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Providing a Method for Tile Troubleshooting Using Thin Display and Image Processing

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Abstract

Due to the rapid development of tile and ceramic production industry and burgeoning increment of demand, quality assessment without the presence of human operator is one of the challenges of this industry. So, to identify flaws in the surface of tile in the production process has been proposed. According to the high variability in color and texture in tiles, this method has been able to specify any inconsistency or heterogeneity in conventional texture of the tile and to provide the tile a qualitative measure or identifies the ruined part of it based on this inconsistency or heterogeneity. In the proposed method, by combining the wavelet, statistical characteristics, derived and gradient operator we could perform a way to determine heterogeneity in the tile texture. It is because the proposed method that acts based on inconsistency in texture is independent of the tile type and therefore is applicable to any tile. Finally, this method was tested on a number of tile images and its resolution was determined. Because of the large number of features in the conducted design properties of sparse matrix was used to reduce the volume of calculations and speeding.

Keywords

Tile, Wavelet Transform, Texture Analysis, Sparse Matrix, Quality Control

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1. Introduction

In recent years, many attempts have been conducted to eliminate methods that were based on the human visual sense. Machine vision is one of the results of these attempts. It has a significant role in the industry, especially in the field of quality control of industrial products [1, 2, 3, 4, 5, 6]. However, inefficiency of optical pattern recognition system is still an important issue and fundamental challenge. Also, attempts to enhance the quality and the performance of such systems are increasing [1]. Among all machine vision systems, the optical inspection system is the most important process in quality control. The quality control process has been designed to ensure the provision of safe and high quality products to customers. Some parts of quality control process have been done in recent years. Now, these activities are automating [7, 8]. The Aim of inspecting the levels is detecting and determining parts of production levels and industrial goods that differ from the safe part of productions and goods [9]. Currently, existing process are used for the purpose of detecting flaws of a huge branch of levels such as fabric, ceramic tile, wood, steel, silicon wafers, paper and leather [2, 6, 10]. Now, all production sectors are automatically done in tile and ceramic factory except the quality control part. First step in building an automated devise is tile calibration, detecting the defects of tiles and ceramics such as cracks and spots by using vision machine. These flaws can be divided into four parts from the

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perspective the impact of imperfection on the tile.

Color defects

These are imperfections such as spots, chipping, not glazed, corner fractures and even cracks and scratches. The most important characteristic of these imperfections is that the color differs from the used colors in tile coloring [11].

Sharp defects:

Like cracks, holes, spots and stains. These imperfections are arisen in images with high contrast structures [11].

Wide defects:

Design imperfections in the patterned tiles [11].

Pattern defect:

Any disobey of the reference pattern in the patterned tiles.

1.1. Conventional Methods in Detecting Colored and Textural Defects

One of the most important parameters in scaling the textural tiles is texture uniformity on the entire surface of tile. Any irregularity in the texture can be easily detected. While there are many different textures, thus providing an algorithm that can detect irregularity in any texture is very difficult. Usually, the texture defects create stain in the images or their color differs from the colors used in tiles. Therefore, these defects are classified in defects of color, size, shape or density. The first group that is related to color defect can be obtained using methods of image detecting, but detection of the second category that is for size, shape or density Sierra requires special algorithms design [12].

The proposed algorithms for detecting color defects were mainly based on clustering colors of tiles and cluster modeling. These algorithms consist of two stages:

Feature extraction: at this stage, a model of used colors in the tiles is obtained using one or more image of perfect tiles [12].

Control: at this stage, using the obtained clusters in the previous step and the nearest neighbor law, the tile image is

Segmented with supervision and it is decomposed into a multilevel image. Each pixel in which the color difference with its cluster centre exceeds the usual limit is known as a defect.

It seems, extracting the color categories is the best and the most applicable way of detecting the color defects. So, different methods of these ideas have been used in most articles [12].

1.2. Conventional Methods in Detecting Sharp Defects of Tiles and Ceramics

Defects such as cracks, spots, holes in the tile image may create sharp edges. These imperfections are known as sharp defects. Different methods have been used to detect the sharp defects. Techniques that have been successful in detecting theses defects are divided into three categories [13].

Detection using the linear filters

The linear filters and convolutions are main algorithm of these methods. This proposed method is simple, because of high speed and low computational volume. The characteristic of these algorithms in detecting defects is their high contrast compared to the rest of image. In tiles that are uniformly stained, the performance of these methods is very impressive, but a more accurate algorithm is needed for detecting the sharp defects in other projects [14].

