SELF-LEARNING SYSTEM FOR SURFACE FAILURE DETECTION

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ABSTRACT

In this article we present a self-learning system for automatic detection of surface failures on ceramic tiles. This system is based on the probabilistic neural network with radial basis. The discrete wavelet transform (DWT) is used as a preprocessing method with good feature extraction possibilities. With an automatic procedure for the production of input vectors for the neural networks training the presented system can adapt itself to different textures. Experimental results of the defect detection for different types of tiles show a high accuracy and applicability of the proposed procedure.

1. INTRODUCTION

In the ceramic tile manufacturing process all phases are completely automated with the exception of the final stage concerned to the visual product control. A manual visual inspection of the tile's surface is subject to mistakes due to workers' fatigue. The goal of the automatic surface failure detection is to insure detection sensitivity at least on the human inspection ability level. A defect on the textured surface is highly masked in dependence on the activity of the surrounding, and it can be very difficult to distinguish between defect and texture of the tiles. For this kind of defects an automatic detection system can be more sensitive than a human visual system.

Different solutions with different levels of complexity are reported in literature, [1,2,3]. All these methods have a limited range of application for some kind of defects and some kind of tiles. In [4] 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. A great complexity of the algorithms is a drawback in the real time application.

In this article we propose a neural network based procedure for detection of different types of failures on plain and textured surfaces. The wavelet transform of the tile image was used as a preprocessing method. This procedure is of moderate complexity and we have achieved good detection results.

2. FEATURE EXTRACTION BY DWT

The discrete wavelet transform - DWT implemented on an image provides a multiresolution analysis. DWT has a good spatial localization for higher frequency components and achieves good frequency localization for low frequency components.

An image is a two-dimensional signal and a two-dimensional DWT has to be performed. One-dimensional filters *h* (low-pass filter) and *g* (high-pass filter) are used in horizontal and vertical direction. That 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 A_1 contains approximation coefficients 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: vertical - V_1, horizontal - H_1 and diagonal - D_1. The filtering process can be preceded on a different level of resolution.

Different wavelet bases with corresponding wavelet filters were constructed, [5]. They differ according to length, smoothness and linearity of the phase. We used Daubeschies least asymmetric wavelet with four filter coefficients. The shortness of its filter enables fast calculation of wavelet coefficients, which is highly important in the failure detection process.

DWT is a good candidate for the image preprocessing method in a surface defect detection process as shown in [6]. Its property of filtering in different directions with a low complex algorithm as well as the conjoint spatial and frequency representation gives a possibility of detecting different kinds of defects. In fact, in random textured surfaces DWT can separate and magnify irregularities as cracks or spots like faults as shown in Figure 1.

We have used the local maximums of the coefficients in subbands V_1, H_1 and D_1 as indicators of the possible defect on the surface. It can be assumed that a defect produces a higher local contrast than the image texture.

To achieve a higher sensitivity level we have divided tile's image in segments, and then used a two-dimensional DWT for every segment. The absolute value of the maximums of the wavelet coefficients in V_1, H_1 and D_1 (further in the text maxV, maxH and maxD), as well as the mean value of coefficients in A_1 (meanA) are used as a measure of distance between the analyzed segment and the referent one. Vector $[\text{maxV maxH maxD meanA}]_k$ of the segment *k* is used as an input vector for the neural network formed for that specific segment.

