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Empirical Investigation of the Impact of the Moving Light Guidance System on Lane-Changing Phenomena

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Abstract

Unintentional speed reductions in bottleneck sections significantly contribute to traffic congestion on freeways. To address this issue, the Moving Light Guidance System (MLGS) has been implemented as a traffic management measure designed to counteract speed reductions and facilitate recovery by adjusting its lighting speed to slightly exceed observed vehicle speeds. This paper investigates the MLGS's impact on lane-changing behavior. Our findings show that, the number of lane changes higher with MLGS than without MLGS. Furthermore, these results suggest that MLGS contributes to inducing lane changes by improving vehicle speed and its homogenization, as well as enhancing the homogenization of headway distances. Additionally, we explore the relationship between traffic states and lane-changing phenomena. The results suggest that MLGS may facilitate lane changes as drivers seek to maintain their desired speed. Furthermore, we analysed the average headway distance between the new leader and new follower during a lane change. It shows that the mean headway distance is smaller, suggesting that MLGS helps create lane-changeable gaps. In summary, the MLGS appears to improve traffic conditions in the passing lane. Under MLGS there are more lane changes likely to be caused by the availability of gaps based on headway distance and the desire to maintain desired speed. This paper shows the mechanisms of MLGS operations and shows that MLGS hence may help reduce traffic disturbances in the other lane, where merging vehicles frequently enter.

Keywords Moving light guidance system · Lane change · Vehicle trajectory data · Freeway

1 Introduction

Unintentional speed disturbance in bottleneck sections of freeways, such as merging zones and tunnels, cause recurrent traffic congestion on freeways. Additionally, inefficient lane changes and weaving, due to short-span diverging and merging areas, also induce bottlenecks [1]. While lane expansion and ramp reconstruction could theoretically mitigate these issues, such solutions are often impractical due to limited land availability. Consequently, freeway administrators employ methods such as speed-reduction warnings and lane utilization adjustments to respond to traffic flow changes over time [2, 3]. Globally, variable speed limits and ramp metering are commonly used for the tools of active traffic management; however, Japanese freeway administrators have not implemented these measures for this purpose, as speed limit authority lies with the police and is primarily intended as a safety measure [4]. Alternatively, since 2013, in Japan the Moving Light Guidance System (MLGS) has been implemented as a traffic flow management measure.

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This system is designed to mitigate speed reductions and promote speed recovery by adjusting the lighting speed to slightly exceed the observed vehicle speed, as illustrated in Fig. 1. This figure shows the MLGS at the Fukae Sag section on the Kobe Route of the Hanshin Expressway, where lighting equipment is installed at regular intervals along the wall, as depicted in the video [5].

This system has been shown to reduce traffic congestion and improve throughput, as evidenced by results from detectors, simulations, and car-following experiments. Masumoto et al. [6] demonstrated that the impact on traffic flow varies with lighting patterns applied in uphill segments of urban highway bottlenecks. Their results showed significant effects when the lighting speed was set slightly above the average vehicle speed per minute, contributing to a 60–70% reduction in daily congestion duration and a 4.3%−7.3% increase in throughput over five-minute intervals. Kameoka et al. [7] conducted operational experiments of the MLGS at sags and tunnel bottlenecks, revealing that the system positively influences throughput under congested conditions, with results showing significance at the 5% level. Terada et al. [8]evaluated the effects of MLGS in mixed traffic environments containing both manually driven and autonomous vehicles. They found that the system led to a reduction in the headway of manually driven vehicles, which subsequently improved overall traffic flow rate. Tabira and Shiomi [9] conducted a quantitative analysis of relative speed variability based on car-following experiments on the freeway under different MLGS operating patterns. Their findings suggest that MLGS contributes to more uniform car-following behavior and enhances sensitivity to relative speed changes.

Based on these examples, MLGS may improve traffic flow and throughput, and its influence on car-following behavior has been demonstrated. Furthermore, Zhang et al. [10] analyzed the effect of MLGS on lane-change behavior through parameter estimation of a lane-changing model using video data. Their results showed that the speed difference and the density differences between the two lanes can be affected by the MLGS. However, to the best of the author's knowledge, its impact on lane-changing behavior from a microscopic perspective remains largely unexplored. Previous research suggests that lane-changing events often cause disturbances in traffic flow [1] by influencing the driving behavior of lane-changing vehicles [11] and the new follower [12]. Additionally, many studies indicate that lane-changing motivations involve feasibility based on density in the original and target lanes [13], the positions and speeds of nearby vehicles and the desire to maintain a target speed [14]. Other studies have shown that using connected vehicle technologies to control merging can help reduce disruptions [15]. Given the findings from previous studies, we hypothesize that MLGS may also positively impact lane-changing dynamics, potentially enhancing overall traffic flow by reducing disturbances. Specifically, we expect the MLGS contributes to the creation of available gaps by homogenizing vehicle speed and headway distance, and facilitates maintaining the desired speed as lane changes are motivated by the increased speed in the target lane. However, the effect of MLGS on lane-changing behavior is still not unveiled.

Fig. 1 Moving light guidance system at the Fukae Sag section on the Kobe Route of the Hanshin Expressway

In this paper, we examine the differences in lane-changing phenomena with and without MLGS, analyzing individual vehicle trajectory data. Based on the findings, we discuss how the MLGS contributes to mitigating traffic congestion, particularly through its influence on lane-changing phenomena.

The remainder of this paper is organized as follows: Section 2 reviews previous studies on lane-change effects and introduces our hypothesis on the impact of MLGS on lane-changing phenomena. Section 3 explains the methods used to assess the MLGS's influence on lane-changing behavior. Section 4 details the MLGS setup, target study section, and all-vehicle trajectory dataset. Section 5 discusses the findings. Finally, Section 6 presents the conclusions, offering insights for future research and operational improvements for MLGS.

2 State-of-the-Art of the Effect of Lane Changes

Lane changes can disrupt traffic flow due to shifts in the driving behavior of vehicles surrounding the lane-changing vehicle. Patire and Cassidy [1] analyzed the impact of lane changes on traffic congestion using trajectory data from a three-lane freeway segment. Their results showed that lane changes towards the shoulder lane to avoid speed disturbances can help prevent deceleration early in the rush. However, as traffic increases later in the rush, these lane changes induce deceleration, which spreads laterally and eventually forms a persistent queue across all lanes. Zheng et al. [11] studied the effects of lane changes by measuring induced transient behavior and changes in driver characteristics. Their findings suggest that lane changes involve a pre-insertion transition followed by a relaxation phase, creating a regressive impact on driver behavior. Chen et al. [12] studied the behavior of the new follower (NF) in the target lane during the pre-insertion process using trajectory data. The results indicated that this process significantly impacts the NF's movement, causing gap creation and speed reduction.

Lane-changing affects the driving behavior of vehicles around a lane-changing vehicle, often negatively impacting traffic flow, for instance by creating voids. Conversely, drivers aiming to change lanes do so based on surrounding conditions. Knoop et al. [13] analyzed lane-change frequency and associated incentives to validate microscopic and macroscopic lane-change models. They found that drivers change lanes approximately once every two kilometers and that lane-change frequency increases with density in both the original and target lanes. Gipps [14] structured drivers' decision processes for lane changes and simulated evaluations, showing that maintaining desired speed is a key factor in lane-changing decisions, even when turns are distant. Kita [16] introduced a game-theoretic model to represent interactions between merging and through cars in merging sections. This model, which considers only the position and speed of adjacent vehicles, was validated through video analysis and demonstrated the model's relevance to driving behavior. Treiber and Kesting [17] proposed a lane-change decision model where drivers maximize utility while ensuring safety. Shiomi et al. [18] introduced a multi-lane first-order traffic flow model depicting lane-change dynamics. In this model, drivers change lanes to optimize their utility, accounting for factors such as the keep-left rule, sensitivity to travel time, and limited information about surrounding traffic. The model demonstrated lane-flow equilibrium and the propagation of congestion queues, offering insights into lane-change behavior and traffic stability.

