Surface defects detection for fired ceramic tiles using Monochrome and Color image processing analysis

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Abstract

One of many applications of vision systems is quality control. Quality control in ceramic tile manufacturing is hard, labor-intensive operation. Ceramic tiles classification depends on three main factors color analysis, dimension verification, and surface defects. Our work introduces enhanced algorithms to detect the color and surface defects in the fired ceramic tiles using principles of image processing analysis. This algorithm assumed as a visual inspection system that helps in the sorting operation before packing operation to improve the homogeneity of batches received by costumer.

Keywords

Quality control, classification, color analysis, surface defect, visual inspection.

1. Introduction

Recently, manufacturing process for the ceramic tiles has been completely automated with the exception of the final stage of production concerned with visual inspection. Defects are viewed as in-homogeneities in regularity and orientation fields, so we can consider that the structural defects are regions of abruptly falling regularity. Human judgment still used in surface and color defects detection but is influenced by expectations and prior knowledge. Such a monitoring task is of course tedious, subjective and expensive but it is based on a long experience and can utilize the huge appreciation and recognition abilities of the human brain [1] and [2].

Surface defects detection operation induces that the entire surface of every tile must be imaged and analyzed. In addition, the color defects detection operation needs that each tile will be captured individually and compared with the reference tile image including all transformation and translation where these caused by movement of line production and the acquisition system we used here in our work [3] and [4].

The visual system introduced in this work depends mainly on the using of image processing techniques to the digital images captured online production [5].

This paper aims to create a visual system that is capable of detecting the color and surface defects for the fired ceramic tiles to ensure that the products are free from defects for the classifying process, which must be effectively, objectively and repeatedly, with sufficient rapidness and low costs giving the ability to adapt autonomously to changes in materials. The techniques used here applied on real surface defects including Long crack, Blob, pinhole and spot defects also a color defects on a plain, and textures tiles.

Finally, the results suggested that the performance is adequate to provide a basis for a viable commercial visual inspection system, as we will see it in the next sections.

2. Image acquisition and capturing

Capturing the tile images in the acquisition using a digital camera creating images that are more suitable for the visual perception, object detection and target recognition. So, the ceramic tiles have been captured through online digital camera held on the line production at the factory.

We get here two kinds of images; the first one is a gray level image that for analysis to extract the surface defects included in the fired ceramic tiles images. We use the first type a gray scale images because this type takes small sizes or small memory size in saving. The second type of images is RGB color image of the fired ceramic tiles that contain color defects like color blob defects, shaded color, water drop color defects, and dirt color defects. After capturing the fired ceramic tiles, we will use many methods in image analysis, mathematical and algebraic operation included in the image processing techniques.

We use in analysis the Image Processing Toolbox in Matlab Software. That gives an output images and programs in M files converted to C code and executable files run directly on computer systems consuming less processing run time because we need less time related to the production line speeds.

3. Image analysis

The basic data structure in MATLAB is the *array*. MATLAB stores most images as two-dimensional arrays (i.e., matrices), in which each element of the matrix corresponds to a single *pixel* in the displayed image [6].

The most important advantage of using matrices is that any number of color transformations can be composed using standard matrix multiplication. If the input image is in a non-linear brightness space RGB, colors must be transformed into a linear space before these matrix operations are used [9].

We use in our work two kinds of images, Intensity images which is a gray scale images used in surface defects detection purposes, and RGB color images which require a three-dimensional array, where the first plane in the third dimension represents the red pixel intensities, the second plane represents the green pixel intensities, and the third plane represents the blue pixel intensities. MATLAB by default, stores most data in arrays of class double. The data in these arrays is stored as double precision (64-bit) floating-point numbers [7] and [8].

3.1 Digital Intensity images for Surface defects detection

Because it is not necessary to take a color images to detect or determine the surface defects laid on the fired ceramic tiles also because of the large size in memory the color images took we use here the digital images for the fired ceramic tiles as intensity images. An intensity image is a data matrix, I, whose values represent intensities within some range. MATLAB stores an intensity image as a single matrix, with each element of the matrix corresponding to one image pixel. The matrix can be of class double, uint8, or uint16. The elements in the intensity matrix represent various intensities, or gray levels, where the intensity 0 usually represents black and the intensity 1, 255, or 65535 usually represents full intensity, or white [10].

