Soft Drink Bottling Plant

Project Report: Image Processing

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Abstract

This project aims to develop an efficient automated system to detect seven different types of bottle defects in soft drink production line. The production line is monitored through a camera which takes a picture for a group of three bottles. The system was designed not only to segment the middle bottle but also to reconstruct and classify the cropped side bottles in the image. It uses a convolution technique in bottle segmenting stage, and Principal Components Analysis(PCA) technique in learning and classification stage.

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1 Introduction

Designing a reliable system that can work efficiently in industrial field is considered a challenging research topic, especially when this system is required to work to detect an industrial faults in mass production line. In this condition, this system have to be real-time, low coast, robust and efficient.

In this report we have worked on detecting seven types of bottle defects for Coca-Cola soft drink production line, and differentiate them from the normal bottles. In this system we have a training set consists of images samples for seven different types of defects and for a normal case bottles. Each image contains a three different bottles. The conventional systems are usually designed to only detect the defects of middle bottle. Since there are some defects on the back of bottle which may cannot be detected by these conventional systems. Our proposed system was designed to also detect the defects of the side bottles. Therefore, each bottle can be rotated 360 degrees in production line, and a triple check can be applied for all view 120 angles.

2 Methodology

In this project we have proposed a system that segments, reconstruct all three bottles by using by using convolution technique. It then uses Principal Components Analysis(PCA) technique for training on set of defects and the normal bottles. Then it classify the normal and defected bottles for new image, based on using generated models from the training stage.

2.1 Bottles Segmentation

In this stage, the left, middle and right bottles are segmented by detect there locations in input image, according to the following algorithm in Figure 1:

- Firstly, the input images are converted from RGB to gray level, as shown in Figure 1 - (a).
- Then the image is binarized by using Otsu thresholding technique, as shown in Figure 1 - (b).
- In Figure 1 - (c), the biggest connected black area is only saved. This area represents the background of the input image.
- In the following stage, the image Figure 1 - (c) is convolved with its mirror as in Figure 1 - (d). By using the following convolution formula.

$$y[n] = \frac{1}{K} \sum_{k=1}^{K} \sum_{m=1}^{M} I_{bw}[m,k] \cdot I_{bw}[m,n-k]$$

where, n is column convolution index, K is number of intersection column pixels, k is pixel intersection index. M is image row size, m is row index and I_{bw} is a binary image.

- Then the maximum peaks of convolution which are spaced 110 at least are detected, as shown in Figure 1 - (e).
- By dividing these peaks location by 2. the center locations and the intersection between all bottles are detected as shown in Figure 1 - (f).

