Machine parts recognition and defect detection in automated assembly systems using computer vision techniques

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Abstract: Assembly line automation gets more significance to cope up with increasing needs of latest technology machines which are used in industry and society. This paper presents a computationally efficient 2D computer vision based approach to recognize the machine parts and detect damaged parts on the assembly line. The image acquisition system which is part of the assembly line setup acquires data from the moving machine parts in line. Captured machine part image data undergoes image preprocessing techniques like background subtraction, binarization, scaling, and noise and holes removal to transform the data suitable for further processing. Then a contour of the machine parts are extracted and normalized by equal part area method to describe the shape. It gives important clues for machine part shape recognition and defect identification. For experimental purpose a model shape for each machine part is developed, the shape recognition and defect detection are performed with only reference to the model shape. The defects in the machine part such as damage, cracks are identified by the similarity measure between model shape and the data extracted from machine part of the assembly line. The detection and identification of defects at the early stage will helps smooth production process, saves production cost and time.

Keywords: Automated assembly systems, machine parts, shape recognition, defect detection, area normalization, computer vision.

1. INTRODUCTION

Today automated assembly systems are widely used in different types of product manufacturing industries (e.g. locks, gear boxes, alarm clocks, engines and motors etc.) and packaging industries with large scale production units. They used mechanized devices such as part feeder, conveyor, image capturing unit, part recognition unit, part selection unit, and intelligent robots that follow fixed sequence of steps to assemble the product.

There are three classes of assembly systems (Lieberman L.I., et al., 1977) with respect to productivity namely high, medium, and low volume production units. In high volume production the assembly systems are fully automated, assembly of parts in other two classes are performed in semi-automated or manual by hand. The variants of these assembly systems are in-line assembly system, dial indexing system, carousel assembly system, and single station assembly system, which is chosen according to the manufacturing process, product, and the production quantity required. The initial investment cost for establishing such systems is high, but it saves time, money, and labor. The advantages of such system are huge quantity of production, stable product design with good quality and reliability.

The machine parts recognition in automated assembly systems is entirely different from general object recognition; moreover the ability of human to distinguish between healthy and unhealthy machine parts are good but it is a complicated task for a machine. In general manual defect detection by human inspectors are impractical with fast moving machine parts on conveyor in addition it is expensive, subjective, inaccurate, eye straining and other health issues to quality control inspectors (Riby Abraham Boby et al., 2011). By considering these issues, a computer vision based non-contact inspection technique is developed for defect detection in industrial machine parts by image processing techniques. The present study will help the industrial robot used in assembly process and industrial inspection systems.

The defect detection is performed on machine parts at early stages of the assembly line to ensure product quality. The schematic diagram for defect detection from machine parts is shown in Figure1. The 2D vision of machine parts which are moved along the conveyor are captured and its boundary characteristics are analyzed to match with its model shape. If there is any deviation in matching result leads to notification of defect which in turn instructs the robot controller to pick up the defective piece from the conveyor and place it in the pallet.

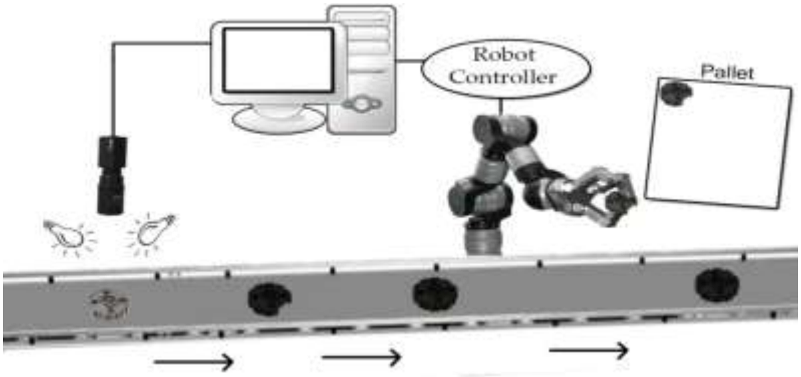


Figure 1. A schematic diagram for machine parts defect detection in model assembly line.

