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AUTOMATED DEFECT DETECTION ON SURFACE OF MILITARY CARTRIDGES

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Abstract. Automated visual inspection systems are widely used to detect defects on the surface of products in real time and separate the defected products at the final stage of the manufacturing line. The product handled in this study is the military cartridge case. The surface defect detection of cartridge cases is a challenging problem. The surface of a cartridge case is metallic, cylindrical, non-uniform textured and highly reflective. Because of these properties, the quality of the captured images can become poor and negatively affect the success of image processing techniques. In this study, an automated visual inspection system, image processing techniques and algorithms are proposed to resolve the problems related to the real-time performance, low accuracy and non-uniform textured, conical shaped and highly reflective surface of products. The experimental results are performed using real images, and satisfactory results were obtained.

Keywords: Surface defect detection, bilateral filter, nonuniform texture, segmentation.
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1 Introduction

Automated visual inspection systems are rapidly becoming important for modern manufacturing processes, which range from automotive and electronics industries to the biomedical industry. These systems improve the product quality, increase the production rate, avoid errors caused by subjectivity, integrate other systems into the production line, and reduce costs Madrigal et al. (2017).

One of the areas that intensively use automated visual inspection systems is the real-time defect detection applications. Automated visual inspection systems enable the users to detect the surface defects during the manufacturing process. Thus, image processing techniques are widely used. The success of image processing techniques to detect defects depends on the quality of the images captured from the product at the final stage of the manufacturing processes. If the product surface is metallic, cylindrical, non-uniform textured and highly reflective, the defect detection problem becomes non-trivial. Capturing proper images on the cylindrical and highly reflective surface needs special illumination and camera set up. Non-uniform textured surface comes from nature of the metallic element surface. It is hard to recognize production defects from the textures of metallic surface. Thus, special automated visual inspection systems and image processing techniques and algorithms should be developed to increase the success of the defect detection process of such surfaces.

The defect detection process aims to segment a possible defective area from the background and classify it in predefined defect categories. In a controlled environment, where the lighting condition is stable and the products are stationary, the simple thresholding techniques are often sufficient to segment the defects from the background. However, such methods are no longer applicable when flash lighting is used and the products are moving. In these much more challenging applications, more elaborate methods are required to ensure stable and reliable defect detection results. The existing methods can roughly be divided into four main categories: statistical, structural, filter-based and model-based methods Weimer et al. (2016). Statistical methods measure the spatial distribution of pixel values. In structural approaches, the texture is characterized by texture primitives or texture elements and the spatial arrangement of these primitives. Filter-based methods apply the filter banks on the image and compute the energy of the filter responses. Model-based methods include fractal models, autoregressive models, random field models, epitome model, texem model, etc. Xie (2008).

The product handled in this study is the military cartridge, which consists of fourelements: case, capsule, ammunition and powder. The subject of this study is the surface defect detection of the cartridge case, which consists of three parts: mouth, surface and primer Aydin et al. (2017), Samet et al. (2016). The surface of the cartridge case is metallic, cylindrical, non-uniform textured and highly reflective. During the manufacturing process, different defects such as corrosion, scratch, crack, split, dent, fold, bulge, buckle, and wrinkle can appear on the surface of the cartridge cases (Military Standard-Visual Inspection Standards for 20mm Ammunition and Components, 1962), (Gainsford, 1958). The automated visual inspection of the cartridge case has some challenges. One challenge is related to real-time manufacturing: the automated visual inspection should support the speed of the manufacturing line. Another challenge is the reflection problem on cylindrical and metallic surfaces because of the illumination. The third challenge is the cylindrical and metallic surface, which has a non-uniform texture. It is difficult to distinguish some defects from the surface texture.

The existing methods are insufficient in many aspects to apply to the cartridge case with a highly reflective surface and non-uniform texture. The required accuracy by military standards cannot be achieved. Most existing methods do not support the real-time manufacturing speed. Their success highly depends on environmental conditions such as the illumination, motion, etc. Finally, there is no study to inspect objects with cylindrical and metallic surfaces.

In this study, an automated visual inspection system, image processing techniques and algorithms are proposed to resolve the aforementioned problems. The proposed system and algorithms contribute to solve the problems related to the real-time performance, low accuracy and non-uniform textured, conical shaped and highly reflective surface of the subject products.

This paper is organized as follows. In Section II, the related works are summarized. In Section III, the architecture of the proposed system is presented. The image processing techniques and algorithms are described in Section IV. The implementation results are shown in Section V. Finally, Section VI concludes the findings.

