Fuzzy Logic based Automation of the Extraction of Surrogate Safety Measures and the Creation of Severity Classification using Video Data

Pushkin Kachroo, Anamika Yadav, Md Mahmudul Islam, Ankit Kathuria, and Shaurya Agarwal

Abstract This paper uses fuzzy logic to create an Artificial Intelligence (A.I.) based automated system that mimics expert rating of traffic conflicts. Video data from multiple sites were collected to study traffic conflicts as surrogate safety measures for traffic collisions. As part of that effort human trained subjects were given instructions to analyze traffic conflicts and assign severity levels to those. This paper proposes a fuzzy logic-based A.I. system that is trained based on such data so that the process of severity assignment can be done by the software system.

Keywords: Safety surrogate, Fuzzy Logic, Classification, Severity

1 Introduction

This paper deals with the automation of severity classification of traffic conflicts using the extraction of safety parameters from traffic videos. Commercial software performs image processing to track vehicles in the videos and creates temporal-spatial numeric data for vehicle movements. Automation is performed using this numeric data as input for processing. Human evaluators assess traffic conflicts based on specific provided criteria in linguistic terms to perform severity classification. Our developed software uses fuzzy logic to mimic that performance for rating.

The traffic data was collected in the field at various intersections of different types using fixed cameras as well as using videos collected by drones. The video data went through image processing to obtain vehicle trajectories, which were further

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processed using the developed algorithms in order to obtain the final results presented in this paper in conjunction with processing of the human analyzed classification. The effectiveness of the algorithms on the collected data is also presented.

2 Background

In this paper we use fuzzy logic principles and techniques to extract information from the vehicle trajectories and then perform automatic classification. The relevant theory and application steps are presented next.

2.1 Fuzzy Set Theory

There are many books and references that provide the fundamentals of fuzzy set theory ([Klir et al.(1997)Klir, St. Clair, and Yuan], [Zimmermann(2010)]). Fuzzy logic is defined on a set $\Omega = \{\omega\}$ with generic elements called a kernel space. Given a set Ω, a fuzzy subset A of Ω is defined by $\{(\omega, \mu_A(\omega)|\omega \in \Omega)\}$, where $\mu_A : \Omega \rightarrow M$ is called the membership function for A, where M is the membership space which for fuzzy subsets usually is $[0, 1]$ and for crisp sets is $\{0, 1\}$. Without loss of generality, we will call fuzzy subsets of Ω to be fuzzy sets.

There are many fundamental fuzzy set relations and operations ([Zadeh(1969)]), such as fuzzy subset, equality, complementation, union, intersection, fuzzy relation, etc. There are many ways these relationships and operations can be built. A very nice way is to use axiomatization using a De Morgan triplet ([Beg and Ashraf(2009)]) which uses T-norm, T-conorm, and negator for the three basic set operations of intersection (conjunction), union (disjunction), and complement respectively.

In the fuzzy set operations that we are using, we have chosen Gödel's fuzzy logic where we have used the minimum function for the t-norm, maximum function for the t-conorm, and $\ltimes(x) = 1 - x$ for the strong negator.

Fuzzy language is built based on linguistic terms, their syntax and their semantic. As an example, we can use a set of *linguistic terms* as T = {Traffic Flow, Low, Normal, High} to represent different fuzzy linguistic variables for traffic flow. Each of the latter three variables will have associated membership function on the numeric values of traffic flow. Fuzzy languages have associated grammars

2.2 Fuzzy Processing Framework

Now, we present how to interface fuzzy logic with the crisp input and output environmental variables [Mamdani(1974), Takagi and Sugeno(1985)]. There are two models for this, namely Mamdani model ([Mamdani(1974)]), and the Takagi-Sugeno-Kang model ([Takagi and Sugeno(1985)]).

