PROBABILISTIC INTEGRATION OF SEISMIC, HYDROACOUSTIC AND INFRASONIC DATA USING THE DEMPSTER-SHAFER RULES FOR COMBINING EVIDENCE

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1.0. ABSTRACT

Identification of suspicious events as nuclear explosions or events of other types is commonly based on incomplete and contradictory data. Although in CTBT monitoring most of the evidence comes from seismic sources, other types of data (hydoacoustic, infrasonic) are often helpful in the classifying an event. The major issue is the manner of merging information from such diverse sources. During this work the Dempster-Shafer (DS) calculus has been implemented as a vehicle for merging information in multi-discriminant schemes. The main motivation for this was that, unlike full Bayesian calculus, DS does not require full knowledge of the conditional probabilities and priors in the problem, the algorithm accepts various combinations of joint probability estimates, and it can merge the information from various independent source regardless of the order of the merging of the data. The final outcome of such calculations is an evidential interval consisting of the support (evidence for) and the plausibility (1-the support against) of simple and composite propositions. Propositions (hypotheses in the parlance of DS) are either simple (the event is an earthquake) or composite, (the event is some kind of explosion). The development of the solutions can be followed as the algorithm processes the various discriminants successively.

In the application of the DS calculus the key inputs are probability masses derived for the various propositions (simple or composite) appropriate to the various (seismic and non-seismic) discriminants. We incorporated several approaches from the general pattern-recognition literature into the estimation of probability masses. Since the seismic discriminants use various aspects of seismograms they can be assumed to furnish independent information as required by the merging process in DS calculus. The same is true for other types of discriminants. The total process is being implemented in MATLAB and includes a graphical user interface. We have found that the output of the process imitates human reasoning quite well for various hypothetical scenarios.

2.0. OBJECTIVES

The objective of this project is to develop a system for event identification by merging information from various seismic, infrasonic and hydroacoustic sources to be used in a practical system for routine discrimination. The basis of the system is formed by the Dempster-Shafer (e.g. Shafer 1976) algorithms which are prominently suitable for combining information from discriminants involving overlapping hypotheses, conflicting and incomplete data. It can also accept rules if stated in terms of stated probabilities (e.g. Dillard 1982).

3 RESEARCH ACCOMPLISHED

3.1 Background

Identifying various types of observed events in the context of a Comprehensive Nuclear Test Ban Treaty (CNTBT) is a classical pattern recognition and data fusion problem. The actual task involves the collection of available observations and the application of various proven discriminants based on previous data.

Presently, the latter come mostly from seismic observations, but other types of data, such as hydroacoustic, infrasonic and radionucleide observations, may contribute. Although considerable work devoted to the statistics of individual discriminants, very little has been done on the joint analyses of multiple discriminants. Moreover, no practical, systematic procedures exist for the merging of information from multiple discriminants especially if these are not very efficient individually (such as the Lg/P discriminant,). Classical Bayesian methods for assessing evidence from multiple sources require the knowledge of the joint statistical distributions of all the quantities measured. This often includes prior probabilities of various hypotheses for which indifferent priors, i.e. assuming that all hypotheses are equally likely, are often employed. In practice, joint distributions and priors are commonly not available, and arbitrary assumptions about them may bias the results.

The DS process of merging evidence from two knowledge source is illustrated in **Figure 1.**. For any knowledge source (discriminant)here may be simple or compound propositions (connected by logical OR's) which are normalized such that they sum to unity. Thus these quantities cannot be called probabilities in the exact sense. Probability weights (masses) are assigned to each proposition. In Figure 1 the probability masses belonging to various combinations of hypotheses are shown along the vertical and horizontal axis, respectively, for the two knowledge sources. We form a product matrix of probability masses and attribute each product to the intersections of the sets in the compound propositions from the two knowledge sources. If these do not overlap, then the product is attributed to the null set. Subsequently, the products corresponding to the same combinations of propositions are summed and the results are divided by the complement of the product masses attributed to the null set. Finally the probability masses attributed to the same subsets of propositions are summed. It can be shown that results will again sum to unity as required by the DS method. There are two main probabilities in DS calculus. The support for a proposition is the sum of all probability masses that contain the proposition and the plausibility is unity minus all the probability masses that support its negation. The interval between these two quantities is termed the evidential interval.