There are various management methods designed to promote efficient lane changes, especially in mixed-vehicle traffic. Scarinci et al. [19] introduced a merging assistant strategy that creates gaps for vehicles entering from on-ramps via traffic light control, reducing traffic disruptions. Simulation results showed this approach decreased congestion and the number of lane-merging vehicles. Letter and Elefteriadou [15] proposed a longitudinal freeway merging control algorithm to maximize the average travel speed of fully automated connected vehicles by optimizing their trajectories, with simulations indicating reduced travel time, higher average speed, and improved throughput during uncongested conditions. Khondaker and Kattan [20] developed an anticipatory Variable Speed Limit (VSL) strategy that minimizes lane changes and braking, using trajectory data from probe vehicles; their findings suggested this approach reduces lane changes and results in smoother acceleration and deceleration patterns. Subraveti et al. [21] introduced a method to strategically induce lane changes near bottlenecks in mixed traffic, which simulation results showed could improve throughput even at low to moderate penetration rates of connected automated vehicles (CAVs). Roncoli et al. [22] proposed a feedback control strategy aimed at maximizing throughput at bottleneck locations while distributing the total density in the bottleneck area across lanes according to a predefined policy through optimal lane assignment of vehicles upstream of the bottleneck. The results demonstrate the effectiveness of this strategy in improving traffic performance.

These studies have shown that strategies like controlled merging gaps and speed regulation can alleviate congestion and improve traffic throughput. In a similar way, we anticipate that the MLGS could positively impact traffic flow and efficiency by influencing lane-changing behavior. According to previous research, MLGS has been shown to improve vehicle speed [6] and throughput [7], as well as affect car-following behavior by enhancing drivers' awareness of relative speed and distance. However, despite the known impact of lane changes on traffic flow [1], there is limited research on the specific influence of MLGS on lane-changing behavior. Inefficient lane changes often disrupt traffic flow, with drivers changing lanes to maintain their desired speed while considering the positions and speeds of surrounding vehicles [14]. Recent studies indicate that lane-changing assistance strategies using connected vehicle technology can help mitigate the adverse effects of lane changes [19].

Given these findings, especially in high lane-changing areas such as merging sections [21], we expect MLGS to support smoother lane changes, which could lead to improved traffic flow and reduced disturbances from lane changes. However, to the best of our knowledge, there are no papers which explicitly address the effect of MLGS on lane changes.

3 Methodology

This section outlines the method used to identify differences in lane-changing behavior, utilizing datasets separated by MLGS operation status (with and without MLGS operation). In short, the method is as follows: First, we compare the average number of lane changes to identify differences in lane-changing phenomena with MLGS. Based on these differences, we then assess traffic conditions in the target lane that receives lane changes, specifically examining variations in average vehicle speed and distance with and without MLGS. Finally, we analyze the relationship between the origin and target lanes during lane changes, focusing on maintaining drivers' desired speeds as a motivation for lane changes. Specifically, we calculate the average speed difference between the origin and target lanes and compare this, along with the related lane change frequency, between MLGS operational and non-operational conditions.

In this paper, we analyze and compare lane change conditions with and without the operation of the MLGS to clarify its impact. The analysis process consists of the steps as shown in Fig. 2. First, assuming that lane changes are influenced by improved traffic flow in the passing lane, we calculate the number of lane changes per target area (defined by unit section and time) and average this count for each density pair (driving lane and passing lane). Next, to assess differences in traffic conditions under MLGS operation and non-operation, we investigate the distribution of average vehicle speed and average headway distance in the passing lane across each target area to assess its traffic conditions. Finally, we hypothesize that improved traffic conditions in the passing lane encourage lane changes, motivated by enhanced lane-change opportunities and drivers' desire to maintain target speeds. To explore this hypothesis, we calculate the average speed difference between the driving lane (origin) and the passing lane (target) and confirm the average frequency of lane changes for each speed difference. Furthermore, we examine the headway distance between the new leader and new follower in the passing lane when a lane change occurs.

Through this process, we aim to clarify the mechanism by which MLGS impacts lane-change phenomena and its potential for optimizing traffic flow on freeways.

3.1 Distribution of Traffic Density

To determine the target density range for analysis, we generate the traffic density distribution for both the driving and passing lanes, and remove these density range that there are a few samples for results not to be affected by scarce data. Traffic density, k, is calculated for each target area, defined by a 10-second interval over a 600-meter section, based on Edie's definition [23]. The frequency of each traffic density pair across the lanes is then recorded. This distribution is visualized in a scatter plot, offering a clear depiction of the available range of density pairs. Traffic density is calculated using Eqs. (1),

$$k_i = \sum_{j \in N_i} t_{ij} / A_i \tag{1}$$

where A_i represents the target area (unit section and time i), t_{ij} is the travel time of each vehicle within A_i, and N_i denotes the set of observed vehicles in A_i.

3.2 Distribution of Average Rate of Lane Changes

At this section, the merging ramp connects to the driving lane, leading to frequent lane changes from the driving lane to the passing lane as vehicles adjust to accommodate merging traffic. To assess differences in lane changes with and without MLGS operation, we calculate the number of lane changes per vehicle-kilometer (LC) for each traffic density pair across both lanes. Specifically, we count the number of lane changes per vehicle and aggregate the total for each target area, following the same approach used in the traffic density pairing calculation, dividing this value by the total distance traveled in the target area. This provides data consisting of traffic density pairs alongside their corresponding lane change counts. Additionally, we exclude data where the density pair's occurrence frequency is below 0.5%, ensuring that low-frequency density pairs do not skew the analysis. The lane change count within the density pair, k_1 and k_2, $LC_{k_1k_2}$, can be formulated as shown in Eq. (2).

$$LC_{k_1k_2} = \sum_{i \in D_{k_1k_2}} c^i_{k_1k_2} / l_{k_1k_2} \tag{2}$$

Where k_1 and k_2 represent the density values for the driving lane and the passing lane, respectively. The variable $c^i_{k_1k_2}$ denotes the total number of lane changes associated with each data i within density pair k_1 and k_2. Meanwhile $l_{k_1k_2}$ represents the total distance traveled of data i in density pair k_1 and k_2 within the dataset, and $D_{k_1k_2}$ refers to the set of data within the density pair. If there is difference between with and without MLGS, to reveal the former conjecture, we investigate the distribution of average speed and headway distance on target lane in section 4.3, and the relationship between speed differences and the number of lane-changes are described in section 4.4.

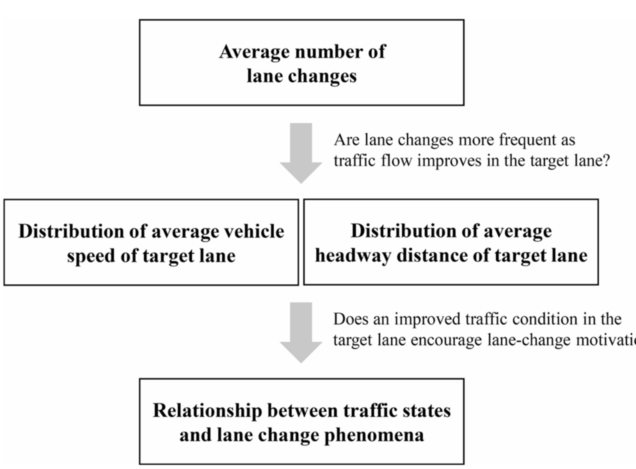


Fig. 2 Hypothesis and analysis method

3.3 Distribution of Average Speed and Average Headway Distance

To evaluate the influence of MLGS on lane-change behavior, we compare the distribution of average vehicle speed and average headway distance in the passing lane between conditions with and without MLGS operation.

