Automatic Inspection of Defects in Plain and Texture Surfaces

Željko Hocenski
Faculty of Electrical Engineering
University J.J. Strossmayer in Osijek
Kneza Trpimira 2B, Osijek, Croatia
zeljko.hoc@etfos.hr

Snježana Rimac-Drlje
Faculty of Electrical Engineering
University J.J. Strossmayer in Osijek
Kneza Trpimira 2B, Osijek, Croatia
snjezana.rimac@etfos.hr

Tomislav Keser
Faculty of Electrical Engineering
University J.J. Strossmayer in Osijek
Kneza Trpimira 2B, Osijek, Croatia
tomislav.keser@etfos.hr

Abstract - The image processing used for visual inspection and quality control in a serial production is described in this paper. We used the discrete wavelet transform - DWT in our failure detection algorithm. To achieve robustness as well as good sensitivity of the algorithm, we divide the images into segments. The difference of the wavelet coefficients maxima for the given segment for images of the tile with and without defects was used for defect detection. The analysis of detection capabilities is done for different segment sizes, different detection sensitivity levels - DSL and for two orthogonal wavelets.

I. INTRODUCTION

The ceramic tiles production is a highly automated process with the exception of the final stage concerned with visual inspection. Chromatic abnormalities, structural abnormalities or both of them can simultaneously cause manufacturing process faults. On-line testing of the surface defects is done at the tile factory by visual testing performed by workers. This way of testing is liable to mistake produced by errors and subjectivity. Furthermore, a high level of inhomogenity within sorted classes of products is present. Finally, this is a hazardous and unhealthy environment for human beings. Therefore, objective inspecting provided by the automatic process gives commercial and safety benefits to the industry. Visual quality testing done by computer vision has to be more robust and provide less costly inspection.

The tile surface quality is described by the surface defects and the intentional effects such as cracks, crazing, dry spots, pin hole, depression, glaze devitrification, blister, etc. [1]. Especially hard is detection of failures on textured tiles when texture is irregular, which is known as random macro texture.

We have derived an algorithm which successfully detects majority of this failure, such as a small pin-hole and cracks, for plain as well as for textured surfaces.

A. Tile defect detection

On the basis of visual inspection tiles can be classified in three classes: first - none or very few acceptable defects, second - few but still acceptable defects, third - waste, unacceptable defects. It is obvius that the classification is based on the visible artifacts on the tile surface. By the proper aquisition camera system that artifact can be captured on the image of the tile. A method for the inspection of the image has to be based on the human visual system (HVS) characteristics. Perception of an image incorporates a large number of different mechanisms. In the first stage HVS has properies of the spatial frequency filter. Furthermore, there is an adaptation to the stimulus dimension [2]. The wavelet transform provides a multiresolution analysis of an image in a similar way as the visual system on the first stage. The variation in the resolution enables the wavelet transform to zoom into image irregularities [3].

It can be assumed that the tile surface failures produce some spots on the tile image. A spot whose luminance is different from the local mean luminance, with sharp edges, corresponds to a sharp contrast and can be detected from the local maxima of wavelet transform coefficients which do not exist for the image of the tile without failures. Our detection algorithm is based on that assumption.

II. DISCRETE WAVELET TRANSFORM

A. Wavelet theory

Wavelets are oscillating functions defined by function ψ - *mother wavelet*, which by dilatation and translation produces basis functions $\psi_{j,k}$ in different scales j and position k.

$$\psi_{j,k}(t) = 2^{j/2} \cdot \psi(2^j t - k) \tag{1}$$

The mother wavelet has to satisfy

$$\int_{-\infty}^{\infty} \psi(t)\,dt = 0 \tag{2}$$

If j decreases, the resolution decreases in the spatial domain and increases in the frequency domain. Functions $\psi_{j,k}$ can be an orthonormal set of the basis functions, so any function in $L_2(R)$ can be expanded as a combination of $\psi_{j,k}$

$$f = \sum_{j,k\in Z} \left\langle f, \psi_{j,k} \right\rangle \cdot \psi_{j,k} \tag{3}$$

where $\langle f,\psi_{j,k}\rangle$ denotes the scalar product of f and $\psi_{j,k}$, and gives details of function f on resolution j

$$x_{j,k}(f) = \left\langle \psi_{j,k}, f \right\rangle = \int \psi_{j,k}(t)\, f(t)\,dt \tag{4}$$

