

Analysis of the possibility of classification the types of utilities networks on the GPR images

Klaudia ONYSZKO and Anna FRYŚKOWSKA-SKIBNIEWSKA, Poland

Key words: geometrical features, object classification, GPR images

SUMMARY

The assessment of the condition of the technical infrastructure is a crucial role in civil engineering, the implementation of BIM technology, 3D cadasters, for the existing infrastructure modernization works and other specialized technical activities. In the time of dynamically developing investment processes, the exact location of the utilities network is important in the context of their subsequent modernization and construction works located in its immediate vicinity. Accurate location data are important not only in the context of construction works, but also in the context of occupational health and safety. In the event of backfilling a non-inventoried underground network, the inventory of such an object may only be performed by non-invasive measurements, e.g. a GPR - Ground Penetrating Radar. Currently, the classification of the network from GPR images was based on the existing reference data obtained from the National Geodetic and Cartographic Resource - NGCR. The aim of the study was to analyze the possibility of using various methods of extraction and classification to distinguish types of utilities networks on the images obtained by GPR. The authors proposed a new algorithm of hyperbolic detection based on appropriate data filtering. It shortened the time of image interpretation and automates the process of selecting underground objects. The authors' motivation to take up the research topic was the automation of the process of detection and classification of underground objects, and thus the reduction of data processing time. GPR test images (radargrams) were acquired in several series of measurements and in various areas located on the campus of the Military University of Technology in Warsaw. The work presents the preliminary results of the detection and classification of objects using geometric, wavelet and fractal analysis and optimization methods based on the analytic hierarchy process (AHP). A new methodology of the detection and extraction of hyperbolas was presented based on the analysis of geometric, radiometric and textural objects contained in GPR images. The detection results are promising as preliminary studies have shown the detection of hyperbolas at 79-91%. The effectiveness of hyperbola detection was assessed by comparing the number of objects detected in the target image and the original image (after pre-processing).

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1. INTRODUCTION

A particularly important aspect in infrastructure modernization works, BIM technology implementation and 3D cadastre is the reliable detection of underground infrastructure present in a given area. There are many cases of accidents or life-threatening situations in the world caused by incorrect location of the underground network or its lack, in particular in the context of construction works related to electricity, heating and gas networks (electric shock, burns with hot water, gas explosion). For this reason, the task of precisely locating underground facilities plays a special role precisely in the context of security.

The main aim of the article was to analyze the possibility of classifying the hyperbolas detected on GPR images according to the type of utilities network (power, gas, water, heating, sewage and telecommunications networks). The basic task of classification is to determine such features of objects that characterize their geometry well - they assume the same values for objects belonging to the same class, while differentiating objects of different classes well. In the analysis of the shape of the hyperbola in GPR images, the authors (Reza et al., 2014) determined the ratio of the hyperbola height to width. The obtained parameter contributed to the authors' estimation of the diameter of detected objects with an estimation error of 12%.

In the publication (B. Jafrasteh, et al., 2016), the authors proposed an algorithm for automatic extraction of geometric parameters, i.e. depth, position and radius of cylindrical underground objects in order to assess their accuracy. The research was carried out on both simulated data and real GPR images recorded on the campus of the Isfagan University of Technology. The results obtained by the authors indicate a higher accuracy of the proposed method in estimating the geometric parameters of underground cylindrical objects than the use of the modified Hough transform (B. Jafrasteh, et al., 2016).

One of the possibilities for object classification is to use the Ring-Projection Technique for reducing the dimension of two-dimensional image into one-dimensional signal. (Suresh Chandra et al., 2016; Yuan Y. Tang et al., 2001) This algorithm is based on taking the summation of all pixels that lie on the circle with radius r and center at the centroid of the object. This process allows to determine the length and height of the obtained signal and its local extremes of function (Guan-Chen Pan et al., 1998).

2. METHODOLOGY

The analysis of the possibilities of object classification (2.2.) must be preceded by image pre-processing (2.1.1.), filtration and extraction of true hyperbolas (2.1.2.), i.e. hyperbolas representing the potential occurrence of utilities networks.

