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Unsupervised Shape Classification of Convexly Touching Coated Parts with Different Geometries

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ABSTRACT

Visual inspection system of various manufactured geometries is widely adopted in industry whereas the inspection system's intelligence is yet to be improved. Mixing of various geometries is a common problem in coating industry and the inspection is carried out manually. This paper gives a framework for classifying the mixed parts from the images captured without prior information of geometries. The parts were segmented from the image using Otsu method followed by morphological operations. Then the borders were extracted and smoothened by Fourier approximation. The touching objects were separated using curvature analysis. Features such as area and skeleton were extracted from the individual parts. The geometries were then classified by k–means clustering successfully. The developed algorithm works for a variety of geometries and is independent of translation and rotation of the parts.

Keywords: shape classification, convex-touching objects, machine vision, inspection.

1. INTRODUCTION

Inspection of manufactured parts is of major importance due to implementation of stringent quality-control measures in industry. Many automobile parts such as nut, bolt, armature, etc. have to be chrome coated before assembling. Such small parts with various geometries are processed in bulk quantities. Ideally there should be unique geometry for each batch or lot. Due to manual transport few parts may remain in the coating instrument resulting in mixing of previous lot geometries with the current one. Geometries that do not belong to the currently inspected geometry (novelty part) have to be rejected during inspection in coating industries. Currently the inspection is carried out manually which is expensive and inaccurate. In this work, a computer aided vision based inspection method for novelty detection for various geometry profiles is proposed, which has advantages like speed, low-cost, repeatability and reliability. The problems associated with the automatic inspection of novelty part using machine vision method are

- Each part cannot be individually checked as the quantum of output is high. Also the parts cannot be constrained in a fixed position.
- The parts may be touching. The touching parts will give wrong segmentation which in turn affects the understanding of the geometrical properties.
- The coated part's geometry may not be always same for all the lots thereby requiring the system to work in an unsupervised way.
- The shape feature extraction from the segmented image has to be robust enough to capture the differences in the shape profile of components.

Hence the solution is not trivial and many state-of-the art geometry based vision techniques should be combined to form an inspection framework.

Machine vision inspection is carried out to measure dimensions or to identify surface defects. For dimensional measurement, the ground truth is defined for a specific part or can be fed by a CAD model [11]. A generic system for detecting defective objects is difficult because most systems often require prior learning specific to the task. Many supervised learning methods have been tested for classification of defective pieces [26].

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Novelty classification was carried out in a supervised way trained by defect free sample. This kind of training is necessary only when there is less number of training samples. Unsupervised classification is necessary for a novelty system to be applied to all systems. Such unsupervised classification is carried out using self-organising map [19].Processing multiple objects at a time poses the problem of touching in segmentation [15]. Touching parts have to be split after segmentation. Different approaches were tried in the literature based on concavity [7,10,23], watershed [14,22,25], mathematical morphology [6], global minimization [1], ellipse-fitting [2,9,27] and elliptic Fourier approximation [15,16]. Defective fruits were classified on the basis of shape [5].

A majority of machine vision systems assumes the parts to be constrained. A generic algorithm for automated visual inspection with unconstrained position of geometries is a long requirement in the industry [17]. Such algorithms should be invariant to translation and rotation of the parts. Since the geometry that is considered for inspection is not known, an unsupervised shape classification has been proposed in this paper. The problem considered here is unique as the requirement is to inspect unconstrained touching geometries in an unsupervised way considering robust shape features.

2. DEVELOPMENT OF INSPECTION FRAMEWORK

The parts have to be segmented from the background and then the touching objects have to be separated. From the image with separated parts, certain shape features have to be extracted. With those features, the parts have to be clustered as novelty and non-defective without any priori information. The techniques used at each step are summarized as a flowchart in Fig. 1.

