Research paper

A vision-based system for inspecting painted slates

Ovidiu Ghita, Tim Carew and Paul Whelan
Vision Systems Group, School of Electronic Engineering, Dublin City University, Dublin, Ireland

Abstract

Purpose – This paper describes the development of a novel automated vision system used to detect the visual defects on painted slates.

Design/methodology/approach – The vision system that has been developed consists of two major components covering the opto-mechanical and algorithmical aspects of the system. The first component addresses issues including the mechanical implementation and interfacing the inspection system with the development of a fast image processing procedure able to identify visual defects present on the slate surface.

Findings – The inspection system was developed on 400 slates to determine the threshold settings that give the best trade-off between no false positive triggers and correct defect identification. The developed system was tested on more than 300 fresh slates and the success rate for correct identification of acceptable and defective slates was 99.32 per cent for defect free slates based on 148 samples and 96.91 per cent for defective slates based on 162 samples.

Practical implications – The experimental data indicates that automating the inspection of painted slates can be achieved and installation in a factory is a realistic target. Testing the devised inspection system in a factory-type environment was an important part of the development process as this enabled us to develop the mechanical system and the image processing algorithm able to perform slate inspection in an industrial environment. The overall performance of the system indicates that the proposed solution can be considered as a replacement for the existing manual inspection system.

Originality/value – The development of a real-time automated system for inspecting painted slates proved to be a difficult task since the slate surface is dark coloured, glossy, has depth profile non-uniformities and is being transported at high speeds on a conveyor. In order to address these issues, the system described in this paper proposed a number of novel solutions including the illumination set-up and the development of multi-component image-processing inspection algorithm.

Keywords Visual perception, Slate, Illuminance, Image processing, Conveyors

Paper type Research paper

1. Introduction

The aims of using automated visual inspection are to classify products for quality so that defective units may be rejected, to measure some properties of the product with a view to controlling the production process, and to gather statistics on the efficiency of the production process. Although slate manufacturing is a highly automated process, in current practice the painted slates are manually inspected by an operator who looks at them as they emerge via a conveyor from the paint process line. Hence, the aim of this work is to develop an online sensor capable of measuring and classifying the slates as having a surface finish of acceptable or not acceptable quality (see Whelan, 1997; Batchelor and Waltz, 2001 for a review of the system engineering issues in industrial inspection).

The authors found no prior relevant work on the inspection of slates. However, there is an abundance of references on the subject of inspection of ceramic tiles. Although the production processes for slates (Fernandez *et al.*, 1998) and ceramic tiles are very different, the visual inspection process for ceramic tiles are broadly applicable to the inspection of slates as both products are rectangular in shape, have textured surfaces and arrive at the inspection point via a conveying system.

One common aspect to emerge from all the work reviewed in the field of ceramics inspection was the difficulty experienced in developing a single processing procedure to detect the wide range of defect types and sizes. The merits of a multi-component inspection were highlighted where each component was tailored to identify a specific category of defects. It is also evident from the literature review that of equal importance to the image processing procedure is the selection of an illumination set-up that minimises spatial and temporal illumination variations. The ceramic inspection systems examined were based on either diffuse or collimated lighting methods. Diffuse lighting methods were usually employed and often in combination with colour cameras. Various implementations used the diffuse lighting method to detect cracks or holes in the tile surface (Peñaranda *et al.*, 1997; Boukouvalas *et al.*, 1997). On the other hand,

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Boukouvalas *et al.* (1999) employed a collimated lighting method where fluorescent lamps were used as a light source to image substrate defects such as lumps and depressions. Their imaging system captures the specular reflections generated by the ceramic tiles surface where the camera and light source angles relative to the normal vector of the surface being inspected are equal.

The second major component of the inspection system is the image processing algorithm that is applied to detect the visual defects. In this regard, Boukouvalas *et al.* (1997) used 1D convolvers to detect the spot and line defect existence on the tile surface. The optimal filter coefficients used in the convolvers can detect features with widths within a factor of 1.5 of the feature for which the filter is optimised. This would restrict the application of this method to slate inspection due to the large range of defect sizes identified on the slate's surface. More complicated techniques based on Wigner distributions were employed to inspect coloured and heavily textured tile surfaces (Boukouvalas *et al.*, 1999). Their implementation used a co-joint spatial frequency representation of the Wigner distribution that was employed to maximise the signature of regular patterns. This method is more applicable to inspection of multi-coloured and textured surfaces and this is a limiting factor in the use of this technique for slate inspection. Peñaranda *et al.* (1997) and Boukouvalas *et al.* (1999) used grey level intensity histograms to identify whether the unit being inspected is defective. Although these methods proved to be reliable when applied to tile inspection, they are less effective in the inspection of slates as the greyscale mean and the standard deviation vary too widely from slate to slate and within each slate.