The study used a total of 105 images of hyperbolas showing various types of underground utilities networks, i.e. power, water, sewage, heating, telecommunications and gas networks. GPR Images were acquired on the Military University of Technology in Warsaw campus at 10 different locations with a Leica DS2000 GPR.

2.1. Extraction of hyperbolas

2.1.1. Imagery Pre-Processing

The image analysis must be preceded by its pre-processing, the aim of which is to eliminate false objects from the point of view of the intended goals of the analysis, as well as to highlight the interesting features of the analyzed image (Gabryś M. et al., 2019). Radargrams obtained in the uNext software were pre-processed with the GRED HD software. This process consisted of the following stages: time zero correction, bandpass frequency filter, gain filter, and background removal (Onyszko K. et al., 2021).

2.1.2. Detection of true hyperbolas

The next stage, right after pre-processing of GPR images, is the extraction of the actual objects. Currently, the process of extracting characteristic areas of interest is usually conducted with use of two methods, i.e., time and frequency analysis and artificial neural networks. The first of them distinguishes fragments of radargrams with similar frequency characteristics with use of wavelet analyzes or Fourier transform (Włodarczyk-Sielicka et al., 2016).

The proposed method of hyperbola detection is based on converting the RGB image to grayscale, background removal, edge detection, fitting the object into the set of detected pixels, and selecting only those hyperbolas that meet the predefined conditions:

- size of the object – (C_S),
- curvature of the object – (C_C),
- depth of the object – (C_D). (Onyszko K. et al., 2021)

The diagram of the detection algorithm is shown in Figure 1.

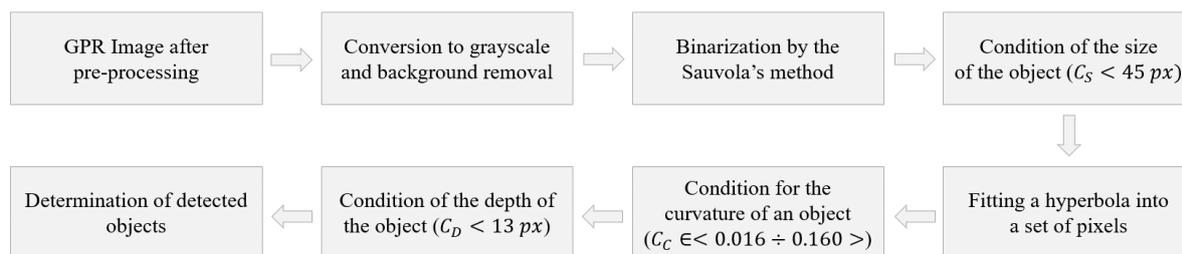


Figure 1. Scheme of the proposed algorithm for the detection of true hyperbolas.

The C_S condition of the size of the objects represented in the image was introduced in order to remove single pixels and small elements that are insignificant in the process of detecting underground utility networks. Based on the analysis of radargrams, it was found that the significant size of true objects is 45 px (Onyszko K. et al., 2021).

The proposed method eliminates hyperbolas whose vertex depth is smaller than 13 px – C_D (it is the equivalent of the Y ordinate, the depth of the location of the object), which corresponds to roughly 35 cm. The value of the introduced criterion (in pixels) was calculated based on a specific vertical resolution, which was determined based on antenna frequency, the rate of propagation of electromagnetic waves, and relative dielectric permittivity (Onyszko K. et al., 2021).

The direction coefficient a , in the form of a general square function of parabola, defines the direction in which the arms of the parabola are pointing. The range of values of the direction coefficient a was calculated based on multiple determinations of its value in test images and the available materials and information obtained from the NGCR (National Geodetic and Cartographic Resource). This allowed for a reliable determination of the range of curvature of true objects – C_C . Regardless of the radiometric span of the image, the range is constant and correct for all radargrams (Onyszko K. et al., 2021).

