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Deriving incline values for street networks from voluntarily collected GPS traces

Steffen John\textsuperscript{a,b}, Stefan Hahmann\textsuperscript{a}, Adam Rousell\textsuperscript{a}, Marc-O. Löwner\textsuperscript{b,c} and Alexander Zipf\textsuperscript{a}

\textsuperscript{a}GIScience Group, Institute of Geography, Heidelberg University, Germany; \textsuperscript{b}Institute of Geodesy and Geoinformation Science, Technische Universität Berlin, Germany; \textsuperscript{c}Institute of Geodesy and Photogrammetry, Technische Universität Braunschweig, Germany

\section*{ABSTRACT}
When producing optimal routes through an environment, considering the incline of surfaces can be of great benefit in a number of use cases. For instance, steep segments need to be avoided for energy-efficient routes and for routes that are suitable for mobility-restricted people. Such incline information may be derived from digital elevation models (DEMs). However, the corresponding data capturing methods (e.g. airborne LiDAR, photogrammetry, and terrestrial surveying) are expensive. Current low-cost and open-licensed DEM (e.g. Shuttle Radar Topography Mission [SRTM] and Advanced Spaceborne Thermal Emission and Reflection Radiometer [ASTER]) generally do not have sufficient horizontal resolution or vertical accuracy, and lack a global coverage. Therefore, we have investigated an alternative low-cost approach which derives street incline values from GPS traces that have been voluntarily collected by the OpenStreetMap contributors. Despite the poor absolute accuracy of this data, the relative accuracy of traces seems to be sufficient enough to compute incline values with reasonable accuracy. A validation shows that the accuracy of incline values calculated from GPS traces slightly outperforms incline values derived from SRTM-1 DEM, though results depend on how many traces per street segment are used for computation.

\section*{Introduction}
Common routing and navigation systems such as Google Maps\textsuperscript{1} or Here\textsuperscript{2} currently do not consider data about elevation or incline when computing routes. Initially, these services were designed primarily for car-based navigation, where incline information in most use cases is not a major concern. However, there are also many routing scenarios where incline is an important factor. For cyclists, pedestrians, and mobility-restricted people such as wheelchair users or people with walking aids, the inclines encountered within a planned route are of high relevance. For instance, the maximum incline a wheelchair user can climb is generally between 3\% and 8\% for manual wheelchairs and up to 10\% for electric ones (Menkens et al. 2011). Cyclists may either prefer mountainous routes for training or flat routes when commuting. Furthermore, energy-efficient routing benefits from incline information. Electric-powered vehicles such as electric cars or wheelchairs have an increased energy demand when going uphill and a limited battery capacity. This is a particular problem as charging stations remain rare. Thus, routing services that use information about the incline of possible routes may be used to predict the required energy demand more accurately and may even compute the most efficient route in terms of power consumption (cf. Franke et al. 2012).

Elevation data may be used to derive incline values within a road network (Schilling et al. 2009). However, the most common sources of elevation suffer from one or more of the following problems: (1) they are too expensive due to the highly specialized and costly sensors involved in data acquisition (satellite missions such as TanDEM-X, airborne LiDAR/photogrammetry, and terrestrial surveying), (2) they are not globally available (e.g. regional open governmental data sets), and (3) they do not have sufficient horizontal resolution or vertical accuracy (e.g. Shuttle Radar Topography Mission [SRTM] and Advanced Spaceborne Thermal Emission and Reflection Radiometer [ASTER]).

Therefore, we investigated whether volunteered geographic information (VGI) may serve as an additional, or even alternative, source of information for low-cost approaches to compute incline. Particularly we focused on voluntarily collected GPS traces. Due to the rapid development of mobile devices with integrated GPS receivers, such traces can easily be recorded on a large scale. The derived incline information will be validated using a high-resolution LiDAR-based DEM, in order to test the feasibility of the approach.
Furthermore, we compared the achieved results to incline values derived from SRTM-1, which currently is one of the best freely available global DEMs in terms of resolution and accuracy. This comparison will provide some insight as to whether crowdsourced GPS data collection already have the potential to substitute costly sensors for the acquisition of incline information.

This contribution is organized as follows. The following section provides an overview and related work. The “Methodology” section describes the methodology of deriving incline values from GPS traces while results are given and discussed in the “Results and discussion” section. The conclusion of this article can be found in “Conclusion” section.

Background and related work

The GPS

The availability of Global Navigation Satellite Systems (GNSS) to end users is a necessary precondition to allow crowdsourced collection of position data. The most widely used GNSS is generally considered as the GPS, which is operated by the US Department of Defense. In its beginning, the accuracy was degraded for civilian use, known as Selective Availability (SA). In the year 2000, SA was switched off, which now enables sufficient accuracy for many standard applications in the private sector, such as navigation and location-based services (Hofmann-Wellenhof, Lichtenegger, and Wasle 2008).

Currently mobile devices that are equipped with low-cost GPS receivers have a horizontal accuracy of 5–10 m and a vertical accuracy of up to 25 m (Liu et al. 2014). The relatively poor vertical accuracy is explained by the constellation of satellites (cf. Langley 1999). In fact, this poor vertical accuracy limits the potential of GPS measurements to derive elevation data. However, in the case of incline computation, this accuracy is not necessarily a problem as long as the vertical error of adjacent points is relatively stable. This is because a similar vertical error would be present in neighboring points, and thus, there would not be a differential inconsistency within the incline computation.

