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Safety justification of train movement dynamic processes using evidence theory and reference models

Yonghua Zhou[a,b,*], Xin Tao[a], Lei Luan[a], Zhihui Wang[a]

[a] Research Center of Rail Transit Signal and Control, School of Electronic and Information Engineering, Beijing Jiaotong University, China
[b] Department of Electronic Information and Control Engineering, Beijing Jiaotong University Haibin College, China

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ABSTRACT

The efficient solution to justify train movement safety is to analyze train movement situations via train operation knowledge and knowledge-based inference tools. In this paper, train operation knowledge is represented as train movement models and conditions, collectively called rule-based train movement reference models. The Dempster–Shafer (D–S) evidence theory is employed to infer the model and condition under which a train is running. Consequently, aberrant models and conditions, potentially endangering train operation safety, are identified in advance so that emergency measures can be taken to prevent train operation accidents. The mass function is defined as the approximation level of the train operation time interval within one block section of a railway line to that obtained from various reference models. The D–S theory is also applied to train movement dynamic processes to gradually identify train operation situations, using the combined section and process mass functions. The proposed inference approach using evidence theory and reference models (ETRM) qualitatively and quantitatively judges the rationalities of train operation control logic and variation tendencies. A case study to prevent the occurrence of the 7/23 railway accident in China demonstrates the validity of the proposed inference approach using ETRM. The analysis and inference centering on train movement situations can meanwhile diagnose the operation status of train onboard and ground control systems.

1. Introduction

The occurrences of disastrous train movement accidents have aroused attention on operation safety by railway transportation administrations and academic research circles. Safety is guaranteed by signal systems in the current railway infrastructure. However, the catastrophic accident of front-rear collision between multiple-unit high-speed trains D301 and D3115 on July 23, 2011 in China, called the "7/23 accident", revealed that signal systems may sometimes be out of normal logical orders, leading to occurrences of railway accidents, especially in heavy rain, snow, and wind. Current train scheduling and commanding systems (TDCS) and centralized traffic control (CTC) systems require a set of effective inference tools to judge whether train control systems are operating according to the preset logical processes, thereby justifying train movement safety or discerning potential safety hazards.

Evidence theory, presented by Dempster [1] and later extended by Shafer [2], known as Dempster–Shafer evidence theory or D–S theory, directly and quantitatively deals with uncertainty and ignorance with regard to possible hypotheses using available and sometimes insufficient evidence. It is one of the widely accepted theories about uncertainty inference and information fusion. D–S theory defines mass functions, which can be interpreted as probability or confidence levels for asserted hypotheses. A mass function is also called basic probability assignment (BPA). It is not necessary to express confidence levels with regard to the hypotheses one by one. The BPA can be also performed over subsets of hypotheses, but the sum of all alleged expressions should be equal to one. The mass functions, from multiple evidence sources over the same framework of discernment, can be synthesized using the Dempster rule of combination. Furthermore, D–S theory defines the uncertain range of confidence level using belief and plausibility functions. It is for these characteristics that D–S theory has been extensively recognized as a powerful inference tool. D–S theory provides a general framework to handle uncertainty inference. A great deal of literature has contributed to perfect the theory on the approaches of BPA [3-12], combination rules of conflicting evidence [13], uncertainty measures using fuzzy and rough sets [14, 15], Bayesian inference [16], classification and clustering [17-25], and other aspects.

* Corresponding author at: Research Center of Rail Transit Signal and Control, School of Electronic and Information Engineering, Beijing Jiaotong University, China.
E-mail address: yhzhou@bjtu.edu.cn (Y. Zhou).

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Mass function definition is a pivotal step to applying D–S theory, and it directly affects the inference and decision efficiency. Bloch [3] defined mass functions using grey-level histograms in a trapezoidal form. Yager [4] employed a fuzzy measure rather than a crisp number to express the uncertainty of belief. Denoeux [5] described mass functions proportional to the decreasing function regarding the distance of a test vector to a training vector. Wang and McClean [6] established a systematic approach to derive mass functions from multivariate data spaces. Masson and Denoeux [7] determined mass functions to minimize the objective of evidential c-means (ECM). Xu et al. [8] established nest-structured BPA functions having normal distribution models for the attributes of training data. Han et al. [9] proposed a novel approach of BPA transformed from fuzzy membership functions. Zhang et al. [10] developed a BPA approach based on the distance between the test data and core samples of training data. Deng et al. [11] constructed mass functions based on the confusion matrix to improve the classification accuracy and sensitivity. Yang and Han [12] represented the uncertainty by utilizing the distance of belief intervals. Mass function definition still remains an unsolved problem; it is domain-specific and has no general solution.

