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Imaging Modes for Ground Penetrating Radar and their Relation to Detection Performance

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***Abstract*— The focus of this paper is an empirical study conducted to determine how imaging modes for ground penetrating radar (GPR) affect buried object detection performance. GPR data was collected repeatedly over lanes whose buried objects were mostly non-metallic. This data was collected and processed with a GPR antenna array, system hardware, and processing software developed by the authors and their colleagues. The system enables GPR data to be collected, imaged, and processed in real-time on a moving vehicle. The images are focused by applying multistatic and synthetic aperture imaging techniques either separately or jointly to signal scans acquired by the GPR antenna array. An image-based detection statistic derived from the ratio of buried object energy in the foreground to energy of soil in the background is proposed. Detection – false alarm performance improved significantly when the detection algorithm was applied to focused multistatic synthetic aperture radar (SAR) images rather than to unfocused GPR signal scans.**

***Index Terms*— ground penetrating radar (GPR), multistatic imaging, synthetic aperture radar (SAR)**

I. Introduction

Ground penetrating radars (GPRs) are useful for buried object detection because they are able to detect not only buried metallic objects, but also buried non-metallic objects with sufficient dielectric contrast against soil. They are widely used for detecting landmines, utility pipes, etc. Buried objects are typically detected in data acquired with a GPR antenna array mounted across the front of a moving vehicle. This paper applies to GPR antenna arrays whose antenna transmit-receive pairs are arranged in a linear sequence.

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Most antenna arrays are designed to operate in monostatic mode, i.e., when a transmitter fires (emits a pulse), only the corresponding co-located receiver listens (receives). A survey of different vehicle mounted GPR antenna arrays and systems can be found in [1]. In multi-monostatic mode, each transmit-receive (TR) pair is activated in succession, producing one sequence of radar return signals (a signal scan) for each TR pair as the vehicle moves along the track. The signal scan for a given TR pair is a 2D array whose columns are radar return signals and whose rows are along the direction of vehicle travel. When signal scan planes for successive TR pairs are placed parallel to one another, the resulting scan volume contains an unfocused GPR image.

GPR images are focused using coherent summation to reinforce radar returns at true locations of buried objects across multiple looks (interrogations) of the sub-surface. This paper considers two well-known coherent summation methods for GPR data, namely multistatic imaging and synthetic aperture imaging. In multistatic imaging, several receivers in the vicinity listen when a given transmitter fires. Multistatic imaging promotes coherent summation in vertical plane images oriented parallel to the cross-track direction. In synthetic aperture imaging, an image is reconstructed from radar return signals acquired not through the linear antenna array at a specific vehicle along-track location (a real aperture), but instead through the area swept out by the antenna array as the vehicle travels over a segment of its traversal path (a synthetic aperture). Synthetic aperture imaging promotes coherent summation in vertical plane images oriented parallel to the along-track direction.

Our system hardware enables multistatic radar return signals to be acquired in real-time through a GPR antenna array that contains as many as $N = 16$ antenna pairs. Each time a transmitter fires, all receivers listen, and all transmitters fire sequentially within ~4ms. Our system hardware can thus acquire one frame of $N^2 = 256$ radar return signals within ~4ms. Also, our imaging software generates multistatic synthetic aperture GPR images in real-time when run on our vehicle-based mobile computing system.

Buried objects are normally detected by applying an energy-based detector to GPR signal scans [2-5]. To improve upon the detection-false alarm rate performance of the detector, a classifier is often used in an attempt to discriminate buried objects detected in GPR signal scans from clutter. Many such classifiers have been proposed [10-27]. Because classification is usually more expensive than detection, the classifier is often only applied to small portions of the signal scans that were pre-screened by the detector.

The approach studied in this paper instead attempts to improve detection-false alarm rate performance by applying an energy-based detector to focused GPR images rather than to unfocused GPR signal scans. Whether detected in GPR signal scans or GPR images, one can always subsequently attempt to discriminate buried objects from clutter using a classifier. The images are focused by applying multistatic and synthetic aperture imaging techniques either separately or jointly to GPR signal scans. Rather than using an energy-based detection statistic derived from GPR signal scans, a GPR image-based detection statistic derived from the ratio of buried object energy in the foreground to energy of soil in the background is used instead.

