Multiple Vehicle Driving Control for Traffic Flow Efficiency

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Abstract—The dynamics of multi-agent in nature have been largely studied for a long time to investigate how the aggregation of agents can move smoothly in complex environments without collision. The main insights can be summarized such that the aggregated dynamics of animals and particles can be explained by an individual’s simple rules. In a similar vein, we conjecture that such simple rules for vehicle maneuvering can accommodate the fluid flow of traffic and reduce car accidents in highway and urban areas. In this paper, we first show the Reynolds’ three rules are applicable to autonomous driving on a single lane. Moreover, we provide additional requirements and algorithms for multiple lanes. Based on these results, we show that the proposed nature-inspired driving maneuver can increase traffic flow by 1) mitigating shockwave at bottlenecks and 2) extending the perception range for better path planning, which requires the support of the vehicle autonomy and wireless communication, respectively. Finally, we prove the feasibility of our work with experiments using multiple UAVs.

I. INTRODUCTION

Modern transportation systems are faced with technical challenges such as traffic flow efficiency, safety enhancement and environmental conservation. To tackle these challenges, the proposed approaches are classified into two parts: a top-down approach and a bottom-up approach. In the top-down approach, a central system provides real-time traffic information to drivers, which is expected to dissipate traffic jam and guide the traffic flow rationally. In the bottom-up approach, vehicle autonomy intervenes in the driving of the vehicle, that is, a vehicle is controlled electronically. The top-down approach has contributed mainly to traffic flow efficiency. In contrast, the bottom-up approach has been used for immediate vehicle safety.

As automotive electronics are beginning to be widely used, there have been several research efforts to increase traffic flow efficiency through vehicle autonomy such as platooning [1] and cooperative adaptive cruise control (CACC) [2]. In platooning, each vehicle is autonomously controlled to adopt the velocity of its predecessor by electronic braking and acceleration, respectively. Finally, we prove the feasibility of our work with experiments using multiple UAVs.

Reynolds’ three rules are applicable to autonomous driving on a single lane. Since Reynolds developed his model for birds in air space, multiple vehicles can achieve any benefit in terms of traffic flow. A bottleneck, caused by several reasons such as accident, lane drop, or lane merging, has been known to be one of the major causes of traffic jams. The bottleneck causes braking-to-stop that affects the reduced gap by platooning increases the traffic density. Each vehicle can sustain the velocity consensus such as a speed limit, which results in an increase of traffic flow [3]. CACC is one of the specific implementations of platooning.

However, the existing platooning is restricted to single lane cases. In general, transportation systems include multiple lanes that have different characteristics and scenarios such as lane drop, lane split, or lane merging. For these lane changing related issues, multiple lanes are much more difficult to deal with analytically and experimentally. The approaches proposed for lane changing issues, in the literature, are too complex to be used in practice. Moreover, a human does not drive in such a complex manner. Instead, a driver abstracts the driving strategy with simple rules, e.g., keeping a safe distance to the predecessor vehicle, braking for collision avoidance, and lane changing for velocity increase.

In this context, there have been many studies that have attempted to explain the aggregate dynamics of multiple agents using simple rules for quite some time [4]–[6]. In particular, animal aggregations have been known to move fast and smoothly in a distributed manner based on a number of simple rules. Reynolds introduced three fundamental laws, separation, alignment, and cohesion, for computer animation of bird flocking in his celebrated paper [7]. The distinct point of Reynolds’ work is that the proposed rules define an individual behavior with no assumption of a centralized coordination. The underlying insight of Reynolds’ work is that an independent individual behavior can achieve a common group goal by simple laws. From the perspective of an individual autonomous agent, the movement for animal aggregation is similar to traffic flow in transportation systems. The difference is whether there is free space or a lane system. These observations motivated us to apply animal aggregation dynamics to vehicle driving in order to increase the traffic flow efficiency in the multiple lane transportation systems.

In this paper, we first show that Reynolds’ three rules are applicable to vehicle driving in a single lane. Since Reynolds developed his model for birds in air space, multiple lanes were not considered in his model. Therefore, we provide additional requirements and algorithms necessary for driving in multiple lanes. The next fundamental question is whether these proposed nature-inspired driving approaches can achieve any benefit in terms of traffic flow. A bottleneck, caused by several reasons such as accident, lane drop, or lane merging, has been known to be one of the major causes of traffic jams. The bottleneck causes braking-to-stop that creates a shockwave [8]. In contrast, the aggregations in
nature smoothly go through bottlenecks in a cooperative manner. However, it is difficult to expect such cooperation on the road since a driver has a short line of sight such that vehicles can only predict short-term traffics in front of them, which can also be explained with the worst-case Nash equilibrium in a non-zero sum non-cooperative game [9].