2 Related Works

A defect detection algorithm was proposed for steel wire rods produced by the hot rolling process (Yun et al., 2014). The steel wire rods are long cylinder rods with a circular cross-section and inconsistent brightness at the sides and center. Moreover, various types of steel wire rods and the presence of scales affect the reflection properties of the rod surface. To resolve these difficulties, the use of dynamic programming and a discrete wavelet transform was proposed. The proposed algorithm has a detection accuracy of 84.7% with 1.5% false alarms. Thus, the proposed algorithm is effective for detecting defects in scale-covered surfaces of steel wire rods.

The work of Chondronasios et al. (2016) investigated the detection of two types of surface defects such as blisters and scratches in extruded aluminum profiles and classified them in three categories: non-defective, blister and scratch. A feature selection was performed for this application. Using two features, the obtained accuracy was 98.6%. This high detection accuracy was achieved by combining the current literature on the field with a new approach to select and manipulate the variables. The values were obtained from the statistical features of co-occurrence matrices on the gradient magnitude of the image as a result of Sobel operator.

In Liu & Yu (2014), the study presents an automated surface defect inspection system for the optical infrared cut-off (IR-CUT) filter, which is applied in all types of color cameras and video devices. The system includes the illumination and imaging module, moving module, flipping module and machine vision algorithm. The introduction of the stationary wavelet transform (SWT) provides a more accurate estimate of the variances in the image and further facilitates the identification of the defected regions. These authors' experimental results on various optical IR-CUT filter samples show an efficiency of 1.05 s per sample and an accuracy of 96.44% of the proposed system.

Xue-Wu et al. (2011) describes the design and testing process of a vision system to detect defects for strongly reflected metal surfaces. A computer-vision-based system to inspect the defects of strongly reflected metal surfaces was developed based on the wavelet transform, spectral measure, and support vector machine. The study used the wavelet smoothing method to eliminate noise from the images. Then, the images were segmented by the Otsu threshold. Finally, five characteristics based on the spectral measure of the binary images were collected and input into a support vector machine (SVM). The classification results demonstrate that the proposed method can effectively identify seven classes of metal surface defects.

The authors in Aarthi et al. (2013) propose a new method to explicitly analyze surface defects. The study developed a discrete wavelet transform technique to diagnose the defect in machineries. In the testing for welding flaws, the reliability and quality of the tests are considerably affected by noise and spurious signals. Thus, signal de-noising and an increase in the signal-noise ratio (SNR) are the key to successful application. Using the discrete wavelet transform, the flaw was isolated using the threshold of the transformed image, and different statistical features were studied.

In Zheng et al. (2002), an inspection system was developed to detect structural defects on bumpy metallic surfaces, particularly holes and cracks on the surfaces of aluminum. Their system is based on the morphology and genetic algorithms and was validated with a database collected from industrially produced aluminum samples. The maximum overall accuracy was 91%.

In Huang & Ye (2015), a machine vision system to inspect the micro-spray nozzle was proposed. Canny edge detection, a randomized algorithm to detect circles, the circle inspection algorithm and the BPNN classifier were used as the image processing algorithms.

The related studies are not efficient for the real-time inspection of cylindrical and metallic objects. The algorithms and methods are not optimized for real-time work. No work has described the entire system for online inspection. In this paper, all required systems are designed, and an applicable algorithm for real-time processes is proposed, which is rarely observed for defect detection.

3 Architecture of the Proposed System

The architecture and scheme of the proposed automated visual inspection system are shown in Figures 1 and 2, respectively.

The proposed automated visual inspection system consists of the mechanical, control and vision subsystems. All subsystems are described below.

3.1 Mechanical Subsystem

The mechanical subsystem consists of the feeder unit, transfer line, and sorter unit (Figures 1 and 2). The feeder unit feeds the transfer line with cartridge cases. The transfer line transfers cartridge cases at a high speed. The sorter unit separates the defected cartridge cases.

