USE OF MACHINE LEARNING AND ROBOTIC SENSING TO TARGET RENEWALS IN CONCRETE GRAVITY SEWERS

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KEYWORDS

Concrete corrosion, machine learning, robotics

ABSTRACT

Sydney Water has approximately 823km of gravity concrete sewers where concrete corrosion is a widespread issue. Early identification of corrosion levels is important to make decisions on fit-for-purpose renewal methods. Sydney Water and the University of Technology Sydney (UTS) have collaborated in developing machine learning models and robotic systems to identify corrosion levels in the carriers as well as to quantitatively measure the depth of corrosion and the depth of reinforcement bars. The machine learning model predicts corrosion hotspots in the carrier, which are further inspected by a manhole deployable robotic system. The new robotic observations are fed back into the machine learning model for continuous improvement. This integrated system has many advantages compared to the current practice.

INTRODUCTION

Sewer corrosion prediction iscritical for water utilities to improve efficiency and save costs in chemical dosing, sewer pipe rehabilitation and sensor deployment [De Muynck et al. (2009), Shook & Bell (1998)]. As sewer corrosion occurs in the presence of gaseous hydrogen sulphide (H2S) generated from sulphur compounds in the sewage, a new and reliable machine learning model has been developed. In this project, the spatiotemporal estimation of H2S and other factors is enabled. Based on the spatiotemporal estimation of factors, the machine learning model could further predict the sewer corrosion level on the entire sewer carriers.

Reliable prediction of H2S and corrosion has often been hampered by insufficient observations for a high level of confidence modelling – a problem commonly referred to as “sparsity” in machine learning [Boon & Lister (1975)]. Therefore, machine learning modelling of spatiotemporal H2S distribution on the entire sewer carriers is nontrivial. Increasing the H2S monitoring sites is also not feasible due to cost and accessibility. Therefore, in this project, an attempt has been made to use emerging machine learning techniques to estimate

Figure 1: The concrete gravity sewers in Sydney Water’s network.

the spatiotemporal distribution of H2S with a limited number of observations. The model does not only estimate the H2S quantity but also estimates the uncertainty associated with the prediction, which is an important measure in decision making.

The length of wastewater piping in Australia can circle the globe more than six times, and 70% of it is underground. Sydney Water estimates it spends $40 million annually rehabilitating sewers, relying on manual inspection to identify damage or areas for concern, with staff required to enter the sewers for a visual inspection. Replacing pipes that are approaching end of life is both costly and disruptive to the community. Sydney Water requires a safe and reliable method of detecting water pipe defects before critical failure in order to apply fit-for-purpose intervention. In this work, we have developed novel sensing and robotic toolkits that assess the condition of concrete sewer pipes. The technology provides Sydney Water with critical data used to inform renewal methods and reduce negative environmental, social, and economic impacts.