Plan identification in frequency space

As mentioned, the convolution methods in plans {schemes} with sharp color changes are without proper performance. Moreover, these drastic changes that their contrast is sometimes less than the defects contrast are a part of the plan. So, the defect of these tiles may not be detected regardless of the plan. In other words, due to the detection of sharp defects in such tiles, the characteristics should be extracted based on the design texture of tile. In the pattern recognition subjects, the effects of regular patterns can be easily separated in the frequency of spatial space, that analysis in the usual frequency is preferred. Because in the current method, in addition to the fact that the image is decomposed into separate frequency components, each energy is also calculated. For this purpose, the noise can be easily removed from a signal. However, the location of prototypes is not detected easily in highly random images. For this reason, removing defects such as cracks using only the information of frequency space will be very difficult [15]. Therefore, the combined frequency and spatial description of the image is used. This method will enhance the separation capability of the pattern structure, because in this way, patterns characteristic structures are separately strengthened [16]. To detect sharp defects in algorithms, the Wigner distribution can be used. In this way, a window is considered around each pixel, so that the pixel is located in the center. Then the window pixels are calculated using nonlinear combinational Fourier transform and the resulting actual distribution is normalized. It is done for maintaining only general and visual specifications of the spectrum. It has been shown that structures such as cracks are detectable by the overall shape of the spectrum and not the values of the feature vector. To detect the lines, the random distribution of these windows is used. The major problem to such algorithms is the high calculation volume. So, to implement this aim, we need a specific processor. However, this way is the most accurate method in detection of the sharp defects [14].

Morphological operators

Using optimization algorithms in this way, masks of morphological operators are selected such that its response to pattern structure occurs at the minimum amount. Then, risk threshold is calculated by applying the mask on the image. If the pixel response to the operator is over the threshold value in the control stage, the pixel can be detected a defect. Contrary to the previous algorithm, this method has very high accuracy and also appropriate algorithm speed.

Despite of the different methods for the detection of sharp defects, these algorithms are usually complementary and a combination of several algorithms is needed in a practical system [17]. Although the detection of high contrast structures by linear filters is a very old method, but the use of these methods in the detection of sharp defects tiles is a new issue. For example, a line detection algorithm to detect cracks and spots in the tiles has been used in ASSIST [15] project. In the current way, two one- dimensional line detection filters are used are applied to the image in vertical and horizontal directions [18].

Each local maximum the possibility of existence of a line and will strengthen the assumption that there is a line in that site. To verify the accuracy of the hypothesis, the output signal is compared to the expected one. The hypothesis is confirmed if the shapes are the same, and otherwise it is rejected. Optimized filters are able to detect structures with the width of a few pixels [15].This method is very fast but its problem is accuracy detection. Thin cracks (with a width of about one or two pixels) ca not be specified.

1.3. Obtaining Tile Images

To obtain a proper image of the tiles and appropriate to apply the algorithm, a camera and the right lighting and strict observance of distances is needed. For this purpose, the camera should be placed close the production line [19].

Distance from the camera usually depends on the size of tile production. For precise lighting, distance between the light source and camera should be less than the distance between camera and the tile surface. Moreover, the light source should as possible be perpendicular to the surface of the tiles, and in such a way that the lighting e is unevenly distributed in the tile and do not create shadow on its surface. To this aim, we need a camera that transfers the received image from a camera to a computer via the pass card use video converter [19]. By eliminating areas on the obtained image that are far from the mean value, the coordinate box of the tile is achieved and the background is removed [20]. At this point we have multiple images for each tile that have been formed while the tile is located in camera scope. The average image of each tile is used for noise removal. To detect flaws in colored tiles, a new algorithm based on the cluster model is proposed in [11]. Color defects are imperfections that their color varies the all colors used in different tiles. The main objective of this method is clustering colors of a perfect tile in the feature extraction level. The result is a number of cluster centers and their corresponding thresholds. The inspection stage, the colorable is applied to the image by the closest neighbor law. Colors with errors more than the corresponding threshold value belong to the defective areas are tiles [12]. Local density of the color levels pixels can be used as a desired feature in the detection. The results reveal that the proposed algorithm is able to detect the defects in a wide range of tiles and does not much computational capacity. Especially, parts of calculations including creating multi vector of the image and extracting the color levels is related to with the color defect detection process. An example is that in addition to revealing the defective area, sometimes the existing algorithms detect the surrounding area [12].

