The Curvelet Transform Application to the Analysis of Data Received from GPR Technique

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***Abstract*—The article presents the analysis of both, synthetic and experimental Ground Penetrating Radar (GPR) data by the use of curvelet transform. The images, received from GPR technique, called B-scans are 2D images, where the first dimension represents time and the other one represents depth. These images are often low resolution and noisy. Besides, B-scans are often very difficult to interpret even for experts. That is why the curvelet transform has been applied to clarify the meaning of images. We have shown that the image analysis process of B-scans can be automated by the use of curvelet transform, which lets us detect the edges in any angle in the image under consideration. It was proven that the proper analysis and the choice of curvelet transform coefficients allows to clearly specify the location of the target. The main advantage of the curvelet analysis is the efficient detection even when we deal with low resolution and noisy images.**

***Index Terms*—GPR, curvelet transform, signal processing, electromagnetic imaging.**

I. INTRODUCTION

The sensors which are used during non-destructive tests work on the base of the detection and the analysis of electromagnetic field scattered from the objects under investigation. In general, the data received from these tests are analyzed and interpreted using advanced signal analysis techniques [1]–[3]. In some cases the buried object detection methods can simultaneously use a few advanced algorithms [4] and advanced data acquisition equipment [5]. In the case of GPR technique the signal analysis can be divided into 2 steps [6], [7], where the objects' parameters are detected or the analysis of raw data is aimed at the detection of the object location [8]. In practice, GPR data interpretation is very sophisticated due to low image resolution and inhomogeneous materials. That is why the experts' knowledge is required. One of the problems connected with GPR technique is also high amplitude of the first response from the object called clutter. Therefore, there are often problems with the detection of the object located near the GPR sensor or near the surface. In order to avoid the problems with clutter two methods are often used:

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1) Filtering;
2) Cutting the signal in the proper time.

The filtering is particularly useful when objects like landmines buried at shallow depths are investigated [9].

Taking the above problems into account different methods are used, which help to interpret the data. One of these methods is the curvelet transform, which was successfully applied to borehole GPR [10] or to the classical impulse GPR [11].

The main shapes which occurred in B-scans are hyperbola-like shapes, which are caused by rebars, tubes and other linear objects. In this case the shape of hyperbola depends on the diameter of a rebar and the EMF velocity in the material surrounding the object.

The resolution of GPR data is approximately equal 1/4 of the length of electromagnetic wave. The higher frequency is used, the better the resolution is, but the depth of penetration is lower. On the other hand, when the frequency is lower, the depth of penetration is deeper, but the resolution is low.

The process of signal interpretation can be divided into a few steps depending on the needs and the kind of problem in question, as follows:

1) Data correlation connected with the imperfection of measurement system;
2) Extraction of noise, disruptions of all sorts and clutter reduction;
3) Image amplification (edge detection, data compression);
4) Temple matching, neural network hyperbola identification;
5) Classification of detected shapes;
6) Object parameters determination by the means of classified shapes (size and object position).

The methods of GPR signal processing depends on the kind of data and can be divided into two groups:

7) Initial A-scan transformation understood as data filtration and deconvolution.
8) B-scan transformation understood as image processing (migration, edge detection) or the methods of image analysis like template matching or artificial neural network.

In our case we have applied B-scan signal analysis method, which is sufficient when hyperbola-like shapes are detected in the images. The detected shapes have let us for later quantitative data interpretation [12], [13].

II. CURVELET TRANSFORM

Curvelet transform belongs to the group of multiresolution transformations, which can be used for the detection of edges in the images under consideration. When comparing this method with another one, but of the same type like, for example wavelets, apart from the scale and the location parameters, there is also a unique parameter of the orientation which lets the image analysis up to 72 different angles when the image resolution is 512 x 512 px. That is why the anisotropic analysis of the images with regard to the edges and shapes, which can occur in the image, is possible. Comparing this with wavelet method, the detected edges do not have to be horizontal or vertical ones, and they do not need to create the same angle. This analysis can be done on different decomposition levels or for different resolutions, which is a very important advantage when GPR data are considered.

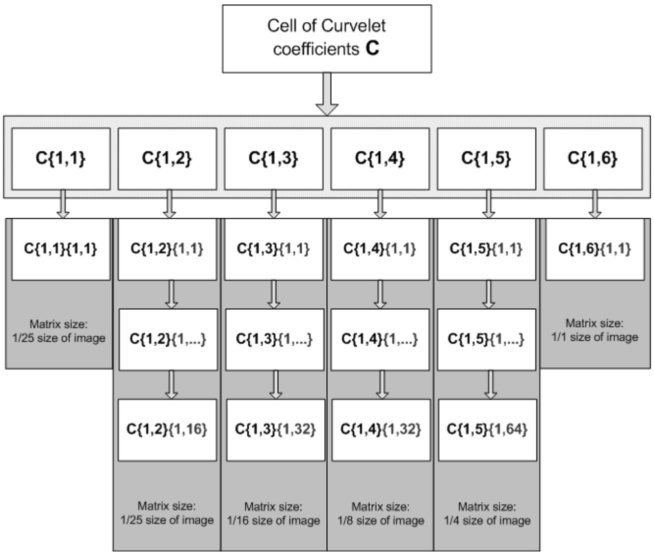


Fig. 1. Curvelet transform coefficients structure.