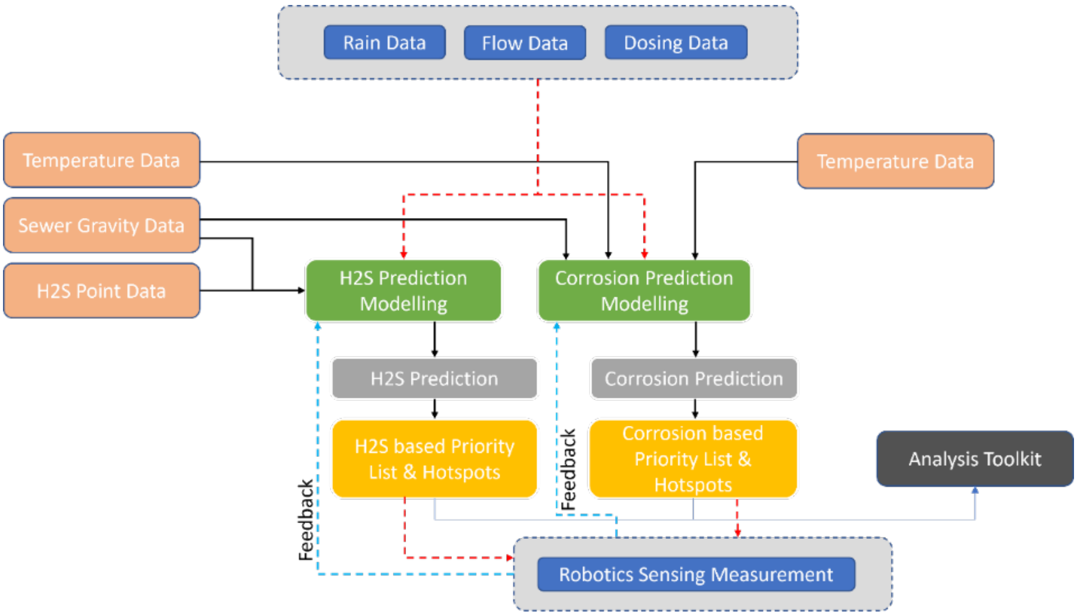

Figure 2: Overall Framework.

HIGHLIGHTS

- Spatiotemporal estimation of corrosion factors on the entire sewer carriers.
- Corrosion level prediction and uncertainty of the prediction on the entire sewer carriers.
- The development of world-leading internal tethered pipe scanning tools.

METHODOLOGY/ PROCESS

Machine Learning Model

This paper demonstrates how to make use of emerging machine learning techniques to estimate the spatiotemporal distribution of H2S with a limited number of observations (as shown in Figure 1). A new and reliable machine learning model, based on a data-driven technique leveraging Gaussian process, has been developed in this project, which enables spatiotemporal estimation of H2S and other factors. Based on the spatiotemporal estimation of factors, the machine learning model could further predict the sewer corrosion level on the entire sewer carriers with high prediction confidence. This work attempts to leverage a Bayesian nonparametric method to predict the sewer corrosion risk on the entire sewer carriers with a limited number of observations. Specifically, this is achieved in two steps: (1) Gaussian Process is used to estimate the distributions of the two influential factors, H2S and temperature, on the entire sewer carriers; (2) Based on the estimation results of influential factors, a second-level Gaussian Process is used to further predict the corrosion risk levels on the entire sewer carriers.

The proposed method has the following desirable properties:

- The method is able to integrate expert domain knowledge (physical model) into the prediction model to alleviate the issue of insufficient data. The adopted machine learning technique is a Bayesian nonparametric method, which provides a way to regularise the prediction with domain knowledge.

- The method is flexible. The prediction model in this work can readily incorporate more factors related to sewer corrosion. Therefore, the model can be easily improved by employing additional data collected in the future. In addition, the proposed model can handle large-scale sewer Carriers, making it widely applicable.

- As the model is built on Gaussian processes, it not only predicts the sewer corrosion level quantitatively, but also estimates the uncertainty of the prediction, as illustrated in Figure 3. This uncertainty is an important measure in decision making and cost-effective sewer operations. For example, it can be used to prioritise high corrosion areas, recommend chemical dosing locations, and suggest the deployment of sensors.

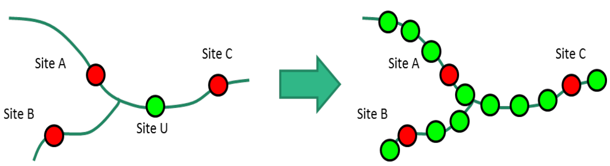

Figure 3: Illustration of Gaussian process on a sewer carrier.

Factor Estimation

This subsection introduces how the Gaussian process has been used to estimate H2S concentration on the entire sewer carriers. In this task, we simply used zero as the mean function (i.e., no prior knowledge is used regarding H2S concentration) and an exponential kernel function as the covariance function described in the following.