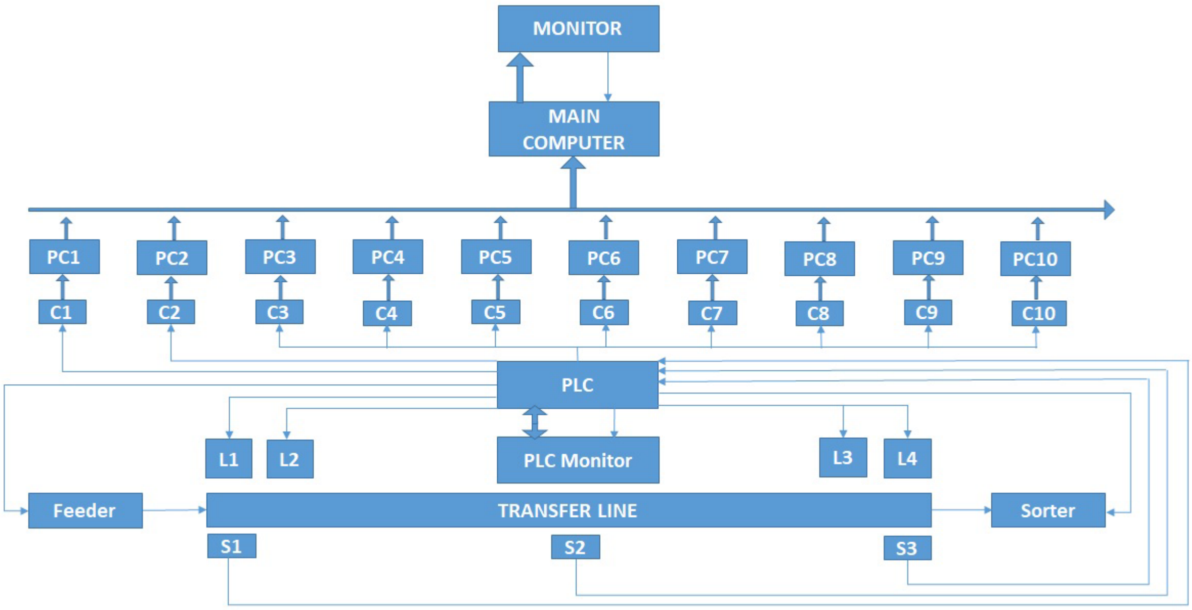


Figure 1: Architecture of the Proposed System

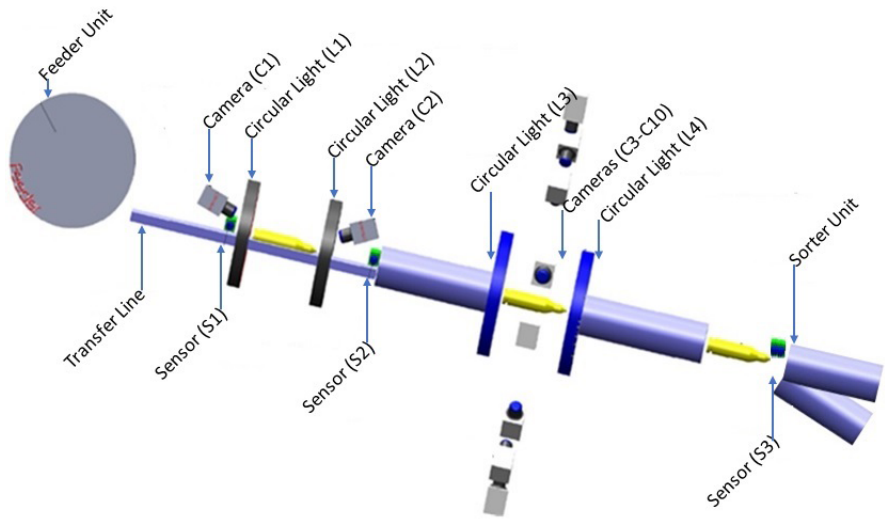


Figure 2: Scheme of the Proposed System

On the one hand, the success of image processing techniques to detect defects directly depends on the quality of the captured images. On the other hand, the image quality directly depends on the stable work of mechanical subsystem. The speed (number of processed cartridge cases per second) of the proposed automated visual inspection system is also defined by the mechanical subsystem. Thus, the mechanical subsystem is an important part of the proposed system.

3.2 Control Subsystem

The control subsystem consists of a programmable logic controller (PLC), sensors (S1-S3) and communication lines (Figure 1 and Figure 2). The control subsystem controls all elements of the system and the defect detection process in real time.

