

Standard Closed-Circuit Television (CCTV) Collection Time Extraction of Sewer Pipes with Machine Learning Algorithm

X. Yin^a, Y. Chen^a, A. Bouferguene^b, H. Zaman^c, M. Al-Hussein^a, R. Russell^d, and L. Kurach^d

^a Department of Civil and Environmental Engineering, University of Alberta, Canada

^b Campus Saint-Jean, University of Alberta, Edmonton, Canada

^c Waste Management, City of Edmonton, Canada

^d EPCOR Drainage Services, Edmonton, Canada

E-mail: xianfei@ualberta.ca, ychen10@ualberta.ca, ahmedb@ualberta.ca, hamid.zaman@edmonton.ca,
mohameda@ualberta.ca, RRussell@epcor.com, LKurach@epcor.com

Abstract –

Closed circuit television (CCTV) is probably one of the most important technologies that is used by municipalities in order to monitor the structural and operational condition of sewer pipes. To be useful, CCTV video footage needs to be collected according to standards, which make such an operation, time consuming especially when pipes have operational issues like debris or tree roots. In this respect, developing benchmarks for data collection can be an important source of information that can improve the efficiency of future surveying campaigns. Computer simulation is an effective method for improving the efficiency of maintenance work schedules. However, CCTV collection data consists of abundant noise (waiting time or defect inspection time) due to the characteristics of pipes in different structural or operational conditions. For example, crawlers equipped with CCTV cameras could be blocked by deposits or serious structural issues in the pipe, which would cost some waiting time for the crawler to proceed with the inspection. In order to extract the standard CCTV collection time, excluding waiting time and defect inspection time a machine learning based approach is proposed in this work in the form of an algorithm commonly known as the Random Sample Consensus (RANSAC). This algorithm is developed to clean the data automatically, arriving at a function of CCTV collection time with two variables (i.e., length of pipe segment and number of taps in the pipe). The results can be fed into a simulation model to imitate the CCTV collection work in future research.

Keywords –

CCTV; Sewer pipes; Time extraction; RANSAC

1 Introduction

The sewer system plays an important role as a type of municipal infrastructure that has a significant influence on the efficiency and quality of our lives. However, the pipes that make up a sewer system undergo deterioration due to aging, external force, excessive demand, and other factors. [1]. This deterioration poses a great challenge for municipal maintenance departments since the maintenance is time-consuming and heavily dependent on capital investment and operating costs. To perform an efficient and quality sewer maintenance job, closed-circuit television (CCTV) is commonly adopted as the pipe condition inspection technique [2–4]. The wide usage of CCTV for pipe inspection has been driven by many practical reasons the most important of which being safety since this monitoring procedure does not require man entry [2]. Furthermore, since the videos are stored on appropriate media, they not only can be visualized for the purpose of inspection or comparison with other techniques (e.g., laser-based system, ultrasonic-based sensors and ground penetrating radar [5]) but more importantly they can serve as accurate historical data.

The CCTV collection process will be discussed in the next section. For this research, it should be noted, we only consider the time period that starting at the beginning of the video to the end. The objective of this research is to extract the standard CCTV collection time, excluding all waiting time, idle time, and other time delays in the collection process. The results can be fed into a simulation model to perform schedule optimization, which is the next stage of our research. In addition, the extracted standard CCTV collection time can be viewed as a benchmark for the CCTV collection process. Management decision can be derived for each

of the CCTV collection job in the perspective of time efficiency. For example, CCTV collection time within in new developed neighborhood should be align to the standard CCTV collection time; while it could be slower in older neighborhood theoretically considering the deterioration of the pipe, since more defects may cause more waiting time.

