Educational Administration: Theory and Practice
2024, 30(5), 4172-4181
ISSN: 2148-2403
https://kuey.net/
Research Article

Level Measurement And Control Using Single Digital Camera Based On Image Processing In Matlab

Mr. Lalit S. Patel[1*], Dr. Utpal T. Pandya[2]

[1*]Assistant Professor, Instrumentation & Control Engineering Department, L.D.Engineering College, Ahmedabad,Gujarat, India,
E-mail: lsp.fetr@ldce.ac.in
[2]Head of Department, Instrumentation & Control Engineering Department,S.C.E.T., Surat, Gujarat, India,
E-mail: utpal.pandya@scet.ac.in

Citation: Mr. Lalit S. Patel, Dr. Utpal T. Pandya, (2024), Level Measurement And Control Using Single Digital Camera Based On Image Processing In Matlab, *Educational Administration: Theory and Practice, 30(5), 4172-4181*
Doi: 10.53555/kuey.v30i5.3603

ARTICLE INFO
Received: 10-04- 2024
Accepted: 11-05- 2024

ABSTRACT

This study examines the effectiveness of image-based level measurement and control using a single digital camera by comparing various segmentation models for liquid level detection. The main goal of this study was to evaluate some common approaches used in segmenting images from single cameras such as simple thresholding, adaptive thresholding, Otsu's thresholding and global thresholding with manual adjustment that will identify liquid levels using blob inside it correctly. All segmentation models consistently show black colour for liquid and white for objects/blobs. In addition, there is a significant correlation between the size of detected objects/blobs and liquid depth suggesting potential use of diameter variations as an indirect measure of changes in liquid depths. Thus, this article presents a technique to compute depth of liquid based on object diameter measured from detected object or blob using height of camera above tank so that one can improve industrial applications involving development of improved level measurement and control systems.

Keywords: Liquid Level Detection, Image Segmentation, Thresholding, Blob, Camera, Image Preprocessing.

1. Introduction

The measurement of liquid level is an essential factor in the monitoring and control of liquid resources. However, manually detecting and getting measurements of liquid levels using visual means may sometimes be a time-consuming and challenging task, mostly related to the positioning of the measuring device or the characteristics of the liquid being measured. Automated measuring systems must accurately identify the liquid level in relation to the associated measuring scale by calibrating the capacity measurements against their scale markings. Hence, it is clear that the conventional methods for detecting liquid levels cannot be used to automate such activities.[1]The most prevalent types of automated water level gauges include the float-type, pressure-type, ultrasonic-type, and radar-type. Their actual uses are often constrained by the expensive cost of equipment and installation, susceptibility to temperature and silt, and the need for frequent maintenance of control systems.There are some circumstances in which mechanical measurement devices, such as pressure sensors, cannot be installed. As a consequence, non-invasive and contactless techniques have been devised that do not involve electrical connections within containers. For this single digital camera is used to measure the liquid level.[2]Single digital camera is a device used to capture the images of the liquid from the top of the tank to measure the level using image preprocessing techniques.

Image Acquisition and Preprocessing

Image processing is a method used to transform visual pictures captured by cameras and video devices into a digital format. This allows for the extraction of significant characteristics or features from the image. Various picture output formats are used in imaging equipment employed in image processing applications.[3] The YUV and RGB camera picture output formats, which use luminance and chrominance data, are widely employed in industrial applications. Semantic data is extracted from pictures by the use of image processing methods, including grayscale conversion, filtering, edge detection, thresholding, and quantification. These techniques are applied to images that have been transformed to either YUV or RGB formats. An important use of image processing methods is the quantification of liquid volume in liquid flow control systems.[4] The VGA resolution camera captures photos to identify the location where the liquid level line in the tanks is located. Measurements are conducted by optimising the camera's distance from the liquid flow system, the angle of view, and the light intensity in the environment.[5] The objective of this study is to use image processing in Matlab to detect and manage the level measurement using a single digital camera. Below are some of the recent literatures conducted liquid level detection using image preprocessing techniques[6] The study's authors introduced an innovative approach that integrates an image processing technique with Node-Red IoT platforms. The primary concept of this work is to use the image of a ruler on the tank to measure the actual height of the liquid level in standardised units. The results of our experiment, which included real-time collection of photos using IoT live-streaming, demonstrate that our suggested approach is very efficient and resilient when used to rulers of varying sizes and shapes. The method is sufficiently precise to enable the practical use of liquid level measurement.[7] The aim of this study is to develop a real-time system for detecting liquid levels using image processing techniques. In addition, this device has the capability to discern the colour of the liquid throughout a chemical reaction. The system was created with visual aid features in LabVIEW and a webcam. With respect to camera resolution, the system achieves an average accuracy of around 99%.

