Knowledge-Based Systems 96 (2016) 40–60

Contents lists available at ScienceDirect

Knowledge-Based Systems

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

Dynamic rule adjustment approach for optimizing belief rule-base expert system

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ARTICLE INFO

Article history:
Received 11 May 2015
Revised 18 November 2015
Accepted 3 January 2016
Available online 8 January 2016

Keywords:
Belief rule-base
Structure learning
Complete structure
Density analysis
Error analysis

ABSTRACT

The belief rule-base (BRB) inference methodology, which uses the evidential reasoning (RIMER) approach, has been widely popular in recent years. As an expert-system methodology using the RIMER approach, BRB is used for storing various types of uncertain knowledge in the form of belief structure. Several structure-learning approaches have been proposed in recent years. However, these approaches are deficient in various aspects, do not have repeatability, hold incomplete data, and are constrained by the associated scale-utility value. Moreover, considering the influence of the number of rules for a BRB system, two scenarios are designed to reveal the relationship between structure feature and fewer/excessive rules. Excessive rules may lead to a BRB that is equipped with an over-complete structure, whereas significantly fewer rules may result in a BRB with an incomplete structure. To solve these problems, we initially proposed to develop an adjusted structure that is leading to the establishment of a complete structure instead of incomplete and over-complete structures. By scenario analysis and experimental verification through parameter learning of BRBs, we summarize several features of two scenarios, which can be used to reveal certain number of key BRB properties. Finally, density and error analyses are introduced to dynamically prune or add rules to construct the complete structure, particularly that of the BRB comprising multiple-antecedent attributes. We verify the effectiveness of the proposed approach by testing its use in a practical case study on oil pipeline-leak detection and demonstrate how the approach can be implemented.

1. Introduction

Dempster–Shafer theory of evidence [1,2], Bayesian probability theory [3], and fuzzy-set theory [4] have been widely employed in handling information under uncertainty. Each of these theories has its own features and is only suitable for a specific application environment [5–10]. When knowledge coexists with different kinds of uncertain information, such as fuzzy, incomplete or ignorant information, none of these theories can represent such knowledge with an applicable scheme. In particular, fuzzy-set theory is known to be valid only in handling fuzzy information because of the vague term of human knowledge, making it inappropriate for cases where information has probabilistic uncertainty [11]. Therefore, developing a hybrid knowledge representation scheme and inference mechanism is highly desired to handle different kinds of information under uncertainty [12,13]. In this regard, Yang et al. [14] proposed the belief-rule-base (BRB) methodology using the evidential reasoning (RIMER) approach. This methodology has its advantages in reflecting the dynamic nature of decision-making problems, particularly information under conditions of fuzziness, ignorance, or incompleteness.

Since then, several powerful approaches have been developed from the improvement of the RIMER approach. In particular, Liu et al. [15] designed an extended belief rule with belief degrees embedded in the consequent terms and in all the antecedent terms. Jin et al. [16] proposed a certainty rule designed with certainty degrees embedded in the antecedent and consequent terms. Calzada et al. [17] formulated a dynamic rule activation method to optimize the rule-inference process. Now, the RIMER approach has been applied in many areas, such as in the safe evaluation of engineering systems [18–20], military capability evaluation [21], pipeline leak detection [22,23], risk analysis [24,25], prediction of consumer preferences [26,27], residual-life probability prediction of metalized film capacitors [28], and basic classification problem [29–31].

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http://dx.doi.org/10.1016/j.knosys.2016.01.003

As an expert system using the RIMER approach, BRB is employed for storing various types of uncertain knowledge in the form of belief structure. The BRB system has the same features as the generalized expert system that it has the universal inferential performance to model and predict the behavior of a complex practical system. However, a complex BRB with thousands of rules should independently consider the parameters of each rule, including the referential values of the antecedent attribute, antecedent-attribute weight, rule weight, and the belief degree in the consequent part. In this case, expert experience is incapable of accurately determining these parameters because of human-knowledge limitations. Therefore, Yang et al. [32] established the first generic BRB parameter-learning framework and the corresponding optimization model, which utilized the Optimization Toolbox of Matlab, to train BRB parameters without expert knowledge. The optimization model of Yang et al. was proven to improve the decisive precision of BRB systems. Moreover, Xu et al. [22] established a BRB parameter-optimization model for pipeline-leak detection. To improve the inferential performance of BRB systems, Chen et al. [33] proposed a modified BRB parameter-learning model to train BRB systems globally; their model is also based on the Optimization Toolbox of Matlab. Zhou et al. [34] argued that the approaches of Yang and Chen essentially employ offline training. When new data become available, retraining the BRB system is necessary. However, the repeated offline training process is highly expensive and time consuming. Therefore, Zhou proposed the first online parameter-learning approach, which is based on the recursive-expectation-maximization algorithm.

