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# FuzzyJam: Reducing Traffic Jams Using A Fusion of Fuzzy Logic and Vehicular Networks

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***Abstract*— Traffic congestion is a growing problem worldwide causing time/fuel waste, pollution, and even stress. Various approaches have been proposed to reduce traffic jams. Recently, researchers have started to employ connected vehicle (CV) technology. Most solutions, however, rely on a binary approach to determine a traffic jam, i.e., whether it exists or not. Accordingly, output given to a driver in the form of driving advisory also tends to be binary and static. However, a traffic jam is a dynamic phenomenon, the intensity of which changes over time depending on various factors including randomness of driving behavior and road conditions. In this paper, we propose to integrate a fuzzy inference system into a traffic-jam-control algorithm such that the dynamics of a traffic jam is effectively represented, thereby providing diversified driving advisory depending upon the intensity of a traffic jam. Through simulations, it is shown that the integrated approach reduces traffic delay by up to 6.5% compared with the state-of-the-art solution.**

## I. INTRODUCTION

Demand for highway travel has grown up significantly [1]. Unfortunately, however, highway capacities of many countries are not commensurate with the growth pace. In the U.S., drivers spent 5.5 billion hours being stuck in traffic jams wasting 2.9 billion gallons of fuel, which costed about $121 billion in 2011 [1]. European countries suffer from lack of available road space as they have recently experienced a dramatic increase in vehicle numbers [2].

Various approaches have been proposed to reduce traffic jams [3][4][5]. Recently, researchers and industry developers started to actively adopt Connected Vehicle (CV) technology. In particular, Knorr *et al.* [6][7] have shown that, using CV technology, traffic jams can be significantly reduced even with small market penetration rates. More specifically, a traffic jam is reduced by advising a vehicle to adjust its gap to the preceding vehicle if the following conditions are met: a traffic jam has been detected (i.e., based on the average speed of preceding vehicles); and the "critical segment" (i.e., a congested road segment) is geographically close and recent enough.

A key observation is that a traffic jam is a dynamic phenomenon that continually changes its intensity depending on dynamic factors such as randomness of driving behavior and road conditions. In other words, a traffic jam is not a binary phenomenon that either occurs or not; therefore determining a traffic jam based on a combination of binary decisions (or a single binary decision), e.g., whether the average speed of preceding vehicles is smaller than a given threshold, potentially leads to inefficient traffic jam control. Similarly, driving advisory must be provided based on different intensity of a traffic jam, rather than relying on a static value.

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Fuzzy logic enables us to make a decision based on fuzzy words rather than crisp numbers, thereby being highly effective in representing a dynamic phenomenon by efficiently mimicking the human ability of exploring imprecision and tolerance. Consequently, resemblance of the human thought process provides traditional expert systems with powerful reasoning capabilities. In this paper, we propose to integrate a fuzzy inference system (FIS) into a traffic-jam-control algorithm to cope with the dynamics of a traffic jam and its fluctuating intensity stemming from randomness of traffic flow. The proposed approach ensures that a driver is provided with differentiated driving advisory according to the different intensity of a traffic jam. Through simulations, it is demonstrated that our proposed system achieves by up to 6.5% smaller traffic delay compared with the state-of-the-art protocol [7]. The contributions of this paper are summarized as follows:

- Identification of sources of inefficiency in the existing binary decision-based protocols
- Design and implementation of a novel fuzzy logic-based protocol
- Verification of the effectiveness of the proposed protocol through simulations

## II. RELATED WORK

We review previous works developed to reduce traffic jams focusing on the approaches based on CV technology. Some works proposed to identify congested road segments using CV technology and to advise drivers to avoid congested areas by providing alternative routes [3][5][4]. Schunemann *et al.* [3] presented an algorithm that allows navigation systems to find routes that circumnavigate congested roads. Lakas and Chaqfeh proposed a communication system that enables effective detection of a traffic jam and efficient dissemination of the information [5]. Narzt *et al.* applied the pheromone principle of ant colonies to traffic systems and developed a decentralized and self-organizing mechanism to avoid traffic jams [4]. However, these solutions may cause another traffic congestion on alternative routes especially when a large number of vehicles are advised to change their routes to the same alternative route. In addition, these solutions are "avoidance-oriented" mechanisms, i.e., they start to operate

