CERAMIC TILE INSPECTION FOR COLOUR AND STRUCTURAL DEFECTS

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ABSTRACT

The ceramic tiles manufacturing process has now been completely automated with the exception of the final stage of production concerned with visual inspection. This paper is concerned with the problem of automatic inspection of ceramic tiles using computer vision. It must be noted that the detection of defects in textured surfaces is an important area of automatic industrial inspection that has been largely overlooked by the recent wave of research in machine vision applications. Initially, We outline the benefits to the tile manufacturing industry. This is followed by a categorisation of typical tile defects. Next, we review a number of techniques recently developed to detect various kinds of defects in plain and textured tiles. The techniques range from pin hole and crack detectors for plain tiles based on a set of separable line filters, through textured tile crack detector based on the Wigner distribution and a novel cojoint spatial-spatial frequency representation of texture, to a colour texture tile defect detection algorithm which looks for abnormalities both in chromatic and structural properties of textured tiles. The above automatic inspection procedures have been implemented and tested on a number of tiles using synthetic and real defects. The results suggest that the performance is adequate to provide a basis for a viable commercial visual inspection system.

1 INTRODUCTION

The ceramic tiles industrial sector is a relatively young industry which has taken significant advantage of the strong evolution in the world of automation in recent years. All production phases have been addressed through various technical innovations, with the exception of the final stage of the manufacturing process. This is still performed manually and is concerned with visual surface inspection in order to sort tiles into distinct categories or to reject those found with defects and pattern faults. This paper addresses the problem of defects and pattern faults by automatic inspection and we review a number of techniques developed to detect various defects in plain and textured tiles.

The research effort expended upon the problem of objectively inspecting, analysing and characterising ceramic tiles is easily justified by the commercial and safety benefits to the industry:

- automation of a currently obsolete and subjective manual inspection procedure
- significant reduction for the need of human presence in hazardous and unhealthy environments
- more robust and less costly inspection
- higher homogeneity within sorted classes of products
- increased processing stability and improved overall production performances through the removal of a major bottleneck
- continuation and consolidation of the leadership currently enjoyed by the European Community in this area

The late rise of the ceramic tile industrial sector means that there has been next to no attempts to automate final product quality inspection. Finney et al.[1] have reported their research on ceramic tableware inspection. The authors discuss the detection of one type of fault only by analysis of the image intensity histogram. In this paper, we present a number of different faults and a range of techniques employed to detect them. The techniques range from small pin-hole and crack detectors for plain tiles, based on a set of separable line filters, through textured tile crack detectors based on the Wigner distribution and a cojoint spatial/spatial frequency representation of texture, to a colour texture defect detection algorithm which looks for abnormalities both in chromatic and structural properties of textured tiles.

2 TILE DEFECTS

The inspection for defect detection has to be carried out at considerable rates of the order of two tiles per second. The objective of inspection is tile classification on the basis of two parameters, namely defects and colour grading. Depending on the number of defects and their dimensions, the tiles are grouped into:

- First Class (none or very few acceptable defects)
- Second Class (few but still acceptable defects)
- Waste (unacceptable defects)

Some of the most common and anti-aesthetic defects found on both plain and textured tiles can be categorised as cracks, bumps, depressions, pin-holes, dirt, drops, ondulations, and colour and texture defects. These are presented in more detail in Table 1.

After defect detection, the inspection process continues with colour shade grading to ensure uniformity of the chromatic properties of the finished product. Details of automatic colour grading of ceramic tiles can be found in a paper by Boukouvalas et al.[2].

3 DEFECT DETECTION ALGORITHMS

In this section we describe several approaches for detecting different types of features in tile images. Later in section 5 we map these features to defects and present more details, including experimental results on the application of each approach to specific tile defects.

