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Changes in VGI Quality over Time: Positional Accuracy Trends in Tehran City

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ABSTRACT

The increasing utilization of Volunteered Geospatial Information (VGI), including data from OpenStreetMap (OSM), raises concerns regarding data quality due to variations in contributors' skills and tools. This study evaluates the positional accuracy of voluntary features in Tehran by comparing them with official datasets. A feature matching approach, employing Hausdorff distance, orientation difference, and buffer overlap—normalized through fuzzy logic—was utilized to assess accuracy. Preprocessing steps included standardizing data extent and coordinate systems, correcting topological errors, and converting datasets into graph structures. The results indicate that most voluntary features exhibited high positional accuracy, with over 87% achieving positional accuracy above 82%. Temporal analysis revealed peaks in voluntary contributions in 2012 and 2017; however, there was a slight overall decline in positional accuracy from 2007 to 2022, as indicated by a negative trend line slope of -0.001834. This study introduces a method for assessing the accuracy of historical data using feature matching across a large area, such as Tehran, to track trends in positional accuracy over time. It emphasizes the necessity for extrinsic assessment in VGI, noting that technological advancements do not always correlate with improved positional accuracy. The comprehensive approach presented in this study provides valuable insights into the quality and reliability of VGI.

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1. Introduction

The rise of Volunteered Geospatial Information (VGI) has revolutionized the field of geospatial information systems (GIS) by enabling widespread public participation in the creation and dissemination of spatial data (Polous, 2023; Zhang, 2020). Coined by Goodchild (2007), VGI leverages the concept of citizens as sensors, where individuals voluntarily collect, share, and contribute spatial data (Forati & Ghose, 2020; Zhang et al., 2021). This grassroots approach utilizes the power of the crowd (Howe, 2006), harnessing the collective knowledge and observations of a large number of participants to build comprehensive and dynamic geospatial datasets (Girres & Touya, 2010; Goodchild, 2007; Sboui & Aissi, 2022).

Among the most prominent VGI platforms is OpenStreetMap (OSM), a collaborative mapping project that allows users worldwide to contribute and edit geospatial information (Chehreghan & Ali Abbaspour, 2018b; Hashemi & Ali Abbaspour, 2015; Yamashita et al., 2023). Since its inception in 2004 (Zhang et al., 2015), OSM has rapidly expanded, amassing a vast repository of user-generated spatial data (Neis & Zielstra, 2014). This democratization of geospatial data production has provided an invaluable alternative to traditional sources (Minghini & Frassinelli, 2019), which are often costly and less accessible (Teimoory et al., 2021). By allowing anyone with internet access to participate, OSM has not only expanded the availability of geospatial data but has also empowered individuals to play an active role in mapping their environments (Ghasemi Nejad et al., 2022; Goodchild & Glennon, 2010).

Despite its many advantages, the quality of VGI remains a critical area of concern and ongoing research (Bai et al., 2024; Goodchild & Li, 2012). Several factors contribute to concerns about the quality of OSM data. First, the contributors to OSM have varying levels of expertise and experience. While some users are highly skilled cartographers, others may have limited knowledge of mapping principles, leading to inconsistent data quality. Second, the equipment used by contributors can vary significantly, from high-precision GPS devices to basic smartphones, resulting in differing levels of quality. Third, the absence of a comprehensive surveillance or verification system for data entry means that errors or intentional inaccuracies can go unnoticed for extended periods (D’Antonio et al., 2014; Girres & Touya, 2010; Haklay, 2010; Senaratne et al., 2017).

Quality in geospatial information encompasses various dimensions, including completeness, consistency, attribute accuracy, semantic accuracy, temporal accuracy, fitness for use, lineage, and positional accuracy (Antoniou & Skopeliti, 2015; Guptill & Morrison, 2013; Kresse & Fadaie, 2004; Van Oort, 2006). Each of these elements plays a crucial role in determining the overall reliability and usability of the data for different applications. As OSM continues to grow, understanding and assessing these quality dimensions is essential for ensuring that the data can be effectively utilized in diverse domains such as urban planning, disaster management, navigation, and environmental monitoring (Aissi & Sboui, 2017; Hong & Yao, 2019; Tavra et al., 2024).

Completeness refers to the extent to which all relevant features are included in the dataset. This component examines the comprehensiveness of the data, identifying which features should be present in the database but are currently missing, and which additional data exist unnecessarily (Chehreghan & Ali Abbaspour, 2018b). Consistency examines the adherence of the dataset to established rules and standards, reducing errors like overlapping features or logical contradictions (Hashemi & Ali Abbaspour, 2015). This includes logical consistency, which ensures topological relationships and structural integrity, and attribute consistency, which verifies that similar features share coherent characteristics. Attribute accuracy ensures that descriptive information, such as names, classifications, or types, accurately reflects real-world features. For example, a highway tag in OSM must correspond to an actual highway. Semantic accuracy focuses on ensuring that the meaning and representation of features in the database align with their real-world counterparts, supporting clarity and proper interpretation (Guptill & Morrison, 2013). Fitness for use evaluates whether the dataset is appropriate for specific applications, recognizing that data suitable for navigation may not meet the requirements of detailed urban planning (Devillers et al., 2007; Sboui & Aissi, 2022). Temporal accuracy assesses whether the dataset reflects real-world changes over time, emphasizing the importance of keeping information current. This is particularly important in dynamic datasets like OSM, where features are frequently updated. Lastly, lineage tracks the dataset’s origin and the processes it has undergone, offering transparency and enhancing trust in its reliability (Kresse & Fadaie, 2004; Van Oort, 2006).

