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A Rust Removed Region Detection for Automated Rust Detection during Grinding Work Process

Yang Tian[1] and Shugen Ma[2]

***Abstract*— In the maintenance task of steel-made infrastructure, such as bridges and towers, the rust removing process is one of the most dangerous and hard works for human beings. The robotic systems can provide a more efficient way to accomplish the tasks. However, the existing robotic systems cannot automatically remove the rust according to the rusted area condition during the rust removing process. As part of the solution, several rust detection methods were proposed. Although they can inspect the rust from a given image, the condition changes during the rust removing process affect the result obviously, which makes them difficult to be utilized in the real application. In our previous research, a rust detection method utilizing a sequence of digital images was proposed by observing the rusted area conditions during the rust grinding process. However, the ROI (Region of Interests) need to be manually set to estimate the change of the rusted area in the previous method. In this paper, we propose a method to determine the cleaned rusted region by an image processing technique with a low pass signal filter. The experiments were conducted on the developed rust grinding platform to show the validity of the proposed method.**

***Index Terms*— Automatic Rust Removing, Rust Detection, Grinding.**

I. Introduction

The collapses of the steel infrastructure are reported worldwide since the ageing problem. A steel bridge named I-35W Mississippi River Bride is collapsed in 2007, which caused a tragic loss of lives and a major disruption of the transportation system. The deterioration of the steel-made infrastructure is most visibly observable in the form of rust [1], [2]. The rust removing is one of important processes in the maintenance work to keep the safety of the facility.

For reducing the burden in the manual labour of rust removing, various robotics systems were developed. For example, the Automated Abrasive Blasting System [3], and the Autonomous eXploration to Build a Map [4] can remove the rust in the manually selected area. Since the work heavily relies on the subjective human vision, it is still not efficient in terms of time and cost.

For realizing the rust detection automatically, several methods [5]–[11] have been proposed to identify the rusted areas in the given images. Without considering the condition changes in the real rust removing process, these methods have shown their potential to apply in the inspection tasks. However, these methods cannot detect the rust during the work process. In our previous research [12], a rust detection method was proposed to robustly

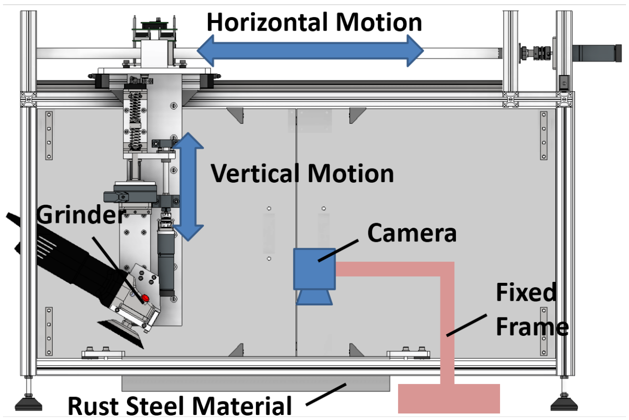

Fig. 1. The grinding robot platform for the rust removing task.

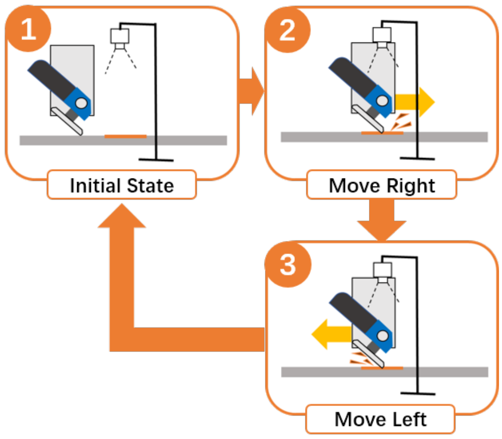

Fig. 2. The horizontal motion in each grinding process.

detect the rusted area during the rust grinding process. Although the experiments result showed its validity, the ROI (Region of Interest) from the original camera image needs to be manually set, which is not efficient in the real working condition.

In this paper, a method is proposed to realize a rust removed region detection for the rust detection during the grinding process. The qualified image without the grinder appeared is utilized as the input of the method. With the image processing technique, the edge of the cleaned region is transferred as a signal. By performing a low-pass filter on the signal, the estimated edge of the cleaned region can be obtained. The experiments were conducted on a developed grinding robot platform to show the validity of the proposed method.

