remote sensing

MDPI

Editorial

GEOBIA 2016: Advances in Object-Based Image Analysis—Linking with Computer Vision and Machine Learning

Norman Kerle [1,*], Markus Gerke [2] and Sébastien Lefèvre [3]

[1] Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, 7500 AE Enschede, The Netherlands
[2] Technical University of Braunschweig, Germany, Institut für Geodäsie und Photogrammetrie, Bienroder Weg 81, D-38106 Braunschweig, Germany; m.gerke@tu-bs.de
[3] IRISA - Université Bretagne Sud, Campus de Tohannic, BP 573, 56017 Vannes, CEDEX, France; sebastien.lefevre@irisa.fr
* Correspondence: n.kerle@utwente.nl; Tel.: +31-53-4876476

Received: 9 May 2019; Accepted: 15 May 2019; Published: 17 May 2019

The 6th biennial conference on object-based image analysis—GEOBIA 2016—took place in September 2016 at the University of Twente in Enschede, The Netherlands (see www.geobia2016.com). In terms of the scope and direction, the meeting departed from earlier editions in the conference series that had established a customary dual focus on studies dealing with technical aspects of image segmentation and object-based classification, shored up with application papers. It had become increasingly clear that in particular technical developments in object-based image analysis proceeded largely independently from similar work in other domains. While GEOBIA research has a distinct spatial focus, the technical and methodological questions share significant commonalities not only with work in computer vision, signal processing, and semantic image analysis, but also the medical imaging field. For that reason, one theme of the conference was synergies, reflecting the aim to attract researchers from beyond the traditional core community. The invitation was particularly directed towards colleagues working in computer vision and machine learning, and the event was also linked to the then ongoing ISPRS 2D semantic labeling benchmark [1]. The main reason for this association was the growing need to depart from highly tailored GEOBIA solutions with limited transferability, towards more generic and robust approaches that also facilitate easier operationalization. This aim illustrates the second theme, solutions. GEOBIA 2016 coincided with a number of exciting relevant developments in the wider geoinformatics arena, with new fields emerging or maturing, such as deep learning, semantic image analysis, cloud-based processing of big data, and development of open-source solutions. All of these themes were mirrored in the very diverse set of 115 papers presented at the conference.

Following the meeting, this Special Issue was launched, and 12 articles were selected for publication. These papers provide a cross-section of the state-of-the art of GEOBIA research and reflect the diversity of work the conference aimed to present. Concerning the solutions theme, 5 papers showed significant developments towards better operationalization. A more standardized sampling and response design and more objective validation of OBIA-based maps were proposed by [2]. The problem of sample selection was also addressed in [3], via template libraries derived from different image types and dates, as well as settings, again aiming at a more robust and transferable analysis. This allows for easier automated topographic map updating, also addressed in [4]. The development of OBIA-based solutions that are available to a wide range of stakeholders is best supported by free and open-source (FOSS) tools. One such solution is the use of Docker images as developed in [5]. For the common problem of urban area classification, [6] showcased a Python-based semi-automatic procedure, implemented as

GRASS add-on. The focus on urban area complexities was supported by the ISPRS benchmark datasets that were used in the studies of [4] and [7]. The data were also used in [8], employing deep learning with a convolutional neural network (CNN) and semantic analysis to guide an adaptive image segmentation, finally also demonstrating transfer learning between different benchmark locations. Semantic classification was also performed in [9], here applied to three-dimensional (3D) point cloud data that are increasingly subjected to OBIA processing (e.g., [10–13]). Transferability of OBIA methods is also furthered though semantic classification with ontologies, as shown in [14], where basic machine learning was also used. Machine learning algorithms were also used in [15] to encode topological relationships between objects, especially helpful when processing images obtained with different sensors. Machine learning can improve the classification efficiency and facilitate the transfer of solutions. An additional obstacle to operationalization that has hampered many OBIA studies is the inefficiency of the multi-resolution segmentation (MRS) conventionally applied. Here, approaches from the signal processing and pattern recognition community offer solutions. Csillik [16] worked with Simple Linear Iterative Clustering (SLIC) superpixels that reduced the time required for segmentation with MRS by 96%, while coupled with random forest analysis achieving comparable accuracy. Superpixels support effective hierarchical multiscale segmentation and have been found to be useful when used in probabilistic modeling and adaptive segmentation [17], especially where object scales are highly variable, such as in complex urbans scenes [18] or damage mapping [19].

GEOBIA 2016 issued a call for interdisciplinary collaboration, and the submitted papers mirror a conference of corresponding diversity. This leads to the question of whether the event had a more lasting effect on the core GEOBIA community and the conference series. The 2018 meeting took place in Montpellier, France, under the theme *GEOBIA in a Changing World*. At this meeting, some trends from 2016 were continued, with several papers focusing on deep learning, semantics, and ontologies, as well as operational handling of big data, embedded in more traditional application work.

