An Accuracy Comparison for the Landslide Inventory with the BPNN and SVM Methods

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ABSTRACT:

Landslides are natural phenomena for the dynamic balance of earth surface. Due to the frequent occurrences of typhoons and earthquake activities in Taiwan, mass movements are common threatens to our lives. In this paper, the interpretation knowledge is quantified into recognition criteria. Multi-source high-resolution data, e.g. a SPOT satellite image, 5m x 5m DTM reduced from a LIDAR data, road and river vector data, are fused to construct the feature space for landslides analysis. Then, those features are used to recognize landslides by a Back-Prapogation Neural Network (BPNN) Method and a Supported Vector Machine (SVM) Method. The extraction results are evaluated in comparison with the manual-interpretation result. The experiments indicate that the conducted method can assist landslide investigation efficiently and automatically. Moreover, the ANN method is better than some statistic classification methods, e.g. Maximum Likelihood method, due to its adaptability for multi-resource data and no predefined assumption.

1. INTRODUCTION

1.1 Motivation

Landslides are natural phenomena for the dynamic balance of earth surface. The potential or intrinsic factors of landslide include geological and morphological factors and the external or triggering factors include earthquake, climate, hydrology, and human activities. The geology is highly fractured and landforms are in high relief in Taiwan. In addition, the frequent earthquakes and heavy rainfalls are together imposing further stress to the earth to break the balance of the nature. And, thus, mass movements such as landslides, slumping, and mudflows take places.

Taiwan has a land area of 36000 m^2, 26.68% of which are covered by plain region, whereas 27.31% of which are hilly and 46.01% are mountainous. By official definition for the purpose of land conservation management, hilly lands refer to the area between 100m and 1000m AMSL or the area under 100m but with a slope more than 5%. Mountainous lands refer to the area with an altitude above 1000m AMSL (Liu et al. 2009).

The complicated landscape of Taiwan is characterized by small drainage basins, highly fractured rock, high relief, and steep stream gradients. Frequent earthquakes due to the collision of Eurasian Plate and Philippine Sea Plate further loosen the top surface of the land. Therefore the lands are particularly sensitive to episodic events such as typhoons and earthquakes, and to various types of anthropogenic disturbance.

In addition, the average annual rainfall of Taiwan is 250.00 cm which is about three times of the average annual rainfall on the earth. Landslides are easily induced by the heavy rainfall come along with typhoons. The consequence is the sedimentation of the reservoirs. And the turbidity of the water in reservoirs becomes a major factor impacting the sustainable operation of water supply reservoirs in Taiwan. Landslides have to be recovered and their hazards have to be mitigated. The necessity of landslide survey is obvious.

It has been a common practice to interpret aerial photographs by visual inspection of an expert geologist. It is a time consuming task. Therefore, the purpose of this study is to implement the human rules and quantifies the criteria with two automatic classification methods, e.g. a Back-Propagation Neural Network (abbreviated as BPNN) and a support vector machine (abbreviated as SVM) methods, to verify their accuracy for the rainfall-induced landslide inventory.

1.2 Overview of related works

Landslides cause approximately 1000 deaths a year worldwide with a property damage of about US$4 billion, and pose serious threats to settlements and structures that support transportation, natural resource management and tourism. In many cases, over-expanded development and activities, such as slope cutting and deforestation, can sometimes increase the incidence of landslide disasters. Recent development in large metropolitan areas intrudes upon unstable terrain. This has thrown many urban communities into disarray, providing grim examples of the

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extreme disruption caused by ground failures (Singhroy and Mattar, 2000).

Aerial photography has been used extensively to characterize landslides and to produce landslide inventory maps, particularly because of their stereo viewing capability and high spatial resolution (Liu, 1985). Aerial photo interpretation has long been adopted for landslide inventory. This conventional method is based on visual perception of colour tone and geo-morphological features of landslides on the aerial photographs. However, the conventional photo-interpretation is a time-consuming and costly approach (Liu, 1987).