2. Background

Measurement of Liquid level based on ImagesSetup of the proposed liquid-level measuring system

Figure 1 illustrates a liquid-level measurement system using a digital camera with a 2hmax view angle, placed above the tank with the optical axis perpendicular to the liquid surface plane. To improve measurement accuracy, consider the distance between the optical origin (OP) and the digital camera's front end (h0). Details on obtaining the essential parameter h0 for a certain camera will be provided later in this work. To overcome the near depth of field (DOF) constraint in present methods, the digital camera has a distance h1 shifted rearward.[8] To avoid liquid contact, place tempered glass between the camera and liquid in the tank for a non-contact measurement method. Mount a mask to protect the digital camera from environmental factors and fluids. The tank is equipped with two spot lights to improve picture quality.

Use a circular non-corrosive float with a specified diameter to measure liquid level. A sinker is placed beneath the float to stabilise it and prevent fluctuations on the liquid surface.[9] The float is a disc with a monochromatic surface, ideally distinct from the tank liquid for easy identification in the picture. The thickness of the float is Hfloat when it is on the tank bottom. Fig. 1 illustrates that the pixel counts of the float diameter, N(ha) and N(hb), at locations Pa and Pb, depend on the photographing distance, ha and hb.

Using the connection between photographing distance and pixel counts, the liquid level may be calculated from the pixel counts of the float's diameter in the camera-captured picture.

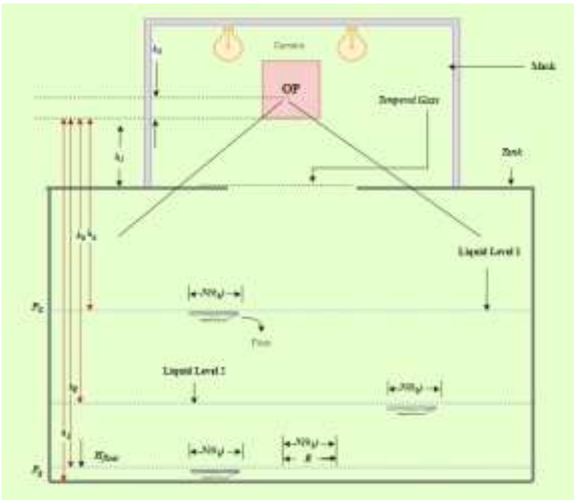


Figure 1 Schematic diagram of the proposed liquid-level measuring system.

Relationship between pixel counts and photographing distance

The pixel counts of the float's diameter, $N(h_a)$ or N(h_b), may be determined by analysing the horizontal scan line of the picture due to the location of the circular float on the liquid's surface. The link between the distance at which a picture is taken and the number of pixels representing objects in the image frame may be used to establish the distance between the float and the digital camera. This information can then be used to calculate the liquid level and, therefore, the volume of the liquid. Figure 2 illustrates the correlation between the distance at which the picture is taken and the number of pixels representing the diameter of the float in an image obtained by the digital camera using the suggested liquid-level measurement system.[10] A muzzle is used to restrict the field of vision to 2hs in order to minimise the radial distortion caused by the lens. Due to the direct correlation between the number of pixels representing an item in a picture frame and its horizontal distance, we have

$$\frac{D_{m1}}{R} = \frac{N_{\max}}{N(h_a)} \quad (1)$$

The variable R represents the diameter of the float. N_{max} refers to the maximum number of pixels in a horizontal scan line of an image frame. This value is fixed and known beforehand, regardless of the distance at which the picture is taken. $N(h_a)$ represents the pixel count of the float's diameter at a certain photography distance, ha. According to the triangle connection shown in below Figure 2, we have:

$$h_0 + h_a = \frac{1}{2} D_{m1} \cot(\theta_s) \quad (2)$$

Dm1 represents the actual horizontal distance in the real world that is created by the field of vision at liquid level 1. By substituting Equation (1) into Equation (2), we can get the distance measurement between the camera and the liquid level at location Pa (liquid level 1) without considering D_{m1}:

$$h_0 + h_a = \frac{1}{2}\left(\frac{N_{\max}}{N(h_a)} R\right)\cot(\theta_s) \quad (3)$$

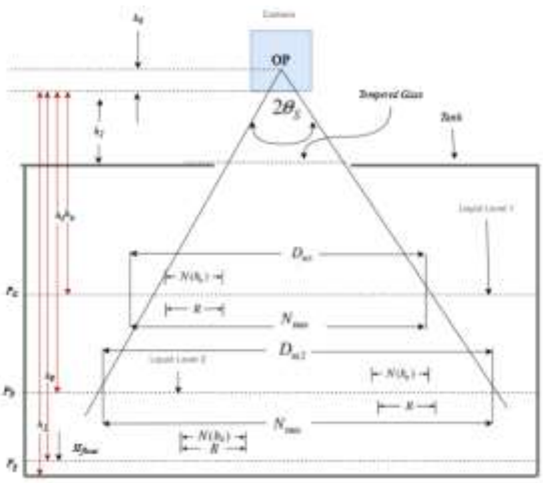


Figure 2 Relationship between float diameter pixel counts and photography distance using the proposed liquid-level measurement method

Subpixel resolution in the determination of the float's diameter

While it is possible to calculate $N(h_a)$ by directly counting the pixels of the float's diameter from the horizontal scan line of the picture, the resulting resolution is unsatisfactory, especially when the photographing distance is considerable. In order to enhance the precision of measurement, the value of $N(h_a)$ may be derived as an alternative by counting the number of pixels occupied by the circular float in the image as:

$$N(h_a) = 2 \times \sqrt{\frac{\sum N_{float}}{\pi}} \quad (4)$$

according to the correlation between the area and radius of a circle, where PNfloat denotes the sum of all pixel counts of the circular float within the image frame at the distance of capture (ha). By doing so, a subpixel resolution has been attained with regard to the measuring precision of the float's diameter in pixel counts. Consequently, the accuracy and precision of measurements in the proposed method can be substantially enhanced.

Measurement of the liquid level

It is important to note that the liquid level is defined as the vertical distance from the bottom of the vessel to the liquid's surface plane. For instance, ht ha and ht hb represent, respectively, liquid levels one and two. By utilising the distance hg, which is commonly understood a priori while the float is positioned at the tank's bottom, the derivation of the liquid level can be further simplified. Equation (3) provides the following expression for the liquid level at position Pa (liquid level 1):

$$h_g - h_a + H_{float} = \frac{1}{2}\left(\frac{N_{\max}}{N\left(h_g\right)} - \frac{N_{\max}}{N\left(h_a\right)}\right).R.\cot(\theta_s) + H_{float}$$

3. Methodology

Methods to produce binary imageSimple Thresholding

Thresholding is the most fundamental technique used for dividing a picture into several segments. Binary pictures may be created from a grey scale image by using thresholding. Colour pictures may be converted into binary images via the process of segmentation. Segmentation is the act of categorising every individual pixel in the original picture into two or more distinct classes. When there are more than two classes, the typical outcome is the generation of several binary pictures. Thresholding is a technique used in image processing to divide a picture into smaller segments, or chunks, by applying a certain colour or grey scale value to determine their boundaries. The primary benefit of first acquiring a binary picture is that it decreases the intricacy of the data and streamlines the procedure of identification and categorization.