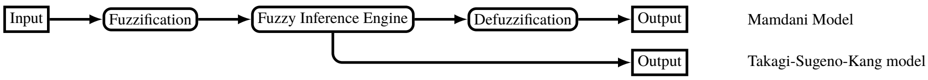


Fig. 1: Fuzzy Processing

3 Application to Field Data

This section provides information on video data collection from several intersections using the drone and video camera and the post-processing of the video data to extract surrogate safety measures. With the surrogate data, we design a fuzzy inference system, which can classify the crash severity ratings based on a couple of inputs.

3.1 Field Data Collection

In the present study, to understand the conflict in a non-lane-based traffic environment, Video data was collected on three unsignalized three-arm intersections which were designated as black spots on National Highway. A variety of motorized and non-motorized vehicles as well as pedestrian interactions were observed at these intersections. The video camera was set up on a high-rise building to capture all the arms of the intersection. Similarly, for the locations where the drone was used for video, drone height and angle were adjusted to capture the whole intersection area. Video data on each location was collected in June 2021 for approximately two hours under clear weather conditions. A brief information of how and where from the video data is collected is given in table 1.

Table 1: Video Data Collection Process from the Roads

Locations	Coordinates	Duration	Road-facility type	Mode of data collection
Cheema bath (NH-3/ AH-1)	Lat: 31°32′11.76″N Long: 75°14′43.23″E	121 min	Three-arm unsignalized intersection	Drone video data
A1-Dhaba (NH-3/ AH-1)	Lat: 31°33′54.51″N Long: 75°4′36.14″E	124 min	Three-arm unsignalized intersection	Drone video data
IIT Jammu (NH-44)	Lat: 32°48′10.88″N Long: 74°53′49.94″E	110 min	Three-arm unsignalized intersection	Video camera

3.2 Data Processing

The captured video data was analyzed using fully automated image processing software DataFromSky (DFS). DFS provides a unique identification number to each road user such that the information on trajectory dynamics such as x and y coordinates, the current speed of the vehicle, acceleration, and deacceleration can be extracted for every unique ID with a precision of 30 frames per second. However, the trajectory data such as speed is presented in the form of a pixel in the image space and is required to be transferred into the coordinate space of the intersection. To transform the data, it is further processed by geo-registering the location with real-world coordinates (latitude and longitude) and establishing their relation with video sequence frame information at a minimum of four positions of the reference image to get the desired detection and tracking of objects of interest (pedestrian, cyclist, and other vehicles). The trajectory data for all categories of road users are detected and classified into different categories such as Motorcycle, Car, Heavy Vehicle, Medium Vehicle, Bicycle, Pedestrian, etc. Further, the processed video is used for extracting useful data such as extraction of indicators like PET, TTC, TIT, TET, etc.

The software detects the vehicle category by processing the image of the vehicle and labeling it with a bounding box to differentiate it from other objects. The size of the bounding box can also be adjusted if the detection of vehicle categories is not properly identified by the software. This issue is major for this study because the software sometimes get confused between the bicycles and the motorcycles. In addition to this, another issue with the image processing software is the requirement of proper illumination as it detects and classifies by processing the image of the vehicle. Night time traffic data is not collected for the chosen locations as the software was not properly tracking and identifying the vehicles due to lack of visibility and it was also allotting double identification numbers to the same road users.

To overcome these issues of multiple tracking and wrong vehicle identifications, data was manually observed by six trained human observers where the vehicles were properly re-categorized and the double identification number vehicles were removed from the final dataset. Data cleaning was carried out by the trained observers. This study only considers two vehicles in a particular interaction and does not include multiple road user interactions. In this study, after the locations were geo-registered with real-world coordinates, the data (trajectory dynamics and safety indicator data like TTC and PET) were exported onto the spreadsheet using CSV file format. These files were further cleaned and saved as excel sheets. However, the speed data corresponding to both the road users for which safety indicators were extracted was manually extracted as for this study, the impact of the speeds on the safety indicators and their classification in severity ranges is also studied.

