An Approach for Parameters Evaluation in Layered Structural Materials based on DFT Analysis of Ultrasonic Signals

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Abstract: An adequate assessment of the condition of versatile structural materials of different origin, from hard biological tissues (cortical bone) to objects of engineering infrastructure facilities (concrete), may encounter difficulties due to their complex and multilayer structure. Traditional ultrasonic testing based on the measurement of single parameters do not allow separating the complex influences of acting factors. Thus, the diagnosis of osteoporosis is complicated by the adverse influence of the thickness of the layer of soft tissue covering bone, when assessing the porosity of the bone. In the evaluation of deterioration processes in concrete, it is important to discriminate the depth of the deteriorated surface layer of concrete and the degree of the material degradation in this layer. The evaluation approach implementing the methods of pattern recognition has been proposed. The initial data set comprised ultrasonic signals obtained at different frequencies in specimens with different values of the parametrs according to a planned grid of the parameters of ineterest. The signals were obtained by surface profiling of the specimens by a pair of emitting and receiving transducers. In this study, an approach to evaluate parameters of interest using pattern recognition methods applied to ultrasonic signals processed by the Digital Fourier Transform was verified. The estimation model was based on the statistical analysis of the magnitude of the spectrum of the original ultrasonic signals. Decision rules were created based on the testing of a number of specimens forming the training set and calculation of the statistical criteria. Comparative testing of examination specimens demonstrated the adequacy of the proposed method as a potentially universal approach for evaluation of different kind of objects.

1 INTRODUCTION

An adequate assessment of the condition of versatile structural materials of different origin may encounter difficulties due to their complex and multilayer structure, where different factors interfere. Ultrasonic testing has established itself as a sensitive tool for characterization of materials' properties and conditions in a broad range of the materials from hard biological tissues (cortical bone) to objects of engineering infrastructure facilities (concrete) (Kundu, 2003). Nevertheless, traditional approaches based on the measurement of single parameters such

as ultrasound velocity, although it is an acknowledged indicator of the material strength, do not allow separating the complex influences of acting factors. This prompts the development of new diagnostic approaches and the use of more sophisticated data processing, in particular, using artificial intelligence methods.

Ultrasonic techniques based on measuring the parameters of elastic waves is a perspective modality to assess bone conditions in respect of osteoporosis (Laugier, 2008). Axial bone ultrasonometers use to measure ultrasound velocity in the compact bone of long bones, such as the tibia and forearm bones.

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Although it demonstrated the sensitivity to osteoporosis and mineralization disorders, its clinical use is compromised by the inability to discern multiple factors influencing the bone condition by this single input. New approaches are focused on the analysis of guided waves propagation at several frequencies that provides extensive information about the bone structure and properties (Tatarinov, 2014). However, discrimination of the factors of interest such as cortical porosity and thickness of the cortical layer against the background of the influence of the surrounding soft tissues requires advanced data processing.

Concrete is the most widely used building material being the basis of industrial and civil buildings and objects of infrastructure. Industrialized countries face the problem of ageing infrastructures that were built mostly in the second half of the 20th century and face deterioration due to environmental and inner factors (Breugel, 2017). Therefore, it is necessary of the adequate quality control and monitoring of the condition. Since the ingress of corrosive species and the harmful influence of water on the porous structure of concretes, especially combined with the action of frost, is initiated at the concrete surface, it is important to know how deep the deterioration processes are expanded into the depth of the concrete bulk. Ultrasound pulse velocity (UPV) has proved itself as an adequate indicator of strength for a certain class of cementation materials such as hardening and mature concretes, cements and etc., where the elastic modulus and strength changed proportionally (Komloš, 1996). However, traditionally used UPV, a single parameter measured at a certain frequency cannot represent the deterioration as a volumetric process, where changes occur gradually from the surface towards inner layers on an unknown depth. The idea of using ultrasonic surface waves at different frequencies has been put forward to assess the condition of the surface layer of concrete by depth is based on the known dependence of the penetration depth of Rayleigh waves its wavelength, inversely proportional to the frequency (Victorov, 1967).

The purpose of this study was to propose within certain limits a universal approach for evaluation at least two independent parameters of an examined object, the values of which are a-priori unknown. To solve this task, the data from a set of similar objects where the values of these parameters are a priori known is used. The very formulation of the problem suggests the need to use pattern recognition methods, but unlike the classical classification problem, in this case there is no need to determine the belonging of the object under study to any known class. In this case, it is necessary to determine only the values of two parameters of the investigated object.