The average vehicle speed V is computed as the mean of vehicle speeds recorded at 0.1-second intervals, aggregated over 10-second periods, based on Edie's definition [23], as shown in Eqs. (3),

$$V_i = \sum_{j \in N_i} d_{ij} / \sum_{j \in N_i} t_{ij} \tag{3}$$

where d_{ij} is the travel distance of each vehicle within the target area (unit section and time i), t_{ij} is the travel time of each vehicle within the target area, and N_i denotes the set of observed vehicles in the target area.

Similarly, the average headway distance is determined as the mean of headway distances between recorded kilo post values at 0.1-second intervals, also aggregated over 10-second periods as shown in Eqs. (4),

$$h_i = \sum_{j \in N_i} (p_{ij} - p_{ij-1}) / a_i \tag{4}$$

where a_i represents the total number of vehicles during the 10-second unit time i recorded every 0.1 s, p_{ij} is the position of each vehicle j within i, p_{ij-1} is the position of each leader vehicle $j-1$ within i, and N_i denotes the set of observed vehicles during i recorded every 0.1 s.

Previous studies [13] indicate that drivers make lane-change decisions based on traffic conditions in the target lane, suggesting that these metrics are key indicators of MLGS impact. For a consistent comparison, the data is categorized into four density ranges: 36–38 veh/km, 38–40 veh/km, 40–42 veh/km, and 42–44 veh/km. The average vehicle speed is calculated by taking the mean of vehicle speeds recorded every 0.1 s, aggregated over 10-second intervals, and the distribution is based on these averaged values. In this table, the number of data points, the mean value, and the standard deviation are presented for conditions with and without MLGS operation. Additionally, the results of a t-test (comparing the mean values) and an f-test (comparing the standard deviations) are included to highlight the differences in means and variances under these conditions.

3.4 Relationship Between Traffic States and Lane Change Phenomena

To assess the MLGS's effect on lane-changing motivation, we calculate the average speed difference by subtracting the driving lane's average vehicle speed from that of the passing lane. The average vehicle speed, as defined in the previous section, is computed based on Edie's definition. Finally, the average number of lane changes occurred at different speed differences is analyzed to see if MLGS impacts the frequency of lane changes by encouraging drivers to switch lanes to maintain their desired speed. The average number of lane changes is calculated by aggregating density values in intervals of 2.5 veh/km. To ensure the reliability of the analysis, we exclude data where the occurrence frequency of the average speed difference, rounded to the nearest integer, is less than one. Additionally, to identify lane-changing conditions focusing on gaps, we calculate the distribution of the gap between the new leader and new follower in the passing lane just before a lane change is implemented. The gap is determined by headway distances between recorded kilopost values of each vehicle at 0.1-second intervals, aggregated over 10-second periods.

4 Overview of MLGS and Data

For this research we look for a section equipped with MLGS and for which individual vehicle trajectories can be recorded. We found that the Higashi-Osaka Route of the Hanshin Expressway.

In this study, we focus on the MLGS-equipped section shown in Fig. 3. This section spans approximately 600 m (from 1.8 to 2.4 kp). It includes a two-lane segment with a merging ramp, where the driving lane, which is connected

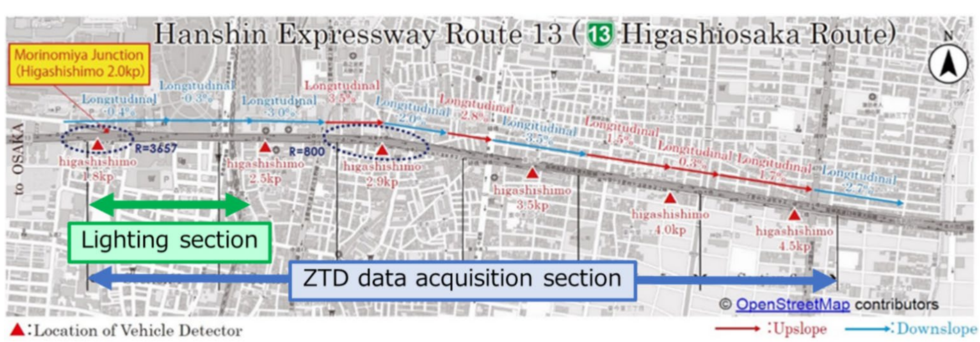


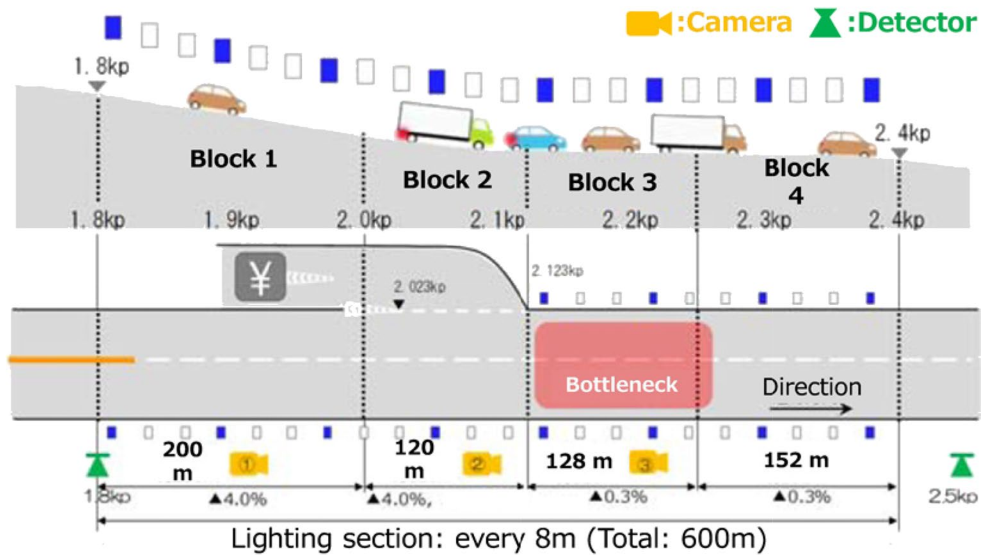
Fig. 3 Subject section

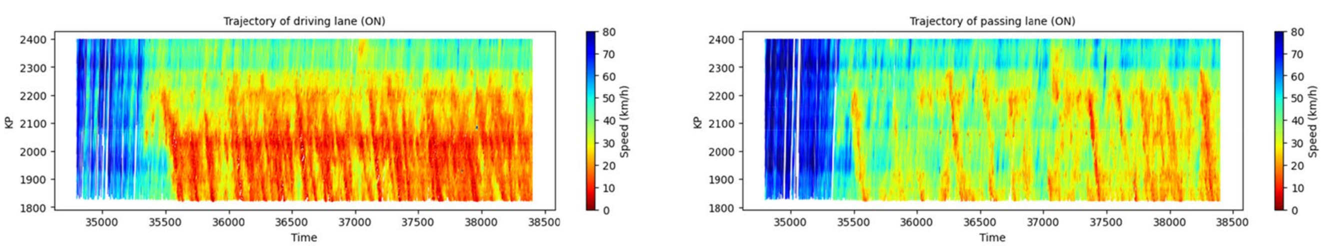
by the ramp, and the passing lane are designed for left-side driving. Due to heavy traffic volumes, this section recurrently experiences congestion.

The MLGS is installed along the wall of the passing lane upstream of the merging lane and along the walls of both lanes downstream. As illustrated in Fig. 4, the system divides the section into four blocks, setting a lighting speed in each block based on average vehicle speeds observed by three cameras. The lighting speed is updated every minute and is slightly faster than the observed speed in Blocks 1–3. In Block 4, the lighting speed is set approximately 5 km/h higher than the speed in Block 3 to facilitate speed recovery.