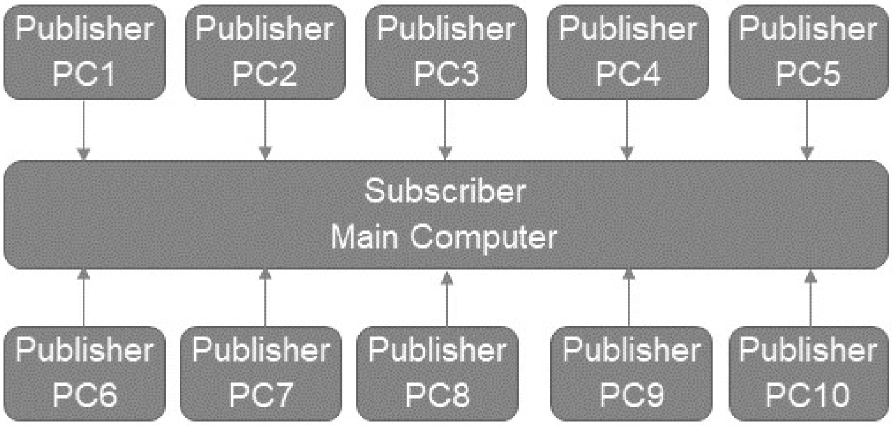


Figure 3: Publisher-Subscriber Architecture for the Control Subsystem

As mentioned, the mechanical subsystem transfers the cartridge cases at a high speed. First, sensor S1 detects a cartridge case and sends this signal to the PLC. Using this signal, the PLC flashes circular lights L1 and L2, which brighten the primer and mouth parts of the cartridge case, respectively. Simultaneously, the PLC triggers cameras C1 and C2, which capture the images from the primer and mouth parts of the cartridge case in the moving state and send them to computers PC1 and PC2, respectively. Then, sensor S2 detects the same cartridge and sends this signal to the PLC. Using this signal, the PLC flashes circular lights L3 and L4, which brighten the entire surface of the cartridge case from both sides. Simultaneously, PLC triggers cameras C3-C10. These cameras immediately take 8 images from the entire surface and send them to computers PC3-PC10. Finally, sensor S3 detects the same cartridge case and sends this signal to the PLC, which commands the sorter unit to separate the cartridge case as defective or non-defective according to the image processing results.

The images captured by cameras C1-C10 are used by the vision subsystem to detect defects. The image processing results from PC1-PC10 are sent to the main computer. The tasks of the main computer are 1) to synchronize all PCs; 2) to evaluate the image processing results; 3) to form the command about the defect; 4) to send this command to the PLC to separate the defective cartridge cases; and 5) to monitor the results.

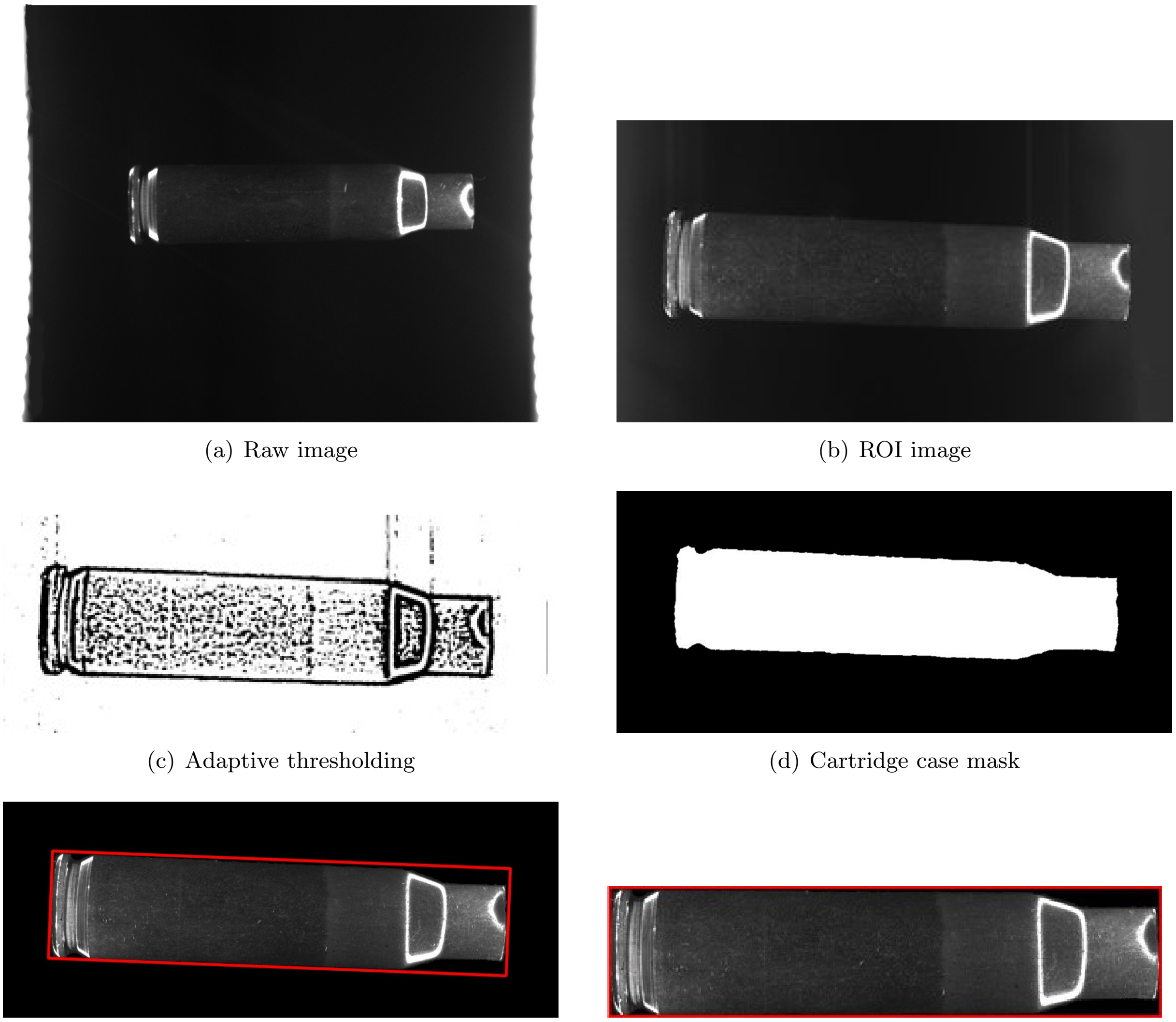
A messaging queue library is used for the communication of the computers. The publisher-subscriber architecture is implemented. The main computer acts as a subscriber. The other computers act as data publishers, which process the images from the cameras. The described publisher-subscriber architecture is shown in Figure 3.

