grass was encroached. As the overall accuracy 66.2% and Kappa statistics 0.52 which is better than MLC result with VITD training. When prior probability is applied, the overall accuracy could be improved at 73.4%, and Kappa statistic 0.60.

5) Discussion

As results, the application of prior probability using VITD have a clearly positive effect on supervised classification of access denied area while the application of training parameter did not give the definite answer. In case of visual supervised training, analysts tend to select the optimized training areas not only considering the assumption of class distribution but also image tone, shape, texute etc. As seen in Table 7, training parameters using VITD polygons have large variances while training parameters using selecting polygons which are produced by clustering or segmentation are similar traditional method. There are small area of builtup in test imagery, and experiment has been done under poor separability between crop and grass. Table 7 shows the separabilities of the values of TD(Transformed Divergence) and by 4 bands combination.

Generally, if the result is greater than 1,900, the classes can be separated. Between 1,700 and 1,900, the separation is fairly good. Below 1,700, the separation is poor. As most of TD values which include crop are under 1700, VITD training has some troubles selecting the crop feature. Crop and Grass features were could not be fully separated in VITD. Also, the spatial resolution of QuickBird imagery has a high spatial resolution to distinguish individual crown. The result of experiment shows that small scale data may not support directly to generate the supervised training parameters. The polygons made by clustering or segmentation can be compared with VITD, and used for precise training as seen by Table 7.

There are many considerations for generating polygons. Also different options for clustering or segmentation lead to the different results. Further study may include several kinds of parameters in clustering and segmentation with the imagery of high spatial resolution especially.

Table 7. Separabilities by training methods applied on this research

(where, 1: forest, 2: grass, 3: water, 4: builtup, 5: crop)

methods	1:2	1:3	1:4	1:5	2:3	2:4	2:5	3:4	3:5	4:5
Training visual interpretation	1895	2000	2000	1999	2000	2000	1814	2000	2000	1666
VITD training	780	1979	1957	1650	1895	1475	944	1920	1875	526
Training clusters+ VITD polygon	1999	2000	2000	2000	2000	2000	1996	2000	2000	1999

4. Conclusion

Satellite classification for access denied area is important at the military application, but has a difficulty in getting the ground truth data. Existing data such as VITD and CADRG can be useful for estimating training parameters or applying prior probability. The research of training automization using several techniques is still an important issue because military requirement and consistent accuracy by analysts' have different expertises and knowledgements. The future study of automatized training process based VITD can be still progressed with object oriented approach.

Acknowledgement

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