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Continuous Monitoring of the Lunar or Martian Subsurface Using On-Board Pattern Recognition and Neural Processing of Rover Geophysical Data

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ABSTRACT

The overall aim of this research is to provide base technology for an automated vision system for on-board interpretation of geophysical data. During the first year's work we have demonstrated that geophysical data can be treated as patterns and interpreted using single neural networks. Research underway at this time is developing an integrated vision system comprising neural networks, algorithmic preprocessing and expert knowledge. This system is to be tested incrementally using synthetic geophysical patterns, laboratory generated geophysical patterns and field geophysical patterns.

SUMMARY OF PREVIOUS WORK

The objectives of the first year funding were threefold. First, develop a continuous profiling EM vision system. Second, develop a continuous profiling sonic system. Third, evaluate pattern recognition and neural network approaches for automated interpretation of continuous profile data. As funding for the first year effort (1989-1990) necessitated a reduction in scope, objectives one and three became the operative objectives for the project.

Combining SERC Funding with funding from several other projects, we purchased a ground penetrating radar (GPR) system for continuous profiling using EM radiation in the 500 MHz and 300 MHz frequency ranges. Extensive experimentation of the GPR system at our geophysical test site and at several sites in Arizona is reported in McGill et al., 1989, McGill et al., 1990, and McGill, 1990.

Research during the first year has also demonstrated that radar signatures can be represented as patterns and interpreted automatically using a single neural network, see Figures 1 and 2. Our increasing experience in the field, however, indicated that GPR signatures can become quite complex, but target shape and aspects of the GPR survey (such as profiling speed) also strongly influence the radar return signatures. Hence, we believe that a single neural network could rapidly become overwhelmed by actual field situations, as we ourselves are at times. This belief has led to this year's project, which has as an objective to develop and incrementally test an integrated vision system comprising neural networks, algorithmic preprocessing and expert knowledge represented by a symbolic paradigm.

SUMMARY OF CURRENT RESEARCH

The research objective of the current reporting period is to develop and incrementally test an integrated vision system comprising neural networks, algorithmic preprocessing and expert knowledge.

VISION SYSTEM

During our previous research, we have demonstrated that GPR patterns are amenable to adaptive pattern recognition using a single neural network. In these experiments a continuous output simulated neural network was used to predict the horizontal and vertical location of a buried plate given the radar signal returned from the irradiated plate.

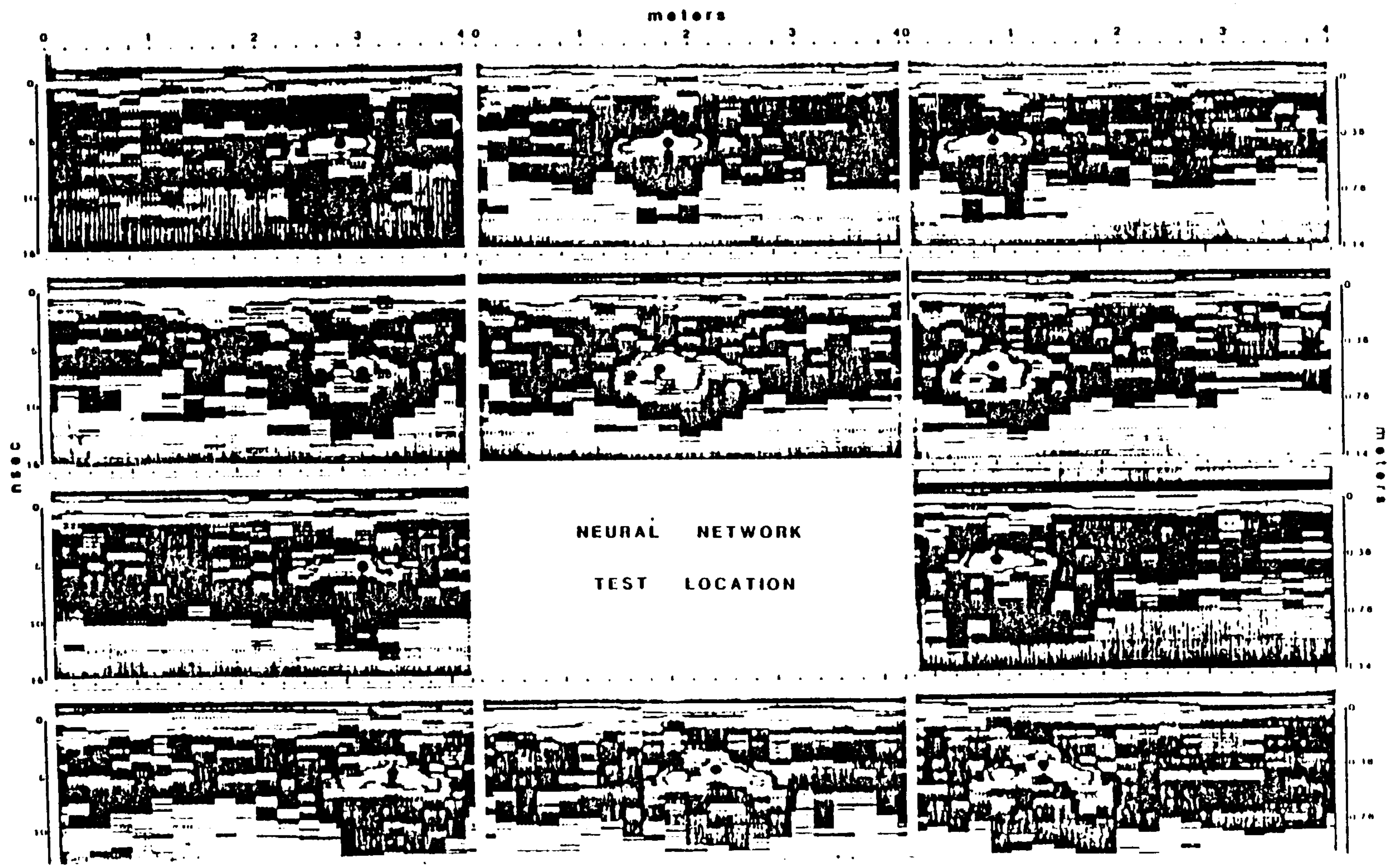

Figure 1. Digital GPR signatures used to train artificial neural networks. The black dot represents the spatial location of the target plate.

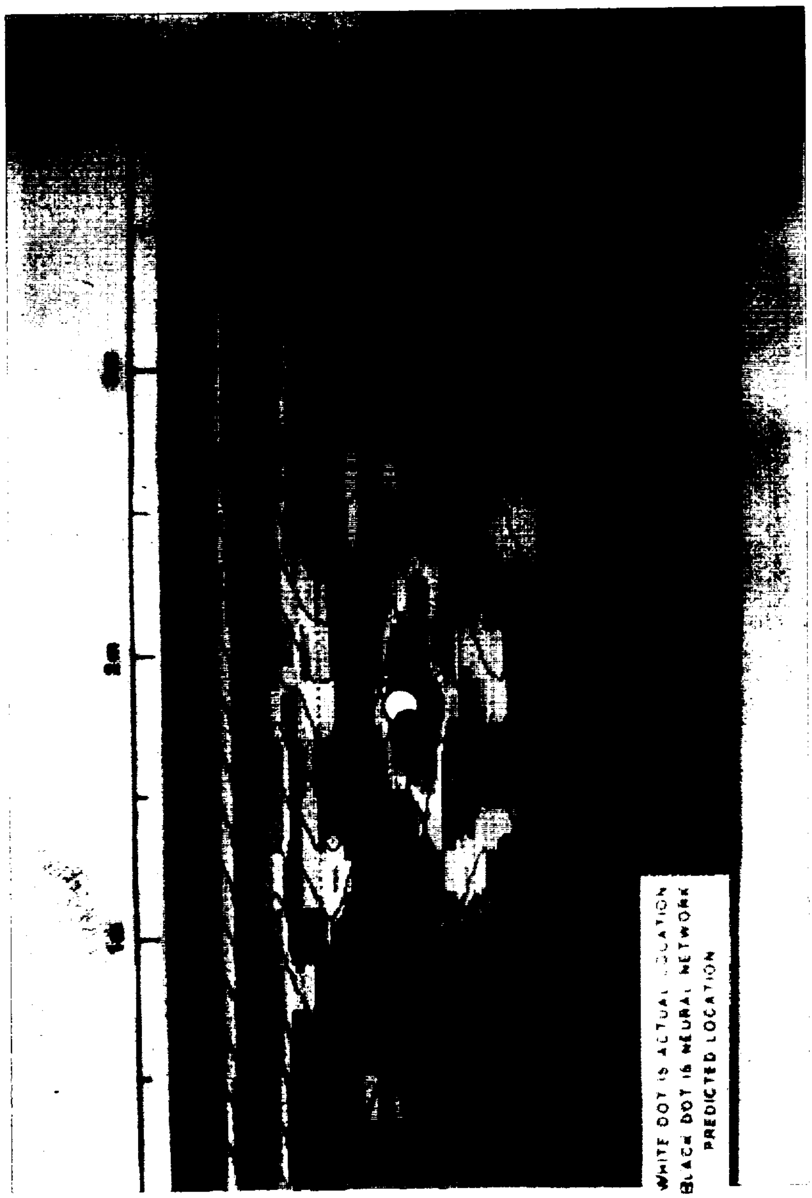

Figure 2. Neural network test profile. The black dot is the target location, the cross is the location predicted by the neural network.

Results from generating synthetic radar signatures over regular geometric shapes, Figures 3 through 7, show that, theoretically at least, far more than the target's spatial location can be derived from the radar pattern. The target shape can be ascertained from the slope of the signature arms, and the vertical and horizontal extent of the target can be calculated from the length and shape of the signature arms. Hence, neural network-based pattern recognition systems should be able to provide more information than our previous experiments have asked of them.

In the field, though, several factors combine to complicate the GPR patterns. First, attenuation in the surrounding soils will limit the radar penetration, thus truncating the anomaly arms. Second, the EM wave velocity of the background soils and the speed of the GPR profile can compress the radar pattern, making shape determination difficult. And third, heterogeneties in the background soils can superimpose noise on the desired GPR patterns.

Because of these difficulties, we have undertaken a program to design a more complex vision system able to incorporate the advantages of neural networks, knowledge base and algorithmic paradigms into a single unit. Neural networks, for example, appear to work best on simple (toy) problems. That is, the simpler the pattern, the more successful neural networks are in recognizing it. Furthermore, the scale of the "toy" (Minskey and Papert, 1968) problem is at a level at which most of the functioning of the human visual system seems to work, i.e., the human visual system appears to be composed of numerous simple neural networks working, for the most part, independently on specific aspects of a pattern.

The complexity of the human visual system seems to reside not as a single huge network, but rather in the complex (and so far little known) way in which the component networks interact or are coordinated. The focus of this effort, then, is on organizing several simple systems into a more effectively complex larger one. Although we are still experimenting with some fundamental uncertainties related to the specifics of how to go about such an organizational task, the following discussion outlines our general approach.

Applying the concept of encapsulation found in object oriented programming, particular domains of the pattern recognition function will be isolated from others to keep the level of inter-model complexity down. We anticipate that higher level objects will be employed to coordinate, or manage, the interaction of simpler objects. Research on the visual system of the horseshoe crab, for example, indicates that the information flow into the crab's visual cortex from its brain exceeds the information flow into its visual cortex from the system of neural networks constituting its optic nerve. Hence, even in simple visual systems there appears to be significant management of image information through knowledge gained from heredity or experience.

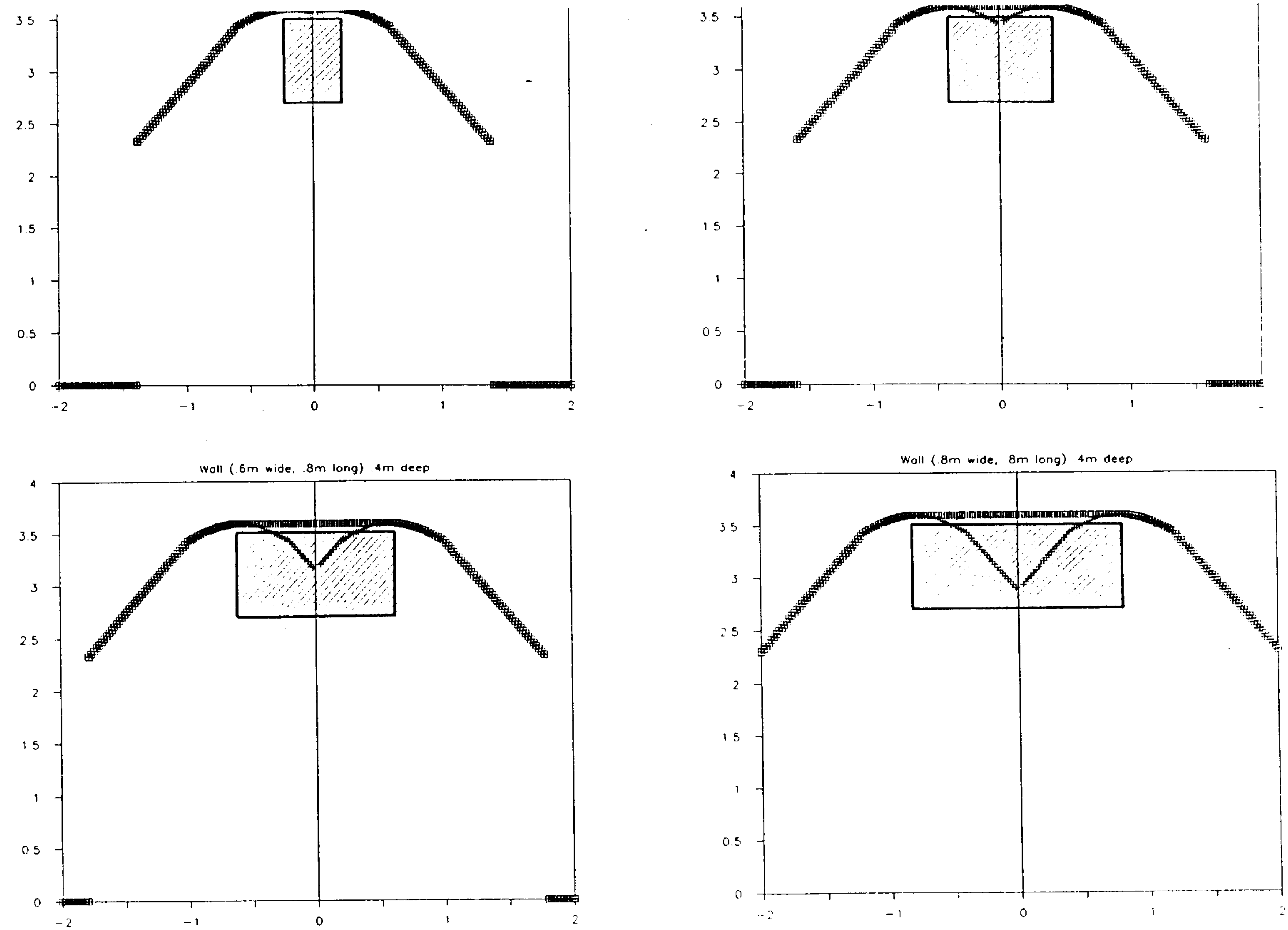

Figure 3. Synthetic GPR profiles over blocks having vertical sides and varying widths, (a) 0.4m, (b) 0.8m, (c) 1.2m, and (d) 1.6m. Reflections from top (squares) and inside surfaces (crosses) are shown.

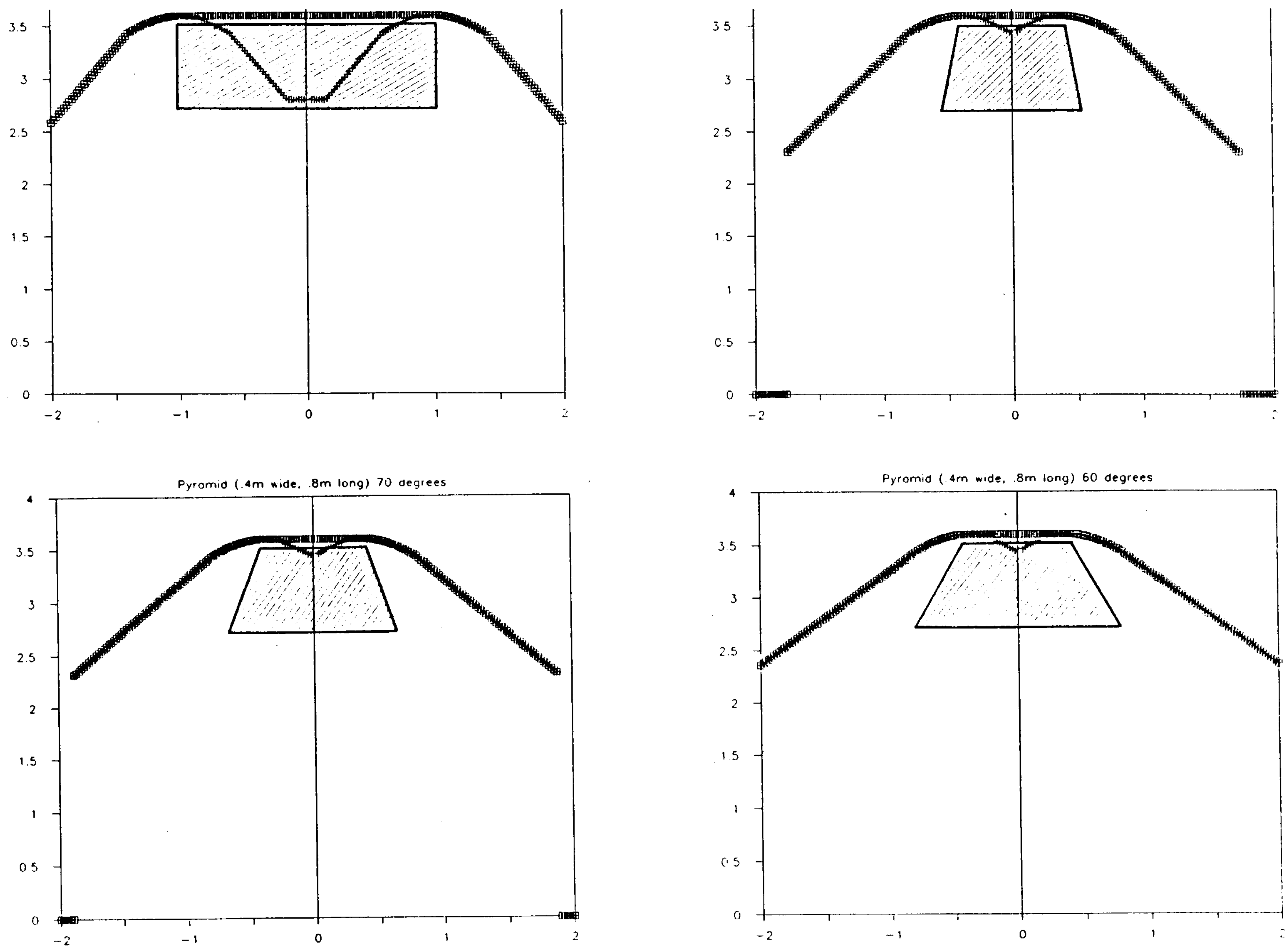

Figure 4. Synthetic GPR profiles over blocks having varying slope angles, (a) 90 degrees, (b) 80 degrees, (c) 70 degrees and (d) 60 degrees. Symbols are described in Figure 3.

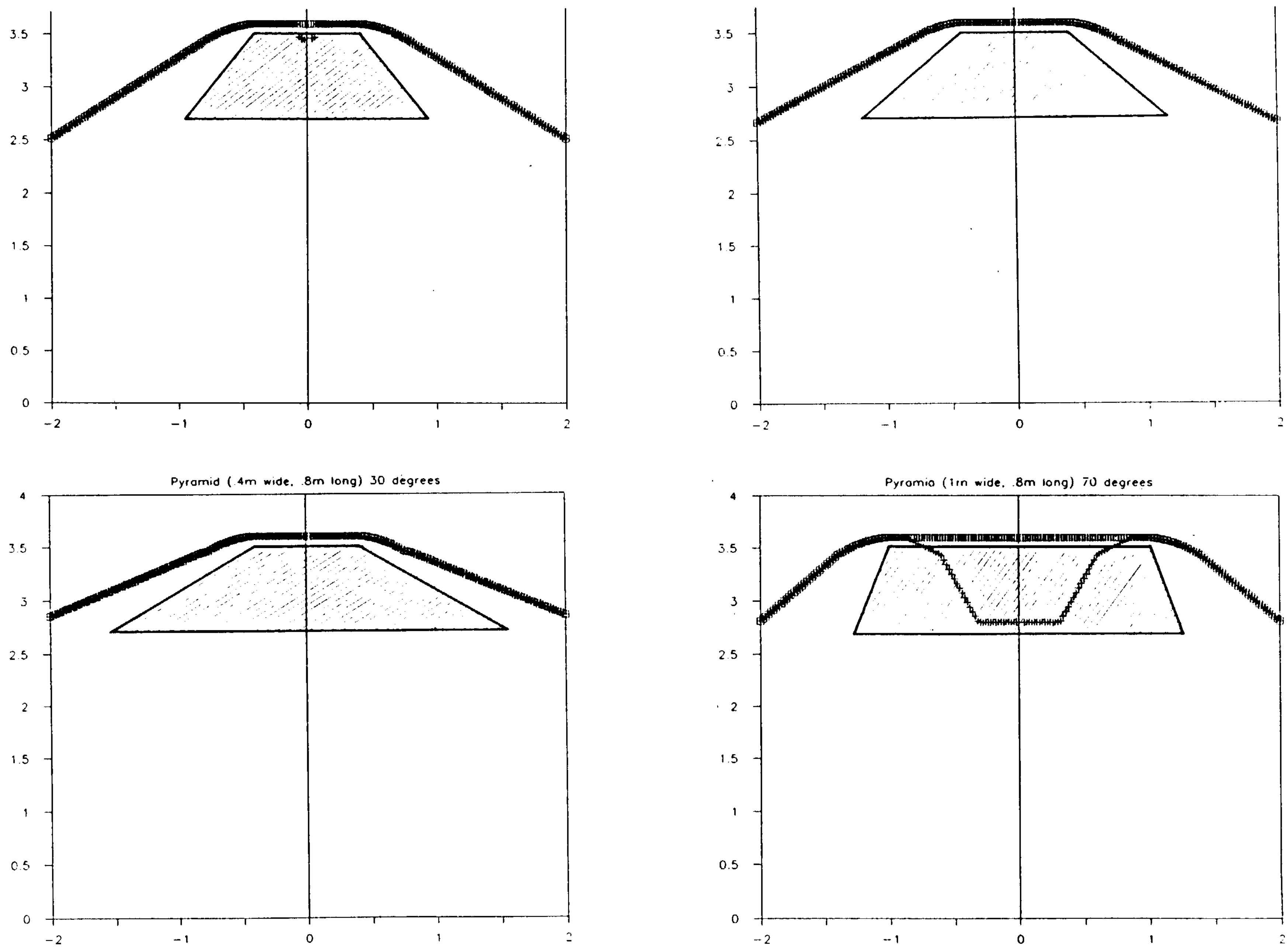

Figure 5. Synthetic GPR profiles over blocks having varying slope angles and widths, (a) 0.8m wide, 50 degrees, (b) 0.8m wide, 40 degrees, (c) 0.8m wide, 30 degrees and (d) 1m wide, 70 degrees. Symbols are described in Figure 3.

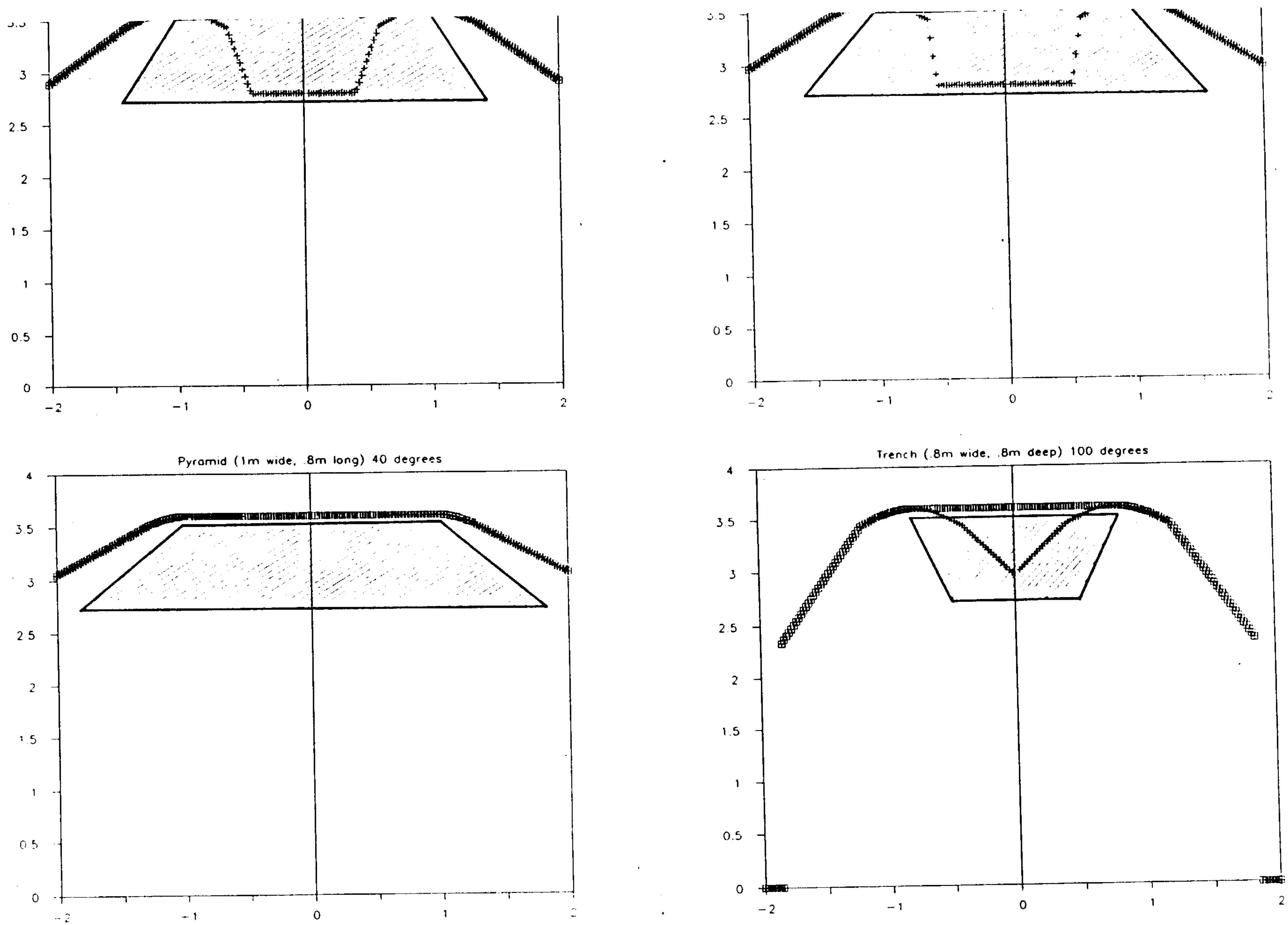

Figure 6. Synthetic GPR profiles over blocks having varying slope angles, (a) 60 degrees, (b) 50 degrees, (c) 40 degrees and (d) 100 degrees. Symbols are described in Figure 3.

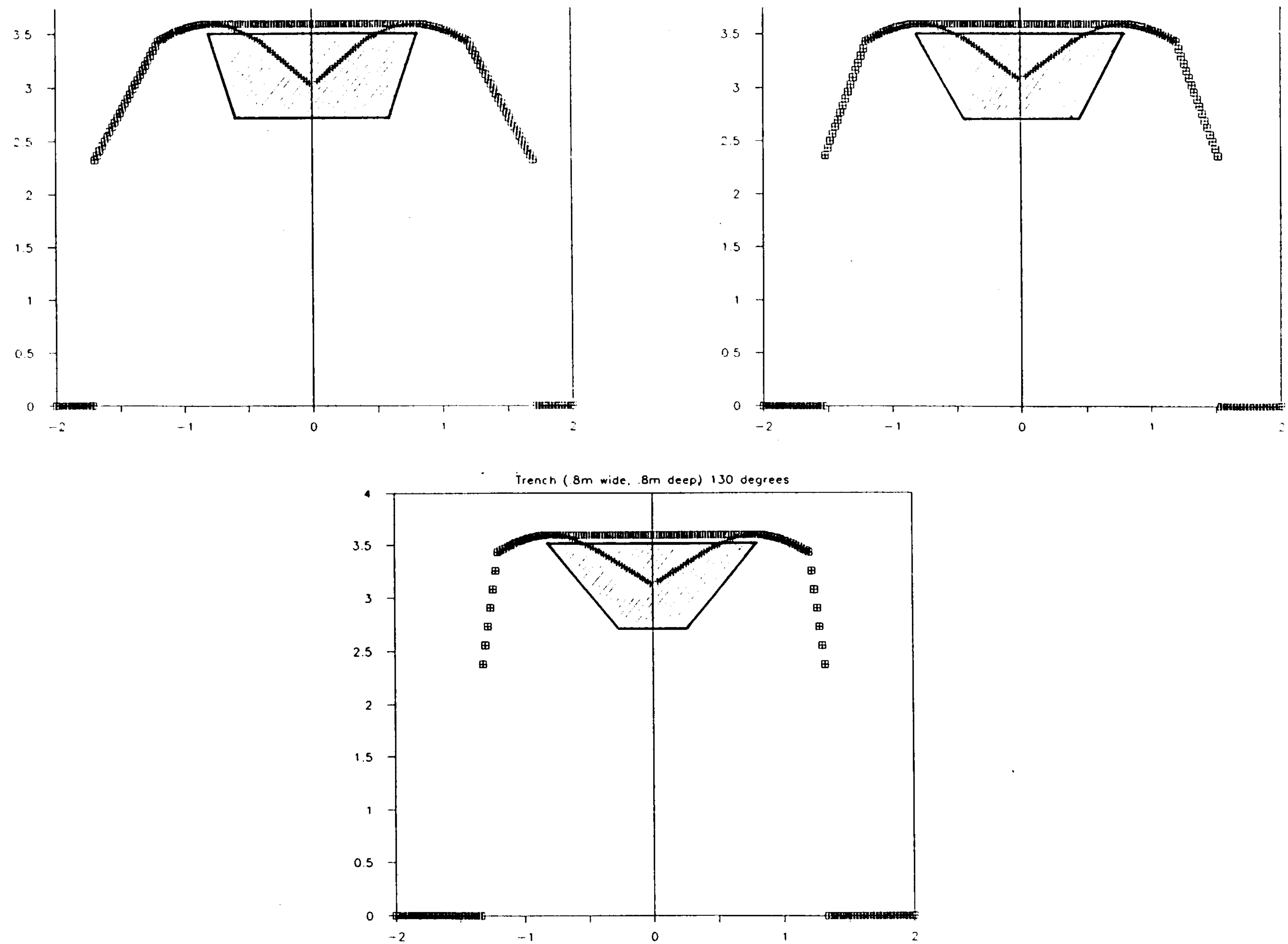

Figure 7. Synthetic GPR profiles over blocks having varying slope angles, (a) 110 degrees, (b) 120 degrees and (c) 130 degrees. Symbols are described in Figure 3.

The basic idea is to use neural network paradigms as separate objects within the object oriented programming environment. Nets for associative memory, nets for self organization and back-propagation nets for discrimination, will ideally be guided and directed in terms of access and activation by expert system modules. At the time of this progress report, a preliminary knowledge base has been assembled, the components (expert system shell, neural network simulation package, and small talk based object oriented programming environment) have been implemented on a Sun Sparcstation, and software to generate synthetic data for neural network training (Figures 3 to 7, for example) has been assembled.

INCREMENTAL TESTING

Synthetic Patterns

Testing of the vision system will interact with system development. Tests will first be completed using synthetic data such as those shown in Figures 3 through 7. That actual GPR patterns look like these synthetic data is demonstrated in Figure 8. The vision system will be supervised until it can perform well on the synthetic data.

Laboratory Test Tank

To test the system in a more natural environment, but still in a well controlled, laboratory situation, we have constructed as part of this project a laboratory GPR test tank shown in Figure 9. The large GPR test tank has been constructed for testing GPR imaging apparatus under well-controlled laboratory conditions.

The test tank consists of a 2.1m high by x 2.1m diameter fiber-glass and polyester mat stock tank. The aqueous, background, solution in the tank has a high permittivity, hence realistic field situations can be scaled within the tank to distances within a few tenths of a meter.

The aqueous solution will serve two purposes: first, to compress the waves enough to present a scaled-down version of an actual field site, and second, to attenuate the waves enough to keep the sides, bottom, and surface reflections small. Because the permittivity of water is generally an order of magnitude greater than that of most rocks. Electromagnetic waves having equal frequencies can be scaled to a third the wavelength. Furthermore, frequencies higher than that in the field can be employed to further decrease wavelength. The medium's skin depth will be adjusted by adding ionic compounds such as HCl to a specified concentration, yielding the necessary conductivity. The model anomalies will be constructed using resin and graphite.

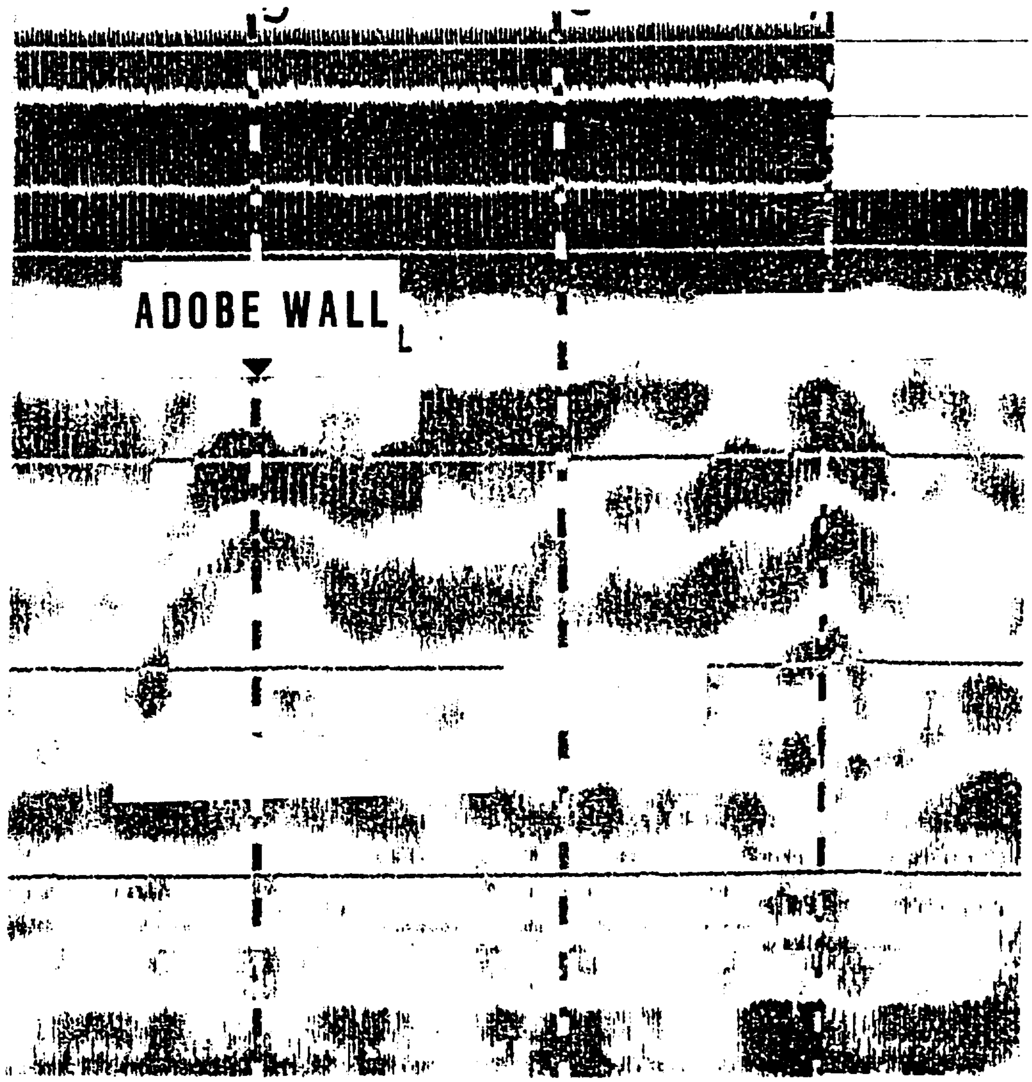

Figure 8. Actual GPR profile from an historical archaeology site at Tubac, Arizona. The adobe wall is similar to the target modeled in Figure 1a.

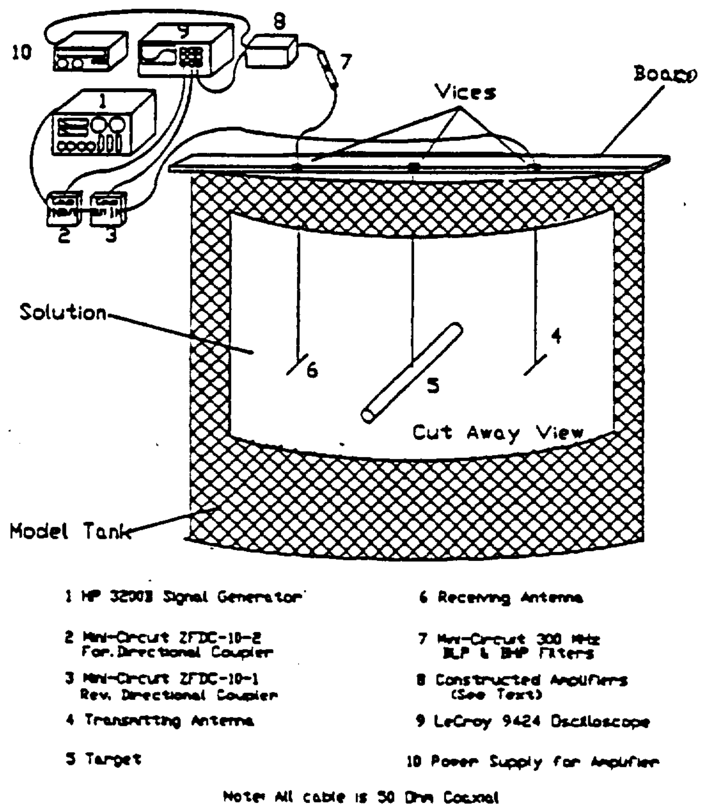

Figure 9. Test tank.