3.1 Line Detection using an Optimal Line Filter

The types of lines representing defects such as long cracks are wide linear structures in contrast to lines obtained from step-edge or ramp-edge filters. The method employed here was developed and reported by Petrou[3]. It consists of two 1D convolutions, in the horizontal and vertical directions respectively. Local maxima indicate the possible presence of a line and trigger the hypothesis that a line is present. The shape of the output signal around a local maximum is compared with the expected shape if a line was present in order to confirm or reject the hypothesis. The convolution filters can be optimised to identify features of up to several pixels wide. Also, they will detect linear features with widths within a factor 1.5 of the width of the feature for which the filters were optimised.

3.2 Spot Detection using an Optimal Spot Filter

On light-coloured plain tiles, small, spot-like faults are of reasonably high contrast against the background. However, due to various sources of noise, e.g. non-uniform illumination, a simple threshold will not serve as an adequate solution to their detection. Thus, an adaptation of the line filter method from section 3.1 was developed for spot-like defects. The only difference is that the tile image is convolved with only one filter which is optimised for spot profiles. The spot peaks thus enhanced are extracted by thresholding.

3.3 Wigner Distribution

In the context of pattern recognition, the signatures of regular patterns can be fairly easily isolated in either the spatial or spatial frequency domain. Spatial frequency analysis is often preferred as it both decomposes the image into individual frequency components and establishes the relative energy of each component. Thus noise effects are also more easily separated. However, in a very randomly textured image, there is no deterministic placement of primitives and no easily identifiable characteristic frequencies of the texture. Thus, defects such as cracks are very difficult to isolate in the frequency domain alone.

Hence, we use the cojoint spatial and spatial frequency representation of the Wigner Distribution[4]. This enhances pattern separability as the patterns' signatures have disjoint support regions in the cojoint representation. According to this method, at each pixel position (x, y) we calculate the Fourier transform of a non-linear combination of pixel values within a window of size $N \times N$ centered at pixel (x, y):

$$W(x,y,p,q) = \sum_{\alpha=-N}^{N} \sum_{\beta=-N}^{N} f(x+\alpha, y+\beta) f(x-\alpha, y-\beta) exp\left(\frac{-j2\pi(p\alpha + q\beta)}{2N+1}\right) \tag{1}$$

where $p, q = 0, \pm1, ..., \pm N$, α and β are spatial displacement parameters, and $f(x, y)$ is the tile image. The Wigner distribution defined above is a real function as it is the Fourier transform of a symmetric function and its components constitute the feature vector at each pixel position. Also, all local Wigner spectral components are normalised by their corresponding dc component, $W(x, y, 0, 0)$, so that only the general shape characteristics of the spectrum are captured. This arose from empirical findings[5] which showed that crack features are encapsulated by the general shape of the spectrum only and not by the exact feature values.

During the off-line training stage, the pseudo Wigner spectrum at each pixel position of a defect-free image is calculated. The covariance matrix of these local features can be singular. Singular value decomposition is used to keep only the most significant features for each pixel and the statistical distribution of these features is computed from the defect-free image. During the testing stage, the Mahalanobis distance of the feature vector of each pixel from this distribution is calculated. The values of this distance are used to form a residual map image. This image is subsequently processed by the optimal linear filter described in section 3.1 to detect the cracks.

3.4 Chromato-Structural Defect Detection

This technique was developed[6] to detect both colour and texture-formation defects in randomly textured ceramic (and granite) tiles. It is based on the image colour and texture information and is a classification solution also consisting of a training and a testing stage.

Using a perfect tile during the training stage, the various colour categories present in the defect-free tile can be identified with the aid of K-means (or ISODATA) clustering in RGB space. The number of these clusters is chosen to be high so that over-segmentation into chromatic classes is obtained, thus minimising (and eliminating) the under-segregation error. Next, these clusters are transformed into CIE-Luv uniform colour space for perceptual merging, i.e. merging of small clusters into super-clusters using Euclidean distance. This is consistent with the fact that Euclidean distance in CIE-Luv uniform colour space reflects perceptual colour discrimination more accurately. Thus, the image is segregated into chromatic categories which are perceptually uniform.