This paper has proposed a method that Is a combination of the tile sparse mapping with the purpose of identifying a wide range of defects with high speed and proper quality that covers faults of the previous methods. As shown in the introduction, all previous method s are all related to a specific type of tiles and are not applicable in all types of defects and tiles and need retraining. While this method is independent of any color, texture, material, pattern, etc.

Rest of this paper is as follows. First, the proposed method and its principles will be expressed. Then the results are simulated and compared with the other papers. The last part of the essay includes collecting results, conclusion and will be terminated.

2. Proposed Method

The proposed method of the paper contains violet and sparse matrix as well as a series of statistical properties and gradient image for detecting the tiles defects. According to the database photographs and absence of noise in the imaging, there is no need for pre-processing of images is. Obviously, changing in scene illumination and imaging conditions might have led to applying different methods, such as histogram correction and noise removal methods. Due to the light uniformity and good quality of images there is no need for pre-processing in the beginning of algorithm.

2.1. Extracting Feature

According to the practical form of this method and the lack of systematic attempts done in previous articles that were mentioned recently, a combination of different wavelet operations was used at this level. The performance of each of these two spaces and also the reason for its application method will be briefly explained. .

Due to color differences between the damaged part of the tile and the usual background color, color channel separation may improve the efficacy of the proposed method. So, these three channels are separated at the first step and of the processing are applied in parallel on the channels. Obviously, if the damage occurred only in a single color, for example, if the color of a part of the tile has been changed quite heterogeneous compared to other tissues, this should be identified as a side effect of the tile and be detected in the algorithm. So, all three channels are separately evaluated and the results are combined. An example of a color image of the database and three separated channels are shown in Figure 1.

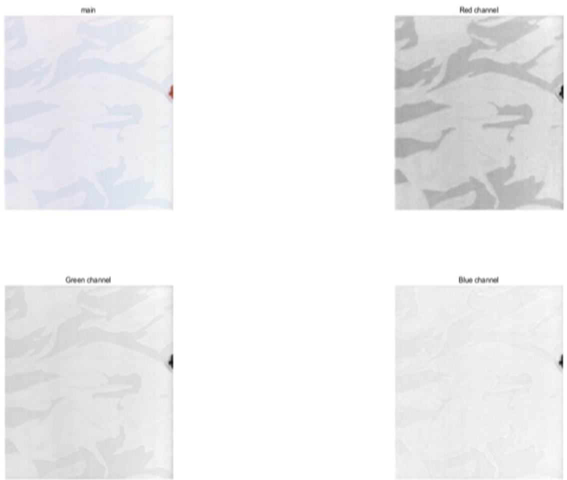

Figure 1. Sample of database images.

2.2. Wavelet Transform

After separation of color channels, features of three channels will be combined as the main vector. In the first phase, based on wavelet transform in simultaneous detection of the frequency changes and time as an efficient space, it was replaced by the Fourier transform. Among the other advantages of wavelet is determining the details of the frequency bands according to difference between the destroyed and safe parts of the image. The only ambiguity in the use of wavelet transform is determining the number of wavelet transform stages and an algorithm that the wavelet transform performs filtering based on it. Windows dimensions are important in some applications. Here, due to the relatively normal size lamb of the images the dimensions of the window was not recognized based on an important simulation parameter. So, the window dimensions were selected 8 × 8 during vacuuming.

Based on the above explanation, various wavelet functions were evaluated in the proposed method the best accuracy percentage and most efficiency was selected in terms of showing appropriate algorithm destruction. The tested wavelet functions include Daubechies (level 1to 45), Coiflets (level 1 to 5), Symlets (level 2 to 45) and the Harr wavelet transform. In the end, among all tested wavelet functions, best result in terms of accuracy and resolution was obtained by db3 algorithm.

The number of acceptable levels based on the maximum window sizes was selected 2 levels. For demonstrating output in a sample mode, the result of the wavelet transform based on db3 algorithm has been shown in Figure 2. In the case of the number of wavelet levels, it is necessary to explain that after the 3th level, the output will not have any useful information. That's because of selected window dimensions 8 × 8. Therefore the wavelet of level 2 was used in all stages. For proving this issue, the wavelet output in levels more than 2 of a sample by a db3 algorithm has been shown in fig 3. It reveals that level 3b will bring us no useful information and the quality of output image is not favorable, therefore the second level is appropriate as the number of numerical selected surface.