The main contribution of this paper is not novel theoretical content, but rather an application-oriented empirical study designed to provide insight into the important topic of how imaging modes for GPR affect buried object detection performance. Our vehicle-based system for real-time detection of buried objects in GPR images is described in Section II. Multistatic and synthetic aperture modes for GPR imaging are described in Section III. A GPR image post-processing method that facilitates separation of buried objects in the foreground from soil in the background is described in Section IV. An energy-based detection statistic derived from GPR images is then developed. Section V compares buried object detection-false alarm rate performance over two lanes, first in unfocused GPR signal scans, and then in GPR images focused using multistatic and synthetic aperture imaging techniques.

II. OVERVIEW OF THE GPR DATA ACQUISITION, IMAGING AND PROCESSING SYSTEM

A real-time GPR data acquisition and processing system was developed at the Lawrence Livermore National Laboratory by the authors and their colleagues. The system components were integrated on a Chevrolet Suburban (Fig.1a). They include a front-mounted GPR antenna array, a navigation system, a rear-mounted ruggedized mobile computing system (MCS), and an in-vehicle operator interface / visualization display.

The GPR antenna array (Fig.1c) contains 16 transmit-receive pairs of resistively loaded vee dipole (RLVD) antennas, such as those described in [28-29]. These antennas have low radar cross section (RCS) and are encased in radar absorbent material (RAM). Multipath reflection artifacts in the GPR return signals are thus limited when the array operates close to the ground. The antenna array includes a customized data acquisition system that contains a field programmable gate array (FPGA) with an embedded PowerPC chip for command and control. The FPGA precisely triggers the 16 transmitters and receivers for acquisition of multistatic GPR data. Our system uses an impulse radar [30-31] that emits extremely narrow pulses with an ultra-wideband (UWB) frequency response (this is in contrast to stepped-frequency radars that emit a sequence of narrow-band pulses whose frequencies increase by a prescribed step size in succession). Specifically, when it receives a trigger pulse, our system produces a transmit pulse of roughly 1 ns in duration (Fig.2a). As shown in Fig.2b, the frequency response of this pulse peaks at ~700 MHz, with 3dB drop-offs at roughly 300 MHz and 1.8 GHz. A receiver samples the return signal when it receives a trigger pulse. A multistatic frame of 16^2 GPR return signals (512 samples per signal and 16 bits per sample) is acquired at a rate of 244 frames per second. All frames are stamped with geo-locations and acquisition times. Data streams from the antenna array are aggregated and distributed through two gigabit Ethernet ports using UDP-based jumbo packet frames.

The navigation system uses commercial components, including a differential GPS, an inertial measurement unit (IMU), and a satellite-based subscription service for real time differential correction to the GPS signals. The position of the GPR antenna array is projected forward from the center of the navigation system and the acquired GPR frames are geo-tagged.

The ruggedized MCS stores and processes the acquired GPR data in real-time (Fig.1b). Each of the two MCS sub-systems uses dual hex core XEON hyper-threaded processors, 24GB of RAM, and solid state drives for the operating system. The storage and track processor (STP) uses two 1.5TB RAID packs of solid state drives for storage of acquired GPR data. The STP geo-tags the multistatic GPR frames and transfers them to the real-time processing and visualization system (RTV).

The RTV processes the acquired GPR data in real-time. The processing pipeline uses a C++ codebase developed by the authors and it has three major elements: (1) signal pre-processing, (2) imaging, and (3) buried object detection (which includes foreground-background separation). Signal pre-processing suppresses antenna coupling, ground bounce, interference and various artifacts in radar return signals acquired by the GPR antenna array. While details of GPR signal pre-processing are beyond the scope of this paper, various aspects are treated in the literature (see [17,33,35] for a discussion of coupling pulse removal, [3,22,33] for interference rejection, [2-5,34] for ground bounce / multipath suppression, and [32] for surface topography correction). GPR images of the sub-surface are reconstructed from pre-processed GPR return signals. Image subtraction and thresholding are then used to remove residual energy (particularly near the surface) from the GPR images. This facilitates separation of buried objects in the foreground from soil in the background, making it easier to detect buried objects in vertical plane images normal to the direction of vehicle travel. Pixel and image dimensions are controlled using software parameters that can be set by the operator. By convention, we use a vehicle-centered *xyz* coordinate system in which the *x* axis points in the instantaneous cross-track direction from the driver to the passenger side of the vehicle, the *y* axis points in the instantaneous along-track direction of vehicle travel, and the *z* (depth) axis points into the ground.

