What You See is What You Map: Geometry-Preserving Micro-Mapping for Smaller Geographic Objects with MAPIT

Falko Schmid, Lutz Frommberger, Cai Cai and Christian Freksa

Abstract Geographic information is increasingly contributed by volunteers via crowdsourcing platforms. However, most tools and methods require a high technical affinity of its users and a good understanding of geographic classification systems. These technological and educational barriers prevent casual users to contribute spatial data. In this chapter we present MAPIT, a method to acquire and contribute complex geographic data. We further introduce the concept of *micro-mapping*, the acquisition of geometrically correct geometric data of small geographic entities. MAPIT is a method for micro-mapping with smartphones with high geometric precision. We show that MAPIT is highly accurate and able to reconstruct the geometry of mapped entities correctly.Please check and confirm the author names and initials are correct.

1 Introduction

Geographic data is the backbone of all geo-spatial applications. However, the collection of geo-spatial information is a resource intense task, traditionally performed by educated specialists employed in companies or national mapping agencies. This practice has changed fundamentally during the last decade: spatial

F. Schmid (✉) · L. Frommberger · C. Cai · C. Freksa
International Lab for Local Capacity Building (Capacity Lab), University of Bremen, Enrique-Schmidt-Str. 5, Bremen 28359, Germany
e-mail: schmid@informatik.uni-bremen.de

L. Frommberger
e-mail: lutz@informatik.uni-bremen.de

C. Cai
e-mail: cai@informatik.uni-bremen.de

C. Freksa
e-mail: freksa@informatik.uni-bremen.de

D. Vandenbroucke et al. (eds.), *Geographic Information Science at the Heart of Europe*, Lecture Notes in Geoinformation and Cartography,
DOI: 10.1007/978-3-319-00615-4_1,

information is increasingly collected and provided volunteers, a phenomenon also known as Volunteered Geographic Information (VGI) (Goodchild 2007). As a result geographic data became openly available for people and services. With the contribution of geospatial data by volunteers, also the nature of data drastically changed: the contributors decided what relevant information is and how to describe it (Haklay 2010). This requires not only the development of flexible services and classification systems, but also tools to collect the data volunteers intend to provide.

There are many different sources and types of VGI data available on different platforms spanning from hiking trails, photos, place information, online sensor data, to rather classical map-data. Volunteerly generated map data typically is collected by means of recording GPS trajectories which then are algorithmically transformed into street information (Ramm et al. 2010; Biagioni and Eriksson 2012). Depending on the accuracy of the received signal, the information has to be manually verified, corrected, and attributed with semantic information like street type, name, etc. to be transformed into useful geo-data.

One prerequisite for VGI being successful is that gathering of geo-data requires little effort. If the workflow is overly complicated, people will not spend their spare time to contribute. Intuitive user interfaces become especially important if the tasks go beyond mapping point- or trajectory-based data, e.g., when mapping extended objects. This usually requires to physically traverse the geographic object to be mapped. Some approaches combine satellite images as baseline data; in this case only immediately visible and conveniently reachable and traversable objects above a certain size are considered. The effort to map small objects is usually too high, as each object to be mapped requires thorough inspection, revision, and attribution.

In this chapter, we introduce the concept of *micro-mapping*, that is, mapping small geometric features in the plane. Examples of such features are vegetable fields in the garden, graves on a graveyard, areas on archaeological sites, fish ponds, flower beds, urban furnitures, etc. Retrieving the geometry of objects of this size can be a cumbersome procedure, as the precision of GPS sensors is not sufficient to provide accurate position information. As a result, such objects are usually mapped as points, or provided with a standard geometric shape.

These workaround solutions are not satisfactory, as in many cases the exact geometry of the objects provides important information. Later generations might want to precisely identify archaeological digging sites, GIS applications require the computation of crop of small agricultural parcels, urban planners benefit from detailed information of urban entities, even on smaller scale like benches or flower beds.

When mapping small features, an easy workflow of the mapping procedure is of even greater importance, because we must expect to have to map many of those small objects. Under this condition, it is infeasible to spend a lot of work on every single object. MAPIT, the method we present in this chapter, reduces the mapping procedure to the simple steps of taking a photo, drawing the outline of the object to be mapped, and label the object by means of a convenient user interface. This allows for mapping many objects in a short time and with high geometric precision.