Algorithm 1: Simple Thresholding for Liquid Level Detection

Input: Image I, Threshold value *T*
Output: Liquid level position *L*

Compute the histogram of the image *I*;
Find the peak corresponding to the liquid level; Let Ppeak be the intensity value at the peak; if P*peakT*then
| Set *L* as the position of the peak;
end
else
| Set L as the highest position with intensity >*T*;
end

This simple thresholding approach uses a certain threshold value to differentiate between the liquid and the background inside a picture. The liquid level location is estimated by analysing the image's histogram and comparing intensity values.

Adaptive Thresholding

Adaptive thresholding is superior than the standard thresholding approach. In a image, some areas may be subject to more shadow, while illuminations may also impact the overall appearance of the image. In the traditional thresholding procedure, a single threshold value, either global or standard, is selected as the mean value. When examining a picture, if the darker portion or pixels have a value that above the threshold value, that specific area of the image will be shown in the foreground. Likewise, if the value is below the threshold value, then that pixel or fragment is considered to be in the background.

Algorithm 2: Adaptive Thresholding for Liquid Level Detection

Input: Image *I*, Window size *W*, Constant *c*
Output: Liquid level position *L*

for each pixel *(x, y)* in *I* do
Compute the local mean *M (x, y)* within the window of size W
centred at *(x, y)*;
Compute the local standard deviation S (x, y) within the
window of size W centred at *(x, y)*;
Compute the threshold value *T (x, y)* = *M (x, y)* - cx *S(x, y)*;
if Intensity of pixel (x, y) >*T (x, y)* then
| Set *I* (x, y) to 1;
end
else
| Set *I(x, y)* to 0;
end
end
Find the position of the liquid level *L* using *I*;

This approach provides a more resilient method for detecting the liquid level in photos, particularly in cases when the images have uneven lighting or noise, as opposed to utilising a set global threshold.

Otsu's Thresholding

Otsu's thresholding approach is based on the linear discriminant criterion, which assumes that the image is composed only of an object (foreground) and a background. This method disregards the heterogeneity and variety of the background. Otsu determined the criterion in order to minimise the overlap between the distributions of the classes. Otsu's method is a technique that divides an image into two regions, T0 and T1. T0 represents the set of intensity levels ranging from 0 to t, denoted as T0 = {0, 1, ..., t}. T1 represents the set of intensity levels ranging from t to l, denoted as T1 = {t, t + 1, ..., l - 1, l}. Here, t is the threshold value and l is the maximum grey level of the image (e.g., 256). T0 and T1 may be assigned to either the object or the background, and vice versa. It is not necessary for the object to constantly occupy the light region. Otsu's thresholding method scans all conceivable thresholding values to find the lowest value for each pixel level on either side of the threshold. Determine the lowest entropy threshold for the foreground-background sum. According to Otsu, the threshold value is dependent on the image's statistical data, which may be used to compute the variance of clusters T0 and T1. To get the optimal threshold value, minimise the weighted group variances, which indicate the probability of the groupings.
Given: p(i) as the histogram probabilities of he observed gray value i=1,...,l

$$P(i) = \frac{number\{(r,c)image(r,c) = i\}}{(R,C)}$$

Where r, c represents the image's row and column indexes, and R and C represent the number of rows and columns, respectively.
wb(t), µb(t), and σ 2 b (t) as the weight, mean, and variance of class T0 with intensity value from 0 to t, respectively. wf (t), µf (t), and σ 2 f (t) as the weight, mean, and variance of class T1 with intensity value from t+1 to l, respectively. σ 2 was the weighed sum of group variances. The best threshold value t* is the value with the minimum within class variance. The within class variance defines as following:

$$\sigma_w^2 = w_b(t) * \sigma_b^2(t) + w_f(t) * \sigma_f^2(t)$$

$$Where,\ w_b(t) = \sum_{i=1}^{t} P(i)$$

$$w_f(t) = \sum_{i=t+1}^{t} P(i)$$

$$\mu_b(t) = \frac{\sum_{i=1}^{t} i * P(i)}{w_b(t)}$$

$$\mu_f(t) = \frac{\sum_{i=t+1}^{t} i * P(i)}{w_f(t)}$$

$$\sigma_b^2(t) = \frac{\sum_{i=1}^{t} (i - \mu_b(t))^2 * P(i)}{w_b(t)}$$

$$\sigma_f^2(t) = \frac{\sum_{i=t+1}^{t} (i - \mu_f(t))^2 * P(i)}{w_f(t)}$$

Global Thresholding with Manual Thresholding

Global thresholding is a method that selects a single threshold value from the histogram of the whole picture. Local thresholding utilises localised gray-level data to choose numerous threshold values, with each value being optimised for a specific tiny location inside the picture. Global thresholding is a more straightforward and convenient method to use, but its outcome is dependent on having a well-distributed lighting. Local thresholding approaches are capable of handling non-uniform lighting, but, they are intricate and time-consuming. In automated visual inspection applications, when regulated lighting conditions ensure that non-uniform illumination is not a problem, global thresholding is often used because to its simplicity and speed.

Algorithm 3: Global Thresholding with Manual Thresholding for Liquid Level Detection

Input: Image *I*, Manual threshold value *T*
Output: Liquid level position *L*
1 for each pixel *(x, y)* in *I* do
if Intensity of pixel *(x, y)* > *T* then
Set *I(x, y)* to 1;
end
else

6 Set $I(x, y)$ to 0;
7 end
8 end
9 Find the position of the liquid level L using I;

The method recognises an image and a predetermined threshold value as input. The image is divided into two regions based on pixel intensity using a threshold value. Pixels with intensities brighter than the threshold are classified as background, while pixels with darker intensities are classified as liquid. The technique achieves the creation of a binary picture by iteratively analysing each pixel in the image and comparing its intensity to the threshold. In this binary image, white pixels represent the backdrop, while black pixels represent the liquid. Ultimately, the liquid level is determined as the demarcation between these two areas in the binary picture. Although this technique provides a direct and simple way to measure liquid levels, it does have several drawbacks. The accuracy of the measurement may be affected by fluctuations in illumination throughout the picture, as well as image noise, which can cause misclassification of pixels.

Edge Detection

Edge detection includes a range of mathematical techniques that seek to find edges, which are defined as curves in a digital picture where there is a sudden shift in image brightness or, more precisely, where there are discontinuities. The identification of discontinuities in one-dimensional signals is referred to as step detection, whereas the identification of signal discontinuities across time is referred to as change detection. Edge detection is a crucial technique used in image processing, machine vision, and computer vision, specifically for identifying and extracting features.

Several studies utilised a Gaussian smoothed step edge (an error function) as the most basic modification of the ideal step edge model for simulating the effects of edge blur in actual applications. A one-dimensional image (f) with a single edge at x=0 may be represented as follows:

$$f(x) = \frac{I_r - I_l}{2}(erf(\frac{x}{\sqrt{2}\sigma}) + 1) + I_l$$

At the left side of the edge, the intensity is $I_l = \lim_{x \to -\infty} f(x)$ and right of the edge it is $I_r = \lim_{x \to \infty} f(x)$.The scale parameter is σ referred to as the blur scale of the edge. It is optimal to set the scale parameter according to the picture's quality in order to prevent the distortion of actual image edges.