Satellite imagery can also be used to collect data on the relevant parameters involved such as soils, geology, slope, geomorphology, land use, hydrology, rainfall, faults, etc. Multispectral images are used for the classification of lithology, vegetation, and land use, Stereo SPOT imagery is used in geo-morphological mapping or terrain classification (Wu et al., 1989; Liang, 1997; Liu, 1999; Hsu et al., 2002). For landslide inventory mapping the size of the landslide features in relation to the ground resolution of the remote sensing data is very important. A typical landslide of 40000 m^2, for example, corresponds with 20x20 pixels on a SPOT Pan image and 10*10 pixels on SPOT multi-spectral images. This would be sufficient to identify a landslide that has a high contrast, with respect to its surroundings e.g. bare scarps within vegetated terrain, but it is insufficient for a proper analysis of the elements pertaining to the failure to establish characteristics and type of landslide (Hsiao et al., 2003). It is expected that in the future the Very High Resolution (VHR) imagery, such as from IKONOS-2, might be used successfully for landslide inventory (Westen, 2000). By using the criteria for visual interpretation, artificial intelligent of expert system and automatic procedures can be developed to improve the efficiency and accuracy of landslide mapping (Kojima et al., 2000; Liu et al., 2001).

In a real case, limitations are due to the spatial and spectral resolutions of the images. More than 50% of the rainfall-induced landslides in Taiwan are less than 50 m in length. Landslides of this scale are not readily identifiable using images of a pixel-size larger than 10 m. By pixel-wise classification, landslides can occupy only individual or just a few pixels without forming an outer shape of landslides. Moreover, commission and omission errors can further complicate the situation.

The classification for the remote sensing data had been developed for a long time ago. Traditional used classification methods, e.g. Maximum Likelihood method is based on statistical analysis. It will be limited by a priori statistical assumption, e.g. probability distribution, and by the Hughes Effect, denoting that increasing data bands imposes a need to increase training samples.

Artificial Neural Networks (ANNs) have been used successfully in many applications such as pattern recognition, function approximation, optimization, forecasting, data retrieval, automatic control and landslide interpretation (Robert, 1990; Zurada, 1992; Chang and Liu, 2004). ANNs have been found to be powerful and versatile computational tools for organizing and correlating information in ways that have proved more useful for solving certain types of problems too complex, too poorly understood, or too resource-intensive to tackle than traditional computational methods. However, it is a black box for the trained network and the derived results will easily tend to local extreme values for the solution (Bischof et al., 1992).

Recently, some variant support vector machine (SVM) methods, based on statistical learning, had been used on the land use/cover classification (Zhu and Blumberg, 2002, Foody and Mathur, 2004, Camps-Valls and Bruzzone, 2005, Chen, 2006). All of their experimental results indicated that the derived results using the SVM method are better than other discriminant-based classification methods.

2. METHODOLOGY

Individual landslides are generally small and located in certain locations of a slope. Landslides occur in a large variety, depending on the type of movement such as (slide, topple, flow, fall, spread), the speed of movement (mm/year-m/sec), the material involved (rock, debris, soil), and the triggering mechanism (earthquake, rainfall, human interaction). Survey methods usually include ground survey, aerial or space-borne survey, or a combination.

Ground survey can be high accurate, but slow. When hazards take places, accessibility is low. Therefore, it is impossible to make the survey in near real-time or in a complete coverage after a torrential rainfall.

Photographic or image interpretation approach can be adopted and implemented manually, automatically, or semi-automatically. Manual interpretation requires well-trained geologist to delineate the landslides under a stereoscopic environment. The advantage of this approach is that individual landslide can be defined very clearly. However, manual interpretation is too slow to meet the requirements for emergency response. Automatic classification of landslides is based on certain criteria and computing algorithms. The advantage for image classification is the objectiveness of the approach. Most of the recent automatic classification methods of landslides using images are based on spectral features other than topographic features. Therefore, the inventory results usually can not meet the requirements for taking engineering measures. A recent study is to establish a hybrid approach to combine the advantages of automatic processes with manual interpretation. A software interface was designed to assist visual interpretation of landslides. Both spectral and spatial parameters are employed for the inputs of the software to assist the interpreter/operator to correctly recognize and delineate landslides (Liu et al., 2009).

