Jurnal
Teknologi

Full Paper

A REVIEW OF VISION BASED DEFECT DETECTION USING IMAGE PROCESSING TECHNIQUES FOR BEVERAGE MANUFACTURING INDUSTRY

Nor Nabilah Syazana Abdul Rahman[a], Norhashimah Mohd Saad[a*], Abdul Rahim Abdullah[b], Norunnajjah Ahmat[c]

[a]Center for Robotics and Industrial Automation, Faculty of Electronic and Computer Engineering, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia
[b]Center for Robotics and Industrial Automation, Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia
[c]Centre for Languages and Human Development, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia

Article history
Received
21 February 2018
Received in revised form
22 January 2019
Accepted
28 January 2019
Published online
18 April 2019

*Corresponding author
norhashimah@utem.edu.my

Abstract

Vision based quality inspection emerged as a prime candidate in beverage manufacturing industry. It functions to control the product quality for the large scale industries; not only to save time, cost and labour, but also to secure a competitive advantage. It is a requirement of International Organization for Standardization (ISO) 9001, to appease the customer satisfaction in term of frequent improvement of the quality of products and services. It is totally impractical to rely on human inspector to handle a large scale quality control production because human has major drawback in their performance such as inconsistency and time consuming. This article reviews defect detection using image processing techniques for beverage manufacturing industry. There are comparative studies on techniques suggested by previous researchers. This review focuses on shape defect detection, color concentration inspection and level of liquid products measurement in a container. Shape, color and level defects are the main concern for bottle inspection in beverage manufacturing industry. The development of practical testing and the services performance are also discussed in this paper.

Keywords: Automatic inspection, beverage manufacturing industry, defect detection

Abstrak

Pemeriksaan kualiti berdasarkan visual muncul sebagai kriteria utama dalam industri pengeluaran minuman. Ia berfungsi untuk mengawal kualiti produk dalam industri yang berskala besar; bukan sahaja untuk menjimatkan masa, kos dan tenaga, tetapi juga untuk memperolehi keboleh bersaing. Organisasi Antarabangsa Standardisasi (ISO) 9001 amat mementingkan kepuasan pelanggan dalam industri yang berkaitan dengan kekerapan penambahbaikan kualiti barangan dan perkhidmatan. Adalah tidak praktikal untuk bergantung kepada pemeriksa manusia untuk mengawal penghasilan barangan berkualiti berskala besar kerana manusia ada banyak kelemahan seperti perkhidmatan yang tidak konsisten dan memakan masa yang lama. Artikel ini mengkaji semula pengesanan kecacatan berdasarkan visual menggunakan teknik-teknik pemprosesan imej untuk industri pembuatan minuman. Terdapat kajian perbandingan teknik-teknik yang dicadangkan oleh penyelidik terdahulu. Kajian ini mengfokuskan kepada pengesanan kecacatan bentuk, kelikatan warna dan pengukuran aras cecair produk. Pembangunan ujian praktikal dan prestasi perkhidmatan turut dibincangkan dalam artikel ini.

Kata kunci: Pemeriksaan automatik, industry pembuatan minuman, pengesanan kecacatan

1.0 INTRODUCTION

Visual-based defect detection is an effective technique to detect and to classify the defect in various industrial product [1]. It can be used for three things such as the quality control program, the data acquisition as well as the data analysis. Visual inspection is a simple technique but its contribution toward industries is surprisingly high [2] because this technology produces a competitive good and produces a standard quality of product [3]. Visual-based defect detection technology improves the quality of the product and the management of industry. Therefore, it has been used widely in the manufacturing industries when it involved the inspection of the quality of the product. This industry demanded a high standard of quality and a strict uniformity index for the product; which means that the good must be produced without defect. Hence, visual-based defect detection is carried out to assess the quality of the product by referring a set of standard products [4]. There are two types of visual-based defect detection; the manual inspection and the automated one. Both kind of inspections have their own advantage and disadvantage towards the manufacturing industry.

The manual inspection is a hundred percents process conducted by a human operator, whose role is to inspect and to monitor the quality of the product [5]. This approach has been used in this industry before the existence of the automatic visual inspection. The activities in this manual inspection will involve search the defect, recognize the fault and make the best decision [6]. Thus, the training for quality inspection is essential to improve the skill of inspection and to reduce errors during the manufacturing process. The human operator has been trained appropriately to enhance their performance during the process of quality inspection. They need to learn how to identify the product with defects and then to make an immediate decision either to accept or to reject or to rework the defect part.

The performance of the human operator are measured based on many aspect such as their skill ability, their knowledge, their health condition, their confidence level and their personal experiences [7]. The affected performance of the manual inspection are due to job-related factors, the managerial factors, the ecological factors, the motivational factors, and the individual factors [8]. Moreover, human inspectors are slow and became ineffective when they are completing the task that required a longer time [9]. They are either affected by fatigue or sickness or human weaknesses [10]. Hence, they need frequent rest to maintain a high-performance level.

The automated inspection, contrarily is using the computer vision to control the product quality during the manufacturing process [11]. This automatic inspection is a monitoring system that improves the quality of operations of the industry [12]. Recently, many manufacturing industries have changed their quality control inspection from the manual inspection into the automated one [13]. As a result, this automated inspection has reduced the execution time and the computational cost as well as achieved a ninety nine percents error free [14]. This automated inspection also gives better and immediate decision-making either to accept or to reject the product.

During the manufacturing process, an automated inspection is integrated with the quality control inspection to achieve the excellent result in detecting the defect of the product [15]. Compared to the manual one, the automated inspection offers more advanced capability including the elimination of human errors and at the same time increased productivity [16]. Thus, the accuracy of inspection increased throughout the usage of the automated inspection in the manufacturing process [17].

An example of automated quality inspection system is illustrated in Figure 1. Based on the figure, the image of the object, which had been carried out using a conveyer, is captured by webcam. In order to ensure that the object image is captured at proper position, a sensor is used to stop the conveyer at the desired place. In addition, a light source is placed together next to the webcam to ensure that the image is getting enough illumination. Then, the captured image will be stored in the personal computer (PC) folder for the next activity, an image analysis.

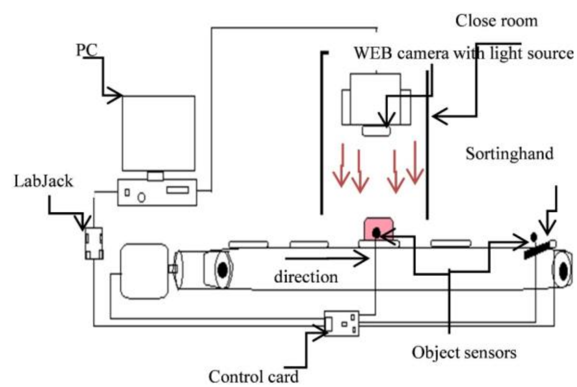


Figure 1 Example of an automated quality inspection system [18]

The defect detection uses integrated technology of image processing, exactitude measure, pattern recognition and artificial intelligence to classify the product quality has been broadly applied in beverages industries [3, 4, 6]. The defect inspection can be categorized into classes such as bottle shape, color concentration, liquid level, bottle cap inspections and label verifications. Currently, the automated inspection system in beverage industry can only be performed in one type of inspection [19, 20]. If the industry has three inspections at one time, three systems are needed to be installed in production line. Hence, additional cost is needed to perform the inspection process. Therefore, appropriate image analysis technique that integrates all inspections at one time with high accuracy is necessary to provide efficient inspection system.

Small and Medium Enterprise (SME) is industry that seen as vital actor in increasing the innovation, competitiveness and establishment for developing economic growth [21]. Generally, SME in beverage industry is fully utilized the manual product inspection due to the lack of capital. However, this limitation has made SME produces the product with low specification and without follow the ISO 9001 standard. By implementing automated inspection, it will be able to control the quality of the products with fast delivery to the customer [22]. Camera based inspection with image processing capability is a valuable tool that can provide SME with vision-based inspection customized exactly to their needs with lower cost.

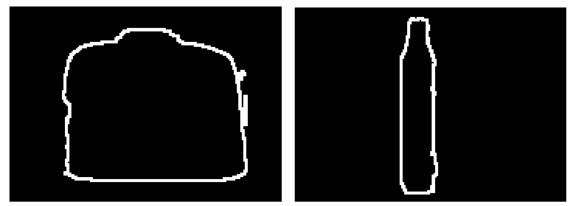
This paper aims to review and discuss the understanding of image processing techniques for product inspection in the beverage manufacturing industry. Furthermore, the explanation of the automated defect detection and segmentation techniques for the inspection system are included. A large number of studies and research activities for product quality improvement are studied. The comparison between certain techniques are described to gain enough information in this field. Thus, this extensive review is carried out in order to provide high accuracy result and able to be implemented in real-time application for beverage manufacturing industry.