In general, defects in machine parts are classified into two types: surface defects and damages. The surface defects are identified by texture and color features, but part damages are identified by shape features. In the present study, a shape feature extraction method is employed which is compact in nature and it is responsive with the speed of the assembly line. The defect detection is performed with reference to a model shape of the machine part. The shape descriptor uses only the boundary information to describe the shape of the machine part. The matching of test shape with model shape is performed using correlation coefficient metric. If any deviation found in the test then it is identified as defective. The status of healthy and unhealthy parts is notified to the robot controller for its appropriate action.

The reminder of this paper is organized as follows. The section 2, presents literature review on part recognition and defect identification in automated assembly lines. Section 3 presents a shape feature extraction method that identifies defects in machine parts. The experimental results are discussed in Section 4. Finally section 5 concludes this paper.

2. LITERATURE REVIEW

The research on automated assembly systems was started long years back; many enhancements are incorporated with respect to the evaluations in the field of mechanical engineering. After the advent of computers, automated inspection of industrial parts is achieved using machine/computer vision techniques. From the literature it is known that lot of research has been done for detecting the defects from the industrial parts using machine vision based non-contact inspection techniques. There are places the machine vision is applied in automated assembly systems (Jim Orrock et al., 1988) part recognition and location, non-contact control to find part orientation, and visual inspection.

This section describes variety of techniques used in defect detection from machine parts. The approaches used for defect detection in automated assembly systems are classified into single feature based or multi-feature based shape description methods.

2.1 Single Feature Based Descriptors

A single feature based techniques are faster and they are capable to work with the speed of the assembly line. An edge based geometric pattern matching method is adapted in (Jun Sun et al.,2009) to inspect the machine parts in assembly lines. An online learning based Principal Component Analysis (PCA) feature is used for recognition and classification of defected patterns, their performance depends on the number of training samples.

In (Riby Abraham Boby et al.,2011) the image analysis techniques such as Fourier filtering (FFT), auto-median, image convolution, and single-step thresholding methods are used for detecting the defects from reflective ring components. In (Hyun S. et al., 1988), a normalized distance-verses-angle signature of length 360 is used for recognition of industrial parts. They compute the distance between shape centroid to all boundary points as a function of angle i.e by linearly increasing the angle value from 0-360 degree value. The farthest contour point is assumed as starting point in the contour. The Discrete Cosine Transform (DCT) and Fisher's Linear Discriminant Analysis (LDA) techniques are used to detect faults in real-time manufacturing environments (Fadel M.Megahed et al., 2012) tolerates any lighting or changes in environmental conditions. The Euclidean distance is used for finding the defects in the projected image with respect to trained samples.

A non-contact automated inspection system to detect defects in moving custom parts was proposed by (Shaniel Davrajh et al., 2008). They have inspected defects by significant Region Of Interest (ROI) feature along with Discrete Fourier Transform (DFT). Similarly in (Abinesh Bhuvanesh et al., 2007) a ROI feature is used for automatic inspection of stamping defects in Integrated Chip(IC) lead-frames. In both methods, a template matching is performed by pixel-wise difference is computed between the test and model images to detect defects. An intelligent robot work-cell described in (Wail Mustafa et al., 2013) uses 3D texlets is a local surface descriptor to recognize industrial parts, they use multiple views of single instance, which uses color and shape separately and are viewpoint invariant. They used Random Forest based learning algorithm for object recognition from few sample models. The fault detection from chemical instruments using Wavelet transformation was described in (Marcos et al., 2005); the correlation coefficient and Euclidean distance metrics are used for similarity matching task.

