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GEBZE TECHNICAL UNIVERSITY

FACULTY OF ENGINEERING

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DEFECT DETECTION ON GLOSSY SURFACES USING THE DEFLECTOMETRY DATA

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GEBZE TECHNICAL UNIVERSITY	GRADUATION PROJECT JURY APPROVAL FORM

This study has been accepted as an Undergraduate Graduation Project in the Department of Computer Engineering on 31/08/2021 by the following jury.

JURY

Member
(Supervisor) : Prof. Dr. Yusuf Sinan Akgül

Member : Dr. Yakup Genç

ABSTRACT

Defect detection is an important task in industrial manufacturing. Despite the importance of the visual inspection of industrial products, many of the visual inspection processes are performed manually. The problem is that human inspection presents some drawbacks, such as being time consuming, the high cost involved, and the lack of standardization. In this context, the development of automated processes for the inspection of industrial products is important.

In this project, the defects on the glossy surfaces were detected by using the images obtained by the deflectometry method. Image processing algorithms were used on the images while detecting defects. To evaluate the performance, F1 score was calculated for each images. The mean of F1 score was calculated as 0.90.

Keywords: Defect detection, deflectometry, image processing.

ÖZET

Hata tespiti, endüstriyel üretimde önemli bir görevdir. Endüstriyel ürünlerin görsel denetiminin önemine rağmen, görsel denetim işlemlerinin birçoğu manuel olarak gerçekleştirilmektedir. İnsan denetiminin zaman alıcı olması, yüksek maliyetli olması ve standardizasyon eksikliği gibi bazı dezavantajları vardır. Bu bağlamda endüstriyel ürünlerin denetimi için otomatik süreçlerin geliştirilmesi önem arz etmektedir.

Bu projede deflektometri yöntemi ile elde edilen görüntüler kullanılarak parlak yüzeylerdeki kusurlar tespit edilmiştir. Hatalar tespit edilirken görüntüler üzerinde görüntü işleme algoritmaları kullanılmıştır. Performansı değerlendirmek için her görüntü için F1 puanı hesaplanmıştır. Ortalama F1 puanı 0.90 olarak bulunmuştur.

Anahtar Kelimeler: Hata tespiti, deflektometri, görüntü işleme.

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I am also indebted to my family and friends for their invaluable support, advice and love during my education.

Esra Eryılmaz

LIST OF SYMBOLS AND ABBREVIATIONS

Symbol or Abbreviation	:	**Explanation**
SDD	:	Surface Defect Detection
AVI	:	Automated Visual Inspection
RGB	:	Red Green Blue
LGD	:	Local Standard Deviation
R-CNN	:	Region Based Convolutional Neural Networks
YOLO	:	You Only Look Once (Real-time Object Detection)
SSD	:	Single Shot Detector
CVPR	:	Conference on Computer Vision and Pattern Recognition
ECCV	:	European Conference on Computer Vision
CAD	:	Computer-Aided Design
GUI	:	Graphical User Interface

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1. INTRODUCTION

1.1. PROJECT DESCRIPTION

Nowadays, the increasing population increases the consumption as well. Manufacturing systems are developing in a fast pace to meet increasing demand of consumption. However, very quick increase of production has surpassed the development speed of currently existing control systems. In manufacturing, since the quality is a very important issue as well as the quantity, the operation of quality control systems must be accelerated and must be accomplished by machines. The idea of our study is based on this thinking.

The glossy surfaces such as refrigerator or car are made high glossy for the good appearance 1.1, but are critical to defects like dent and uneven surface. In today's industry, the defect of the products produced can create very important problems in terms of both the customer and the subsequent processes of production. [1]–[3]

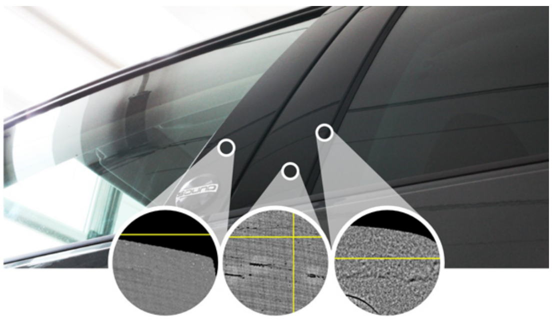

Figure 1.1: A high glossy door of car

Surface Defect Detection (SDD) is an important part of industry quality control. SDD's manual control has many disadvantages, such as subjectivity, variable standards, and high costs. Until recently, this process was carried out manually. Manual control can be subjective because it depends on many factors such as employee experience and motivation. Fine defects appearing on a low-contrast surface cannot be visibly defined even with a well-trained inspector. Therefore, the development of automation systems which are not affected by working time, fatigue and stress can objectively carry out this process.