For multiresolution analysis of a function one needs two functions: the mother wavelet ψ and the scaling function ϕ. The scaling function also generates a set of basis function as a dilated and translated version of itself

$$\phi_{j,k}(t) = 2^{j/2} \cdot \phi(2^j t - k) \tag{5}$$

For fixed j, $\phi_{j,k}$ are orthonormal, and

$$\int_{-\infty}^{\infty} \phi_{j,k}(t)\,dt = 1 \tag{6}$$

The scalar product of the function f and scaling functions $\phi_{j,k}$ gives approximation coefficients x_A of the image on the resolution j.

$$x_{A\,j,k}(f) = \langle \phi_{j,k}, f \rangle = \int \phi_{j,k}(t) f(t)\,dt \tag{7}$$

A connection between the mother wavelet and the scaling function is given by the *wavelet equation*

$$\varphi(t) = 2^{1/2} \sum_k g(k)\phi(2t-k) \tag{8}$$

Scaling functions also satisfy the *dilatation equation*

$$\phi(t) = 2^{1/2} \sum_k h(k)\phi(2t-k) \tag{9}$$

Coefficients g(k) and h(k) have to be chosen in such a way to satisfy the orthogonality condition for wavelet and scaling functions, as well as conditions (2) and (6). Furthermore for most of the applications the wavelets with the finite support are needed, as well as a level of smoothness of the wavelet and scaling basis functions. These requests on the wavelets give constructions of different wavelets with different coefficients g(k) and h(k) [4], [5].

A discrete function f can be analysed by the discrete wavelet transform through the fast recursion algorithm [6].

$$x_{j,k}(f) = \sum_n g_{2k-n}\, x_{A\,j-1,k}(f) \tag{10}$$

$$x_{A\,j,k}(f) = \sum_n h_{2k-n}\, x_{A\,j-1,k}(f) \tag{11}$$

Equations (10) and (11) present convolution, and this calculation of the coefficients $x_{j,k}$ and $x_{A\ j,k}$ corresponds to digital filtering followed by the downsampling (decimation). In this case filters characteristics are connected to g(k) and h(k)

$$H(\omega) = 2^{-1/2} \sum_k h(k) e^{-j\omega k} \tag{12}$$

$$G(\omega) = 2^{-1/2} \sum_k g(k) e^{-j\omega k} \tag{13}$$

Filter $H(\omega)$ is a lowpass filter and filter $G(\omega)$ is a highpass filter.

B. DWT of an image

DWT of an image may be represented [5] as filtering with a four-channel perfect reconstruction analysis/synthesis filterbank. Lowpass filter H and highpass filter G are applied in two dimensions: horizontal (frequency u) and vertical (frequency v), and the downsampling operation is applied in both directions, as shown in Fig. 1. That results in four transform components – frequency subbands, which consist of all possible combinations of high- and low- pass filtering in two dimensions, called orientations. The lowest frequency subband contains wavelet coefficients X_A of an image approximation on a lower resolution. Another three subbands contain wavelet coefficients of details in three orientations: X_V- vertical, X_H – horizontal and X_D – diagonal.

