RUST SURFACE AREA DETERMINATION OF STEEL BRIDGE COMPONENT FOR ROBOTIC GRIT-BLAST MACHINE

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ABSTRACT

There has been increasing interest in the use of robotic machines, and several prototype robotic machines have been developed to automate the grit-blasting process for the purpose of steel bridge maintenance. To utilize such a robotic grit-blast machine effectively, the first consideration is automating the determination of the rust surface area to blast, on the basis of standards of practice, in a rapid manner. This study aims to propose a method to rapidly and accurately determine the rust surface area on steel bridges to blast, with consideration for the standards of practice, from images acquired via a blasting machine. The first step is to perform a color space conversion to transform the input image from a red/green/blue (RGB) color space to a hue/saturation/intensity (HSI) color space. The next step is to detect the presence of rust, using pixel-level classification via the C4.5 decision tree algorithm. Then it is necessary to confirm the blasting area by verifying whether the rust detection result satisfies the specified criteria on the basis of standards of practice. The proposed method was validated on 39 test images with various characteristics with respect to the degree of rusting and rust distribution type. The experimental results showed that the average accuracy rate of rust area classification was about 97.63%, and the success rate of the final decision of blasting area determination was 100.00% for 39 test examples. The whole processing time took an average of only 0.86 seconds per image. The preliminary results demonstrated that the proposed method not only determined whether rust was present in an image and the amount of rust but also indicated whether blasting was necessary, and, if necessary, it rapidly specified the rust surface area that should be blasted on the basis of standards of practice. The proposed method could be successfully incorporated into a robotic grit-blast machine.

KEYWORDS

Robotic grit-blast machine, Rust detection, Rust surface area determination, Steel bridge inspection and maintenance, Surface painting

INTRODUCTION

The deterioration of a steel bridge surface is most visibly observable in the form of rust (Chen et al., 2011; Lee, 2011). Rust decreases the coating quality, which can affect the service life of a steel bridge (To et al., 2010; Paul et al., 2011). If the surface rust on a steel bridge is not removed, it can severely reduce the structural strength of the bridge, which is the primary cause of failure in such bridges (Shih et al., 2006; Liu et al., 2008). Therefore, the surface rust should be removed, and then the blasted area should be repainted. In practice, such rust removal is done by manual grit-blasting; however, it is dangerous because workers are exposed to harmful substances, including lead and asbestos (To et al., 2010; Paul et al., 2011). Furthermore, manual grit-blasting is an extremely labor-intensive and time-consuming process (Liu et al., 2008). When considering the number of steel bridges that must be maintained, the problem becomes much worse.

To solve this problem, there has been increasing interest in the use of robotic machines, and several grit-blast machines have been developed to automate the grit-blasting process. Examples of these machines include the Robotic Bridge Maintenance System (Lorenc et al., 2000), Automated Abrasive Blasting System (Echt et al., 2000), and Autonomous eXploration to Build a Map System (Paul et al., 2011). Typically, these machines automatically blast a defined rust surface area selected by a remote operator based on a map obtained through sensors mounted on the robotic machines. Because the remote manipulator relies heavily on subjective human vision to select the rust area for grit-blasting, it is difficult to select an accurate and optimized area (Shih et al., 2006). Moreover, such a manual process is repetitive; as a result, it remains ineffective in terms of time and cost. Therefore, in utilizing a robotic grit-blast machine, the first consideration is the automation of the determination of the rust surface area for blasting.

In recent years, several studies have proposed methods to automatically detect rust on a steel bridge (for example, Lee et al., 2006; Chang et al., 2011; Ghanta et al., 2011; Chen et al., 2012). These studies show the potential for automatic rust detection via image processing techniques in an outdoor environment that includes various disturbances, such as illumination variance and various rust colors. However, there is a lack of consideration of time spent to detect the presence of rust in the image. Because steel bridges may have considerable surface areas, the rust detection process should be capable of near real-time performance. Although near real-time rust detection is desirable, previous studies have focused solely on rust detection accuracy.