The raw data were presented by sets of ultrasonic signal acquired stepwise by surface profiling of the object in the pitch-catch mode. The discrete Fourier transform (DFT), one of the recognized methods of signal analysis, transforming the signals from time to frequency domains was used (Stone, 2021). A set of statistical parameters was extracted from the set of magnitude signals, thus forming a set of features describing the object. Extracting statistical parameters from each object in the set, decision rules are created to be the instrument for the evaluation of parameters of interest in the examined objects.

To show the universality of the approach, its performance was tested in two different materials, which had different parameters of interest and belonged to different areas. The first class of objects was bone tissue in respect of osteoporosis, the problem related to medical diagnostics. The osteoporosis condition was modelled by tissue mimicking phantoms. The second class of objects was concrete with gradually deteriorated surface layer, both by the material quality and by expansion of deterioration in depth, the problem of technical diagnostics in construction and maintenance of infrastructure.

2 PROPOSED APPROACH

The proposed approach for evaluation for object parameters in two experiments is based on the principles of pattern recognition. The evaluation method consists of two parts: creating a set of decision rules using the data for a training set of specimens and validation the set of decision rules by substitution the data for an examination specimen to make sure that the proposed approach is correct.

2.1 Ultrasonic Testing

Acquisition of ultrasonic signals was carried out by the surface profiling of specimens by a pair of emitting and receiving ultrasonic transducers. To vary the wavelength and thus the penetration depth of ultrasonic surface wave into the object, the testing was repeatedly done at two ultrasonic frequencies: 100 and 450 kHz I bone phantoms and 50 and 100 kHz in concrete specimens. The excitation signals were two-period sine tone-bursts. The signals were recorded by moving the receiver from 20 to 120 mm

far from the emitter with a step of 5 mm by the specimen's surface.

Two series of objects of interest were investigated:

a) Bone phantoms modelling osteoporosis, where 3 grades of bone condition were simulated by thin polymer plates with gradually varied inner porosity of 0, 10 and 25%. The specimens were covered by natural soft tissues of thicknesses 0, 2 and 5 mm. The parameters of interest in the evaluation were the bone condition on the scale "norm-osteoporosis" and the thickness of the soft layer. Thus, the grid in the training set of specimens included 3 grades of bone condition and 3 grades of soft tissue thickness, totally 9 objects.

b) Deteriorated surface of concrete, where 7 grades of depths of deterioration from 0 to 40 mm and 4 grades of the material quality in the weak surface layer (cement-to-sand ratios 1:3; 1:4; 1:7 and 1:12) were provided in a series of concrete specimens. The grid of the training series contained 21 object.

2.2 Creation of Decision Rules

Step 1: For one specimen with a priori known thickness of the "weak" concrete layer, three signals were recorded at frequencies of 50, 100 and 200 kHz. The result was three discrete signals $s(t)$.

Step 2: Each of the discrete signals $s(t)$ ($t \in [t\_min; t\_max]$) is converted by discrete Fourier transform (DFT) into the spectral signal $M(\omega)$, ($\omega \in [\omega\_min; \omega\_max]$) describing the magnitude spectrum:

$$M(\omega) = \sqrt{\left(Re(\omega)\right)^2 + \left(Im(\omega)\right)^2}$$

where:

$$Re(\omega) = \sum_{t=t\_min}^{t\_max} s(t) \cdot cos\left(\frac{2\pi \cdot t \cdot \omega}{t_{max} - t\_min}\right)$$

and

$$Im(\omega) = \sum_{t=t\_min}^{t\_max} s(t) \cdot sin\left(\frac{2\pi \cdot t \cdot \omega}{t_{max} - t\_min}\right)$$

In further processing, the considered interval ω satisfied the following conditions:
$M(\omega) \geq \varepsilon 1 \cdot max\{M(\omega)\}$ and
$\omega \leq 0{,}5 \cdot (\omega\_max - \omega\_min)$

Step 3: In the selected interval ω, the values of three functions were calculated:

$$F\_max(\omega) = max\{M(\omega)\};$$
$$F_{avr(\omega)} = average\{M(\omega)\} \text{ and}$$
$$F\_min(\omega) = min\{M(\omega)\}$$

Step 4: Statistical tests were performed in the interval ω selected in Step 3.

