# Integration of Multi-Source Data for Wastewater Network Management

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**Abstract.** This paper focuses on the integration of multi-source data for managing wastewater network information. The data come from various sources such as maps, photographs, videos, and geographic information systems (GIS). These sources are heterogeneous in quality and often contain imprecise, inconsistent, or missing data. Leveraging the complementarity of these sources is essential to reduce inconsistencies, improve data accuracy, particularly regarding the geographic location of manholes and pipes, and thereby enhance the overall understanding of the network. We concentrate on two specific types of data. The first is geographic information systems (GIS), which manage detailed information on manholes and pipes across separate, comprehensive datasets. The second consists of television inspection videos (ITV) of pipes from a specific area within the Montpellier metropolitan region. Recent studies have enabled the generation of a graphical representation of the wastewater network in the inspected area based on ITV videos. However, the manholes visible in the videos lack precise geographic coordinates, making accurate localization challenging or even unfeasible. The goal is to integrate GIS and ITV data to achieve the most accurate and comprehensive representation possible of the wastewater network, with a particular focus on precisely determining the geographic locations of the manholes identified in the ITV data.

**Keywords:** ITV videos· GIS Data· Data integration.

## 1 Introduction

A large number of wastewater pipeline networks are aging and require continuous monitoring to ensure their structural integrity and operational performance, which makes their maintenance an increasingly critical concern for municipalities. This challenge is further exacerbated by increasing demand, limited financial resources, and the tightening of environmental and public health regulations [7]. Consequently, ensuring the proper functioning of these systems requires regular and thorough inspections to detect potential issues early and prevent severe, costly damage.

The scale of this challenge is well illustrated by a 2019 report from the United States, which noted that over 4,692 miles of wastewater pipelines were repaired or replaced that year, amounting to an estimated cost of USD 3 billion [1].

Effective maintenance strategies depend heavily on strong pipeline integrity management, with inspection playing a central role [2]. Among available techniques, closed-circuit television (CCTV) inspections have become the most widely used method for assessing internal pipe conditions and detecting structural defects. A wide range of affordable CCTV systems, designed by leading manufacturers, can accommodate various pipe diameters and configurations. These systems enable the identification of physical deterioration, such as corrosion, cracking, or deformation, and support engineers in deciding whether to proceed with rehabilitation or conduct further structural assessments [12].

Beyond inspection, the management of wastewater networks can be greatly enhanced through the integration of multiple data sources. In particular, combining geographic information systems (GIS), CCTV inspection data, and hydraulic modeling provides a more holistic understanding of network condition and performance [21]. While GIS offers a spatial framework for organizing and analyzing infrastructure data, CCTV and hydraulic models supply real-time insights into system behavior [15]. CCTV inspections also prove particularly useful for detecting internal issues such as obstructions or sediment accumulation that could lead to blockages. Early detection of these problems can help prevent incidents like flooding and minimize damage to surrounding properties. A key factor in managing these underground assets is the ability to accurately locate them. Precise knowledge of pipe coordinates not only improves condition assessment but also reduces the costs associated with inspection and maintenance. However, uncertainties often remain regarding the precise position of underground elements, particularly when relying on observations made from the surface.

In this context, geographic information systems (GIS) play a pivotal role by enabling interaction between databases and spatial maps. GIS is an information system that manages spatially distributed elements and processes, allowing users to gather, store, retrieve, analyze, and visualize geographic data. Through GIS, diverse data sources such as GPS coordinates, digital images, video footage, and field inspection records can be integrated into a single, easily navigable platform. Furthermore, GIS can be employed as a document management system for handling TV inspection data. Valuable information extracted from video footage can be converted into structured digital data, making it more accessible for analysis and decision-making [18]. In the pursuit of sustainable urban development, traditional procedures must be rethought. This requires not only the integration of environmental data into infrastructure planning and evaluation but also a clear understanding of the central role GIS plays in this transformation [13].

In this study, we focus on using Geographic Information Systems (GIS) to enhance the value of TV inspection (ITV) data. GIS makes it possible to accurately locate and map manholes, even when coordinate data is missing. As illustrated in Figure 1, the TV inspection process examined in this study includes several steps, labeled from (a) to (f). The videos collected during inspections are first reviewed by an operator. Based on the results of text recognition, useful textual information is automatically extracted. This step is represented in parts (c) and (d) of Figure 1. From the extracted data, which includes ITV distances and manhole identifiers, a graph of the wastewater network is created, as shown in part (e) of the figure [17]. Using the algorithms developed in this paper, the graph can then be transformed into a map where each manhole is assigned geographic coordinates. The final output includes the latitude and longitude of the manholes.

