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Image processing based concrete crack classification using Logistic Regression model

Phân loại vết nứt trên cấu kiện bê tông sử dụng kỹ thuật xử lý ảnh và mô hình hồi quy lô-git-tíc

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Abstract

Computer vision models have been proven to be productive as well as effective for concrete crack detection. This study develops an alternative model based on image edge detection, projection integral, and logistic regression approaches for recognizing and categorizing cracks on concrete surface. The integrated model has been developed using Visual C#.NET and tested with 200 real-world image samples. Experimental results point out that the new model has attained a good predictive performance with a classification accuracy of 92.5%.

Keywords: Computer vision; Concrete crack detection; Edge detection; Projection integral; Logistic Regression.

Tóm tắt

Các mô hình thị giác máy tính đã được chứng tỏ là những phương pháp hiệu quả cho việc phát hiện vết nứt trên bề mặt bê tông. Nghiên cứu này của chúng tôi phát triển một mô hình dựa trên các kỹ thuật phát hiện cạnh trên ảnh, tổng hình chiếu độ sáng, và phân tích hồi quy lo-git-tic. Mô hình mới được xây dựng với ngôn ngữ Visual C# .NET và được kiểm chứng bởi 200 mẫu ảnh thực tế. Kết quả nghiên cứu chỉ ra rằng mô hình này đạt được kết quả phân loại vết nứt tốt, với độ chính xác là 92.5%.

Từ khóa: Thị giác máy tính; Phát hiện vết nứt; Phát hiện cạnh; Tổng hình chiếu độ sáng; Phân tích hồi quy Lô-gít-tic.

1. Introduction

Large concrete structures with considerable surface areas are widely encountered in high-rise buildings, retaining walls, bridges, etc [1, 2]. Because of the combined effects of aging, intensive usage, and inclement climate conditions, their structural heath deteriorates over time. Therefore, maintaining an acceptable level of integrity of these structures is a crucial task for civil engineers [3]. To fulfill this task, civil engineers need to be well informed about the current status of concrete structures.

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Therefore, periodic condition survey based on visual inspection is very important to provide civil engineers with accurate and timely information regarding the structural heath condition.

Based on literature review, a considerable number of previous works have dedicated in computer vision based crack detection for concrete structures [3-9]. It is because cracks are a major concern when considering the safety, durability, and serviceability of reinforced concrete structures. Another reason is that computer vision is a means to improve the productivity of the surveying process and to eliminate subjective judgment of human technicians [10]. Timely identification of surface cracks is a crucial step in structure diagnosis and remediation. Information regarding cracks (e.g. position, types, etc.) provides helpful data for civil engineers to analyze and prevent potential structure failures.

This study develops an alternative computer vision based approach for crack detection relying on image processing techniques of edge detection and projection integral. In addition, the logistic regression training with the state-of-the-art adaptive moment estimation (Adam) is used for crack pattern recognition.

2. Research method

2.1 Canny edge detection approach

Given an image sample, the first task of crack recognition is to highlight crack patterns. To do so, this study relies on the Canny edge detection approach proposed by Canny [11]. This is a multi-step algorithm for edge detection [12]. In the first step, a Gaussian convolution is applied to the image sample. The employed Gaussian filter is given by [5]:

$$g(m,n) = G_\sigma(m,n) * \mathrm{f}(\mathrm{m},\mathrm{n}) \quad (1)$$

where $G_\sigma = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{m^2+n^2}{2\sigma^2})$. m and m denotes pixel locations. (2)

In the second step, the gradient of $g(m,n)$ using a certain gradient operator (e.g. Sobel) can be applied as follows:

$$g_{m,n}(\mathrm{m},\mathrm{n}) = \sqrt{g_m^2(\mathrm{m},\mathrm{n}) + g_n^2(\mathrm{m},\mathrm{n})} \quad (3)$$

2.2. Projection Integral (PI)

PI is an effective method for recognizing shape and texture [13-16]. This image processing approach has been widely used in computer vision based structure health monitoring [17-19]. Given an image $I(x,y)$, the horizontal PI (HP) and vertical PI (VP) given by:

$$HP(y) = \sum_{i \in x_y} I(i,y) \quad (4)$$

$$VP(x) = \sum_{j \in y_x} I(x,j) \quad (5)$$

where HP and VP denote the horizontal and vertical PIs, respectively; x_y and y_x are the set of horizontal pixels at the vertical pixel y and the set of vertical pixels at the horizontal pixel x, respectively.

It is noted that the HP and VP are helpful for recognizing longitudinal crack and transverse crack. A longitudinal crack case and a transverse crack case typically feature one peak of intensity in VP and HP, respectively [20]. Moreover, as shown in [18], diagonal projections (DP) with +45^o and -45^o can also be computed to enhance the discriminative power of the extracted feature set.

2.3. Logistic Regression model

A LR model can be used to construct a classification model that assigns data samples to two prespecified categories of 0 and 1. This classifier is relatively simple to program and its model structure is also easily comprehensible [21-23]. The class output of a LR model (*y*) is denoted as 1 for a positive class and 0 for a negative class. A vector of feature is expressed as $x_i = x_{i1}, x_{i2}, ..., x_{iD}$ where *D* denotes the number of the features used for classification [24]. $\theta = \theta_0, \theta_1, \theta_2, ..., \theta_D$ denotes the model parameters.

Given a feature vector x_i, a LR model calculates $h_\theta(x_i)$ which represents the probability of the positive class output. $h_\theta(x_i)$ is computed as follows [24, 25]:

$$h_\theta(x_i) = h_\theta(x_{i1}, x_{i2}, ..., x_{iD}) = \frac{1}{1+\exp(-\eta_i)}$$

$$= \frac{1}{1+\exp(-\theta^T x_i)} \quad (6)$$

where $\eta_i = \theta_0 + \theta_1 x_{i1} + \theta_2 x_{i2} + ... + \theta_D x_{iD} = \theta^T x_i$.

$g(\eta_i) = \frac{1}{1+\exp(-\eta_i)}$ denotes the logistic function; its derivative is given by [26]:

$$g'(\eta_i) = g(\eta_i) \times (1 - g(\eta_i)) \quad \textbf{(7)}$$

3. Experimental results

To test the capability the computer vision based model for recognizing concrete crack patterns, this study has collected image samples from high-rise buildings in Da Nang city (Vietnam). All of the image samples with their ground truth status of transverse crack and longitudinal crack have been assigned by human inspectors. The image size is set to be 64x64 pixels to facilitate the computing process. For each class label of concrete crack, 100 image samples have been collected. Therefore, the image dataset includes of 200 samples. The collected image dataset is demonstrated in **Fig. 1**.

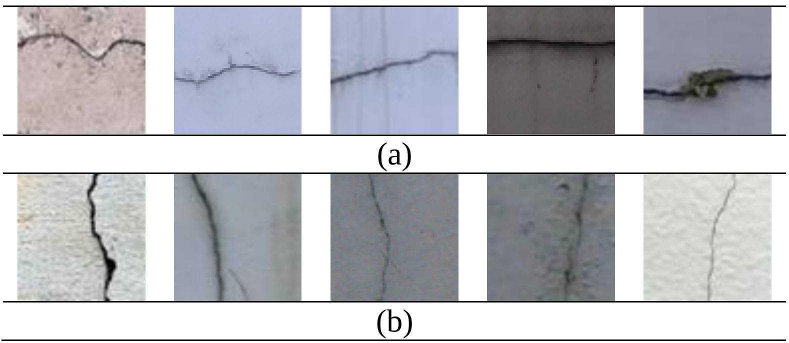


Fig. 1 Image samples: (a) Transverse crack and (b) Longitudinal crack

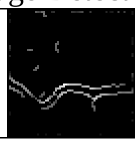
Original Image	Gray-Scaled Image	Edge Detection
		

Fig. 2 Image processing results for an image sample containing a transverse crack

