Accident Analysis and Prevention 90 (2016) 41–49

Contents lists available at ScienceDirect

Accident Analysis and Prevention

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

Fuzzy logic inference-based Pavement Friction Management and real-time slippery warning systems: A proof of concept study

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ARTICLE INFO

Article history:
Received 18 October 2015
Received in revised form 10 February 2016
Accepted 15 February 2016
Available online 22 February 2016

Keywords:
Friction
Pavement Friction Management (PFM)
Locked-wheel
Fuzzy logic
Connected vehicles
HSIP

ABSTRACT

Minimizing roadway crashes and fatalities is one of the primary objectives of highway engineers, and can be achieved in part through appropriate maintenance practices. Maintaining an appropriate level of friction is a crucial maintenance practice, due to the effect it has on roadway safety. This paper presents a fuzzy logic inference system that predicts the rate of vehicle crashes based on traffic level, speed limit, and surface friction. Mamdani and Sugeno fuzzy controllers were used to develop the model. The application of the proposed fuzzy control system in a real-time slippery road warning system is demonstrated as a proof of concept. The results of this study provide a decision support model for highway agencies to monitor their network's friction and make appropriate judgments to correct deficiencies based on crash risk. Furthermore, this model can be implemented in the connected vehicle environment to warn drivers of potentially slippery locations.

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1. Introduction

Friction is known to be an important factor affecting the risk of vehicle crashes (Flintsch et al., 2013; Mayora and Piña, 2009; Henry, 2000). Minimizing roadway crashes and fatalities is one of the Federal Highway Administration's (FHWA) and U.S. Department of Transportation's (USDOT) top priorities (Federal Highway Administration, 2014). The FHWA's Highway Safety Improvement Program (HSIP) policy states that 'each State shall develop, implement, and evaluate on an annual basis a HSIP that has the overall objective of significantly reducing the occurrence of and the potential for fatalities and serious injuries resulting from crashes on all public roads' (FHWA T5040.38). Furthermore, HSIP project locations shall be selected based on 'crash experience, crash potential, or other data supported means as identified by the State, and establishes the relative severity of those locations' (FHWA T5040.38). To achieve this to the greatest extent possible, State highway agencies will require the development of a Pavement Friction Management (PFM) program.

The FHWA has implemented various policies throughout the years to minimize friction-related vehicle crashes (Najafi et al., 2011). In 1980, the FHWA introduced the Skid Accident Reduction Program (SARP) (FHWA T 5040.17). The goal of the SARP was to minimize wet-weather skidding accidents. A subsequent publication supplied new guidelines for selecting appropriate treatments to achieve optimum surface textures for providing a high level of wet friction and a low level of tire-pavement noise (FHWA T5040.36). In 2010, the agency canceled the SARP and introduced the PFM program (FHWA T5040.38). The new program introduces a more proactive and systemic approach to identifying and correcting friction deficiencies and prioritizing resources based on needs.

FHWA technical advisory T5040.36 and the American Association of State Highway and Transportation Officials (AASHTO) Guide for Pavement Friction Management have presented several approaches to defining minimum and desirable friction levels (Hall et al., 2009). Most approaches require historical friction and accident data, which may not be readily available. In a previous study, authors suggested using an Artificial Neural Network (ANN) to model the relationship between friction and vehicle crashes and used the model to define a desirable network level friction threshold and while an ANN provides high prediction accuracy, it requires high computational power. Fuzzy logic models, on the other hand, require less computation power and can be easily stored in microchips and vehicle's on-board computers. This makes them very appealing for real-time applications such as connected vehicles technology.

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http://dx.doi.org/10.1016/j.aap.2016.02.007
0001-4575/Published by Elsevier Ltd.

Recently, the USDOT has begun promoting the concept of connected vehicles to improve the safety of, and ease of mobility throughout, the transportation infrastructure system. Connected vehicles can increase drivers' awareness and reduce the risk of crashes through vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) data transmission. This application will inform drivers of roadway hazards in real-time. According to the USDOT, 'combined V2V and V2I systems potentially address about 81% of all-vehicle target crashes; 83% of all light-vehicle target crashes; and 72% of all heavy-truck target crashes annually' (US Department of Transportation, 2015).

The USDOT has also performed a safety pilot study to collect V2V and V2I data under real-world conditions. The safety applications evaluated in the safety pilot include the following: Blind Spot Warning/Lane Change Warning (warns drivers if there is a car in the blind spot during an attempted lane change), Forward Collision Warning (warns drivers when a vehicle in their path is stopped or is traveling slower and they fail to brake), Electronic Emergency Brake Lights (notifies the driver when a vehicle ahead of them is braking hard), Intersection Movement Assist (warns the driver if it is unsafe to enter an intersection), Do Not Pass Warning (warns drivers if they attempt a lane change when there is another vehicle coming from the opposite direction in the passing zone), Control Loss Warning (warns the driver if another adjacent vehicle has lost control) (US Department of Transportation, 2015). This study aims to introduce a slippery spot warning system under a proof concept to be implemented in connected vehicle research.