The image can then be split into a stack of binary images one for each chromatic category. We perform morphological smoothing on each binary image to remove noise before characterising the structure of the left-over blobs. For each blob we compute as structural features its area, perimeter fractality, elongatedness, and some spatial information about the distribution of other blobs around it. Finally, assuming that these attributes are normally distributed, we extract their mean and covariance matrices and save them for the testing phase.

During testing, the image pixels are classified into the chromatic categories defined during the training stage using the nearest neighbour rule. Any unclassified pixels are rejected and considered as colour defects. Morphological smoothing is then performed on each colour category binary image. The structural features of each resulting blob are then computed and any blob-like texture defects are identified by means of the Mahalanobis distance function using the structure statistics saved in the training phase.

4 TILE IMAGE CAPTURE AND SENSOR RESOLUTION

Given the extremely small sizes of some of the defects, it is imperative that a camera with very high resolution is used. For example, we need to detect holes of size $0.2mm$ on tiles of size $200 \times 200mm$. For the final system, the intention is to use both a colour camera and a black and white camera of very high resolution for detection of colour defects and all other defects respectively. However, in our experiments reported here, we used a Canon CLC 500 flatbed scanner by placing the tiles directly on the scanner. This provides fairly sharp images of resolution 1024×682, although they do suffer from non-uniform scanning illumination as well as other forms of noise. Nevertheless, we still obtained very good results which are presented in the next section.

On very dense and randomly textured tiles some defects are too small even after close and lengthy examination by human inspectors. These defects are too well hidden within the random texture primitives of the tile. The same difficulty arises for dark plain tiles given the present noisy scanning method used. For these particular cases we make use of the specularly reflective properties of the surface of a ceramic tile to view only the defects. A perfect tile is expected to reflect light at the same angle as it came in. Any defects causing an uneven surface, such as cracks, bumps, and depressions, will reflect light in a different direction to the rest of the surface (Figure 1). Thus, by positioning the camera where reflected light is not expected, any light seen by the camera can be appertained to defects. Once an image is captured as such, our techniques can be applied to them as before. For this purpose we used a standard CCD camera with a 512×512 resolution.

5 RESULTS

The tiles used in our experiments are of size $200 \times 200mm$ and are either plain or textured. The colours of plain or textured tiles are expected to span a wide range. In the images shown in this paper, some defects may not be easily visible and we have randomly encircled some of them for saliency. In most defect images a dilation operation is carried out to enhance the results. All detected faults correspond to true faults.

5.1 Small spots

It can be seen from Table 1 that some faults are of extremely small and similar dimensions. This similarity allows defects such as very small cracks, depressions, pin-holes, dirt, and small drops to be categorised together and detected as small spots. Also, these faults are primarily visible only on light plain tiles or lightly-textured tiles captured using the Cannon scanner. Examples of plain white, plain yellow, and lightly textured tiles with detected defects are shown in Figures 2-8. In Figures 9 and 10 images of textured tiles captured using the method illustrated in Figure 1 are displayed. Note that the real texture of the tiles is not visible as light is only received from the defective areas. We used the optimal spot detector in all the cases in Figures 2-10. The filter is tuned on a corresponding perfect tile before application during the test stage.

5.2 Short and long cracks

We had no examples of tiles with real defects of such nature, so we superimposed such defects on images of real tiles to exemplify the power of our algorithm.

In Figures 11 and 12 two textured tiles are shown with progressively longer cracks; Figure 11 contains a one cm and rather wide crack and Figure 12 contains a thin (single pixel width) crack running almost across the entire length of the tile. These were both detected by using the modified pseudo Wigner distribution and optimal line filter post-processing (displaying the capability of the filter in detecting lines of various widths). We experimented with various window sizes for the windowing function of the Wigner distribution and found a 7×7 size provides the best discrimination of defects.