Due to the constraints of the carriers structure, we first compute the shortest geodesic path between any two points on the carriers as the distance between these two points. Then, the exponential kernel can be defined in terms of the shortest geodesic distance:

$$K_{i,j}^{Geo} = \exp(-d_{ij}/\sigma^2) \tag{1}$$

where K^{Geo} denotes the $N \times N$ kernel matrix, $K_{i,j}^{Geo}$ denotes the element in the i-th row and the j-th column, d_{ij} is the shortest geodesic distance from point i to point j and σ is the band-width of the exponential kernel.

In order to take into account the flow directions between two points, we have adopted two band-widths $\{\sigma_1, \sigma_2\}$ to differentiate the sewer flow direction: σ_1 for the case where there is no reverse flow direction from one point to the other, and another σ_2 for the case where there is a reverse flow direction from one point to the other. As a result, the above kernel function should be written as

$$K_{i,j}^{Geo\prime} = \exp(-\mathbf{1}_{noreverse} \cdot \frac{d_{ij}}{\sigma_1^2} - \mathbf{1}_{reverse} \cdot \frac{d_{ij}}{\sigma_2^2}) \tag{2}$$

where $\mathbf{1}_{noreverse}$ and $\mathbf{1}_{reverse}$ are indicator functions – if the statement is true, the function returns 1, otherwise 0. After computing the kernels of all pairs on the entire sewer carriers we can obtain a $N \times N$ kernel matrix $K^{Geo\prime}$.

Based on the H2S concentration values y_L^{H2S} of the observed sites, we can estimate the values y_U^{H2S} of the unobserved sites using the following equation:

$$y_U^{H2S} = K_{UL}^{Geo\prime}(K_{LL}^{Geo\prime} + \sigma_0 \cdot I)^{-1} y_L^{H2S} \tag{3}$$

where $K_{LL}^{Geo\prime}$ denotes the kernel matrix between the observed sites and $K_{UL}^{Geo\prime}$ denotes the kernel matrix between the unobserved sites and the observed sites. Note that both $K_{LL}^{Geo\prime}$ and $K_{UL}^{Geo\prime}$ are submatrices of $K^{Geo\prime}$; σ_0 is a constant parameter and I denotes an identity matrix.

By using Equation (3), we can estimate the H2S concentrations on the entire sewer carriers. Temperature can be estimated in the same way by inputting the observed temperature y_L^{Temp}.

Corrosion Prediction

We have also used the Gaussian Process to estimate the deterioration rate (Structure Grade loss per year). In this GP, we have the following settings. The mean function is set as the physical model derived from the University of Newcastle [Wells & Melchers (2016)]:

$$CR = A \times [H2S]^{0.5} \times \frac{(0.1602H - 0.1355)}{(1 - 0.977H)} \times e^{(-45{,}000/RT)} \tag{4}$$

where A is a constant parameter determined empirically, $H2S$ is the H2S concentration, H is the fractional relative humidity of the sewer atmosphere, R is the universal gas constant, and T is the absolute temperature.

The kernel function is set as the linear combination of three kernels, which is defined as

$$K^{CR} = \alpha_1 \cdot K^{Geo\prime} + \alpha_2 \cdot K^{H2S} + \alpha_3 \cdot K^{Temp} \tag{5}$$

where $K^{Geo\prime}$ is the exponential kernel defined above, K^{H2S} is the Gaussian kernel with the difference of $H2S$ concentration as the distance, K^{Temp} is the Gaussian kernel with the difference of $Temperature$ as the distance, and $\alpha_1, \alpha_2, \alpha_2$ are the coefficients (constant parameters) for the linear combination of the three kernel matrices. In other words, we define the "distance" between two points on the sewer carriers in terms of geodesic distance, H2S difference, and temperature difference (unobserved H2S/temperature is filled in with the estimation obtained using the factor estimation model introduced in the previous section) – If two pipes are close and have similar H2S and temperature values, they are likely to have similar deterioration rates.