With more studies conducted on learning and training for the BRB parameters, the researcher determined that BRB would be oversized when excessively numerous antecedent attributes or the initial manual BRB structure are unavailable for use in the BRB systems. For a complex system, expert knowledge and historical data sets may not be perfect, and may only lead to the construction of inappropriate BRB structure. Hence, an initial BRB may be overfitting or underfitting because of the unreasonable number of rules. Consequently, such a BRB system cannot achieve excellent inferential performance BRB training through existing parameter-learning approaches. To solve this problem, Li et al. [35] formulated a belief K-means clustering algorithm, which can adjust the distribution of referential values for each of the antecedent attributes and improve the inferential accuracy and decision quality through mining historical data sets. Chang et al. [36] proposed a structure-learning approach using grey targets, multidimensional scaling, isomaps and principle component analysis, all of which can efficiently downsize the number of antecedent attributes. Zhou et al. [37] suggested the concept of “statistical utility,” which can determine whether a rule should be kept or reduced by calculating the utility value. Yang et al. [38] devised a structure-learning approach for the BRB comprising a single antecedent attribute. To date, these existing approaches not only statistically tune parameters for a given set of rules but also adjust the BRB structure.

Several challenges should still be addressed to achieve the optimization of BRB systems. First, merely training BRB parameters is insufficient; adjusting the BRB structure is necessary, especially that of the BRB comprising multiple-antecedent attributes. Moreover, the effectiveness of parameter learning is usually based on the initial BRB structure. For example, in the case of pipeline-leak detection, two antecedent attributes (i.e., pressure difference and flow difference) should include eight referential values and seven referential values in the initial structure, respectively, so that the BRB system can accurately estimate the leak size of the pipeline. If each antecedent attribute would only involve one referential value in the initial structure, the BRB system will lose its estimated accuracy. Second, only a few structure-learning approaches are applicable. Since the conceptualization of “structure learning” in recent years, only Li et al. [35], Chang et al. [36], Zhou et al. [37], and Yang et al. [38] have made contributions to the structure learning of BRB systems. Third, the available structure-learning approaches possess several inherent disadvantages. Particularly, the approach of Li et al. [35] is restricted by the subjectivity in determining the number of referential values because of its basis on the K-means algorithm. The approach of Chang et al. [36], which is only suitable for simplifying the BRB structure, lacks repeatability. The approach of Zhou et al. [37] is affected by the scale-utility construction. The approach of Yang et al. [38] is only applicable for the optimization of BRBs with single-antecedent attribute. Finally, the available structure-learning approaches lack a scheme that ensures the ability of the BRB systems to estimate any complex system, which usually involves multiple-antecedent attributes, with arbitrary accuracy. Moreover, these approaches only consider the reduction of the number of rules.

In this context, the current study aims to propose a new structure-learning approach that addresses the aforementioned challenges. Essentially, this approach should have the ability to overcome the shortcomings of the existing strategies. By contrast, Chen et al. [39] have already proven the existence of several properties in the BRB system, such as continuity property, boundedness property, and universal approximation. However, they did not elaborate the relationship between exceedingly many/few rules and the universal inference performance of BRB systems. Thus, the present study initially design two scenarios to reveal the relationship between structure feature and number of rules, the first scenario is designed under the condition that the number rules is fewer and the number of training data is sufficient. And the second scenario is designed under the condition that the number of rules is excessive and the number of training data is insufficient. By scenario analysis and experimental verification for parameter learning in BRB systems, we finally divide the BRB structure into three categories based on the number of rules while the number of training data is a given value. The incomplete structure is the name of the first category, which is associated with too few rules; the over-complete structure is the name of the second category, which is related to too many rules; and the other category, namely the complete structure, contrast to the former two structures. The complete structure renders the BRB system capable of providing excellent inferential performance. To distinguish three category structures, we suggest that the number of rules in the complete structure is always lower bounded and upper bounded. Hence, the number of rules in the complete structure is not a specific value. Instead, its number of rules is an interval. To enable a BRB to achieve the complete structure, the current study analyzes a large quantity of trained BRB systems and summarizes several BRB features equipped with the incomplete or over-complete structure. On the basis of these features, this paper proposes a dynamic rule adjustment approach, which mainly includes density and error analyses, to construct the complete structure of a BRB. Notably, density analysis is employed to prune the belief rules, whereas error analysis is used to add the belief rules to the complete strategy. The addition of new belief rules must consider multiple-antecedent attributes. Both analyses are the important components of the dynamic rule adjustment approach. To verify the effectiveness of this approach, we investigated the widely used case of oil pipeline-leak detection. The best BRB decision structure is then constructed from the incomplete or over-complete structure. By comparing with the existing BRB on oil pipeline-leak detection, the new BRB system constructed through the proposed approach exhibits excellent estimation performance and a compact BRB structure for BRB.

The rest of the paper is organized into sections. Section 2 introduces the RIMER approach. Section 3 presents the over-complete and incomplete structures. Section 4 proposes the dynamic rule adjustment approach in obtaining a BRB complete