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Automated Training from Landsat Image for Classification of SPOT-5 and QuickBird Images

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Abstract : In recent years, many automatic classification approaches have been employed. An automatic classification method can be effective, time-saving and can produce objective results due to the exclusion of operator intervention. This paper proposes a classification method based on automated training for high resolution multispectral images using ancillary data. Generally, it is problematic to automatically classify high resolution images using ancillary data, because of the scale difference between the high resolution image and the ancillary data. In order to overcome this problem, the proposed method utilizes the classification results of a Landsat image as a medium for automatic classification. For the classification of a Landsat image, a maximum likelihood classification is applied to the image, and the attributes of ancillary data are entered as the training data. In the case of a high resolution image, a K-means clustering algorithm, an unsupervised classification, was conducted and the result was compared to the classification results of the Landsat image. Subsequently, the training data of the high resolution image was automatically extracted using regular rules based on a RELATIONAL matrix that shows the relation between the two results. Finally, a high resolution image was classified and updated using the extracted training data.

The proposed method was applied to QuickBird and SPOT-5 images of non-accessible areas. The result showed good performance in accuracy assessments. Therefore, we expect that the method can be effectively used to automatically construct thematic maps for non-accessible areas and update areas that do not have any attributes in geographic information system.

Key Words : Automated Training, GIS Data Revision, Non-accessible Area.

1. Introduction

Accurate and timely geospatial information is necessary in order to carry out military operations. Generally, geospatial information of most areas is easily acquired; however, it is difficult to get information for non-accessible areas, such as demilitarized zones (DMZ). For these cases, high resolution satellite images used for the acquisition of geospatial information could be the solution. In

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particular, commercially available high spatial resolution multispectral images, obtained from QuickBird, IKONOS, KOMPSAT-2, and SPOT-5, etc., can provide detailed ground information in a timely manner (Huang, 2007).

Manual classification performed by a trained expert is labor-intensive (hence impractical for processing large amounts of data), highly subjective, and non-reproducible (Zijdenbos *et al.*, 1998; Zijdenbos *et al.*, 2002). An automatic classification, which does not need an operator, can be an effective way to update geographic information system (GIS) data in military maps, both saving time and producing objective results. In recent years, many approaches have been used for automatic classification using high resolution satellite images. Most of the approaches utilize existing ancillary data, such as GIS data. Ancillary data is used to automatically extract training data by being entered as either attribute data or as knowledge to identify some of the features in a supervised classification process (Di *et al.*, 2000; Xiao and Raafat, 1992; Walter, 1998; Eo *et al.*, 2008). However, these methods have the limitation that they are unable to be directly applied to high resolution images because of scale differences between the high resolution image and the ancillary data. Due to the more heterogeneous spectral-radiometric characteristics within land-use/land-cover units portrayed in high resolution images, many applications of traditional single-resolution classification approaches have also led to unsatisfactory results (Barnsley and Barr, 1996).

In order to overcome this problem, this paper proposes a automated training method using Landsat images as the medium between the small-scale ancillary data and the high resolution satellite image. The proposed method consists of three processes. An overview of the method is shown in Fig. 1. The first step was to apply a maximum likelihood classification

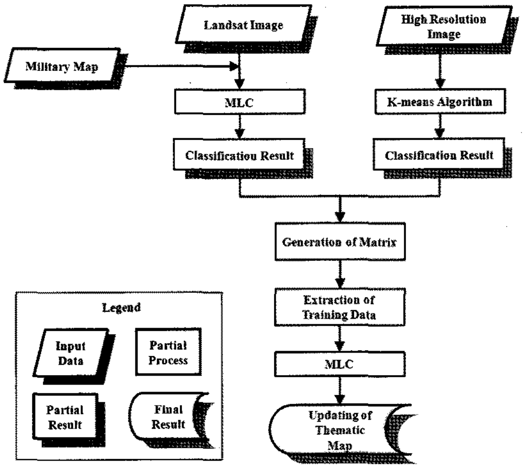


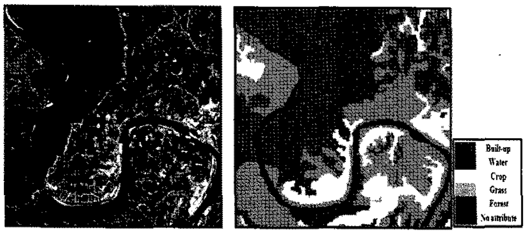
Fig. 1. Flowchart of the classification method based on automated training.

