Study of automated defect detection methods for OBACHT

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Abstract

This paper describes my summer student work dedicated to systematic study of different methods of automated defect detection on high-resolution optical images of Nb inner cavity surfaces. Three method, i.e. Eigenfaces, Segmentation and Viola-Jones were throughly investigated and tested using real images from the actual cavity production process for the Europian XFEL project. Detailed description of the methods as well as achieved defect detection results and detailed comparision between them are presented and discussed.

Contents

Introduction

The world-wide physics community looks forward to a slite of new generation of accelerator projects. The 1.3GHz superconducting Nb cavities are the basic for the actually under construction European X-ray free electron laser XFEL[1] as well as for the planned future International linear collider ILC[2]. 800 cavities of the EXFEL should operate at 23.5 MV/m while 16 000 cavities of the ILC are foreseen to operate at 31.5MV/m average acceletating gradient.

It has been observed[3] that surface defects in the range of a few microns to several millimeters may limit the perfomance of the cavities. Assuming just 10% of cavities to be optically inspected for the ILC, the total amount of images produced by OBACHT would be increadible and manual processing of the images is not further practical and should be automated.

The **o**ptical **b**ench for **a**utomated **c**avity inspection with **h**igh resolution and short **t**imescales (OBACHT) is a robot developed at DESY and based on KEK camera system. For fully automated optical inspection of the cavities OBACHT uses linear and rotational drivers to position the camera inside the cavity (see Fig. 1). The camera system resolves structures on the surfaces down to 5 microns for properly illuminated surfaces, single image consists of 3488x2616 pixels. The ability of the system is illustrated on Fig. 2, where the high-resolution image of a welding seam and a defect location compated with an earlier image from the same area taken with boroscope. The boroscopes are actually used to examine the quality of the inner surface at companies producting e.g. XFEL cavities. A total number of 2790 images are usually taken per cavity to map out the equators (9x90 images) with the two adjacent heat-affected zones (2x9x90 images) and the irises between two elliptical cells and the beam pipe (10x36 images). Manual analysis of such amount of pictures is not longer seasible.

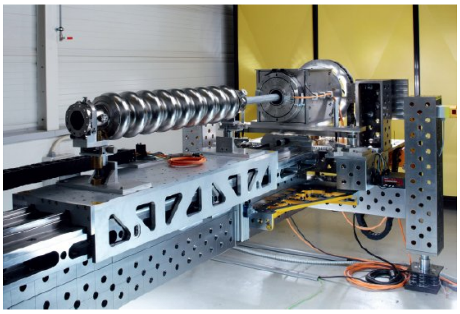

Figure 1: The robot OBACHT for automatic scan of cavity inner surfaces.

The purpose of the research is to automatically classify the defects on the images and produce statistics of the defects distribution on the cavities. The statistics could be used as a feedback to the cavity production. This paper is mainly dedicated to using different

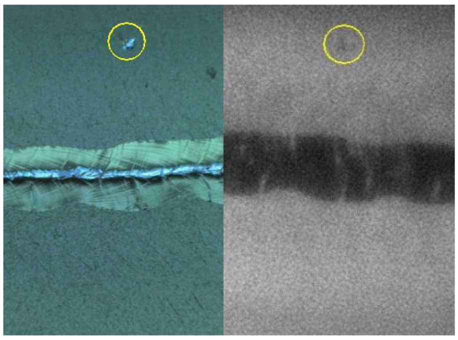

Figure 2: Image of a welding seam taken with OBACHT (left) and with a boroscope (right), courtesy E.Zanon. A suspicious spot (yellow circle) is indicated in both images.

methods of defect detection on a cavity surface images, such as eigenfaces, segmentation and Viola-Jones method.

1 OBACHT images and typical defects

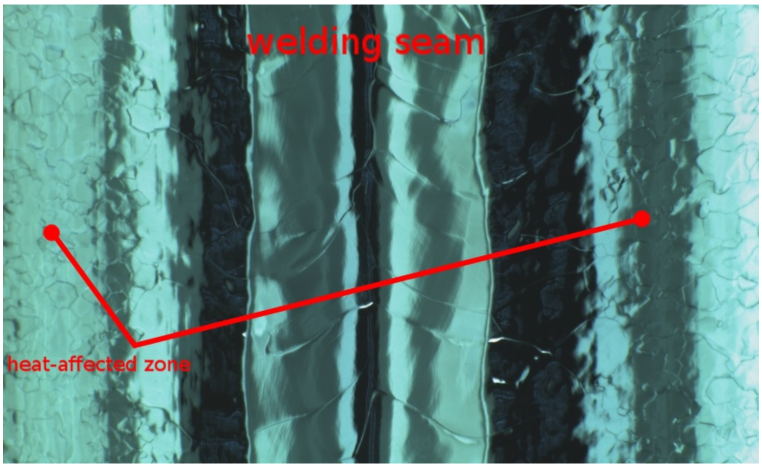

Figure 3: Layout of an equator: the welding seam in the center and so-called heat-affected zones on the sides.