2 Related Work

During the last decade, the generation, distribution, and usage of geographic information has dramatically changed. With the availability of affordable geodetic equipment, such as GPS devices and smartphones, and the availability of web-based data sharing platforms, the collection of geographic data became a phenomenon known as Volunteered Geographic Information (VGI) (Goodchild 2007; Sui 2008). VGI is a crowdsourcing movement, thus the collection of data by volunteers all over the world cooperating via web based platforms. One of the largest and most prominent VGI projects is OpenStreetMap[1] (OSM). OSM allows everybody to contribute geographic data of any kind. What started as a project collecting street map data quickly developed into a complex topographic mapping project with a huge amount of all kinds of mapped spatial entities. So far there are basically three different ways to provide geographic data to VGI platforms:

- *Geotagging*: Geotagging denotes the annotation of any kind of media or information (pictures, facts, etc.) with geographic coordinates to express its place of creation or relevance (e.g. Elwood 2008; Luo et al. 2011). Projects like EpiCollect (Aanensen et al. 2009) use geotagged form data to collect information about animal disease distribution, street art locations, archaeological digging sites, etc. Geo-tagging is an appropriate way to involve amateurs to provide non-spatial data, or whenever exact geo-spatial classification of the recorded entities is not important. However, this approach is limited in accuracy and expressiveness because no geometric information is provided. It is not possible to describe the geometry or orientation of the respective entities. We need additional information if the entity is supposed to be rendered on a map, or if properties need to be analyzed.
- *GPS-Trajectory*: A common practice to record geo-spatial data is to physically walk around the entity to be mapped and to record the complete GPS trajectory or only fixes that are required to describe the geometry of the entity, e.g., (Ramm et al. 2010; Turner 2006). The data of the tracks can then be analyzed and fused to richer data sets describing street networks or any other spatial entity to be mapped (Biagioni and Eriksson 2012).
- *Satellite Imagery Annotation*: An alternative method to create geo-spatial data is to analyze satellite imagery by means of crowdsourcing. With this approach, instead of physically traversing entities, contributers manually extract entities and their geometries from satellite images, e.g., (Maisonneuve and Chopard 2012).

With close range photogrammetry, a technique so far not explored for VGI, it is possible to obtain geographic data from camera systems (Luhmann 2010). Methods of this field are applied in traffic accident reconstruction (Du et al. 2009;

[1] http://www.openstreetmap.org

Fraser et al. 2008), and architectural engineering, e.g., bridge measurement (Jiang et al. 2008), 3D building reconstruction (Asyraf et al. 2011).

Once the data is collected it needs to be classified according to the addressed geographic specification system, such as OSM, CityGML,[2]ATKIS,[3] or the OS MasterMap.[4] However, those specifications are complex systems to formally describe possible spatial entities. Due to the complexity, it is hard for non-experts to contribute data with correct annotation. Once data is classified incorrectly, it will not be detected by algorithms for analysis or rendering. As studies on quality of OSM data show, the collection of complex geo-data by amateurs requires appropriate mechanisms to ensure quality (Goodchild 2009; Haklay 2010). However, human computer interaction aspects or human spatial conceptualizations of space are not very well studied and addressed in VGI literature and practice so far (Jones and Weber 2012). One approach to support this process is to incorporate ontological reasoning in the classification process, e.g., (Brando et al. 2011; Schmid et al. 2012). In addition to the classification process, geo-spatial editors and workflows are typically complex and hard to use. Without training and experience it is hard to collect, classify, and contribute spatial data to a platform like OSM. These educative and usability barriers prevent potential casual contributers to provide even only small bits of information to VGI platforms. However, in many cases, the inclusion of people at a grassroots level is the only possibility to gather and map expert data from agriculture, seasonal phenomena, land use, soil quality, disaster impacts, etc. (see Frommberger et al. 2012, for example).

3 mapIT: A Micro-Mapping Approach

In this chapter we present mapIT, a new approach for capturing, classifying, and contributing geographic data for Volunteered Geographic Information (VGI) initiatives. The purpose of mapIT is what we call *micro-mapping*: recording geometrically correct data of small geographic entities. *Small* entities in the context of micro-mapping are objects which size is too meaningful such that they could be represented as a point, but small enough to easily fit to one camera image (Schmid et al. 2012).

The design of mapIT follows the idea of WYSIWYG[5] editors: collecting, editing and contributing geo-spatial data are no separate steps in mapIT, but integrated in one seamless workflow in which users can directly contribute geometric data from camera images of any entity in the surrounding environment.

