Fast normalized cross correlation for defect detection

D. M. Tsai and C. T. Lin
Machine Vision Lab.
Department of Industrial Engineering and Management
Yuan-Ze University, Chung-Li, Taiwan, R.O.C.
E-mail: iedmtsai@saturn.yzu.edu.tw

ABSTRACT

Normalized cross correlation has been used extensively for many machine vision applications, but the traditional normalized correlation operation does not meet speed requirements for time-critical applications. In this paper, we propose a fast normalized cross correlation computation for defect detection application. A sum-table scheme is utilized, which allows the calculations of image mean, image variance and cross-correlation between images to be invariant to the size of template window. Given larger images of size $M \times N$ and the neighborhood window of size $m \times n$, the computational complexity can be significantly reduced from $O(m \cdot n \cdot M \cdot N)$ with the traditional normalized correlation operation to only $O(M \cdot N)$ with the proposed sum-table scheme.

Keywords: Normalized cross correlation; Defect detection; Sum tables

1. INTRODUCTION

Normalized cross correlation (NCC) has been commonly used as a metric to evaluate the degree of similarity (or dissimilarity) between two compared images. The main advantage of the normalized cross correlation over the cross correlation is that it is less sensitive to linear changes in the amplitude of illumination in the two compared images. Furthermore, the NCC is confined in the range between –1 and 1. The setting of detection threshold value is much easier than the cross correlation. The NCC does not have a simple frequency domain expression. It cannot be directly computed using the more efficient FFT (Fast Fourier Transform) in the spectral domain. Its computation time increases dramatically as the window size of the template gets larger.

Correlation-based methods have been used extensively for many applications such as object recognition (Ooi and Rao, 1991), face detection (Brunelli and Poggio, 1993), motion analysis (Giachetti, 2000) and industrial inspections of printed-circuit boards (Kim *et al*., 1996), surface-mounted devices (Gallegos, *et al*., 1996), wafers (Cai, *et al*., 1994), printed characters (Penz, *et al*., 2001), fabrics (Yazdi and King, 1998), ceramic tiles (Costa and Petrou, 2000), etc. The traditional normalized correlation operation does not meet speed requirements for industry applications. In this paper, we present a fast normalized cross correlation for defect detection.

In object recognition or pattern matching applications, one finds an instance of a small reference template in a large scene image by sliding the template window in a pixel-by-pixel basis, and computing the normalized correlation between them. The maximum values or peaks of the computed correlation values indicate the matches between a template and subimages in the scene. The normalized cross correlation used for finding matches of a reference template $t(i, j)$ of size $m \times n$ in a scene image $f(x, y)$ of size $M \times N$ is defined as

$$d(x,y) = \frac{\sum_{i=-m/2}^{m/2} \sum_{j=-n/2}^{n/2} f(x+i, y+j) \cdot t(i,j) - m \cdot n \cdot m_f \cdot m_t}{\left\{ \left(\sum_{i=-m/2}^{m/2} \sum_{j=-n/2}^{n/2} f^2(x+i, y+j) - m \cdot n \cdot {m_f}^2 \right) \cdot \left(\sum_{i=-m/2}^{m/2} \sum_{j=-n/2}^{n/2} t^2(i,j) - m \cdot n \cdot {m_t}^2 \right) \right\}^{1/2}}$$

$$\textit{for all } (x,y) \in M \times N \qquad (1)$$

where

$$m_f(x,y) = \frac{1}{m \cdot n} \sum_{i=-m/2}^{m/2} \sum_{j=-n/2}^{n/2} f(x+i, y+j)$$

$$m_t(x,y) = \frac{1}{m \cdot n} \sum_{i=-m/2}^{m/2} \sum_{j=-n/2}^{n/2} t(i,j)$$

The template size $m \times n$ is smaller than the scene image size $M \times N$.

Pixel-by-pixel template matching is very time-consuming. For a scene image of size $M \times N$, and the template of size $m \times n$, the computational complexity is $O(m \cdot n \cdot M \cdot N)$. In order to alleviate the drawback of long processing time in template matching, the coarse-to-fine and multi-resolution search approaches (Gross and Rosenfeld, 1987; Crowley and Sanderson, 1987; Penz *et al.*, 1999; Bonmassar and Schwartz, 1998) have been widely used to reduce computation burden. Such algorithms first scan the image quickly and find all promising areas in the rough resolution, and then search for more accurate patterns and locations in the fine resolution.