To solve the problem, we proposed two approaches: 1) vehicle autonomy support and 2) perception range extension. First, vehicle autonomy intervenes in a bottleneck situation to reduce shockwave. In this paper, we show how smoothly the proposed nature-inspired driving strategy passes the bottleneck in a cooperative manner with experimental results using multiple unmanned autonomous vehicles (UAVs). Moreover, our approach is not too complex to apply to driving strategies of UAVs thanks to the simplicity of the Reynolds’ rules. Second, we conjecture that traffic flow is increased by the proposed vehicle aggregation movement laws with the support of long range sensing or wireless communication. We also prove this conjecture experimentally.

The contributions of this paper can be summarized as follows:

- This paper suggests an open problem of how vehicle autonomy contributes to traffic efficiency, particularly in terms of vehicle autonomy.
- We show that Reynolds’ three rules are applicable to unmanned autonomous automotive vehicle driving in a single lane.
- Based on the rules for a single lane, we provide additional requirements and algorithms necessary for multiple lane scenarios.
- We show the proposed nature-inspired driving strategy can increase traffic flow with the support of vehicle autonomy and wireless communication.
- We provide experimental results and scientific explanations from real experiments using the solutions and 4WD autonomous automotive vehicles.

The remainder of this paper examines the proposed nature-inspired driving strategy in more detail. Section II and III deal with driving in single and multiple lanes respectively. Section IV provides experimental verification of our work. Section V concludes this paper.

II. DRIVING IN A SINGLE LANE

In this section, a system model for autonomous driving in a single lane is provided. Based on the model, a decision making process is provided for obtaining the proper controls.

A. Reynolds’ Rules for Automotive Vehicles

Although Reynolds’ rules are intended to model bird flocking, the rules are applicable to automotive vehicles, specifically corresponding to the functionality of ACC\(^1\) and LKS\(^2\).

Not surprisingly, if ACC and LKS are supported for a vehicle, autonomous driving is possible in a single lane. For vehicle actuation, three independent control inputs are necessary: brake, throttle valve and steering wheel. The brake and throttle valve correspond to longitudinal control. Likewise, the steering wheel corresponds to lateral control. ACC and LKS take responsibility of longitudinal and lateral controls, respectively.

Reynolds’ rules are decomposed into three steps: separation, alignment, and cohesion. Separation corresponds to braking for maintaining a given safety gap. Alignment corresponds to adjusting the steering wheel toward the predecessor vehicle while staying in the current lane. Lastly, cohesion corresponds to opening the throttle valve up for maintaining the safety gap. ACC accommodates separation and cohesion, and LKS conducts alignment. ACC and LKS can achieve autonomous driving in a single lane. Consequently, driving in a single lane is explained by Reynolds’ rules.

B. System Model

To realize the autonomous driving, a system for longitudinal and lateral controls is described as follows:

1) Longitudinal Control: Necessary equations for longitudinal vehicle control have been derived from [14] and some changes have been made for our model. The longitudinal control is described as follows:

\[ \nu_k = \nu_{k-1} + \tau \cdot a_{k-1} \]  

where \( \nu_k \) is the vehicle speed at time \( k \), and \( \tau \) is a unit time, e.g., 1 s. \( a_k \) denotes the acceleration input at time \( k \), which is determined by

\[ a_k = \min(a_v, a_d) \]  

where \( a_v \) is the acceleration necessary to achieve the desired speed from the current speed. \( a_v \) is described as follows:

\[ a_v = \alpha \cdot (\nu_{\text{max}} (1 - e^{-R}) - \nu) \]  

where \( \alpha \) is a constant-speed error factor, \( \nu_{\text{max}} \) is the maximum allowable speed and \( R \) is the curvature radius. \( a_d \) is the acceleration necessary to adopt to the speed of the predecessor vehicle. If a predecessor vehicle exists, the acceleration demand \( a_d \) is described as follows:

\[ a_d = a_o \cdot a_p + a_p \cdot (\nu_p - \nu) + a_d \cdot (\tau - r_s) \]  

where \( a_o \) and \( a_p \) denote the acceleration and the speed of the target predecessor vehicle, respectively; \( a_d = \infty \), otherwise. \( r \) is the distance between the ego and the predecessor vehicle. \( a_o, a_p \) and \( a_d \) are constant factors. \( r_s \) is the minimum safe distance from the target predecessor, which is described as

\[ r_s = \frac{\nu^2}{2} \left( \frac{1}{a_p} - \frac{1}{a_d} \right) \]  