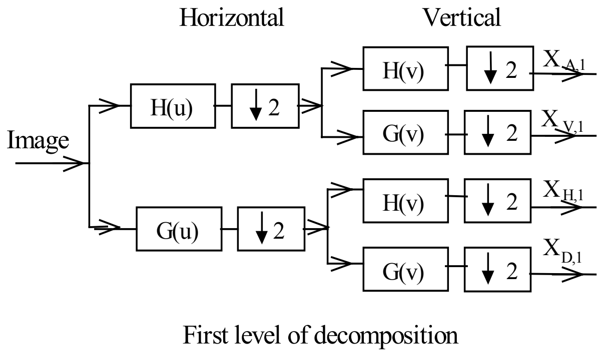


Fig. 1. Discrete wavelet transform of an image

C. Surface failure detection using DWT

The local contrast of an image is often more informative than the light intensity values. The wavelet transform measures gray level variations on different scales. The edges of the image structures are given with sharp variation on a slowly variable background. The variation in resolution enables the wavelet transform to zoom into these image irregularities. Visibility of these irregularities depends on the HVS sensitivity, and according to [7], one can calculate wavelet coefficients which correspond to the visibility thresholds.

It can be assumed that the tile surface failures produce some spots on the tile image. A spot with the luminance different from the local mean luminance, with sharp edges correspond to a sharp contrast. It can be detected from the local maxima of a wavelet transform which do not exist for the image of the tile without failures.

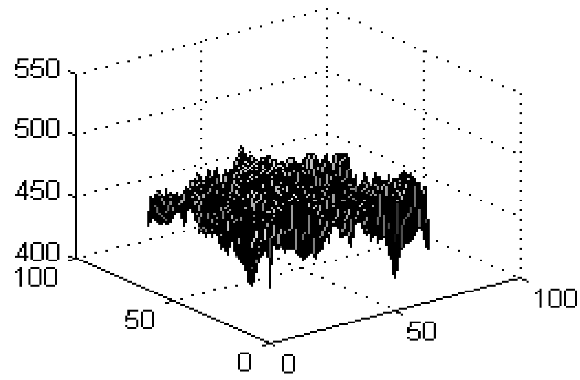
An example of the images of a tile with small defects is given in Fig. 2.

a) b)

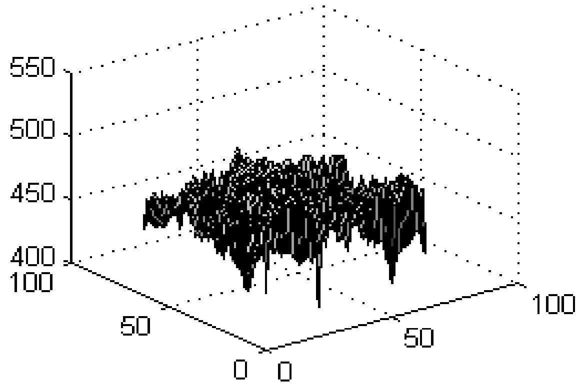
Fig. 2. a) Tile withouth surface failures; b) tile with a small defect

The size of the defect is around 0.3 mm in diametar, and the contrast of the corresponding spot in the image of the tile is around 10% of the local background. Although the spot is visible a simple thresholding and comparison in the image domain is not adequate because the colour of the spot is in the range of the colour in the image of the correct tile. For this type of the tile with a macro texture the analysis on the pixel to pixel base could not give proper results in an inspection procedure. Namely, only the smallest translation of the tile images, even less than one milimetar, gives difference between images of the tiles. The advantage of the DWT usage for an amplification of the structural irregularities is clearly shown in Fig. 3.

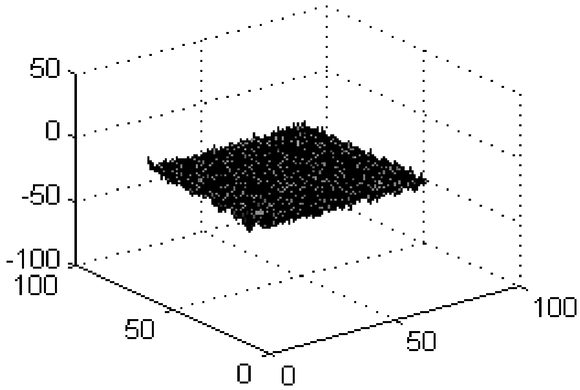
Approximation coefficients follow the textured structure of the original image and a diagnosis of faults is difficult. But coefficients of details X_H*, X_V* and/or X_D* for the image with a defect show a high enhancement in the area of the spot. For the tiles without a fast transition of contrast the coefficients X_H, X_V and X_D are very close to zero. So detection of the spots can be done by detection of the high wavelet coefficients.