All image pixels have width Δ_x in the cross-track dimension and height Δ_z in the depth dimension. Successive image frames are separated by a fixed distance of Δ_y along the track. For all images in this paper, we used Δ_x = 6.875 cm, Δ_y = 2 cm and Δ_z = 2 cm. For an antenna array of length 2.2 m, Δ_x = 6.875 cm corresponds to images with $2N = 32$ columns in vertical planes orthogonal to the direction of vehicle travel.

The operator interface and visualization display uses a tablet PC and resides in the vehicle (Fig.1d). The interface has user selectable tabs for real-time display of signal scans along the track, GPR images of the sub-surface (both horizontal and vertical plane views along the track), and a time series of detection statistics (with audible alarms).

III. GPR Imaging Modes

The imaging modes for GPR are (1) monostatic vs. multistatic imaging on the one hand, and (2) imaging through a real vs. synthetic aperture on the other. The GPR antenna array mounted to the front of a moving vehicle contains N transmit-receive (TR) pairs at height $|z_A|$ meters above ground level separated by Δ_A meters in the cross-track (x) direction. The reconstructed 3D image of the subsurface is a sequence of 2D images (xz image frames) in vertical planes oriented parallel to the cross-track direction. Each xz image frame is reconstructed from a *multistatic data matrix* (*MDM*), i.e., an NxN frame of radar return signals whose rows correspond to different transmitters and whose columns correspond to different receivers. Each element of an MDM thus contains the radar return signal for a specific TR pair (m samples per signal). Prior to image reconstruction, the signal scan along the track for each TR pair is pre-processed in order to suppress ground bounce, flatten the surface (equalize the surface time of arrival), and remove various artifacts [2-5,17,22,33-35].

In *real aperture radar* (*RAR*) imaging mode, the image frame at $y = y_k$ is reconstructed from the signal frame acquired through the antenna array at $y = y_k$ (a real aperture). In *synthetic aperture radar* (*SAR*) imaging mode, the image frame at $y = y_k$ is reconstructed from signal frames acquired through the area swept out by the antenna array at $y = y_{k-\Delta_k} \dots y_k$ (a synthetic aperture). Specifically, the SAR image at $y = y_k$ is generated by combining RAR images reconstructed from signal frames acquired at $y = y_{k-\Delta_k} \dots y_k$.

RAR images can be either *monostatic* or *multistatic*. Monostatic (multistatic) SAR images are generated from sequences of monostatic (multistatic) RAR images. In monostatic imaging mode, only the corresponding receiver is activated when a transmitter fires (emits a pulse). In multistatic imaging mode, multiple receivers (typically one or more to either side of the transmitter) are activated when a transmitter fires.

A. *Multistatic Imaging*

For a uniform medium with refractive index $\eta \geq 1$, the radar return time delay from transmitter at (x_T, y, z_A) to point scatterer at (x_S, y, z_S) to receiver at (x_R, y, z_A) (all of which lie in the same vertical xz plane) is the travel distance from transmitter to point scatterer to receiver divided by the radar propagation velocity c/η in that medium. Points in the vertical xz plane at antenna array along-track location y whose time delay is the same as for the point scatterer all lie on an ellipse in the xz plane whose foci are the locations of the transmitter and receiver (Fig.3a). For non-uniform media, η can vary spatially and the ellipse becomes distorted.