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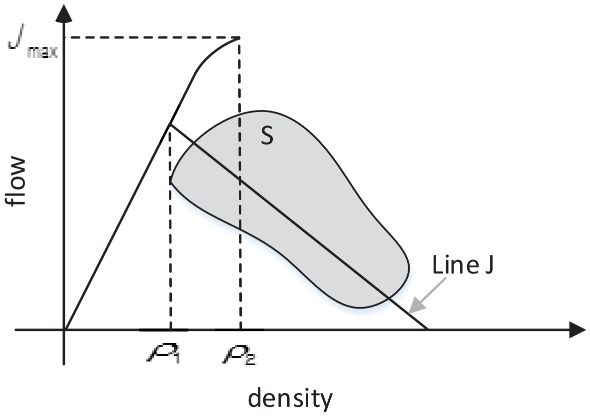

Fig. 1: The fundamental diagram [10]

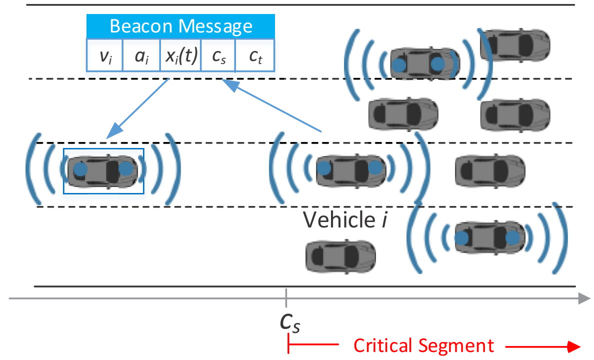

Fig. 2: An example of traffic jam control

only after a traffic jam is determined to be significantly aggravated.

There are more "proactive" approaches that reduce traffic jams by instantaneously providing driving advisory to drivers as a traffic jam arises [8][9][6][7]. Kerner *et al.* [8] proposed an algorithm designed to advise drivers to keep a certain gap to the preceding vehicle when a traffic breakdown occurs and showed that traffic jams are significantly reduced. The proposed algorithm, however, assumes 100% penetration ratio. Fekete *et al.* [9] developed a recommended speed as a convex combination of the desired speed and average speed of other vehicles. They showed that a traffic jam is effectively reduced by advising the recommended speed to drivers. Although Fekete *et al.*'s solution provides fairly good performance with relatively small penetration rates, more than 60% of market penetration rates are still necessary. Knorr and Schreckenberg [6] have successfully reduced traffic jams using inter-vehicle communications with penetration rates of below 50%. In their recent work [7], they improved [6] by considering human limitations like reaction time in adapting driving behavior; they also considered realistic radio propagation and mobility models.

## III. Background and Motivation

### A. Three-Phase Traffic Theory

Kerner [11][10][12], in his pioneering work, has shown, with empirical evidence, that traffic flow on a highway is characterized by space-time transitions between three phases: free flow (F), synchronized flow (S), and moving jam (J). In the F phase, vehicles arbitrarily accelerate/deccelerate and change lanes due to low traffic density. The curve with a positive slope in the flow-density graph shown in Figure 1 corresponds to the F phase. As shown, as the traffic density increases, the flow rate linearly increases; however, at densities between $\rho_1$ and $\rho_2$, the free flow can be easily broken: The F phase is transitioned to the S phase mostly at highway bottlenecks or on/off ramps, where the traffic flow is perturbed significantly and traffic breakdown arises. In the S phase, average vehicle speed is sharply decreased but no significant stoppage is observed. The 2D region labeled S in Figure 1 represents the S phase. Within the region of synchronized flow, self-compression, also often called pinch region arises, where the local density is increased and average speed is even further decreased, often causing stoppage. The pinch region starts to propagate to upstream and the width of the propagation wave becomes larger – thus being called "wide moving jam". Consequently, the S phase is transitioned to the J phase.

Kerner and Boris show that the wide moving jam (i.e., the transition from S to J) can be prevented by enforcing strong speed adaptation to the vehicles within synchronized flow (i.e., vehicles close to a critical segment) [13]. In other words, a larger gap to the preceding vehicle potentially decreases the probability of further traffic break down and propagation of the traffic jam.

