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Adaptive Image Processing Technique for Quality Control in Ceramic Tile Production

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Preliminary notes

Automation of the visual inspection for quality control in production of materials with textures (tiles, textile, leather, etc.) is not widely implemented. A sophisticated system for image acquisition, as well as a fast and efficient procedure for texture analysis is needed for this purpose. In this paper the Surface Failure Detection (SFD) algorithm for quality control in ceramic tiles production is presented. It is based on Discrete Wavelet Transform (DWT) and Probabilistic Neural Networks (PNN) with radial basis. DWT provides a multi-resolution analysis, which mimics behavior of a human visual system and it extracts from the tile image the features important for failure detection. Neural networks are used for classification of the tiles with respect to presence of defects. Classification efficiency mainly depends on the proper choice of the training vectors for neural networks. For neural networks preparation we propose an automated adaptive technique based on statistics of the tiles defects textures. This technique enables fast adaptation of the SFD algorithm to different textures, which is important for automated visual inspection in the production of a new tile type.

Adaptivna tehnika obrade slike za kontrolu kvalitete u proizvodnji keramičkih pločica

Prethodno priopćenje

Automatizacija vizualne provjere za kontrolu kvalitete u proizvodnji materijala s teksturama (pločice, tekstil, kože, itd.) nije široko primijenjena u praksi. Za ovu namjenu potreban je sofisticirani sustav za snimanje slika, kao i brza i efikasna procedura za analizu tekstura. U ovom je radu predstavljen algoritam za detekciju površinskih oštećenja (SFD) u proizvodnji keramičkih pločica. Temelji se na diskretnoj valićnoj transformaciji (DWT) i probabilističkim neuronskim mrežama (PNN) s radijalnim bazama. DWT omogućava više-rezolucijsku analizu koja oponaša ljudski vizualni sustav i izdvaja iz slike pločice značajne za detekciju oštećenja. Neuronske mreže se koriste za klasifikaciju pločica ovisno o postojanju oštećenja. Efikasnost klasifikacije najviše ovisi o odgovarajućem odabiru vektora za učenje neuronskih mreža. Za pripremu neuronskih mreža predlažemo automatiziranu adaptivnu tehniku koja se temelji na statistici tekstura oštećenja na pločicama. Ova tehnika omogućava brzu adaptaciju SFD algoritma na različite teksture, što je posebno važno za automatiziranu vizualnu provjeru u proizvodnji novog tipa pločica.

Keywords

Automated visual inspection
Discrete wavelet transform
Probabilistic neural network
Quality control in tile production

Ključne riječi

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1. Introduction

Visual inspection is an important part of the quality control in different manufacturing processes. Traditionally, human has carried out this inspection but performances of a human inspector are highly influenced by emotional, physical and environmental distractions. Automated visual inspection based on the machine vision system is already widely used for quality control of products such as printed circuits boards, automotive parts and products labels. On the other hand, trained human inspectors still largely accomplish inspection of products having natural textured surfaces. Products such as tiles, parquet slabs, textile and leather are covered with textures that cannot be described by regular textures and an automated control is quite demanding task in these cases.

This paper deals with the quality control of the textured ceramic tiles. Some of the most common defects found on tiles can be categorized as cracks, bumps, drops,

Symbols/Oznake

a_j	- wavelet approximation coefficient - valićni aproksimacijski koeficijentni
$\mathbf{A}_1$	- matrix of the approximation coefficients at scale 1 - matrica aproksimacijskih koeficijenata na sakali 1
C	- number of training vector class I - broj trening vektora klase I
d_j	- wavelet detail coefficients - valićni koeficijenti detalja
$\mathbf{D}_1$	- matrix of the diagonal detail coefficients at scale 1 - matrica koeficijenata dijagonalnih detalja na sakali 1
D	- number of training vector class II - broj trening vektora klase II
FDR	- false detection ratio - omjer pogrešne detekcije
g	- high-pass filter impulse response - impulsni odziv visoko-propusnog filtra
$G(z)$	- high-pass filter transfer function in z domain - prijenosna funkcija visoko-propusnog filtra u z- domeni
$H(z)$	- low-pass filter function in z domain - prijenosna funkcija nisko-propusnog filtra u z- domeni
$\mathbf{H}_1$	- matrix of the horizontal detail coefficients at scale 1 - matrica koeficijenata horizontalnih detalja na sakali 1
NDR	- non-detection ratio - omjer ne-detekcije
$\mathbf{H}_1$	- matrix of the vertical detail coefficients at scale 1 - matrica koeficijenata vertikalnih detalja na sakali 1
$X_{i,j}$	- feature vector - vektor značajki
$w_{i,j}$	- neural network weighting coefficient - težinski koeficijent neuronske mreže
σ	- spread of the Gaussian function - raspršenje Gaussove funkcije

Indices/Indeksi

$_j$	- scale of the DWT decomposition - skala DWT dekompozicije
$_{i,j}$	- block number - broj bloka

holes, dirt, spots and depressions with sizes ranging from quarters of a millimeter to several centimeters. A failure on the textured surface can be highly masked because of the surrounding with a high activity level. This makes automated inspection more difficult, but detection of the defects becomes a hard task for human, too.