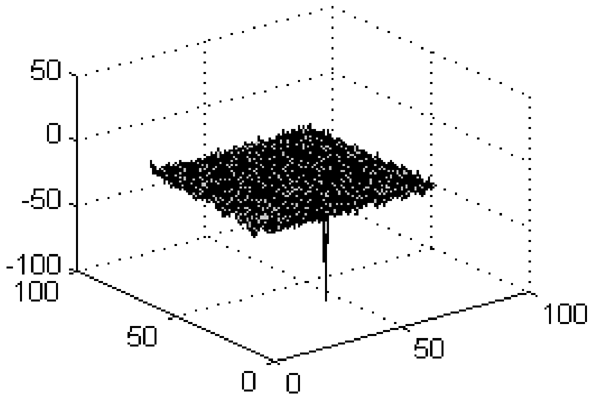
a) approximation coefficients X_A of the correct tile image



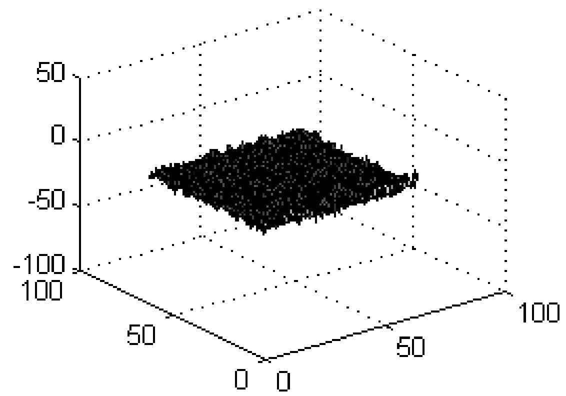
b) approximation coefficients X_A* of the image with a defect



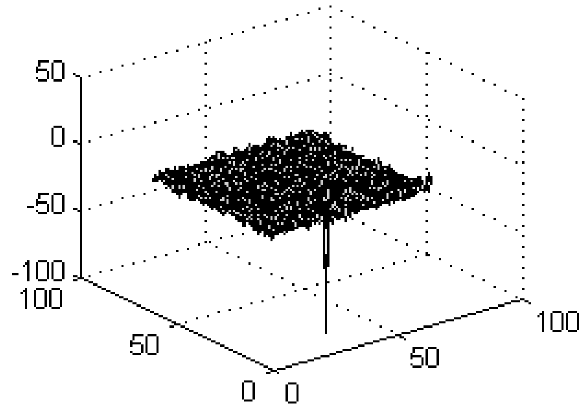
c) wavelet coefficients X_H of the correct tile image



d) wavelet coefficients X_H* of the image with a defect

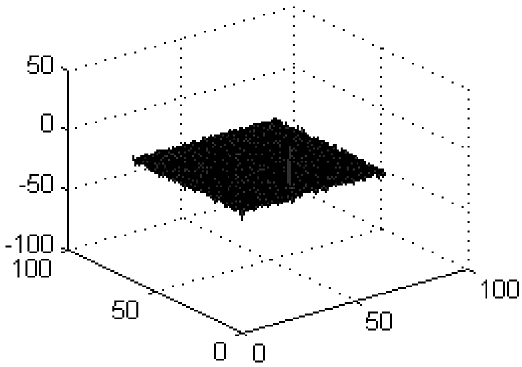


e) wavelet coefficients X_V of the correct tile image

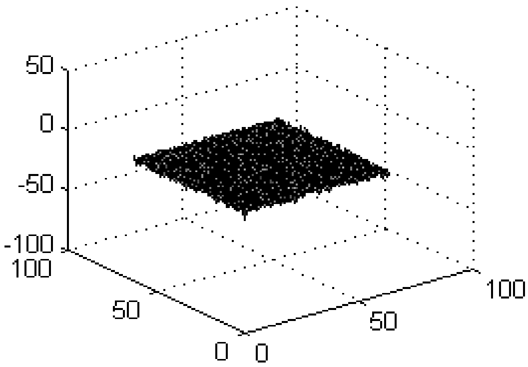


f) wavelet coefficients X_V* of the image with a defect

Fig 3. a), b), c), d), e), f) Wavelet coefficients X_A, X_H and X_V of the correct tile image and wavelet coefficients X_A*, X_H * and X_V * of the image with a defect



g) Wavelet coefficients X_D of the correct tile image



h) wavelet coefficients X_D * of the image with a defect

Fig 3. g) Wavelet coefficients X_D of the correct tile image; h) wavelet coefficients X_D * of the image with a defect

Fig. 3 g) and h) show wavelet coefficients X_D and X_D*. For the presented defects (Fig. 2) coefficients X_D* do not show any enlargement in comparison to the coefficients X_D. Anyway, the detection of the large coefficients X_V* or X_H* is sufficient for defect detection. For a different kind (shape and orientation) of the failure at least one of the X_V*, X_H* or X_D* consists of enhanced coefficients.

III. FAILURE DETECTION ALGORITHM

Wavelet coefficients of the details point to every irregularity in the texture, and we use that property in our failure diagnostic algorithm. To improve sensitivity of our algorithm we use relative differences between wavelet coefficients of a correct image and an image with a defect. Furthermore, to achieve robustness of the algorithm to the images translation we divide images to the segments and we compare maxima of the wavelet coefficients in the corresponding segments. In such a way local properties of the image are taken into account what improves robustness as well as sensitivity of the algorithm. Relative differences between the corresponding maxima for given segments are used in the detection procedure. Those differences are defined separately for horizontal, vertical and diagonal coefficients.

$$RDH = \frac{\max|X_H| - \max|X_H *|}{\max|X_H|} \tag{14}$$

$$RDV = \frac{\max|X_V| - \max|X_V *|}{\max|X_V|} \tag{15}$$

$$RDD = \frac{\max|X_D| - \max|X_D *|}{\max|X_D|} \tag{16}$$

An error is detected if relative differences are higher than the determined detection sensitivity level (DSL).

$$If\ [RDH\ or\ RDV\ or\ RDD] > DSL \qquad error\ detected$$

To analyse effectiveness of our failure detection algorithm we changed the segment size **bs**, as well as the sensitivity level DSL. This diagnostic procedure begins with loading of the referent and a tested image. The processing parameters are the segment size **bs**, starting sensitivity level $\mathbf{DSL_{min}}$, final sensitivity level $\mathbf{DSL_{max}}$ and the diagnostic step $\mathbf{DSL_{step}}$.

Diagnostic procedure

- *Preparation for analysis*
  - *load reference image*
  - *load inspected image*
  - *set parameters of analysis*
    - *set block size*
    - *set minimal tolerance level of the coefficient differences (*$\mathbf{DSL}_{min}$*)*
    - *set maximal tolerance level of the coefficient differences (*$\mathbf{DSL}_{max}$*)*
    - *set increment amount of tolerance level of the coefficent differences (*$\mathbf{DSL}_{step}$*)*
- *Cropping image segments*
  - *crop one image segment from reference image*
  - *crop correspondent image segment from inspected image*
  - *discrete wavelet transformation of segments*
- *Perform calculation of coefficient differences*
  - *calculate horizontal coefficient differences*
  - *calculate vertical coefficient differences*
  - *calculate diagonal coefficient differences*
- *Decision algorithm*
  - *compare calculated coefficient differences with tolerance level of the coefficient differences*
  - *if any of three calculated coefficent differences are greater than or equal to tolerance level of the coefficient differences then mark image segment from inspected image as segment with an error*
  - *else mark segment as segment without error*
- *Increment tolerance level of the coefficient differences then jump to decision algorithm*
- *Set crop coordinate for next image segments then jump to croping image segment routine*