Criterion #1: the number of ω values that fulfill the condition:

$$F_{max(\omega)} \geq average\left(F\_max(\omega)\right), (cr\#1);$$

Criterion #2: the ratio between the maximal values of the functions $F\_min(\omega)$ and $F\_max(\omega)$:

$$cr\#2 = \frac{max\left(F\_min(\omega)\right)}{max\left(F\_max(\omega)\right)}$$

Criterion #3: the ratio of the maximum derivative value for the function $F\_max(\omega)$ to the maximal value for the function $F\_max(\omega)$:

$$cr\#3 = \frac{max|dF\_max(\omega)|}{max\left(F\_max(\omega)\right)}$$

where:

$$dF\_max(\omega) = F\_max(\omega) - F\_max(\omega - 1) .$$

Criterion #4: the ratio of the maximum derivative of function $F\_avr(\omega)$ to the maximal value for the function $F\_max(\omega)$:

$$cr\#4 = \frac{max|dF\_avr(\omega)|}{max\left(F\_max(\omega)\right)}$$

where:

$$dF\_avr(\omega) = F\_avr(\omega) - F\_avr(\omega - 1) .$$

Criterion #5: the ratio of the maximum derivative of function $F\_min(\omega)$ to the maximal value for the function $F\_max(\omega)$:

$$cr\#5 = \frac{max|dF\_min(\omega)|}{max\left(F\_max(\omega)\right)}$$

where:

$$dF\_min(\omega) = F\_min(\omega) - F\_min(\omega - 1) .$$

Critera #6, #7 and #8: approximation of function $F\_max(\omega)$ by quadric polynomial:

$F_{MLS}(\omega) = cr\#6 \cdot \omega^2 + cr\#7 \cdot \omega + cr\#8$, where polynomial coefficients can be found using the method of least squares:

$$\begin{pmatrix} cr\#6 \\ cr\#7 \\ cr\#8 \end{pmatrix} = [W]^{-1} \cdot \begin{pmatrix} \sum_i \omega_i^2 \cdot F\_max(\omega) \\ \sum_i \omega_i \cdot F\_max(\omega) \\ \sum_i F\_max(\omega) \end{pmatrix}$$

where:

$$[W] = \begin{pmatrix} \sum_i \omega_i^4 & \sum_i \omega_i^3 & \sum_i \omega_i^2 \\ \sum_i \omega_i^3 & \sum_i \omega_i^2 & \sum_i \omega_i \\ \sum_i \omega_i^2 & \sum_i \omega_i & \omega_{max} - \omega_{min} \end{pmatrix}$$

Criterion #9: the ratio between the maximal values of functions $F\_avr(\omega)$ and $F\_max(\omega)$:

$$cr\#9 = \frac{max(F\_avr(\omega))}{max(F\_max(\omega))}$$

Criteria #10 - #13: the integral criteria defined as the ratios of the areas bounding functions $F\_min(\omega)$, $F\_avr(\omega)$ and $F\_{max(\omega)}$. The criteria were calculated as follows:

$$cr\#10 = \frac{S_{min}}{S_{max}}; \quad cr\#11 = \frac{S_{avr}}{S_{max}};$$
$$cr\#12 = \frac{S_{max} - S_{avr}}{S_{max}}; \quad cr\#13 = \frac{S_{avr} - S_{min}}{S_{max}}$$

where:

$$S_{min} = \frac{1}{max\{F\_max(\omega)\}} \cdot \sum_{\omega=\omega\_min}^{\omega\_max} F\_min(\omega)$$

$$S_{avr} = \frac{1}{max\{F\_max(\omega)\}} \cdot \sum_{\omega=\omega\_min}^{\omega\_max} F\_avr(\omega)$$

$$S_{max} = \frac{1}{max\{F\_max(\omega)\}} \cdot \sum_{\omega=\omega\_min}^{\omega\_max} F\_max(\omega)$$

