Quality Assessment of Remote Mapping in OpenStreetMap for Disaster Management Purposes

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ABSTRACT

Over the last couple of years Volunteered Geographic Information (VGI) and particularly OpenStreetMap (OSM) have emerged as an important additional source of information in disaster management. The so-called OSM Crisis Maps are primarily developed by OSM contributors who work remotely. While local OSM contributors know their area of interest and rely upon local knowledge, often the sole basis for the remote mapping is satellite imagery. This fact may raise doubts about the quality of the Crisis Maps. This study introduces an experimental approach to assess the data quality that remote mappers produce. In an experimental setting, data sets produced by a group of remote mappers are evaluated by comparing them to data sets created by a selected expert mapper with local knowledge. The presented approach proved to be useful for assessing data quality of remote mapping and can be used to support decisions about the suitability of crowdsourced geographic data.

Keywords

OpenStreetMap, Volunteered Geographic Information, Crisis Maps, Remote Mapping, Disaster Management

INTRODUCTION

Natural and man-made disasters are a known reality of our world. However, with disasters and their settings being extremely multifaceted, disaster management is to-date a very complex task. Especially in disaster response dependable data to create situational awareness is crucial as reaction time is sparse and response actions need to be organized based on accessible information. Generally, this data should be provided by official sources. With this official data oftentimes not being available or accessible, during the last couple of years, humanitarian aid organizations recognized the potential of Volunteered Geographic Information (VGI) for disaster management purposes.

Due to new technologies and the public accessibility to VGI platforms, international volunteers can also actively support disaster response remotely, using their internet connection and satellite imagery. These publicly accessible applications can help the humanitarian aid organizations and emergency response teams to improve their situational awareness and coordinate their disaster response measures (Meier, 2012). The collaborative maps of OpenStreetMap in particular proved to offer great potential in disaster scenarios. Ever since 2010 when the crowdsourced map was initially implemented for a crisis situation after the earthquake in Haiti, numerous OSM contributors provided their support in mapping events in the aftermath of a disaster, producing the so-called Crisis Maps. This engagement attracted serious interest in academic circles as well as on the side of humanitarian aid organizations (Harvard Humanitarian Initiative, 2011; United Nations Office for the Coordination of Humanitarian Affairs, 2013). However, while one main advantage of OSM is that their contributors mainly focus on their well-known local surroundings (Goodchild, 2007; Neis and Zipf, 2012), Crisis Maps originate largely from mappers that work remotely. These contributors have not necessarily been to the place in question and may not have any country-specific knowledge. Consequently, their digitization solely relies on satellite imagery and Global Positioning System (GPS/GPX) tracks that locals may have created. Additionally, due to the lack of time in disaster situations, the data of remote mappers cannot be examined by local mappers, which is the usual quality assurance procedure in OSM.

Due to the fact that OSM is a crowdsourced map and that a main part of the data in Crisis Maps originates exclusively from contributors that work remotely, humanitarian aid agencies and first responders have doubts about the quality of the OSM data and therefore sometimes refrain from utilizing it (Harvard Humanitarian Initiative, 2011). Furthermore, activity areas of remote mappers generally lack official cross-reference data, making it difficult to apply usual quality assessment methods, which are based on comparisons with reference data.

Against this backdrop, this paper introduces a methodology to assess the remote data quality with an empirical approach.

After presenting the related work in the following chapter, the empirical setting as well as the method that was applied for the quality analyses and the results will be introduced. The usability and possible further applications of the methodology will then be discussed in the final chapter.

RELATED WORK / BACKGROUND

The increasing popularity of OSM prompted to a considerable number of researchers to investigate the OSM data quality (Arsanjani, Barron, Bakillah and Helbich, 2013; Barron, Neis and Zipf, 2013; Fan, Zipf, Fu and Neis, 2014; Girres and Touya, 2010; Haklay, 2008; Neis, Zielstra and Zipf, 2013). The so-called extrinsic quality assessments were in general conducted by comparison of the OSM data to official data sets (Fan et al., 2014; Girres and Touya, 2010; Haklay, 2008; Neis et al., 2013). The result of these studies proved that the OSM data quality is relatively high and comparable to the quality of official data in densely populated regions with a high number of OSM contributors.