2.2 Multi - Feature Based Descriptors

Some assembly systems does not rely only on a single feature, instead they integrate several features to utilize today's fast computing facilities. In general, many authors incorporated global shape properties like eccentricity, compactness, Euler number, convex hull etc to enhance the performance. A coded descriptor in (Palkush Ra et al., 2012), groups with simple geometric features like length, angle, lines and circles into coded matrix to describe the machine parts. In (Jim Orrack et al., 1988), a model based approach is used for part images matching. It uses the following global geometrical features: area, perimeter, length-to-width ratio, major/minor axis length etc. In 1977, Yachida et al. recognized complex industrial parts with respect to template shapes using object shape, area and thinness ratio features.

A machine vision based approach for finding a specified machine part among different machine parts on a moving conveyor was proposed by (Saburo Okada et al., 1994) which uses neural network and fuzzy inference based learning method for machine part discrimination. They have used following features set: {number of holes, number of corners, area, peripheral length, maximum radius, centroid, centroid of each hole}. In (Kouichi Nakano et al.,1992), the length of edge line and angle at a corner are the geometric features extracted from machine parts. Further neural network based learning is applied on the Fourier descriptor, area, and perimeter features for shape recognition.

An automated classification of dismantled small parts such as bolts, nuts, washers, spacers, brackets etc. from small Jet engines was performed by (Thomas C. Muhlbauer et al.,1996). They have used machine vision approach to sort the parts and place them in appropriate bins. The features used are number of holes, and centroid distance. These sorted parts are again reused for engine reassembly. Similar to machine parts, the surface defects found in manufactured web materials such as plastic, paper, pipe, steel strips etc. are detected in (Francisco G.Bulnes., 2014) using the following parameters: length, width, area, position, average grey level of the pixels, and length-width ratio. The authors have used sparse matrix data structure to store the information about detected defects; this data structure handles large volume of data and supports fast access.

The surface defects in industrial parts are recognized and retrieved by (Kunttu I. et. al., 2007) using angular radius Fourier Descriptor(FD) which is compact in nature and integrates directional angle and centroid distance of the contour with FD. They have tested their approach in web materials for example, to find paper defects such as holes, wrinkles and dirt parts. Moreover they integrated different shape signatures like centroid distance, area function, angular function, complex coordinates, polar coordinates, and angular radial function for experimentation. The surface defects found in gun barrels are identified and classified using texture features such as energy, uniformity, correlation, contrast, and entropy (Rajalingappaa Shanmugamani et al., 2014). They have used Sequential Forward Selection (SFS) algorithm for selection of best features set. For defect classification, the Naïve Bayes, k-Nearest Neighbor, Artificial Neural Network and Support Vector Machine classifiers were used. Similarly machine learning based surface defect detection and classification described in (S. Ravikumar et al., 2010) used a decision tree instead of SFS for selection of histogram features that represents magnitude of pixel values, and for classification purpose C4.5 and Naïve Bayes classifiers were used.

2.3 Challenges and Issues

Apart from features count, a good recognition and defect identification method poses the three factors (Hyun S. et al., 1988): a) it is insensitive to variances in rotation, scaling, and translation (RST), b) the ability to handle huge variety of shape objects, and c) simplicity and efficiency to work with real-time applications. All the existing methods found in the literature are testing their approach on very few image samples, so it loses the generality of applications. In most of the existing methods that works on industrial inspection system are using very simple elementary features and advanced image analysis techniques are not extensively used. The proposed approach addresses the above challenges and works with defect detection in industrial inspection systems.

In the next section a shape based machine vision system is presented, which uses contour information of machine parts to detect the defects. The machine parts images are preprocessed and object shapes are extracted; then partition the object shape into predefined number of equal part area segments with respect to shape centroid using sector area approach. The corner contour points of the segments are called normalized contour points. The distance between centroid to all normalized contour points forms a feature vector to describe the machine parts. A model shapes dataset is created from all the machine parts under test. A correlation coefficient metric is used to compare the model shape and the shape of the machine part under test. If perfect matching exists, there is no defect found. Otherwise the machine part is identified as defective and this information is passed to robot controller which removes it from the assembly line.

