THE APPLICATION OF EVIDENTIAL REASONING IN A PORTABLE MAINTENANCE AID

William R. Simpson
John W. Sheppard
Advanced Research and Development Group
ARINC Research Corporation
2551 Riva Road
Annapolis, Maryland 21401

ABSTRACT

As part of its Independent Research and Development program, ARINC Research Corporation is applying alternative approaches to artificial intelligence (AI). Our research on theorem proving, pattern recognition, and expert systems has resulted in the development of several AI-based tools. Some of the problem domains explored are diagnostics, sensor fusion, reliability-centered maintenance, and dynamic reconfiguration.

Our primary approach developed to address these problems incorporates a form of knowledge representation that uses a binary matrix. This type of matrix provides a compact means of storing logical relationships between elements in the knowledge base. In addition, inferences are drawn using an efficient algorithm for processing known information in conjunction with the binary matrix. However, because the algorithm assumes complete confidence in the evaluation of the premises, there is no facility for reasoning under uncertainty.

Recently, an approach has been developed that incorporates reasoning under uncertainty in the matrix-based approach to inferencing: the Dempster-Shafer method of evidential reasoning. Discussions in this paper include an overview of the inference process, a review of the principal components in the evidential reasoning process, and an application of the approach to an ARINC Research-developed diagnostic aid. A review of areas for future research is also provided.

INTRODUCTION

In the past, maintaining complex systems has required a mixture of science and art. Among the maintainability issues requiring the most art have been those concerning diagnosis and prognosis. Prognosis, which is not discussed in this paper, involves gathering system data and recognizing trends that may be used to predict a future failure or maintenance need. Diagnosis, the subject of the paper, involves gathering system facts and using these facts to draw conclusions about failures in the system.

A number of portable maintenance aids use rules, models, or both to combine facts and draw conclusions. These inferential processes provide, for the most part, successful diagnostic tools. There exists a class of problems, however, where the inferential process is inadequate.

In the inferential process, the line of reasoning that leads to drawing a conclusion assumes that the relationships between tests and failures are clearly discernible, well defined, and unambiguous. These relationships are, however, frequently not so well defined. For example, when diagnosing a problem, the technician performing a test may not be convinced that the resulting test output is correct. In addition, the technician may not believe that the output list of potential causes of anomalies is complete for this test. Finally, the technician who interpreted the test outcome may not have the experience necessary to reliably interpret the output. For many important problem domains, including testability, similar uncertainty in relations and indications is a prevalent characteristic. A diagnostic tool should incorporate a methodology for including uncertainty in both the statements of relationships and the interpretation of test indications in order to draw conclusions.

The class of problems typified by uncertain test outcomes, inadequate skill levels to test and interpret the results, and even uncertain elements in the model is generally addressed as "reasoning under uncertainty." A number of approaches exist for applying reasoning under uncertainty to diagnostic aids.

The approach we use to address the problem of uncertainty is Dempster-Shafer evidential reasoning.[1,2] The Dempster-Shafer approach involves evaluating information sources in terms of evidence obtained, applying a confidence value to the outcome, and allocating the confidence-modified evidence to the set of conclusions. ARINC Research Corporation is using the Dempster-Shafer approach in our Portable Interactive Troubleshooter (POINTER™) System. This paper describes the Dempster-Shafer approach to reasoning under uncertainty and the steps taken to incorporate it in POINTER.

THE INFERENTIAL PROCESS

The inferential process used in the tools developed by ARINC Research is a set membership process. If premise A is true, it implies one of *n* causes. If premise B is false, it implies one of *m* causes. If both premise A is true and premise B is false, this implies that only members of both *m* and *n* are possible conclusions. The inferential process seeks the intersection of the possible conclusion sets; we have reduced the inferential reasoning process to a set intersection process. This paradigm has been sufficient to solve a large number of problems in the area of testability and fault isolation.[3-6] The line of reasoning that leads to a conclusion typically assumes that the relationships between tests and failures are clearly discernible, well defined, and unambiguous.

The class of problems typified by uncertain outcome of tests—inadequate skill levels with which to perform a test and interpret the results, and even uncertain elements in the model—is usually considered to be reasoning under uncertainty, for which a number of approaches exist. Some basic approaches include certainty factors, Bayesian probabilities, and weighted causal networks. Also, there are various logics that allow some aspects of uncertainty, such as predicate calculus, multivalued logic, modal logic, nonmonotonic reasoning, and intuitionist logic. Three of the more advanced categories that have influenced our thinking have been "truth maintenance,"[7,8] "fuzzy logic,"[9,10] and "theory of evidence."[1,2] The latter has had the most profound effect. We modified Dempster's rule of combinations[2] for our application.

