3D Micro-Mapping: Crowdsourcing to Support Image and 3D Point Cloud Analysis

Bernhard Höfle, Katharina Anders, Lukas Winiwarter

3DGeo Research Group, Institute of Geography, Heidelberg University

Crowdsourcing of geospatial data aims at (geo)information extraction performed by humans. It includes the key characteristics that potentially large and diverse user groups are involved, users can have a lack of formal training and special knowledge and usually Web 2.0 technology is utilized (Heipke 2010). The science of crowdsourcing is a multi-dimensional one, which includes technical-, data- and social aspects, as well as integrated views (Fig. 1). The integrated issues are of high importance such as how a crowdsourcing task shall be designed. The design is not only determined by the actual task (e.g. mapping of trees) but also by the input data (e.g. image vs. point clouds), the tools that are used and also by the expected skills of the target crowd (Fig. 1).

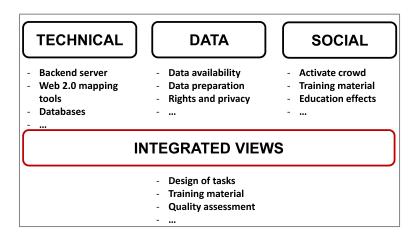


Fig. 1: Dimensions of crowdsourcing.

A special case of crowdsourcing is '3D micro-mapping', which means mapping and extraction of 3D geoinformation within a few seconds using web technology, which can also be done by non-experts (Herfort et al. 2018). In our definition, 'micro' refers to the effort and time that is needed to solve a single crowdsourcing task. A task could be the annotation of an image or 3D view or the mapping of a single geographic feature by clicking into an image. This effort is 'micro' and thus the task is designed such that it can be solved within a few seconds. Micromapping makes primarily sense for tasks that are easy to understand and to be solved by human interpreters and are difficult to be solved by algorithms in an automatic manner. Users make use of their visual interpretation strength and they might provide local and context knowledge that can be incorporated in a beneficial way.

3D micro-mapping can be divided into three main concepts how 3D-geoinformation is derived from remotely sensed data (Fig. 2): a) Mapping can be done in the original image space (e.g. photo) and results are transformed to geographic 3D space - using monoplotting or other methods to solve the mathematically ill-posed problem (cf. Griesbaum et al. 2017), b) 3D data is converted into 2D image space (e.g. cross-section of point cloud) and then converted back to geographic 3D space (Fig. 2), c) mapping is performed directly – and interactively – in 3D (cf. Herfort et al. 2018).

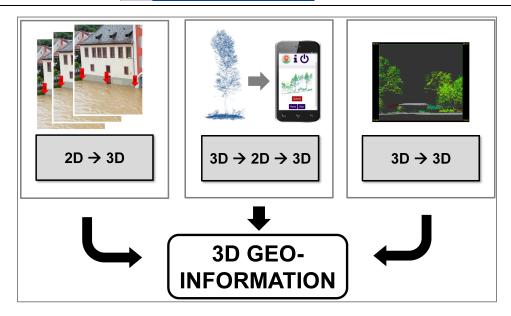


Fig. 2: Main concepts of 3D micro-mapping.

Most micro-mapping projects share a similar structure (Fig. 3). The project consists of single tasks which are solved by users and generate none, one or more contributions to a single task. All contributions per task need to be aggregated to derive the resulting 3D geoinformation. Commonly employed aggregation functions are majority vote, mean values, etc. (Herfort et al. 2018). The choice of aggregation influences the completeness and precision of the results. Depending on the use of data the appropriate aggregation function must be chosen.

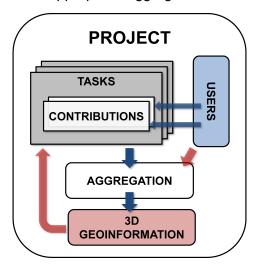


Fig. 3: General structure of 3D micro-mapping as crowdsourcing projects.

Common challenges (according to Barrington et al. 2011) are the questions, a) how the overall project objective can be split into micro-tasks, b) how the contributions can be aggregated and c) how a large group of people can be organized.

In order to set up a micro-mapping project, a minimum technical system with the following components is needed (Fig. 4), which implements the general structure as shown in Fig. 3. The input data (e.g. 3D point cloud) has to be prepared and split into the single tasks (e.g. single cross-sections through point cloud). Usually a web frontend is used to display the tasks to the users and to offer a tool to map and submit the answer to the task. A core part is the logic and system for task management. This includes e.g. how tasks are selected from the

overall set of open tasks, how often tasks are shown to users and whether tasks are closed after a certain number of contributions. The geo-database holds the prepared base data for mapping and also stores the contributed results. Already in the geo-database, the users' contributions can be converted to 3D geographic space. Alternatively, it is done later in the post-processing step, which also consists of applying the aggregation function in order to derive the final 3D geo-information output.

