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

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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 how to merge information from such diverse sources. The Dempster-Shafer (DS) calculus has been implemented as a vehicle for merging information in this application. The reason for this that, unlike full Bayesian calculus, it does not require full knowledge of the conditional probabilities or priors in the problem, it accepts various combinations of joint probability estimates, it merges the information form 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.

The key inputs in the application of the DS calculus are probability masses derived for the various propositions (simple or composite) appropriate to the various (seismic and non-seismic) discriminants. We are in the process of finding the best ways to produce probability masses for the various standard discriminants. Although statistical discriminants based on Gaussian-distributed are often effective, we do not depend solely on such models. Instead, 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.

Key Words: data fusion, discrimination, inference

INTRODUCTION

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 dicriminants. Presently, the latter come mostly from seismic observations, but other types of data, such as hydroacoustic, infrasonic and radionuclide observations may contribute. Unless the event is very large (in such cases discrimination is a relatively easy task) the set of available observation is limited and often contradictory. The other basic question is how to combine the available information in an objective manner. Studies of poorly identified events (e.g. Ryall et al 1996) typically involve lengthy discussions and weighting all of the available information with discriminatory value. It happens frequently that different investigators come to drastically different conclusions because they attach different weight to various kinds of observations.

There are various basic issues that have to be addressed in applying discriminants. Typically, most seismic discriminants are affected by the variability of propagation through the Earth. Thus transportability of discriminants cannot be assumed a priori. In applying discriminants one needs data for various types of events, preferably from the same region involving similar propagation paths. The prior data are in the form of populations of data points with poorly defined statistical distributions. Assumption of normality is merely convenient and mathematically tractable, but in most cases there is not enough data to prove normality, often the distribution is visibly not normal. Nevertheless, statistical discrimination methods seem to be appropriate in many cases as long as not much emphasis is placed on the computed 'confidence limits' and 'linear discriminants'. The aura of precision and rigor that is often attached to statistical discrimination studies is rarely justified.

Simply comparing the *available* data to new data has its own pitfalls. A famous old Ms-mb discrimination study has found that nuclear explosions and earthquakes can be reliably discriminated in western North America. Closer examination of the data showed that all the *available* explosions had higher magnitudes than the available earthquakes and the formal separation was mostly based on magnitude. Once the magnitude difference was removed, or smaller explosions were included the discrimination capability was found to be much reduced. On the other hand, one could argue that large events must be explosions since large earthquakes are rare in the region, thus magnitude has a discriminant value. Whether to accept this premise or not is a matter of personal taste. This argument implicitly considers *a priori* probabilities, that most people prefer to disregard, otherwise 95% of all events could be reliably classified as earthquakes without any data analysis at all.

Therefore, when depending on previous experience in a given region for discrimination one must make sure that discrimination does not depend on the limited extent of previous data. If the physical factors playing role in a discriminant are well understood, then it is possible, through physical modeling, to characterize the nature of possible data sets even though the amount of available data is limited (e. g. Barker 1996). Unfortunately, the physical basis of many of the regional discriminants is poorly understood.

Another issue is what discriminants can be considered as independent pieces of information. Clearly the M0-mb and related discriminants and the Pn/Sn spectral ratios can be considered to be independent pieces of information. On the other hand, the numerous values of the latter in various frequency bands are not, since they are similar and seem to furnish the same kind of information. For such redundant information a reduction in the dimensionality by combining such evidence is appropriate, as we shall demonstrate below.

DEMPSTER-SHAFER RULES FOR COMBINATION OF EVIDENCE

Dempster-Shafer (DS) calculus is a generalization of Bayesian methods of inference (Dempster 1968, Shafer 1976). In order to differentiate it from standard statistical methods DS has its own version of terminology. In DS parlance hypotheses are called propositions, the equivalents of probabilities are termed probability masses. In typical usage of DS each knowledge source (KS) contributes a set of single or combined propositions (so called general propositions that have probability masses assigned to disjunctions of several single propositions). Generally such sets are incomplete (not all combinations of propositions are represented).