REASONING UNDER UNCERTAINTY

In our review of processes that might contribute to our approach, we were drawn to Shafer's evidential approach[1] because it uses two variables to describe uncertainty: support and plausibility. With the identification of the dependency relationships, we are able to ascribe support to some conclusions and deny other conclusions when we determine a test outcome. Under Shafer's formulation, we assign a confidence [0 . . . 1] to each outcome and compute the support and denial of each conclusion. Further, Dempster worked out an elegant way to combine test results when we have two or more outcomes (called Dempster's rule of combinations).

Although adapting Shafer and Dempster's concepts contributed to our approach, six problems were discovered in using the inferential process:

- Providing good user interface
- Controlling the calculation space
- Starting the evidence-gathering process
- Avoiding disappearing uncertainty
- Choosing a source of evidence
- Recognizing an answer

PROVIDING GOOD USER INTERFACE

The major effect on the success of any software project lies at the user interface. If the system is too difficult to operate and understand, it will not be used. This is especially true when solving complex problems. When providing an application for reasoning under uncertainty, we assume it unrealistic to have the maintenance technician provide confidence factors for test results. However, a large part of what provides a confidence measure in a test is related to the specific context taking place at the time the test is conducted.

Much of the difficulty associated with determining confidence factors can be eliminated by incorporating elements of Zadeh's"fuzzy" logic.[7] As part of our user interface, we provide the technician with a list of qualifiers that describe possible test outcomes. The qualifiers may be test-specific or taken from a set of generic defaults.

We have listed in Table 1 an arbitrary set of default qualifiers for a test outcome together with the associated confidence factors. These associated confidence factors can then be modified by using set membership properties. For example, the test may approach the limit of the skill level of the technician (the threshold here is a variable). Under these circumstances, confidence may be reduced. Further, time to execute may be extensive (more than expected) or quick (less than expected), reducing confidence in the test. Finally, the test may have an inherent confidence level that ranks it at less than 100% confidence under the most optimistic circumstances. Since we began to use default qualifiers to aid technicians, results indicate that these qualifiers are easy and comfortable forms of interface for users.

TABLE 1. DEFAULT QUALIFIERS FOR A TEST OUTCOME

Qualifier	Descriptor	Initial Confidence
Certain	There is little doubt in the test's outcome.	1.00
Somewhat Certain	There is some doubt in the test's outcome.	0.67
Somewhat Uncertain	There is considerable doubt in the test's outcome.	0.33
Uncertain	The outcome of the test is essentially unknown.	0.00

CONTROLLING THE CALCULATION SPACE

The most difficult mathematical problem in an evidential process is identifying the conclusions, observations, and relationships that should be involved in a given process. Without limits, the required calculations quickly escalate to unwieldy numbers. Too severe a limit may result in ignoring important evidence. We proceeded in our approach with the assumption that the relationships identified in the binary matrix knowledge base are correct and absolute (strong), but the interpretation of a premise has a variable degree of certainty. (We expect incorrect modeling of relations to contribute to the level of conflict experienced when using the model for collecting evidence. We have not fully explored the situation in which a relationship is weak.)

We also incorporated a single-conclusion assumption, which reduces the calculation space and simplifies the evidential calculations. This assumption limits the inference process to identifying a single answer for a particular problem instance. This restrictive assumption is somewhat relaxed by the modeling technique, which allows specified multiple conclusions to be included in the model as separate conclusions. This approach is discussed in detail in reference 11.

STARTING THE EVIDENCE-GATHERING PROCESS

For the inferential process (perfect information assumed), we cannot make an assessment (i.e., draw a conclusion) until a minimum number of premises have been evaluated. The evidential process, however, can provide an answer that is based on the evaluation of one premise (credible or not). We addressed this by using the inferential process to start the problem. Evidence is computed at each step of the process, but an answer is not offered until the inferential process can provide one. (If the process has not gathered enough information to get an answer using perfect information, the computer does not offer the answer provided by the evidential process but continues testing.)

AVOIDING DISAPPEARING UNCERTAINTY

In our scheme for processing evidence, we need an indicator that measures how well the modeled relationships match the problem to which they are being applied. An example of when there is an obvious mismatch is when successive evaluations of the same premise conflict. Our first choice for this indicator was the uncertainty measure. However, we found that uncertainty could only decrease with each additional premise, independent of the evaluation sequence, when calculated using Dempster's rule of combinations under our assumptions. To solve this problem, we created an additional conclusion, the "unanticipated result," which measures evidence of conflict outside of the Dempster combination. This new conclusion contributes to the evidence accumulation process by decreasing the relative weight of evidence that can be assigned to the other conclusions. This "unanticipated result" conclusion was supported by any outcome that was in direct conflict with all of the current hypotheses. This definition of support fits well with the inferential start-up of the evidential process, and we used the inferential result to generate our initial hypothesis.

