BAYESIAN MODELING:
AN AMENDMENT TO THE AI-ESTATE STANDARD

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Abstract–Recent advances in diagnostic technology have resulted in the need to examine these technologies for expanding current work in diagnostic standards. Specifically, the use of Bayesian networks for system diagnosis is becoming more common, thus warranting consideration of a Bayesian modeling within IEEE Std 1232 (AI-ESTATE). In the following, we present a discussion of Bayesian diagnosis as a basis for introducing a new information model to support exchange Bayesian knowledge. We also describe a simple extension to the model to support system prognosis. Finally, we discuss recent initiatives within the IEEE to update their standard exchange mechanisms to support XML as "preferred" medium.

INTRODUCTION

Efforts by the Department of Defense to increase use of commercial or dual-use technologies have resulted in the levying of new requirements on automatic test systems. One of the areas where requirements are being levied is in the exchange of diagnostic information. The IEEE Standards Coordinating Committee 20 (SCC20) on Test and Diagnosis for Electronic Systems has been developing standards for diagnostic knowledge exchange and diagnostic services with their IEEE Std 1232-2002 Standard for Artificial Intelligence Exchange and Service Tie to All Test Environments (AI-ESTATE). Because of the new DoD requirements, it was determined that an amendment to the AI-ESTATE standard was required.

In addition to the new exchange requirements, members of the diagnostic community have indicated an interest in defining a standard for Bayesian diagnostics. Bayesian diagnostic models involve specifying random variables corresponding to tests and diagnoses utilizing a network structure to relate the random variables to one another. With each node in the Bayesian network is the specification of a set of conditional probabilities, prescribing the conditional probabilities of each of the values of that node given the "parent" (or dependent) nodes in the network.

In a companion paper in this conference, details on the specification, population, and use of a Bayesian diagnostic model is provided. In this paper, we expand upon that discussion and describe how the Bayesian diagnostic model is being standardized within SCC20. We describe the process of utilizing formal information models to capture the semantics of Bayesian diagnosis. We then provide a detailed discussion of the structure and definition of the AI-ESTATE Bayes model, relate the elements of the model to existing information models within AI-ESTATE, and explain how to use the Bayesian model in the context of an AI-ESTATE conformant diagnostic reasoner. Given recent emphasis on prognostics, we also explain how to extend the AI-ESTATE Bayes model to incorporate constructs for prognosis based on the concept of a Dynamic Bayesian Network (DBN). Finally, we provide a discussion of the new XML-based exchange format being incorporated into AI-ESTATE to satisfy exchange requirements under the DoD and industry-led Automatic Test Markup Language (ATML) initiative.

DIAGNOSTIC STANDARDS

The SCC20 Diagnostic and Maintenance Control (DMC) subcommittee is developing a family of standards ([2], [3]) that are product information exchange standards for test, diagnosis, and maintenance. The original standards developed by the DMC, the 1232 series, provided a means of exchanging information between diagnostic reasoners. The complete 1232 standard, which was published in November 2002 as a full-use standard, contains the diagnostic information models and formally defines a set of standard software services to be provided by a diagnostic reasoner in an open-architecture test environment. As the information models for the 1232 standards were developed, it became apparent that these models could be used for standardizing testability and diagnosability metrics as well as maintenance history information.

In 1997, the DMC began to work on a new standard focusing on expanding the work of the cancelled testability standard, MIL-STD 2165 [3]. The approach taken to develop this replacement standard involved defining testability and diagnosability metrics based on standard information models. Specifically, it was found that the AI-ESTATE models provided an excellent foundation for defining these metrics. AI-ESTATE provides formal definitions of the same information required for determining the testability and diagnosability of a system. With these formal definitions, the constraint language of EXPRESS can be applied directly to define metrics and characteristics of testability and diagnosability. This standard was recently published by the IEEE Standards Association as a "trial use" standard.

The Management of Test and Maintenance Information Standard (formerly IEEE P1389) is being re-worked and expanded as IEEE P1636 Software Interface for Maintenance Information Collection and Analysis (SIMICA). As a member of the SIMICA family, IEEE P1636.1 defines an exchange mechanism for test results using XML. This standard is intended to serve as a replacement for the recently withdrawn IEEE Std 1545-1999, Standard for Parametric Data Logging [4].