In addition, a common limitation of these studies is the lack of consideration of practical requirements. In practice, the determination of the area to blast is accomplished based on the standards of the American Society for Testing and Materials (ASTM, 2012) and the Steel Structures Painting Council (SSPC, 2000). According to these standards, the percentage of rusting as well as the rust distribution type are considered in determining the rust surface area for blasting. Although there is a need for a subsequent procedure and method to determine automatically and objectively the area to blast, based on the standards, previous studies have limited themselves to detecting the presence of rust in the image.

The aim of this study is to propose a method for reliable and near-real-time determination of the rust surface area to blast from images acquired via a camera mounted on a robotic grit-blast machine on a steel bridge. The following chapter describes the framework of the proposed rust surface area determination method. The next section then presents the experimental results obtained through the proposed framework. The paper closes with conclusions and recommendations for future research.

FRAMEWORK OF THE PROPOSED RUST SURFACE AREA DETERMINATION METHOD

The proposed method not only determines whether rust is present in an image, along with the amount of rust but also indicates whether blasting is necessary and, if necessary, where blasting should be performed. First, a color space conversion transforms the input image from an RGB color space to an HSI color space. Then pixel-level classification is performed to detect the presence of rust. For this process, we need to choose the most appropriate classifier to use, achieving both speed and performance. Therefore, this study selects the best classifier by computing and comparing the performance of rust classification models from six different classifiers via 10-fold cross validation. The classifier selection process is performed only once. After that, the rust surface area is determined by verifying whether the rust detection result satisfies the specified criteria. The specified criteria used in this approach are based on the degree of rusting on a scale of 0 to 10 and the rust distribution type (i.e., spot rusting, general rusting, and pin-point rusting) as defined by the ASTM (2012), also referred to in Chen et al. (2012), and the SSPC (2000). A detailed description of the processes and methods are provided in the following sections.

Color Space Conversion

The robotic grit-blast machine for steel bridge maintenance acquires color images in an outdoor environment, where the appearance of objects is affected by changes in illumination and causes false detection. Therefore, the acquired image is converted to the HSI color space, which is invariant to illumination changes (Wesolkowski, 1999). The RGB color space can be converted to the HSI color space using the following formula (Cheng et al., 2001):

$$H = \arctan\left(\frac{\sqrt{3}(G-B)}{(R-G)+(R-B)}\right), S = 1-\frac{\min(R,G,B)}{I}, I = \frac{(R+G+B)}{3}$$

Classification of Rust Area

To detect the presence of rust in the input image, a rust classification model is trained from the training set. Then the trained classification model is used to classify each pixel in the input image as belonging to rust or the background. In this study, the rust classification model is trained via the best classifier in terms of speed and performance. For this purpose, this study considered a total of six different classifiers—support vector machine (SVM), artificial neural network (ANN), decision tree (C4.5), naïve Bayesian (NB), logistic regression (LR), and k-nearest neighbor (KNN)—which are grouped into the categories of support vector machines, neural networks, tree-based methods, statistical approaches, and nearest-neighbor methods (Lessmann et al., 2008). To select the most appropriate classifier for the classification of rust areas, a total of 8,792,081 rust pixels and 14,978,012 background pixels were collected. Then, the rust and background pixels were resampled into 100,000 pixels each.

Using the data set comprising the 100,000 rust pixels and 100,000 background pixels, we evaluated SVM, ANN, C4.5, NB, LR, and KNN via 10-fold cross validation and compared their performances. Table 1 summarizes the evaluation results of the six classifiers in terms of the cross-validation accuracy and test time.

Table 1 – Accuracy and speed performance comparison of six different classifiers

Classifier	Accuracy Rate (%)	Test Time (s)	Classifier	Accuracy Rate (%)	Test Time (s)
SVM	91.58	911.98	NB	78.56	1.36
ANN	86.38	0.55	LR	63.96	0.64
C4.5	97.39	0.56	KNN	96.86	1,642.12

Figure 1 illustrates the results of this comparison on a two-dimensional (2D) chart. The x-axis of this chart is the accuracy rate, and the y-axis is the logarithmic scale of the test time. Among them, the C4.5 decision tree algorithm is at the far bottom right area of this chart. Compared with all classifiers, C4.5 was much faster and also more accurate. As a result, C4.5 was selected as the best classifier for our method and the rust classification model is trained via the C4.5 decision tree algorithm.