2.1 Artificial Neural Network method

An Artificial Neural Network (ANN) is a simulation of the functioning of the human nervous system that produces the required response to input (Robert, 1990). ANN is able to provide some of the human characteristics of problem-solving ability that are difficult to simulate using logical, analytical techniques. One of the advantages of using ANN is that it doesn't need a predefined knowledge base. ANN can learn associative patterns and approximate the functional relationship between a set of input and output. A well-trained ANN, for example, may be able to discern, with a high degree of consistency, patterns that human experts would miss. In a neural network, the fundamental variables are the set of connection weights. A network is highly interconnected and consists of many neurons that perform parallel computations. Each neuron is linked to other neurons with varying coefficients of connectivity that represent the weights (sometime is refereed as strengths in other literature) of these connections. Learning by the network is accomplished by adjusting these weights to produce appropriate output through training examples fed to the network (Zurada, 1992).

The multilayer perceptron (MLP) is one of the most widely implemented neural network topologies. The article by Lippman is probably one of the best references for the computational capabilities of MLPs. Generally speaking, for

static pattern classification, the MLP with two hidden layers is a universal pattern classifier. In other words, the discriminant functions can take any shape, as required by the input data clusters. Moreover, when the weights are properly normalized and the output classes are normalized to 0/1, the MLP achieves the performance of the maximum a posteriori receiver, which is optimal from a classification point of view. In terms of mapping abilities, the MLP is believed to be capable of approximating arbitrary functions. This has been important in the study of nonlinear dynamics, and other function mapping problems. The MLPs are trained with error correction learning, which means that the desired response for the system must be known, as well known as backpropagation algorithm (Zurada, 1992). The objective of learning is to minimize the error (RMS in this case) between the predicted output and the known output.

An MLP type neural network model was utilized in this work using the Neural Net function in ENVI 4.3 software (Research System, Inc., 2006). The Neural Net technique uses standard back-propagation for supervised learning. You can select the number of hidden layers to use and you can choose between a logistic or hyperbolic activation function. Learning occurs by adjusting the weights in the node to minimize the difference between the output node activation and the output. The error is back-propagated through the network and weight adjustment is made using a recursive method. You can use Neural Net classification to perform non-linear classification.

2.2 Support Vector Machine (SVM) method

The SVM method is a classification system derived from statistical learning theory. It separates the classes with a decision surface that maximizes the margin between the classes. The surface is often called the optimal hyper-plane, and the data points closest to the hyper-plane are called support vectors. The support vectors are the critical elements of the training set (Research System, Inc., 2006; Chen, 2006).

You can adapt SVM to become a nonlinear classifier through the use of nonlinear kernels. While SVM is a binary classifier in its simplest form, it can function as a multiclass classifier by combining several binary SVM classifiers (creating a binary classifier for each possible pair of classes). ENVI's implementation of SVM uses the pair-wise classification strategy for multiclass classification. SVM classification output is the decision values of each pixel for each class, which are used for probability estimates. The probability values, stored in ENVI as rule images, represent "true" probability in the sense that each probability falls in the range of 0 to 1, and the sum of these values for each pixel equals 1. ENVI performs classification by selecting the highest probability. An optional threshold allows reporting pixels with all probability values less than the threshold as unclassified.

SVM includes a penalty parameter that allows a certain degree of misclassification, which is particularly important for non-separable training sets. The penalty parameter controls the trade-off between allowing training errors and forcing rigid margins. It creates a soft margin that permits some misclassifications, such as it allows some training points on the wrong side of the hyper-plane. Increasing the value of the penalty parameter increases the cost of misclassifying points and forces the creation of a more accurate model that may not generalize well.

The ENVI's SVM classifier provides four types of kernels: linear, polynomial, radial basis function (RBF), and sigmoid. The default is the radial basis function kernel, which works well in most cases.