Among the various elements of geospatial data quality, positional accuracy is a fundamental aspect. Positional accuracy refers to the degree to which the reported locations of features in a dataset correspond to their true positions on the Earth's surface (Antoniou & Skopeliti, 2015; Kresse & Fadaie, 2004; Van Oort, 2006). High positional accuracy is essential for applications that require precise spatial information, such as navigation systems, cadastral mapping, and emergency response. Conversely, low positional accuracy can result in significant errors and misinterpretations, potentially undermining the effectiveness of these applications.

This study investigates the positional accuracy of OSM linear data and its evolution over time. By examining the temporal changes in positional accuracy, we aim to gain insights into the reliability of OSM as a geospatial data source and identify trends that may indicate improvements or declines in data quality. To achieve this, we will employ a feature-matching method to identify corresponding linear features in both official datasets and OSM. By computing the spatial similarity between matched features, we can quantify their positional accuracy.

The feature matching method entails comparing linear features, such as roads, across different datasets. By analyzing the spatial correspondence between these features, we can assess the positional accuracy of OSM data. Additionally, by examining the registration or modification timestamps of features within the OSM dataset, we will investigate trends in positional accuracy over time. This temporal analysis will enable us to determine whether the quality of OSM data is improving, declining, or remaining stable as more contributions are made. To ensure a comprehensive assessment, this research will leverage OSM history file and official reference data. The OSM history file is a dataset containing all registered or modified versions of features within the OSM project. By systematically comparing these features across different time periods, we can identify trends and patterns in positional accuracy. The findings will offer valuable insights into the reliability of OSM as a geospatial data source.

Understanding the temporal dynamics of positional accuracy can help identify periods of significant improvement or decline, which may be associated with changes in technology, contributor behavior, or community guidelines within the OSM platform. For instance, advancements in Global Navigation Satellite System (GNSS) technology, increased awareness of data quality issues among contributors, or modifications to OSM's mapping guidelines could all influence the accuracy of the data.

In conclusion, evaluating the positional accuracy of OSM data over time is essential for understanding its suitability for various applications. This research aims to provide a systematic assessment of trends in positional accuracy, offering insights into the reliability and potential of OSM as a geospatial data source. By focusing on this critical aspect of data quality, we hope to contribute to ongoing efforts to improve the usability and effectiveness of VGI.

The organization of this paper is structured as follows: Section 2 provides a comprehensive review of the existing literature on the quality assessment of VGI, with a focus on extrinsic evaluation methods and their relevance to positional accuracy. Section 3 outlines the methodology, detailing the data acquisition process, preprocessing techniques, and the proposed feature matching framework. Section 4 discusses the implementation of the methodology, highlighting significant findings, including the results of the positional accuracy analysis and its temporal trends. Finally, Section 5 concludes the study by summarizing the key findings, their implications, and offering recommendations for future research.

2. Related work

Volunteered Geographic Information (VGI), particularly exemplified by OpenStreetMap (OSM), has significantly transformed the methodologies for geospatial data collection and application (Hecker et al., 2018). The open-access and frequently updated nature of OSM data has led to its widespread use across various disciplines, with a notable emphasis on urban studies (Zhang & Malczewski, 2017). However, the quality of OSM data raises substantial concerns, primarily due to the diverse expertise and backgrounds of its contributors (Azariasgari & Hosseinali, 2023; D'Antonio et al., 2014). This paper aims to examine extrinsic evaluation techniques that assess the quality of OSM data by comparing it with official datasets.

Several studies have employed extrinsic methods to assess the quality of OSM data by comparing it to authoritative and official sources. Haklay (2010) was among the pioneering researchers in this domain. His study compared OSM data with Ordnance Survey (OS) data in London. Haklay evaluated the completeness and positional accuracy of OSM data, finding that while OSM data was generally accurate, with features approximately six meters away from their true locations, there were still significant discrepancies. Notably, about 80% of OSM highway features overlapped with the OS dataset. This study set a precedent for subsequent research by highlighting both the strengths and limitations of OSM data compared to official sources.

Following Haklay, Zielstra and Zipf (2010) conducted a comprehensive comparison of OSM data with commercial TeleAtlas data. Their study aimed to evaluate OSM's potential as an alternative to commercial datasets. Although they found OSM to be highly detailed and valuable, especially for urban areas, the data did not fully replace commercial datasets, particularly in rural regions. This study illustrated the challenges in relying solely on VGI for comprehensive geospatial coverage and quality.

Girres and Touya (2010) extended this line of research by assessing OSM data quality in France, comparing it with high quality data from the French national mapping agency. They used a broader set of quality metrics, including positional accuracy, attribute accuracy, semantic accuracy, temporal accuracy, consistency, completeness, and lineage. Their findings indicated that while OSM data had several strengths, including frequent updates and broad coverage, there was a notable variability in quality. They emphasized the need for balancing contributor freedom with regulatory frameworks to enhance the data's overall reliability.