Automated control systems using image processing can overcome most of the disadvantages of manual control and offer manufacturers the opportunity to significantly improve quality and reduce costs. [4]–[6]

1.2. PROJECT PURPOSE

Surface defect detection have importance in terms of sectoral quality. Automatic systems are developed on the defect detection, in this regard many methods are tried to obtain high precision with image processing studies.

Our aim to get more successful results than manual inspection and it is aimed to be done in a shorter time. By using image processing techniques, it is aimed to detect such defects like cracks, smudges, broken points on the surfaces in the manufacturing field, where the products are continuously moving on a conveyor, and we utilized reflected pattern image. In this study finding the most optimal input values for the image processing algorithms and creating an output image with marked defects is our main goal.

In this way, defective products are prevented from reaching the customers and detection of surface defects becomes automatic from manual.

2. LITERATURE REVIEW

Manual surface inspection methods performed by quality inspectors do not satisfy the continuously increasing quality standards of industrial manufacturing processes. Defect detection is an integral part of quality control process in any manufacturing industry. Machine vision provides a solution by using an automated visual inspection (AVI) system to perform quality inspection and remove defective products.

The machine vision system has the advantages of high precision, high efficiency, high speed and continuous detection, non-contact measurement, etc. Thereby, a large variety of solutions and applications has been inspired and utilized in this field since the 1980s, and their number has continued to grow. European and North American market data reveal that the growth of machine vision applications generally outperform the overall economic growth. Moreover, China has also become a major market for machine vision in recent years. According to, the size of the global machine vision market was approximately USD 7.2 billion in 2017, growing 6.8% year-on-year. [4], [6]–[10]

2.1. SURFACE DEFECT TYPES

Surface defects can be divided into ten categories with the following characteristics.2.1

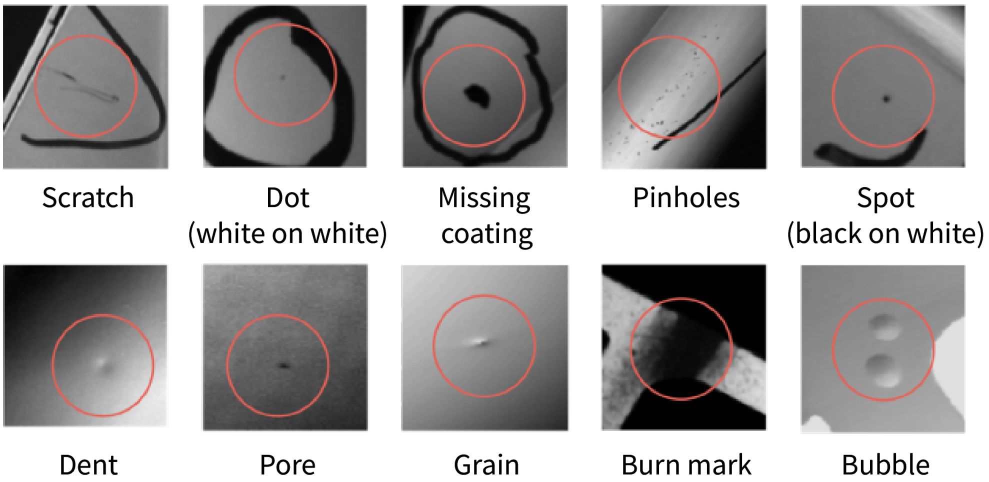

Figure 2.1: Defect Types

Descriptions of the most common defects :

- Scratch : A scratch is a shallow, long defect made by something thin and sharp.
- Dot : Dot defects occur during the production process
- Pinholes : Pinhole is a quality fault appearing as small holes on the product surface. Pinhole sizes are typically less than one millimeter.
- Dent : Dents are mainly produced by a low-velocity impact event.
- Burn mark : Burn marks are discolorations, usually rust colored, that appear on the surface of the injection molded prototypes. Burn marks can also be caused by the overheating of trapped air, which etches the surface of the molded part.
- Bubble : Bubble refers to the phenomenon in which the surface of a molded product bulges.

In this context, research has been done on defect detection using image processing techniques and deep learning techniques.

2.2. DEFECT DETECTION USING IMAGE PROCESSING TECHNIQUES

Defect detection techniques is one of the segmentation process that becomes the most important steps in image analysis. Generally, the main function of the segmentation is to reduce and to compress the image information for easy analysis of the image. Image segmentation can be classified into two categories of techniques which are the thresholding-based technique and the clustering-based one.
[11]–[15]

2.2.1. 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. 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. [16]

2.2.1.1. ADAPTIVE THRESHOLDING

An adaptive thresholding technique uses the local threshold value to segment the image. The local threshold value of each pixel in the image is depending on the intensity of the neighbouring pixel. A study by Peuwnuan et al 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. 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.

2.2.1.2. 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.