It is a property of the DS method that the final results do not depend on the order of combination. Moreover, even though algorithms for merging multiple sources were developed, the final result will be the same as that obtained by chaining the merging process by merging only two knowledge sources at each step, i.e. merging the result of the last step with the probability masses from the next knowledge source (**Figure 2**). These properties are, of course, to be expected for any reasonable algorithm for merging evidence. Nevertheless, the intermediate results will strongly depend on the order of the consideration of various types of evidence. For instance, if we merge all the evidence favoring a given proposition first, the probability mass for it will reach high values, only to be diminished when unfavorable evidence is merged later.

3.2. Work accomplished

During this project

a) We have built a Dempster-Shafer inference engine in MATLAB complete with user interfaces
b) Implemented various algorithms from the pattern recognition literature to estimate probability masses directly from the previously analyzed data in the region of study.
c) Tested and evaluated the behavior of the system with synthetic data using various realistic scenarios
d) We have added algorithms to evaluate the uncertainties in the results by repeating the calculations iteratively using perturbed probability masses

The final product is a practical system designed to evaluate new events by automatically comparing them to pre-existing data from the same region. Most of the remaining work involves the development of rules and statistical-pattern recognition analyses to be stated in terms of probabilities to be entered into the fusion process.

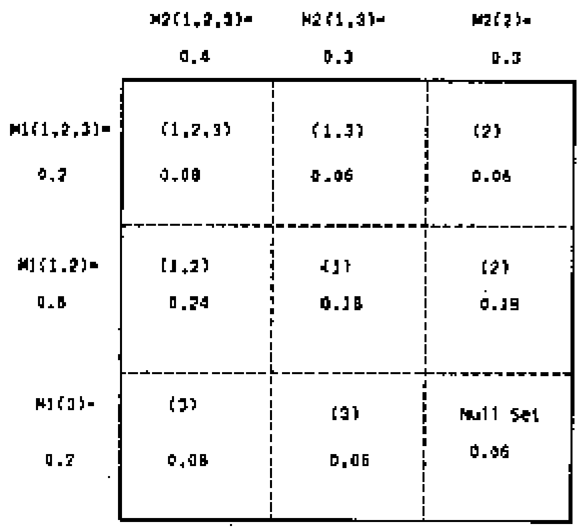


Figure 1. A numerical example for merging evidence from two knowledge sources (discriminants). The two sets of probability masses are shown along the two axes with their assignments to propositions 1,2,3 in parentheses. Note the assignment of cross products.

Flow diagram of the merging process

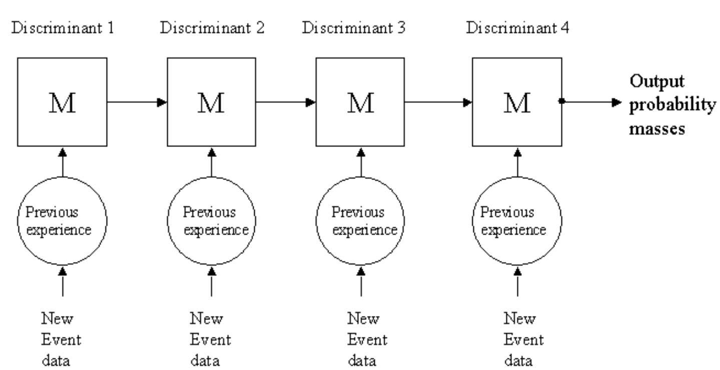


Figure 2. The probability masses from successive knowledge sources are merged chainwise, the order is immaterial. If the overlap of propositions in the discriminants are chosen appropriately at the final step we shall have probability masses assigned to all simple propositions (i.e. the discriminants are able to separate all of these).

3.3. SIMULATIONS OF THE REASONING PROCESS.

3.3.1. Discriminants

We have implemented a simple prototype demonstration system for identifying seismic events that incorporates the following discriminants.

