A novel underwater dam crack detection algorithm based on sonar images

Pengfei Shi[1 2, a], Xinnan Fan[2, b] and Gengren Wang[2, c]

[1] College of Computer and Information, Hohai University, Nanjing, 210098 China

[2] College of IOT Engineering, Hohai University, Changzhou, 213022 China

[a]flyshn@hotmail.com, [b]fanxn519@163.com, [c]wanggr_hhuc@163.com

Keywords: Sonar Image; Dam Crack; Detection; AUV

Abstract. As underwater environments are complex and time-varying, and the target is randomness and diversity. Underwater dam crack detection based on autonomous underwater vehicle (AUV) equipped with sonar is a challenging task. In this paper, a novel crack block tree (BT) algorithm utilized in sonar images is proposed to detect underwater dam crack. Firstly the low-resolution sonar images should be pre-processing, then the images are divided into image blocks for clustering analysis. After that, an adaptive fracture fragments based on tensor voting is put forwarded to combine the crack segment. At last, a minimum spanning tree is used to obtain the cracks. By comparing the crack BT with other algorithms, the results show that the proposed approach can deal with the crack detection more effectively.

Introduction

Dam crack detection is an important work to ensure the dam safety [1] The dam crack is a mutation in the process of its internal damage accumulation [2]. Thus, it is always used to indicate the danger degree of the dam damage which is attracted by many scholar's attention. Recently, the underwater dam crack detection with sonar images has become one of the most important methods for its nondestructive, intuitive, convenient and efficient [3]. However, underwater environments are complex, time-varying and full of interference [4-6] which will lead to the measurement signal submerged by noise. Besides, the unstructured crack is random and diverse leading to the difficulties to describe the cracks.

Aimed at those problems mentioned above, various methods have been proposed. Chen, et al. [7] presented an adaptive underwater dam crack edge detection algorithm based on multi-structures and multi-scale elements. Bernstone, et al. [8] proposed a digital image analysis technique for crack monitoring using a standard web-camera to acquire continuous data sets in concrete dams. Xu, et al. [9] suggested an integrated model used digital image processing in developing the numerical representation of concrete structures defects. However, most of the traditional detection are proposed by exploiting characteristics which always submerged by noise. It will lead to low detection rate and high false alarm rate.

In this paper, a novel crack detection algorithm called crack BT is proposed. Section 2 illustrates the basic idea of the crack BT. Section 3 gives the result of proposed algorithm and analysis.

The crack BT

Before the crack BT, some prior knowledge about crack can be introduced: 1) the image regions are darker than their surroundings; 2) the connected domain of the crack region is slender than other regions. The workflow chart of the proposed approach is shown in Fig. 1, which will be introduced in details as follows.

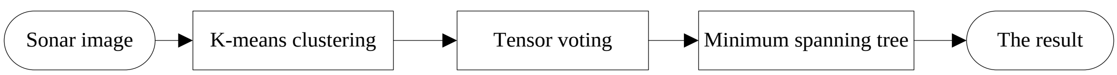

Fig.1. The workflow of the crack BT

Clustering analysis of the image blocks. The sonar images should be pre-processing first, and the details can be seen in previous work [9]. After that, the image is divided into nonoverlapping image blocks which is shown in Fig. 2(b). Three characteristic matrices are computed for each block: 1) the mean value matrix (Mm); 2) the standard deviation matrix (STDm); 3) the information entropy matrix (IFE). A clustering analysis method is used to distinguish crack (crack-like) from background with the 3-D space classifiers, and each point identifies one image block. Then the feature set in the 3-D space is defined as:

$$F = \{(V_1, y_1)\cdots(V_n, y_n) : V_i \in R^3; y_j \in \{c_1, c_2\}\} \tag{1}$$

where n is the number of block points for the pattern vector V, which is constructed by Mm, STDm and IFE; y_i corresponds to the i th block. The blocks are divided into two classes, c_1 and c_2, denoting blocks carrying non-crack information and the blocks containing with cracks information respectively.

Furthermore, the K-means classification approach is used to make the clustering analysis [10]. The clustering result in the 3-D feature space is shown in Fig. 2(i). The classes that are labeled with red circle in the 3-D feature space are the target class c_2. The final results of the target blocks are shown in Fig. 2(c), which are marked with red squares.

Adaptive tensor voting of the crack fragments. Cracks marked with independent segments after clustering analysis are actually an integrated crack. It will affect the understanding of the crack if the segments are not connected. The spatial proximity and the gliding property of the crack fragments is the main difference with the interference. Thus, a self-adaptive tensor voting algorithm is put forwarded. The images can be expressed in a tensor field which contains ball tensor and stick tensor. The two tensors can be defined as follow:

Ball tensor: if point P is an isolated point, the tensor is expressed as $\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$.