Mathematical morphology is feature extraction method based on preliminary information about the geometry of the object. A morphological operation is defined as the examination of image set by using a small cluster called configuration element. The basic operations of mathematical morphology are expansion, erosion, opening and closing. [17]

2.2.1.3. 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. 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.

2.2.2. LEVEL DEFECT DETECTION TECHNIQUES

The Sobel edge detection, the Canny edge detection and the Hough transform are proposed.

2.2.2.1. 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 Sobel operator when applied to gray-scale images calculates the gradient of the brightness intensity of each pixel, giving the direction of the greater possible increase of black to white, and in addition calculates the amount of change of that direction.

The Sobel operator performs a 2-D spatial gradient measurement on an image. Typically, it is used to find the approximate absolute gradient magnitude at each point in an input gray scale image.

The Sobel edge detector uses a pair of 3×3 convolution masks, one estimating the gradient in the x-direction (vertical) and the other estimating the gradient in the y-direction (horizontal). A convolution mask is usually much smaller than the actual image. As a result, the mask is slid over the image, manipulating a square of pixels at a time. The Sobel masks are shown in figure 2.2. [18]

-1	0	1
-2	0	2
-1	0	1

Vertical

1	2	1
0	0	0
-1	-2	-1

Horizontal

Figure 2.2: Convolution template of Sobel operator

2.2.2.2. 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.

The Canny operator works in a multi-stage process. First of all the image is smoothed by Gaussian convolution. Then a simple 2-D first derivative operator is applied to the smoothed image to highlight regions of the image with high first spatial derivatives. Edges give rise to ridges in the gradient magnitude image. The algorithm then tracks along the top of these ridges and sets to zero all pixels that are not actually on the ridge top so as to give a thin line in the output, a process known as non-maximal suppression. The tracking process exhibits hysteresis controlled by two thresholds: T1 and T2, with T1 > T2. Tracking can only begin at a point on a ridge higher than T1.

Tracking then continues in both directions out from that point until the height of the ridge falls below T2. This hysteresis helps to ensure that noisy edges are not broken up into multiple edge fragments. [19]

2.2.2.3. HOUGH TRANSFORM

One of the famous statistical technique is Hough transform that generally used for straight line detection. 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.

This method aims to construct a control chart that is able to monitor the highest number of votes in the Hough space (Hough matrix). This statistic is calculated for each defect map, and an alarm will be raised when it is larger than the control limit, indicating that a pattern has been detected. An approximate distribution of this statistic is developed and the control limit can thus be estimated. Compared to existing techniques, this method has the following characteristics.

1. It focuses on detecting specific spatial patterns of defects instead of only detecting the existence of clustering.

2. The detection is realized through an easy-to-use control chart and the monitoring statistic is intuitive and easy to compute.

3. A quantitative design procedure is also provided, which relates the Type I and Type II errors to the design parameters.

[20]

2.2.3. 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. 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. 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). A variety of color detection technique is proposed in the past decade ago and in order to retrieve information and detect the color of the image.

2.2.3.1. 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. 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. 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. [21]

2.2.3.2. OTSU'S THRESHOLDING

Among the available visual inspection techniques, automatic thresholding is a commonly used approach for defect detection because of the simplicity in terms of its implementation and computing.

The Otsu's thresholding is one of the common techniques used in image segmentation application. This technique works under automatic threshold value. It is known as a global thresholding and it depends on the gray pixel value of the image. Based on a review made by, 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 . The optimal threshold value is automatically chosen by maximizing the weighted sum between class variance pixels.

2.3. DEFECT DETECTION USING DEEP LEARNING

Deep learning, which has rapidly developed because of its efficient feature extraction ability, can be applied to the defect detection of tiny parts. The Faster R-CNN, YOLO, and SSD are currently the most popular methods for object detection. In 2015, Shao et al. proposed the Faster R-CNN deep learning object detection algorithm. However, the Faster R-CNN has a slow detection speed.

In 2016, Redmon et al. proposed the object detection algorithm YOLO at an international conference on computer vision and pattern recognition (CVPR). In the same year, Wei Liu et al. proposed the object detection algorithm SSD at a European conference on computer vision (ECCV). YOLO and SSD detect objects using regressions, and deep learning is used for real-time detection. The Faster R-CNN is

a two-step object detection algorithm that detects objects through classification and regressions. The SSD algorithm is a one-step object detection algorithm that directly detects objects using regressions. Therefore, we apply an SSD object detection method to improve the real-time performance of tiny part defect detection. A complete part defect detection system considers the feature extraction ability and real-time performance of the detection algorithm. The stability and defect detection ability of the algorithm are indispensable key factors.
[22] [23]

In this project, image processing algorithms were applied to detecting defects, instead of deep learning techniques.