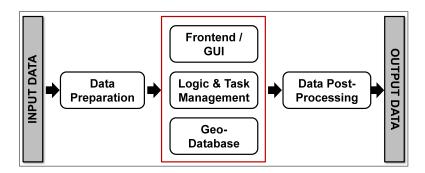


Fig. 4: Minimal technical system for 3D micro-mapping.

The theoretical considerations of 3D micro-mapping will be discussed in more detail based on two selected research studies: The first study investigates three experiments of 3D micro-mapping, which deal with airborne LiDAR point clouds of single urban trees that have been derived automatically by point cloud segmentation (see algorithm in Höfle et al. 2012). One of the experiments is a full-3D task where the users are asked to determine the crown base height of trees (Koma et al. 2016) by interactive plane adjustment in a web app. Further details are published in Herfort et al. (2018).

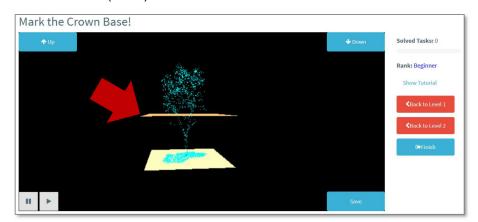


Fig. 5: Experiments on 3D micro-mapping for crown base height estimation (Herfort et al. 2018).

The second study deals with mapping and localization of trees in a mixed forest that was scanned with UAV-LiDAR under leaf-on conditions. This crowdsourcing study will also contribute to the SYSSIFOSS research project, which has the objective to develop a method to generate synthetic structural remote sensing data for improved forest inventory models (https://uni-heidelberg.de/syssifoss). The objective of a single task is to click on tree stems in cross-sections cut from the forest point cloud. The main hypothesis is that humans can detect trees in relatively sparse UAV point clouds better than automatic approaches, which are already challenged by high-density TLS data as input data (Liang et al. 2018). The upcoming 3D tree mapping crowdsourcing project will be released for mapping at the Phowo 2019 conference. Conference participants will be contributing to novel scientific dataset that will help to a) identify challenging issues for users while mapping, b) evaluate different aggregation methods of user contributions, and c) assess mapping accuracy by comparison with TLS-

captured trees. Furthermore, we expect valuable insights to push forward the combination of automatic methods and crowdsourcing in hybrid and integrated algorithms. For example, Herfort et al. (2019) found that the combination of deep learning and micro-mapping can drastically reduce the effort for crowdsourcing (by 80 %).





Fig. 6: Upcoming research study on crowdsourcing of tree stem locations in UAV-LiDAR point clouds of a mixed forest. Left: web browser interface, right: smartphone view.

The web app for 3D micro-mapping of tree mapping in UAV-LiDAR point clouds can be accessed here (Fig. 6): https://uni-heidelberg.de/3dgeo. Contributions are gratefully welcome.

References

Barrington, L., Ghosh, S., Greene, M., Har-Noy, S., Berger, J., Gill, S., Lin, A. & Huyck, C. (2012): <u>Crowdsourcing earthquake damage assessment using remote sensing imagery</u>. *Annals of Geophysics*. Vol. 54 (6), pp. 680-687.

Griesbaum, L., Marx, S. & Höfle, B. (2017): <u>Direct local building inundation depth determination in 3D point clouds generated from user-generated flood images</u>. *Natural Hazards and Earth System Sciences*. Vol. 17 (7), pp. 1191-1201.

Heipke, C. (2010): <u>Crowdsourcing geospatial data</u>. *ISPRS Journal of Photogrammetry and Remote Sensing*. Vol. 65 (6), pp. 550-557.

Herfort, B., Höfle, B. & Klonner, C. (2018): <u>3D micro-mapping: Towards assessing the quality of crowdsourcing to support 3D point cloud analysis</u>. *ISPRS Journal of Photogrammetry and Remote Sensing*. Vol. 137, pp. 73-83.

Herfort, B., Li, H., Fendrich, S., Lautenbach, S. & Zipf, A. (2019): <u>Mapping Human Settlements with Higher Accuracy and Less Volunteer Efforts by Combining Crowdsourcing and Deep Learning</u>. *Remote Sensing*, Vol. 11 (15), 1799.

Höfle, B., Hollaus, M. & Hagenauer, J. (2012): <u>Urban vegetation detection using radiometrically calibrated small-footprint full-waveform airborne LiDAR data</u>. *ISPRS Journal of Photogrammetry and Remote Sensing*. Vol. 67 (0), pp. 134-147.

Koma, Z., Koenig, K. & Höfle, B. (2016): <u>Urban Tree Classification Using Full-Waveform Airborne</u>
<u>Laser Scanning</u>. In: *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences*. Vol. III-3, pp. 185-192.

Liang, X., et al. (2018): <u>International benchmarking of terrestrial laser scanning approaches for forest inventories</u>. *ISPRS Journal of Photogrammetry and Remote Sensing*. Vol. 144, pp. 137-179.