5.3 Water Drops and Ondulations

Both Figures 13 and 14 show the application of the chromato-structural defect detection algorithm to plain white tiles with water drop and ondulation defects.

5.4 Random Texture Abnormalities

Figures 15 and 16 also show texture abnormalities detected using the chromato-structural defect detection algorithm. For example, the image in Figure 15(a) is split into 11 distinct colour categories and following morphology and Mahalanobis distance comparison of blob characteristics, the faults in Figure 15(b) are detected.

5.5 Colour

The image in Figure 16(a) contains a spot-like colour abnormality besides the obvious large blob defect. It can be seen in Figure 16(b) that this spot defect was also detected at the time of colour category classification when it was rejected as a colour not identified during the training process. Figure 16(c) shows a 5×5 zoomed region of the blue-band of the image around this defect to demonstrate the sensitivity of the algorithm.

6 SUMMARY AND CONCLUSIONS

The automation of the inspection stage will play a crucial role in advancing the development of the ceramic tile manufacturing process. In this paper we have shown a number of techniques developed for the detection of a multifarious range of ceramic tile defects.

We described optimal spot and line detectors used independently and as post-processing stages to our other techniques. The Wigner distribution used for crack detection is effectively the Fourier transformation of a non-linear function of the tile image function. It is a very accurate approach but it is computationally demanding. We have considered alternative and faster methods which will be reported soon. We also presented a framework for the detection of defects in randomly textured images based on their colour and texture information. Also, the approach has addressed the problem of colour segmentation as a by-product.

It is hoped that the considerable advance achieved in overall production through the automation of ceramic tile inspection will eliminate an estimated 70-80% customer complaint rate regarding product quality[7]. Furthermore, the spin-offs of the findings of this project can have an impact in other industrial fields presenting similar problems; for instance in the textile industry for defect detection, loose threads detection, and colour shading classification on fabrics, the agro-food industry for visual analysis of crops such as apples/oranges/pears/etc, the wood industry for texture and colour classification, and in a number of other industries.

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7 REFERENCES

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Table 1 - Typical Ceramic Tile Defects

Defect	*Description*	*Size*
cracks	breaks, slits, fissures and cuts	few tenths of mm to some cms
bumps	reliefs of the glazed surface with respect to the planar surface of tile	few tenths to some mms
depressions	general depression of glazed surface with a circular shape	radius usually $<$5mm
holes	pin-tips, small bubbles, holes, craters	minimum 0.25mm
dirt	dust particles or dried glaze residuals	few tenths to some mms
drops	drops during glaze application	few tenths to very low mms
water drops	irregular shapes (condensation drops)	few mms to cms
ondulations	longitudinal bars, rills and imperfect glaze laying	widths and lengths of few cms
colour	spots of various colours	few tenths of mm to cms
texture	blobs discernible from regular texture	few tenths of mm to cms

