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Interpretation of Ground Penetrating Radar Dataset using Normalised Cross-Correlation Technique

W. A. Wahab, W. Z. Zakaria, R. C. Omar, R. Roslan, J. Jaafar, A. M. Suldi

Abstract: Ground Penetrating Radar (GPR) is one of the latest non-destructive geophysical technology and most widely used in detecting underground utilities. GPR can detect both metal and non-metal, however, it is unable to identify the type of underground utility object. Many researchers come out with their techniques to interpret the GPR image. The current method requires experience in interpretation. Thus, in this study, a new method to detect underground utility utilizing the Normalised Cross-Correlation (NCC) template matching technique is proposed. This technique will reduce the dependency on experts to interpret the radargram, less time consuming and eventually save cost. Upon detection, the accuracy of the system is assessed. From the accuracy assessment performed, it is shown that the system provides accurate detection results for both, depth and pipe size. The Root Mean Square Error (RMSE) for the buried pipe depth obtained by using the proposed system is 0.110 m, whereas the highest percentage match obtained is 91.34%, the remaining 8.66% mismatched might be due to the soil condition, velocity or processing parameter that affected the radargram. Based on the assessment, the developed system seems capable to detect the subsurface utility if the radar image and template image used is acquired using the same antenna frequency, point interval, and similar GPR instrument.

Keywords: Ground Penetrating Radar,underground utility, radargram, template matching, normalized cross-correlation

I. INTRODUCTION

Ground Penetrating Radar (GPR) generated images called radargram [1] which contains hyperbolas that represent object beneath the earth's surface. These hyperbolas are formed by the reflection of signals emitted by the GPR device. A radargram is complex [2] and is difficult to be comprehended [3] by a common user. Interpretation of these datasets (radargram) in detecting underground utility is a tedious process [4], where such operations would require a considerable amount of time and effort.

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W. A. Wahab, Institute of Energy Infrastructure, UniversitiTenaga Nasional,43000 Kajang, Malaysia
W. Z. Zakaria, Institute of Energy Infrastructure, UniversitiTenaga Nasional,43000 Kajang, Malaysia
R. C. Omar, Institute of Energy Infrastructure, UniversitiTenaga Nasional,43000 Kajang, Malaysia
R. Roslan, Institute of Energy Infrastructure, UniversitiTenaga Nasional,43000 Kajang, Malaysia
J. Jaafar, Department of Surveying Science and Geomatics, UniversitiTeknologi MARA, 40450 Shah Alam, Malaysia
A. M. Suldi, Department of Surveying Science and Geomatics, UniversitiTeknologi MARA, 40450 Shah Alam, Malaysia

Moreover, the interpretation of the radargram is highly subjective and is based primarily on an interpreter's ability to recognise patterns in a radargram [5]; thus, making the whole process subject to human inaccuracy and slowness. Detection and interpretation based on manual interpretation techniques can lead to inconsistent results. However, the interpretation of radargram in detecting underground utility is a crucial task. By identifying the type and location of underground utility before construction, the possibility of underground utility damage caused by miss digging, and disruption to existing utility services as well as risks to workers can be reduced [6]. To overcome this situation, the automatic handling of such operations is investigated. In recent years, many forms of automatic detection and interpretation systems were proposed and successfully applied.

Normalised Cross-Correlation (NCC) is a signal processing technique [7] used as a similarity measure to determine the matching point between template and image [8]. Although this technique is computationally slow, NCC is robust under uniform illumination changes [9] where it is less sensitive to linear changes in the amplitude of illumination between two matched images [10]. Moreover, this technique is more accurate and provides the best performance in all image categories [9]. Due to the NCC robustness on previous researches, the approach was taken to assist in achieving the objectives of this study.

II. METHODOLOGY

The methodology of this research is shown in Fig. 1.