3. PROPOSED APPROACH: MACHINE PARTS RECOGNITION AND DEFECT IDENTIFICATION

A non-contact machine vision based defect detection system is proposed in this section. The following assumptions are considered in the present study. The objects moving in the conveyor are captured by vertical direction of the overhead camera in the automated assembly lines. The machine parts are placed on the conveyor with predetermined sequence and the timing is synchronized with operation of assembly system. Here the objects on the conveyor are not occluded and they posses rotational orientations. That is, machine part to be captured and the camera are stationary; this simulates the situation in which the camera will extract the exact shape from the top view and only one part is present per view.

The sequence of steps followed in the proposed system is: image capturing, image preprocessing, contour extraction, area normalization, centroid distance calculation, similarity matching, machine part recognition, and defect detection. These steps are summarized in flow diagram form in Figure 2.

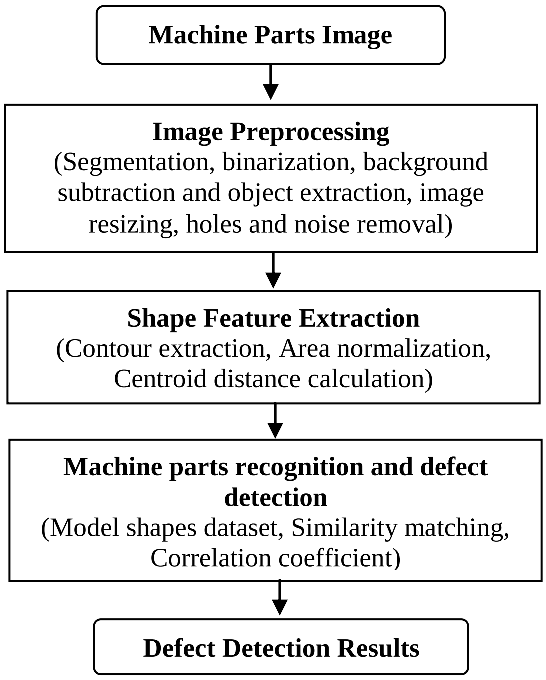


Figure 2. A flow diagram for the proposed machine vision based defect detection system.

3.1 Image Preprocessing

The machine parts are captured under different lighting conditions which may cause the image to be noisy and blurred. The image preprocessing techniques used will enhance the image and make them suitable for further steps. The preprocessing techniques used in this paper are segmentation, binarization, background subtraction and object extraction, image resizing, holes removal, and noise removal.

A. **Segmentation:** It is a process by which the image regions having similar pixel characteristics are grouped together to partition the image into meaningful parts. The segmentation process is performed by using color and texture features of the image. In this paper the images used in experimentations are pre-segmented images.

B. **Binarization:** The color or grey scale image is converted into black & white or binary image. A binary image is obtained by setting a threshold value. For example set threshold value of 128, the image pixels having the threshold value less than 128 are converted into the value 0 (black) and greater than threshold value are converted into 1 (white).

C. **Background subtraction and object extraction:** From the binarized image this step removes the background details and object of interest is extracted using bounding box method.

D. **Image Resizing:** The object shape images are converted into standard size to avoid scale changes. All the shapes in model shapes dataset and the shape of all the machine parts under test are resized.

E. **Holes removal:** In this paper a contour based shape feature extraction is employed, which uses only boundary information of the shape and the edges present inside the shape are not required. The details present inside object shape are removed and contour of the object is produced by holes removal process.

F. Noise Removal: Noise removed image is the final output of image preprocessing. The unwanted artifacts found on the object shape are removed and contour curve is smoothed by Gaussian filter.

3.2 Shape Feature Extraction

The shape feature extraction is applied on preprocessed images. It starts with fixing a starting point on the contour by assuming farthest contour pixel point to the shape centroid. Then contour pixel coordinates of the shape is extracted in clock-wise direction from the farthest contour pixel point. The extracted contour is a closed curve, which is represented in parametric form or non-parametric form. The parametric representation is popular and it is suitable for geometrical processing on object curves. The parametric equation of the curve is represented in (Yang Mingqiang et al., 2007) as given bellow,

$$\Gamma(\mu) = [x(\mu),y(\mu)] \quad (1)$$

where $\mu \in \{1,2,\ldots N\}$ and (x, y) are contour pixel coordinates which in turn describe the contour with respect to the parameter μ. The contour tracing algorithm is used to extract the boundary pixels of the shape which represents the object shape by ($\Gamma_{\mu+i}$, $i \in \{0,1,2,\ldots n\text{-}1\}$) where 'n' is number of boundary pixels.

