Analysis of Image Processing techniques for Machinery Part detection :A Review

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Abstract: *Detecting an object is an acute job in the automation industry, and when it comes to the machinery parts then one has to know when an object has reached at a expected location. In the automation industry , the objects or the parts of the objects are detected based on the object passing by on a conveyor, the closure of a door, or the arrival of a carrier at a stop. Such machine part recognition and defect detection involves the specific models or shapes of machine parts. These are then generated as dataset that are created from the good machine parts. In turn such model/ shapes are used during the similarity matching process. Assembly line automation are significant to handle the day by day demands of latest technology machines that can utilize the image processing techniques Artificial neural networks ,machine learning etc., which are used in industry and society. The detection and identification of defects in these machinery parts helps in smooth manufacturing process if they are detected at the a very early stage and these in turn saves production cost and time. This paper is a review of such techniques that are used to detect machinery parts and then the obtained image is processed by different image processing methods.*

Keywords: Fuzzy C-means, Support Vector Machine, Artificial Neural Network, Object detection and identification.

1. Introduction

In today's reasonable atmosphere, quality of manufactured products plays an important role in the economy of the country. In most of the industries specifically in the automotive industry, which in a no man operative mode , one has to deal with safety equipment's for which the quality is a mandatory requirement that directly decreases probable dangers. In certain cases the automotive parts may be small in size, and nevertheless they establish a vital role with high requirement on their production systems. Furthermore, the smaller the component, the difficult is the inspection for the quality since the algorithms need to be strong to identify the parts. Machine vision technology inspecting defects have been continuously advanced along with science and technology. Automation of the inspection process with a suitable algorithm will bring the classification process to a more skilled and precise. The biggest problem lies in differentiating the foreground from the background. Human observation can perform this separation very skillfully, and with a machine it still remains a major trial for the researchers. As is often the case with planned faults, these are slight difference and hide in background texture.

This paper is organized as follows. Section 2 gives the related work details in machinery part detection . Section 3 describes comparison of all papers. The conclusion is given in Section 4.

2. Related Work

P.Arjun, T.T.Mirnalinee: This paper deals with the aim of present research in Assembly line automation for which the following steps are done in the sequence such as with image acquisition with preprocessing, contour extraction and normalizing the area, distance calculation using centroid, matching process for similarity, machine part recognition and defect detection. The image is applied with shape feature extraction in order to find the contour in images by getting a farthest pixel from centroid and moving ahead in clockwise direction. In order to inspect the parts a reference model is required. Such reference dataset are made from the good parts of machine parts of concern. The defects are detected by observing the deviations with the results of the part and the reference template. Coefficients of correlation metric helps in comparing the feature vectors of the machine part and referenced .This measures the similarity between the two. RST (Rotation, Scaling, Translation) invariance and defect detection test are performed on a machine part image. Geometrical transformation are used for rotation of the images and image interpolation used for scaling of the images. For translation invariance no experiment is required because it does not affect the characteristics of the image. 10 RST transformed images are created, 5 rotation transformed (0, 90,180,270,360 degree), 5 scale transformed (0.2, 0.4, 0.6, 0.8, 1.0).An efficient 2D based approach to detect the damage is presented here . Damage, cracks are identified by scanning the shape of the object this generates the feature vector. The feature vectors contain the 1D information about the contour of the shape present in the image. The correlation coefficient is used for comparing the images. 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.

This method is insensitive to variances in rotation, scaling, and translation, ability to handle huge variety of shape objects, simplicity and efficiency to work with real-time applications. Converting the image into shape contour neglects some surface defects which include minor cracks, defect present in the area masked by the contour. Expanding the range of defects that can be detected. Detecting surface defects and methods to identify the defects those are masked by the conversion to 2D contour could be the future scope[1].