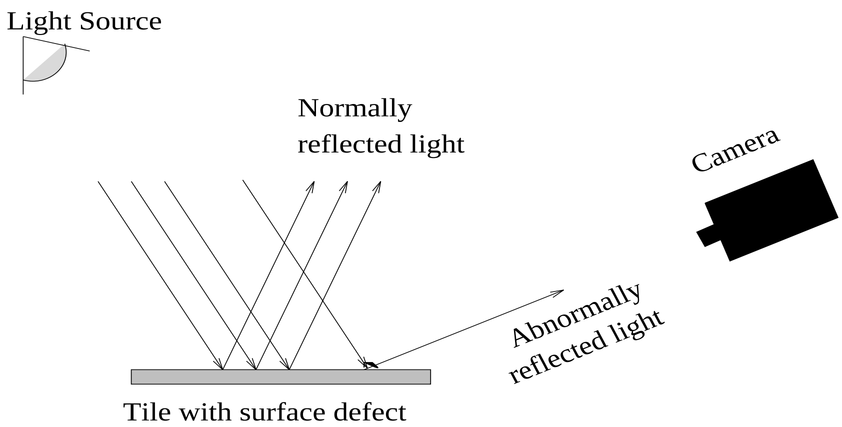


Figure 1: Special image accquisition arrangement for certain defects

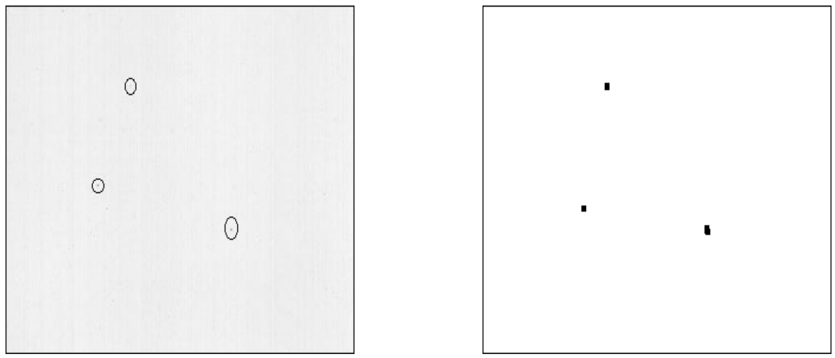


Figure 2: Plain white tile with small crack and spot defects

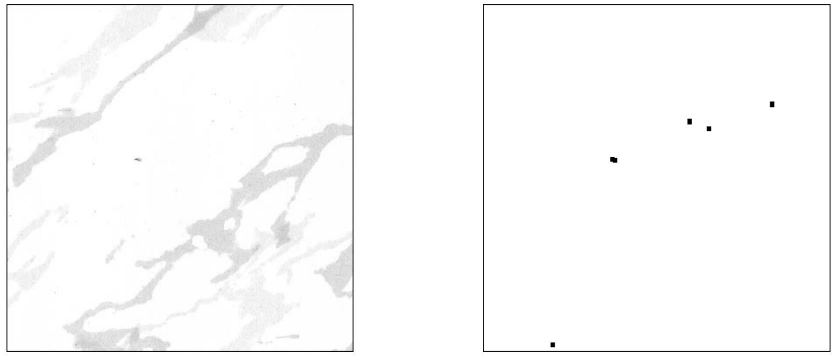


Figure 3: Carrara light-textured tile with crack and spot defects

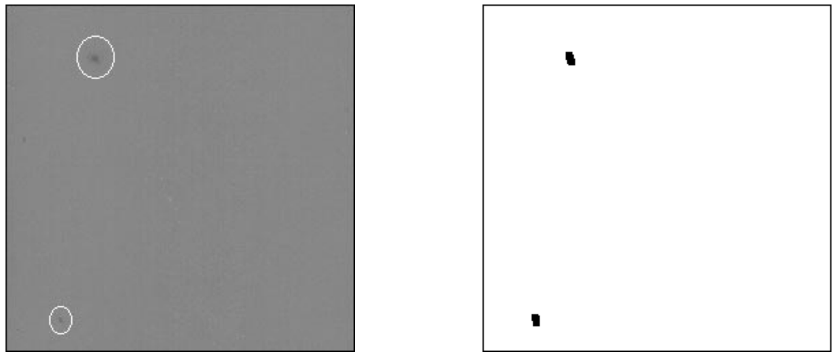