### B. Connected Vehicle (CV) Technology

A recent work [7], based on the three-phase traffic theory, effectively uses CV technology to reduce traffic jams. More specifically, a vehicle $i$ periodically broadcasts a beacon message containing its velocity $v_i$, acceleration $a_i$, position $x_i(t)$ at time $t$ as illustrated in Figure 2. A beacon message additionally contains, if any, the upstream front location $c_s$ and time stamp $c_t$ of a "critical segment", a road segment with congested traffic. Upon receiving a beacon message, a vehicle calculates the average speed $\overline{v}(t)$ of all vehicles ahead. If $\overline{v}(t)$ is smaller than a given threshold $T_v$ more than two consecutive intervals (i.e., $\overline{v}(t-\delta t) < T_v$ and $\overline{v}(t) < T_v$), the vehicle marks the critical segment by setting $c_t$ as $t$ and $c_s$ as $x_p(t) + \gamma$, where $\gamma$ is the communication range.

Once a critical segment is determined, vehicles are enforced to adapt their speed if the critical segment is recent and they are geographically close enough to the critical segment. More specifically, if the following conditions are satisfied:

$$t - c_t < T_t \text{ and } 0 < c_s - x(t) < T_s,$$

where $T_s$ and $T_t$ are the spatial and temporal thresholds, the vehicles are advised to keep a larger headway distance. Based on the intuition that *a larger gap has the smaller probability of the occurrence of "overdeceleration effect"*, Knorr *et al.* [7] modified the Comfortable Driving Model (CDM) [14], which is based on Nagel-Schreckenberg's cellular automation [15], to apply and simulate the advised driving behavior. The original CDM contains a probabilistic component $p$ which reflects driver's inability to keep a constant speed:

$$p \leftarrow \begin{cases} p_b & \text{if } l_{n+1} = \text{true AND } t_h < t_s \\ p_0 & \text{if } v_n = 0 \text{ AND NOT} \\ & (l_{n+1} = \text{true AND } t_h < t_s) \\ p_d & \text{otherwise,} \end{cases}$$

where $t_h$ is the time headway; $t_s$ is the interaction horizon; and $l_{n+1}$ is the preceding vehicle's braking status. So $p_b$ is the probability of braking, used when the preceding vehicle is within interaction horizon and the preceding vehicle is braking; $p_0$ simulates the *slow-to-start*, i.e., delayed acceleration although there is no obstruction ahead. Knorr *et al.* [7] basically introduced a probability $p_c$ to model the advised driving, i.e., smaller probability of the occurrence of "overdeceleration effect":

$$p \leftarrow \begin{cases} p_b & \text{if } l_{n+1} = \text{true AND } t_h < t_s \\ & \text{AND } gap_n \leq v_n t_r \\ p_c & \text{if } l_{n+1} = \text{true AND } t_h < t_s \\ & \text{AND } gap_n > v_n t_r \\ p_0 & \text{if } v_n = 0 \text{ AND NOT} \\ & (l_{n+1} = \text{true AND } t_h < t_s) \\ p_d & \text{otherwise,} \end{cases}$$

where $t_r$ is the driver's reaction time which is set as 1 second. By introducing $p_c$ (which is set as $0.8 \cdot p_b$), the model reduces the probability of braking if the headway distance is greater than $v_n t_r$ (i.e., the desired gap).

### C. Motivation

There are two key observations regarding the above-mentioned approach. First, a traffic jam is determined based on a combination of binary decisions, i.e., $t - c_t < T_t$, $0 < c_s - x(t) < T_s$, and $\overline{v}(t) < T_v$. As a result, we obtain only a binary output, i.e., whether a traffic jam has occurred or not. However, considering the fact that a traffic jam is a dynamic process that continually changes its intensity, the binary decision does not effectively represent the dynamics of a traffic jam. Second, the driving advisory is given as a fixed value represented by probability $p_c$. However, as a traffic jam has varying intensity, the driving advisory needs to be diversified depending on the intensity.

## IV. Fuzzy Logic

In this section, we briefly review fuzzy logic to help readers better understand our contributions. For more details on fuzzy logic, please refer to [16].

### A. Fuzzy Set

A crisp set defines only membership and non-membership of an element, in the form of a membership function $\mu_A(x)$, i.e., given a crisp set $A$, $\mu_A(x) = 1$ if $x \in A$ and $\mu_A(x) = 0$ if $x \notin A$. In contrast, a fuzzy set extends a crisp set by introducing partial membership, i.e., the membership function $\mu_A(x)$ of a fuzzy set $A$ takes values in the interval $[0, 1]$; that is, a fuzzy set can be written as a set of ordered pairs: $A = \{(x, \mu_A(x))|x \in U\}$.