3. METHOD AND SYSTEM ARCHITECTURE

3.1. SYSTEM REQUIREMENTS

Software and hardware requirements :

1. High resolution image display,
2. Sufficient storage space,
3. Sufficient computer powering,
4. Memory transfer bandwidth,
5. OpenCV version 4.1.x (4.1.0 or 4.1.1 will both work fine),
6. Python version 3.6 (any Python version 3.x will be fine).[24]–[26]

3.2. ARCHITECTURE

The SDD process includes different steps according to the data set used, the defect examined, the method used and the intended results. If we summarize this process in general, the model given in Figure 3.1 can be used.

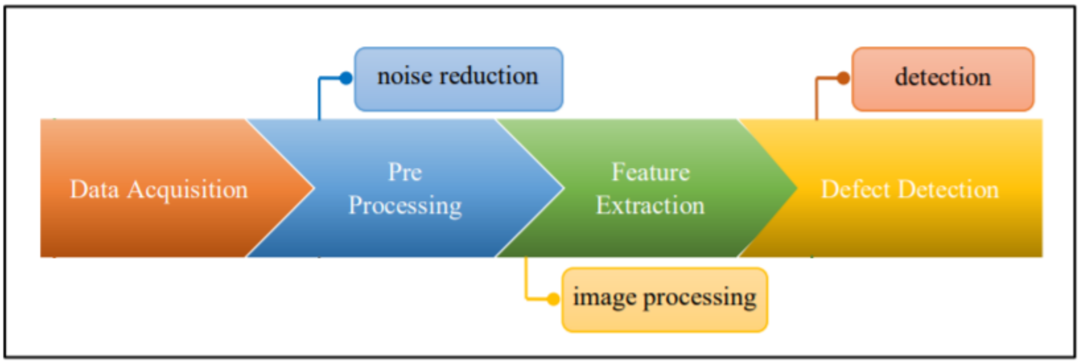

Figure 3.1: Defect Defection Method

3.2.1. DATA ACQUISITION

The data acquisition step in the SDD model includes the acquisition of the dataset to be used.

The deflectometry data of the study was obtained from Surfvis firm through the supervisor. Surfvis as a Deep Tech startup develops intelligent Surface Inspection solutions for the manufacturing industries; its solutions pave the way to fully digitalized quality inspection, especially in the automotive and electrical appliances industries. [27]

A dataset containing 50 images in total was collected.

3.2.1.1. DATASET

The dataset containing 50 pairs of images (RGB and deflectometry image) is shown in the figure 3.2.

Figure 3.2: Dataset

3.2.2. PRE PROCESSING

One of the biggest drawbacks in data processing processes is the removal of the unnecessary parts of the data that will affect the result. Furthermore, the data is ready for feature extraction. Data are pre-processed to avoid these drawbacks. There is no obligation to use this process. In the SDD process, pre-processing allows the removal of the noise contained in the image or filtering out the parts that do not have an effect on the result by the filtering and various changes (color mode, size etc.) on the image. Some methods in the pre-processing step (gabor filtering, fourier transform, etc.) are also used in the feature extraction step. In some studies, pre-processing and feature extraction are carried out in the SDD process.

The method used for pre-processing in the SDD process is noise reduction in this project.

3.2.2.1. NOISE REDUCTION

Noise reduction is important preprocessing operations for defect detection. Noise reduction used to remove the pixels on the image that have a negative effect. There are several methods available for noise reduction; thresholding, wavelet, deep neural network, etc.

It is very difficult to remove noise from the digital images without the prior knowledge of filtering techniques. Filters are most commonly used for noise reduction and blurring.

Filtering image data is a standard process used in almost every image processing system. Filters are used for this purpose. The choice of filter depends on the filter behaviour and type of data.
Noise is abrupt change in pixel values in an image. So when it comes to filtering of images, the first intuition that comes is to replace the value of each pixel with average of pixel around it. This process smooths the image. In this project I consider two assumptions.

Assumptions:

- The true value of pixels are similar to true value of pixels nearby
- The noise is added to each pixel independently.

A mask is a filter too. Concept of masking is also known as spatial filtering. In this project with this statistical concept I just deal with the filtering operation that is performed directly on the image. The masking algorithm finds the mean and standard deviation of the color spaces and ignores anything out of the ordinary points. 3.3