The interactions takes under consideration both evasive action and non-evasive action based conflicts using the manual observations to understand the anomalies in non-evasive interaction as well which makes them critical. Some scenarios that were noted during the observation of video data:

Scenario 1: A vehicle waiting on the median opening to cross starts moving before the other vehicle passes the conflict zone. It does not change the path or the speed but based on its estimation of the vehicle passing the zone before it arrives at the conflict point, it comes dangerously close to the passing vehicle in . Here no evasive action has been taken but this interaction is dangerous as this may have resulted into a serious conflict.

Scenario 2: A parked vehicle on the road suddenly starts moving when the other vehicle is passing from its side. This interaction is not critical unless due to sudden throttle the vehicle comes in the path of the vehicle coming from the back. Vehicle from the back only sees a parked vehicle and hence no evasive action appropriate is taken if the parked vehicle suddenly starts moving but the interaction is quite critical when observed manually.

The following key points were noted for assigning the Ratings value during the manual observation of the collected video data to categorize the interactions into severe, and normal interactions:

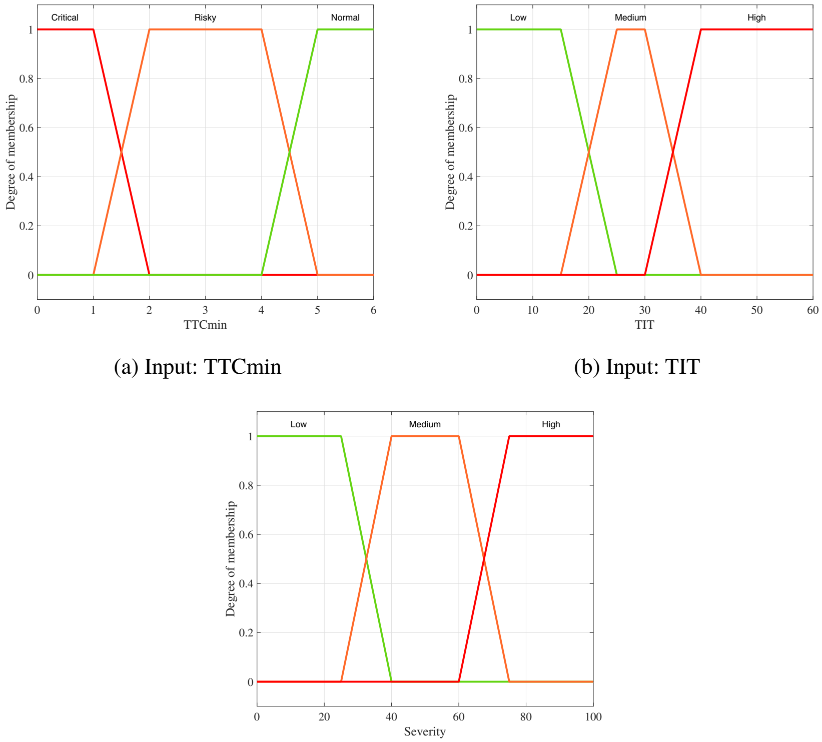
Highly Severe Interaction (2): When the two road users (at least one or both road users are motorcyclist) crosses the conflict zone, one or both of them changes their path or increase/decrease their speed to avoid the collision.

Severe Interaction (1): When two road users cross the conflict zone, they are in such close proximity that a slight variation in their speed or path may result in a collision.

Normal Interaction (0): When two road users cross the conflict zone without any impact on each other’s speed or path and neither they are in close proximity on road.

3.3 Results

To design the fuzzy inference system, we chose the two most important time-based surrogate safety measures: minimum Time to Collision (TTCmin) and Time Integral Time to Collision (TIT) as the input for the fuzzy system. For both the input, we define three membership functions, for TTCmin these are *Critical*, *Risky*, and *Normal* whereas for TIT these are *Low*, *Medium*, and *High*. The TTCmin and TIT membership function values are taken from the dataset we obtained through data processing mentioned in the above subsection. If the value of the TTCmin is lower, it indicates there is a higher chance of a crash. On the contrary, a higher value of TIT indicates a greater probability of a crash or the interaction is quite severe. For the output, we design the crash severity ratings into three membership functions: *Low*, *Medium*, and *High*. The severity values reflect the crash severity ratings, which are given in percentage; the higher the percentage value, the more severe the interaction is, and vice versa. The input and output membership functions are shown in figure 2.