For our analysis, we use trajectories of the dataset as collected in Zen Traffic Data (ZTD) and the MLGS operational log dataset. ZTD provides detailed trajectory data for all vehicles within the targeted section, including each vehicle's position, speed, lane, and kilo-post every 0.1 s through image sensing technology. Additionally, the dataset includes vehicle type (differentiated by vehicle length over or under 6 m) and information on longitudinal and lateral gradients. This dataset has previously been utilized for studies on flow breakdown characteristics [24] and data-driven car-following behavior modeling [25]. In this study, we examine six one-hour data sets from the subject section: two of these datasets recorded under active MLGS operation, as shown by the trajectories in Figs. 5 and 6, and four datasets recorded without MLGS operation, as shown by the trajectories in Figs. 7, 8, 9 and

Fig. 4 Overview of MLGS operation

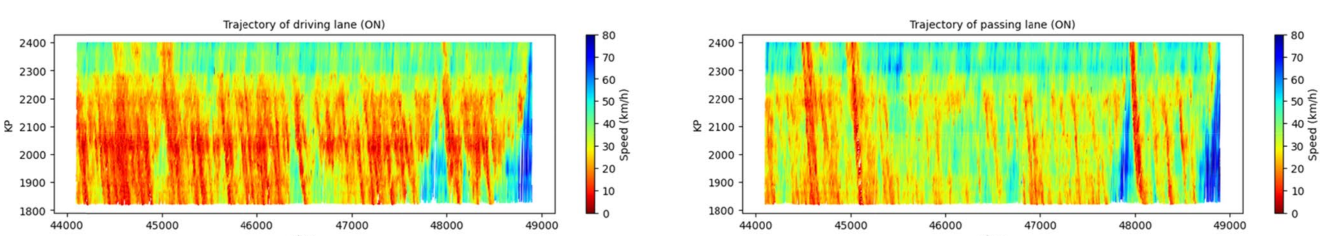




(a) Driving lane

(b) Passing lane

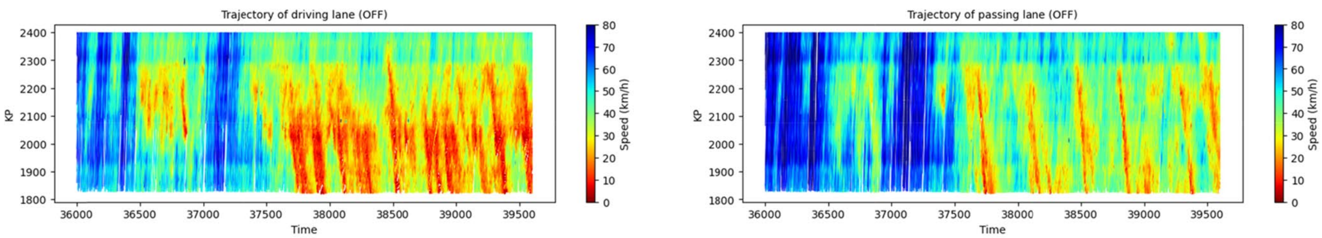
Fig. 5 Trajectory data (dataset 1, with MLGS)



(a) Driving lane

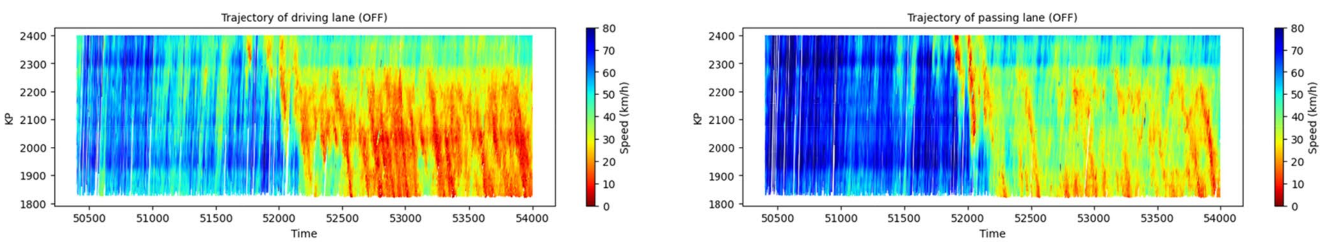
(b) Passing lane

Fig. 6 Trajectory data (dataset 2, with MLGS)



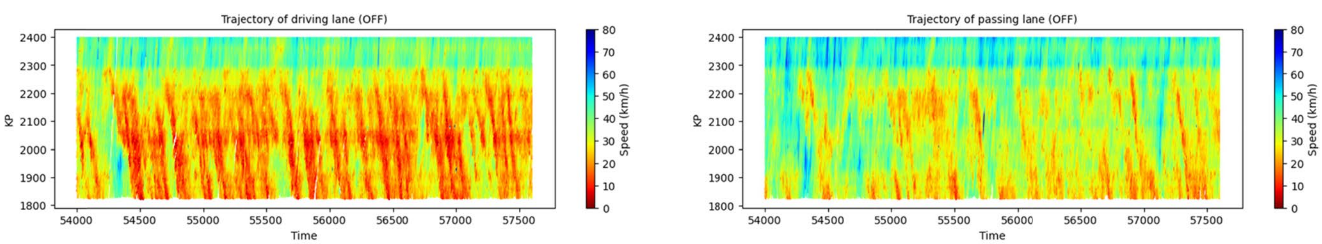
(a) Driving lane (b) Passing lane

Fig. 7 Trajectory data (dataset 3, without MLGS)



(a) Driving lane (b) Passing lane

Fig. 8 Trajectory data (dataset 4, without MLGS)



(a) Driving lane (b) Passing lane

Fig. 9 Trajectory data (dataset 5, without MLGS)

10. The fundamental diagrams for each lane are presented in Fig. 11, where the vertical axis represents the number of vehicles of each lane, and the horizontal axis represents density of vehicles of each lanes, defined by 10-second intervals over a 600-meter section.

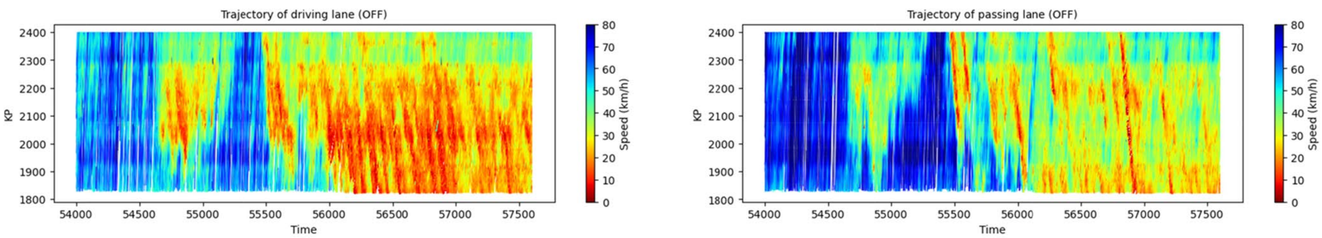
5 Results

5.1 Distribution of Traffic Density

The results of the traffic density distributions with and without MLGS operation are illustrated in Fig. 12a and b, respectively. In these figures, the vertical axis represents the density of the driving lane, the horizontal axis represents the density of the passing lane, and the color gradient from red to blue indicates the frequency of density-pair occurrences. In Fig. 12a, the driving lane's traffic density ranges from 10 to 60 vehicles per kilometer (veh/km), while the passing lane's density varies between 0 and 65 veh/km. Figure 12b shows a similar distribution for the driving lane, but the passing lane density is slightly narrower, ranging from 5 to 50 veh/km. Notably, there is not sufficient frequency of density occurrences except between 35 and 55 veh/km in the driving lane and 30 and 50 veh/km in the passing lane. Therefore, we focus on these density ranges for the following analyses. As shown in Fig. 11, these data include both congested and non-congested conditions, under MLGS operation as well as without it, and lane-changing behavior can differ between these conditions. Since the MLGS is intended to improve traffic flow under congested conditions, we select these target density ranges for further analysis.