An alternative strategy to reduce the computational load of the normalized cross correlation is to reduce data dimensionality by converting the 2D image into a 1D representation. Gallegos *et al*. (1996) generated a linear projection of the image along the major axis of the object under detection so that the 2D correlation can be converted into a 1D correlation. Tsai and Tsai (2002) used ring projection to reduce image dimensionality. The ring projection representation converts the 2D image in a circular window into a 1D gray-level signal as a function of radius. The feature of each ring with a specific radius is given by the average gray value of pixels on the ring. 1D representation can significantly reduce computational complexity. However, reduction in image dimensionality also reduces spatial information between pixels in the 2D image, and may result in false detection.

Lewis (1995) presented an algorithm for fast calculation of the normalized correlation using two sum tables over the image function f and image energy f^2. The sum tables are pre-computed integrals of f and f^2 over the search image. For a window of size $m \times n$, it can efficiently reduce the arithmetic operations from $m \cdot n$ to only three addition/subtraction operations once the sum tables are established. Lewis' sum-table approach can be used to efficiently calculate the denominator (image variances) of eq. (1). However, it cannot be directly applied to compute the cross correlation between images f and t, as the one shown in the numerator of eq. (1). The computational inefficiency of the NCC remains. Briechle and Hanebeck (2001) further presented a sum table-based algorithm for fast calculation of the NCC, and applied it to the problem of object recognition. The computation of the numerator in eq. (1), i.e., the cross correlation between images f and t, is simplified by the weighted sum of rectangular basis functions, i.e.,

$$\sum_{i=1}^{K} k_i \sum_{(x,y)\in R_i}\sum f(x,y),$$

where R_i defines the rectangular area of basis function i. This allows the sum table to be applied to the scene image f. The estimation of the coefficients k_i for the K basis functions is a non-trivial problem, and the result is only an approximation of the cross correlation. This approach is not practical for defect detection application since one may have to estimate $M \cdot N$ sets of coefficients k_i given a scene image of size $M \times N$.

In the correlation-based defect detection applications, a reference image and a scene image, both of sizes $M \times N$, are compared in a pixel-by-pixel basis. Two small windowed subimages of coincident pixel locations from the two respective compared images are used to compute the normalized cross correlation. The computation process is repeated by taking each coordinates (x, y) as the center of the neighborhood window so that the normalized correlation value of each pixel in the scene image can be evaluated. A pixel with NCC value below some specific threshold is then classified as a defective point. The location of a local defect in the scene image can be effectively detected in this manner. The normalized cross correlation used for detecting defects between a reference image $r(x, y)$ and a scene image $f(x, y)$ is defined as

$$d = \frac{\sum_{i=-m/2}^{m/2}\sum_{j=-n/2}^{n/2} f(x+i, y+j)\cdot r(x+i, y+j) - m\cdot n\cdot m_f \cdot m_r}{\left\{\left(\sum_i\sum_j f^2(x+i, y+j) - m\cdot n\cdot m_f^{\,2}\right)\cdot\left(\sum_i\sum_j r^2(x+i, y+j) - m\cdot n\cdot m_r^{\,2}\right)\right\}^{1/2}}$$

where $m \times n$ is the size of the neighborhood window; m_f and m_r are the gray-level averages of the windowed subimages from the scene and the reference, respectively. In this paper, we show that both the denominator (variances) and numerator (cross variance) of the normalized correlation formulation in eq. (2) can be calculated with the sum-table operation for defect detection application. The proposed sum-table scheme reduces the computational complexity of the traditional normalized cross correlation from $O(m \cdot n \cdot M \cdot N)$ to only $O(M \cdot N)$, given that the image of size $M \times N$ and the neighborhood window of size $m \times n$ The proposed method is invariant to the window size, and results in significant savings of computation time. This paper is organized as follows: Section 2 presents the sum-table scheme for NCC computation. The computational complexity and computation time between the proposed method and the traditional operation are also evaluated. The paper is concluded in Section 3.