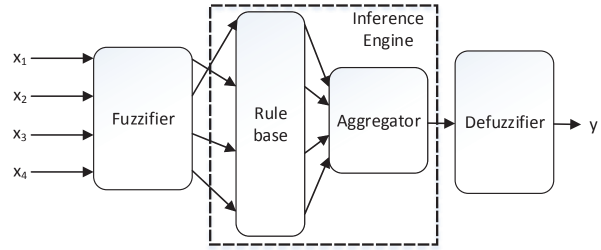


Fig. 3: A diagram of a fuzzy inference system

### B. Fuzzy Inference System

A fuzzy inference system (FIS) is basically a mapping of a vector of input data into a scalar output. Figure 3 depicts a diagram of a general FIS. The FIS is composed of fuzzifier, rule base, aggregator, and defuzzifier. The fuzzifier maps a vector input of scalar values into corresponding fuzzy sets. The rule base has linguistic rules called fuzzy rules that are often defined by domain experts. More specifically, let $T(\mathbf{x}) = \{T_x^1, T_x^2, ..., T_x^n\}$ be the term set for input vector $\mathbf{x} = \{x_1, x_2, ..., x_n\}$ (e.g., if $x_1$ is a temperature, $T(x_1)$ is {"cold", "hot"}). A fuzzy rule is in the form of a simple *if-then* rule (e.g., "if $x$ is $T_x$ then $y$ is $T_y$). More formally, denote fuzzy rules by $R = (R_1, R_2, ..., R_n)$. The $i$-th fuzzy rule can then be written as:

$$R_i = \text{ if } (x_1 \text{ is } T_{x_1}, \text{ and } ..., x_p \text{ is } T_{x_p})$$

$$\text{then } (y_1 \text{ is } T_{y_1}, \text{ and } ..., y_q \text{ is } T_{y_q}).$$

Each rule yields a single number which is the firing strength of the rule. When multiple antecedents are present in a rule, fuzzy operation (e.g., min or product) is applied to find a single firing strength. Now given a set of output fuzzy sets with corresponding firing strength, the aggreator combines the output fuzzy sets into a single set. The defuzzifier then translates the output fuzzy sets into a crisp number, which is the final output of FIS.

## V. Protocol Design

This section presents the design of our proposed protocol called Fuzzy Logic-Based Traffic Jam Control (FuzzyJam). We provide an overview of FuzzyJam followed by the details on its design.

### A. Overview

FuzzyJam resembles the design of [7] in how it detects a traffic jam (See Subsection III-B). A key difference lies in the transformation of variables $\overline{v}(t)$, $t - c_t$, and $c_s - x(t)$ into membership functions denoted by $\mu_v, \mu_t$, and $\mu_s$ respectively. Using the membership functions, FuzzyJam effectively represents the intensity of a traffic jam rather than relying on the binary decision. Accordingly, drivers are

