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Improved Laser Scan for Pitting Corrosion Measurement by Using Super Resolution Technique

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Abstract

To characterize the pitting corrosion of metallic pipe, high-resolution laser scan is indispensable. In many cases, only low-resolution scan can be obtained due to the limitations of the scanning equipment or time constraint. Although interpolation method can be applied to enlarge the low-resolution image, the enlarged laser scan loses the details of surface topography, which are important to calculate the parameters of pitting corrosion. In this paper, a single-frame super resolution method is proposed to infer a high-resolution laser scan from the low-resolution input. The relation between the low-resolution input and high-resolution result is modeled with a Markov random field (MRF) with the aid of a training set built in advance. A belief propagation algorithm is implemented to infer the super-resolved result. The experiments demonstrate a good performance of the proposed method in comparison with the traditional interpolation methods.

Keywords:

Ductile iron pipe, performance assessment, pitting corrosion, image super resolution, Markov random field

1. Introduction

Since 1960s, ductile iron (DI) became a popular pipe material in many municipalities, because the ductile iron pipe is stronger and easier to tap, requires less support and provides greater flow area than the pipe made from other materials. It is better than the PVC, concrete, polyethylene, or steel pipe in difficult terrain. Buried metallic pipes are subject to the pitting

corrosion by which cavities or holes are produced (Roberge, 2010). Pitting corrosion is known as a factor governing the pipes' long-term durability and is affected by many factors, including the electrochemical and physical properties of surrounding soils (Liu et al., 2008). However, the mechanism of pit growth has not been fully explored and understood. The quantification of the temporal and spatial distribution of pitting corrosion as well as the pitting growth rate still remains a challenge for pipe residual life prediction. It is of importance to quantify the pitting corrosion for further analysis such as understanding the relations between the current conditions of pipes and corrosion rates with existing soil properties (Najjaran et al., 2006; Kleiner and Rajani, 2001).

Laser rang / displacement sensors can accurately measure the surface of a sand blasted ductile iron pipe. From the acquired laser range image, the pitting corrosion can be further characterized or quantified with area, pit depth, percentage of material loss, etc. To accurately characterize pitting corrosion, highly dense range measurements (i.e. high-resolution laser scan/image) of pipe are desired. Since a laser scan system scans the pipe surface line by line, it is time consuming to acquire a high-resolution (HR) laser scan image. It may take half an hour to scan a half meter long pipe segment. If a shorter time of scan is expected, only a sparsely-scanned image (i.e. low-resolution laser scan/image) can be obtained. Thus, a solution, which can obtain a high-resolution scan in a short time, is preferred. Generating a high-resolution scan from the low-resolution one may solve this problem.

In past decades, extensive work has been carried out to enhance the resolution of laser images (Diebel and Thrun, 2005; Yang et al., 2007; Garro et al., 2009; Schuon et al., 2009, 2008; Jil et al., 2006). The resolution enhancement techniques for a laser image can be roughly classified into three categories: interpolation methods, multi-sensor super resolution, and multi-frame super resolution. Interpolation methods, which include the linear interpolation, polynomial interpolation, cubic interpolation, etc., are the simplest methods to generate a high-resolution image from the low-resolution one. However, detail of the surface roughness can be lost when interpolation techniques are used. Therefore, pitting corrosion cannot be accurately characterized. Multi-sensor super resolution combines a low-resolution laser scan and a high-resolution color image to infer the enhanced laser image. In (Diebel and Thrun, 2005; Yang et al., 2007; Garro et al., 2009), the authors presented a technique combining registered time-of-flight (ToF) image with its color counterparts acquired by high-resolution cameras. Figure 1 illustrates

the process of multi-sensor super resolution. However, the assumption that color is correlated with depth may not be correct. The quality of the result is poor when a discontinuity in depth is not visible in the color channel. Moreover, the registration of a color image and a laser scan still remains a challenge for computer vision research. Multi-frame super resolution exclusively uses multiple laser scans to improve the resolution. This method registered and fused multiple low-resolution laser scans of the same scene to achieve an improved resolution in the final result (Schuon et al., 2009, 2008; Jil et al., 2006). The multi-frame super resolution process is illustrated in Fig. 2. This method needs to scan the object couple of times and it is time consuming. The registration problem still exists.

Figure 1: Multi-sensor super resolution.

Figure 2: Multi-frame super resolution.