1) P wave complexity
2) Modulation
3) S/P spectral ratios
4) Lg-P spectral ratios
5) Ms-mb
6) Lg spectral ratio
7) Location
8) Hydroacoustic detection
9) Infrasonic detection

The individual discriminants is our simulations have assumed properties that are based on previous experience and physical insight. A few examples of these are described briefly below.

P wave complexity has been found to be effective in dicriminating earthquakes from quarry blasts in Scandinavia (Blandford 1993). P wave from earthquakes tend to have more gradual onset of amplitudes that explosions. These observations were made visually. In order to parametrize complexity we have computed the ratio of the first moment of the seismogram Pn power centered on the arrival time to that of the total power all within the time interval between the arrival time and two seconds after the arrival. This gave us a complexity parameter of 0.7 for impulsive arrivals that decayed after the arrival, 0.9 for arrivals that started abruptly but remained at constant amplitude and 1.5 for arrivals that built up gradually (as unity minus exp(at)) in amplitude from arrival onset within the following 2 second interval. We assumed that these characteristics has a considerable overlap, because P waves from many earthquakes in other regions are quite impulsive too.

Spectral modulation distinguishes single explosions and earthquakes from multiple mining explosions and underwater explosions. The cause for spectral modulation in multiple mining explosions is ripple firing (Baumgardt and Ziegler 1986, Smith 1993, Kim et al 1994) while spectra of underwater explosions are modulated because of multiple bubble pulses and water reverberations (Baumgardt and Der 1999). This discriminant was parametrized as the maximum cepstral amplitude, this spectral modulation parameter varied between zero to 0.7 in our simulations, the latter value was assigned as the mean value for underwater explosions and quarry blasts. Low values of these parameter were assigned to earthquakes and single explosions. Moderate amount of overlap between these two groups of population was assumed in our simulations. Other, equally efficient, possibilities for modulation-based discriminants exist however (Hedlin 1998).

Sn/Pn spectral ratios are commonly given as vectors of values for various frequency bands, the remarks with regards to the reduction of dimensionality made above apply to this discriminant as well. Because their values depend only weakly on frequency the values in various bands but are similar for the same events these can be combined to form a univariate discriminant. This can be accomplished by the standard procedure of computing the covariance matrix between the vector components for a large data set (containing all kind of events) and projecting the individual event vectors along the eigenvector corresponding to the largest eigenvalue. This is done in the system automatically for this types of discriminants. Sn/Pn discriminant tends to separate single explosions on one hand from earthquakes and multiple mining explosions (Sereno et al 1998). Some studies indicate that mine bursts are less earthquake-like than most earthquakes, and multiple explosions (quarry blasts) are also intermediate in character.

Ms-mb. This is a member of a family of discriminants that essentially compare the spectral energy of seismograms in the short and long period bands. Its various versions (mb-ML, mb-M0) are effective discriminants that can separate earthquakes from all kinds of explosions over wide magnitude ranges. For this discriminant we have incorporated the following features; we assumed that the Mb for quarry blast was slightly lower than for single blasts (the P waveforms from various sub-explosions destructively interfere) thus making the Ms-mb values more earthquake-like. Mine bursts were also assumed to be more earthquake-like.

Intelligent systems for monitoring also apply numerous rules, besides standard discriminants, in assessing the nature of an event. Although many of such rules are formulated a deterministic decisions, many of these can be recast in forms of probability statements and thus integrated into our data fusion scheme.

Instead of probability mass assignments based on the statistical of pattern analyses of previous evidence, which may not exist at all, one may have to make probability mass assignments based on some physical models. These may take the form ‘if we have not detected a hydroacoustic signal happens then we assign the probability mass to Proposition 4 of .2 and .7 to the combination of Propositions 1,2,3,5’. These probability mass assignments can then be combined the same way as those derived before.

3.3.3. Propositions.

With regards to event type the following single propositions (with their abbreviations) were assumed;

1) Single explosion on land…………….EX
2) Single underwater explosion…..……UWX
3) Mining explosion (multiple)…………QB
4) Mine burst……………………………MB
5) Earthquake……………………………EQ

Note that nuclear explosions are not mentioned as a separate category in this case. It is not possible to discriminate nuclear explosions from large single chemical explosions using the discriminants listed here, as evidenced by the studies of the large chemical explosion NPE. Individual discriminants such as those described above are generally not able to separate the individual probability masses appropriate to all these propositions. For instance, Ms-mb is able to separate most explosions from earthquakes, but may not be able to attribute proability masses to each type of explosion. Moreover spectral modulation is a property of both underwater explosions and quarry blasts. Thus the problem is posed in the manner of the combination of simple and/or compound propositions as shown in Figure 1.