Other related implementations include the application of the grey level difference method (Tobias *et al.*, 1995), morphological methods (Müller and Nickolay, 1994), local binary pattern methods (Ojala *et al.*, 1996; Mäenpää *et al.*, 2003) and texture analysis (Mandriota *et al.*, 2004; Lu and Tsai, 2005). The grey level difference methods were ineffective because of the significant variations in acceptable grey level mean values between successive slate images. Key to the successful application of morphological methods is the selection of structuring elements matched to the size and shape of the defect features (Patek *et al.*, 1998; Whelan and Molloy, 2000). However, this was considered unfeasible given the vast range of defect shapes and sizes.

This paper is organised as follows. Section 2 describes the typical slate defects. Section 3 details the development of the prototype inspection system. Section 4 presents the adopted illumination arrangement. Sections 5 and 6 describe the image-processing algorithm. Section 7 presents several challenges introduced to the system by the factory environment. Section 8 discusses the experimental results and Section 9 concludes this paper.

2. Description of slate defects

The manufactured slates are painted on a high-speed paint line and are manually inspected as they emerge from the paint line via a conveyor system. Visual inspection is carried out manually where human inspectors make a decision as to whether each individual slate is defect free and removing the slates not meeting the inspection criteria.

Slates have a rectangular shape and their top surface is painted black or grey and has a high gloss finish. The painted surface is nominally flat. The slate surface defects are broadly classified into two categories: substrate and paint. Substrate defects include incomplete slate, lumps, depressions and template marks. Paint faults include no paint, insufficient paint, paint droplets, efflorescence, paint debris and orange peel.

These defects can have arbitrary shapes and their sizes range from sub-millimetre to hundreds of square millimetres. A selection of representative defects is shown in Figure 1, where Figure 1(a) shows a defect free (reference) image section.

3. Description of the prototype inspection system

The prototype inspection system was built to replicate the factory environment (Newman and Jain, 1995) and is shown in Plate 1. The 2 m long belt conveyor transports the slates to the inspection line at speeds in the range 15-50 m/min. The slate is illuminated using a 762 mm wide fibre optic line light where the light is collimated by a cylindrical lens. The sensing device is a Basler 2k-pixel line-scan camera fitted with a 28 mm lens. The line-scan camera operates at a scan frequency of 2.5 KHz. A micro-positioner was attached to the camera to facilitate fine adjustment of camera view line. A Euresys frame grabber is used to interface the camera to the PC. The slate is aligned by a guide placed on one side of the conveyor and an optical proximity sensor triggers the image capture immediately prior to the arrival of the slate at the inspection line. When the image transfer is complete, the slate image is processed using the image-processing routines that will be detailed in Sections 5 and 6.

4. Illumination set-up

The strategy used to image the slate relies on the strong reflecting properties of the slate's surface. Light incident on the slate will be reflected and the angle of reflection is equal to the angle of incidence if the slate surface is acceptable. The principle of operation is shown in Figure 2 using the Phong illumination model described by Davies (1997).

Generally speaking, paint defects have reduced gloss levels, except for paint droplets that may have a higher gloss level than the slate areas of acceptable quality. Substrate defects are associated with uneven slate surfaces that are generated by an incorrect drying/formation process. The resulting appearance of these defects translates into a reduction of light arriving at the sensing device. For this implementation, a collimated light source was used. One of the challenging problems we encountered was the variation in depth profile across the slate due to slight but acceptable slate bowing that is sometimes present in the inspected slate. This raises and lowers the absolute position of the band of light relative to the camera view position. As a mechanical solution to force the slate into a uniform flat position is not feasible, we decided to defocus the lens that is used to collimate the light. This produces a wider band of light and reduces collimation. The resulting reduction in light intensity was compensated for by using the spare capacity in the lamp controller. A simple trigonometric calculation was employed to determine the width of the band of light required to make the system sufficiently insensitive to depth profile non-uniformities. To this end, the lens was defocused such that the resulting width