The most important part of the automatic defect detection is feature extraction of the features which makes possible a distinction between tile texture and the area with defects. In the literature one can find several approaches to that problem [1–6]. In [1], Jahanbin et al. proposed a computer vision algorithm based on extraction of texture features by using second-order statistics after Discrete Wavelet Transform (DWT). This algorithm successfully detected 87.5 % of defects, but computing complexity is rather high.

In [2], Boukouvalas et al. give the solution of the ceramic tile quality inspection and show very good results for different kinds of textured and plain tiles. They used a different detection algorithm for a different type of defects. For detection of cracks with a linear shape in uniformly colored tiles they used filtering in vertical and horizontal direction. For detection of cracks detection in textured tiles a more sophisticated approach was used. The conjoint spatial and spatial frequencies representation of the Wigner distribution was used to enhance pattern separability. This solution has high reliability and good performance results compared to the human accuracy, but great complexity of the algorithms used in the classification process is a drawback in the real time application. It is especially true when the type and the color of the tile are often changed in the production process.

In [3], the failure detection algorithm based on Discrete Wavelet Transform (DWT) and Probabilistic Neural Network (PNN) is described. The proposed algorithm yielded good results in failure detection on textured surfaces. Anyway, optimal parameters in this algorithm have to be found for each type of texture (i.e. type of tile). In the production process it can be a serious drawback because of a great number of textures, especially when the new products are launched. We have found that defects occurring on tiles, have similar features regardless of the tile color or texture. Based on these conclusions, an innovative adaptive technique for tile inspection is proposed in this paper.

The organization of the paper is as follows. In Section 2, an overview of the basic algorithm for the surface failure detection (SFD) is given. In Section 3, the influence of the algorithm parameters on the classification process performance is discussed. In Section 4, the optimization procedure for the adaptive parameter tuning is proposed, which is followed by conclusions goven in Section 5.

2. Surface Failure Detection (SFD) algorithm

All procedures developed for the detection of failure on the tile surface are based on some kind of a digital image processing technique. Therefore, the first step of an automatic visual inspection system is the image acquisition. Success of inspection highly relies on this step. The image acquisition is not an easy task because of the need for proper illumination, spectral properties of camera sensors, resolution and the shooting angle. Dust in the industrial plant and vibration of an assembly line carrying the tiles make the image acquisition even more demanding. In this research we have assumed that the image acquisition system picks up all surface failures that is visible to a trained human inspector.

The SFD algorithm used in this paper is based on the algorithm given in [5] and [6]. It consists of three stages (as shown in Figure 1.):

1. Multi-resolution analysis;
2. Feature extraction;
3. Failure detection (classification by neural networks).

The multi-resolution analysis is inspired by human visual system (HVS) behavior. Namely, the first stage of the HVS provides a multi-resolution processing by multi-channel decomposition of the image. In the SFD algorithm DWT is used as an image preprocessing method because of its property of filtering in different direction with a low complex algorithm as well as the conjoint spatial and frequency representation of the image.

The second stage of the SFD algorithm is feature extraction. This stage reduces the amount of data by feature extraction, which is the most important part of the algorithm for defects detection. Details of this stage are given further in the text.

Finally, probabilistic neural networks with radial basis are used for classification of tiles into two classes: class I (tiles without failures) and class II (tiles with failures).

2.1. Multi-resolution analysis

Discrete wavelet transform (DWT) can be presented as digital filtering by low-pass and high-pass filters on different scales. Wavelet coefficients at finer scales are appropriate for micro-texture modeling while the coarser ones can capture macro-texture attributes. In opposition to a window Fourier transform, that has a fixed resolution in the spatial and frequency domains, DWT has a good spatial localization for higher frequency components and a good frequency localization achieved for low frequency components.

The hierarchical signal analysis by using DWT can be implemented by iterative filtering and a down-sampling operation with low-pass and high-pass filters h and g. A mathematical algorithm, invented by Mallat [7], enables a fast calculation of wavelet coefficients a_j and d_j on the scale j as given by (1):

$$a_j(k)=\sum_m h(2k-m)\cdot a_{j-1}(m)\,, \tag{1}$$

$$d_j(k)=\sum_m g(2k-m)\cdot a_{j-1}(m)\,, \tag{2}$$

where g and h presents impulse response of high-pass and low-pass wavelet filters, respectively. These filters satisfy the general constraint for perfect reconstruction which is in z-transform domain given as follows:

$$H(z)\tilde{H}(z^{-1})+G(z)\tilde{G}(z^{-1})=1\,. \tag{3}$$

Coefficients a_j represent an approximation of a signal on the scale j. The highest order approximation coefficients a_0 can be understood as digital presentation of a signal (in our case it is the image of a tile). Coefficients d_j obtained by high-pass filtering, contain information of the signal details.

An image is a two-dimensional signal and a two-dimensional DWT has to be performed. Usually, one-dimensional filters h and g are used in horizontal and vertical direction as shown in Figure 1.