2. THE SUM-TABLE SCHEME FOR NCC COMPUTATION

As aforementioned, the computational complexity of the traditional normalized cross correlation directly depends on the size of the neighborhood window. It is a common practice to use a small window size for time-critical applications. A small size of neighborhood window may contribute to computational efficiency, but it also degrades the effectiveness of defect detection.

Model images defined in a small window contain only little structure, and do not have enough information contents for robust detection. For a neighborhood window that contains $m \times n$ sample pixels, the error between the sampled correlation coefficient d and its continuous version r can be expressed by (Weatherburn, 1962; Betke and Makris, 1995)

$$E\left[(d-r)^2\right] = \frac{1-r^2}{\sqrt{m \cdot n}} \tag{3}$$

The evaluation of d relies on the window size. False detection can be avoided if the neighborhood window is sufficiently large. Figure 1(a) shows the image of a faultless PCB used as a reference, and Figure 1(b) is a defective PCB that involves a missing IC component. Both images are 400×400 pixels wide. In order to visualize the detection results, the resulting normalized correlation values are displayed as a function of intensity, where brightness is linearly proportional to the magnitude of the normalized correlation d. The darker the intensity in the resulting image, the stronger the evidence of a defect. Figures 1(c)-(f) show the detection results from window sizes of 5×5, 15×15, 20×20 and 35×35 pixels, respectively. The results reveal that an overly small window size can not generate reliable correlation values. Although the defective region can be notable detected with a small window size, noisy points are also signified in the resulting image. This may cause serious false alarm. The effect of noise is significantly reduced as the window size increases.

In this paper, we present a sum-table scheme that allows the calculation of the normalized cross correlation in eq. (2) to be invariant to the neighborhood window size so that the efficiency and effectiveness of the NCC for defect detection can be simultaneously retained. Given a two-dimensional discrete function $g(x, y)$, $x = 0, 1, 2, \cdots, M-1$ and $y = 0, 1, 2, \cdots, N-1$, the sum table associated with $g(x, y)$ is constructed by (Lewis, 1995)

$$S(x, y) = g(x, y) + S(x-1, y) + S(x, y-1) - S(x-1, y-1) \tag{4}$$

with $S(x, y) = 0$ when either $x, y < 0$.

The sum of $g(x, y)$ over limited ranges of x and y can then be calculated from the sum table, i.e.,

$$\sum_{i=-m/2}^{m/2} \sum_{j=-n/2}^{n/2} g(x+i, y+j) = S(x+m/2, y+n/2) - S(x-m/2-1, y+n/2) - S(x+m/2, y-n/2-1) + S(x-m/2-1, y-n/2-1) \tag{5}$$

Note that the original computation of the sum of $g(x, y)$ over the size of $m \times n$ involves $m \cdot n$ addition operations. It is dramatically reduced to only 3 addition/subtraction operations, and is invariant to the window size $m \times n$ with the help of the sum table.

The normalized correlation operations in eq. (2) involve the calculations of the image means and image squares for both the reference $r(x, y)$ and the scene $f(x, y)$ and the cross correlation between f and r, i.e.,

$$\sum_{i=-m/2}^{m/2} \sum_{j=-n/2}^{n/2} f(x+i, y+j) \tag{6}$$

$$\sum_{i=-m/2}^{m/2} \sum_{j=-n/2}^{n/2} f^2(x+i, y+j) \tag{7}$$

$$\sum_{i=-m/2}^{m/2} \sum_{j=-n/2}^{n/2} f(x+i, y+j) \cdot r(x+i, y+j) \tag{8}$$

and

$$\sum_{i=-m/2}^{m/2} \sum_{j=-n/2}^{n/2} r(x+i, y+j) \tag{9}$$

$$\sum_{i=-m/2}^{m/2} \sum_{j=-n/2}^{n/2} r^2(x+i, y+j) \tag{10}$$

Note that the image mean and image square (eqs. (9) and (10)) for the reference image $r(x, y)$ can be pre-calculated off-line. They do not cost the computation time in the inspection process. Since the normalized cross correlation is applied for defect detection, the image mean and image square for the scene image $f(x, y)$, and the cross-correlation between f and r (eqs. (6)-(8)) can be efficiently calculated by constructing three sum tables as follows:

$$S_m(x, y) = f(x, y) + S_m(x-1, y) + S_m(x, y-1) - S_m(x-1, y-1)$$

$$S_s(x, y) = f^2(x, y) + S_s(x-1, y) + S_s(x, y-1) - S_s(x-1, y-1)$$

$$S_c(x, y) = f(x, y) \cdot r(x, y) + S_c(x-1, y) + S_c(x, y-1) - S_c(x-1, y-1)$$

with $S_m(x, y)$, $S_s(x, y)$ and $S_c(x, y)$ = 0 if either $x, y < 0$. Therefore, eqs. (6)-(8) can be calculated from the sum tables $S_m(x, y)$, $S_s(x, y)$ and $S_c(x, y)$, respectively. That is,

$$\sum_{i=-m/2}^{m/2}\sum_{j=-n/2}^{n/2} f(x+i,y+j) = S_m(x+m/2,y+n/2) - S_m(x-m/2-1,y+n/2) - S_m(x+m/2,y-n/2-1) + S_m(x-m/2-1,y-n/2-1)$$

$$\sum_{i=-m/2}^{m/2}\sum_{j=-n/2}^{n/2} f^2(x+i,y+j) = S_s(x+m/2,y+n/2) - S_s(x-m/2-1,y+n/2) - S_s(x+m/2,y-n/2-1) + S_s(x-m/2-1,y-n/2-1)$$

$$\sum_{i=-m/2}^{m/2}\sum_{j=-n/2}^{n/2} f(x+i,y+j)\cdot r(x+i,y+j) = S_c(x+m/2,y+n/2) - S_c(x-m/2-1,y+n/2) - S_c(x+m/2,y-n/2-1) + S_c(x-m/2-1,y-n/2-1)$$

For two compared images of size $M \times N$, and a neighborhood window of size $m \times n$, the required arithmetic operations between the traditional normalized correlation and the proposed sum-table scheme are summarized in Table 1. It can be seen from Table 1 that the proposed sum-table scheme takes only $18 \cdot M \cdot N$ addition/subtraction and $2 \cdot M \cdot N$ multiplication operations, whereas the traditional normalized correlation involves $3 \cdot m \cdot n \cdot M \cdot N$ addition and $2 \cdot m \cdot n \cdot M \cdot N$ multiplication operations. The overall improvements of the proposed method over the traditional normalized correlation are $m \cdot n/6$ in addition/subtraction and $m \cdot n$ in multiplication. The computational complexity can be significantly reduced from $O(m \cdot n \cdot M \cdot N)$ to only $O(M \cdot N)$, i.e., the computation of NCC is invariant to the window size $m \times n$. This allows a user to select a sufficiently large neighborhood window for obtaining the best detection effectiveness, while maintaining the computational efficiency.

Given a scene image of size 400×400 pixels, the computation times from the proposed sum-table scheme and the traditional NCC operation on a personal computer with a Pentium III-1000MHz processor are presented in Table 2. The results reveal that the computation time of the traditional method is dramatically increased as the window size gets larger. However, the computation time of the proposed method is a constant, regardless of the changes in window size.

3. CONCLUSION

The traditional normalized cross correlation is one of the most effective and commonly used similarity metrics in computer vision. However, it does not meet speed requirements for time-critical applications. In this paper, we have proposed a fast normalized cross correlation based on the sum-table scheme for the application in defect detection. The use of the sum tables for the calculations of image mean, image variance and cross correlation introduces substantial computation savings. The computational complexity can be dramatically reduced from $O(m \cdot n \cdot M \cdot N)$ with the traditional normalized correlation operation to only $O(M \cdot N)$ with the proposed sum-table scheme, given that the scene image of size $M \times N$, and the neighborhood window of $m \times n$. Since the proposed method is invariant to the window size, a user can select a proper window size to maximize the detection effectiveness for the object under inspection without trading off the computational efficiency. The proposed sum-table scheme makes the normalized cross correlation applicable for on-line defect detection applications.