Use the Pyramid Levels field to set the number of hierarchical processing levels to apply during the SVM training and classification process. If this value is set to 0, ENVI processes the image at full resolution only. The default is 0. The maximum value is dynamic; it varies with the size of the image you select. The maximum value is determined by the criteria that the highest pyramid-level image is larger than 64 x 64. For example, for an image that is 24000 x 24000, the maximum level is 8.

3. CASE STUDY

3.1 Test area and experimental materials

A test area located at the Alishan up-stream basin in central Taiwan had been used. Its area is about 36 square kilometres. In the study area, the accumulated rainfall had reached 811mm in 24 hours and 1200 mm in 48 hours since 9th June 2006. This heavy rainfall event, so called "6-9 torrential rainfall", induced enormous amount of debris flows and slides. LiDAR data and aerial photographs were taken on 18th June, 20th June and 22nd June of 2006, respectively. Moreover, a SPOT-5 mosaic satellite image, shown as figure 1, taken on the relative time, was also used to test automatic classification methods. There had been no records of heavy rainfall events one year prior to this event. The landslides observed with these datasets can be solely attributed to this torrential rainfall event.

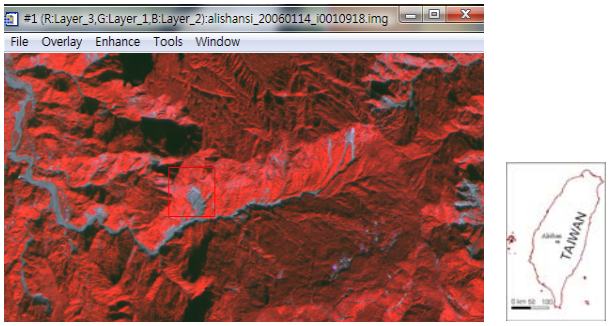

Figure 1. SPOT-5 image for the test area

The orthophotos used in this study, shown in figure 2, are generated by aerial photographs taken by directly geo-referencing technique and orthorectified by LiDAR DSM without using ground control points. Photography and laser scanning are synchronized. Because airborne LiDAR is equipped with GPS and IMU, an event mark is given when photography system triggers a Transistor-Transistor Logic pulse. Thus, the instantaneous GPS and IMU information can be used to resolve the exterior orientation of the photo frame, i.e. x, y, z, ω, ψ, κ. Subsequently, the true-ortho ground surface model, e.g. LiDAR DSM is used for the ortho-rectification..

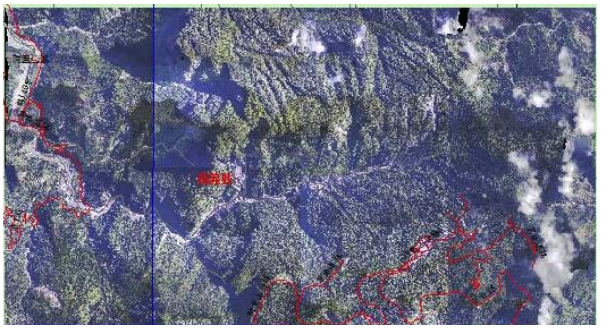
Figure 2. True-ortho aerial photos for the test area

Leica ALS50 airborne LiDAR system used in this study is consisted of 2 major parts, i.e. a laser scanning assembly and a Position and Orientation System (POS). The former one is for triggering laser pulses, controlling the range, the swath, the field of view (FOV), the scan rate and the pulse rate. These parameters decide how fast we can make a complete coverage of the survey area. The second part is critical to the positioning accuracy.