Figure 1 Representative defects found on the slate surface

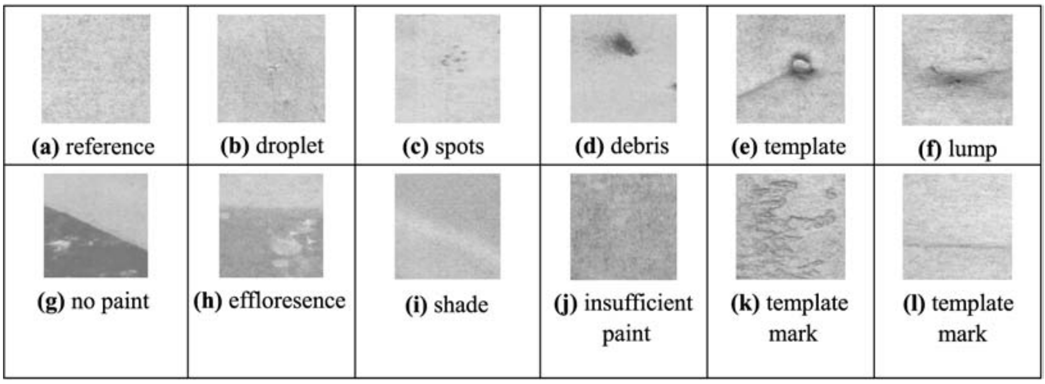
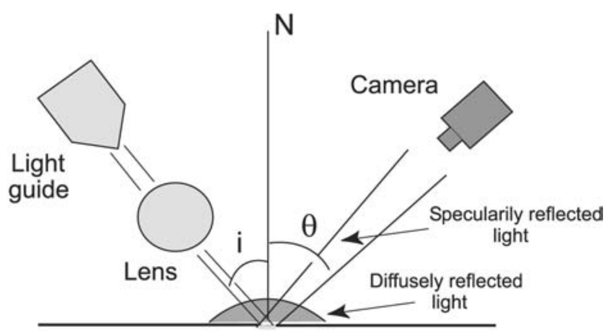


Plate 1 Conveyor and slate inspection system

Figure 2 Model of reflectance for slate surface



of the light band was made equal to 25 mm. For this implementation, the illumination set-up comprises two Fostec DCR III 150 W lamp controllers, a Fostec 30" fiber optic light line and a cylindrical lens. It is useful to mention that the developed inspection system uses collimated light, and this implies that changes in the ambient light have a negligible influence on the light reflected by the slate back to the camera. In our experiments, the system was tested under various ambient lighting conditions and it was found to be insensitive to changes in the ambient lighting.

5. Segmentation of slate image from background

The first step of the devised image processing procedure involves the identification of slate boundaries. Slate edge detection was facilitated by cutting slots in the conveyor base and ensuring the belt width is less than that of the slate. The light intensity signal arriving at the sensing device from these slots is close to the camera black level when no slate is present and a sharp signal transition is sensed when a slate arrives in the field of view. Therefore, a simple threshold operation is sufficient to identify the slate edges. Corners are located by tracking the horizontal and vertical edge lines to their end positions.

To verify if the slate is defect free, initially, a straight line between the detected corner positions was drawn and the inspection start locations were set relative to this line. Rotation is accounted for using the equation of a straight line. After this operation, the slate is segmented from the background and the four-component algorithm described in Section 6 can be applied.

6. Image processing algorithm

In order to devise an efficient solution to identify defective slates, the grey level signals from hand selected reference slates and defective slates were analysed. Experimental data indicated that the mean grey level of successive reference slates can vary by up to 20 grey levels where the average grey level was 167. These variations are not generated by imperfections in the optical or sensing equipment but rather due to acceptable variation in slate surface colour. As such the image processing algorithm has to accommodate these variations. In order to identify the computational components of the inspection algorithm, the grey level histograms of slate images containing paint and substrate defects were investigated. This enabled us to draw a number of conclusions:

- the grey level mean is different for each reference slate;
- the limit of this variation can be determined by experimentation; and
- the average grey level value of the defect pixels is generally lower than the average grey level value of the background pixels.