Other studies also included intrinsic analyses of the OSM quality (Arsanjani et al., 2013; Barron et al., 2013) applying a temporal approach, which focuses on analyses of the attributes and of the contributors themselves. While these studies provided insights about the different levels of experience and the behavior of contributors, they did not address remote mappers in particular.

Since OSM data became a new and innovative source of information in crisis situations, there have also been several research studies further analyzing this phenomenon and the general perception of this new concept (Kawasaki, Bermann and Guan, 2013; Zook and Graham, 2010). These studies investigated the interoperability of the humanitarian aid organizations and the volunteers and technical communities and also explained that OSM data, and VGI in general, is often perceived as inaccurate and error-prone by the humanitarian aid agencies and emergency responders. Nevertheless, these studies do not provide any information about the actual quality of the OSM data.

Thus, although the data quality of OSM and its use in disaster management as well as the OSM contributors have been investigated, there have been no studies assessing the data quality that can be expected in Crisis Maps, i.e. in the maps produced by volunteers for coping with crises.

This research gap, especially with regards to remote mapping in places where there is no critical mass of local mappers, cannot be addressed using the existing research approaches, since official data for referential comparison is often not available in many places that are considered to be activity areas of remote mappers. An intrinsic analysis cannot be conducted as remote mapping does not contain much attribution. This information is generally added by local mappers. Additionally the data contributed by remote mappers often is the first digitization in an area, which makes a temporal approach impractical. Therefore, this study addresses remote mapping quality using an empirical and experimental approach.

EMPIRICAL SETTING

The experiment to evaluate the data quality of remote mapping for disaster management purposes was conducted during a course in “VGI in humanitarian aid and disaster management” as part of a graduate program in Geography in the Geographical Institute of Heidelberg University, Germany.

As part of this course the eight seminar attendants participated in a remote mapping exercise which was organized in cooperation with the non-profit organization Kathmandu Living Labs[1]. With this partner organization being based in Kathmandu in the Federal Democratic Republic of Nepal, Kathmandu also is the research area of this paper. The data sets created during this exercise constitute the remote mapping data for the experiment.

The students received a short introduction into the editing tools and the exercise before then starting a task in the OSM Tasking Manager, an online application that was developed by the Humanitarian OpenStreetMap Team[2] and is also used in disaster situations to organize and coordinate OSM mapping activities. The task itself was developed by Kathmandu Living Labs. The students were asked to remotely digitize buildings in the less populated southern and western areas of Kathmandu using the Java OpenStreetMap Editor (JOSM) and the satellite imagery provided by BING as a base map. The BING satellite imagery by Microsoft Cooperation and its data suppliers is provided freely in the OSM editors. The imagery of Nepal was panchromatic but enhanced resolution to 25cm.

Students were given an hour to apply themselves to the task. The activity areas of the students, acting as remote mappers, are presented in Figure 1 (lowest density is highlighted in blue, highest density is highlighted in red). The data created by remote mappers was retrieved from OSM using the Overpass Turbo application[3].