The subscriber decides the defected cartridge case by evaluating the results from all publishers. Ten publishers process ten images from different parts of the same cartridge case. All publishers form binary signal 0 (defective) or 1 (non-defective) and send them to the subscriber, which executes logical operation AND using binary signals received from all publishers. If the result is “logical 1”, the cartridge case under control is non-defective; otherwise, it is defective.

3.3 Vision Subsystem

The vision subsystem consists of the main computer, personal computers (PC1-PC10), cameras (C1-C10) and ring lights (L1-L4), as shown in Figures 1 and 2. The vision subsystem is used to capture and process the images taken from the mouth (one image), primer (one image) and entire surface (eight images) of the military cartridge case on ten computers PC1-PC10 in parallel by the proposed algorithms. These algorithms detect different defects of military cartridge cases.

In this chapter, the architecture of the automated visual inspection system is proposed. This system aims to detect defects on the mouth, primer and entire surface of the cartridge



(a) Raw image (b) ROI image

(c) Adaptive thresholding (d) Cartridge case mask

(e) Obtaining the minimum area rectangle (f) Segmented and oriented object

Figure 4: Segmentation of the Cartridge Case

case, which has a metallic, cylindrical, non-uniform textured and highly reflective surface.

4 Image Processing Techniques and Algorithms

Defect detection algorithms are the most critical part of the proposed system. In this section, the image processing techniques and algorithms to detect defects are proposed. The image processing procedure is divided into four main stages: preprocessing, segmentation, defect detection, classification.

4.1 Preprocessing

The captured image (Figure 4 (a)) should be reduced from noise, and the region of interest (ROI) should be extracted during the preprocessing stage. The extracted image (Figure 4 (b)) is used for the segmentation stage. After the ROI is obtained, the Gaussian blur is applied to remove some noise in the image.

4.2 Segmentation

The cartridge case should be segmented from ROI (Figure 4 (b)). To this end, followings steps should be applied: a) Adaptive thresholding; b) Morphological closing; c) Obtaining the cartridge case mask; d) Obtaining the minimum area rectangle; e) Rotation.

a) Adaptive thresholding: Adaptive thresholding is applied after a preprocessing with Gaussian blurring. The result of operation gives the edges of the cartridge case (Figure 4 (c)).

b) Morphological closing: Morphological closing makes the edges thicker. There can be some gaps on the edges because of background intensity after adaptive thresholding process. These gaps on the edges of the cartridge case are closed by morphological closing (Figure 4 (c)).

c) Obtaining the cartridge case mask: The cartridge case mask is obtained by filling the inside of thick edge and applying morphological erosion operation. After that, the template mask of military cartridge case comes out (Figure 4 (d)).

d) Obtaining the minimum area rectangle: Obtaining minimum area rectangle is a simple task after coming out cartridge case mask. It can be calculated by finding minimum and maximum corner points of the mask (Figure 4 (e)).

e) Rotation: Rotation is done by calculating the angle between the minimum area rectangle and horizontal plane (Figure 4 (f)).