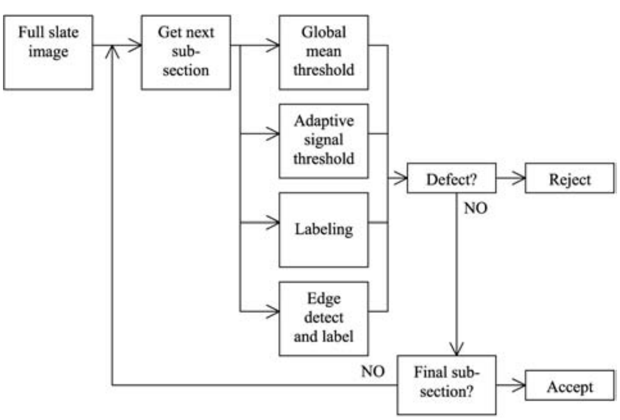
Also, it has been observed that the majority of defects are negligibly small relative to the whole slate image. This indicated that it would be desirable to inspect the slate image for defects in small image sub-sections as the relative impact of a defect on the grey level statistics of the image is increased. The slate image was divided into smaller segments of size 128×128 pixels and each segment was processed separately.

The devised algorithm is shown in Figure 3 and consists of four distinct components with each component designed to detect specific defect types. The components are global mean threshold method, adaptive signal threshold method, labelling method and edge detection method. Each component of the algorithm is applied to each image segment and the results are compared to experimentally determined thresholds. If any result exceeds the predefined threshold then the image segment and hence the slate is considered defective. Each component of the algorithm is briefly explained in the following sections.

6.1 Global mean threshold method

This method investigates the grey level mean of an image section. If the computed mean is lower than the experimentally determined mean then the image section belongs to a defective slate. This method is used to detect gross defects such as missing paint, orange peel, efflorescence, insufficient paint and shade variation. Although very simple, this method proved to be the most effective solution to robustly detect these types of defects.

Figure 3 Slate defect detection block diagram



6.2 Adaptive signal threshold method

Experimental measurements indicated that the slate texture noise is found in the band (mean $-$ 30, mean $+$ 30) and to avoid the incidence of any false positives, the signal thresholds were experimentally selected as (mean $-$ 40, mean $+$ 60). This method was designed to detect defects such as missing paint (where less than 50 per cent of the image section is defective), debris, droplets and spots. This method is primarily designed to detect the substrate defects that are generated by an incorrect slate formation process. Depending on severity, defects such as efflorescence, shade variation and insufficient paint are sometimes detected by this method.

6.3 Labelling method

Connected component labelling (Dillencourt *et al.*, 1992) is an efficient method for detecting the imaged defects that are immersed in noise. This method consists of several steps that are shown in Figure 4.

The first step converts the input image into binary by applying an adaptive thresholding technique. The second step is applied to reduce the level of noise in the binarised image by applying a morphological opening operation. The aim of this operation is to remove the small un-connected features. The filtered image is labelled and for each connected group of pixels, the algorithm assigns a unique label. The labels are ordered in accordance with the size of the detected blobs. Generally speaking, the small blobs may be associated with slate texture and the large blobs may be associated with defects. Thus, in order to eliminate the influence of the irrelevant small features, the total area of the largest ten blobs is used as the discriminative feature to classify the image section as acceptable or defective. This method proved to be very effective for detection of high contrast defects such as debris, droplets, spots and no paint.

6.4 Edge detection method

The previous methods detailed before are not effective in detecting small narrow defects. Hence a fourth image processing component was added to the algorithm. Initially, the image is filtered with a median filter and this is followed by the application of the Sobel edge detector. The edge structure returned by the Sobel edge detector contains gaps that are bridged by applying a morphological closing operation. Sometimes the defects have shallow intensity profiles and the gaps in the edge data are too large to be closed by the morphological operator and the resulting data will consists of a collection of small unconnected edge segments. To circumvent this problem, the image resulting after the application of closing operation is labelled and the total area of the largest ten blobs is used to grade the image section as acceptable or defective. The sequence of operations required by this method is shown in Figure 5.

Figure 4 Labelling method

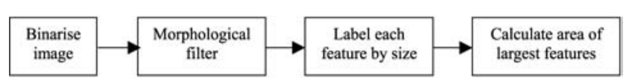
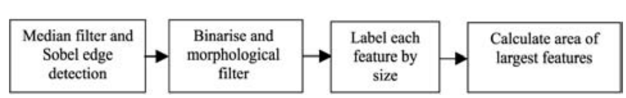


Figure 5 Edge detection method



7. Challenges introduced by factory conditions

7.1 Effect of depth profile variation and vibration on edge detection

The devised slate segmentation method described in Section 5 worked very well for flat slates but resulted in false triggers for slates having significant depth profile variation. If the slate is affected by depth profile variations, the captured image follows the curve of the slate and false rejections occur when there are large differences between the assumed straight edge and the imaged curved edge (Figure 6). An example of false defects caused by the edge checking method is shown in Figure 7.