We can estimate the deterioration rate and its variance as follows:

$$y_U^{DetRate} = K_{UL}^{CR}(K_{LL}^{CR} + \sigma_0 \cdot I)^{-1} y_L^{DetRate} + CR_U$$
$$[\sigma_U^{DetRate}]^2 = K_{UU}^{CR} + \sigma_0^2 - K_{UL}^{CR}(K_{LL}^{CR} + \sigma_0 \cdot I)^{-1} K_{LU}^{CR} \tag{6}$$

where $y_L^{DetRate}$ denotes the observed deterioration rates on the set of ground truth sewer pipes (which have two records of Structure Grade in the traverse reports), K_{LL}^{CR} denotes the kernel matrix between the observed sites and K_{UL}^{CR} denotes the kernel matrix between the unobserved sites and the observed

Figure 4: CRAFT V1 with scissor lift expansion arms to handle sensor payload, 100m Cable reel with power and communication to CRAFT.

sites, and CR_U denotes the prior values calculated using Equation (4).

By using Equation (6), we can estimate the deterioration rates of pipes on the entire sewer Carriers. As the deterioration rate is per year, we need to use the following equation to compute the Structure Grade of a pipe at any month t:

$$STRgrade(t) = STRgrade(t_0) + \frac{1}{12}\sum_{t_0<t'\leq t} DetRate(t') \quad (7)$$

where $DetRate(t')$ denotes the deterioration rate of a pipe at month t', which is regarded unchanged during the investigation period, that is $DetRate(t') = y_U^{DetRate}$. Given the Structure Grade at month t_0 and the deterioration rate $y_U^{DetRate}$, the Structure Grade of the pipe at month t can be obtained using Equation (7).

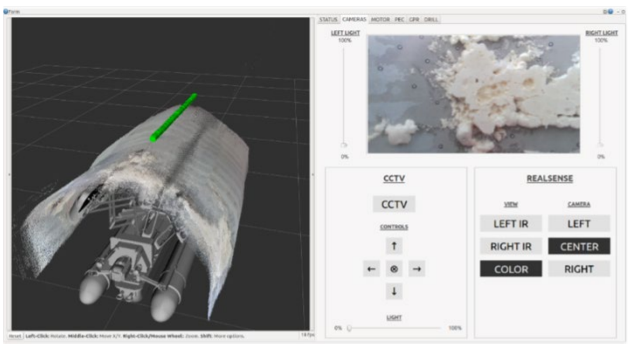

Figure 5: CRAFT V1 tested in a DN1200 concrete pipe with rebar under lab conditions.

Robotic Sensing:

The NDT contact-based sensors need to be scanning the pipe surface to quantitatively estimate the good concrete over the rebar, therefore the need for a state-of-the-art robotic platform that can handle these sensor payloads is important. A floating platform with active manipulation of sensor payload has been identified as the most feasible design approach and CRAFT platform (Figure 6) has been developed to meet the design specifications. A multi-actuator expansion module has been integrated into CRAFT robot to provide the dexterity required to navigate through the sewer pipeline and handle the sensor suite to collect NDT measurements.

Figure 6: CRAFT V1 deployed at Fairfield West Carrier – Sydney in Mar 2021.

The sensing suite on CRAFT comprises of Ground Penetrating Sensor (GPR) and Pulsed Eddy Current Sensor (PEC) which work in unison to provide estimate of the soft layer thickness and good concrete cover over the rebar in the pipe. GPR sensor operates at a frequency range of 200 – 4000 MHz (central frequency of 2000MHz), with a supply voltage of 12V and peak power of 3W. These signals are reflected from different layers of the concrete and provide a unique signature correlating to the characteristics of the material beneath the wall surface. PEC sensor includes sensor coils, driver circuit to control the excitation pulses and process the received pulses including the signal conditioning and ADC modules are packed into a compact form factor that can detect and estimate the distance to rebar up to 90mm with high resolution. A custom UI has been developed (Figure 4) to control and monitor various operations of the platform with several tabs including Status, Camera, Motor, PEC and GPR.