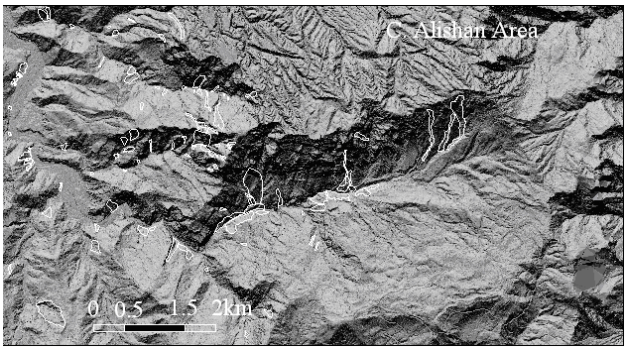

Figure 3. The DTM generated from the LiDAR sensor

Point density is an important indicator for the spatial resolution of LiDAR DEM and DSM. An understanding of the forest closure and crown density can be obtained by preliminary inspection of the point-density distribution of point clouds (Means et al., 2000; Naesset, 2002). In this study, the point density is around 4 points/m^2. The upper envelope of the point clouds is interpolated to form a digital surface model (abbreviated as DSM), whereas the point clouds that hit the bare ground or that are filtered to eliminate off-ground points are interpolated to form a Digital Elevation Model (abbreviated as DEM). In other words, DEM denotes the bare ground surface. Sometimes, it is also known as digital terrain models, abbreviated as DTM. The accuracy of the DEM and DSM can be varied due to the change of land-cover types and density of vegetation. For assuring the accuracy, ground survey with total stations was carried out for 347 selected samples. The RMSE is 0.82m, and mean error is 0.73m (Table 1). On basis of field observation, the errors are attributed to the dense low bushes underneath the tree-canopies. This over-estimation of DEM is a noteworthy phenomenon especially for tropical and sub-tropical forest. In general, for bare ground, the accuracy is about 0.15m (Liu et al., 2009).

Table 1. Accuracy assessment of the digital elevation models

Locations	Sample size	Average error (m)	RMSE (m)	Standard Error (m)
Tree base	219	0.70	0.77	0.33
Open Ground	128	0.79	0.90	0.43
Total	347	0.73	0.82	0.37

3.2 The Ground Truth generated by visual interpretation

The perception of landslides from a bird-eye view of aerial photographs is also largely depending on the scale or spatial resolution of the photographs. Landslides can not be mapped properly when they are smaller than a minimum mapping unit. In general, four factors affect the quality of the mapping results, namely the scale, the time lag between the landslide event and the aerial photography, the used film type, and the overall quality of the photographs. Six criteria can be used for the recognition of landslides on aerial photographs, including tone, location, shape, direction, slope, and shadow effects. The result of manual air-photo interpretation shown as Figure 4 can be used as the ground truth for the following tests.

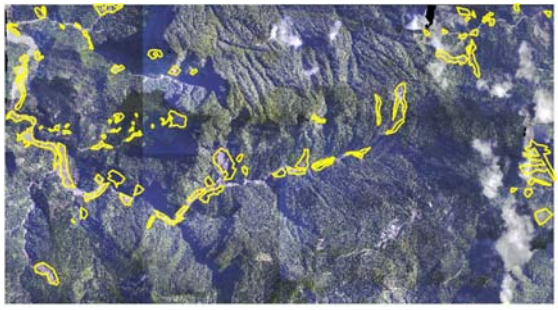

Figure 4. The ground truth derived by manual interpretation

4. RESULTS AND ANALYSIS

4.1 Creation of the training ROIs

To create training sites for each class, the ROI tool function was used to define the regions what we interested. In the preliminary study, six classes were set as shown as Table 2. The pixel size and its colour used for each class are listed in the table. All training ROIs are shown as Figure 5. Through the training and classification procedures, the results will be reclassified into collapse and non-collapse two classes.