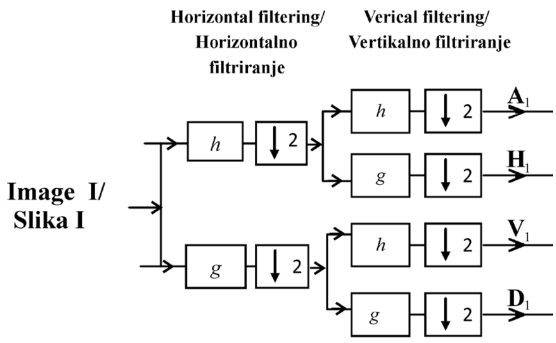


Figure 1. Discrete wavelet transform of an image

Slika 1. Dvodimenzionalna valićna transformacija slike

For the resolution level j this results in four frequency subbands (e.g. four sets of the wavelet coefficients) as a combination of low-pass and high-pass filtering in two dimensions. The lowest frequency subband presented by matrix $\mathbf{A}_1$ contains wavelet coefficients a_l and presents the image approximation at the lower resolution. Another three subbands contain wavelet coefficients and present the details of the image in the three orientations: $\mathbf{V}_1$, $\mathbf{H}_1$ and $\mathbf{D}_1$. Coefficients in $\mathbf{V}_1$ are a result of filtering by low-pass filter h in vertical direction and high-pass filter g in horizontal direction. Coefficients in $\mathbf{H}_1$ are calculated by low-pass filtering in horizontal direction, and high-pass filtering in vertical direction, since coefficients in $\mathbf{D}_1$ are calculated by high-pass filtering in both directions. The filtering process can proceed on a different level of resolution. In the SFD algorithm only the first level of decomposition is used with satisfying results.

Different wavelet bases and corresponding wavelet filters have been constructed as presented in [8]. They differ according to length, smoothness of the wavelet functions and linearity of the phase. We have found out that Daubechies least asymmetric wavelet with four filter coefficients as well as Haar wavelet with two coefficients in both low-pass and high-pass filters achieve very good results in the SFD algorithm. The shortness of their filters enables fast calculation of wavelet coefficients, which is highly important in the failure detection process.

2.2. Feature extraction

The DWT property of filtering in different directions with a low complex algorithm as well as the conjoint spatial and frequency representation gives possibility of the detecting of different kinds of defects. In fact, in random textured surfaces DWT can separate and magnify irregularities as cracks or spots like faults. Sensitivity of that separation depends on the local contrast between defects and the background. An example of DWT for a tile with a pinhole defect is given in Figure 2. Although the contrast between a defect and its surrounding is not very high (it is even hardly observable), the pinhole defect produces a high level of wavelet coefficients in $\mathbf{V}_1$ on the spot which corresponds to the defect position.

This is quite similar to the human visual system behavior. Perception of a varying illuminant surface by the human visual system incorporates a large number of different mechanisms that have properties of the spatial-frequency filter, as well as DWT, [7]. The wavelet transform of an image measures the light intensity variations on different scales, and wavelet coefficients have maximum on the edges of the image structures because of the local contrast enhancement. Therefore, SFD uses local maximums of the coefficients in subbands $\mathbf{V}_1$, $\mathbf{H}_1$ and $\mathbf{D}_1$ as indicators of a possible defect on the surface. It can be assumed that a defect produces a higher local contrast than the image texture. That is certainly that is true for most of the defects with exceptions of the blob-like defects. This type of defects usually occupies a larger area so it changes the local mean level of pixels intensity. Since coefficients in the lowest frequency band $\mathbf{A}_1$ incorporate information of the local mean intensity, we have also used those coefficients in our detection algorithm.

To achieve a higher detection sensitivity level the image of the tile is divided into blocks of size M×N pixels, and then the two-dimensional DWT is used for each block (block DWT). For an image of size WxH pixels, the number of blocks are W/M×H/N = BM×BN.

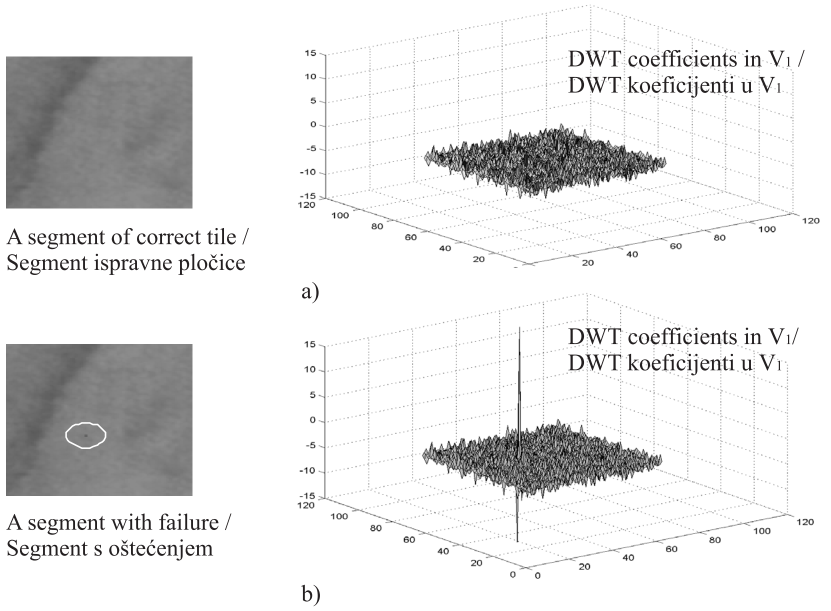


Figure 2. Image and corresponding DWT coefficients in V1 for: a) tile without failure; b) tile with a failure.

Slika 2. Slika i odgovarajući DWT koeficijenti u V1 za: a) pločicu bez oštećenja; b) pločicu s oštećenjem.

