

Inferring Bottom Acoustic Properties from AN/SQQ-32 Sonar Reverberation Data in Order to Reduce False Targets in Bottom/Buried Mine Detection*

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ABSTRACT

Bottom/sub bottom geoacoustic properties must be determined to high spatial resolution in order to reduce false targets for bottom/buried mine detection.

Inversion techniques (ITs) are used to infer bottom geoacoustic properties using AN/SQQ-32 beam reverberation level (RL) time series data acquired in Rhode Island Sound in February 1993. A technique was developed wherein the deviation of the RL for an individual ping and beam from an area-wide average RL is used to generate geo-referenced maps illustrating the relative reflectivity of the seabed. These geo-plots not only agree with existing descriptions of the sediment distribution, but also provide a highly detailed spatial representation of the bottom geoacoustic distribution. The plots highlight the gross inadequacies, particularly in spatial resolution, of existing information on bottom geoacoustic properties and the difficulties of using such algorithms as Lambert's Law to characterize the RL.

These plots, when produced using appropriately small sample intervals, have sufficient spatial resolution to reveal MCM clutter density information. Geo-referenced maps of relative reflectivity can be an invaluable aid to in developing “realistic” mine hunting time lines especially in a route-survey mode or as a surveying tool to compare clutter densities. These clutter densities are used as a basis for change detection algorithms applied to bottom/buried mine detection. Additionally, they can also be used to identify appropriate geoacoustic parameter inputs for accurate sonar model performance predictions and to provide real time performance monitoring and assessment, (i.e. a capability to revise and modify the search strategy).

INTRODUCTION

In shallow water, acoustic sensors are particularly influenced by geoacoustic interactive processes with the sea floor including transmission into the sediment and reflection and scattering at the water-sediment interface. Backscatter from this interface can often severely degrade acoustic sensor performance. Planning for MCM operation can be unduly restricted due to lack of knowledge of the sediment composition and roughness and its spatial variability. Bottom sediment property maps generally are based on large area averages derived from a few in-situ observations. Such maps have only limited value when confronted with solving the problem of mine detection and classification in an area of high bottom roughness, or one containing numerous false targets or high clutter density or operating in areas of potential mine burial. A high priority exists to develop high-resolution maps of bottom characteristics as an aid to pursuing all aspects of mine warfare (MIW).

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This paper presents an alternative approach using inversion technology to infer bottom sediment characteristics from the beam reverberation data recorded from medium (ASW) or high (MIW) frequency active sonars.¹ Such data may be acquired "in stride" and displayed "in real time" to sonar operators/mission planners or can be archived in the tactical route survey data base for later generation of high-resolution geoacoustic plots of sediment properties such as its reflectivity, roughness and clutter density.

CONCEPT

The inversion technique employed in this study is based on the premise that in-situ beam RL data can be used to characterize seabed geoacoustic properties, principally its relative reflectivity. This technique is based on the assumption that backscattering from the sea surface and water column (volume) remains spatially and temporally invariant over the short duration and limited area of the exercise or survey. Hence, any variation in RL, from beam to beam and ping to ping, may arise only due to changes in the reflective properties of the sea floor, (i.e., spatial variations in bottom composition).

This technique also invokes several other assumptions, none of which are particularly limiting: (a) the sound speed profile was invariant both spatially (~3 km² area) and temporally (duration <2 hr), (b) the source level, although varied during the measurement period, was invariant in azimuth (beam to beam) and (c) no significant topographical features were present, (i.e., the bottom was essentially flat).

The methodology and analysis is based on creating a characteristic or area-wide RL curve, determined from the average of many pings and beams, and comparing smoothed individual beam RL curves against the area-wide mean curve. (see Howell¹ for more details). Each data point in the smoothed single beam RL curve has an associated range and bearing which corresponds to a unique geographic position. Hence, any deviation of a single beam RL curve from its area-wide mean can be interpreted as a local difference in bottom sediment characteristics. For example, Figure 1(a) shows areas where the backscattering from beam 21 (from Ping 107 during Event 1) is both greater than and lesser than that of the Event 1 overall mean RL curve. Regions of anomalously lower beam RL are associated with areas containing less reflective (more absorptive) sediments and conversely. Area-wide plots of relative reflectivity can then be generated by combining the beam RL data from many pings.