For instance, Proposition 1 may be that a given event is an earthquake (single proposition) while Proposition 2 may be that the given event is either a quarry blast or nuclear explosion (combined or general proposition). Prior to processing by the DS method all the available probability masses, single and combined, are normalized such that they sum to unity. The uncertainty in a proposition A is reflected by the evidential interval defined by its support and plausibility. Support is defined as the sum of probability masses m for propositions that include A and the plausibility is unity minus the sum of probability that do not include A, that is the support for its negation, 1-s(~A).

The following equations define the DS rule for combining information from two independent knowledge sources (Dillard 1982). The combined probability mass of the general proposition B is

$$m(B) = \sum_{B' \& B'' = B} m_1(B')\, m_2(B')/\, C \qquad (1)$$

where B' and B" vary over the general propositions supported by KS1 and KS2, respectively, and

$$C = \sum_{B' \& B'' \neq \sim\Theta} m_1(B')\, m_2(B'') \qquad (2)$$

Letting F(B) denote the numerator of equation (1) [i.e. F(B)=C *m(B)], we can write

$$C = \sum F(B) \qquad (3)$$

where the sum is over all valid general propositions. The resulting support for the general proposition B is

$$s(B) = \sum_{B' \& B = B'} m(B). \qquad (4)$$

Equation (4) also needed in the calculation of the plausibility *p* (not probability!) of the single proposition A_i which is

$$p(A_i) = 1 - s(\sim A_i) \qquad (5)$$

Similar, more complex, equations may be written for multiple independent sources KS1, KS2…. KSn. Because the combining of the evidence from independent sources by DS rules is commutative and associative, i.e. the order and grouping is immaterial, we chose to combine sources in pairs, each new source to the previously combined sources. This not only makes the combination of evidence simpler, but allows one to follow the development of the solution easier. It is also easy see how the addition of another piece of evidence changes the reliability of combined solution.

Even though in the notation shown above the combining process may appear complex, it is quite straightforward as a worked numerical example published by Cleckner (1985) demonstrates.

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

These individual discriminants 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 parameterize 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.

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 parameterized 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. Other possibilities for modulation-based discriminants exist however (Hedlin 1998).

S/P 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.

Lg/P spectral ratios are employed similarly to the Sn/Pn ratios. They are also commonly given as vectors of values in several frequency bands which need to be reduced in dimensionality also. Typically this discriminant is expected to have larger values for earthquake-like events than for explosions.

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.

Lg spectral ratio was found to be effective in the western United States and New England (Li et al 1996).

It is easy to add more discriminants to the system. In the near future we plan to include probability estimates for hydroacoustic and infrasonic measurements The role of the discriminants is to provide probability masses for the various single and combined propositions based on the data from a given new event by using the statistical parameters derived the pre-existing data from the given, presumably homogeneous with respect to propagation characteristics, region. We assume that propagation anomalies, distance corrections and transportability were adequately considered before entering into the DS merging scheme.

With regards to event type single propositions were assumed
1) Single explosion on land
2) Single underwater explosion
3) Mining explosion (multiple)
4) Mine burst
5) Earthquake

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.

In all cases the discriminants will provide probability masses to the DS fusion process based on past experience in the region. Mathematically the most expedient way to define probability masses is to evaluate Gaussian probability densities at the parameter values corresponding to the event to be classified and this was done in this report. The Gaussian densities (single or multiple dimensional) would be fitted to sets of data points for the various available event types accumulated from past experience in the region. Naturally, the sets of probability masses, which will be incomplete with regards to all the possible propositions, will have to be normalized prior to entering into the DS fusion process. The various discriminants generally do not always provide probability masses for each individual simple proposition, but often give those appropriate to compound propositions. For example, modulation characterizes both quarry blasts and underwater explosions, quarry blasts (multiple explosions) and single explosions tend to have P waves with low complexity. Moreover, if the parameter populations are distinctly non-Gaussian 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).

IMPLEMENTATION OF THE SYSTEM

A simple prototype system for merging information from various sources was implemented in MATLAB utilizing the GUI generating software (GUIMAKER) by Marchand (1996). The system processes the information by stepping through all the available discriminants, presenting the supporting regional data, estimates the probability masses for the new event. The probability masses are merged with those of the preceding discriminants in each step. Discriminants that are not available for a given event are simply skipped in combining the evidence.