[2] http://www.citygml.org/

[3] http://www.adv-online.de

[4] http://www.ordnancesurvey.co.uk/oswebsite/products/os-mastermap/index.html

[5] WYSIWYG: "What-You-See-Is-What-You-Get"

MAPIT is designed to be barrier-free, i.e., it only requires little general knowledge to be used and no education in geographical classification systems. With MAPIT contributors can collect and contribute geo-data in situ, thus while being present in the environment. However, it is also possible to classify and contribute the data at any point in time.

3.1 What You See is What You Map

MAPIT is developed to integrate visual data capture, intuitive classification, and contribution in a single process. The idea of MAPIT is to enable the mapping of entities within the current vista space of users: that is, users can map spatial objects and phenomena when they see them. This method has several advantages compared to the alternative methods of GPS-trajectory based annotation, satellite image annotation, and geo-tagging.

- *Advantages Compared to Geo-Tagging* Geotagged information can be images, tweets, lexical entries, etc. Points of interest (POIs) are a particular form of geo-tagged entities, as they are primarily created to be used in geographic information systems. With geotagged information it is not possible to describe complex geometry. With MAPIT it is possible to contribute complex geometry also for entities until now considered to be to small to map geographically and geometrically correct.
- *Advantages compared to GPS-Trajectory recording* In areas with outdated, no, or not sufficient coverage by satellite imagery, entities have to be captured by means of recording the GPS trajectories of users surrounding the entity. With MAPIT users do not have to traverse the outline of the object and record GPS trajectories, but only have to take a photo of them. This is especially beneficial in cases when entities are hard to reach, e.g., when they are located in only hardly accessible marsh land. Additionally, due to the relatively small size of entities we are aiming at, the GPS data is usually highly scattered and require manual reconstruction of the geometry.
- *Advantages Compared to Satellite Imagery Annotation* In the last years, satellite images became the one of the most important sources for geo-spatial data. Data captured by GPS is verified with satellite images, but satellite images are also used to extract spatial features directly from the photo. These methods are very powerful to align scattered data correctly to the shapes of entities, and to create data along their visual outlines. However, this method is sensible to coverage, quality, and the frequency of updates of the underlying image material. In some cases the entities to be mapped cannot be recognized on the images due to resolution problems, in some cases the objects are occluded by entities located above (e.g., a pond located in a forest), in some cases the entities are not yet covered due to outdated images, and in some cases the entities are only seasonal phenomena (like flooding areas in rainy seasons), or even invisible (such as contaminated soil).

In general, mapIT is a suitable method whenever smaller entities have to be mapped that have to be geometrically accurate, up-to-date, are visually occluded for satellites, are changing or seasonal features, or are even invisible such as contaminated sites or archaeological digging sites.

4 mapIT: Workflow and Technical Details

mapIT is a VGI method to enable also casual contributors to provide correct geospatial data. We set three requirements for our method: (a) the mapping process should not require any geographical expert knowledge (for example, about geographic classification), (b) it should not be required to type in names or numbers, and (c) it has to run on low-cost smartphones with usual sensory capabilities (that is, GPS, compass, camera, tilt sensors). Thus, we develop a camera and speech-recognition based mapping application for Android phones (see Fig. 1): The user only has to take a picture of the entity to map (Fig. 1a), trace its outline on the touchscreen (Fig. 1b), and finally speak the type of the object into the phone (Fig. 1c). After these intuitive and barrier-free steps, the entity can immediately be uploaded to a server and is ready for further processing and inspection (Fig. 1d). Geometry and location of the entity are derived from GPS signal, geometric projection of the finger-trace on the touchscreen, camera lens properties, and information of the tilt sensors.

4.1 In-Situ, Ex-Situ, Online, and Offline Functionality of mapIT

Some of the components of mapIT obviously require internet connectivity, e.g. uploading data to a server. Mapping with mapIT is designed to work in-situ and ex-situ, as well as online and offline. Pictures of spatial entities taken with mapIT can be used at any point later to extract spatial information from it. This also holds for the speech recognition component based on the Android speech-to-text component[6]; in-situ speech labeling is only possible when a connection to the internet is available. If there is no connection available, the user can either label manually, by entering the label with a keyboard or use the speech functionality later when being connected to the internet again. Every picture taken with mapIT can be used to extract as many entities as wanted.