In principle, a component GPR xz image frame may be reconstructed from the radar return signal for a specific TR pair (m samples per signal) by tracing m concentric elliptical (or distorted elliptical) arcs on the image half-plane below the surface. Arc geometries are prescribed by η and the time delays of the associated samples. Arc brightnesses are set to the amplitudes of the associated samples. An xz GPR image frame may be reconstructed from return signals for multiple TR pairs by adding component image frames. Component image frames tend to add coherently (i.e., reinforce or focus) at actual scatterer locations and incoherently at other locations, thereby increasing the ratio of energy from scatters in the foreground to energy from soil in the background. The basis for multistatic imaging is the idea that in theory, one can exploit coherent summation at fixed array location along the track to improve this ratio by increasing the number of receivers to either side of a transmitter that observe a scatterer when the transmitter fires.

The multistatic imaging parameters N_T and N_R have non-negative integer-values. Each column of an xz image frame has an associated transmitter T that it lies closest to. $N_T \in [0,N)$ is the maximum number of transmitters to either side of T that can contribute to values of pixels on that column when the image is reconstructed. GPR images are thus reconstructed from $\min(2N_T+1, N)$ *looks* (interrogations). Similarly, the *multistatic degree* N_R is the number of receivers to either side of each contributing transmitter whose return signals can contribute to values of pixels on that column.

Table 1 lists various modes for GPR imaging through a real aperture. By definition, $N_R = 0$ for monostatic imaging and $N_R > 0$ for multistatic imaging. One extreme ($N_R = N_T = 0$) is for degenerate monostatic imaging. In this mode, the value of a pixel in an xz image frame is the value of a specific sample on a specific GPR return signal. We refer to this mode as the signal scan mode or unfocused image mode because it produces xz image frames that resemble unfocused GPR signal scans (2D arrays whose columns resemble GPR return signals). The other extreme ($N_R = N_T = N{-}1$) is for full multistatic imaging. In this mode, all TR pairs can contribute to every column in an xz image frame. For full multi-monostatic imaging, $(N_R, N_T) = (0, N–1)$. In this mode, all transmitters can contribute to every column, but only the corresponding receiver is activated when a transmitter fires.

Table 1: Modes for GPR Imaging through a Real Aperture

N_R	N_T	Description of Imaging Mode
0	≥0, <*N*	general monostatic mode
>0, <*N*	≥0, <*N*	general multistatic mode
0	0	degenerate monostatic (i.e., signal scan or unfocused image) mode
0	*N*–1	full multi-monostatic mode
N–1	*N*–1	full multistatic mode

Fig.4 depicts MDM masks for an antenna array with $N = 6$ TR pairs. Mask rows correspond to transmitters, mask columns correspond to receivers, and mask elements of value one correspond to active TR pairs. Mask (a) is for the full multi-monostatic mode $(N_R, N_T) = (0, N–1)$ (i.e., *N* looks and 1 receiver per look). Mask (b) is for the full multistatic mode $(N_R, N_T) = (N–1, N–1)$ (i.e., *N* looks and *N* receivers per look). Mask (c) is for the degree 1 multistatic mode $(N_R, N_T) = (1, N–1)$ (i.e., *N* looks and up to 3 receivers per look). The mask sequence in (d) is for the degree 1 multistatic mode $(N_R, N_T) = (1,1)$ (i.e., up to 3 looks and up to 3 receivers per look). This mode contains one mask for each of 6 transmitters, and the mask that applies to a given image column is associated with the transmitter closest to that column.

B. Synthetic Aperture Imaging

In what follows, $u_R(x,z; y_k)$ refers to the RAR image at vehicle along-track location y_k, *x* refers to the cross-track coordinate (column) of a pixel, and *z* refers to the depth coordinate (row) of a pixel. The contribution that the GPR return signal associated with TR pair (*i*,*j*) makes to pixel (*x*,*z*) at vehicle along-track location y_k is expressed symbolically as $u_{i,j}(x,z; y_k)$. This term represents the value of the sample associated with a specific time delay in the TR pair (*i*,*j*) return signal. The time delay is computed as the cumulative radar time delay (a) from transmitter *i* to the surface (through air), (b) from the surface to subsurface pixel (*x*,*z*) (refracted through soil), (c) from subsurface pixel (*x*,*z*) back up to the surface (through soil), and (d) from the surface back up to receiver *j* (through air). Time delay calculations through soil require an estimate of the soil dielectric constant. The time delay calculations are discussed in [6,8-9].

