Real-Time Object Detection Using Dynamic Principal Component Analysis

Gülay Büyükaksoy Kaplan, Oğuz İçoğlu, Ahmet Burak Yoldemir, Mehmet Sezgin
TÜBİTAK UEKAE
Gebze, Kocaeli, Turkey
gulay.kaplan@bte.tubitak.gov.tr, oguz.icoglu@bte.tubitak.gov.tr, burak.yoldemir@bte.tubitak.gov.tr, mehmet.sezgin@bte.tubitak.gov.tr

***Abstract*—In this work, we contribute to the real-time detection of buried objects, with special emphasis on explosive ones, using the ground penetrating radar (GPR). When the buried objects have explosive substance, the moment of detection becomes vital. Therefore, we start the detection process right after the very first GPR signals begin to return from the buried objects. For this purpose, we adopted the studies focusing on the online process monitoring methods using principal component analysis (PCA), and adapted them to the dynamic conditions of the ground. Different objects with varying dielectric properties are buried in the test environment and used for the evaluation of the proposed method. With the observed results, it is validated that, the proposed method is employable towards the real-time object detection.**

***Keywords*-Ground Penetrating Radar, Principal Component Analysis (PCA), Buried Explosive Object Detection.**

I. INTRODUCTION

The detection of buried objects is one of the principal branches in real-time search applications [1]. This branch of search application has a broad usage in various fields. It is used in archeology for detection of antiques under the ground [2], in pipeline installations for detection of pipes under the earth and within the walls [3], or in security domain for detection of buried explosives [4]. In each case, the type of the object to be detected varies; stones or marble objects in archeological studies, metallic tubes in pipeline installations or metallic and plastic mines in military and humanitarian applications.

Since these miscellaneous objects possess distinct attributes, it gets difficult to propose a generic answer for all of the detection problems in the aforementioned cases. However, ground penetrating radar (GPR) offers a promising solution since it is designed primarily to investigate the shallow subsurface of the earth, building materials, roads and bridges. GPR is an electromagnetic technique that has been developed over the past forty years for shallow, high resolution investigations of the subsurface [5].

The representative diagram of an underground object detection using GPR sensor is given in Fig. 1. As denoted in the figure, the system firstly generates the GPR signal by the transmitter and emits it to the ground via its transmitting antenna. The GPR sensor used in this study has a frequency band between 0.4 and 2 gigahertz. Then, the receiving antenna collects the reflected signals including antenna coupling, soil surface reflection and target reflection signals. The receiver unit digitizes the incoming raw GPR signal to process it in the signal processing unit in the next step. In our study, the raw GPR signals are handled by the help of a controller card that transforms the continuous GPR signal into 16-bit digital values with such a frequency that results in a collection of 256 GPR samples for each signal emitting. Consequently, with respect to the GPR values, the signal processing unit instantaneously decides whether there is a buried object or not. In this paper, we aim to present our study concentrated on the detection of surrogate mines buried under the ground.

The paper hereafter is organized as follows. It depicts the motivation beneath this study in Section 2, and defines the proposed method towards the pivotal points in our motivation in Section 3. The application of the method and the exploited test environment are explained in Section 4. Finally, the experimental results and the conclusions are given in Section 5 and 6 respectively.

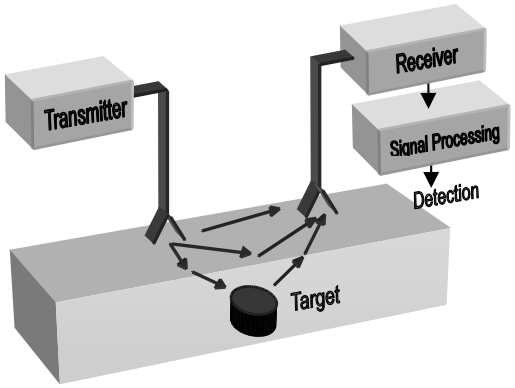

Figure 1. Representative diagram of underground target detection using GPR

II. ONLINE DETECTION REQUIREMENT

A. Motivation

As mentioned before, the study presented in this paper is focused on the detection of surrogate mines buried under the ground. When the buried objects contain explosive substance, an instantaneous decision has to be made. In this case, the detection system does not have the opportunity to collect a vast history of data and construct a comprehensive control dataset, which forms the ground truth. Also, it does not have the opportunity to make a decision by acquiring all of the near

978-1-4244-4605-6/09/$25.00 ©2009 IEEE

region samples and judge with respect to the general layout of the input dataset. Therefore, the system should immediately construct its control dataset and process the streaming input samples in real-time so as not to put the operator at risk. Such a requirement enforces the system to be developed so that it can process the data online.