The shape descriptor discussed in this section will normalize the contour by means of partitioning the shape area into 'N' number of equal part area segments using sector area approach (Arjun P. et al., 2014). It requires following three parameters: centroid (G), total object area (S), equal part area (S_{part}) and compute the sector area of the segments.

3.2.1 Centroid (G)

The geometric centre of a shape object is called Centroid. In this paper Centroid plays two major roles, 1) computation of farthest contour point, and 2) computation of distance values for each normalized contour point. The centroid (G) of the shape with 'R' pixels is calculated as mean values of (x, y) coordinates of the shape object and is calculated using the equation (2).

$$G_x = \sum_{i=1}^{n} \frac{x_i}{R} \quad \text{and} \quad G_y = \sum_{i=1}^{n} \frac{y_i}{R}$$

$$\text{Centroid (G)} = (G_x, G_y) \quad (2)$$

3.2.2 Total object area (S)

The structure of machine part shapes are not just like basic shapes such as circle, square, rectangle etc. For basic shapes well defined formulas are available to compute the area which is more faster. In case of machine part images the area is computed by counting all pixels enclosed within the shape object. The following equation (3) computes total object area (S) of the machine part image $I(x,y)$ is given by,

$$S = M_{00} = \sum_x \sum_y x^0 y^0 I(x,y) \quad (3)$$

3.2.3 Equal part area (S_{part})

The equal part area 'S_{part}' is a reference value in which the machine part shape object is partitioned. Before segmenting a shape into number of equal part area segments, the normalization factor value 'N' is chosen. Number of normalized contour points and number of equal part area segments produced after OAN is equal to the normalization value 'N'. The total object area 'S' obtained from equation (3) is divided by normalization value 'N' gives S_{part} value is given in equation (4). This S_{part} value is used at the time of OAN process to divide the machine part shape into 'N' equal part area segments with respect to the shape centroid.

$$S_{part} = \frac{S}{N} \quad (4)$$

3.2.4 Sector area

The core part of OAN process is to partition the shape object into 'N' number of equal part area segments. The partitioned segments are in triangular format with one point as a centroid and remaining two points are present at the contour of the shape. There are two approaches are available to find the equal part area segments which are triangle area approach (Yang Mingqiang et al., 2007) and sector area approach (Arjun P. et al., 2015). In this paper, a sector area approach is used because it preserves the shape information more accurately than triangle area approach. The sector area of a equal part area segment (G,P_1,P_2) is calculated using equation (5).

$$SectorArea(G,P1,P2) = \frac{1}{2} \times \left(\frac{r_{P1} + r_{P2}}{2} \right)^2 \times \theta \quad (5)$$

where (r_{P1}, r_{P2}) are distance between G to P_1 and G to P_2 respectively, and 'θ' is angle between the straight lines (G,P_1) and (G,P_2). The normalized contour is represented by the vector ($P_{\mu}, P_{\mu+1}, P_{\mu+2}, \ldots P_{\mu+N-1}$). The next step is to compute the shape descriptor from normalized contour points. The distance between centroid '*G*' to all normalized coordinates 'P_i' is calculated using Euclidean distance.

$$D(G, P_i) = \sqrt{(G - P_i)^2} = |G - Pi| \qquad (6)$$

The extracted shape descriptor is stored in 1D array of length 'N' e.g. {$D(G,P_1)$, $D(G,P_2)$, $D(G,P_3)$, … $D(G,P_N)$}. This shape descriptor is further used in machine parts recognition and defect detection process.