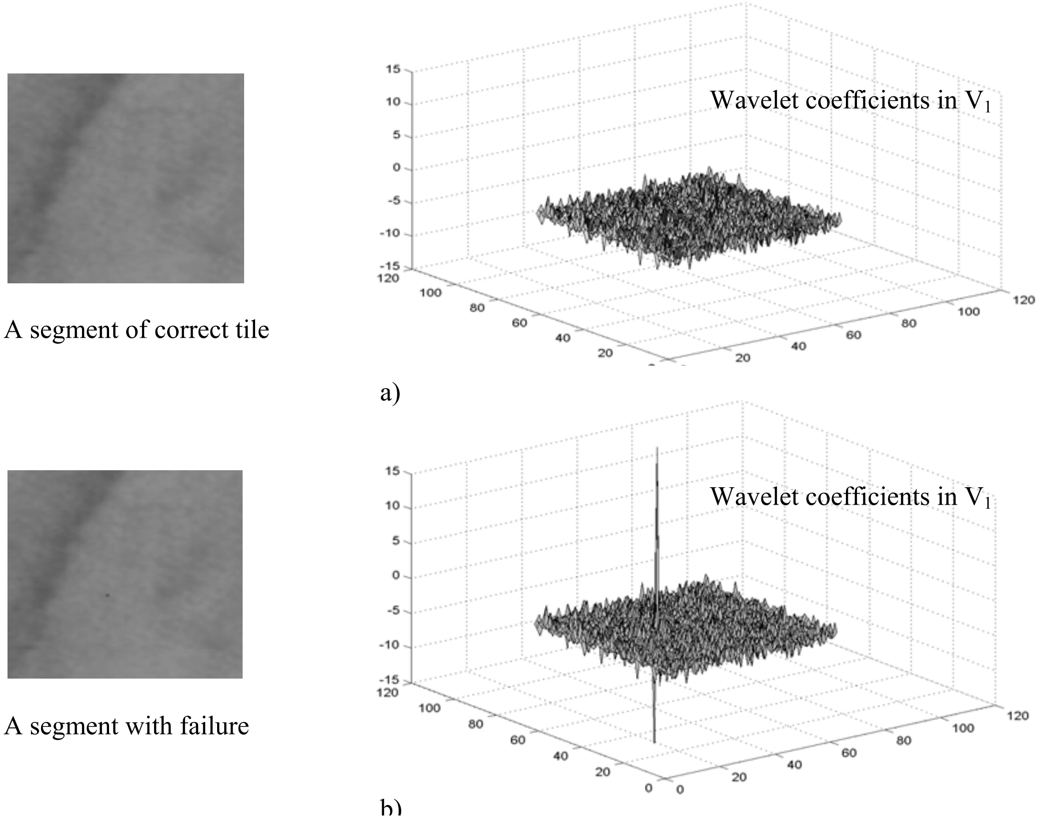

Figure 1. A segment of size 120x120 pixels (10mmx10mm) and corresponding wavelet coefficients in subband V1 for: a) the tile without failure; b) the tile with a failure

3. NEURAL NETWORK BASED DETECTION ALGORITHM

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. In the problem of classification the probabilistic neural networks with the radial basis function (PNN-RBF) give good results.

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

$$h(d) = e^{-\left(\frac{d}{\sigma}\right)^2} \qquad (1)$$

where d presents the Euclidean distance in multidimensional space R^n:

$$d_i = \|x - x_i\| \qquad (2)$$

In (2) x presents an n-dimensional input vector and x_i are n-dimensional training vectors. Since d_i is input to the activation function *h(d),* the output of the first layer is higher if distance d_i is closer to 0. Parameter σ in (1) defines a spread of the Gaussian function and allows adjustment of neuron sensitivity.

The output layer of the PNN-RBF network is a competitive layer. This layer sums $h(d_i)$ that corresponds to the specific class to produce a vector of probabilities as its net output. 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 a 0 for the other classes.

The structure of the PNN-RBF network was adopted for the defect detection, as shown in Figure 2. The defect detection