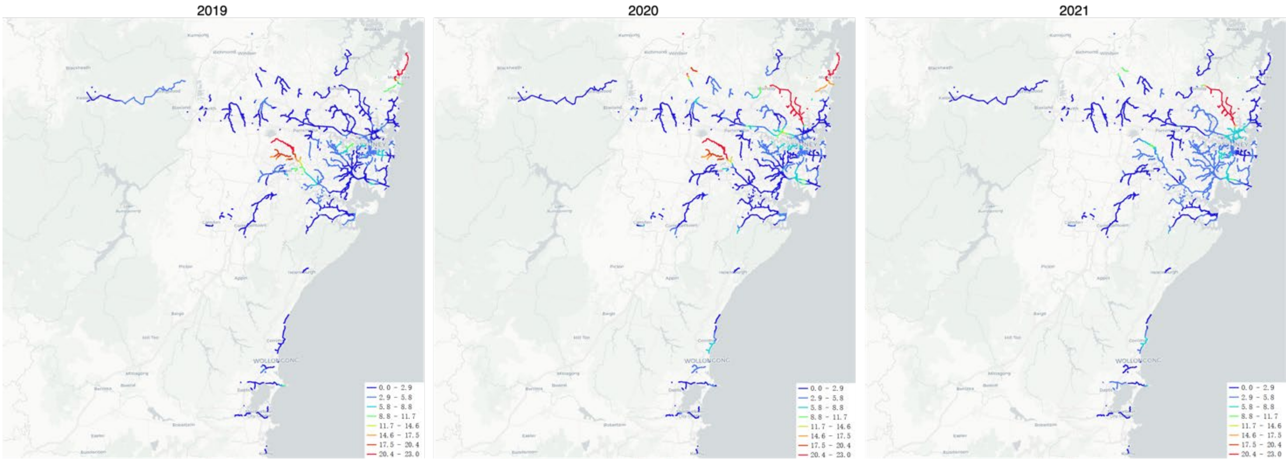

Figure 7: H2S Prediction results 2019-2021.

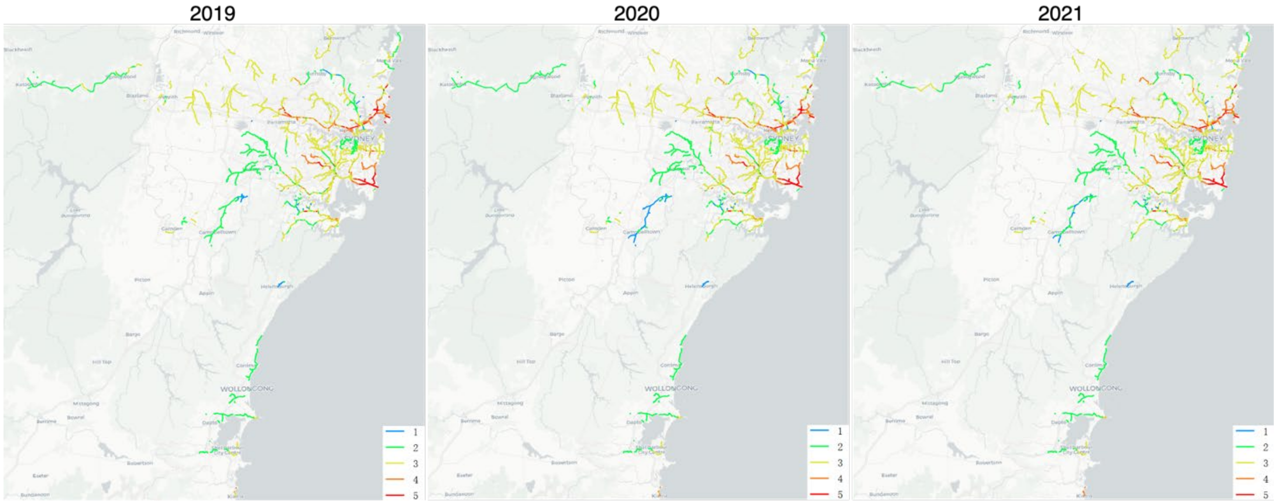

Figure 8: Corrosion level prediction results 2019-2021.