[6] http://developer.android.com/reference/android/speech/tts/TextToSpeech.html

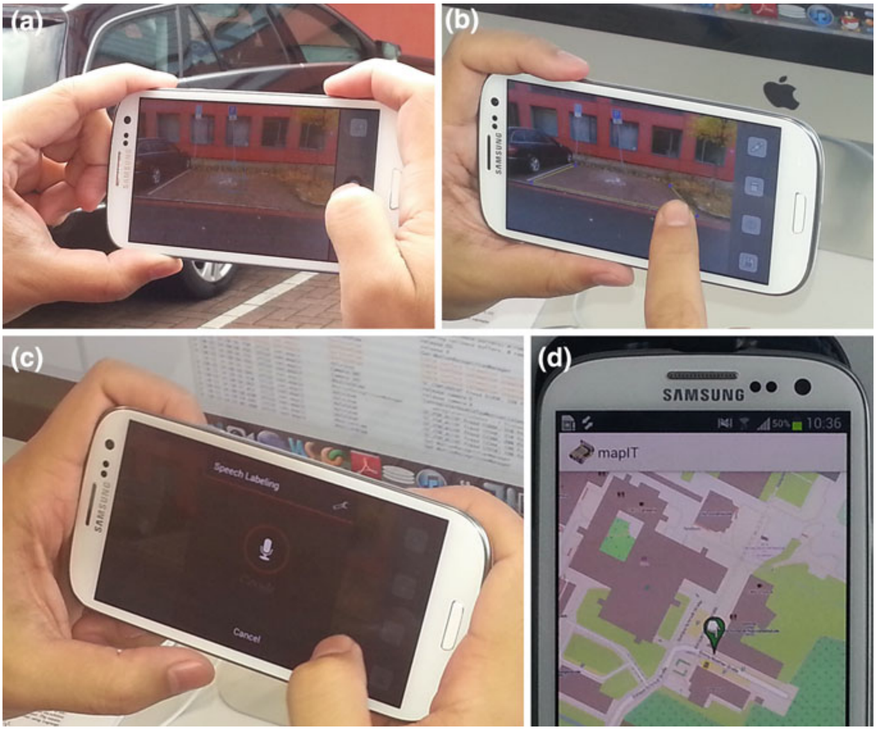

Fig. 1 Mapping requires little effort: The user just has to take a photo (**a**), outline the entity (**b**), annotate it via speech (**c**), upload it to a geo-server and check the entity on map (**d**)

4.2 Sensor Data Filtering

For geographic location calculation, a variety of sensor data is required, such as GPS and orientation sensor data. These sensor results are inevitably affected by hardware accuracy, environmental facts etc. Instead of simply accepting the raw sensor data, we adopt different methods of sensor fusion against different sensor types, in order to filter noise.

In particular, GPS signals inevitably suffer from noise and are known to be less reliable. To stabilize out readings, we record a series of GPS location estimates from the time the image capture starts until the shutter is pressed. From this series, we eliminate obvious outliers and smooth the remaining estimates by a weighted sum in favor of the latest estimates, following the assumption that later sensor readings provide a more reliable result. This considerably improved location estimates.

4.3 Projection to World Coordinates

In order to integrate the marked object into a geo-data set, it needs to be converted into a geographic location L. We now describe how we can retrieve the world coordinates of the marked object from the outline information of the camera image. The outline is a closed polygon, a set P^* of (x, y) coordinates in the image plane. In the first step, we reduce the number of points of P^* by applying the Douglas-Peucker algorithm (Douglas and Peucker 1973) for shape simplification and obtain a new, smaller set $P = \{P_0, P_1, \ldots, P_n\}$, $P_i = (x_i, y_i)$. This implements shape simplification directly on the smartphone.

The task to calculate the real world coordinates of the object outlined by P is an inverse perspective transformation (Foley et al. 1990, e.g.). For calculating the geographic location, distance and bearing angle from observer's location P_{camera} to every target point P_i is required. In the local coordinate system, $P_{\text{camera}} = (0, 0, h)$, with h being the height of the camera above the ground.[7]

Figure 2 depicts the projection from the image coordinate system to a local coordinate system, that is, from a point P_i in the image coordinate system to a point P'_i in the local coordinate system. The fact that the object is known to be in the xy-plane considerably reduces the complexity of the calculation.