5.2 Distribution of Average Rate of Lane Changes

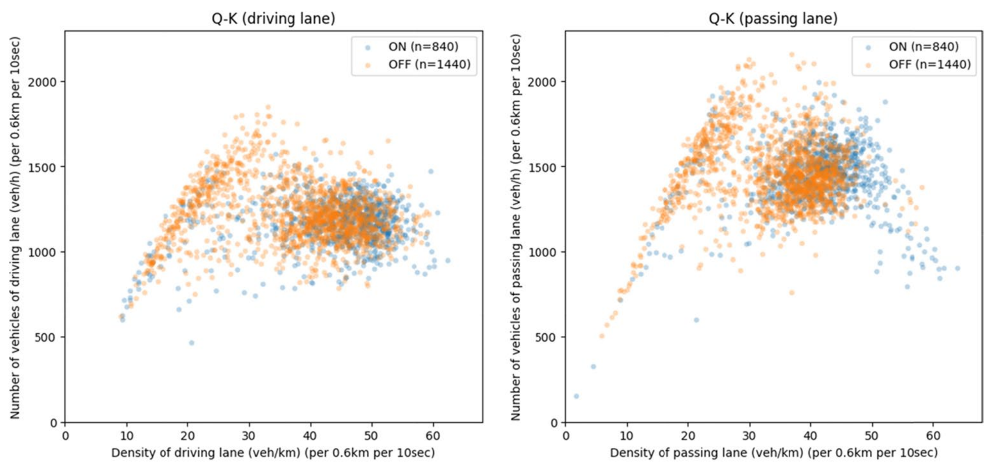
The lane change rates in each traffic density pair, is illustrated in Fig. 13a and b, representing conditions with and without MLGS operation, respectively. In both figures, the vertical axis represents the density of the driving lane, the horizontal axis represents the density of the passing lane,



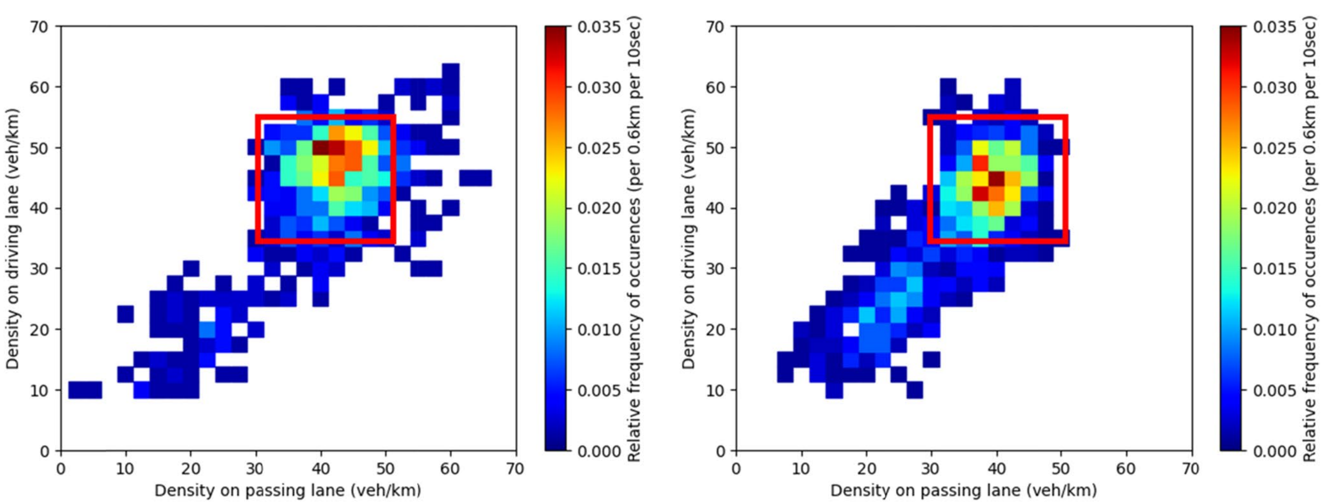
(a) Driving lane (b) Passing lane

Fig. 10 Trajectory data (dataset 6, without MLGS)