3.3.4. Methods for the estimation of probability masses

In all cases the discriminants will provide probability masses to the DS fusion process based on past experience in the region. The computation of the probability masses, i. e. relative weights of the applicable single or compound propositions, can be accomplished by the use of the various classification methods described in the pattern recognition literature.

Mathematically, the most expedient way to define probability masses is to fit Gaussian probability densities to pre-existing data sets, previous experience, from the same region. The Gaussian probability densities of these distributions at the parameter values corresponding to the new event may be used as probability weights in such a scheme. In using Gaussian statistics we are not attempting to decide at each step which of the relevant propositions are the most likely, but only to provide relative weight in the combination process. Naturally, the sums of probability masses, which will be incomplete with regards to all the possible propositions, will have to be normalized to unity prior to entering into the DS fusion process.

If the parameter populations are distinctly non-Gaussian, however, then one has to use other methods for computing probability masses. The pattern recognition literature provides numerous approaches to the problem, it includes methods such as the nearest neighbor classification, potential functions, smoothed empirical distributions and neural networks (e.g. Tou and Gonzalez 1974, Theodoridis and Koutroumbas 1999). We are in the process of implementing several of ones briefly described below. These provide options in the processing flow that the operator may chose.

Another issue is the questions of which of the discriminants can be considered as independent pieces of information. The Dempster-Shafer formalism used in our work requires that the information merged from various sources be independent. Clearly, the M0-mb and related discriminants and hydroacoustic data can be considered to be independent pieces of information since they were derived from different sensors. The same is true for the Pn/Sn spectral ratios vs Lg spectral ratios since they were derived from different parts of seismograms. The case of Sn/Pn and Lg/Pn ratios is less clear, since they both involve the Pn spectra. In this work we shall still treat them as independent pieces of information since both also involve different parts of the seismograms. On the other hand, the numerous values of the same kinds of spectral ratios (such as Sn/Pn) in various frequency bands are clearly not independent , since they tend to be similar for a given events and depend only slightly from frequency, and thus seem to furnish the same kind of information. For such redundant information that a reduction in the dimensionality by combining such evidence is appropriate. Typically it can be shown by eigenanalysis that the information is almost entirely contained in the first few eigencomponents (often in one!) and thus spectral ratio information over numerous frequency bands can be stated in terms of one or two variables.

3.5. A few examples.

In order to demonstrate the workings of the system, we have generated synthetic data and 'previous experience' for the set of discriminants listed above. In order to have sufficient realism in these simulations, the synthetic data were made conform with the published results by a number of investigators (Li et al 1996, Sereno et al 1998, Fisk 1994, Fisk et al 1994, Bennett et al 1994, Barker 1996, Barker et al 1993). In most areas no results are available for all the discriminants above. In actual applications, ideally, standardized reference data sets should be accumulated within geophysically well defined regions. The 'new data' for one synthetic set displays consistently the properties of a single explosion. The other set has contradictory characteristics in the various discriminants. We must remind the reader, however, that these are totally made-up data.