Stick tensor: if P is the point on the curve, the tensor is expressed as $\begin{bmatrix} \cos^2\theta & \sin\theta\cos\theta \\ \sin\theta\cos\theta & \sin^2\theta \end{bmatrix}$.

θ is the tangent angle between the tangent and the horizontal direction.

The stick tensor along the y-axis from the coordinate origin O, and the voting strength from P can be calculated by degradation function [11]:

$$DF(s, k, \sigma) = e^{-\left(\frac{s^2 + ck^2}{\sigma^2}\right)} \tag{2}$$

where σ is the voting scale, $s = \dfrac{\theta l}{\sin\theta}$ is the arc length, $c = \dfrac{-16\log 0.1 \times (\sigma - 1)}{\pi^2}$ controls the degradation speed of the function curvature, $k = \dfrac{2\sin\theta}{l}$ is the curvature. σ is the only free parameter as the voting field design, it directly controls the size scales of voting field. In the previous studies, σ is usually given by the prior knowledge, but the prior knowledge is difficult to get in the underwater dam crack detection. Thus, a parameter adaptive fracture fragments is put forwarded based on the clustering analysis. The scale of voting field determines how much neighborhood that the corresponding point impacts to the neighbors, which also determines how much neighborhood that the corresponding point is affected by neighbors. As can be seen from the experiment, the quantity of the marked cracks is inversely with voting field scale. Thus, the voting field scale is gained by

$$\sigma = k / n_2 \tag{3}$$

where k is the adjustment coefficient and n_2 is the number of c_2 that gained from the clustering step.

Then minimum spanning tree and edge pruning is used to further remove the image noise and other false positives [12]. The whole method is shown in the flow chart in Fig. 2 to illustrate.