Volunteered Geographic Information (VGI)

The term “Volunteered Geographic Information” was introduced by Goodchild (2007). It describes a special case of user-generated content (UGC). The latter term emerged in the mid-1990s and describes content of any type in the Internet which is produced by the user (Bauer 2010) of respective web services. The phenomenon of VGI has also been referred to as “crowdsourcing geospatial information” by Heipke (2010) and Ramm, Topf, and Chilton (2011). Sui (2008) describes the recent development as the “wikification of GIS” and points out that the actors and methods for collecting geographic information have changed. While previously only experts like surveyors or cartographers acquired and processed geodata, today there is a large group of mostly untrained people who are also acquiring and processing this kind of data without any financial compensation. Budathoki, Bruce, and Nedovic-Budic (2008) refer to this phenomenon of a melting border between users and producers of geodata with the term “produser” of geodata. Due to its nature, VGI is typically heterogeneous in terms of accuracy and coverage (Sester et al. 2014). Depending on the number and motivation of contributors, some regions may be covered with more data and thus may be more complete than others.

Different forms of VGI acquisition can be differentiated. For instance, Sester et al. (2014) distinguish between participatory and opportunistic acquisition of VGI. While the participatory acquisition happens intentionally and is dedicated to a certain purpose, opportunistic data collection is a process where a user more or less unconsciously collects relevant data. Here, we present research on data of the latter category, since the analyzed GPS data has not been acquired for the specific purpose under investigation, i.e. the computation of road incline.

Figure 1 shows an example of the VGI data set that we use for our research. It can be seen that there is a higher density of available information than is contained in the SRTM-1 DEM (horizontal resolution = 1″ ~ 30 m, indicated by the grid lines) in the same region. Particularly beneficial for our approach is that many GPS track points are located along streets, which is exactly where the information for street incline computation is needed. However, it may also be seen that the density of measurements is not the same for all streets and at times can be quite poor.

OpenStreetMap (OSM)

The OSM project was founded in 2004 and can be seen as the most-popular VGI project (Haklay and Weber 2008). Three main methods of data acquisition may be distinguished: (1) digitizing based on previously recorded GPS traces, (2) digitizing based on satellite or aerial imagery, and (3) data donations of companies as well as open data provided by public agencies. It has been shown that the quality and completeness is varying for OSM data (e.g. Neis, Zielstra, and Zipf 2012).
Nevertheless, the OSM data set can be used for various applications – cf., e.g., Neis and Zielstra (2014b) and Arsanjani et al. (2015) for an overview. The OSM database stores both the map features and the user-generated GPS traces. These GPS traces are stored as a collection of files in the GPS Exchange format (GPX).

Currently, street incline values are assigned to the respective features using key-value pairs (tags) as is done for any semantic information in the project. According to the project documentation, the key is supposed to be “incline” and the corresponding value is ideally the actual incline value given in percent or degree.  

If a street geometry does not have a constant incline, the geometry should be split at the location of incline change.

Information regarding the incline of ways is scarce in the OSM data set and when it is present, it is in many cases not very specific. Only 0.2% of the highway features in OSM have an “incline” tag, while the majority of these tags (~75%) only specify “up” or “down.” For the remaining 25%, which is only 0.05% of all highway features, the incline is mainly given as a percentage or degree. However, it has also been found that non-numeric incline values (such as “moderate” or “extremely steep”) have been found. This may be due to several reasons. On the one hand, the contributors are often not too concerned with tags which will not be displayed on the map. On the other hand, incline values cannot simply be digitized from GPS traces or aerial imagery like other features. They need to be estimated on-site with the help of tools such as inclinometers or gyroscopes, which can now be found built into common smartphone models.

**3D routing**

One particular use case that would benefit from the availability of incline information for the complete street network is that of 3D route computation. As a 3D routing scenario, Müller et al. (2010), Neis and Zielstra (2014a), and Weyrer, Hochmair, and Paulus (2014) investigated routing algorithms that meet the requirements of mobility-restricted people. Beside this use case, incline is also relevant for route computation of electric-powered vehicles. One of the reasons why people are still skeptical about such vehicles is the poor prediction of distance range before a charge of the power source is required (Bachofer 2011). In order to improve this prediction, it is important to generate an accurate estimation of the energy consumption. In that calculation, incline is an important factor. Franke et al. (2012) introduced a routing algorithm that computes the most energy-efficient route and also provided the total energy consumption. To calculate the incline information, a high-resolution DEM acquired from LiDAR measurements was used. However, many other approaches in 3D routing (cf., e.g., Kono et al. 2008; Sachenbacher et al. 2011; Schilling et al. 2009) make use of different DEMs with a horizontal resolution of 90 m (i.e. SRTM, ASTER).

**Extraction of street attributes from user-generated movement trajectories**

Extracting street information out of user-generated GPS traces, as we do in this article, has already been investigated by several researchers. However, the focus of these studies was mainly on deriving semantic...
information, and at the time of writing, no literature was found that made use of user-generated GPS traces for generating incline values. van Winden (2014) proposed several algorithms to automatically derive different road attributes from GPS traces, such as the direction of the road (one or two way), speed limit, or number of lanes. He used GPS trajectories acquired from 800 people within a certain time span. Furthermore, Zhang, Thiemann, and Sester (2010) used GPS traces from OSM to derive street attributes such as the number of lanes as well as turning restriction and tried to automatically correct the street’s centerline. They discovered that motorways are covered by 30–80 corresponding traces, whereas streets within cities in average have less than 20 corresponding traces. Minor streets especially in residential areas often only have only a few or no corresponding traces.