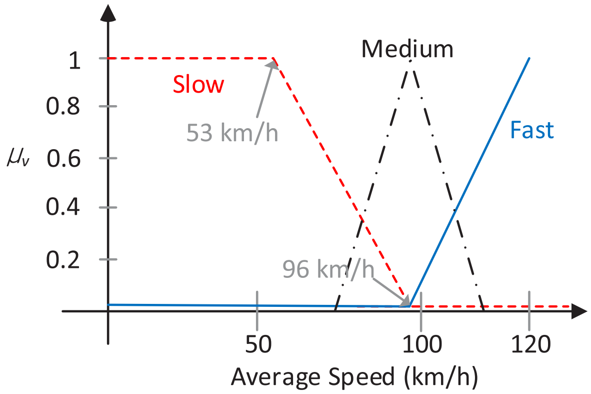


Fig. 4: The membership function for average speed

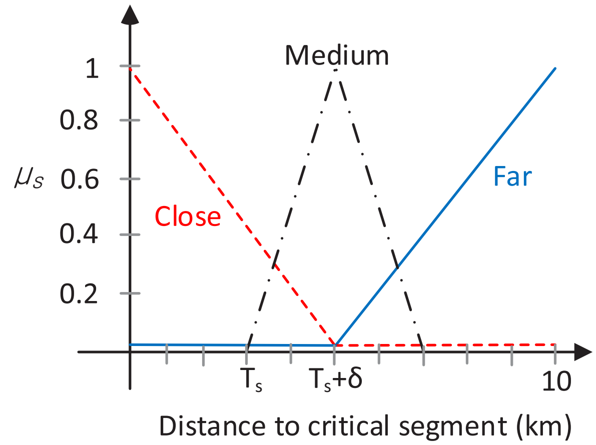


Fig. 5: The membership function for the distance

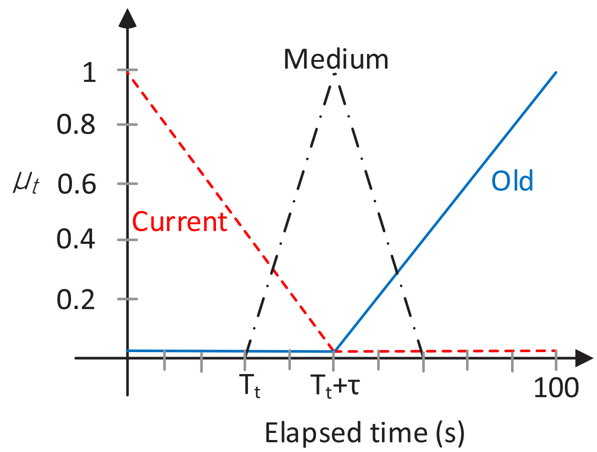


Fig. 6: The membership function for the elapsed time

provided diversified driving advisory that more accurately reflects the current traffic condition. More specifically, a driving advisory is given as a fuzzy set which is determined by evaluating the fuzzy sets representing $\overline{v}(t)$, $t - c_t$, and $c_s - x(t)$. The driving advisory is then periodically updated given new $\overline{v}(t)$, $t - c_t$, and $c_s - x(t)$ to cope with dynamically changing intensity of a traffic jam. In the following subsections, we will describe in details the design of the membership functions, rule-base, and defuzzifier.

### *B. Membership Functions*

The current design of the membership functions targets general U.S. highways – It should be noted that we intend to show the advantages of our fuzzy-logic-based approach through an example design, and therefore, there can be different approaches for designing membership functions depending upon diverse operators and highway conditions.

We first discuss the design of membership function $\mu_v$, i.e., the membership function for the average speed of preceding vehicles. The average speed is represented using three linguistic terms: $\{SLOW, MEDIUM, FAST\}$. To distinguish between $FAST$ and $SLOW$, we adopt the definition of congestion from [17]: Chen *et al.* defines that traffic on a highway is called congested if the average vehicle speed is smaller than 96 km/h (which coincides with Los Angeles highways). Consequently, the speed of 96 km/h is used as the boundary value between $FAST$ and $SLOW$. For the minimum speed on a highway, we refer to the report published by U.S. Department of Transportation [18]. The report provides a list of top 25 congested highway locations and corresponding average speed [18]. We take the average of the 25 congested highways and use it as the index for the minimum speed (53 km/h). Also we refer to the speed limit of the states [19]. According to the speed limit report, we adopt the average speed limit of 120 km/h (75 mph) as the maximum possible speed for our membership function. Figure 4 depicts the resulting membership function $\mu_v$.

For the design of membership function $\mu_s$ (i.e., membership function for the distance to a critical segment), we represent the distance using three linguistic terms $\{CLOSE, MEDIUM, FAR\}$. Basically we adopt the threshold $T_s = 3$ km from [7] to determine if a given distance is $CLOSE$ or $FAR$ from a critical segment. However, instead of making a binary decision, i.e., saying that the distance is $CLOSE$ if it is smaller than $T_s$, we fuzzify the distance using $T_s + \delta$ as the boundary value as shown in Figure 5, where $\delta$ is a system parameter which allows for easy adoption of the membership function for different traffic circumstances.

The membership function $\mu_t$ (i.e., membership function for the elapsed time for a critical segment) is similarly designed with $\mu_s$. The elapsed-time is described using three linguistic terms $\{CURRENT, MEDIUM, OLD\}$; the boundary value differentiating $CURRENT$ and $OLD$ is defined by adopting the threshold $T_s = 30$s from [7], i.e., using $T_s + \tau$ as the boundary value, where $\tau$ is a system parameter. The resulting membership function is shown in Figure 6.