Fig. 11 Fundamental diagram in volume-density plane



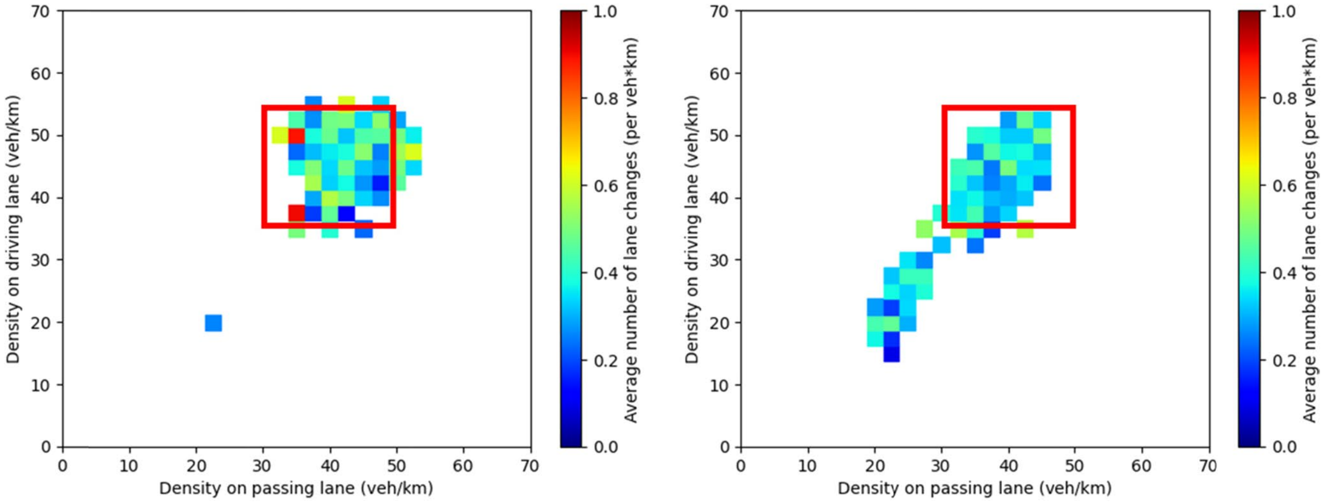
(a) Driving lane (b) Passing lane



(a) With MLGS (b) Without MLGS

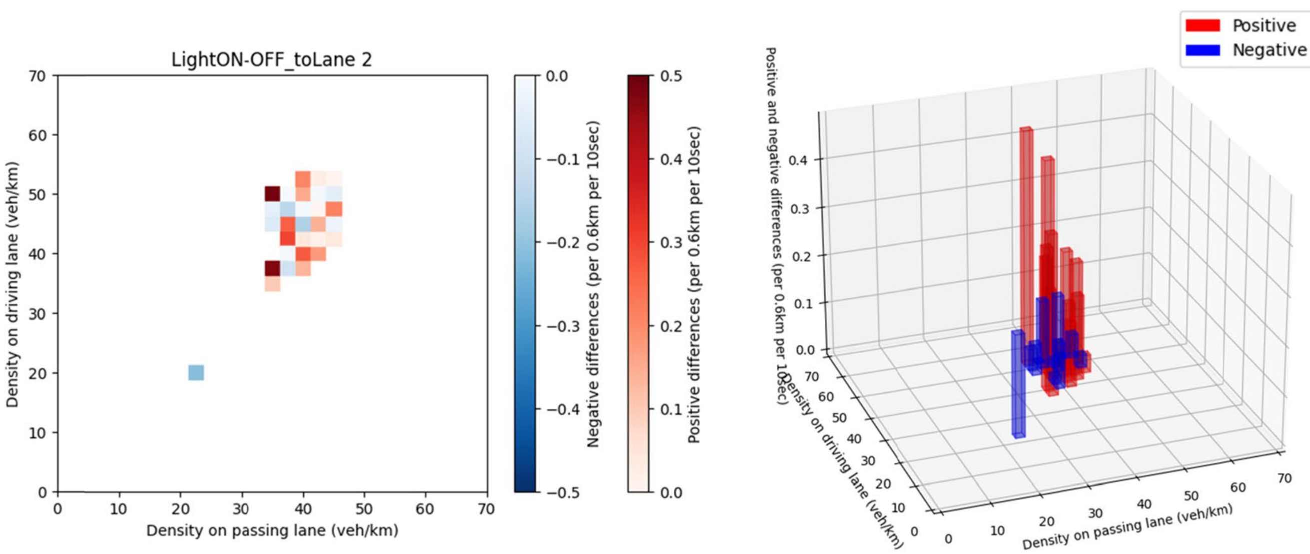
Fig. 12 Distribution of traffic density

and the average rate of lane changes are indicated by a gradation color from red to blue. Within the designated focus area (traffic densities between 35 and 55 veh/km on the driving lane and between 30 and 50 veh/km on the passing lane, as outlined in Section 5.1), it was observed that the number of lane changes was slightly higher under MLGS operation, although the trend was not distinctly clear. To further clarify any potential effects, Figure 14 displays the difference in lane changes calculated by subtracting the values without MLGS from those with MLGS operation, for each density pair. Positive differences, meaning that the lane-change rate increases more with MLGS than without MLGS in the



(a) With MLGS (b) Without MLGS

Fig. 13 Distribution of rate number of lane changes



(a) Scatter plot graph (b) Bar graph

Fig. 14 Difference in lane changes calculated by subtracting the values without MLGS from those with MLGS operation

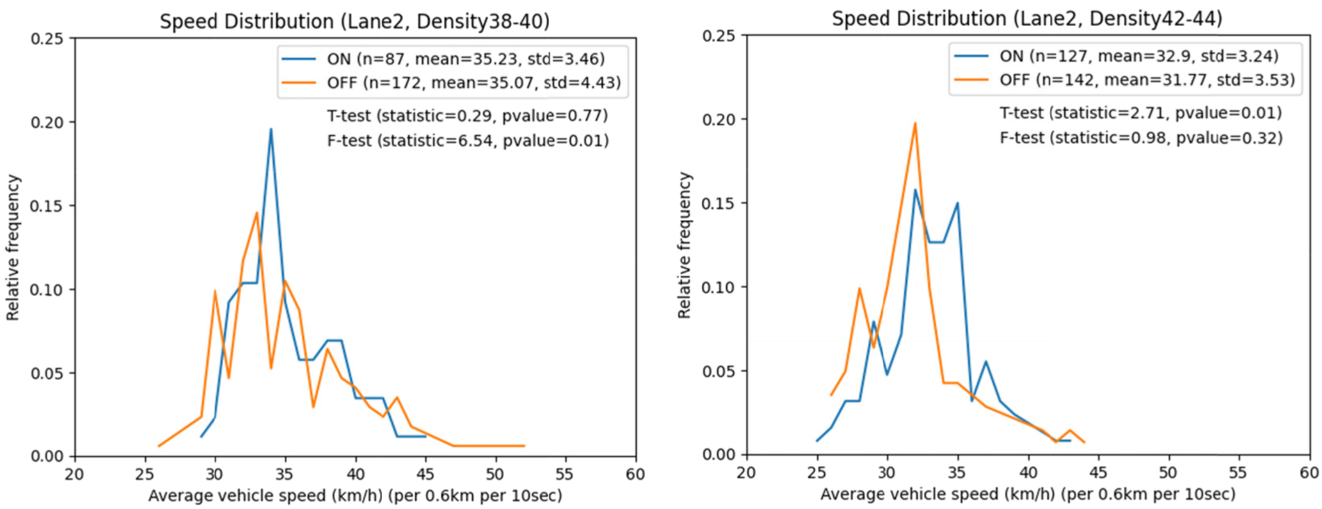
specific density pairs, are shown in red, and negative differences in blue, with density representing the magnitude, particularly as shown in Figure 14(a). In Figure 14(b), while it presents the same results as Figure 14(a), the absolute value of positive and negative differences is depicted by the height of each bar. These results indicate that the overall lane change rate is higher under MLGS. We did not find a specific trend how this depends on the density in either lane. This fact implies that MLGS works to promote lane-changes from the driving lane to the passing lane. It is naturally conjectured that lane-changes increase when the available gaps on the target lane increases and/or the motivation of lane-changes such as improvement of driving speed gets higher.

5.3 Distribution of Average Speed and Headway Distance on Target Lane

Table 1 presents the basic statistics of the distribution of average vehicle speed in the passing lane. The results indicate that the mean average vehicle speed is higher under active MLGS operation, except within the 36–38 veh/km density range. Statistically significant differences at the 5% level, confirmed by t-test results, are observed particularly within the 42–44 veh/km density range. Additionally, the standard deviation of average vehicle speed is consistently smaller when the MLGS is active, with statistically significant differences at the 5% level confirmed by f-test results,

Table 1 Distribution of average vehicle speed

Density on passing lane (veh/km)	With MLGS			Without MLGS			T-test (P value)	F-test (P value)
	Number of data	Mean value (km/h)	Standard deviation (km/h)	Number of data	Mean value (km/h)	Standard deviation (km/h)		
36-38	68	36.25	3.58	180	36.33	4.05	0.89	0.24
38-40	87	35.23	3.46	172	35.07	4.43	0.77	0.01*
40-42	110	34.05	3.33	187	33.19	3.89	0.05	0.07
42-44	127	32.9	3.24	142	31.77	3.53	0.01*	0.32



(a) Density interval on passing lane: 38-40 veh/km

(b) Density interval on passing lane: 42-44 veh/km

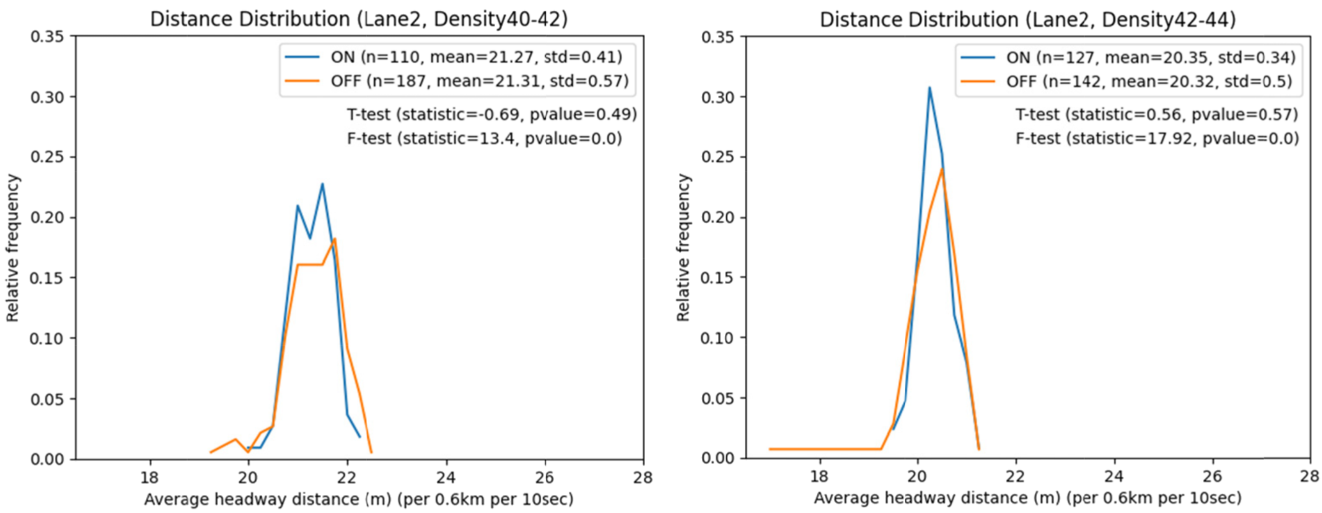
Fig. 15 Distribution of average vehicle speed