Common elevation data sources

Digital elevation models (DEMs) are a common source of elevation data. DEMs may be distinguished into digital surface models (DSMs) and digital terrain models (DTMs), depending on if they are representing the Earth’s surface including objects on it (e.g. building and trees = DSM) or not (=DTM). A very high accuracy and resolution can be achieved using airborne techniques, such as laser detection and ranging (LiDAR) or photogrammetry. However, these methods are expensive and thus not globally applicable.

Spaceborne satellite missions may gather elevation information at global scale. Examples are the “Shuttle Radar Topography Mission” (SRTM, Farr et al. 2007), the “Advanced Spaceborne Thermal Emission and Reflection Radiometer” (ASTER, Abrams et al. 2010), and “TerraSAR-X add-on for Digital Elevation Measurement” (TanDEM-X). The data of the latter one has been used to derive a global DTM with 4 m vertical accuracy and 12 m horizontal resolution. It is globally available but comes with license costs and is thus not feasible for low-cost use cases. The SRTM DSM and ASTER DSM are open-licensed; however, their horizontal resolution is only 30 m and their vertical accuracy only 6.2 m (SRTM, cf. Farr et al. 2007), 4.0 m (SRTM, Gesch et al. 2012), and 9 m (ASTER, Meyer 2011; Gesch et al. 2012), respectively. Whereas in flat areas, these inaccuracies may level out, for areas that include relatively quick elevation changes such as hilly and mountainous regions, this data might not be sufficient to derive the incline of streets with an acceptable accuracy. Also, in forested and residential areas, these data sets might not be sufficient, since by their nature as DSMs, they represent the elevation, including buildings, trees, and other objects.

Alternatively to DEMs, the incline may also be derived using terrestrial measurement methods, such as differential GPS or satellite-based augmentation systems (Han and Rizos 1999; Boucher 2013). However, those methods are very costly and therefore not applicable to larger areas or for low-cost use cases.

Map matching

A necessary precondition to attach information derived from GPS traces to corresponding street segments is the process of linking the traces to the street segments. This process is generally known as map matching (e.g. Marchal, Hackney, and Axhausen 2005; Quddus, Ochieng, and Noland 2007). In navigation applications, these algorithms are used to predict the user’s location within a street network. An example of a GPS traces and corresponding matched street segments is shown in Figure 2. Map matching is a challenging task if GPS data has insufficient accuracy. In these cases, several street segments are eligible as being the one that is being traveled.

Map matching algorithms can be categorized into different groups: geometric, topological, probabilistic, and other advanced algorithms (Quddus, Ochieng, and Noland 2007). For all approaches, it is assumed that the carrier of the GPS device is traveling on a street that is contained in the street network. Geometric approaches are generally faster in processing and easier to implement, since they simply compare the distances between two points, two curves, or a point and curve (e.g. White, Bernstein, and Kornhauser 2000). In addition to the distance between a GPS trace and street segment,
topological algorithms further consider the topological relationship (e.g. touching and disjoint) between the segments of a street network (e.g. Quddus et al. 2003). In probabilistic approaches (e.g. Ochieng, Noland, and Quddus 2003), the error ellipse of GPS track point is used to find intersecting street segments, which serve as matching candidates. Advanced algorithms use additional techniques such as Kalman filtering or other mathematical models (e.g. Krakiwsky, Harris, and Wong 1988).

Methodology

Pilot region

The pilot region of our study is an area around Heidelberg in the southwest of Germany. Figure 3 shows the extent of the region, which is 497 km² in size. It is characterized by mountainous and forested areas in the east as well as flat urban areas and farm-land in the west. This mixture makes the area particularly suited for this research, since it allows differentiating the results between different land-use classes and terrain characteristics.

Input data

Crowdsourced GPS traces

There are several platforms and applications that enable users to collect GPS traces for different purposes. In OSM, GPS traces are collected to support mapping. Besides that, there are sport tracking apps for smartphones (e.g. Strava and Runkeeper) which track routes to provide statistics about the user’s training (average speed and elevation profile). On platforms such as komoot or Gpsies, GPS traces can be recorded or uploaded to share and recommend routes with other users.

Mobile devices often have integrated low-cost GPS receivers (Heipke 2010). Usually, the elevation measurement is derived directly from the GPS signal or from an additionally built-in barometer. Some applications also derive elevation information from DEMs, e.g. Runkeeper and Strava, while sometimes the exact source of the information remains unclear. Moreover, the devices deal differently with the vertical datum. While some devices record the ellipsoidal height (also due to misconfiguration) above the reference ellipsoid defined by the World Geodetic System 84 (WGS 84), others internally transform the measured ellipsoidal

Figure 3. Pilot region Heidelberg/Germany (Map: OSM).
height from WGS 84 datum to mean sea level (MSL) using a geoid model. The GPS traces that we use for our study were taken from the OSM project. In general, these GPX files neither contain information about the elevation datum nor about the sensor. Thus, elevation data acquisition remains largely a black box. However, for this study, we assume an internal transformation to MSL for the majority of tracks.

