

SEMI-AUTOMATIC CLASSIFICATION PROCEDURE FOR UPDATING LANDUSE MAPS WITH HIGH RESOLUTION OPTICAL IMAGES

Claudia Notarnicola^a, Annett Frick^b, Steve Kass^a, Philipp Rastner^a, Giuseppe Pulighe^a, Marc Zebisch^a

^a EURAC-Institute Applied Remote Sensing, Viale Druso 1, 39100 Bolzano (Italy)

^b LUP - LUFTBILD UMWELT PLANUNG GmbH, Potsdam, Germany

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1. INTRODUCTION

This paper presents a semi-automatic procedure for the classification of high resolution images in order to obtain a fast update of land cover – land use maps. The adopted methodology can be considered as both recursive and hierarchical. It is hierarchical because it is developed as a top-down procedure starting from the main classes and moving down toward the smallest ones in three levels. It is recursive because in each level the classification procedure is applied until a fixed accuracy threshold is reached by considering the results of different classifiers. Innovative aspects of the classification procedure are the use of the old land-use map as a kind of a-priori information and the development of a land use model which indicates according to the landscape characteristics the probability to have a certain class. An object-oriented procedure has been also developed for the post-processing phase and the detection of the mixed forest stands. The study is carried out on six test sites located in northern Italy. Due its variability in landscape, the sites were chosen in order to cover all the natural characteristics as well as all the possible land use classes. The procedure is applied to 6 SPOT V images (10-meter resolution), which cover the whole test sites and were all acquired in summer 2006.

2. METHODS

The overall classification process, illustrated in fig.1, is mainly divided in three basic levels and a fourth level for the post-processing. A particular strategy is designed for the sampling step. Quality, quantity and representativeness of the samples strongly affect the performance of both classification and validation. Since manual delineation of training and test areas cannot guarantee the fulfilment of those criteria, we develop an automated sampling method. First an unsupervised ISODATA clustering [1] is performed. An intersection of those clusters with the old land use map determines spectrally homogeneous sub-classes. The minimum of 50 samples per class is then obtained by a stratified random sampling taking into account all spectral variants. After the samples are thus generated a visual interpretation of Level 1 and Level 2 classes is carried out, based on Orthofotos and additional information as well as ground truth data. An interpretation guideline is developed to maximise objectivity. Finally all samples are divided into a training set to be used for Level 1 and Level 2 classification and a test set to be used solely for validation.

3.1 Level 1 processing

The Level 1 classification stands for the derivation of masks for further subdivision on Level 2. The classes water, urban, agriculture, wood and non-vegetated areas are identified on this level. We develop a fully automated iterative procedure by combining two different classification methods with auxiliary data. First a Maximum Likelihood classification is performed based on signatures from the training samples. Second the decision tree approach See5 [2] is applied on the same training samples. After the first classification run the two classification results and the old land use map are intersected. Pixels which belong to the same Level 1 class in all three datasets are considered to be correctly classified and are either used as final masks or as training samples for the next run. All other pixels are regarded as unclassified. If the validation of the intersection result with the test samples yields an overall accuracy > 90% and if the unclassified pixels amount to less than 10% of the whole scene, the result from the first run is considered as final masks and Level 2 classification begins. If these criteria are not matched, the process continues with the second run. Two major changes are introduced in the second run: all pixels considered as correctly classified after the first run are taken as new additional training information and instead of the old land use map, a segment-based See5 classification is used. This ensures that classification results can differ from the old map, since now only image-related information is involved in the mask generation. The second run is iterated until the accuracy criteria are finally met.