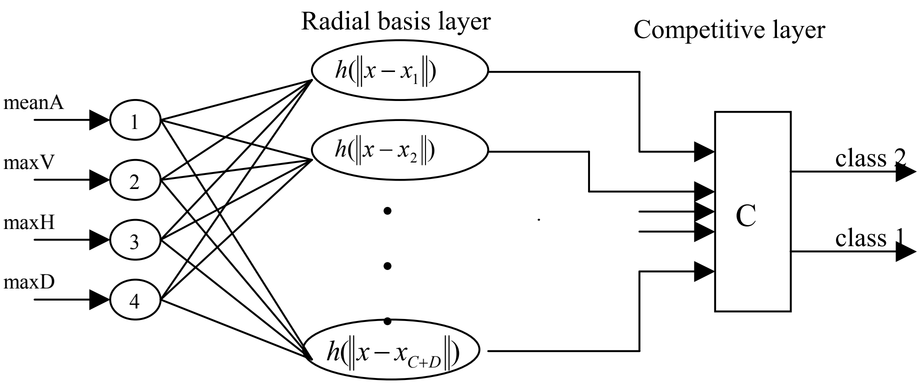

Figure 2. Structure of the neural network used in detection algorithm

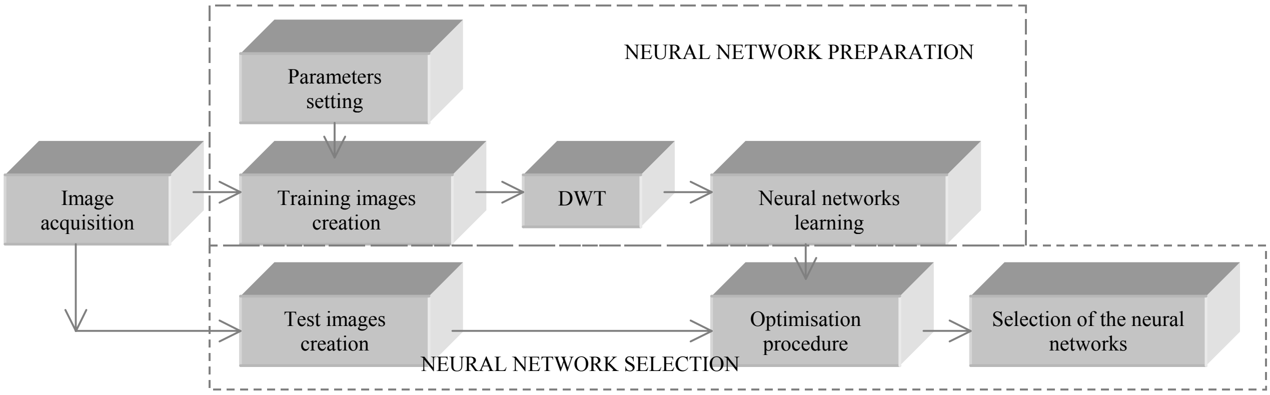

Figure 3. Self-learning procedure

problem is solved as a classification of tiles in class 1 - correct tiles, and class 2 – tiles with defect. Due to high differences of features across the tile surface, an image of the tile is divided in segments and a neural network is produced for each segment. Training vector x_i has four elements: maxH, maxV, maxD and meanA of the specific segment. The set of training vectors consists of C vectors of defect free segments, and D vectors of segments 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. The number of training vectors defines the number of neurons in the hidden layer. A tile is proclaimed as correct if for all segments networks classify their own segments to class 1 (as correct segments).

4. SELF-LEARNING PROCEDURE

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 self-learning procedure consists of two parts: the neural networks preparation and the neural network selections as shown in Figure 3.

4.1 Neural networks preparation

The neural networks learning begins with the tile's image acquisition and proceeds with the computer guided creation of the training images. The defect free images include translation, rotation and changes in brightness, while in the image with defects our program forms different kinds of defects in the random manner. Three different kinds of defects are used in this procedure: spot like, line like and blob like defects. The choice of the defects type is based on an analysis of the real defects statistics. 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. Sizes of the defects range from 0.2 millimeters to few millimeters and occur with different orientation and in randomly chosen position. The smallest defects and defects with the smallest contrast fall on the border of visibility for the human observer. The images with these defects define a sensitivity of the detection algorithm. Training vectors produced with images with larger and darker defects are used for better covering of the area of a more visible defect. Produced training images are used for the neural network learning. In this phase of the self-learning procedure several networks sets are made with a different number of training vectors and different segment sizes. These networks are used later in the optimization procedure and the network with the best detection ability is used in the failure detection process.

4.2. Neural network selection

After neural networks preparation a set of 100 test images with and without failures are made. The failure free images are made on the same way as the training defect-free images. For the preparation of the test images with failures we used 14 different algorithms to achieve similar morphology of the defects as we found in the real tile's production. Type and position of the failure are chosen randomly. An example of the actual and artificially generated defective tile images is shown in Figure 4.