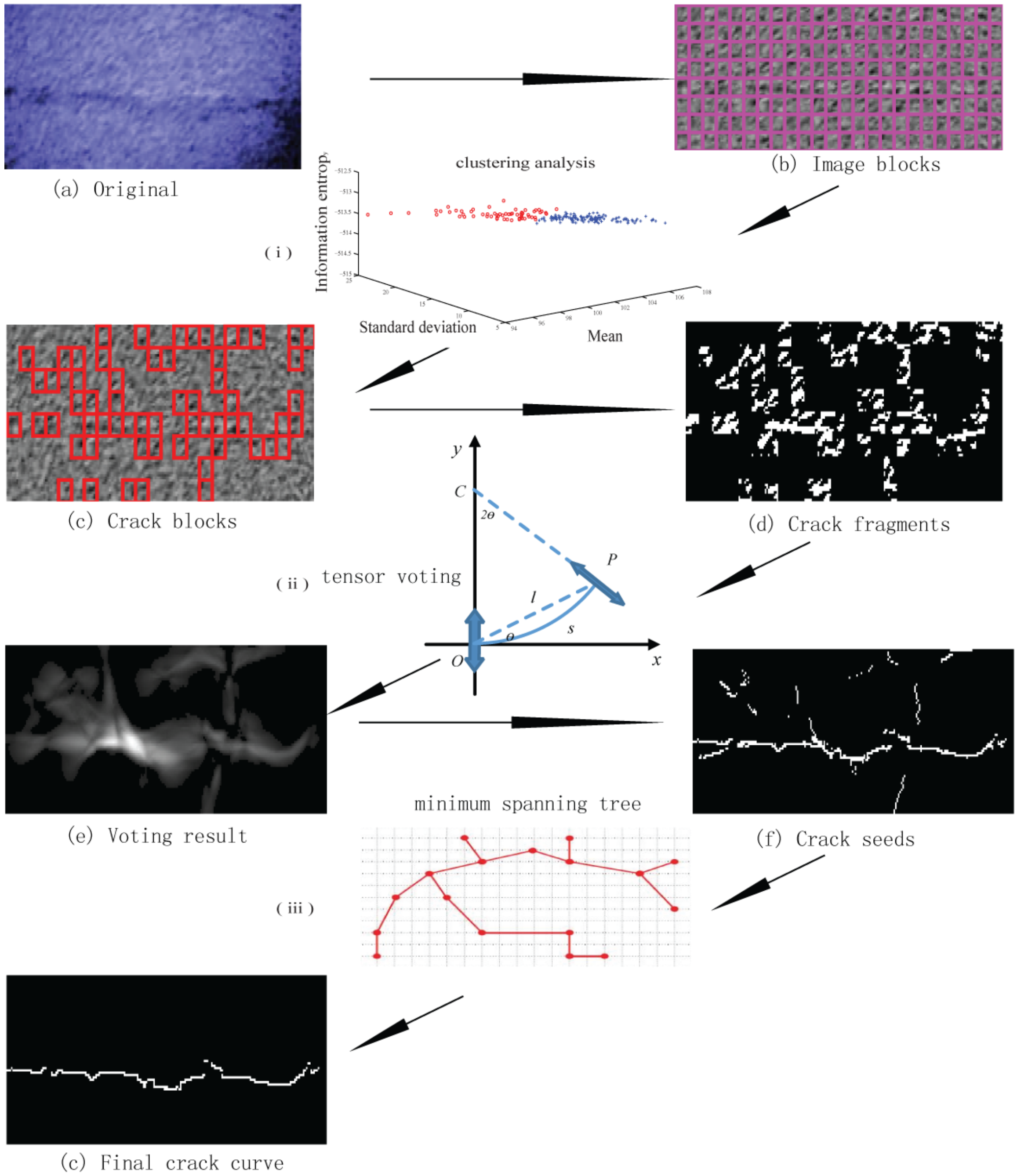

Fig.2. Flow chart of the crack BT. (i) three-dimensional clustering analysis, (ii) adaptive tensor voting, (iii) minimum spanning tree and edge pruning.

Experiments and analysis

In this section, the proposed algorithm is used to analyze three typical cracks of underwater dam surface images captured from a dam hydropower project: the first one is that the sonar dam image contains a huge cracks with a complex background (see a(i) in Fig. 3); the second one is that the sonar dam image contains a normal crack (see a(ii) in Fig. 3); the third one is that the sonar dam image contains a tiny crack (see a(iii) in Fig. 3). First of all, the three original sonar images are pre-processing and blocking. After that, the images are divided into image blocks for clustering analysis so as to mark the block which contains cracks. And then, the adaptive fracture fragments is used to connect the marked crack fragments. At last, the minimum spanning tree and edge pruning is used to get the cracks mark, and the result is shown in Fig. 3(d).

To test the performance of the proposed approach, it is compared with the tensor voting [13] and wasp algorithm. The results are shown in the Fig. 3. As we can see, the wasp algorithm is unable to deal with the crack detection. The tensor voting is able to detect huge cracks, but it can not deal with the normal crack especially the tiny one. The results show that the proposed approach can solve the crack detection problem effectively.