The effectiveness of hyperbol detection in GPR images depends on the length of the measurement distance. For evaluation a parameter M (Equation 1) was suggested, comparing the M_1 – the number of objects detected in the target image (i.e., after the pre-processing stage, filtration, and the application of conditions C_S , C_C , and C_D) and M_2 – the number of objects detected in the output image (i.e., after pre-processing).

$$M = \frac{M_2 - M_1}{M_2} \cdot 100\% \quad (1)$$

The values of M were calculated for the results obtained from 10 radargrams, and the obtained average values are presented in Results (Onyszko K. et al., 2021).

2.2. Methodology of the classification possibilities

The main task of object classification analysis is to determine features of objects that assume the same values for objects of the same class and at the same time distinguish objects of different classes. The main aim of the presented research was to assess the possibility of geometric features of objects in classification using GPR images from binarization (2.2.1) and one-dimensional data (2.2.2).

2.2.1. Geometrical feature extraction

Geometric features show the geometric properties of objects in the image and are related to their shape. The process of dimensioning a hyperbola makes it possible to obtain quantitative values describing specific features of the analyzed object. The work developed methods for determining the geometric features of objects on digital images obtained from GPR (Fig. 2). We propose to analyze the proper hyperbolas on the basis of the following features:

- curvature (C_C),
- size (C_S),
- completeness (C) and symmetry of the hyperbola (S),
- width (W) i height (H),
- depth (C_D),
- thickness of the hyperbola – counted at its vertex (t),
- the signal length – (L).

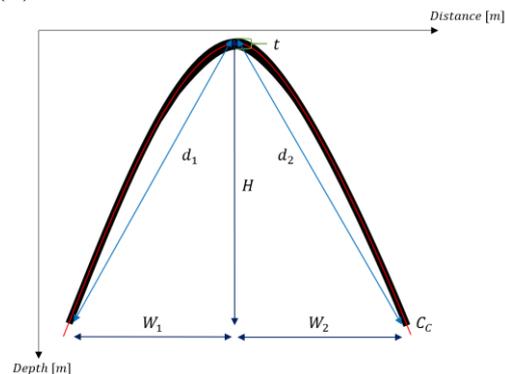


Figure 2. Definition of hyperbola characteristic parameters.

The features of the hyperbola were determined on the basis of analyzes of test images, and their results were verified on the basis of reference data of underground utilities networks obtained from NGCR. Figure 3 shows examples of the different types of networks: Figure 3a for the electricity network, Figure 3b for the telecommunications network, Figure 3c for the water supply network, Figure 3d for the sewer network, Figure 3e for the heating network and Figure 3f for the gas network. These are images obtained by recognition after prior processing of the images, after filtration and the introduced conditions: C_S , C_D i C_C .

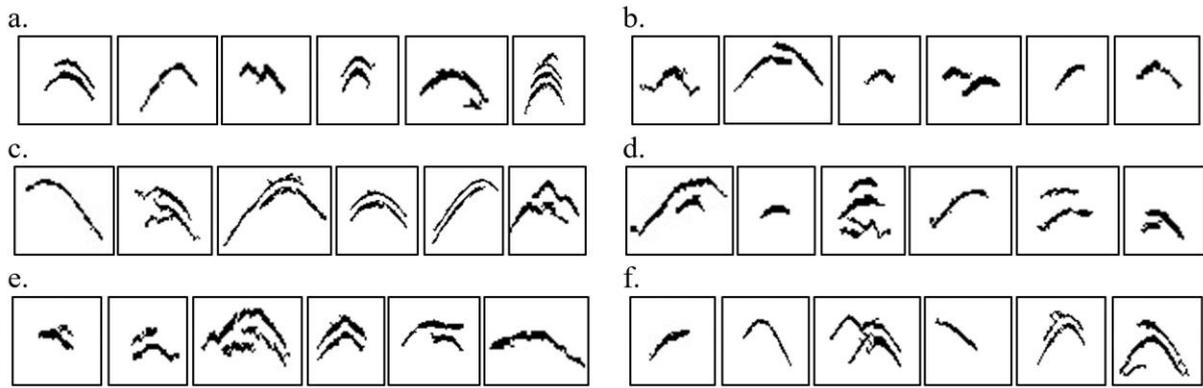


Figure 3. Test hyperboles representing different network types: (a) electricity network, (b) telecommunications network, (c) water supply network, (d) sewer network, (e) heating network, (f) gas network.