B. Online Process Control

As mentioned above, the requirements specific to the detection of objects with dangerous substance entail the system to be developed for real-time operations. To this end, the employable methods are investigated and the ones used in the online process control applications are found out to be effective since they also address a similar problem. Online process control methods are used in the industry for detecting faults originating from the production. Similar to our case, the production line cannot be stopped, and the system must detect the deficiencies on a streaming line within very short time periods. However, the online process control methods benefit from a previously constructed control dataset that is valid throughout the entire detection phase. The control dataset in online process control is comprised of the data bunch containing the known correct production attributes. In our case, the control dataset contains the varying attributes of the ground. This enforces us to modify the methods used in the online process control and adapt them to satisfy our dynamic needs.

III. The Proposed Detection Method

In this study, we adapted online process control approach to the detection of the buried surrogate mines. In our case, the number of attributes that define the GPR data are large and using all of them for detection is time consuming and ineffective. Therefore, principal component analysis (PCA) is used to extract the most effective components within these GPR attributes.

A. Principal Component Analysis (PCA)

PCA is a popular technique for reducing the dimensionality in data analysis. It has three major advantages. First, the PCA parameters can be calculated directly from the data. Second, in terms of mean squared error, it is the optimal linear method for dimensionality reduction. Third, once the PCA parameters are calculated, construction and reconstruction become computationally easy operations [6].

PCA transforms the original process variables in a new set of uncorrelated variables that explains the trend of the process. Consider an $n \times p$ data matrix X, where n denotes the number of observations (samples) and p denotes the number of variables. Before employing PCA, the values are normalized to zero mean and unit variance. Next step is to calculate the covariance matrix in order to get the eigenvalues and eigenvectors. The covariance matrix is given as

$$S = \frac{1}{n-1} X^T X. \tag{1}$$

The covariance matrix S is then decomposed into its eigenvalues and eigenvectors. The chosen k eigenvectors of S constitute the columns of the $p \times k$ loading matrix P, which transforms the original $n \times p$ data matrix X into an $n \times k$ matrix which has a reduced dimensionality.

$$Y = XP \tag{2}$$

The coordinates in the principal component space are often called as *scores*. Scores are values of the original measured data that have been transformed into a space having fewer dimensions. This matrix is composed of the uncorrelated components of the original data. The scores can be transformed back to the original space using

$$\hat{X} = YP^T. \tag{3}$$

The original data matrix X can be reconstructed using

$$X = \hat{X} + E \tag{4}$$

where E is the residual matrix that denotes the difference between the original data matrix X and the reconstructed data matrix $\hat{X}$.

In signal processing applications, the signal to noise ratio (SNR) is aimed to be increased since a high value of SNR represents a high degree of information within the data. SNR is elevated by imposing high variance, and the variable that maximizes the data variance is called a *principal component* of the data. Thus, in order to obtain the principal components of a dataset, we search for the uncorrelated linear combinations of the original variables whose variances are as large as possible.

Since each principal component corresponds to a certain amount of variance of the whole dataset, we use the cumulative percent variance (CPV) approach to verify the effectiveness of the selected components, which is given as

$$CPV(k) = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{p} \lambda_i} \cdot 100. \tag{5}$$

The *CPV* value denotes the ratio of the sum of the selected eigenvalues to sum of all eigenvalues. This value should be greater than 90% in order to prevent loss of information [7].