3.2 Digital RGB images for Color defects detection

An RGB image, sometimes referred to as a “true color” image, is stored in MATLAB as an m-by-n-by-3 data array that defines red, green, and blue color components for each individual pixel. RGB images do not use a palette. The color of each pixel is determined by the combination of the red, green, and blue intensities stored in each color plane at the pixel’s location. This yields a potential of 16 million colors. The precision with which a real-life image can be replicated has led to the commonly used term “true color image.”

An RGB MATLAB array can be of class double, uint8, or uint16. The three-color components for each pixel are stored along the third dimension of the data array. To further illustrate the concept of the three separate color planes used in an RGB image, the code sample in (Figure 1) creates a simple RGB image containing uninterrupted areas of red, green, and blue, and then creates one image for each of its separate color planes (red, green, and blue). It displays each color plane image separately, and displays the original image [10].

Notice that each separated color plane in (Figure 1) contains an area of white. The white corresponds to the highest values (purest shades) of each separate color. For example, in the “Red

Plane" image, the white represents the highest concentration of pure red values. As red becomes mixed with green or blue, gray pixels appear. The black regions in the image shows pixel values that contain no red values, i.e., R == 0.

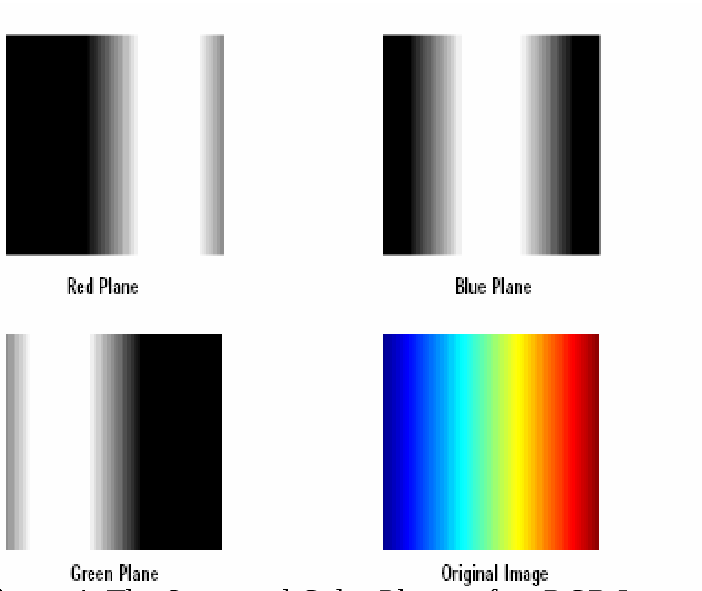


Figure 1. The Separated Color Planes of an RGB Image

Finally, we could say when the RGB stored as in class Unit 8, and Unit 16, the image is an m-by-n-by-3 array of integers in the range [0, 255] or [0, 65535]. However, if it is stored in class double, the image is an m-by-n-by-3 array of floating-point values in the range [0, 1]. (Figure 2) shows the RGB color cube for Unit 8 image analysis.

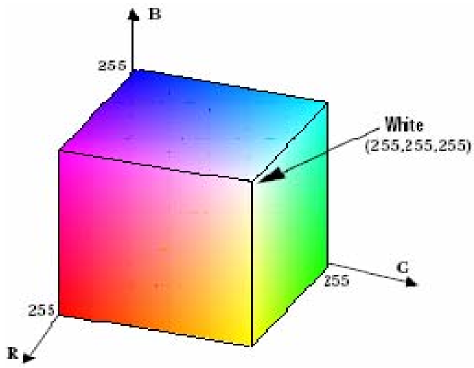


Figure 2. RGB color cube for Unit 8 images

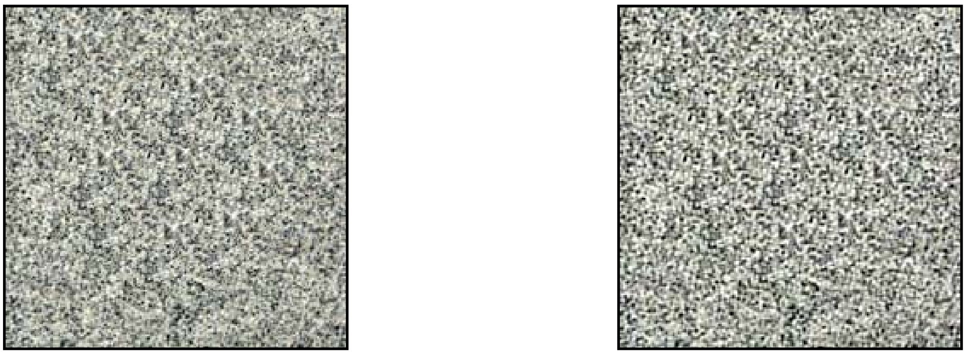
4. Template Matching

Due to their time–frequency localization properties, discrete wavelet transforms have been proven appropriate starting points for the classification of the measured signals. They allow the extraction of richer problem-specific information from sensor signals than earlier methods for many practical applications [11].