It is hard to compare the size, width and height of a hyperbola due to the completeness of the extracted objects. For this reason, the hyperbol characteristics were classified into 3 groups (Figure 4):

- complete objects (with a vertex and two arms of a hyperbola) – Group I,
- nearly complete objects (with the vertex and the left or right arm of the hyperbola) – Group II,
- incomplete objects (with only one arm or the apex of the hyperbola) – Group III.

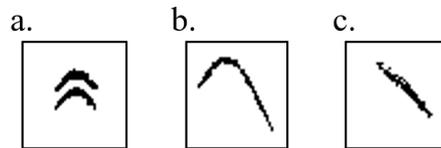


Figure 4. Completeness of extracted hyperboles: (a) Group I, (b) Group II, (c) Group III.

For each detected hyperbola a K parameter was defined which represents the ratio of the hyperbola height (H) to width (W) – Equation 2. The results of the determined K -values are given in the chapter Results.

$$K = \frac{H}{W} \quad (2)$$

where:

H – the hyperbola height (H_1 – for the left half of the hyperbola, H_2 – for the right half of the hyperbola) [px],

W – the hyperbola width (W_1 – for the left half of the hyperbola, W_2 – for the right half of the hyperbola) [px].

On the basis of the obtained values of the K parameter (Chapter Results), it was found that hyperboles representing utilities networks are symmetrical. Therefore, in further analyses (determining the size, height and width of the object), the authors included only halves of hyperbola, thus not excluding group II objects from the analysis. Objects from group III were rejected, and in further analysis included objects in groups I and II. In the case of completeness

of the object (group I), height and width were averaged for the left and right halves of the hyperbola.

2.2.2. Ring-Projection Algorithm

To determine another characteristic of the hyperbola (i. e. the length of the signal – L), the image of the hyperbola was reduced to a one-dimensional pattern using the Ring-Projection-Wavelet-Fractal method. The first step to reduce the dimension from 2D to 1D is to determine the center of mass (M_O) for each object using a density function of mass distribution on the plane. On this basis, Cartesian coordinates are converted into a polar system (from x-y space to $\gamma - \theta$ space) using formula 3 (Guan-Chen, P.).

$$\begin{cases} x = \gamma \cos\theta \\ y = \gamma \sin\theta \end{cases} \quad (3)$$

where:

$$\gamma \in [0, \infty),$$

$$\theta \in (0, 2\pi].$$

Then, rings with radii $(r + \Delta r)$ centered at the point M_O are created. In the last step of the algorithm, the number of pixels in the range of the given ring is counted for each value of the radius r . Figure 5 shows a diagram of the reduction of the image dimension to one-dimensional data on the example of a selected hyperbola, which is an energy network.