\(^1\)An adaptive cruise control (ACC) maintains appropriate distance from a predecessor vehicle [10], [11]. With the support of steering, the yaw-rate sensor, and the range sensor input, ACC recognizes the immediate predecessor in the same lane. Accordingly, throttle valve and electric brake input messages are generated to sustain a safe distance from the predecessor vehicle. ACC deals with only longitudinal vehicle control.

\(^2\)A lane keeping system (LKS) recognizes the current lane and then calculates the amount of errors from the reference point and angle. The reference point is typically the center point of the lane. The reference angle is typically the tangential angle of the lane. The sensing method of recognizing the lane is largely classified into vision-based [12] or LIDAR-based approaches [13].
where \( d_p \) and \( d \) denote the deceleration capabilities of the ego and the target vehicle, respectively.

2) Lateral Control: We derive the following equations for lateral vehicle control from [1] with some changes to apply our scenario. Figure 1 shows a system model of LKS whose desired path is the center of the lane. The system dynamics for UAV lateral control is described as follows:

\[
\dot{x} = Ax + B\delta + C\dot{\Psi}_{des}
\]

where \( x = [e_1, e_1, e_2, e_2] \), \( e_1 \) is the lateral position error, and \( e_2 \) is the yaw angle difference between the current heading and the tangential line of the desired path. \( A, B \) and \( C \) are described as follows:

\[
A = \begin{bmatrix}
0 & 1 & 0 & 0 \\
0 & -c_f + c_r & 0 & 0 \\
0 & 0 & 0 & -c_f + c_r \\
c_l & -c_f + c_r & -c_l - c_f & -c_f + c_r + c_l
\end{bmatrix}
\]

\[
B = \begin{bmatrix}
0 \\
0 \\
c_l & 0 \\
c_l & 0
\end{bmatrix}
\]

\[
C = \begin{bmatrix}
0 & 0 & 0 & -\nu \\
c_f + c_r & -c_f + c_r & -c_l - c_f & -c_f + c_r + c_l
\end{bmatrix}
\]

where \( c_f \) and \( c_r \) are front and rear cornering stiffness, respectively. \( I \) denotes the yaw moment of inertia and \( m \) is the vehicle mass, \( \nu \) denotes a vehicle velocity, \( l_f \) and \( l_r \) are the longitudinal distance from the center of gravity to front and rear tires, respectively.

\( \delta \) is the front wheel steering angle input, and \( \dot{\Psi}_{des} \) is the desired yaw rate, which is defined as follows:

\[
\dot{\Psi}_{des} = \nu / R
\]

where \( R \) is the curvature radius, which can be estimated if more than three points are given on the desired path, as shown in Figure 2. The points can be provided by foresight sensing data. The curvature radius \( R \) is formulated as follows:

\[
\cos^{-1}\left(\frac{2R}{l_1}\right) + \cos^{-1}\left(\frac{2R}{l_2}\right) = \pi - \theta
\]

where \( l_1 \) and \( l_2 \) are the distances between given points on the desired path (see Fig. 2). Note that (8) is not a closed-form.

Consequently, control variables are the steering angle \( \delta \) and the longitudinal velocity \( \nu \) in (6). The longitudinal velocity \( \nu \) is determined by the acceleration input \( a_k \) shown in (1). The control variables at time \( k \) are rewritten in a recursive form as follows:

\[
(\delta_k, a_k) = (\delta_{k-1} + \Delta\delta_k, a_{k-1} + \Delta a_k).
\]

The problem is redefined as finding the sequence of optimal control vector \( \Delta u_k = [\Delta\delta_k, \Delta a_k] \).

C. Measurement Model

The proposed system detects the lane using vision camera. The vision camera derives \( s_l \) and \( s_r \), shown in Fig. 1, i.e., how distant the ego vehicle is located from the left and the right lane, respectively. The measurement vector at time \( k \) is written as \( y_k = [s_l, s_r] \), which is formulated by

\[
\begin{bmatrix}
s_l \\
s_r
\end{bmatrix} = \begin{bmatrix}
\frac{r_w}{\cos c_2} - \frac{l_w}{2} & \frac{r_w}{\cos c_2} - \frac{l_w}{2} \\
\frac{s_l}{\nu} & \frac{s_r}{\nu}
\end{bmatrix} + \begin{bmatrix}
\nu^l_k \\
\nu^r_k
\end{bmatrix}
\]

where \( l_w \) is the width of the ego vehicle and \( r_w \) is the lane width. \([\nu^l_k, \nu^r_k]^T\) is the measurement error vector. Note that the measurement model (10) is non-linear.