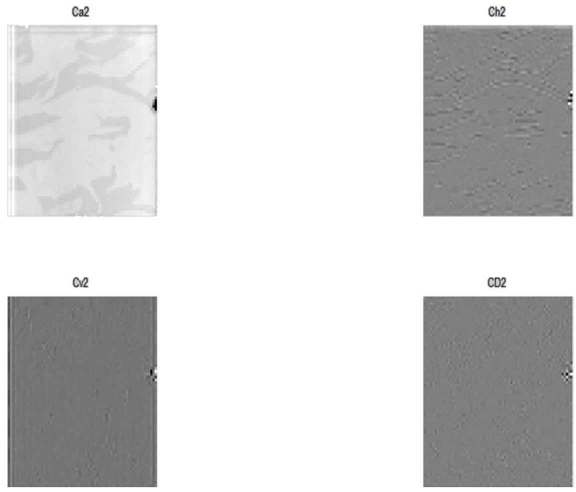

Figure 2. Wavelet transform result at level 1 based on db3 algorithms.

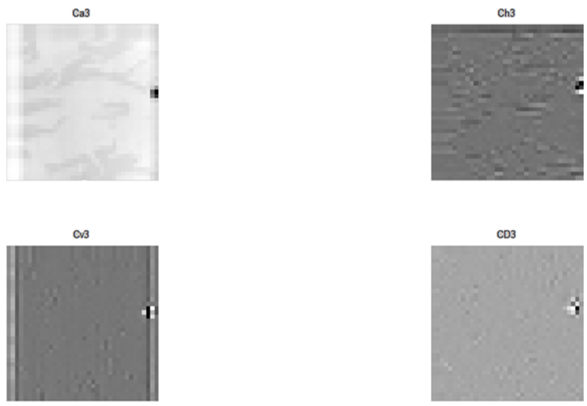

Figure 3. Wavelet output at levels above 2 for a sample image using db3 algorithms.

2.3. Suitable Feature Extraction of Wavelet

According to a previous step, overall, 7 output images is obtained between the two wavelet transform channel and this number will be 8 by considering the main image.

Based on Ramos reference 2012 [21], methods such as Entropy, energy, average set, variance set and cluster trend are used for the aim of proper extraction in the wavelet field. All of the relations represent changes in a homogenous texture and this is exactly what we need in detecting defect in the tile surface. In the formulas 1 and 2, p and μ respectively represent a M × N sized window and absolute value of probabilities, and are used for creating an input and extraction of tissue based quintet features.

$$p_{x+y}(k)=\sum_{\substack{i=1\\i+j=k}}^{M}\sum_{j=1}^{N}p(i,j) \qquad k=2,3,\ldots,M+N \tag{1}$$

$$\mu=\sum_{i=1}^{M}\sum_{j=1}^{N}\left|p(i,j)\right| \tag{2}$$

Table 1. Formulas related to the extracted features.

Formula	Descriptor
$f_1=\sum_{i=1}^{M}\sum_{j=1}^{N}p(i,j)\log(p(i,j))$	Entropy
$f_2=\sum_{i=1}^{M}\sum_{j=1}^{N}[p(i,j)]^2$	Energy
$f_3=\sum_{k=1}^{M+N}kp_{x+y}(k)$	Total average
$f_4=\sum_{k=1}^{M+N}(k-f_3)^2\,p_{x+y}(k)$	Total variance
$f_5=\sum_{i=1}^{M}\sum_{j=1}^{N}(i+j-2\mu)^2\,p(i,j)$	Cluster orientation

{Descriptor, entropy, energy, total average, total variance, cluster tendency}

Table 1 separately shows formulas related to the extracted features. Given the number of totally 8 images in this step, we will have 40 different features that will be used for calculating the final matrix. In addition to the 5 features that are of high statistical levels, we also used characteristics of mean and variance of 8-matrix and wavelet transforms as relatively efficient properties. In justifying this issue we will argued that we can expect an approximately zero variance for tiles with uniform tissue, and if the ratio of the variance to the mean increases then this ratio will be very superficial in situations where there is o destruction. Regarding this feature ad the 5 previous, we will have 7 features. Considering the 8 images we will totally have 56 images in this level.