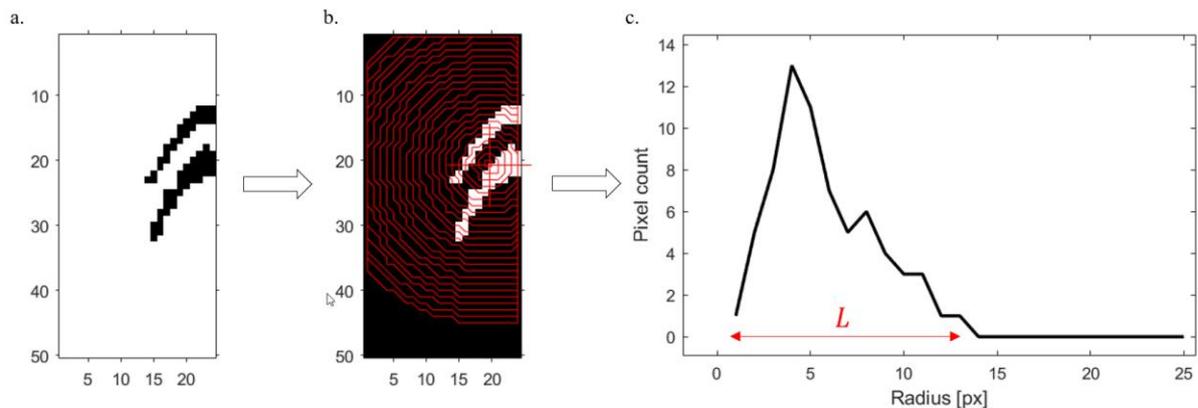


Figure 5. Scheme of reduction of image dimension to signal: (a) binary image of hyperbola, (b) the centroid of the mass distribution on the x-y plane with the rings of given radius, (c) the ring-projection of the image of hyperbola.

Based on the obtained one-dimensional data, the signal length (L) was determined for each half of the hyperbola, which is the last feature that mathematically describes the research object. The results of the obtained lengths are presented in the Results chapter.

2.3. Proposed Method of Automated Classification of True Hyperbolas

The proposed methodology for the classification of objects is based on multi-criteria optimization. Moreover, we developed the classification coefficient Q (Equation 4) which automates and supports the process of detecting and identifying underground utility networks by inexperienced operators by means of assigning the hyperbolas detected in the image to classes of significance. The Q classification criterion automates the classification process by making the selection more effective by increasing the certainty of its occurrence:

$$Q = w_{C_S} \cdot C_S + w_{C_C} \cdot C_C + w_{C_D} \cdot C_D \quad (4)$$

Where:

C_S – condition for the size of the object,

C_C – condition for the curvature of the object,

C_D – condition for the depth of the object,

The values of variable weight coefficients ($w_{C_S} = 0.24$, $w_{C_C} = 0.52$, $w_{C_D} = 0.24$) may be determined with the use of statistical methods or substantive analyses. The weights were introduced based on the analysis of 10 test images. The weights of attributes was determined with use the analytic hierarchy process – *AHP* method (Yuzhen H. et al., 2018; Shenghua X. et al., 2021; Stefanów P., 2007).

For the results obtained with algorithm 1 the following ranges (Q) are proposed for the classification of objects detected in the radargram:

- For $Q \leq 20,0 \rightarrow$ certain point ($G1'$),
- For $Q \in (20,0; 23,0 > \rightarrow$ uncertain point ($G2'$),
- For $Q > 23,0 \rightarrow$ least certain point ($G3'$) (Onyszko K. et al., 2021).

3. RESULTS

The effectiveness of the detection of hyperbolas in GPR images ranges from about 79 to about 99 %. For longer measurement routes (above 80 m) the effectiveness of the detection of hyperbolas decreased.

In this paper, methods are developed to determine the geometric features of objects extracted from GPR images. Table 1 summarizes the results of the determined geometric features of the hyperbolas for each type of network: power (e), telecommunications (t), gas (g), water (w), heating (h), and sewage (s).

Table 1. Ranges of values of determined geometric features of hyperbolas for each type of networks.

Geometric feature of a hyperbola	Type of network						
	e	t	g	w	h	s	
Depth [px]	Min.	19	15	28	49	49	47
	Max.	46	82	84	121	145	124

Geometric feature of a hyperbola		Type of network					
		<i>e</i>	<i>t</i>	<i>g</i>	<i>w</i>	<i>h</i>	<i>s</i>
Curvature	Min.	0.0189	0.0234	0.0171	0.0168	0.0185	0.0169
	Max.	0.1256	0.1436	0.0922	0.0882	0.0846	0.0707
Thickness [px]	Min.	2	3	2	1	3	1
	Max.	6	6	5	7	7	7
Size [px]	Min.	21	27	48	40	42	37
	Max.	87	80	76	150	112	119
Width [px]	Min.	6	6	10	8	7	4
	Max.	21	19	21	42	24	39
Height [px]	Min.	5	7	13	5	8	6
	Max.	26	18	30	50	34	35
1D signal length	Min.	6	4	11	6	9	6
	Max.	25	23	25	38	32	28

The distinguishing feature of the power and telecommunications network is the curvature of the hyperbola, which takes values above 0.10. The curvature values of the hyperbolas representing the other network types do not exceed 0.10.