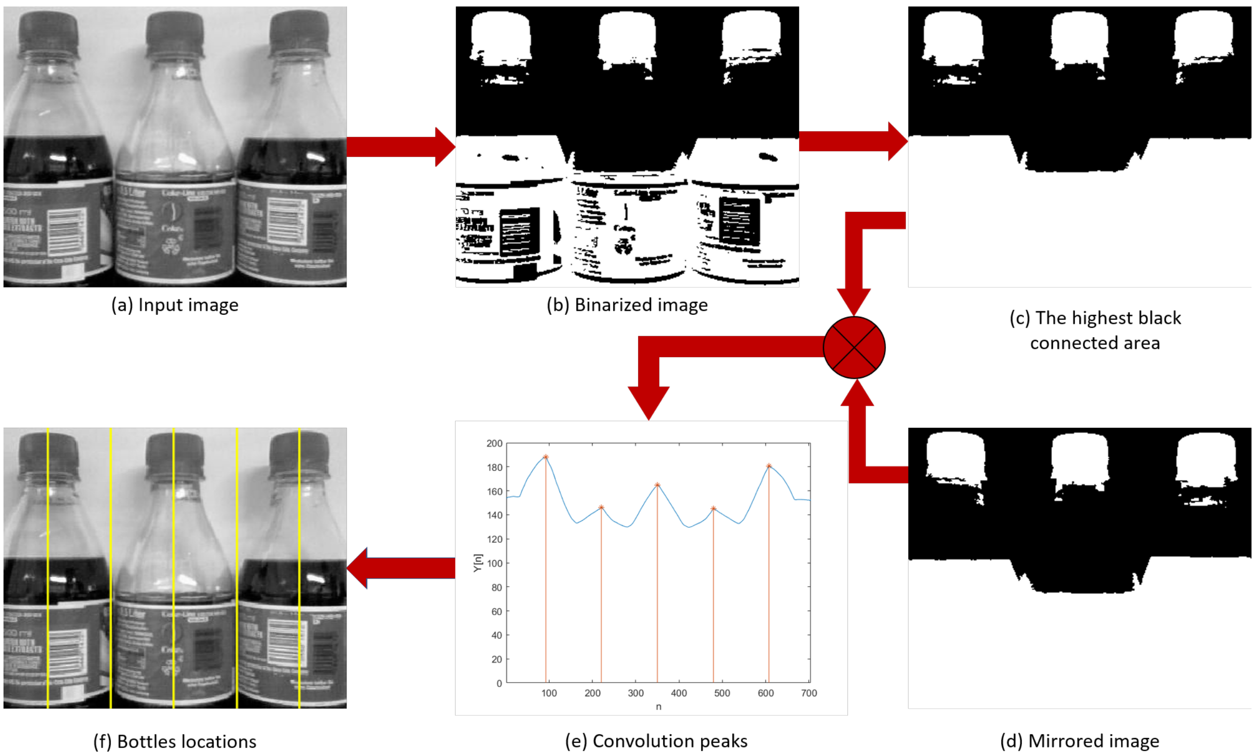


Figure 1: OpenGL Viewport and Graphic Window Adjustment

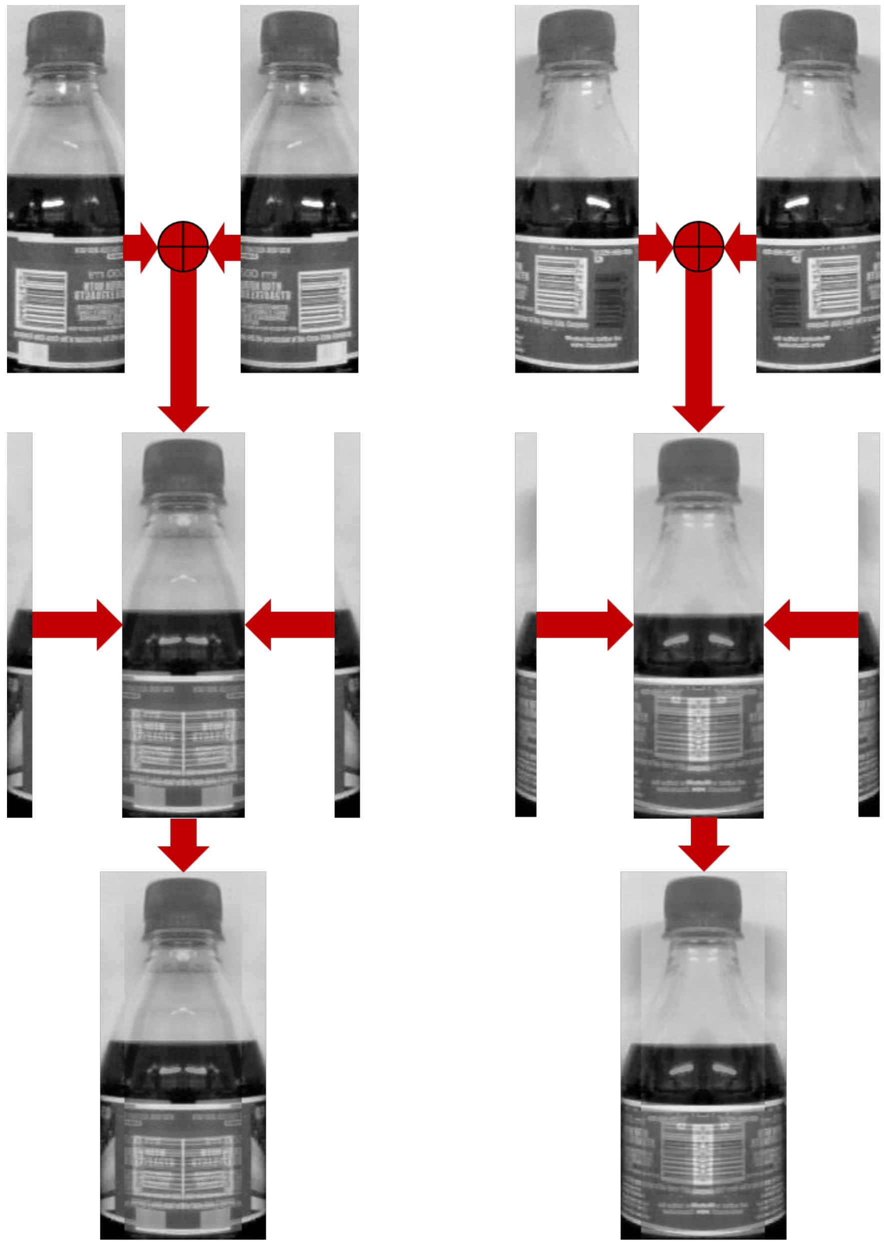
2.1.1 Middle Bottle Segmentation

The middle bottle location from the localization stage would be from the 3rd peak, then the image is cropped 115 column pixels towards the left and the right because the PCA stage requires a fixed window. Therefore, the middle bottle image dimensions would be 288 x 130 as shown in Figure 2