Forghani and Delavar (2014) explored OSM data quality in an area of Tehran by comparing it with municipal reference maps. They introduced a fuzzy logic-based assessment method to evaluate the consistency and accuracy of OSM data. Their study revealed that while the overall quality was relatively high, spatial uncertainty varied across different areas. The research highlighted the importance of addressing spatial variability and uncertainty in the evaluation of crowdsourced data.

Graser et al. (2014) developed an open-source toolbox for evaluating street networks, focusing on OSM data in Vienna, Austria. This toolbox, based on the Sextant framework for QGIS, allowed for the comparison of network characteristics such as completeness and connectivity. Their study found that OSM data was highly accurate in representing major highways, though there were differences in attribute completeness compared to official datasets. This work underscored the utility of specialized tools for assessing the quality of network-based data.

Dorn et al. (2015) assessed land use data quality in southern Germany by comparing OSM data with the ATKIS dataset. Their study revealed high completeness and accuracy for forested areas, but significant gaps in agricultural areas, suggesting that the quality of OSM data is influenced by population density and land use type. This study provided insights into how different types of land use affect the quality of VGI.

Ballatore and Zipf (2015) introduced the concept of conceptual quality, which emphasizes how cultural and contextual factors influence data interpretation. They developed a multi-faceted framework for assessing conceptual quality, including metrics such as accuracy, granularity, completeness, consistency, conformity, and richness. Their study demonstrated that quality is not only a function of data accuracy but also of how well it fits within different cultural and contextual frameworks.

Zhou (2017) investigated the use of buffer zones to measure spatial accuracy in New Zealand. His study employed a buffer zone approach to evaluate how much OSM road data fell within a defined distance from authoritative road networks. Zhou found that without proper feature matching, the buffer zone approach could lead to inaccuracies in assessing positional accuracy. He recommended pre-matching features to improve the reliability of this method.

Mobasheri et al. (2018) innovated by examining sidewalk data quality in Heidelberg, Germany, using data collected via GPS-equipped wheelchairs. They compared this crowdsourced data with official municipal data, finding a high level of completeness (96%) and a low root mean square error (RMSE) of 0.93 meters for spatial accuracy. This study highlighted the effectiveness of using specialized data collection methods to enhance the quality of VGI.

Chehreghan and Ali Abbaspour (2018b) developed an automated feature matching technique to assess the completeness of OSM data within a specified area (District 6) in Tehran city. Their approach leveraged geometric properties to identify and align corresponding features between OSM and reference datasets. Their findings indicated that 92% of the OSM objects corresponded to those in the reference dataset, with the total length of matched objects representing 87% of the total length of all objects. Additionally, the spatial similarity between the matched objects in both datasets averaged 0.86°. Furthermore, an evaluation of OSM data spanning from 2013 to 2017 demonstrated an 87.2% increase in user participation in creating objects, accompanied by an improvement of 0.15 in the average spatial similarity degree.

Xie et al. (2019) proposed a novel method combining deep learning with high-resolution satellite imagery to evaluate the quality of building data in Las Vegas, Nevada. Their approach used convolutional neural networks to extract building footprints from satellite images and compared these with OSM data. The study demonstrated that this method was effective in identifying and correcting errors, thus improving the overall quality of OSM data.

Hashemi and Ali Abbaspour (2015) explored logical consistency. They developed a framework to identify logical inconsistencies in OSM data using directional, topological, and metric distance relationships. Their study found that such inconsistencies could significantly impact data interpretation and analysis, emphasizing the need for improved consistency checks in VGI.

Feature matching has proven to be a valuable approach for extrinsic quality assessment, particularly in evaluating positional accuracy and completeness. As a contribution to VGI quality research, this study employs feature matching (Chehreghan & Ali Abbaspour, 2017, 2018b) to assess positional accuracy as a key element of spatial quality. Moreover, analyzing the positional accuracy of features over time using historical data files offers a novel perspective that has not been extensively explored. While a few studies have examined positional accuracy trends over time, significant drawbacks and gaps remain: no research has yet investigated a large area, such as an entire metropolis with a high volume of features, over an extended period (e.g., 15 years). Additionally, the results of prior research have become outdated, underscoring the need for a new and comprehensive assessment.

3. Proposed method

Feature matching is a valuable technique for extrinsic assessment, particularly in analyzing positional accuracy over time by utilizing the historical data of features across extensive areas, such as metropolitan regions. This study aims to evaluate the positional accuracy of all versions of volunteered geospatial features within the OSM project over time, employing a feature matching approach. This method is fundamental, significant, and complex, making it essential for effective extrinsic evaluation.

The feature matching approach is central to this research, as it identifies corresponding features between OSM and the official dataset. This process enables the calculation of positional accuracy for volunteered features that have official counterparts. Subsequently, the registration or modification date for each volunteered feature with a corresponding official feature is obtained, allowing for the determination of the positional accuracy trend for all versions of these features over time. This trend is then statistically analyzed to assess its significance. The general workflow of this research is illustrated in Figure 1.