The OSM GPS data contains more than 2.5 billion track points all over the world, collected by thousands of users. However, the majority can be found in Europe (cf. Figure 4). A dump of all GPX files is available for download with the latest version of this file dating from April 2013. Within our pilot region, 4194 GPS traces have been identified. About 86% (3606) of them also contain elevation information. Given the density of the GPS track points within the pilot region (over 2 million), and the region’s size of 497 km², this would theoretically result in a resolution of 1 point every 15 × 15 m grid square, assuming an even distribution of the GPS measurements.

**Street network**
The main purpose of computing the incline in this study is to allow the enrichment of a street network with the derived data. For simplicity, we chose to use the OSM street network as test data set. We have extracted all features of the OSM data set which are tagged as “highway,” leading to a total of over 57,000 features with a length of 5336 km. Table 1 shows the classification of the street segments and their share within the pilot region.

### Table 1. Values of highway tag and their share of length in percent.

<table>
<thead>
<tr>
<th>Value</th>
<th>Verbal description</th>
<th>Share in %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Track</td>
<td>Agricultural, forestry streets</td>
<td>44</td>
</tr>
<tr>
<td>Residential</td>
<td>Streets within residential areas</td>
<td>18</td>
</tr>
<tr>
<td>Path</td>
<td>Mainly hiking trails and small paths</td>
<td>9</td>
</tr>
<tr>
<td>Footway</td>
<td>For pedestrians only</td>
<td>7</td>
</tr>
<tr>
<td>Secondary</td>
<td>Country road of second priority</td>
<td>4</td>
</tr>
<tr>
<td>Tertiary</td>
<td>Country road of third priority</td>
<td>3</td>
</tr>
<tr>
<td>Cycleway</td>
<td>For cyclists only</td>
<td>3</td>
</tr>
<tr>
<td>living_street</td>
<td>Streets, where pedestrians have priority over cars</td>
<td>2</td>
</tr>
<tr>
<td>Motorway</td>
<td>Equivalent to autobahn</td>
<td>3</td>
</tr>
<tr>
<td>Unclassified</td>
<td>Roads with minor priority than tertiary</td>
<td>3</td>
</tr>
<tr>
<td>Primary</td>
<td>Country road with highest priority</td>
<td>1</td>
</tr>
<tr>
<td>Others</td>
<td></td>
<td>3</td>
</tr>
</tbody>
</table>


In order to analyze dependencies of our results to different land use classes, we extract this information from the OSM data set using the corresponding tags. In our study area, the mapping of land use within OSM is relatively complete. Where small gaps occur in the

Figure 4. Screenshot of a grid map, showing the number of GPS points per grid cell.
data set, we have buffered the existing land-use polygons to complete the coverage. Whereas rural areas such as farmlands and allotments are characterized by fields and mainly low buildings, residential or commercial areas often have taller buildings and urban canyons (Langley 1999) where multipath and shadowing effects are more likely to occur. This may affect the GPS accuracy and consequently the accuracy of derived incline information.

As a reference data set for validating a high-resolution DTM is used, the DTM was derived from official airborne LiDAR measurements and represents the terrain, excluding buildings and vegetation. The DTM covers the entire pilot region with a horizontal resolution of 1 m and a vertical accuracy of 0.5 m. In addition, the SRTM-1 DEM has been used to calculate incline values and to compare them to the results derived from the GPS measurements. This will indicate whether our approach can generate more accurate results than those contained in current openly available data sets.

**Workflow and implementation**

**Overview**

The process of deriving incline values consists of multiple steps (cf. Figure 5). First of all, the GPS data and the street network are imported into a database. This step has the option to filter GPS data contained within a specific bounding box and to skip data which does not contain elevation information. After this preprocessing step, both input data sets are linked to each other via map matching techniques. This is a necessary precondition to performing the sequential calculation of an incline value for each segment within the street network. Finally, we validate our results. In the following sections, we describe each of these steps.

**Import and preprocessing**

We imported both street network and GPS traces into a common database as this simplifies all following remaining steps. Prior to writing the GPS traces to the database, we check if two conditions are met: (1) an individual trace needs to contain elevation information and (2) the trace needs to intersect the specified bounding box. All GPS traces are stored as 3D linestrings in the database.

Once imported, some preprocessing steps are performed on the data. A trace may be interrupted due to the loss of the GPS signal (e.g. when passing a tunnel) which causes missing points within a track. Consequently, we do not have any elevation information along these sections. Therefore, we do not include them in the incline computation. The respective interruptions can often be identified through a long distance between two consecutive track points. The traces are split if the distance between two adjacent points in a trace is exceeding a certain threshold. This is an iterative process and an individual trace may be split in multiple parts. The threshold values are chosen to be 300 m for the maximum distance between consecutive points as proposed by Zhang, Thiemann, and Sester (2010).

After splitting, the elevation data within each trace segment is smoothed to reduce the high-frequency noise. For this step, a weighted moving average filter has been applied. The following set of weights $W$ has been used for the window:

$$W = \{0.1, 0.125, 0.15, 0.25, 0.15, 0.125, 0.1\}$$

The smoothed elevation value of a point is calculated as follows:

$$e^*_n = \sum_{m=1}^{7} (e_{n+(m-4)} * w_m)$$

where

- $e^* = \text{smoothed elevation}$,
- $e = \text{original elevation of data points}$,
- $w = \text{weights}$, and
- $n = \text{number of track point}$.

For the first and last three values of each trace, we only use the available adjacent values for the calculation of the weighted average. Figure 6 shows an elevation profile of a GPS trace and its smoothed representation. For comparison, the elevation profile

![Figure 5](image-url)
of the corresponding path derived from the reference DTM is also depicted. It may be seen that the GPS measurements show a rather constant offset.