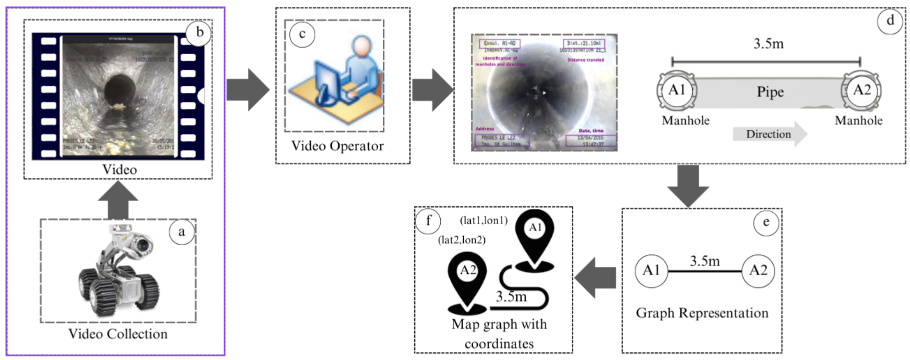


Fig. 1: TV inspection workflow to find the geographic coordinates of manholes

This work leverages Geographic Information Systems (GIS) to enhance graphs derived from television inspections by precisely identifying the locations of manholes and integrating them into a spatial mapping system. The data collected during inspections are represented as graphs, allowing operators to detect anomalies and prioritize necessary actions. Once linked to GIS, these graphs provide spatial context that facilitates problem localization and the planning of appropriate interventions. This visual format also improves communication with stakeholders and supports more effective decision-making.

The rest of the paper is organized as follows. Section 2 reviews related work in the fields of TV inspection and GIS. Section 3 describes the methodology. Section 4 presents the implementation of the proposed approach in the city of Montpellier, France, focusing on how coordinates of manholes are identified by matching GIS and inspection videos data. Finally, Section 5 presents the conclusions.

## 2 Related works

Several studies have explored aspects related to TV inspection data and Geographic Information Systems (GIS). For instance, Bruslund et al. [9] provide a comprehensive review of image-based automation techniques in CCTV and Sewer Scanner and Evaluation Technology (SSET) inspections, covering evaluation protocols, database architectures, and algorithmic processing pipelines.

Uzair et al. [18] contributed to thematic mapping of manhole and sewer inspection data, emphasizing the use of TV inspections for managing maintenance work orders and generating service lateral maps from sewer inspection records.

In the field of computer vision, various approaches have been applied to automate sewage network analysis. Techniques such as crack detection [8] and image segmentation [10] have been investigated, while Biswas et al.[3] addressed the specific challenges of sewer inspection videos. Kumar et al.[11] developed a deep learning-based system to localize and classify sewer faults using CCTV data, showing improvements in the speed and consistency of condition assessments.

Wang et al.[19] proposed a framework for tracking multiple sewer defects within inspection videos. Meanwhile, Yin et al.[20] focused on automating the interpretation of CCTV footage beyond simple image-based fault detection, converting video data into structured textual information. Similarly, Dang et al. [4] introduced a text-recognition-based framework to streamline CCTV inspection evaluation. Moradi et al. [14] presented a multi-method approach employing support vector machines and other techniques to automatically detect and locate anomalies in sewer inspection videos. Zhang et al. [16] proposed a comprehensive data-driven framework integrating GIS, CCTV, and hydraulic modeling for wastewater system monitoring and management. Finally, Tran-Nguyen et al. [17] used inspection videos to extract the structural topology of wastewater networks, modeling it as graphs that may then be integrated into GIS to support improved network management.

## 3 Methodology

The objective of this research is to integrate wastewater TV inspection (ITV) data with Geographic Information Systems (GIS) to estimate the geographical coordinates of manholes observed in inspection videos. As illustrated in Figure 1, the proposed methodology can be divided into three main stages:

- **TV inspection and data extraction:** Analyzing inspection videos to detect and extract relevant features such as manholes and pipe segments.
- **Linking GIS and ITV data:** Establishing correspondences between features identified in the ITV videos and existing GIS records, enabling integration of both datasets.
- **Geolocation based on distance matching:** Using distance measurements, including computations from the Haversine formula, as key criteria to define algorithms that match and estimate the geographic coordinates of manholes observed in the ITV data, thus enhancing GIS accuracy.

