Fencing Virtual Landscapes: Using GIS to Identify and Classify Fences and Hedges for More Accurate Landscape Visualizations

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Abstract: Fences are a fundamental part of our landscapes. They delineate, protect, distinguish and give order. However, GIS data on fences and hedges is sparse. This becomes especially apparent in landscape visualizations. Even with highly detailed building information, land-cover data, and infrastructure information, a rural landscape without fences and hedges looks clearly incomplete. In this article, we describe a method for generating large-scale high-coverage barrier data from the Austrian cadastre dataset and other publicly available GIS data. We evaluate this data statistically against three manually mapped regions, as well as visually in our GIS-based landscape visualization. The results show that the approach works well in regions dominated by single-family homes, but that the assumptions generally do not apply in more rural regions with alpine pastures.

Keywords: Open data, feature extraction, mapping, GIS, VR, 3D visualization

1 Introduction

Fences delineate, protect, distinguish and provide order in our landscapes (NASSAUER 1995, PICKARD 1994). Especially in rural and suburban areas, they are so ubiquitous that they characterize the landscape perhaps more than the houses they guard. As John Brinckerhoff Jackson put it in "Discovering the vernacular landscape":

"*Boundaries stabilize social relationships. They make residents out of the homeless, neighbors out of strangers, strangers out of enemies. They give a permanent human quality to what would otherwise be an amorphous stretch of land. Those roughly geometrical enclosed spaces are a way of rebuking the disorder and shapelessness of the natural environment; seeing them from outside, the alien wanderer wishes he too belonged.* (JACKSON 1984)"

But perhaps it might be their ubiquity that causes barriers to be often overlooked. While OpenStreetMap (OPENSTREETMAP CONTRIBUTORS 2024) contains meticulous data for buildings, roads, power lines and a number of other landscape-relevant elements, entries containing barrier tags are severely lacking. While cities sometimes keep official records of fences which are then reflected in the OpenStreetMap, smaller towns and villages rarely contain any data for barriers. Neither commercial map services like Google Maps nor governmental data sources provide any better coverage of fences.

In addition to their cultural and visual significance, fences and hedges have important ecological impacts, both positive and negative. Fences regulate human-wildlife-interactions, reduce predation, and prevent access to dangerous areas such as roads. However, they also pose a risk to wildlife through collision and entanglement with fences, as well as indirect ecological damage by fragmenting landscapes and restricting movement, leading to stress and habitat loss (JAKES et al. 2018).

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Given this cultural, ecological, and aesthetic value of fences, the lack of fence data is a curious gap in spatial and ecological analysis. It becomes especially apparent when analyzing openness and accessibility of landscapes or creating 3D visualizations based on geodata: Even with highly detailed building information, land-cover data, and infrastructure information, a rural landscape visualization without fences and hedges can appear incomplete, and it is challenging to orient oneself in a fence-less town (KELLY et al. 2021). This may be related to the neurology of the brain itself, which uses specialized *boundary cells* – cells whose firing rate correlates to the proximity to a boundary in the surrounding landscape – for navigation (LEVER et al. 2009).

Large-scale 3D landscape visualizations where manual mapping or detailed 3D scanning is infeasible typically use broadly available GIS data such as height maps, orthophotos, land cover data and building footprints, often focusing on the depiction of terrain and vegetation (CLASEN 2011, LANGE 2001, SCHAUPPENLEHNER, LUX & GRAF 2019). The resulting virtual environments can be valid and useful representations, but it has been argued that achieving high realism is easier in the middle- or background due to the lack of foreground detail. We suggest that fences are a key component of this usually lacking foreground detail.

The objective of this article is to work towards filling this gap by assessing whether it is possible to automatically generate accurate barrier datasets based on pre-existing GIS data. We conceptualize and implement an algorithm based on four assumptions and evaluate the results statistically against manually mapped test regions as well as visually in a large-scale landscape visualization. The result is a description of a potential method for generating large-scale high-coverage fence datasets from GIS data that is publicly available in Austria. Landscape visualization is our primary motivation for developing this method, but as noted above, accurate large-scale fence datasets may also be useful for other fields such as ecology.