Image of a defect varies depending on the illumination of the camera, location and the nature of the defect. The illumination of the camera is normally constant and only depends on the relief of a cavity. An equator is the area where two half-cells of a cavity are welded. This area could be devided into two subareas: welding seam and heat-affected zone (see Fig. 3). The bright and dark stripes on the Fig. 3 are optical effects

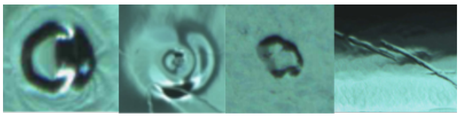

Figure 4: Defect classification (from left to right): "cateye", pit, welding spatter, and scratch.

related with a fixed shutter spead of the camera and the most common defects are shown on the Fig. 4.

2 False positive and hit ratio

In this paper true and false positive rates are used to estimate the effectiveness of a defect detection algorithm. Let us pretend there are 100 images and 90 of them contain defects. Let us also preted an algorithm identified all 90 images with defects and falsely 5 more images without them. The rest 5 images are truly refused by the algorithm as not containing defects. The true positive rate (or detection rate) and false positive rate (or false alarm rate) are defined as:

True positive rate = # true positives / (# true positives + # false negatives) = 90 / (90 + 0) = 1,
False positive rate = # false positives / (# false positives + # true negatives) = 5 / (5 + 5) = 0.5.

True positive means correctly identified, false positive - incorrectly identified, true negative - correctly rejected and false negative - incorrectly rejected.

3 The problem of image classification

The problem of image classification in this paper is defined as follows: given a set of images X and a set of classes Y that classifies images. There is a relationship between X and Y given by function $Y^* : X \to Y$. The goal is to find a function f that takes a vector of features of $\forall x \in X$ that truly classifies $\forall x \in X$. That function should truly classify images from any other set.

When an image is classified as a defect or non-defect ($Y = \{-1, +1\}$) then "classification" is substituted with "detection" to simplify the meaning of a problem.

4 Detection methods

4.1 Eigenfaces

Eigenfaces are a set of eigenvectors that are derived from the covariance matrix of the probability distribution of the high-dimensional vector space of possible faces of human beings. The approach of using eigenfaces for recognition was developed by Sirovich and Kirby (1987) and used by Matthew Turk and Alex Pentland in face classification[4]. A set of eigenfaces can be generated by performing a mathematical process called principal component analysis (PCA) on a large set of images depicting different human faces. The result of PCA analysis under a set of images is a set NxM eigenfaces (eigenvectors) and the same number of eigenvalues, where N and M are the width and the heigt of images. Practically a few first eigenfaces with the largest eigenvalues are responsible for the major variance of the original data in the eigenface subspace. A projection of an original image into the eigenface subspace produces approximatelly the same image. Informally, eigenfaces can be considered as a set of "standardized face ingredients", derived from statistical analisys of many pictures of faces. Any human face can be considered to be a combination of these standart faces. The dimension reduction of the original data allows to select strongly marked features of an image ignoring nose distortion.

An example of a set of eigenfaces is shown on the Fig. 5. Notice that the different eigenfaces seem to accentuate features of the face. Some focus more on the eyes, others on the nose or mouth and some a combination of them. The rest eigenfaces would more accentuate on noise and hight frequency features.

The face recognition princple is following. A large set of pictures of human beings

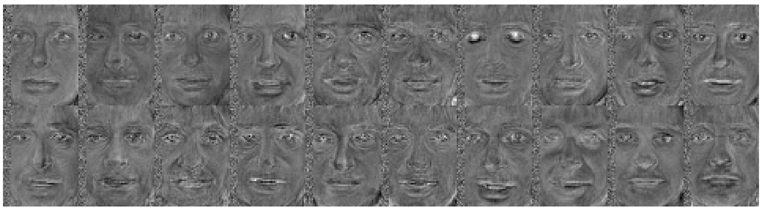

Figure 5: Eigenfaces generated by PCA

undergo PCA analysis and only eigenfaces responsble for highest variation are retained for further analysis. A set of pictures of a specific person is projected now to the low-dimensional subspace composed of the selected eigenvectors. The coordinates of each picture in this subspace are features of the picture. Practically the feature vector of an image consists of 10-20 variables. Points with coordinates of the feature vectors of the detecting person in the subspace are collected in a cluster with small deviation. When a picture of another person is projected to the same subspace its point is located outside the cluster. The distance between the nearest to the testing face point and a point from the cluster of identified person can characterise similarity between testing and identified person.