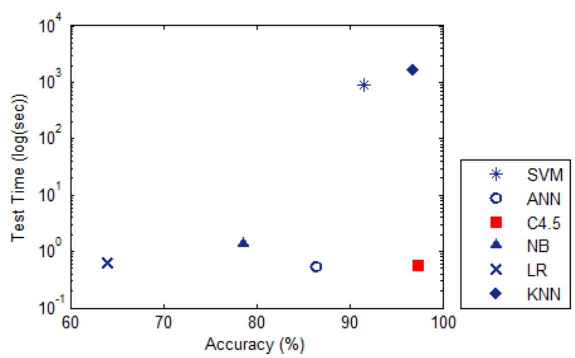


Figure 1 – Accuracy and speed performance comparison of six different classifiers

Determination of Blasting Area

The previous step classified the presence of rust in the image at the pixel level. This indicates where rust exists, but does not determine whether or where to blast. In practice, the percentage of rusting and the rust distribution type in the image are considered in determining whether blasting the surface in the image area is necessary in whole, in part, or at all. In this study, by computing the percentage of rusting and the rust distribution type in the image, the final decision of determining the area to blast is made automatically. First of all, the percentage of rusting in the image is computed by calculating the percentage of rust pixels compared with the total number of pixels in an image. Then, the result is categorized into eleven cases—degree of rusting from 0 to 10—which the ASTM defines in document D610 for standard practices for evaluating the degree of rusting on painted steel surfaces (see Table 2) (ASTM, 2012).

According to the practices, if the image contains less than 0.3% rust pixels (the image is categorized as a degree of rusting from 7 to 10), the final decision—that blasting is unnecessary—is made immediately, without further processing (Tam and Stiemer, 1996). If the image contains more than 33.3% rust pixels (degree of rusting from 0 to 2), the final decision—that blasting is wholly necessary—is made immediately, without further processing (Tam and Stiemer, 1996). If the image contains equal to or more than 0.3% and equal to or less than 33.3% rust pixels, the rust distribution type should be further considered to make a final decision.

Table 2 – Scale and description of rust ratings (ASTM, 2012)

Degree of Rusting	Description
10	No rust or less than 0.01% rust
9	Minute rust, less than 0.03% rust
8	Few isolated rust spots, less than 0.1% rust
7	Less than 0.3% rust
6	Extensive rust spots, less than 1% rust
5	Less than 3% rust
4	Less than 10% rust
3	Approximately 1/6 of surface rusted
2	Approximately 1/3 of surface rusted
1	Approximately 1/2 of surface rusted
0	Approximately 100% of surface rusted

Once the image is categorized as having equal to or more than 0.3% and equal to or less than 33.3% rust pixels (degree of rusting from 3 to 6), the image is examined further to determine its type of rust distribution. According to the ASTM (2012) and the SSPC (2000) standards, rust distribution types are divided into three groups: spot, general, and pin-point rusting. Spot rusting consists of rusting concentrated in a few localized areas (see Figures 2(a) and 2(d)). General rusting consists of rusting with rust spots of various sizes and shapes that are randomly distributed across the surface (see Figures 2(b) and 2(e)). These two types of rusting have characteristics that occur locally in a few areas; therefore, blasting is necessary only for the rusted areas. Unlike spot or general rusting, pin-point rusting consists of small, isolated spots of rust that are distributed across the surface. An example of this type of rust distribution is depicted in Figures 2(c) and 2(f). If pin-point rusting has occurred, corrosion has spread across the entire image, so blasting is necessary for the whole image, because corrosion will continue.