### 3.1 Video Inspection(ITV)

Using ITV data, our objective is to generate a graphical representation of the wastewater network within the inspected area. However, the manholes visible in these inspection videos are not associated with precise geographic coordinates, which complicates their accurate localization. As illustrated in Figure 2, the ITV data include valuable attributes such as addresses, manhole identifiers, flow directions, and travel distances, elements that are essential for infrastructure mapping. The process of labeling and interpreting events occurring in the video footage is known as *video annotation*, a crucial aspect of data annotation. In our context, each ITV segment corresponds to a connection between two manholes. A graph-based representation of the wastewater network has been developed from these annotations, with nodes corresponding to manholes and edges to the inspected pipe segments [17].


Fig. 2: Annotated TV inspection

### 3.2 Linking GIS and ITV

Figure 3 illustrates how the GIS data of the wastewater network can be enriched by integrating external sources such as ITV. The graph extracted from ITV annotations provides complementary structural information that can enhance GIS databases, in which details about manholes and inspection lines are often managed separately. The aim is to combine GIS and ITV data to accurately estimate the spatial coordinates of manholes identified in inspection videos. This geolocation step enhances the spatial consistency of the wastewater network representation and supports more efficient infrastructure management.
As illustrated in Figure 4, the process of extracting graphs from ITV data begins with retrieving address information in JSON format. This information is then processed using QGIS, a free and open-source desktop GIS application that enables visualization and editing of both raster and vector data.

### 3.3 Haversine formula

The Haversine formula is widely used to calculate the great-circle distance between two points on the Earth's surface. It provides the shortest "as-the-crow-flies" distance, ignoring elevation and terrain variations. The calculations, as shown in Equations 1–3, are based on latitude and longitude coordinates:

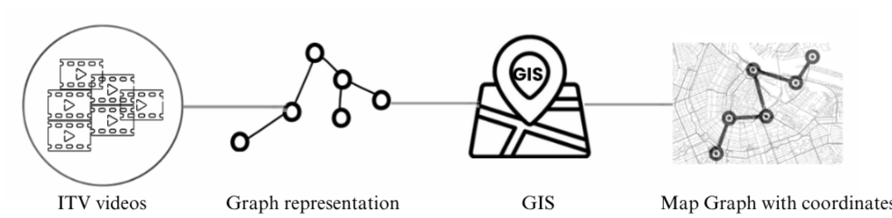


Fig. 3: Linking GIS and ITV

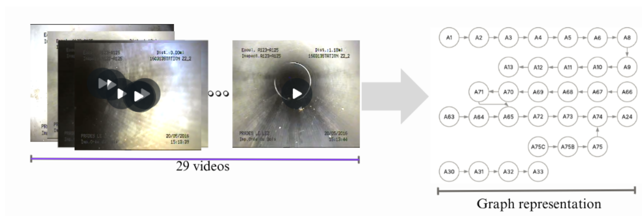


Fig. 4: An example of the process of the graph extraction from the ITV

$$a = \sin^2\left(\frac{\Delta\phi}{2}\right) + \cos\phi_1 \cdot \cos\phi_2 \cdot \sin^2\left(\frac{\Delta\lambda}{2}\right) \tag{1}$$

$$c = 2 \cdot \text{atan2}\left(\sqrt{a}, \sqrt{1-a}\right) \tag{2}$$

$$d = R \cdot c \tag{3}$$

where $\phi$ is the latitude (in radians), $\lambda$ is the longitude (in radians), and $R$ is the Earth's mean radius (6,371 km). Additionally, the initial bearing between two points, often used in navigation, can be calculated using Equation 4:

$$\theta = \text{atan2}\left(\sin\Delta\lambda \cdot \cos\phi_2, \cos\phi_1 \cdot \sin\phi_2 - \sin\phi_1 \cdot \cos\phi_2 \cdot \cos\Delta\lambda\right) \tag{4}$$

where $(\phi_1, \lambda_1)$ is the starting point, $(\phi_2, \lambda_2)$ is the destination point, and $\Delta\lambda$ is the difference in longitude.