B. Using PCA for Online Process Control

Although PCA is known as a data reduction method, it is one of the diagnostic algorithms for fault detection in process control [9]. PCA can be used in real-time online process monitoring and fault diagnosis to detect changes in normal operation conditions. PCA transforms the original process data into a new data consisting of uncorrelated attributes. A smaller amount of data facilitates process control and also speeds up the fault detection procedure. Detection of changes in the online process control is done using two statistics: Hotelling's T^2 and Q statistics. T^2 statistic represents the major variation in the data. On the other hand, Q statistic represents the total sum of the residual error, namely it shows the inadequacy of the model generated with PCA. Q statistic of the samples given in matrix X can be calculated as

$$Q = (X - \hat{X})^T (X - \hat{X}). \tag{6}$$

The Q statistic gives the amount of the variation in each sample which is not captured by the k principal components retained in the model. Q statistic offers a way to test if the process data has shifted outside the normal operating space. On the other hand, T^2 statistic provides an indication of the unusual variability within the normal subspace. The sum of normalized squared scores, known as Hotelling's T^2 statistic, gives the amount of the variation of the samples within the PCA model [10]. T^2 statistic can be calculated as

$$T^2 = x^T P \Lambda_k^{-1} P^T x \tag{7}$$

where, Λ_k is a matrix formed by the first k rows and columns of the diagonal eigenvalue matrix Λ, which is acquired from the covariance matrix given in (1).

In order to diagnose an abnormality in process conditions, first, the region of the normality should be defined. Confidence limit for Q statistic (Q_{lim}) is given as

$$Q_{\lim} = \theta_1 \left[\frac{h_0 c_\alpha \sqrt{2\theta_2}}{\theta_1} + 1 + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1^2} \right]^{\frac{1}{h_0}} \tag{8}$$

$$\theta_i = \sum_{j=k+1}^{p} \lambda_j^i \qquad h_0 = 1 - \frac{2\theta_1\theta_3}{3\theta_2^2} \tag{9}$$

where c_α is the value of the normal distribution with α being the level of significance [11]. Confidence limit for T^2 statistic (T^2_{lim}) is defined as

$$T^2{}_{\lim} = \frac{k(n+1)(n-1)}{n(n-k)} F_\alpha(k, n-k) \tag{10}$$

where $F_\alpha(k,n\text{-}k)$ is the F distribution with n and n-k degrees of freedom and α is the level of significance [12].

In the previous section, it has been denoted that a high value of SNR represents a high degree of information within the data, namely the normal operating conditions. In the PCA approach, the valuable information in the data is extracted by retaining the principle components with larger associated variances. Therefore, it is assumed that the eliminated principle components with low associated variances correspond to the noisy part of the data. As shown in (8), (9) and (10), the Q_{lim} is determined by the eliminated principle components, and T^2_{lim} is determined by the retaining ones. Hence, data with a high SNR implies a low Q_{lim} value and a high T^2_{lim} value.

When a new sample is acquired, the new Q statistic, Q_{new} (or the new Hotelling's statistic, T^2_{new}) is determined. By comparing Q_{new} with confidence limit $Q_{\lim}$ (or T^2_{new} with T^2_{lim}), a decision on the similarity of the new sample to the normal operating conditions is made. The $Q_{\text{new}} < Q_{\lim}$ condition means that the new sample is close enough to the space defined by the k principal components, hence, can be considered to fit the model. Similarly, $T^2_{\text{new}} < T^2_{lim}$ condition means that the projection of the new sample into the space defined by the k principal components is close enough to the origin of the space, hence, can be considered to fit the model. When an abnormal event occurs, Q_{new} gets greater than $Q_{\lim}$ (or $T^2_{\text{new}} > T^2_{lim}$) and this measurement is considered as an alarm condition.

An example is given in Fig. 2 to depict the situation given above. In the figure, the original data space is 3D, and it is reduced to 2D with PCA, which enforces the data elements to fit on a plane. The ellipse on this plane denotes the confidence limit for the T^2 statistic. This figure is particularly given for T^2, however, there is also a 3D confidence limit for the Q statistic concentric with the given PCA axes which is not shown on the figure. The new data samples that fall beyond these borders (denoted as *outliers* in the figure) are considered as alarm conditions.

