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Image Classification with Higher-Dimension Watershed Classifier: A Test to Malaysian National Land Use Classification Scheme

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Abstract

Recent image classification based on *watershed* algorithm (Watson et. al.,1992) has reported as a potential method for producing accurate method of classifying satellite images. This method, however, can only be applied to 2-D feature space and hence several independen analysis had to be combined to give acceptable results. In this paper, a generalizat n of the *watershed* algorithm to enable classification of any n-D feature space is presented and analysed. Results are presented for 3 different models of classification: (i) maximum likelihood, (ii) combinations of 2-D *watersheds,* and (iii) n-D *watershed,* tested over a relatively heterogeneous land cover of Malaysia. It is shown that the n-D *watershed* method is the most superior, although it has not reported a substantial improvement in the classification accuracy from the 2-D approach. Given the elaborate computational time taken by the n-D watershed, it is concluded that the n-D watershed is no better than the 2-D approach.

1.0 INTRODUCTION

The application of satellite remotely sensed data for land cover mapping has long been recognized (Haralick and Fu,1983; Thomas et. al.,1987), although the search for operational and robust technique for extracting this information still continues (Townshend,1992). Among others, the poor classification accuracy is mainly due to the assumption made by most classifiers such as the widely used maximum likelihood technique that classes within an image are multi-normally distributed or composed of finite number of classes. The spectral data rarely, if ever, can conform to these assumptions. Image classification which use these assumptions, often end up with large errors (Ince,1987; Mather,1990), and even if manual editing is performed in the training collection as in the parametric approach where a strict threshold for each class is enforced, then it usually leaves the image not fully classified. The unclassified pixels are usually the classes which are inadequately represented by this normal statistics especially in the higher resolution of the new generation satellite data like Landsat TM and SPOT (Bolstad and Lillesand, 1991).

Numerous attempts have used multi-temporal, multi-resolution, and prior probabilities (Strahler,1980; Maselli,et.al.l992) in an attempt to improve classification, but the results have been so far poor from the operational point of view. Apart from the above mentioned conventional classification, the recent *watershed* method proposed by Watson et. al. (1992) has shown a potential for producing accurate classification. The watershed classifier is a pattern recognition technique which use a particle detection procedure to construct spectral classes which then can be assigned to the ground truth classes. The watershed algorithm without any prior assumptions of the classes parameters seems to be one of the promising methods, however, it can only be applied to 2-D feature space and hence several independent analysis had to be combined to give best results (Watson et. al.,1992). In addition, the watershed method has not been demonstrated on large operational sizes of more than 512x512 extract. Consequently, this paper will examine the generalization of watershed method using input from n-D feature space for scene covering the size of one operational land use map of Malaysia.

2.0 THE WATERSHED CLASSIFICATION METHOD

The watershed classification method segments the image into discrete classes directly from analysis of the feature space on the connectivity basis as in algorithms of Beucher (1982). The basic idea of segmenting using watershed is to partition the feature space based on the analogy of water flows over a complex surface. Figure 1 illustrates the visualization of the watershed and its associated terms used in describing the method. When water flows over the surface, it firstly streams down, reaching the deepest point (minimum or sink) where it stops. With each minimum, a locus of points from which the water may flow-in can be identified. This locus is referred to as *catchment*. Several catchments can overlap, and their common points form the *watershed.*

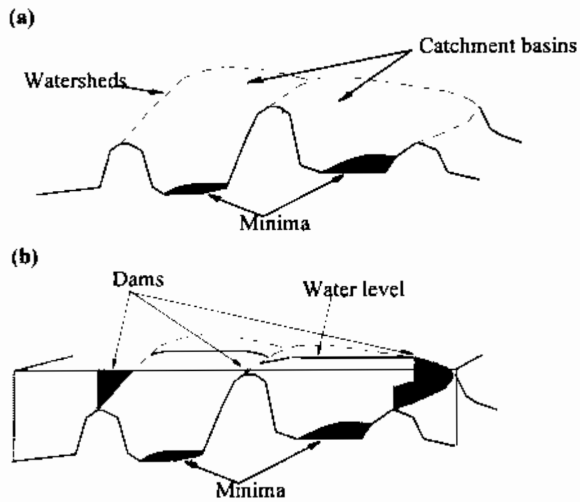

Figure 1 : Illustration of watershed. (a) shows the minima, catchment basins and the watersheds. (b) Building the dams at places where water coming from two different minima would merge, where the analogy used in the immersion simulation algorithm for formation of watershed in the n-D feature space. Please refer texts for descriptions. (after Vincent and and Soille,1991).

In adapting the watershed analogy in partitioning the feature space of remotely sensed data, the aim is firstly to locate the minimum points (sinks), and secondly to find the watersheds. To enable this, however, two processing prerequisites must be fulfilled : (i) the random access to any pixels within the image, and (ii) direct access to the neighbours of a given pixel. As such, for the purpose of classifying multispectral images of satellite remotely sensed data, only two approaches of watershed formation are of interest here ; (i) the 2-D watershed, and (ii) the n-D watershed.