To determine the possibilities of the classification of the hyperbolas according to the type of network, one must be based on the minimum depths of the location of underground utilities networks:

- separate telecommunication duct systems – 0.5 m,
- mains telecommunication duct systems and in-ground cables – 0.7 m,
- power supply cables up to 1 KV and over 1 KV – 0.7–1.0 m,
- lighting cables – 0.5 m,
- remotely controlled heating ducts starting from the manhole cover – 0.5 m,
- gas networks – 1.0–1.2 m,
- water supply networks (depending on pipe diameter) – 1.4–1.8 m,
- sewers—the depth is calculated so as to maintain the proper inclination of these points – 1.4 m.

Based on the analyzed values of hyperbola depth, it can be observed that district heating, water supply and sewage networks are usually deeper than the other types of networks. The indicated types (*h*, *w* and *s*) are also distinguished by signal length (*L*) and object size.

The following tables show the results of the parameter *K* representing the ratio of the hyperbola height (*H*) to width (*W*) for the resulting complete (Table 2) and nearly complete (Table 3) hyperbolas.

Table 2. The results of the ratio of the complete hyperbola height (H) to width (W) for each types of networks.

Type of network	K	
	Min.	Max.
<i>e</i>	0.79	1.64
<i>t</i>	0.88	1.60
<i>g</i>	0.76	0.85
<i>w</i>	0.48	0.93
<i>h</i>	0.85	1.19
<i>s</i>	0.67	1.15

Table 3. The results of the ratio of an almost complete hyperbola height (H) to width (W) for each types of networks.

Type of network	K	
	Min.	Max.
<i>e</i>	0.71	1.43
<i>t</i>	0.95	1.18
<i>g</i>	0.63	1.31
<i>w</i>	0.69	1.27
<i>h</i>	0.71	1.55
<i>s</i>	0.56	1.22

If the height of the hyperbola obtained in the measurement greater value than its width then the parameter K took values higher than 1. Due to the analysis of the parameter K values for the halves of hyperbolas obtained results for complete and almost complete hyperbolas are similar to each other.

The classification of hyperbolas by the multi-criteria optimization method resulted in an average classification efficiency of certain (about 58%), uncertain (about 39%), and least certain (about 48%) objects, with respect to the reference data from NGCR. The lowest effectiveness of classification was noted for uncertain objects, whose parameters are on the boundary between classes in the proposed automated algorithm. This results from the fact that a vast majority of objects in this class have a radiometric and geometric structure that is difficult to determine.

4. CONSLUSIONS

The hyperbola images analyzed in the classification process were extracted with the use of the proposed detection algorithm, which included filtration, binarization and detection of true hyperbolas based on the introduced conditions: C_S , C_C i C_D . The proposed algorithm of

automatic detection of true hyperbolas allows for their detection with the efficiency (parameter M) from about 79% to about 99%.

The authors also proposed the classification of the hyperbola into certain, uncertain and least certain objects (parameter Q). The effectiveness of the hyperbolic classification was, respectively: about 58% (for certain objects), about 39% (for uncertain objects) and about 48% (for least certain objects).

The article presents the methodology for possibilities of classification of the types of underground utilities based on the geometric features of a hyperbolas. The paper provides an overview about reducing the dimension of two-dimensional image into one-dimensional signal, which allowed to characterize the hyperbola by the length of the signal. The results obtained showed significant differences between the parameters characterizing the shape and size of individual hyperbolas.

The performed analyses are the basis for further research on possibilities of classification of network types on the basis of GPR images. Further research in this field might allow us to present a methodology for automatic classification of hyperbolas according to the type of land development network.

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BIOGRAPHICAL NOTES

Klaudia Onyszko – Graduate from the Military University of Technology in Warsaw, Poland. She received the MSc degree in geodesy and cartography in 2019. Currently, she has been working as a Research Assistant at the same university and is responsible for teaching remote sensing and engineering geodesy. Her research interests include GPR detection, laser scanning, image processing and data analysis.

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