GEOBIA is a niche community with limited output and reach. A simple literature analysis shows that under the core (GE)OBIA label, only 100–150 papers have been published annually since the 2016 conference, in contrast with approximately 4000 segmentation-based works on computer vision or machine learning, many of which also have a spatial focus. It is thus important that the GEOBIA community is clear about its identity and future direction. The 2016 conference showed that there is significant interest in the various spatial data segmentation-focused communities coming together. For the 2020 GEOBIA conference and beyond, it will be critical to make optimal use of the rapid technical developments, especially in computer vision and machine learning, to stay relevant. Continued cross-fertilization, and, in particular, incorporating the rapid advances of CNN for visual perception, will be necessary.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Rottensteiner, F.; Sohn, G.; Gerke, M.; Wegner, J.D.; Breitkopf, U.; Jung, J. Results of the isprs benchmark on urban object detection and 3d building reconstruction. *ISPRS-J. Photogramm. Remote Sens.* **2014**, *93*, 256–271. [CrossRef]
2. Radoux, J.; Bogaert, P. Good practices for object-based accuracy assessment. *Remote Sens.* **2017**, *9*, 646. [CrossRef]
3. Tiede, D.; Krafft, P.; Fureder, P.; Lang, S. Stratified template matching to support refugee camp analysis in obia workflows. *Remote Sens.* **2017**, *9*, 326. [CrossRef]
4. Höhle, J. Generating topographic map data from classification results. *Remote Sens.* **2017**, *9*, 24.
5. Knoth, C.; Nust, D. Reproducibility and practical adoption of geobia with open-source software in docker containers. *Remote Sens.* **2017**, *9*, 290. [CrossRef]
6. Grippa, T.; Lennert, M.; Beaumont, B.; Vanhuysse, S.; Stephenne, N.; Wolff, E. An open-source semi-automated processing chain for urban object-based classification. *Remote Sens.* **2017**, *9*, 358. [CrossRef]

7. Jarzabek-Rychard, M.; Maas, H.G. Geometric refinement of als-data derived building models using monoscopic aerial images. *Remote Sens.* **2017**, *9*, 282. [CrossRef]
8. Audebert, N.; Le Saux, B.; Lefevre, S. Segment-before-detect: Vehicle detection and classification through semantic segmentation of aerial images. *Remote Sens.* **2017**, *9*, 368. [CrossRef]
9. Weinmann, M.; Weinmann, M.; Mallet, C.; Bredif, M. A classification-segmentation framework for the detection of individual trees in dense mms point cloud data acquired in urban areas. *Remote Sens.* **2017**, *9*, 277. [CrossRef]
10. Kamps, M.T.; Bouten, W.; Seijmonsbergen, A.C. Lidar and orthophoto synergy to optimize object-based landscape change: Analysis of an active landslide. *Remote Sens.* **2017**, *9*, 805. [CrossRef]
11. Zou, X.L.; Zhao, G.H.; Li, J.; Yang, Y.X.; Fang, Y. Object based image analysis combining high spatial resolution imagery and laser point clouds for urban land cover. In *Xxiii isprs Congress, Commission iii*; Halounova, L., Schindler, K., Limpouch, A., Pajdla, T., Safar, V., Mayer, H., Elberink, S.O., Mallet, C., Rottensteiner, F., Bredif, M., et al., Eds.; Copernicus Gesellschaft Mbh: Gottingen, Germany, 2016; Volume 41, pp. 733–739.
12. Lin, Y.B.; Wang, C.; Cheng, J.; Chen, B.L.; Jia, F.K.; Chen, Z.G.; Li, J. Line segment extraction for large scale unorganized point clouds. *ISPRS-J. Photogramm. Remote Sens.* **2015**, *102*, 172–183. [CrossRef]
13. Yang, B.S.; Dong, Z.; Zhao, G.; Dai, W.X. Hierarchical extraction of urban objects from mobile laser scanning data. *ISPRS-J. Photogramm. Remote Sens.* **2015**, *99*, 45–57. [CrossRef]
14. Gu, H.Y.; Li, H.T.; Yan, L.; Liu, Z.J.; Blaschke, T.; Soergel, U. An object-based semantic classification method for high resolution remote sensing imagery using ontology. *Remote Sens.* **2017**, *9*, 329. [CrossRef]
15. Cui, Y.W.; Chapel, L.; Lefevre, S. Scalable bag of subpaths kernel for learning on hierarchical image representations and multi-source remote sensing data classification. *Remote Sens.* **2017**, *9*, 196. [CrossRef]
16. Csillik, O. Fast segmentation and classification of very high resolution remote sensing data using slic superpixels. *Remote Sens.* **2017**, *9*, 243. [CrossRef]
17. Hossain, M.D.; Chen, D. Segmentation for object-based image analysis (obia): A review of algorithms and challenges from remote sensing perspective. *ISPRS-J. Photogramm. Remote Sens.* **2019**, *150*, 115–134. [CrossRef]
18. Cheng, G.L.; Zhu, F.Y.; Xiang, S.M.; Wang, Y.; Pan, C.H. Accurate urban road centerline extraction from vhr imagery via multiscale segmentation and tensor voting. *Neurocomputing* **2016**, *205*, 407–420. [CrossRef]
19. Vetrivel, A.; Gerke, M.; Kerle, N.; Vosselman, G. Identification of damage in buildings based on gaps in 3d point clouds from very high resolution oblique airborne images. *ISPRS-J. Photogramm. Remote Sens.* **2015**, *105*, 61–78. [CrossRef]