2. Background

Fuzzy logic systems are based on traditional rules-based expert systems and can use approximate data and 'linguistic rules' to drive human-like decisions (Zadeh, 1965). Experts' opinions can be incorporated into the fuzzy logic system through these linguistic rules (Flintsch and Chen, 2004). The fuzzy logic inference system consists of a fuzzifier, fuzzy inference engine, fuzzy rules and defuzzifier (Suman and Sinha, 2012).

The fuzzifier converts the numerical input values into linguistic variables. Linguistic variables take word or sentences values versus numerical values (e.g. very young, young, middle age, versus 20, 30, 50 years old) (Zadeh, 1975). Several linguistic sets can be defined for each variable. Input variables can partially belong to more than one linguistic set. The belonging of any input variable to a certain linguistic set is defined as the degree of membership to that set and can take any value in the [0,1] interval (i.e., the degree of membership will be zero if the value does not belong to the set) (Suman and Sinha, 2012). The inference engine transforms the inputs into the linguistic set of output based on linguistic rules. Fuzzy rules can be defined based on expert opinion or based on the observed relationship between the input variables and the outputs. Finally, the defuzzifier converts the fuzzy output set to a single 'crisp' value (Suman and Sinha, 2012).

Over the last few years, several researchers have proposed a fuzzy decision-making approach to determining pavement maintenance and safety needs based on various pavement characteristics (Sandra et al., 2010; Chassiakos, 2006; Chen, 2007; Suman and Sinha, 2012; Xiao et al., 2000). Sandra et al. developed a fuzzy logic-based decision making tool to prioritize pavement needs based on the severity of various pavement distresses (Sandra et al., 2010). Chen used a fuzzy approach to predict the life-cycle cost of various pavement maintenance strategies based on pavement condition (Chen 2007). Both studies used expert opinion to develop fuzzy rules. Xiao et al. used fuzzy-logic to predict the risk of wet pavement crashes (Xiao et al., 2000). The researchers used accident and traffic data from 123 sections of highways in Pennsylvania, collected from 1984 to 1986. Researchers' results showed that fuzzy-logic can, indeed, be used to predict the rate of crashes. Furthermore, they found that fuzzy-logic can also be used to determine the corrective action(s) that should be taken to improve safety (Xiao et al., 2000).

Fig. 1. Locked-wheel skid trailer.

3. Objective

This paper uses a fuzzy logic inference system to model friction's relationship to speed limit, traffic volume, and crash rate. Mamdani and Sugeno fuzzy controllers are used to develop the proposed model, which provides a reliable and customizable tool that agencies can use to establish a relationship between crash rate and friction level and also employ as a scale to prioritize safety projects based on crash risk. Furthermore, the model can be used in real-time crash warning systems to alert drivers to potential slippery spots. The application of the proposed fuzzy system in a real-time crash warning system is demonstrated as a proof of concept.

4. Data Collection

The data for this study were provided by the New Jersey Department of Transportation (NJDOT). The friction data were collected every 0.16 kilometer (km) on more than 3,218 km of urban arterial roads using an ASTM E-501 ribbed-tire locked-wheel skid trailer (Fig. 1) *(*Najafi et al., 2014*)*. The data also included crash location (route and milepost), accident type (fatal, injury-causing, etc.), roadway surface condition at the time of accident (wet, dry, etc.), annual average daily traffic (AADT), and speed limit. Weather information was extracted from the National Oceanic and Atmo-

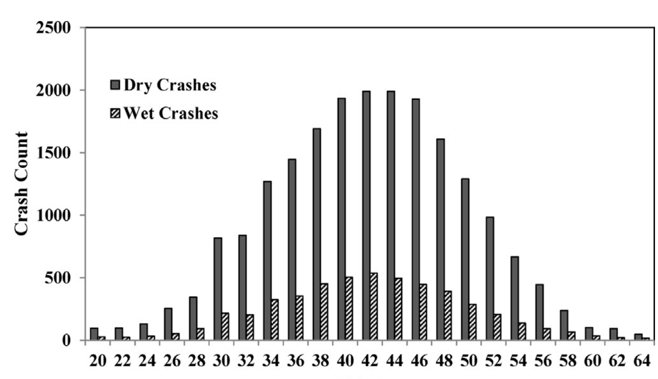

Fig. 2. Crash distribution for fatal and injury causing crashes.