In order to address this problem, the slate's edge has been divided into shorter line lengths of 30 mm length and the location for these short edge segments is verified. The image sub-sections that will be analysed by the inspection algorithm are positioned adjacent to these detected short segments. This will avoid the inclusion of background information in the image sub-section that may cause false triggers when the image data is analysed by the inspection algorithm.

7.2 Effect of variation in speed profile

The conveyor speed was set at 38 m/min and camera exposure was set to 400 μs giving a scan frequency of 2.5 KHz. The cross direction resolution was 0.221 mm and the moving direction resolution was 0.244 mm. The constancy of conveyor speed was measured by imaging the same slate several times and by imaging 16 slates in succession. The timing of image capture is under digital control and is repeatable. Measurements for the repeatedly imaged slate ranged from 298.3 to 300.7 mm while the measurements for 16 reference slates ranged from 295.9 to 300.1 mm. These variations are generated by the conveyor speed variations and the change in image resolution in the moving direction is very small (approx. 0.8 per cent) and does not have any negative effect on the inspection results.

8. Robustness tests

The inspection system was developed on 400 slates to determine the threshold settings that give the best trade-off between no false positive triggers and correct defect identification. Then the system was tested on more than 300 fresh slates and the success rate for correct identification of acceptable and defective slates was 99.32 per cent for defect free slates based on 148 samples and was 96.91 per cent for defective slates based on 162 samples.

The classification of defective and defect free slates was performed by an experienced operator based on a visual examination. A detailed performance characterisation is depicted in Table I where the detection rate for each category of defect is presented. The system failed to identify one defective slate that had a shallow depression that was

Figure 6 False triggers generated by slate's depth profile variation

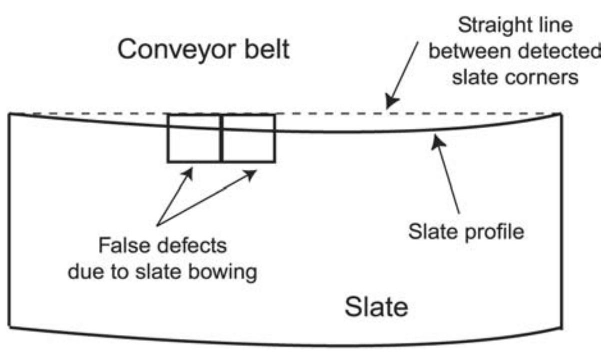
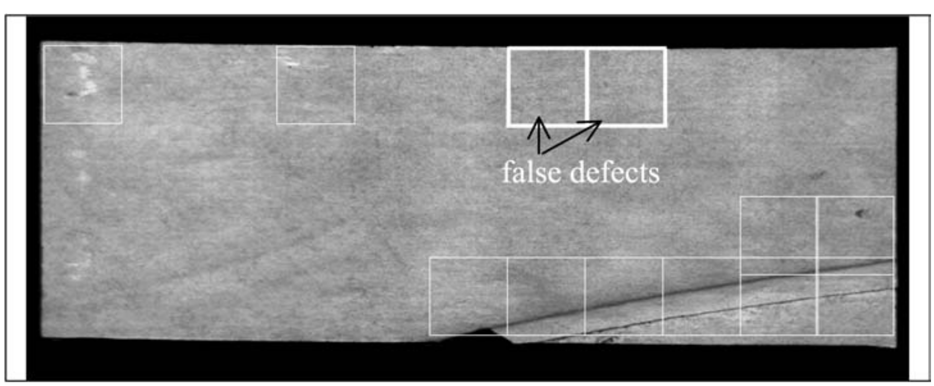


Figure 7 False defect generation due to depth profile variation



Note: The white box is drawn around 128 × 128 pixel image sub-sections considered to be defective. True positive defects are correctly detected as indicated by the faint boxes

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Table I Summary of defect detection rates