2 CCTV Collection Process

CCTV operators travel to inspect sewer pipes at the assigned locations as per the schedule set up by the municipal maintenance department. In general, before beginning the video collection phase, the pipes to be inspected are cleaned in advance by means of flushing equipment, in order to eliminate deposits and obstacles in the pipes which in turn ensures that the conditions for data collection are acceptable [6,7]. Following flushing activities, operators begin set-up work for CCTV data collection on the ground. The setup includes adjustment of a remotely controlled robot equipped with a specialized television camera. Next the camera begins to record a video for the observed pipe from the start point. In the process, the operators need to adhere to standards such as those described in National Association of Sewer Service Company (NASSCO) in order to obtain quality information that can be accurately analyzed later in the process. For instance, four primary categories of pipe defects are listed based on the pipeline assessment and certification program (PACP) [8]: that is, (i) structural defects, (ii) operation and maintenance defects, (iii) construction defects, and (iv) miscellaneous defects. While collecting the video, the technologist controlling data acquisition can decide to spend more time on serious defect such as those referred to as pipe broken or substantial deposits. The total CCTV collection time can be derived by means of Equation (1), $Time_n = a \cdot L_n + b \cdot T_n + W_n + C + \varepsilon_n$ (1) where $Time_n$ represents the total CCTV collection time for pipe segment, n ; L_n is the length of the pipe segment; T_n is the number of taps of this pipe segment; W_n is the total waiting time, which may include the time for inspection of severe defects, adjustment of camera, etc.; C is the fixed time for the CCTV collection process, which may include time for equipment setup and other routine processes; and ε_n is an error representing the uncertainties regarding this process.

From a theoretical viewpoint, if there are no serious defects or other accidents that hinder the CCTV collection process observed in one pipe, a CCTV collection time can be generally described in Equation (2),

$$Time_n = a \cdot L_n + b \cdot T_n + C + \varepsilon_n \quad (2)$$

The waiting time is eliminated in this equation. $Time_n$ is denoted as standard CCTV collection time. The data points that contain waiting time are the noisy points that we want to exclude. The standard CCTV collection time extraction is conducted by the RANSAC algorithm, which will be described in the next section.

3 RANSAC Model

In order to extract the standard CCTV collection time, this research applies the Random Sample Consensus (RANSAC) algorithm to clean the raw data automatically. RANSAC, proposed by Fischler & Robert in 1981, is a non-deterministic approach to use the smallest initial dataset to determine the parameters of a model, then repeat the process until it reaches the predefined criterion [9]. Unlike linear regression using least-squares estimation, which seeks to minimize the distance from all the data points to the fitted function, RANSAC model searches for the best fitted function without considering the outliers (see Figure 1). From Figure 1. we can see that the solid line constructed by the RANSAC algorithm is better at describing the trend for all five points than the dotted line developed by least-square estimation. The outlier is called a noise point in this scenario, and it is these noise points that are supposed to be eliminated in constructing this regression model.

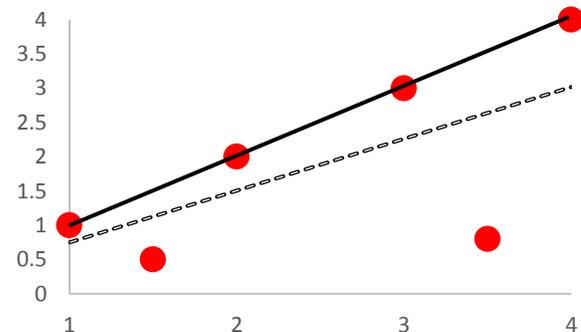


Figure 1. Comparison of least-square estimation and RANSAC.

The mechanism of the RANSAC algorithm is presented in Figure 2. The algorithm starts with selecting X points (where $X = \text{number of independent variables} + 1$). For instance, two points are needed to fit a line (2-dimensional problem) while three points are needed to fit a plane (3-dimensional problem). From Equation (2), we know that the extraction of the standard CCTV collection time is a problem with two independent variables, namely, the length of the pipe segment associated with video (L), and the number of taps within the pipe segment (T). Therefore, three points

need to be selected for each iteration. An objective function (Y_i) can be formed based on the selected points. Then, the Euclidean distance of each point to the objective function is calculated. A threshold (t) should be selected in order to decide whether the point is an inlier or an outlier. If the distance is within the threshold, it is an inlier; otherwise, it is an outlier. The number of inliers (N_i) should be counted and compared with the N_{i-1} (i.e., the greatest number of inliers among all the historical iterations). If the N_{i-1} is bigger, we save the N_{i-1} as N_i , and Y_{i-1} as Y_i . Otherwise, we update the N_i and Y_i accordingly. The process is repeated until the predetermined number of iterations (N) is reached. As for the number of iterations (N), it can be calculated by means of Equation (3) [10].

