Engineering Applications of Artificial Intelligence 60 (2017) 136–150

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Bayesian and Dempster–Shafer reasoning for knowledge-based fault diagnosis–A comparative study

K. Verbert*, R. Babuška, B. De Schutter

Delft Center for Systems and Control, Delft University of Technology, Mekelweg 2, 2628 CD Delft, The Netherlands

ARTICLE INFO

Keywords:
Fault diagnosis
Uncertainty reasoning
Bayesian inference
Dempster-Shafer inference
Condition-based maintenance

ABSTRACT

Even though various frameworks exist for reasoning under uncertainty, a realistic fault diagnosis task does not fit into any of them in a straightforward way. For each framework, only part of the available data and knowledge is in the desired format. Moreover, additional criteria, like clarity of inference and computational efficiency, require trade-offs to be made. Finally, fault diagnosis is usually just a subpart of a larger process, e.g. condition-based maintenance. Consequently, the final goal of fault diagnosis is not (just) decision making, and the outcome of the diagnosis process should be a suitable input for the subsequent reasoning process. In this paper, we analyze how a knowledge-based diagnosis task is influenced by uncertainty, investigate which additional objectives are of relevance, and compare how these characteristics and objectives are handled in two well-known frameworks, namely the Bayesian and the Dempster-Shafer reasoning framework. In contrast to previous works, which take the reasoning method as the starting point, we start from the application, knowledge-based fault diagnosis, and examine the effectiveness of different reasoning methods for this specific application. It is concluded that the suitability of each reasoning method highly depends on the problem under consideration and on the requirements of the user. The best framework can only be assigned given that the problem (including uncertainty characteristics) and the user requirements are completely known.

1. Introduction

Condition-based maintenance is a promising preventive maintenance strategy to reduce system downtime and costs. An important task within the condition-based maintenance process is the determination of the actual system health based on measurement data, hereafter referred to as "fault diagnosis". In practice, fault diagnosis is a challenging task, among other things, due to the presence of uncertainty. Especially for safety-critical systems, like medical devices, railway systems, and nuclear reactors, is it important to deal with the uncertainty in an adequate way.

Although a lot of research has been devoted to fault diagnosis, relatively little attention has been paid to the consequences of uncertainty. Many existing methods account for part of the uncertainty, e.g. methods based on Kalman filters (Chen and Patton, 1996; Li et al., 2012; Mrugalski, 2013; Combastel, 2015) or methods based on set-membership approaches (Puig, 2010; Blesa et al., 2011). Such methods however adopt strong assumptions regarding the type of uncertainty present, and require that the system can be described by a specific model, often a linear state space model. Besides, data-based methods, e.g. methods based on neural-networks (Tayarani-Bathaie et al., 2014; Du et al., 2014), have been proposed that may implicitly account for various types of uncertainty. However, such methods are, in general, not able to clearly express the uncertainty in the diagnostic result, yielding that the uncertainty cannot be adequately accounted for in the subsequent decision making process.

Because of the aforementioned drawbacks of existing methods with respect to uncertainty handling, in this paper we focus on uncertainty reasoning for *knowledge-based fault diagnosis*. Knowledge-based diagnosis is considered because in many practical applications not enough knowledge is available to define a quantitative model required by model-based approaches. Knowledge-based fault diagnosis is influenced by uncertainty in various ways: First, the available measurement data may be incomplete, incorrect, or imprecise, e.g. due to sensors with a limited accuracy; Second, knowledge is needed to infer system health from these uncertain data. Also this knowledge is generally uncertain, i.e. (partly) incorrect, subjective, or incomplete.

Despite of the development of various methods for reasoning under uncertainty and the many discussions about the correctness and usefulness of these methods (Lindley, 1987; Cheeseman, 1985; Smets, 1992, 1994; Dubois et al., 1996; Ferson and Ginzburg, 1996; Dubois and Prade, 2001; Cobb and Shenoy, 2003), no agreement has

* Corresponding author.
E-mail addresses: k.a.j.verbert@tudelft.nl (K. Verbert), r.babuska@tudelft.nl (R. Babuška), b.deschutter@tudelft.nl (B.De Schutter).

http://dx.doi.org/10.1016/j.engappai.2017.01.011
Received 31 May 2016; Received in revised form 27 November 2016; Accepted 16 January 2017

been reached regarding a consistent and uniform framework to handle problems under uncertainty. In particular the disagreement about the correctness and usefulness of the Bayesian and the Dempster-Shafer framework has led to debates. Bayesian proponents claim that the Bayesian theory is the optimal framework to handle all kinds of uncertainty (see e.g. the works by Lindley (1987); Cheeseman (1985)). To quote Dennis Lindley, an eminent probabilist (Zadeh, 2008), "probability is the only sensible description of uncertainty and is adequate for all problems involving uncertainty. All other methods are inadequate" and "anything that can be done with fuzzy logic, belief functions, upper and lower probabilities, or any other alternative to probability can better be done with probability." While Bayesian proponents are convinced about their framework, shortcomings are claimed by many researchers (see e.g. the works by Smets (1992, 1994); Dubois and Prade (2001); Dubois et al. (1996); Ferson and Ginzburg (1996); Cobb and Shenoy (2003); Haenni (2003); Shafer (1990)). For example, Smets (1992, 1994); Haenni (2003); Shafer (1990) argue for the need of belief functions and for their added value over probabilities. Especially, they promote belief functions for being superior in representing incomplete and partially reliable knowledge. Dubois et al. (1996) conclude that the Bayesian approach is tailored for decision making, but not necessarily for other kinds of reasoning. Ferson and Ginzburg (1996); Dubois and Prade (2001) consider different sources of uncertainty, all having their own characteristics, and they argue that each of these uncertainty sources requires another reasoning strategy. In contrast, Cobb and Shenoy (2003) advocate that the Bayesian and Dempster-Shafer frameworks have roughly the same expressive power.

