Application of PCA in Concrete Infrared Thermography Detection

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Keywords: Infrared Thermography, Concrete, Non-destructive Testing, Principal Components Analysis.

Abstract. Infrared thermography has been a very important nondestructive evaluation (NDE) in the detection of concrete due to its non-contactness, rapidity, capability of imaging large area. More generally, there are some frames in the infrared image sequence. It costs more time to read the information behind the infrared image directly, and the result is influenced by subjective factors in the most degree. Principal component analysis (PCA) is used to convert an infrared image sequence into a set of principal components. Then, the detection result can be got quickly by keeping the lower principal components and ignoring the higher ones.

Introduction

The defects in a RC bridge are hard to detect with existed testing equipment for the detailed positions and severity of damage, so they are easy to be ignored during daily maintenance. But the risk from internal defects is larger than surface defects on a bridge, which is the meaning to study the assessment method for internal defects of a bridge, and research condition evaluation, defect detection, daily maintenance with the non-destructive and visual detecting equipment.

In case of heat input into a concrete member that may have discontinuous defects inside such as the cavity, the thermal conductivity, specific heat and so on of the defect are different from the part without any defect, thereby temperatures of various concrete surface areas are different. Those temperature distribution areas on concrete surface are closed related with defects inside concrete, so they generally can be the important basis for determining internal conditions of concrete. The infrared thermography detection technology can detect temperature distribution on concrete surface through measuring infrared radiation energy, and then judge the possible defect inside, which is the fundamental principle of infrared thermography detection. The advantages of the infrared thermography technology are scanning the object surface quickly, non-destructive, with non-contactness and large area, the results are visual, therefore automation and real-time observation can be achieved. By the end of 1970s, there have been scholars to diagnose thermal loss, roof water seepage, wall defect and subsurface defect of a road, etc. with the infrared imagery technology [1-3]. For more than 20 years, the researchers in China combine the infrared thermography detection technology and civil engineering to carry on the application study on concrete defect detection and construction quality, etc. [4-6]

In general, there are many frames in the infrared image sequence. It costs much more time to read the information behind the infrared image directly, and the result is influenced by subjective factors in the most degree. As technology to analyze and simplify a data set, the principal component analysis (PCA) is often used to reduce the dimension of a data set, and keep the feature that contribute most to the variance of the data set by keeping the lower principal components and ignoring the higher ones, Li Junmei, et al. [8] study application of PCA in object identification; Hua Shungang, et al. [9] apply the PCA technology in the IR thermal graphic face recognition; both of them achieve good results. But the report concerned applying the PCA technology for infrared thermography detection for concrete internal defects has not been found yet.

Theory of PCA

The PCA may reduce the dimension of the data set, and keep the features that contribute the variance of the data set most, thereby dozens frames of infrared image sequence are compressed to several principal components that may show the essence of the sample.

The specific procedure of the PCA:

Form sample matrix. Assume there are p infrared images with the pixel of m×n per frame, then the temperature matrix of infrared image i is shown as Formula (1).

$$\mathbf{A_i}=\begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} \qquad i=1,2,\ldots,p \tag{1}$$

Perform vectorization to the temperature matrix of each infrared image stacked by column to get the sample vector $\mathbf{x_i}$, as shown in Formula (2).

$$\mathbf{x_i}=\begin{pmatrix} a_{11} \\ \vdots \\ a_{m1} \\ \vdots \\ a_{1n} \\ \vdots \\ a_{mn} \end{pmatrix} \qquad i=1,2,\ldots,p \tag{2}$$

Combine p sample vectors to the sample matrix X:

$$\mathbf{X}=\left(\mathbf{x_1},\quad \mathbf{x_2},\quad \ldots,\quad \mathbf{x_P}\right)^{\mathrm{T}} \tag{3}$$

Form covariance matrix. Perform centralization to the sample, viz. each column of the sample matrix **X** subtracts the average to guarantee the deviations in all dimensions are based on zero. Form the covariance matrix **C** as shown in Formula (4).

$$\mathbf{C}=\frac{1}{p-1}\sum_{i=1}^{p}\left(\mathbf{x_i}-\overline{\mathbf{x}}\right)\left(\mathbf{x_i}-\overline{\mathbf{x}}\right)^{\mathbf{T}} \tag{4}$$

Where, $\overline{\mathbf{x}}=\frac{1}{p}\sum_{i=1}^{p}\mathbf{x_i}$ is the average of the sample vector in each column.