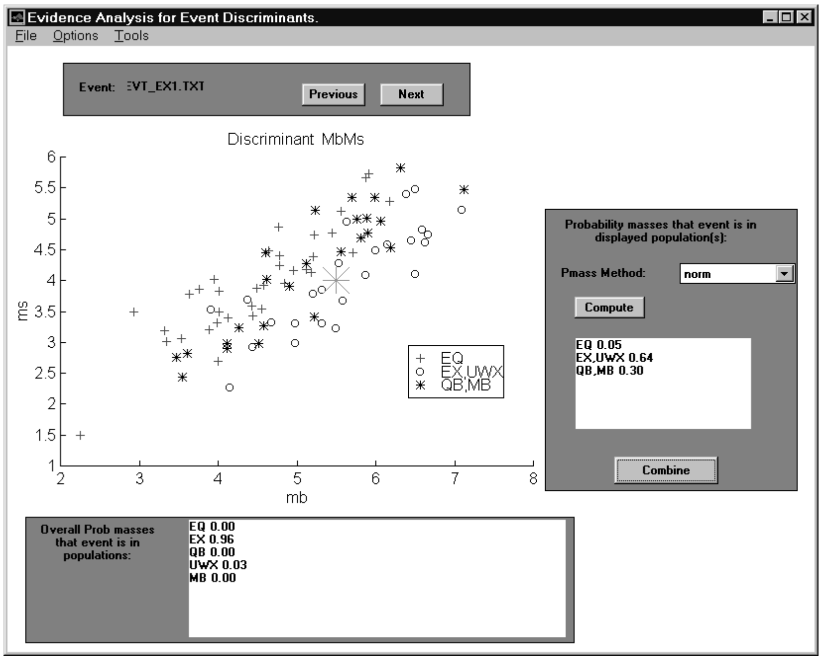
As we mentioned before, the various discriminants are used to separate various sets (combined propositions) of event types. These sets often overlap but are not identical for the various discriminants. This allows one to compute the probability masses for the simple propositions. For instance, applying the Ms-mb discriminant may resolve the question whether a given event is an earthquake, but will provide much less information about the type of explosion one is examining. Modulation is commonly more characteristic explosions, quarry blasts and underwater explosions, than earthquakes, but an observation of a hydroacoustic signal and location in a water-covered area will lead to the decision that it is an underwater explosion. The application of multiple discriminants that use various sets of propositions is actually needed to identify the probability masses for the single propositions. In some cases the set of discriminants available for an event may not be sufficient to identify it as one of the event types listed above. In such cases only a combined proposition (such as it is some kind of explosion) can be proven. In order to prove decisively that an event is a nuclear, rather than chemical, explosion some corroboration in the form of radionucleide release is needed, although the location and event size may be a factor in the decision.

Working with the first set, we show the Ms-mb data and the data point in **Figure 3** (top). The Sn/Pn spectral ratio data is assumed to be available for five frequencies (Figure 1 bottom). The latter is reduced to a single dimensional Gaussian distribution in the process as described above. As we step through the various discriminants the probability mass for the proposition 1 (EX single explosion) steadily increases (**Figure 4**), but starts at low values because the single proposition of EX has not been isolated yet. On the other hand, the probability mass for the proposition 5 (EQ earthquake) starts at a higher value, since the first discriminant gives a probability mass to it, and steadily diminishes as more and more evidence is merged contradicting it (Figure 2).

Note that after the application of the first few discriminants the inferred probability masses for some of the single proposition of EX remains low. This is because these discriminants can separate only subsets of single propositions and provide no information about the probabilities of the single proposition such as those listed above for explosions.

The second data set, combined with the same 'previous experience' was designed to give much less consistent result (displays of the system for the contradictory discriminants Ms-mb and Sn/Pn spectral ratios are shown in **Figure 5**). The history of the proposition 1 (EX) shows an increase for modulation and

Sn/Pn which support it, followed by a sharp decline as conflicting data for the Lg/Pg spectral ratios, Ms-mb and Lg spectral ratios are merged. The best fit is to the properties of a mine tremor but with a low probability.