INFORMATION MODELS

The purpose of an information model is to identify clearly the objects in a domain of discourse (e.g., diagnostics) to enable precise and unambiguous communication about that domain. Such a model comprises objects or entities, relationships between those objects, and constraints on the objects and their relationships. When taken together, these elements of an information model provide a complete, unambiguous, formal representation of the domain of discourse. In other words, they provide a formal language for communicating about the subject of interest or domain [5].

Using information models, information exchange can be executed in two ways. The first is through a set of exchange files. Specifically, information can be stored by one party in a file and read by a second party. The exchange file format is derived directly from the information model and defines the syntax of the message contained within it. The semantics of the message (i.e., the interpretation of the information contained within the file) is derived from the semantics of the model.

The second means of information exchange is through a set of services defined for a hardware or a software component as accessed via some communications infrastructure. The interface definition for the component is derived from the information model and, once again, defines the syntax of the message. As before the interpretation of the message is derived from the semantics of the model.

Three advantages to using standard information models to define the communications mechanism are evident. First, since standards are published documents, a large audience has access to the standard. By specifying standards in procurement documents or design documents, the designers know the basis for communication before detailed design begins.

Second, a software standard defines a contract between an application and a user of that application. This contract has the advantage of having been validated and legitimized by the fact that a community of experts in the domain have gathered and agreed upon the content of the standard. Consequently, users of the standard can trust that a) the standard is technically correct, and b) the community of those using the standard believes the standard is useful; therefore, users of the standard have the added benefit that they need not re-invent the technology covered by the standard.

Third, standards are typically endorsed and accredited by an independent accrediting body. Such endorsement certifies that the standard was developed according to an open process designed to keep the best interests of the community in mind. Examples of such accrediting bodies include IEEE, ANSI, ISO, and IEC.

The EXPRESS information modeling language [5], standardized by ISO, was designed for formally defining information in support of exchanging that information between two or more parties.

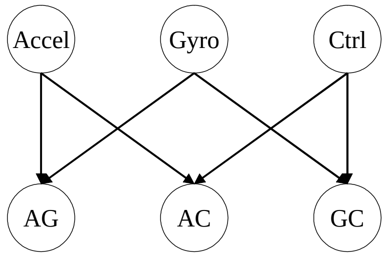

Fig. 1. Simple stability augmentation system BBN.

EXPRESS is object-oriented in flavor but focuses on defining the semantics of the information modeled. In addition, rules have been defined for deriving exchange files and services for information exchange directly from the EXPRESS models.

BAYESIAN NETWORKS

There are many diagnostic systems that allow for reasoning under uncertainty; however, the natural approach that uses probabilities directly is the Bayesian Belief Network (BBN) [6]. Formally, a $\mathrm{BBN} = \langle \mathbf{V}, \mathbf{E}, \mathbf{C} \rangle$ is a *Bayesian Belief Network*, where

- $\mathbf{V}$ is a set of vertices corresponding to random variables $V_i \in \mathbf{V}$,
- $\mathbf{E}$ is a set of directed edges $e_{ij} \in \mathbf{E}$ relating pairs of vertices V_i and V_j, where the source of the edge corresponds to V_i, the destination of the edge corresponds to V_j, and the edge represents a conditional dependence relationship of V_j on V_i,
- $\mathbf{C}$ is a set of conditional probability tables $C_{\mathrm{Pa}(i)} \in \mathbf{C}$ where each entry provides the probability of V_i given the set of parents of V_i ($\mathrm{Pa}(i)$).

An example of a Bayesian network is given in Fig. 1, taken from [11].

If we continue to assume that tests are performed independently from one another, then we connect tests (as random variables) to possible diagnoses (as random variables). Usually, we can also assume that the diagnoses are independent from one another (i.e., the existence of one fault does not cause another fault to occur). Thus the only dependence relationships modeled are between tests and diagnoses. Note that these two assumptions are not necessarily true, and in general such dependence relationships, when known, can be modeled directly by the BBN by inserting appropriate edges between pairs of tests or between pairs of diagnoses. In addition, we must find a way to handle the relationships between the intended states of the tests and the observations of those tests.

The diagnostic problem consists of inferring the probability of each of the diagnoses in the BBN given the test results. Note that the joint probability distribution over all of the variables in the BBN, $\Pr(\mathbf{V})$, is given as the product of the probability distributions of each over each of the vertices (random variables) conditioned on their parents, i.e.,

$$\Pr(\mathbf{V}) = \prod_{V_i \in \mathbf{V}} \Pr(V_i \mid \mathrm{Pa}(V_i))$$

Assume we subdivide the set of random variables $\mathbf{V}$ into two subsets, $\mathbf{T}$ and $\mathbf{D}$ corresponding to tests (e.g., BIT indications) and diagnoses respectively. Further, assume that $\mathbf{T} \cup \mathbf{D} = \mathbf{V}$ and $\mathbf{T} \cap \mathbf{D} = \varnothing$ (i.e., $\mathbf{T}$ and $\mathbf{D}$ are disjoint but define the entire set of random variables $\mathbf{V}$). Finally, assume $\mathbf{T}$ contains the set of observations (e.g., the evidence from BIT) and $\mathbf{D}$ contains everything else (including, if needed, random variables representing the "true" states of the tests as if we were able to know the underlying state perfectly). Given a target set of test results, τ, we calculate $\Pr(\mathbf{T}' = \tau)$ (where $\mathbf{T}' \subseteq \mathbf{T}$) by marginalizing out the remaining variables given by $\mathbf{V} \backslash \mathbf{T}'$. Marginalization is carried out by summing over all $\Pr(\mathbf{V} \backslash \mathbf{T}', \mathbf{T}' = \tau)$, where "\" denotes set difference:

$$\Pr(\mathbf{T}' = \tau) = \sum_{\mathbf{V} \backslash \mathbf{T}} \Pr(\mathbf{V} \setminus \mathbf{T}', \mathbf{T}' = \tau)$$

For this model, we note the prior probabilities for the diagnoses D_i, are given by the probabilities derived from reliability estimates. The probabilities for $\Pr(T_j \mid D_i)$ arise from constructing the appropriate diagnostic model and reflect the causal nature of the faults.

$$\Pr(o(T_i) \mid \mathrm{Pa}(o(T_i)) = \Pr(o(T_i) \mid \mathbf{D}_{T_i}) = \prod_{D_j \in \mathbf{D}_{T_i}} \Pr(o(T_i) \mid D_j)$$

where $\mathbf{D}_{T_i}$ is the specific set of diagnoses (i.e., a subset of all diagnoses in the model), all of which must "pass" to observe the dependent test passing (i.e., $\mathbf{D}_{T_i} = \mathrm{Pa}(o(T_i))$).

Given the conditional independence of the diagnoses, we can then compute the posterior probabilities of each of the diagnoses given the test results as follows. First, we partition the random variables into three sets: $\mathbf{D}$ (the diagnoses), $\mathbf{T}$ (the true test states), and $\mathbf{O}$ (the test observations). The evidence variables will be restricted to $\mathbf{O}$.

$$\begin{aligned}\Pr(D_i \mid \mathbf{O}) &= \alpha \Pr(\mathbf{O} \mid D_i)\Pr(D_i) \\ &= \alpha[\Pr(\mathbf{O} \mid \mathbf{T})\Pr(\mathbf{T} \mid D_i)\Pr(D_i)] \\ &= \alpha \Pr(D_i)\sum_{T_j \in \mathbf{T}} \Pr(o(T_j) \mid T_j)\Pr(T_j \mid D_i)\end{aligned}$$

Here, α is a normalizer (to restore the computed values to probabilities) over the set $\mathbf{D}$, equal to

$$\alpha = \sum_{D_i \in \mathbf{D}} \Pr(D_i)\sum_{T_j \in \mathbf{T}} \Pr(o(T_j) \mid T_j)\Pr(T_j \mid D_i)\,.$$

Observe that $\Pr(T_j \mid D_i) \in \{0, 1\}$ as described earlier, so the members of the sum are restricted only to those tests that observe D_i. Then we only need to consider $\Pr(D_i)$, which corresponds to the prior probability for D_i based on failure rate, and $\Pr(o(T_j) \mid T_j)$, which corresponds to the confidence value assigned to the observed test result. Using the Baye's maximum *a posteriori* hypothesis, we determine the most likely diagnosis simply as

$$D_{MAP} = \arg\max_{D_i \in \mathbf{D}}\{\Pr(D_i \mid \mathbf{O})\}\,.$$

In other words, we provide the most probable diagnosis as a means of minimizing expected error (i.e., risk) in the diagnostic process.