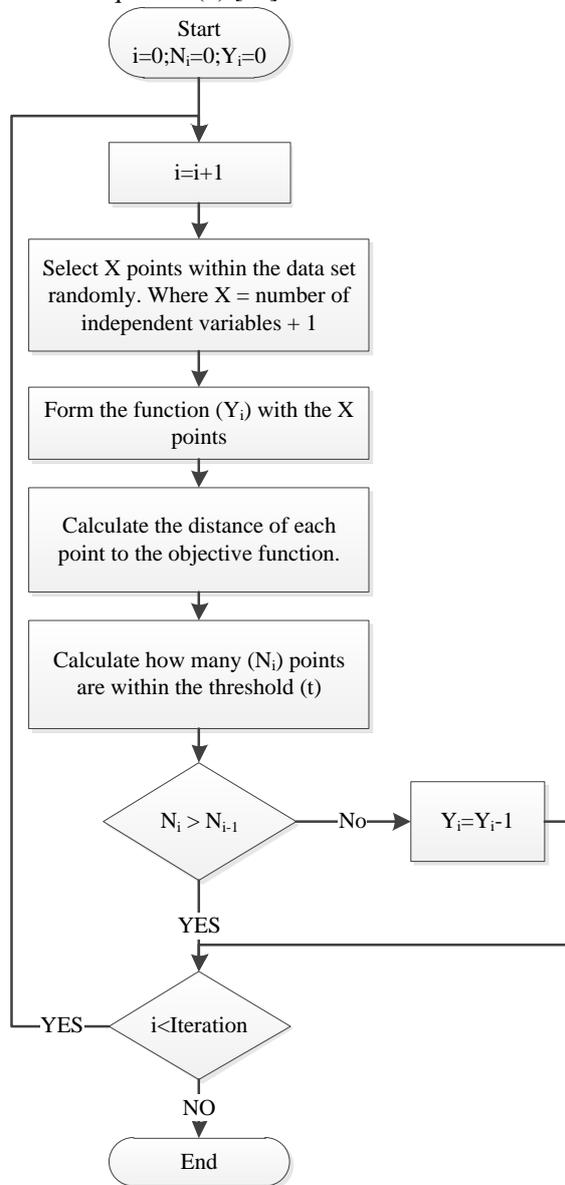


Figure 2. Flow chart of RANSAC algorithm.

$$1 - p = (1 - \lambda^X)^N \Rightarrow N \geq \frac{\log(1 - P)}{\log(1 - \lambda^X)} \quad (3)$$

where X is the number of points needed to construct the objective function; N is the number of iterations; P is the probability that at least one of the objective functions built in all N iterations is constructed by X inliers; and λ is the inlier ratio, which can be calculated using Equation (4). Although a priori it is an unknown ratio, it can be updated during the algorithm progress [11].

$$\lambda = \frac{\text{Inliers}}{\text{Inliers} + \text{Outliers}} \quad (4)$$

Considering the probabilistic nature of the RANSAC algorithm, the parameters (e.g., a and b) of the objective function will vary from one time to another if the algorithm runs multiple times. Therefore, the mathematical expectation of each parameter can be calculated from a large number of run-times of the algorithm. The mathematical expectation of the parameters will be used to form the objective function for the convenience of constructing the simulation model in the future research.