3.3 Machine parts recognition and defect detection

The machine parts recognition and defect detection requires model shapes of machine parts. Model shapes dataset is created from healthy machine parts. These model shapes are used during the similarity matching process. Two kinds of processes are performed for feature extraction from the machine part images. The shape feature extraction techniques mentioned above are applied to all the shapes in model images dataset. This process is performed at earlier and is called offline process. When a shape feature extraction is performed from the machine parts on the conveyor is called online process. The machine parts recognition is the first step which confirms the identity of a machine part; and the defect detection process will identify the defects by any deviation in the matching results. The feature vectors of the machine parts (P) and model shape (Q) are compared using correlation coefficient metric. The correlation coefficient 'r' measures the similarity between two shapes P and Q which is determined by the equation (7).

$$r(f_p, f_q) = \frac{\sum_{p,q=0}^{N-1} (f_p - \bar{f}_p)(f_q - \bar{f}_q)}{\sqrt{\left(\sum_{p=0}^{N-1} (f_p - \bar{f}_p)^2\right)\left(\sum_{q=0}^{N-1} (f_q - \bar{f}_q)^2\right)}} \qquad (7)$$

Where (f_p, f_q) are feature vectors and (f'_p, f'_q) are its mean values of the shapes P and Q respectively. The correlation coefficient results are bounded within the range of -1 to +1, where total negative correlation is -1 and total positive correlation is +1. The degree of closeness between the shapes is represented by intermediate values of correlation result 'r'.

4. EXPERIMENTAL RESULTS

The experiments are conducted on Internal Combustion (IC) engine machine part images. The experimentations are focused on two major aspects such as ability of the shape descriptor to support RST invariance and accurately detect the defects in the form of parts damage. An example machine part (Part1.gif) and its damaged counterpart (Part2.gif) used in the experiments are shown in Figure 3a, and 3b. Preprocessing techniques are applied on the input images, segmented and background subtracted images are shown in Figure 3c, 3d, and binarized, resized, holes and noise removed images are shown in Figure 3e, 3f.

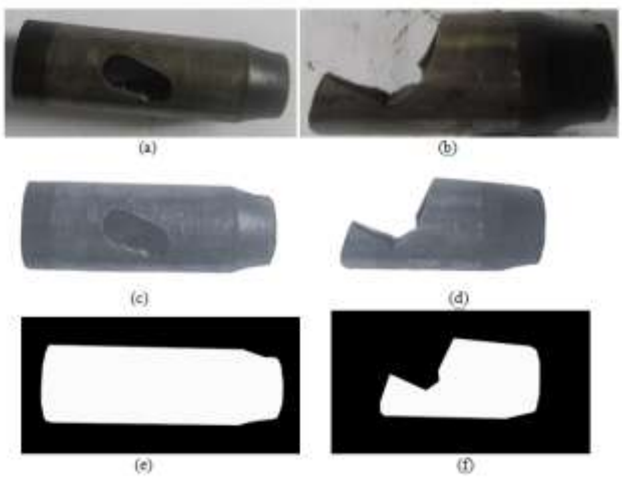
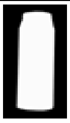
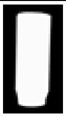


Figure 3. (a)Healthy machine part image (b) Damaged machine part image. (c)-(f) are the results of image preprocessing.

From the Figure 3e, 3f, contour pixels of the machine parts are extracted in clockwise direction using contour tracing algorithm. It produces the boundary pixel coordinates of the shape in sequence from a specified starting point. The starting point is the farthest point on the contour from the shape centroid. The Euclidean distance metric is used to find the distance between centroid to the farthest point. The length of the contour depends on size/area of the shape and the amount of deep convexity/concavity of the curves. This contour information of the shape is only considered for shape descriptor generation, machine part recognition and defect detection. During feature extraction, the closed contour of the shape object is normalized into 'N' number of samples by sector area based OAN process. The right selection of 'N' value is very important because it influence time complexity and effectiveness of the shape descriptor. The contour of all shapes are normalized with the normalization factor value N=64. It produces 64 number of equal part area segments and 64 number of normalized boundary coordinates to represent the object shape.