2.0 AUTOMATED QUALITY INSPECTION TECHNIQUES

Several automated quality inspection techniques such as an adaptive thresholding, a gray level co-occurrence matrix, a morphological operation and an Otsu's thresholding are proposed by previous researchers for defect detection [23]. There are many types of focus in the product quality inspection such as shape, texture, color, level, size, and material. However, only three types of inspections are focused in these researches which are shape, color, and level defects because this three categories are the main concern for bottle inspection in beverage manufacturing industry [24]–[26].

2.1 Shape Inspection

Shape is a visual image of the basic feature used to describe image information [27]. The variety of shape features are evaluated by how accurately the similar shape is retrieved from the designated database. Reviews from previous research made some comparison on the shape inspection system technique. Ramli *et al.* [28] proposed the shape detection using a partial erosion-based technique to automate the shape segmentation process of plastic bottle. This technique involved a morphological and an erosion process to segment the bottle shape and to extract the features from the segmented image as illustrated in Figure 2. In classifying the shape of the bottle, the multilayer perception (MLP) neural network is applied because of its preciseness for feature recognition tasks. The accuracy of the proposed technique is more than eighty percents. It shows that the partial erosion-based will give better segmentation result in detecting the shape of plastic bottle either broad or slim. However, the partial erosion-based technique is inefficient as well as gives a bad effect to the image especially when the partial erosion is set less than fifty percents or more than hundred percents.



(a) (b)

Figure 2 Bottle image: (a) Broad bottle, (b) slim bottle Ramli *et al.* (2012)

The statistical histogram based Fuzzy C-means (SHFCM) is suggested by Moradi *et al.* [29] to identify the apple defect for fruit quality inspection. The process started with the conversion of red, green and blue (RGB) image into L*a*b color space. Then, use the active counter model (ACM) to segment the apple shape. Lastly, SHFCM is used to classify the healthy and the defect apple. The experimental result shows that the accuracy achieved to detect the healthy apple is 96% and the defect apple is 91%. This proposed technique proves the capabilities to characterize the apple based on healthy or defective condition. It is also consuming less time to process the algorithm. Nevertheless, SHFCM is the combination of the statistical histogram and the fuzzy c-means which makes the algorithm is more complex and prone to misclassified as a healthy and a defective apple.

Gonydjaja *et al.* [30] developed an automatic rectangularity defect detection for ceramic tile using the morphological operation technique. The image analysis includes pre-processing, segmentation, feature extraction, defect measurement and ceramic quality classification. In order to separate the tile object and the background image, the morphological operation is performed using the operation opening, the filling and the closing. The rule-based classifier is used to classify the quality of the ceramic tile. The defect and the standard measurement are compared and reached 93% accuracy for rejected ceramic tile. The experimental result shows that the proposed technique can be applied in ceramic tile classification system. The limitation of morphological operation is difficult to detect small defect and inefficient to be implemented for real-time processing.

Different to Abdellah *et al.* [31], they proposed support vector machine (SVM) approach to detect a defect and to identify textile fabric. The pre-processing step has convert RGB image into a greyscale image and has enhanced the contrast of the image by using histogram equalization technique. Then, the Otsu's thresholding is applied to segment the image into several regions in order to locate the spot of the defect in the textile fabric image. The morphology operator is used to remove the noise and the unwanted small object that present in the image. The classification results of this experiment obtained 95% accuracy in detecting the defect of the textile fabric. It proves that this proposed technique is successful to classify the defect and also successfully function for the textile fabric detection system. However, this technique needs to combine with other appropriate technique in order to get the high-quality image in large of numbers. The combination of two techniques will produce a highly competent system in computational complexity.

Sahar *et al.* [32] used an adaptive thresholding and the morphological operation techniques to develop an automated system to detect breast cancer lesions. The adaptive median filter is applied at the pre-processing stage to reduce the unwanted noise and maintain the quality of the image pixels. The segmentation process is using the adaptive thresholdng to separate the intended object and the background image. In extracting the image features, the morphological operations is used to extract the features such as region, shape and size from the breast cancer image. The results obtained are then compared to the manual Region of Interest (ROI) which was done by an expert. This technique has achieved 95.19% and proves that the system is competent to detect the breast cancer lesion. But, the disadvantages of this system is it could not segment the breast cancer lesion properly at the high-intensity area of image and it is incapable to detect the small object. Table 1 summarize the review for shape inspection system.

Table 1 Summary of shape for quality inspection system

No.	Title	Year	Author	Technique	Results
1	Plastic Bottle Shape Classification using Partial Erosion-based Approach	2010	Ramli *et al.*	• Partial Erosion • Multilayer Perception (MLP) Neural Network	• The accuracy achieved is more than 80%
2	Apple Defect Detection using Statistical Histogram based Fuzzy C-Means Algorithm	2011	Moradi *et al.*	• Active Contour Model (ACM) • Statistical Histogram based Fuzzy C-Means (SHFCM)	• The accuracy achieved is 96% (healthy apple) and 91% (defect apple).
3	Rectangularity Defect Detection for Ceramic Tile using Morphological Technique	2014	Gonydjaja and Kusuma	• Morphological Operation • Edge corner counting value	• The accuracy achieved is 93% (reject tile)
4	Defect Detection and Identification in Textile Fabric by SVM method	2014	Abdellah *et al.*	• Otsu's thresholding • Support Vector Machines (SVM)	• The accuracy achieved 94.84% (defect fabric).
5	Automated Detection of Breast Cancer Lesions using Adaptive Thresholding and Morphological Operation	2016	Sahar *et al.*	• Adaptive Thresholding • Morphological Operation	• The accuracy achieved 95.19%.

2.2 Colour Inspection

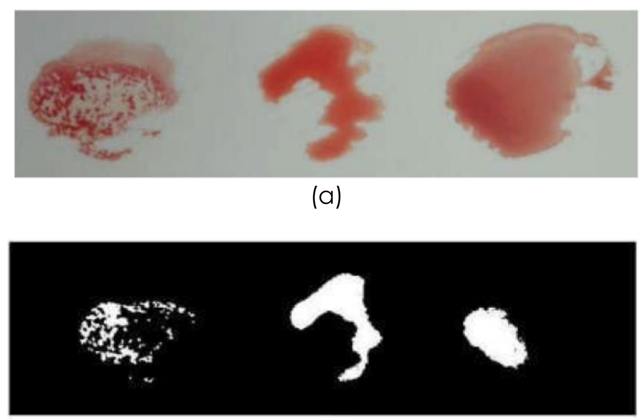
Most of the foods and the beverage products are part of the color inspection system. The color inspection using image processing technique is applied to inspect the defective color on the surface of the product [33]. Previous researchers have developed different systems for different applications in inspecting color of the product. Tang [34] proposed region growing technique to segment the color image in order to increase the color image application. The process started with the conversion of a color image into specific color range. Then, the watershed technique is applied to initialize segmentation process. Next, it will automatically select the seed region by referring certain condition and grow the region until the latter become consolidate. The results show that the proposed technique can obtain better segmentation and can be implemented for color image application. However, this technique required longer time to process the algorithm and sometimes it over- segment the image.

Wang *et al.* [35] recommended fuzzy c-means (FCM) with support vector machine (SVM) to segment and to classify the color image. The first stage of the process is putting the pixel level and the texture of color image extracted by using local homogeneity model and Gabor filter. Then, the process is continuing with FCM clustering technique to segment the color image and then, the segmented image will be used as training sample. In obtaining the classification results, SVM is employed to classify the color of the image based on the pixel level information. The accuracy of the experimental result is 96%. It proves that the proposed technique offers high accuracy segmentation result. Nevertheless, the higher number of training sample takes longer time to process the sample. The proposed technique also is less effective on the noise image.

A study of Dubey *et al.* [36], suggested K-means clustering technique for the infected fruit part detection and to replace the manual inspection that has been used in the industry. The transformation of RGB color image into L*a*b color space is applied in the pre-processing stage. In order to classify the colors, K-Means clustering technique is used and the other two different colors are measured by using Euclidean distance metric. Each pixel is labeled with its cluster index by referring to the K-means result. The segmented images are then separated according to the pixel label. The cluster number is applied to show the result of a different images. Based on the performance evaluation, the proposed technique shows it can segment the color precisely in order to detect the fruit defect. But, the unsuitable K-value selection may causes under-segmentation or over-segmentation for the image.