D. Decision Making Process

In (10), the variable control \( \Delta u_k \) is obtained in real-time by the following formulation:

\[
\Delta u_k^* = \arg\min_{\Delta u_k} \| r_k - y_k \|_p + q \| \Delta u_k \|_p,
\]

where \( r, q \in \mathbb{R}^+ \), and \( \| \cdot \|_p \) is p-norm. In our work, \( p = 2 \). The reference value \( r_k \) is the desired path that is defined as

\[
r_k = \begin{bmatrix}
\frac{r_w - l_w}{2} \\
\frac{r_w - l_w}{2}
\end{bmatrix}^T.
\]

Finally, longitudinal and lateral control inputs are obtained on-line by solving (11) and (12). Although this section investigated a single lane scenario, the lane width \( r_w \) can be unavailable in some scenarios such as partially removed lane markings, or disturbances from sun-light or shadows. To solve this problem, we recovered removed lane markings with an interpolation method and mitigated disturbances with vision filters (see Fig. 5.) If we consider beyond a single lane, a special path planning algorithm necessary to obtain a desired path. However, this is quite complex because of the various scenarios such as intersections, junctions, or no lane space. Path planning itself is beyond the scope of this paper. Note that we focus on single lane and multiple lanes in this paper.
III. DRIVING IN MULTIPLE LANES

In the previous section, it was shown that ACC and LKS are sufficient conditions for autonomous driving in a single lane. In this section, lane changing issues are addressed in terms of the requirements and algorithms, which are necessarily incurred for driving in multiple lanes.

A. Lane Changing Problem

In autonomous driving in a single lane, the references for the longitudinal and lateral control are definitely always provided, as addressed in Sec. II. On the other hand, driving in multiple lanes is not straightforward. Lane changing is decomposed into two parts. First, a driver has to constantly make the decision of whether to keep the current lane or change into another lane. Second, the driver has to decide how to change lanes if lane changing is decided.

1) Lane Changing Decision Problem: The major reason for lane changing is the expectation of some benefits by moving into another lane. In this paper, vehicle velocity is considered as the benefit. The best strategy is to keep the current lane, if a certain amount of velocity increase is not expected by lane changing, or a certain amount of velocity decrease is not expected by lane keeping. The real-world examples where lane changing has to be considered are typically a low-speed predecessor vehicle or obstacles in the same lane, and a bottleneck caused by accidents, lane-drop or lane-merging. If there is no obstacle in front, a vehicle can increase the velocity up to the speed limit. Figure 3 shows the sequence diagram to deal with the above mentioned scenarios.

Suppose that no predecessor vehicle is in front of the ego-vehicle (S1). The vehicle is accelerated up to maximum speed keeping the current lane if there is no lane drop or merging (S2). Otherwise, the vehicle notifies a lane drop to the successor vehicles typically through wireless communications (S3). The bottleneck notification is intended to mitigate the shockwave incurred by the sudden braking of the predecessor vehicles. Likewise, the vehicle can predict the traffic flow and lane situation in front if there is any information delivered from the predecessor vehicles (S4). In our experiments, we use a Fuzzy logic controller proposed in [16]. The longitudional controller has a role in avoiding collisions between vehicles during lane changing. For vehicle collision avoidance, the lane changing maneuver has to control its speed to maintain a minimum spatial safety gap and safety level proposed in [17], [18]. We implemented all these considerations for the real experiments.

B. Long-term Perspective Driving

One thing not explained in Fig. 3 is the part about the information from predecessors. Before we propose our schemes, we will introduce the concept of short and long term perspective driving first. Let us see (13) from the view point of $T_s$. $T_s^{l}$ and $T_s^{s}$ represent a long-term and short-term perspective, respectively, i.e., $T_s^{l} > T_s^{s}$. With $T_s^{l}$ and $T_s^{s}$, a lane changing decision can be formulated as follows. The

\[
V(C, T_s, \phi) = \frac{1}{|T_s|} \sum_{i \in C} \int_{T_s} a_t(i, \phi) dt,
\]

Fig. 3. Procedure of cooperative vehicle controller.

changing by the ego vehicle, which is represented as follows:

\[
\phi = \arg \max_{\phi_l, \phi_c, \phi_r} \{ V(\phi_l), V(\phi_c) - \eta, V(\phi_r) \},
\]

where $\phi_l$, $\phi_c$, and $\phi_r$ represent a left, current and right lane, respectively, $\eta$ is the threshold for mitigating oscillation, i.e., frequent lane changing.