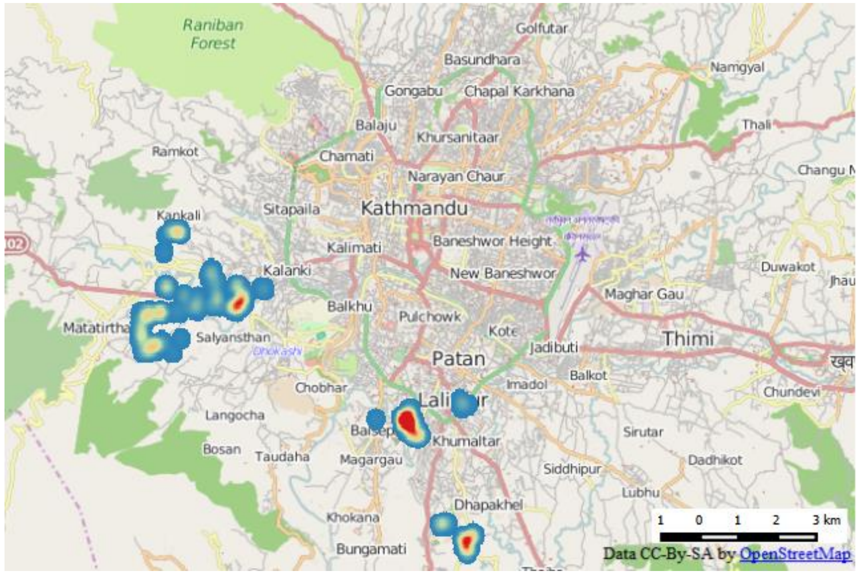

Figure 1: Kernel density of the Activity Areas of Remote Mappers (radius=300m)

The second part of the experiment was conducted in the Kathmandu Valley. The data sets of the remote mappers were loaded into an additional layer in the JOSM editor and in turn digitized using the BING satellite imagery by an experienced OSM mapper with what we call “purposeful local knowledge”.

While natural local knowledge is acquired by living in an area and observing it unconsciously, this mapper visited and observed the activity areas of the students before starting to digitize the corresponding features himself. Thus, the mapper

[1] www.kathmandulivinglabs.org Accessed 26.2.2015.

[2] http://hot.openstreetmap.org/ Accessed 30.01.2015.

[3] http://overpass-turbo.eu/ Accessed 30.01. 2015.

acquired the local knowledge deliberately and for a specific reason.

The data of the experienced mapper is expected to be of high quality and can therefore be used as the reference data set to conduct the data quality assessment.

METHODOLOGY

The methodology to conduct the quality assessment is divided into three main sections: (1) preprocessing to generate the data sets for the quality evaluation of remote mapping and (2) qualitative analysis and (3) quantitative analysis. The workflow followed in the methodology is presented in Figure 2.

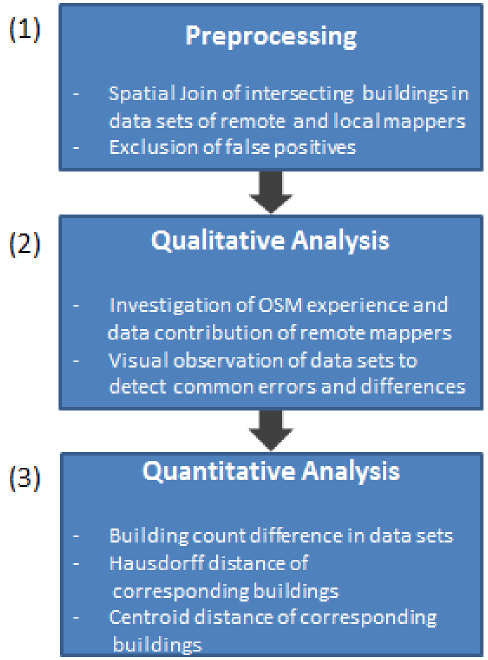

Figure 2: Overview of the Methodology

1. Preprocessing

Before starting the automated quantitative assessment, the data sets of the remote and local mappers were loaded into QGIS to perform a qualitative analysis.

The ensuing quantitative analysis was conducted in a Postgre/PostGIS database. The data sets were imported into the data base using the PostGIS Shapefile downloader plugin and projected to the Universal Transversal Mercator Projection WGS1984_UTM45N which is commonly used for the Central Region of Nepal.

In the quantitative analysis, corresponding features are compared automatically, therefore the congruent features in the data sets need to be identified beforehand. All features with an intersecting area were selected and joined conducting an intersect query in PgAdmin. This intersection was followed by a spatial join to merge the corresponding buildings in the data sets. The result of these queries is a table containing all buildings with an area overlap with another building in the corresponding data set. This method can cause mismatches in the corresponding data set when the building density is high. Thus, in a second step these mismatches are identified by loading the congruent data sets of the remote and local mappers in QGIS and visually identifying the features with the highest overlap. The additional mismatched buildings with lower area overlap were declared false positives and deleted from the table created in the spatial join.