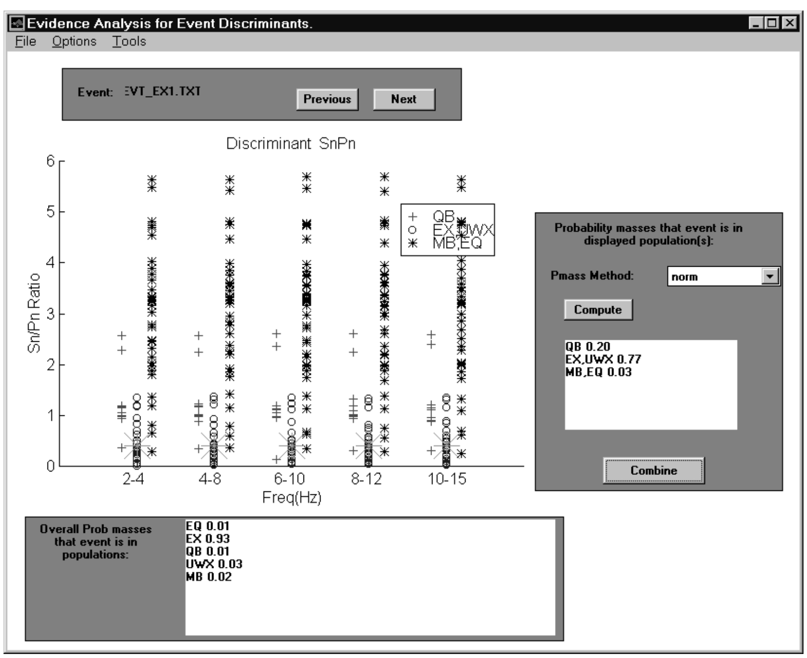
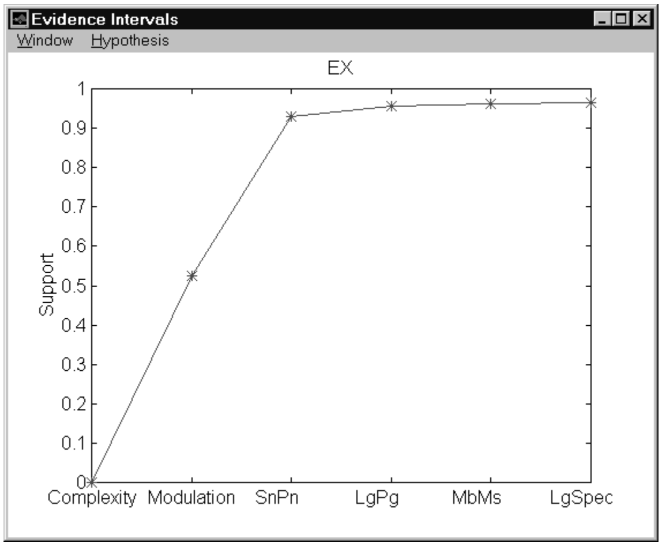


Figure 3. Synthetic Ms-mb (top) and Sn/Pn spectral ratio (bottom) populations. The Ms-mb were assumed to be well separated for earthquakes and single explosions but mixed for quarry blasts and mine bursts. The large stars correspond to the assumed data. The panels show the GUI presentation, allowing the combination of evidence (Compute button), changing of the method for computation of probability masses.



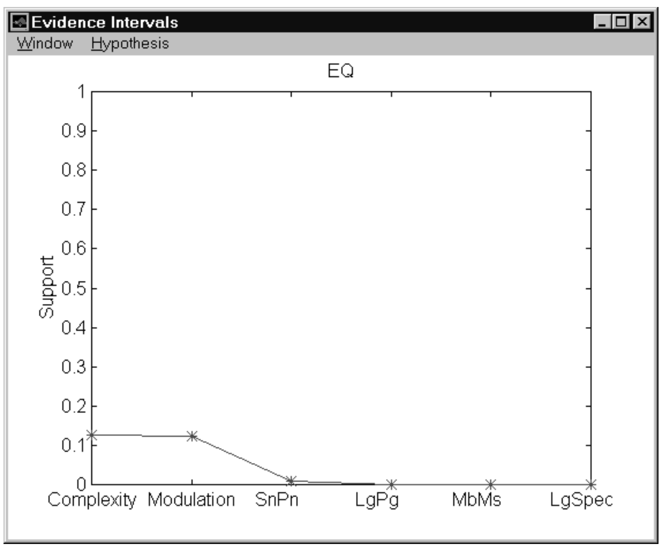


Figure 4. The time histories of supports for the #1 proposition (EX single explosion) and those for the proposition #5 (EQ earthquake). Note the monotonous increase of the first and the decrease of the second. This is due to the fact that all the data support proposition #1.