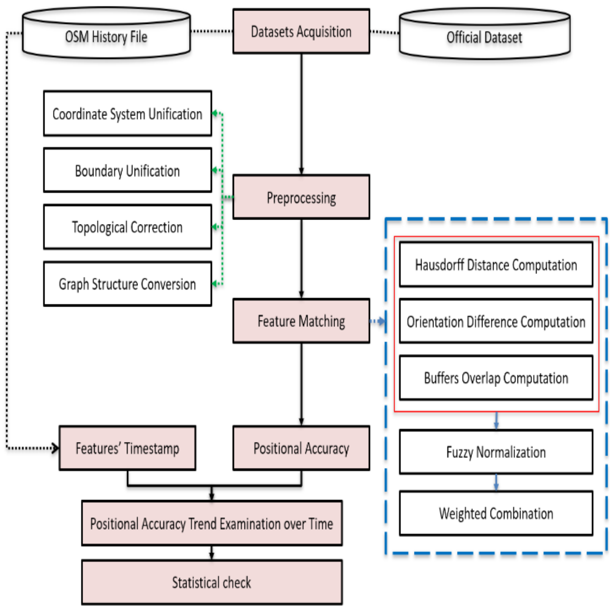

Figure 1. Workflow for Assessing OSM Positional Accuracy Over Time

As shown, the first step involves acquiring the necessary volunteered and official datasets. The history of the OSM dataset is available for free download in Protocolbuffer Binary Format (PBF), containing all registered versions of volunteered features globally. After obtaining this OSM history file, features relevant to the study area are extracted and converted into a suitable format such as ESRI Geodatabase for further analysis. The official and verified dataset for the study area must also be obtained from authoritative mapping organizations and converted into a compatible format like ESRI Geodatabase.

The next step involves a series of preprocessing procedures applied to both datasets to minimize structural differences and reduce ambiguity. Initially, the coordinate systems and projections of both the volunteered and official datasets are standardized. The boundaries of both datasets are then precisely aligned with the study area. Topological errors, such as pseudo-nodes and dangling edges, are corrected. Finally, all linear features in both datasets are segmented and converted into a graph structure, ensuring that there are no mid-line intersections.

The feature matching approach is applied to identify corresponding features between the volunteered and official datasets. This method, which is based on three geometric criteria—Hausdorff distance, orientation difference, and buffer overlap—utilizes fuzzy normalization to standardize the resulting values. The choice of these criteria for feature matching and computing positional accuracy was informed by a comprehensive examination of various geometric measures. Visual inspections conducted in a small test area indicated that these three criteria exhibited the most effective matching performance. Their selection also considered the large number of features analyzed and the computational efficiency necessary to manage the dataset.

Among the various spatial distance concepts introduced by researchers, the Hausdorff distance is considered a useful metric for the feature matching process of linear features. It measures the maximum deviation between two polyline features, indicating their spatial proximity. The values obtained for Hausdorff distance in this paper are in meters. A smaller Hausdorff distance value signifies greater spatial similarity and, consequently, higher positional accuracy of the volunteered feature. The Hausdorff distance calculation identifies the maximum of the shortest distances between points on one polyline feature and another. This is known as the Directed Hausdorff Distance. To compute it between two polyline features, volunteered and official, the process involves calculating the distance from each vertex of the volunteered feature to all vertices of the official feature and selecting the minimum distance for each vertex. In the end, the directed Hausdorff distance from the volunteered feature to the official feature equals the largest of these minimum distances. This process is repeated in reverse, from the official to the volunteered feature. Additionally, if the directed Hausdorff distance from the volunteered feature (V) to the official feature (O) is denoted as $h(V,O)$, its mathematical expression is given in Equation 1 (Chehreghan & Ali Abbaspour, 2018a; Min et al., 2007).

$$h\left(V,O\right)=\max_{P_V\in V}\left\{\min_{P_O\in O}\left\{d\left(P_V,P_O\right)\right\}\right\} \qquad (1)$$

Similarly, the directed Hausdorff distance from the official feature to the volunteered feature, denoted as $h(O,V)$, is expressed mathematically in Equation 2 (Chehreghan & Ali Abbaspour, 2018a; Min et al., 2007).

$$h\left(O,V\right)=\max_{P_O\in O}\left\{\min_{P_V\in V}\left\{d\left(P_O,P_V\right)\right\}\right\} \qquad (2)$$

Finally, the Hausdorff distance is the maximum value obtained from both directed distances, as expressed mathematically in Equation 3 and denoted by $HD(O,V)$ (Chehreghan & Ali Abbaspour, 2018a; Min et al., 2007).

$$HD\left(O,V\right)=\max\left\{h\left(V,O\right),h\left(O,V\right)\right\} \qquad (3)$$

Another useful criterion that can be used in the feature matching approach is the orientation difference criterion. To compute the orientation difference between a volunteered and an official linear feature, the direction of each feature is first determined by connecting its endpoints with a line and calculating the angle with the horizontal axis. The orientation difference is then obtained in degrees by comparing these angles. A smaller orientation difference value signifies greater spatial similarity and, consequently, higher positional accuracy of the volunteered feature. If the volunteered line is denoted by V and the official line by O, with the direction of the volunteered line represented by A_v and the direction of the official line by A_O, then the orientation difference between these two lines, denoted as $OD(V,O)$, is calculated according to Equation 4 (Chehreghan & Ali Abbaspour, 2018a).