The matrix containing information of blocks is presented by **IB** in the scheme of the scheme of the SFD algorithm presented in Figure 3. The result of the DWT multi-resolution analysis is matrix **WC** which contains matrices $\mathbf{A}_1$,$\mathbf{V}_1$, $\mathbf{H}_1$ and $\mathbf{D}_1$. **WC** matrix can be presented as follows:

$$WC = \begin{bmatrix} \left[A_1\ V_1\ H_1\ D_1\right]_{1,1} & \cdots & \left[A_1\ V_1\ H_1\ D_1\right]_{1,BM} \\ \vdots & & \vdots \\ \left[A_1\ V_1\ H_1\ D_1\right]_{BN,1} & \cdots & \left[A_1\ V_1\ H_1\ D_1\right]_{BN,BM} \end{bmatrix}, \quad (4)$$

The maximums of the wavelet coefficients in $\mathbf{V}_1$, $\mathbf{H}_1$ and $\mathbf{D}_1$ (further in the text referred to as max(**V**), max(**H**) and max(**D**)) for a given block, as well as the mean value of coefficients in $\mathbf{A}_1$ (mean(**A**)) are used to form a measure of distance between the analyzed block and the referent one. In the SFD algorithm, vector $X_{i,j}$ is defined for block i,*j* as:

$$X_{i,j}=\{\text{mean}(\mathbf{A})_{i,j}, \max(\mathbf{V})_{i,j}, \max(\mathbf{H})_{i,j}, \max(\mathbf{D})_{i,j}\}. \quad (5)$$

$X_{i,j}$ is used as a feature vector in the input of the probabilistic neural network trained for the given block *i,j*. The result of processing in the feature extraction part is the matrix **FC:**

$$FC = \begin{bmatrix} X_{1,1} & \cdots & X_{1,M} \\ \vdots & & \vdots \\ X_{N,1} & \cdots & X_{N,M} \end{bmatrix}. \quad (6)$$

2.3. Failure detection by neural networks

Generally, an artificial neural network associates the output vector to the input data vector, where dimensions of these vectors are most often different and their functional relationship is nonlinear. Neural networks have been used for the approximation of multivariable, nonlinear functions. In the problem of classification, the probabilistic neural networks with the radial basis function (PNN-RBF) give good results [9–10].

PNN-RBF has one hidden layer (radial basis layer) of neurons with radial basis activation functions *h(d)* (Figure 4). A Gaussian function is usually used as a radial basis function:

$$h(d) = e^{-\left(\frac{d}{\sigma}\right)^2}, \quad (7)$$

where *d* presents the Euclidean distance in multidimensional space R^n. In the SFD algorithm a neural network is used for each block *i,j,* so *d* is calculated as the distance between a four-dimensional input vector $X_{i,j}$ and a four-dimensional training vector $X_{i,j}^*$.

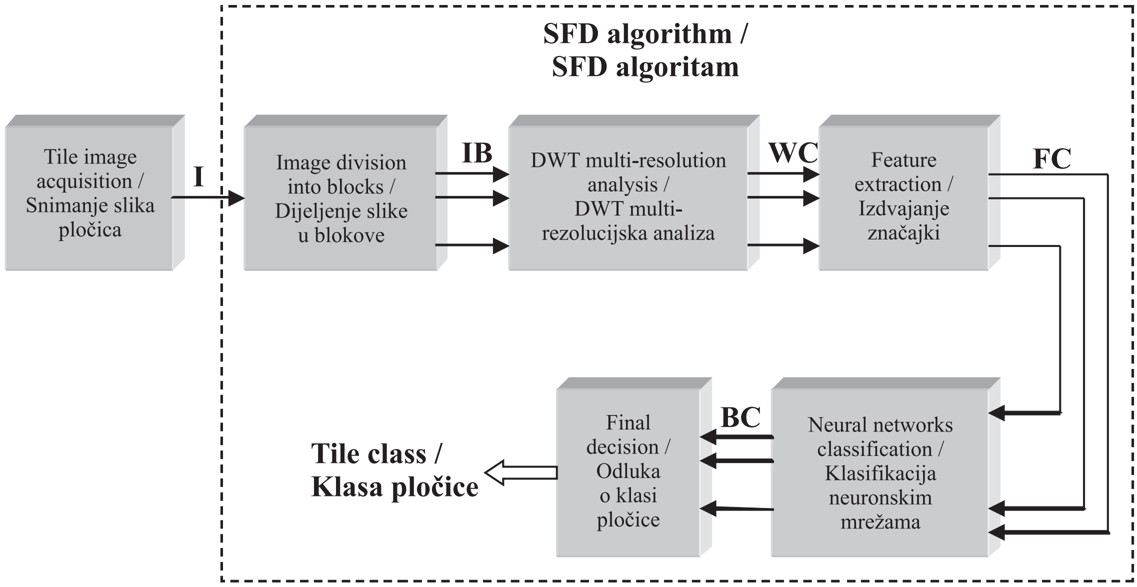


Figure 3. Surface failure detection (SFD) algorithm
Slika 3. Algoritam za detekciju površinskih oštećenja (SFD)

Training vectors and their number have to be chosen carefully to obtain good classification behavior of a neural network. For a block *i,j* the distance between input vector $X_{i,j}$ and training vector $X_{i,j}^*$ is given as follows:

$$d_{i,j} = \left\| X_{i,j} - X_{i,j}^* \right\| \tag{8}$$

Since $d_{i,j}$ is the input to the activation function *h(d)*, the output of the first layer is higher if distance $d_{i,j}$ is closer to 0 (which means that input vector $X_{i,j}$ is closer to vector $X_{i,j}^*$). Parameter σ in (4) defines a spread of the Gaussian function and allows adjustment of neuron sensitivity. Based on the network training procedure, the weighting coefficient w_i is associated to the each output of the radial basis layer.

