COLOR AND LIDAR DATA FUSION: APPLICATION TO AUTOMATIC FOREST BOUNDARY DELINEATION IN AERIAL IMAGES

Zuyuan Wang, Ruedi Boesch, Chritian Ginzler

Dept. of Land Resource Assessment, Swiss Federal Research Institute WSL,
zuyuan.wang, ruedi.boesch, christian.ginzler@wsl.ch

KEY WORDS: Forest Boundary Delineation, Gabor Filters, LIDAR, Aerial images, Data Fusion

ABSTRACT:

Forest boundary delineation is one of the key issues of forest management for Swiss National Forest Inventory (NFI). The proposed approach in this paper focuses on the delineation of forest boundaries with special emphasis on spatially contiguous and reproducible results by using both aerial images and LIDAR data. The used Green Vegetation Index (GVI) is helpful to find green vegetation areas. With the information provided by canopy height model (CHM) obtained from LIDAR data, the forest area where CHM has a regular density can be detected successfully. The selected JSEG segmentation method has been found to produce useful homogenous sub-areas. The combination of JSeg segmentation result and the texture features extracted by Gabor wavelet leads to the whole forest area detection and obtain proper forest boundaries. Preliminary results are encouraging, regarding an automatic process and delivers robust delineation of forest boundaries. Future research is focused on appropriate Gabor filter selection to reduce computation burden and other better data fusion methods to obtain more accurate forest boundary delineation.

1. INTRODUCTION

A third of Switzerland is covered in forest which is a complex ecosystem. Forest performs various tasks such as providing protection (e.g. against avalanches), wood production, non-wood production like game, honey, and mushrooms, amenities for rest and recreation, biodiversity and landscape variety. Since the forest has many functions that are important to people, it is necessary to continuously monitor the condition of the ecosystem "forest" and to understand the cause of changes. Consequently the Federal Council decided to carry out the first National Forest Inventory (NFI) in 1981. The NFI(Bachofen et al., 1988; Brassel, 2001; Brassel and Brändli, 1999.) is intended to record the current state and the changes of the Swiss forest in all its functions. With the ongoing third NFI (NFI3), there are about 7000 aerial images covering the whole of Switzerland which can be used for extracting forest features.

Forest stand delineation is one of the key issues of forest management. The NFI ranges on a rectangle 500m×500m spaced grid and each sample plot of 50m×50m containing all measured landscape variables. With such a coarse grid of the sampling design in NFI, it is not suitable for local assessment of forest stands, hence spatially contiguous and automatic boundary detection of forest-stands is one of the prerequisites to overcome such limitations.

So far there are different approaches to achieve forest boundary delineation with various image resolutions. Direct forest stand delineation can be found such as by image segmentation of satellite data (Hagner, 1990)or by analysis of single tree crown (Leckie et al., 2003) for delineating forest borders. The other is by implementing traditional classification methods(Haapanen et al., 2004), or finding an optimal delineation threshold to achieve successful forest/nonforest classifications(Peterson et al., 2004).

Benefited from the high spatial resolution of NFI images, the texture within forest areas can be additional features to characterize the forest. Furthermore, LIDAR data provide rich information on the vertical structure of forest.(Wulder and Seemann, 2003) The goal of this paper is to investigate the fusion of available LIDAR canopy height model (CHM) and aerial images features extracted from color and texture for forest boundary delineation. The merging of aerial images and LIDAR data give opportunities to make advantages of both data sets. Empirical tests show that the proposed method offers an automatic process of forest boundary detection for various aerial images in a promising way.

2. MATERIALY AND METHODS

2.1 Study Data Sets

The aerial images in our database have been made available by the Swiss Federal Office of Topography with a scale of 1:30000. Testing Aerial images are with 0.5m resolution, varying luminance and green color distribution. Most of the images are located in the middle part of the Switzerland and the forest type belongs to deciduous low land forest.

2.2 Green Vegetation Index

Color is an important feature which we use to filter non-green vegetation areas in this paper. Simple image transformation may be useful in understanding image data. For instance, ratios might be helpful in enhancing difference between features in scenes. As we know, the Normalized Difference Vegetation Index (NDVI) is a measure of the amount and vigour of vegetation at the surface. NDVI is a non-linear transformation of the visible (red) and near-infrared bands of satellite information. Since the available true-color RGB aerial images don't allow calculating the widely used NDVI, we suggest an index which we name Green Vegetation Index (GVI) based on the use of green and red bands. For each aerial image, GVI is calculated as the ratio between green and red. Suppose R represent red, G represents green, then

$$GVI = G / R \qquad (1)$$

Let $m = mean(GVI)$, then we define a threshold *th*,

$$th = \delta \times m \tag{2}$$

Depending on this threshold, we can filter non-green vegetation areas from the aerial image. Fig. 1 shows the result of the detected green vegetation area of one aerial image.

Fig.1.a original image   Fig. 1.b detected green vegetation areas

It can be seen from Fig.1.b, that the detected green vegetation areas include forest, croplands, etc. The results successfully remove building area which is helpful for forest detection. Depending on the specific forest definition in Swiss NFI, the dominant height of the stocking within the forest boundary-line is 3m. Hence we use the DTM (Digital Terrain Model) and DSM (Digital Surface Model) to generate CHM and obtain the pixels that belong to the forest. Unfortunately, the density of the available CHM is not regularly distributed for different images. In some forest areas, the data can be completely missing. If it is only based on CHM, the whole forest area can hardly be detected at all. Fig.2 shows the CHM and detected forest area based on CHM.
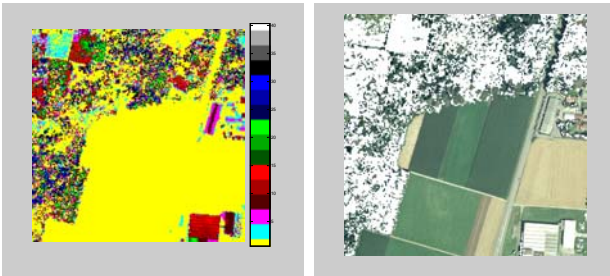

Fig.2.a CHM   Fig.2.b detected forest area

2.3 Jseg Segmentation

Segmentation is the process that subdivides an image into homogenous regions. JSEG (Deng and Manjunath, 2001) is one of the color image segmentation methods which provide robust segmentation results on a large variety of color images. First the image is quantized using an unsupervised color quantization algorithm based on human vision perception(Deng et al., 1999). Following quantization, the reduced colors define color class labels while the color class number for each image is different. The image pixel colors are replaced by their corresponding color class labels which construct a class-map image. Let Z be the set of all image data points in the class-map, and $z = (x, y)$, m be the mean,

$$m = \frac{1}{N} \sum_{z \in Z} z \tag{3}$$

Suppose color has been quantized into C level, Z_i, $i = 1,2......C$. Let m_i be the mean of the N_i data points of class Z_i,

$$m_i = \frac{1}{N_i} \sum_{z \in Z_i} z \tag{4}$$

Let

$$S_T = \sum_{z \in Z} \|z - m\|^2 \tag{5}$$

and

$$S_W = \sum_{i=1}^{C} S_i = \sum_{i=1}^{C} \sum_{z \in Z_i} \|z - m_i{}^2\| \tag{6}$$

S_T is the variance of points within the same class. S_W is the total variance of points belonging to the same class. Define,

$$J = S_B / S_W = (S_T - S_W) / S_W \tag{7}$$

It essentially measures the distance between different classes S_B between the members within each class S_W. A higher value of J implies that the class values are more separated from each other and members within each class are closer to each other and vice versa. The J-image is calculated over a moving window centered on the J - values. The size of the window is depending on the scale that is needed to segment an image. Normally, the basic window at the smallest scale is a 9×9 window without corners. A region growing and merging step based on the color similarity is used to segment based on the J-image. The color histogram for each region is extracted and the Euclidean distance in the color space is calculated and saved in a distance table. Each pair of regions with the minimum distance is merged together if the distance value reaches a threshold. One of the threshold parameters in JSEG controls the region merging within a range [0, 1.0]. Fig. 3.a shows the segmentation results of one aerial image without region merging.

Fig.3.a Jseg segmentation result   Fig.3.b detected forest areea

The selection of an invariant value for the region merging parameter *th* is too much dependent on the single image content. For the purpose of forest detection, we choose the initial segmentation without any region merging. After we get the segmentation results, then these areas with the percentage of forest pixel is larger than a predefined threshold λ will belong to forest. Fig.3.b shows the detected forest areas (indicated by

white lines).

2.4 Texture Features Extracted by Gabor Wavelet Transformation

Texture is another important feature which can be extracted from the images by different analysis algorithms. A large number of techniques have been proposed in the past two decades ranging from statistical approach to filtering approach. Gabor Filter (A.C.Bovik et al., 1990; A.K.Jain and F.Farrokhnia, 1991) belongs to one of the filtering approaches inspired by the multi-channel filtering mechanism discovered in neurophysiology which suggests that the visual system decomposes the retinal image into a set of sub-bands. A two dimensional Gabor function $g(x, y)$ and its Fourier transform $G(u, v)$ can be written as:

$$g(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right)\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right) + 2\pi jWx\right] \quad (8)$$

$$G(u,v) = \exp\left\{-\frac{1}{2}\left[\frac{(u-W)^2}{\sigma_u^2} + \frac{v^2}{\sigma_v^2}\right]\right\} \quad (9)$$

where $\sigma_u = 1/2\pi\sigma_x$ and $\sigma_v = 1/2\pi\sigma_y$. Let $g(x, y)$ be the mother Gabor wavelet, then this self-similar filter dictionary can be obtained by appropriate dilations and rotations of $g(x, y)$ through the generating function:

$$g_{mn}(x,y) = a^{-m}G(x', y'), \ a > 1, \ m, \ n = \text{integer}$$
$$x' = a^{-m}(x\cos\theta + y\sin\theta), \text{ and } y' = a^{-m}(-x\sin\theta + y\cos\theta) \ (10)$$

where $\theta = n\pi/K$ and K is the total number of orientations. The scale factor a^{-m} in (10) is meant to ensure that the energy is independent of m. Such strategy as to ensure that the half-peak magnitude support of the filter responses in the frequency spectrum touch each other can be used to reduce the redundant information in the filtered images(B.S.Manjunath and Ma, 1996). This result in the following equations to calculate the filter parameters σ_u and σ_v.

$$a = (U_h/U_l)^{-\frac{1}{S-1}}, \ \sigma_u = \frac{(a-1)U_h}{(a+1)\sqrt{2\ln 2}}$$

$$\sigma_v = \tan\left(\frac{\pi}{2K}\right)\left[U_h - 2\ln\left(\frac{\sigma_u^2}{U_h}\right)\right]\left[2\ln 2 - \frac{(2\ln 2)^2\sigma_u^2}{U_h^2}\right]^{-\frac{1}{2}} \quad (11)$$

where $W = a^m U_l$, U_h and U_l denote the lower and upper center frequency of interest. K is the number of orientation and S is the number of scales in the multi-resolution decomposition and $m = 0,1,......S-1$. In our experiments, $K = 6$ and $S = 4$.

Using the Gabor filter set defined above, there are all 24 filtered images for an input aerial image. Since the local texture region of each sub-area after Jseg segmentation is homogeneous, the mean value μ_{mn} and the standard deviation σ_{mn} of the transform coefficients are used to present the sub-region. A feature vector constructed by μ_{mn} and σ_{mn} is represented as

$$f = [\mu_{00}\sigma_{00}\mu_{01}\sigma_{01}......\mu_{35}\sigma_{35}] \quad (12)$$

2.5 Forest Detection

In 2.3, since regions that belong to the forest have been detected using CHM, let

$$f_{forest} = [\mu_{f00}\sigma_{f00}\mu_{f01}\sigma_{f01}......\mu_{f35}\sigma_{f35}] \quad (13)$$

For each sub-area after Jseg segmentation with a feature vector:

$$f_{sub-area} = [\mu_{s00}\sigma_{s00}\mu_{s01}\sigma_{s01}......\mu_{s35}\sigma_{s35}] \quad (14)$$

consider the distance between the two feature vectors defined as:

$$d(f_{forest}, f_{sub-area}) = \sum_m\sum_n d_{mn}(f_{forest}, f_{sub-area}) \quad (15)$$

$$\text{where } d_{mm}(f_{forest}, f_{sub-area}) = \left|\mu_{mn}^{forest} - \mu_{mn}^{sub-area}\right| + \left|\sigma_{mn}^{forest} - \sigma_{mn}^{sub-area}\right| \quad (16)$$

if the distance d smaller than a predefined threshold ξ, then the corresponding sub-area will belong to the forest, otherwise, it will belong to non-forest areas. Based on the above analysis, Fig.4 summarizes the flow chart of our forest delineation algorithm.
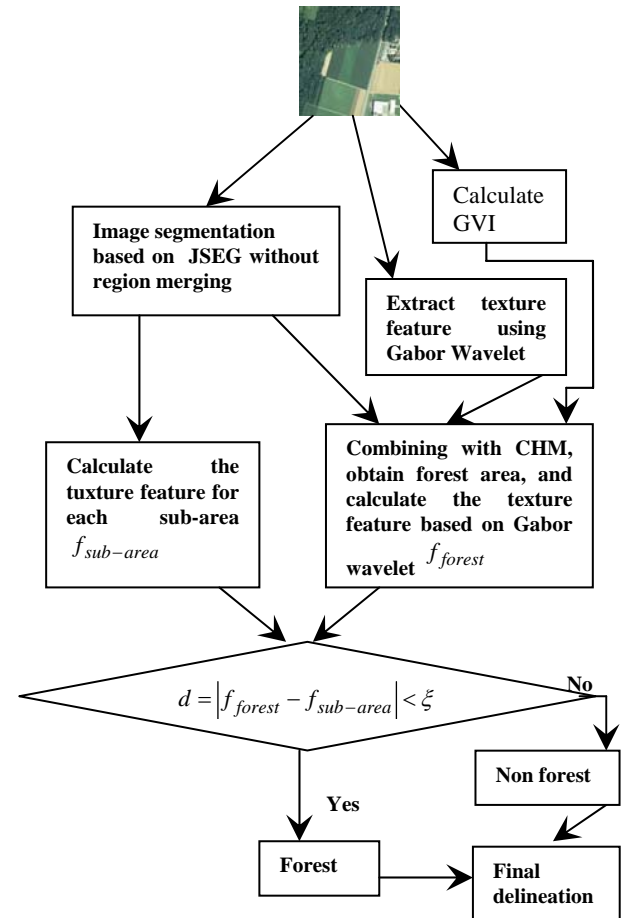

Fig. 4 Experimental flow chart

3. EXPERIMENTAL RESULTS AND CONCLUSION

Examples of the delineation results (indicated by white lines) are shown in Fig.5. The thresholds were empirically chosen as: $\delta = 0.85$, $\lambda = 0.4$ and $\xi = 150$.

The experimental results indicate that combining with LIDAR data, after extending JSEG region merging with Gabor wavelet texture features, forest areas can be distinguished in a more robust way. The introduction of GVI is quite helpful for urban area with building's removing. Obviously, the efficient integration of CHM which doesn't contain any color information but true object height information give chances to detect real forest area which constructed a feature vector

represented forest with the efficient integration of CHM. The distance measure finds sub-areas which are more similar to the detected forest pattern. The additional texture features are suitable to make discrimination between forest and the other landscapes. The approach presented in this study offers an automatic process and delivers robust delineation of forest boundaries based on JSEG and Gabor wavelets texture features.
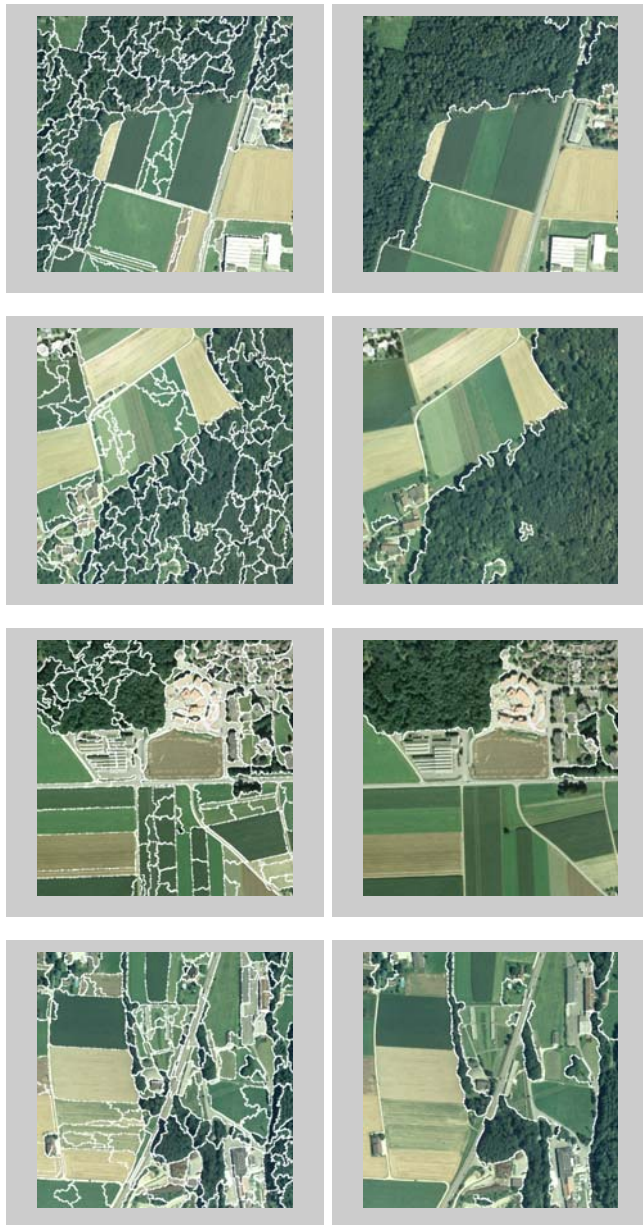

Fig. 5 Forest delineation results

The dimension of the texture features extracted from Gabor wavelet is at least 48 for each different region. Because the textures may share the same spatial frequency properties over bands and orientations, some filtered images may show similar response to different textures. Therefore, not all the 24 filtered images are always useful. How to make a useful filter selection will be helpful to reduce the computational burden for large aerial images. Later on, further research is needed to find out whether or not other segmentation methods will be more suitable for homogeneous texture pattern detection which

maybe helpful for more accurate forest area delineation. In our experimental, we found that if the available CHM is completely lost in specificl area, the corresponding forest area will not be detected correctly. Or if there are some years delay between the CHM data and the aerial images, there will be also some wrong forest detection. Hence how to find other better data fusion methods or add interactive experts' knowledge will be another research focus. Currently, only typical midland areas have been investigated in detail, therefore how to extend the test area to alpine regions will be important for further verification of the method.

References

A.C.Bovik, M.Clark and W.S.Geisler, 1990. Multichannel texture analysis using localized spatial filters. *IEEE Transaction on Pattern Analysis and Machine Intelligence*, 12: pp. 55-73.

A.K.Jain and F.Farrokhnia, 1991. Unsupervised texture segmentation using gabor filters. *Pattern Recognition*, 16(12): pp. 1167-1186.

B.S.Manjunath and Ma, W.Y., 1996. Texture Feature for Browsing and Retrieval of Image Data. *IEEE Transaction on Pattern Analysis and Machine Intelligence*, 18(8): pp. 837-842.

Bachofen, H., Mahrer, F. and al., e. (Editors), 1988. *Schweizerisches Landesforstinventar Ergebnisse der Erstaufnahme 1982-1986*. Kommissionsverlag Flück-Wirth, Teufen.

Brassel, P. (Editor), 2001. *Swiss national forest inventory: methods and models of the second assessment. Swiss Federal Research Institute WSL*, Birmensdorf.

Brassel, P. and Brändli (Editors), 1999. *Schweizerisches Landesforstinventar Ergebnisse der Zweitaufnahme 1993-1995*. Haupt, Bern.

Deng, Y., Kenney, C., Moore, M.S. and Manjunath, B.S., 1999. Peer group filtering and perceptual color image quantization, *Proc. of IEEE International Symposium on Circuits and Systems (ISCAS)*, pp. pp. 21-24.

Deng, Y. and Manjunath, B.S., 2001. Unsupervised segmentation of color-texture regions in images and video. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 23(8): pp. 800-810.

Haapanen, R., R.Ek, A., Bauer, M.E. and Finley, A.O., 2004. Delineation of forest/nonforest land use classes using nearest neighbor method. *Remote Sensing of Environment*, 89: pp. 265-271.

Hagner, O., 1990. Computer aided forest stand delineation and inventory based on satellite remote sensing, *Proceeding from SNS/IUFRO workshop in Umeå 26-28 February 1990: The usability of remote sensing for forest inventory and planning*, Umeå: Swedish University of Agricultural Science, Remote Sensing Laboratory, pp. pp. 94-105.

Leckie, D.G., Gougeon, F.A., Walsworth, N. and Paradine, D., 2003. Stand delineation and composition estimation using semi-automated individual tree crown analysis. *Remote Sensing of Environment*, 85: pp. 355-369.

Peterson, U., Püssa, K. and J. Liira, 2004. Issues related to delineation of forest boundary on Landsat Thematic Mapper winter images. *International Journal Remote Sensing*, 25(24): pp. 5617-5628.

Wulder, M.A. and Seemann, D., 2003. Forest inventory height update through the intergration of lidar data with segmented Landsat. *Canadian Journal Remote Sensing*, 29(5): pp. 536-543.