Separating mounds from mounds

Combining LiDAR with land use models for automated detection approaches

M. Fabian MEYER-HEß, Ruhr University Bochum, Germany[1]
Ingo PFEFFER, LWL-Archaeology, Germany
Carsten JÜRGENS, Ruhr University Bochum, Germany

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Introduction

LiDAR-derived digital terrain models revolutionized archaeological prospection in the last two decades. Using the new technique, area-wide detections of field monuments hidden under dense vegetation became possible and archaeologists found new sites even in well-known areas. Concerning the drawbacks of the commonly used hill shading visualization, many other visualizations were invented to enhance visibility of interesting structures. However, analysing terrain models is still mostly done by hand in well-defined investigation areas. Vice versa, for a province-wide detection of field monument, automated approaches are necessary to fully exploit their potential. This also applies to the state of North Rhine-Westphalia (NRW) in western Germany. On the one hand, archaeologists benefit from the Open Geodata principle, which provides up-to-date spatial data, such as digital terrain models, free of charge. On the other hand, there are not enough resources to take the chance for a province-wide prospection using these data in a reasonable amount of time.

Therefore, geographers from the Ruhr University Bochum and archaeologists from the Westphalian archaeological agency are developing workflows for an automated and time-efficient analysis of the available terrain models. To reduce processing time, e.g., settlements and other sealed areas are rejected. Finally, potential field monuments are flagged and sorted by probability. This way, archaeologists are able to interpret the most promising results at first without losing those that appear eroded. Some of the preliminary results were already published in Meyer et al. (2019).

This paper will demonstrate two things. Firstly: discriminating between archaeological interesting and uninteresting areas is possible and appropriate to avoid misclassifications. Secondly: the topics of LiDAR visualization and automated detection are interdependent. More precisely, traditional

[1] M. Fabian Meyer-Heß, Ruhr University Bochum, Department of Geography, Universitätsstraße 150 / Building IA, 44801 Bochum, matthias.meyer@rub.de.

hillshade visualizations should not be used for Object-based Image Analysis (OBIA). E.g., Difference Maps should be preferred.

Determining archaeological interesting areas

The government of NRW provides a variety of spatial datasets free of charge. The land use model *BasisDLM* is used to determine archaeological interesting areas (*positive*) and to reject those where field monuments cannot be preserved in the terrain (*negative*).

The land use model consists of a bunch of shapefiles, each including a certain type of land use as polygon-, line- or point features. Evaluating polygons, such as forests, pastures or residential areas, is relatively easy because unsealed areas are most likely to be positive, whereas the others are negative. Line and point features, however, have no width or diameter, in contrast to their modern real-world counterparts such as streets or windmills. Therefore, their width has to be derived from the attribute table or determined as precise as possible for every type of object. These width values are then used as radii for buffer zones, representing the negative area around each feature (Fig. 1). Starting with well-defined investigation areas to derive the width of all features, the buffering was finally done for the whole province of Westphalia. This way, most non-archaeological mounds and other modern structures are rejected from the detection (Fig. 2, Meyer-Heß, 2020).

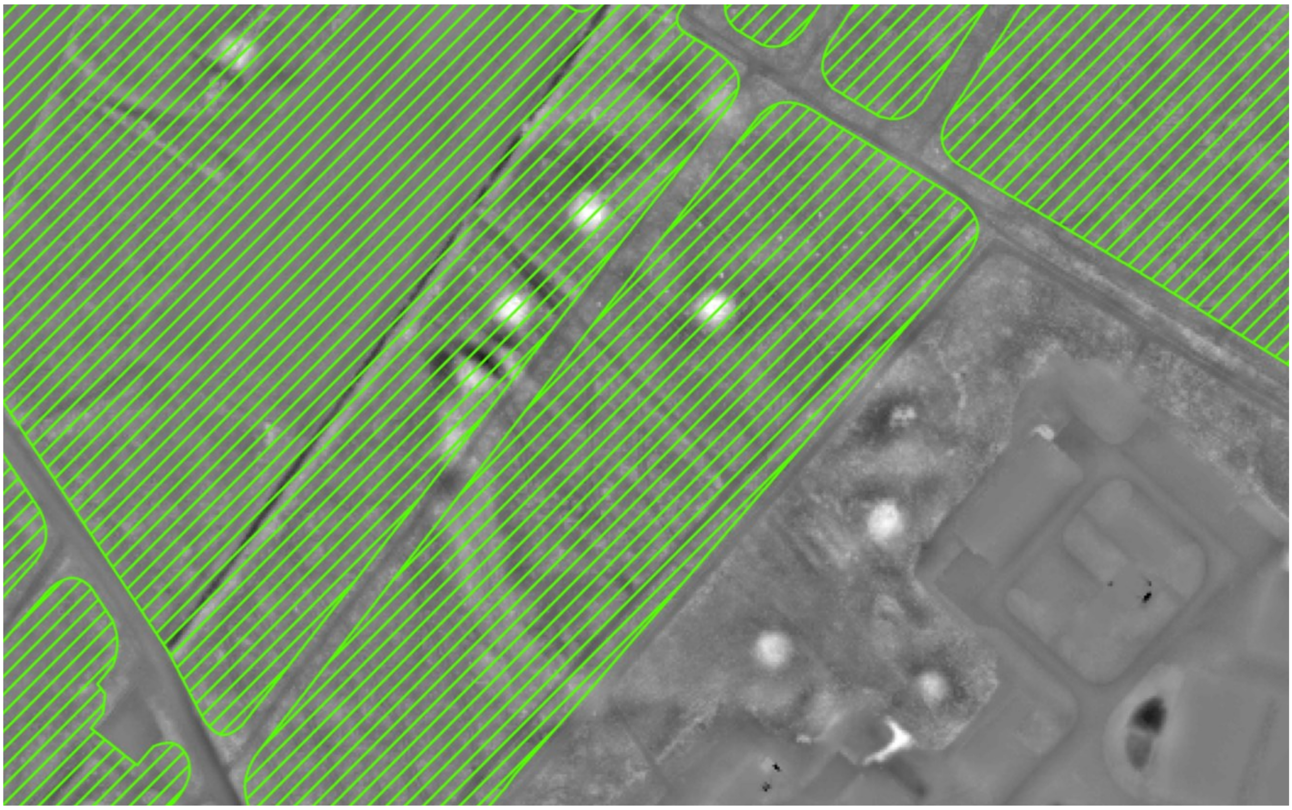

Fig. 1. Difference Map of an investigation area in Haltern. The brighter a pixel, the more elevated it is compared to the surrounding relief, whereas dark colors are below. The positive layer, to which the search is limited to (green), is overlaying (Data Source: Land NRW, dl-de/by-2-0).

Fig. 2. Non-archaeological mound made of asphalt in Wuppertal (© M. Fabian Meyer-Heß).

Automated detection using OBIA

For the classification, OBIA, implemented in *eCognition Developer* by Trimble, is used. This technique does not classify single pixels but objects representing homogeneous areas within an image. In a DTM, they correspond to areas of the same height. Objects are generated in the initial segmentation step that is executed perfectly when the object borders match those of their corresponding real-world objects.

Afterwards, statistical values are calculated for every object. Some of which refer directly to the object (e.g. length and width) and some to its neighbors (e.g. rel. border to brighter objects). From these, the user can choose features to describe classes. This is the advantage over pixel-based approaches because objects can be addressed in a relation to their neighbors and therefore be discriminated by their location, which is essential for the detection of field monuments. In terms of OBIA, remnants of a Motte-and-Bailey castle can be described as a local maximum (the motte) or as an object completely surrounded by darker (lower) objects, which is in close proximity from a ring-shaped local minimum (a ditch surrounding the motte). All steps are included in a *ruleset* that runs fully automated, exports the classification results to GIS-compatible shapefiles and can be transferred to other projects.

OBIA and its dependencies on visualizations

Although OBIA does not ‘see’ an object in the way the human eye does, it nevertheless benefits from special terrain visualizations like the Difference Map that was originally developed for manual interpretation. Because hills and valleys are removed, contrast increases significantly but most importantly, all monuments appear in a levelled situation.

This is necessary because object borders in LiDAR datasets follow the contour lines, making field monuments invisible to OBIA if they are located on a hillside. Fig. 3 demonstrates this issue as the castle on the left side (a) cannot be detected because the objects where derived from a regular DTM. On the right side (b) the hill is removed (Difference Map) and motte and bailey stand out against the surrounding area even though they are almost eroded completely.

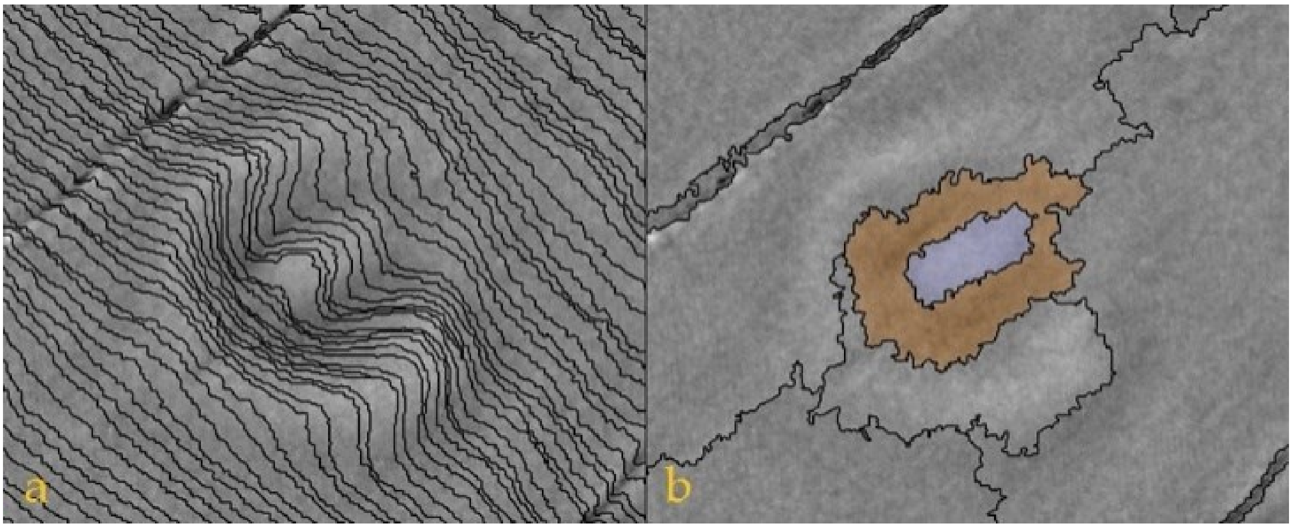

Fig. 3. Difference Maps of a highly eroded Motte-and-Bailey castle on a hillside in Warburg with overlaying objects derived from a regular DTM (a) and from a Difference Map (b) (Data Source: Land NRW, dl-de/by-2-0).

Mound detection

Mound detection in OBIA is relatively straightforward. In terms of OBIA, the task is to find round local maxima. They are not classified binary but in five classes, that were derived from reference mounds in different stages of erosion. This is a similar result organizing approach to that of Trier et. al. (2015).

Table 1 provides an idea of what is possible under good circumstances. The overall decreasing correctness is no surprise because the class descriptions get wider in order to find possible eroded mounds as well. Completeness is 100 % by definition, because all 173 reference mounds defined the classes. The black numbers where generated using the outdated workflow without considering the land use, whereas the blue numbers are considering the additional information. These are significantly higher demonstrating that land use models are useful and should be used not only for mound detections but for manual prospection as well.

Class	TP	FP	Total	Correctness	Δ
1) ideal	14	1 / 0	15 / 14	93 % / 100 %	+ 7 %
2) …	20	19 / 10	39 / 30	51 % / 67 %	+ 16 %
3) …	65 / 64	260 / 147	325 / 211	20 % / 30 %	+ 10 %
4) …	52	578 / 415	630 / 467	8 % / 11 %	+ 3 %
5) highly eroded	22	1227 / 911	1249 / 933	2 % / 2 %	+ 0 %
Total	173 / 172	2085 / 1483	2258 / 1655	8 % / 10 %	+ 2 %

Table 1. Results of a mound detection in Haltern. Blue numbers were generated using the land use model.

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