If *K* is the number of classes in which we want to classify input vectors, then training vectors $X_{i,j}^*$ have to be a good presentation of these classes. Also, *K* is the number of output layer neurons.

The output layer of the PNN-RBF network is a competitive layer. This layer sums contributions for each class of inputs to produce a vector of probabilities as its net output. Classification is based on the highest output of neurons in the output layer. A competitive transfer function on the output of the second layer picks the maximum of these probabilities and produces a 1 for that class and 0 for the other classes.

The input of the neural networks classification part of the SFD algorithm is matrix **FC** that contains feature vectors for all blocks. The output of that part is matrix **BC** with information of the blocks classes. The failure detection problem in the SFD algorithm is solved as a classification of tiles in class I - correct tiles, and class II – tiles with defects.

Due to high differences of features across the tile surface a neural network is produced for each block. The set of training vectors is made for each block and it consists of C vectors of the defect-free block, and D vectors of the given block with defect(s). Images of the defect-free tiles differ mutually because of the variations in the illumination intensity during the inspection process and because of small differences of the tiles position in front of the acquisition camera. Therefore, a sufficient number of vectors describing the defect-free block have to be used.

Furthermore, to achieve a good classification result one has to use a proper choice of defects for the training vectors preparation. The defects of different sizes, contrasts and shapes have to be included.

The number of training vectors defines the number of neurons in the hidden layer.

The number of neurons in the first layer is equal to the length of the input vector and in this case it is four. The number of neurons in the output layer is equal to the number of quality classes and in this case it is two.

For a given input vector X_n the neural network gives an output equal to 1 for the neuron associated to the most probable class. A tile is proclaimed as correct if for all blocks its networks classify them to class 1 – correct block.

2.4. Experimental results and discussion

The main challenge in the SFD algorithm implementation is a proper choice of the algorithm parameters. Parameters that mostly influence algorithm detection capability, sensitivity and calculation

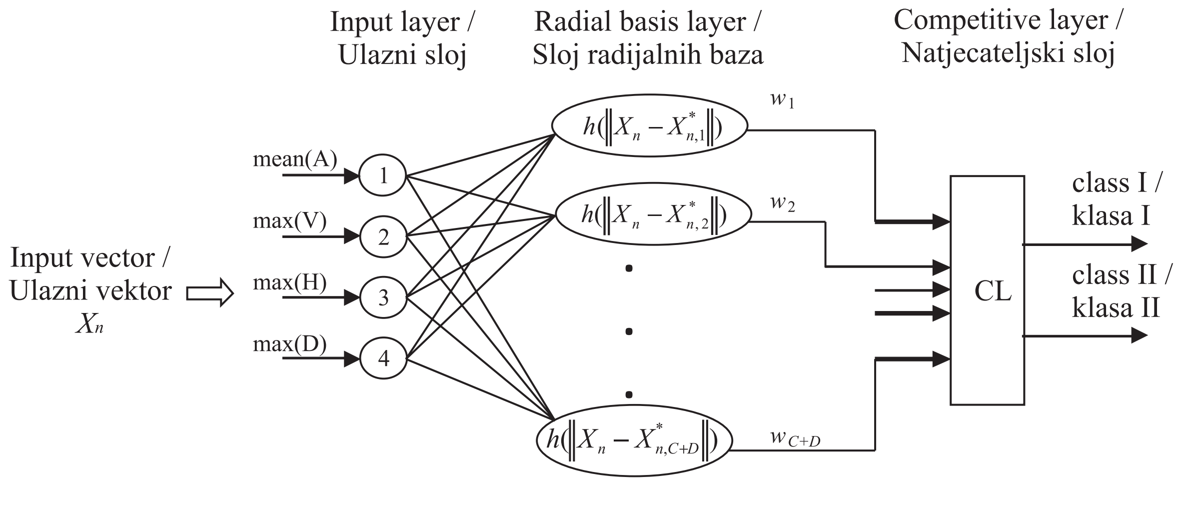
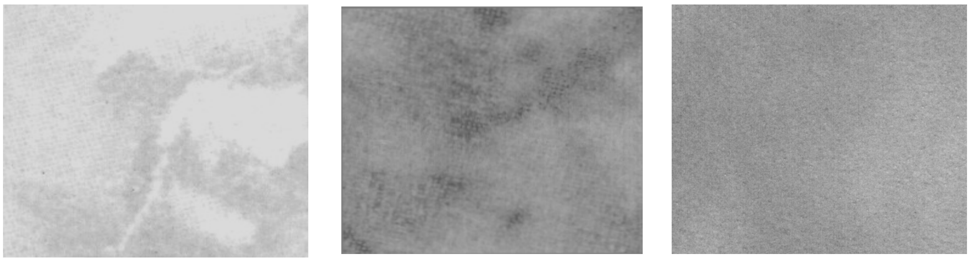


Figure 4. Structure of the neural network used in the SFD algorithm

Slika 4. Struktura neuronske mreže korištene u SFD algoritmu



a) b) c)

Figure 5 a) A clip of T1 tile; b) a clip of T2 tile c) a clip of T3 tile.