TEMPLAR is an iterative, linear time algorithm that combines the edge detection property of wavelets with MDL (Minimum Description Length) complexity-regularization to learn a low dimensional template that is automatically inferred from the data. Once the template has been learned, the resulting model can be used for pattern synthesis or pattern classification. TEMPLAR enables a large reduction of the wavelet transform data while retaining problem-specific information, which facilities an efficient pattern recognition process.

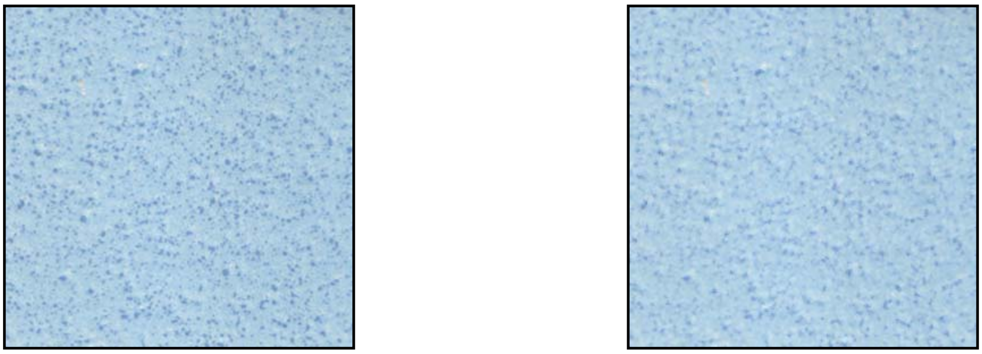
Using the principles of wavelet 2D analysis by the TEMPLAR software, which creates a clear and clean template image from four to thirty-six images, could be taken for the reference defect free ceramic tile image.

Generating the artificial template from training data, which contains randomly translated, noised and rotated tile images, with variable background, and lighting conditions. We observe that the final template does not represent any of the clutter present in the training images. We will see in the next figures the difference between the original reference tile images and its artificial templates for the same tile's images [12].



(a) (b)

Figure 3. (a) Original tile image (Series 1) (b) Artificial template for tile image (Series 1)

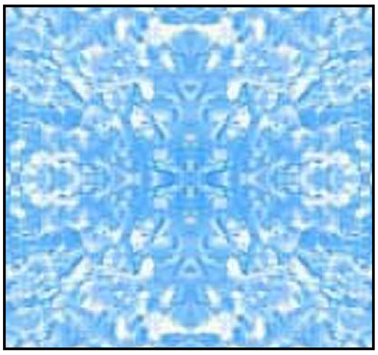


(a) (b)

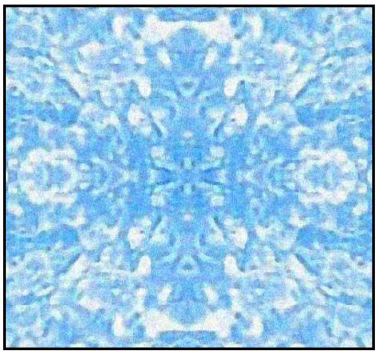
Figure 4. (a) Original tile image (Series 2) (b) Artificial template for tile image (Series 2)

(a) (b)

Figure5. (a) Original tile image (Series 3) (b) Artificial template for tile image (Series 3)

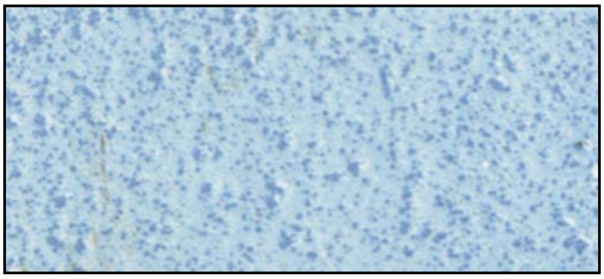


(a)