(MLC) to Landsat image with the military map. Then, a K-means algorithm was applied to a high resolution image. In second step, a matrix that shows the relation of each class in the two results was generated and then, necessary training parameters for the high resolution image's MLC process were extracted based on the matrix. Finally, the classification of the high resolution image was conducted using the training parameters from the preceding step, and the military map was updated. All of the processes were conducted using the MATLAB R2008a program and ENVI 4.5 software with Windows XP operating system.

2. Study area and data set

The experimental dataset are a QuickBird image and a SPOT-5 image as the high resolution image, Landsat TM and a military map. There were two study areas for this study. The first area was Yeoncheon in South Korea, which has an area of 100 km^2, including built-up, water, crop, grass and, forest features (Fig. 2). The second area was Cheorwon in South Korea, which has an area of 64 km^2, including built-up, water, grass and, forest features except grass (Fig. 3). These areas are a non-accessible DMZ.

A military map is comprised of small-scale vector data and provides land cover information of non-accessible areas. The feature codes of a military map follow FACC (Feature Attribute Code and Catalogue) and were integrated to built-up, water, crop, grass, and forest class. These data are of different spatial resolution to each other. Table 1 presents information of datasets used in this paper. Although there is a difference of acquisition time among data, we assume that there is little land cover change because of the restraint of development in the DMZ.



(a) (b)

Fig. 2. Study area 1. (a) QuickBird (3, 2, 1 band composite) image, (b) Military map.

(a) (b)

Fig. 3. Study area 2. (a) SPOT-5 (3, 2, 1 band composite) image, (b) Military map.

Table 1. Information about the Data Set

Sensor/Source	Time	Location
QuickBird	August on 2004	Yeoncheon in South Korea
SPOT-5	October on 2005	Cheorwon in South Korea
Landsat TM	April on 2009	Above two sites
Military Map	2003	Above two sites

3. Experimental method

In this paper, an MLC was used for classification of the Landsat image, and a K-means clustering algorithm was applied to the high resolution image. Then, the training data of each class was extracted through a matrix that showed the relationship between the above two results. Finally, a high resolution image was classified using the training data, and the military map was subsequently updated.

1) Classification of the Landsat image with ancillary data

The result of MLC using Landsat image with military map plays a role as a medium for automated training of high resolution image. The military map attributes were used as training data and prior probabilities for the MLC of the Landsat image. Prior probabilities of each class were calculated by the area proportion of each class in the military map. The Landsat image used for the MLC included six bands excluding the thermal band.

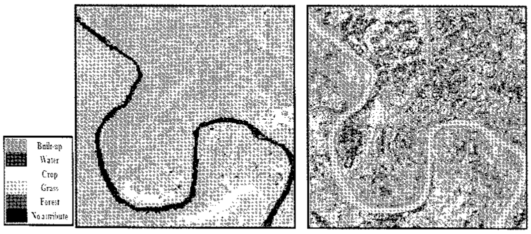
2) Classification of the high resolution image using a K-means algorithm

The K-means algorithm has been shown to be effective in producing good clustering results for many practical applications. In this paper, a K-means algorithm was applied to the QuickBird image and SPOT-5 image. The parameters of the K-means algorithm are detailed in Table 2.

Figs. 4 and 5 show the results of the MLC for the Landsat image and the results of the K-means algorithm for the QucikBird image (study area 1) and

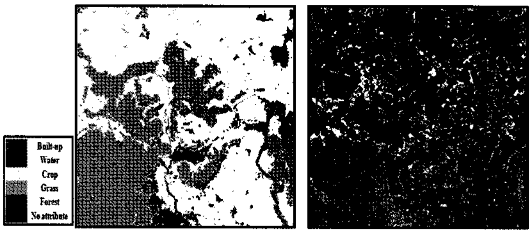
Table 2. Parameters of the K-means Algorithm

Number of Classes	10 (QuickBird), 8 (SPOT-5)
Change Threshold	0.5%
Iteration	50



(a) (b)

Fig. 4. The classification results of study area 1. (a) MLC result for the Landsat image, (b) K-means result for the QuickBird image.