2.1 2-D Watershed

In the 2-D approach, Watson et. al. (1992) used the Golay L (Golay,1969) structuring element to form the watersheds. This is carried out by first constructing a bivariate histogram of the two features input where the local highs are located instead of the minimum, and repeatedly connected to these local high any point which is one less in height and is uniquely adjacent to the high point. These local high groups are then expanded to the next lower height until zero is reached. When two groups have the topological criteria such that they start competing for the same conditions, then L structuring element will automatically detect such conditions, and set them to zero. The processing is carried out reiteratively as each of the grey level of the bivariate histogram is scanned down, and those points that are not connected to any group is then formed as a seed for further generating other groups. As the grey level is descended, the number of groups formed will increase and such that when there is no further possible regrouping or when zero is reached.

The only limitation of this method is that it can only be applied to 2-D feature space and hence several independent analysis had to be combined to give acceptable results. For example, for a six TM bands, 15 bivariate histograms are needed to be formed when all the six are to be used in the classification, hence producing 15 classified images. This, however, is not as critical as all the classified images can be labelled by an object labelling program, where a unique thematic map can then be produced (Watson,1987). Data compression technique might be another alternative to this problem. For example, the principal component transformation can be used to compressed multispectral band, although total solution of capturing all the information from this transformation is normally up to only 95% for first two components derived. The third component would have the remainder, and again if this component is to be considered into the classification, two classified spectral images are then produced. In such a case, labelling more than one classified images containing spectral groups according to ground truth is then necessary. This, however can be optimally labelled simultaneously using object labelling program mentioned earlier.

2.2 n-D Watershed

In the higher dimension watershed, the histogram is inverted, mathematically so that the peaks of the histogram become the sinks of the sinks immersion. The process of finding the sinks and the growing process to form the watersheds remain the essential elements of the problem as described earlier, but the region growing process is based on *immersion simulation* algorithm (Vincent and Soille,1991). Finding watersheds by this algorithm is best described by analogy piercing holes in each sinks (local minima) of an image (see Figure 1-b). Immersing this surface into a lake, the water starts filling the surface through the pierced holes, filling up firstly the local minima of the lowest altitude and then continue progressively filling the different catchment basins. If *dams* are builts at each pixel where water from two different minimas emerged, then at the end of the immersion process, each of the local minimum is surrounded by dams; which is termed in mathematical morphology as catchment basin. Thus, the dams that have been built provide a tessellation of the surface into its different catchment basins and these dams correspond to watersheds of the image.

By using the immersion simulation algorithm, the two prequisite steps remain unchanged. First, the pixel intensity vectors of the input image is sorted in the accumulative manner, where for each sorted grey level, an arbitrary labels are initially assigned. For the selected initial number of arbitrary labels in the accumulated grey level, a significant distance between them must also be imposed. This sorting ensure the access to any pixels and its neighbourhood within the input image, even if an n-D input is used. Secondly the growing of the watershed, referred to as *flooding* in the immersion simulation algorithm is determined by computing the *geodesic influence zones* of the minimas. Detailed descriptions of the rules can be found in Vincent and Soille (1991).

To implement n-D watershed method on the image processing system, a computer program was written in the Sun Sparc-5 worksation. The program accepts variable input features. The sorting of the intensity vectors of the input image is achieved using the hash-table technique (Shlien,1975). The access to the neighbouring pixels during the flooding process is controlled by the connectivity parameter. Small connectivity ensures more detailed classification than larger connectivity but it takes more computational time. Test of the connectivity parameters with respect to computational time is given in the evaluation section. During the flooding process, the above topological measure - geodesic influence zones are used to connect a pixel to the appropriate class if it satisfies all the topological conditions within the n-D feature space. If a pixel cannot be connected to any existing class within the feature space, it is then set to a new class, and the whole flooding process is repeated until all the feature space is divided into separate watersheds or spectral classes. The output of the processing is a single classification label for each pixel. As such, the n-D watershed produced much simpler output than the combined 2-D procedure.

3.0 APPLICATION TEST

3.1 Study area

To test the applicability of the n-D watershed, a Landsat TM sub-scene measuring 1024x1024 pixels of Malaysia was used in this test. The corresponding land-use map where the classes were compiled using the national land use classification scheme (Wong,1971) was used to evaluate the tested classifiers. The land-use map were digitised and rasterized to the equivalent image spatial resolution. The image data were later geometrically-corrected by registering the prominent points in the image to the corresponding features in the digitized land use map.

A total of 13 land cover types, namely the agricultural land use classes were tested in this study. To avoid any uncertainty that these defined classes can adequately be delineated from spectral data, an independent set of pixels for each land use class categories were collected by visual analysis and used as test sets. This test set were later verified for their validity on the ground, and are hereafter, referred to as image truth. It is noteworthly to mention that all the 13 tested classes, have not ever been successfully delineated either with parametric or nonparametric approach of digital classification (Hashim et. al.,1992).