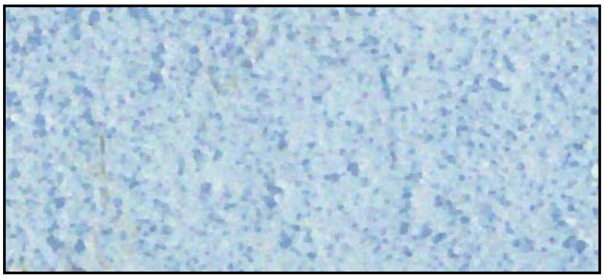


(b)

Figure 6. (a) Original tile image (Series 4) (b) Artificial template for tile image (Series 4)



(a)



(b)

Figure 7. (a) Original tile image (Series 5) (b) Artificial template for tile image (Series 5)

Template matching uses correlation. Correlation subtracts the mean and generally does normalize. For discrete images, always requires a specific scale. "Inner scale" is the original pixel grid. Size of the kernel determines scale. We assume that the original reference image for the fired ceramic tiles and the artificial template are the background for any correlation operation.

5. Surface defect detection

A subtraction algorithm used here between the defect free tile image (reference image) and the defective tile image. The reference image is considered as a background image. We can use an artificial template for the defect free tile image also as a background image. Because of the images stored as arrays (i.e. matrices) so, the subtraction will be contrary between each element in the two matrices of the two images.

We apply this algorithm on many series of tiles where they are plain tiles and textured tiles. Now subtract the background image from the original image to create a uniform image containing only the defect. First, change the storage class of I (Intensity image) to double, because subtraction can only be performed on double arrays.

I = im2double(I); % Convert I to storage class of double

Now subtract (background image) from I and store it in a new array, I2.

I2 = I – (background); % Subtract the background from I

Subtracting (background) from I may yield some out-of-range values in the image. To correct the dynamic range of pixel values, use the max and min functions to clip pixel values outside the range [0,1].

I2 = max(min(I2,1),0); % Clip the pixel values to the valid range

Now display the image with its uniform background. The ease with which we can subtract one image from another is an excellent example of how MATLAB matrix- based design makes it a very powerful tool for image processing [8].

6. Color defect detection

Whatever their chemical composition, whatever their mechanical properties, ceramic tiles are most often selected by the users according to their aesthetical properties. Mean prevailing color, colored patterns, color texture are important features to be controlled by the producer in order to fully satisfy his customers [13]. Some colored patterns must be recognized and considered as defects. Commonly detected defaults in commercialized machines are:

1. Large-area and local color variations
2. splintering
3. stains, dots, dirt
4. color blobs

This is why automated quality control systems must be able to measure the shade of a tile with precision and reliability. There are various marketing policies concerning embedded imaging devices [14].

Since each color has different sensitivity and responsivity characteristics, it is necessary to tune each color in the camera for the maximum dynamic range of all colors for a given light source or colored tile [15]. However, it is not possible to perform robust color measurements without using an adequate lighting system. In a few words, the lighting must be perfectly homogeneous, stabilized, diffuse and powerful.

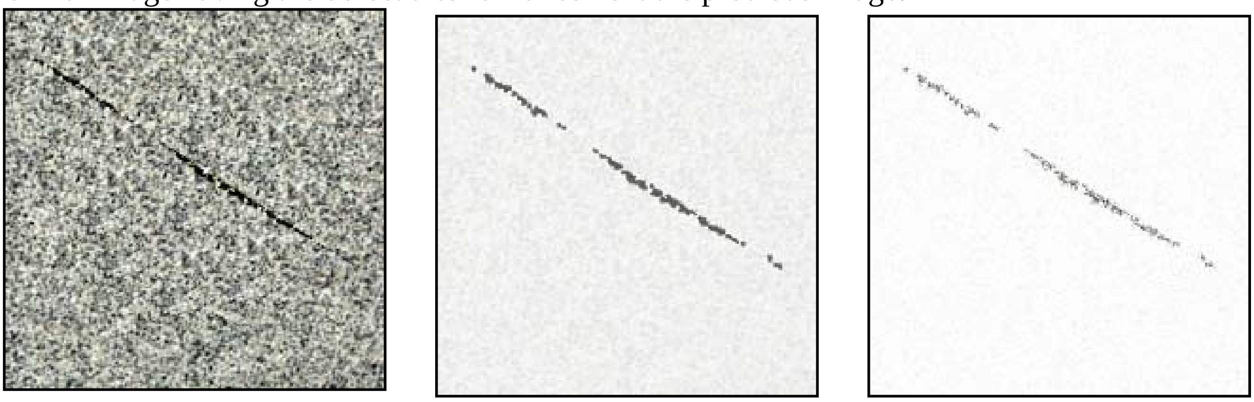
The main work here is making the correlation for each item in the three matrices R, G, and B between the original reference images for fired ceramic tile (defect free tile image), the artificial template and the defective tile image.