2.1. Image Capture

Images of various combinations of different geometries were captured in a laboratory image acquisition setup (Fig. 2(a).). A ring white LED light was used as illumination for the image acquisition. Various parts collected from coating industry such as nut, bolt, armature, screws along with few novelty parts were captured as colour images. Fig. 2(b). shows one such image with nuts as non-defective and screws as a novelty part. The background was kept as black to avoid shadows in the image. The aperture was maintained small to reduce specular reflections from the reflective coatings.

2.2. Segmentation and Morphological Operations

Segmentation of the objects from the background can be achieved by various methods [18,28]. In this paper the segmentation of the parts from the background is carried out using Otsu method [20]. Otsu method automatically finds the threshold by minimizing the intra class variance of the histogram. Otsu method was observed to be accurate for this application. A binary image is obtained by applying the threshold determined by Otsu method (Fig. 3(a).). The binary image obtained is further subjected to morphological operations such as closing, opening and filling [8] to remove the noise and the operations are shown in Fig. 3(b-d).

2.3. Border Smoothening

Shape based algorithms [7,24] otherwise known as clump splitting algorithms split the touching objects

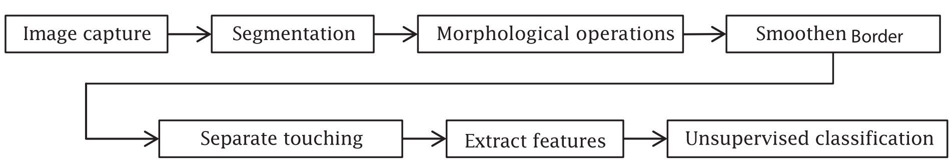

Fig. 1: Flowchart of the inspection framework.

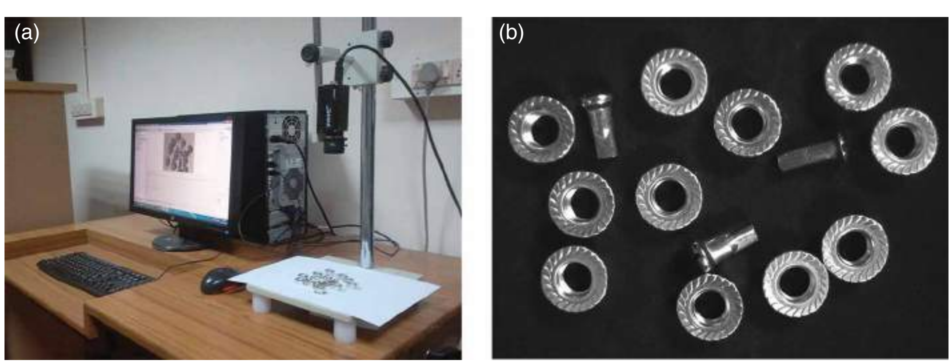

Fig. 2: Image acquisition: (a) Laboratory setup, and (b) Image with novelty parts.

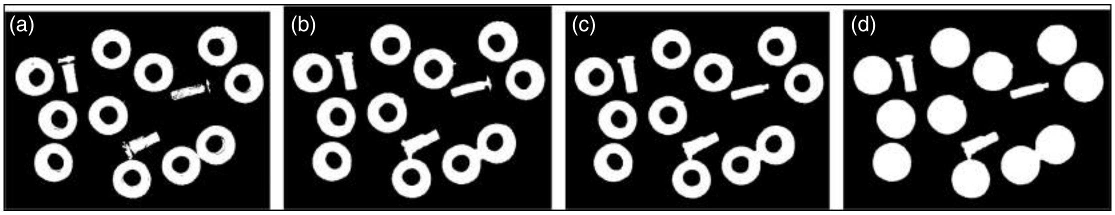

Fig. 3: Image segmentation: (a) Otsu segmentation, (b) Closing operation, (c) Opening operation, and (d) Filling operation.