Namrata Varad Mhapne, Harish S V, Anita S Kini, Narendra V G:This paper uses the method in four stages: Image acquisition, Image pre-processing, Image segmentation, Classification. In Image Acquisition stage the images of apple with and without defects are taken and kept in the system for further classification. In Image pre-processing the image contrast is adjusted using histogram equalization. For this the image is converted into YC_bC_r color space and then histogram equalization is applied on the C_b space. In case of Image segmentation the equalized image is segmented using clustering. K-means clustering assigns K clusters and Xi data points. The data point is assigned to the cluster with value closest to the data point. This step is repeated and data points are assigned to the clusters until convergence is achieved. Fuzzy C-means clustering is another compelling clustering algorithm. During Classification process the segmented images from the previous step are used for the classification purpose the respective apples are then classified into healthy and defective classes. As a result, the accuracy when using K-means clustering is lower than that of FCM. K-means with equalization has no effect on the accuracy but decreases the computing time. FCM with equalization improves accuracy to a certain extent and also reduces the computing time. We see that accuracy increase with cluster size and attains constant value at some cluster value.

The above performance concludes that the K-means clustering with and without preprocessing lacks in accuracy compared to FCM. FCM shows increase in accuracy and computational speed with the pre-processing. Therefore FCM will be optimal for detecting defects in apple. The efficiency of the algorithm can be increased by initially determining the cluster centres. This gives rise to certain advantages and disadvantages:

a) Efficient and uniform quality inspection tool

b) Improved time complexity and accuracy of the clustering algorithm

Even with the proper clustering algorithm the accuracy is not 100% hence must work on a way to increase the accuracy. Performance can be further tested by validating and using few channels for L*a*b or YC_bC_r color space instead of considering full color space information[2].

Syahril Anuar Idris, Fairul Azni Jafar, Seha Saffar: This paper displays the area of corrosion in the two images using red channel histogram algorithm. Accuracy of detection between filtered and unfiltered image will be justified with the validation steps. The images used for this purpose are taken inside the nickel tube. The raw image are put through the red channel histogram. The Filtered image are then subjected to enhancement Filters based on the highest PSNR value presented by the filter. Both images of area of corrosion are then compared based on the extracted area for corrosion. As a result, the image from the test bed is used to obtain the accuracy of the corrosion area based on red channel histogram. The result is compared side by side to show significant difference in the detected area. Filter enhancement is used to improve the accuracy of the visual inspection. The filter is selected based on the Peak Signal to Noise Ratio. Higher the value of the PSNR better is the filtered image. From the result, it can be concluded that the visual inspection accuracy can be improved using the image enhancement filter. Here the Enhancement algorithm is not limited to corrosion inspection. It enhances the image quality and improves the error measurement easier. It has the ability to adapt to the environment. Some images are over exposed which increases the brightness level this reduces the corrosion area detected. The enhancement ability is limited and for small corrections only. Furthermore, the variety of filter could provide flexibility of the inspection system[3].

Ira C. Valenzuela, John Carlo V. Puno, Argel A. Bandala1,Renann G. Baldovino: 1. Methodology: The methodology for assessing the quality of lettuce crop health predominantly includes, digital image processing and backpropagation artificial neural network. Focusses on the design of the Neural Network, and Classification of Crop Quality. The images of the lettuce are taken using a generic camera with a fixed zoom in the ratio of 1:1. This is typically done to reduce the optical distortion. These images range from having very little to very large defects. The Image Pre-processing step mainly consists of, noise cancellation, binarization and blob extraction. On the other hand, the extracted features from the feature extraction process, provides the arithmetic mean of the red, green, blue, hue, saturation and value color components of the defected areas present in the samples of lettuce images. Based on the RGB and HSV components the Artificial Neural Network is used to classify the quality of lettuce. The backpropagation is made up of, 6-neurons in the input layer, 10 neurons in hidden layers and 2 neurons in the output layer. Backpropagation is mostly used as it has the capability to adjust its weights and biases which in turn increases the efficiency of the model learning. Random predictions of outcomes are done initially by the neural network based on the input patterned images. And, with the delta leaning rule, adjustments of weights are possible, which thus improves the performance of the model. The gradient is used to update the weights and biases during the iterations. Once the training is complete, the classifier classifies the lettuce as “0” and “1”. “0” – indicates that there is no defect in the lettuce sample and thus, is termed to have a good crop quality“1” – indicates defects and, is thus considered to have poor crop quality. As a result, the traditional way of identifying the defects in a lettuce gave a relatively higher error rate. The reasons for the same were, the different visual perceptions of humans and varying lighting conditions. On the contrary, the use of machine visual system with artificial neural network gave a minimum relative error rate of 0.051.Hence, it can be concluded that, this method is the easiest alternative in assessing the quality of lettuce. Wherein, the samples are classified as ‘Good’ (0) and ‘bad’ (1). This method helps the farmers to access the quality of the crops while growing it, the relative error rate in assessing the crop quality is minimized , and the subjective assumptions in identifying the crop quality is eliminated. Backpropagation ANN was unable to identify the number of defects in a lettuce sample. Thus, the future research may focus on this topic, specifically on grading the affected areas[4].