4 Case study

4.1 Data description

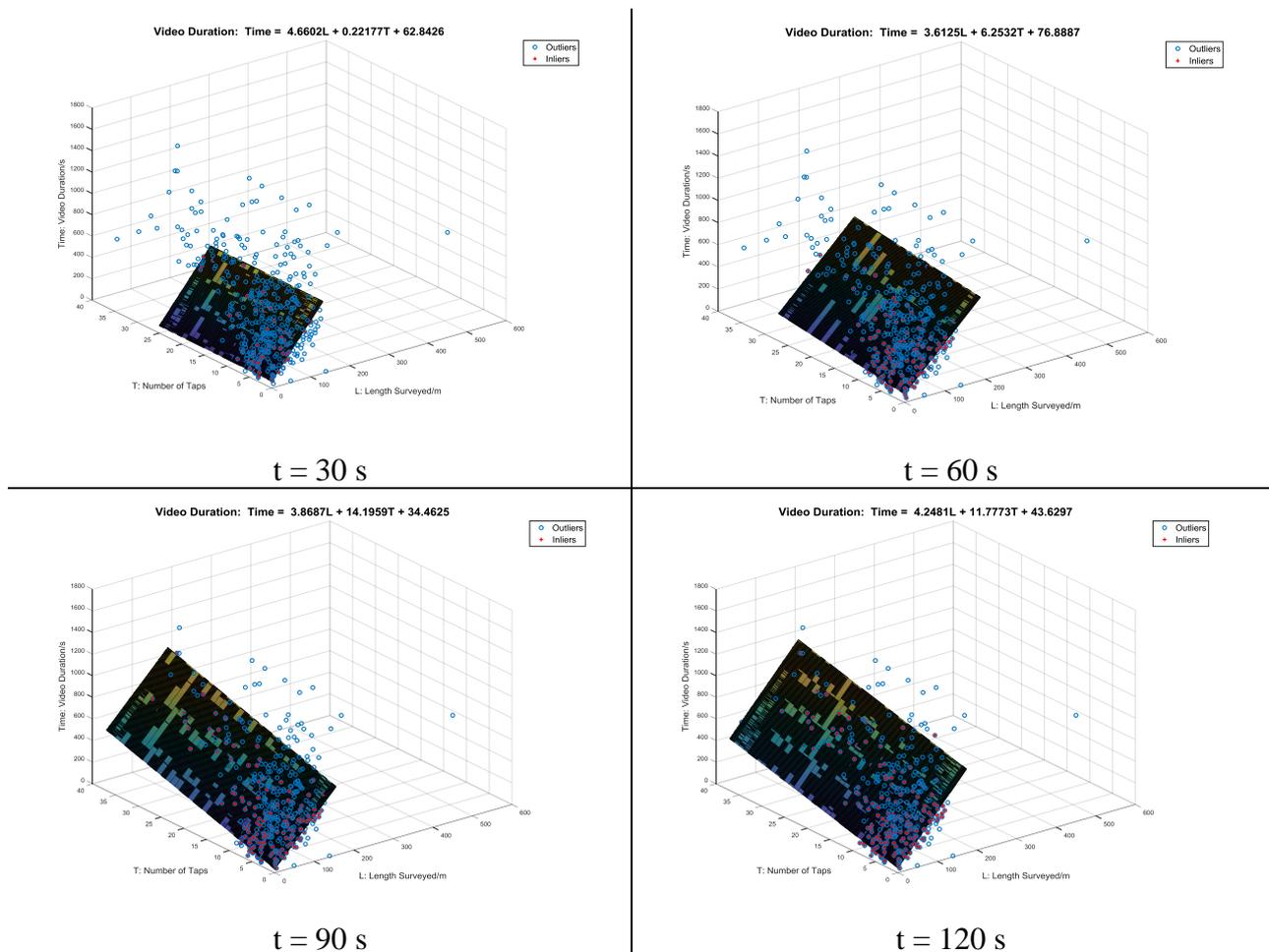
The data used in this research was collected by EPCOR Drainage Services, which is responsible for the operation and maintenance of the sewer infrastructure in Edmonton, Canada. For each pipe segment, the data is provided in two formats (two types of files), namely, Microsoft Access (.mdb), and video file (.mp4). The video duration (in seconds) and length of pipe segment surveyed (in meters) can be retrieved from the Access database directly. The number of taps is counted by a count query (combining all kinds of code associate with taps, such as Breaking-In/Hammer, Factory-made, Saddle, etc.) in the database in order to derive the total number of taps in a given pipe segment. Other attributes associated with the pipe segment can be derived from the Access database as well, such as the number of defects, location, and material type. The CCTV video serves as the validation function; that is to say, it is used to check the validity of the data recorded in the Access database either through manual viewing and analysis of the CCTV footage or by means of algorithms. In this research, we consider three attributes— video duration (s), length of pipe segment (m), and number of taps. 540 data records are fed into the RANSAC model to capture the relationship described in Equation (2) by excluding

any data records that contain forms of waiting time as described above.

