Neurocomputing 123 (2014) 406–414

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

A sparse representation based fast detection method for surface defect detection of bottle caps

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ARTICLE INFO

Article history:
Received 16 February 2013
Received in revised form
12 June 2013
Accepted 3 July 2013
Communicated by Pingkun Yan
Available online 29 August 2013

Keywords:
Fast detection
Bottle cap
Surface defect
Circular region projection histogram (CRPH)
Sparse representation

ABSTRACT

A practical machine-vision-based system is developed for fast detection of defects occurring on the surface of bottle caps. This system can be used to extract the circular region as the region of interests (ROI) from the surface of a bottle cap, and then use the circular region projection histogram (CRPH) as the matching features. We establish two dictionaries for the template and possible defect, respectively. Due to the requirements of high-speed production as well as detecting quality, a fast algorithm based on a sparse representation is proposed to speed up the searching. In the sparse representation, non-zero elements in the sparse factors indicate the defect's size and position. Experimental results in industrial trials show that the proposed method outperforms the orientation code method (OCM) and is able to produce promising results for detecting defects on the surface of bottle caps.

1. Introduction

The cap is an important part of bottling product packaging. The pattern of the cap's surface normally includes a company logo, and possibly defects such as surface scratch, distortion, stains, printing deviation and other faults that occur during the production (e.g. stamping and plastic injecting). Therefore, inspection of defected caps is of crucial importance for quality control. Machine vision based inspection technique is a promising solution to replace human vision. Defect detection has been studied intensively in many areas, such as fabric [1], glass panel [2], sheet steel [3], agricultural [4,5], food [6], electronics [7], lumber [8,9], and bottling industries [10]. However, few studies have addressed automatic inspection of the surface of bottle caps.

Most automated visual inspection systems for complicated textured surfaces generally attempt to identify defects by building adequate templates of feature representation from sample images. This representation is called feature dictionary, which is used to analyze a sample image for detecting anomalies. Detection accuracy is dependent on the adequacy and generalization of the dictionary. Generally, the selection of an adequate feature set in the training process requires the assistance of complicated classifiers such as Bayes [11], maximum likelihood [12], and neural networks [13] for classifying sample and template features. The entire process is of high computational complexity and time-consuming. In the meantime, however, the production of caps is very fast. At least 2600 caps will be produced per minute. The time left to deal with each single cap is less than 24 ms. Thereby, a simple and high-speed detection method is desirable. Typically, the process of defect detection requires at least two steps [14]. In the first step, the sample image is rotated and translated to be aligned with the template image. In the second stage, the two images are matched point by point. Thus, fast and precise alignment is very critical. In this paper, we propose a novel circular region projection histogram (CRPH) method and a fast detection algorithm based on sparse representation of the defects of bottle cap surface. The main idea of the paper stems from the work reported in [14,15].

We propose a circular region projection histogram method that is similar to the orientation code histogram method proposed in [14]. In [15], text and piecewise smooth contents in an image are separated into two different images. Different dictionaries were used for different contents, such as a dictionary of bi-orthogonal wavelet transforms (OWT) for piecewise smooth contents and a dictionary of discrete cosine transform (DCT) for texture contents. In our method, the image center is firstly located, and then the appropriate radius

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0925-2312/$ - see front matter
http://dx.doi.org/10.1016/j.neucom.2013.07.038

circle range is extracted as the template region of interesting (ROI) on the standard cap's surface. The ROI is projected as histograms along different directions that are rotated around the image center. The histograms are the arrays that model the true distribution by counting the occurrences of pixel values that fall into each bin. These arrays are regarded as atoms that compose the template dictionary similar to the one developed in [15]. Secondly, the image of the sample cap is captured whilst the sample ROI is extracted. Then, the ROI is projected at vertical and horizontal directions to get two 1D arrays as sample project histograms. Finally, the defect can be found through matching the atoms in the template dictionary to the sample histogram using a developed sparse representation method. The experimental result shows that the CRPH method and the developed sparse representation algorithm are effective for finding the defect on the cap's surface.

The rest of this paper is organized as follows. Section 2 reviews the challenges and presents corresponding solutions based on sparse representation. Section 3 discusses the process of extracting ROI and introduces a novel method CRPH for feature matching, while the template and the defect dictionaries are built, respectively. The fast match algorithm is proposed in Section 4. Experimental results and their analysis are shown in Section 5 and Section 6 concludes the paper with a summary of the proposed work and discussions.

2. Sparse representation method

Sparse representation methods have drawn a lot of attention in recent years. The problem is solved by searching for the most compact representation of a signal in a dictionary [16]. Suppose that an arbitrary bottle cap has a surface image X which contains a template pattern marks X_t and a defect component X_d. As such, the bottle cap's surface can be denoted as follows:

$$X = X_t + X_d. \tag{1}$$

The defect detection is a process of separating the template image X_t and defect image X_d from the sample image X. We can use a sparse representation to solve this equation.