The first intermediate step is to project P from the image coordinate system to a point $P_{3d} = (x_{3d}, y_{3d}, z_{3d})$ in a 3D coordinate system (defined by the blue axes in Fig. 2). For this we need the height *height* and width *width* of the camera image in pixels, the angle α from the phone's orientation sensor, and the camera lens parameter angles γ and δ that define the device's camera frustum. Then we get:

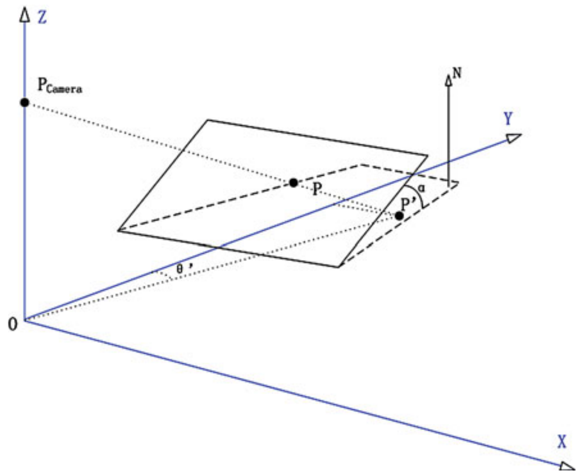

Fig. 2 Projection from image coordinate system to local coordinate system in the plane

[7] At the current state, the parameter h has to be set manually.

$$x_{3d} = x - \frac{\text{width}}{2} \tag{1}$$

$$y_{3d} = \frac{\text{width}}{2} \tan(\frac{\gamma}{2} + (\text{height} \ - y) \sin \alpha) \tag{2}$$

$$z_{3d} = (\text{height} \ - y) \cos \alpha \tag{3}$$

P'_i is the intersection point of the straight through P_{camera} and P_{3d} with the xy-plane. N is the normal vector of the xy-plane.

$$P' = P_{\text{camera}} + \frac{-P_{\text{camera}} \cdot N}{(P_{3d} - P_{\text{camera}}) \cdot N}(P_{3d} - P_{\text{camera}}) \tag{4}$$

With $P' = (x', y', z')$, we can finally retrieve θ':

$$\theta' = \arctan(\frac{x'}{y'}) \tag{5}$$

The distance d_i between P_{camera} and P'_i is

$$d_i = \frac{h \cdot \arctan \alpha'}{\cos \theta'} \tag{6}$$

with

$$\alpha' = \alpha - \frac{\delta}{2} + \delta | \frac{y' - y_{max}}{y_{max}} | \tag{7}$$

and y_{max} being the maximal y coordinate in the projected polygon.

With lat_o and lon_o being the latitude and longitude taken from the GPS estimate of the observer's position and R=6371004 being the equatorial radius of the earth in meter, we retrieve $L = (lat_i, lon_i)$ for every P'_i:

$$lat_i = \arcsin(\sin lat_o \cos \frac{d_i}{R} + \cos lat_o \sin \frac{d_i}{R} \cos \theta') \tag{8}$$

$$lon_t = lon_o + \ \text{atan2} \ (\sin \theta' \sin \frac{d_i}{R} \cos lat_o, \cos \frac{d_i}{R} - \sin lat_o \sin lat_t) \tag{9}$$

We repeat this procedure for every point in the object's outline and connect the points in the projection following the input sequence.

5 Evaluation

To show the feasibility of MAPIT we evaluated the accuracy of the collected geodata under everyday conditions. We collected defined real-world geometric data under controlled and varying conditions and compared the real world entity

Fig. 3 The satellite image used to verify the mapped parking lots. Each of them is 5×2.35 m

and the reconstructed entity with respect to accuracy of *angles*, *area*, and *perimeter*. We did not take the positional offset introduced by the GPS sensor into account, since potential errors are not introduced by the MAPIT approach but by the sensor unit itself. Any GPS-based approach depends on the accuracy of the sensor and cannot improve the physically limited result. However, we observed the usual offsets for the non-survey grade GPS units built in smartphones varying between near 0 m up to 10 m of positional displacement. With our filtering as outlined in Sect. 4.2, we obtained offsets of 1–4 m.

The aim of MAPIT is to enable micro-mapping, thus geometrically correct mapping of small spatial entities. For testing the precision we chose parking lots as reference objects, as they have a defined rectangular shape, are of a well-matching reference size of 5×2.35 m, and are visible on satellite imagery (see Fig. 3). All entities have been recorded using MAPIT running on a Samsung Galaxy Nexus 2 with Android 4.0. Our sample size was $p = 50$ measurements.