Table 2. Six classes for the selected ROIs of training samples

Class	Code	Pixel size	Colour
Collapse	R1	121	Red
Aspect surface of woods	R2	161	Green
Back-light surface of woods	R3	186	Blue
Building	R4	124	Yellow
Cloud	R5	72	Magenta
River	R6	114	Sea Green

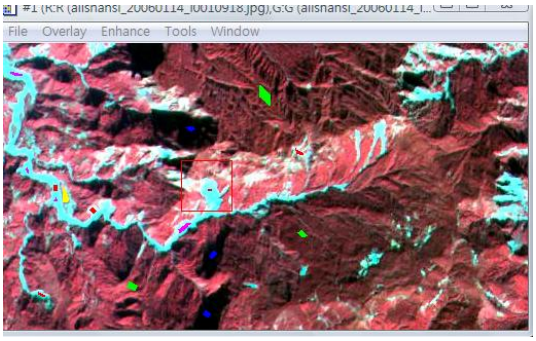

Figure 5. The ROIs of training samples

4.2 Classification results

Using the above mentioned training ROIs, the classification results for the BPNN, SVM methods are derived as shown as Figure 7 and 8. In many test results for the BPNN method, the best chosen parameters and its corresponding result are shown as Table 3 and Figure 6, respectively. However, the default parameters for the SVM method are used to get the result (Figure 7). Meanwhile, the result for the Maximum Likelihood (ML) method, shown as Figure 8, also implemented for the comparison.

Table 3. The best parameters setup for the BPNN method

Parameter name	Value
Training Threshold Contribution	0.8
Training Rate	0.8
Training Momentum	0.5
Training RMS Exit Criteria	0.01
Number of Hidden Layers	1
Number of Training Iterations	20000

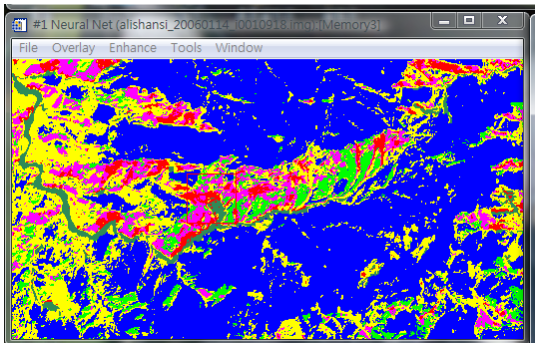

Figure 6. The classification result for the BPNN method

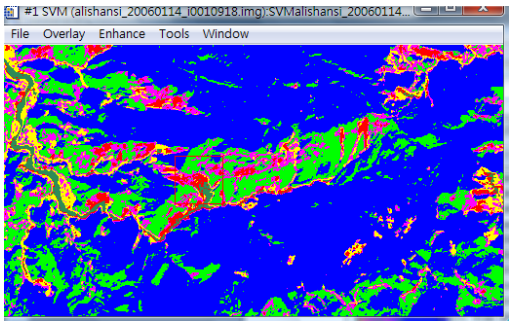

Figure 7. The classification result for the SVM method

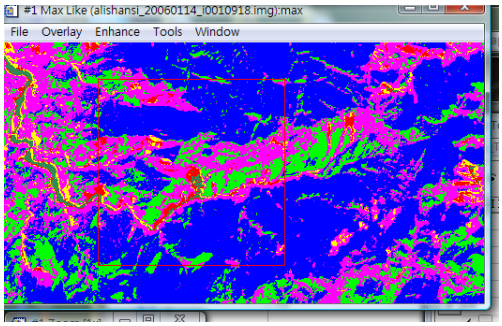

Figure 8. The classification result for the ML method

4.3 Visual comparisons

For the accuracy assessment of different classification methods, the result for each method is overlaid with the ground truth. The visual comparison result for the ML, BPNN, and SVM method are shown as Figure 9 - 11, respectively. The black polygons in the figures represent landslide areas in the ground truth.

In the overall comparison, the result for the SVM method is better than the results derived from other two methods. Moreover, there is some erroneous judgement for the "cloud" and "aspect surface of woods" classes as shown in figure 9. Although decreasing the erroneous judgement of the "cloud" class in figure 10, but increasing the erroneous judgement of the "building" class. Due to the similarity of colour tone between the river valley and the landslide areas, it leads to a different level of confused results for three methods.