Slika 5: a) isječak pločice T1; b) isječak pločice T2; c) isječak pločice T3.

complexity are: choice and number of training vectors, size and number of blocks, spreading parameter σ and type of wavelet. The optimal parameter set highly depends on the type of texture on the tile. As a measure of the efficiency two results have been used: 1. Percent of the tiles erroneously proclaimed as impaired ones – False Detection Ratio (FDR) ; 2. Percent of undetected impaired tiles – Non-Detection Ratio (NDR). The efficiency of the algorithm rises if both percentages decrease, and the goal is to find such a set of parameters where both percentages are close to zero.

The tiles used in our experiment were ceramic of size 200 x 200mm, with different textures as shown in Figure 5. Tile's images are of sizes 2500 x 2500 pixels. We have analyzed the influence of each parameter to the algorithm performance for three tile types with significantly different textures (Figure 5).

2.5. Influence of the training vectors

The most important part of the SFD algorithm is the network training and in connection with that the choice of training vectors. Training vectors fall into two classes. We used C vectors of defect-free images (class I) and D vectors of the images with defect (class II). Vectors from class I define a cluster in a multidimensional space for the defect-free images and vectors from class II define a cluster for the images with defect. (Precisely, due to image segmentation these clusters are formed for each block independently).

The results of the detection procedure for T1 tiles are given in Table I , for a different number of training vectors. The experiment was done for C= 5, 10, 15 and 20, and for D= 5, 10, 15 and 20. Images used for the creation of training vectors included the translation, rotation and intensity changes for the defect-free tiles, and different kinds of defects (according to shape, size, level of contrast and position) for the tiles with defects. Contrast of the defects to surroundings is 20% of the local mean for the first 8 training vectors, and up to 100% for the remaining vectors. Size of the defects ranges between 0.2 millimeters to few millimeters and defects occur with different orientation and in a randomly chosen position. The testing set of tiles consisted of 50 defect-free tiles and 50 tiles with defects. The training set was not included in the testing set. The spread of the Gaussian radial basis function σ=0.826/7, and the size of segments was 60x60 pixels. One can notice that for a larger number of class I training vectors (C) the FDR (percentage of the false detected tiles) decreases very fast. The influence of the number of class II vectors (D) highly depends on the number of the class I vectors. For small C a rise of D even increases the percentage of a false detection. For C=20 (20 class I vectors) we had zero percent of the false detection for all numbers of class II vectors used in the experiment. Furthermore, for almost all combinations of C and D the percentage of non-detection (NDR) is zero, so it can be concluded that for this kind of tiles and this set of parameters (σ=7, block size 60x60) the detection algorithm has a high efficiency. If twenty vectors of class I are used, then FDR will be negligible.

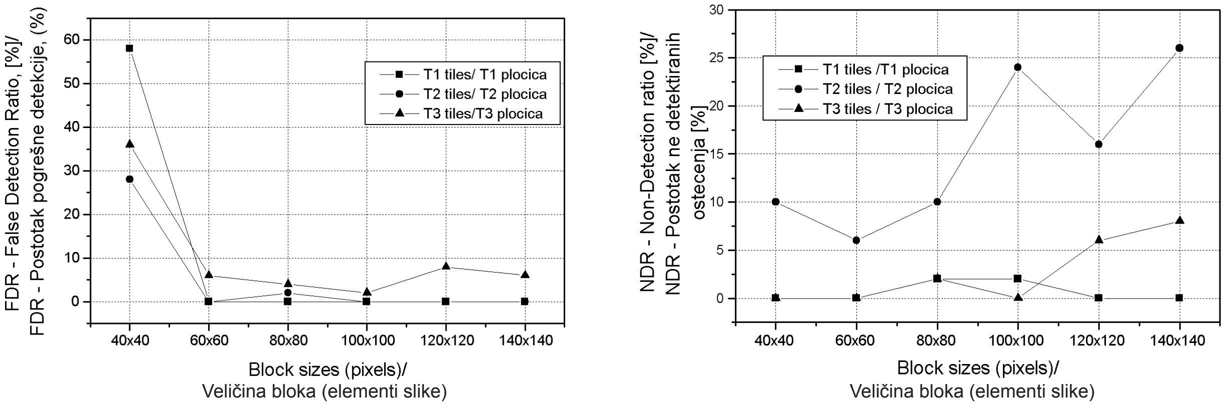
2.6. Influence of the segment size

The detection procedure was conducted for different blocks sizes and for three types of tiles (Figure 5). The results for FDR and NDR for different block sizes and different-tiles are shown in Figure 6. It can be observed that FDR is the lowest for block sizes between 60x60 and 100x100. Sensitivity of the algorithm falls for larger blocks because in the textured surfaces the local contrast in the defect-free blocks can be even higher than the contrast of the defects in that block. Probability of such condition rises with the size of the blocks. Hance as sensitivity falls, the value of NDR (percentage of non-detected failures) rises. It influences the most failure detection for T2 tiles which have heavier texture than other two types of tiles. Also, because of the lower sensitivity for larger blocks the SFD algorithm achieves a lower level of FDR in that case. Smaller blocks are more influenced by translations and rotation of the tile images, whereas larger blocks have a lower level of sensitivity.