Depending on the resolution of the analyzed image the patters of the image are identified (grouped) in the separated matrixes. The discrete parameters of orientation are grouped on different levels in a way that every matrix sequence has data of different image patters. In the presented work the authors used FDCT (Fast Discrete Curvelet Transform) algorithm via Wrapping implemented in CurveLab [14] library which belongs to MATLAB. The structure of curvelet transform coefficients which have been received on the base of CurveLab are shown in Fig. 1. The detail structure explanation of curvelet transform coefficients and their features can be found in [11], [14]–[17].

III. GPR DATA

The application of curvelet transform to the data analysis from GPR has been done for two cases: synthetic data generated in GprMax software [18] and experimental data. In both cases the monostatic configuration has been used (see Fig. 2), where one antenna works as receiver and transmitter. During GPR measurements the antenna from position N =*1* is moved to position *N=41*.

In our case the model of concrete slab with dimensions of 0.6 x 0.3 meter and perfectly conducting scatter (rebar) of various radius ϕ (from 0.005 to 0.03 m) have been used (see Fig. 3). Moreover, the rebar was located in different depths and positions with regard to the air bubbles understood as the distortion. The following dielectric parameters have been assigned to the concrete: ε_r = 6 and σ = 0.01 S/m. To simulate GPR antenna at center frequency of f = 900 MHz a ricker (I) source has been applied

$$I = -2\zeta\sqrt{\frac{e}{2\zeta}}e^{-\zeta(t-\chi)^2}\left(t-\chi\right) \tag{1}$$

where: $\zeta = 2\pi^2 f^2$, $\chi=1/f$ and f is the center frequency of electromagnetic field.

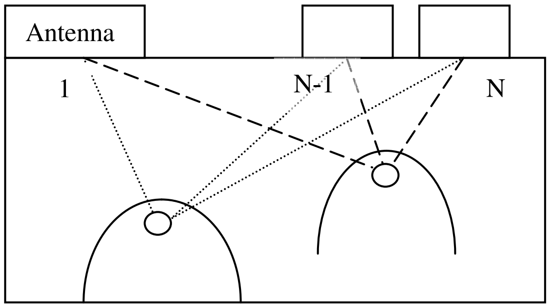
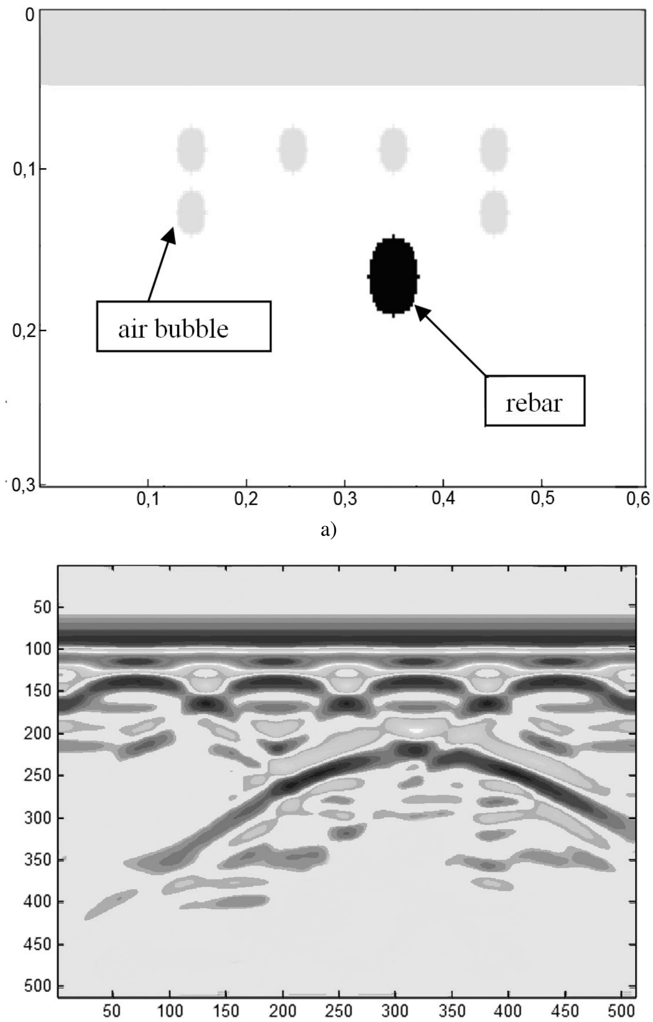


Fig. 2. GPR measurement setup.



a)

b)

Fig. 3. The rebar in the concrete surrounded by the air bubbles (a) – the model, b) – B-scan received from simulation.

