Information Sciences 346–347 (2016) 275–285

Contents lists available at ScienceDirect

Information Sciences

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

A multicriteria approach for analysis of conflicts in evidence theory

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ARTICLE INFO

Article history:
Received 2 June 2015
Revised 22 January 2016
Accepted 29 January 2016
Available online 6 February 2016

Keywords:
Dempster–Shafer theory
Classification of conflict
Multi-criteria classification
MCDM
ELECTRE TRI

ABSTRACT

Dempster–Shafer Theory (DST) or Evidence Theory is regarded as one of the leading theories for modeling uncertainty in imprecise situations. The main advantage of this theory arises from the possibility of combining different bodies of evidence originally developed by using Dempster's combination rule. However, this rule leads to counter-intuitive results when the bodies of evidence conflict with each other to a high degree. Thus, different combinations of conflict management rules have been developed over the years where, regardless of the method used, what should be identified first of all is the level of conflict between the bodies of evidence. Therefore, different metrics were used to classify or quantify the conflict but no single one of these was successful because it is impracticable to represent all situations of conflict in this theory by using only one metric. Therefore, the contribution of this article is to analyze conflict within DST by using a multi-criteria analysis, for which the Multi Criteria Decision Making (MCDM) method considered was ELECTRE TRI. On modeling the problem, three classes of conflict (low, medium and high), were considered. To validate the model, a numerical analysis was conducted that included the use of a method to point up conflict so as to infer parameters.

1. Introduction

Since its development in the 60s, Dempster–Shafer Theory (DST) or Evidence Theory [30], has been seen as one of the main tools for dealing with situations of uncertainty which classical probability theory has difficulty in modeling. Situations like vagueness, ignorance and others cannot be modeled by classical Probability Theory given their axiomatic premises. As a counterpoint, DST does not require the axioms of additivity and completeness to be adhered to, thus allowing a wider range of situations to be modeled. Therefore, this theory can be used for research studies in very different areas: image processing [17]; group decision using multiple criteria [12,29]; maintenance [2]; neural networks [1] etc.

Despite all these characteristics, the main advantage of DST comes from Dempster's Rule of Combination (DRC) which allows two belief functions or independent bodies of evidence to be merged. From a practical point of view in DRC, the presence of an *a priori* distribution to establish a merger between two bodies of evidence is not necessary, while Bayesian Theory does require this. However, the application of this rule generates counter-intuitive results when the two bodies of evidence, involved in the merger, conflict with each other to a high degree [40].

The combination of bodies of evidence arises in many contexts when aggregating expert's knowledge. There are several studies which address this matter in a fuzzy context, for example [20,22–24,35]. Herrera-Viedma et al. [14] present a

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http://dx.doi.org/10.1016/j.ins.2016.01.080
0020-0255/

review of fuzzy approaches for aggregating expert's knowledge using group decision making and fuzzy logic through soft consensus, thereby pointing towards new trends and challenges within this fuzzy context, while Cabrerizo et al. [4] analyze different consensus approaches in fuzzy group decision making problems, including partial consensus, full consensus and soft consensus.

When considering the DRC there are two main approaches that have been developed over the years in order to overcome the issues that arise whenever there is a high degree of conflict. The first class of approaches focuses on modifying DRC which has generated a real jungle of combination rules in the literature [31,10,39,19,5]. The second focuses on administering the conflict without necessarily modifying DRC [31,37,28,25].

As to the first approach, the change in DRC is proportional to some constant that expresses the level of conflict between two bodies of evidence. The first natural metric developed for this is the normalization constant of DRC that some authors associate with the level of conflict between two bodies of evidence. However, as demonstrated by Liu [18], this constant does not capture all the possible existing conflict situations in this theory, although it may do so to a certain extent. This impossibility within the normalization constant caused authors to investigate or develop another way to measure the conflict between two bodies of evidence [15,18]. Given the computational complexity present in DST, it is complex from the computational point of view to represent all possible conflict situations using a single metric.