CHOOSING A SOURCE OF EVIDENCE

In the literature on evidence combination that we examined, nothing addressed selecting a source of evidence. The source of evidence is independent of evidence combination. In our applications, we are concerned with selecting the next premise (or source of evidence) to evaluate, and we have a good method for selecting the next premise in the strictly inferential domain. However, when we move into the evidential domain, that method is discarded. To choose a source of evidence, we modify the method to recognize a current hypothesis and select a premise that considers the best potential for supporting or denying the hypothesis.

RECOGNIZING AN ANSWER

The last problem we addressed was how to recognize when the evidential collection process should end. There are obvious stopping points, such as when there is only one conclusion that is plausible and is supported. Usually there is an assortment of conclusions that have varying levels of both support and plausibility. Sometimes two or more conclusions will have identical evidence. To know when to stop collecting evidence, we trained a neural network, by back propogation,[12] to recognize that an answer has occurred. We trained the network with computed and random data that were evaluated by expert model builders. The trained network is accessed by POINTER, the ARINC Research-developed portable maintenance aid.

EVIDENTIAL REASONING IN DIAGNOSTICS

The technique of matrix-based inferencing has been most heavily used in two ARINC Research-developed tools—the System Testability and Maintenance Program (STAMP®) and POINTER. POINTER was derived from STAMP. STAMP is a set of computer-based analysis techniques and tools that are used to conduct testability analyses and develop fault-isolation strategies to improve system maintenance. The tools and techniques work from a functional dependency model of the system being analyzed. Because the functional model is the primary input to STAMP, a wide variety of systems may be analyzed, including digital, analog, hybrid, electromechanical, and electrohydraulic. In addition, STAMP may be used to analyze systems during the various stages of the acquisition process: preliminary design, prototype, redesign, and operational.

ARINC Research continues to develop STAMP and has been performing research in the area of interactive maintenance aids in general and intelligent portable maintenance aids in particular. An interactive maintenance aid is an electronic presentation of fault-isolation and repair material that assists a maintenance technician in diagnosing faults and repairing faulty systems. It is most effective when resident on a small portable computer.

POINTER is a model-based, intelligent maintenance aid, hosted on a PC-386, that dynamically computes fault-isolation strategies on the basis of a STAMP model, the problem context, and user input. It allows a full range of user options for both isolation and repair and can be tied to logistics documentation systems. It can be completely tailored to the individual application through a series of application-specific menus. A particularly powerful feature is the ability to run separate programs from within POINTER.

Currently, the evidential calculations have been implemented in STAMP and may be invoked when STAMP is run in an interactive mode. The calculations are also being implemented in POINTER. As tests are chosen and evaluated, the user is asked to select results from among several qualifying terms such as those listed in Table 1. Confidence in the test outcome is based on these qualifiers. The confidence is the basis for calculating support and plausibility of the results. When STAMP or POINTER forms a hypothesis (after completing a parallel inferential analysis of the test outcomes), the data are given to the neural network for evaluation. If the neural network declares an answer, the user is presented a list of possible diagnostic conclusions together with probabilities of each as the answer set. A user may request further testing at any time.

SUMMARY

The capability to develop portable maintenance aids containing uncertainty calculations has become a reality, because a number of specific problems have been overcome. A major problem was the user interface requirement for field technicians to supply uncertainty information. In addition, our work has shown that no single AI technique currently meets all of the requirements for a portable maintenance aid.

The current implementation of POINTER contains a number of techniques that work together to achieve the specific purpose of a portable maintenance aid—to provide technical assistance in a troubleshooting and repair environment.

FUTURE DIRECTIONS

In the inferential mode, POINTER includes learning test times and failure rates as well as some limited ability to modify dependency relationships using repair data. Using the evidential process, these learning factors can be expanded to include certainty factors and some enhanced relationship learning, although the exact interrelationships may be difficult to derive. Evidential reasoning may also be used to recognize deficiencies and trends as well as differences among individual technicians.

In cases where a diagnostic aid is dedicated to one specific (serial number) system, the aid will have adequate data to attempt prognostication. At first this may be simply exponential failure prediction based upon current operating hours and failure history, but it may later be expanded to trending analysis for incipient failures. Trending analysis has had some success in turbine engine monitoring but has not yet been incorporated into a portable maintenance device.

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