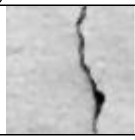
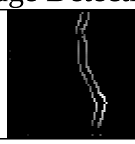
Original Image	Gray-Scaled Image	Edge Detection
		

Fig. 3 Image processing results for an image sample containing a longitudinal crack

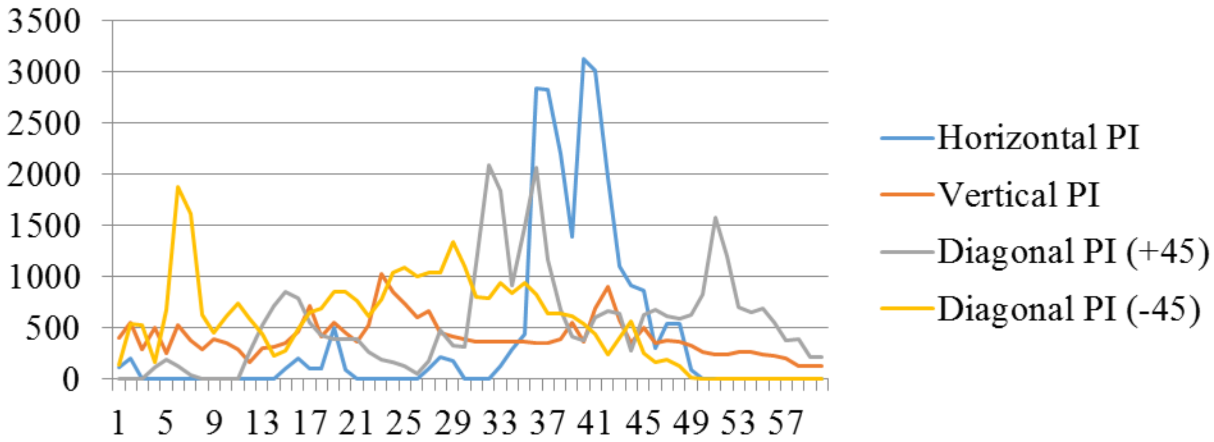


Fig. 4 Projection integrals of an image sample containing a transverse crack

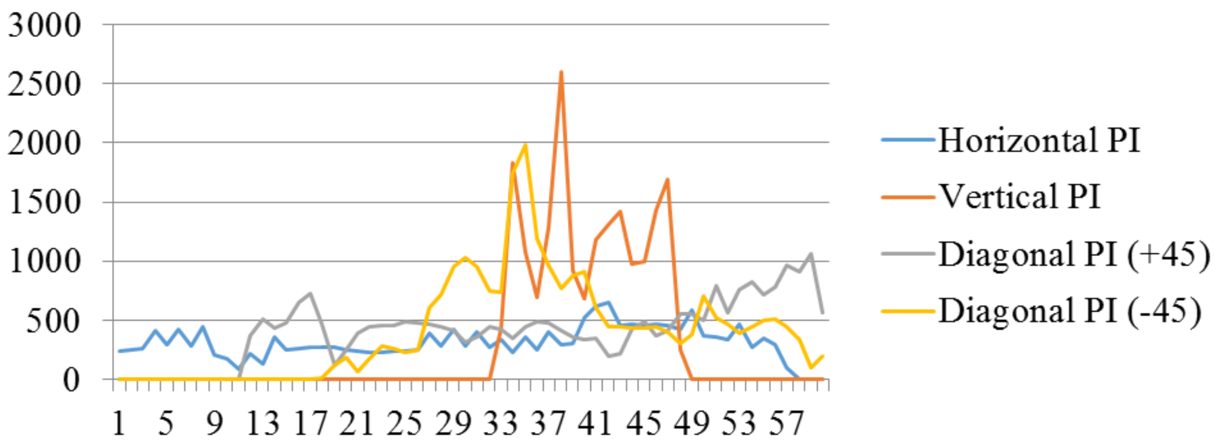


Fig. 5 Projection integrals of an image sample containing a longitudinal crack

For each image sample, the Canny edge detection approach is first used to process the image and highlight edges (refer to **Fig. 2** and **Fig. 3**). Subsequently, the PI technique is used to extract numerical features (refer to **Fig. 4** and **Fig. 5**). Moreover, to standardize the input feature, the numerical features are normalized by the Z-score equation [27]. To evaluate the LR based classifier, Classification Accuracy Rate (CAR), true positive rate TPR (the percentage of positive instances correctly classified), false positive rate FPR (the percentage of negative instances misclassified), false negative rate FNR (the percentage of positive instances misclassified), and true negative rate TNR (the percentage of negative instances correctly classified) are also widely used [28]. Based on the outcomes of the TP, FP, and FN, the Precision and Recall can also be computed to express the model predictive capability [29, 30].