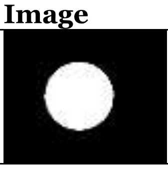
Algorithm 4: Edge Detection for Liquid Level Detection

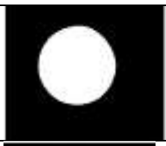
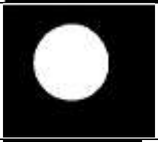
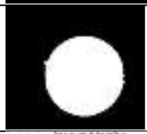
Input: Image I
Output: Liquid level position L
1 Apply an edge detection algorithm (e.g., Canny, Sobel, etc.) to detect edges in I;
2 Threshold the edge-detected image to obtain binary edges;
3 Find the position of the highest edge in the binary image along the vertical axis as the liquid level L;

The method provides a direct way to detecting the liquid level in an image using edge detection. Although it offers a reasonably straightforward and effective approach, its precision may be hindered by variables such as picture noise and fluctuations in lighting conditions. To achieve more reliable liquid level detection, particularly in unpredictable conditions, it may be important to consider alternate methods such as adaptive thresholding or machine learning approaches.The following section displays the results of liquid level detection and diameter measurement.

6. Results

The Segmentation of the images was done in Matlab 2023 version, which is installed in windows 10 pro operating system with 16 GB of RAM and I3-6th generation processor.

Methods	**Segmented Image**	**Diameter in meters**	**Depth in meters**
Simple Thresholding		0.0487515429	0.3456

Adaptive Thresholding		0.0634874058	0.3383
Otsu's Thresholding		0.0635470429	0.3382
Global Thresholding with Manual thresholding		0.052473569	0.3438
Edge Detection		231.1994	0.5785

The findings suggest that the liquid contained within the vessel is consistently identified as black by the segmentation models, whereas the objects or clumps present in the liquid are identified as white. Additionally, upon analysis, a significant correlation is observed between the profundity of the liquid and the diameter of the detected object or mass. An observation is made that the diameter of an object or mass increases with increasing depth, and conversely, decreases in depth result in decreasing diameter. This observation highlights the possibility that variations in diameter could be employed to deduce differences in the profundity of a liquid.

By utilizing the diameter of the detected object or object and the height of the camera positioned above the tank, the liquid's depth is determined. This study provides significant contributions to the understanding of the correlation between liquid depth and object diameter by means of rigorous analysis. As a result, level measurement and control systems can be enhanced in terms of precision and dependability. Furthermore, the assessment of segmentation models in comparison offers valuable insights that may facilitate the selection of the most appropriate method according to the particular requirements.