The optimization begins by inspecting the test images with the networks learnt for the smallest number of segments (a higher size of segments) and with the smallest number of

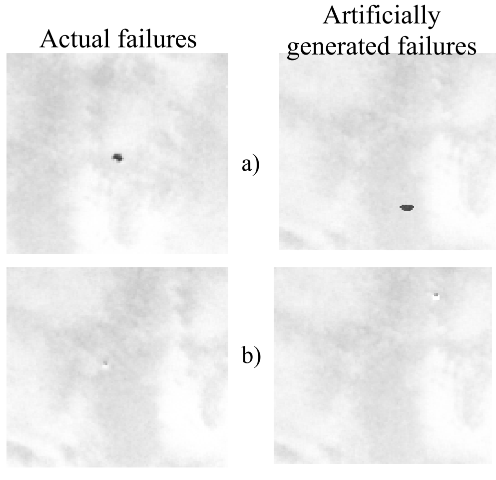

Figure 4. Actual and artificially generated failures: a) glaze defect; b) pin-tip defect

Table I. Detection results for different segment sizes and different number of the training vectors C and D

Segment size	C=12, D=8		C=15, D=10		C=20, D=15		C=25, D=20	
	False detection	Non-detection	False detection	Non-detection	False detection	Non-detection	False detection	Non-detection
40x40 pixels	2%	3%	2%	2%	0%	2%	0%	2%
60x60 pixels	0%	3%	0%	2%	0%	2%	0%	4%
80x80 pixels	0%	3%	0%	0%	0%	0%	0%	1%
120x120 pixels	0%	3%	0%	0%	0%	0%	0%	0%

training vectors. The algorithm effectiveness is measured by two results: 1. Percent of the tiles erroneously proclaimed as impaired ones – called false detection in further text; 2. Percent of undetected impaired tiles – or non-detection in further text. The efficiency of the algorithm rises if both percentages decrease, and the percentages are close to zero. If percentages of both the false detection and non-detection are below the predetermined threshold this neural network is chosen for the detection process. If these percentages are above the threshold the optimization procedure is conducted with networks learnt for same size of segments but with more training vectors. If these networks fail too, the optimization process is continued with smaller sizes of segments until a successful networks set are found. 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 the successful networks set is not found in this second trial, an operator gets message of the non-adjustment of detection procedure to the current type of tiles

5. EXPERIMENTAL RESULTS

Experimental results of the detection of defects on Sky Green tiles (250x200 mm) made by neural networks learnt with a different number of training vectors and different segment sizes are given in Table I. This detection is done on images of 100 defect-free tiles and 100 tiles with some failure. Tiles with failure are chosen carefully to represent different types of defects. Images are scanned during production by Uniline 2048 CCD monochrome line scan camera with 2048 pixels resolution. Experimental results show the best behavior of the algorithm for the segments of sizes between 80x80 pixels to 120x120 pixels, and for C=20 and D=15. We obtained similar results for different types of tiles, except for very dark tiles where DWT could not discriminate failure from surroundings. Anyway, success of the detection depends of acquisition system ability to record failures as contrast difference on the tile image. Some failures can not be visible on the image without special acquisition method. The number of segments and the number of training vectors increase the number of mathematical operations and increase proportionally the memory occupation for neural networks parameters. Therefore the optimization algorithm is incorporated in the self-learning procedure. In practice our self-learning detection procedure successfully works on 87% of the tiles with a different random texture produced by the ceramic industry “KIO” in Orahovica, Croatia. The detection process on actual tile images results in less than 2% of non-detection and less than 2% of false detection for these tiles, which is bellow the human observer results. The failure detection for the rest of the tiles we plan to solve with the second camera acquisition system.

6. CONCLUSIONS

The proposed defect detection procedure based on the probabilistic neural network with the radial basis function and DWT preprocessing shows good detection results. The efficiency of the algorithm is defined by the percentage of the tiles erroneously proclaimed as impaired ones and by the percentage of undetected tiles with defect. An optimization process achieves adaptation of the algorithm parameters to different textures. In this process a set of neural networks is done. Networks mutually differ according to segments sizes and the number of the training vectors. The best result in our experiments attains the network with segment sizes 120x120 pixels and for C=20 and D=15 training vectors. Therefore, the optimization procedure begins with the network with such parameters. Results of our detection system show applicability for almost 90% of the tiles type we inspected with false detection below 2%.

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