Table 1. FDR and NDR ratios for tile T1 with block size 60x60 pixels

Tablica 1. FDR i NDR omjeri za pločicu T1 s veličinom blokova 60x60

Number of training vector class II/ Broj trening vektora klase II	FDR/ FDR				NDR/ NDR			
	Number of training vector class I/ Broj trening vektora klase I				Number of training vector class I/ Broj trening vektora klase I			
	C=5	C=10	C=15	C=20	C=5	C=10	C=15	C=20
D=5	24 %	24 %	8 %	0 %	0 %	0 %	0 %	0 %
D=10	42 %	6 %	2 %	0 %	0 %	2 %	2 %	2 %
D=15	48 %	30 %	10 %	0 %	0 %	0 %	0 %	0 %
D=20	48 %	30 %	26 %	0 %	0 %	0 %	0 %	0 %



a) b)

Figure 6. a) FDR – False Detection Ratio for T1, T2 and T3 tiles with different block sizes;b) NDR – Non-Detection Ratio for T1, T2 and T3 tiles for different block sizes

Slika 6. a) FDR – Postotak pogrešne detekcije za T1, T2 i T3 pločice s različitim veličinama blokova; b) NDR – Postotak nedetektiranih oštećenja za T1, T2 i T3 pločice s različitim veličinama blokova

2.7. Influence of spread σ

Spread σ of the Gaussian radial function defines the width of an area in the input space to which each neuron responds. In Figure 7. FDR dependence on the spread σ is shown, as well as NDR dependence on σ. The results are given for tiles T1, for C=20 and D=15, and for block sizes 60x60 and 100x100 pixels. Results show that for a small value of the spread the number of the undetected failures is high due to low sensitivity of neurons. In that case the network has the ability of a good classification only for the training set and even a small distinction of the test image from the training set can cause a wrong decision. A higher level of σ can cause an increase of the undetected failures (NDR) because sensitivity of neurons rises and every input vector stimulates all neurons. As a result, the network makes a wrong classification.

For tiles used in the experiment networks with σ between 3 and 7 obtain the best behavior. These values correspond to the smallest distance between two classes.

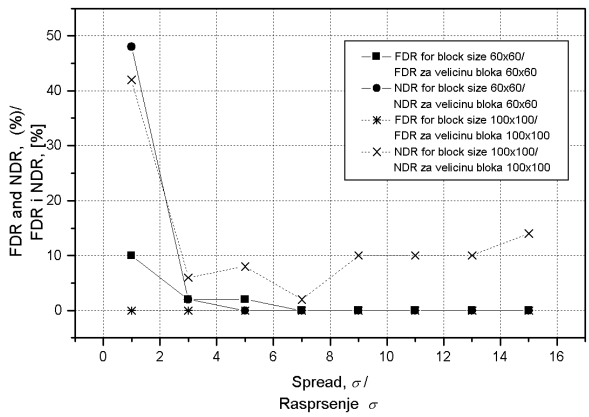


Figure 7. FDR and NDR dependence on the spread σ

Slika 7. Ovisnost FDR i NDR o raspršenju σ

3. Adaptive SFD

The SFD algorithm possesses good failure detection capability as shown by experimental results. Anyway, its success highly depends on the optimal parameters setting. In fact, each texture demands a specific neural network. In the ceramic tiles production process the type and the color of the tiles are often changed, therefore a failure detection procedure has to be flexible and adaptable. We have used self-learning capability of the neural networks to achieve such procedure.

The most critical part in the neural network learning process is the training vectors preparation. Training vectors have to present common defects on tiles as well as acceptable differences in luminance, color and texture of the tiles. Also, differences in position of the tile image, which occur during the image acquisition, have to be incorporated in vectors for defect-free tiles as well as in vectors for tiles with defects. An extensive statistical analysis has to be made before making a choice of the training vectors. For a new product, i.e. a new tile type, there are no statistical data to make this choice. The solution for this problem has been found in the knowledge of the statistical features of defects which occur on tiles. Although the textures of tiles differ, types and features of the defect are the same for almost all tile types. By knowing the statistical features of the defects occurring most frequently on tiles we have developed software for artificial generation of the image of tiles with defects. For a new tile production a usage of this Artificial Defects Generator (ADG) can drastically reduces time for automated vision inspection. The adaptive SFD algorithm, which includes ADG, is explained in the following text.

3.1. Feature extraction from the defects statistical data

Analysis of the defect statistical features perfomed on 114 samples of the tiles with defects. Firstly, defects are classified according their shape and size. For each class of defect the first and the second statistical moments (mean and variance) of the intensity histogram are calculated. Also, second-order statistic based on Haralick features is used for a better insight into defects texture. Haralick texture features are calculated from intensity level co-occurrence matrices, [11]. We have found that correlation, contrast and uniformity are the most interesting features.

Statistical information of the real defects is used for construction of the artificial defects with the same characteristics. The idea is to mimic actual defects that occur during the tile production. These artificially made defects are superposed to images of the correct tiles by software we have named Artificial Defects Generator (ADG). Generation of the artificial defects copies statistical feature of the actual defects, but it also reaches their randomness in statistics and position.

3.2. Optimization procedure for adaptive SFD parameters setting

For the preparation of the neural networks included in the SFD algorithm we have developed an optimization procedure (Figure 8). It consists of a few stages:

- Training images preparation by using ADG – parameters of ADG are tuned to produce training vectors of different kinds and visibility of defects;
- Testing images preparation by AFD for SFD validation;
- Neural network learning on training vectors;
- Failure detection of testing images by SFD algorithm;
- Validation of the SFD results;
- If FDR and NDR are below predetermined thresholds, the SFD algorithm is prepared for use in the production process;
- If FDR and NDR are above predetermined thresholds, the optimization routine is repeated with different parameters.