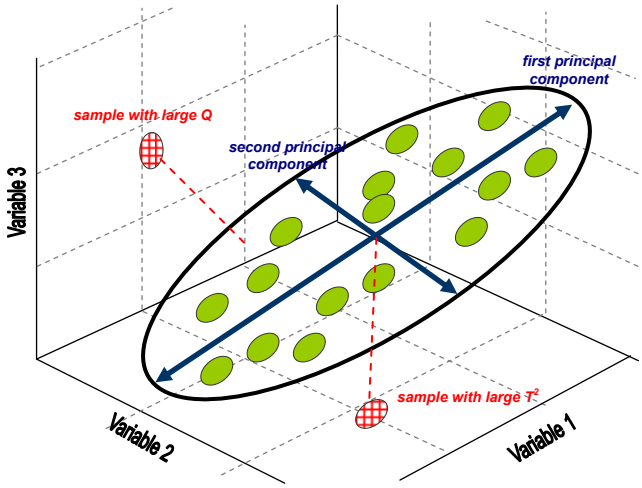

Figure 2. Graphical representation of the PCA model with three variables, including Q and T^2 outliers

C. *Real-Time Object Detection Using Dynamic PCA*

In this work, we adopted the abovementioned technique to detect the existence of an anomaly, especially a surrogate mine under the ground. The identification of the type of the object is the subject of another work. In this study, we focused on detecting the inhomogeneities under the ground since any buried object causes an anomaly in the GPR response. This is similar to the approach used in the online process control where the process flows in a stream as the GPR signals do in our system, and the normal conditions (correct production process) correspond to the GPR response from the ground without any buried object, and the abnormal conditions (faulty production process) correspond to the GPR response from the ground with a buried object.

In order to decide on fault detection, the online process control benefits from a previously constructed control dataset that is used to set the confidence limits and this dataset is valid throughout the entire detection step [13]. This control dataset in online process control consists of the data having the correct production attributes. In our case, the control dataset involves the data bunch containing the characteristics of the GPR response of the ground. However, the ground is changeable and there is no static control dataset as in the online process control. Therefore, an initial control dataset is constructed and it is constantly updated with the new data that has been marked as target-free after the detection process. Therefore, we call the

method as dynamic PCA which is also called as recursive PCA in the literature [14].

The detection method can be explained in detail as follows. The initial control dataset is composed of the first GPR responses. Although we cannot know exactly what lies beneath the first scans, we are sure that there is no dangerous object since the operator stands on this region. Thus, the safe starting region is accepted as the control dataset of the normal operation for our case. In our real-time GPR application, during the formation of a B-scan (2D GPR image composed by concatenating the vertical 1D GPR responses, each of which is called as an A-scan), the safe region is also slid towards the scanning direction. Q and T^2 values of the new input are compared to the limits obtained from the Q and T^2 statistics of this sliding safe region. If they exceed the limits, this measurement denotes the existence of a buried object or simply an inhomogeneity under the ground.

Fig. 3 gives the flow diagram of this technique. First, a window is constructed that holds n A-scans from the safe region. Second, the GPR data within this window is normalized to zero mean and unit variance. As the third step, the principal components for the scans within the window are analyzed, and k principal components with major eigenvalues are selected. With respect to these principal components, the limit values Q_{lim} and T^2_{lim} are calculated. Fourth, the GPR signal from the current scan is acquired and normalized like the samples in the window. Fifth, the Q and T^2 statistics of the new sample are calculated with respect to the principal components obtained from the window, namely the safe region.