<u>RESULTS/ OUTCOMES</u>

H2S & Corrosion Prediction: Our model enables evaluation of optimisation via the facility to upload a second H2S data set for comparison. This allows the user to directly compare the diurnal average H2S before and after a dosing change has been implemented. We have evaluated the proposed H2S prediction model using the real data provided by Sydney Water (Figure 7). Based on our experiments, 20% of the predicted high risky pipes in our model cover 52.64% of the observed risky pipes (Structure Grade level 4 & 5) in three years (Figure 9). The machine learning engine uses the estimations of H2S and other parameters such as temperature and hydraulic information to predict corrosion levels on the entire carriers. The output of the evaluation is a map of structure grade for the entire sewer carriers. We have summarized and compared the predicted structure grade and the ground-truth structure grade of each of the pipes traversed in 2020 (Figure 8). One can see that the majority of predictions have less than a 4% difference compared to the corresponding ground truths. In average, the prediction error is less than 4% (0.2/5 = 4%) as shown in Figure 9.

In Australia, the total length of sewer pipes is over 110,000 km and the value of wastewater infrastructure construction completed across Australia amounted to around 3 billion Australian dollars in the 2020 fiscal year. The annual cost due to the failure of water/wastewater pipelines alone in Australia was estimated to be over $250 million. The proposed machine learning model for corrosion level prediction has been deployed in a Sydney sewer carriers. The evaluation results have demonstrated the high prediction level of confidence in the proposed machine learning model, with an average Structure Grade conficence level of 52.64% with only 20% pipes selected from our predicted priority list for Sydney Water. With a suitable, validated model, Sydney Water could defer as much as $16M annually from its current rehabilitation cost which vary between $60-80M annually.

Robotic Sensing: We have deployed the CRAFT V1 in the sewer carriers at Fairfield West Carrier in March 2021 (Figure 10) which has a downstream length of 200m and validated the operation of the platform sub-systems, deployment strategies, data collection, platform stability and sensor evaluation.

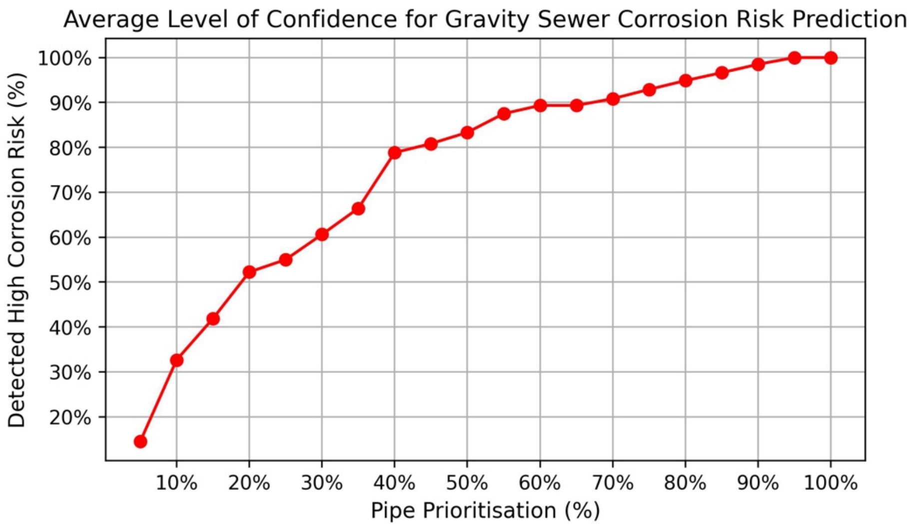

Figure 9: The average level of confidence for corrosion prediction.