Before curvelet transformation application these data have to be carefully prepared because they possess negative values, which do not occur in classical digital images. The initial image analysis based on curvelet transform is connected with the contrast and features amplification, which are used in further analysis. In this way the image interpretation becomes easier for GPR operator.

In our case the images were initially transformed to 512x512 pixels, then the clutters have been excised. All the images show the case of a metallic object (rebar) in the concrete with air bubbles as the source of noise (Fig. 2). In this case the classical B-scan will present the sequence of hyperbola-like shapes. One of the cases which were investigated in this work can be seen in Fig 3. The model configuration can be seen in Fig. 3a and its B-scan generated with GPRMax software in Fig. 3b. The interpretation of this image will be based on the finding of hyperbolas maximums, understood as the object findings.

IV. Synthetic Data Analysis

During the investigation presented in this work the sequence of matrixes and their coefficients, which determine the information about the object localization has been established. By the use of curvelet transform we have observed diagonal coefficients of the matrix sequence, which are important for searching the localization of the objects.

The coefficients of curvelet transform consist of 146 matrixes describing transform development with regard to every level of the resolution (scale) and the orientation. The first matrix consists of the coefficients on the lowest degree of decomposition, while 146th matrix consists of the coefficients on the highest level of the decomposition. The matrixes from the second to 145th consists of the coefficients which take into account the orientation parameter i.e. every matrix consists of the coefficients describing the details in the B-scan image under the specified angle. For example, matrixes: 4, 22, 54 and 90 contain the coefficients which are responsible for the horizontal details in the image, for different levels of the resolution, from the lower to higher ones, respectively. Analogously, the matrixes 7, 29, 61 and 105 contain the coefficients responsible for the vertical details in the image. During the investigation on the presented task, we have established the matrixes which contain the coefficients of curvelet transform which carry important information about the object localization.

In our case we have used all the features of curvelet transform with regard to the shapes identification in the images under investigation. For the cell coefficients which contain 146 matrixes the thresholding of coefficients has been done. In this way, after inverse curvelet transform hyperbola, shapes can be retrieved without the noise. The choice of threshold values for the coefficients in the different matrices was made experimentally.

In Fig. 4 and Fig. 5 the effects of curvelet transform application to the rebars with different diameters in concrete are presented. Because the rebar was located in different depths we were able to observe different positions of hyperbolas tips. We have also investigated rebar diameter influence on the parameters of reconstructed hyperbolas. It was concluded that there is no influence of rebar diameter on detection.

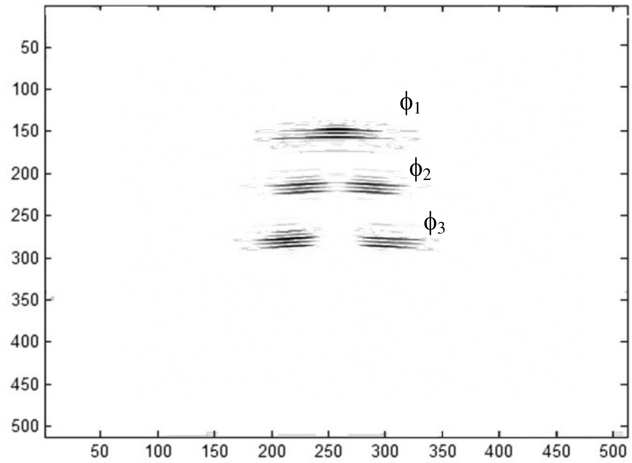


Fig. 4. The reconstructed hyperbola-like shapes received from the inverse curvelet transform with thresholding applied to the rebar in the concrete. The diameters (ϕ) and the depth (d) of three rebars are varied ($\phi_1 > \phi_2 > \phi_3$ where $\phi_1=50$, $\phi_2=125$, $\phi_3=300$mm), ($d_1<d_2<d_3$, where $d_1=40$, $d_2=100$, $d_3=160$ mm).