BAYESIAN INFORMATION MODEL

The intent of the AI-ESTATE standard [2] is to provide a formal information model for the diagnostic domain to support unambiguous exchange of diagnostic information and a consistent software interface for diagnostic systems [12]. Currently SCC20 is amending AI-ESTATE to include a model to cover Bayesian diagnosis. In Fig. 2, we present a new information model that extends the AI-ESTATE standard such that Bayesian networks can be represented. This figure depicts the model using a graphical modeling language called EXPRESS-G [5], which corresponds to a subset of EXPRESS.

The Bayesian network model information model captures information necessary for creating diagnostic Bayesian networks. Assumptions made with this model include that random variables corresponding to tests can only depend on diagnosis variables and other test variables. Diagnoses have no dependencies. In addition, the probability tables are to be fully explicated (including closure, i.e., summing to one across dependent joint distributions), and *array position* in the probability array corresponds to *array position* in the dependence array.

Tests and diagnoses are incorporated from the AI-ESTATE Common Element Model with two types of attributes added to these entities. First, probabilities are associated with test outcomes (e.g., PASS and FAIL) and diagnosis outcomes (e.g, GOOD, CANDIDATE, and SUSPECT). These probabilities, defined as a set, provide the conditional probability tables for the respective random variables. These tables go with the second attribute—the "depends_on" attribute—that identifies the dependence relationship between random variables. Note that The original confidence attribute on these entities corresponds to $\Pr(o(P))$ (or $\Pr(o(F))$) and $\Pr(D_i)$ respectively, all of which are specified in the full lexical EXPRESS model.

AI-ESTATE (i.e., IEEE Std 1232-2002) also defines several "standard services" for a diagnostic reasoner to use within a larger test environment. The reason for defining such services is to facilitate "plug-and-play" compatibility across reasoners. These standard services work directly with the extended model [2]. First, all "accessor" services are defined relative to any entity or attribute within the AI-ESTATE information model (including extended models). Second, the higher-order services, related to reasoner control and diagnostic inference, do not depend on the specifics of the underlying model. In other words, the services do not specify whether the inference process is using a fault tree, a diagnostic inference model, or a Bayesian network; therefore, the same services will work directly with the new model.

Note that the model shown in Fig. 2 is slightly different from that discussed above. Specifically, the model presented assumes there are no dependence relationships between tests where the model in Fig. 2 allows for such dependencies (by including the attribute "`depends_on_test S[0:?]`" on `bayes_test`). One can argue that such dependence relationships are not required. In fact, including them could add unnecessary computational burden to any inference algorithm that processes the network; however, SCC20 decided to include the relationships to provide a more general structure in the event some tests within the system are not conditionally independent.

A MODEL FOR PROGNOSIS

Using the ideas discussed in the companion paper in this conference [11], the model shown in Fig. 2 can be extended to include prognosis as well. The idea is to extend the Bayesian network such that diagnoses depend on other diagnoses in a temporal relationship and construct what is called a "Dynamic Bayesian Network" [6], [10]. Capturing prognostic (i.e., temporal) relationships can be done simply by including a new dependence relationship in the model, as shown in Fig. 3. What is interesting to note is that the only change is the specification of this new relationship on the entity "`bayes_diagnosis`" (i.e., the attribute "`previous_time S[1:?]`").

As described in [11], prognosis can be performed using the DBN structure by "chaining" successive diagnosis BBNs together in this manner. Under the first-order Markov assumption, we only need to represent two slices of the DBN and then "unroll" as necessary in processing the model. Note that only the diagnoses are linked through time since they reflect change in state directly. Changes in observation state are derived from the underlying state changes in the system.