The segmentation of streets within data sets is usually defined by semantics (e.g. street name) and not according to the characteristics of the terrain. Therefore, a street segment may span several valleys and peaks, which leads to wrong incline estimation due to a single incline being assigned to the segment as a whole. To reduce this effect, streets within our data set are split into segments at the intersection points with other streets. We do not further split the street segments into smaller pieces as this would lead to only a few corresponding GPS points for each segment and would consequently lower the accuracy of incline estimation. Instead, an average incline for each segment between street intersections is stored.

Map matching
In order to link GPS traces with corresponding street segments, we apply a simplified version of the map matching approach described by Zhang, Thiemann, and Sester (2010). The algorithm consists of three steps (cf. Figure 7).

1. The street segment is buffered and all traces are selected as matching candidates which intersect this buffer (Figure 7(a)). We used a buffer size of 50 m.

2. Profile lines for each node of the street segment are computed which are perpendicular to the segment and centered at the node (Figure 8(b)). We choose the length of these lines to be 30 m, considering the horizontal accuracy of the GPS measurement and the width of typical streets. If a GPS trace intersects most of the profile lines, it is considered to be a matching trace.

3. Profile lines that are (not) intersected by a candidate trace are counted. All candidate traces that intersect at least 70% of the perpendicular lines are considered as matched traces (Figure 7(c)). A lower threshold would result in a higher matching rate at the cost of more false positives, particularly for streets that only have two nodes. A higher threshold would be too restrictive, considering the inaccuracies of GPS and the remaining positional errors of the street segments.

We skip the detection of lanes and directions of streets that is also described by Zhang, Thiemann, and Sester (2010), since this is not relevant for our use case.

Calculation of incline
The incline values are calculated for each street segment individually. The entire process is shown in Figure 8 and will be explained in the following section.
For each street segment, the matched preprocessed GPS traces are selected. Since a trace usually spans multiple street segments, the traces need to be clipped in order to only use relevant elevation information for the segment in question. To clip the GPS traces, we use a buffer around the street with a size of 30 m (cf. Figure 9).

For each of the clipped traces, the incline ($i^t$) is calculated by averaging the incline values ($i^p$) of consecutive GPS track segments. Since the distance between the track points is not equal, $i^p$ is weighted according to the distance and normalized with the full length of the trace. The calculation may be expressed using following formula:

$$i^t = \frac{\sum_{m=1}^{n-1} \left( \frac{d_{m,m+1}}{l} \right) \left( \frac{e_{m+1} - e_m}{d_{m,m+1}} \right)}{\sum_{m=1}^{n-1} \left( \frac{d_{m,m+1}}{l} \right)},$$

where

- $i^t =$ incline of GPS trace segment in percent,
- $i^p =$ incline of two consecutive GPS track points in percent,
\[ n = \text{number of track points}, \]
\[ e = \text{elevation of track point}, \]
\[ d = \text{horizontal distance between two track points}, \]
\[ l = \text{horizontal length of GPS trace segment}. \]

In OSM, the street segments are directed from the first node of the segment to the last node. Consequently, it has to be checked whether the GPS trace was recorded in the same or the opposite direction of the street. This is done by a comparison of the average bearing of the street segment and the GPS trace. If the difference in bearing (\( \alpha \)) is greater than a certain threshold, it is assumed that the GPS trace follows the opposite direction and the calculated incline value is inverted. Based on tests with individual samples, we have chosen a threshold of 40°.

The next step is to average all incline values computed from the individual traces (\( i_t \)) to get a value that represents the incline of the street segment (\( i_s \)). Since the length of the trace may vary, the average is weighted based on the length of each trace. The following formula has been used for averaging the incline values of the individual traces:

\[
i_s = \frac{\sum_{a=1}^{k} (i_t^a) \left( \frac{l_a}{\sum_{a=1}^{k} l_a} \right)}{\sum_{a=1}^{k} \left( \frac{l_a}{\sum_{a=1}^{k} l_a} \right)},
\]

where
\[ i_s = \text{incline of street segment in percent}, \]
\[ i_t = \text{incline of GPS trace in percent}, \]
\[ k = \text{number of corresponding traces}, \]
\[ l = \text{horizontal length of trace}. \]

In order to evaluate the results, we also compute the incline for each street segment using the given DTMs. For this purpose, the elevation values within the DTMs along the street segments are determined with a sampling distance of 3 m. These values are used to compute elevation differences, which subsequently allow computing an average incline for each street segment.

**Results and discussion**

**Analysis of elevation data of crowdsourced GPS traces**

We use a total of 3606 GPS traces comprising of over two million track points within our pilot region of Heidelberg (cf. Figure 10). We evaluate the accuracy of this input data using a high-resolution DTM. There are two aspects relating to the accuracy of the data: (1) the absolute error of the elevation measurements compared to this DTM and (2) the relative accuracy. The latter refers to the error of the differences of elevation between two adjacent points. It has to be noted that the horizontal inaccuracies of the GPS points influence this evaluation, since especially in mountainous areas an error in horizontal positioning also leads to an erroneous elevation value picked from the reference data set. Furthermore, the high-resolution DTM used for evaluation suffers from some inaccuracies as it reflects the actual terrain of the earth and consequently does not contain all structures on the earth’s surface, such as buildings, trees, or bridges. This leads to errors, particularly in the case of bridges, where ground elevation is interpolated. Besides elevation accuracy, we also evaluate the GPS traces in terms of coverage and density.