In order to evaluate MAPIT under realistic conditions we applied three different mapping variations:

- *Multiple perspectives*: we recorded 8 parking lots from 4 different perspectives in varying distances between 3 and 8 m in order to rule out influences on perspective adaptation of the method, see Fig. 4. This resulted in 32 individual measurements.
- *Multiple distances*: we recorded 4 parking lots from 3 different distances (5, 10, 15 m), however each from the same perspective (see Fig. 5). This resulted in 12 individual measurements.
- *Multiple entities from one photo*: we recorded 3 photos and mapped 2 distinct parking lots within each of them (see Fig. 6). This resulted in 6 individual measurements.

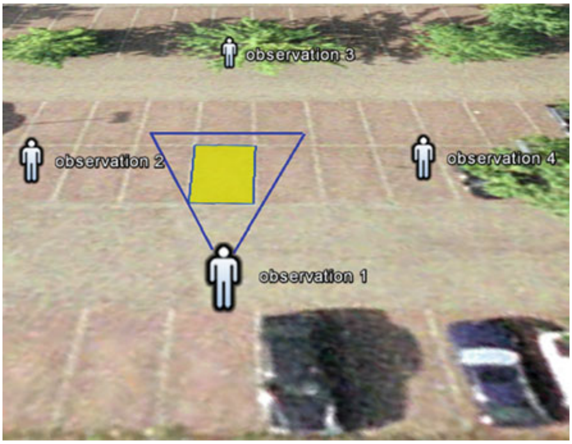

Fig. 4 Mapping an entity from 4 different perspectives

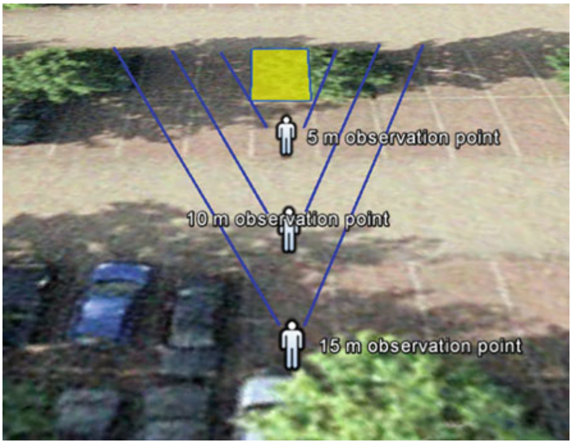

Fig. 5 Mapping an entity from three different distances (5, 10, 15 m)

After the recording of the photos with MAPIT (which includes the sensory information for geometric reconstruction) we manually set the four corner points of the parking lot on a large 20” screen with a computer mouse. This deviation from the original workflow (segmenting the entity directly on the touchscreen) was necessary to rule out errors introduced by inaccuracies of the touchscreen or during finger-based pointing. Defining the edges with greatest possible precision allows to analyze the results of the method without the influence of technical limitations of the interface. The four corner points where used as the input for the projection introduced in Sect. 4.3.

We then analyzed the resulting 50 reconstructed rectangles (32 multiple perspectives, 12 multiple distances, 4 multiple entities) with respect to their accuracy (each original parking lot is 5×2.35 m). We measured:

Fig. 6 Mapping of multiple objects from one photo

- the absolute angular deviation of each of the four inner angles of each reconstructed rectangular parking lot. Ideally each internal angle is exactly 90°. We compared 200 individual angles.
- the absolute areal deviation of each reconstructed rectangular parking lot. Ideally each entity has an area of 11.75 m^2. We compared 50 areas.
- the absolute side-length deviation of all sides of the reconstructed rectangular parking lot. Ideally each entity has two sides with 5, and two with 2.35 m length. We compared 200 individual side-lengths.