by finding the concave points. Error in finding concave points due to improper segmentation affects the efficiency of clump splitting. Watershed based methods [14,25] are found to be satisfactory for some unique applications. Watershed segmentation is less efficient producing over segmentation when the change in gradient of the two touching objects is low. Various morphological operators in different sequences were experimented on the image to split the objects [6]. A long chain of objects reduces the efficiency of morphological operators. The global minimization based method [1] is not satisfactory except few cases. The lesser the gradient of the objects the more the minimization method will fail in splitting. Ellipse fitting method [2,9] is followed to fit the objects thereby achieving split which is time consuming. Obviously the algorithm accuracy decreases as the object deviates from the shape of an ellipse or a circle. A combination of watershed and concavity is time consuming [29]. Elliptic Fourier approximation based technique [15,16] is robust, fast and can handle large input with varied geometrical features. Elliptic Fourier approximation was tested on plastic bottles and grain kernels. In this work elliptic Fourier approximation is used to separate the touching objects.

In the segmented binary image, few parts (appearing as white blobs) are touching (Fig. 3(d).). These blobs have to be separated assuming that they touch convexly. The curvature at those touching points significantly differs from rest of the points on the border of the white blobs. To obtain the curvature, a smooth border is needed. To transform the blobs with a smooth border the following procedure was followed. The boundaries were extracted from the binary image using the canny edge operator [4]. Fig. 4(b). shows the edge of single blob.

The shape signature of the boundaries can be described by elliptic Fourier descriptor. The chain code was calculated from the boundary image. The chain code was converted to Fourier domain by Fast Fourier Transform. The Fourier series of the border is given by Eqn. (1)

$$x_N(t) = A_0 + \sum_{n=1}^{N} a_n \cos\left(\frac{2n\pi t}{T}\right) + b_n \sin\left(\frac{2n\pi t}{T}\right) \tag{1.1}$$

$$y_N(t) = C_0 + \sum_{n=1}^{N} c_n \cos\left(\frac{2n\pi t}{T}\right) + d_n \sin\left(\frac{2n\pi t}{T}\right) \tag{1.2}$$

Where N is the number of harmonics in Fourier approximation, A_0 and C_0 are coefficients of zero frequency.

Various percentages of the frequencies were retained while it is converted to chain code by Inverse Fast Fourier Transform as shown in Fig. 4(c-e). The chain code was converted back to binary image with smoothened borders. By eliminating the high frequency information, smoothened borders were obtained. Fig. 4(d-e) shows the effect of Fourier descriptors. Fig. 4(f-g). show the edge detection and smoothening for the whole image.

2.4. Separation of Convexly-touching Points

The curvature was then calculated for all points in the border of each blob using the formula in Eqn. (2)

$$\kappa(t) = \frac{dx(t)d^2y(t) - d^2x(t)dy(t)}{(dx(t)^2 + dy(t)^2)^{3/2}} \tag{2}$$

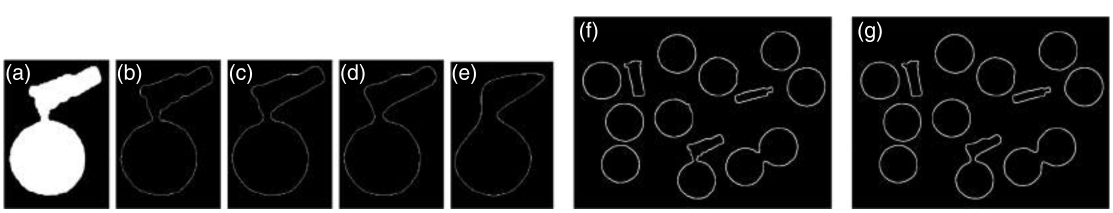

Fig. 4: Edge detection and Smoothening of border: (a) Binary blob, (b) Border obtained from Canny edge operator, (c) Border reconstructed from 50 % of Fourier descriptors, (d) Border reconstructed from 30 % of Fourier descriptors, (e) Border reconstructed from 10 % of Fourier descriptors (f) Edges of whole image, and (g) Smoothened borders with 50 % of Fourier descriptors.