**Absolute elevation accuracy**

For the assessment of the absolute elevation accuracy of the GPS measurements, we compute the root-mean-square-error (RMSE) on the data set as a whole and

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**Figure 10.** Visualization of GPS track points, color coded according to elevation (green = low, red = high).
then the errors on the GPS measurements classified by the land-cover area that they fall into (cf. Table 2):

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (e_{i}^{GPS} - e_{i}^{DTM})^2}{n}},
\]

where

- \(e_{i}^{GPS}\) = GPS elevation measurement of the GPS point,
- \(e_{i}^{DTM}\) = elevation value derived from the DTM at the location of the GPS point, and
- \(n\) = total number of GPS points.

The RMSE, i.e. the square root of the mean of the squared residuals, is a common measure of difference in spatial analyses. In our case, it provides a measure of the differences between GPS and DTM elevation values. For the calculation of the RMSE, only 90% of the residuals have been used whereas 10% have been excluded as severe outliers. Possible reasons for these outliers may be wrongly calibrated (in the case of barometric measurements) or misconfigured devices, or values that may not have been recorded on the Earth’s surface (e.g. in an airplane).

With 27 m, the overall RMSE is slightly worse than 15–20 m as found out in previous studies (Liu et al. 2014; Zhang, Thiemann, and Sester 2010). A possible reason may be that crowdsourced traces are prone to be recorded under heterogeneous conditions. Furthermore, the diversity of devices and the unknown geodetic datum degrade the accuracy.

We observe that track points in forests seem to be more accurate than track points in the land-use classes “grass” and “allotments.” This contradicts our expectations (due to a more visible sky generally leading to better GPS signals) and may be explained with the sample sizes of GPS track points. “Forest” is one of the land-use classes with the most GPS track points, whereas “allotments” and “grass” have only a few and thus might be more influenced by outliers.

Figure 11 depicts a histogram of the differences in elevation between the GPS and DTM data sets. It can be seen that there is a peak and a normal distribution around 0 m. In addition to that, however, there is also a second peak and a second normal distribution around 48 m. This may be explained by devices that have recorded ellipsoidal elevation values according to the WGS 84 ellipsoid. The geoid undulation in region of Heidelberg is equivalent to this offset of 48 m. In general, we can assume that the majority of the GPS elevation measurements have been recorded according to the geoid.

### Table 2. Absolute elevation accuracy of crowdsourced GPS track points, differentiated by land use class.

<table>
<thead>
<tr>
<th>Land-use class</th>
<th>RMSE (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Allotments</td>
<td>35</td>
</tr>
<tr>
<td>Commercial</td>
<td>34</td>
</tr>
<tr>
<td>Grass</td>
<td>30</td>
</tr>
<tr>
<td>Overall</td>
<td>27</td>
</tr>
<tr>
<td>Residential</td>
<td>25</td>
</tr>
<tr>
<td>Forest</td>
<td>22</td>
</tr>
<tr>
<td>Industrial</td>
<td>22</td>
</tr>
<tr>
<td>Farmland</td>
<td>21</td>
</tr>
</tbody>
</table>

Relative elevation accuracy

The obtained absolute accuracy of 27 m within the GPS data set appears to be very large, especially when compared to the vertical accuracy of the SRTM-1 DSM (6.2 m) which could also be used for low-cost approaches. However, since for the calculation of incline only the difference in elevation of two adjacent track points is used, only the relative elevation accuracy...
is of major concern. We evaluate this relative accuracy as follows: for each GPS track point, the difference of elevation $\Delta h_{GPS}$ to the next track point of the trace has been calculated. This value, with regard to the distance between the points, reflects the actual incline of the terrain including the remaining noise of the GPS measurements after filtering. The difference of elevation $\Delta h_{DTM}$ was derived from the reference data (i.e. high-resolution DTM) and is the difference of elevation derived from the GPS measurements $\Delta h_{GPS}$. This results in the GPS error $e_{\Delta h}$:

$$e_{\Delta h} = \Delta h_{GPS} - \Delta h_{DTM}$$

We have computed $e_{\Delta h}$ for all track points. To reduce the effect of severe outliers, we only use 90% of the values to compute the RMSE (as mentioned earlier). The results can be seen in Table 3 together with the analysis of the impact of the relative elevation accuracy on the incline error.

### Coverage and density

In order to get an idea of how many streets are covered with how many traces and how dense the GPS track points are, we investigated coverage and density. The coverage is analyzed using the results of the map matching. It has to be noted that due to the $n$ to $m$ relationship, GPS traces may be matched to more than one street.

A large share of streets does not have any corresponding trace although many streets are covered with at least one trace in the pilot region. Streets with higher priorities generally have more corresponding traces (e.g. motorway), whereas residential streets only have a few or even none (cf. Figure 12). Particularly, motorways are completely covered by at least 25 traces. Also, primary streets have 100% coverage with at least 5 traces. Approximately 95% of the street types “secondary,” “tertiary,” and “cycleways” are covered with at least 1 trace and 80% with at least 5 traces. The lowest coverage (40–60% with at least 1 trace) is observed for the feature types “residential,” “footpath,” and “path.” In general, it can be said that streets of higher priority have more matching GPS traces. Residential streets that can be used by bicycles perform as well as secondary and tertiary streets. Paths that are dedicated to pedestrians only are comparable to residential streets in terms of trace coverage. However, this may even be a side effect of the matching algorithm, which assigns traces to both the residential street and the parallel footpath due to their close proximity.