The eigenface decomposition can be fairly applied to the problem of defect detection

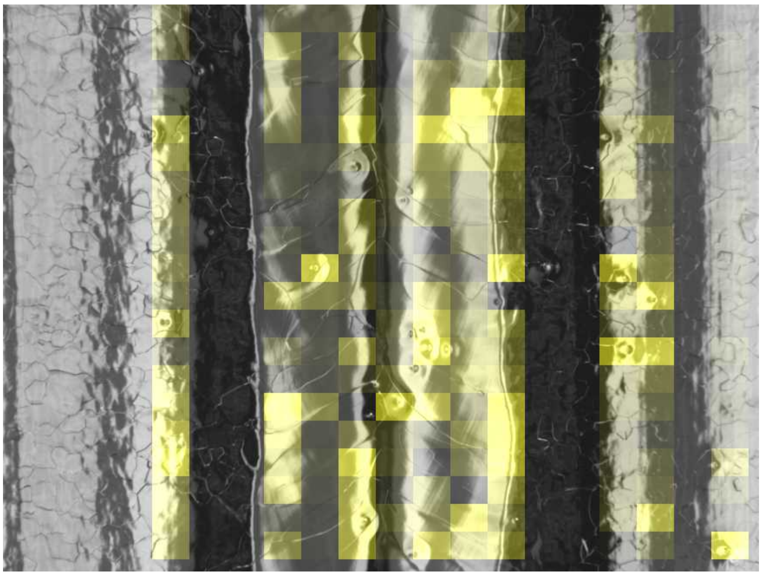

Figure 6: A result of the eigenface defect recognition. The brighter square the higher irregularity is.

on the cavity surface images. It is seen that the image of an equator on Fig. 3 consists of several vertical zones (stripes) that could be treated as “faces”. The rest images of equators are typical and well aligned. Then an image is splitted into N vertical zones and that zones to M tiles. In this case “pure” tiles without defects on the surface are used to train the algorithm to detect irregular tiles, i.e. tiles with defects. Each vertical stripe is analysed separatly from others. When the eigenfaces for the stripes are calcu-

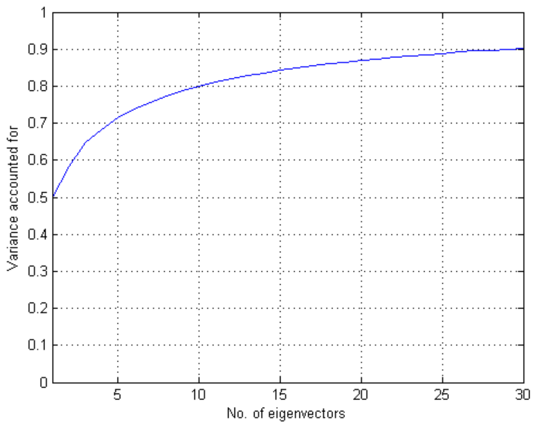

Figure 7: Variance distribution among eigenfaces.

lated, testing tiles are projected to corresponding subspaces. If the standart deviation of a stripe withing a single image exceeds the threshold then the stripe is suspected to have irregularities. The minimal euclidian distance between suspected tile and each of the "good" tiles defines the irregularity of the tile. Euclidian distance is given by

$$r = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_K - y_K)^2}$$

On the Fig. 6 tiles of suspected stripes are marked with yellow squares, the brighter square the higher irregularity is. For the algorithm training normally 5-7 pure images are selected within an equator. The main parameters to play with are the grinding ratio of an image and number of eigenfaces used for decomposition. According to the Fig. 7, the first 30 highest eigenvalues are account for 90% of the variance in the data set. Small number of eigenfaces increase false positive detection ratio, so the first 30 eigenvectors accounting for the highest variance are retained for the defect detection.