In this paper, a new method is proposed to enhance the resolution of laser scan in the application of pipe performance assessment. Different from multi-frame approaches, this method infers a high-resolution laser scan from a single laser scan of low resolution with the available information from a training set, which includes low- and high-resolution pairs of laser scans. The training set can be prepared in advance. Figure 3 is a schematic drawing of the process. In detail, interpolation operation is first applied to enlarge the input laser scan. A Markov random field model established with the laser scan pairs in the training set is employed to present the relation between the low-resolution input and expected high-resolution result. Belief propagation algorithm is implemented to infer the result, which is a super-resolved laser scan with more detailed information for pitting corrosion.

The rest of the paper is organized as follows. The laser scan system for the ductile iron pipe is described in section 2. Section 3 details the procedure to process the acquired laser scan. A new technique to enhance the resolution

Figure 3: Single-frame super resolution process.

of acquired laser scan is introduced. The experimental results on simulated and real pipe laser scans can be found in the section 4. The final section concludes this paper.

2. Laser scan system for pitting corrosion

As a part of a research project sponsored by American Water Works Association Research Foundation (AwwaRF) and National Research Council (NRC) Canada on long-term performance of ductile iron pipe, a field testing program was initiated to investigate the soil environment and determine the corrosion rates from selected locations for ductile iron pipe segments. To quantify pipe pitting corrosion, a scanning system was developed at the NRC Institute for Research in Construction (IRC).

The laser scan system consists of a laser displacement sensor head mounted on a linear track that travels parallelly to the pipe surface at distance of $50 \pm 10 \text{ mm}$. Figure 4(a) and 4(b) show the laser scan system and the laser displacement sensor respectively. Data obtained from the laser scanner is a measure of the distance (at an accuracy of $30 \text{ }\mu\text{m}$) from the known position of the scanner to a point on the external surface of the pipe. A data point is sampled every millisecond. The scanning system has the ability to accommodate pipe sections of up to 1050 mm in length with diameters that range from 100 mm to 400 mm . Each pipe section will be mounted on the scanning rig to scan the external pipe surface. The average time required to scan a pipe section with a 1.5mm resolution, ranges from 20 to 40 minutes, depending on diameter and length of the pipe.

Pipe scanning involves a back and forth movement of the laser displacement sensor mounted on a track that is placed parallel to the longitudinal pipe axis. When the laser sensor reaches either end of the pipe, the pipe rotates a specified amount. After the pipe is rotated, the scan continues in the opposite direction. For each data point the scanner records three pieces of data, longitudinal distance along the pipe x , pipe rotation θ , and the distance from the sensor head to the pipe surface ρ as illustrated in Fig. 5. The pipe scanning process terminates when the pipe has gone through one whole turn, i.e. θ reached 360 degrees. This is only in the case where the full pipe is being scanned. The user can select a subset of the pipe to scan. The

⁰Now, American Water Works Association Research Foundation is known as Water Research Foundation (WaterRF).

Figure 4: Laser pipe scanning system at NRC IRC.

scanning resolution depends on the self rotation amount and the linear track speed. The faster the track moves and the larger the increment of rotation, the lower the resolution. Therefore, the higher the resolution, the more time the scan takes.

Figure 5: Scanning data.

3. Processing laser scan

The overall procedure to process laser scan is shown in Fig. 6. Pre-processing is a step to remove the noise and correct the laser scan. The details of this process can be found in reference Liu et al. (2008); Rajani et al. (Will be published by WRF). The next step is the implementation of the proposed approach in this paper, which is to enhance the resolution of laser scan by using single-frame super resolution. A training set containing LR and HR

laser scan image pairs is built in advance. More details unavailable in a low-resolution laser scan image are learned from the high-resolution laser scan images in the training set. With the derived super-resolved laser scan image, we can obtain the corrosion parameters to analyze pipe corrosion rates and conditions, but this is beyond the scope of this paper. Readers are referred to report Liu et al. (2008) for the details.

Figure 6: The procedure to enhance laser scan image.

3.1. The general process

The process of a laser scan is in analogy to the formation process of a regular color image. A low-resolution laser scan S_L can be produced from its corresponding high-resolution S_H under the following generic model:

$$S_L = FS_H + n \quad (1)$$

where n denotes noises. In the super-resolution process of a regular color image, F usually consists of a down-sampling and a blur matrix (Jil et al., 2006). However, in this study we assume that F only refers to a down-sampling matrix. The super-resolution process for a laser scan image is to infer the high-resolution one from its low-resolution counterpart, which is acquired during the inspection. Solving S_H in Eq. (1), given S_L and F , is an ill-posed inverse problem, which means many S_H may satisfy the constraint of equation (1). We can formulate this as a maximum a posteriori (MAP) problem, which can be expressed as:

$$\hat{S}_H = \arg \max_{S_H} P(S_H | S_L) \quad (2)$$

According to the Bayes' theory, there is:

$$P(S_H|S_L) = \frac{P(S_L|S_H) P(S_H)}{P(S_L)} = \frac{P(S_L, S_H)}{P(S_L)} \quad (3)$$

where $P(S_L, S_H)$ is the joint probability of S_H and S_L . $P(S_L)$ is priori probability of S_L , which is a scaling factor. Therefore, Eq. (2) can be equivalently written as:

$$\hat{S}_H = \arg \max_{S_H} P(S_H, S_L) \quad (4)$$

Thus, the enhancement of a laser scan image converts to the problem of estimating S_H by maximizing joint probability $P(S_H, S_L)$.

In this study, a graphical model, namely Markov random field (MRF), is employed to model the relationship between the low-resolution input and the expected high-resolution result, i.e. super-resolved laser scan, with the information derived from the laser scans in the training set.

Since a single distance measure conveys little information and the distance measure in a laser scan is strongly correlated to its adjacent distance measures, we use image patch instead of single distance measure as the process unit for the laser scan. We assume that the super-resolved laser scan patch should satisfy two conditions: 1) similar to the formation process of laser scan, the down-sampled patches of the super-resolved laser scan should be similar to its low-resolution inputs; and 2) each super-resolved patch should be compatible with its adjacent patches to avoid block effect. Based on these conditions, the MRF model is built to model the relationship between the super-resolved laser scan and the low-resolution input patch by patch. Figure 7 illustrate the MFR structure, where each patch is represented as a node in the model.

To formulate these two conditions, two types of compatibility measurement are considered. One is the compatibility measurement ϕ between low- and high-resolution patches; the other is the compatibility measurement ψ between adjacent high-resolution patches. Specifically, the compatibility measurement ϕ is of the form:

$$\phi(\hat{S}_H^i, \hat{S}_L^i) = \exp \left(\frac{-|\hat{S}_H^i - \hat{S}_L^i|^2}{2\sigma_k^2} \right) \quad (5)$$

where $\hat{S}_H^i$ is a super-resolved high-resolution patch, and $\hat{S}_L^i$ is its down-sampled counterpart. The superscript i refers to the index of the patch. σ_k

Figure 7: Structure of Markov random field model.

a parameter in this equation. Equation (5) denotes that if $\hat{S}_L^i$ is more similar to the input low-resolution patch S_H^i , $\hat{S}_H^i$ will have a higher probability to be the super-resolved patch.

The compatibility measurement ψ can be expressed as:

$$\psi(\hat{S}_H^i, \hat{S}_H^j) = \exp\left(\frac{-|d_{ij} - d_{ji}|^2}{2\sigma_x^2}\right) \quad (6)$$

where $\hat{S}_H^i$ and $\hat{S}_H^j$ are adjacent patches overlapped with each other and d_{ij} is the overlapped area in $\hat{S}_H^i$. In contrast to d_{ij} , d_{ji} is the overlapped area in $\hat{S}_H^j$. Figure 8 shows the two adjacent patches and the overlapped area highlighted with shadow. Compatibility function ψ describes how adjacent patches agree with each other. If the overlapped areas of neighboring patches are more similar, the neighboring patches will be more compatible to be the super-resolved patches.

Figure 8: Adjacent patches and overlapped area.

In the MRF model, the joint probability over the low- and high-resolution laser scan can be written as (Freeman et al., 2002):

$$\begin{aligned}
\hat{S}_H^1, \hat{S}_H^2, \dots, \hat{S}_H^N &= \arg \max_{S_H} P(S_H, S_L) \\
&= \arg \max_{S_H^1, S_H^2, \dots, S_H^N} P(S_H^1, S_H^2, \dots, S_H^N, S_L^1, S_L^2, \dots, S_L^N) \\
&= \arg \max_{S_H^1, S_H^2, \dots, S_H^N} \prod_{N_b(i,j)} \psi(S_H^i, S_H^j) \prod_i \phi(S_H^i, S_L^i)
\end{aligned} \tag{7}$$

where S_H^i and S_L^i are the patches in S_H and S_L respectively. $N_b(i, j)$ indicates that patch i, j are neighbor patches and N is the number of patches.