Basic image gradient is also used for feature extraction and gradient will lead to highlighting the image changes and it also will result in extracting the edges in horizontal, vertical and diameter mode. This method can be useful in the precise detection of unwanted changes in normal tissue of the image. Consider highlighting of the tile defect in fig 4. Obviously, according to the gradient operator the tile defect is highlighted and it is clear in feature extraction phase. By adding the tile image gradient to the uses images in the feature extraction phase and having 8 images, the total number of images will be 9. Since we totally have 3 color channels, so the number of 27 images are resulted from three different channels. Five basic features of table 1, average and variance can be extracted from each image. It will lead to a 189 vector of the image characteristics. These vectors are arranged based on the 8 × 8 windows extracted from the image, and will be used to determine heterogeneity of the texture of tile image. Also, the destruction spot of the tile will be used.

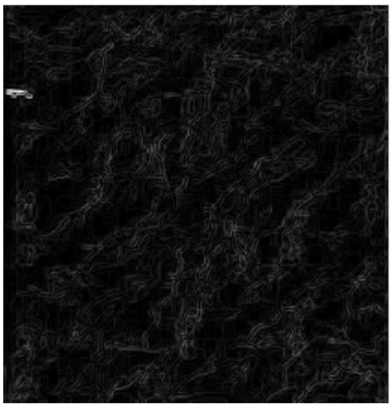

Figure 4. Gradient image of the tile.

2.4. Detecting Inconsistency

In two previous episodes it was explained that some of the text feature of the image will be interpreted by applying the Wavelet transform and the Gradient operator. These features show the texture profile. Clearly there will be an evident difference among tiles, because the pattern and used color in tiles is not similar. The obvious point in the field of destruction or defection on the tile is that the smooth normal texture of the surface will be different in other parts and the human eye can also detects specify the imperfections on the tile surface using this change.

According to this description, the extracted features including entropy, the tendency of the cluster, variance and etc are not able to show Heterogeneity in the image texture. So, after calculating these features in each 8 × 8 non- overlapping window of the image, the standardized images 256 × 256 that now have become a 32 × 32 feature matrixes due to the dimensions of the window, will be regularly arranged and then we will derive from a two- dimensional 32 × 32 matrix resulted from the image. A 189 feature vector is considered for each array of the matrix. Two- dimensional derivative is able determine changes to the adjacent neighborhoods.

To calculate the two-dimensional derivative, the operator or the Sobel mask was used. With this method the applied derivative will be able to demonstrate both horizontal and vertical changes. Also, it can easily show all the changes of an 8 neighborhood of an 8×8 window.

Table 2. Sample values of the table 1 characteristics before and after mapping.

	Name Features	Its value before mapping	Value after mapping
The second level wavelet approximation channel	Entropy	38184.39	4.582
	Energy	3968575	6.599
	Total average	558289.5	5.747
	Total variance	2.22e16	16.347
	Cluster orientation	1.61e13	13.209
	Variance	16.016	1.205
	Average	248.984	2.396

After calculating the two-dimensional derivative of the image, it can be argued that in defection points, derivative features that are more consistent with the defect are necessarily more than the rest of the image with no destruction. It should be noted that some mentioned features have high numerical value in positive and negative, and this relatively large changes may effect on the derivative efficiency. To remove these changes, all features were turned into a positive number by a simple shifting. Then the large changes were almost removed by applying logarithm to base 10. To justify it, the actual values of features before and after the mapping were shown in table 2. It reveals that by applying this mapping, features will reasonably be placed in a fair numerical interval.

2.5. Sparsity

The derivative is computed using Sobel operator for two-dimensional of the 32- matrixes of feature values vectors related to 8×8 window of the tile image. If the tissue is perfectly matches with the surrounding tissue, it is expected that derivative tends to zero in that window or cell. This issue must be true in all channels and features. Then, all derivative value per 189 available features related to different channels and properties of the image based on gradient and wavelet were completely and linearly added. It will be criteria for showing text changes caused by damage. If that reasoning is correct, we expect the derived values to be close zero and have slightly higher values than the rest in the point with damage or defect.