Singular value decomposition. Perform the singular value decomposition (SVD) to the covariance matrix **C**, as shown in Formula (5).

$$\mathbf{C}=\mathbf{U\Sigma V^T} \tag{5}$$

Where, $\mathbf{U_i}$ in Column *i* of Matrix **U** is the principal component vector No. *i*, reset it to the m×n matrix $\mathbf{B_i}$, then $\mathbf{B_i}$ is the No. *i* image of principal component, as shown in Formula (7).

$$\mathbf{U_i}=\begin{pmatrix} u_{i,1} \\ u_{i,2} \\ \vdots \\ u_{i,\mathrm{mn}} \end{pmatrix} \qquad i=1,2,\ldots,p \tag{6}$$

$$\mathbf{B_i}=\begin{pmatrix} u_{i,1} & u_{i,\mathrm{m}+1} & \cdots & u_{i,(n-1)\mathrm{m}+1} \\ u_{i,2} & u_{i,\mathrm{m}+1} & \cdots & u_{i,(n-1)\mathrm{m}+2} \\ \vdots & \vdots & \ddots & \vdots \\ u_{i,\mathrm{m}} & u_{i,2\mathrm{m}} & \cdots & u_{i,\mathrm{mn}} \end{pmatrix} \qquad i=1,2,\ldots,p \tag{7}$$

Select quantity of valid principal components. The element λ_i at the diagonal of the matrix $\mathbf{\Sigma}$ is called the singular value, which is the nonzero square root of the eigenvalue $\mathbf{CC}^{\mathrm{T}}$ and $\mathbf{C}^{\mathbf{T}}\mathbf{C}$, and corresponding to the row vector of **U** and **V**. The singular value λ_i shows the size of the information quantity, and defines the variance contribution rate α_i, where the principal component is the ratio between No. *i* singular value λ_i and the total singular value, as shown in Formula (8).

$$\alpha_i = \lambda_i / \sum_{i=1}^{p} \lambda_i \qquad i = 1, 2, \ldots, p \tag{8}$$

The variance accumulative contribution rate $\varphi(q)$ of the first *q* principal components is shown in Formula (8).

$$\varphi(q) = \sum_{i=1}^{q} \alpha_i = \frac{\sum_{i=1}^{q} \lambda_i}{\sum_{i=1}^{p} \lambda_i} \qquad (q < p) \tag{9}$$

When the accumulative contribution rate $\varphi(q)$ of the first *q* principal components is more than the preset threshold (Here is 85%), the original variable information can be reflected sufficiently. $\varphi(q) > 85\%$ shows that there are 85% energy on the projection of the first *q* eigenvector set.

Through the above mentioned calculation, *q* images for principal components can be obtained, which can be used to reduce the dimension of a data set, and keep the feature that contribute most to the variance of the data set; by keeping the lower principal components and ignoring the higher ones, So the positions of possible internal defects can be judged clearly through those principal component images.

Experimental verification

Preparation of sample and heating equipment. Prepare the concrete sample. The sample is 480mm long, 240mm wide and 160mm high with neat surface. The concrete grade is C40. Embed 3 foamed plastics to simulate the internal defects. The depth of the defect in the sample is *H*=60mm, the thickness of the defect is *h*=40mm, and the side lengths are 20mm, 60mm and 100mm respectively. Make and position the defects accurately. Set a rebar lifting ring on the side without rebar. Refer to Fig. 1.

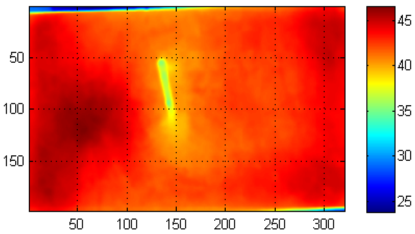
(a)The artificial defects (b) Visible-light image

Fig. 1 Concrete sample

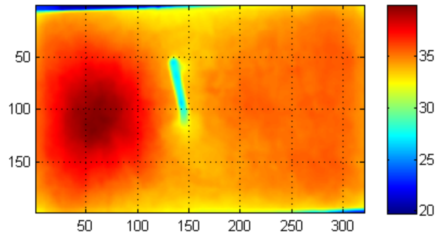
The concrete IR thermal imaging NDT heating device is formed by 45 ceramic radiators in 9 lines and 5 rows. The surface average thermal power density of the ceramic radiators is 16kW/m^2. The heating equipment is shown in Fig. 2.

Fig.2 Heating device and InfRec R300 infrared thermal imager

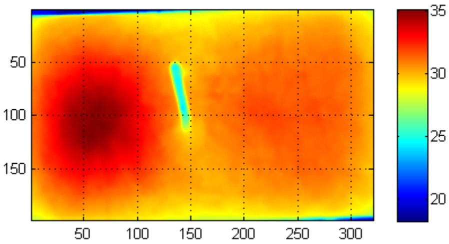
Test results. Test the side with the rebar lifting ring of the sample. Set the temperature of the heating array to 350℃, heat the concrete horizontal surface for 10min and then remove the heating device. Take an IR image every other 1min, record the cooling down process for 60min, and get 60 IR image sequence. Select image No. 7, 17, 27 and 60 as Fig. 3 shown.



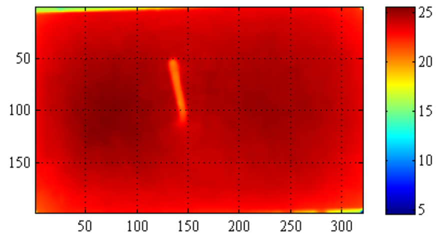
(a)No. 7



(b)No. 17



(c)No. 27



(d)No. 60

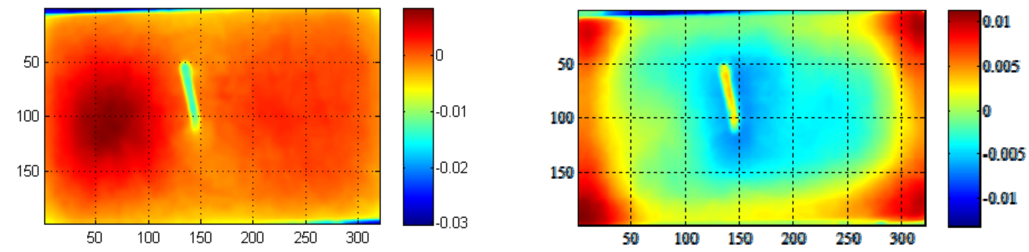
Fig.3 Infrared thermal images

When the equipment is removed newly, except for the exposed rebar lifting ring, the temperature on the concrete sample surface is average, there is no obvious high-temperature and low-temperature areas; when the heating device is removed for 7min (No. 7), there has been the local high-temperature area on concrete sample surface, but the border of it is not obvious; when the heating device is removed for 17min (No. 17), the border of the local high-temperature area has been very obvious, which corresponds the actual positions of the defects; when the heating device is removed for 27min (No. 27), the border of the local high-temperature area of the concrete sample surface has been diffused, the position of the border cannot be identified clearly; when the heating device is removed for 60min (No. 60), the temperature of concrete sample surface reaches unanimity again, there is no obvious high temperature and low temperature areas.

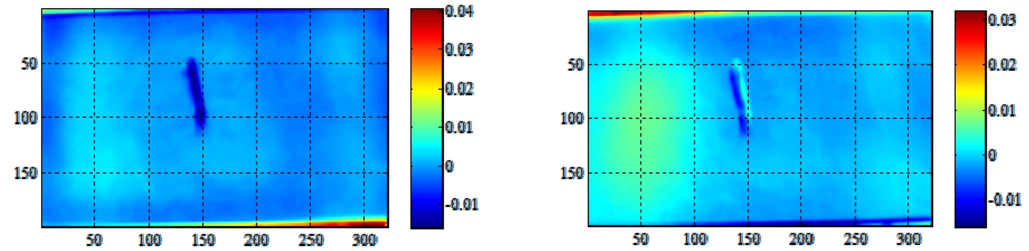
In addition, only the largest defect (With the side length 100mm) of the 3 ones in the sample can be detected, while the smaller defects (B with the side length 60mm and C with the side length 20mm) have no obvious surface temperature difference during the entire test procedure. The temperature difference information from defects are covered by outside noise (Uneven heating, etc.), the positions and sizes of defects cannot be judged from the thermography. Along with enlargement of defect geometric sizes, the defect outlines become obvious. At the same time, the exposed rebar lifting ring can be regarded as an additional external heat source, which affects identification of Defect B, and disturbs other defect detection results

PCA results. The traditional analytical method for internal defect identification directly by the infrared image sequence heavily relies on the clearest one in the sequence, there are large subjectivity and possibility of misjudge and misdetection.

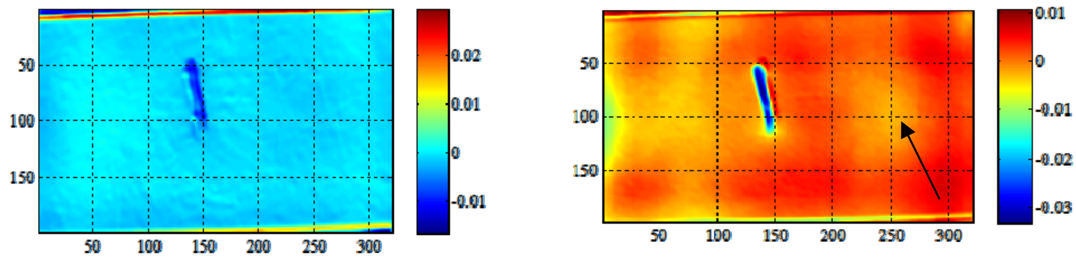
The results shown in Fig. 4 can be obtained by PCA to the infrared image sequence. Here the principal component result diagrams with the weight of principal components more than 2% (With the accumulative contribution rate 87.9%) is listed. Where the first principal component (With the contribution rate 50.5%) and the fourth principal component (With the contribution rate 6.5%) reflect the internal defect A with the side length 100mm; the sixth principal component (With the contribution rate 2.4%) reflects the internal defect with the side length 20mm; all the 3 ones are helpful principal components that reflect the internal defects; the second principal component (With the contribution rate 17.5%) reflects boundary heat effect, the third principal component (With the contribution rate 6.9%) reflects environmental conditions outside the sample, the fifth principal component (With the contribution rate 4.1%) reflects surface conditions of the sample, while all the 3 ones are noise components.



(a) The first principal component 50.5% (b) The second principal component 17.5%



(c) The third principal component 6.9% (d) The fourth principal component 6.5%



(e) The fifth principal component 4.1% (f) the sixth principal component 2.4%

Fig.4 Principal Component Analysis

Because the temperature changing regularity in various areas are different, different areas can be taken respectively from the IR images by PCA. Thereby defects that are hard to be detected by other methods can be identified better, for example, the internal defects with the side length 20mm can be detected with the sixth principal component, it is difficult to identify with other methods. At the same time, all images in the infrared image sequence are used, so information waste is avoided.

Summary

Here PCA is applied to the IR thermography detection for concrete internal defects, and the following conclusions are drawn:

(1) PCA can be used in IR thermography detection for concrete internal defects with better results;

(2) Information of all images is used adequately to avoid information waste;

(3) PCA can reduce subjective factors in IR thermography feature judgement to avoid misjudge and misdetection;

（4） By PCA, different areas in the IR images can be taken respectively, thereby defects that are hard to be identified by other methods can be identified better.

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