The system assumes that we have previous experience (data populations) for various single and multiple types of events in the area. The discriminants for a given new event are read in and the probability masses for the various appropriate single and compound propositions are computed by comparing it with the previous experience. The method of comparison can be selected for each discriminant, in this report we assumed Gaussian probability distributions for the data. The probability masses are merged with the previous merged results as the new discriminant is considered. Finally, the time evolution of the support (belief) for all user-selected single and multiple propositions can be displayed. A file is written to record the history of the reasoning process. This file includes all the input data for the event, the probability masses, all the beliefs for the set of all available single and combined propositions.

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.

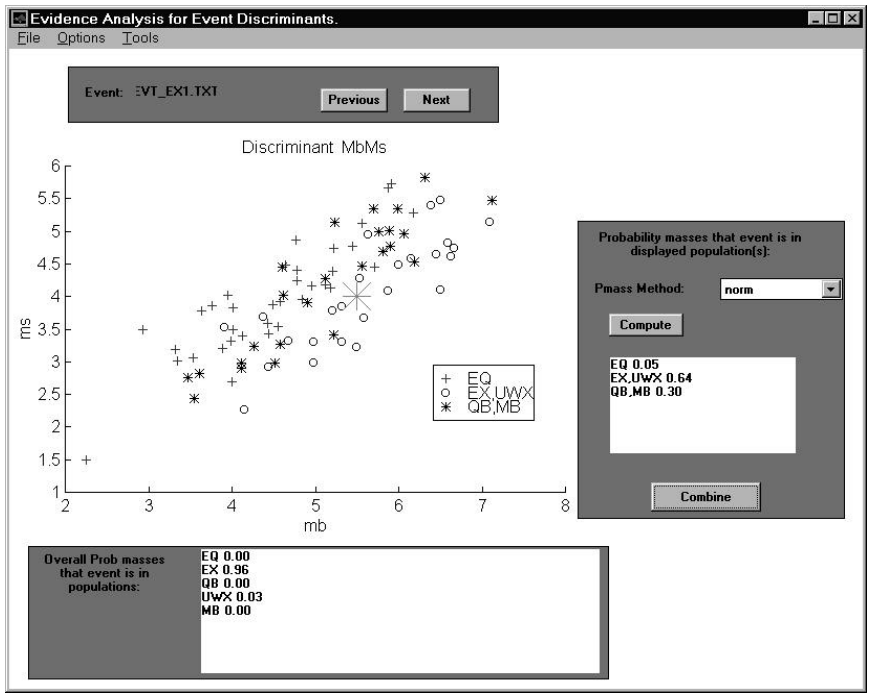
Working with the first set, we show the Ms-mb data and the data point in **Figure 1** (top). The Sn/Pn spectral ratio data is assumed to be available for five frequencies (Figure 1 bottom). The latter is reduced to a single dimensional Gaussian distribution in the process as described above. As we step through the various discriminants the probability mass for the proposition 1 (EX single explosion) steadily increases (**Figure 2**).
On the other hand the probability mass for the proposition 5 (EQ earthquake) steadily diminishes as more and more evidence merged contradicting it (Figure 2).

The second data set, combined with the same 'previous experience' gives a much less consistent result (displays of the system for Ms-mb and Sn/Pn spectral ratios are shown in **Figure 3**). 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 4**).

CONCLUSIONS AND FUTURE PLANS

The work presented shows that the DS rules for combining evidence from multiple independent sources provide a natural framework for identifying events on the basis of various types of seismic, infrasonic and hydroacoustic observations. The methodology naturally accommodates incomplete and contradictory data and overlapping 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 next step is to formulate probability mass computations for non-seismic data using sources such as Brown et al 1998, Chael and Lohr 1998, Dighe et al 1998, and Herrin 1998.