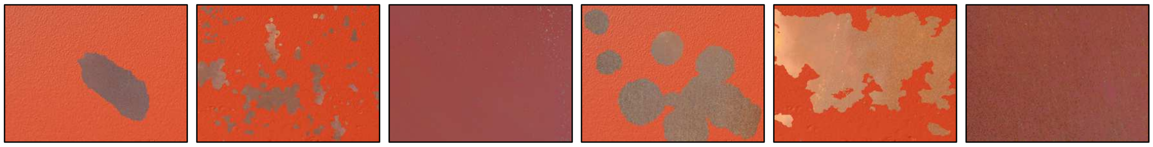
To determine the rust distribution type, this study uses density, a geometric feature, to understand the characteristics of the image (El-Naqa et al., 2004; Wei et al., 2009). From the three-dimensional (3D) histogram of different rust distribution types, given that the bin size is 15×15 pixels, we found that, unlike the spot or general rusting types, a 3D histogram of pin-point rusting is spread over a relatively smaller range of values. Density is measured by the standard deviation of the rust pixels' distribution in the 3D histogram, then use a threshold value to determine whether the type of rust distribution is pin-point rusting or not (spot or general rusting). A pre-defined threshold value was obtained from the experiment and was set to 20. If the calculated density value of the rust detection result is less than 20, the rust distribution type of the image is determined to be pin-point rusting. In this case, the final decision is made that blasting is wholly necessary. If the calculated density value of the rust detection result is equal to or more than 20, the rust distribution type of the image is spot or general rusting. The final decision is made by providing the exact areas in the form of a pixel to blast.

EXPERIMENTAL RESULTS

An experiment was performed to validate the effectiveness of the proposed method for rust surface area determination. To collect representative rust samples for the experiments, images were acquired by keeping the grit-blast machine 0.4m from the steel component surface under various illumination conditions. The color images acquired by the digital camera had a resolution of 480×640 pixels. Rust images were made by manually cropping rust regions based on the rust distribution type defined in the ASTM (2012) and SSPC (2000) standards from each image with a resolution of 480×640 pixels. Background images were collected by manually selecting images without rust acquired from red and brown steel bridges which have not yet been validated by research.

Among the images, we combined the rust pixels in one image with a resolution of 480×640 resolution and background images with a resolution of 480×640 pixels for use as test images. To generalize the validation result, the experiment was designed to cover various possible cases in terms of the degree of rusting and the rust distribution type. A total of 39 test images were selected, showing different degrees and types of rust distribution. Figure 2 shows six examples among 39 test images used in our experiment.

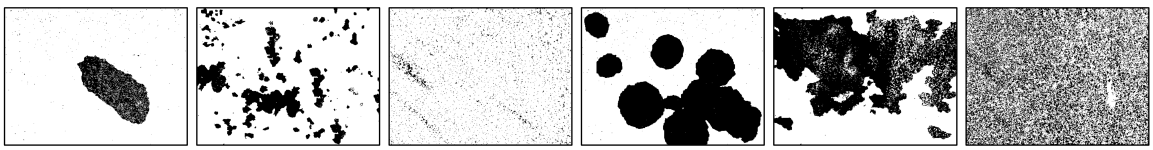
As the first step of the proposed method for rust surface area determination, the color space conversion was performed to transform the image from the RGB color space to the HSI color space for each image.



(a) (b) (c) (d) (e) (f)

Figure 2 – Six test examples: (a) Spot rusting (10.93%); (b) General rusting (16.46%); (c) Pin-point rusting (2.74%); (d) Spot rusting (36.93%); (e) General rusting (55.30%); (f) Pin-point rusting (45.86%)

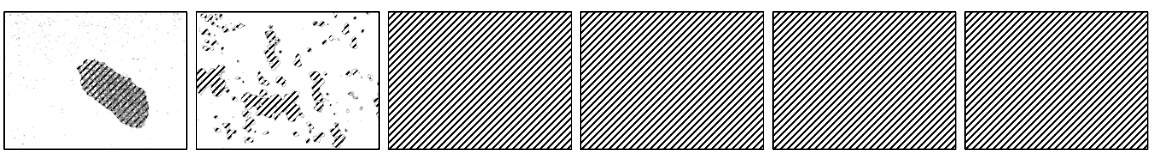
The trained classification model via the C4.5 decision tree algorithm was used to classify each pixel in the test images as belonging to rust or the background. For 39 test images, the average rust detection accuracy rate was 97.63% (the standard deviation was 2.29). Figure 3 shows the results of rust area classification for six examples illustrated in Figure 2.