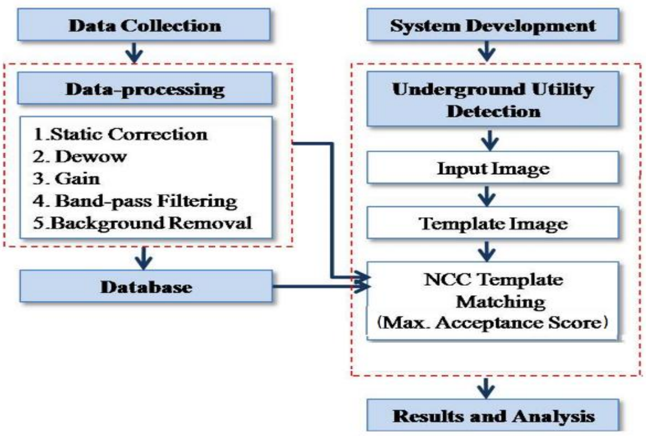


Fig. 1Theworkflow of the research methodology

Data Collection

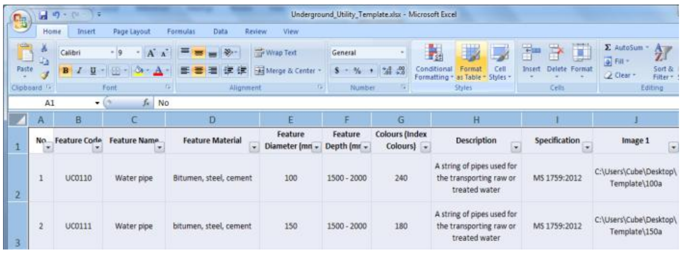
Different sizes of buried utility were observed by the GPR, with more than five (5) readings for each utility and at a different location. The size of the utility observed is known, including the buried depth, feature name, feature code, and material.

Data Processing

The ReflexW 6.5 version software was used in the pre-processing phase. This software was chosen based on its capabilities to enhance and improve the quality of GPR dataset quickly and easily [11]. The software was specially designed for processing and interpretation of seismic, acoustic, electromagnetic reflection, refraction, and transmission data [12].

Database

Underground utility database contains all information about the underground utility such as the utility code, name, material, diameter of the utility (mm), the depth that the utility is buried, and the color index of the utility on the map or plan, the description of the utility, their specifications as well as the hyperbola shape from radargram. The information involved in the database is gathered from various sources such as from JabatanKerja Raya (JKR), Syarikat Bekalan Air Selangor (SYABAS), currently known as Air Selangor, SIRIM (MS 1759:2012, MS 1034:1986 and MS 930:2010) and, JabatanUkurdanPemetaan Malaysia (JUPEM). This information was standardised by JKR and SIRIM. The hyperbolic shapes of radargram were collected for known pipes and sizes. The hyperbola radargram is used to represent the sizes of pipe and cable. Fig. 2 illustrates the underground utility template database.



No	Feature Code	Feature Name	Feature Material	Feature Diameter (mm)	Feature Depth (mm)	Colours (Index Colours)	Description	Specification	Image 1
1	UC0110	Water pipe	Bitumen, steel, cement	100	1500 - 2000	240	A string of pipes used for the transporting raw or treated water	MS 1759:2012	C:\Users\Cube\Desktop\Template\100a
2	UC0111	Water pipe	bitumen, steel, cement	150	1500 - 2000	180	A string of pipes used for the transporting raw or treated water	MS 1759:2012	C:\Users\Cube\Desktop\Template\150a

Fig. 2 The underground utility template

System Development

This study developed a system based on NCC to detect the hyperbola from radargram more rapidly and accurately.

Underground Uility Detection

In this detection technique, the matching percentage implies the degree of similarity between two images. The results which are closer to 100% indicate that the image is very similar to the other one while the lower the percentage obtained implies a low similarity between two images. Zero percent (0%) matching shows that they are completely uncorrelated. The lower the percentage obtained, the lower the image matching accuracy. Fig. 3 represents the pipe detection results by using the Automatic Detection System for GPR Dataset.