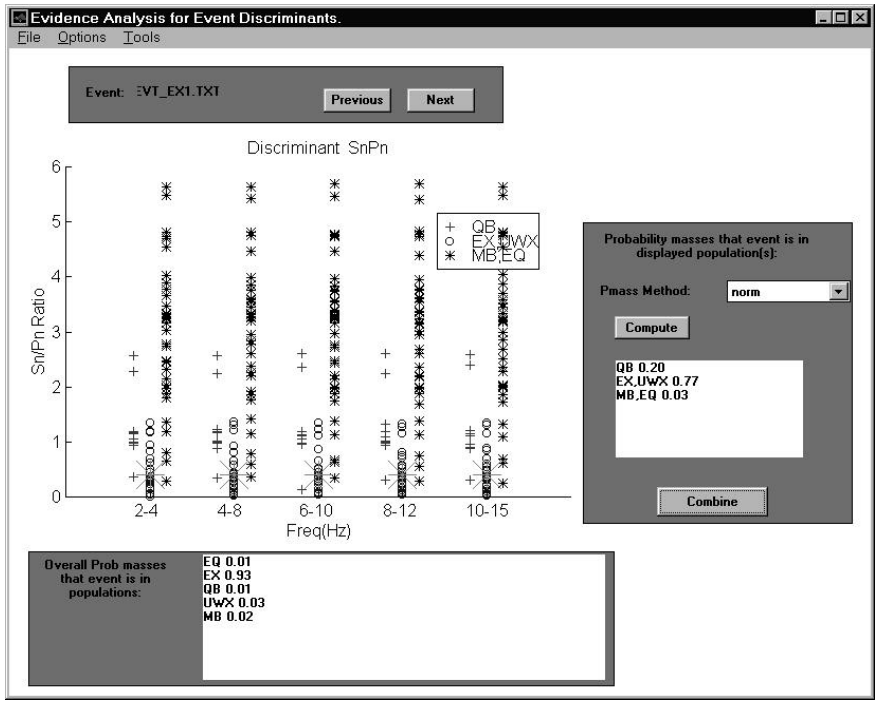
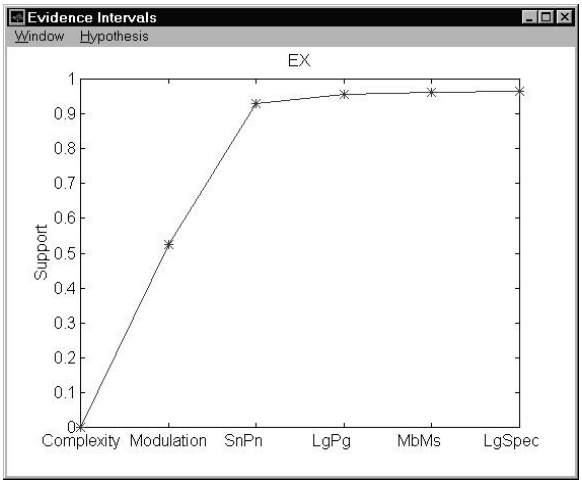


Figure 1. Synthetic Ms-mb (top) and Sn/Pn spectral ratio (bottom) populations. The Ms-mb were assumed to be well separated for earthquakes and single explosions but mixed for quarry blasts and mine bursts. The large stars correspond to the assumed data. The panels show the GUI presentation, allowing the combination of evidence (Compute button), changing of the method for computation of probability masses.



