Model-based Diagnosis: A Probabilistic Extension

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Abstract. The present study treats model-based diagnosis as an uncertain reasoning problem. To handle the uncertainty in model-based diagnosis effectively, a probabilistic approach serves as a point of departure. The use of probabilities in diagnosis has proved beneficial to the performance of diagnostic engines. We extend the use of probabilities to reflect the aging processes affecting component lifetimes. Unexpected failures signal unusual operating conditions possibly due to the failure of other subsystems. The diagnostic system architecture proposed here is capable of detecting failures that are difficult to detect using a conventional diagnostic engine. Moreover, ascribing a statistical interpretation to nonmonotonic reasoning, allows us to use a hybrid (probabilistic-logical) inference engine at the heart of this system.

1 Diagnosis and Uncertain Reasoning

Diagnosing a system is the process of identifying a set of components whose failure explains the faulty system performance. Generally, model-based diagnosis consists of a cyclic process of making assumptions (regarding the faultiness or faultlessness of components), predicting the system behavior under these assumptions, observing actual system behavior, and adjusting the assumptions. This cycle is repeated until a set of faulty components is identified, and the failure of this set of components explains the observed abnormal behavior. As described, model-based diagnosis is deducing some hidden properties based on some observed ones and a causal understanding of the function of the system and its components.

Hidden properties cannot be determined with certainty. Hence the assumptions made regarding which components might be faulty are at best uncertain. Another source of uncertainty is introduced in the diagnostic cycle by the prediction phase. The behavior of a faulty component is hard to predict. It can be identical to the correct behavior for some inputs, but very different from it given another input. However, the faulty behavior is constrained by physical constraints. Attempts to perform diagnosis based on the correct behavior alone, have typically generated a large number of possible diagnoses, including some physically impossible ones. The incorporation of failure modes into the system description has been driven by the need to weed out physically impossible diagnoses [9]. Another constraint that is usually imposed on nonmonotonic diagnostic
engines is the minimality constraint. A set of components forming a diagnosis \( \Delta \) is minimal if it does not contain any component \( X \) such that the set \( \Delta - X \) can explain the observed behavior. Other potential sources of uncertainty in a diagnostic process are the unreliability of observations, the stochastic nature of the system under diagnosis, and intermittent failures.

Here, we approach the diagnostic problem as a problem of reasoning under uncertainty. The problem readily yields itself to probabilistic approaches [17], [12], and [24]. Moreover, a statistical interpretation for nonmonotonic reasoning allows us to consider nonmonotonic systems, such as GDE [10], as performing some form of uncertain reasoning. Casting diagnosis as a problem of reasoning under uncertainty justifies both the minimality and failure mode requirements. Adding components to a minimal diagnosis reduces the probability of the set (the probability of a diagnosis is the product of the independent probabilities of failure of its components) which justifies the minimality requirement. Moreover, the probability of a physically impossible failure mode is zero, which guarantees the elimination of any explanation involving such failure modes.

Further advantages can be achieved from a probabilistic formulation of diagnosis. These advantages include choosing the most informative tests using entropy measures [10], reducing the time required for diagnosis and the costs of diagnosis [17], and optimizing the diagnostic decision making to maximize some utility [8]. The following paragraphs shed some light on these advantages, and the rest of this work introduces a new one: the detection of premature failures resulting from the failure of other subsystems.

A diagnostic engine has to determine which measurement to take next. One approach to guiding the diagnostic process is to select the measurement that would provide most information [10]. Using a probabilistic representation, it is easy to select such measurement based on entropy. The minimum entropy corresponds to maximum information.

Performing the most informative test first is attractive because it allows the diagnostic engine to limit the search and therefore provide a superior average performance. However, in practical situations, performing the most informative test may be too costly, or difficult. Choosing to optimize cost instead of information results in a different strategy for selecting the measurement/test to perform next. The decision tree appropriate for analyzing the next measurement decision has a branch corresponding to each test. Each test has a cost and a duration associated with it. Each component has a probability of failure. Tests determine the status of tested components. The minimum average testing cost (or duration) can be achieved by testing the components with the highest probability of failure to testing cost (testing duration) ratio [17]. More elaborate decision-theoretic approaches create diagnosis and repair plans optimized to minimize down time, costs due to failure, and repair costs [8]. These techniques rely heavily on the availability of probabilistic information.