(a) (b)

Fig. 5. The classification results of study area 2. (a) MLC result for the Landsat image, (b) K-means result for the SPOT-5 image.

SPOT image (study area 2). The two results were then used to construct a matrix.

3) Generation of Matrix

This method produces a matrix in order to better understand the relationships between the classes of two results. The process of making a matrix in this study is as follows: First, a COUNT matrix was made by counting the pixels of the K-means class in each of the MLC class after overlaying two results of preceding step (Tables 3, 5). In the next step, a ROW matrix was made by dividing the components of each row by the sum of the row in the COUNT matrix. As with the ROW matrix, the COLUMN matrix was made by dividing the components of each column by the sum of the column in the COUNT matrix. Finally, a RELATIONAL matrix was generated by multiplying each component of the ROW and COLUMN matrices. This process, therefore, has an effect that considers the weight of each component in the COUNT matrix. Table 4 and Table 6 show the final RELATIONAL matrix of study area 1 and study area 2.

Table 3. COUNT Matrix of Study Area 1

MLC \ K-means	1	2	3	4	5	6	7	8	9	10	sum
Built-up	1664	8248	4049	7328	5997	12043	10602	23776	18837	37423	129967
Water	4575	368641	6084	7729	2316	16779	6630	22180	10628	18817	464379
Crop	2142	11243	6038	23818	108212	63825	103641	87098	38842	37470	482329
Grass	391642	101923	715444	1006880	1264196	1285680	1228656	822757	316603	149101	7282882
Forest	730595	16125	974461	796840	593499	347721	248388	117453	47595	17766	3890443
sum	1130618	506180	1706076	1842595	1974220	1726048	1597917	1073264	432505	260577	12250000

Table 4. RELATIONAL Matrix of Study Area 1

MLC \ K-means	1	2	3	4	5	6	7	8	9	10
Built-up	1.88E-05	1.03E-03	7.39E-05	2.24E-04	1.40E-04	6.47E-04	5.41E-04	4.05E-03	6.31E-03	4.14E-02
Water	3.99E-05	5.78E-01	4.67E-05	6.98E-05	5.85E-06	3.51E-04	5.92E-05	9.87E-04	5.62E-04	2.93E-03
Crop	8.41E-06	5.18E-04	4.43E-05	6.38E-04	1.23E-02	4.89E-03	1.39E-02	1.47E-02	7.23E-03	1.12E-02
Grass	1.86E-02	2.82E-03	4.12E-02	7.55E-02	1.11E-01	1.31E-01	1.30E-01	8.66E-02	3.18E-02	1.17E-02
Forest	1.21E-01	1.32E-04	1.43E-01	8.86E-02	4.59E-02	1.80E-02	9.92E-03	3.30E-03	1.35E-03	3.11E-04

4) Extraction of training data

Training data from the high resolution image was automatically extracted using regular rules based on a RELATIONAL matrix that showed the relationships between the two results. The procedure for training extraction was as follows:

1) Find the biggest value row of each class in RELATIONAL matrix
2) If the biggest values exist in the same column, choose the value that has bigger difference compared with second biggest value in the row. Then, the class of MLC result having the second biggest value in the column selects the second biggest value in the row.

This procedure is ended at the first step, if there is the only biggest value in the column.

The chosen pixels of each class shown in Table 4, 6 were used as training data in the MLC processing of the high resolution image.

4. Result and discussion

The proposed method was applied to two different scenes from two different sensors and the results were validated by visual interpretation and quantitative assessment. Additionally, it was compared with the result that is extracted through the manual method of ENVI 4.5 software. To conduct a quantitative assessment, we chose a photo-interpretation approach rather than a field survey method to verify the proposed method because of the access constraints. We selected the 789 and 492 reference points to compose the confusion matrix from high resolution image. But we assumed that bare soil feature classified into built-up class were correctly classified because the list of classes classified is already set from military map and the spectral characteristic of bare soil feature is similar to built-up feature than other features in the image.