After the initial settings of parameters the algorithm starts the analysis. From both images, the referent and the tested image, the segments of declared size **bs** are determined. DWT is applied to both segments, resulting in horizontal, vertical and diagonal coefficients. The coefficients with the maximum amount are selected and used to calculate the difference between the corresponding coefficients on both images. If the difference is higher than the given DSL, the tested segment is proclaimed as a defect segment. The analysis of the sensitivity level DSL is finished. After that the sensitivity level is increased for the value DSL_{step} and the analysis of the same segment is repeated. When all the segments are analysed, the values of the segment size **bs** is changed and the diagnostic procedure is repeated.

IV. EXPERIMENTAL RESULTS

A. Textured surface

The influence of the segment size **bs** to the analysis results is presented in Fig. 4. The results are given for the segment sizes 17x17, 35x35, 47x47 and 65x65 pixels, and for DSL between 0.2 and 5.4. DWT is done by the Daubechies wavelet with minimum phase db2 [4]. Coefficients h(k) and g(k) for that wavelet are given in Table I.

TABLE I
Coefficients of the wavelet filters for the wavelet db2

h(k)	-0.1294	0.2241	0.8365	0.483
g(k)	-0.483	0.8365	-0.2241	-0.1294

The aim of the algorithm is to find all defect segments, but some of the correct segments can be declared as defect too if the DSL is too small. The percentage of the detection of the segments with defect is given in Fig. 4 a), and the percentage of the false detected segment (correct segments declared as segments with defect) is given in Fig 4. b). From Fig. 4 a) one can see that with rising DSL the probability of the nondetection of segments with a defect increases. That increasing is the smallest for the lowest segment size 17x17. That can be explained with a lower sensitivity to the image translation and a good capture of the local statistical properties for a small segment. However, for DSL ≤ 1.1 even the segments with sizes 35x35 and 47x47 give 100% defects detection. The processing time increases as the segments size falls, so the larger segment can be better for the analysis. In the same time the percentage of false proclaimed segments decreases for a higher DSL and it falls faster for the larger segments. For DSL = 1.1 and bs=35x35 pecentage of false detection is 2.96%. For DSL = 1.1 and bs=47x47 that percentage is 1.6%. For DSL ≤ 3.6 and bs=17x17 algorithm finds all defect segments, and for DSL = 3.6 percentage of false detection is 0.75%. If we decreased the algorithm processing time bs=17x17 would give the best results. Even for a smaller DSL the percentage of false detection does not rise rapidly, so we can obtain proper detection of the defect segments (which corelate to the tiles with surface defects) with a small percentage of the false proclaimed segments.

The influence of the wavelet to the diagnostic result is shown in Fig. 5. We used two wavelets for analysing: db2 wavelet and the Haar wavelet [5]. Haar wavelet has filter coefficients h(0)=h(1)=0.5, g(0)=-g(1)=0.5. For bs=47x47 the percentage of the detected segments with a defect is shown in Fig. 5 a). A higher percentage of detection is obtained for the Haar wavelet, but the percentage of false detection falls fast for db2 wavelet (Fig. 5 b). We can conclude that for the Haar wavelet a good choice for DSL is 1.5 where the percentage of detection is 100% and the percentage of false detection is 1.5%. For the db2 wavelet and DSL=1.1, percentage of detection is 100% and the percentage of false detection is 1.85%. These results are similar, but the advantage of the Haar wavelet is in its shortness which improves the algorithm speed.