2. Qualitative Analysis

The buildings of the remote and local mappers were visually observed in QGIS to identify differences and errors in the individual data sets and to recognize patterns and weaknesses in the remote mapping.

3. Quantitative Analysis

In the quantitative analysis the corresponding data sets and especially the number of corresponding buildings are compared to the total number of buildings in the data of the remote and local mapper to detect falsely identified features.

Afterwards the corresponding features were compared using the Hausdorff distance function (Rucklidge, 1996). This function implements an algorithm which is also known as the Discrete Hausdorff distance. The computation is therefore limited to discrete points for one polygon of the corresponding pair. The Discrete Hausdorff distance provides information about the positional correspondence as well as the similarity of their orientation and shape of two geometries. The result of the Hausdorff distance calculation will present the maximum distance from one point in a polygon to the nearest point in the corresponding feature and thereby allows the evaluation of how similar the two compared features are regarding their positional accuracy and shape (Rucklidge, 1996). Additionally, the centroid distance of the features in the data sets is calculated to investigate the positional accuracy in particular.

RESULTS

In this section the results of the analyses are presented starting with the qualitative and then turning to the results of the quantitative analysis.

1. Qualitative Assessment

The qualitative analysis showed great variations within the remote mappers group concerning the number of features the different mappers identified during the remote mapping exercise and their experience in OSM (Table 1).

More than half of the remote mappers had not contributed to OSM before taking part in the experiment. This experience however does not seem to correlate with the number of features the mappers contributed in the experiment.

Subject	**Number of Digitized Buildings**	**Number of days since registration in OSM**
Mapper 1	49	1
Mapper 2	135	174
Mapper 3	33	131
Mapper 4	15	1
Mapper 5	198	1
Mapper 6	93	1
Mapper 7	123	200
Mapper 8	6	1

Table 1: Identified Buildings and Experience in OSM of the Remote Mappers

A comparison of the total building numbers that were identified by the remote and local mappers shows that there are variations in the number of identified features, although both data sets were contributed from the same areas.

These irregularities can be explained when exploring the corresponding data sets visually. In various cases the remote mappers falsely digitized a single building as consisting of a group of buildings, thereby leading to n:1 relations and resulting in an imbalance in building numbers in the corresponding data sets. One example of this occurring is presented in Figure 3. The red marked polygons represent the digitization of the mappers with the BING satellite imagery in the background as a base layer.

Figure 3: Digitization of Buildings by Local Mapper (left) and Remote Mapper (right)

While the local mapper identified and therefore digitized two buildings, the remote mapper identified three buildings.

In contrast, in other cases the remote mappers digitized a group of buildings or houses in a row as being connected and therefore being only a single building complex. This misinterpretation caused n:1 relations and consequently again led to an imbalance in building numbers in the compared data sets. An example for this issue is presented in Figure 4. While the local mapper digitized six buildings, the remote mapper interpreted these buildings as only one.

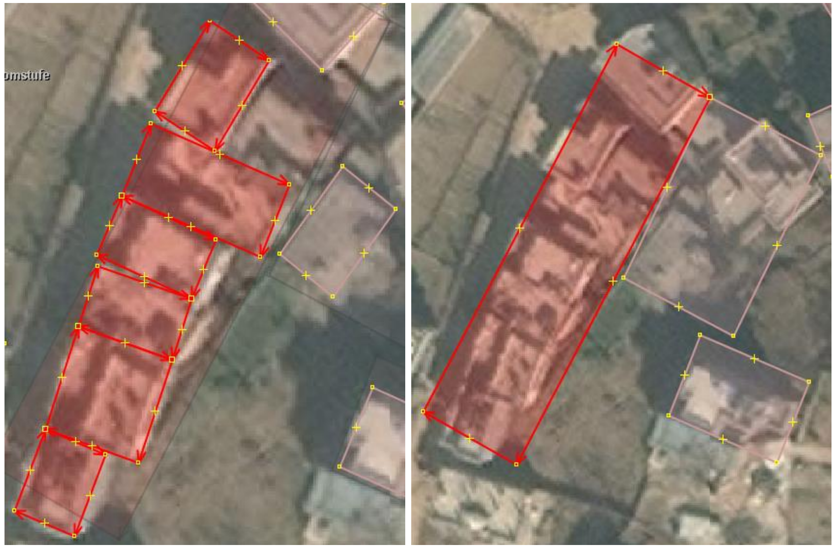

Figure 4: Digitization of Building Complex by Local Mapper (left) and Remote Mapper (right)

2. Quantitative Assessment

Before conducting the quantitative assessment, the corresponding buildings were identified by intersecting and merging the corresponding buildings, thereby identifying first deviations in the data sets. While the total number of buildings that were digitized by the local and remote mappers was nearly equal, due to the misinterpretations that were also recognized in the qualitative analysis, in total around 10% of the buildings that were correctly identified and digitized by the local mapper were in turn not identified and therefore not digitized by the remote mappers (Table 2).

Description	Number of Buildings
Buildings digitized by remote mappers	652
Buildings digitized by local mappers	659
Corresponding buildings in both data sets	620
Misinterpreted buildings	71

Table 2: Deviation in Building Counts in Compared Data Sets

After the corresponding features were detected, the data sets were compared using the Hausdorff distance. Figure 5 shows a histogram with the deviation of the Hausdorff distances in which the blue bars represent the frequency of the Hausdorff distance within all data sets, the red line represents the cumulated percentage of the data sets compared to the total number of features. More than half of the features the remote mappers contributed showed a Hausdorff distance of less than 4 meters to the corresponding features in the data set of the local mapper, 74% of the total data was off less than 6 meters. The average Hausdorff distance in the compared data sets is 4.94 meters, the standard deviation is 3.96 meters.

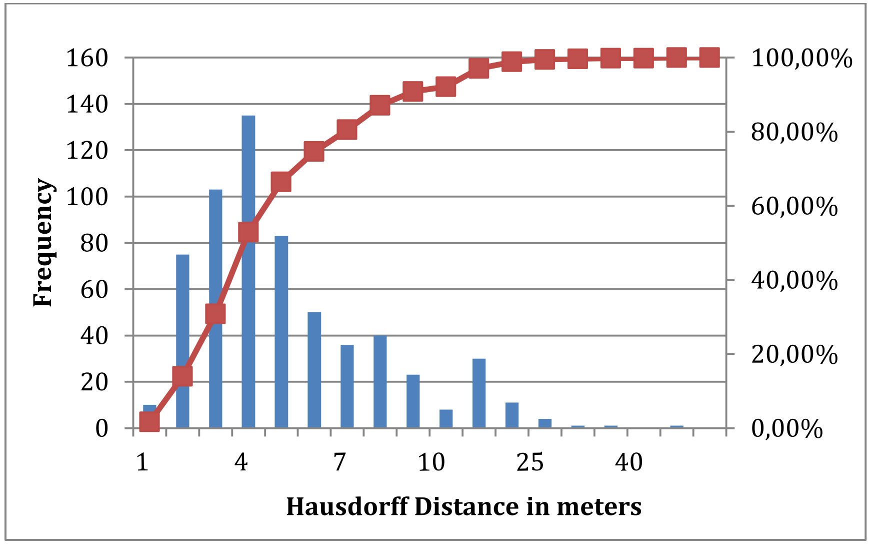

Figure 5: Histogram presenting the Hausdorff Distances

Furthermore the positional accuracy was investigated by calculating the centroid distance of the features in both data sets (Figure 6). This analysis shows that the centroid distance could be an influential factor for the results in the Hausdorff distance. The average deviation in the centroid distance being 3.36 meters and the standard deviation being 2.60 meters, the centroid distance already constitutes around 75% of the Hausdorff distance. Thus, the positional deviation seems to be more pivotal than differences in shape.

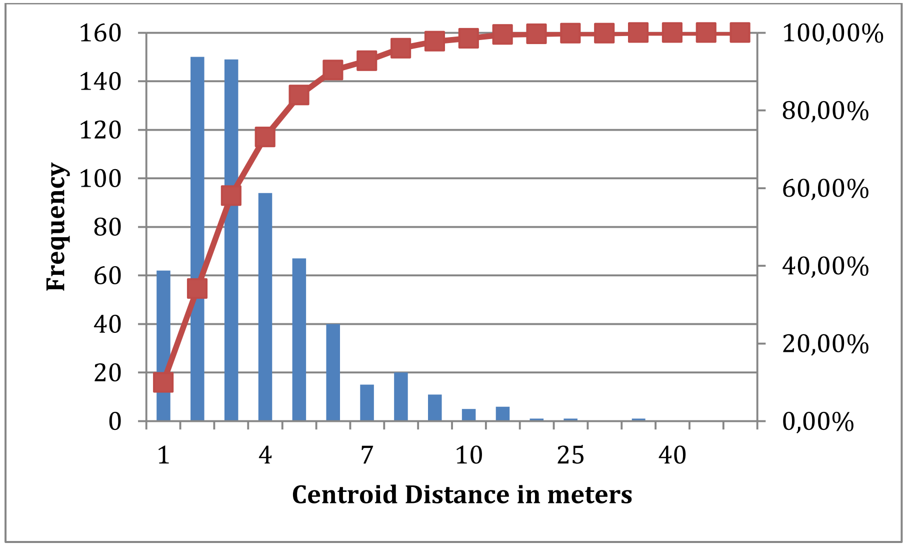

Figure 6: Histogram presenting the Centroid Distances

DISCUSSION AND CONCLUSION

The presented study introduces an experimental approach to evaluate the quality of the OSM data contributed by remote mappers. The fact that the assumptions that were made in the qualitative analysis were confirmed by the quantitative assessment, as well as the additional results of the presented analyses indicate that the presented methodology can be seen as a useful way to evaluate the data quality of remote mapping and could lead to revealing results.

To achieve more representative results, this methodology needs to be applied to larger research groups, preferably participants in disaster mapping events. That way a high number of remote contributors and their contributions could be tested while working under crisis mapping conditions. However, this possibility can only be applied if an appropriate group of experienced local mappers is available to validate the data of the remote mappers. OpenStreetMap does not collect any information about the home location or local knowledge of contributors. While there have been attempts to acquire this information using the main activity area of the OSM contributors (Neis et al., 2012), mappers that are mainly active in disaster mapping and therefore contributing data to OSM way outside their area of local knowledge, can cause a considerable number of errors. This issue can be avoided when having a group of remote mappers and a local mapping community to validate the data of the remote mappers.

The qualitative assessment of the data sets suggests that a misinterpretation of buildings can cause a strong deviation in building numbers in comparison to the ground reality. This problem could be approached by providing country specific training material in which the mappers learn about common features in the foreign country and how to digitize these features correctly. The usefulness of such training material could be tested by applying the approach and method that was presented in this study. Data sets of remote mappers without any country specific knowledge and data sets of remote mappers that receive country specific training material could be separately compared to data sets that were generated by a mapper with purposeful local knowledge. Appropriate training material for Nepal is currently being developed by the author and will be tested in future work.

Additionally other factors that could likely be influential for the quality of remote mapping, e.g. the experience in OSM or remote sensing and the influence of building density on the mapping accuracy, could be further investigated by conducting surveys and statistical analyses.
The presented methodology proved to be useful for evaluation of data quality of remote mapping. However, if this data quality is to meet the requirements in disaster management, it needs to be directly checked against specific criteria and needs of practitioners in this field.

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