Type	Undetected	Detected	Correct result (per cent)
Missing paint	0	4	100
Insufficient paint	0	9	100
Efflorescence	0	15	100
Shade variation	0	12	100
Nozzle drip	0	14	100
Droplets	0	8	100
Dust	0	4	100
Wax	1	7	87.5
Template marks	2	33	94.28
Template marks II	0	5	100
Lumps	0	13	100
Depressions	1	3	75
Bad edge	0	18	100
Misc. types	1	12	92.30
Total	5	157	96.91

positioned parallel to the direction of slate travel. However, the system was able to identify this defect when the slate was rotated about 90° (i.e. the slate was imaged with the 300 mm edge facing forward) as the defect was clearly imaged. Also the system was not able to identify two slates that present tiny marks (approx. 1 mm^2) on their surface. These defects were undetected because the resolution provided by the present imaging system was not sufficient to image them accurately.

Typical inspection results are shown in Figure 8 for defect types efflorescence, lump, damaged edge and template marks. White lines are drawn around the image sub-sections found to be defective. Codes highlighting which of the algorithm components were triggered are shown for edge and lump defects in Figure 9. The code for global mean threshold is 1, adaptive signal threshold is 2, label method is 4 and edge method is 8. A defect can trigger more than one component. The lump defect generated a code of 14 indicating it had triggered the mean threshold method (one) and the label method (four). The image output and defect pixel count for lump and edge defects of each image-processing component are shown in Figure 9.

Real-time operation is a realistic target although some challenges remain to produce an industrial system. The reduction of the processing time is in progress and currently the inspection takes 0.8 s for analysing a slate image (the algorithm was executed on a Pentium II 600 MHz PC with 128 MB RAM). Also, some processing can be implemented in hardware and this will assure real-time operation.

9. Conclusions

The experimental data indicates that automating the inspection of painted slates can be achieved and installation in a factory is a realistic target. Testing the devised inspection system in a factory-type environment was an important part of the development process. It enabled us to verify that the devised mechanical system and the image-processing algorithm are feasible to be implemented in an industrial environment. The overall performance of the slate inspection system indicates that the proposed solution can be considered as a replacement for the existing manual inspection system.

Figure 8 Typical inspection results. From top left, efflorescence, lump and damaged corner, template mark and template mark