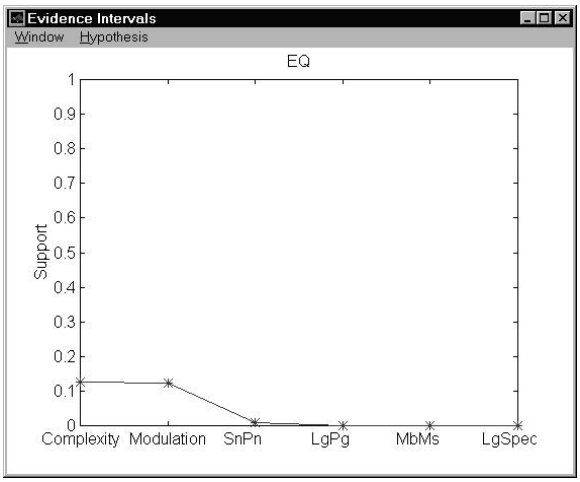
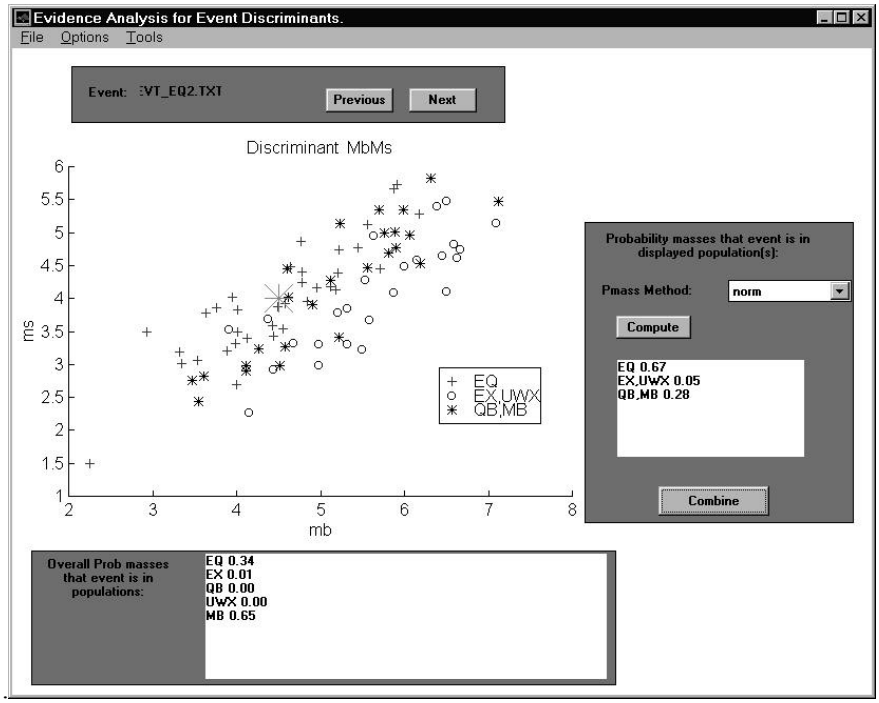


Figure 2. The time histories of supports for the #1 proposition (EX single explosion) and those for the proposition #5 (EQ earthquake). Note the monotonous increase of the first and the decrease of the second. This is due to the fact that all the data support proposition #1.