Moreover, to automatically implement the LR model, a software program has been developed in .NET framework 4.6.2. The Graphical user interface (GUI) of the software program is shown in **Fig. 6**. It is noted that the Adaptive Moment Estimation (Adam) has been used to train the LR model used for crack pattern recognition [31-33]. The model classification results are reported in **Table 1** which shows the outcomes of the training and testing phases. It is noted that 90% of the collected has been used for model training. The rest of the data is used for model testing. As reported in **Table 1**, the developed model has achieved a good predictive accuracy with CAR = 92.50% and F1 score = 0.93.

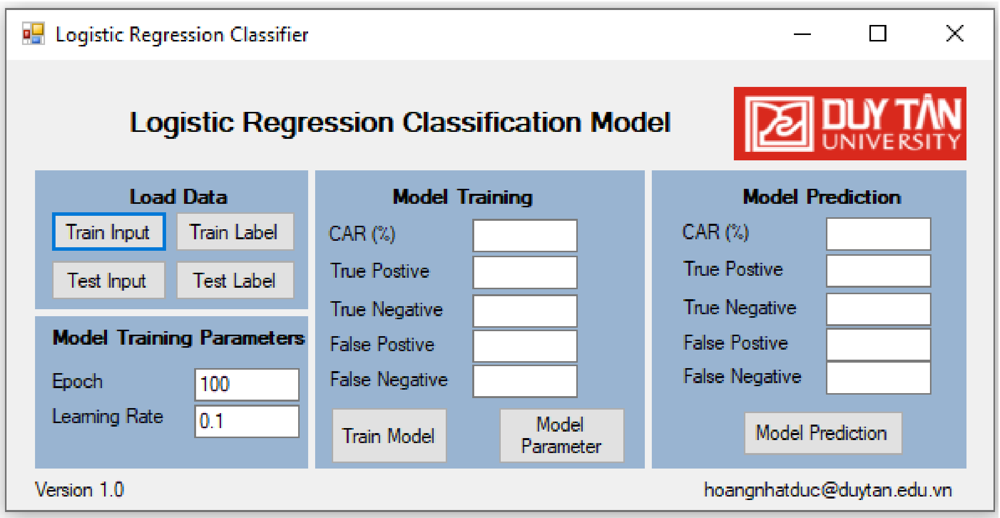


Fig. 6 The Logistic Regression Classification program

Table 1. Experimental results

Phases	Index	CAR (%)	TP	TN	FP	FN	Precision	Recall	NPV	F1 Score
Training	Mean	99.72	89.50	90.00	0.15	0.35	1.00	1.00	1.00	1.00
	Std.	0.37	1.83	1.73	0.36	0.65	0.00	0.01	0.01	0.00
Testing	Mean	92.50	9.65	8.85	0.70	0.80	0.93	0.93	0.92	0.93
	Std.	5.36	1.82	1.80	0.56	0.98	0.06	0.09	0.10	0.05

4. Conclusion

Crack detection is a crucial task in periodic structure health survey. This study investigates the capability of a computer vision based model for enhancing the productivity of the periodic structure health survey process. The model is constructed by an integration of the Canny edge detection, PI, and LR classification approaches. Experimental results with real-world image samples demonstrate the potential of the model developed in this study.

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