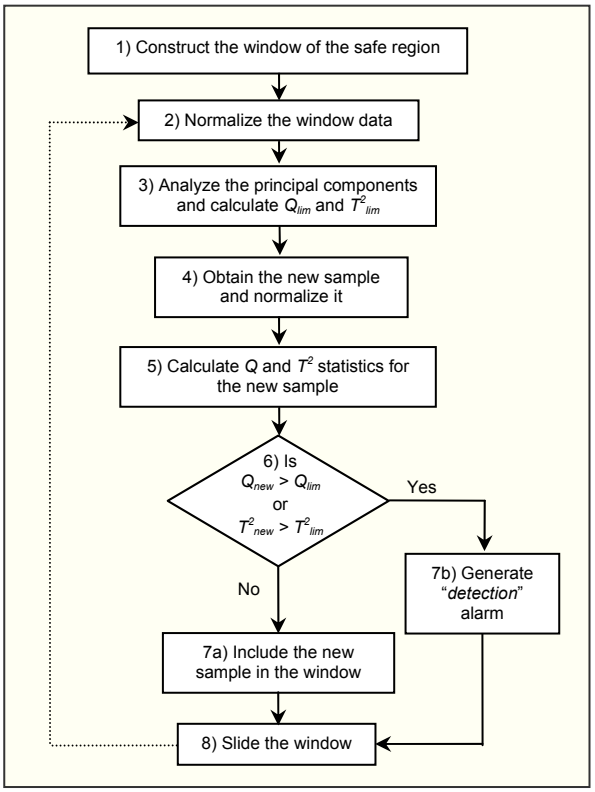

Figure 3. Flow diagram of the detection method

It should be noted that, in our technique, there are t scans between the new scan and the window, in other words, the window follows the current scan with t scan latency. The reason for applying latency is that, GPR is capable of surveying an area before passing over it. Hence, with the early approach to the buried object, target signatures begin to emerge. When these responses are included in the window, they distort the control dataset with the attributes of the buried object. In order to prevent this perturbation, the window follows the current scan with t scan latency.

As the sixth step, the Q and T^2 statistics of the new sample are compared with the limit values, Q_{lim} and T^2_{lim}, and if either of these exceeds these limits, a decision of detection is made. It should be noted that, in the online process control, the window is static, thus, Q_{lim} and T^2_{lim} limits are always constant, and the Q and T^2 statistics of the new sample are always calculated with respect to the same principal components since the attributes of the correct production are constant in online process control. However, in our application, the attributes of the safe ground are not constant, and may vary as the scan advances, and this entails the composition of a new safe region. In order to implement this requirement, the window that holds the safe ground attributes is slid in each new scan (seventh step), and the new A-scans, whose statistics do not exceed the limits are included in the window. This ensures that only the GPR scans that belong to the safe ground are added to the window. In the next run, the new principal components are analyzed and the new Q_{lim} and T^2_{lim} values are calculated.

IV. Application

A. Test Environment and Data Collection

Our test environment is comprised of two pools; one of them has sand and the other has mould. The pools occupy a volume 1 meter high, 2 meters long and 3 meters wide. The test environment is constructed in such a way as to minimize the external influences. We collected the data using a robotic system which our GPR system is fixed to. The robotic system moves with a constant speed of 0.2 meters per second. Each B-scan is composed of the GPR responses taken within 1 meter distance. During the scanning, the robotic system holds the GPR's scanning head approximately 5 centimeters above the ground surface.

During the experiments, four objects, which are equivalent to M14, TS50, VS50 and DM11AT mines, and two nonexplosive objects, namely a stone and a glass bottle were buried in the pools at different depths. For each object, 10 B-scans were collected in horizontal and vertical directions.

B. Application of the Technique

In our dataset, each B-scan is composed of 240 GPR A-scan signals, each of which is composed of 256 samples. In order to reduce the effects of the echo from the ground surface, a time-gating procedure is applied on the variables acquired in each A-scan [7]. The width of the safe region window is chosen as 40 GPR A-scans. Actually, for real-time applications, this value can be increased. The width of the safe region window also determines the number of the principal components since PCA can reduce the dimensionality of the variables at most to the number of samples without loss of

information [8]. Empirically, the number of principal components is determined as 30, t is set as 10, and consequently the proposed method is applied with steps as depicted in Fig. 3. During the calculation of the confidence limits for Q statistic (Q_{lim}) and T^2 statistic (T^2_{lim}), the level of significance (the value of α given in (8) and (10)) is selected as 95%.

V. EXPERIMENTAL RESULTS

In Figures 4 through 8, one example within 10 results obtained for each buried object is given. In the figures, the first image shows the B-scan after the time-gating procedure. The detection results of Q and T^2 statistics are given in the second and third parts respectively. The detection decision is made after 5 sequential detection alarms. The detection performance of Q and T^2 statistics are given in Table I, together with the false alarm rates. Each detection decision that falls before or after 10 centimeters apart from the buried object is considered as a distinct false alarm. In Table I, *Q_Det* and *T_Det* stand for the detection rates of Q and T^2 statistics respectively. Similarly, *Q_FA* and *T_FA* are the false alarm rates of Q and T^2 statistics.