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The modeling scheme will be chosen to provide an attenuation per wavelength similar to that found in the field. In this way, the same conditions encountered in the field can be modeled in a controlled environment. Using this unique facility, the influence of EM wave velocity, profiling speed and background attenuation on GPR patterns can be assessed while still maintaining homogeneous background conditions. The research during this phase will evaluate the ability of the GPR vision system to extrapolate from synthetic patterns to real, but still ideal, patterns. This phase will also be interactive as the system is adjusted to improve performance.

FIELD TEST

As a final test, the GPR system will be applied using the GPR test facility at the San Xavier Geophysical Test Site. This test facility has been designed specifically for our SERC GPR work (Figures 10, 11, and 12). Details of this site are provided in McGill, 1990.

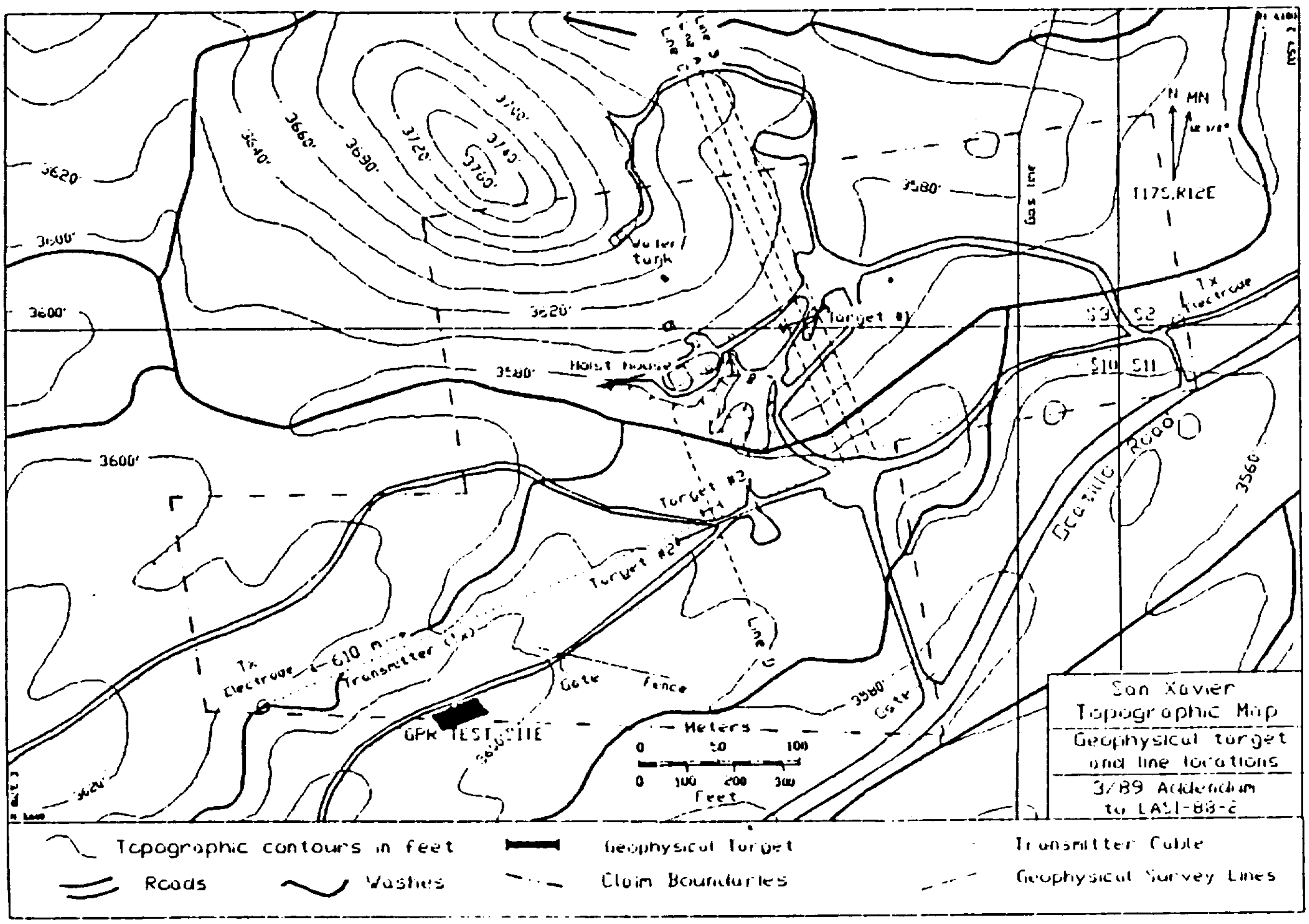

Figure 10. Location of the SERC, GPR test site at the San Xavier Geophysical Test Facility.