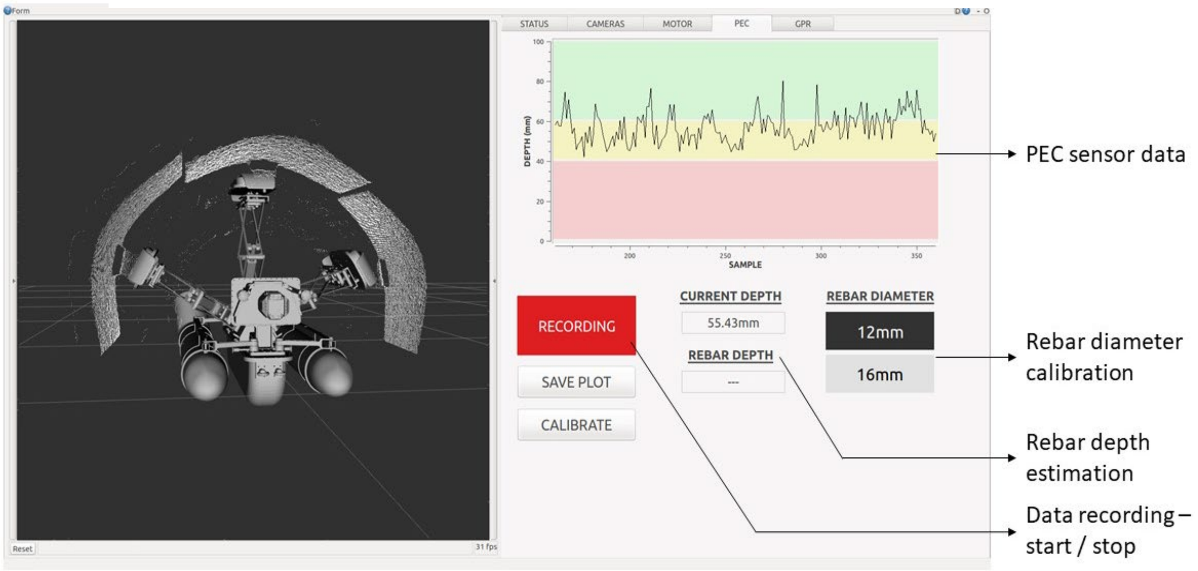

Figure 10: CRAFT UI – PEC sensor control tab

The PEC tab in the UI (Figure 11) plots the live sensor data and colour coded with green, yellow and red with preset rebar depth values. Any depth less than 40mm is marked as red showing that the concrete cover is less and needs attention. “Rebar Diameter” is selectable between “12 and 16mm” which loads the corresponding calibration file. GPR tab controls has time resolution of the GPR sensor that can be switched between Default and Custom which corresponds to lower and higher depth penetration of GPR signals. For near-surface detection, the default option can be used. The “FILTER” button enables the inbuilt filter which processes the GPR scans through the time window and provides better visualization of the data in the window above. Filter coefficients can be configured using the + and – buttons at the bottom.

CRAFT V2 is in the developmental stage based on the field deployment learnings of CRAFT V1. The scissors lift mechanism is replaced with a robotic manipulator. Figure 12 shows the CRAFT V2 prototype.

CONCLUSION

With a limited number of monitoring sites, it is a challenge to predict H2S concentration and sewer corrosion levels on the entire carriers. A machine learning model based on a Gaussian process, was used to predict spatio-temporal H2S and corrosion hot spots with > 80% confidence on the three gravity concrete sewer systems of Sydney Water. The predicted results can help to prioritise high-risk areas, recommend chemical dosing locations, and suggest the deployment of robotic sensors. Applying robotic sensing and advanced signal processing to the ground penetrating radar and pulse eddy current sensor data provides an estimation of the depth of the soft concrete layer and the distance to reinforcement bars. These methods can be used for 900 – 1500mm concrete sewers, and for > 1500mm traversable sewers with handheld tool kits. This