The result of correlation operation is a new image containing only items with the same size of the main matrices values at pixels, which have the defect. We can control the threshold of correlation to be more sensitive to small variations or less sensitive to small variations up to classes we want or accuracy achieved by this algorithm. We apply this algorithm on many batches and series for fired ceramic tiles where they are plain and textured fired ceramic tiles.

7. Experimental results

The two techniques have been developed for the detection of various range of ceramic tile defects (Surface defects and Color defects). We have described the algorithm used in detecting the surface defect including many types of defects such Cracks, Long cracks, Spot, and Blob defects.

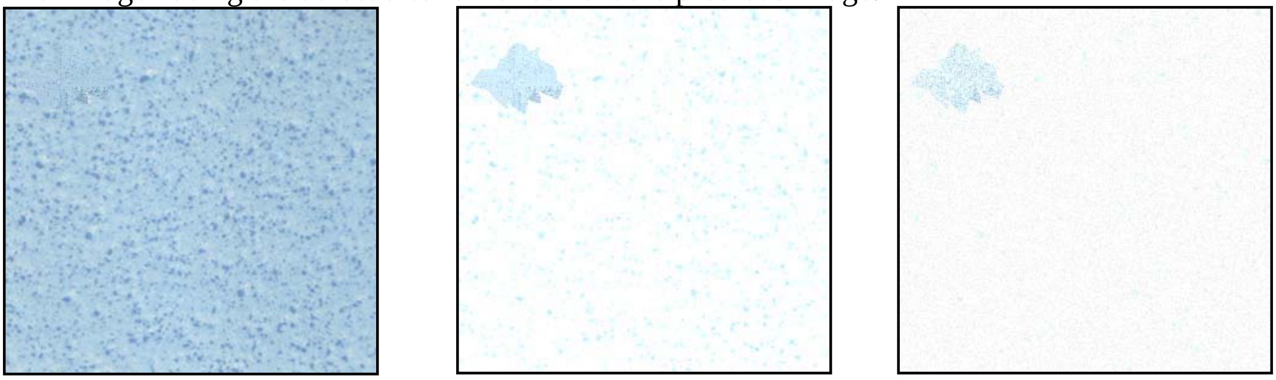
(Figure 8a) shows the Long crack defect in the defective tile image, (Figure 8b) shows the new resultant image using the detecting algorithm having only the defect and (Figure 8c) shows the final image having the defect after enhancement the previous image.



(a) (b) (c)

Figure 8. (a) Long crack defective tile image (b) Isolated defect (c) Isolated defect with enhancement

(Figure 9a) shows the Blob defect in the defective tile image, (Figure 9b) shows the new resultant image using the detecting algorithm having only the defect and (Figure 9c) shows the final image having the defect after enhancement the previous image.



(a) (b) (c)

Figure 9. (a) Blob defective tile image (b) Isolated defect
(c) Isolated defect with enhancement

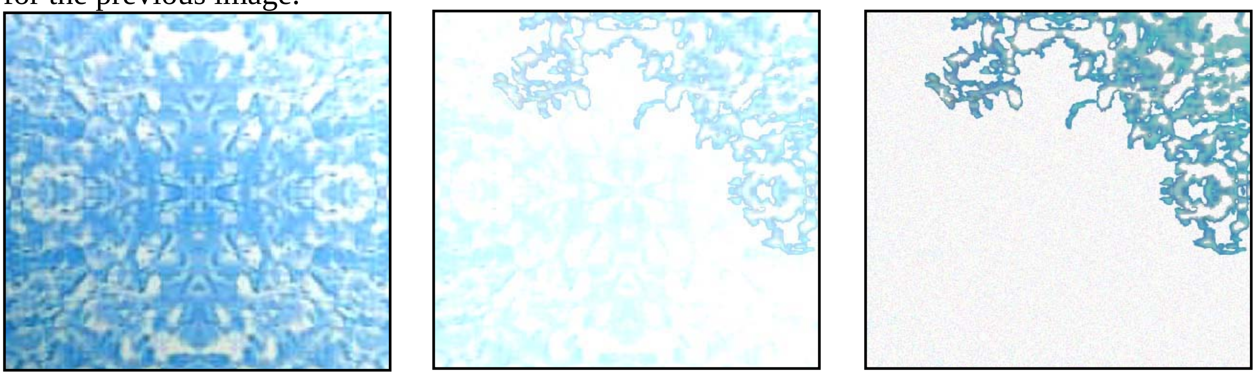
(Figure 10a) shows the Crack defect in the defective tile image, (Figure 10b) shows the new resultant image using the detecting algorithm having only the defect and (Figure 10c) shows the final image having the defect after enhancement the previous image.