2 Materials and Methods

2.1 Assumptions and Data

Fences generally delineate the borders of private property surrounding residential buildings. Therefore, the Austrian cadastre dataset (FEDERAL OFFICE OF METROLOGY AND SURVEYING (BEV) 2023b), which contains the legal boundaries of land ownership, is at the core of our automatic fence classification process. Buzzard et al. (2022) use a similar approach to map fences in the USA, focusing on wire fences in regions dominated by large-scale agriculture. Xianghuan et al. (2016) have used the reverse assumption in their article: They used point cloud data to detect fences, which they then used to build a cadastre dataset. This supports our claim that legal boundaries and fences correlate, leading to our first assumption: **Assumption 1: Fences generally run along legal boundaries**.

If a road is in the immediate vicinity or within a legal boundary, a fence usually accompanies this road. Therefore, we also use a national road dataset for the fence classification. **Assumption 2: Fences generally run right between properties and roads.** This requires road widths: these are available for all roads in Austria, but when using OpenStreetMap data, the width may need to be estimated based on other attributes.

We also use building data from OpenStreetMap (OPENSTREETMAP CONTRIBUTORS 2024) and assume that inhabited properties are always fenced, unless they are very large. **Assump-**

tion 3: Properties with a building inside are always fenced unless they exceed a certain area.

To differentiate fences from hedges, we propose surveying height data and true-color composite aerial imagery. For height data, a normalized digital surface model (nDSM) is used since it provides the difference between surface heights and terrain heights, yielding the height of whatever is placed on top of the terrain. Hedges are generally higher than fences, and because of their width, they are more likely to be visible in this height data, whereas thin fences generally do not clearly appear in nDSMs with typical resolutions of 1 or 2 meters (we use height data at 1 meter resolution, which is available for all of Austria). Furthermore, the area around a hedge line should be largely green in the aerial image. **Assumption 4: Hedges have higher values in the elevation dataset than fences and appear green in the aerial imagery.** If near-infrared data is also available, the Normalized Difference Vegetation Index (NDVI) may provide an even more accurate way of identifying hedges (HUANG et al. 2021). It should be noted that while the combination of height and color should be sufficient to differentiate fences surrounded by short vegetation from hedges, it is infeasible to detect combinations of fences and hedges with this method, as fences disappear in the aerial imagery when surrounded by dense shrubbery.

2.2 Processing

This section outlines a GIS processing workflow to obtain classified fence and hedge line data from the input data and assumptions described above First, the cadastre and road data are used to generate unclassified barrier lines:

1. Download and crop the cadastre dataset, i. e. the legal boundaries, for the region of concern. (Assumption 1)
2. Subtract road areas (road lines buffered by road width) from the cadastre polygons to identify fences accompanying the roads. (Assumption 2)
3. Select cadastre polygons with an area of less than 300 ha and a building inside as fence candidates. (Assumption 3)
4. Turn the fence candidate polygons into lines.
5. Remove overlapping building polygon regions from the fence lines.

Then, this line data describing barriers is classified into *fence* or *hedge* based on additional data (height and orthophoto) as follows:

1. Buffer fence lines generated in the first step by 1m.
2. Calculate zonal statistics for nDSM and orthophoto within those barrier polygons.
3. Classify as hedge if the nDSM mean is high enough (we assume 1.2m) and the orthophoto contains more green than red on average (we use 4 percent). (Assumption 4)

We use QGIS and Python with the Fiona library to run these processing steps. Using QGIS' command line program "qgis_process", the process is fully automated into a single script that generates fence and hedge lines for a given region.

2.3 Validation

To assess the accuracy of the data generated with the approach described above, a dataset close to the ground truth is needed to compare against. As noted in the introduction, OpenStreetMap (OPENSTREETMAP CONTRIBUTORS 2024) data on fences is sparse, but some regions of good coverage exist. In addition, it has been shown that manually detecting fences from high-resolution aerial imagery is feasible (HOLLAND, BOYD & MARSHALL 2006). Therefore, we access OpenStreetMap data and manually refine it, adding missing fence lines and correcting existing ones by hand, using the Austrian orthophoto at 0.2m resolution (FEDERAL OFFICE OF METROLOGY AND SURVEYING (BEV) 2023a) and the Austrian Basemap Orthophoto (GEOLAND.AT 2024) as references. Lastly, these results are visually verified with street-level imagery such as Google StreetView where possible. While this dataset is also prone to errors – in areas not covered by street-level imagery, especially small fences (e. g. grazing fences) can be very difficult to identify – we will use this as our "ground truth" data to compare our automatically generated barriers against.