In this study, we have a few different sets of information:

- **Coordinate Data ($F_C$):** For each uniquely identified manhole, this dataset provides its latitude, longitude, and corresponding address, obtained here from GIS datasets.
- **Distance Data ($F_D$):** This dataset includes the computed distances between pairs of manholes, derived from the coordinate data $F_C$ (and hence from GIS datasets).

- **Given Distances and Addresses ($F_G$):** Extracted from the ITV inspection videos, this dataset contains distances and associated addresses. It serves as reference information for matching ITV observations with corresponding manholes in the GIS data.
- **Output Data ($F_O$):** This dataset contains the final matched pairs of locations, established by comparing distances and addresses from both the GIS and ITV data. It represents the outcome of the matching process, linking manhole identifiers extracted from ITV inspection videos with their corresponding identifiers in the GIS dataset.

## 4 Algorithmic Approach

### 4.1 Overview and Intuition

We describe here the algorithmic approach used to estimate the geographic coordinates of manholes identified in ITV (Inspection TéléVisée) videos. This process relies on matching distances observed in the videos with pairwise distances between known locations on a map. To improve robustness, address matching is also incorporated. We distinguish between trivial helper functions and more complex decision, making algorithms. The trivial functions are treated as atomic and will not be expanded in code; instead, we present their role, notation, and purpose.

The core idea behind this approach is to correlate partial information extracted from the ITV videos, namely a target distance $g$ and an observed address $a$, with structured geographic data. Since the ITV footage lacks GPS coordinates, we attempt to infer likely geographic positions by searching for known location pairs whose spatial distance approximates $g$ and where at least one location corresponds to address $a$. The process follows several stages:

1. **Distance matching:** For a given $g$, we extract all location pairs from a dataset $F_D$ whose distances are approximately equal to $g$, within a configurable tolerance $T$.
2. **Address filtering:** We then refine the candidate list by selecting only those pairs where at least one of the two places is associated with the address $a$, using metadata from $F_C$.
3. **Deduplication and saving:** As a technical safeguard, before writing any candidate pair to the output dataset $F_O$, the algorithm performs a simple check to ensure that the same pair has not already been processed. This lightweight step prevents redundant entries without affecting the core matching logic.
4. **Incremental search:** In certain cases, for a given distance value $g$, no exact correspondence exists in $F_D$ within a strict initial tolerance. This makes the definition of a suitable tolerance a delicate matter. To handle this, the algorithm performs an incremental search: it begins with a small tolerance value and gradually increases it in fine steps until a match is found or a maximum threshold is reached (e.g., 8 meters). This progressive relaxation

allows the system to balance matching accuracy and completeness while minimizing false positives.

5. **Batch processing:** This logic is applied iteratively to each $(g, a)$ entry found in the ITV-derived dataset $F_G$.

This approach of combining spatial approximation with semantic filtering helps reliably recover geographic positions from imperfect visual data.

### 4.2 Algorithms

The following basic functions are considered *immediate* or *atomic*, and will be referred to directly in the subsequent algorithms.

– **ApproxEqual(**$d_1$**,** $d_2$**,** $T$**)**: Returns `True` if the absolute difference between two distances $|d_1 - d_2|$ is less than or equal to a given tolerance $T$, otherwise returns `False`.
– **CheckPair(**$F_O$**,** $e$**)**: Returns `True` if the pair $(id1, id2, d)$ from element $e$ already exists in the output file $F_O$, and `False` otherwise.
– **Save(**$F_O$**,** $D$**)**: Appends a list $D$ of rows to the output CSV file $F_O$. If $F_O$ is empty, it first writes a header row.

**Algorithm 1 – CompDists:** Given a set of precomputed distances between pairs of locations $F_D$, a target distance $g$ (from the ITV video), and a tolerance $T$, this algorithm identifies all pairs whose distance is approximately equal to $g$. The comparison is done using ApproxEqual. The result is a list $L$ of tuples $(id1, id2, d)$.