The RST invariance and defect detection test are performed on a machine part image as shown in Figure 3a. In terms of RST invariance test the machine parts recognition task is accomplished. The RST includes three transformations namely rotation, scaling, and translation. The geometrical transformations are used to create rotation transformed images and image interpolation techniques are used to create scale transformed images. For translation invariance no experiment is required because it does not affect the size, area, orientation and other characteristics of the shape but the object is moved from one coordinate position to other inside the image. For an input image 10 RST transformed images are created, 5 rotation transformed (0, 90,180,270,360 degree) and 5 scale transformed (0.2, 0.4, 0.6, 0.8, 1.0) images as shown in Table 1. The table also illustrates the one-to-one correspondence between query image with its rotate, scaled, and defective versions are calculated by correlation coefficient metric given in (7).

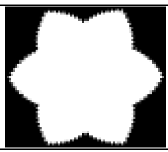
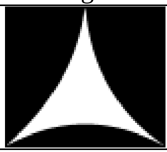
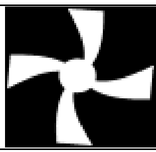
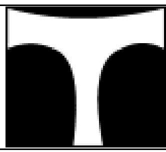
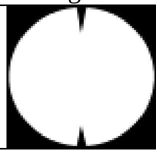
Table 1 Correlation coefficient results for rotated, scaled, and defective versions of query shape.

Query Image	Transformed Image	Transform Factor	Correlation Coefficient
		Rotate_0	1.00
		Rotate_90	1.00
		Rotate_180	1.00
		Rotate_270	1.00
		Rotate_360	1.00
		Scale_0.2	0.74
		Scale_0.4	0.99
		Scale_0.6	0.90
		Scale_0.8	0.97
		Scale_1.0	1.00
		Defective	-0.078

The Table 1 shows experimental results of the OAN shape descriptor on a machine part image along with correlation results. In terms of RST invariance test, first the rotation invariance is tested with five different angles, in all the cases it produces maximum correlation result which is +1. For scale invariance test, it performs well for higher scale values. If the scale value reduced to very small range then the performance is slightly degraded e.g. scale_0.2. The defect detection is performed between the query shape and defective shape is shown in last row of the above Table 1. The structure of the defective shape is entirely different than normal healthy machine part and it gives negative correlation result which is '-0.078' confirms the defect in the machine part. Moreover the method gives good recognition results for rotated and scaled images. Degradation in performance is noticed when matching very small scaled images. In defect detection process, a threshold value ‘t’ is set to determine the defect status of machine parts. The threshold is introduced to tolerate with small variances and distortions occurred due to poor lighting, and viewpoint changes. If correlation value ‘r’ is greater than ‘t’ then the machine part is healthy otherwise it is defective. This status of healthy and unhealthy parts is notified to the robot controller for its appropriate action.

The OAN shape descriptor is furthermore tested on MPEG-7 CE Part-B dataset images. It is a benchmark dataset consist of 1400 images categorized into 70 classes (Latecki L.J. et al., 2000). This dataset includes different varieties of shape objects including machine part images. From the literature, it is known that the quality assessment of any shape descriptor developed is experimented with this dataset. The performance metrics considered is Bulls-Eye-Retrieval (BER) rate, it is a measure calculated from percentage of correctly retrieved images from the top 40 retrieval results. Maximum number of correct retrieval is 20 images from each class. Several machine part images from this dataset along with their BER retrieval rates of the OAN shape descriptor is given in the Table 2.

Table 2 BER rates of the shape descriptor on machine part images of MPEG-7 CE Part-B dataset.