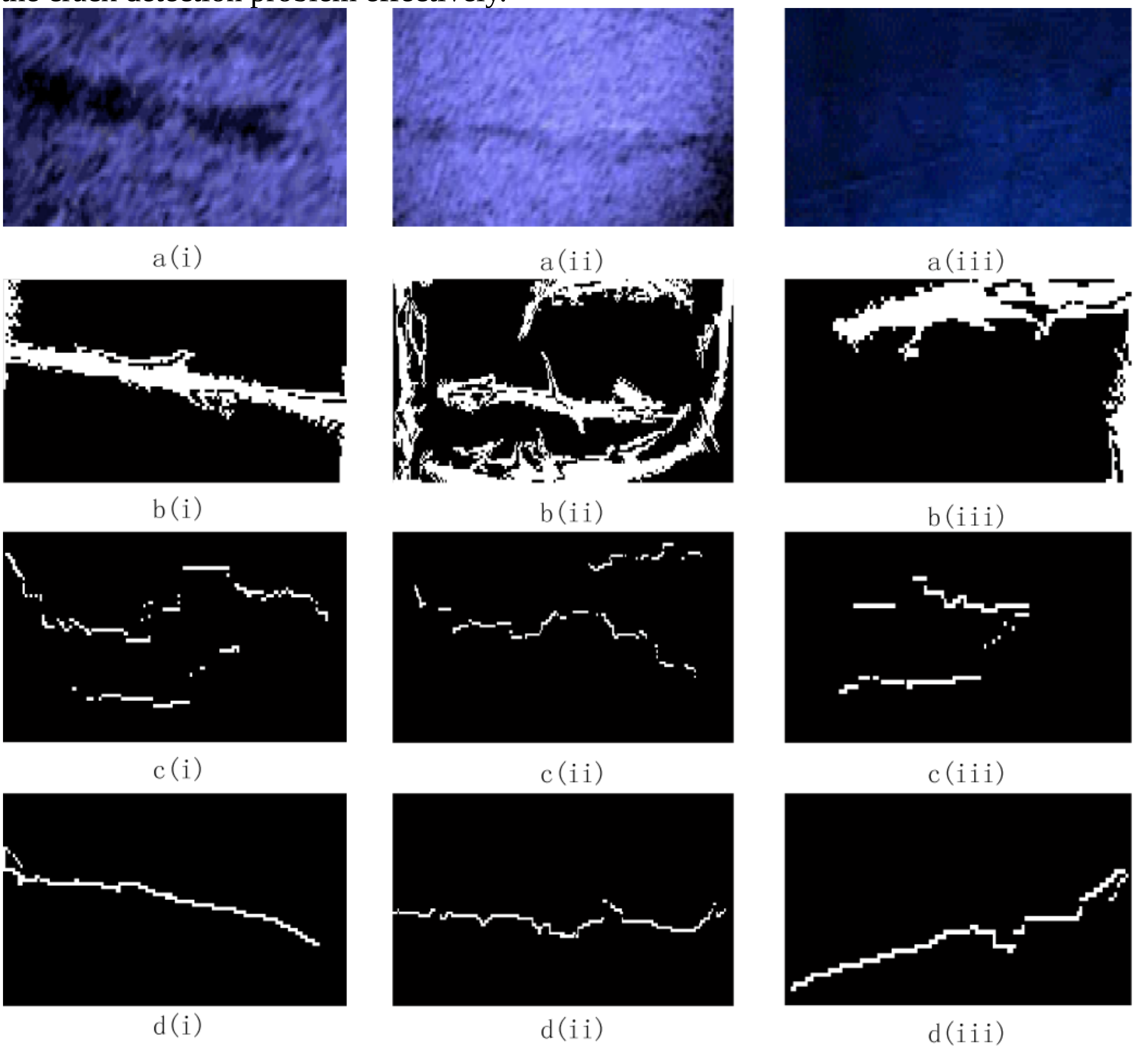

Fig.3.Image detection results comparing the proposed method and other classical method: (a) Original image, (b) Wasp Algorithm, (c) Tensor voting and (d) The crack BT.

Conclusion

The underwater dam crack detection is considered and a novel approach is proposed. In the proposed crack BT algorithm, the sonar image blocks is used for the crack clustering analysis. Then the adaptive fracture fragments based on tensor voting is used to connect the crack fragments. The proposed crack detection algorithm can handle sonar images with low resolution. The experiments show that the proposed method can detect the underwater dam crack efficiently when the environments are complex and the cracks are tiny.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (61573128) and the colleges and universities in Jiangsu province plans to graduate research and innovation (CXZZ120255).

References

[1] Branko Glisic, Daniele Inaudi. Development of method for in-service crack detection based on distributed fiber optic sensors [J]. Structural Health Monitoring. 11(2):161–171, 2012.

[2] Wang ShanShan and Ren QingWen. Dynamic response of gravity dam model with crack and damage detection [J]. Science China Technological Sciences . 54(3):541–546, 2011.

[3] Thomas Stephan, Peter Fruehberger, Stefan Werling, and Michael Heizmann. Model based image restoration for underwater images [C]. In SPIE Optical Metrology 2013, pages 87911F–87911F. International Society for Optics and Photonics, 2013.

[4] Congping Chen, Jian Wang, Lei Zou, Jun Fu, and Cong ji Ma. A novel crack detection algorithm of underwater dam image [C]. In Systems and Informatics (ICSAI), 2012 International Conference on, pages 1825–1828, May 2012.

[5] Prateek Prasanna, Kristin J. Dana, Nenad Gucunski. Automated Crack Detection on Concrete Bridges [J]. IEEE Transactions on Automation Science and Engineering, DOI: 10.1109/TASE, 2014.

[6] R.R. Murphy, E. Steimle, M. Hall, M. Lindemuth, D. Trejo, S. Hurlebaus, Z. Medina-Cetina, and D. Slocum. Robot-assisted bridge inspection after hurricane ike [C]. In Safety, Security Rescue Robotics (SSRR), 2009 IEEE International Workshop on, pages 1–5, Nov 2009.

[7] CongPing Chen, Jian Wang, Lei Zou, and FaFun Zhang. Underwater dam image crack segmen-tation based on mathematical morphology [J]. Applied Mechanics and Materials, 220:1315–1319,2012.

[8] Christian Bernstone and Anders Heyden. Image analysis for monitoring of crack growth in hydropower concrete structures [J]. Measurement, 42(6):878–893, 2009.

[9] Xue-jun Xu and Xiao-ning Zhang. Crack detection of reinforced concrete bridge using video Image [J]. Journal of Central South University, 20(9):2605–2613, 2013.

[10] Xinnan Fan, Peng Wu, Jianjun Ni, and Pengfei Shi. An illumination balance algorithm based on improved affine shadow formation model for underwater image [C]. In Image and Signal Processing(CISP), 2013 6th International Congress on, volume 2, pages 910–916, 2013.

[11] H. Oliveira and P.L. Correia. Automatic road crack detection and characterization. Intelligent Transportation Systems [J], IEEE Transactions on, 14(1):155–168, March 2013.

[12] Hatem A. Rashwan, Miguel A. Garcia, and Domenec Puig. Variational Optical Flow Estimation Based on Stick Tensor Voting [J]. IEEE Transactions on image processing, 22(7): 2589–2599, JUL 2013.

[13] Qin Zou, Yu Cao, Qingquan Li, Qingzhou Mao, and Song Wang. Crack Tree: Automatic crack detection from pavement images [J]. Pattern Recognition Letters, 33(3):227–238, 2012.