Figure 2: The segmented middle bottle

2.1.2 Side Bottles Segmentation

In order to segment the left and right bottles, the localize the peaks locations are also used in this stage. Since the left bottle is cropped from the left-side an the right bottle is cropped from the right side, these side requires an image reconstruction technique as shown in Figure 3. In the case of the left bottle, the first peak location represents the center of the bottle. Then the image width from the center toward the left image boundary (the first image column) is calculate which is w_{left}, and the image is cropped from 1 to $2 \times w_{left}$. The cropped image would be the bottle center. Next, the average between the bottle center image and its mirror is calculated. After that, the reset right side of the left bottle from $2 \times w_{left}$ to the second peak is cropped and mirrored. Finally, The mirror cropped right-side image, the center mean right-side image and cropped right-side image are concatenated together, and additional pixels are added and subtracted from the reconstruction windows boundaries to fit the PCS window size 288 x 130. The similar stage are also applied to the right-side bottle in order to segment and reconstruct it.



(a) Left bottle reconstruction

(b) Right bottle reconstruction

Figure 3: Side bottle segmentation and reconstruction

2.1.3 Missing Bottle

In the case of missing bottle image the number of detected peaks would be less than 5. It supposed to be three but after biarization stage the writings on the image logo would be connected to with the segmented black background area. It will affect the convolution peaks locations as shown in Figure 4.The left and right bottles cannot be segmented in this condition.

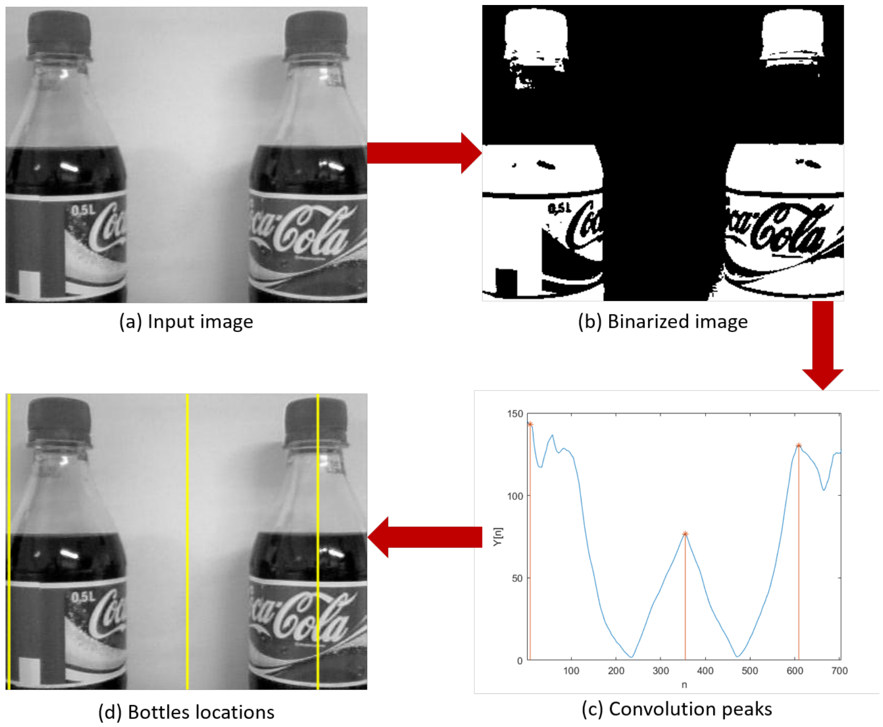


Figure 4: Missing bottle image fault locations

2.2 PCA (Principal Components Analysis)

The PCA is applied on the segmented bottles images from the previous stage. It is divided into two sub-stages which are the training stage and the testing stage, which are explicated in this section.