Figure 4: Plain yellow tile with depression defect

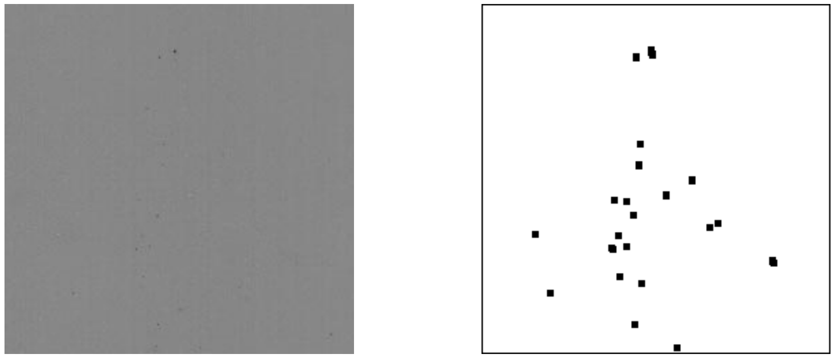


Figure 5: Plain yellow tile with dirt defects

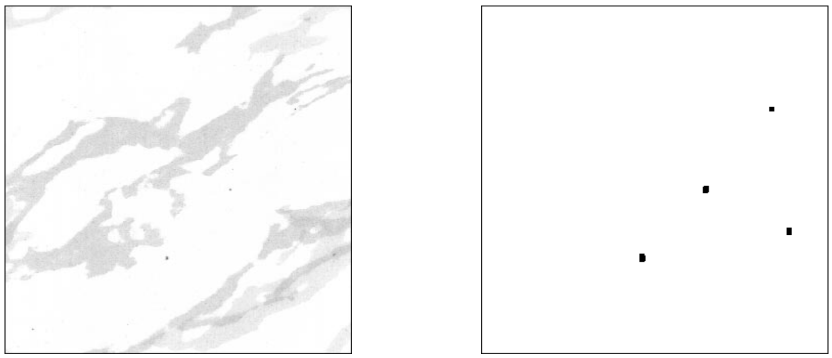


Figure 6: Carrara lightly textured tile with holes defects

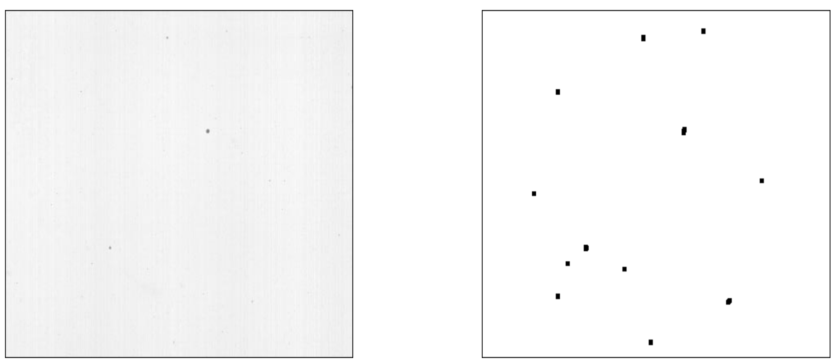


Figure 7: Plain white tile with drops defects

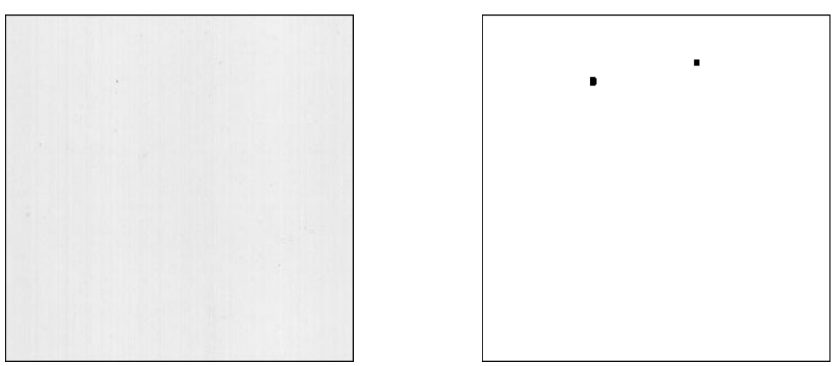


Figure 8: Plain white tile with pin-hole defects