With regard to point density, we have analyzed the average distance between adjacent GPS track points for the street type. While there is an average distance of 14 m in the whole data set, we find that this distance is much higher for motorways (36 m) than for instance for paths (8 m) and residential streets (10 m). Thus, it can be concluded that the point density depends on the average speed of vehicles on the corresponding street types.

### Analysis of incline values derived from GPS traces

We have computed incline values for the street network using the GPS traces and the method described in section “Calculation of incline”. If we consider all street segments that are covered by at least one trace, we can compute incline values for a total length of 3064 km, which is equivalent to 57% of the complete street network of 5338 km in the pilot region.

### Pre-evaluation processing

A high-resolution DTM derived from airborne LiDAR measurements has been used for evaluation. Though generally highly accurate, the use of this LiDAR data set for the evaluation of our results is not without

<table>
<thead>
<tr>
<th>Land use</th>
<th>RMSE $e_{\Delta h}$ (m)</th>
<th>Average distance (m)</th>
<th>$\Delta$ incline error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>0.3</td>
<td>14</td>
<td>2.4</td>
</tr>
<tr>
<td>Allotments</td>
<td>0.2</td>
<td>11</td>
<td>2.2</td>
</tr>
<tr>
<td>Commercial</td>
<td>0.2</td>
<td>10</td>
<td>2.4</td>
</tr>
<tr>
<td>Farmland</td>
<td>0.2</td>
<td>17</td>
<td>1.0</td>
</tr>
<tr>
<td>Forest</td>
<td>0.5</td>
<td>11</td>
<td>4.3</td>
</tr>
<tr>
<td>Grass</td>
<td>0.2</td>
<td>29</td>
<td>0.8</td>
</tr>
<tr>
<td>Industrial</td>
<td>0.2</td>
<td>10</td>
<td>2.4</td>
</tr>
<tr>
<td>Residential</td>
<td>0.3</td>
<td>10</td>
<td>2.7</td>
</tr>
</tbody>
</table>

Figure 12. The coverage with GPS traces for different street types.
issues. Figure 13 shows an example of a motorway junction with the underlying DTM. Here, the incline derived from the DTM is calculated erroneously with a value of 30%. Due to the characteristics of the pilot region, streets with an incline of more than 20% are likely to exist only rarely. However, for about 0.4% of the street segments, the DTM-derived incline values have been estimated as being above 20% and in some cases even above 100%. As these errors would influence the results of the validation, we exclude street segments that have an incline derived from the DTM of above 20%.

Likewise, we assume that street segments with an incline steeper than 35% do not exist in the pilot region. Therefore, street segments with GPS-derived incline values or SRTM-derived incline values of above 35% are also excluded from the evaluation.

Impact of relative elevation accuracy on incline error
In section “Relative elevation accuracy”, we have already introduced how we analyze the relative elevation accuracy of consecutive GPS measurements. In order to estimate the impact of the error $\Delta h$ on the actual incline values, we have also calculated the average distance between two adjacent points (cf. Table 3). We divide the error $\Delta h$ by this average distance to estimate the incline error that is caused by the relative elevation inaccuracy of adjacent GPS measurements. Overall, we estimate that the impact of the relative accuracy of the GPS elevation measurements on the computed incline values results in an error of 2.4% incline. The smallest impact is in areas of the land-use classes “grass” and “forest” with an error of equal or less than 1% incline. In forested areas, an error of over 4% incline is estimated based on the relative accuracy assessment. All values within the other areas are in a range between 2.2% and 2.7% incline. Thus, we can conclude that the relative accuracy of GPS elevation measurements depends on the surrounding land-use class. Land-use classes characterized by less obstructing structures (e.g. buildings and trees) perform better.

Comparison of GPS incline and high-resolution DTM incline
The comparison of the inclines derived from GPS traces and the high-resolution DTM is realized by the calculation of the incline differences. The result is expressed as an incline error $e_i$ (unit = %). The following formula is used:

$$e_i = \frac{i_{GPS} - i_{DTM}}{i_{DTM}}$$

where

- $e_i$ = incline error in %,
- $i_{GPS}$ = incline, derived from GPS traces,
- $i_{DTM}$ = incline, derived from DTM.

Figure 14 shows the street network color coded by the GPS incline error. Due to the incomplete coverage of GPS traces, the incline could not be calculated for all streets within the network. It may be observed that street segments having a medium or large error are not equally distributed in this area. In the western part (flat terrain and mainly farmland) only a few and short street segments with a high error have been found. However, more streets with a larger error value have been detected in the eastern part, i.e. mountainous terrain and forest. This may be explained by the decreased relative vertical accuracy of GPS track points in forested areas (cf. Table 3).

A histogram with the distribution of the GPS incline errors, which is normally distributed around the mean...
of 0 m, is depicted in Figure 15. The distribution has a standard deviation of \( \sigma = 4.0 \). When recalculating the standard deviation with only 95% of the data, it results in \( \sigma_{95\%} = 2.3\% \) incline.

Table 4 shows the absolute length in kilometers of the street segments for which the incline was calculated below the error, given in the first column. The third column represents the resulting share of street segments for which it was possible to derive the respective incline information in reference to the total length of 3064 km where at least one trace was available.