(a) Input: TTCmin

(b) Input: TIT

(c) Output: Crash Severity

Fig. 2: Membership Functions

We have defined three simple rules for the fuzzy inference system. Firstly, the severity will be *High* if either the TTCmin is *Critical* or TIT is *High*. Secondly, the severity will fall in the *Medium* category when one of the value of the TTCmin and TIT fall in the *Risky* and *Medium* category, respectively. And the lastly, if either the TTCmin is *Normal* or TIT is *Low* then the severity will be *Low*. The rules of the fuzzy inference systems are defined as follow:

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Rule 1: If TTCmin is Critical or TIT is High then Severity is High.
Rule 2: If TTCmin is Risky or TIT is Medium then Severity is Medium.
Rule 3: If TTCmin is Normal or TIT is Low then Severity is Low.
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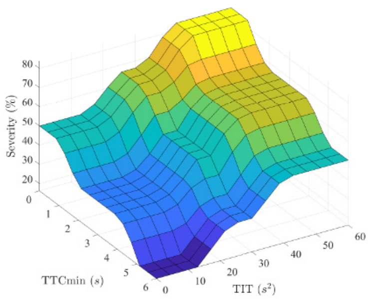
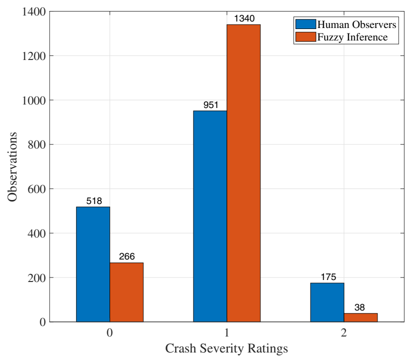
After defining the membership functions and the rules for the fuzzy inference system, it provides the model, shown in figure 3a. Now, using this model, we can get the percentage of the crash severity provided with the TTCmin and TIT values as input. The output we will get from this model is in percentage form. For example, if the TTCmin is $6s$ and TIT is $0s^2$, the severity will be 20%. We applied a simple rule to get the ratings from this severity percentage. If the severity is less than or equal to 33% then it will be considered as normal interaction (0), if it is more than 33% and less than or equal to 66% then the interaction will be severe (1), and for other cases, the interaction will be highly severe (2).



(a) Fuzzy Inference Model



(b) Comparison: Human Observers and Fuzzy Output

Fig. 3: Fuzzy Output and Human Observations

Finally, we have generated the crash severity ratings using the fuzzy inference model for all the observations. In total, there were 1644 observations available in the dataset, and human observers provided a rating for each observation. Human observers classified 518 interactions as normal, 951 interactions as severe, and 175 interactions as highly severe. Whereas, The fuzzy inference system gave 266 interactions as normal ratings, 1340 interactions as severe ratings, and the rest 38 interactions as highly severe ratings. The comparison between the human observers and the fuzzy inference model is shown in figure 3b. If we compare the output of the fuzzy inference model with the human observers, we can see that the accuracy for classifying the interactions is about 55% for the fuzzy inference model.

4 Conclusions

In this paper, we developed an Artificial Intelligent (A.I.) system using the fuzzy logic inference model to provide ratings for traffic conflicts. We have used TTCmin, and TIT surrogate safety measures as the input for the fuzzy inference system, and the output is defined as the severity of the traffic conflicts. We have used three membership functions for each input and output, which helps to convert the crisp information into fuzzified input and fuzzified output to crisp output. The output from the fuzzy inference model shows that it successfully mimics around 55% of the human observer's ratings.

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