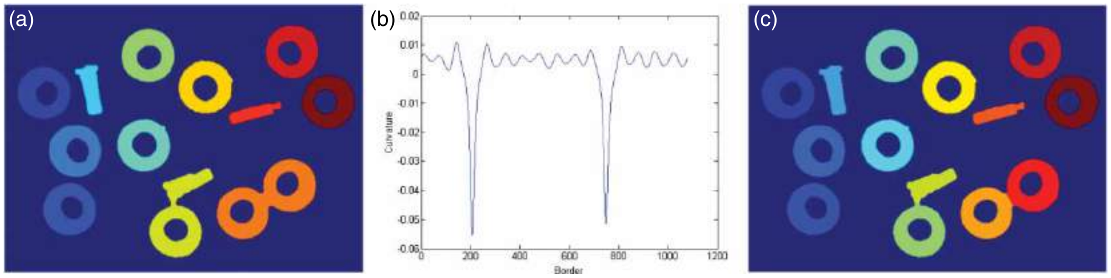

Fig. 5: Separate convexly touching objects: (a) Touching objects in same colour, (b) Curvature along the smoothened border of 2 touching objects blob shown in Fig. 3(c)., and (c) Touching objects separated by thresholding the curvature shown in different color.

where $\kappa(t)$ is curvature, $dx(t)$, $dy(t)$, $d^2x(t)$and $d^2y(t)$ are the first and second derivatives of the coordinates x and y. Points that were below the threshold of -0.01 curvature are considered as concave or nodal points. The unit of curvature is pixels. The curvature varying along the border of a convexly touching blob is shown in Fig. 5(b). The touching parts were then separated along the nodal points as shown in Fig. 5(c). The assumption about the shape of the touching objects is that the border should be always convex (i.e there are no concavities and concavity is defined by the curvature $< -.01$). If more than two objects are touching, this method will not work. Existing methods such as ellipse fitting [2], nearest concave points [16] for separating more than two parts were tested and found to be inconsistent across all trial cases. The assumptions of objects resembling ellipse shape and nearest concave points belong to the same object are the reasons for the failure of the methods.

2.5. Feature Extraction and Unsupervised Classification

Skeleton based matching and clustering using probabilistic techniques were proven to be successful [3, 21]. The area of each blob is then calculated by adding the pixels in each blob. The medial axis or skeleton is calculated using thinning operation (Fig. 6(a).) [8]. The area and medial axis were considered as features and clustered with unsupervised k-means algorithm [12]. The medial axis obtained from the image is converted to feature space by branch information and normalised by vector quantization. K–means is a clustering algorithm which finds the mean vectors of the expected number of clusters (k) by iterative process. The Euclidean distance is used as a metric. The k was selected as 2 because only the novelty had to be classified from the rest (i.e. there are only two classes). The classifier returns a null cluster when there was no novelty part. The result of shape classification is shown in Fig. 6(b). K-means initialization was done by Mersenne Twister algorithm [13] for consistent random number generation.

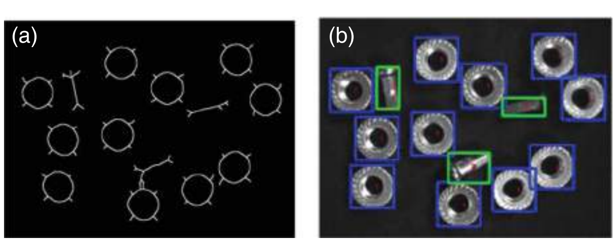

Fig. 6: Skeleton detection and shape classification: (a) Skeleton/ Medial axis (b) Unsupervised classification by k-means and labeling.

3. RESULTS AND OBSERVATIONS

Various geometries and mixed combinations were tested and are shown in Fig. 7. 50 % of frequencies were retained as a uniform for all the images.