2.3 Use of Decision Rules

The approach to assess the parameters of object using decision rules consisted of the following steps.
Step 1: For the examination specimen, which is a test for the decision rules, steps 1-4 from the section "Creation of decision rules" (3.1.) were repeated.
Step 2: The values set of parameters was divided into a certain number of intervals. In each interval of parameters, each i-th statistical criterion of the control specimen $cr\#x[i]$ was compared with the corresponding i-th decision rule $Rule[i]$ within the accuracy range $\pm\Delta$:
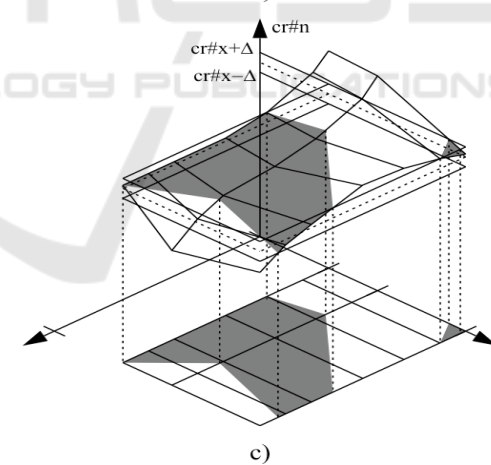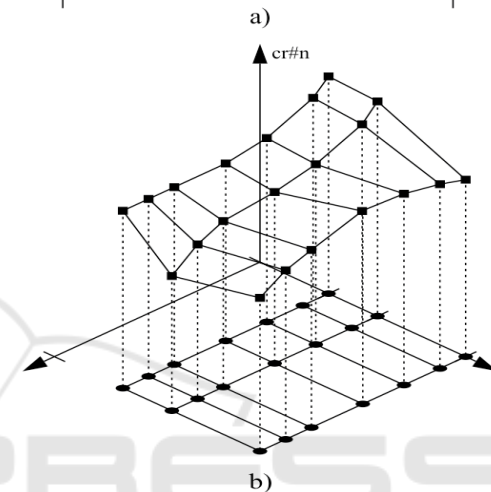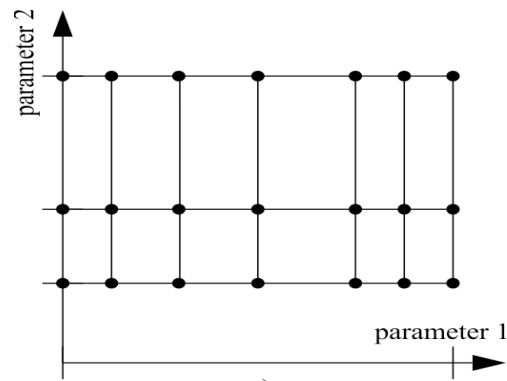

Figure 1: a) Topology of initial data, b) decision rule for selected criterion c) use of decision rule for a recognition case.

$$\{cr\#x[i] - \Delta \leq Rule[i] \leq cr\#x[i] + \Delta\}$$
$$= \begin{cases} true & s\_cr[i] = 1 \\ false & s\_cr[i] = 0 \end{cases}$$

where:

$$\Delta = 0{,}5 \cdot \varepsilon2 \cdot (max(Rule[i]) - min(Rule[i]))$$

$\varepsilon2$ – the relative error of value $cr\#x[i]$;

s_cr – the number of intersections in the interval.
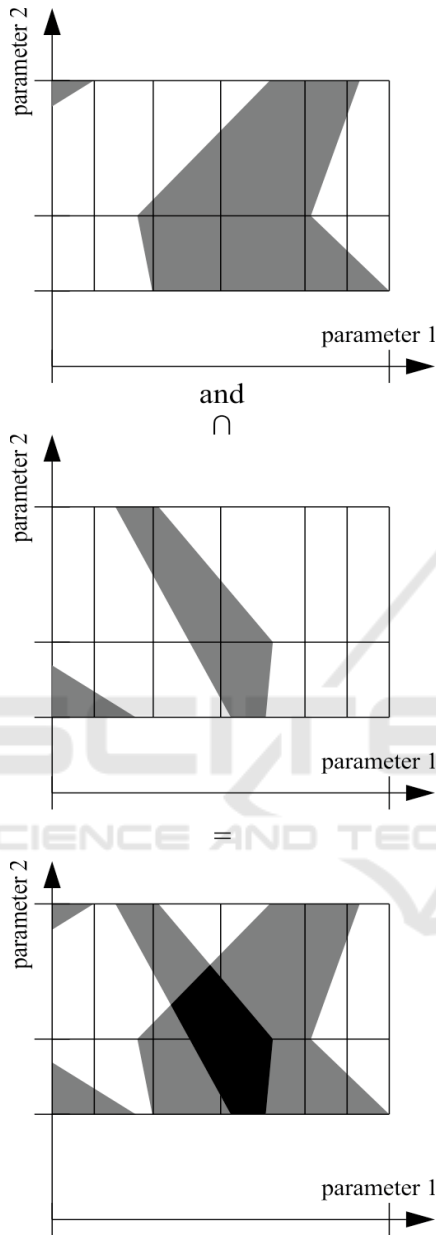Fig.2 illustrates the use of the decision rule sum for two criterion.

