Information Sciences 253 (2013) 110–125

Contents lists available at ScienceDirect

Information Sciences

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

An evidential network approach to support uncertain multiviewpoint abductive reasoning

Felipe Aguirre [a,*], Mohamed Sallak [a], Frédéric Vanderhaegen [b,c], Denis Berdjag [b,c]

[a] University of Technology of Compiègne, HEUDIASYC, UMR CNRS 7253, Compiègne, France
[b] UVHC, LAMIH, UMR CNRS 8201, F-59313 Valenciennes, France
[c] Univ Lille Nord de France, F-59000 Lille, France

ARTICLE INFO

Article history:
Received 24 April 2012
Received in revised form 1 July 2013
Accepted 26 July 2013
Available online 6 August 2013

Keywords:
Abductive reasoning
Model-based diagnosis
Uncertainty
Evidential network
Belief functions theory
Valuation based system

ABSTRACT

The paper proposes an approach to support human abductive reasoning in the diagnosis of a multiviewpoint system. The novelty of this work lies on the capability of the approach to treat the uncertainty held by the agent performing the diagnosis. To do so, we make use of evidential networks to represent and propagate the uncertain evidence gathered by the agent. Using forward and backward propagation of the information, the impact of the evidence over the different symptoms and causes of failure is quantified. The agent can then make use of this information as additional hints in an iterative diagnosis process until a desired degree of certainty is obtained. The model is compared with a deterministic one in which evidence is represented by binary states, that is, a symptom is either observed or not.

1. Introduction

Diagnosis is a complex function that demands an important cognitive effort. It consists of an iterative process in which we attempt to identify the cause of a failure or an accident from the available evidence at hand. The process starts with an initial set of observed symptoms that suggest a first list of possible failures. Thanks to these suspected failures, some symptoms become either more or less likely, thus, the agent performing the diagnosis has additional hints at hand to continue the iterative process. Newly observed symptoms reduce the list of possible failures and the iterative process goes on until a desired degree of certainty about the possible failures is obtained, that is, until the cause has been identified.

The so-called model-based diagnosis approaches are aimed at replicating human reasoning during a diagnosis process [4,9,16,33,39,40,43–45]. The human diagnosis is based on observations, thus uncertain observations may hinder diagnosis accuracy. Several techniques exist to treat such uncertainty: the Bayesian network based approaches [5,20,22,24], the probability based approaches [7,17,18], the subjective evaluation based approaches [41], the belief based approaches [25,30,32], the possibility based approaches [6,12,14,15], the evidential network based approaches [3,19], etc. This paper is about uncertainty treatment using an evidential network for multiviewpoint abductive diagnosis.

In [16,39,40], a multiviewpoint abductive diagnosis is proposed in which symptoms and possible failures are represented by events related to each other through different viewpoints and different levels. The several viewpoints are represented by an oriented graph in which terminal events represent the failures and intermediary events the symptoms. Inference is

* Corresponding author. Tel.: +33 3 44 23 46 45.
E-mail addresses: faguirre@utc.fr (F. Aguirre), sallakmo@utc.fr (M. Sallak), frederic.vanderhaegen@univ-valenciennes.fr (F. Vanderhaegen), denis.berdjag@univ-valenciennes.fr (D. Berdjag).

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http://dx.doi.org/10.1016/j.ins.2013.07.014

performed by applying FOCUS and EXCLU mechanisms that refines the list of possible failures given the observed symptoms. The observations are of a binary nature, that is, the agent either confirms an observed symptom (FOCUS mechanism) or excludes a symptom (EXCLU mechanism). This means that the agent cannot represent his degree of uncertainty about the observations he makes. This is one of the major drawbacks of this method, for instance, the agent may want to quantify to what extent he believes that a given symptom is observed or not. Even more, he may want to quantify his degree of ignorance about a specific observation.

In this article we propose to enhance this method using *evidential networks* (EN) thanks to its superior uncertainty representation and propagation. An EN is a graphical tool for representing and managing uncertainty using *valuation-based systems* (VBS) as a framework and *belief functions theory* (BFT) as a tool to interpret and combine the information. Briefly, a VBS is a framework used to represent and reason under uncertainty proposed by Shenoy [22,23]. Within this framework, knowledge is represented by objects consisting of a set of *variables* and a set of *valuations* affected to the variables. Finally, inference is drawn by using two operators called *combination* and *marginalization*. By using these objects and operators, VBS can represent different types of uncertain knowledge in different domains including probability theory [24], belief functions [25,32], Zadeh–Dubois–Prade's possibility theory [11,48], etc. In VBS, the graphical representation is called a *valuation network*, and the method for solving problems is called the *fusion algorithm*.