4.2 Results and findings

As discussed in section 3, three parameters need to be determined for the RANSAC model: the number of points needed to form the candidate objective function (X), the number of iterations (N), and the threshold (t). In this case, $X = 3$ since there are two independent variables in this model, as per Equation (2). The lower boundary of the number of iterations, meanwhile, can be calculated from Equation (3). Considering the positive correlation between the number of iterations and the probability of obtaining the optimal results, along with the size of the dataset and CPU processing time, an iteration number of 100,000 was selected. As for the threshold, several experiments were conducted with different values of t (see Fig 3).

From Figure 3, we can see that the objective function can be plotted as a plane in a 3D space. The video duration (time) increases with an increase in the length of pipe segment (L), and number of taps (T), a finding which aligns with reality, since an increase in either the length of pipe segment or the number of taps will increase the CCTV collection time. The red dots represent the pipe segments classified as inliers; that is to say, these pipes are in good condition since there are no severe defects or other accidents that would lead to significant waiting time during the inspection process. Similarly, the blue dots represent the pipe segments that are classified as outliers, which means that these inspections must have been delayed by some extenuating circumstances (either severe defects within the pipe or other accidents such as equipment failure). The inliers and outliers are tabulated in Table 1.



*Note that the red dots are the inliers (within the threshold) and the blue dots are outliers (outside of the threshold).

Figure 3. Results of RANSAC model with different values of threshold (t)

Table 1. Number of inliers and outliers at different thresholds.

Threshold	30 s	60 s	90 s	120 s
Inliers	130	217	285	335
Outliers	410	323	255	205

Comparing the results in Figure 3 and Table 1, we can see that, as the value of the threshold grows, the number of inliers shows an increasing trend. The information in Figure 3 and Table 1 can be interpreted as follows: with the relaxation of the conditions, the number of pipe segments classified as being in good condition increases. A box-plot can be plotted based on the inliers at the four threshold values, along with the original video duration in the original 540 data (see Fig 4). Obviously, the original dataset has the highest median video duration, while the dataset has the lowest video duration when the threshold is set at the lowest value (30 s). The medians of the last three scenarios ($t = 60$ s, $t = 90$ s, and $t = 120$ s) do not vary significantly compared with the variation between the first two scenarios ($t = 30$ s and $t = 60$ s). Similar relationships for the 75th quantile of the video duration in the box-plot can be observed. The threshold selection is subjective due to the nature of this algorithm. Although a smaller threshold ensures that all the inliers are classified correctly, it may lead to the loss of points that should have been classified as inliers in reality. On the contrary, if the threshold is greater, it may include points that should have been classified as outliers in reality. Identifying the optimal tradeoff between accuracy and completeness in this threshold selection process requires several experiments and statistical analysis at the same time. Ultimately the threshold of 60 s was selected, as it contains the inliers that take part in around 40% of the total data points, which is aligned with the empirical judgment from the dataset.

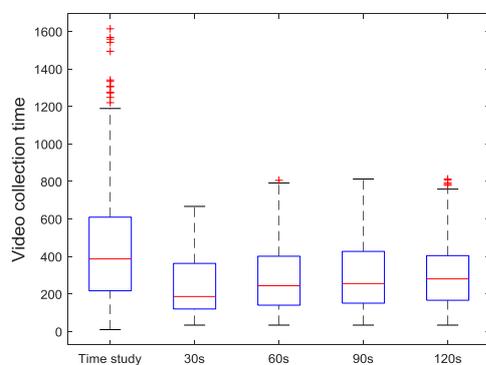
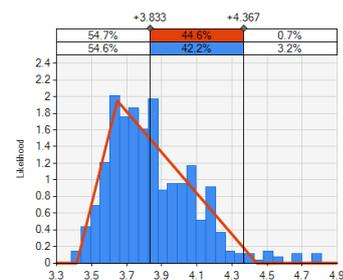


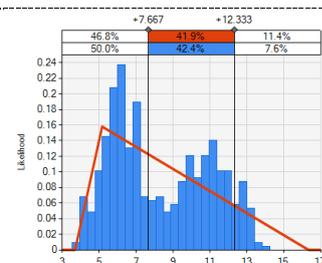
Figure 4. Box-plot of video durations of inliers in four scenarios, along with original

dataset.