Capizzi *et al.* [37] proposed the automatic fruit defect classification based on gray level co-occurrence matrix (GLCM) and the radial basis probabilistic neural network (RBPNN) to be applied in fruit industrial application. The fruit is classified based on shape, color and texture. To determine the shape features, RGB image is converted into a grayscale image and the threshold value is set 1 or 0. Color features are extracted by using the conversion of RGB image to HSV image. The mean and the standards deviation value are calculated to classify the color of the fruit. GLCM technique is applied on the image to extract the texture features. The results from the shape, the color and the texture features are classified using RBPNN classifier technique. Through this technique, 97.25% accuracy is achieved. Due to high number of samples available, a large memory size is required and a lot of time is needed to complete all the process.

Yamin *et al.* [38] suggested blood group detection as shown in Figure 3(a), to classify the blood group color detection. The pre-processing step introduces conversion of RGB image into hue, saturation and value (HSV) image. Then, the HSV image is converted into a grayscale image to calculate the threshold value of the image. The morphological operation technique is applied to segment the image by removing the unwanted object and to restructure the image as shown in Figure 3(b). The vertical histogram is developed to identify the region of blood image. The density of the white pixel and total number of the object in a segmented image are calculated and will be used in the classification stage. For the classification of blood group, the rule-based classifier technique is implemented by setting the density threshold value and the objects threshold value. The result obtained a 98% high accuracy from the performance verification. However, using the proposed technique will reduces the quality of the image and it became inefficient during real-time processing. Table 2 summarize the review for the color inspection system.



(a)

(b)

Figure 3 Blood image: (a) Blood sample, (b) blood detection Yamin *et al*. (2017)

Table 2 Summary of colour for quality inspection system

No.	Title	Year	Author	Technique	Results
1	A Color Image Segmentation Algorithm Based on Region Growing	2010	Tang	• Watershed • Region growing	• Better segmentation result for color image.
2	Color Image Segmentation using Pixel Wise Support Vector Machine Classification	2011	Wang et al.	• Fuzzy C-Means • Support Vector Machine (SVM)	• The accuracy achieved is 96%.
3	Infected Fruit Part Detection using K-Means Clustering Segmentation Technique	2013	Dubey et al.	• K-means Clustering • Euclidean distance	• Precise in segmentation and in fruit defect detection.
4	Automatic Classification of Fruit Defects based on Co-Occurrence Matrix and Neural Networks	2016	Capizzi et al.	• Gray Level Co-occurrence Matrix (GLCM) • Radial Basis Probabilistic Neural network (RBPNN)	• The accuracy achieved is 97.25%.
5	Image Processing Based Detection & Classification of Blood Group using Color Images	2017	Yamin et al.	• Morphological Operation • Rule-based	• The accuracy achieved is 98%

2.3 Level Inspection

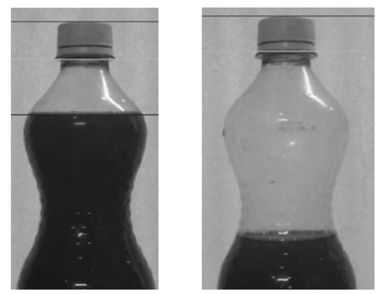
Water level inspection is preferred to measure and to monitor the water level of the product in order to equalize the level of water for all products [39]. The level inspection has been widely used in many industries over the years. Hence, previous research is reviewed to improvise the previous level inspection. Pithadiya *et al.* [40] has developed a liquid level inspection system based on infinite symmetrical edge filter (ISEF) detection technique to replace the traditional quality inspection performed by human operator. The process includes of image cropping and normalizing it, or filtering and detecting the image. In obtaining the detection result, the features of the bottle is extracted by calculating the average distance from the center of the ROI. Then, ISEF edge detection (Shen Castan algorithm) technique is applied to detect the liquid level either it shows an overfill or an underfill level using the average distance value. The analysis results show that the proposed technique is better in detecting the overfill and the underfill liquid level. But, this technique is not suitable for the quality image because it will give an over-segment image. Complex computation also become one of the limitation of this technique.

Yazdi *et al.* [41] has proposed the feature extraction and the edge detection algorithm to inspect fill level and to inspect the cap level in bottling machine. The captured image is going through several image processing steps such as the image enhancement, the segmentation, and the classification. By applying this edge detection technique, the image is segmented into several regions to locate the position of the level and the cap. For liquid level, a vertical and a horizontal reference line technique is used for the detection. The features of the segmented image are extracted and will be used for the classification process. The classification of the liquid level and the cap closure are done by using neural network (NN) technique. This technique proves that it can inspect the liquid level and the cap of bottle accurately. Nevertheless, the lower or the empty liquid level could not be detected and will face too many pre-processing techniques which will reduce the image quality.

According to Hies et al. [42], they suggested the edge detection technique to detect the water level for the real-time system. The process started with the transformation of the captured image into two-dimensional (2D) views. From the image, ROI has been selected automatically for analysis. The edge detection technique aims to obtain the edge of the image by assuming the changing intensity pixel of the image. The longest straight line in the image is calculated using Hough Transform technique in order to detect the lines of the water level. The experimental results show high accuracy and reliable to be used for the water level detection system. The disadvantages of this technique as it required a large memory size and it also give a misleading result because of the unsuitable technique used for segmentation process.

Dave and Hadia [43] has developed an automated liquid level and the cap closure inspection system using the image processing technique to automate the filling water system in the beverage industry. In orer to determine the proper segmentation, the captured image is filtered for noise reduction and the contrast enhancement is applied too, will increase the quality of the image. Color cropping technique is used by selecting a designated area of the image. The comparison of color range and the captured image is done to detect the liquid level. The detection of the cap's position is inspected based on the vertical and the horizontal reference line. The condition of the bottle cap either presentable or no presentable cap or no proper cap detected by using RGB matrix technique. This technique demonstrated precise detection of the liquid level and of the cap and thus, is suitable to be used for beverage application. The limitation of this technique is it could not segment it properly when the noise is spotted in the image.

Sharma et al. [44] proposed the automated bottle inspection system for the empty and the filled water in the manufacturing process. The automated system is implemented to overcome the problems created from the manual inspection due to its limitations. The process is classified into three types of inspections which covers the empty bottle shape inspection, the top and the bottom inspection, the fill level inspection and the cap placement inspection. For the empty bottle shape inspection, the morphological opening technique is used to remove the small noise in the image and to draw the line of the bottle shape. Then, the boundary of the bottle is extracted and calculated to determine the defective area. The Hough transform and the canny edge technique are applied for the top and the bottom inspection in order to find and to detect the circle edge in the image. The fill level and the cap placement inspection use the same technique which is the canny edge detection which offers sharp edge detection. The average accuracy of this system is 92%. However, this system needs a large memory of size and it takes longer time to finish all the image analysis process. An example of the level defect detection is illustrated in Figure 4. Table 3 summarize the review of the level inspection system.



(a) (b)

Figure 4 Bottle image: (a) Normal level (b) underfilled level [43]

Table 3 Summary of colour for quality inspection system

No.	Title	Year	Author	Technique	Results
1	Machine Vision Based Liquid Level Inspection System using ISEF Edge Detection Technique	2010	Pithadiya et al.	• ISEF Edge Detection • Vertical and Horizontal Reference Line	• Better detection result of overfill and underfill bottle.
2	Feature Extraction Algorithm for Fill Level and Cap Inspection in Bottling Machine	2011	Yazdi et al.	• Sobel Edge Detection • Vertical and Horizontal Reference Line • Neural Network (NN)	• Accurate inspection for liquid level and cap of the bottle.
3	Enhanced Water-Level Detection by Image Processing	2012	Hies et al.	• Edge Detection • Hough Transform	• Higher accuracy and reliability
4	Liquid Level and Cap Closure United Inspection using Image Processing	2015	Dave and Hadia	• Color cropping • RGB matrix • Vertical and Horizontal Reference Line	• Precisely detect liquid level and cap position
5	Empty and Filled Bottle Inspection System	2015	Sharma et al.	• Canny Edge Detection • Hough Transform	• The average accuracy achieved is 92%.