5.1 Results & Discussion

Table 1 shows the result of the evaluation for each mapping variation. It shows the mean deviation across all measurements of one mapping condition, and in the bottom row the overall mean across all mapping conditions. Although showing slight differences in the conditions, MAPIT performs uniformly well. The areal deviation across all three mapping variations is clearly below 4 %, in the multiple perspective condition even just 3.44 %. The same picture can be found in the side-length (perimeter) evaluation. In all three conditions the perimeter of the mapped entity is preserved to a very high degree: the summary deviation across all conditions is 4.33 %, in the multiple entities condition just 3.84 %. The angular accuracy of in all conditions is only slightly worse, however can still reconstruct

Table 1 Evaluation result

Variation	Area (%)	Perimeter (%)	Angle (%)
Multiple perspectives	3.44	4.46	5.99
Multiple distances	4.30	4.25	5.88
Multiple entities	4.90	3.84	6.26
Overall Deviation	3.82	4.33	5.99

angles to a very high precision; the deviations are only around 5.99 % across all conditions.

When we have a closer look at the distribution of the deviations across the conditions, we can get a better understanding of the composition of the results.

The chart for the angular error in Fig. 7a, shows that 50 % of the measurements only have a deviation between 0 to 2 %. The second peak is around a deviation of 10 %. After reviewing the data set, it turns out that the angles far from the observing points tend to have a greater deviation. In contrast, the angle of vertex turns out the better outcomes with 2 % in error. The chart for the side-length error in Fig. 7b shows a monotonly declining distribution of the deviation with about 70% of the measurements deviating below 5 %. A slightly different picture shows the chart for areal deviation in Fig. 7c.

Figure 8 shows visual results of the numbers presented above. All originally mapped parking lots are outlined by yellow line and filled with dots. The green polygons are the results of the mapping and geometric reconstruction with MAPIT. The geometry of the entities is very well reconstructed. We can observe a slight positional offset due to the GPS accuracy. However, even with the entities shifted from the original locations, our approach is capable of reconstructing complex topologies, such as neighboring parking lots on a parking ground.

6 Application Example

In this section we want to point to an application example where the approach shown in this chapter becomes a useful tool. We refer to a project we are working on in rural Laos where we are working with an educational program by the Lao government to enable poverty reduction work in the villages. Within the scope of this project, the problem of having an insufficient amount of protein in the daily food supply was prototypically tackled by installing small fishponds in the backyards of villager's houses to ensure an additional protein source (see Fig. 9). This idea turned out to be a successful and was quickly adopted by other villagers and across villages.

A major task in such kind of development work is monitoring the success and the impact of actions taken. In this case, this would mean to monitor the how the ponds spread over the area over time, their number, and the total amount of protein they can supply. To determine the latter number, it is essential to know the size of

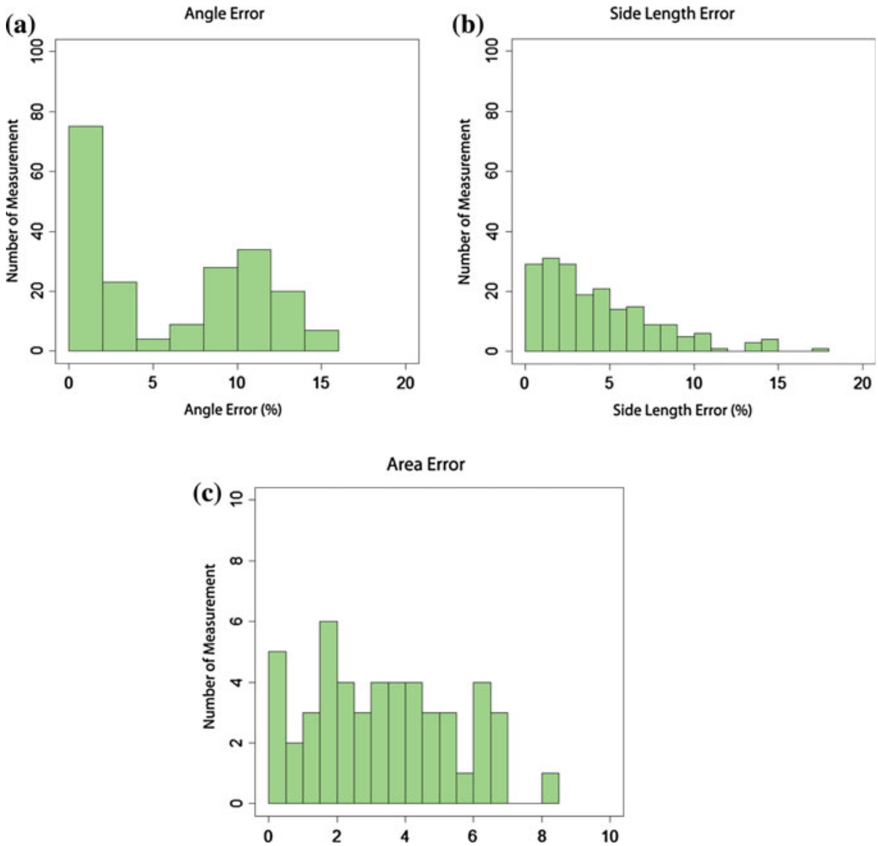

Fig. 7 The evaluation results: absolute internal angle deviation (**a**), absolute side-length (perimeter) deviation (**b**), absolute areal deviation (**c**)