(a) (b) (c)

Figure 10. (a) Crack defective tile image (b) Isolated defect
(c) Isolated defect with enhancement

Color defects detecting algorithm applied on many tiles containing several color defects like Color variations, Blob color, and Dirt.

(Figure 11a) shows the Color variation defect in the defective tile image, (Figure 11b) shows the resultant image when applying the detecting algorithm also it shows the location of defects and its size, and (Figure 11c) shows the final image having the defect after enhancement for the previous image.



(a) (b) (c)

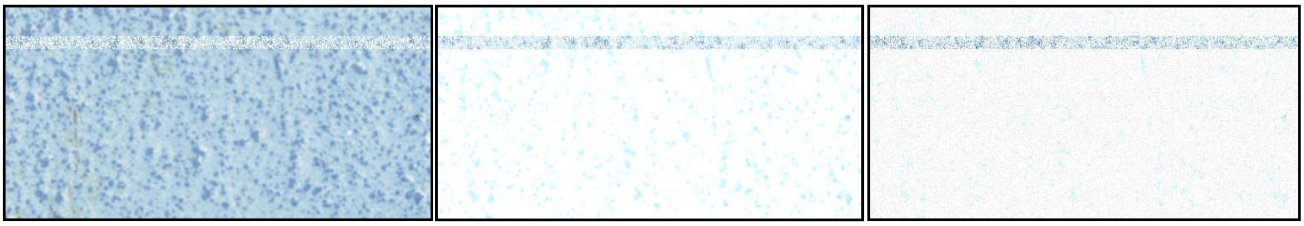
Figure 11. (a) Color variation defective tile image (b) Isolated defect
(c) Isolated defect with enhancement

(Figure 12a) shows the Blob color defect in the defective tile image, (Figure 12b) shows the resultant image when applying the detecting algorithm, also it shows the location of defects and its size, and (Figure 12c) shows the final image having the defect after enhancement the previous image.

(a) (b) (c)

Figure 12. (a) Blob defective tile image (b) Isolated defect
(c) Isolated defect with enhancement

(Figure 13a) shows the Dirt color defect in the defective tile image, (Figure 13b) shows the resultant image when applying the detecting algorithm, also it shows the location of defects and its size, and (Figure 13c) shows the final image having the defect after enhancement the previous image.



(a) (b) (c)

Figure 13. (a) Dirt color defective tile image (b) Isolated defect
(c) Isolated defect with enhancement

The result of the project is a prototype analyzer technique with some major simplifications compared to the solutions currently available on the market using an algorithm for detecting the defects in fired ceramic tile. The acquisition technique allows the system to be installed without having to make mechanical or electrical modifications to the sorting line. These results translated indirectly to a lower costs and means that the system can be moved when required.

8. Conclusions

We introduce two algorithms for isolating the surface defects and color defects displayed in new images for the classification process. Automated sorting systems would bring numerous benefits to the entire sector with major economic advantages. We apply the new algorithms on a many batches and series of fired ceramic tiles. Using the new algorithms keep miss sorting at extremely low levels.

We succeeded in isolating different kinds of defects in ceramic tiles images including the surface defects such Cracks, Long cracks, Blobs, and pinhole also color defects like Blob color, Dirt, and color variation defects. Using the new images, we could calculate the area of defects and distribution of the defect adding this factor to classification algorithm to classify the tiles to one of determined classes: Class I, Class II, Class III, and Waste tiles. Automated sorting systems would bring numerous benefits to the entire sector with major economic advantages, also guarantee product quality, increase plant efficiency and reduce fixed and periodic investments.

9. References

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