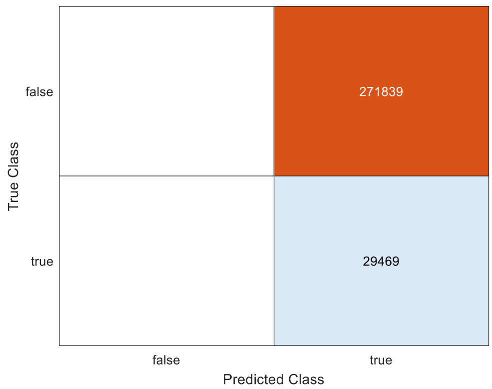


Figure 2 Global Thresholding Confusion Matrix

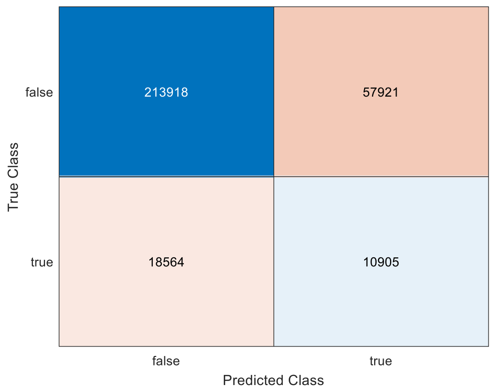


Figure 3 Edge Detection Confusion Matrix

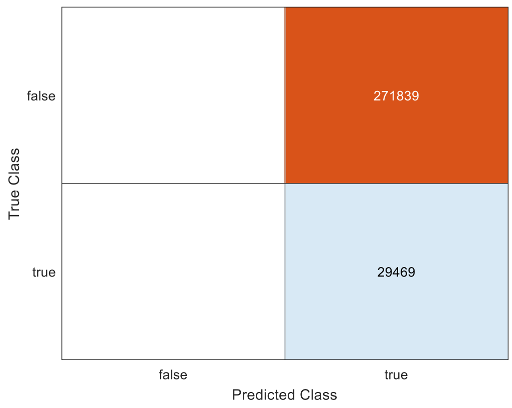


Figure 4 Simple Thresholding Confusion Matrix

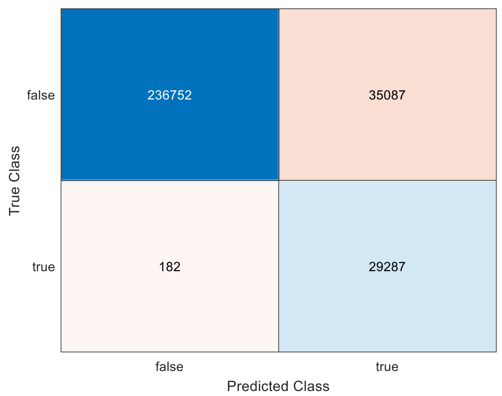
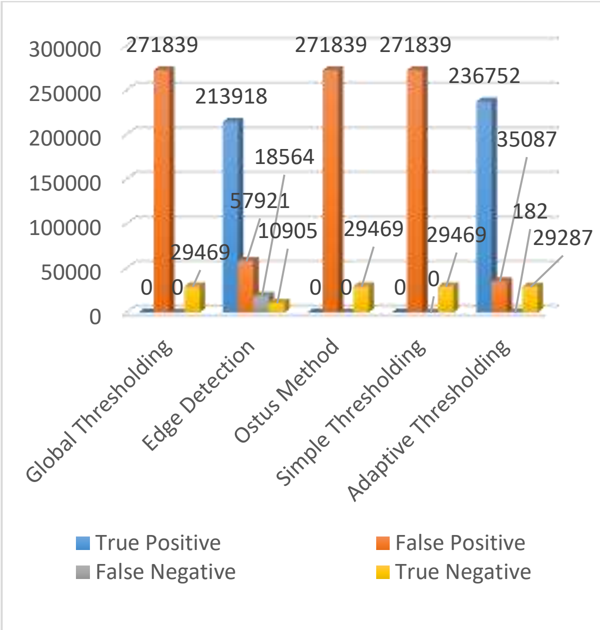


Figure 5 Adaptive Thresholding Confusion Matrix

The above confusion matrices shows the True Positive, True negative, False Positive and False negative values. The rows in the confusion matrices represent the actual classes, and the columns represent the predicted classes. The diagonal of the matrix shows the number of correct predictions and the off-diagonal elements shows the number of incorrect predictions. In the above global thresholding method the values on the diagonal are highest that means the model is performing well at predicting the correct classes. In global thresholding the false positive and true positive values are 271839 and 29469. There are no miss classificatios, so the model performs well. In Edge detection confusion matrix true positive value is 213918, False positive value is 57921, False Negative value is 18564 and True Negative value is 10905. This method has some miss classifications or predictions. The next confusion matrix is simple thresholding confusion. This confusion matrix does not have any missing classifications. In this false positive and true negative are 271839 and 29469. The next confusion matrix is Adaptive Thresholding confusion matrix. The vale for true positive, False positive, False Negative and True Negative are 236752, 35087, 182 and 29287. There are some miss classifications in this model also. So it is not performing better than Global and simple thresholding Models.