With this background, the RAR image reconstruction process can be simply expressed in mathematical terms. The index i_x of the transmitter closest to image column *x* is

$$i_x = 1 + \text{round}\,(x\Delta_x/\Delta_A) \in [1, N] \tag{1}$$

Then

$$u_R(x,z; y_k) = \underset{(i,j)\in\Omega(x)}{\text{mean}}\; u_{i,j}(x,z; y_k) \tag{2}$$

$$\Omega(x) = \{\, (i, j)\text{: } \max(i_x–N_T, 1) \le i \le \min(i_x+N_T, N),\ \max(i–N_R, 1) \le j \le \min(i+N_R, N) \,\} \tag{3}$$

In practice, equations (1)-(3) can be realized using (i) migration techniques in the spatial domain [6-7] or (ii) plane-to-plane propagation [38-41].

In a uniform medium, the radar return time delay from transmitter at (x, y_T, z_A) to point scatterer at (x, y_s, z_s) back to the co-located receiver at (x, y_T, z_A) (all of which lie in the same vertical *yz* plane) is twice the travel distance from transmitter to point scatterer divided by the radar propagation velocity in that medium. As the vehicle passes by, the distance from the transmitter to the point scatterer decreases to a local minimum and then increases along a hyperbolic arc ("smile") in the vertical *yz* plane at cross-track location *x* (Fig.4b). In non-uniform media, the hyperbolic arc becomes distorted.

Short distances of vehicle travel along the track are essentially linear. Pixel *p* on a specific column of the *xz* SAR image at $y = y_k$ may thus be computed as the sum of pixels on the same column from *xz* RAR images at nearby along-track locations $y = y_{k–\Delta_k} \ldots y_k$ that lie on the *yz* vertical plane hyperbola (or distorted hyperbola) that contains *p*. Successive image frames tend to add coherently (i.e., reinforce or focus) along hyperbolic arcs associated with scatterers and incoherently along arcs associated with soil, thereby increasing the ratio of energy from scatters in the foreground to energy from soil in the background. The basis for SAR imaging is the idea that because a scatterer will be observed repeatedly by an antenna pair as it passes by, one should theoretically be able to increase this ratio by exploiting coherent summation along hyperbolas in vertical planes oriented along the track.

The synthetic aperture integration formula generates a SAR image $u_S(x,z; y_k)$ at vehicle along-track location y_k from a sequence of RAR images as

$$u_S(x,z; y_k) = \sum_{j = k–\Delta_k}^{k} u_R(x, z'(y_j, z); y_j) \tag{4}$$

where *z* is the depth of a pixel in the image plane associated with current antenna array along-track location y_k, and $z'(y_j,z)$ is the depth of the corresponding pixel in the image plane associated with some previous antenna array along-track location y_j. For an antenna array at height $|z_A| > 0$ above ground level with forward tilt angle $0 \le \phi_A < \pi/2$ from vertical, the image plane associated with along-track location *y* is, by our convention, the *xz* vertical plane at along-track location

$y + |z_A| \tan\phi_A$ where the forward line-of-sight perpendicular to the antenna array intersects the surface of the ground (see Fig.4). In this case, at fixed cross-track location x, $z'(y_j,z)$ is computed such that the radar time delay from the transmitter at (y_j, z_A) to the point $(y_k + |z_A| \tan\phi_A, z)$ at depth z on the image plane associated with along-track location y_k is the same as the delay to the point $(y_j + |z_A| \tan\phi_A , z'(y_j,z))$ at depth $z'(y_j,z)$ on the image plane associated with along-track location y_j. Mathematically, $z'(y_j,z)$ satisfies the equation

$$\text{delay}\,[\,(y_j, z_A) \text{ to } (y_k + |z_A| \tan\phi_A, z)\,] = \text{delay}\,[\,(y_j, z_A) \text{ to } (y_j + |z_A| \tan\phi_A , z'(y_j,z))\,] \quad (5)$$

where delay(A to B) is the time delay of the radar wave in traveling from point A to point B (typically through air and then refracted through soil).

The number of successive RAR image frames that combine to form a single SAR image frame (Δ_k+1 in (4)) is based on z_A, ϕ_A, the effective beam width θ_A of the antenna, and the fixed spacing Δ_y between successive xz image frames in the along-track direction. As shown in Fig.5 for $0 \le \phi_A,\theta_A < \pi/2$,

$$\Delta_k = \text{round}\,(\,|z_A|\,[\tan\phi_A + \tan(\theta_A - \phi_A)] / \Delta_y) \quad (6)$$

To first order, our RLVD antennas have an omni-directional beam pattern. However, when encased in RAM, the modified beam pattern has an effective beam width of $0 < \theta_A < \pi/2$ as measured, for example, from the boresight axis to the off-axis 3dB point.

IV. GPR Image-Based Detection Statistic

Even in GPR images reconstructed from signal scans that were pre-processed, residual energy associated with ground bounce and artifacts that were not completely removed from the pre-processed signal scans can still be significant, especially near the surface. Residual energy can make it more difficult to separate buried objects in the image foreground from soil in the background. As a first step towards GPR image-based detection, our system uses image post-processing to facilitate foreground-background separation and reduce this residual energy (Fig.6).

The spatial distribution of energy within sequences of GPR xz image frames along short segments of the traversal path tends to be highly correlated. This phenomenon is not unique to spatial sequences of GPR image frames, but also occurs, for example, in temporal sequences of video frames. In video, there is precedent for subtracting from each pixel, the mean of corresponding pixels from previous frames in order to track motion (i.e., to separate movement in the foreground from stationary background) [42-43]. For spatial sequences of GPR image frames that contain buried objects with small along-track extents, the analogy is to facilitate separation of buried objects in the foreground from soil in the background by subtracting from each GPR image frame, an estimate of the background formed by computing the mean of previous GPR image frames. Specifically, the mean of pixels (x,z) over GPR image frames $y_{k-n} \ldots y_{k-n_0}$ is subtracted from pixel (x,z) in GPR image frame y_k, where n and $n_0 < n$ are the along-track window and guard band parameters. Large positive differences suggest a foreground anomaly in frame y_k. Negative differences are set to zero. The guard-band separation between GPR image frames y_k and y_{k-n_0} should be close to the expected along-track extent of a buried object, whereas the along-track separation between GPR image frames y_k and y_{k-n} should be perhaps an order of magnitude greater.

Next, μ_k and σ_k^2 are recursively updated as the running mean and variance over all nonzero pixels in the GPR difference image frames at $y_0 \ldots y_k$. Pixels in frame y_k with energies deemed statistically insignificant are suppressed by setting all pixels of value less than μ_k+$n\sigma_k$ from frame y_k to zero (n = 2 by default). Region growing is used to segment the resulting 2D image frame into foreground regions (spots) that contain pixels with nonzero values. Fig.7 shows reconstructed and post-processed image cubes and overhead views for a buried non-metallic object. Energy inside the cubes is projected onto the three visible faces.

Spot centroid location and energy-based detection features are computed for each GPR xz image frame at $y = y_k$ as each frame k is received. One obvious image-based detection feature is the *spot energy* $f_k \ge 0$ (i.e., the sum of pixel values for the spot extracted from the non-negative post-processed xz image frame at $y = y_k$). While f_k is a measure of energy in the foreground, the median $b_k \ge 0$ of pixels in the reconstructed xz image frame at $y = y_k$ is a measure of energy in the background (the reconstructed images generated by our system using plane-to-plane propagation are non-negative [40]). The non-negative *spot ratio* detection feature

$$r_k \overset{\Delta}{=} \begin{cases} f_k / b_k & b_k > 0 \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

is a measure of the foreground-to-background ratio.

Spots associated with buried objects of limited along-track extent persist within short sequences of GPR xz image frames. Buried object detections can thus be represented volumetrically as sequences of overlapping spots extracted from successive GPR xz image frames. While the point location of a spot extracted from a GPR xz image frame in 2D can be taken as its centroid, we take the point location of the 3D volumetric representation of a buried object detection as the centroid of the spot in the GPR image frame sequence with the largest spot ratio value (the local maximum). In practice, locations and spot ratios for these strongest spots can be estimated by applying a peak filter of half-width w to the time series $\{r_k\}$ of spot ratio values. The peak filtered version of

$\{r_k\}$ is a time series of *detection statistics* (i.e., a detection time series) whose nonzero spot ratio values are separated by at least w meters along the track. To compute the detection statistic (a peak filtered spot ratio) for a specific along-track location, the vehicle must therefore first travel w meters beyond that location along the track. This latency (or lag) of w meters is related to the along-track extent of visibility to the GPR for typical buried objects.

Each nonzero detection statistic in the detection time series has an associated vector of spot features. The spot feature vector contains the spot frame index, spot acquisition time, spot energy, spot ratio, spot pixel centroid, spot (easting, northing, depth) location, and potentially other features (such as spot size, spot orientation, spot extent, etc.). These features can be used to relate detected objects to one another or to discriminate buried objects from clutter.

V. DETECTION PERFORMANCE VS. GPR IMAGING MODE

This section considers tracks along two lanes. Lane 1 is a relatively flat gravel lane (~1.2 km in length), and Lane 2 is a somewhat bumpier dirt road (~1 km in length). Lane 2 is considered more challenging than Lane 1, as it is less improved and more bumpy. We assumed a soil dielectric constant of $\eta^2 = 6$ for both lanes.

The 42 Lane 1 objects were all ≤ 15 cm in depth to the top, and 28 of them (roughly two thirds) were non-metallic. The 77 Lane 2 objects were all ≤ 20 cm in depth to the top, and 57 of them (roughly 75%) were non-metallic. Non-metallic objects tend to have lower dielectric contrast against soil and can thus be more difficult to detect with a GPR than metallic objects.

Detection time series were generated for single traversals of each lane with various GPR imaging modes enabled. The horizontal axis of a detection time series represents the GPR *xz* image frame index (which is proportional to distance traveled along the path), and the vertical axis represents detection statistic strength (a peak filtered spot ratio value). We used a peak filter that separates all nonzero time series samples by at least $w = 0.7$ m along the track. Each detection time series is annotated with locations of objects that the antenna array actually passed over (blue diamonds). Although detection time series plots provide a convenient snapshot of run performance, they are one-dimensional and provide no indication of cross-track locations (from the driver to the passenger side of the vehicle) for either objects or detections.

ROC curves were generated for each lane by combining multiple traversals. Lane 1 was traversed 3 times (twice forward and once backward) for a total travel distance of ~3.6 km. Lane 2 was traversed 4 times (twice forward and twice backward) for a total travel distance of ~4 km. Each ROC curve is a plot of detection probability (P_D) vs. the number of false alarms per kilometer (N_{FA}) of vehicle travel along-track. For each ROC curve, an uncertainty radius of 1 meter (in location of detections relative to objects) was used in calculating detection probability.

Lane 1 detection performance is summarized in Fig.8-9. Fig.8 shows Lane 1 detection time series for the unfocused RAR imaging mode $(N_R, N_T) = (0,0)$ and the multistatic SAR imaging mode $(N_R, N_T) = (2,15)$. One can deduce by visually inspecting the plots that the foreground-to-background ratio is higher for the multistatic SAR imaging mode.

Fig.9 shows Lane 1 ROC curves for various GPR imaging modes. The advantage of SAR imaging is demonstrated in Fig.9a-c for the unfocused imaging mode $(N_R, N_T) = (0,0)$, the monostatic imaging mode $(N_R, N_T) = (0,15)$, and the multistatic imaging mode $(N_R, N_T) = (2,15)$. The advantage of multistatic imaging for RAR images is demonstrated in Fig.9d, which shows improvement in detection performance from the unfocused imaging mode $(N_R, N_T) = (0,0)$ to the monostatic imaging mode $(N_R, N_T) = (0,15)$ to the multistatic imaging mode $(N_R, N_T) = (2,15)$. A similar multistatic imaging advantage for SAR images is demonstrated in Fig.9e. However, there is less performance improvement from the monostatic imaging mode $(N_R, N_T) = (0,15)$ to the multistatic imaging mode $(N_R, N_T) = (2,15)$.