This paper is organized as follows. In Section II, we introduce the rust grinding platform and the rust detection method. In Section III we introduce the proposed rust

[1]Y. Tian is with the Department of Robotics, Ritsumeikan University, Shiga, 525-8577, Japan. `tian@fc.ritsumei.ac.jp (Y. Tian)`

[2]S. Ma is with the Department of Electrical Engineering and Automation, Tianjin University, 300072, China. He is also with the Department of Robotics, Ritsumeikan University, Shiga, 525-8577, Japan. `shugen.ma@ieee.org (S. Ma)`

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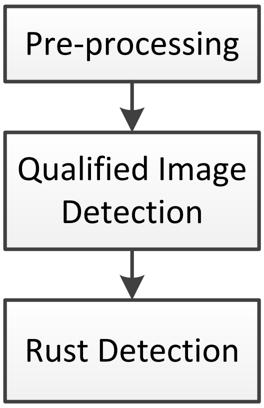


Fig. 3. The workflow for the robust rust detection method.

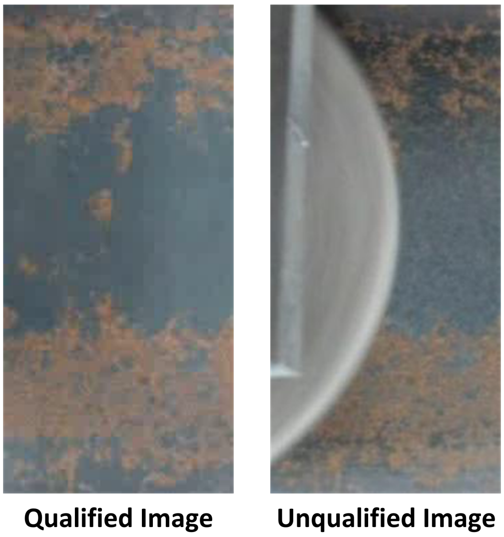


Fig. 4. The example of the qualified image and the unqualified image.

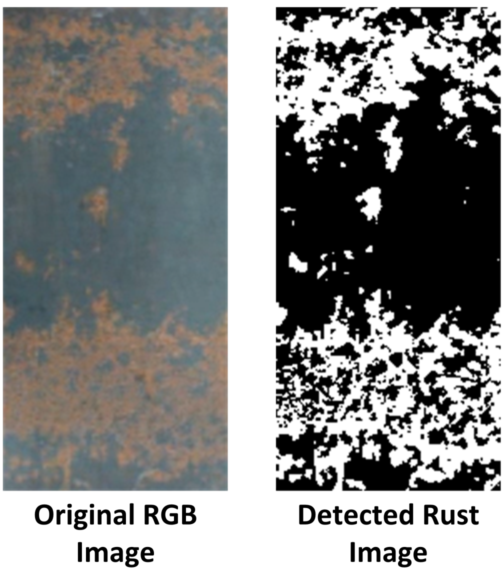


Fig. 5. The example of the robust rust detection result.

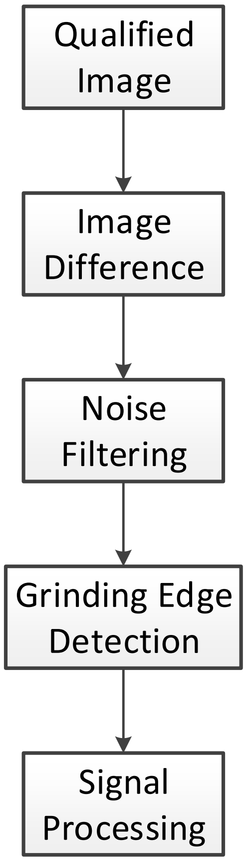


Fig. 6. The workflow for the rust grinding area detection.

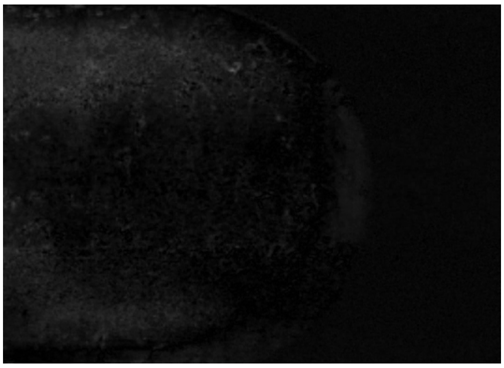
removed region detection method with an example. In Section IV, we show the results of the experiments in the developed grinding platform. The conclusion is presented in Section V.