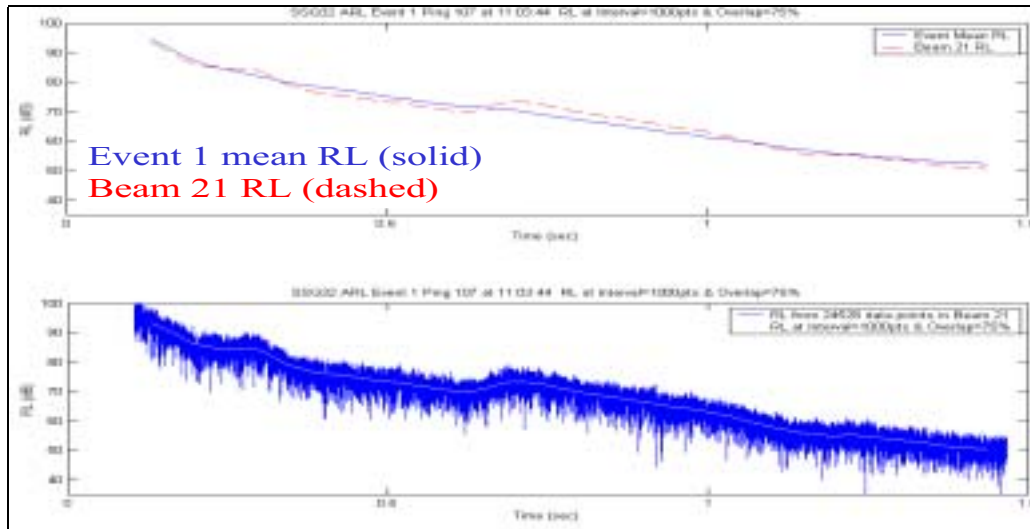


Figure 1. (a) Smoothed RL (dashed) for beam 21, ping 107 compared the event 1 mean RL curve (solid) illustrating regions of greater and lesser reflectivity; (b) raw and smoothed RL curves for beam 21, ping 107 based on 1000 point, 75% overlap smoothing.

DATA

Beam-formed reverberation level (RL) data were acquired by the USS AVENGER (MCM-1) AN/SQQ-32 sonar suite for four periods during 19 February 1993 while the vessel was operating in Rhode Island Sound (Figure 2). The backscattered energy from 601 pings was recorded while the ship traversed 1500 m on a westward course in water 25-27 m deep. Data were recorded from 28 beams, each 2.5° wide, resulting in a 70°-wide azimuthal arc extending approximately 1100 m in range. The 12° depression angle was used to ensure strong bottom interaction of the outgoing pulse. Table 1 lists the particulars associated with each of the four measurement periods or events. The total area ensonified during the entire experiment encompassed a narrow rectangle approximately 3000 m long by 1000 m wide. Positional information for each ping was derived from the ship's GPS navigational log. The raw RL data were later corrected for application of a time varying gain and receiver sensitivity.

Track	Event	Start Time	End Time	Number of Pings	Pulse Length	Power Setting	Source Level
1	1	11:02:15	11:05:26	109	11ms	Med	215dB
1	2	11:05:26	11:12:20	228	11ms	Low	210dB
1	3	11:12:20	11:14:53	88	11ms	Med	215dB
2	4	12:45:09	12:49:36	156	2ms	High	220dB

Table 1. Details of Recorded AN/SQQ-32 Transmissions on 19 February 1993.

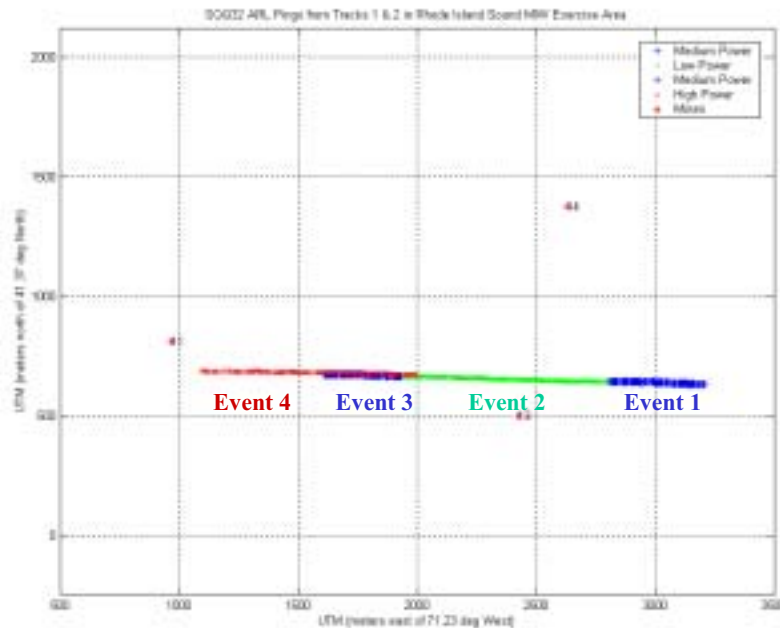


Figure 2. Ship track for each event, 1100-1300 local time, 19 Feb 1993 in Rhode Island Sound.

Each ping represented 28 time series, one for each beam, of about 25,000 samples per beam. At a sound speed of 1500 m/s, this represents a reverberation signal of about 1.5 s duration or 1100 m in range. To produce the mean RL curve for each beam, we employed a smoothing technique that segmented the RL time series into 1000 sample point intervals corresponding to a distance of about 40 m. In addition, we applied an overlap of 75% to each segment. Various combinations of segment length and overlap percentage were explored with the above values providing the best trade off between data preservation and computational efficiency. Figure 1(a) illustrates the raw and smoothed beam RL curves for Beam 21 of Ping 1 during Event 1.

ANALYSIS

Following the procedures described above, comparisons of single ping RL data to area- or event-averaged RL data were conducted. The data from ping 107 of Event 1 (Figure 3) are illustrative of features found in all the beam RL data sets. The warmer (yellow/red) areas are regions of greater than average backscattering and conversely for the blue-toned regions. The red areas contain a sediment structure that is 4 to 5 dB more reflective than the area mean. The entire ensounded area exhibits a dynamic range of about 10 dB in relative reflectivity.

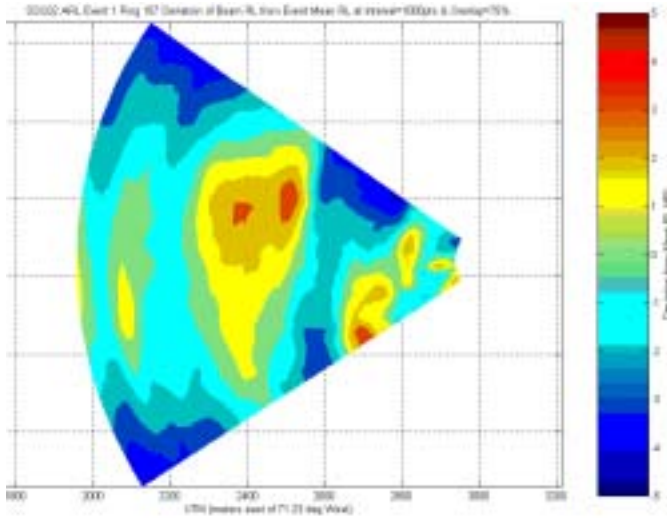


Figure 3. Contour plot of relative reflectivity based on the 28 beams of ping 107 compared to the event 1 mean RL curve. Note the area of increased (4 to 5 dB) reflectivity near 2400 m east of the grid origin.

The geographic consistency of regions of high/low relative reflectivity can be demonstrated by sequentially overlaying contour plots from a series of sequential pings (Pings 59, 86, 113, 140 and 167) spanning just under 2 min or 200 m of ship movement to the west (Figure 4). Regions of high/low backscatter appear consistently in the same geographic location over a number of pings.

If the RL curves from all the pings comprising event 1 (109 pings) are combined into a composite plot (Figure 5), the resultant averaging will eliminate some features present on the contour plots constructed from individual pings; these features are not geographically consistent. Thus the contours in Figure 5 lose some detail relative to a single ping plot but significant areas of high/low relative reflectivity are still well preserved.

By employing the technique described above to all the pings along Track 1 a contour plot of relative reflectivity can be generated for the entire area, a distance of about 2.5 km, (Figure 6). Because of the differences in power setting during this sequence of 425 pings (Table 1), the RL curves were normalized to a standard (medium power) setting. The major features present in the single ping and Event 1 composite plots are readily discernable even when an area-wide mean RL curve is employed.