There is a dependency between the number of GPS traces used for the calculation of the incline values and the share of street segments for which the incline can be derived with certain accuracy. Figure 16 shows this dependency with the example of the share of street segments with an incline error of less than 2% incline. An increase of the threshold of the number of GPS traces used for the computation of the incline values results in a higher share of correctly estimated incline values. However, at the same time, the share of street segments that would be covered by this amount of GPS traces is decreasing. Thus, the incline computation using voluntarily collected GPS traces is a trade-off between accuracy and coverage.

**Comparison of GPS incline and SRTM incline**

In this section, we compare the incline derived from the GPS traces to the results derived from SRTM-1 DSM. For this purpose, we compute the errors of the SRTM incline
values analogously to the errors of the GPS incline values (cf. section "Comparison of GPS incline and high-resolution DTM incline"). Table 5 shows that the GPS incline performs slightly better than the SRTM incline; however, the coverage is more complete with SRTM.

Table 6 shows the comparison of the standard deviations for both input data sources distinguished by land-use classes. They have been calculated using 95% of the data to reduce the effect of outliers. The three columns contain the standard deviation of the SRTM incline computation $\sigma_{\text{SRTM}}$, the standard deviation of the GPS incline $\sigma_{\text{GPS}}$ computation using street segments covered by at least one trace, and the standard deviation of GPS incline computation using street segments with at least 5 GPS traces ($\sigma_{\text{GPS}5T}$). The overall results ($\sigma_{\text{SRTM}} = 3.1\%$, $\sigma_{\text{GPS}} = 2.3\%$, and $\sigma_{\text{GPS}5T} = 1.6\%$) show that from the GPS data, the incline values can be computed with higher accuracy than using SRTM. This holds true for all land-use classes.

A possible reason for this result is that the SRTM-1 DEM is a DSM, which means that all structures on the earth surface are represented in the data set. Due to the low horizontal resolution of 30 m of SRTM, this DEM contains many mixed pixels that do not only cover street segments, but also buildings and trees that are next to these street segments. In contrast to this, the GPS track points are recorded on the earth surface, or more precisely on a constant height above the ground (e.g. in a car or back pack). Moreover, the SRTM data in general suffers from a vertical accuracy of 6.2 m, which is a relatively large error in comparison to the relative accuracy of the GPS measurements with 0.6 m within the same distance of 30 m (0.3 m within 14 m distance, cf. Table 3).

A final analysis was performed to evaluate the influence of the type of terrain on the results. For this purpose, standard deviations achieved in flat areas (DTM incline <2%) and mountainous areas (DTM incline >5%) have been compared. As shown in Table 7, both input data sources perform better in flat areas. However, in mountainous regions, the GPS incline computation does not outperform the SRTM incline computation and, in fact, performs slightly worse.

### Limitations of approach

There are some limitations to our approach that are inherent in our methodology. In the OpenStreetMap-Wiki, a convention regarding the incline of streets is given. When adding incline information to OSM-Ways, the street segment is supposed to be split at the beginning and at the end of the inclined part and the maximum incline shall be assigned as an attribute. However, in our approach, we only compute the average incline per street segment. This results in erroneous incline estimations if a street segment spans parts with different incline values. However, a modification of our approach to compute the maximum incline value of street segment would be possible. Nevertheless, such modification would trigger the need for another evaluation of the results.
Conclusion

Within our analysis of crowdsourced GPS traces, we have discovered that the absolute accuracy of 27 m (RMSE) is worse than usual for low-cost GPS devices. This may be due to a mixture of (unknown) measurement methods (GPS measurement, barometric measurement, and elevation databases), misconfigured or wrongly calibrated devices, or due to a mixture of the vertical datum (WGS 84 ellipsoid, MSL). However, the relative accuracy, which is of importance for deriving incline values, has an RMSE value of 0.3 m which is sufficiently high. Hence, it is possible to derive incline values for street segments to a reasonable accuracy if the streets are covered with multiple GPS traces. In comparison to the SRTM-1 DSM, the GPS incline performs better in flat regions and equally in mountainous region. However, the coverage is significantly lower since voluntarily collected GPS traces are not available for a significant share of street segments. This coverage may be increased if further sources of user-generated GPS traces are taken into account.

As a more general conclusion, we can say that these results show that today it is possible to achieve comparable or even slightly better results for incline computation using recent VGI compared to data acquired by a specialized research satellite 15 years ago (i.e. the SRTM satellite, 1999). Of course, also for VGI, we need an operative satellite system, such as the GPS satellites. However, this study underlines the potential that VGI can be used in cases that were not the primary reason for the initial collection. In our case, this was the calculation of incline, but further use cases are easily imaginable, particularly considering the fact that the crowd of volunteers is continuing to collect data.

We see a future research strand in the fusion of openly available DEMs, such as SRTM or open data, with the information of voluntarily collected GPS data. This could make use of the advantages of both data acquisition approaches. Moreover, this could not only yield a more accurate and complete incline estimation for street networks, but also create an improved global and openly available DEM.

Disclosure statement

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ORCID

Stefan Hahmann http://orcid.org/0000-0002-8145-7090

References


Notes

13. For a more detailed description of the workflow and implementation, readers are advised to consult John (2015).
15. The tool for preprocessing is available at https://github.com/GIScience/osmgpxpreprocessor.
17. The tool for calculating the incline value is available at https://github.com/GIScience/osmgpxinclinecalculator.