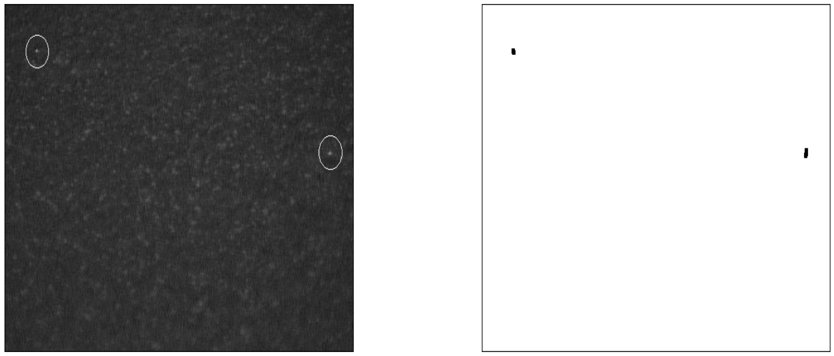


Figure 9: Donizetti textured tile with crack and bump defects

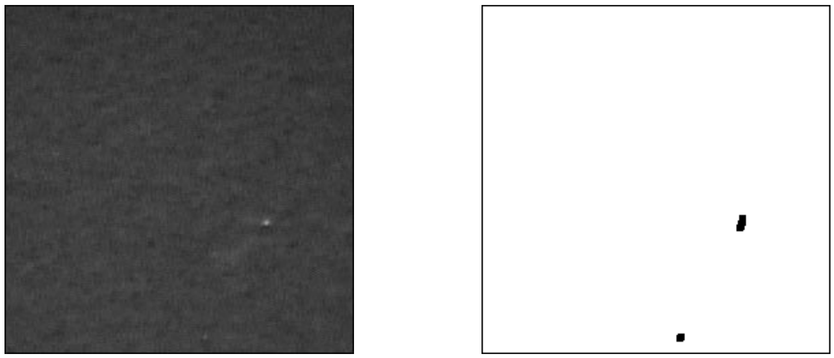


Figure 10: Puccini textured tile with bump defects

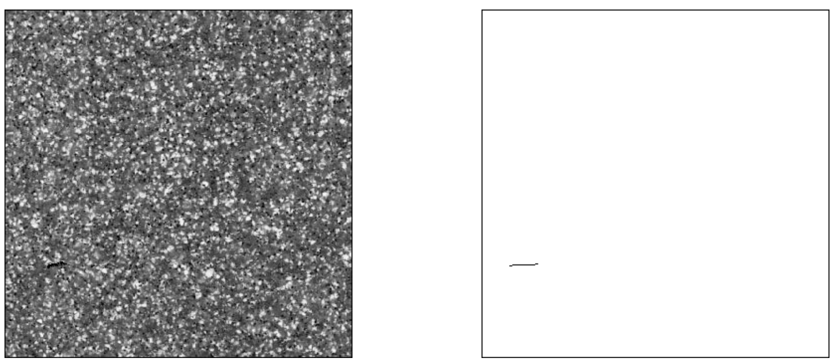


Figure 11: Rossini textured tile with short crack defect

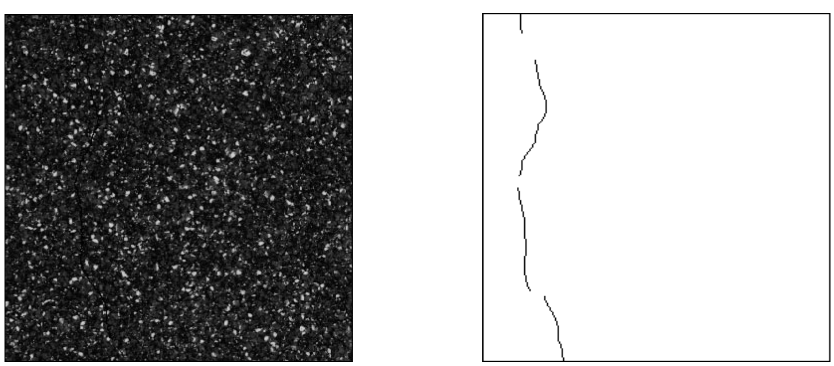


Figure 12: Donizetti textured tile with long crack defect