2) Execution of Lane Changing: A lane changing controller includes a lateral and longitudinal controller. In this paper, no special lateral controller is newly proposed. For our experiments, we used a Fuzzy logic controller proposed in [16]. The longitudional controller has a role in avoiding collisions between vehicles during lane changing. For vehicle collision avoidance, the lane changing maneuver has to control its speed to maintain a minimum spatial safety gap and safety level proposed in [17], [18]. We implemented all these considerations for the real experiments.

\[
\sum_{i \in C} a_t(i, \phi) dt,
\]

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where $T_s^{l}$ and $T_s^{s}$ represent a long-term and short-term perspective, respectively, i.e., $T_s^{l} > T_s^{s}$. With $T_s^{l}$ and $T_s^{s}$, a lane changing decision can be formulated as follows. The

\[
V(C, T_s, \phi) = \frac{1}{|T_s|} \sum_{i \in C} \int_{T_s} a_t(i, \phi) dt,
\]

where $\phi_l$, $\phi_c$, and $\phi_r$ represent a left, current and right lane, respectively, $\eta$ is the threshold for mitigating oscillation, i.e., frequent lane changing.

Fig. 3. Procedure of cooperative vehicle controller.
vehicle moves from the current lane \( \phi_c \) to \( \phi \) if

\[
V(C, T_s^c, \phi) > V(C, T_s^c, \phi_c) + \Delta \omega_{lh},
\]

where \( \Delta \omega_{lh} \) is used to avoid oscillation and reflect opportunity costs. Since \( T_s^l > T_s^c \), the vehicle makes a decision for a long-term benefit rather than a short-term one. The next question is how to make \( T_s^l \gg T_s^c \). Perception range extension, e.g., multi-hop sensing or wireless communications, is one of the major methods to achieve a large \( T_s^l \). In this paper, we conducted experiments with wireless communications. We will show the results in the next section.

C. Lane Drop and Smooth Merging

A bottleneck is known as one of the major causes of a traffic jam. If the successor vehicles can predict a lane drop or merging, they can prepare in advance for the bottleneck point. Arem et al. showed that bottleneck notification through communication could increase traffic flow in the case of a high CACC penetration rate [3]. However, the authors mentioned no specific algorithm for a lane changing strategy to cope with bottlenecks.

Figure 4 shows the proposed lane merging method in the case where four vehicles are in two lanes. Concisely, two cars in the left lane can join the right lane smoothly without braking like in the bottom of Fig. 4, if \( d_1, d_2, d_3 \) are positive and \( v_1 = v_2 = v_3 = v_4 \). \( v_{1,...,4} \) denotes the velocity of the vehicles from right to left in Fig. 4, respectively.

For such smooth merging, vehicles have to know not only the fact that a lane drop will appear but its position as well. One typical solution is to rely on GPS and navigational maps. One of the other solutions is that a predecessor vehicle perceiving a coming lane drop delivers the lane drop and its position to the successors through wireless communications. The advantage of this method is that it works even if GPS is unavailable or a navigational map is incorrect.

Before the lane drop notification is given, an individual vehicle maintains a certain sized safety gap with the predecessor vehicle in the same lane. Note that the vehicle has to conduct ACC with the predecessor in the adjacent lane shown in the upper road of Fig. 4. We call this as a zig-zag formation. If all vehicles achieve a speed consensus and zig-zag formation, the vehicle platoon can merge smoothly shown in the bottom of Fig. 4. We also implemented this smooth lane merging successfully, which is provided in detail in the following section.
Fig. 5. On-line post-processing results of (a) current lane and vehicle detection, and (b) multiple lanes detection. The green line depicts the center of the lane, i.e., the desired path $r_k$.

Fig. 6. Test-bed for multiple unmanned autonomous ground vehicles.

B. Evaluation

First of all, we experimentally proved that Reynolds’ three laws were sufficient conditions for autonomous ground vehicle driving in a single lane. In Sec. II.A, we explained that multiple vehicles embedded with ACC and LKS can achieve fast and smooth driving in a single lane. In the case of a single lane, the lane and predecessor vehicles always give references such as a desired path and minimum safety gap. Therefore, a single lane can be somewhat straightforward. However, the case of multiple lanes is much more complicated.