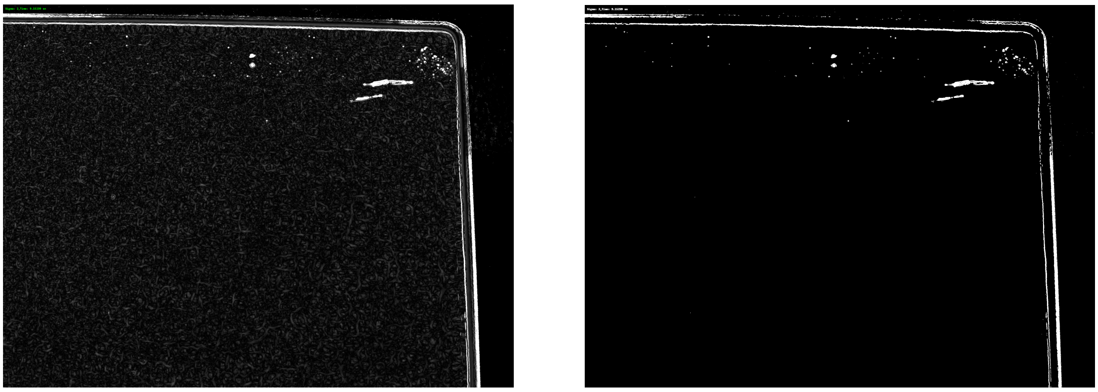

Figure 3.3: Deflectometry image & Noise reduced image

3.2.3. FEATURE EXTRACTION AND DEFECT DETECTION

There are various methods that can be used for defect detection in the SDD process. These methods, statistical, spectral, model-based and learning-based can be divided into 4 groups. Which of these methods will be used depends on the expert's opinion, outcome success and data. For example, learning-based methods or spectral methods can be used to find a defect in a standard pattern. Or, structural or model based methods can be used for deformation on the steel surface.

Statistical defect detection was used in this project. The procedures applied after the noise reduction is as follows :

- CAD models of the images were created. These CAD models of the images contains only the edges of the images. CAD models were created manually on the computer. 3.4
- These edges should not be counted as defects. To neglect these edges, the program takes two images, the first one is noise reduced deflectometry image and the second one is CAD image of the original image. The program compares these two images. Edges coming from the CAD image are omitted on the deflectometry image.

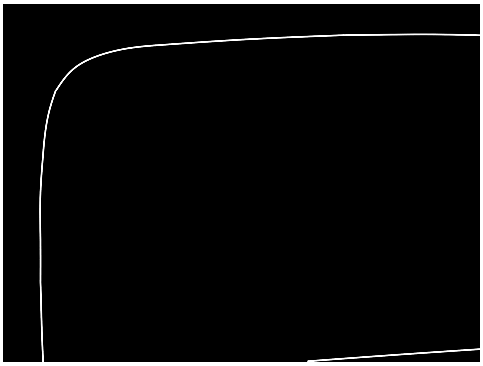

Figure 3.4: CAD Model Example

- Lastly, the places other than the omitted edges are marked as defects. The starting point, ending point, width and length of these marked rectangles are saved in the excel file in order to be able to calculate the performance.

3.3. IMPLEMENTATION DETAILS

Firstly 50 deflectometry images from the dataset were send to the noise reduction function and results saved.

```
def noise_reduction(image) :
    im = cv2.imread(image)
    # or COLOR_BGR2YUV, should work equivalently here
    yuv = cv2.cvtColor(im, cv2.COLOR_BGR2YCrCb)
    mean = np.mean(yuv, axis=(0,1))
    std = np.std(yuv, axis=(0,1))
    # EDIT: there needs to be an abs() on that difference, we want
   magnitudes, no signs
    mask = (np.abs(yuv - mean) / std >= 4.5).any(axis=2)
    mask_u8 = mask.astype(np.uint8) * 255

    return mask_u8
```

Listing 3.1: Python noise reduction implementation

After the noise reduction I created CAD models of the images manually.(CAD models includes just edges of the images because edges are not defects so they should not be counted as defects) 3.4

Then in the find_defects() function the CAD models and the noise-reduced images were compared. The edges of the objects coming from the CAD models are removed and the remaining white areas are counted as defects. Also the positions of the defects on the images were recorded in this function.

```
def find_defects(imB, imA):
    imageB = cv2.imread(imB)
    imageA = cv2.imread(imA)

    grayA = cv2.cvtColor(imageA, cv2.COLOR_BGR2GRAY)
    grayB = cv2.cvtColor(imageB, cv2.COLOR_BGR2GRAY)

    (score, diff) = ssim(grayA, grayB, full=True)

    # convert the array to 8-bit unsigned integers in the range [0,255] before we can use it with OpenCV
    diff = (diff * 255).astype("uint8")

    # threshold the difference image, followed by finding contours to obtain the regions of the two input images that differ
    thresh = cv2.threshold(diff, 0, 255, cv2.THRESH_BINARY_INV | cv2.THRESH_OTSU)[1]
    contours = cv2.findContours(thresh.copy(), cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)
    contours = imutils.grab_contours(contours)

    # find largest area contour,those from the edges are omitted.
    max_area = -1
    for i in range(len(contours)):
        area = cv2.contourArea(contours[i])
        if area>max_area:
            cnt = contours[i]
            max_area = area

    tw,ht=550,750
    # image = cv2.rectangle(image, start_point, end_point, color, thickness)
    # loop over the contours
    for c in contours:
        (x, y, w, h) = cv2.boundingRect(c)
        if w < tw and h < ht:
            #original
            cv2.rectangle(imageA, (x, y), (x + w, y + h), (0, 0, 255), 2)
            #modified
            cv2.rectangle(imageB, (x, y), (x + w, y + h), (0, 0,
```

```
    255), 2)

    return imageB
```

Listing 3.2: Python finding defects implementation

At the end, in order to measure performance, since no learning is used in the project, the manually created defect list compared with the found defect list.