Obviously, if the image tissue be uniform and perfect then almost the whole derivative texture will be zero and the resulting matrix represents a zero matrix. If certain parts of the image are defected or damaged then the safe points will be zero and only a few elements of the resulting matrix will be non-zero. This is a quiet spars Matrix and its properties should be used for processing and saving it. If the matrix is processed with these small numbers, then processing speed will be descended and calculation volume will increase. That is n what we expect. If these values be set to zero and we use the properties of sparse matrix during storage, then the calculation volume will be decreased and there will be the possibility of review and correction of the line results. At this level, to demonstrate the efficiency of sparse matrix operator than the simple arithmetic operator, the processing was performed once and was normally saved. In this case, the resulting matrix was related to database set containing 38 photos and 46 MB memory. In the second phase, after changing unimportant elements to zero and removing the extra components of sparse matrix with elements of the first phase, only the space of 1.5 MB was occupied after saving. It is a reduction of about 30 times and clearly indicates that efficiency and speed calculation is greatly increased using the sparse matrix properties during saving and reloading this information.

Table 3. Shows the number of non-zero elements for top 10 features of the sample images.

	number of zero elements	number of non-zero elements	Zero percent	Percent of non-zeroes elements
Features (1)	1022	2	99.8	0.2
Features (2)	1022	2	99.8	0.2
Features (3)	1023	1	99.9	0.1
Features (4)	1023	1	99.9	0.1
Features (5)	1022	2	99.8	0.2
Features (6)	1017	7	99.32	0.68
Features (7)	1022	2	99.8	0.2
Features (8)	1021	3	99.71	0.29
Features (9)	1019	5	99.51	0.49
Features(10)	1021	3	99.71	0.29

According to the dimensions of the resulting 2- matrix after processing window with a 32- matrix and 1024 natural number, the sparseness or being zero of matrix elements can easily be determined by dividing the number of non-zero elements. As shown in table 3, based on the threshold level, number of non-zero elements is very high. Therefore to store, retrieve and re- analyze the derivative matrix effective and beneficial, using this algorithm can be beneficial.

2.6. Detection of Defect

After the stage of putting the threshold level and disregarding the elements with low range, to detect the defects considering that the size of all features are almost on a conventional level after mapping, all values are added together and then the image is drawn as a gray image. Obviously it is expected that is the non-zero elements are more in point or parts of the image then color of that region tends to be 1, otherwise 0. Finally, this color change in the grey area can be a proper criterion for heterogeneity detection and change in conventional texture of the image. Given that the conducted design is completely based on the changing structure in the texture and there has been no previous training in this field, so it is certainly a method without guide and can easily detect any change in the texture, regardless of type, color, texture and tile material.

3. Results

According to the explanations the proposed method was applied to some sample images and the results have been shown in Figures 5 and 6. Naturally, all defected images or some of them can be easily specified and it can also be a standard for tile quality based on the number of defections. Program was designed to set the highest lack of coordination in the texture is depicted and determined as a defection, provided that the number of non-zero elements of the sparse matrix in the block be more than 10. In Figure 6, the defected area has been marked with white color. This region will be clearer than the other parts of the left picture, and also it has been determined as a window in the main image. If the defect is more intense then this difference will be very evident.

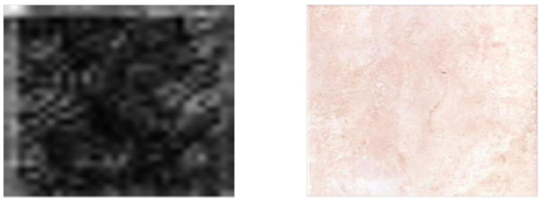

Figure 5. Safe tile and not specified defection region.

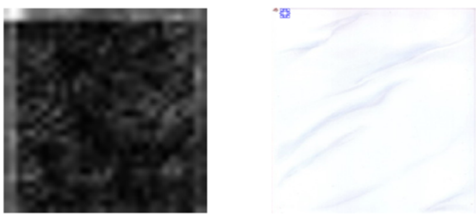

Figure 6. Defected tile and determining the area of damage.

4. Conclusions

In this article by combining wavelet operators, texture, deviation and gradient energy operator a method was designed to determine any change or heterogeneity in the conventional texture of image using the same image and without the need of previous knowledge and also detect the tile defects. Considering that average of the image texture is used as a criterion and threshold level, so this method is adaptive and has compliance adaptability in any texture, color, shape and design. To improve the method efficiency and decrease the volume of calculations, the properties of sparse matrix was used. Finally the method was implemented on the sample database images in different scenarios and its efficiency was determined.

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