To perform inference with the DBN (and thereby predict future states), first infer the current state (i.e., the state in the current time slice) from the test observations using any Bayesian inference algorithm. Next, the DBN is "unrolled: to the desired number of time slices (assuming the state progressions occur in discrete time steps—DBNs can handle continuous time, but the computation is more complex). Then, beliefs are propagated through time by observing that

$$\begin{aligned}\Pr(D_i^{t+1}) &= \Pr(D_i^{t+1} \mid D_i^t)\Pr(D_i^t) \\ &\quad + \Pr(D_i^{t+1} \mid \neg D_i^t)\Pr(\neg D_i^t).\end{aligned}$$

In fact, given the assumption that only diagnoses progress in state through time and that a diagnosis only depends upon itself in the previous time step, this part of the model reduces to a simple Markov chain, which can be either discrete time or continuous time.

Key to constructing the DBN is defining the temporal transition probabilities (i.e., the probabilities of transitioning from a given state to its next state). In the simplest case, failure probabilities can be used. When better information is available (e.g,. based on historical data), probabilities derived from this information can be used. The point is that the DBN is fully general and can be adapted to available knowledge about the system being analyzed. Theoretically, causal relationships between faults (i.e., a fault at time step t causes another fault to occur at time step $t + 1$) can be represented directly with the DBN as well (even though such models are rarely useful).

MODEL EXCHANGE THROUGH XML

Recent work within the IEEE has embraced developing exchange formats based on the eXtensible Markup Language (XML). This work is being supported through an industry consortium feeding XML schemata to IEEE SCC20 known as the Automatic Test Markup Language (ATML) consortium. The mission of ATML is to "define a collection of XML schemas that allows ATE and test information to be exchanged in a common format adhering to the XML standard [1]." The XML schemata are being provided as part of the new IEEE P1232a, an amendment to IEEE 1232-2002. This amendment will incorporate both the new Bayesian model (Fig. 2) and the specific XML schemata for the Bayesian model as well as *all* information models currently defined in [2].

As stated in the above "mission statement," the principal goals of the ATML project focus on information exchange [1]. Specifically, to goals related to diagnostics that ATML seeks to achieve are:

1. Establish an industry standard for test information exchange
2. Allow for managed extensibility of test information
3. Ensure compatibility with other ATE information-based standards
4. Allow for information exchange with legacy systems
5. Create modular descriptions for test environments
6. Leverage existing technologies in creating test environments
7. Allow for the use of dynamic test sequences that can change with historical data
8. Allow for the use of optimization techniques such as artificial intelligence