Figure 2: Illustration of finding the area of a probable solution using the superposition of two decision rules.

Step 3: At each interval, the number of intersections of the set of statistical criteria with the corresponding decision rules was computed as

$$sum = \sum_i s\_cr[i]$$

The interval, where the number of the intersections *sum* is maximal, gives the final estimate of the factors of interest of parameters for the control specimen.

3 RESULTS

The validation of the proposed approach comprised two types of experiments:

1) assessment of the state of the bone phantom by the parameters of interest: the degree of inner porosity (the parameter of the main diagnostic interest) and the thickness of the soft tissue layer (a side factor).
2) assessment of concrete condition by the parameters of interest: the thickness of "weak" concrete layer or the depth of the deterioration and the quality of "weak" concrete in terms of its composition. Both parameters are diagnostically important in this case.

In each of the experiments, the datasets in each object were obtained at two ultrasonic frequencies:

- 100 kHz and 450 kHz in bone phantoms;
- 50 kHz and 100 kHz in concrete specimens.

3.1 Evaluation of Bone Phantom's Parameters

Based on the obtained 13 decision rules, a test was made on 3 samples with the values of osteoporosis grade and soft tissues thickness, which were not presented in the training set (Table1).

Table 1: Parameters of test bone phantoms.

Object	Osteoporosis grade	Soft tissue thickness, mm
X	1	3
Y	2	4
Z	5	1

An example is given in Figure 3, where the area of possible solutions is shown in red, the correct answer is shown in a blue rectangle.

Experiment #1.
In the first experiment, a frequency of 100 kHz and bilinear interpolation in the decision rules were chosen. The values of ε2 s for all objects of the examination sample were chosen experimentally 0.03. Regions of probable solutions for 3 examination objects in the test series are given in Figure 4 and correspond to the highest concentration of

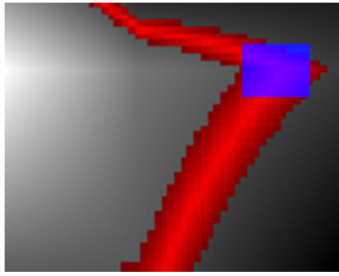intersections of all decision rules. The known values of parameters are shown by blue rectangles.

Figure 3: Region of interest for cr#5, Y object and bilinear interpolation.

Figure 4: Results of Experiment#1 for 3 test cases (X, Y, Z in Table 1). The abscissa shows the values of the thickness of the layer of soft tissues in ascending order from left to right, along the ordinate the values of porosity are plotted in ascending order from top to bottom.

As it is seen in Figure 4, objects X and Y are classified quite accurately. Object Z has large extra regions at the top and right bottom corner of the field that may misinterpret the evaluation.

Experiment #2.