3.4. USER INTERFACE

Python offers multiple options for developing GUI (Graphical User Interface). Out of all the GUI methods, tkinter is the most commonly used method. It is a standard Python interface to the Tk GUI toolkit shipped with Python. Python with tkinter is the fastest and easiest way to create the GUI applications.
[28][29]

The interface was created using tkinter (Tk). This interface allows to select deflectometry images with "Browse Image" button and with the "Find Defects" button it allows to finding defects on that image and displayed. It also shows the performance results on that image with the "Show Details" button.3.5

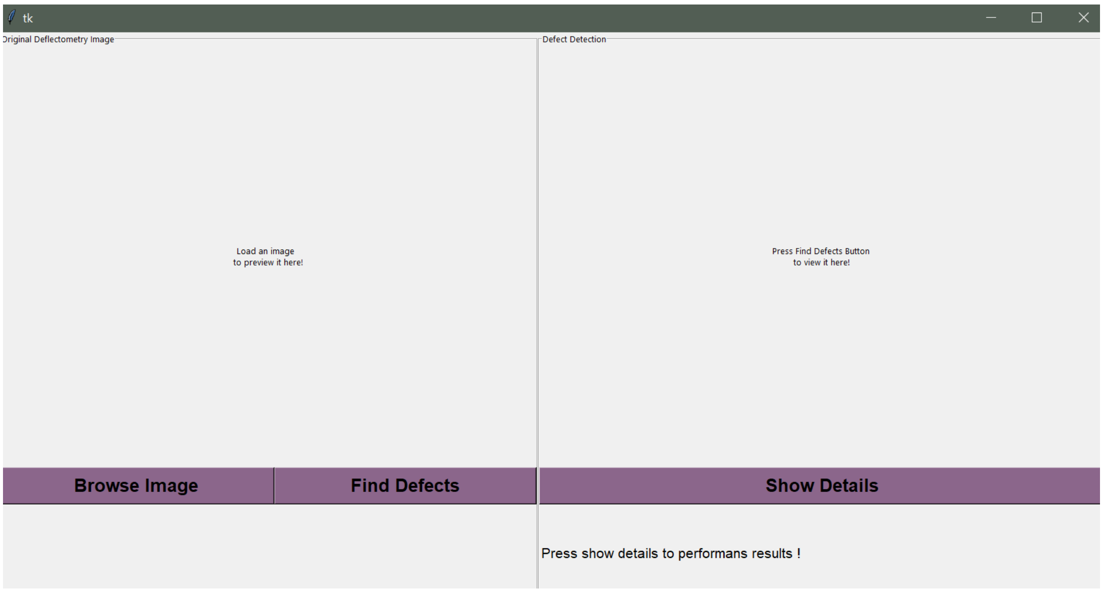

Figure 3.5: User Interface

The sample output is shown in Figure 3.6

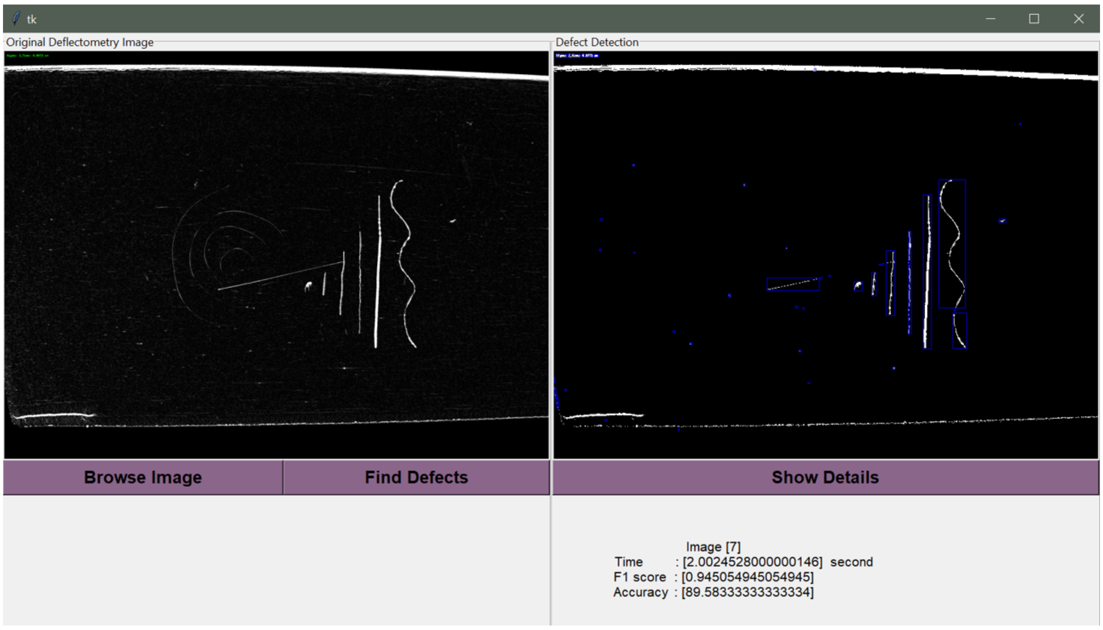

Figure 3.6: User Interface Output

4. EXPERIMENTS

- On the first practises I was manually marking defects and finding those parts. Because manual marking is difficult, I changed the method and find it automatically.

- In the noise reduction step, firstly Otsu's Thresholding Algorithm were used. When the results were examined, it was found that this algorithm also deleted some of the defects besides the noises. After that for the noise reduction, statistical methods which includes an algorithm that found mean and standard deviation of the color spaces and ignore anything out of the ordinary points were used.

- Connected component analysis is performed to identify the edges in the images before the CAD models creation. Basic idea is to traverse through the image and find the connected pixels. Each of the connected components (blobs) are labelled as edges and extracted. Then I changed my method of removing edges because defects can be long connected pixels sometimes and it removes that defects too.

4.1. RESULTS

The RGB and deflectometry images, CAD models and the results of the phases they went through are given below figures 4.14.24.3