II. Rust Grinding Platform and Rust Detection

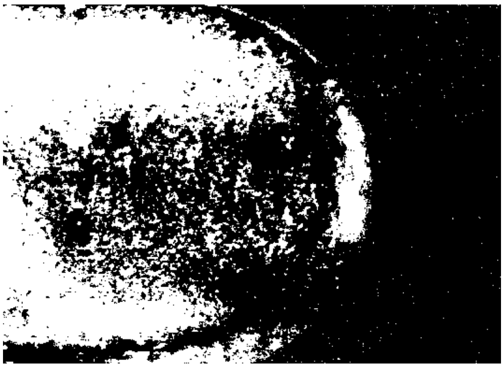
A rust grinding robot platform which can remove the rust on a flat steel surface has been developed with a movable grinder, as shown in Fig. 1. The rusted steel material can be placed on the bottom of the platform. The grinder can be moved in the vertical direction and the horizontal direction with two individual actuators. In the vertical direction, a force sensor is mounted to measure the pressing force of the grinder. A camera is fixed on a base without vibration. The camera faces the surface of steel material to observe the condition of the rusted area.

In each grinding time, the mounted grinder is moved horizontally with a rotating brush, as shown in Fig 2. The grinder is moved between the initial position and the desired position. The range of the motion and the speed of the motion can be set according to the requirement. The horizontal position estimation on the platform is realized by using the mounted distance laser sensor. The PD control of the motor with the encoder feedback is applied for the horizontal speed control.

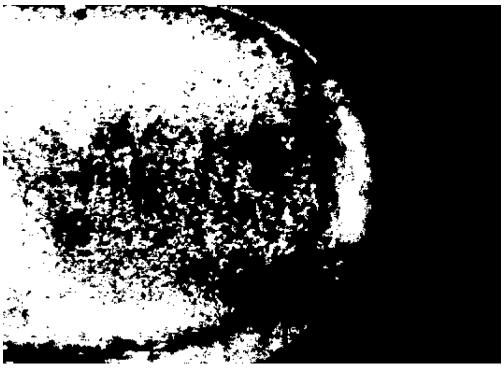
In our previous rust detection method, the workflow can be divided into three parts, as shown in Fig. 3. Firstly, the



(a)



(b)



(c)

Fig. 7. The example of the output image in each step. (a) Image Difference (b) Binarization (c) Noise Filtering

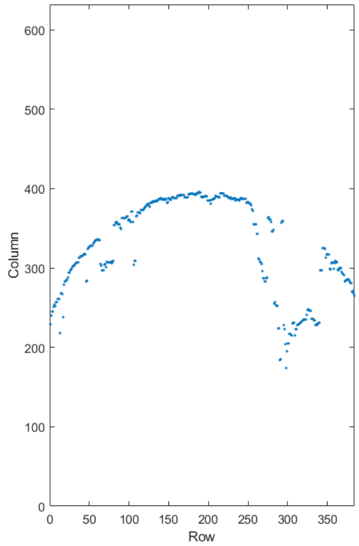


Fig. 8. The example of the grinding edge detection result.

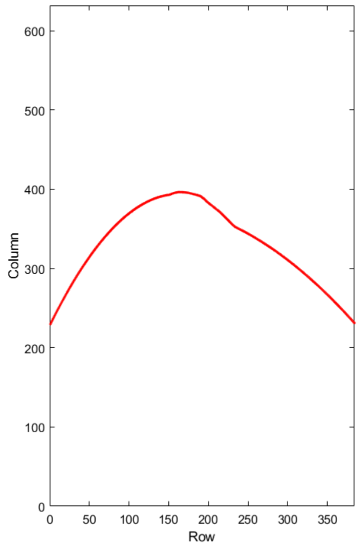


Fig. 9. The example of the smoothing filtered result.

original RGB camera image is pre-processed to obtain a monocular image within the ROI. This step is called pre-processing. Secondly, the pre-processed image is further processed to obtain a metric value to judge whether the grinder is projected in the image. The step is named Qualified Image Detection (QID). If the grinder is shown in the image, the image is judged to be an unqualified image. On the other hand, the image only showed the rusted steel plate is the qualified image. An example of the qualified image and the unqualified image is shown in Fig. 4. Finally, the qualified image is processed to estimate the amount of rust in the image, as shown in Fig. 5. This

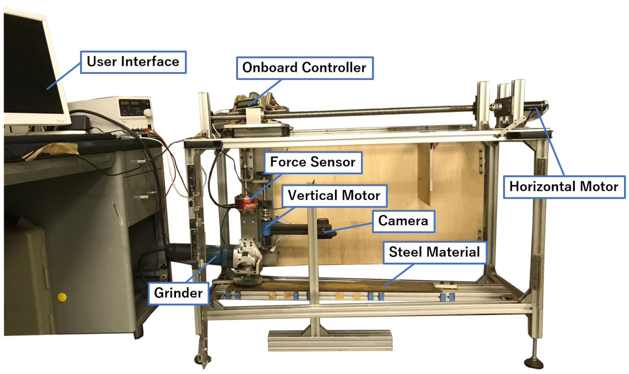


Fig. 10. The developed grinding robot platform utilized in the experiments.