$$OD(V,O) = \left| A_V - A_O \right| \tag{4}$$

The buffer overlap criterion is also considered one of the most important criteria used in the matching approach and has received significant attention in previous research. The buffer overlap criterion refers to the overlapped area between the buffers of the volunteered and official features. To calculate this criterion, buffers with a predetermined radius are created around both features. The ratio of twice the area of the overlapping buffer to the total buffer areas indicates the buffer overlap criterion, inherently normalized between 0 and 1. A value closer to 1 indicates higher spatial similarity and, consequently, higher positional accuracy of the volunteered feature. In mathematical terms, if the area of the buffer around the volunteered feature is denoted by S_V, the area of the buffer around the official feature by S_O, and the area of the overlapping region by S_{V-O}, then the buffer overlap criterion, denoted as $BO(V,O)$, is derived from Equation 5 (Chehreghan & Ali Abbaspour, 2018b; Teimoory et al., 2021).

$$BO(V,O) = \frac{2(S_{V-O})}{S_V + S_O} \tag{5}$$

After computing the geometric criteria, the values of these three criteria must be normalized to ensure they share the same scale and structure for effective combination. Since the buffer overlap parameter is inherently normalized, with values ranging from 0 to 1, only the non-normalized criteria (Hausdorff distance and orientation difference) require normalization. For these, fuzzy normalization is applied using a Z-shape membership function, as illustrated in Figure 2. (Chehreghan & Ali Abbaspour, 2017, 2018b; Teimoory et al., 2021). This theory, first introduced by Professor Zadeh (1965), has gained significant attention for normalization in recent decades. Among various normalization methods, the efficient performance of fuzzy normalization in similar previous studies led to its selection for normalizing the criteria values in this research.

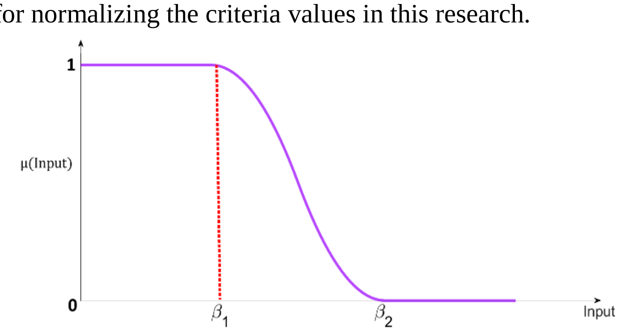

Figure 2. Z-Shape Membership Function

In Figure 2, as input values increase from zero to β_1, the membership value is set to 1. Between β_1 and β_2, the membership value decreases as per equation 6 (Chehreghan & Ali Abbaspour, 2017, 2018b; Teimoory et al., 2021). Values beyond β_2 are assigned a membership value of 0. The parameters β_1 and β_2 are determined through expert consultation and trial and error for each geometric criterion.

$$\mu_A(x) = \begin{cases} 1, & x \le \beta_1 \\ 1 - 2\left(\dfrac{x-\beta_1}{\beta_2-\beta_1}\right)^2, & \beta_1 \le x \le \dfrac{\beta_1+\beta_2}{2} \\ 2\left(\beta_2 - \dfrac{x}{\beta_2-\beta_1}\right)^2, & \dfrac{\beta_1+\beta_2}{2} < x \le \beta_2 \\ 0, & x > \beta_2 \end{cases} \tag{6}$$

To establish correspondence between the volunteered and official features, each volunteered feature undergoes several steps to find its official counterpart. Initially, a buffer with a specified radius, determined through trial and error and literature review, is created around each volunteered feature. Official features within this buffer are considered candidate matches. The spatial similarity between the volunteered feature and each candidate official feature is then calculated using a weighted combination of the three geometric criteria. The inherent normalization of the buffer overlap criterion and fuzzy normalization of the Hausdorff distance and orientation difference facilitate this calculation, resulting in a normalized positional accuracy value between 0 and 1. To better understand this weighted combination, if the orientation difference criterion is denoted as OD, the Hausdorff distance as HD and the buffer overlap as BO with corresponding weights as w_{OD}, w_{HD} and w_{BO} then spatial similarity, denoted as SP can be calculated using the weighted average in Equation 7. The mentioned weights have been determined based on consultations with experts and trial and error.

$$SP = \frac{w_{HD} \times HD + w_{OD} \times OD + w_{BO} \times BO}{w_{HD} + w_{OD} + w_{BO}} \tag{7}$$

The official feature with the highest spatial similarity above a threshold of 0.7 is selected as the matching feature for the volunteered feature. The ID of the volunteered feature, its matching official feature, and their spatial similarity (normalized positional accuracy) are recorded.

A key aspect of the matching approach used in this research is that some volunteered features are broken into a graph structure during preprocessing. For analysis, the positional accuracy of the original features is needed. To achieve this, the positional accuracy of the original feature is determined by calculating a weighted average of the positional accuracies of the graph segments that comprise the original feature, with the weights being proportional to the lengths of the respective segments.

After calculating positional accuracy, the registration or modification dates of volunteered features with matching official features are extracted. Each version of the volunteered features in the OSM history dataset, which includes timestamp information, is categorized by the year of registration or modification. This process creates multiple categories, each containing features corresponding to a specific year of creation or modification. For each category, the average positional accuracy is computed, providing yearly values for comparison. These averages are plotted in a chart to reveal the trend of positional accuracy over time. To better visualize this trend, a line is fitted to the data, indicating the change in mean positional accuracy across the years. The statistical significance and reliability of the observed trend are then analyzed to ensure robust findings.