The above table presents a comparission of the performance of different image segmentation methods. It includes the following metrics: true positive, false positive, false negative, and true negative outcomes. The depicted Global Thresholding produces an output of false negatives and zero true positives, signifying an incapability to identify relevant elements within the image. However, the considerable quantity of 271,839 false positives indicates a substantial problem with over segmentation, as it inaccurately detects insignificant characteristics. In contrast, Edge Detection exhibits a higher level of performance, as evidenced by its significantly higher count of 213,918 true positives and comparatively lower count of 18,564 false negatives. With this enhancement, the approach continues to log a significant 57,921 false positives, demonstrating the need of additional refinement. Otsu's Method and Simple Thresholding exhibit similar deficiencies to Global Thresholding, including a significant occurrence of false positives and null true positives. On the other hand, Adaptive Thresholding demonstrates its superior performance as the most effective method, yielding a noteworthy 236,752 true positives, a comparatively modest 182 false negatives, and 35,087 false positives. The obtained outcomes demonstrate the effectiveness of Adaptive Thresholding in precisely detecting pertinent features while reducing errors in segmentation.

7. Conclusion

In conclusion, the results of our investigation into image-based level measurement and control using a single digital camera highlight the effectiveness of segmentation models in accurately detecting liquid levels and objects within the liquid. Through comparative analysis, we observed consistent detection of liquid as black and objects or blobs as white across various segmentation methods, including simple thresholding, adaptive thresholding, Otsu's thresholding, and global thresholding with manual adjustment.

Furthermore, our findings reveal a significant correlation between the diameter of detected objects or blobs and the depth of the liquid. Notably, as the depth of the object or blob decreases, its diameter tends to decrease, and conversely, as the depth increases, the diameter increases. This observation suggests the potential utility of diameter variations as a reliable indicator of changes in liquid depth.

By calculating the liquid depth based on the detected object or blob diameter and the camera height above the tank, our study provides valuable insights into improving level measurement and control systems in industrial settings. These insights enable more accurate and reliable monitoring of liquid levels, facilitating informed decision-making and enhancing process efficiency.

8. References

[1] H. K. Singh, S. K. Chakroborty, H. Talukdar, and N. M. Singh, "A New Non-Intrusive Optical Technique to Measure Transparent Liquid Level and Volume," vol. 11, no. 2, pp. 391–398, 2011.

[2] W. Zhang, M. Dong, L. Zhu, Y. Guo, and H. Chang, "Research on dynamic Method of Liquid Level Detection based on the Probe Type Capacitance Sensor," *Procedia - Soc. Behav. Sci.*, vol. 3, pp. 546–552, 2012, doi: 10.1016/j.aasri.2012.11.086.

[3] B. Aksoy, O. Khaled, and M. Salman, "A New Hybrid Filter Approach for Image Processing," vol. 3, no. 3, pp. 1–9, 2020, doi: 10.35377/saucis.03.03.785749.

[4] B. A. Seyit Ahmet İNAN1*, "Real-time analysis of liquid level and flow rate using image processing techniques," 2023.

[5] D. Lkxl, P. K. F. Pdlov, W. Hgx, F. Q. Olkxlshqj, W. Hgx, and P. O. Vhjphqwdwlrq, “Vision Based Liquid Level Detection and Bubble Area Segmentation in Liquor Distillation,” pp. 3–8, 2019.
[6] T. H. Le, P. T. Ngo, V. N. Tran, and V. H. Tran, “Liquid Level Detection via Node-red and Automatic Image Processing System,” pp. 73–84, 2022.
[7] F. E. Samann, “Real-time Liquid Level and color Detection system using Image Processing,” pp. 2–6, 2018.
[8] M. Lu, C. Hsu, Y. I. N. Y. U. Lu, T. K. Rd, and T. County, “Improvements and Applications of the Image-Based Distance Measuring System,” 2007.
[9] T. Wang, M. Lu, C. Hsu, C. Chen, and J. Tan, “Liquid-level measurement using a single digital camera,” *Measurement*, vol. 42, no. 4, pp. 604–610, 2009, doi: 10.1016/j.measurement.2008.10.006.
[10] C. Hsu, M. Lu, W. Wang, and Y. Lu, “Distance measurement based on pixel variation of CCD images,” *ISA Trans.*, vol. 48, no. 4, pp. 389–395, 2009, doi: 10.1016/j.isatra.2009.05.005.