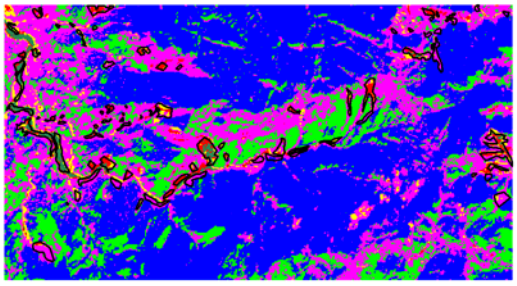
Figure 9. The visual comparison result for the ML method

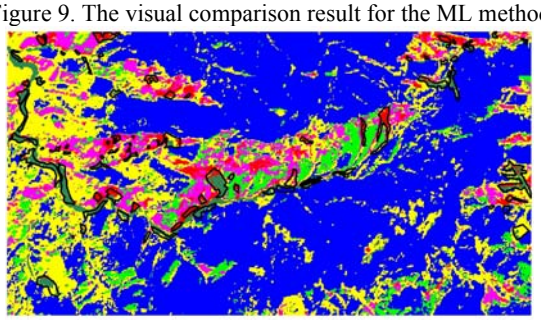
Figure 10. The visual comparison result for the BPNN method

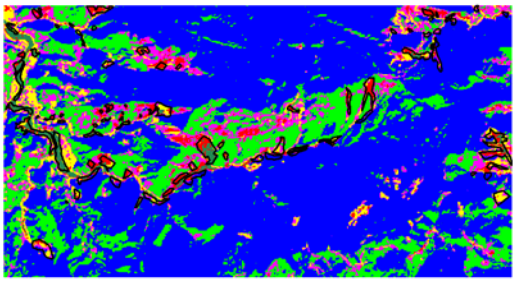
Figure 11. The visual comparison result for the SVM method

It is proved that the morphological features of rainfall-induced landslides are useful in the automatic recognition of landslides. However, they have to be defined in related to local conditions and the specific events triggering the landslides (McKean and Roering, 2004; McKean, et al., 2005; Liu et al., 2009). In the future, some significant geo-morphological features will be added to improve the classification accuracy. And some quantitative assessment for the classification accuracy will be given.

5. CONCLUSIONS AND SUGGESTIONS

5.1 Conclusions

1. The procedures for the rainfall-induced landslide interpretation had been figured out using automatic

classification methods including BPNN and SVM methods. Specific parameters are tested and tuned in this study.

2. The visual comparison results indicate that SVM method gives a better result than the ones derived from both BPNN and ML methods.

5.2 Suggestions

1. In the future, some significant geo-morphological features will be added to improve the classification accuracy in this work.
2. The causes of erroneous judgements, quantitative assessment for the landslide inventory should be further confirmed in the proceeding research.

6. REFERENCES

Bischof, H., W. Schneider, and A. J. Pinz, 1992. Multispectral Classification of Landsat-images Using Neural Networks, *IEEE trans. on Geoscience and Remote Sensing*, 30(3), pp. 482-490.

Camps-Valls G. and L. Bruzzone, 2005. Kernel-Based Methods for Hyperspectral Image Classification, *IEEE trans. on Geoscience and Remote Sensing*, 43(6), pp. 1351-1362.

Chang, K T and J K Liu, 2004. Landslide features interpreted by neural network method. In: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Istanbul, Turkey, Vol. XX, Part B7, pp.574-579.

Chen, C. C., 2006. Rice Paddy Identification using the Support Vector Machine and Plausible Neural Network, MSc thesis, Dept. of Civil Eng., NCTU, HsinChu, 109p (in chinese).

Foody, G. M. and A. Mathur, 2004. A Relative Evaluation of Multiclass Image Classification by Support Vector Machine, *IEEE trans. on Geoscience and Remote Sensing*, 42(6), pp. 1335-1343.

Hsiao, K. H., C. Y. , Yin, J. K. , Liu, M. F. , Yu, and C. L. Wang, 2003. *Landslide Identification Using SPOT Imageries and Aerial Photographs*, Journal of Photogrammetry and Remote Sensing, 8(4), pp. 29-42. (in chinese)

Hsu, L. D., C. C. Chen, J. P. Tsao, S. Chen, 2002. *Multi-annual SPOT images for monitoring large-scaled landslide*. In: *Proceedings of symposium of annual meeting of Chinese Association of Geographic Information System*. Taichung.