Amany Khaled, Mostafa R.A. Atia, Tarek Moussa:An inverted microscope INNOVATEST IN-MM600 was used to capture images of different grades of Grey Cast Iron (GCI)microstructure. Image Enhancement was required so that all the images had the same levels of contrast and brightness, thus ensuring a fair decision about its grade type and categorization n. This technique involved contrast adjustment approaches like piecewise linear and logarithmic transformations. Histogram equalization was used as the final enhancement step. Statistical features were extracted from grey level co-occurrence matrices which was used for decision making through ANN and SVM. These features can define and distinguish between textures by Harralick. SVM and ANN are supervised learning approaches. Two datasets were prepared one of each of the learning approaches. SVM used only two features namely dissimilarity and entropy for classification of the sample as GCI or ductile cast iron. Inputs for the Feed Forward Artificial Neural Network were the six chosen features i.e. contrast, correlation, energy entropy, homogeneity and dissimilarity. The output for this method was to grade the percentage of the sample between texture grades from A to E according to expert’s eye decision. SVM showed 100% efficiency for classification of ductile cast iron images. But for GCI, the classifier failed to identify only one image out of around 40 test images that were given for testing.

Validation of NN output was carried out using two datasets. One approach was using 15% of the dataset already proposed for training. Every time training was carried out, data was randomized and therefore, the validation dataset in this approach was not fixed. Other approach was a dataset of 40 new images not involved in any of the training steps of the neural network to be under test for neural network validation. It was observed that Metavision assessed 6 samples in a wrong way out of 13 samples which means that 46%

of the decisions were wrong compared to the manual assessment. On the contrary, the automatic gray Cast Iron Multi-Assessment(CIMA) has assessed one sample only out of the 13 samples in a wrong way, which means that 7.5% of the decisions were wrong compared to the manual assessment. SVM and ANN were trained and tested using separate validation datasets. Tests have successfully shown that the AVM has identified DCI with 100% efficiency while GCI was identified with a percentage of error of about 2.3%. As for the grading section, ANN tests have proven 98% efficient identification of the submitted samples with 3-4% error. This method has overcome the problems faced during the traditional way of visual inspection such as human error, biased categorization, lack of experience, variations in performance levels and quality of decisions. Automation of the inspection process with a suitable classifier brought the categorization process to a more professional and accurate level illuminating the probability of biased selection of samples. ANN has an advantage over other decision-making techniques that is it can retrained on a wider range of data. It also has the capability of solving complex problems correctly even if the inputs are not included in the training dataset from the start[5].

Kimiya AOKI, Takuma FUNAHASHI, Hiroyasu KOSHIMIZU, Yasuhiko MIWATA: It involves:

1. Generating integral image
2. Constructing image lattice
3. Out image with KIZUKI map

The integral image is generated to calculate the sum of intensity of each square of lattice array. This calculation is done in various phases and sizes in the lattice array, by changing the phase and scaling the integral image. After various phase shifts and scaling this down sampled image is then binarized using discriminant analysis (Otsu's method), adaptive dynamic thresholding etc. This saliency map is incremented by one if the corresponding pixel is found in the binary image. The saliency map is then normalized and then converted to a pseudo-colour image which is named "KIZUKI" map and normalized saliency map is inverted and subtracted from the original image to get the pop-out image. This results in the input images include irregularities at certain regions. These regions are marked based on the binary image which gives us KIZUKI map and pop-out image. The experiment had many trial images with some irregularities. The input images are about 640x480 pixels and the computational time required is 20sec. "KIZUKI" process of defect detection is very simple and effective, it is easily incorporable into different visual examination systems. So the "KIZUKI: model has proved to be a reasonable approach for defect detection. And since the program is very simple and effective, it can be widely incorporated with different visual examination systems. Retaining the information at all scales during Down-sampling for peripheral vision and improving performance of eye micro-vibrations which is simulated through phase shifts could be the future scope[6] .