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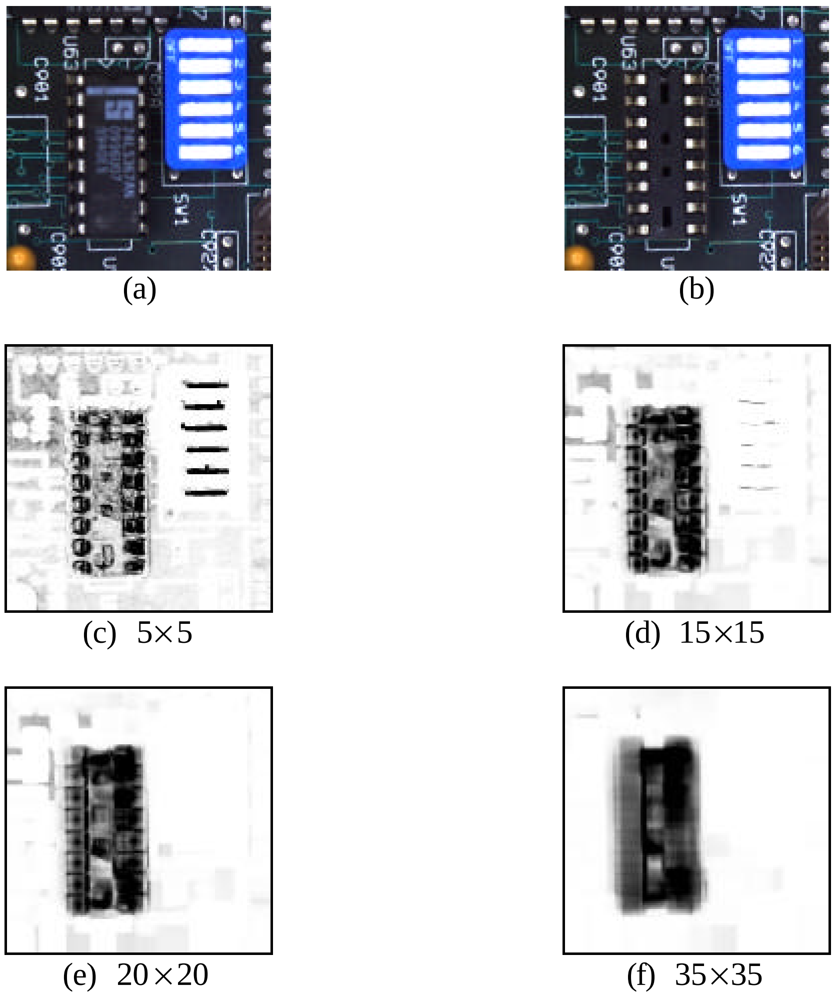

Figure 1. The effect of changes in window size: (a) the reference image; (b) the scene image involving a missing IC component; (c)-(f) detection results from window sizes of 5×5, 15×15, 20×20 and 35×35 pixels, respectively.

Table 1. The comparison of arithmetic operations between the proposed sum-table scheme and the traditional normalized correlation.

Image size : $M \times N$ Window size : $m \times n$		The proposed method		The traditional method	
		Addition/ subtraction	Multiplication	Addition/ subtraction	Multiplication
Construction of sum-tables	S_m	$3 \times M \times N$	0	0	0
	S_s	$3 \times M \times N$	$M \times N$	0	0
	S_c	$3 \times M \times N$	$M \times N$	0	0
Calculation of NCC	$\sum\sum$	$3 \times M \times N$	0	$m \times n \times M \times N$	0
	$\sum\sum f^2$	$3 \times M \times N$	0	$m \times n \times M \times N$	$m \times n \times M \times N$
	$\sum\sum f \cdot r$	$3 \times M \times N$	0	$m \times n \times M \times N$	$m \times n \times M \times N$
Total		$18 \times M \times N$	$2 \times M \times N$	$3 \times m \times n \times M \times N$	$2 \times m \times n \times M \times N$

Table 2. The comparison of computation times (based on a personal computer with a Pentium III 1000 MHz process).

Image size :400×400 Window size :	The proposed method (seconds			The traditional method (seconds
	Construction of um-tables	Calculation of NCC	Total	
15×15	0.16	0.44	0.60	64.47
25×25	0.16	0.44	0.60	151.58
35×35	0.16	0.44	0.60	267.82