2.2.1 Training Stage

In the training stage the features dimension of the image is reduced, and training models (features classes) are created for normal and defected bottles training images. This stage is only applied on the segmented middle bottle, and it explained as in following steps

- The segmented middle bottle is re-sized by scaling factor s to reduce the computational time, and it is converted from 2D matrix to a row vector. This row vector dimension would be $1 \times (s * M * N)$, where M and N is the the image dimension.
- Then, all the row vector images are organized in 2D Matrix. Since there are 9 images for each 7 defect condition and 24 normal images, the result 2D training matrix D_{train} size would be $87 \times (s * M * N)$.
- In order to remove the common features between images, each image in D_{train} matrix

is normalized by subtracting it from the mean of all training images.

$$D(i) = D_{train}(i) - d_{mean}$$

- The covariance matrix A is calculated by multiplying D by its transpose as shown in the following equation, and its dimension would be 87×87

$$A = D \times D^T$$

- Next, the first 36 eigenvalues U_i and eigenvectors V_i are calculated for matrix A as they contain the significant features for the training images data. The eigenvector dimension would be 87×36. The number of eigenvalues are calculated initially by finding the summation of eigevalues which achieves the 95% of the trace of eigenvalues matrix.

- In order to reversed back the eigenvectors needs to the higher dimension space, it is multiplied by the the feature matrix D as shown in the following equation. The dimensions of extracted eigenvector matrix $V_{extract}$ dimension would be $(s*M*N) \times 36$.

$$V_{extract} = D^T \times V_i$$

- Finally, the training images features space is projected on the PCA space by multiplying the projection matrix D by the extracted eigenvectors $V_{extract}$, as shown in the following equation. The projection eigenvector matrix size $V_{proj-train}$ would reduced to 87×36.

$$V_{proj-train} = D \times V_{extract}$$

2.2.2 Testing Stage

In the testing stage, all three bottle images are segmented. Each bottle is resized by the same scaling factor as in the training stage. Then, it transformed from 2D matrix to a row vector, and they are subtracted from the training set mean d_{mean}. Then, the resultant testing image vector d_{test} is also projected on the extracted eigenvector matrix $V_{extract}$ and the output vector size would be 1×36.

$$d_{proj-test} = d_{test} \times V_{extract}$$

Finally, the euclidean between the projected testing vector $d_{proj-test}$ and all the training vectors in projection matrix $V_{proj-train}$ is calculated. The minimum euclidean distance represents the closest train image which matches the testing image, and it is classified according to the corresponding defects or normal class.

3 Experimental works

In this project, the MATLAB is used as a programming language to develop and evaluate the proposed system. The scaling factor is selected to equal 0.5 in order to decrease the computational time. The training set of the system consists of 9 images for 7 different types of defects which are ('UnderFilled', 'OverFilled','NoLabel','NoLabelPrint','LabelNotStraight','CapMissing' and 'DeformedBottle'). In addition, a training set consists of 24 of 'Normal' bottle. Another set was used in the testing stage. It consists of 15 images a normal bottle in the middle, and defected and normal bottles on the sides.

In order to evaluate the system, the system accuracy, specificity and sensitivity were calculated. The defected bottles are considered as a positive case, while the normal bottles are considered as a negative case. The system showed 100 percent accuracy in classifying the center and the side bottles as shown in the following table:

	Defected bottle	**Normal bottle**
Detected defected bottle	20	0
Detected not defected bottle	0	25
	Sensitivity = 100%	Specificity = 100%

The following table shows the classification accuracy for each type of defect bottle:

Defect Type	**Number of defects**	**Classified correctly**
Under Filled	3	3
Over Filled	2	2
No Label	4	4
No Label Print	4	4
Label Not Straight	2	2
Cap Missing	4	4
Deformed Bottle	1	1

4 Conclusion

In this project, we have designed proposed a technique to detect the industrial defects by segmenting and classify all the the 3 bottles. The experimental results showed a 100% accuracy for all three bottles with the side defected bottles testing set. The following points states the advantages of the proposed system, and the drawbacks with the suggested future works to enhance the the system.

Advantages

- The proposed data segmentation technique by using convolution successfully localized, segmented and reconstructed all the three bottles images for different types of defects.
- The system was designed to decrease undetected defects by applying triple check on the same bottles in the production line, which would enhance the production system

efficiency.

- The PCA technique is high efficient for detecting different types of defects with high accuracy. Moreover, it works on the complete segmented image is more robust than using a techniques which works on a small windows, especially when it works in variable industrial environment.

Drawbacks and Future Works

- The convolution segmentation technique needs to be modified to work on the case of missing bottle.
- The proposed technique can be modified to work on segmenting and detecting a higher number of bottles per one image in order to increase the system efficiency.
- The proposed system needs to be evaluated by using huge database.