4. Implementation

This section outlines the implementation of the proposed methodology. The first step involves selecting Tehran, the capital city of Iran, known for its diverse participation patterns and high engagement in the OSM project, as the study area. A satellite image of Tehran, along with its location in Iran, is shown in Figure 3.

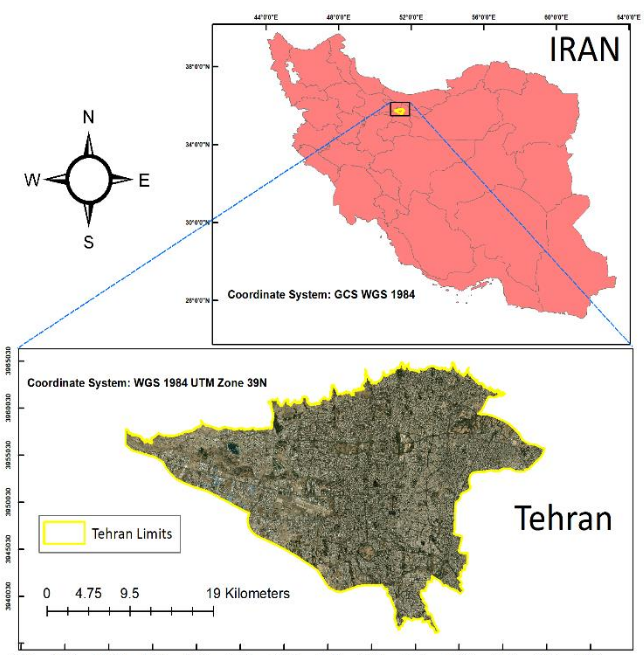

Figure 3. Satellite image of Tehran and its location in Iran

To implement the proposed approach, voluntary and official datasets for Tehran need to be acquired. The OSM history file was downloaded from the OSM Planet website, and all versions of the voluntary features related to Tehran were extracted and processed into a suitable format, as shown in Figure 4.

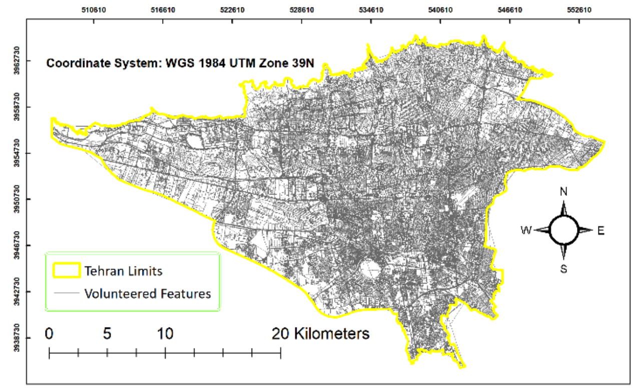

Figure 4. Volunteered OSM features for Tehran.

The official dataset, at a 1/2000 scale of Tehran's road network produced by the Tehran Municipality in 2002, was also obtained and is presented in Figure 5.

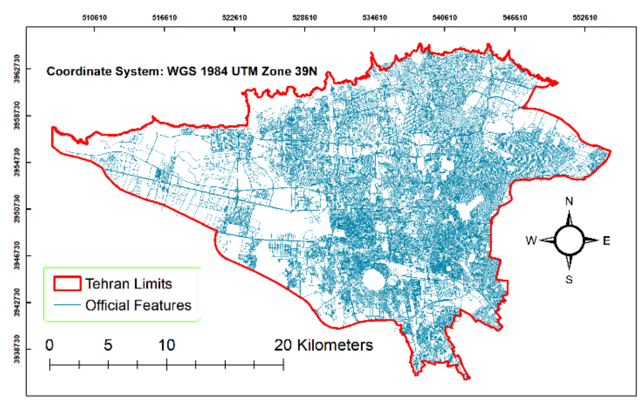

Figure 5. Official dataset of Tehran's streets

With both the OSM history dataset and the official dataset for Tehran, the preprocessing steps described in the proposed methodology section are applied, including standardizing the coordinate systems and extents, fixing topological errors, and converting both datasets to graph structure. The feature matching process was then performed using the geometric criteria of orientation difference, Hausdorff distance, and buffer overlap as described earlier. The resulting positional accuracy map for all versions of the voluntary features with corresponding official features is shown in Figure 6. There are 71,761 voluntary features with corresponding official features. As seen in the figure, the calculated positional accuracy is normalized, with values closer to one indicating higher positional accuracy.

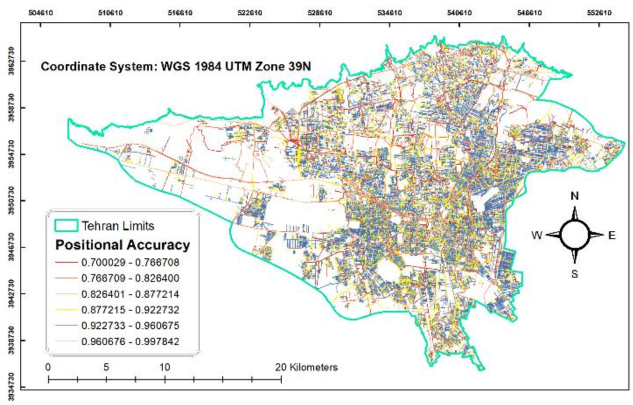

Figure 6. Positional Accuracy Map for Voluntary Features Across All Years

Figure 6 illustrates that the majority (57%) of voluntary features with corresponding official features have a positional accuracy above 92%, and most (87%) have an accuracy above 82%, which is also reflected in the histogram in Figure 7.