3.0 DEFECT DETECTION TECHNIQUES

Defect detection techniques is one of the segmentation process that becomes the most important steps in image analysis [45]. Generally, the main function of the segmentation is to reduce and to compress the image information for easy analysis of the image [46]. Image segmentation can be classified into two categories of techniques which are the thresholding-based technique and the clustering-based one. The thresholding-based technique is divided into two classes which are the global thresholding and the local thresholding. The global thresholding can be set manually or automatically but the local thresholding is determined by calculating the local intensity of each pixel of the different threshold value [47]. The clustering technique is mainly applied for image analysis of high-dimensional measurement patterns. It is used to group the pixels of the image that consists of similar features [48]. This research focuses on three types of quality inspection inclusive of the shape, the color and the level of the image bottle.

3.1 Shape Defect Detection Techniques

The popularity of the shape defect detection technique in the image processing is increasing after the edge-based segmentation is introduced in the early 90's. By partitioning the image plane, the specific object of a specific area in the image can be observed [49]. The capability of the shape defect detection technique, in detecting the complex surfaces such as sphere, linear extrusion, and helix makes these techniques become a common in many applications [50]. The shape defect detection techniques i.e., the adaptive thresholding [51], the morphological operation [52] and the local standard deviation (LSD) [53] are presented in this research for the development of the product quality inspection system.

A. Adaptive Thresholding

An adaptive thresholding technique uses the local threshold value to segment the image [54]. The local threshold value of each pixel in the image is depending on the intensity of the neighbouring pixel [55]. A study by Peuwnuan *et al.* [56] stated that they implemented the image thresholding concept to classify the image pixels either in dark or in light. The pixel distribution of the images is divided into two values in order to obtain the level of gray, black and white in binary form [32]. The image intensity value which has above threshold value is characterized as a foreground value and the remaining pixels is a background value. The minimization of the variance sum of two levels as the threshold value for each image can give a better accuracy during segmenting the object [57].

Saad *et al.* [51] applied the adaptive thresholding technique to detect and to classify brain lesion based on diffusion-weighted imaging (DWI). The result analysis shows that this technique provides a higher performance in terms of segmentation for hyperintensity lesions. Besides, this adaptive thresholding has a lower illumination effect when varying lighting condition and when doing changing background [58]. Roy *et al.* [59] applied hybrid technique by combining the adaptive thresholding technique with the optimal technique in order to improve the results of the experiments. According to Zhao *et al.* [60] the adaptive thresholding is ineffective during processing at the intersection with many lines due to the incomplete shape assumption. Moreover, it could not give a good segment for the image which has a high-intensity area.

B. Morphological Operation

The morphological operation technique is widely adopted in many applications i.e. the mobile photogrammetric systems, the sewer pipes detection system and the industrial object detection [61]. Ritchey [52] in his study summarized the morphological analysis in image processing wherein focusing on the object arrangement and the structure. The analysis using the morphological operation technique required conversion of the images in the binary and in grayscale form. From the set of mathematical formulation using lattice algebra and integral, the gray levels of an image in pixel (on a scale of 0 – 255) between dark and bright regions are separated from the threshold value [62], [63]. In addition, selecting the appropriate neighbor shape is required for the morphological operation technique to identify specific shape of the image [64].

In characterizing the iris region for biometric application, Mira and Maye [65] discovered a morphological operation technique and it has shown advantages in term of low computational complexity. The flexibility of hardware integration put this technique as suitable tool for the real-time monitoring system. The difficulty in selecting the optimum threshold value became a drawback for this technique. In addition, over-segmentation can cause inaccurate results for shape detection [66]. Pesaresi and Benediktsson [67] employed the morphological operation technique in detecting the complex satellite image. In experiment, the result shows a low accuracy achievement when they are using a high-resolution image. Therefore, the multiscale morphological operation is proposed to reduce the over-segmentation problem. However, this operation will leads to high computational complexity.

C. Local Standard Deviation

The contrast enhancement which is applied in the image has used the intensity modification approach to remove the noise and the uneven brightness presented in the image [68]. This contrast enhancement can be divided into two categories which are global contrast enhancement and local contrast enhancement. The global contrast enhancement is used in many applications that increase the image quality; but the local contrast enhancement is implemented to acquire detailed information of an image [69]. The local standard deviation (LSD) is one of the local contrast enhancement technique used to improve the low-quality image which has low contrast image. LSD is applied to adjust the amplification coefficient and to obtain higher enhancement in low contrast areas and low enhancement areas at high contrast areas [70].

The capability of LSD in using the local contrast enhancement to analyze the image makes it suitable to be employed in various application. Noise reduction in the image is the main advantage of this technique. Singh and Kumar [53] used the combination of the global and the local contrast enhancement to enhance the low contrast image. The local contrast enhancement using LSD technique shows its capability to remove noise in the image while the contrast enhancement is obtained from the removal of the divided by zero condition. The divided by zero condition is removed in order to increase the contrast enhancement level for different region and the result is a clear image with low noises [71]. This technique showed a fast and an effective contrast enhancement. However, the higher complexity the analysis makes, the image become longer [72]. In addition, some of the image pixels may get result in the LSD's as 0's if the smooth and the high-quality image is applied. But, this limitation can be neglected because the output may produce a undesired image [73].

3.2 Colour Concentration Defect Detection Techniques

With the increasing demand for many pattern recognition and computer vision applications, color image processing is a major concern of the researchers [34]. It is because the color is one of the features which can provide additional information and can be used for the further image analysis process [74]. The color detection technique is applied in the image in order to detect and to classify different types of color in the image. In image processing, the color of the image is the combination of three basic colors insitu, which are red, green and blue (RGB) [75]. A variety of color detection technique is proposed in the past decade ago and in order to order and to retrieve information and detect the color of the image. The different color detection technique namely Otsu's thresholding [76] and K-means clustering [77], [78] are used in previous research in characterizing the image color for image analysis which is important in the automated product quality inspection system.

A. K-Means Clustering

The clustering is a technique which classifies the color of the image by dividing the individual of a population into several groups base on the quantitative comparisons for different population characteristics [75]. The purpose of data clustering is for natural classification, underlying structure, and compression. By combining the K-means to measure the similarities between each group, the image pixel conditions either in low or in high level can be labeled [77], [78]. In image processing, the K-means clustering technique will analyze the image and generate the superpixel region resulting in a high quality of image feature. However, generating the superpixel images is slow to compute and inefficient in memory. Therefore, Achanta *et al.* [79] came with a solution which is proposing a new superpixel algorithm namely simple linear iterative clustering. But, K-means clustering technique is still adapted for the classification of the color image. This algorithm will limit the boundary of the images to the desired location and overcome the weakness.

In separating the bone, the fat, the tissue and the background, an analysis base on two-dimensional magnetic resonance images are conducted by [80] using K-means clustering technique. The particular regions are separated with different set of colors such as red, green and blue taken from the selected K value. Hence, it gives an advantage for a reduction for the over and the under-segmentation error. According to Zhang *et al.* [81], the improved K-means will perform better results hence, makes this technique is selected in the image processing analysis. Likas *et al.* [82] in their experiment, implementing K-means clustering technique for the different data set such as iris, synthetic and the image segmentation. From the data set, the clustering error is calculated on the number of clusters. At the end of the experiment, the authors conclude that the improper choice at K-means may yield to inaccurate result from high clustering error.

B. Otsu's Thresholding

The Otsu's thresholding is one of the common techniques used in image segmentation application. This technique works under automatic threshold value [83]. It is known as a global thresholding and it depends on the gray pixel value of the image. Based on a review made by [76], Otsu's thresholding used a comprehensive algorithm to obtain the global optimal threshold of the image. The image is separated into two classes in gray levels which are foreground and the background [84]. The optimal threshold value is automatically chosen by maximizing the weighted sum between class variance pixels [85]. Almisreb and Tahir [86] applied Otsu's thresholding in the pre-processing stage to adjust the contrast and to remove the pupil of the iris image. The result from pre-processing stage shows that the Otsu's thresholding can be adapted and to be used in image analysis.

In a study conducted by [87] Otsu's thresholding, is proposed to segment the image for apple sorting and grading. The optimal threshold will select automatically around the apple boundary to make it produce a better segmentation result [88]. Sindhuri and Anusha [89] suggested Otsu's thresholding to be used for separating document text. It is because Otsu's thresholding is capable to extract the document text from the noisy image background by segmenting the brightness object and removing the darkest object in the image. Otsu's thresholding offers simple algorithm and is an effective technique to segment the noisy image, so it has been used widely in the image segmentation application [90]. Nevertheless, Zhang and Hu [91] analyse thing using the Otsu's thresholding and found out that it is time-consuming in multilevel threshold selection. This matter can be improvised by adapting the 2D Otsu's adaptive threshold algorithm which can improve time processing during segmentation process [92].