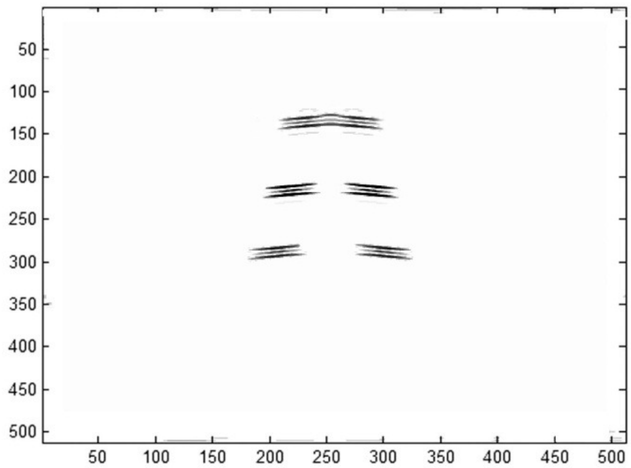


Fig. 5. The reconstructed hyperbola-like shapes received from the inverse curvelet transform with thresholding applied to the rebar in the concrete. The diameters (ϕ) of three rebars are constant ($\phi_1= \phi_2= \phi_3=125$ mm) and the depth (d) are varied ($d_1<d_2<d_3$, where $d_1=40$, $d_2=100$, $d_3=160$ mm).

V. Experimental data analysis

On the base of the analysis carried out in the previous section we have established the threshold values of coefficients, which have been used in the analysis of the experimental data. In this way we were able to clearly identify the locations of the hyperbolas' tips in experimental data. The interpretation of this type of images is easy for GPR operator, it lowers the risk of mistakes, and finally enables a large data analysis.

The reconstructed image based on curvelet transform is shown in Fig. 7 and its B-scan in Fig. 6. Because of B-scan was of low resolution in the cell of curvelet transform coefficients, the matrixes describing high resolution details did not contain any significant coefficients. The information about hyperbola-like shape was contained in the matrixes describing the low resolution details. That is why the result of inverse curvelet transform application is of lower resolution when it is compared with synthetic data analysis.

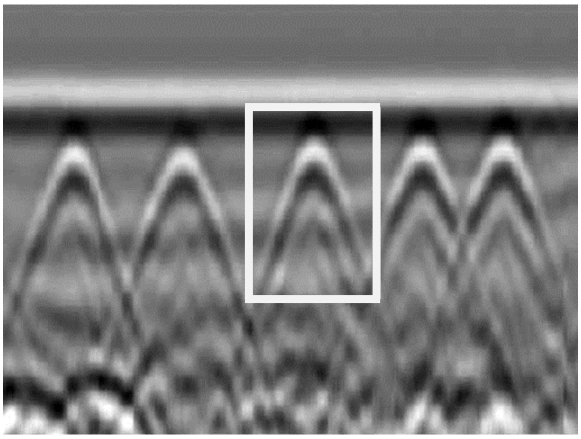


Fig. 6. The B-scan received from measurements - the rebar in the concrete. The white frame indicate the case under consideration.

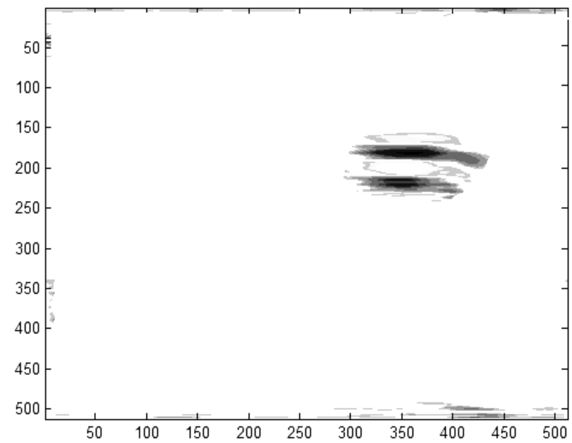


Fig. 7. The reconstructed hyperbola-like shape received from the inverse curvelet transform with thresholding applied to the rebar in the concrete.

VI. CONCLUSIONS

The article presents the application of curvelet transform to the analysis of GPR images received from synthetic and experimental data. The investigation has allowed us to point out the features of curvelet transform of GPR technique. We have shown that the application of culvelet transform to B-scans images with many disturbances like, for example, air bubbles can properly eliminate most of the visual artifacts and recover more details from the image. This allows us to clearly detect the buried scatterer, which belongs to the class of searched objects.

On the base of the former data we have established the coefficients set of curvelet transform, which were applied to the latter data. We have shown that curvelet transform enables to detect the edges of different shapes and spatial orientation in B-scans. Moreover, the research enables us to choose the proper coefficients and decomposition levels that mirror physical phenomenon as well as possible. In this way we have shown that B-scan image analysis can be understood as a special case of inverse problem.

A number of simulated cases let us transform the results from numerical experiments into real ones. Finally, the process of hyperbola tips detection can be automated. When the parameters of the process are known (spatial and time resolution), and by using the experience received during computer based experiments, we are able to set optimum values of curvelet transform coefficients, which are necessary to establish proper detection.

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