At the end of segmentation operations, the cartridge case is extracted from background (Figure 4 (f)).

4.3 Defect Detection

The proposed algorithm includes the following steps: a) Bilateral filtering; b) Sobel filtering; c) Thresholding; and d) Morphological closing.

a) Bilateral filter: Gaussian blurring is the simplest method to smooth an image; each output image pixel value is a weighted sum of its neighbors in the input image. The core component is the convolution by a kernel, which is the basic operation in linear shift-invariant image filtering. At each output pixel position, it estimates the local average intensity and corresponds to the low-pass filtering. An image filtered by Gaussian convolution is given by Paris et al. (2009) as Eq. 1:

$$GC\left[I\right]_p = \sum_{q \in S} G_\sigma\left(\|p-q\|\right) I_q, \tag{1}$$

where $G_\sigma(x)$ denotes the 2D Gaussian kernel, I_p is the image intensity value at pixel position p, S is the set of all possible image locations that are named as the spatial domain, $|.|$ is the absolute value, and $\|.\|$ is the L2 norm. $G_\sigma(x)$ is defined as Eq. 2:

$$G_\sigma\left(x\right) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{x^2}{2\sigma^2}\right). \tag{2}$$

Gaussian filtering is a weighted average of the intensity of the adjacent positions, where the weight decreases with the spatial distance to the center position p. The weight of pixel q is defined by the Gaussian $G_\sigma\left(\|p-q\|\right)$, where σ is a parameter that defines the neighborhood size.

Bilateral filtering is the improved version of Gaussian blurring and a technique to smooth images while preserving the edges. The bilateral filter is also defined as a weighted average of nearby pixels, which is notably similar to the Gaussian convolution. The difference is that the bilateral filter considers the difference in value with the neighbors to preserve the edges while smoothing. The key idea of the bilateral filter is that for a pixel to affect another pixel, it should occupy a nearby location and have a similar value.

$$GC\left[I\right]_p = \frac{1}{W_p}\sum_{q\in S} G_{\sigma_s}\left(\|p-q\|\right) G_{\sigma_r}\left(\left|I_p - I_q\right|\right) I_q,$$

where normalization factor W_p ensures that the pixel weights sum to 1.0:

$$W_p = \sum_{q\in S} G_{\sigma_s}\left(\|p-q\|\right) G_{\sigma_r}\left(\left|I_p - I_q\right|\right).$$

Parameters σ_s and σ_r will specify the amount of filtering for the image I. G_{σ_s} is a spatial Gaussian weighting that decreases the effect of the distant pixels, and G_{σ_r} is a range Gaussian that decreases the effect of pixels q when their intensity values differ from I_p.

A common approach for defect detection is to apply a smoothing filter on the preprocessing step. However, although the smoothing operation improves the result by eliminating redundant noise, smoothing also removes some fine details that are notably important for the problem. The proposed algorithm uses bilateral filtering to solve this problem. The bilateral filter provides great results on non-uniform textured surfaces. While it suppresses the noise and non-uniform texture, it renders defects as distinguishable. The bilateral filter creates an effect on the image like a cartoonizer by compressing the noise and clarifying the defects.

b) Sobel filter: After the bilateral filter, the defects can be detected. The first derivative edge detector or Sobel filter is used to detect the defects of the surface. Its calculation is notably simple and fast to detect high frequencies. The proposed algorithm calculates the gradient magnitude. The Sobel filter is generally accepted as a good method to calculate the gradient. Two kernels are used in the Sobel operator. The edge magnitude obtained by the Sobel operator is used to calculate the features of the sample data. The calculation is done using the following equation Chondronasios et al. (2016).