Against this background, another approach to identifying conflict is needed. The first is contained in the paper by Liu [18] which receives support from the results of the study by Jousselme and Maupin [15], in which they set out a way to measure conflict by using two metrics plus a numerical threshold of subjective conflict. Following a different line, Destercke and Burger [9] develop an interval metric based on axioms while Fu et al. [13] focus on separating the internal conflict from the external one.

Regardless of the method for measuring conflict, two situations are always present when analyzing conflict in DST: more than one metric is needed to measure the conflict in this theory; and, at the same time, there is some degree of subjectivity involved when determining what the conflict is.

An important point to consider is what the precise meaning of the conflict metric is and how this might best be quantified and aggregated with other types of metrics that seek to capture different types of conflict situations.

Using this prism, the classification of conflict in DST can be seen as a problem of multi-criteria classification. By taking this view, this paper seeks to expand how conflict in DST can be measured by using a multi-criteria method of classification. To this end, the suitability of using such a method when analyzing conflict in DST is ascertained.

Within the various multicriteria approaches, it is a non-compensatory methodology that would be the most appropriate for addressing the issue raised in this paper, as it does not consider tradeoffs [7] between criteria. Thus, more than two conflict metrics can be aggregated so as to tackle conflict measurement in DST, which is what this article proposes.

With this in mind, the ELECTRE TRI method was chosen. This Multi Criteria Decision Making (MCDM) method uses an outranking relationship where each measure of conflict is defined by using a pseudo-criterion in order to integrate the subjective imprecision into assessing what the conflict is.

This article is divided into six sections including this Introduction. Section 2 presents the basic elements of DST and DRC. Section 3 discusses conflict and how it is measured in the literature. In Section 4, the ELECTRE TRI method is introduced while Section 5 sets out both how the problem is structured and a numerical application of the proposed model. Finally, the conclusion discusses the method and what studies could be usefully undertaken in the future.

2. Basic concepts

DST is defined on a non-empty finite, exhaustive and mutually exclusive set, $\boldsymbol{\theta}$**,** of elementary events. This set is called a "frame of discernment" and the set formed by all possible subsets of $\boldsymbol{\theta}$ is called a power set, $2^{(|\boldsymbol{\theta}|)}$. To see how the two sets are related, consider the case where $\boldsymbol{\theta}$ has three elements, $\boldsymbol{\theta} = \{\theta_1, \theta_2, \theta_3\}$, in this case $2^{|\boldsymbol{\theta}|}$ will have 2^3 elements defined as follows: $2^{|\boldsymbol{\theta}|} = \{\emptyset, \{\theta_1\}, \{\theta_2\}, \{\theta_3\}, \{\theta_1, \theta_2\}, \{\theta_1, \theta_3\}, \{\theta_2, \theta_3\}, \boldsymbol{\theta}\}$. Based on the $2^{|\boldsymbol{\theta}|}$ set, the basic probability assignment function, m, is defined and is given in (1) and (2)

$$m : 2^{|\boldsymbol{\theta}|} \to [0, 1] \tag{1}$$

$$\sum_{\boldsymbol{A}\in\boldsymbol{\theta}} m(\boldsymbol{A}) = 1 \tag{2}$$

The function *m (A)* can be interpreted as the degree of belief that the system has in a certain element A belonging to the $2^{|\boldsymbol{\theta}|}$ set. If $m\ (A) > 0$, then set A is called the focal element. Using the function m, two other functions are defined: The belief function *Bel(A)* and the plausibility function *Pl (A)*. The *Bel (A)* function is defined as the total of belief that is attributed to set A, which is calculated by the expressions in (3) and (4)

$$Bel : 2^{|\boldsymbol{\theta}|} \to [0, 1] \tag{3}$$

$$Bel(A) = \sum_{B\subseteq A} m(B) \tag{4}$$