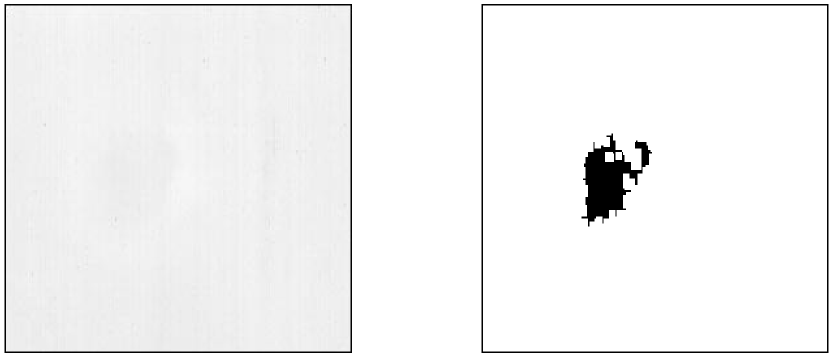
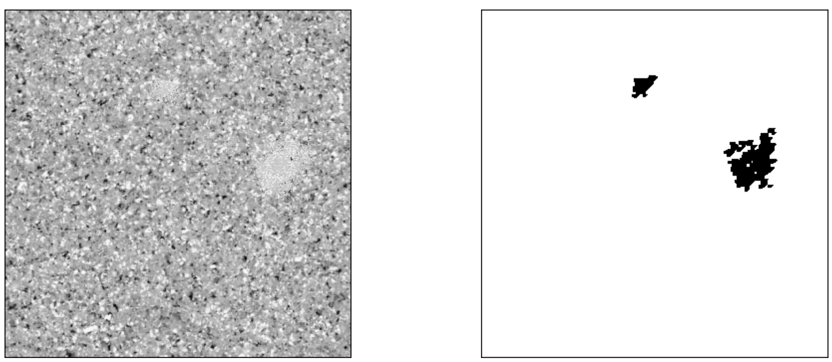


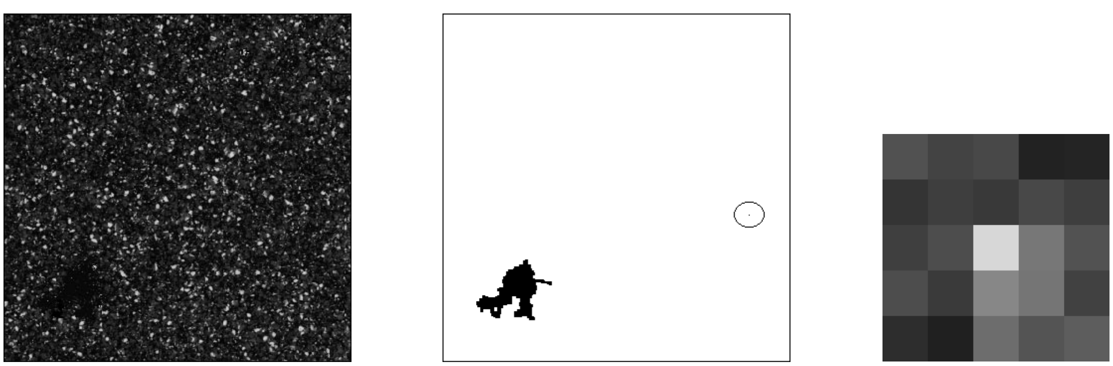
Figure 13: Plain white tile with large water drop defect

Figure 14: Plain white tile with ondulation defect



(a) (b)

Figure 15: Puccini textured tile with blob defect



(a) (b) (c)

Figure 16: Donizetti textured tile with blob and colour defects