Three 1.5 x 1.5-kilometer regions with comparatively good OpenStreetMap coverage were selected and manually refined using the approach described above:

- **Elsbach**: a typical eastern Austrian town with flat relief, dominated by single-family homes.
- **Bad Hofgastein**: a village in an Alpine valley with scattered settlements.
- **Schlaming**: a rural region on an Alpine hillside dominated by pastures and farmhouses.

To aid future research, this manually mapped "ground truth" data was made available as open data.[1]

The manually surveyed data is compared against our automatically generated barriers, created for the same regions by the process described in section 2.2, to assess **accuracy** and **completeness** of the automatic process. Accuracy is measured by assessing how many automatically generated barriers correspond to an existing barrier (true positives versus false positives). Completeness is evaluated by calculating how many existing barriers were also generated using our automatic approach (detected versus not detected).

To account for small offsets (e. g. caused by imprecise manual digitization or inaccuracies in the data), the dataset which is being compared against is buffered by 4 meters. By carrying out *intersection* and *difference* operations in GIS, we evaluated whether barriers of one dataset are also present in the other dataset. As a result, each dataset is classified into two categories (covered or not covered by the other dataset).

To measure *attribute accuracy* (whether fences and hedges were correctly distinguished), the attribute values in all true positives are compared, resulting in a percentage of correct classifications.

2.4 Visualization

As noted in the introduction, our primary motivation for acquiring barrier data is landscape visualization. Our visualization software, which is developed with the game engine Godot and a custom plugin for loading GIS data[2], renders barriers from GIS lines by repeating a single object (a 3-dimensional model of a fence or hedge segment) along a line. By matching the distance between objects to the size of the segments, a continuous fence is created. To take the relief into account, each individual segment is placed on the ground by reading from the digital terrain model at its location. If the terrain model is noisy, this can result in an uneven fence line; to prevent this, the height difference between two segments can be dampened by using an average of the previous and current height.

1 Available online: https://github.com/boku-ilen/brace-data
2 Geodot Plugin: https://github.com/boku-ilen/geodot-plugin/

The specific types of fence and hedge segments used in a given landscape can be assigned randomly from a pool of typical barriers for a specific region. Figure 1 shows examples of such segments.

Fig. 1: Examples of the 3D models used as fence and hedge segments in the visualization

3 Results

Evaluation of accuracy, completeness, and attribute accuracy was carried out as described in section 2.3, comparing "generated barriers" (data generated by the method described in section 2.2) to "existing barriers" (our manually mapped ground truth data). The total length of all lines in each class was measured; the results are provided in Tables 1, 2, and 3. Some extracts of the GIS data are shown in Figure 2.

The accuracy varies significantly between the three regions. With 75.8%, the accuracy is fairly high in Elsbach, a town dominated by single-family homes which are relatively clearly demarcated from the agricultural fields in the surroundings. Accuracy is lower in Bad Hofgastein with 53.8%. A qualitative visual survey of the results (see Figure 2), indicates that the accuracy is good in the vicinity of residential homes, while the false positives are primarily caused by fences around pastures: when they have a field barn inside, they are not filtered by assumption 3. Consequently, the accuracy is also low in Schlaming at only 17.0%, since this region is dominated by pastures and contains almost no detached houses, where the automatic barrier generation works well.

Table 1: Evaluation of accuracy. Length of true positives (generated barriers where an existing barrier is nearby) and false positives (generated barriers with no existing barrier nearby) in meters

	true positives (m)	**false positives (m)**	**% true**
Elsbach	28887	9243	75.8%
Bad Hofgastein	32697	28107	53.8%
Schlaming	2729	13340	17.0%
Total	64313	50690	55.9%

The results for completeness are similar, though the automatically generated data scores higher in this metric in all regions: approximately 80% of all "ground truth" barriers were also identified by our automatic approach in Elsbach and Bad Hofgastein. Undetected barriers primarily consist of fences along or within specific types of fields: for example, in Elsbach, individually fenced parcels in a horse farm were not identified. On the other hand, our approach missed three quarters of "ground truth" barriers in the Schlaming region, where most fences surround pastures rather than residential gardens.