In the second experiment, a frequency of 450 kHz and bilinear interpolation in the decision rules were chosen. Regions of probable solutions for 3 examination objects in the test series known values of parameters compared to known values of parameters (blue rectangles) are shown by blue rectangles are given in Figure 5. The highest concentration of intersections of all decision rules allow accurate the classification of the test objects. However, in this
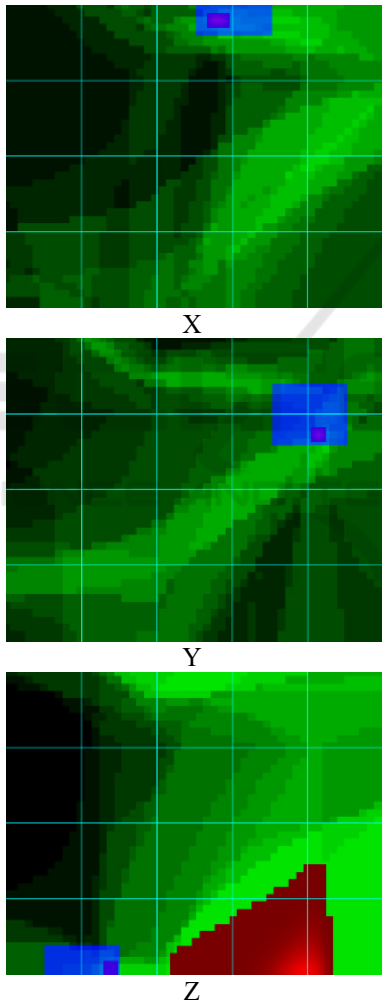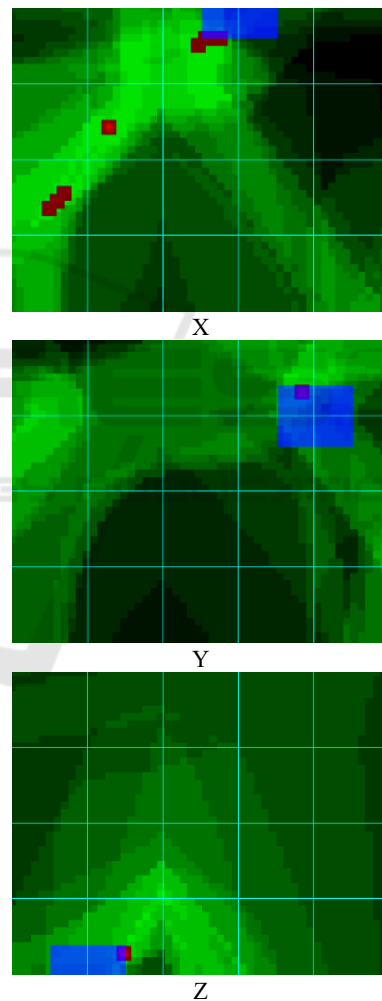

Figure 5: Results of Experiment#2 for 3 test cases (X, Y, Z in Table 1) The abscissa shows the values of the thickness of the layer of soft tissues in ascending order from left to right, along the ordinate the values of porosity are plotted in ascending order from top to bottom.

experiment as well, there are extra intersections that do not correspond to the right solutions in all objects.

The results of Experiment#1 and Experiment#2 obtained at different frequencies mostly coincide. Meanwhile, the areas of false intersections of decision rules are located differently. The combination of data of the both experiments allow to find the correct solution with the best coincidence and to reject false intersections that are not confirmed by the results obtained at another ultrasonic frequency.

3.2 Evaluation of Concrete Parameters

Experimental verification of the proposed method included several practical experiments. The initial data contained a set of signals in 7x3=21 specimens with thickness of the "weak" concrete 0, 3, 5, 12, 20, 25, 30, 35, 40 mm and quality of concrete (ratio "cement/sand") 1/12, 1/7 and 1/4. The data for each specimen was composed of 3 discrete signals obtained at ultrasonic frequencies 50, 100 and 200 kHz, consequently.

This set of specimens was divided into the training and examination sets. The total number of specimens in the training set was 21. The examination set included 3 specimens of thicknesses of the "weak" concrete layer 3 and 25 mm and different grades of the cement/sand ration. The error values in all experiments were selected ε_1=0,08 and ε_2=0,05.

Experiment #3.
In the 3rd experiment, a specimen with a "weak" concrete layer thickness of 3 mm and ratio "cement/sand" of 1/7, scanning frequency 50 kHz was selected as an examination one.

The results of final evaluation for the examination specimen and an illustration of computation of the segment of interest by using all 13 decision rules for frequency 50 kHz are shown in Figure 6. The taken result shows that proposed approach gives the evaluation with an approximately error of 1 mm by thickness and approximately 0.1 by the ratio "cement/sand".

Experiment #4.
In the 4th experiment, a specimen with a "weak" concrete layer thickness of 25 mm and ratio "cement/sand" of 1/7, scanning frequency 50 kHz was selected as an examination one.

The results of final evaluation using 13 decision rules for frequency 50 kHz are shown in Figure 7. The proposed approach gave the specimen evaluation with approximately error 5 mm by the thickness and approximately 0.1 by the ratio "cement/sand".
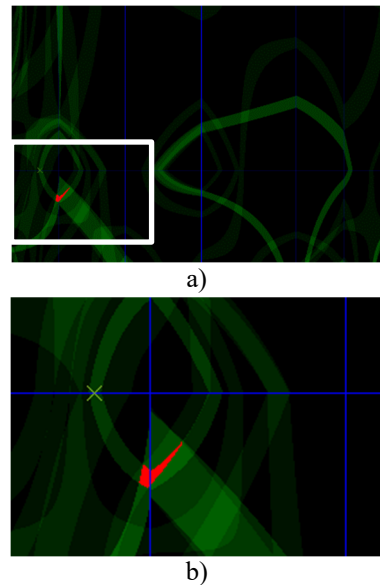

Figure 6: Results of Experiment#3, a) original, b) enlarged fragment. The abscissa shows the values of the thickness of the "weak" concrete layer in ascending order from left to right, along the ordinate the values cement/sand ratio are plotted in ascending order from top to bottom.