To calculate Eq. (7), a process to estimate $\hat{S}_H^i$ needs to be defined. A straightforward way is to consider each patch of the high-resolution laser scan in the training set as one state of $\hat{S}_H^i$. Therefore, each node in the MFR model will have millions of states, which may introduce a very intensive load of computation. To tackle this problem, only certain number of high-resolution patches from the training set are considered as states of $\hat{S}_H^i$. To this end, we search for each S_L^i the most similar n patches $\hat{S}_L^t, t = 1, 2, \dots, n$ from the low-resolution patches in training set. Then the corresponding high-resolution patches $\hat{S}_H^t$ are considered as states of $\hat{S}_H^i$.

It is still difficult to calculate Eq. (7) directly and approximation could be a good solution in this case. Hence, an iterative algorithm named belief propagation (BP) is employed to infer the result. The BP algorithm is efficient and usually takes 3-4 iterations to converge. Readers are referred to reference (Freeman et al., 2002) for the details of the belief propagation algorithm.

3.2. Details of the procedure

The high-resolution laser scan can be expressed as:

$$S_H = E(S_L) + S_D \tag{8}$$

where $E(\cdot)$ refers to an interpolation function and S_D is the difference between S_H and the interpolated result from S_L . According to Eq. (8), inferring S_H is equivalent to inferring the difference image S_D . Thus, we can infer difference image S_D rather than inferring S_H directly. To estimate S_D , a feature map extracted from the input laser scan with a difference of Gaussian (DoG) filter is used to estimate S_D .

The overall enhancement process can be implemented in two steps: the training and the inferring step.

Training step. The training step is to build databases with the laser scan patches derived from the low- and high-resolution laser scan pairs in the training set. The training step is illustrated with the flowchart in Fig. 9. Usually this step can be accomplished in advance. Every laser scan pair in the training set is processed as follows:

1. Enlarge the input low-resolution image S_L to the same resolution of the high-resolution image S_H by an interpolation method.
2. Obtain the difference image S_D by subtracting the interpolated image ($E(S_L)$) from S_H .
3. Divide S_D into $N \times M$ patches, i.e. there are N and M patches for each row and column respectively, and all the patches are used to build a difference patch database D^H .
4. Use *DoG* filter to extract feature map for the enlarged image $E(S_L)$.
5. Divide the derived feature map into $N \times M$ patches, and all the patches are used to build a feature patch database D^L .

Inferring step. Inferring is the major step in the resolution enhancement for laser scan. The inferring step is illustrated in Fig. 10. The low-resolution input together with the two databases D^L and D^H are fed to the MRF model to infer the high-resolution result. The following processes are carried out:

1. Enlarge the low-resolution input image S_{TL} to the same zoom number as the training process.
2. Extract the feature map from the enlarged image $E(S_{TL})$ with a *DoG* filter.
3. Divide the feature map into $N \times M$ patches.
4. Search n most similar low-resolution patches $\hat{S}_L^t$, $t = 1, 2, \dots, n$ from D^L for each patch S_{TL}^i in S_{TL} . And find their corresponding high-resolution patches $\hat{S}_H^t$ from D^H .
5. Apply BP algorithm to infer difference image patches with the MFR model.
6. Integrate the patches obtained from previous step into the difference image S_{TD} .
7. Combine the inferred S_{TD} and $E(S_{TL})$ to generate the super-resolved image.

The output of the inferring step is the super-resolved laser scan.

Figure 9: The training step of resolution enhancement for laser scan.

Figure 10: The inferring step of resolution enhancement for laser scan.

4. Experimental results

In the experiments, we tested the proposed method on simulated and real laser scan of a ductile iron pipe. The first experiment is with the simulated pipe laser scan. In this experiment, we only have real high-resolution laser scans, whose low-resolution counterparts can be obtained by down-sampling operation. The laser scans were acquired from the field scan of ductile iron pipe segments in Louisville, Kentucky, USA. The spatial resolution is 1.5 mm/pixel along the longitudinal and latitudinal directions.

We randomly selected twenty laser scans as high-resolution images in the training set. These images were down-sampled to resolution 3, 6, 9, 12, and 15 mm/pixel along both directions. The down-sampled images were used as the low-resolution counterparts. Another five randomly picked-up laser scans were down-sampled and used as inputs. The resolution enhancement results from 3 and 6 mm/pixel to 1.5 mm/pixel are given in Fig. 11 and 12 respectively. The linear and cubic interpolation methods were also applied for comparison. However, these two methods blurred most of the details of the laser scan while the super-resolved laser scan obtained with the proposed method reflects most details.