### *C. Rule Base*

We have described the membership functions that constitute the fuzzifier of FuzzyJam. Once crisp input values are fuzzified into corresponding fuzzy values using the fuzzifier, the rule-base of FuzzyJam comes into

TABLE I: Rule base

| | Avg. Speed | Distance | Time | Driving Advisory |
|---|---|---|---|---|
| Rule 1 | Slow | Close | Current | Strong |
| Rule 2 | Slow | Close | Medium | Strong |
| Rule 3 | Slow | Close | Old | Medium |
| Rule 4 | Slow | Medium | Current | Strong |
| Rule 5 | Slow | Medium | Medium | Strong |
| Rule 6 | Slow | Medium | Old | Medium |
| Rule 7 | Slow | Far | Current | Strong |
| Rule 8 | Slow | Far | Medium | Medium |
| Rule 9 | Slow | Far | Old | Medium |
| Rule 10 | Medium | Close | Current | Medium |
| Rule 11 | Medium | Close | Medium | Medium |
| Rule 12 | Medium | Close | Old | Medium |
| Rule 13 | Medium | Medium | Current | Medium |
| Rule 14 | Medium | Medium | Medium | Medium |
| Rule 15 | Medium | Medium | Old | Weak |
| Rule 16 | Medium | Far | Current | Medium |
| Rule 17 | Medium | Far | Medium | Weak |
| Rule 18 | Medium | Far | Old | Weak |
| Rule 19 | Fast | Close | Current | Weak |
| Rule 20 | Fast | Close | Medium | Weak |
| Rule 21 | Fast | Close | Old | Weak |
| Rule 22 | Fast | Medium | Current | Weak |
| Rule 23 | Fast | Medium | Medium | Weak |
| Rule 24 | Fast | Medium | Old | Weak |
| Rule 25 | Fast | Far | Current | Weak |
| Rule 26 | Fast | Far | Medium | Weak |
| Rule 27 | Fast | Far | Old | Weak |

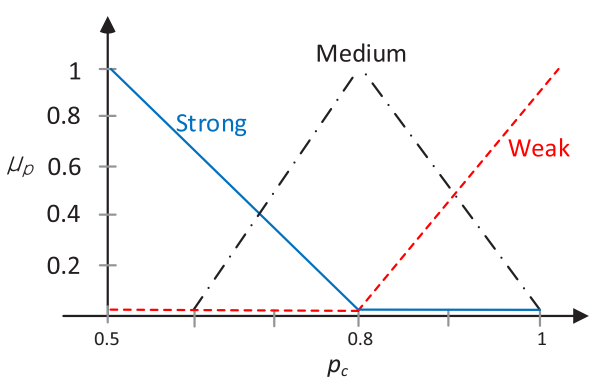

Fig. 7: The membership function for the driving advisory

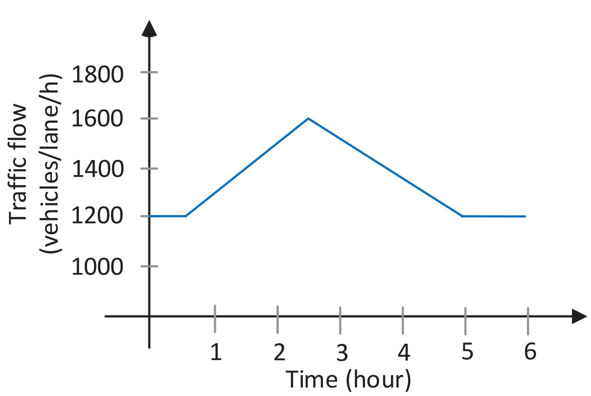

Fig. 8: Traffic flow of main road

TABLE II: Simulation setup - traffic

| | |
|---|---|
| **Lane** | 2 lanes |
| **Length** | 18Km (12,000 cells) |
| **Vehicle speed (car)** | 34m/s |
| **Vehicle speed (truck)** | 26m/s |
| **Vehicle length (car)** | 4m |
| **Vehicle length (truck)** | 12m |
| **Portion of trucks** | 10% |
| **Operation time** | 6.5 hours |