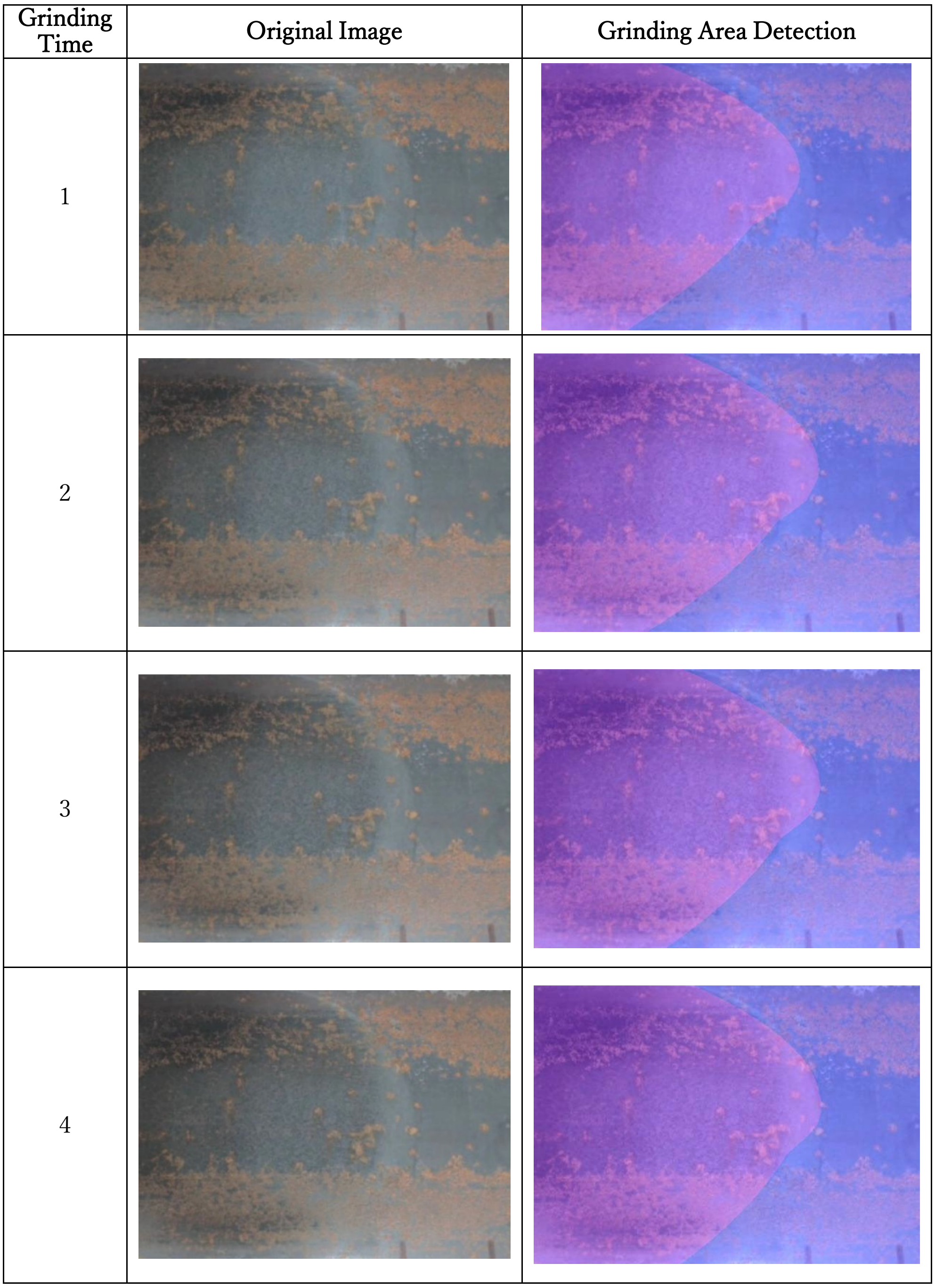


Fig. 11. The developed grinding robot platform utilized in the experiments.

step is called rust detection. In this step, the brightness unifying technique is applied to deal with intensity non-uniformity problem. The detected rust image is a binaries image, which the white pixels represent the rusted area. In this part, the effect of the rust powder produced by the grinding process is decreased by processing the current image with the previous image.