3.3 Level Defect Detection Technique

The level detection technique has played an important role in the bottle filling inspection system in beverage manufacturing industries. The variation of water level is measured in three conditions which are normal, underfill and overfill [41]. While inspecting the level of water, the level detection technique is proposed because it is able to recognize the line of water in three conditions [92]. Each condition of the water level has its own threshold value to be used for detection and for classification process. The Sobel edge detection [93], the Canny edge detection [94] and the Hough transform [95] are proposed because they are capable to segment the water level accurately [43], [44]. The level detection technique also become one of the major interest in inspecting the water level for the bottling system.

A. Sobel Edge Detection

The Sobel edge detection is a gradient-based technique that used a derivatives operation to perform the edge detection of the image in x-direction and y-direction. The 2-D pixel array is transferred into statistical data set to enhance and to remove the redundant data which is required by digital image [96]. Generally, it is applied to determine the gradient magnitude at each point of the grayscale image. The calculation of the gradient of image intensity will produce darker or brighter contrast to represent the area of edges [97]. The Sobel operator has used two convolution template mask that consists 3x3 kernels to calculate the approximations for x and y-direction [98]. Based on a comparison of edge detection technique made by [99], sobel edge detection is adopted because it has simple algorithm and simple processing time.

The advantages of the Sobel edge detection is described by [93] in their studies of shark fish classification. Sobel operator offers simple algorithm and low in computational complexity. Vincent and Folorunso [100] used the same to detect the edge of various types of image. The result shows that it can produce better detection of the edge area with simple computation. Hence, it can be used by the industrial inspection for the edge detection application. The Sobel edge detection also has a limitation in detecting small edges of the image. Jin-Yu *et al.* [101] employed this detection to detect the edge of the human image. The sobel operator shows the difficulty to remove noise in the image. Hence, it may cause the sobel to be misclassified the edge of the object. In the study made by [102], the sobel edge detection demonstrate high sensitivity to noise which makes it less accurate to detect the edge of the image.

B. Canny Edge Detection

Another common technique of the edge detection is the canny edge detection. This detection is one of the optimal edge detection and is widely used in the image processing tools. This technique provides convolution filter which can smooth the noise and to detect the edge of the image [103]. For smoothing process, the canny edge detection used a Gaussian mask with two-dimensional pixel array. The Gaussian mask is applied to reduce and to eliminate the noise, thus overcoming the limitation of the sobel edge detection [104]. In detecting the edge of the image, the local maxima of gradient magnitude are computed at each pixel in both directions of x and y. Hence, the edge of the image is identified when the gradient magnitude is above than threshold value [105]. The Canny edge detection is an effective technique too because it can provide adjustable parameter without affecting the pixel value of the image [106].

Several previous researchers have recommended the canny edge detection because of its capability to detect edge area of the image. According to Ogawa *et al.* [107], they proposed the canny edge detection as a detector which offers a good extraction of optimal edges and it can achieve accurate detection of the edge area. Gentsos *et al.* [108] implemented the canny edge detection for field programmable gate array (FPGA) in detecting the edge of the high-resolution image. The experimental results show that the canny edge detection has obtained high accuracy by eliminating all the unwanted edges and has identified all the significant edges. Besides, the ability to detect the edge of the noisy image makes this technique resistant to a noisy environment [109]. The major drawback of this canny edge detection is its time consuming problem due to its complex computation. Therefore, this technique is difficult to be implemented in the real-time system.

C. Hough Transform

One of the famous statistical technique is Hough transform that generally used for straight line detection [110]. The Hough transform is an automatic detection of lines by estimating the arbitrary shape parameters of its boundary points. This technique involves the conversion of figure point form into a straight-line form. The parameters such as angle of the line and the origin distance is described in parameter space [111]. Besides, the Hough transform used slope-intercept parameters in two-dimensional array to extract the information lines in the image. In order to find the line in the image, three steps need to be done which must be performed in accumulation way, find the peak values, and peak values verification [112].

The performance of the Hough transform was explained by [113] which has used Hough transform to detect building line and pedestrian. The probabilistic interpretation of Hough-based is applied to assume the value of parameters. Better accuracy in detecting multiple object has been achieved compared to others technique. The promising performance of the Hough transform also has been described by [114] in classifying and localizing human actions. Zhang et al. [95] proposed the Hough transform for the line detection because of its robustness to noise and its capability to detect object line even though without enough information. However, the study conducted by [42], stated that Hough transform is time consuming due to its complexity in computation. This limitation can be improved by using generalized Hough transform that allows the reduction of time and memory size [115].

4.0 CONCLUSION

The quality of the product using image processing techniques are presented. Vision-based inspection is categorized into two inspections which are the manual inspection and the automated inspection. The manual inspection in the manufacturing process is conducted by human operator while the automatic inspection has used computer vision for product quality classification. As discussed earlier, the performance of the manual inspection can be affected by many factors which make this type of inspection is inefficient to be used in manufacturing industry. Therefore, the automated inspection is proposed to overcome the limitation of the manual inspection.

A number of studies on product quality inspection techniques were reported for the development of real-time monitoring system. The studies are a focus on the inspection for shape, color and level in determining the defect on the beverage product. An accurate, low cost, fast speed and multi-function system are needed for a quality inspection standard. Based on the review from previous researchers, the inspection system is developed only to inspect the product quality either for the shape, the color or the level of the product. Thus, the system makes it less efficient and not reliable to be implemented in inspecting the quality of the product. For some reasons, the system is less capable of classifying the defect on the product because of the inappropriate technique was chosen.

The common techniques were presented by the previous research such as the adaptive thresholding and the morphological operation for the shape detection technique. Both techniques provide better segmentation result, but it has difficulty to segment the important edges or the region because the optimal threshold value could not be obtained. Therefore, LSD is proposed to improve low contrast image in order to get a good result of segmentation. In addition, the capability to reduce the noise and the ringing will leads to the high accuracy in segmenting the shape of the beverage product. Meanwhile, a technique based on the color detection technique such as K-means clustering and Otsu's thresholding are introduced to make a comparison for both techniques. K-means clustering technique shows potential to segment the color in the image very well. However, to select a suitable K-value has become a limitation to this technique. It is because the inappropriate K-value will produce over-segmentation or under-segmentation of the image. Thus, Otsu's thresholding is proposed to overcome the limitation of K-means clustering technique. The use of histogram analysis has make Otsu's thresholding to be able to separate the object and the background image easily. On the other hand, the optimum threshold value can be obtained automatically and is applicable in the real-time monitoring system.

The frequent techniques for the level detection of beverage product are the sobel edge detection, the canny edge detection and the Hough transform. These techniques have a promising a good result of edge area detection. Nevertheless, the sobel edge detection could not give a well segmentation for the noisy image while the canny edge detection is very time-consuming due to the complex computation. Hence, the Hough transform is suggested because of its capability to detect the level of water accurately. The simple algorithm makes this technique process the image in a very short of time. Thus, it is a reliable and an effective technique to be used for the beverage manufacturing industries.

Acknowledgement

The authors would like to thank the Universiti Teknikal Malaysia Melaka (UTeM), UTeM Zamalah Scheme, Rehabilitation Engineering & Assistive Technology (REAT) research group under Center of Robotics & Industrial Automation (CeRIA), Advanced Digital Signal Processing (ADSP) Research Laboratory and Ministry of Higher Education (MOHE), Malaysia for sponsoring this work under project

GLuar/STEVIA/2016/FKE-CeRIA/I00009 and the use of the existing facilities to complete this project.

References

[1] Yun, J. P. 2009. Vision-based Defect Detection of Scale-covered Steel Billet Surfaces. *Optical Engineering*. 48(3): 37205.

[2] Koch, C., Georgieva, K., Kasireddy, V., Akinci, B., and Fieguth, P. 2015. A Review on Computer Vision based Defect Detection and Condition Assessment of Concrete and Asphalt Civil Infrastructure. *Advanced Engineering Informatics*. 29(2): 196-210.

[3] Prabuwono, A. S., Sulaiman, R., Hamdan, A. R. and Hasniaty, A. 2006, November. Development of Intelligent Visual Inspection System (IVIS) for Bottling Machine. *TENCON 2006-2006 IEEE Region 10 Conference IEEE*. 1-4.

[4] Baudet, N., Maire, J. L., and Pillet, M. 2013. The Visual Inspection of Product Surfaces. *Food Quality and Preference*. 27(2): 153-160.

[5] Hassan, M. H., and Diab, S. L. 2010. Visual Inspection of Products with Geometrical Quality Characteristics of Known Tolerances. *Ain Shams Engineering Journal*. 1(1): 79-84.