In this paper, we compare Bayesian and Dempster-Shafer reasoning from an application-oriented point of view. In contrast to previous works, which take the reasoning method as the starting point and use examples to illustrate the effectiveness of the method, we start from the application, i.e. knowledge-based fault diagnosis, and examine the effectiveness of different reasoning methods for this specific application. More specifically, the contributions of this paper are:

1. We analyze how the available data and knowledge are influenced by uncertainty;
2. We compare how the knowledge-based fault diagnosis task fits within the Bayesian and Dempster-Shafer reasoning framework;
3. We present additional objectives (e.g. clarity of inference) and analyze how they are accounted for in both reasoning frameworks.

Note that our aim is not to deeply discuss uncertainty methods nor to advocate one of the methods in general. We focus on a specific problem with the related objectives, for which we assess under which circumstances which method is most suitable to reach these objectives.

Note that this paper is an improved and extended version of our conference paper (Verbert et al., 2015). In particular, the current paper adds the following elements: a thorough analysis of the knowledge-based fault diagnosis problem in both the Bayesian and the Dempster-Shafer framework, as well as a more extensive comparison and example.

The remainder of this paper consists of three parts: The first part (Section 2 till Section 4) discusses general concepts regarding reasoning under uncertainty. In the second part (Section 5 till Section 7), we analyze the uncertain reasoning problem of knowledge-based fault diagnosis. The third part (Section 8) covers a specific fault diagnosis example for railway track circuits.

2. Classification of uncertainty

According to e.g. Zadeh (2008); Dubois and Prade (2001); Dubois et al. (1996); Ferson and Ginzburg (1996) various sources of uncertainty need to be treated differently. A distinction is made between the following sources of uncertainty:

1. Randomness;
2. Incompleteness;
3. Imprecision;
4. Conflict.

Randomness, also called intrinsic variability, refers to the situation that a future outcome is uncertain, but a probability distribution of the outcome is available, e.g. throwing a known fair die. *Incompleteness* means that an outcome (or probability distribution) is defined, but the information available is not sufficient to identify this outcome (or probability distribution). For example, the evidence that the winner of a competition is a male is only sufficient to identify the winner in the case that there is only one male candidate winner. Otherwise, this evidence only allows to exclude candidate female winners. *Imprecision* refers to the situation that the outcome is known, but with finite precision. For example, we know that the current outside temperature is between 25.5 and 26.5 degrees Celsius. Finally, uncertainty can arise due to (partially) *conflicting* information. For example, two experts give a different answer to a particular question.

For reasoning purposes, uncertainty is often classified into the following two classes (Kiureghian and Ditlevsen, 2009; Billinton and Huang, 2008):

1. Aleatory uncertainty;
2. Epistemic uncertainty

Aleatory uncertainty, also called statistical uncertainty, represents intrinsic variability – i.e. the differences that are observed each time the same experiment is repeated. *Epistemic uncertainty*, also called systematic uncertainty, arises due to a lack of knowledge. This is the uncertainty about things that we could in principle know, but in practice we do not know. The two are often distinguished using the fact that epistemic uncertainty can be reduced by gathering more knowledge or more data, whereas aleatory uncertainty cannot be reduced (Kiureghian and Ditlevsen, 2009; Ferson and Ginzburg, 1996). To illustrate this, consider the example of throwing a die. When we throw a die of which we know the underlying model, each time we get a different outcome, but throwing it more often will not provide information to reduce uncertainty about the outcome of a future throw. So, the uncertainty referred to is of the aleatory type. In contrast, when we throw an unknown die and we want to construct a probabilistic model of the outcome of a throw, then the more data we gather, the less uncertainty we have in our model. Here, the uncertainty referred to is of the epistemic type. Ideally, we would like to eliminate all epistemic uncertainty, so that only aleatory uncertainty remains. In practice, which part of the uncertainty actually can be reduced depends on the particular problem, practical constraints, and the assumptions adopted (Kiureghian and Ditlevsen, 2009).

Considering the different uncertainty sources: both imprecision, incompleteness, and conflict refer to a lack of knowledge and they can be regarded as epistemic uncertainty, whereas randomness can be regarded as aleatory uncertainty.

3. Methods for reasoning under uncertainty–an overview

For completeness and to make a link between the different uncertainty sources and the different reasoning frameworks, in this section, we briefly introduce four common frameworks for reasoning under uncertainty, namely the Bayesian framework, the Dempster-Shafer framework, possibility theory, and fuzzy logic. Later on in Section 4, we motivate our choice to focus on Bayesian and Dempster-Shafer reasoning in this paper. Extensive discussions of the frameworks compared in this work, i.e. Bayesian and Dempster-Shafer reasoning, can be found in Appendix A and Appendix B respectively.