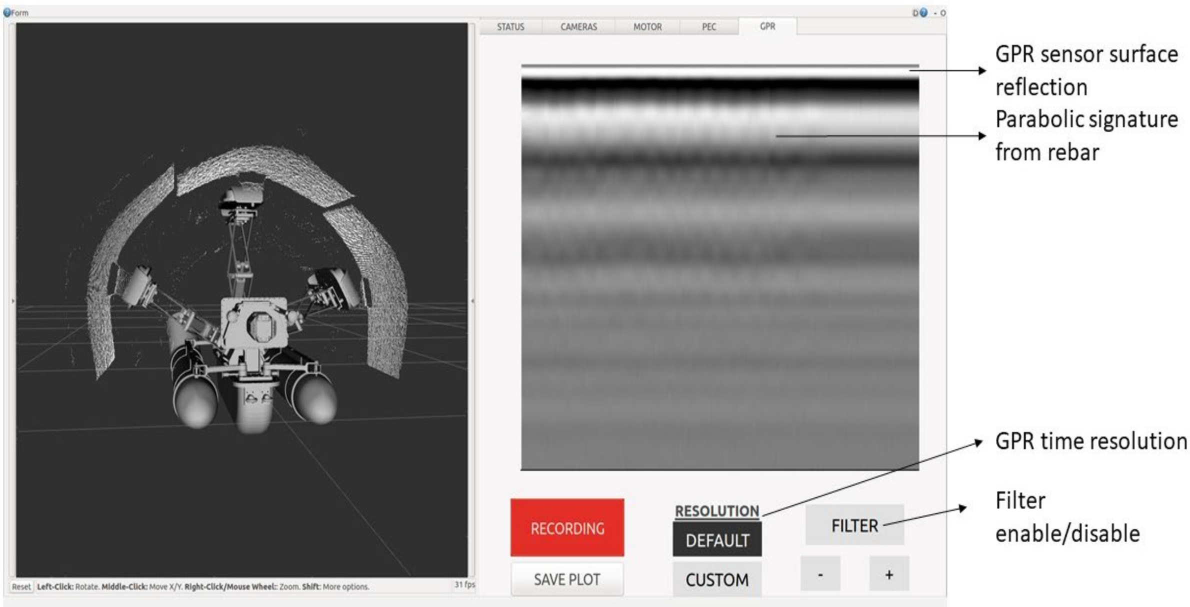

Figure 11: CRAFT UI - GPR sensor control tab.

world leading ability to non-destructively measure soft concrete depth with an interface that allows the operator to assess the performance while the measurement is carried out is a significant innovation in action. The remaining life of the concrete pipes can then be calculated by integrating the fit-for-purpose coating decision-making process.

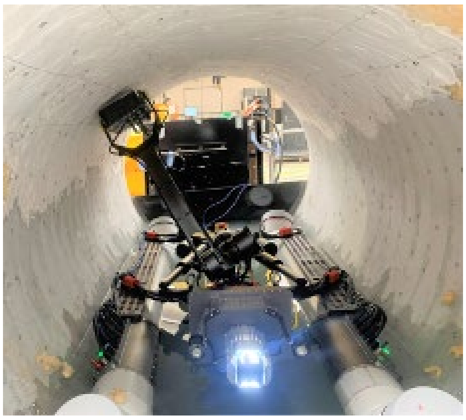

Figure 12: CRAFT V2 prototype.

REFERENCES

Wells, T., Melchers, R. 2016. Concrete sewer pipe corrosion findings from an australian field study. Proceedings of the Ozwater. Aust Water Association, Sydney, NSW, Australia.

Boon, A., Lister, A. 1975. Formation of sulphide in rising main sewers and its prevention by injection of oxygen. Prog. Wat. Tech. 7(2), 289–300.

De Muynck, W., De Belie, N., Verstraete, W. 2009. Effectiveness of admixtures, surface treatments and antimicrobial compounds against biogenic sulfuric acid corrosion of concrete. Cement Concr. Compos. 31(3), 163–170.

Shook, W.E., Bell, L.W. 1998. Corrosion control in concrete pipe and manholes. Tech-nical Presentation, Water Environmental Federation, Florida.