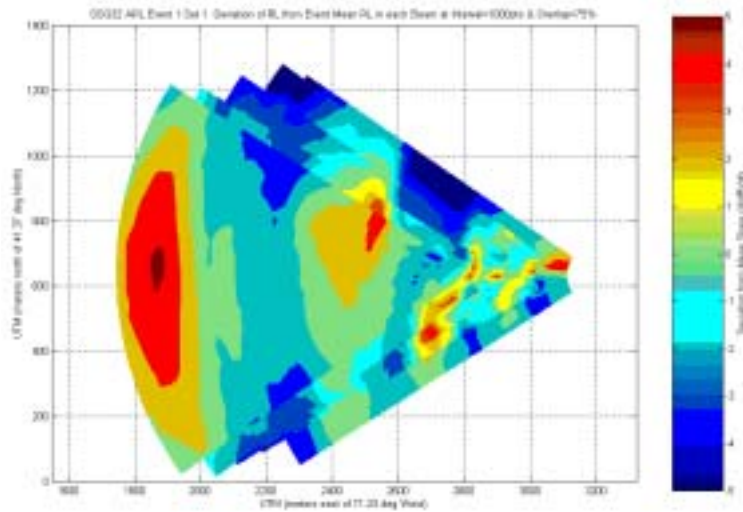


Figure 4. Overlay of five contour plots from selected pings during event 1 illustrating the geographical consistency of areas of high/low reflectivity.

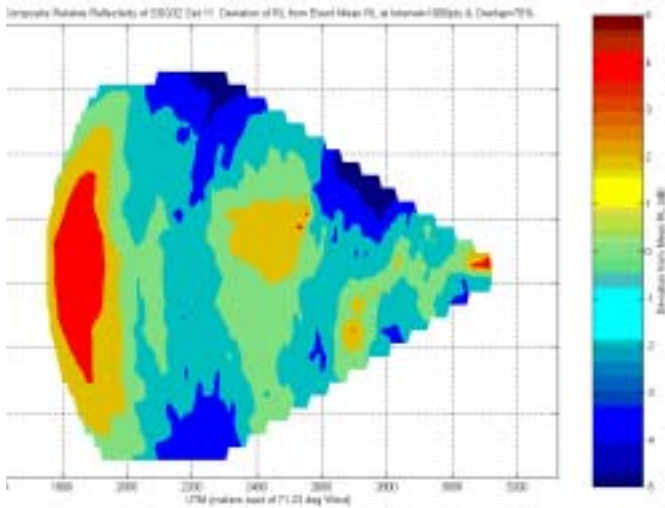


Figure 5. Contour plot for all pings of event 1. Note some resolution is lost compared to Fig 4 but overall the geographical consistency is maintained.

The features seen in Figure 6 agree qualitatively with the broad scale surface sediment description of the area.² The most prominent feature is the 200-300 m wide highly reflective band observed mid-way in the survey area. Its reflectivity and size suggest this is either an exposed rock outcrop or ancient reef structure or more likely a mixed rock and gravel glacial moraine. The presence of a moraine-like feature is supported by noting that this band is coincident with the area of greatest bathymetric variation.³ The area to the west of the moraine is relatively featureless, exhibiting low reflectivity of limited dynamic range (1-2 dB). This is most likely a large region covered by a smooth sand sediment layer as suggested by the NAVOCEANO mine warfare pilot chart.² To the east the RL data describe a seabed of highly

variable reflective characteristics. Regions of low reflectivity are interspersed with irregular patches of quite high reflectivity. The latter are likely areas of uncovered (or thinly covered) rock, rocky patches or gravel/pebble fields surrounded by depressions or basins filled with finer grained sediments or mud in the areas of minimal relative reflectivity (-3 to -4 dB).

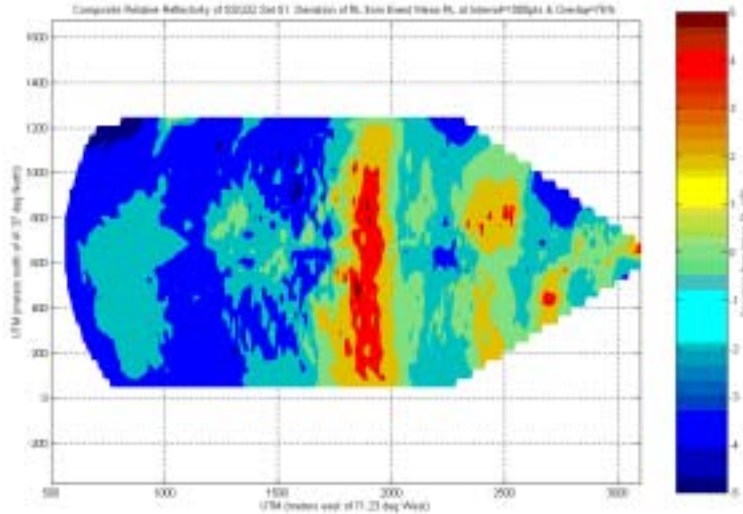


Fig. 6. Relative reflectivity contour plot from all pings of events 1,2, and 3 based upon an area-wide mean RL. Geographically consistent regions of high/low reflectivity are seen throughout the 1000 m by 3000 m survey area.

The geographic contour plot of relative reflectivity agrees well with the limited picture that can be gleaned from analysis of observed sedimentary data such as described by References 2 and 3. The major benefit of this technique is the far greater spatial detail of sediment distribution that can be acquired just by recording beam RL data while conducting routine or survey operations.

DISCUSSION

This "through the sensor" technique to measure the relative reflectivity of the seabed has wide spread application to all aspects of undersea warfare. If *a priori* geophysical observations have been conducted in a given region, then high frequency RL contour plots such as in Figure 6 can be calibrated against these data to provide absolute contours of reflectivity. High spatial resolution maps of the surface sediment geoaoustic distribution can then be inferred from calibrated contour plots.

Lower frequency sonars such as the 3.5 kHz AN/SQS-53C found on most Navy destroyers can be used to produce similar bottom reflectivity mosaics but with the added advantage of deeper penetration into the sediment (several meters).⁴ Vertical gradients of sediment properties can be assessed as well. Not to be overlooked is the much larger area encompassed by each ping from the 53C sonar, (e.g., tens of km², enabling a much larger area to be surveyed in a shorter time). Interesting bottom/sub-bottom features can later be examined in more detail with the use of the high-resolution SQQ-32 sonar or a side scan sonar to provide high definition pictographs of the bottom roughness or clutter density.

Future evolution of this inverse technology is to fuse simultaneous beam RL data measured from a suite of sensors, each at a different frequency, to provide a three dimensional view of the sediment properties (Fig. 7). High frequency sonar images will provide information concerning the bottom roughness and clutter density while medium and lower frequency sonars will provide information on bottom and sub-bottom reflectivity and embedded features.

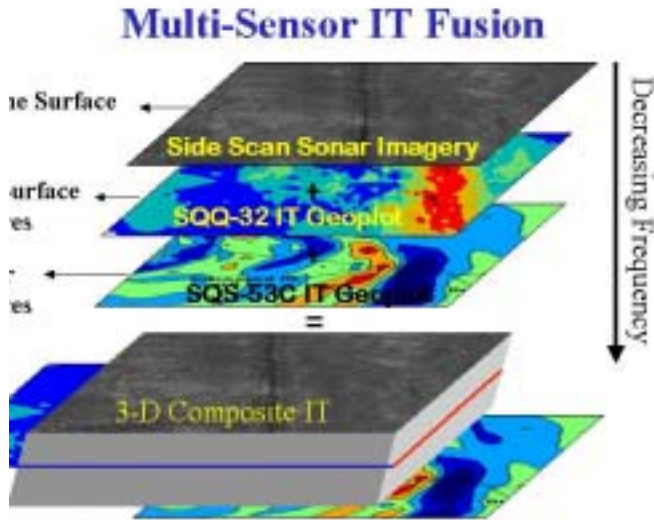


Figure 7. Data fusion schematic illustrating a three-dimensional view of bottom roughness, clutter density and reflectivity that can be obtained from a suite of multi-frequency sensors.

APPENDIX A – AUTOMATED BOTTOM/BURIED MINE DETECTION/CLASSIFICATION

TECHNICAL DESCRIPTION

MIW sonars with automated detection/classification (AUTOCLAS) algorithms to detect bottom/buried mines can reduce or eliminate operator involvement in the target decision process. NSI is developing AUTOCLAS as an automatic buried/bottom mine detection algorithm using Barron Associate's (BAI)⁵ polynomial neural network (PNN) synthesis software toolkit (GNOSIS)⁶ for automated synthesis and analysis of computation models to detect bottom/buried mines. The high spatial resolution map of the bottom 3D geoaoustic properties using the IT algorithm described in the previous section will help reduce the probability of false targets.