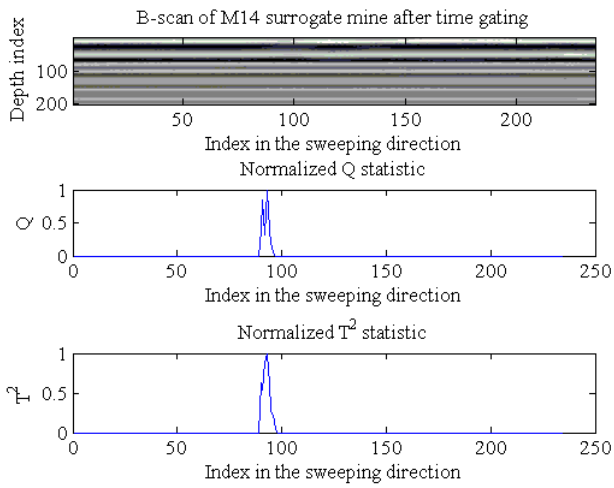

Figure 4. The graphical result for M14 surrogate mine

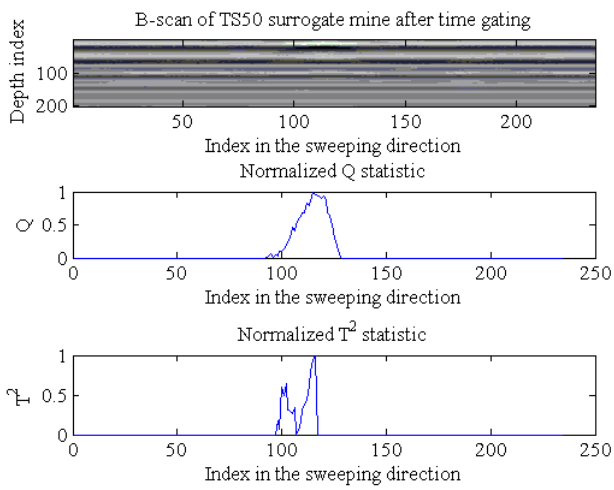

Figure 5. The graphical result for TS50 surrogate mine

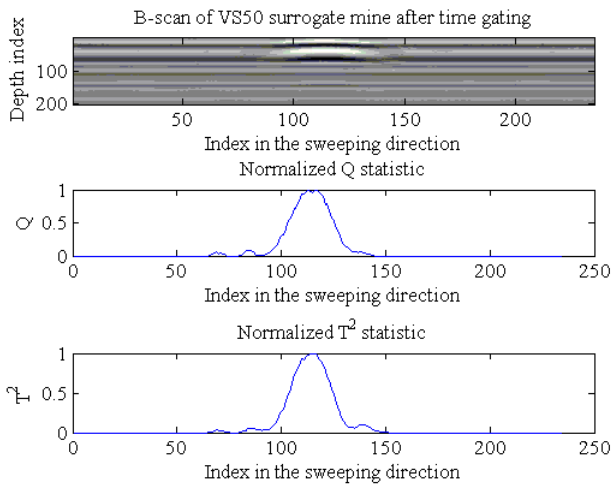

Figure 6. The graphical result for VS50 surrogate mine

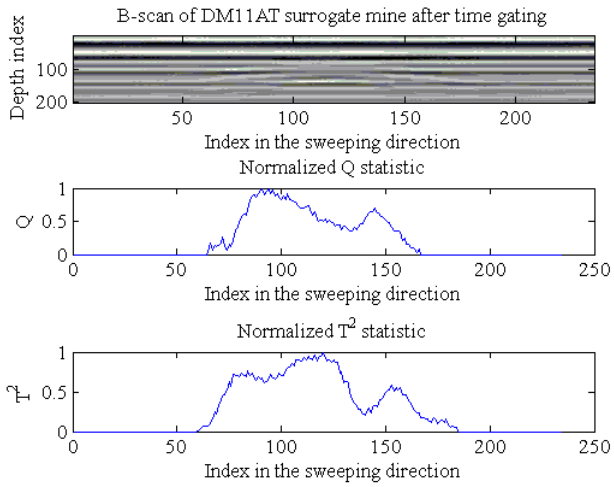

Figure 7. The graphical result for DM11AT surrogate mine

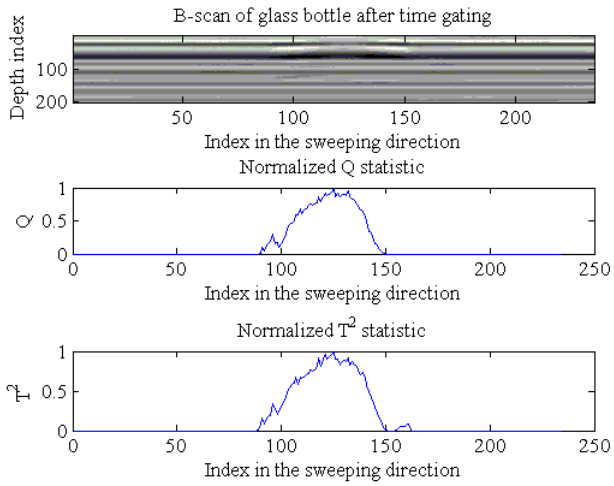

Figure 8. The graphical result for glass bottle

The M14 surrogate mine is a small object which has a diameter of 5.6 and a height of 4 centimeters, and its burial depth is 7 centimeters. So, its detection is quite challenging, the

effect of lumps or inhomogeneties under the ground can cause a similar effect with the M14 surrogate mine. As seen in Table I, the detection rate of the Q statistic is higher than that of the T^2 statistic.

The TS50 surrogate mine is also buried at the same depth, but it is of greater size compared to M14 surrogate mine. Therefore, the detection performance of the Q statistic is increased to 100% for both pools, and the performance of the T^2 statistic is increased to 100% in sand and to 70% in mould.

During the experiments, we buried the VS50 surrogate mine in only the sand pool. The size of this object is same as the TS50 surrogate mine but it involves more metallic content. Both statistics detect this object perfectly.