B. Plain surfaces

The proposed algorithm is suitable for the plain surface too. However, sensitivity of the algorithm is much higher because of very small values of the X_H, X_V and X_D (ideally these are equal to zero). So a modification of the algorithm has to be done. More relevant for detection is the absolute not relative difference, and we define

$$DH = \max|X_H| - \max|X_H*| \tag{17}$$

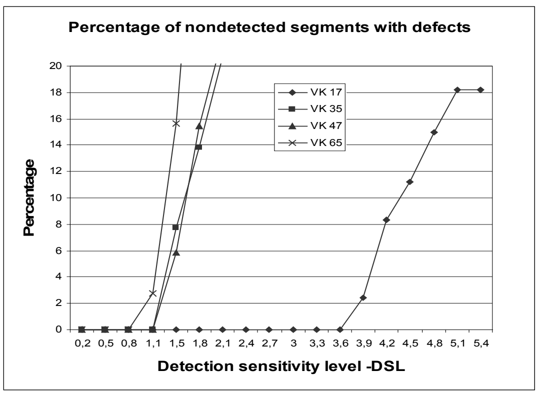
$$DV = \max|X_V| - \max|X_V*| \tag{18}$$

$$DD = \max|X_D| - \max|X_D*| \tag{19}$$

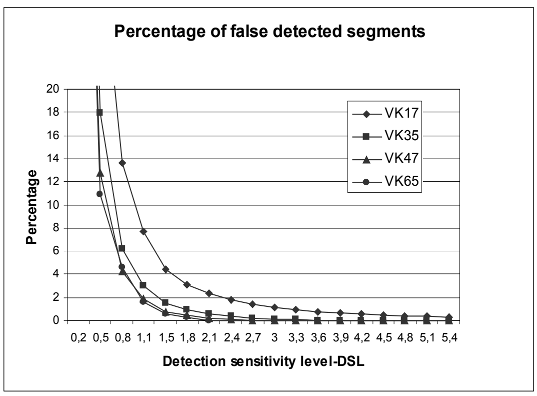
An error is detected if the absolute difference is higher than the determined detection sensitivity level (DSL).

$$If\ [DH\ or\ DV\ or\ DD] > DSL \qquad error\ detected \tag{20}$$

With that modification we obtained 100% detection of the defects and a decrease of false detection. For the plain surface we can define DSL as a function of the visibility of defects. Very small defects with a low contrast are not visible. Furthermore, because of very high algorithm sensitivity for plain surfaces nonhomogenity in the image aquisition can produce false detection. So

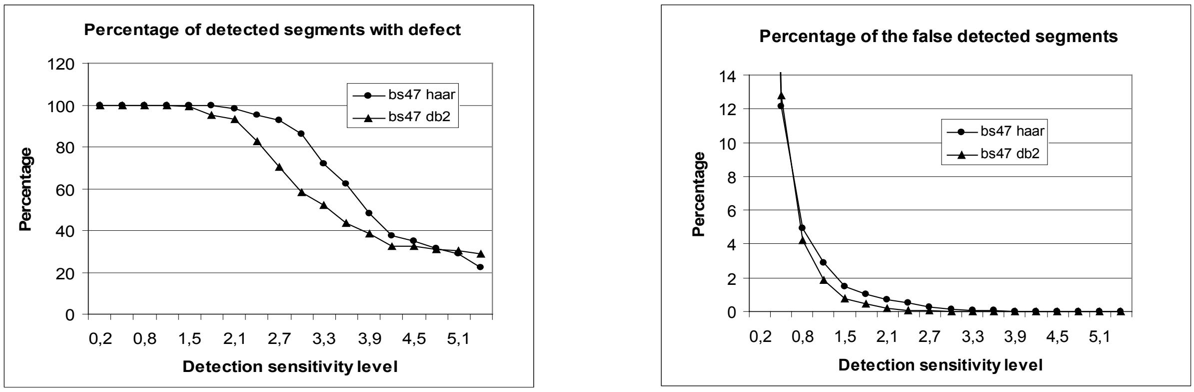


a)



b)

Fig. 4 a) The percentage of detected segments with a defect; b) the percentage of false proclaimed segments as segments with a defect



a) b)