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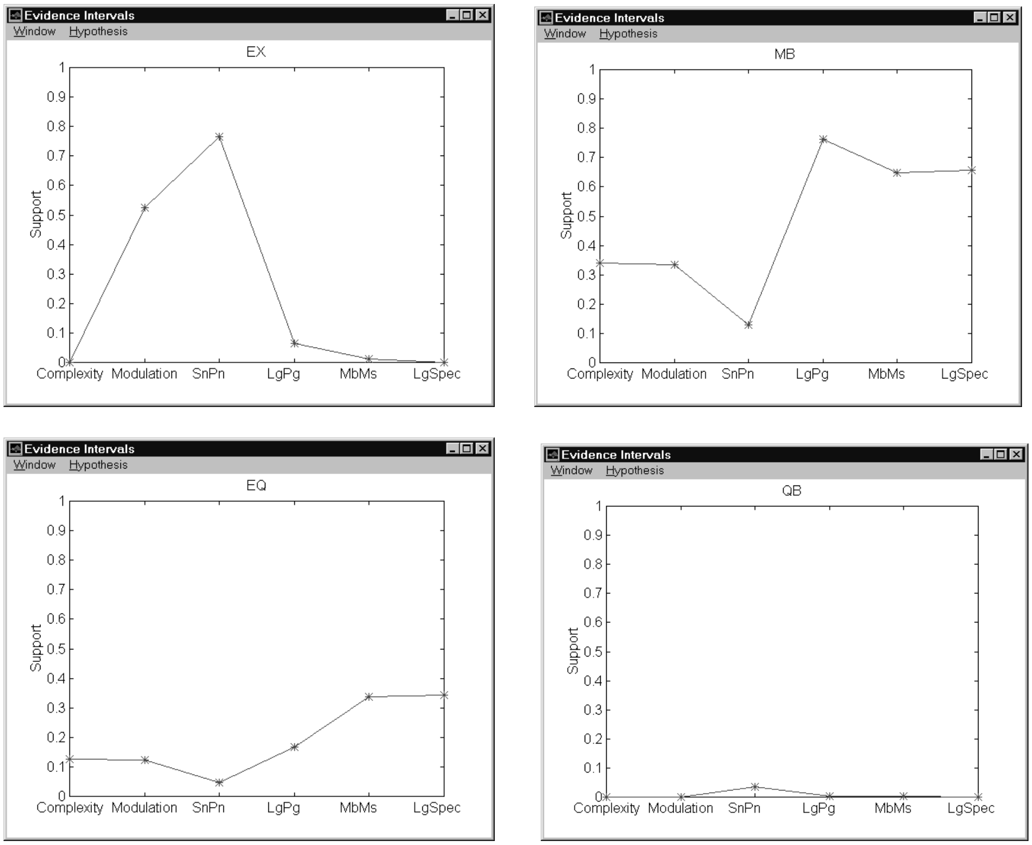

Figure 5. The time histories of supports (support) for the #1 proposition (EX single explosion), #4 (MT mine tremor), #5 (EQ earthquake) and #2 (QB quarry blast or multiple explosion) for the second set of assumed data. Because of the conflicting data the support for each is changing non-monotonously and none reach a high value.

Figure 5 shows the time histories of support for a case where the data were inconsistent with any of the single propositions. In such cases the support fluctuates, increases where the data are consistent with a proposition, only to decrease again when new, contradictory evidence is introduced.

Assessment of the uncertainties in the results of the DS merging process.

We have added some important new features to the DS process by incorporating the uncertainties in the estimated probability masses. The estimates of the probability masses from the acquired empirical data in a given region are point estimates giving no hint of their uncertainties. Consequently, the final results of the merging process may be severely biased or unreliable. It is a simple matter, however, to estimate the uncertainties in these probability masses by resampling schemes such as bootstrap or jackknife (Efron 1982). Such schemes would be quite helpful in cases where the ‘previous experience’ consist if small data sets. It does not add much to the computing time if the probability masses are perturbed using their estimated uncertainties and the merging process is repeated many times in a Monte-Carlo scheme. The results will then be populations of probability mass estimates for the various propositions and will give a much better assessment of the given discrimination problem.