Our experiments were also conducted on multiple lanes with three UAVs. To evaluate our works, we measured traffic flow at the end of a lane drop, i.e., the flag in bottom right of Fig. 7. More specifically, traffic flow was defined as the inverse of the arrival time gap between the first and third vehicles at the flag point in Fig. 7. Hence, the unit of traffic flow is $s^{-1}$. The arrival time was independently measured outside of the UAVs. To mitigate the effect of the initial conditions, three UAVs started at the flag and turned counterclockwise. Then, we measured the arrival time after driving the whole track once.

The starting point was the flag point in the bottom right of Fig. 7. At that point, the vehicles form a single lane platoon. At a lane split point, the second vehicle changed to the right lane according to S1-S5-S6-Lane changing in Fig. 3. Right before the lane drop, the first and second vehicle recognized the lane drop and then sent this lane drop detection to the successor vehicle, i.e., the third vehicle. All vehicles formed the zig-zag formation in a distributed manner.

Figure 8 shows the traffic flow according to the target vehicle speed and safety gap that correspond to $v_{\text{max}}$ in (3) and $r_s$ in (5), respectively. Note that we can see that there is an optimal control point to maximize the traffic flow in Fig. 8. Figure 9 shows the traffic flow according to the target speed at the end point of the lane drop. As the average speed is increased, the total traffic flow also increased. At relatively low speed, i.e., up to 0.8 m/s, traffic flow increased roughly linearly. From 0.8 m/s, the second derivative of the traffic flow was negative.

The major reason is that the high speed makes vehicle control difficult. Each UAV has collision avoidance mechanisms whose priority is the highest. If an UAV recognizes the high probability of collision, the UAV immediately slows down. Therefore, under high speed, a frequent shockwave is incurred by sudden braking for vehicle collision avoidance. Note that given the vehicle speed, traffic flow is not increased according to the growth of the safety gap. Let us investigate the impact of the safety gap.

Figure 10 shows the traffic flow from the perspective of the safety gap. In Fig. 10, there is an optimal safety gap to maximize the traffic flow. Intuitively, the traffic flow decreased according to the growth of the safety gap from 0.6 m to 1.0 m. However, the traffic flow also decreased in situations with a safety gap that was too small from 0.4 m to 0.6 m. Similar to high speed in Fig. 9, an insufficient safety gap can incur sudden braking for collision avoidance. Smooth lane merging without shockwave requires a certain sized safety gap. A marginal safety gap from the sufficient safety gap, e.g., 0.6 m in Fig. 10, contributed to the decrease in traffic density. For a given safety gap, the traffic flow did not increase according to the growth of the vehicle speed.
Consequently, the proposed smooth lane merging method minimizes the shockwave at a bottleneck, which can achieve fluid traffic flow. We also discovered that there is an optimal consensus for vehicle speed and the safety gap to maximize the traffic flow at a lane drop point. One could say that the speed of our UAVs was not fast enough to compare to road traffic. However, the size of our vehicle was less than ten times a real vehicle. Considering the size of the vehicle, the authors think that the speed was fast enough and the results are scalable to road traffic. In addition, a longer platoon is known to be more susceptible to the propagation of shockwave. We will further investigate the relationship between upstream shockwave propagation and platoon size theoretically and experimentally based on this work.

V. CONCLUSION

In this paper, we investigated how vehicle autonomy can contribute to traffic flow efficiency. To answer the question, ACC and LKS were derived from Reynolds’ three laws as minimum requirements for autonomous single lane driving. To cope with autonomous driving in multiple lanes, we derived LCS as a required component and proposed algorithms for multiple vehicles in multiple lanes. In addition, we proposed the concept of smooth lane merging and long-term perspective driving. Long-term perspective driving is expected to encourage voluntary cooperation on road. One of the major methods to provide such long-term perspective is to let the following vehicles know in-front traffic and road situations through wireless communications. In this context, the role of wireless communication was investigated.

We verified all these proposal and deduction with UAVs on a test track including various scenarios on the road. The experimental results show the proposed requirements and algorithms works well in multiple lanes as well as a single lane. In particular, the proposed smooth lane changing explicitly contributes to traffic flow increase by shockwave mitigation due to an optimal safety gap and velocity consensus.

REFERENCES