Fig. 5 a) The percentage of detected segments with a defect for the haar and db2 wavelet; b) the percentage of false proclaimed segments as segments with a defect for the haar and db2 wavelet

DSL has to be chosen quite high and it depends on HVS sensitivity to the wavelet. The border of visibility t_V for a wavelet can be calculated as shown in [7]

$$t_{r,o} = \sqrt{\frac{0.48 \cdot 3 \cdot u_{\max} \cdot v_{\max}}{\int_0^{v_{\max}} \int_0^{u_{\max}} \frac{9.63}{(1 + 5.74 \cdot 10^{-3}(u^2 + v^2))^{6.57}} \cdot \left| F_{r,o}(u,v) \right|^2 du dv}} \tag{21}$$

Index r represents the level of decomposition (we used only r=1) and o represents orientation. u_{max} and v_{max} are the maximal horizontal and vertical spatial frequencies and they depend on viewing distance. $F_{r,o}(u,v)$ are two dimensional wavelet filter characteristics. Since $F_{r,o}(u,v)$ is different for a different wavelet and it differs for different orientation of wavelet coefficients the DSL has to be settled for every orientation separately. An error has to be detected if the absolute differences are higher than the determined $t_o = t_{1,o}$.

$$If \ \left[DH > t_H \ \ or \ \ DV > t_V \ \ or \ \ DD > t_D \right] \qquad error\ detected \tag{20}$$

V. CONCLUSION

In this article the diagnostic algorithm based on the discrete wavelet transform (DWT) is described. The images are divided to segments and two-dimensional DWT is applied to them. The decision of the failure is made by comparing the wavelet coefficients of the tested segment for the reference image and image with failures. An error is detected if the determined detection sensitivity level (DSL) is less than the relative difference between wavelet coefficient maxima for the given segment. We have investigated the influence of the DSL and segment size to the effectiveness of failure detection. We have found out that the probability of false failure detection is lower for greater segments and higher DSL. However, the probability of nondetection of the failures increases as a function of DSL. For greater segments the number of nondetected failures is also higher. Optimal values for DSL depend on the segment size and we proposed DSL=1.1 for 35x35 and 45x45 segments, and DSL=3.6 for 17x17 segments. Furthermore, we investigated the influence of different wavelets to the diagnostic results and we found out that short wavelets are suitable for analysis (such as the Haar wavelet) and the optimal DSL depends on the wavelet too. For the plain surfaces DSL has to be chosen depending on the visibility of the failure. The proposed algorithm can be used not just for detection but also for the classification of the tiles, so that our further research is planned to be carried out in that direction.

REFERENCES

[1] C. Boukouvalas, J. Kitter, R. Marik, M. Petrou: "Automatic colour grading of ceramic tiles using machine vision", IEEE Trans. Industial Electonics, Feb. 1997.

[2] S. Mallat: "Wavelets for a vision", Proc. of the IEEE, vol. 84, pp. 604-614., 1996.

[3] L. Gaudart, J. Crebassa, J.P. Petrakian: "Wavelet transform in human visual channels", Applied Optics, vol.32, no.22, pp. 4119-4127, 1993.

[4] I. Daubechies, Ten lectures on wavelets, no. 61, CBMS-NSF Regional conf. series in appl. math., 1990.

[5] M. Antonini, M. Barlaud, P. Mathieu, I. Daubechies, "Image coding transform using wavelet transform," IEEE Trans. on Image Processing, vol.1, no.2, pp. 205-219, 1992.

[6] T.K. Sarkar, C.Su, R. Adve, M. Salazar-Palma, L. Garcia-Castillo, R.R. Boix, "A tutorial on wavelets from electical engineering perspective, part1: Discrete wavelet techniques", IEEE Antennas and Propagation Magazine, vol.40,, no.5, pp. 49-68, 1998.

[7] S Rimac-Drlje:"Influence of wavelet quantization noise to image quality", dissertation, University of Zagreb, Faculty of Electical Engineering and Computing, Zagreb, 2000.