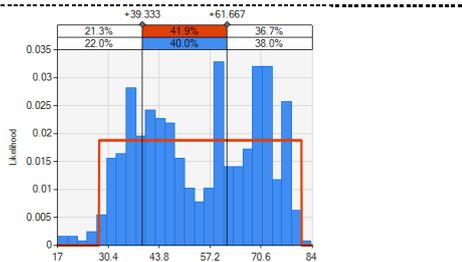
As discussed in Section 3, due to the probabilistic nature of the RANSAC algorithm, multiple runs are needed to capture the distribution of the three parameters (a, b and C) in Equation (2). Figure 5. shows the results of 500 runs of the RANSAC algorithm with the threshold of 60 s. Parameters a and b are both fitted with triangular distribution, with the mathematical expectation of 3.84 and 8.34 separately. Parameter C conforms to the uniform distribution with an expectation of 54.56. Therefore, the objective function can be summarized as $Time_n = 3.84 \cdot L_n + 8.43 \cdot T_n + 54.56$. The statistical analysis can be interpreted as follows: for one meter of pipe segment in good condition, it takes 3.84 s to finish the CCTV collection process; if there is one tap present within the pipe segment, it takes 8.43 s to finish the inspection; the fixed duration for the CCTV collection process is 54.56, which may include equipment setup time, camera adjustment time, and other routine processes. With the function derived from the RANSAC model, theoretical video collection time can be calculated with the two inputs (L and T). A histogram (see Figure 6.) can be constructed to show the performance of the RANSAC model by comparing the distribution of video collection time of the original data (inliers) and the theoretical results calculated from the RANSAC model. We can see from Figure 6 that the two histograms are largely co-terminous, which means that the results from the model are quite close to reality.



Parameter a: Triangular distribution; Expectation (a) = 3.84



Parameter b: Triangular distribution; Expectation (a) = 8.34



Parameter c: Uniform distribution; Expectation (a) = 54.56.

Figure 5. Results of the parameters in RANSAC model.

This function can be fed into a simulation model to model the CCTV collection process. In addition, it can be used as a classifier to distinguish whether or not a given pipe segment being inspected by CCTV is in good condition.

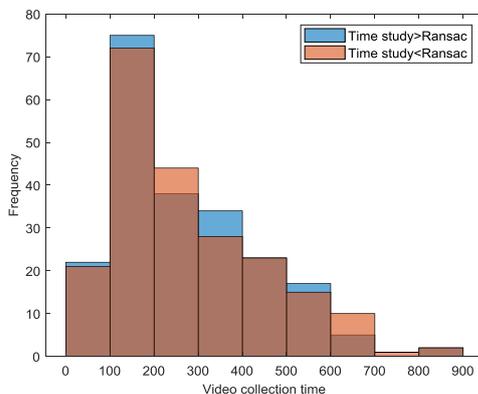


Figure 6. Histogram of RANSAC model and original time study.

5 Conclusion

Exclusion of noisy data is the objective of this research, so the RANSAC algorithm is utilized to exclude all data points that contain noise of any form. The CCTV collection process is summarized as a background of this study. Followed by the interpretation of the RANSAC model, focusing on the mechanism of the algorithm and the implementation process. Three key parameters need to be determined based on the nature of the problem and the authors' subjective judgment, namely, the number of points needed in order to form the candidate objective function (X), the number of iterations (N), and the threshold (t). A case study was performed to show the application of the RANSAC algorithm. Five hundred-forty data records collected by EPCOR Drainage Services were utilized to build the model, leading to a linear function that describes

the relationship among CCTV collection time (Time), length of pipe segment (L), and number of taps (T). The results can be used in a simulation model to simulate the CCTV collection process in future research.

Acknowledgments

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