**Algorithm 1:** CompDists: Compare distances to find approximate matches

**Input:** $F_D$ (set of distance records), $g$ (target distance), $T$ (tolerance)
**Output:** $L = \{(id1_i, id2_i, d_i)\}$, the list of matching pairs
**Data:** $L \leftarrow \emptyset$
**for** *each row* $(id1, id2, d)$ *in* $F_D$ **do**
    **if** *ApproxEqual*$(d, g, T)$ **then**
        $L \leftarrow L \cup \{(id1, id2, d)\}$
**return** $L$

**Algorithm 2 – CompAddrs:** Filters a list $M$ of matching distance pairs to retain only those where at least one location has the same address as the target address $a$ (extracted from the ITV video). The coordinates and addresses are taken from $F_C$. In this algorithm, for a pair of points $(id_1, id_2)$, the notations $(x_1, y_1, a_1)$ and $(x_2, y_2, a_2)$ respectively represent the coordinates and address of the first and second points in the pair. These notations allow precise handling and comparison of geographic and semantic information during data processing[1].

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**Algorithm 2:** CompAddrs: Filter matching distances based on address

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**Input:** $F_C$, $M = \{(id1_i, id2_i, d_i)\}$, $a$
**Output:** $L = \{(id1_i, id2_i, d_i, x1_i, y1_i, a1_i, x2_i, y2_i, a2_i)\}$
**Data:** $C \leftarrow \{(id, (x, y, address))$ for each row in $F_C\}$
**Data:** $L \leftarrow \emptyset$
**for** *each* $(id1, id2, d)$ *in* $M$ **do**
  $(x1, y1, a1) \leftarrow C[id1]$;
  $(x2, y2, a2) \leftarrow C[id2]$;
  **if** $a1 = a$ *or* $a2 = a$ **then**
    $L \leftarrow L \cup \{(id1, id2, d, x1, y1, a1, x2, y2, a2)\}$
**return** $L$

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**Algorithm 3 – MatchingPair:** Given a target distance $g$ and an address $a$ from an ITV video, the algorithm incrementally searches for a unique pair of locations on the map whose distance is approximately $g$ and where at least one of the two places matches address $a$. It starts with a small tolerance (e.g., $T = 0.01$) that gradually increases until a satisfactory pair is found or the maximum allowed tolerance is exceeded. In rare cases where multiple matching pairs are found, ideally, all possible pairs should be considered and evaluated collectively to select the best overall match. However, this exhaustive approach is computationally impractical. In this study, we adopt a simpler approach by treating all matches as valid solutions and selecting the first one found. A more thorough exploration involving the development of appropriate heuristics for optimal pair selection is left for future work.
Finally, if the tolerance value reaches a maximum threshold without finding any match, the algorithm returns a failure. This situation can be explained by different cases: manholes present in one source but missing in the other, which is the most plausible scenario, or simply errors in the geographic coordinate data. In the first case, the combined use of GIS and ITV data is fully justified, as it offers complementary information for a better understanding of the wastewater network.

**Algorithm 4 – Process:** This is the top-level routine. For each ITV video record (a pair of target distance $g$ and address $a$), it simply calls the MatchingPair algorithm to attempt finding a matching location pair.

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[1] In this paper, addresses are compared using exact matching. However, this approach can be easily extended to support approximate matching in case exact matches fail.

**Algorithm 3:** MatchingPair: Incremental matching using distance and address

```
Input: F_D, g, a, F_C, F_O
Data: T ← 0.01, maxT ← 8.0
while T ≤ maxT do
    M ← CompDists(F_D, g, T);
    L ← CompAddrs(F_C, M, a);
    if |L| = 1 then
        if CheckPair(F_O, L[0]) = False then
            Save(F_O, L);
            return
    else if |L| > 0 then
        for each e in L do
            if CheckPair(F_O, e) = False then
                Save(F_O, [e]);
                return
    T ← T + 0.01
Output: No matching pair found
```

**Algorithm 4:** Process: Apply matching to each ITV distance-address pair

```
Input: F_G, F_D, F_C, F_O
for each row (g, a) in F_G do
    MatchingPair(F_D, g, a, F_C, F_O)
```

## 5 Experimental Results

The data for our study was collected from the wastewater network in the Montpellier Mediterranean Metropolis area of France. Let us start with a concrete example to illustrate the matching process.

*Matching Based on Distance and Address* In the first step, considering only the distances with a tolerance of 0.01, Figure 5 shows a set of 8 possible matching pairs. Among these, the closest pair by IDs was (46958, 46957), based solely on distance. However, when we incorporate address information from the ITV data, specifically the address *Impasse de la Mayre* with a distance of 26.46 m, only one candidate remains that matches both the distance and the address criteria. This final matching pair corresponds to IDs (46572, 46573). *id1 = 46572, id2 = 46573, address1 = Impasse de la Mayre*. Figure 6 further illustrates the GIS manholes associated with street names extracted from the videos.