Label Name	device1-2.gif	device4-11.gif	device5-3.gif	device8-12.gif	device9-1.gif	key-1.gif
Image						
BER Rate	90%	85%	100%	100%	90%	100%

Finally, the discriminative power of the descriptor is analyzed by the graphical representation of its features as shown in Figure 4. The OAN descriptor for the four shapes (a) Query image and its (b) Rotate, (c) Scale, and (d) Defective versions of the images from the Table I are plotted in Figure. 4. From the graphs, the x-axis represents index of normalized contour points of the shape object and y-axis represents centroid distance values. The distance values in y-axis of Figure 4(c), (d) are not same with query image because the shape in 4(c) is resized and 4(d) is defected shape. The graph results of 4(b), 4(c) shows the rotated and scale transformed images which are exactly matched with graph of query image. The graph result in 4(d) for defected image is deviated from graph of query image, it will show the machine part tested is unhealthy i.e., defective machine part.

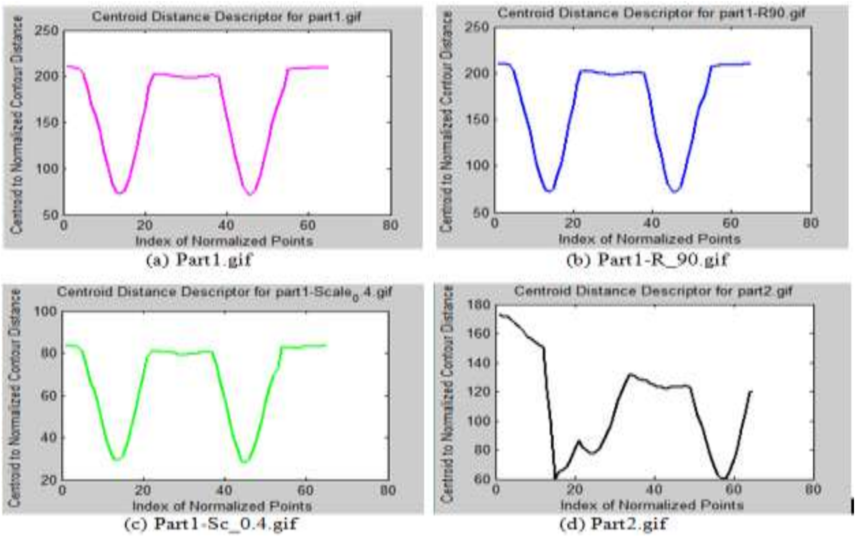


Figure. 4. (a) The OAN Shape descriptor is plotted in graph representation for query image from Table I (b)-(d) rotated, scaled, and defective versions of the query image.

The above Tables and Figures show the validity of the OAN shape descriptor for recognizing the machine parts which undergoes RST transformation and accurately detecting the defects and damages in machine parts. The experiments reveal that the OAN based shape descriptor for defect detection in automated assembly systems works well on geometrically transformed images. It further justify that this method can be applied to recognize the machine parts captured in different viewpoints. The performance of the shape descriptor used in this paper is depends on the Normalization value ‘N’ and the transformation parameters used in the experiments. The advantage of OAN shape descriptor is very small in size and it operates with the speed of assembly line operations. In addition, it will be used for defect detection in industrial inspection systems.

5. CONCLUSIONS

In this paper, a computationally efficient 2D computer vision based approach to recognize the machine parts and detect damaged parts in automated assembly systems has been presented. The machine part defects in the form of damage, cracks are identified by scanning the shape of the object and a feature vector is generated from the shape. The shape descriptor discussed is simple, compact, and fast one dimensional feature vector which preserves the shape information using contour pixel coordinates of the shape. The shape descriptor was generated by partitioning the shape object into fixed number of equal part area segments with respect to centroid using sector area approach. The feature vector is a 1D array consists of distance between centroid to subsequent normalized contour points. Two kinds of tests were performed on the machine part images to confirm the validity of the descriptor; namely RST invariance test and defect detection test. The correlation coefficient metric was used for comparing the images for recognition and detection of defects in machine part. From the experiments, the centroid to normalized contour points distance shape descriptor performs good for machine parts recognition and defect detection. Future work will be focused on development and integration of multiple features from equal area normalization descriptor to further strengthen it in terms of accuracy and efficiency.

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