TABLE III: Simulation setup - network

| | |
|---|---|
| **Pathloss** | Nakagami-m |
| **TX power** | 17dBm |
| **Antenna gain** | 0dBm |
| **Sensitivity threshold** | -90dBm |
| **Reception threshold** | -81dBm |
| **MAC Protocol** | DSRC |
| **Beacon interval** | 240ms+random(0,10)ms |
| **Beacon size** | 500Bytes |

play to determine the level of traffic jam and corresponding driving advisory which is represented using the terms $\{STRONG, MEDIUM, WEAK\}$. The rule-base is shown in Table I. For example, if the fuzzifier provides $SLOW$ average speed, $CLOSE$ distance, and $CURRENT$ up-to-dateness, $STRONG$ driving advisory is recommended. The fuzzy driving advisory in turn is translated into a corresponding crisp value using the membership function for the driving advisory; as explained in Subsection III-B, the degree of driving advisory is controlled by parameter $p_c$, i.e., smaller $p_c$ means the smaller probability of "overdeacceleration effect", thus representing stronger advisory. Figure 7 displays the membership function for the driving advisory. As shown, the membership function selects the suggested value of $p_c$ (i.e., $0.8{\cdot}p_b$) by [7] as the boundary value between $STRONG$ and $WEAK$ driving advisory.

### *D. Aggregator and Defuzzifier*

For determining the firing strength, we use the commonly used *MIN* method, and for the *aggregation* method, we use the *MAX* method – due to space constraints, we omit the details of the methods; see [16] for details. There are various methods for defuzzification such as maximum-decomposition method, center of maxima, and height defuzzification. We use the centroid method because it finds the "balance" point of the solution while other methods are limited to a narrow spectrum of applications. In the centroid method, the defuzzifier uses the center of gravity $y'$ of $\mu_p$ as the output of the fuzzy inference system. Formally, in a continuous fuzzy set, the center of gravity is computed as:

$$y' = \frac{\int_x y_i \mu_p(y) dy}{\int_x \mu_p(y) dy}.$$

## VI. Performance Evaluation

We evaluate the performance of FuzzyJam by comparing with the state-of-the-art traffic jam control protocol [7]. In particular, we measure the average travel time

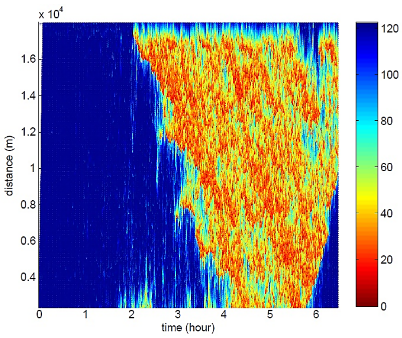


Fig. 9: Illustration of traffic jam

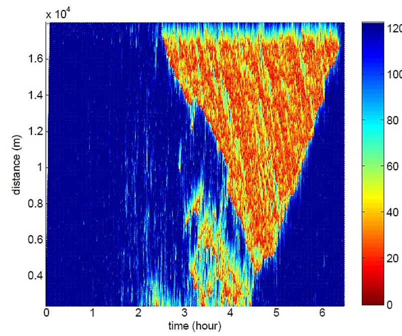


Fig. 10: After applying [7]

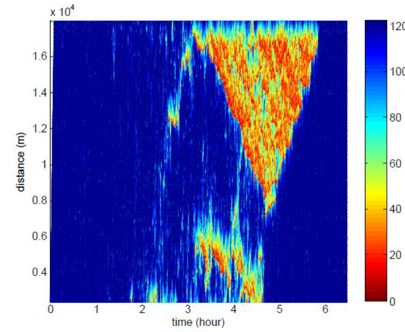


Fig. 11: After applying FuzzyJam

for different penetration rates. For the evaluation, we use JiST/SWANS [20][21] with extension by Ibrahim and Weigle [22] and Kilot [23].

### A. Simulation Setup

We consider a two-lane highway segment which spans 18Km. This segment has a 300-m-long on-ramp located 1.5Km from the downstream boundary. The on-ramp has a traffic flow of 450 vehicles/h. The traffic flow of the main road is adjusted as shown in Figure 8 such that a traffic jam is created. The traffic scenario used for this experiment is summarized in Table II. Vehicles communicate using DSRC protocol [24]. We use the Nakagami-m [25] for modeling the physical layer. Other network-related simulation settings are summarized in Table III. We use $\delta = 2$ and $\tau = 20$ for our simulations. We acknowledge that data communications failure can lead to the degraded performance of our protocol - however, due to space constraints, we leave the investigation on the effect of packet delivery ratio as our future work.