[6] Patel, K. K., Kar, A., Jha, S. N., and Khan, M. A. 2012. Machine Vision System: A Tool for Quality Inspection of Food and Agricultural Products. *Journal of Food Science and Technology*. 49(2): 123-141.

[7] Skinner, N., Roche, A., O'Connor, J., Pollard, Y. and Todd, C. 2005. Workforce Development TIPS (Theory into Practice Strategies): A Resource Kit for the Alcohol and Other Drugs Field. Adelaide, Australia: National Centre for Education and Training on Addiction (NCETA): Flinders University.

[8] Salas, E., Maurino, D. and Curtis, M. 2010. Human Factors in Aviation: An Overview. Human Factors in Aviation. Academic Press. 3-19.

[9] Mak, K. L. and Peng, P. 2008. An Automated Inspection System for Textile Fabrics based on Gabor Filters. *Robotics and Computer-Integrated Manufacturing*. 24(3): 359-369.

[10] Kujawińska, A. and Vogt, K. 2015. Human Factors in Visual Quality Control. *Manag. Prod. Eng. Rev.* 6(2): 25-31.

[11] S.-H. Huang and Y.-C. Pan. 2015. Automated Visual Inspection in the Semiconductor Industry: A Survey. *Comput. Ind.* 66: 1-10.

[12] Al Kamal, I. and Al-Alaoui, M. 2008. Online Machine Vision Inspection System for Detecting Coating Defects in Metal Lids. *Proceedings of the International MultiConference of Engineers and Computer Scientists.* II: 19-21.

[13] Noor Khafifah Khalid, M. S. Z. A., Zuwairie Ibrahim. 2008. An Algorithm to Group Defects on Printed Circuit Board for Automated Visual Inspection. *International Journal of Simulation: Systems, Science and Technology.*

[14] Ravikumar, S., Ramachandran, K. I. and Sugumaran, V. 2011. Machine Learning Approach for Automated Visual Inspection of Machine Components. *Expert Systems with Applications*. 38(4): 3260-3266.

[15] Edris, M. Z. B., Zakaria, Z., Zin, M. S. I. M., and Jawad, M. S. 2015. Automated Deform Detection on Automotive Body Panels Using Gradient Filtering and Fuzzy C-Mean Segmentation. *Jurnal Teknologi*. 9: 47-50.

[16] Mera, C., Orozco-Alzate, M., Branch, J., and Mery, D. 2016. Automatic Visual Inspection: An Approach with Multi-instance Learning. *Comput. Ind.* 83: 46-54.

[17] Park, M., Jin, J. S., Au, S. L., Luo, S., and Cui, Y. 2009. Automated Defect Inspection System by Pattern Recognition. *Proc. 5th Int. Conf. Image Graph. ICIG 2009.* 2(2): 768-773.

[18] Marhoon, A. F., Younis, A. N. S., and Taha, F. T. 2013. Automated Visual Inspection System for Specifying Brick Quality. *Journal of Sensor Technology.* 3(December): 110-114.

[19] Li, X., Qiao, T., Pang, Y., Zhang, H., Yan, G. 2018. A New Machine Vision Real-time Detection System for Liquid Impurities based on Dynamic Morphological Characteristic Analysis and Machine Learning. *Measurement.* 124: 130-137.

[20] Huang, B., Ma, S., Wang, P., Wang, H., Yang, J., Guo, X., Zhang, W., Wang, H. 2018. Research and Implementation of Machine Vision Technologies for Empty Bottle Inspection Systems. *An International Journal Engineering Science and Technology.* 21(1): 159-169.

[21] Wang, Y., Li, K., Gan, S. and Cameron, C. 2019. Analysis of Energy Saving Potentials in Intelligent Manufacturing: A Case Study of Bakery Plants. *Journal of Energy*.

[22] Jahanshahi, A. A., Gashti, M. A. H., Mirdamadi, S. A., Nawaser, K. and Khaksar, S. M. S. 2011. Study the Effects of Customer Service and Product Quality on Customer Satisfaction and Loyalty. *International Journal of Humanities and Social Science.* 1(7): 253-260.

[23] Kefer, M. and Tian, J. 2016, August. An Intelligent Robot for Flexible Quality Inspection. *2016 IEEE International Conference on Information and Automation (ICIA) IEEE.* 80-84.

[24] Shafait, F., Imran, S. M., and Klette-Matzat, S. 2004. Fault Detection and Localization in Empty Water Bottles through Machine Vision. *E-Tech 2004.* 30-34.

[25] Tachwali, Y., Al-Assaf, Y. and Al-Ali, A. R. 2007. Automatic Multistage Classification System for Plastic Bottles Recycling. *Resources, Conservation and Recycling.* 52(2): 266-285.

[26] González Ramírez, M. M., Villamizar Rincón, J. C., and Lopez Parada, J. F. 2014. Liquid Level Control of Coca-Cola Bottles Using an Automated System. *CONIELECOMP 2014 - 24th Int. Conf. Electron. Commun. Comput.* 148-154.

[27] Zhang, D. and Lu, G. 2004. Review of Shape Representation and Description Techniques. *Pattern Recognition.* 37(1): 1-19.

[28] Ramli, S., Mustafa, M. M., Hussain, A., and Wahab, D. A. 2012. Plastic Bottle Shape Classification Using Partial Erosion-based Approach. *Modern Applied Science*. 6(4): 77-83.

[29] Moradi, G., Shamsi, M., Sedaaghi, M. H., and Moradi, S. 2011. Apple Defect Detection using Statistical Histogram based Fuzzy C-means Algorithm. *Inst. Electr. Electron. Eng.* 11-15.

[30] Gonydjaja, R. and Kusuma, T. M. 2014. Rectangularity Defect Detection for Ceramic Tile Using Morphological Techniques. *ARPN Journal of Engineering and Applied Sciences.* 9(11): 2052-2056.

[31] Abdellah, H., Ahmed, R., and Slimane, O. 2014. Defect Detection and Identification in Textile Fabric by SVM Method. *IOSR Journal of Engineering*. 4(12): 69-77.

[32] Sahar, M., Nugroho, H. A., I, Tianur, Ardiyanto, and Choridah, L. 2016. Automated Detection of Breast Cancer Lesions Using Adaptive Thresholding and Morphological Operation. *Int. Conf. Inf. Technol. Syst. Innov*. 27-30.

[33] Yam, K. L. and Papadakis, S. E. 2004. A Simple Digital Imaging Method for Measuring and Analyzing Color of Food Surfaces. *Journal of Food Engineering.* 61(1): 137-142.

[34] Tang, J. T. J. 2010. A Color Image Segmentation Algorithm based on Region Growing. *Comput. Eng. Technol. (ICCET), 2010 2nd Int. Conf.* 6: 634-637.

[35] Wang, X.-Y., Wang, T., and Bu, J. 2011. Color Image Segmentation Using Pixel Wise Support Vector Machine Classification. *Pattern Recognition*. 44(4): 777-787.

[36] Dubey, S. R., Dixit, P., Singh, N., and Gupta, J. P. 2013. Infected Fruit Part Detection using K-Means Clustering Segmentation Technique. *The International Journal of Interactive Multimedia and Artificial Intelligence*. 2(2): 65.

[37] Capizzi, G., Lo Sciuto, G., Napoli, C., Tramontana, E., and Wozniak, M. 2015. Automatic Classification of Fruit Defects based on Co-Occurrence Matrix and Neural Networks. *Proc. 2015 Fed. Conf. Comput. Sci. Inf. Syst. FedCSIS 2015.* 5: 861-867.

[38] Yamin, A., Faisal Imran, Akbar, U., and Tanvir, S. H. 2017. Image Processing Based Detection & Classification of Blood Group Using Color Images. *Int. Conf. Commun. Comput. Digit. Syst.* 293-298.

[39] Kreutzer, J. F., Flaschberger, J., Hein, C. M., and Lueth, T. C. 2016. Capacitive Detection of Filling Levels in a Cup. *BSN 2016 - 13th Annu. Body Sens. Networks Conf.* 31-36.

[40] Pithadiya, K. J., Modi, C. K., and Chauhan, J. D. 2010. Machine Vision Based Liquid Level Inspection System using ISEF Edge Detection Technique. *Proceedings of the International Conference & Workshop on Emerging Trends in Technology (ICWET).* 601-605.

[41] L. Yazdi, A. S. Prabuwono, and E. Golkar. 2011. Feature Extraction Algorithm for Fill Level and Cap Inspection in Bottling Machine. Proc. 2011 Int. Conf. Pattern Anal. Intell. Robot. ICPAIR 2011. 1(June): 47-52.