3.2 Classification Approach

All the six TM bands (excluding the thermal) of the study area are classified using the two above-mentioned watershed methods. In the 2-D watershed, 3 band pairings - bands 1-4, bands 2-5, and bands 3-6 are used after been priorily identified as having the least correlations among them. Three sets of spectral groups were produced from the three band pairings. In the n-D approach, all the six bands are processed simultaneously, producing a single classified spectral image.

Apart from the two watershed classification methods, the widely used maximum likelihood classification (MLC) was also carried out so as to enable comparison of the earlier two watershed methods to be made. The MLC was performed using the combined unsupervised/supervised approach where it involve two procedures, starting with clustering the input image into initial 100 spectral clusters. These spectral clusters are then used as trainings in the following maximum likelihood classification (Richards,1986).

The classified spectral groups produced by the three classification methods (2-D, n-D, and MLC) are then labelled using an object labelling program. The program divides the image into two mutually exclusive sets : one the training set and the other the test set. The training set allows the arbitrary spectral class labels to be translated into ground truth labels for each method. The last set was then used to evaluate the accuracy for each method.

3.3 Evaluation

The classification accuracy is determined by analysing the classification error matrix and Kappa coeficient of agreement (Hudson and Ramn,1987). Ten random classification assessments using the image truth set are used in the accuracy analysis. The average of the ten error matrices was then used in the computing the kappa coefficeient of agreement. Apart from these two assessments, the processing times were also noted for the classification methods.

4.0 RESULTS AND DISCUSSION

The classification accuracy is summarised in Table 1. The classified images of the study area using the three classification method were shown in plate 1. For presentation convenience only 500x300 image is shown. The corresponding land use map used as the classification labels and the image truth where the test pixels for the accuracy assessments are seleceted shown are also in plate 1.

The n-D approach reported the best classification accuracy (k=0.703) compared to the 2-D watershed (k=0.627). Judging at individual classes accuracies, the n-D feature space where the classes were initially grown are far more sensitive to the delineation of classes that contain minimum delineations such as in the case of 1u, 1t, 2h and 7c. Field checks conducted confirm that these classes have very similar landscape characteristics that they are not able to be separated by spectral data alone without experiencing large errors. The major classes depicted in the study area were the 3o, 3g, 7f and 8. It is interesting to note that these classes are much better classified with the n-D. The MLC only reported identifying only 6 classes with lowest classification accuracy of 57 per cent (k=0.568) compared to the previous two watershed methods. The MLC only recognised big contiguous classes, and relatively small classes were not successfully delineated at all.

Apart from the better classification accuracy shown by the n-D approach, the formation of the watersheds in the n-D feature space was very time consuming. In initial stage of this study, the n-D was run on the *Microvax4000* worskstation but due to the excessively time consuming, the classification was then hosted on the *Sun Sparc-5* workstation. The processing time taken for classifying the image was directly proportional to the image size, connectivity and the number of input features. The connectivity is the level of which the watersheds to be formed. Connectivity 1 will get all adjacent pixels in proximity of 1 to be part of the catchment basin if they fulfilled the topological requirement (see Figure 1) Computational time recorded by the n-D watershed in classifying various image sizes with different connectivity parameters and numbers of feature input is given in Table 2.

The classification time of the 2-D watershed method, on the other hand, was relatively fast compared to the n-D, even running the classification only on the Microvax 4000 system. Three 2-D watersheds was produced by the 2 band pairings in less than two hours, and it took another 10 minutes for labelling the three watersheds to produce final labelled classification. Having noted processing time using the two watershed approaches and the marginal classification accuracy increment of 9 per cent, the previous 2-D method in this case is still considered better means of classification from the practical point of view.

The quite low overall average accuracy of both the watershed methods tested are very much contradicting to the accurate classification as reported by Watson et. al.(1992). Cursory examination of the data, however, revealed that there exists a relatively high spectral fragmentations within the spectral image data Although the inclusion of pixel in forming a class is determined by the connectivity factor, but the isolated pixel that are distinctive in their intensity compared to the neighourhood will be still classified as a single-pixel end class in the n-D watershed method. Table 3 below tabulates the number of single-pixel end class tested using different iage extract with various connectivity factors and numbers of feature input. Reducing the number of these single-classes would gives a simple means of lowering the spectral fragmentations, hence if this procedure is sucessfully implemented, an accurate classification (in excess of 95 per cents) can thus be achieved.

5.0 CONCLUSION

In this paper, the attempt to generalize the watershed classification method using more than 2-D feature input have been presented. The results have shown that n-D watershed method can be implemented and yield better classification accuracy, even in a highly spectral fragmented Landsat TM data over the Malaysian heterogeneous landscape. The n-D watershed, however, takes more computational time compared to the previous 2-D approach. In addtion, the n-D watershed method also requires at least hardware that is equivalent to the Sun Sparc-5 workstation. Having seen marginal accuracy improvement (9 percent) over the previous 2-D approach, the special hardware requirement and the time taken by the n-D watershed approach is therefore not reasonably justifiable from the prcatical point of vew. However, further development of the n-D method, particularly on ways to expedite the processings are very much recommended, as to in-line with current trend of hyperspectral sensor development.

5.1 Acknowlegments

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