Fig. 6 is the result applied to the QuickBird image of study area 1. In study area 1, built-up, water, grass, and forest features were well classified. According to the characteristics of high resolution images, the result provided more detailed and accurate

Table 5. COUNT Matrix of Study Area 2

MLC \ K-means	1	2	3	4	5	6	7	8	sum
Built-up	389	946	1754	4398	8115	6525	3124	2946	28197
Water	7837	853	372	1532	760	537	248	125	12264
Crop	5492	9793	5197	34431	63628	95883	106062	55960	376446
Forest	29751	95862	62510	17762	11176	3814	1613	605	223093
sum	43469	107454	69833	58123	83679	106759	111047	59636	640000

Table 6. RELATIONAL Matrix of Study Area 2

MLC \ K-means	1	2	3	4	5	6	7	8
Built-up	1.23E-04	2.95E-04	1.56E-03	1.18E-02	2.79E-02	1.41E-02	3.12E-03	5.16E-03
Water	1.15E-01	5.52E-04	1.62E-04	3.29E-03	5.63E-04	2.20E-04	4.52E-05	2.14E-05
Crop	1.84E-03	2.37E-03	1.03E-03	5.42E-02	1.29E-01	2.29E-01	2.69E-01	1.39E-01
Forest	9.13E-02	3.83E-01	2.51E-01	2.43E-02	6.69E-03	6.11E-04	1.05E-04	2.75E-05

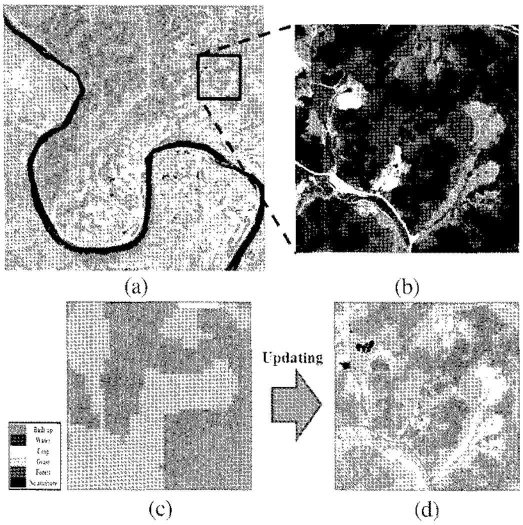


Fig. 6. The results of the proposed method(study area 1) (a) classification results of the QuickBird image, (b) magnified subimage of the original image, (c) magnified subimage of the military map, (d) magnified subimage of the classified image.

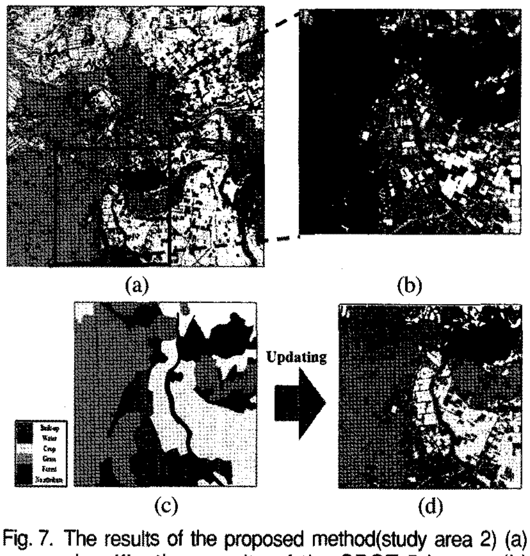


Fig. 7. The results of the proposed method(study area 2) (a) classification results of the SPOT-5 image, (b) magnified subimage of the original image, (c) magnified subimage of the military map, (d) magnified subimage of the classified image.

information than the military map. However, the crop feature was misclassified into the grass class because they have similar spectral characteristics during summer. Fig. 7 is the result applied to the SPOT-5 image of study area 2. In study area 2, the proposed method showed good performance for all features. But the case of crop feature that was not harvested showed a tendency to be classified into the built-up class.