Table 2: Evaluation of completeness. "Detected" are existing barriers which were spotted by our automatic approach, "not detected" are existing barriers where our approach did not estimate a barrier (length in meters)

	detected (m)	not detected (m)	% detected
Elsbach	34840	7721	81.9%
Bad Hofgastein	35638	9438	79.1%
Schlaming	2678	7971	25.1%
Total	73156	25130	74.4%

The classification into "fence" or "hedge" was correct in about 75% of the generated barriers. This attribute accuracy is lowest in Bad Hofgastein; it is unusually high in Schlaming with 99.0%, but it should be noted that the sample of true positives was far smaller in this region than in the others and the ground truth data contained almost no hedges, so this result is less significant than the others.

Particularly for the visual impression, the ratio of fences to hedges is also important. In our predicted data, approximately 11.4% of barriers are classified as hedges, while the remaining 89.6% are fences. In the "ground truth" data, hedges are slightly more prevalent, with 16.5% hedges and 83.5% fences.

Table 3: Evaluation of the classification into fence and hedge, comparing our generated data with the ground truth data (length in meters)

	class correct (m)	class incorrect (m)	% correct
Elsbach	23074	5813	79.9%
Bad Hofgastein	21481	11216	65.7%
Schlaming	2702	27	99.0%
Total	47257	17056	73.5%