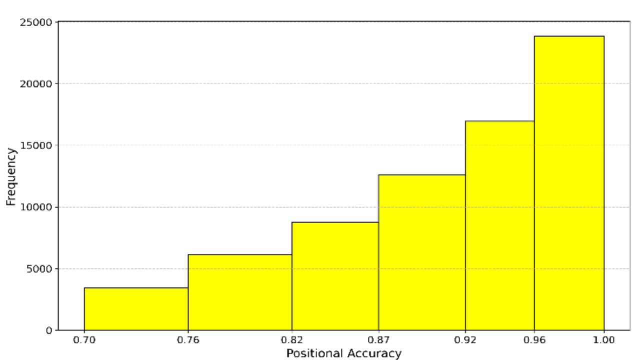

Figure 7. Histogram of Calculated Positional Accuracy for Voluntary Features Across All Years

A validation procedure was conducted to assess the accuracy of the implemented matching process. For this, 2,500 random features were selected and visually inspected. The results revealed 821 true positives (real matches correctly identified as matches) and 276 false positives (real matches incorrectly identified as non-matches). Additionally, 193 false negatives (real non-matches incorrectly identified as matches) and 1210 true negatives (real non-matches correctly identified as non-matches) were found. Based on these results, the matching process achieved an overall accuracy of 0.812, calculated by dividing the total number of correct matches (true positives and true negatives) by the total number of comparisons.

In the next phase of the proposed approach, the year of creation or modification for voluntary features with corresponding official features from 2007 to 2022 was extracted and is shown in the map in Figure 8.

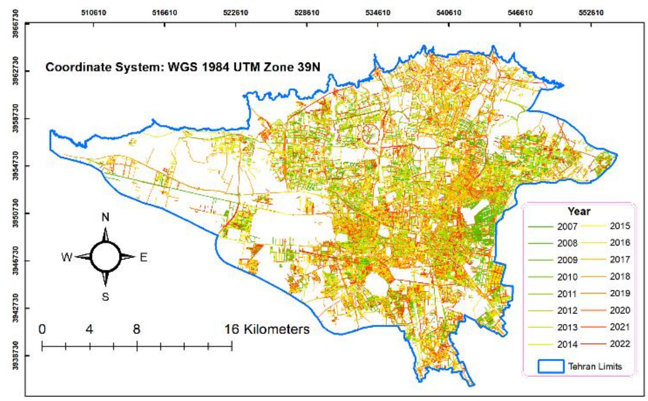

Figure 8. Map of Voluntary Features by Year of Creation or Modification

Figure 9 presents the histogram of the creation or modification years for the voluntary features with corresponding official features in Tehran. It shows that the number of voluntary features with corresponding official features was higher in the years 2012 and 2017 compared to other years.

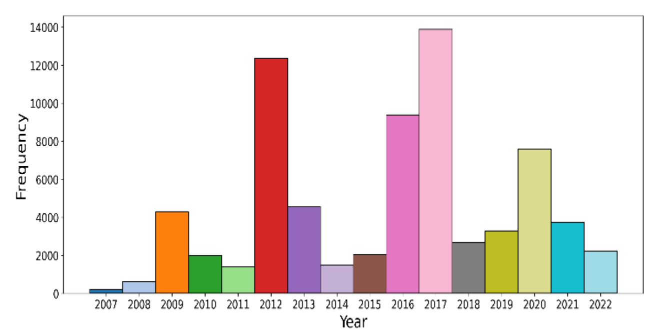

Figure 9. Histogram of Voluntary Features by Year of Creation or Modification

To analyze the trend of positional accuracy over time, voluntary features with corresponding official features were grouped based on their creation or modification year, and the average positional accuracy for each group was calculated and plotted in Figure 10 along with the number of features in each group. This figure shows the trend of positional accuracy of voluntary features with corresponding official features over the years, with several fluctuations.

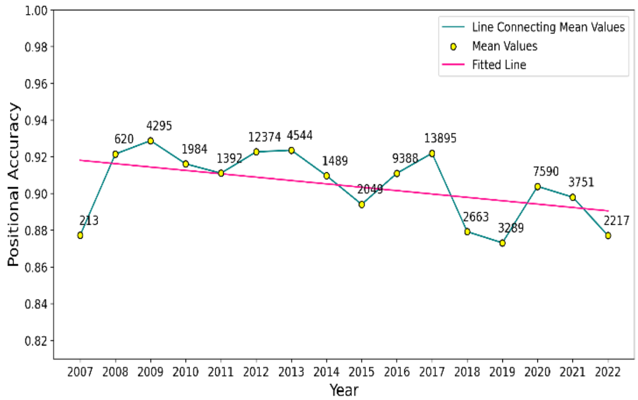

Figure 10. Trend of Positional Accuracy for Voluntary Features Over Time

In Figure 10, a line was fitted to the data to visualize the trend of positional accuracy over time. The slope of -0.001834 indicates a slight downward trend in positional accuracy from 2007 to 2022. The equation of the fitted line is depicted in Equation 8. This downward trend is visually apparent in Figure 10. Thus, it can be concluded that the positional accuracy of voluntary features has slightly decreased over time.