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * A, \text{ and}$$

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} * A$$

where A is the original image. The gradient image is calculated as Eq. 3:

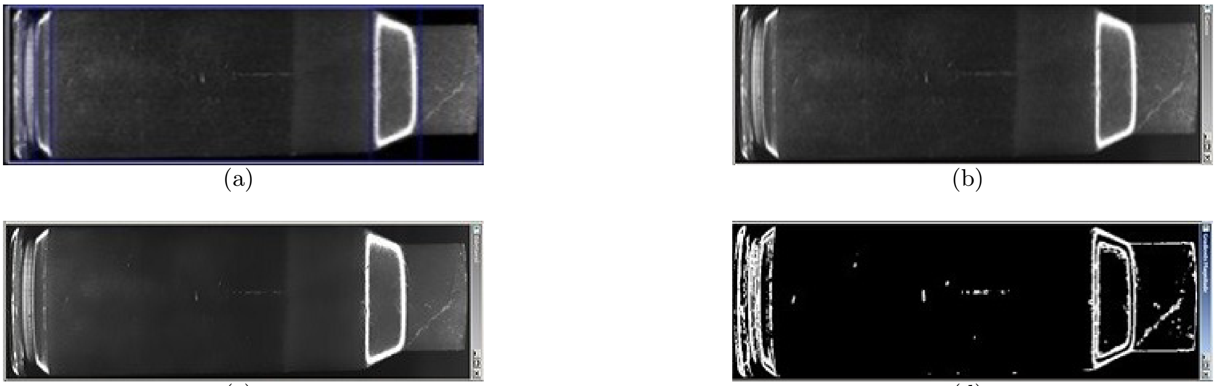
$$G = \sqrt{{G_x}^2 + {G_y}^2}. \tag{3}$$

c) Thresholding: A global threshold is applied to the gradient image. The threshold value is adjusted by the operator. In the result, the defective areas are indicated by white pixels.

d) Morphological Closing: It is better to merge some close defective pixels for demonstration. This process can be performed by morphological closing.

4.4 Classification

Different defect types such as corrosion, scratch, crack, split, dent, fold, bulge, buckle and wrinkle can appear on the surface of the cartridge cases. Contour-based features of the defects are used for classification. The extracted features of contours are the hu-moments, contour area, contour perimeter, contour approximation, and convex hull. The support vector machine (SVM) is used for classification.



(a) (b) (c) (d)

Figure 5: Implementation results: a) Original cartridge case; b) Gaussian smoothing; c) Bilateral filter; d) Detected defects

5 Implementation Results

The following platform is used to implement the proposed image processing techniques and algorithms. We used software such as Windows 10, C++, OpenCV, QT and ZeroMQ libraries. The OpenCV library was used for the image processing tasks. The QT library was used for the user interface tasks. The ZeroMQ library was used for the multi PC synchronization. The hardware included 10 fanless embedded PCs Vacow with Intel i7 processor, PLC S200, 10 Cameras Point Gray with 1.3 MegaPixels, 4 ring lights, and different sensors. For the data set, 800 non-defective and 200 defective real military cases were used.

At the beginning, the user should determine some parameters of the algorithm. For example, the user can adjust the sensitivity for defect detection via an operator screen of the developed software. The developed software enables the users to set the threshold, defect the area size, defect the length, etc.

An example of the implementation results for the surface inspection of the cartridge case is shown in Figure 5.

First, 10 cameras capture 10 images (1 for primer, 1 for mouth and 8 for surface parts) from cartridge cases in the moving state. Figure 5 (a) shows an example for the image captured from the surface part of the original cartridge case. Then, Gaussian smoothing was applied to the captured images. Figure 5 (b) shows an example for results after Gaussian smoothing. Next, the bilateral filter was applied to the images obtained after Gaussian smoothing. Figure 5 (c) shows an example of the results after the bilateral filter. Finally, the defects were detected on the base of images obtained after the bilateral filter. Figure 5 (d) shows an example of the detected defects.

Figure 6 shows an example of the user interface. As observed in Figure 6, defects were detected on 8 images (one for the mouth and 7 for the surface) for the same cartridge case. The mouth was detected as defective because it was not circular, i.e., the mouth is deformed. Defects were detected on 7 surfaces because there are scratches on the surface of the cartridge cases. There is no defect on the primer and only on one surface. The cartridge case was separated as a defective one because there are defects on 7 images of the surface and mouth part.

The obtained results were evaluated using the confusion matrix theory Parker (2001). The confusion matrix is shown in Table 1. The results for 1000 cartridge cases (800 non-defective and 200 defective) are shown in Tables 2 and 3.