D-S theory appoints an intelligent inference mechanism to data processing and information utilization. It has been applied to various fields such as medical treatment [26], equipment manipulation [27] and economic analysis [28]. Very few studies have addressed the application of D–S theory to railway traffic. Oukhellou et al. [29] applied D–S theory to the classification fusion of track circuit fault diagnosis. Xu et al. [30] utilized D–S theory to locate faults in power transmission lines. Train operation knowledge can facilitate the management of railway transportation [31, 32]. The application of D–S theory depends on domain-specific knowledge for proposition inferences.

In order to prevent the reoccurrences of similar railway accidents, some techniques have been explored for analyzing accident causes [33-36]. Baysari et al. employed the human factors analysis and classification system (HFACS) to analyze rail accidents/incidents in Australia [33]. Ouyang et al. established an analysis approach to railway accidents using the system-theoretic accident models and process (STAMP) [34]. Belmonte et al. utilized the functional resonance accident model (FRAM) to perform the safety analysis of automatic train supervision (ATS) systems [35]. Fan et al. developed an accident causal loop model using a system thinking approach to perform a thorough analysis of 7/23 accident between multiple-unit trains in China [36]. Those methods address how to learn from railway accidents to improve railway operation safety.

In this paper, we attempt to employ D–S theory and train operation knowledge to judge train movement status based on intermittent information feedback, in order to infer potential safety hazards of train operations and thereby provide decision grounds to take measures to avoid accidents. The train movement reference models are established to act as various kinds of sensors, providing multisource information for D–S theory to evaluate train movement status from respective angles using train movement models [37, 38]. The current leading control modes of train operations cannot access the continuous train position information, which signifies that the only known position information regards what section of a railway line a train locates at within a time interval. With regard to this characteristic of information feedback, a mass function is proposed, which measures the differences between the movements of an actual train and reference models. Moreover, decision making cannot often be accomplished at one time, and involves dynamic evolutions. The combined *section and process mass functions* are further defined to represent individual decision activities and accumulated decision consequences. With the process advancement of train movements, train movement status will be gradually revealed from decision ignorance to sufficient confidence. This paper ultimately establishes the safety inference framework utilizing evidence theory and train movement knowledge. The validity of the framework is demonstrated through a case study of the disastrous 7/23 railway accident in China.

The rest of this paper is organized as follows. Section 2 outlines the basic principle of evidence theory. Section 3 develops the rule-based reference models of train movements. Section 4 elucidates the reference model-based inference framework for safety justification of train movements. Section 5 demonstrates the validity of the proposed framework using case study. The final section discusses the conclusions.

2. Evidence theory

2.1. Mass function

D–S theory defines a frame of discernment Θ, which is a set of mutually exclusive and exhaustive hypotheses and constructs the domain that a mass function concerns. If Θ has N elements, 2^N possible subsets can be formed using these elements, called power set 2^Θ. If one subset contains only one element of Θ, it is called a singleton.

A mass function is a mapping from the power set 2^Θ to [0, 1], denoted as $m: 2^\Theta \to [0,1]$. It stands for the probability or confidence level assigned to a subset, also called BPA. If A is a subset of Θ, then BPA should satisfy the following conditions:

$$m(\phi) = 0 \tag{1}$$

$$\sum_{A\subseteq\Theta} m(A) = 1 \tag{2}$$

If $m(A) > 0$, A is called a focal element.

2.2. Rule of evidence combination

With regard to multiple evidence sources, the corresponding mass functions defined over the same framework of discernment Θ can be merged together using Dempster's rule of combination based on an orthogonal sum. Suppose m_1 and m_2 are the defined mass functions. The combined mass function $m = m_1 \oplus m_2$ is calculated as

$$m(A) = \frac{\sum_{B\cap C=A} m_1(B)m_2(C)}{1-k} \tag{3}$$

$$k = \sum_{B\cap C=\phi} m_1(B)m_2(C) \tag{4}$$

where A, B and C are subsets of Θ. k describes the sum of basic probabilities for the subsets without intersections over which m_1 and m_2 are defined, and it should be excluded for the combined mass functions because Eqs. (1) and (2) must hold.

2.3. Measures of belief degree

In D–S theory, two measures of belief degree are defined to represent the uncertain range of an inference, i.e., the belief function and plausibility function. The belief function of A is defined as

$$Bel(A) = \sum_{B\subseteq A} m(B) \tag{5}$$

The plausibility function of A is defined as

$$Pl(\phi) = 0 \tag{6}$$