The DM11AT surrogate mine which has a diameter of 30 centimeters is buried at the depth of 25 centimeters. It is a completely nonmetallic object. As can be seen in Fig. 7, as the size of the object increases, number of samples exceeding the statistic limits increases. The performances of both methods are 100% in sand and 90% in mould.

When the results are analyzed taking soil types into account, it is observed that the detection performance obtained in mould, which contains more inhomogeneities, is lower than that of the sand, which has a more homogeneous structure. In sand, the detection rate of Q statistic is 91.6% and T^2 statistic is 83.3%. Meanwhile, the false alarm rate of Q statistic is 5% and T^2 statistic is 8.3%. In mould, the detection rate of Q statistic is 71.6% and T^2 statistic is 53.3%, and the false alarm rate of Q statistic is 20% and T^2 statistic is 13.3%. All these numerical results show that the soil characteristic affects the detection rate. In the overall analysis, the detection rate of the Q statistic is higher than the T^2 statistic; nevertheless, the T^2 statistic is better than the Q statistic in terms of the false alarm rate, especially in the mould. Generally, inhomogeneities in the ground cause the false alarm rate to increase. Therefore, the increase in the false alarm rate in mould is expected and also observed in Q statistic results. However, it is not valid for false alarm rate of T^2 statistic, as T^2 statistic internalizes the inhomogeneities by including them in the normal operation conditions region.