The template image X_t only contains an original pattern which is flawless. The sparse decomposition matrix $D_t \in M_t^{N\times L}$ is written as [17]

$$X_t = D_t\alpha_t, \tag{2}$$

where α_t is known as the template's sparse factor, D_t is the template dictionary.

Similarly, for the defect image on the cap's surface, the sparse decomposition matrix $D_d \in M_d^{N\times K}$ is written as

$$X_d = D_d\alpha_d, \tag{3}$$

where α_d is the defect's sparse factor. D_d is the defect's dictionary. So, X can be denoted as follows:

$$X = D_t\alpha_t + D_d\alpha_d. \tag{4}$$

To seek a sparse representation over a combined dictionary containing both D_t and D_d, one of the popular methods is to use the L_0-norm as a definition of sparsity. Hence, the following equations need to be solved:

$$\begin{aligned}&\{\alpha_t, \alpha_d\} = \arg\min\|\alpha_t\|_0 + \|\alpha_d\|_0\\ &\text{s.t.}\quad X = D_t\alpha_t + D_d\alpha_d.\end{aligned} \tag{5}$$

Eq. (5) only refers to an ideal case. In practice, due to light intensity changes, density changes and distortion, the image X cannot be fully decomposed into the template and the defect images. Instead, X is represented as [18]

$$\begin{aligned}&\{\alpha_t, \alpha_d\} = \arg\min\|\alpha_t\|_0 + \|\alpha_d\|_0\\ &\text{s.t.}\quad \|X - D_t\alpha_t - D_d\alpha_d\|_2 \le \varepsilon\end{aligned} \tag{6}$$

where the parameter ε stands for the residual that is the tolerance between the sample and the template images. Using this way, the decomposition of the image is only an approximation.

As well known, the problem formulated in (6) is non-convex and intractable. Its complexity grows exponentially as the number of columns in the overall dictionary increases. In order to obtain a tractable convex optimization solution, the basis pursuit (BP) method [19] reveals the replacement of the L_0-norm with an L_1-norm [20]. Eq. (6) is re-written as a linear programming problem:

$$\begin{aligned}&\{\alpha_t, \alpha_d\} = \arg\min\|\alpha_t\|_1 + \|\alpha_d\|_1,\\ &\text{s.t.}\quad \|X - D_t\alpha_t - D_d\alpha_d\|_2 \le \varepsilon.\end{aligned} \tag{7}$$

The methods introduced above are effective in defect detection. However, they have high computational complexity and is time-consuming. They are still far from real-time applications. One of the reasons is that the dictionaries are redundant and overcomplete. The dictionary size determines the time complexity and quality of matching. The more atoms there are in a dictionary, the better the search precision may be. This is the reason that an overcomplete dictionary is usually adopted [21]. However, the overcomplete dictionary is always large, and it increases computational complexity. Therefore, a trade off is needed between matching precision and computational complexity. In this paper, a novel dictionary is proposed which is compact and simple. A simple dictionary may sacrifice the accuracy of separation but will help to achieve real-time process. Another contribution of this paper is to use circular region projection histogram (CRPH) as the matching features, which can speed up the rotating match.

3. Feature extraction and dictionary construction

Searching and extracting circular region is the key point to improve the overall speed of the detection algorithm. The projective transformation is performed on the circular region of interest (ROI). Apparently, this approach can save a lot of computing time since the ROI has a smaller size than the entire image. Fig. 1 shows the process of ROI extraction. This process includes four steps: (a) Acquisition of the original images. (b) Searching the edge points and center of the cap image. (c) Positioning the ROI. (d) Extracting the ROI.

The second step above is very critical as the positioning accuracy of the cap center determines the quality of further tasks. In order to obtain the cap center, the cap's edge points are searched firstly. The searching path is along the radius from the outside to the inner as shown in Fig. 1(b). The light cross symbols indicate the edge points of the cap. Due to the fact that the edge points have the maximal changes in brightness, the second-order Gaussian function is used to search for the singular points (edge points). The mathematical expression of the singular points is given as follows [22]:

$$\frac{\partial^2 g(t)}{\partial t^2} = 0 \quad \text{s.t.}\ \frac{\partial g(t)}{\partial t} > 0 \tag{8}$$

where $g(t)$ denotes the density at point t, which is the index position on the radius line. Eq. (8) suggests that the search direction is along the radius from the outside to the center and the density changes from low (or dark) to high (or bright) in finding the extremum points, and the points are ignored where the density changes from high to low. Due to the special shape characteristics of the crown cap, the image intensity changes significantly from dark to bright at the circle edge along the radius from the cap edge to the cap center. In Fig. 1, a search path is pre-planned in which the search direction is almost orthogonal to the edge so that the edge points can be found easily and the search speed is improved. The search path is shown in Fig. 1(b), the radius of external circle used in the search path needs to be as large as possible in order to ensure that the search path always starts from outside the cap, and ends inside the cap. In order to avoid