In [25], Shenoy described how Dempster–Shafer's BFT fits in the framework of VBS (thus, giving birth to EN). Dempster's rule of combination and the marginalization within BFT are used as the operators and Basic Belief Assignements (BBAs) as valuations. The advantage of BFT is its superior capabilities to handle epistemic and aleatory uncertainty at the same time. The former being caused by imperfect information or the lack of it, and the latter being caused by the natural variability of a process.

In [1,3], Benavoli & al. used an EN to develop an information fusion system that aims at supporting a commander's decision making by providing an assessment of threat. Threat is modeled in the framework of VBSs by a network of entities and relationships between them. In [19], Laamari et al. compares two architectures for belief propagation in ENs applied to reliability analysis under uncertainty. In [46], Xu uses ENs in decision analysis using BFT to model a decision maker's degree of belief about which state of affairs will prevail. In the present work, we apply EN to the diagnosis process and discuss the advantages of taking into account uncertainty in the process. This is done by comparing the results with the initial model presented in [16,40,39].

In Section 2 we present the multiviewpoint based approach for abductive diagnosis. In Section 3 we extend this approach using evidential networks to treat uncertainty. In the final section we compare both methods with an example of application in railway systems.

2. The principle of a multiviewpoint based abductive diagnosis

The multiviewpoint abductive diagnosis uses an initial set E of known events e_i ($E = \{e_i / i \in [1, 2 \ldots, n]\}$ where n is the number of known events in E). Relations between events are applied in a hierarchical way using oriented graphs. These relations can be causal, temporal or functional among others. There are for instance relations such as $e_i \rightarrow e_j$ and $e_k \rightarrow e_j$. Then, the abductive diagnosis suggests that e_i or e_k are plausible given the observation of e_j. The events can be thoughts, components, facts, images. They can relate to the failed or the successful functions of the system, to the structural human or machine components of the system, to the sequences between events or the similarity level between these sequences, to the probability of occurrence of the events, to the consequences or the causes of these events, etc.

Different viewpoints are applied to the set E dividing it into several oriented graphs. Each of them contains a root (the name of the viewpoint), terminal events (the subset of possible events to diagnose) and intermediary events (forming links between the root and terminal events). Therefore, there are as many graphs as viewpoints for a given model and the graphs may be connected between each others if the intersection of their set of terminal events is not empty—that is, they have some terminal events in common but not the intermediary events. Intermediary events are organized in different levels. Higher levels are less specific and as you approach the terminal events, the information is more specific.

As an example, lets say that we saw an animal and that we want to identify it. One viewpoint could refer to the *morphology* of the animal, a first level of this viewpoint could suggest that the animal has *members* and a next level could be more specific and indicate what kind of members: *legs*, *wings*, *fins*, etc. Here we recognize *morphology* as the root, *members* as a first level and $\{legs, wings, fins\}$ as second and parallel levels. They could be connected with different terminal events as for example: $\{Trout, Flamingo, Elephant, \text{etc.}\}$.

The set of suspected events is noted S_e and represents the domain of interest of the model. The objective of the multiviewpoint abductive diagnosis is to reduce the set S_e by applying some several actions as evidence comes to the hand of the agent so as to identify one of the terminal events as the cause of the situation to be diagnosed. The evidence corresponds to information gathered about the different intermediary events. If the evidence suggest that an event e_i is observed, the FOCUS mechanism reduces the set S_e keeping only the terminal events linked to the observed event e_i. On the other hand, if the evidence excludes an event e_i, the EXCLU mechanism is applied to exclude the terminal events linked to e_i.

The $MASK(e_i)$ of an event e_i contains all the actions that justify the rejection of e_i. PV is a viewpoint and $e_i(PV)$ is a possible event of PV. $e_i(PV)$ can then be the root, an intermediary event or a terminal event of the viewpoint. The $CHILD(e_i(PV))$ function gives all the events of Se that are linked with $Ef(PV)$. The following actions are possible: