FUSION OF LiDAR AND HYPERSPECTRAL DATA FOR 3D SEGMENTATION OF INDIVIDUAL TREES

Eduardo Tusa[1,2,3], Jean-Baptiste Barré[1], Jean-Matthieu Monnet[1], Mauro Dalla Mura[2,4], Frédéric Berger[1], Jocelyn Chanussot[2]

[1]Univ. Grenoble Alpes, Irstea, LESSEM, 38000 Grenoble, France
[2]Univ. Grenoble Alpes, CNRS, Grenoble INP*, GIPSA-lab, 38000 Grenoble, France.
*Institute of Engineering Univ. Grenoble Alpes
[3]Universidad Técnica de Machala, Facultad de Ingeniería Civil, AutoMathTIC, Machala, Ecuador
[4]Tokyo Tech World Research Hub Initiative (WRHI), School of Computing, Tokyo Institute of Technology, Tokyo, Japan

OBJECTIVE

The availability of remotely-sensed data with high spatial and spectral resolution are becoming more widespread in forestry management, having important contributions in the development of new applications for monitoring these ecosystems. In particular, it is possible to consider studies of an entire stand by elaborating findings at tree level. However, it raises the question about the data fusion from different sensors such as LiDAR and Hyperspectral images (HI). This study shows the preliminary results previous a fusion methodology between high-density LiDAR data - (45 pts/m² minimum) and VNIR HI - (0.80 m spatial resolution) acquired on French Alpine forests along an altitude gradient. The methodology is based on the integration of HI and LiDAR data at low level of fusion by following the idea of non-parametric clustering based on Mean Shift (MS). We are interested on evaluating the effect of considering all the spectral information together with the AMS in the 3D segmentation which takes into account spatial data provided by the LiDAR data.

SEGMENTATION BASED ON MEAN SHIFT

ALGORITHM

Mean shift algorithm finds the maxima of a density function by applying an iterative method for every observation, *x*. The re-estimation of the mean uses a kernel function, $K(x_i - x)$, to determine the weight of nearby observations. The weighted mean is given by

$$m(x) = \frac{\sum_{x_i \in N(x)} K(x_i - x) x_i}{\sum_{x_i \in N(x)} K(x_i - x)}$$

where *N(x)* is the neighborhood of x. In [1], they propose a multivariate kernel

$$K(x_i - x) = \frac{C}{h_s^2 h_r^p} k_s \left(\left\| \frac{x_i^s - x^s}{h_s} \right\|^2 \right) k_r \left(\left\| \frac{x_i^r - x^r}{h_r} \right\|^2 \right)$$

k_r : spatial kernel function
k_s : range kernel function
h_s : spatial bandwidth
h_r : range bandwidth
$x_i^s - x^s$: spatial distance
$x_i^r - x^r$: range distance

3D LiDAR SEGMENTATION

In [2,3], an adaptive mean shift is designed based on the following kernel criteria:

Spatial kernel function

$$k_s(x_i^s - x^s) = e^{\left(-\gamma \left\| \frac{x_i^s - x^s}{h_s} \right\|^2 \right)}$$

Range kernel function

$$k_r(x_i^r) = 1 - \left\| 1 - dist(x_i^r, x^r, h_r) \right\|^2$$

$dist(x_i^r, x^r, h_r)$ is the distance between the point and the mask boundary of the cylindrical profile.

Spatial bandwidth: $h_s = s^s x_i^r$

s^s: slope of the linear regression between the crown radius and the tree height.

Range bandwidth: $h_r = s^r x_i^r$

s^r: slope of the linear regression between the crown height and the tree height.

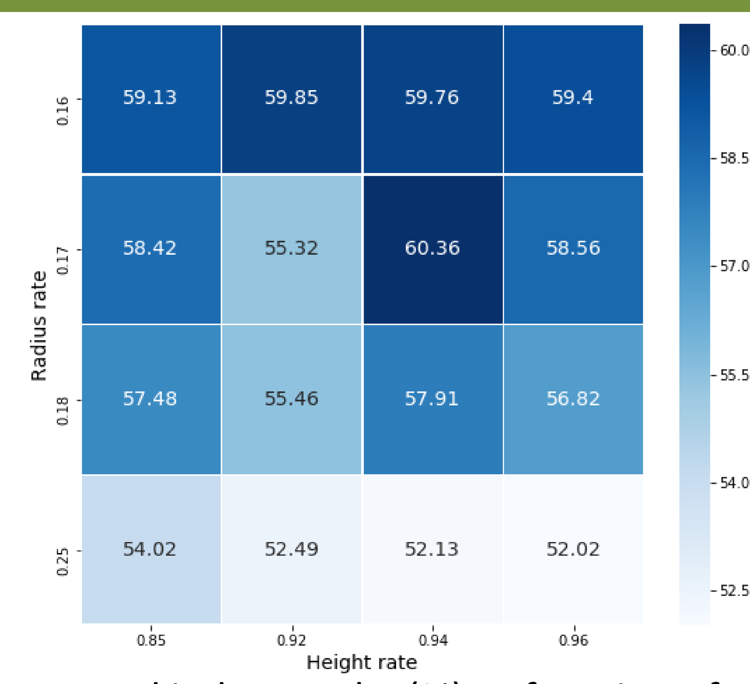

Fig. 1. Jaccard index results (%) as function of spatial bandwidth (radius rate) and range bandwidth (height rate)

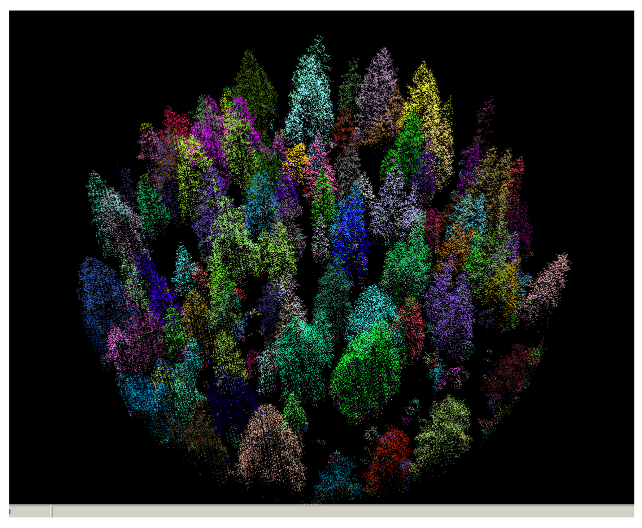

Fig. 2. 3D point cloud segmentation

HYPERSPECTRAL SEGMENTATION

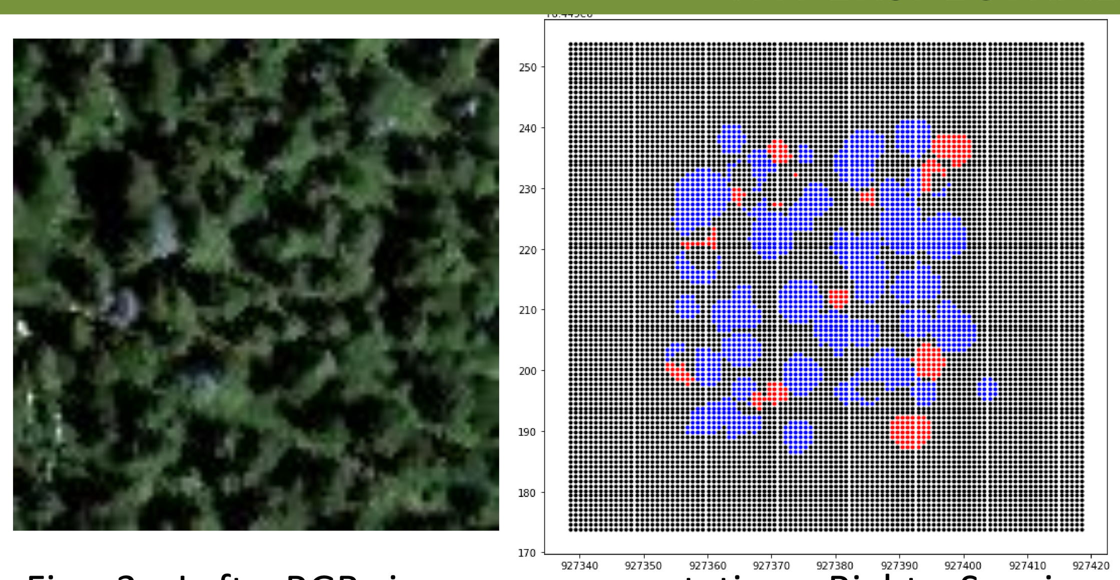

Fig. 3. Left: RGB image representation. Right: Species ground truth: Norway spruce in blue and Silver fir in red.

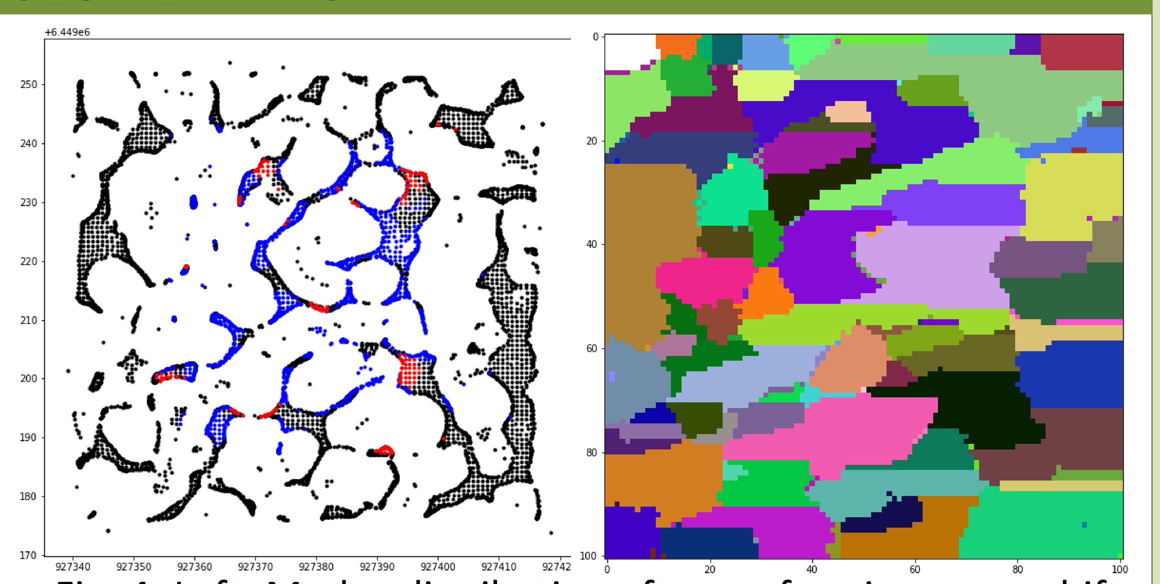

Fig. 4. Left: Modes distribution after performing mean shift with hs=4.8m and hr=0.018. Right: Segmented regions.