III. Automated Rust Removed Region Detection

In our practical experiments, we found that the selective of ROI is not convenient since the rust removed region is changed during the grinding process. As a solution, the function of ROI is realized by a grinding region detection method to automatically detect where the rust has been cleaned.

The principle of the method is to check the change of the rusted area during the grinding process to estimate the grinding region in the given image. Technically, an image comparison between the initial image and the image after the grinding is the key point of the method.

The workflow of the method is shown in Fig. 6. The qualified image (the image without grinder) is selected as the input of the method. With calculation of the absolute difference between the pixel intensity of the qualified image and the initial image, the change of the steel plate

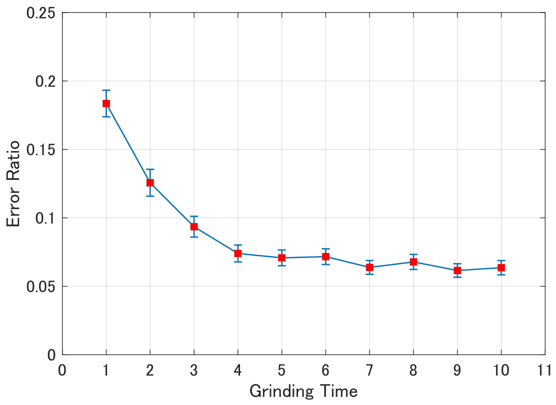


Fig. 12. The error ratio of the result of the grinding area detection according to the grinding time.

after the grinding process can be obtained. The example of the absolute difference image is shown in Fig. 7(a). It is clear to see that the image difference is not obvious since the amount of the removed rust is small. The binarization need to be performed to acquire a more specific result.

After the binarization with a suitable threshold, the image shown the result of image difference can be generated. The example of the binarization result is shown in Fig. 7(b). It is clear to see that some noise is exist in the generated image. This kind of noise comes from the generated rust powder attached to the steel plate. For preventing the effect of the image noise in the grinding region estimation, a noise filter is applied to the output image.

In the noise filtering, an opening closing process is performed. The example of the noise filtering result is shown in Fig. 7(c). Since the image difference is highly depends on the position of the rusted area, it is difficult to obtain a continuous area from the image processing to estimate the grinding region. Instead, we try to estimate the edge of the grinding region. Since the rusted area is not continuous, it is still difficult to acquire a continuous edge of the grinding region with the existing edge detection method. A technique utilizing transfer the image to a signal to obtain the continuous edge is performed.

The grinding edge detection process obtain the first true pixel (equal to 1) from the opposite direction of the grinding direction in the image and transfer it to a signal. The x axis of the signal is the row of the image. The y axis of the signal is the column of the image. The example of the grinding edge detection result is shown in Fig. 8. It is clear to see that the edge is not continuous in some parts. For smoothing this signal, the Savitzky Golay Finite Impulse Response smoothing filter [13] is applied to obtain a smooth edge of the grinding region. The example of the smoothing filtered result is shown in Fig. 9. It is clear to see that the a smooth estimated edge of the grinding region is obtained.

IV. Experiments

For showing the performance of the proposed method, experiments were conducted on the developed grinding robot platform, as shown in Fig. 10.

The result of the rust grinding region detection in first 4 times grinding process is shown in Fig. 11. In the row of Grinding Area Detection, the blue mask on the image represents the uncleaned region. The purple mask on the image represents the cleaned region by the grinder. Although the difference between the original images in each grinding time is not obvious, the result of the grinding region detection changes according to the grinding time.

With the calculation of the difference between the estimated edge of the grinding region and the ground truth in each column in the image, the error ratio can be obtained by the ratio of the difference and the row size of the image.

The error ration according to the grinding time is shown in Fig. 12. The red points represent the mean error ratio in each image, and the error bars mean the 95% confidence intervals of the t-distribution of the error. It is clear to see that the estimation accuracy is increased according to the grinding time. This phenomenon is easy to understand since more rust is removed with more grinding times. It causes the difference between the initial image and the image after the grinding process becomes larger according to the grinding time.

V. Conclusion

In this paper, a rust grinding region detection method for the rust detection during the grinding process is introduced. The image processing techniques and the signal processing techniques are applied to automatically detect the grinding region. The experiments with the developed rust grinding platform were conducted. The performance was analyzed with the ground truth to show the accuracy of the method.

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