Table 2 Distribution of average headway distance

Density on passing lane (veh/km)	With MLGS			Without MLGS			T-test (P value)	F-test (P value)
	Number of data	Mean value (m)	Standard deviation (m)	Number of data	Mean value (m)	Standard deviation (m)		
36-38	68	23.51	0.63	180	23.49	0.72	0.84	0.23
38-40	87	22.26	0.58	172	22.38	0.57	0.12	0.78
40-42	110	21.27	0.41	187	21.31	0.57	0.49	>0.01*
42-44	127	20.35	0.34	142	20.32	0.50	0.57	>0.01*

especially within the 38–40 veh/km density range. This is evidential to see the distribution on Figure 15a for the density intervals of 38- 40 veh/km and Figure 15b for 42-44 veh/km. In these figures, the horizontal axis represents the average vehicle speed, the vertical axis represents the relative frequency of these values, and the blue line and orange line indicate the conditions with and without MLGS operation, respectively. Since the mean vehicle speed tends to be faster and the standard deviation tends to be smaller under MLGS operation, this implies that the MLGS contributes to both improving vehicle speed and enhancing vehicle speed homogenization.

Similarly, Table 2 presents the distribution of average headway distances in the passing lane. The average headway distance is calculated by taking the mean of headway distances recorded at 0.1-second intervals, aggregated over 10-second periods, and the distribution is derived from these averaged values. We calculate this distribution for each density range, and the results show that each density range exhibits similar headway distances. There are no differences in the mean average headway distance between with and without MLGS – as should be because the same density (defined by the bin) must yield the same distance headway, and as confirmed by t-test results. Additionally, the standard deviation of average headway distance is consistently smaller under MLGS operation, except within the 38–40 veh/km density range. Statistically significant differences at the 5% level, confirmed by f-test results, are particularly evident within the 40–42 veh/km and 42–44 veh/km density ranges. The distribution of the headway distances are illustrated in Figure 16a for the 40–42 veh/km density intervals and Figure 16b for the 42–44 veh/km density intervals, respectively. According to these results, particularly the effect of the smaller standard deviation of headway



(a) Density interval on passing lane: 40-42 veh/km

(b) Density interval on passing lane: 42-44 veh/km

Fig. 16 Distribution of average headway distance

Table 3 Distribution of average vehicle speed differences

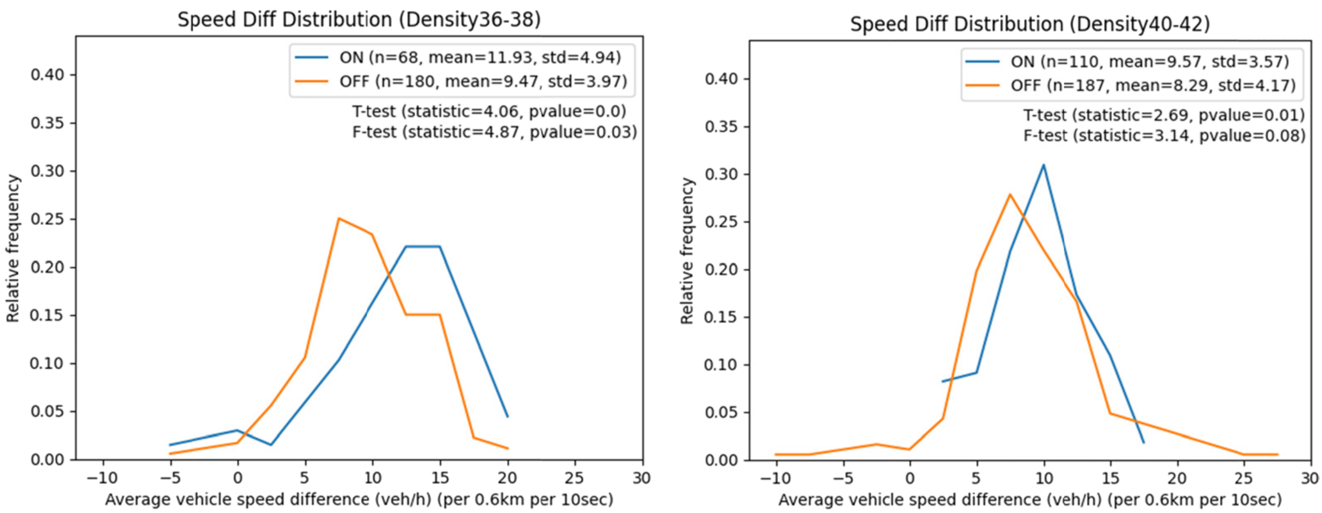
Density on passing lane (veh/km)	With MLGS			Without MLGS			T-test (P value)	F-test (P value)
	Number of data	Mean value (m)	Standard deviation (m)	Number of data	Mean value (m)	Standard deviation (m)		
36-38	68	11.93	4.94	180	9.47	3.97	>0.01*	0.03*
38-40	87	10.31	3.94	172	9.32	3.94	0.08	0.18
40-42	110	9.57	3.57	187	8.29	4.17	0.01*	0.08
42-44	127	8.86	3.9	142	8.10	3.37	0.09	0.09

distance under active MLGS operation, it can be inferred that the MLGS contributes to enhancing headway distance homogenization. This suggests that the system helps reduce variability in the spacing between vehicles.

These results suggest that the MLGS can influence lane-changing behavior by fostering more uniform traffic flow. Specifically, improvements in vehicle speed and its homogenization in the passing lane, as indicated by the smaller standard deviation, may heighten drivers' intention to maintain their desired speeds, while enhanced headway distance homogenization may create adequate space in the target lane for lane-changing vehicles. To determine whether homogenized traffic flow impacts lane-changing phenomena, we analyze the relationship between average speed differences and the average number of lane changes, as well as the headway gap between the new leader and new follower when a lane change occurs, as detailed in Section 5.4.

5.4 Relationship Between Traffic States and Lane Change Phenomena

The distribution of average vehicle speed differences calculated by subtracting the average vehicle speed of the driving lane from the average vehicle speed of the passing lane are shown in Table 3. The average speed difference is calculated by subtracting the driving lane's speed from the passing lane's recorded at 0.1-second intervals, aggregated over 10-second periods, and the distribution is derived from these averaged values. The mean value of the distribution with MLGS is larger than that without MLGS, and there are significant differences of that in the range of traffic density 36–38 veh/km and 40–42 veh/km based on the results of the t-test as shown in the table. However, no clear trend was observed in the standard deviation of the average speed difference. This is illustrated in Fig. 17a for the 36–38 veh/km density interval and Fig. 17b for the 40–42 veh/km density interval. Since the MLGS is installed on the passing lane throughout the subject section, the results suggest that the average vehicle speed in the passing lane benefits more significantly from MLGS operation compared to the driving lane, where MLGS is only installed downstream of the merge section. This is consistent with the findings on the improvement in the mean average vehicle speed distribution in the passing lane, as discussed in Section 5.3. Consequently, this fact may influence lane changes from the driving lane to the faster passing lane, motivated by the desire to maintain a driver's desired speed.