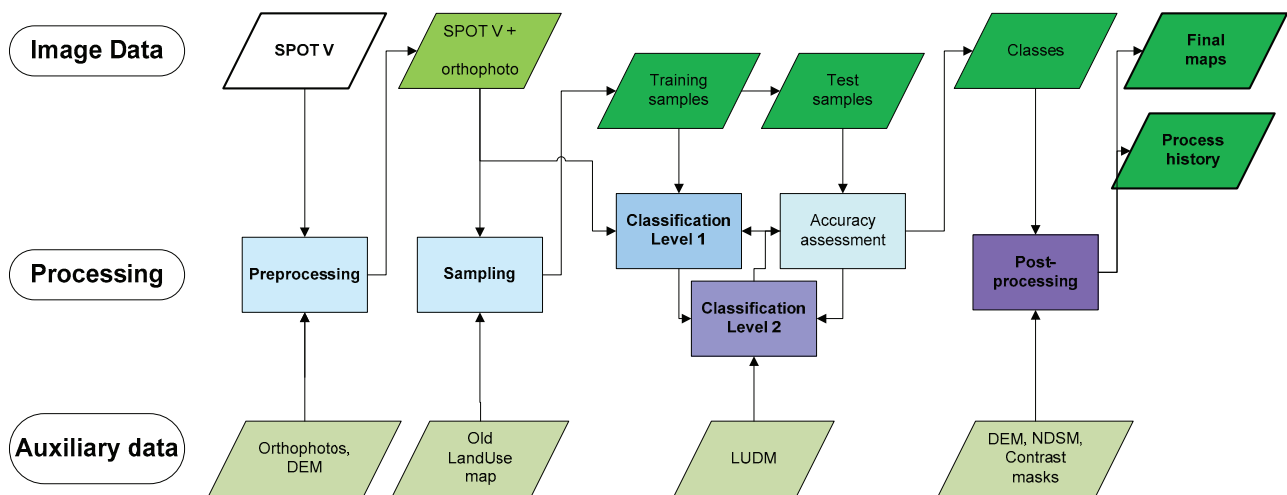


Fig.1. Overview of the classification scheme.

3.2 Level 2 processing

The level 2 classification is carried out within each mask determined in level 1 by using a standard Maximum Likelihood classifier. In a second step in order to improve the separability among some specific classes (e.g. intensive and extensively used grassland, different species of forest stands) a land use distribution model (LUDM) has been added as additional layers in the classification. The methodology applied for the derivation of the Land Use Distribution Model (LUDM) is the Weights of Evidence (WofE) method depending on Bayesian probability model with assumption of conditional independence [3]. The method uses the statistical association between a training points theme, such as a theme showing site occurrence to determine the weights. The final product is a map of posterior probabilities of occurrence based on the altitude, slope and aspect for each class and calculated for each map unit (e.g. the pixel). A secondary product is the contrast mask, indicating the pixels with the highest reliability in the probability map.

3.3 Post-processing

The Post-processing procedure is built up on an object-oriented rule based Process tree. Beside Spot images and the classification results, additional layers like the contrast and probability masks from the land-use model (LUDM) are used as well as the Digital elevation model (DEM) and the normalized digital surface model (NDSM). Mixed forest is derived by a moving window filter technique with object-oriented classification procedure. Mixed forest definition is given on a Minimum Map Unit (MMU) of 2500 m² when a forest class (broadleaf or coniferous) was below 75%. To determine this quantity, a chessboard segmentation of 5x5 pixel (MMU) is carried out and set in relation to a lower chessboard segmentation (Pixelbased) to quantify the respectively areas and to derive if the MMU is mixed. To consider all direction, the MMU chessboard segmentation is shifted in all direction of almost 2 pixels and each time quantified, if mixed forest is given or not. Finally, the middle pixel is considered as Mixed forest, when it overlapped at least 7 times (>60%) with given mixed forest, if not, the initially classification remained the same. Finally all classes were cleaned up by a conventional majority filter procedure.

3. RESULTS

The overall accuracy reached after post-processing ranges from 90% up to 94% and the kappa coefficient from 0.88 to 0.93. The major problems are encountered for the classification of particular forest classes such as dwarf-shrubs and natural grassland in comparison to extensively used grassland. A net improvement in the classification of these classes is obtained in the level 2 by using the LUDM information and subsequently in the post-processing phase with the use of the NDSM.

A statistical analysis carried out on the final classified image indicate that the LUDM influenced the 40 up to 60% of pixels, providing useful information that in some cases can only be reached by using multi-temporal datasets.

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