This addition to the algorithm enables the user to relate new data to the previous experience in the region in a more quantitative manner. The results thus obtained reflect the uncertainties due to scatter in the empirical data and the limitations imposed by sparse data sets. **Figure 6** shows a synthetic example of the merging procedure using a Monte-Carlo scheme where the computation was repeated many times with randomly perturbed probability masses. Since all discrimination problems involve relatively small amounts of data, this calculation can easily be done on small computers.

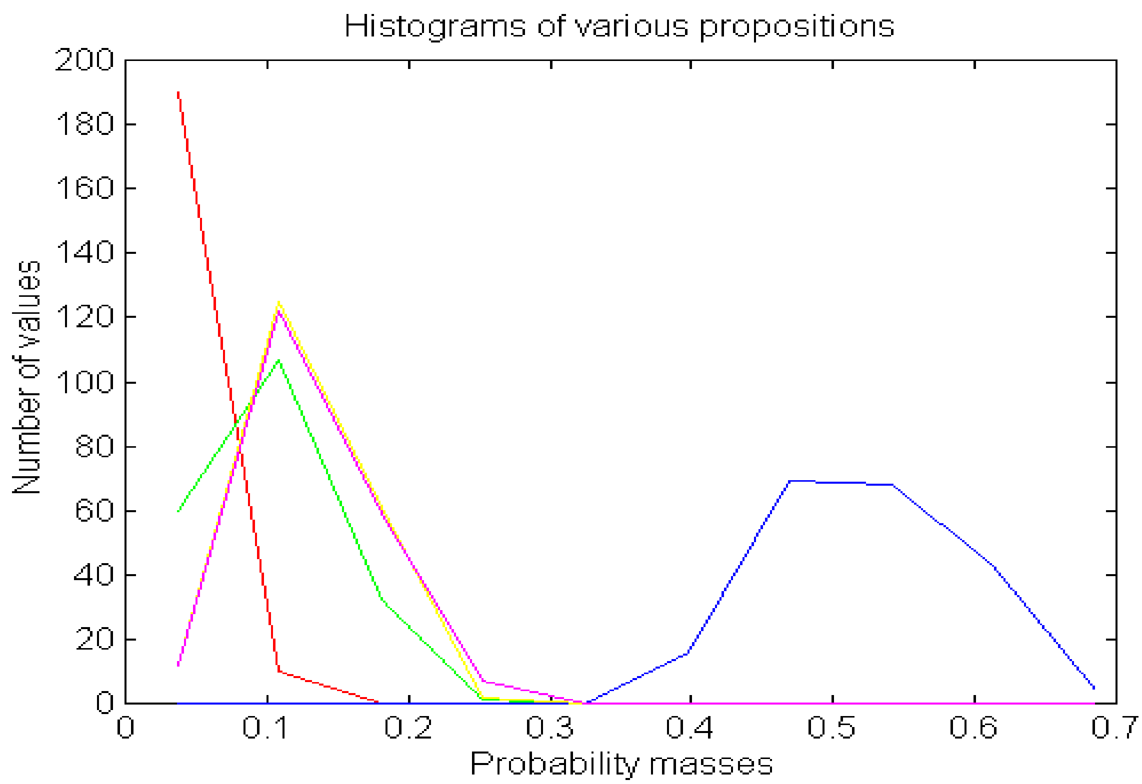

Figure 6. Populations of probability masses for four propositions, one very unlikely, two about equally unlikely and one the most probable. The populations were generated by randomly perturbing the original probability masses.

4.0. CONCLUSIONS AND RECOMMENDATIONS

The work presented shows that the DS rules for combining evidence from multiple independent sources provide a good framework for identifying events on the basis of various types of seismic, infrasonic and hydroacoustic observations. The methodology easily accommodates incomplete and contradictory data and overlapping sets of single propositions. The development of belief and plausibility estimates as more discriminants are added reflect the internal consistency of the data set. In the cases where conflicting pieces of information must be reconciled a widening of the evidential interval and the lowering of belief indicates a reduction in the reliability of the conclusions.

The results shown above demonstrate that the DS calculus is eminently suitable for merging information from various discriminants and it simulates the human reasoning process quite well. The relatively low computational efficiency of the DS process relative to other methods is immaterial in nuclear monitoring where speed of computation is not an issue.

Key Words; nuclear monitoring, data fusion, discrimination, inference

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