(a) (b) (c) (d) (e) (f)

Figure 3 – Results of rust area classification for six test examples, accuracy rate of: (a) 97.89%; (b) 99.72%; (c) 98.82; (d) 99.87%; (e) 92.43%; (f) 94.65%

Once classification of rust area was done, the results were further processed to determine the rust areas to blast. Figure 4 shows the results of blasting area determination for six examples from rust area classification results illustrated in Figure 3. The diagonal stripes visually represent the rust surface area to be blasted. The degree of rusting (7 to 10, 3 to 6, and 0 to 2) and the rust distribution type of the image (spot, general, or pin-point rusting) allow six cases in total. The final decision is broadly divided into three categories: blasting is unnecessary, blasting is necessary in the whole image, and blasting is necessary only for specified areas.



(a) (b) (c) (d) (e) (f)

Figure 4 – Blasting area determination results: (a) Necessary only for specified areas; (b) Necessary only for specified areas; (c) Necessary in the whole image; (d) Necessary in the whole image; (e) Necessary in the whole image; (f) Necessary in the whole image (Note: The diagonal stripes represent the rust surface area to be blasted.)

Table 3 shows the success rate of the final decision of blasting area determination for each of the six cases in terms of the degree of rusting and the rust distribution type.

Table 3 – Success rate of the final decision of blasting area determination (The number of images yielding correct decisions/the number of test images)

Rust Type / Degree of Rusting	Spot or General	Pin-Point
7 to 10	4/4, 100%	2/2, 100%
3 to 6	7/7, 100%	7/7, 100%
0 to 2	12/12, 100%	7/7, 100%

Table 4 shows the average processing time for 39 test examples. In summary, the average processing time from color space conversion to blasting area determination took less than one second on average, requiring only 0.86 seconds (the standard deviation was 0.07). From a practical viewpoint, one can conclude that the proposed method can be used to determine rapidly and accurately the rust surface to blast from the image.

Table 4 – Statistical data on the performance of the proposed method for rust surface area determination

Color Space Conversion	Rust Detection	Basting Area Determination	Total
0.10	0.52	0.24	0.86

CONCLUSIONS

The advantages of the automated robotic grit-blast machines for steel bridge maintenance are clear. Recent field trials of a full-scale robotic grit-blast machine for steel bridge maintenance appear to support this conclusion as well. In this study, we proposed a method to determine rapidly and accurately the rust surface area to blast on steel bridges. The experimental results of the proposed method showed that the average accuracy rate of rust area classification was about 97.63%, and the success rate of the final decision of blasting area determination was 100.00% for 39 test examples. The whole processing time took only an average of 0.86 seconds. The proposed method can reduce labor and increase the productivity of the automated robotic grit-blasting process. This shows that the proposed method will result in significant potential cost savings. Furthermore, the proposed method can minimize environmental impacts related to waste and harmful materials, such as lead and asbestos, by optimizing the blasting area.

In this study, spot, general, and pin-point rusting constitute the primary target. However, hybrid rusting, a mixture of two or three rust distribution types, occasionally occurs. Therefore, in future research, a method that includes a rust surface area determination method for hybrid rusting will be developed to consider every rust distribution type that occurs on steel bridge surfaces. In addition, a path planning method for blasting will be developed, based on the rust surface area determined by the proposed method.

ACKNOWLEDGMENTS

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2010-0023229).

REFERENCES

American Society for Testing and Materials (ASTM) (2012). *Standard Practice for Evaluating Degree of Rusting on Painted Steel Surfaces[1] (D610-08).* In Annual Book of ASTM Standards (Vol.06.01ASTM). West Conshohocken, PA.

Chang, L. M., Shen, H. K., & Chen, P. H. (2011, July). Automated Rust Defect Recognition Method Based on Color and Texture Feature. *International Conference on Image Processing, Computer Vision, and Pattern Recognition*, Las Vegas, NV.

Chen, P. H., Shen, H. K., Lei, C. Y., & Chang, L. M. (2011). Fourier-Transform-Based Method for Automated Steel Bridge Coating Defect Recognition. *Procedia Engineering*, 14, 470–476. doi: 10.1016/j.proeng.2011.07.058

Chen, P. H., Shen, H. K., Lei, C. Y., & Chang, L. M. (2012). Support-Vector-Machine-Based Method for Automated Steel Bridge Rust Assessment. *Automation in Construction*, 23, 9–19. doi: 10.1016/j.autcon.2011.12.001

Cheng, H. D., Jiang, X. H., Sun, Y., & Wang, J. (2001). Color Image Segmentation: Advances and Prospects. *Pattern Recognition*, 34, 2259–2281. doi: 10.1016/S0031-3203(00)00149-7

Echt, A., Dunn, K. H., & Mickelsen, R. L. (2000). Automated Abrasive Blasting Equipment for Use on Steel Structures. *Applied Occupational and Environmental Hygiene*, 15, 713–720. doi: 10.1080/10473220050129310

El-Naqa, I., Yang, Y., Galatsanos, N. P., Nishikawa, R. M., & Wernick, M. N. (2004). A Similarity Learning Approach to Content-Based Image Retrieval: Application to Digital Mammography. *IEEE Transactions on Medical Imaging, 23,* 1233–1244. doi: 10.1109/TMI.2004.834601

Ghanta, D., Karp, T., & Lee, S. (2011, May). *Wavelet Domain Detection of Rust in Steel Bridge Images*. International Conference on Acoustics, Speech and Signal Processing, Boston, MA.

Lee, S., Chang, L. M., & Skibniewski, M. (2006). Automated Recognition of Surface Defects Using Digital Color Image Processing. *Automation in Construction*, 15, 540–549. doi: 10.1016/j.autcon.2005.08.001

Lee, S. (2010, April). Automated Defect Recognition Method by Using Digital Image Processing. *International Conference on Associated Schools of Construction*, Boston, MA.

Lessmann, S., Baesens, B., Mues, C., & Pietsch, S. (2008). Benchmarking Classification Models for Software Defect Prediction: A Proposed Framework and Novel Findings. *IEEE Transaction on Software Engineering*, 34, 485–496. doi: 10.1109/TSE.2008.35

Liu D. K., Dissanayake, G., Manamperi, P. B., Brooks, P. A., Fang, G., Paul, G., Webb, S., Kirchner, N., Chotiprayanakul, P., Kwok, N. M., & Ren, T. R. (2008, Dec). A Robotic System for Steel Bridge Maintenance: Research Challenges and System Design. *Australasian Conference on Robotics and Automation*, Canberra, Australia.

Lorenc, S. J., Handlon, B. E., & Bernold, L. E. (2000). Development of a Robotic Bridge Maintenance System. *Automation in Construction*, 9, 251–258. doi: 10.1016/S0926-5805(99)00040-0

Paul, G., Webb, S., Liu, D., & Dissanayake, G. (2011). Autonomous Robot Manipulator-Based Exploration and Mapping System for Bridge Maintenance. *Robotics and Autonomous Systems*, 59, 543–554. doi: 10.1016/j.robot.2011.04.001

Shih, C. Y., Hung, S. L., Garrett Jr, J. H., Soibelman, L., & Dai, J. S. (2006, June). Steel Bridge Corrosion Detection by Wavelet Transform Theory. *Joint International Conference on Computing and Decision Making in Civil and Building Engineering*, Montréal, QC.

Steel Structures Painting Council (SSPC). (2000). *Standard Text Method for Evaluating Degree of Rusting on Painted Steel Surfaces*. SSPC Publication No. 00-08 from SSPC: The Society for Protective Coatings, Pittsburgh, PA.

Tam, C. K., & Stiemer, S. F. (1996). Development of Bridge Corrosion Cost Model for Coating Maintenance. *Journal of Performance of Constructed Facilities*, 10, 47–56. doi: 10.1061/(ASCE)0887-3828(1996)10:2(47)

To, A. W. K., Paul, G., & Liu, D. (2010, June). Image Segmentation for Surface Material-type Classification Using 3D Geometry Information. *2010 IEEE International Conference in Information and Automation*, Harbin, China.

Wei, C. H., Li, C.T., & Li, Y. (2009). Content-based Retrieval for Mammograms. *Artificial intelligence for maximizing content-based image retrieval* (1st ed., pp. 313–339). In M. Zongmin (Ed.), Hershey, PA: Idea Group Publishing.

Wesolkowski, S. B. (1999). *Color Image Edge Detection and Segmentation: A Comparison of the Vector Angle and the Euclidean Distance Color Similarity Measures*, Master's Thesis. Waterloo University, Waterloo, Ontario.