Lane 2 detection performance is summarized in Fig.10-11. Fig.10 shows Lane 2 detection time series for the unfocused RAR imaging mode $(N_R,N_T) = (0,0)$ and the multistatic SAR imaging mode $(N_R,N_T) = (2,15)$. As for Lane 1, one can deduce by visually inspecting the plots that the foreground-to-background ratio is significantly higher for the multistatic SAR imaging mode.

Fig.11 shows Lane 2 ROC curves for various GPR imaging modes. As for Lane 1, the advantage of SAR imaging is demonstrated in Fig.11a-c for the unfocused imaging mode $(N_R, N_T) = (0,0)$ the monostatic imaging mode $(N_R, N_T) = (0,15)$, and the multistatic imaging mode $(N_R, N_T) = (2,15)$. As for Lane 1, the advantage of multistatic imaging for RAR images is demonstrated in Fig.11d, which shows improvement in detection performance from the unfocused imaging mode $(N_R, N_T) = (0,0)$ to the monostatic imaging mode $(N_R, N_T) = (0,15)$ to the multistatic imaging mode $(N_R, N_T) = (2,15)$. A similar multistatic imaging advantage for SAR images is demonstrated in Fig.11e. However, while there is improvement in detection performance from the unfocused imaging mode $(N_R, N_T) = (0,0)$ to the monostatic imaging mode $(N_R, N_T) = (0,15)$, the multistatic imaging mode $(N_R, N_T) = (2,15)$ provides little additional improvement.

After extensive exploration of the (N_R, N_T) space of possible multistatic imaging modes, we found the multistatic imaging mode (N_R, N_T) = (2,15) to be nearly optimal for this study. By comparing the red ROC curves in Fig.9d (Lane 1) and Fig.11d (Lane 2) to the green ROC curves in Fig.9e and Fig.11e, one can get an overall sense of the improvement in detection – false alarm rate performance possible by applying energy-based detection to multistatic SAR images rather than to unfocused RAR images (signal scans). For example, on Lane 1, the false alarm rate dropped by nearly a factor of 10 at $P_D = 0.7$, and the detection rate increased by 33 percentage points at $N_{FA} = 10$. On Lane 2, the false alarm rate dropped by nearly a factor of 4 at $P_D = 0.7$, and the detection rate increased by 17 percentage points at $N_{FA} = 10$.

The experiments clearly show that for the case of one look and one receiver per look (unfocused GPR image frames), detection performance in SAR images was significantly better than in RAR images. However, for the case of many looks and many receivers per look (multistatic), the benefit of SAR vs. RAR imaging was less. The full benefits of SAR imaging can only be realized when one knows the dielectric properties of the sub-surface. At present, we model the subsurface as uniform with an assumed dielectric constant of η^2. If the subsurface is non-uniform or η^2 is in error, synthetic aperture integration results will be computed along the wrong distorted hyperbola, and this will limit the increase in foreground-to-background ratio (FBR) possible with SAR imaging (or even cause it to decrease). Even if the dielectric properties of the sub-surface were known, one can expect the theoretical limit of increase in the FBR to be lower for multistatic SAR vs. RAR than for unfocused SAR vs. RAR because one would expect the FBR to be larger in multistatic RAR images than in unfocused RAR images to begin with.

VI. SUMMARY

The relation between GPR imaging mode and detection-false alarm rate performance for buried objects was studied using GPR data collected repeatedly over lanes whose buried objects were mostly non-metallic. The data was acquired with a real-time vehicle-mounted GPR data collection and processing system developed at Lawrence Livermore National Laboratory by the authors and their colleagues. The GPR imaging algorithms focus the acquired signal scans by applying multistatic and synthetic aperture imaging techniques either separately or jointly. Detection-false alarm rate performance improved significantly when the detection algorithms were applied to multistatic SAR images rather than to unfocused GPR signal scans. Further performance improvements may be possible by (i) adopting an algorithm that extracts buried object locations and extents directly from 3D images of the sub-surface, and (ii) using change detection to exploit detection results from previous road traversals.

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