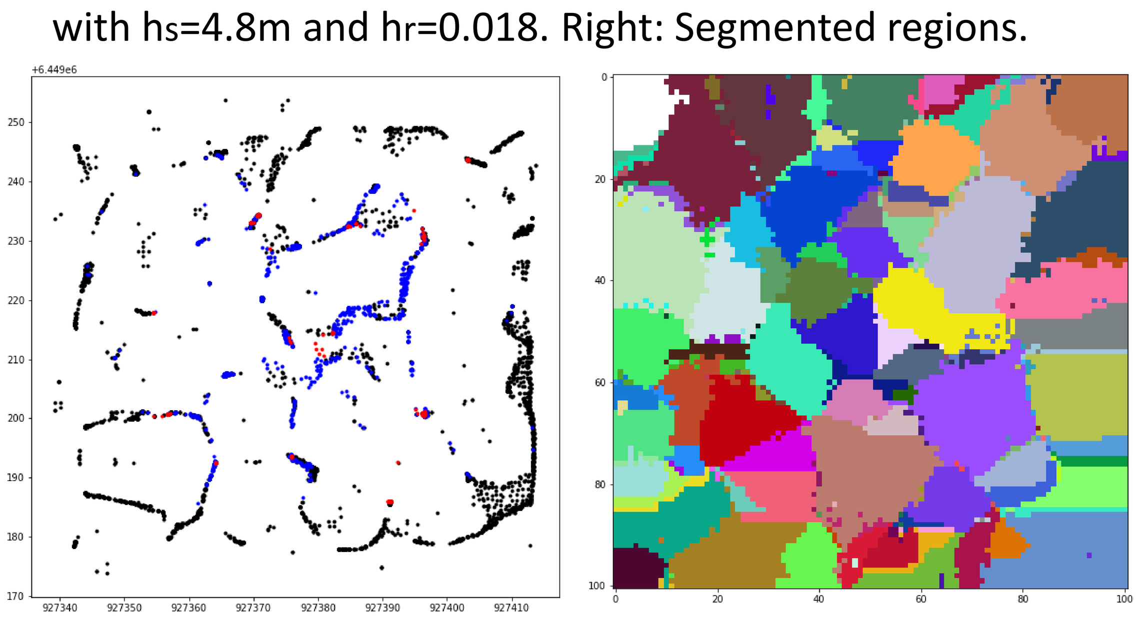

Fig. 5. Left: Modes distribution after performing mean shift with range kernel only. Right: Segmented regions.

Spatial kernel function

$$k_s(x_i^s - x^s) = e^{\left(-\gamma \left\| \frac{x_i^s - x^s}{h_s} \right\|^2 \right)}$$

Range kernel function

$$k_r(x_i^r - x^r) = e^{\left(-\gamma \left\| \frac{cos\_dist(x_i^r, x^r)}{h_r} \right\|^2 \right)}$$

$cos\_dist(x_i^r, x^r)$ is the cosine distance in a circular profile.

PERSPECTIVES

- In LiDAR and hyperspectral segmentation, the modes are grouped based on spatial criteria (nearest neighbor). A spectral criteria for merging regions is being tested.
- The fusion strategy of LiDAR and hyperspectral data is oriented for discriminating species. A set of LiDAR features based on point density will be included in order to provide robustness to the specie characterization.

References

[1] D. Comaniciu and P. Meer, “Mean shift: A robust approach toward feature space analysis,” IEEE Trans. Pattern Anal. Mach. Intell., no. 5, pp. 603–619, 2002.
[2] A. Ferraz et al., “3-D mapping of a multi-layered Mediterranean forest using ALS data,” Remote Sens. Environ., vol. 121, pp. 210–223, Jun. 2012
[3] A. Ferraz, S. Saatchi, C. Mallet, and V. Meyer, “Lidar detection of individual tree size in tropical forests,” Remote Sens. Environ., vol. 183, pp. 318–333, Sep. 2016.

GROUPE HYPERSPECTRAL DE LA SOCIÉTÉ FRANÇAISE DE PHOTOGRAMMÉTRIE ET DE TÉLÉDÉTECTION

SFPT- Groupe Hyperspectral
9 - 10 Juillet 2019
Toulouse

Communauté UNIVERSITÉ Grenoble Alpes

gipsa-lab

irstea

EUROPEAN UNION
Interreg
Alpine Space
Links4Soils

ACKNOWLEDGEMENT

LabEx OSUG@2020

Observatoire des Sciences de l'Univers de Grenoble

This work has been supported by a grant from LabEx OSUG@2020 (Investissements d'avenir - ANR10 LABX56)