In terms of the accuracy assessments, the overall accuracy and Kappa coefficient of the proposed method for study area 1 were respectively 78.7% and 0.73 (Table 7). The overall accuracy and Kappa coefficient of the manual method were respectively 89.2% and 0.86 (Table 8). The proposed method showed lower accuracy than the manual method. In the cases of built-up, water, and forest classes, high accuracies were seen, while crop and grass classes had relatively low accuracies including commission and omission errors due to their spectral characteristics. Crop and grass features have similar spectral characteristics during the summer season and

Table 7. Confusion Matrix of Study Area 1 by proposed Method

	Built-up	Water	Crop	Grass	Forest	User's Accuracy (%)
Built-up	**185**	0	0	0	0	100.0
Water	0	**115**	0	0	0	100.0
Crop	1	2	**12**	31	0	26.1
Grass	0	0	130	**127**	3	48.6
Forest	0	0	0	1	**182**	99.5
Producer's Accuracy (%)	99.5	98.3	8.5	79.9	98.4	**78.7** (Overall)

Kappa coefficient = 0.73

Table 8. Confusion Matrix of Study Area 1 by Manual Method

	Built-up	Water	Crop	Grass	Forest	User's Accuracy (%)
Built-up	**181**	0	0	0	0	100.0
Water	0	**96**	0	0	0	100.0
Crop	5	0	**107**	17	0	83.0
Grass	0	12	34	**140**	5	73.3
Forest	0	9	1	2	**180**	93.8
Producer's Accuracy (%)	97.3	82.0	75.3	88.1	97.3	**89.2** (Overall)

Kappa coefficient = 0.86

this led to a low separability between crop and grass. This situation was also evident in the results of the manual method. Thus, we expect that this problem is solved by using other seasonal images.

In the case of study area 2, the overall accuracy and Kappa coefficient of the proposed method were respectively 88.4% and 0.84 (Table 9). The overall accuracy and Kappa coefficient of the manual method were respectively 90.1% and 0.87 (Table 10). The two methods appeared to provide high overall accuracy in study area 2. The principal reason is that the SPOT-5 image was taken during autumn and homogeneity was increased due to the lower spatial resolution of the SPOT-5 image. In addition, separability among all classes was better at study area 2 than at study area 1 because there were only four classes but no grass class in the military map. Therefore, the proposed method showed good performance for study area 2.

Table 9. Confusion Matrix of Study Area 2 by proposed Method

	Built-up	Water	Crop	Forest	User's Accuracy (%)
Built-up	**84**	4	19	3	76.3
Water	1	**112**	0	3	96.6
Crop	25	0	**136**	0	84.5
Forest	1	1	0	**103**	98.1
Producer's Accuracy (%)	75.7	95.7	87.7	94.5	**88.4** (Overall)

Kappa coefficient = 0.84

Table 10. Confusion Matrix of Study Area 2 by Manual Method

	Built-up	Water	Crop	Forest	User's Accuracy (%)
Built-up	**108**	26	15	5	70.1
Water	0	**91**	0	0	100.0
Crop	3	0	**140**	0	97.9
Forest	0	0	0	**104**	100.0
Producer's Accuracy (%)	97.3	77.8	90.3	95.4	**90.1** (Overall)

Kappa coefficient = 0.87

5. Conclusion

In this paper, an automated training method was proposed to classify high resolution image of non-accessible area. The proposed method can be effective and time-saving and produce the objective results due to the exclusion of operator interventions. Additionally, by utilizing commercially available high resolution images, we were able to produce better detail and more accurate information.

The proposed method performs an automated supervised classification by automatically extracting training data through RERATIONAL matrix that shows the relation between classes of the result classified. This method was applied to a QuickBird image and a SPOT-5 image. In order to validate, both visual interpretation and quantitative assessment of the results were conducted with the manual method. As the result, we concluded that the proposed method can advantageously be used to automatically revise and update GIS data of non-accessible areas.

The one drawback in using this method is that it tends to show low accuracy in the classifications of crop and grass classes during the summer season because of their similar spectral characteristics. Therefore, in order to solve this problem, future work will focus on raising the accuracy of classification for these two classes through the use of other methods, such as shape and texture based methods.

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