Fig. 7. shows the classification result of similar geometry. Though the skeleton is uniform (Fig. 7(c)) for the parts the 'area' feature distinguishes them. Fig. 8(a). is captured at a different magnification with different parts and the classification gives a good result. The framework developed here is invariant to position, translation and rotation of the objects with uniform scaling. The algorithms for constrained objects lack these qualities [17]. Multiple parts can be inspected in a scene in comparison to inspection of single objects. The speed of the algorithm is faster than algorithms with higher order feature extraction and ranking methods [3]. There is no training required which makes the framework generic to multiple objects. In contrast, most of the defect classification algorithms require training [26].

The limitations of the proposed inspection framework are occlusion, overlap of parts, high intensity illumination, assumption of convex shaped objects and mix-up of more geometry. -If an object is above another (occlusion), the numbers of true negatives or false positives are likely to increase because multiple parts will be segmented as one blob which in turn alters the area and medial axis. As the parts were not occluded due to their circular geometry, this algorithm worked well in coating industry case. Flat parts might be occluded at times. In that case, use of range cameras will be useful to get the shape. Any

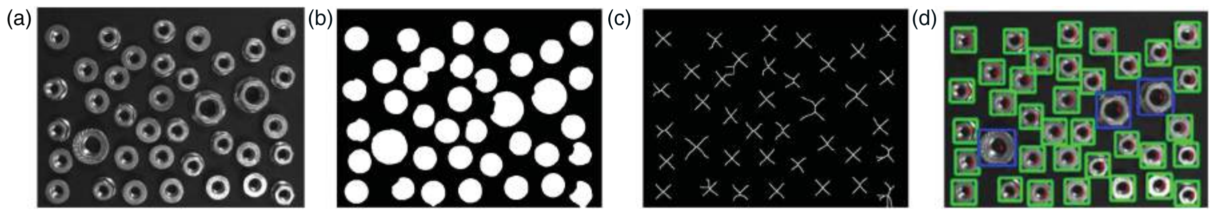

Fig. 7: Classification results for nuts of varying size: (a) Original image, (b) Parts segmented and the touching parts were separated, (c) Skeleton, and (d) Classification.

holes in the object should be free of other objects. Since the holes are filled, the smaller part will be missed from classification. A high intensity of incident light produces more bright spots on the specular coated surface. Bright spots degrade the segmentation and in turn may affect the overall efficiency of the method. More than 2 parts should not be touching. If more than 2 geometries are mixed, a manual input is required to guess the number of geometries (k).

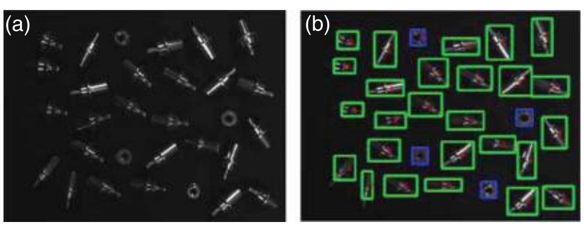

Fig. 8: Classification result for mixed armature and nuts: (a) Original image (b) Classification result.

4. CONCLUSIONS

The novelty part detection problem in industry is prototyped in laboratory environment. Images of various geometries like nut, bolt, armature, screws were captured along with various novelty geometries. The segmentation of the geometries from background is based on histogram properties. Fourier elliptic shape descriptor along with curvature information works well to separate different or same touching geometries. The feature space is contributed by area and skeleton of the geometries providing a large intra-class variance and hence k-means algorithm classifies the shapes with high accuracy. The proposed algorithm works well on a broad variety of situations such as different geometries and rotation of the parts. Overall the proposed inspection scheme forms a generic novel framework that has a potential for automation in industries.

ACKNOWLDEGEMENT

The authors would like to express their sincere thanks to Durga Metal Finish Private Limited, Ambattur, India for supplying the coated parts.

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