Kojima, H., C. F. Chung, and C. V. Westen, 2000. Strategy on the Landslide Type Analysis Based on The Expert Knowledge and the Quantitive Prediction Model, International Archives of Photogrammetry and Remote Sensing, Vol. XXXIII, Part B7, pp. 701-708, Amsterdam.

Liang, L. S., 1997. *Satellite images as applied to the investigation of landslides and hot springs*. MSc. Thesis, Institute for Applied Geology, National Central University.

Liu, J. K., 1985. Remote Sensing for Landslide Identification and Prediction – cases from Taiwan. In: *Proceedings of Advanced Technology for Monitoring and Processing Global Environmental Data*, the University of London, UK and CERMA, USA, pp. 223-232.

Liu, J. K., 1987. Automation for landslide analysis using digital images, Remote Sensing, Vol. 8, pp. 60-90. (in chinese)

Liu, J. K., 1999. *A practical approach to the installation of a national landslide database on basis of a SPOT mosaic*. Proceedings of the 18th symposium on survey and mapping. Ilan, p.561-570.

Liu, J. K., S. J. Wong, J. H. Huang, M. J. Huang, 2001. Images analysis for landslides induced by torrential rainfall. In: *Proceedings of symposium on civil engineering technology and management for 21 century*. Hsin-chu. P.C-21~C-31.

Liu, J. K., K. T. Chang, J. Y. Rau, W. C. Hsu, Z. Y. Liao, C. C. Lau, T. Y. Shih, 2009. *The Geomorphometry of Rainfall-Induced Landslides in Taiwan Obtained by Airborne Lidar and Digital Photography*, Geoscience and Remote Sensing, In-Teh, Inc. (in press)

Means, J. E., Acker S.A., Fitt B.J., Renslow M., Emerson L., Hendrix C.J., 2000. Predicting forest stand characteristics with airborne scanning lidar. *Photogrammetric Engineering & Remote Sensing*, 66(11), pp. 1367- 1371.

McKean, J. and J. Roering, 2004. Objective landslide detection and surface morphology mapping using high-resolution airborne laser altimetry. *Geomorphology*, 57, pp. 331-351.

McKean, N. F., D. R. Streutker, J. Chadwick, D. J. Glenn, G. D. Thackray, and S. J. Dorsch, 2005. Analysis of LiDAR-derived topographic information for characterizing and differentiating landslide morphology and activity. *Geomorphology,* 73, pp. 131–148. DOI: 10.1016/j.geomorph.2005.07.006.

Naesset, E. 2002. Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. *Remote Sensing of Environment*, 80(1), pp. 88-99.

Research System, Inc., 2006. ENVI Online Help.

Robert, H. N., 1990. *Neurocomputing*, Addison-Wesley Pub. Co., pp. 21-42.

Singhroy, V. and K. Mattar, 2000. SAR Image Techniques for Mapping Areas of Landslide, In: *International Archives of Photogrammetry and Remote Sensing*, Vol. XXXIII, Part B7, pp. 1395-1398, Amsterdam.

Westen, C. V., 2000. Remote Sensing for Natural Disaster Management, International Archives of Photogrammetry and Remote Sensing, Vol. XXXIII, Part B7, pp. 1609-1617, Amsterdam.

Wu, J. S, J. H. Tsai, J. D. Hu, 1989. *Landslide investigation of the slopelands in Taiwan*. Agriculture Council, Bureau of Soil and Water Conservation.

Zhu, G. and D. G. Blumberg, 2002. Classification Using ASTER Data and SVM Algorithms; The Case Study of Beer Sheva, Israel, *Remote Sensing of Environment*, 80(2), pp. 233-240.

Zurada, J. M., 1992. Introduction to Artificial Neural Systems, West Pub. Co., pp.163-248.