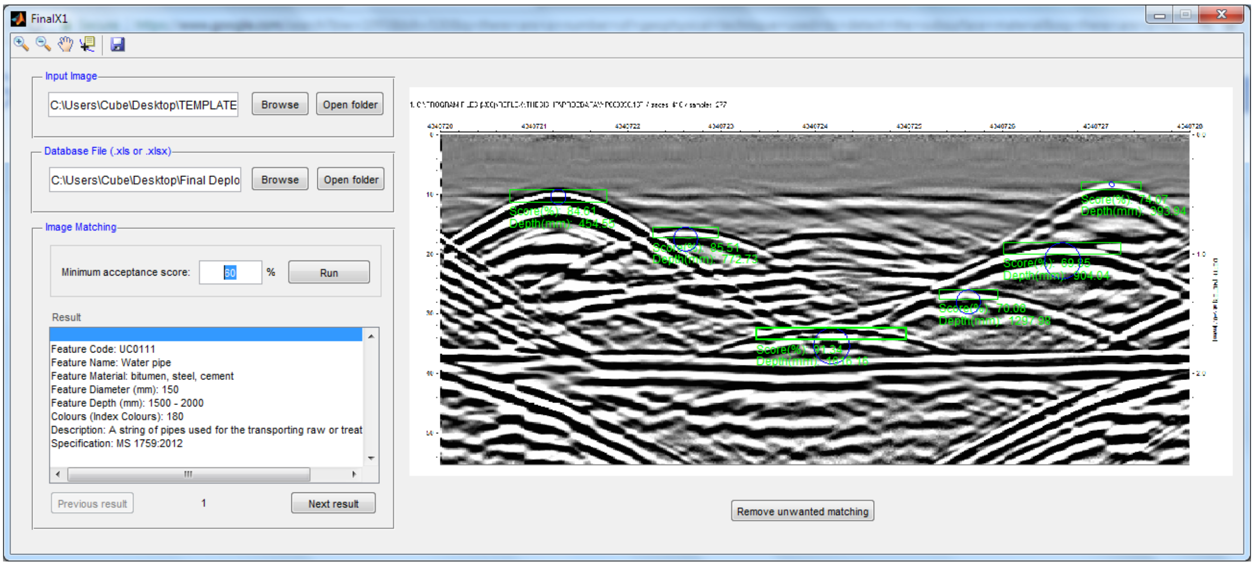


Fig. 3The Result of Pipe Detection using the Automatic Detection System for GPR Dataset

From Fig. 3, it can be seen that the system is capable of detecting similar hyperbola between the input image and the template image. Moreover, the system can provide the information of detected hyperbola as well as the depth and the percentage of the match. However, to investigate the capability of the system over other detection systems, this system will be compared with two other techniques; hyperbola fitting and pixel-by-pixel (direct comparison) template matching.

III. RESULTS AND ANALYSIS

Pipes Detection by Using Pixel-By-Pixel (Direct Comparison) Template Matchingand Automatic Detection System for GPR Dataset

The Automatic Detection System for GPR Dataset has been compared with the pixel-by-pixel (direct comparison) template matching in detecting the depth of the buried pipes. The actual depth of hyperbolas involved in this comparison is known. The results of depth obtained by using pixel-by-pixel (direct comparison) template matching and Automatic Detection System for GPR Dataset including the errors of depths were tabulated in Table I.

Table. 1 The Results of Depth Obtained by Using Pixel-by-Pixel (Direct Comparison) Template Matching and Automatic Detection System for GPR Dataset

No.	Actual Depth (m)	Pixel-by-Pixel Template Matching		Normalised Cross-Correlation (NCC) Template Matching	
		Depth Obtained (m)	Error (m)	Depth Obtained (m)	Error (m)
P1	0.46	0.481	0.021	0.472	0.012
P2	1.00	1.250	0.250	0.950	0.050
P3	2.48	2.570	0.090	2.530	0.050
P4	1.97	2.260	0.290	1.895	0.075
P5	1.26	1.429	0.169	1.270	0.010
P6	0.3	0.455	0.155	0.373	0.073
RMSE			**0.398**		**0.110**
Percentage Error (%)			**13.052**		**3.605**

Table I represents the results of depth obtained by pixel-by-pixel (direct comparison) template matching and Automatic Detection System for GPR Dataset. The results indicated that the RMSE for pixel-by-pixel (direct comparison) template matching is 0.398 m whereas the RMSE for Automatic Detection System for GPR Dataset is 0.110 m. For depth less than 1.2 m, the acceptance accuracy of the utilities is ±150 mm and an accuracy of ±300 mm for depths greater than 1.2 m. From the results, it can be concluded that the Automatic Detection System for GPR Dataset gives the accurate depth and it is in the acceptable range. The percentage error in detecting the object depth using pixel-by-pixel (direct comparison) template matching is 13.052%. The percentage error of the depth detection by Automatic Detection System for GPR Dataset is 3.605%. The RMSE value from Automatic Detection System for GPR Datasetis lower than the RMSE value provided by the pixel-by-pixel (direct comparison) template matching.

The Comparison of Actual Pipe Size with the Pipe Size Obtained from Hyperbola Fitting, Pixel-by-pixel (Direct Comparison) Template Matching and Automatic Detection System for GPR Dataset

The results of pipe size detection, detected by hyperbola fitting, pixel-by-pixel (direct comparison) template matching and Automatic Detection System for GPR Dataset is compared with the actual pipe size (ground truth). The dataset used in this test is obtained at the real site. Table II represents the comparison of the pipe size obtained using three (3) different techniques.

Table. 2 The comparison of detection results obtained by using hyperbola fitting, pixel-by-pixel templatematching and automatic detection system for gpr dataset and the actual pipe size (ground truth)

No.	Actual Size (mm)	Hyperbola Fitting		Pixel-by-pixel Template Matching		Automatic Detection System for GPR Dataset	
		Detection (mm)	% Match	Detection (mm)	% Match	Detection (mm)	% Match
1	100	105.86	94.14	100	43.00	100	85.00
2	150	157.08	92.92	150	59.00	150	91.34
3	500	509.24	90.76	500	41.00	500	84.10
4	700	710.64	89.36	700	52.00	700	87.21
5	1100	1114.52	85.48	1100	47.00	1100	86.43
	Average Matching Percentage		**90.53**		**48.40**		**86.82**

Referring to Table II, the comparisonbetween hyperbola fitting, pixel-by-pixel template Matchingand Automatic Detection System for GPR Datasetwith the actual value, indicates that thehyperbolafitting provides a higher percentage match as compared to the pixel-by-pixel (direct comparison) template matchingfor GPR Dataset with the average percentage match of 90.53%. The pixel-by-pixel template matchinggives the average percentage match of only 48.40%.The NCC template matching, on the other hand, provides 86.82%of average matching percentage. Despiteshowing a higher matching percentage results, the hyperbola fitting method requires user interventionto cut the hyperbola before estimating the size of the pipe. This might affect the pipe size estimation result. The pixel-by-pixel template matchingshowsa low matching percentage of matches. This mightbe so since the direct comparison of pixel values are sensitive to noise, object motion and the grayscale difference between the input image and the template image. From these three techniques, Automatic Detection System for GPR Dataset is the best to be used in interpreting the radargram.

From the overall results, it can be seen that the developed system is unable to detect similar hyperbola between the input radargram and the template image from the database at 100% acceptance score. This may occur due to the effects of noise, clutter, undesired frequencies and various unwanted echoes that are still lagging after the data processing. This problem possibly will affect the match results between template images and input images.

Cost-Benefit Analysis

Cost-benefit analysis (CBA) was performed to calculate and compare the benefits and costs of the developed system. The benefits and costs are expressed in monetary terms and are adjusted for the time value of money [13]. In this study, the comparison was carried out between the current GPR interpretation practices (manual interpretation) and the Automatic Detection System for GPR Dataset. Table III elaborates the comparison in term of software cost, and manpower between the manual interpretation and the Automatic Detection System for GPR Dataset development.

Table. 3 The Comparison Betweenthe Manual Interpretation and the Automatic Detection System for Gpr Dataset Development, in Term of Software Cost and Manpower

Subjects	Manual Interpretation			Automatic Detection System for GPR Dataset		
	Cost per Unit (RM)	Unit	Price (RM)	Cost per Unit (RM)	Unit	Price (RM)
1. ReflexW GPR/Reflection Seismic With 2D Data Analysis	6498.46	1	6498.46	6498.46	1	6498.46
2. Matlab and Simulink Student Suite	-	-	-	213.40	1	213.40
3. Microsoft Office Excel	-	-	-	500.00	1	500.00
4. Radargram Interpreter Cost/Day	200.00	1	200.00			
Total			**6698.46**			**7211.86**

From Table III, it can be seen that the ReflexW GPR/Reflection Seismic With 2D Data Analysis is involved in both interpretation techniques. As for the Matlab and Simulink Student Suite, and the Microsoft Office Excel, the cost of the software was only applicable to the Automatic Detection System for GPR Dataset technique since it was used to develop the system. In terms of radargram interpreter cost, the cost was only applicable for the manual interpretation as it requires an expert to interpret and determine the type of utility represented by the hyperbola that were found in the radargram. Referring to the total cost of both interpretation techniques, it shows that the cost of manual interpretation is 7% lower than the Automatic Detection System for GPR Dataset. The manual interpretation cost, however, will increase with the increasing number of working days for the interpreter. The benefit of the system was also being assessed in terms of the interpretation time.The comparison between the two techniques is shown in Table IV.

Table. 4 The Comparison Between The Manual Interpretation And The Automatic Detection System For Gpr Dataset In Term Of The Interpretation Time

Subjects	Manual Interpretation	Automatic Detection System for GPR Dataset
Interpretation Method	Interpret the radargram manually	Automatically
Interpretation Verification	Ground truth	Automatically
Radargram Interpretation Time	Depends on earth surface or soils type, density of the utility, and interpreter.	Depends on the size of the radargram

From Table IV, it can be seen that the manual interpretation, manually interprets the radargram. The manual interpretation might lead to an inaccurate result. This will cause damage to the underground lines during excavation or underground utility repairs. Manual interpretation is also tedious and time-consuming, where it involves an experienced interpreter. As for the Automatic Detection System for GPR Dataset, the interpretation is done automatically. For the verification task, the ground-truth is used to verify the interpretation results from the manual interpretation method. No ground-truthing is needed for the Automatic Detection System for GPR Dataset technique as it was done during the system and database development phase. In manual interpretation technique, the interpretation time depends on earth surface or soils type, the density of the utility, and interpreter. The poorer the site condition, the longer it takes to interpret the radargram. Utility density also causes a delay in the interpretation process. As for the Automatic Detection System for GPR Dataset technique, the interpretation time depends on the size of the radargram involved.

In the Automatic Detection System for GPR Dataset system, apart from saving costs for long-term underground utility detection project in terms of manpower and reducing the interpretation time, it can also be applied in various applications. One of the applications that can apply this technique is fingerprint identification. The system can be used, too, by the forestry department to identify tree species. However, users need to change the database based on the application involved.

IV. CONCLUSION

The focus of this study has largely been on the development of an automatic detection system for GPR dataset (underground utility). The study highlights the importance of automation in GPR data interpretation. The automation of GPR data interpretation is necessary to ensure consistency in the interpretation results. The Automatic Detection System for GPR Dataset provides benefits in terms of cost, time and manpower. The developed system can also be used in other applications such as to detect buried landmines, buried oil tanks, and classification of tree species through leaf venation and shape. However, future studies need to be done to improve the methods used as well as to have better interpretation results.

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