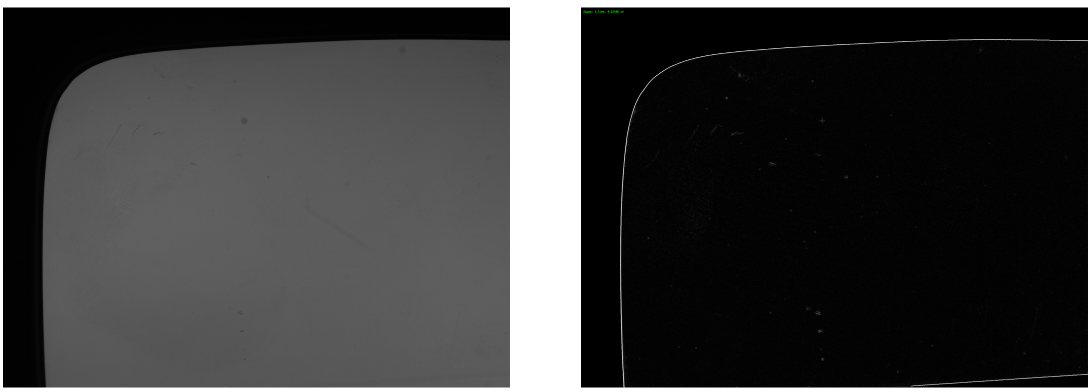

Figure 4.1: RGB image & Deflectometry image

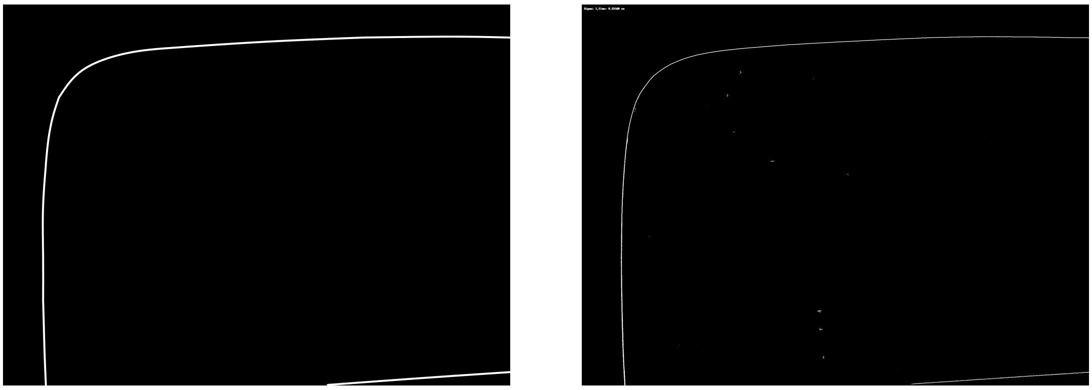

Figure 4.2: CAD image & Noise reduced image

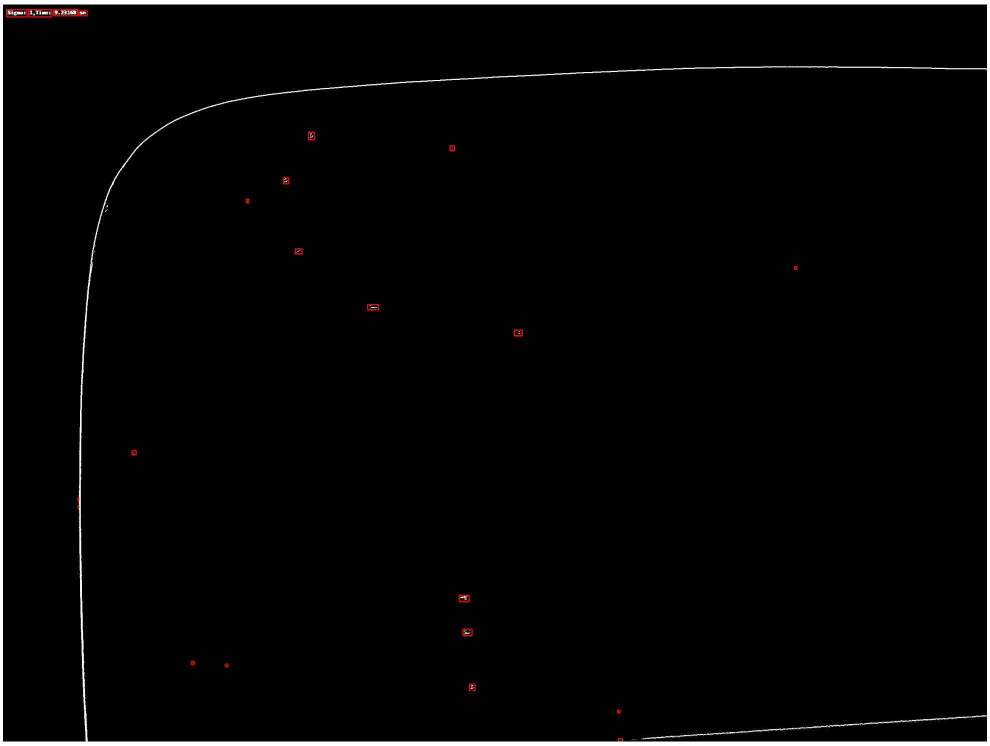

Figure 4.3: Output image

4.2. PERFORMANCE MEASUREMENTS

In order to measure performance, since no learning is used in the project, the manually created defect list compared with the found defect list.
While calculations confusion matrix values in figure 4.4 are recorded and used.

Average F1 score was calculated as 0.9. 4.6

Average accuracy was calculated as 83%. 4.5

TRUE CLASS

PREDICTED CLASS	Positive	Negative
Positive	True Positive (TP)	False Positive (FP)
Negative	False Negative (FN)	True Negative (TN)

Figure 4.4: Confusion Matrix

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Figure 4.5: Accuracy Rate

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Figure 4.6: F - Score

The time of the functions calculated, average was found as 1.95 seconds.

5. EVALUATION OF SUCCESS CRITERIAS

1. As a consequence , the first success criterion, catching at least 85% of surface defects was approached. Numerical results indicate that the implemented image processing algorithms have 83.33% accuracy. In fact, the numerical results were compared with the correct defect list created by manually when calculating. It should be taken into account when evaluating this criteria.

2. The second success criterion, fault detection time should be 0.1 seconds at most. It was not approached because the images are have large dimensions which is 2592 x 1944 pixels. And the time took an average of 1.95 seconds for each image. The dataset contains 3 small dimension images which is 1000 x 600 pixels and the time took an average of 0.3 seconds for these images.