Figure 9 depicts the spatio-temporal changes of vehicular speed for the generated traffic. As shown, as the traffic flow increases, about 2 hours later a traffic jam appears at the on-ramp area. Figures 10 and 11 show samples of traffic generated by using the state-of-the-art approach and FuzzyJam, respectively. In the following section, we provide a detailed analysis on the difference.

### B. Average Travel Time

Figure 12 shows the average travel time for varying penetration rates. Each point represents the average of 30 simulation runs. The average travel time for Knorr *et al.* is reduced by up to 12.21% (compared with no solution applied) when 40% of penetration rate is used, whereas FuzzyJam reduces it by up to 17.782%. We observe that in all penetration rates, FuzzyJam outperforms Knorr *et al.*'s protocol; FuzzyJam has as much as 6.5% smaller average travel time. We also observe that the error bars (i.e., representing standard deviation) become smaller as the penetration rates increase, which indicates that the system shows higher reliability with higher penetration rates, although both protocols show significant improvement of the average travel time with even small penetration rates.

The average travel time is compared with the ideal travel time, which is measured by not increasing the traffic flow as suggested in Figure 8, i.e., by providing moderate traffic flow which does not cause traffic congestion. Consequently, we obtain the ideal travel time of 364 seconds. Figure 13 shows the travel time increase compared with the ideal travel time. As shown, FuzzyJam achieves nearly 10% improvement in all penetration rates compared with Knorr *et al.*

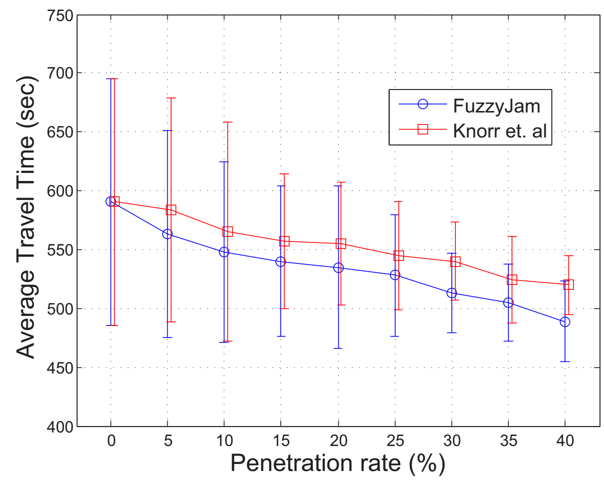


Fig. 12: Average travel time per penetration rate

## VII. Conclusions

We have presented FuzzyJam, a traffic jam control protocol using a fusion of CV technology and Fuzzy Logic. Based on an observation that Fuzzy Logic is better suited for representing the dymanics of a traffic jam, Fuzzy Logic is integrated into a CV-technology-based traffic jam control. Consequently, FuzzyJam achieves higher efficiency compared with the state-of-the-art traffic control protocol. As future work, we will apply FuzzyJam to realistic traffic data obtained from various traffic environments and analyze its performance to show its generality and practicality. We will also investigate the effect of driver model, i.e., on how driver reaction to driving advisory affects the performance.

## Acknowledgment

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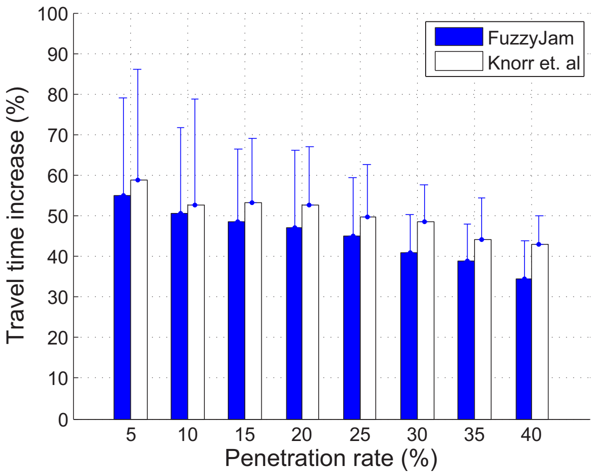


Fig. 13: Comparison with ideal traffic

by MSIP of Korea (2013K1A1A2A02078326). We would also like to thank the authors of [7] for generously providing their simulation code.

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