$$Y = -0.001834X + 4.6 \qquad (8)$$

In the final step of analyzing the positional accuracy trend of voluntary features over time, the observed trend must be statistically validated to determine its significance. Since the data pertains to features in a specific region and has a large sample size, the central limit theorem allows us to approximate the data distribution as normal. Therefore, parametric tests are suitable. Considering the interval nature of the positional accuracy criterion and having more than two groups, either ANOVA or Welch ANOVA statistics tests are applicable depending on the variance equality assumption (McCrum-Gardner, 2008; Montgomery & Runger, 2010).

Initially, Levene's test was conducted to assess the assumption of equality of variances among groups. The test yielded a P-value of 0.000 (less than the significance level of 0.05) and a test statistic of 81.81, indicating unequal variances. Thus, the Welch ANOVA test was used. The P-value in this section is displayed as 0.000 due to its ridiculously small value beyond computer representation. The results of the Welch ANOVA test are shown in Table 1.

Table 1. Welch ANOVA Test Results

Statistical Metrics	Calculated Values
P-value	0.000
F-value	213.74
DF DEN	8065.66
DF NUM	15

The parameters in Table 1 include the P-value, indicating the probability of observed results under the null hypothesis, with values below 0.05 confirming statistical significance. The F-value measures the ratio of variance between groups to variance within groups, testing differences among group means. The degrees of freedom are divided into two components: DF NUM (Numerator), representing the number of independent groups being compared minus one (15 in this case, as there are 16 groups), and DF DEN (Denominator), which reflects the degrees of freedom related to variability within the groups, based on the sample size (8065.66 here, indicating a large dataset and complex variance structure).

According to the Welch ANOVA test results in Table 1, the P-value of 0.000 is less than the significance level of 0.05, rejecting the null hypothesis (Greenland et al., 2016) and confirming that there are statistically significant differences among the mean positional accuracies of the groups. This indicates that the observed trend of positional accuracy over time is statistically significant.

5. Conclusion

This study aimed to evaluate the positional accuracy of VGI, with a specific focus on OSM data for Tehran, utilizing an extrinsic evaluation method. By employing a systematic approach that included data extraction, preprocessing, and advanced feature matching, we analyzed the temporal trends in the positional accuracy of OSM features.

The preprocessing steps included critical tasks such as standardizing coordinate systems, aligning data extents, correcting topological errors, and converting both OSM and official datasets into graph structures. These steps were essential to ensure the integrity and compatibility of the datasets.

Using a feature-matching approach that incorporates Hausdorff distance, orientation difference, and buffer overlap—normalized through fuzzy logic—we developed a comprehensive method for assessing the normalized positional accuracy of voluntary features in comparison to official records. The results indicated that the majority of voluntary features corresponding to official features in Tehran demonstrate high positional accuracy, with values exceeding 82%, and a significant proportion surpassing 87%.

Furthermore, the analysis of temporal trends revealed that the number of voluntary features corresponding to official features peaked in specific years, notably 2012 and 2017. However, an examination of the overall trend in positional accuracy from 2007 to 2022 indicated a slight yet statistically significant decline. The fitted trend line, which has a negative slope of -0.001834, illustrates this downward trajectory, suggesting a gradual decrease in the positional accuracy of OSM data over time. Additionally, no significant fluctuations in the positional accuracy trend were observed in any particular year that could be attributed to external factors.

Statistical validation using the Welch ANOVA test confirmed that the differences in mean positional accuracy across the years are significant, underscoring the importance of continuous monitoring and quality assurance in VGI projects. The results of this study highlight that while OSM data generally maintain a high level of volunteer accuracy, there are fluctuations that require further investigation and potential intervention to sustain data quality.

A noteworthy finding of this research is that advancements in technology do not necessarily lead to higher quality features in recent years compared to those recorded or modified in earlier years. Despite the availability of enhanced surveying tools and data collection methods, the accuracy of voluntary features has not demonstrated consistent improvement. This indicates that factors such as contributor expertise, the nature of the editing process, and the complexity of urban environments play significant roles in determining data quality.

The novel aspect of this research lies in its comprehensive analysis of the positional accuracy of historical OSM data over an extended period. This study offers valuable insights into the evolution of data quality in a major metropolitan area. This approach not only enhances the understanding of VGI accuracy but also provides a robust framework for future studies aimed at improving the reliability of geospatial data contributed by volunteers.

In conclusion, the feature matching methodology presented in this study demonstrates its effectiveness as an extrinsic assessment tool for evaluating the accuracy of VGI. By leveraging historical data, this research offers a nuanced perspective on how the quality of voluntary contributions fluctuates over time. As urban areas continue to expand and evolve, ensuring the accuracy of VGI becomes increasingly critical for urban planning, disaster management, and various other applications. Future research should concentrate on developing strategies to address the observed decline in accuracy and investigate the underlying causes of these temporal trends to enhance the overall quality of VGI.

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