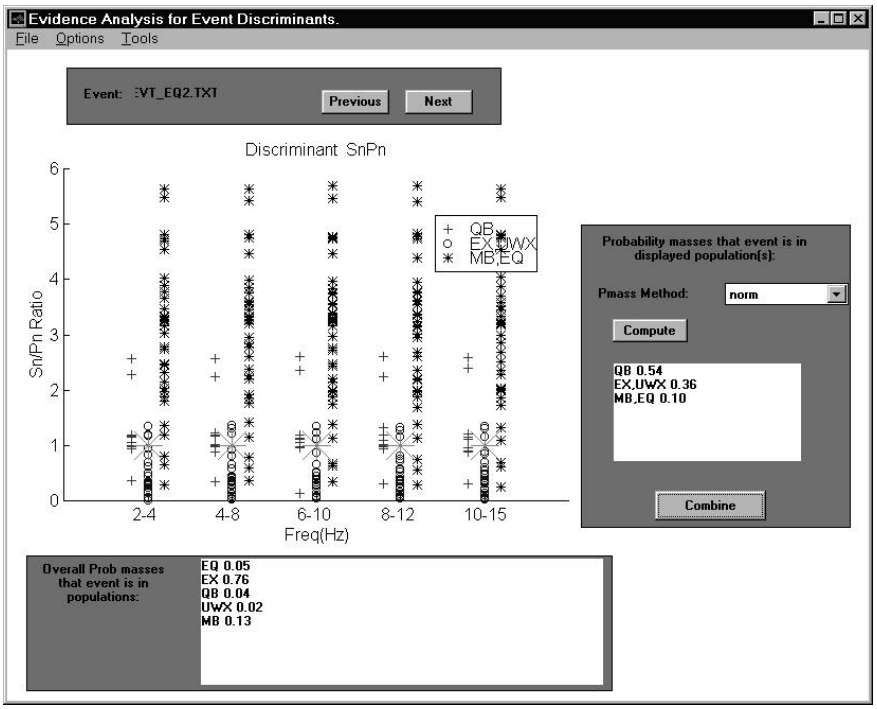


Figure 3. Synthetic Ms-mb (top) and Sn/Pn spectral ratio (bottom) populations. The Ms-mb were assumed to be well separated for earthquakes and single explosions but mixed for quarry blasts and mine bursts. The large stars correspond to the assumed data. Not that in this case there is a conflict between these two sets of data.

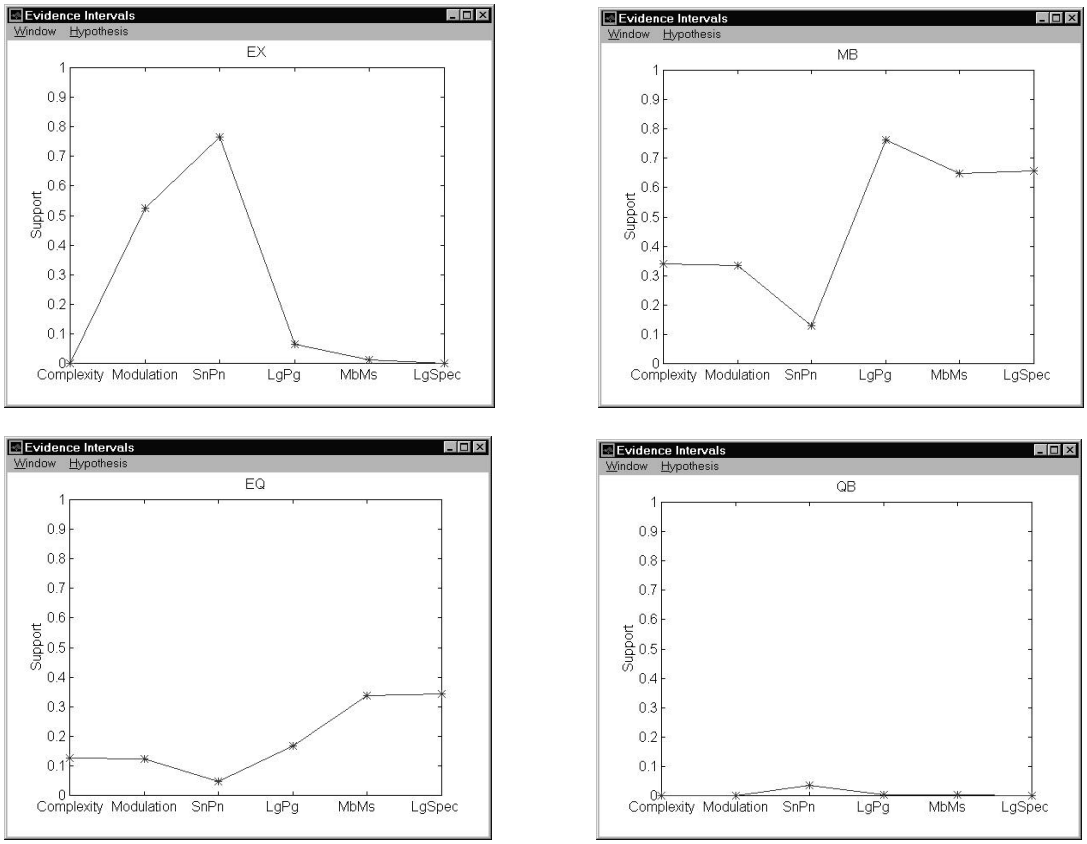


Figure 2. The time histories of supports (belief) for the #1 proposition (EX single explosion), #4 (MT mine tremor), #5 (EQ earthquake) and #2 (QB quarry blast or multiple explosion) for the second set of assumed data. Because of the conflicting data the support for each is changing non-monotonously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

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