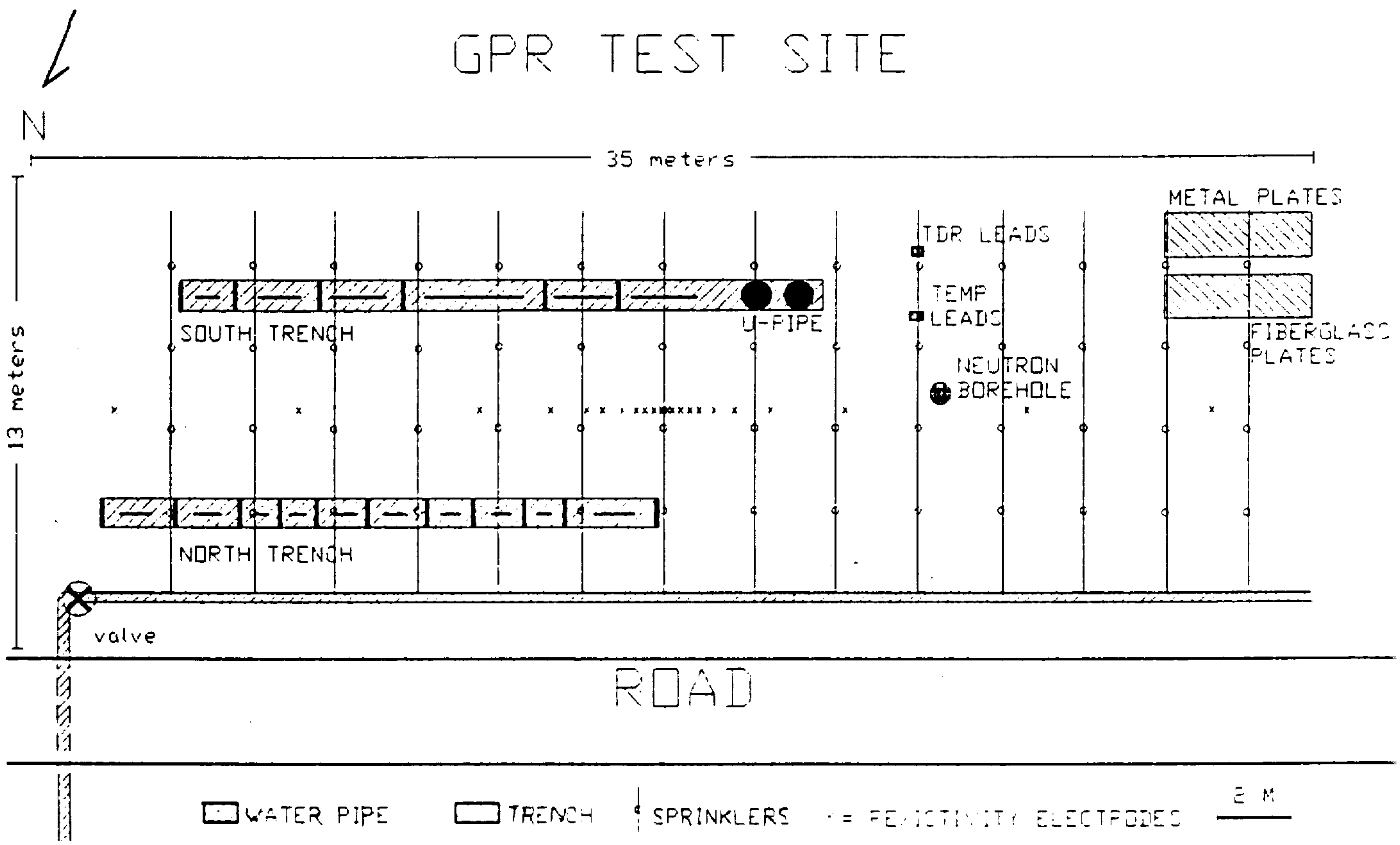

Figure 11. Plan view of the SERC, GPR test site.

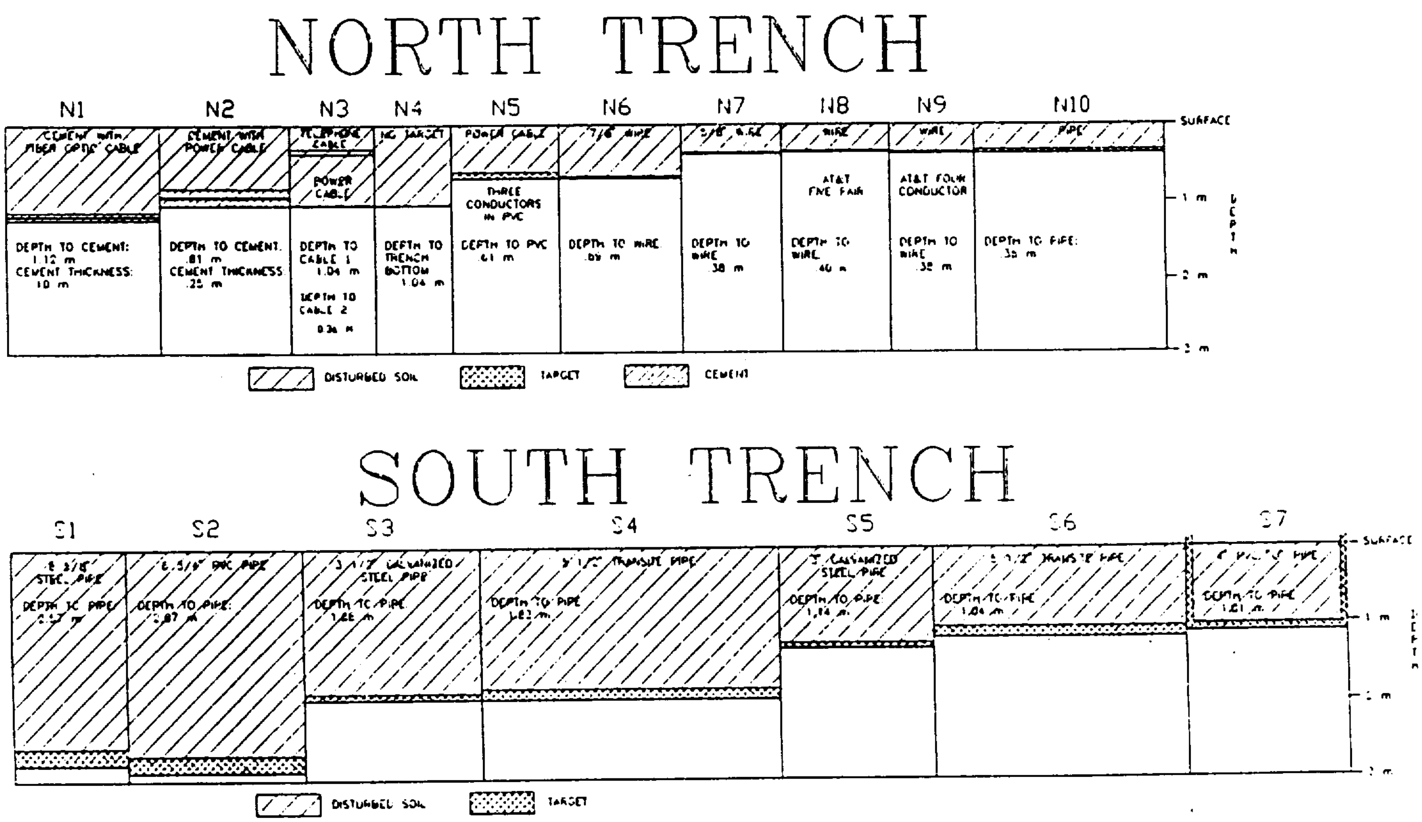

Figure 12. Cross-section of the targets at the SERC, GPR test site.

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