[42] Yazdi, L., Prabuwono, A. S., and Golkar, E. 2011. Feature Extraction Algorithm for Fill Level and Cap Inspection in Bottling Machine. P*roc. 2011 International Conference on Pattern Analysis and Intelligent Robotics 2011.* 1(June): 47-52.

[42] Hies, T., Babu, P. S., Wang, Y., Duester, R., Eikaas, H. S., and Meng, T. K. 2012. Enhanced Water-Level Detection by Image Processing. *10th International Conference on Hydroinformatics HIC 2012. January 2012.*

[43] Dave, V. A., and Hadia, P. S. K. 2015. Liquid Level and Cap Closure United Inspection using Image Processing. *International Journal of Innovative Research in Science, Engineering and Technology*. 1(12): 62-68.

[44] Sharma, S., Krupa, K. V., Gandhi, R., Jain, A., and Shah, N. 2015. Empty and Filled Bottle Inspection System. *J. Image Video Process.* 1122-1126.

[45] Aghajari, E. and G. Chandrashekhar, D. 2017. Self-Organizing Map based Extended Fuzzy C-Means (SEEFC) Algorithm for Image Segmentation. *Applied Soft Computing.* 54: 347-363.

[46] Yogamangalam, R. and Karthikeyan, B. 2013. Segmentation Techniques Comparison in Image Processing. *International Journal of Engineering and Technology (IJET).* 5(1): 307-313.

[47] Zhang, J., Yan, C. H., Chui, C. K., and Ong, S. H. 2010. Fast Segmentation of Bone in CT Images using 3D Adaptive Thresholding. *Computers in Biology and Medicine*. 40(2): 231-236.

[48] Choy, S. K., Lam, S. Y., Yu, K. W., Lee, W. Y., and Leung, K. T. 2017. Fuzzy Model-based Clustering and Its Application in Image Segmentation. *Pattern Recognit*. 68: 141-157.

[49] Cremers, D., Rousson, M., and Deriche, R. 2007. A Review of Statistical Approaches to Level Set Segmentation: Integrating Color, Texture, Motion and Shape. *International Journal of Computer Vision*. 72(2): 195-215.

[50] Gelfand, N. and Guibas, L. J. 2004, July. Shape Segmentation using Local Slippage Analysis. *Proceedings of the 2004 Eurographics/ACM SIGGRAPH Symposium on Geometry Processing ACM*. 214-223.

[51] Saad, N. M., Abu-Bakar, S. A. R., Muda, A. F., S. Muda, and Syafeeza, A. R. 2015. Automatic Brain Lesion Detection and Classification Based on Diffusion-weighted Imaging using Adaptive Thresholding and a Rule-based Classifier. *International Journal of Engineering and Technology.* 6(6): 2685-2697.

[52] Ritchey, T. 2006. Problem Structuring using Computer-aided Morphological Analysis. *Journal of the Operational Research Society.* 57(7): 792-801.

[53] Singh, A. and Neeraj Kumar. 2012. A Comprehensive Method for Image Contrast Enhancement based on Global-local Contrast and Local Standard Deviation. *International Journal of Engineering Research & Technology*. 2319-1163.

[54] Saad, N. M., Bakar, S. A. R. S. A., Muda, A. S., and Mokji, M. M. 2015. Review of Brain Lesion Detection and Classification using Neuroimaging. *J. Teknologi.* 74(6): 73-85.

[55] Bradley, D. and Roth, G. 2007. Adaptive Thresholding using the Integral Image. *J. Graph. Tools.* 12(20): 13-21.

[56] Peuwnuan, K., Woraratpanya, K., and Pasupa, K. 2016. Modified Adaptive Thresholding using Integral Image. *The 13th International Joint Conference on Computer Science and Software Engineering, JCSSE 2016*. 2-6.

[57] Jansi, S. and Subashini, P. 2012. Optimized Adaptive Thresholding based Edge Detection Method for MRI Brain Images. *International Journal of Computer Applications*. 51(20): 1-8.

[58] Yazid, H. and Arof, H. 2013. Gradient based Adaptive Thresholding. *Journal of Visual Communication and Image Representation*. 24(7): 926-936.

[59] Roy, P., Dutta, S., Dey, N., Dey, G., Chakraborty, S., and Ray, R. 2014. Adaptive Thresholding: A Comparative Study. *International Conference on Circuits, Communication, Control and Computing II.* 1320-1324.

[60] Zhao, M., Yang, Y., and Yan, H. 2000. Adaptive Thresholding Method for Binarization Blueprint Images. *Pattern Recognition Letters.* 2(2000): 931-934.

[61] Kowalczyk, M., Koza, P., Kupidura, P., and Marciniak, J. 2008. Application of Mathematical Morphology Operations for Simplification and Improvement of Correlation of Images in Close-range Photogrammetry. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. 37: 153-158.

[62] Soille, P. 2000. Morphological Image Analysis Applied to Crop Field Mapping. *Image and Vision Computing.* 18(13): 1025-1032.

[63] Diaz-Huerta, C. C., Felipe-Riveron, E. M., and Montaño-Zetina, L. M. 2014. Quantitative Analysis of Morphological Techniques for Automatic Classification of Micro-calcifications in Digitized Mammograms. *Expert Systems with Applications*. 41(16): 7361-7369.

[64] Elbehiery, H., Hefnawy, A., and Elewa, M. 2005. Surface Defects Detection for Ceramic Tiles Using Image Processing and Morphological Techniques. *Proceeding World Academy of Science, Engineering and Technology.* 5(5): 158-162.

[65] de Mira Jr, J. and Mayer, J. 2003. Image Feature Extraction for application of Biometric Identification of Iris - A Morphological Approach. *Proc. XVI Brazilian Symposium on Computer Graphics and Image Processing*.

[66] Mukhopadhyay, S., and Chanda, B. 2003. Multiscale Morphological Segmentation of Gray-scale Images. *IEEE Transactions on Image Processing*. 12(5): 533-549.

[67] Pesaresi, M., and Benediktsson, J. A. 2001. A New Approach for the Morphological Segmentation of High-resolution Satellite Imagery. *IEEE Transactions on Geoscience and Remote Sensing*. 39(2): 309-320.

[68] Singh, A. and Kumar, N. 2014. A Global-local Contrast based Image Enhancement Technique based on Local Standard Deviation. *International Journal of Computer Applications.* 93(2): 8-12.

[69] Shah, N., and Dahiya, V. 2015. Comparison of Global – Local Contrast Enhancement in Image Processing. *Int. J. Appl. or Innov. Eng. Manag.* 4(11): 16-22.

[70] Yang, Y. and Zhou, Z. 2012. Research and Implementation of Image Enhancement Algorithm Based on Local Mean and Standard Deviation. *IEEE Symp. Electr. Electron. Eng*. 375-378.

[71] Singh, S. S., Devi, H. M., Singh, T. T., and Sinam, T. 2012. Local Contrast Enhancement using Local Standard Deviation. *International Journal of Computer Applications.* 47(15): 31-35.

[72] Zheng, D., Wang, J., and Xiao, Z. 2005. Image Enhancement Based on Local Standard Deviation. *Journal of Information and Computing Science*. 2(June): 1-10.

[73] Cvetkovic, S. D., Schirris, J., and De With, P. H. N. 2007. Locally-adaptive Image Contrast Enhancement without Noise. *IEEE International Conference on Image Processing* 557-560.

[74] Cheng, H.-D. C. H.-D. and Sun, Y. S. Y. 2000. A Hierarchical Approach to Color Image Segmentation using Homogeneity. *IEEE Transactions on Image Processing*. 9(12): 2071-2082.

[75] Cheng, H., Jiang, X., and Wang, J. 2002. Color Image Segmentation based on Homogram Thresholding and Region Merging. *Pattern Recognition*. 35(2): 373-393.

[76] N. I. Conference and H. I. Systems. 2009. Otsu Method and K-means. 2.

[77] Jain, A. K. 2010. Data Clustering: 50 Years Beyond K-means. *Pattern Recognition Letters*. 31(8): 651-666.

[78] Zhang, D., Islam, M. M., and Lu, G. 2012. A Review on Automatic Image Annotation Techniques. *Pattern Recognition.* 45(1): 346-362.

[79] Achanta, R., Shaji, A., Smith, K., Lucchi, A., Fua, P., and Süsstrunk, S. 2011. SLIC Superpixels Compared to State-of-the-Art Superpixel Methods. *IEEE Transactions on Pattern Analysis and Machine Intelligence.* 34(11): 2274-2282.