TABLE I. DETECTION RESULTS OF THE USED TECHNIQUES

Object	*Soil type*	*Depth*	*Q_Det*	*Q_FA*	*T_Det*	*T_FA*
M14	Sand	7 cm	6/10	2/10	3/10	0
M14	Mould	6 cm	6/10	1/10	0/10	0
TS50	Sand	7 cm	10/10	0	7/10	0
TS50	Mould	7 cm	10/10	7/10	10/10	2/10
VS50	Sand	10 cm	10/10	0	10/10	0
DM11AT	Sand	25 cm	10/10	0	10/10	3/10
DM11AT	Mould	25 cm	9/10	0	9/10	5/10
Glass bottle	Sand	9 cm	10/10	0	10/10	0
Glass bottle	Mould	9 cm	10/10	6/10	8/10	1/10
Stone	Sand	9 cm	9/10	1/10	10/10	2/10
Stone	Mould	9 cm	8/10	1/10	8/10	0
RESULT			**89/100**	**14/100**	**72/100**	**11/100**

VI. CONCLUSION

In this work, we adopt one of the online process control methods to the detection of buried explosive objects. Since the metallic and dielectric properties of the ground are not constant, in contrast to the online process control, there is no static normal operation condition region for our task. We assume the beginning part of each scan as the normal operating region, and the new sample (which is very close to this normal region) is compared with this region via two statistics. By sliding the normal operation region throughout the scanning process, we adapt the normal region to the dynamic condition of the ground.

In the application of the T^2 statistic, we make a simplification about the construction of the control region. Namely, according to Mason and Young [11], the outliers of the control region should also be detected and removed from the control region before detecting the anomalies. Applying the outlier exclusion will be the subject of our future work.

ACKNOWLEDGMENT

The authors wish to thank to Orhan Baykan, Nedret Pelitçi and Sencer Melih Deniz who performed the data collection activities.

REFERENCES

[1] D. J. Daniels, *Surface Penetrating Radar*, IEE Radar Sonar Navigation and Avionics Series 15, 2004.

[2] G. S. Baker and H. M. Ambrose, "Ground penetrating radar imaging of a 4th Century Roman Fort, Humayma, Jordan," in *Proc. 4th Int. Workshop on Advanced Ground Penetrating Radar,* Naples, Italy, 2007.

[3] X. Zeng, "GPR characterization of buried tanks and pipes," *Geophysics*, vol. 62, pp. 797-806, 1997.

[4] K. C. Ho and P. D. Gader, "A linear prediction land mine detection algorithm for hand held ground penetrating radar," *IEEE Trans. Geosci. Remote Sensing*, vol. 60, pp. 1374-1384, June 2002.

[5] J. J. Daniels, "Ground penetrating radar fundamentals," Department of Geological Sciences, The Ohio State University, U. S. EPA Tech. Rep. Region V, Nov. 25, 2000.

[6] J. E. Jackson, *A user's guide to principal components*, John Wiley & Sons, New York, 1991.

[7] P. Gader, L. Wen-Hsiung, N. J. Wilson, "Detecting landmines with ground-penetrating radar using feature-based rules, order statistics and adaptive whitening," *IEEE Trans. Geosci. Remote Sensing*, vol. 42, pp. 2522-2534, Nov. 2004.

[8] M. Ringner, "What is principal component analysis?," *Nature Biotechnology*, vol. 26, pp. 303-304, 1998.

[9] S. Roweis, "EM Algorithms for PCA and SPCA," in *Proc. Advances in Neural Information Processing Systems 10*, 1997.

[10] J. Liu, KW Lim, R. Srinivasan, X.T. Doan, "On-line process monitoring and fault isolation using PCA," in *Proc. IEEE International Symposium on Intelligent Control*, pp.658-661, 2005.

[11] D. G. Alvarez, "Fault detection using principal component analysis (PCA) in a wastewater treatment plant (WWTP)," in *62th Int. Student's Scientific Conf.*, Saint-Petersburg, Russia, 2009.

[12] R.L. Mason, J.C. Young, *Multivariate statistical process control for industrial applications*, ASA-SIAM, Pennsylvania, 2002.

[13] V. Venkatasubramanian, R. Rengaswamy, K. Yin, S. N. Kavuri, "A review of process fault detection and diagnosis Part I: Quantitative model-based methods," *Computers and Chemical Engineering*, vol. 27, pp. 293-311, 2003.

[14] W. Li, H. H. Yue, S. V. Cervantes, S.J. Qin, "Recursive PCA for adaptive process monitoring," *Journals of Process Control*, vol. 10, pp. 471-486, 2000.