The first disadvantage is the feature of eigenface decomposition method and the second is the normal irregularity of the seam picture which often treated as a defect. On the Fig. 8 it is seen that the algorithm falsely treats edges of the seam as containing defects because the edge is not regular The highlited zones in the heat-affected area are also problematic.

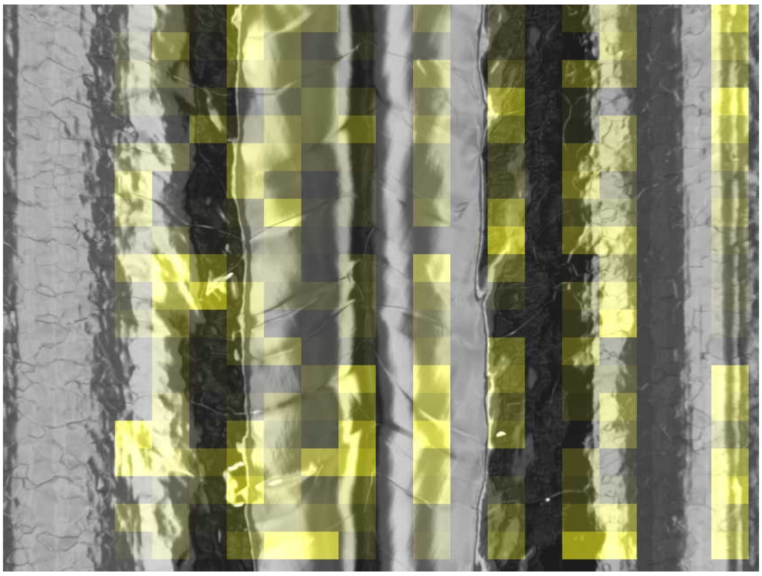

Figure 8: High false positive detection ratio of eigenface defect recognition method.

4.2 Segmentation

The main disadvantage of the eigenfaces method is a high false positive rate. The idea of the segmentation method is extraction of objects with definite intensities of pixels and further selection by their geometrical parameters.

Defects on the surfaces usually reflect light due to illumination effects. The bright

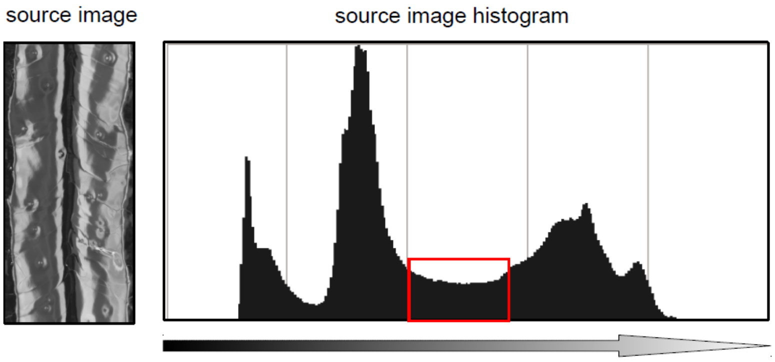

Figure 9: Grayscale to black/white image convertion

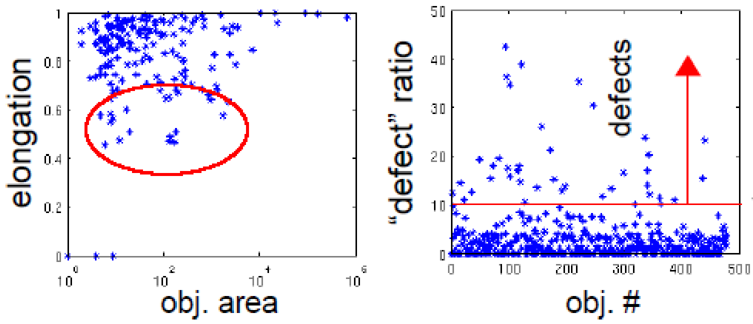

Figure 10: Geometrical properties of found objects on a black/white image. The red line on the right plot indicated the threshold of treating objects as defects.

areas of defects that reflect light are extracted from the source image after applying a threshold filter (see Fig. 9). The highest pick on the histogram accounts for the middle tones, the left pick for the dark tones and the pick on the right accounts for the bright tones on a welding seam. As most defects are located in the middle tone area of welding seams this area is converted to black color to locate defects with lower color intencities (shadows of defects). Pixels with intensities outside the defined range are white. On the Fig. 11 traces of the defects are seen the white spots. Then the algotithm for searching for connected pixels extracts white "islands" from black/white image and calculate their geometrical properties. It is known that an ellipse describing a defect has a relatively small elongation. To skip small objects like alone pixels with lowest elongation the value of area of an object is combined with the elongation to filter undesired objects (non-defects). These two parameters are used to calculate the ratio of "defectness" of an object:

$err = \frac{log(Area)}{a/b}$.

The logarithm in the formula is used to reduce large influence of the area of an object due to large variance in the values of area among objects. a and b are major and minor axis of the describing object ellipse relatively. The left plot on the Fig. 10 shows the relationship between the elongation and the value of area of found black objects. Suspicious objects are marked with red circle on the left plot, they have relatively small elongation and large enough area. The right plot shows the relationship between the ratio of "defectness" and the object number. Objects with the ratio upper the experimentally found value (threshold) are treated as defects and marked with colour spots on the Fig. 10.

The main disadvantage of this method is high false negative rate: after black/white

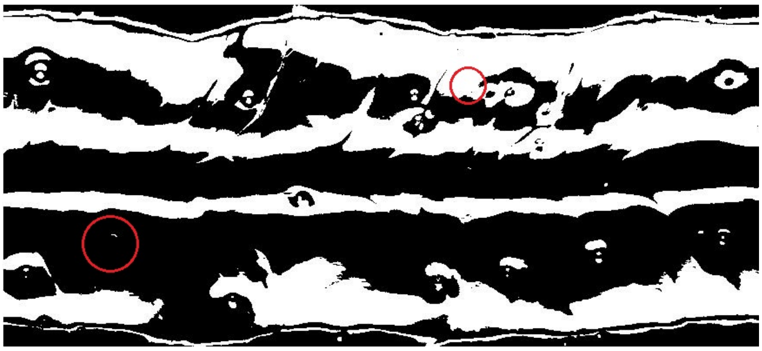

Figure 11: Loss of a defect track (left circle) and defect merger with white "island" (right circle) on black/white image

convertation defects with diffuse edges merge with bright spots of the welding seam. This effect is demonstrated on the Fig. 11. After the merger the defect (its track) is missed as the algorithm omits objecs with extra large size. A result of the segmentation

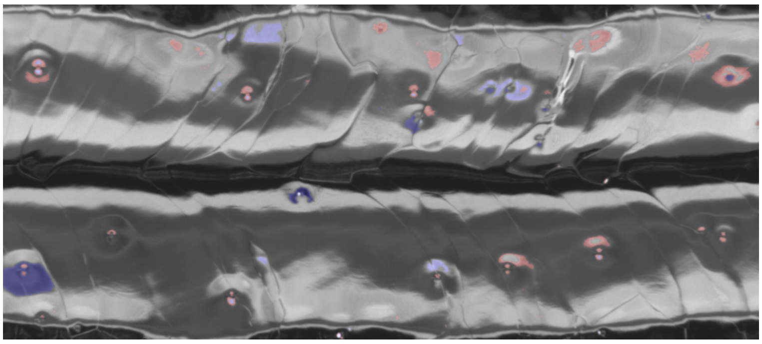

Figure 12: Loss of a defect track (left circle) and defect merger with white "island" (right circle) on black/white image

method is shown on the Fig. 12. The red spots indicate objects treated as defects on normal image and the blue spots for the inverted image.

4.3 Viola-Jones method

The Viola-Jones (as names of the authors Paul Viola and Michael Jones who proposed this object detection framework in 2001[5], further V-J) method is the most successive aproach mentioned in this work for the defect detection problem. Initially the method was designed for the human face detection and nowadays it remains one of the most efficient real-time framework for the image classification problem. In this work V-J is successfully used for the defect classification problem.

For image classification V-J uses so called strong classifier that is trained to classify an image as, for example, a defect or non-defect. The method uses sliding window to probe a testing image. To detect objects of different scales the window also changes its size instead of the original image size. Then the probe is scanned for the detecting object features presence and in case the probe has all the features the algorithm treats it as a defect. V-J method uses Haar-like features for calculating gradietns of the testing image in definite areas. On the Fig. 13 some Haar-like features are demonstrated on a human face: one of the wanted features for the human face recognition is a high gradient between eyes and forehead (right bottom picture on the Fig. 13). The value of a feature

Figure 13: Haar-like features used to detect a human face.

is calculated as (give a formula)

$F = X - Y,$

where X is the sum of pixel intensities under the white and Y under the black regions of the Haar primitive.

To reduce the false positive ratio V-J uses cascade classifier that consists of several so called weak classifiers. The purpose of a weak classifier is to make a "weak" guess whether the image is wanted or not. A weak classifier uses several Haar-like primitives to extract features of the image to make a guess. To make a more precise guess weak classifiers are combined into a strong classifier - a stage, where each weak classifier is a layer of the stage. A stage must satisfy the preset detect ration and false alarm. Further enhancement of object detection is achieved creating new stages and connecting them to a cascade. The first stage in a cascade is designed to rapidly skip images that are unlikely the detecting objects. As far as an image goes through stages, the task for the next stage is more difficult, because highest stages have to choose the detecting object among similar images. The work of creating such an effective chain of stages is assigned to the AdaBoost technique (give a link). False alarm and detection rates for a cascade are

$$FA = FA_1 \cdots FA_N,$$
$$DR = DR_1 \cdots DR_N,$$

where FA_i and DR_i are false alarm and detection rates of the i^{th} stage. For example, if the false alarm is equal to 0.5 for each stage and the hit rate is equal to 0.97 then for 10-stage cascade the false alarm is less than 0.001 and the hit rate more than 0.7.

The training algorithm uses positive and negative images to build a cascade of classifiers. Positive images are images containing only detecting objects while negative images are arbitrary images without detecting objects. To train an efficient classifier order of thousands positive and negative images could be required. In this work 1500 positive and negative images (3000 in the sum) are used to train 20-stage classifier with false alarm 0.5 for each stage. To enhance the training and detection only one type of defects ("pits") in definite area of a cavity surface image (illuminated part of the welding seam) are used to train a single cascade. For futher defect classification different types of defects could be collected and used for training new cascades.

An example of defect detection by V-J method is shown on the Fig. 14. The algorithm

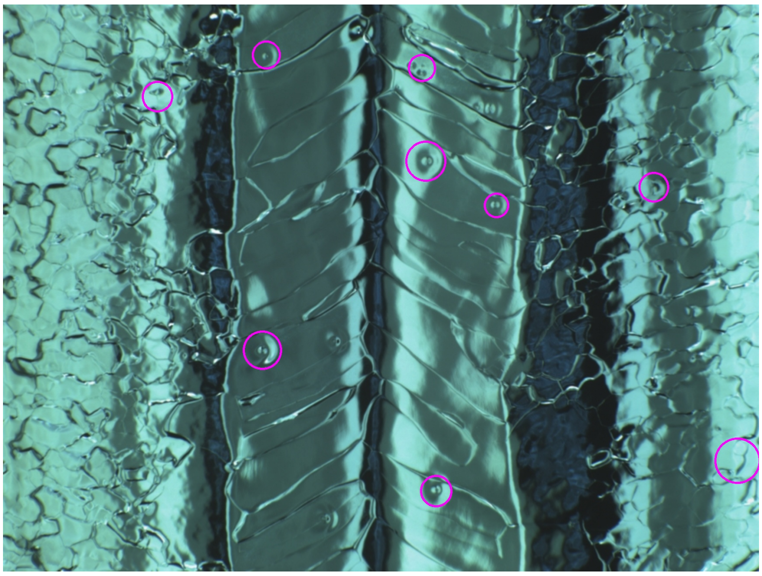

Figure 14: Detection of "pits" using Viola-Jones method.

detected all the evident "pits" and four structures reminding "pits". Since the cascade used for the defect detection is trained to recognise only "pits" in the illuminated part of the welding seam, other "pits" in shadow are not detected in this example.

5 Summary

Three different methods of defect detection were studied. Eigenfaces method showed undesirably high false positive rate but relatively small training time. Unlikely to eigenfaces and Viola-Jones methods, segmentation method does not use training but it has relatively high false negative rate. The most promising results showed Viola-Jones method. It has extrimely small false positive rate and sufficiently high true positive rate. Tab. 1 contains the main features of each method.
The source code of the considered methods could be found in an AFS directory `/afs/desy.de/group/fla/cavity` or in GitHub `http://www.github.com/duburlan/`.

Table 1: Feature comparision of the considered defect detection methods. FA and DR are false alarm (false positive rate) and detection rate (true positive rate).

Method	FA	DR	training	testing
Eigenfaces	high	low	fast	<1 second
Segmentation	medium	medium	-	>1 second
Viola-Jones	low	high	3 days	<1 second

In this work failsafe parameters were used for training the cascade for "pits" detection. Optimisation of the parameters (number of stages deduction, pure negative images, deverse positive images) should increase precision of the detection.

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