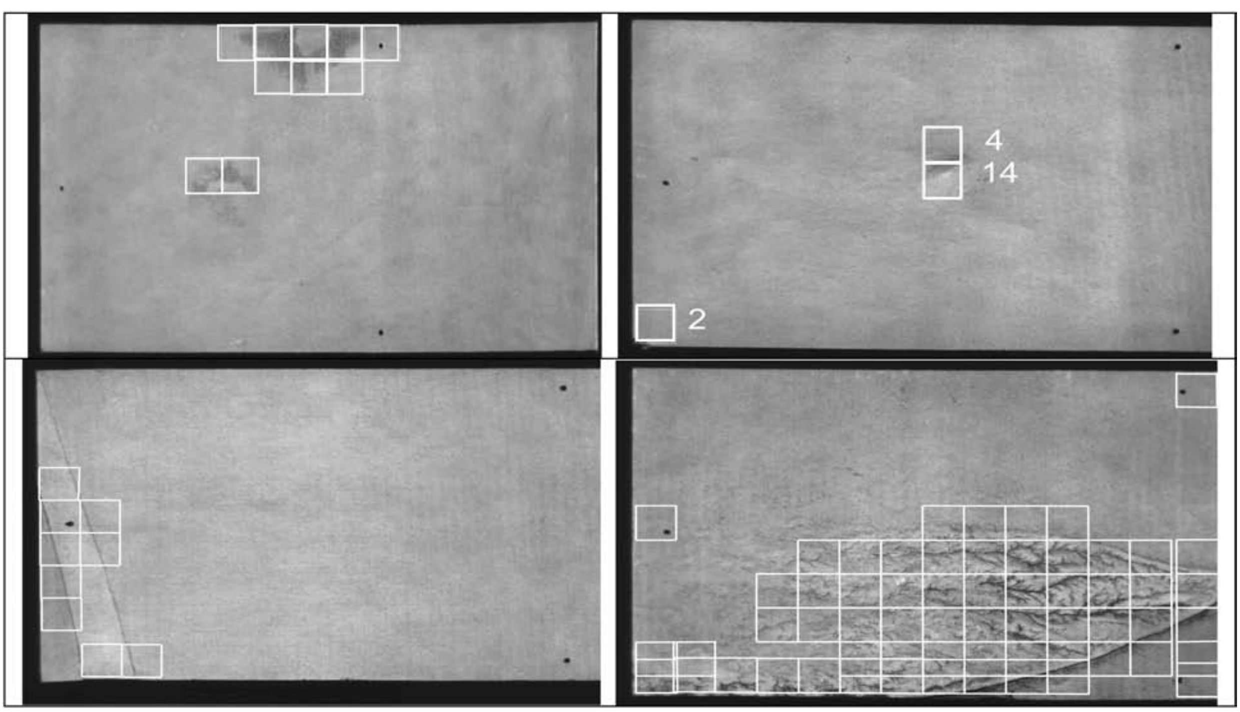
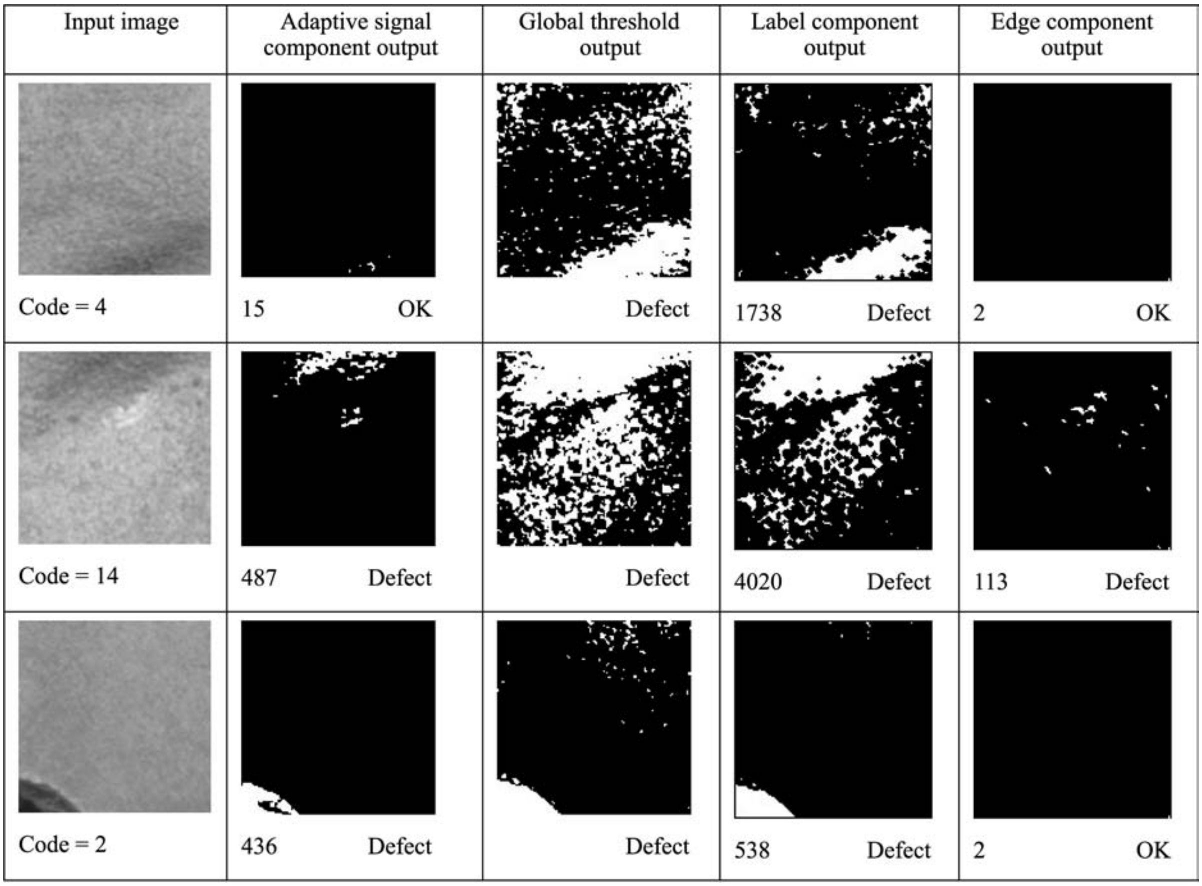


Figure 9 Image output of each algorithm component for defective image sub-sections of lump and edge fault slate shown in Figure 7



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Corresponding author

Ovidiu Ghita can be contacted at: ghita@eeng.dcu.ie