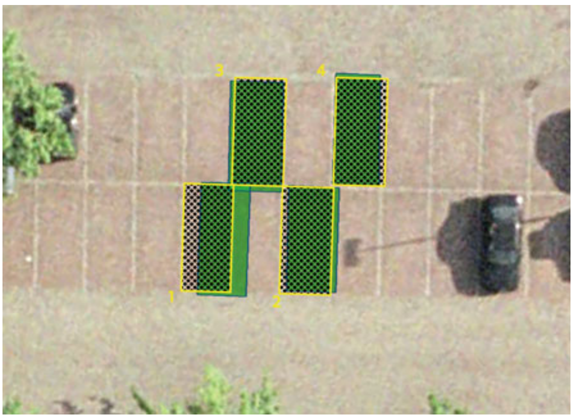

Fig. 8 This figure illustrates the reconstruction of four parking lots: the areas with *yellow outlines* and *filled with yellow dots* are the original parking lots to be mapped, the *green areas* are the same lots recorded and reconstructed with MAPIT. Note the accuracy of the geometric reconstruction. Only slight positional offsets are recognizable due to GPS filtering

Fig. 9 Backyard ponds in a village in rural Laos

the ponds in order to estimate how many fish can breed there. Thus, the application presented in this chapter can be a great help to perform this kind of monitoring. It runs on any low-cost Android smartphone, such that it is not expensive to equip local stakeholders with the needed technology. The mapping procedure is simple and intuitive and can be performed by laymen. People working there can assess the whole development of the pond project by simply going around, taking pictures, drawing the outlines, and label them as ponds. This data then can be aggregated on remote servers, visualized on dynamic maps, and protein supply can be estimated by determining the overall size of ponds in an area.

7 Conclusions & Future Work

Geo-spatial information is the basis for manifold applications in industry, development, and research. In contrast to past decades, the acquisition, availability, and usage of geographic data is anchored in a broad global movement of volunteers. Everybody can contribute the kind of data required for particular usage. However, until now there exists no easy-to-use method to record and contribute small geographic features with full geometric information. Due to the high effort required to map small entities, they have largely been ignored in the data collection process although there exist a large number of use cases for it.

In this chapter we introduced the concept of *micro-mapping*, the geometric correct acquisition of small spatial entities. We developed MAPIT, a method for rapid, barrier-free acquisition and contribution of small spatial entities with full geometric information. MAPIT is based on everyday smartphone technology and applies inverse perspective transformation to project coordinates of a photo to geographic space. We showed that the results of MAPIT are highly accurate, and we could reconstruct the original geometries of sample entities with high precision. The angular deviation between original and reconstructed entity is only 5.99 %, the side-length error 4.33 %, and the areal deviation is only 3.82 % between original and reconstructed entity.

mapIT is designed to facilitate barrier-free contribution of geo-spatial data. It does not require more hardware than an ordinary smartphone and provides an easy workflow that allows acquisition of geo-data by non-experts. This can make mapIT a valuable tool in low-resource settings and facilitates the exploitation of geographical information in larger contexts that actually are unable to benefit from it—even in fields that usually do not much rely on technology, such as in agricultural development.

In order to make data processable it is necessary to classify it correctly. However geographic classification systems are complex and still hard to use for uneducated users. We plan to develop an ontological reasoning component to automatically translate natural language into a properly classified object.

Acknowledgments We gratefully acknowledge support by the University of Bremen, the German Research Foundation (DFG) within the SFB/TR8 Spatial Cognition and the International Research Training Group on Semantic Integration of Geospatial Information (GRK 1498), and support by the European Union Seventh Framework Programme—Marie Curie Actions, Initial Training Network GEOCROWD under grant agreement No. FP7-PEOPLE-2010-ITN-264994.

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