Anugool Thamna, Pornsak Srisungsitthisunti, Surangsee Dechjarern: In this paper, The conveyor is passed with the Bullet cartridges through the sensors. In turn the sensor passes signal to the programmed software and it helps the camera to acquire images. PLC receives signals from camera as an indication to start the inspection process and reject bullets if it has any defects. Bullets are usually made of brass and they are highly reflective hence most care to be taken in the finalization of position of light source and that is ensured by providing an even bar type lighting. This system detects, inspect and classify the defects of the bullets to improve the quality control of bullet cartridges. Based on their classification, systems were determined and eliminate the causes of defects. This kind of system is proves to be of high speed and the accuracy is high. Due to visual defect inspection relied on sharp image the speed of entire processes depend on camera frame rate. Image quality is based on sufficient lightning and stability of the bullets. In this paper, inspection was performed on 120 bullets to detect the accuracy of our system. Out of 120 bullets there are 20 dents, 20 tears, 20 creases, 20 mismatch lengths are detected on bullets and also there are 40 non defective bullets. The system performed five tests for each condition and we get an inspection result. After inspection it revealed that out of 80 bullets, 68 defective bullets detected and out of 40 non defective bullets, the 36 non defective bullets are detected. This research has developed detection inspection and automatic classification parts of the system. After detection of bullet there were four types of defect were found on the bullet surface i.e. Dents, crashes, tears, mismatch length. The inspection speed was 2 bullets per second with accuracy of 85 % and undetectable rate is 12.5 %.The accuracy for detection of different types defect were 86.7%.It is difficult to detect the certain position of bullet because of the rotation of bullet along with conveyor belt were harder so that the bullet may not be fully detected. Moreover, some errors were caused during inspection of bullet due to reflection of light from the bullets which directly interfere on the defect spots[7].

Vikas Chaudhary, Ishan R. Dave and Kishor P. Upla: In this paper, the bottom of the bottle is fixed in size and circular and hence the ROI is extracted by combination of circle detection and size. 2IHT algorithm has two steps, radius detection and centre detection. Compared to Hough circle detection this algorithm is efficient and even utilizes less memory space. Central panel and annular region are the two classified regions after localization as the measurement regions. The annular region is classified further as annular panel region and annular texture region. So the defect in these three regions is detected separately. Template matching has three steps viz., regular texture localization, template extraction and template matching and these are used in case of Annular texture region for defect detection. If these is any deviation from the correlation coefficient then it is declared to be defects in the template matching process. Multiscale mean filtering that has three steps viz., Projection and mean scale filtering, comparing projection profile and filtering result, are used for annular panel region for defect detection by obtaining maxima for final defect classification. The final result is computed by

$$(y) = \arg max \mathrm{SDmin<bi<SDmax} \{D(y, bi)\} \qquad (1)$$

Where {D (y, bi)}is the difference between the projections profile and the filtering results. Values of R(y) are high in the defective region and low in the normal region. Saliency detection methods like Region Growing Geodesic Saliency (RGGS) and Region Growing Euclidean Saliency (lRGES) are used for Central panel defect detection .After classification of all detected defects are classified into different classes. The proposed algorithm (image registration, Pre-processing, Image segmentation, Defect detection, Defect classification) were used which takes 2.528s to execute the inspection of PCB image. The algorithm is able to perform inspection even captured test (defective) image is rotated, scaled and translated. Since this algorithm utilizes minimum time and its robust as a result, the proposed algorithm is suitable for automatic visual inspection of PCB. Using referential inspection method, it is possible to detect and classify all the 14 types of defects of PCB. After detecting defects each defect is classified like number connected components, shape based descriptors and area. Using various region properties like the algorithm is useful in electronics manufacturing industries to inspect PCB quickly and accurately, that may lead to reduced production time and improvement in overall quality and reliability of product. Here PCB inspection process is fast and reliable using automatic visual inspection (AVI) systems. The algorithm is able to perform inspection even when captured test image is rotated, scaled and translated[8].

