Dempster-Shafer and Bayesian Networks for CAD-based Feature Extraction: A Comparative Investigation and Analysis

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Introduction

Information pertaining to real world problems often contains noises and uncertainties. This has been a major challenge faced by the contemporary AI researchers. Of various paradigms developed for handing uncertainties, the Dempster-Shafer theory (DS) and the Bayesian Belief Networks (BBN) have received considerable attention in the AI community recently. They have been successfully applied to problems in medical diagnosis, decision-making, image understanding, machine vision, etc.. Despite their obvious success, blindly using them without understanding their limitations may result in computational difficulty and unsatisfying inference results. The aim of this paper is to analyze and compare the performance of the two paradigms in extracting manufacturing features from the solid model descriptions of objects. Such a comparison will serve to identify their strengths, weakness, and appropriate application domains.

Problem Domain and Formulation

A major difficulty faced by the previously proposed methods for feature extraction has been the interaction between features. Feature interaction introduces uncertainties to feature representation, making their recognition very difficult [Ji, 1993]. We propose to recognize interacting features by identifying a set of correct virtual links, based on generating and combining geometric and topological evidences.

A DS approach was developed in this research that can correctly identify multiple virtual links simultaneously by overcoming the mutual exclusiveness assumption. The approach constructed a frame of discernment consisting of the subsets of all potential virtual links. Domain-specific knowledge was used to prune the original frame to a manageable size. A key component of this approach is the *principle of association* we developed for interpreting evidences and for assigning bpas to proper hypothesis sets. Virtual links were determined through evidence aggregation. An approximate method was developed to reduce the evidence aggregation from exponential to linear time by replacing the newly-generated focal elements with their existing nearest supersets.

A hypothesis space consisting of subsets of potential virtual links was used to construct an initial BBN. The casual-consequence relationship between any two connected nodes was represented by the whole-part relationship. Heuristic knowledge was then applied to prune the initial network into a singly-connected BBN for effective belief propagation. To identify multiple virtual links, the belief revision algorithm [Pearl, 1988] was employed for belief propagation, resulting in an optimal state for each node in the network that best explained the observed evidences. Virtual links were subsequently determined from the optimal state of each hypothesis.

Comparison and Conclusion

The measures used for comparison include informational complexity, time complexity, and robustness. Informational complexity study reveals that BBNs require a complete probabilistic model to initiate an inference while DS can function under incomplete model. Furthermore, the auxiliary information required by BBNs may sometimes prove to be difficult and expensive to obtain. In time complexity, both mechanisms are NP-hard in general. While linear time may be achieved for special cases, approximate methods are normally employed for general cases. The robustness study indicates that BBNs tolerate large deviations in prior probability and link matrices. DS, on the other hand, is very sensitive to input data change and conflicting evidences.

This research concludes that while both mechanisms can overcome the mutual exclusiveness assumption to identify multiple virtual links, the BBNs are well suited to applications where probabilities are known or can be acquired, and where human subjective opinions are important. On the other hand, the DS theory is a good choice for applications where uncertainty is best thought of as being distributed in power sets, and where no prior knowledge is available. One disadvantage with DS is that it still stays in lifeless number manipulation while the BBNs use intuitively meaningful semantic networks. In certain fields however, both algorithms can be applied, and the qualities of the results often depend on the skill of the users in adapting the basic theories to their particular problems.

References

Q. Ji, 1993. Bayesian Methods for Machine Understanding of CAD Models. MS thesis, Dept. of Electrical and Computer Eng., Univ. of Arizona.

Pearl, J., 1988. *Probabilistic Reasoning in Intelligent System*, Morgan Kaufmann Publishers, INC.