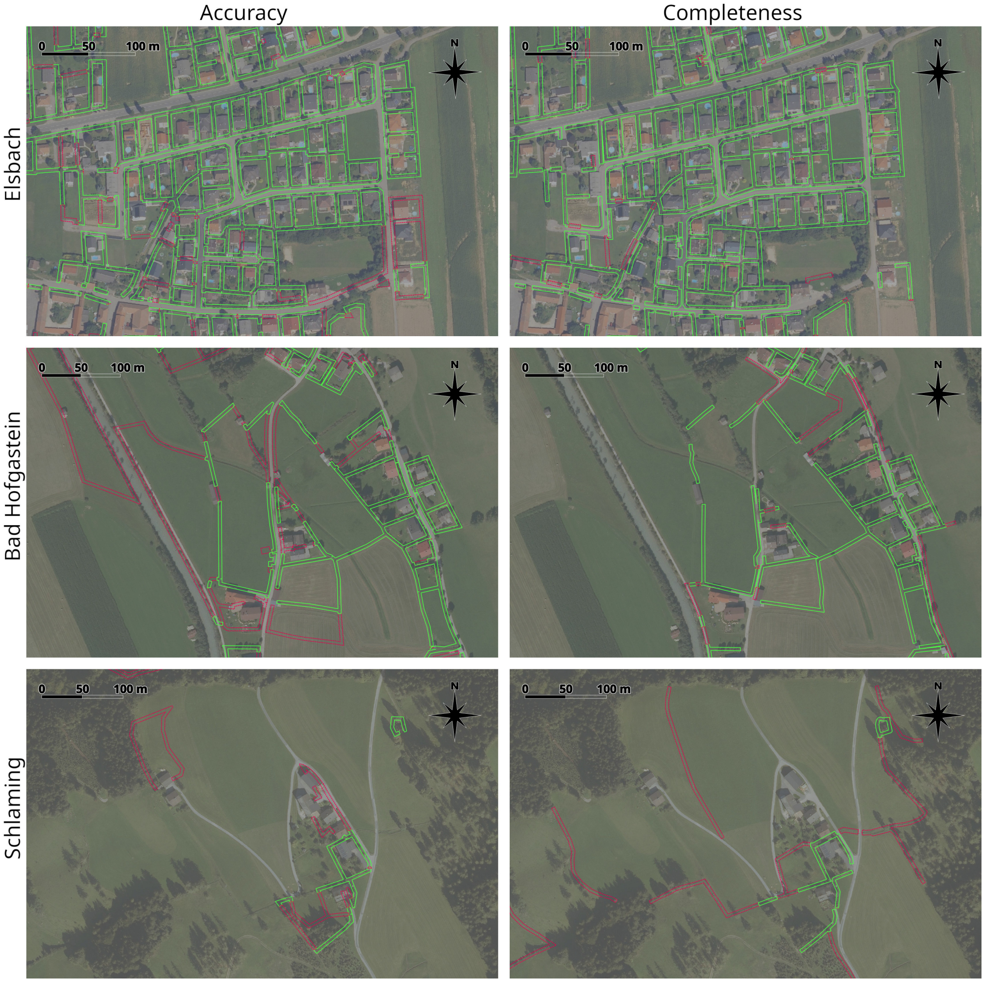

Fig. 2: Accuracy (generated lines classified into true (green) and false (red, dashed) positives) and completeness (manually surveyed lines classified into detected (green) and not detected (red, dashed)) of exemplary sections within the three regions (Background: BEV Orthophoto)

In addition to this statistical analysis, we used our GIS-based landscape visualization software to compare rural and suburban landscapes with and without fence representations based on our automatically created fence dataset. Figure 3 shows one such comparison of a photograph to a visualization in the Elsbach region. Note that the specific fence types were assigned randomly.

Fig. 3: Comparison of a street-level photograph in the Elsbach region (left, source: Mapillary, licensed CC BY-SA) to a visualization of the same area including our estimated barrier dataset (center) and without barriers (right)

4 Discussion

In all regions, the completeness of barriers was higher than the accuracy. In Elsbach and Bad Hofgastein, the two regions dominated by single-family homes, the automatically generated barriers were about 80% complete, but only approximately 76% and 54% accurate respectively. This suggests that the approach is well suited for identifying barriers in such regions, but that additional measures are needed to filter improbable barriers. In Schlaming, a rural area characterized by farms and pastures, both accuracy and completeness were low at around 17% and 25% respectively. This suggests that barriers on and around pastures in rural alpine regions follow a different logic than barriers in more densely populated areas, and our assumptions do not apply there. Therefore, a different approach may be needed there.

A possible alternative approach uses street-level imagery for automatically surveying fences, as shown by (Ypenga, Sukel & Alavi 2023) with good results. However, the coverage with street-level imagery is very poor in rural areas, so this approach is not a solution for these regions. Furthermore, these approaches cannot recognize barriers that are outside the visibility from the road. (e. g. between and behind buildings).

To create the validation dataset, we combined volunteered geographic information from OpenStreepMap with remote sensing data. Field surveys may be more accurate, though (Cherrill & McClean 2001) argue that even there, small fences are generally not mapped. Still, systematically mapped fences in the field would contribute to a more accurate ground truth data to compare our results against. Particularly in areas not covered by street-level imagery, some false positives are likely due to the fact that the fences are not recognizable on the aerial images. In addition, there are often temporal inconsistencies between the data, which means that, for example, fences around new buildings that were recorded by OpenStreepMap mappers on site are not yet present on older aerial images. Such temporal differences are a challenge for both the manual survey and the automatic processing.

Additionally, our control sample is relatively small due to the high effort of manually identifying and mapping fences in aerial images. A larger control sample, especially a larger number of different regions, would strengthen the statistical significance of the results. We expect that the approach produces good results in any region with a typical European rural or suburban structure dominated by single-family houses; it would be interesting to verify this by conducting similar statistical analysis in other countries where similar data is available.

Fences and hedges are important landscape elements for which there is practically no or only very incomplete data. With our automated approach, we provide a viable way to fill this data gap in rural regions. While other approaches are still needed to increase accuracy and completeness in some landscapes, both the statistical evaluation and visual impressions of the generated barriers in a landscape visualization show that the fences and hedges are an important addition to the accurate representation of rural landscapes at scales where manual mapping or detailed 3D scanning is infeasible. However, this is only one of the many potential use-cases for a high-coverage fence dataset. We hope that our method inspires future work in this underappreciated field of remote fence sensing.

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