To understand the performance of these methods, the root mean squared error (RMSE) was computed for the obtained results and listed in Table 1. The RMSE between the enhanced laser scan and its high-resolution reference is defined as:

$$\text{RMSE} = \sqrt{\frac{\sum_{i,j} (S_o(i,j) - S_e(i,j))^2}{MN}} \quad (9)$$

where $S_o(i,j)$, ($i = 1, 2, \dots, N$; $j = 1, 2, \dots, M$) is the high-resolution laser scan image of size $M \times N$. $S_e(i,j)$ is the super-resolved laser scan image. A small RMSE value indicates a better result.

Table 1: Comparison of resolution enhancement methods with simulated laser scan.

Resolution (mm/pixel)	Root mean square error		
	Linear interpolation	Cubic interpolation	Proposed method
3	0.377	0.386	0.254
6	0.548	0.580	0.378
9	0.629	0.673	0.501
12	0.647	0.689	0.547
15	0.659	0.705	0.571

(a) Down-sampled laser scan

(b) Linear-interpolated result

(c) Cubic-interpolated result

(d) Super-resolved result

(e) High-resolution reference

Figure 11: Resolution enhancement results (with simulated laser scan from 3 mm to 1.5 mm) achieved with (a) linear interpolation, (b) cubic interpolation, and (c) the proposed method. The reference laser scan is shown in (e).

(a) Down-sampled laser scan

(b) Linear-interpolated result

(c) Cubic-interpolated result

(d) Super-resolved result

(e) High-resolution reference

Figure 12: Resolution enhancement results (with simulated laser scan from 6 *mm* to 1.5 *mm*) achieved with (a)linear interpolation, (b) cubic interpolation, and (c) the proposed method. The reference laser scan is shown in (e).

The second experiment deals with “real” examples. The pipe segment was scanned at resolution 1.5, 3, 6, 9, 12 and 15 $mm/pixel$ in both directions. The laser-scan of resolution 1.5 $mm/pixel$ served as high-resolution reference while the others were used in low-resolution inputs. The training set generated in the first experiment was still used in this experiment. Figure 13 and 14 show the enhanced results with resolution increased from 3 and 6 $mm/pixel$ to 1.5 $mm/pixel$. More details were presented in the super-resolved results. Table 2 listed their corresponding RMSE results.

In both experiments, the proposed method achieved the best results in terms of the RMSE. We also can find that the RMSEs in first experiment (with simulated data) are smaller than the RMSEs in second experiment (with real world data). That is because in first experiment, we only have the high-resolution laser scans. Their low-resolution counterparts are obtained through down-sampling. In this process, there is no noise introduced. However, in second experiment both the high- and low-resolution laser scan images are acquired through different scanning processes, which inevitable result some noise and increase the RMSE value.

Table 2: Comparison of resolution enhancement methods with real laser scan.

Resolution ($mm/pixel$)	Root mean square error		
	Linear interpolation	Cubic interpolation	Proposed method
3	0.564	0.573	0.400
6	0.871	0.888	0.642
9	0.933	0.951	0.877
12	1.18	1.222	0.983
15	1.31	1.366	1.075

The quality of the enhanced laser scan image degrades with the decreased resolution of the input. Most details are preserved in the enhanced laser scan image, whose resolution is increased from 6 $mm/pixel$ to 1.5 $mm/pixel$. The proposed method can restore most of the characters of the pitting corrosion from the training set only if the corroded areas are large enough. However, when the resolution of the input laser-scan is lower than 6 mm , the pitting corrosion cannot be restored.

5. Concluding remarks

In this paper, we present a new method to enhance the resolution of pipe laser scan. Different from other enhancement approaches, the proposed

(a) Down-sampled laser scan

(b) Linear-interpolated result

(c) Cubic-interpolated result

(d) Super-resolved result

(e) High-resolution reference

Figure 13: Resolution enhancement results (with real laser scan from 3 mm to 1.5 mm) achieved with (a) linear interpolation, (b) cubic interpolation, and (c) the proposed method. The reference laser scan is shown in (e).

(a) Down-sampled laser scan

(b) Linear-interpolated result

(c) Cubic-interpolated result

(d) Super-resolved result

(e) High-resolution reference

Figure 14: Resolution enhancement results (with real laser scan from 6 *mm* to 1.5 *mm*) achieved with (a) linear interpolation, (b) cubic interpolation, and (c) the proposed method. The reference laser scan is shown in (e)

method infers a high-resolution laser scan from the low-resolution input with the aid of a train set by using single-frame super resolution. The super-resolved laser scan has a better quality compared with those obtained by traditional interpolation methods in terms of root mean square error. This super-resolution based enhancement can achieve the same quality as high-resolution scan while save the pipe scanning time. It typically takes $3 \sim 5$ minutes to scan a pipe segment, which originally needs $10 \sim 20$ minutes to complete the scan.

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