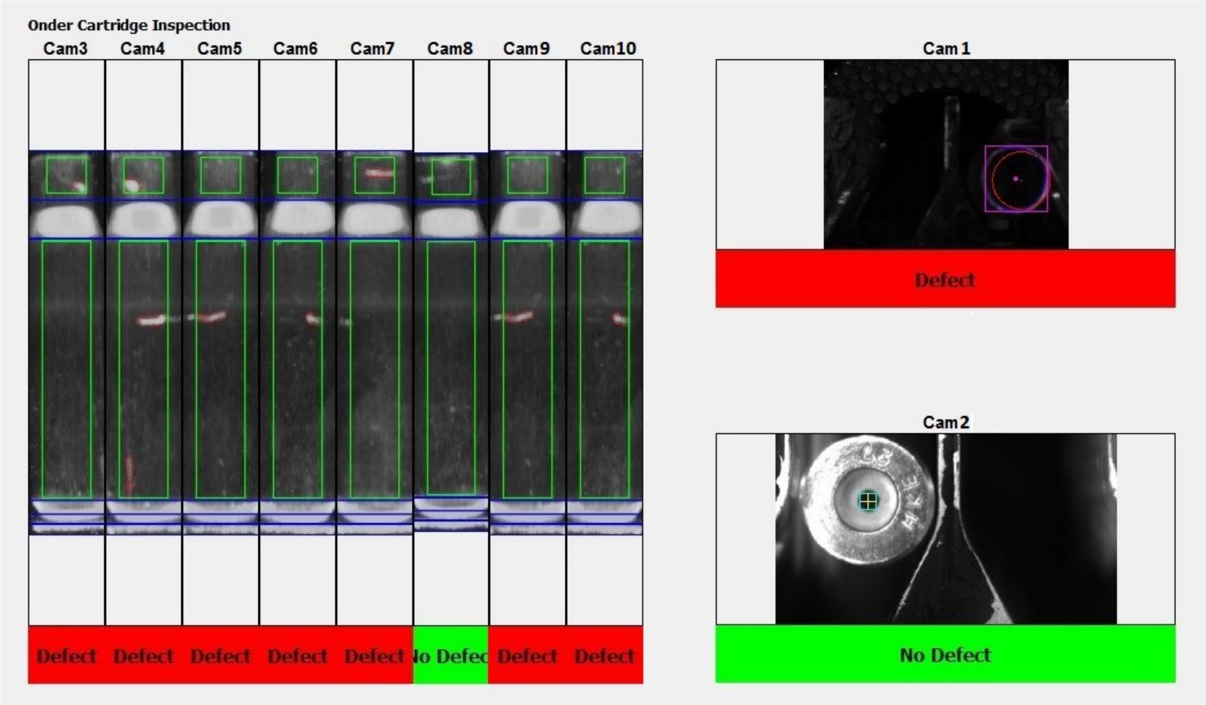


Figure 6: User Interface

Table 1: Confusion matrix

	Results of algorithm		
Actual defects of case		***Defect***	***Non-Defect***
	Defect	TP	FN
	Non-Defect	FP	TN

Table 2: Results for the confusion matrix

	Results of algorithm		
Actual defects of case		***Defect***	***Non-Defect***
	Defect	19%	1%
	Non-Defect	3%	77%

Table 3: Results of the proposed methodology

Error Rate	Recall	Precision	F-measurement
0.04%	0.95	0.86	0.90

The obtained results show that the proposed automated visual inspection systems and image processing techniques/algorithms have provided the high performance with the processing speed of 5 cartridge cases per second and 96% accuracy.

6 Conclusions

Military cartridge cases have metallic, cylindrical, non-uniform textured and highly reflective surface. These features make the defect detection process difficult. To effectively solve this problem, a new automated visual inspection system has been proposed for the real-time inspection of defects on the mouth, primer and surface parts of the cartridge cases during the manufacturing process. The architecture of the proposed automated visual inspection system was designed and implemented. The success of the defect detection process depends on the quality of the captured images, which depends on the stable work of mechanical subsystem. Because of the stable work of the designed and implemented mechanical subsystem, the high speed of the manufacturing process and high quality of the captured images have been achieved.

The proposed image processing techniques and algorithms have provided high-accuracy defect detection on the metallic, cylindrical, non-uniform textured and highly reflective surface of military cartridge cases.

The implementation results show that the proposed automated visual inspection system works with the high speed of 5 cartridge cases per second, provides a high accuracy of 96% and satisfies the NATO standards. The proposed system can be adapted for the defect inspection of other products such as screws, nails, and covers with some modification. As future work, deep learning techniques will be implemented for defect detection on metallic, cylindrical, non-uniform textured and highly reflective surfaces. ACKNOWLEDGMENT This work has been funded by Ministry of Science, Industry and Technology of Turkey under grant San-Tez 0018.STZ.2013-1.

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