Using GNOSIS for developing a classification PNN provides numerous advantages over other methodologies. GNOSIS uses a generalized network structure that permits the use of a variety of basis functions, nonlinear transformations, and network interconnections (including delays and feedbacks). It grows the network structure from zero complexity to a level of just sufficient complexity to ensure optimal performance without overfitting that would result in performance degradation on unforeseen data. GNOSIS uses a constrained logistic-loss fitting criteria that is statistically well suited for classification problems. It uses a regularized Gauss-Newton method for estimating the network weights that is orders of magnitude faster than gradient-decent methods such as backpropagation.

PNN synthesis has been the basis for over 30, 11, 6 SBIR Phase I, II, III awards, respectively, since 1987. For example, U.S. Air Force contract FO8627-96-C-6013⁷ showed that AUTOCLAS has the potential to detect buried mines. GNOSIS developed signal processing algorithms and PNN modes that correctly classified 92.5% of subsurface ordnance detected by ground-penetrating radar during field experiments.

Applications modelling of sonic returns were demonstrated by the DARPA Acoustic Non-Traditional Exploitation System (DANTES) program. GNOSIS helped develop an automatic classification algorithm for transient and other broadband acoustic sources. Its classification accuracy was validated during sea trials. Of special interest is that the DANTES PNN can be trained or re-trained at sea in near real time. AUTOCLAS will have similar capabilities.

At this time NAVSEASYS COM is implementing a PNN-based technology for voltage transient suppression in a DD-51 ship.

Based on its extensive research in coastal waters, from the surf zone and outward, NSI is confident that it can overcome any technical issues, and, for the first time, develop an AUV-deployable AUTOCLAS.

NSI is attempting to obtain funding to perform the following steps:

A. Develop a detailed work plan, including creation of a location and methodology sensor data base for PNN training, and develop a technical approach. Substantial challenges exist in selecting, acquiring and operating one or more sonars. Further challenges are in designing the field test, selecting a test site, acquiring mine shapes, and ensuring that sufficient test data will be recorded. NSI will creatively minimize time and resources. For example, under certain conditions, valid data might result from placing and retrieving targets from pier side.

B. Determine type(s) of sonars and unmanned under water vehicles (UUVs) to demonstrate AUTOCLAS performance. Potential sonars include:

- Marine Sonics Side Scan Sonar - SAHRV
- JHU/APL high frequency imaging sonar - CETUS II
- HF and VHF Side Scan Sonars - MORPHEUS
- KLINE 5400 Side Scan Sonar - BPUUV
- Multibeam 400 KHz Sidescan Sonar - UPAUV
- AN/SQS SQQ-32 Fleet mine hunting sonar

NSI will use a higher frequency sonar (> 400 kHz) for its potential detailed characterization of a mine's structure. A lower frequency (≤ 35 kHz) sonar will image buried mines but with less image information (and thus less classification capabilities).

C. Develop the buried and unburied PNN training data using dummy mines and similarly sized typical bottom debris. For the buried and unburied cases, a data base of about 100 event signals from 20 different targets may be sufficient. More data may be desirable for a robust evaluation database, but techniques such as the iterative jack-knife procedure could support classification PNN evaluation by compensating for limited data.

D. Develop detection/classification models. For developing AUTOCLAS with candidate

mine targets the GNOSIS neural network will process an input data vector of sonar signals to output a vector that indicates the target classification. If, for example, AUTOCLAS were to have only two different mine shapes, the classification neural network model has two outputs. In principal, the k th output would be exactly unity from data collected over a target of the k th class. All other outputs would be exactly zero. A set of training data will be established that consists of N (2) pairs of input and output vectors. These vectors incorporate the inputs (features) and outputs (class, e.g., 2). Feature extraction for each will incorporate time-domain signals (either directly or by transformation into the frequency domain). Another approach may be to synthesize spatial domain signals by selecting samples with identical indexes from each waveform in a target response. Data fusion may be used to combine feature sets. The target data will be randomly partitioned into training and evaluation sets. The GNOSIS logistic-loss network will correctly map its output into $\{0,1\}$.

The synthesis or training algorithm builds a neural network structure, beginning with a single layer of processing elements and adding layers until additional network complexity is no longer justified by data. In this manner GNOSIS will allow the PNN to grow to a just-sufficient level of complexity. An information theoretic criterion developed by Akaike⁸ prevents over fitting the training data. The classification model outputs will be a direct estimate of the probabilities of class membership. The developed AUTOCLAS is then evaluated using the evaluation data set.

ACKNOWLEDGEMENTS

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