[80] Ng, H. P., Ong, S. H., Foong, K. W. C., Goh, P. S., and Nowinski, W. 2006. Medical Image Segmentation Using K-Means Clustering and Improved Watershed Algorithm. *IEEE Xplore Proceedings*. 61-65.

[81] Zhang, Z., Zhang, J., and Xue, H. 2008. Improved K-Means Clustering Algorithm. *2008 Congress on Image and Signal Processing*. 169-172.

[82] Likas, A., Vlassis, N., and Verbeek, J. J. 2003. The Global k-means Clustering Algorithm. *Pattern Recognition*. 36(2): 451-461.

[83] Guo, W. Y., Wang, X. F., and Xia, X. Z. 2014. Two-dimensional Otsu's Thresholding Segmentation Method based on Grid Box Filter. *Optik (Stuttg).* 125(18): 5234-5240.

[84] Jenifer, S., Parasuraman, S., and Kadirvelu, A. 2015. Otsu's Method for Clip Limiting Histograms for Contrast Enhancement of Digital Mammograms. *2014 IEEE International Conference on Computational Intelligence and Computing Research, IEEE ICCIC 2014.* 6-9.

[85] Wang, X. and Xue, Y. 2016. Fast HEVC Intra Coding Algorithm based on Otsu's Method and Gradient. *2016 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB) IEEE*. 1-5.

[86] Almisreb, A. A., and Tahir, N. M. 2013. Enhancement of Iris Boundary Detection based on Otsu Method. *IEEE Symp. Comput. Informatics, ISC. 2013.* 143-146.

[87] Mizushima, A., and Lu, R. 2013. An Image Segmentation Method for Apple Sorting and Grading using Support Vector Machine and Otsu's Method. *Computers and Electronics in Agriculture.* 94: 29-37.

[88] Vala, M. H. J. and Baxi, A. 2013. A Review on Otsu Image Segmentation Algorithm. *International Journal of Advanced Research in Computer Engineering & Technology*. 2(2): 387-389.

[89] Zhang J., and Hu, J. 2008. Image Segmentation based on 2D Otsu Method with Histogram Analysis. *2008 International Conference on Computer Science and Software Engineering Image*. 1: 105-108.

[90] Lu, J. and Hu, R. 2012. A New Image Segmentation Method Based on Otsu Method and Ant Colony Algorithm. *Int. Conf. Comput. Sci. Inf. Process*. 767-769.

[91] Sha, C., Hou, J., Cui, H., and Kang, J. 2016. Gray Level-Median Histogram Based 2D Otsu's Method. *Proceedings of the 2015 International Conference on Industrial Informatics - Computing Technology, Intelligent Technology, Industrial Information Integration. ICIICII 2015.* 30-33.

[92] Lin, F., Chang, W.-Y., Lee, L.-C., Hsiao, H.-T., Tsai, W.-F., and Lai, J.-S. 2013. Applications of Image Recognition for Real-Time Water Level and Surface Velocity. *2013 IEEE Int. Symp. Multimed.* 259-262.

[93] Shrivakshan, G. T., and Chandrasekar, C. 2012. A Comparison of Various Edge Detection Techniques used in Image Processing. *International Journal of Computer Science Issues.* 9(5): 269-276.

[94] Ogawa, K., Ito, Y., and Nakano, K. 2010. Efficient Canny Edge Detection Using a GPU. *2010 First Int. Conf. Netw. Comput*. 279-280.

[95] Zhang, Q., Yeo T. S., Tan, H. S., and Luo, Y. 2008. Imaging of a Moving Target with Rotating Parts based on the Hough Transform. *IEEE Transactions on Geoscience and Remote Sensing.* 46(1): 291-299.

[96] Gupta, S. and Mazumdar, S. G. 2013. Sobel Edge Detection Algorithm. *International J. Comput. Science Manag. Res*. 2(2): 1578-1583.

[97] Vijayarani, S. and Vinupriya, M. 2013. Performance Analysis of Canny and Sobel Edge Detection Algorithms in Image Mining. *International Journal of Innovative Research in Computer and Communication Engineering.* 1(8): 1760-1767.

[98] Abdel-Qader, I., Abudayyeh, O., and Kelly, M. E. 2003. Analysis of Edge-detection Techniques for Crack Identification in Bridges. *Journal of Computing in Civil Engineering.* 17(4): 255-263.

[99] Sharifi, M., Fathy, M., and Mahmoudi, M. T. 2002. A Classified and Comparative Study of Edge Detection Algorithms. *Proceedings Information Technology Coding and Computing*. 5-8.

[100] Vincent, O. R., and Folorunso, O. 2009. A Descriptive Algorithm for Sobel Image Edge Detection. *Proceeding Informing Science & IT Education Conference 2009*. 1-11.

[101] Zhang, J. Y., Yan, C., and Huang, X. X. 2009. Edge Detection of Images based on Improved Sobel Operator and Genetic Algorithms. *Proceeding 2009 International Conference on Image Analysis and Signal Processing, IASP 2009.* 3: 32-35.

[102] Gao, W., Yang, L., Zhang, X., and Liu, H. 2010. An Improved Sobel Edge Detection. *2010 3rd IEEE International Conference on Computer Science and Information Technology, ICCSIT 2010.* 5: 67-71.

[103] Pithadiya, K. J., Modi C. K., and Chauhan, J. D. 2011. Selecting the Most Favourable Edge Detection Technique for Liquid Level Inspection in Bottles. *International Journal of Computer Information Systems and Industrial Management Applications (IJCISIM).* 3(December): 34-44.

[104] Abdul Kadir Jumaat, Siti Salmah Yasiran, Aminah Abdul Malek, Wan Eny Zarina Wan Abdul Rahman, Norzaituleha Badrin, Siti Hajar Osman, Siti Rohaina Rafiee, Rozi Mahmud 2014. Performance Comparison of Canny and Sobel Edge Detectors on Balloon Snake in Segmenting Masses. 2014 *International Conference on Computer and Information Sciences, ICCOINS 2014 - A Conference of World Engineering, Science and Technology Congress, ESTCON 2014 - Proceedings.*

[105] Ali, M., and Clausi, D. 2001. Using the Canny Edge Detector for Feature Extraction and Enhancement of Remote Sensing Images. *Geoscience and Remote Sensing Symposium 2001.* 2298-2300.

[106] Wang, B., and Fan, S. 2009. An Improved CANNY Edge Detection Algorithm. *2009 Second International Workshop on Computer Science and Engineering*. 497-500.

[107] Ogawa, K., Ito, Y., and Nakano, K. 2010. Efficient Canny Edge Detection Using a GPU. *2010 First International Conference on Networking and Computing*. 279-280.

[108] Gentsos, C., Sotiropoulou, C. L., Nikolaidis, S., and Vassiliadis, N. 2010. Real-time Canny Edge Detection Parallel Implementation for FPGAs. *2010 IEEE International Conference on Electronics, Circuits and Systems, ICECS 2010 - Proc.* 499-502.

[109] Tsanakas, J. A., Chrysostomou, D., Botsaris, P. N., and Gasteratos, A. 2015. Fault Diagnosis of Photovoltaic Modules through Image Processing and Canny Edge Detection on Field Thermographic Measurements. *International Journal of Sustainable Energy*. 34(6): 351-372.

[110] Fernandes, L. A. F., and Oliveira, M. M. 2008. Real-time Line Detection through an Improved Hough Transform Voting Scheme. *Pattern Recognition.* 41(1): 299-314.

[111] Agan, I., Lenglet, C., Jahanshad, N., Yacoub, E., Harel, N., Thompson, P. M., Sapiro, G. 2011. A Hough Transform

Global Probabilistic Approach to Multiple-subject Diffusion MRI Tractography. *Medical Image Analysis*. 15(4): 414-425.

[112] Borrmann, D., Elseberg, J., Lingemann, K., and Nüchter, A. 2011. The 3D Hough Transform for Plane Detection in Point Clouds: A Review and a New Accumulator Design. *3D Research*. 2(2): 1-13.

[113] Barinova, O., Lempitsky, V., and Kohli, P. 2010. On Detection of Multiple Object Instances using Hough Transform. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 34(9): 1773-1784.

[114] A. Yao, J. Gall, and L. Van Gool. 2010. A Hough Transform-Based Voting Framework for Action Recognition. *Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference*. 2061-2068.

[115] Mukhopadhyay, P. and Chaudhuri, B. B. 2015. A Survey of Hough Transform. *Journal of Pattern Recognition Society*. 48(3): 993-1010.