3. The third success criterion, dataset should be collected from at least 10 different physical parts. The number of images will be around 50. It was approached. Data generated using the Deflectometry method were obtained through the supervisor. A dataset contains 50 images in total was collected.

6. DISCUSSION AND 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.

In this project, detection of glossy surface defects were investigated, it is aimed to get more successful results than manuel inspection and it is aimed to be done in a shorter time. Image processing algorithms are applied for detecting defects, i.e., hole, scratch, dent and spot. A set of 50 glossy surface defect images were used for testing the proposed method.

- Firstly, noise reduction techniques were applied on the dataset and the noise in the images was reduced.
- Afterwards, CAD images of the images were created.
- The defect-free parts, i.e. edges, in deflectometry images are omitted through these CAD images.
- Lastly, the remaining parts are called defects.
- In order to measure performance, since no learning is used in the project, the manually created defect list compared with the found defect list

The results show that the applied algorithms have a good performance on glossy defect detection. In fact, the numerical results were compared with the correct defect list created by manually when calculating. Numerical results indicate that the implemented image processing algorithms have 83.33% accuracy respectively on the hole, scratch, dent and spot defect.

As further work, deep learning models can be applied to the system to increase the success rate and to measure success automatically. Since the dataset is small, results can be obtained through transfer learning using similar problems.

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