*Tolerance values:* The above represents an ideal case where matching is achieved directly using measured distances and street names. This situation accounts for the majority of cases. In a few instances, larger tolerances are required due

| id1 | id2 | distance | x1 | y1 | address1 | x2 | y2 | address2 |
|---|---|---|---|---|---|---|---|---|
| 46958 | 46957 | 26.360263975274133 | 3.8682638301 | 43.6873972978 | Impasse Lou Triol, Prades-le-Lez | 3.8685677369 | 43.687308392 | Impasse Lou Triol, Prades-le-Lez |
| 46578 | 46579 | 26.455733367726104 | 3.8676162034 | 43.6940991508 | Rue de la Mayre, Prades-le-Lez | 3.8679335929 | 43.6940363525 | Rue Jean Moulin, Prades-le-Lez |
| 46765 | 46762 | 26.472847836075577 | 3.8611429951 | 43.6917719703 | 48, Rue des Érables, Prades-le-Lez | 3.861468512 | 43.6917361795 | 48, Rue des Érables, Prades-le-Lez |
| 46843 | 46842 | 26.43244066253357 | 3.8737160042 | 43.6942095837 | Rue Gaspard Monge, Prades-le-Lez | 3.873965289 | 43.6943645681 | Rue Gaspard Monge,Prades-le-Lez |
| 46327 | 46328 | 26.36976657044073 | 3.8642081936 | 43.6965154791 | Rue des Aramons, Prades-le-Lez | 3.864526351 | 43.6964578122 | Rue des Aramons,Prades-le-Lez |
| 46537 | 46535 | 26.398629219598995 | 3.8646316748 | 43.6985338752 | Rue Jean Jaurès, Prades-le-Lez | 3.86431098 | 43.6985849143 | Rue Jean Jaurès, Prades-le-Lez |
| 46537 | 46494 | 26.369825736302182 | 3.8646316748 | 43.6985338752 | Rue Jean Jaurès, Prades-le-Lez | 3.8647264499 | 43.69876091 | Rue Georges Brassens,Prades-le-Lez |
| 46572 | 46573 | 26.478719257987763 | 3.8689829795 | 43.6942426745 | Impasse de la Mayre, Prades-le-Lez | 3.8693056809 | 43.6942902652 | Impasse de la Mayre, Prades-le-Lez |

Fig. 5: Example of manhole pairs with coordinates and addresses

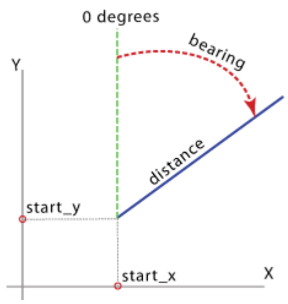

Fig. 6: GIS manholes related to the extracted street names in ITV videos

to slight inconsistencies or noise in the data. With the tolerances applied and without reaching the maximum allowed threshold, our algorithm was able to identify almost all manhole coordinates from the ITV videos, relying primarily on distances and street names.

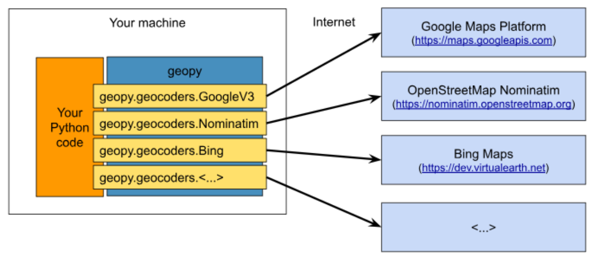
*Handling Missing Street Names: Bearings and Graph Reconstruction* Some rare cases cannot be resolved using the previous method due to missing or incorrect street names, or when only the initial coordinate is available. To handle these cases, we incorporate directional information (bearings), which allows us to reconstruct the manhole positions using distances and angles.

Street names in the videos are sometimes unreadable due to text orientation, low contrast, font variability, or background noise. When reliable address information is missing, we cannot rely on street names alone.

Instead, we use the coordinates of a known starting point (a manhole) and the distances between consecutive manholes. Bearings, defined as angles measured clockwise from north, add the necessary directional component. This combination enables accurate placement of subsequent points, even when street names are unavailable. This method is illustrated in the following figures: Figure 7a shows the bearing calculation concept, and Figure 7b shows the geocoding tools used to retrieve addresses when coordinates are known.