Figure 7: The result of final evaluation for test specimen (thickness = 25 mm, ratio = 1/7), a) original, b) enlarged fragment. The abscissa shows the values of the thickness of the "weak" concrete layer in ascending order from left to right, along the ordinate the values cement/sand ratio are plotted in ascending order from top to bottom.
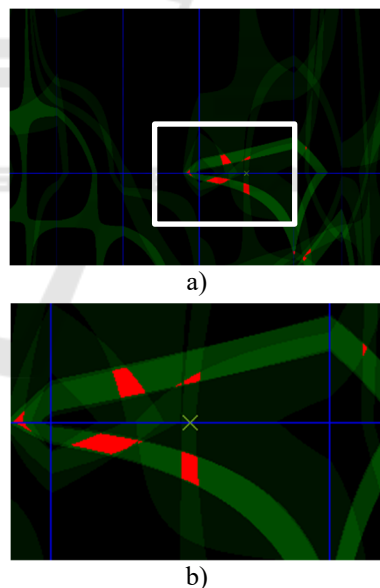
Experiment #5
In the next experiment, two specimens with a "weak" concrete layer thickness of 3 mm and ratios

"cement/sand" of 1/7 and 1/4 were evaluated using the data obtained at ultrasonic frequency 100 kHz. The results of final evaluation are shown in Figure 8. In specimen 1/7 (Figure 8a), an approximately equivalent evaluation was obtained comparing with the same evaluation in Experiment#3 at 50kHz despite the fact that pattern lines of the decision rules intersections at 50 and 100 kHz had completely different patterns. The specimen with the ratio 1/4 (Figure 8b) had at least two distant solutions, where only one was adequate within the accuracy tolerance. This emphasizes the need to improve algorithms and, in particular, to introduce various influence weights for informative rules.
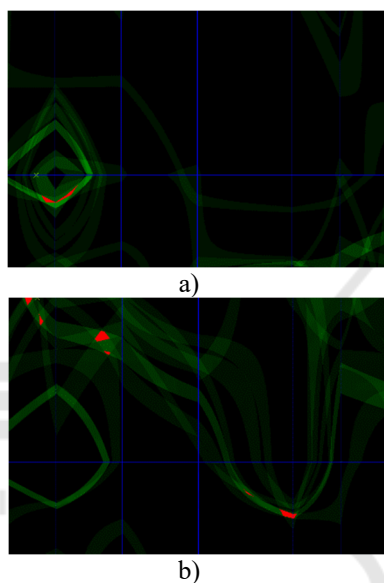

a)

b)

Figure 8: The result of final evaluation for test specimen (thickness = 3 mm,), a) ratio = 1/7, b) ratio = 1/4. The abscissa shows the values of the thickness of the "weak" concrete layer in ascending order from left to right, along the ordinate the values cement/sand ratio are plotted in ascending order from top to bottom.

4 CONCLUSIONS

Despite the small number of initial experimental data, the proposed approach based on DFT analysis of sets of ultrasonic signals demonstrated an adequate estimate of the parameters of interest in different classes of materials and different diagnostic tasks. The method proposes a perspective for the implementation both in biomedical area, particularly, for the diagnosis of the state of bone tissue, and in technical expertise for testing the quality of surface layers of structural materials (concrete) and assessing the degree of their degradation. The approach was principally verified in bone phantoms modelling the osteoporosis condition and in concrete specimens with the gradually degraded surface layer. The parameters of interest were determined with a satisfactory accuracy within a reasonable tolerance. A complex use of ultrasonic signals in the surface transmission at different frequencies can help finding the only correct solution and avoidance of false ones. Improvement of the reliability and accuracy of the proposed approach can be achieved by: a) increase of the number of specimens in the training group and the number of measurements in the initial data sets; development a mathematical method for evaluation of the reliability of each statistical criterion and decision rule and development of additional statistical criteria.

ACKNOWLEDGEMENTS

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