The optimization procedure begins with a small number of training vectors and a high block size. A good starting point can be C=5, D=5 and BM=BN=120. With these values a neural network has a low number of neurons in the hidden layer and it works faster. Also, the number of blocks is low which further improves calculation speed. For some textures these parameters can make a sufficiently efficient SFD algorithm and further optimization is not necessary. If FDR or NDR are above the predetermined threshold (the percentage of acceptable false and non-detection ratios), optimization proceeds with a higher number of C and D vectors, and a smaller block size. If none of the created networks set works well, new sets of networks are made with different spread σ of the Gaussian radial basis function and the optimization procedure is conducted again. If a successful networks set is not found in this second trial, an operator gets the message of non-adjustment of the detection procedure to the current type of tiles.

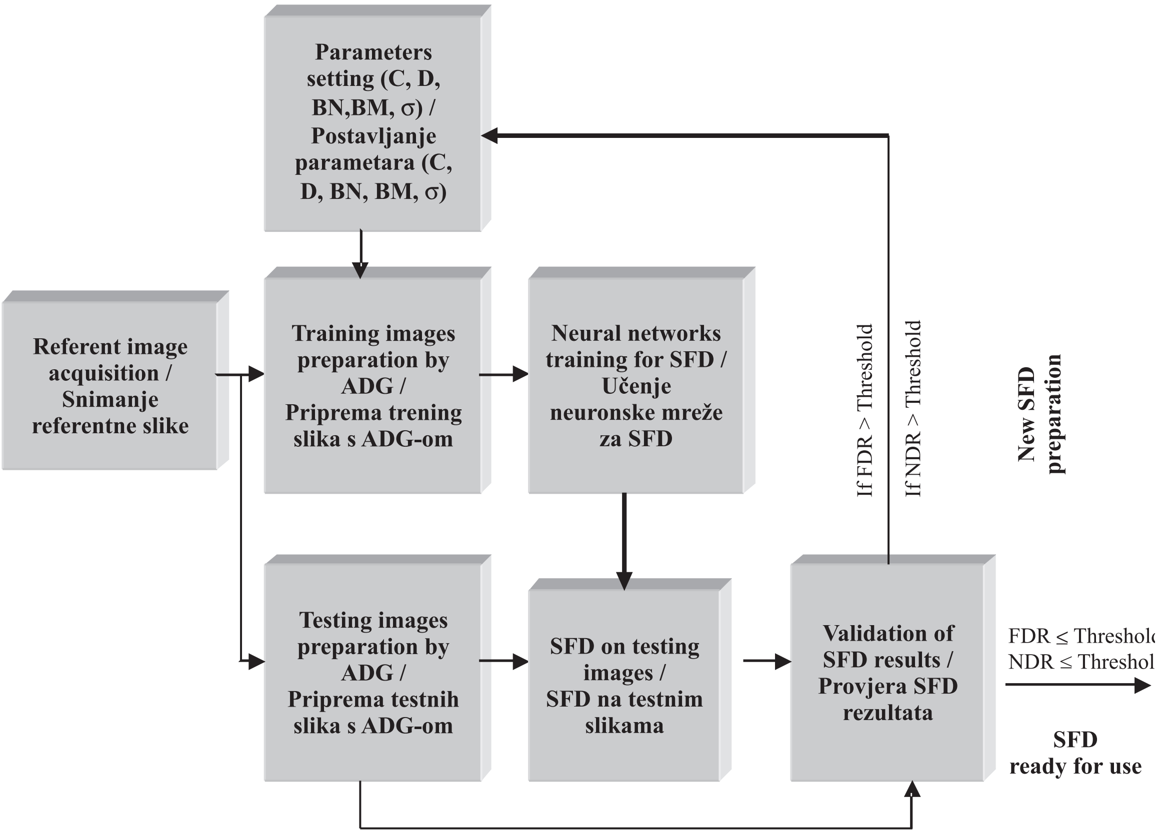


Figure 8. Optimization procedure for adaptive SFD parameters setting.

Slika 8. Optimizacijska procedura za određivanje parametara SFD-a.

4. Conclusion

By using DWT which behaves like a human visual system in the feature extraction process and the probabilistic neural networks for classification purposes, the surface failure detection algorithm SFD achieves good results in the classification of ceramic tiles with textures. The algorithm is of moderate complexity and its success highly depends on the proper choice of parameters. Different textures demands different parameters and the most important ones are: the number of the training vectors from class I (vectors from images without failures) and class II (vectors from images with failures), blocks size and spreading factor (in Gaussian function used in the hidden layer of neural networks). The choice of the training vectors is also of crucial importance.

To make the SFD algorithm adaptive to the new tiles we have developed an optimization procedure for automated SFD parameters setting. Optimization utilizes the Artificial Defect Generator (ADG) which is based on the knowledge of the ceramic tiles defects statistics. Statistical parameters used for defects characterization are: shape and size of defect, mean and variance of the intensity histogram, as well as contrast, correlation and uniformity of its co-occurrence matrices. By using the artificial images made by ADG, an automatic optimization of SFD parameters can be conducted

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