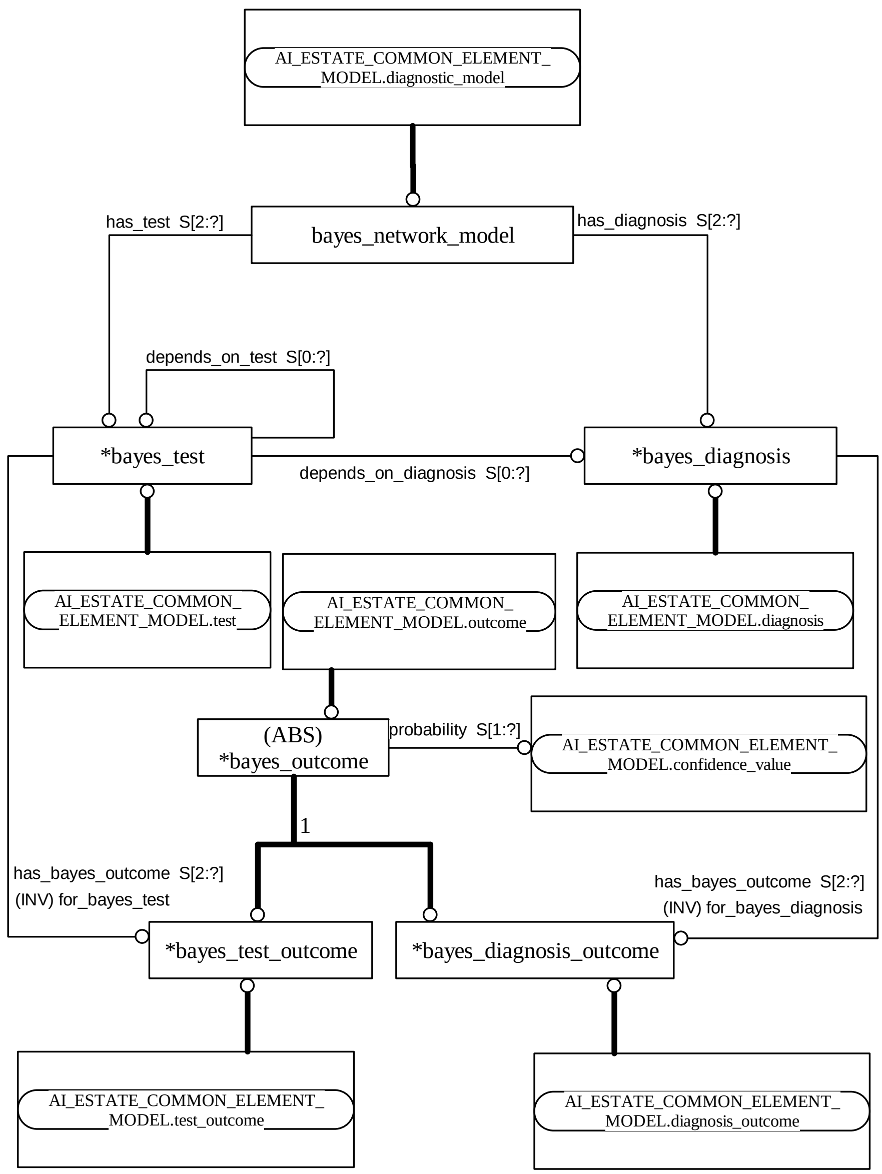

Fig. 2. New AI-ESTATE model to provide for Bayesian diagnosis.

The focus of the P1232a amendment is on goals 1–8 with particular emphasis placed on 7 and 8 (the scope of the Diagnostic and Maintenance Control subcommittee of SCC20).

SUMMARY

The IEEE SCC20 has been creating of information exchange standards in system test and diagnosis and automatic test equipment for almost 30 years. The Diagnostic and Maintenance Control (DMC) subcommittee of SCC20 is chartered with defining information standards in the areas of system diagnosis and diagnostic maturation. Recent work within the DMC has been in response to requirements to extend their models to more modern methods of system diagnosis (namely, Bayesian diagnosis) as well as requirements to update their information exchange medium through widely-used standards such as XML.

In this paper, we focused on the new information model for exchanging information in support of

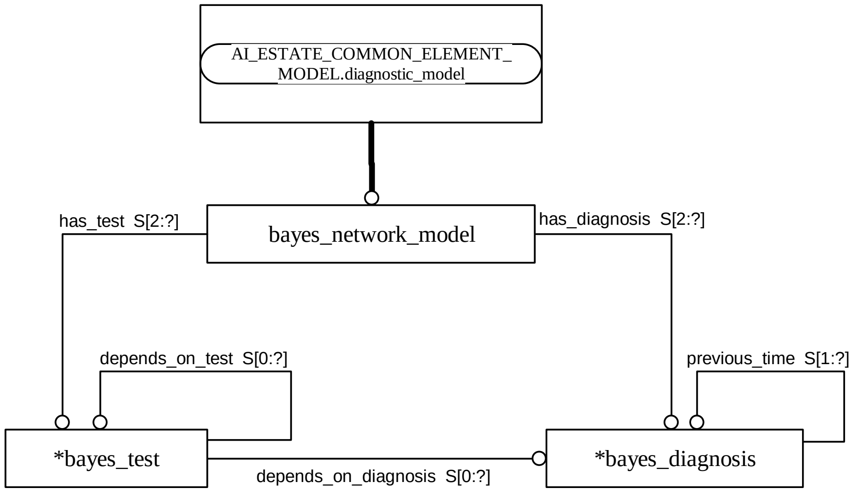

Fig. 3. Extended AI-ESTATE model extract to provide for Bayesian prognosis.

Bayesian diagnosis. This model extends other work in Bayesian diagnosis as described in [10] and [11]. In addition, we presented a simple extension to the Bayesian model that would support use in Bayesian prognosis. This model extension is based on the application of Dynamic Bayesian networks to model system changes through time. Finally, we discussed recent work within the ATML consortium and SCC20 to specify information exchange through XML schemata. The specification of XML for model exchange provides a widely available medium for information exchange coupled with a formal semantic model (not typically provided by XML schemata) to ensure data integrity.

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