Oleksandr Semeniuta , Sebastian Dransfeld, Petter Falkman:In this paper, It implements Functional prototype for star washer picking by involving star washer identification, Circular object analysis, Classification of star washers' orientation and Inspection of star washer teeth. Star washer identification uses Otsu's method for optimal thresholding in order to separate the connected components and result is a labeled image.Polar representation is used for circular object analysis for the metallic part of the image. The metal washer is of keen interest and not the hole in the centre. The Machine learning models are trained on the feature vectors generated by the reference image and images in which washers are disoriented and the high-resolution image of star washer is investigated to segment each star tooth, the analysis results are two angles $\theta star$,$stop$

$$\theta \text{start} = \text{ytop } 2\pi/\text{n\_angles} \quad (2)$$

$$\theta\text{\_start}=(\text{y\_top}+\text{h})2\pi/\text{n\_angles} \quad (3)$$

Using these angles each star tooth can be segmented into an individual image to give start and end of the tooth. The task carried out at inspection rig is parts identification, machine learning based classification, objects image analysis and star washer teeth segmentation. Solution to overcome this problem following tasks is carried out: identification of star washers on the feeder, classification of their orientation, and segmentation of star washer's teeth as a part of close-range inspection. To differentiate the orientation of star washers, there are no clear visual clues. By using a machine learning system it is possible to achieve classification results satisfactorily[9].

3.Comparison

Table 1 details the brief comparison of the techniques that are employed machinery part detection using image processing systems. The complexity of the design system is judged based on no of stages involved.

In 1 the machine parts are inspected for damages using computer vision tool that uses template matching for identifying the defect. This paper uses shape contour to identify the shape of the part in the image. Whereas in 2 the defects in the apple are identified using clustering algorithm after proper pre-processing techniques and in 3 the paper is focused on increasing the accuracy of the visual inspection using filter enhancement technique where appropriate filter is selected based on the PSNR value.

Table 1: Comparison

	Authors	Techniques used for inspection	Performance metrics	Performance values
1	P.Arjun, T.T.Mirnalinee	Contour extraction, Template Matching	Correlation metric	0.74-1.00 (non-damaged) and Less than 0 (if damaged)
2	Namrata Varad Mhapne, Harish S V, Anita S Kini, Narendra V G.	Clustering (K-means, Fuzzy C-Means)	Accuracy of classification	66.11-93.88 (these values differ based cluster sizes)
3	Syahril Anuar Idris, Fairul Azni Jafar, Seha Saffar.	Filter enhancement based on PSNR	PSNR	74.19-109.98 (These PSNR values differ based on the image and filters)
4	Ira C. Valenzuela, John Carlo V. Puno, Argel A. Bandala1,Renann G. Baldovino	Backpropagation	Relative error plot, T-Test	a minimum relative error rate of 0.051.
5	Amany Khaled, Mostafa R.A. Atia, Tarek Moussa	Support Vector Machine, Feed Forward Artificial Neural Network	Accuracy of the classifiers	AVM has identified DCI with 100% efficiency while GCI was identified with a percentage of error of about 2.3%.
6	Kimiya AOKI, Takuma FUNAHASHI, Hiroyasu KOSHIMIZU, Yasuhiko MIWATA	"KIZUKI" Processing	--	640x480 pixels and the computational time required is 20sec

From 4 to 6, in visual inspection of bullet it is difficult to detect certain position of bullet because rotation of bullet along with conveyor belt made it harder to detect defect in serial time hence bullet may not be fully detected. Conversely, in visual inspection of PCB the proposed algorithm is able to perform inspection even when capture test image is rotated, translated and scaled. For inspection of small components, this paper focuses on concept of multi camera or multipose inspection for star washers.

4.Conclusion

Above study assessed the performance and accuracy of the processing techniques. In PCB a Novel algorithm classifies all type of defects which is robust to defect appearance and severity. This is useful in electronics manufacturing industries to inspect PCB . SVM and ANN are used in building up a software to decide the microstructural category in case of grey cast iron grades. Image filter enhancement techniques are used to improve visual inspection accuracy. "KIZUKI" helps develop irregular region extraction programs based on human visual architectures The main objective behind this study is to give more accurate, effective and less time-consuming technique for identifying the machinery parts to make it useful for automation industries.

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