(a) Bearing and distance construction parameters [5]




(b) Geocoding services [6]

*Network Reconstruction from Coordinates and Bearings* Using Equations 1–4, we computed the estimated coordinates of each manhole based on the distances and bearings. These were visualized as a reconstructed graph (Figure 8) (and were stored in an excel file). n our study, we relied on GIS data associated with manholes for nearly all cases to build the network structure. However, in the hypothetical scenario where manhole shapefiles are unavailable, it is still possible to reconstruct the network using only the pipe shapefile, as illustrated in Figure 9. For a clear initial view, the maps are centered using the average latitude and longitude of all points. This average serves to center the map over the area of interest at load time.

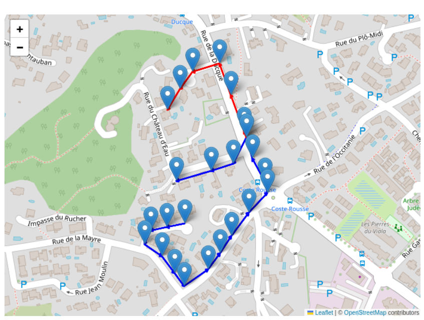


Fig. 8: Reconstructed graph of manholes based on distance and bearing

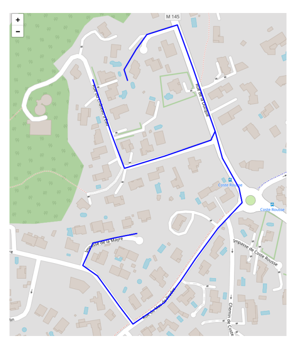


Fig. 9: Graph structure based only on pipeline data

*Spatial Overview* Figure 10 and Figure 11 provide a visual overview of the spatial layout of manholes and pipelines in the selected study area.

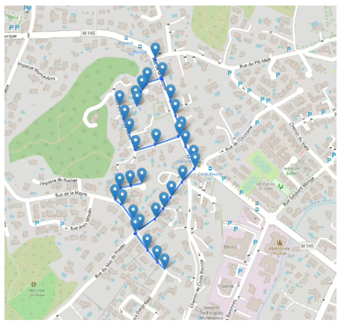


Fig. 10: Mapping the manholes

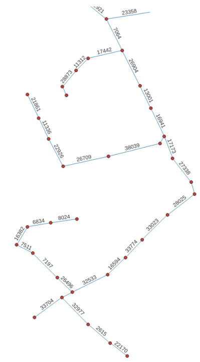


Fig. 11: Pipelines in selected zone in GIS

## 6 Conclusion

This study proposed a method to align and localize manholes in video inspections (ITV) by integrating them with Geographic Information System (GIS) data. Our approach combined street names and inspection distances to perform reliable matching between video-based observations and geospatial manhole records. In most cases, this matching was successful using only two main criteria: the travel distance and the extracted address. For rare cases where street names were missing or unreliable, we incorporated bearing calculations along with known coordinates to simulate the likely positions of manholes.

However, several challenges emerged during the analysis. First, the travel distance reported in ITV data often represents a minimum rather than the true distance between manholes, as inspections may stop before reaching the second manhole. Second, some manholes referenced in ITV records do not appear in the GIS database, and conversely, some manholes in the GIS shapefiles are not mentioned in any video inspections. These discrepancies make exact matching more complex and emphasize the need for flexible, tolerant algorithms.

Additionally, this study focused almost exclusively on GIS shapefiles describing manholes. While this dataset was sufficient to establish spatial relations and validate most ITV information, a more complete representation of the network could be achieved by incorporating GIS pipe data. Pipe shapefiles contain valuable structural details (e.g., length, type, connectivity) and could provide a more robust framework for graph simulation, network integrity checks, and visual validation. Including such data would allow us to cross-verify assumptions, detect anomalies, and better reconstruct missing elements in the network.

Looking ahead, several perspectives can extend this work. First, integrating machine learning or probabilistic models could improve matching in ambiguous or incomplete cases. Second, by incorporating dynamic data (such as flow direction or video metadata), future work could enhance the accuracy and completeness of network reconstructions. Finally, broader deployment of this methodology could support maintenance planning, anomaly detection, and infrastructure upgrades in other urban networks where data gaps are common.

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