(a) Density interval on passing lane: 36-38 veh/km

(b) Density interval on passing lane: 40-42 veh/km

Fig. 17 Distribution of average vehicle speed differences

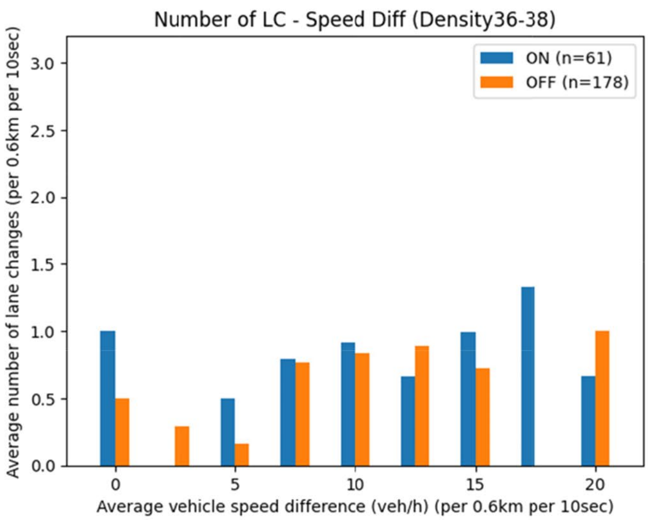
To explore this further, we sort the number of lane changes per average vehicle speed difference between the driving lane and the passing lane, grouping the data into density intervals of 2.5 veh/km. The relationship between the speed differences and the number of the lane-changes as shown in Figure 18. It shows the average number of lane changes increases in proportion to the values of vehicle speed difference, suggesting that the MLGS facilitates lane changes motivated by the desire to maintain a desired speed by improving traffic flow in the passing lane. However, under MLGS operational conditions, lane changes tend to occur more frequently even at smaller speed differences, indicating that the MLGS may also influence lane-changing motivations beyond simply maintaining a desired speed. These findings suggest that lane-change motivation may be encouraged not only by improved average speed in the target lane but also by an increased availability of gaps, providing greater opportunities for lane changes. Additionally, in this target section, which includes a merging area, lane-change motivation from the driving lane to the passing lane may also be influenced by the desire to avoid merging vehicles from the ramp.

Furthermore, to examine whether a homogenized headway distance in the target lane (passing lane) supports lane changes, we analyze the distribution of the headway distanace between the new leader and new follower in the passing lane when a lane change occurs, as summarized in Table 4. The headway distances are calculated as the differences in recorded kilopost values for each vehicle, and the distribution derived from these values indicates that the mean headway distance is smaller under active MLGS operation, with statistically significant differences at the 5% level, as confirmed by t-test results, particularly within the 42–44 veh/km density range. Moreover, the standard deviation of the headway gap is consistently smaller under MLGS operation, with statistically significant differences at the 5% level confirmed by f-test results across all density ranges. These findings are illustrated in Fig. 19, where the horizontal axis represents the headway gap, the vertical axis represents the relative frequency of these values. Since the mean and standard deviation of headway distance tends to be smaller under MLGS operation, these suggest that MLGS contributes to the creation of number of lane-changeable gaps, even if they are small, by homogenizing vehicle speed and the headway distance in the passing lane.

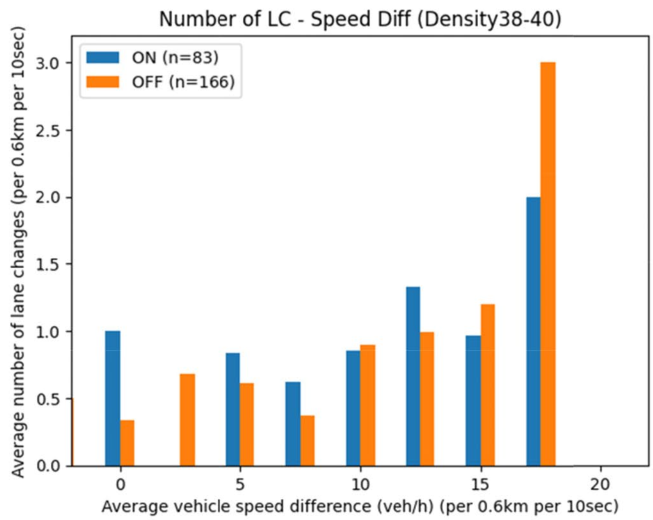
In general, when the speed difference between two lanes is large, lane-change motivation increases, as is the case without MLGS operation. Under MLGS operation, a greater number of acceptable gaps may be available even at smaller speed differences. Therefore, the effect of vehicle speed differences between these lanes on lane changes is less apparent under MLGS operation. This aligns with the findings in Section 5.3, where MLGS was shown to enhance the homogenization of both vehicle speed and headway gaps.

6 Conclusion

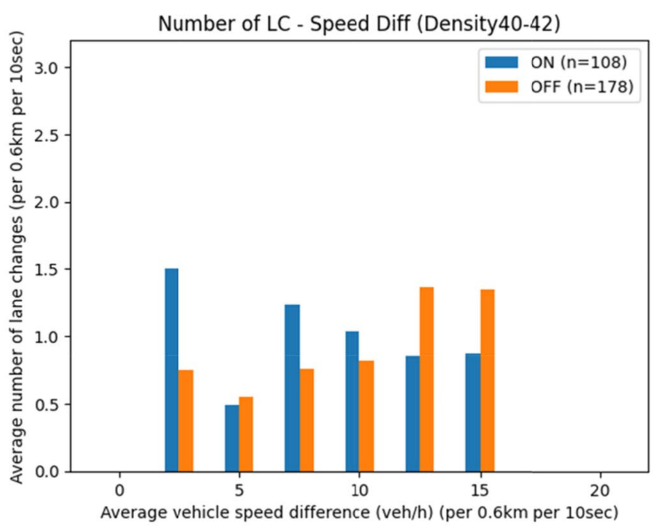
The findings indicate that the MLGS contributes to improvement of traffic flow. Notably, the number of lane changes per density pair (comprising densities in the driving and passing



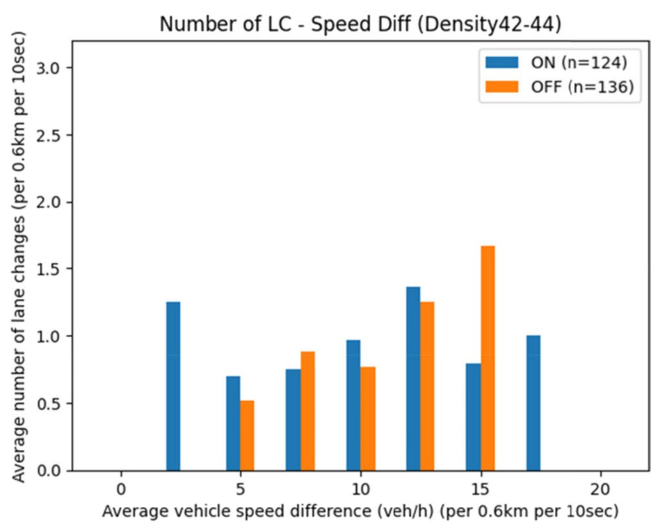
(a) Density interval on passing lane: 36-38 veh/km



(b) Density interval on passing lane: 38-40 veh/km



(c) Density interval on passing lane: 40-42 veh/km



(d) Density interval on passing lane: 42-44 veh/km

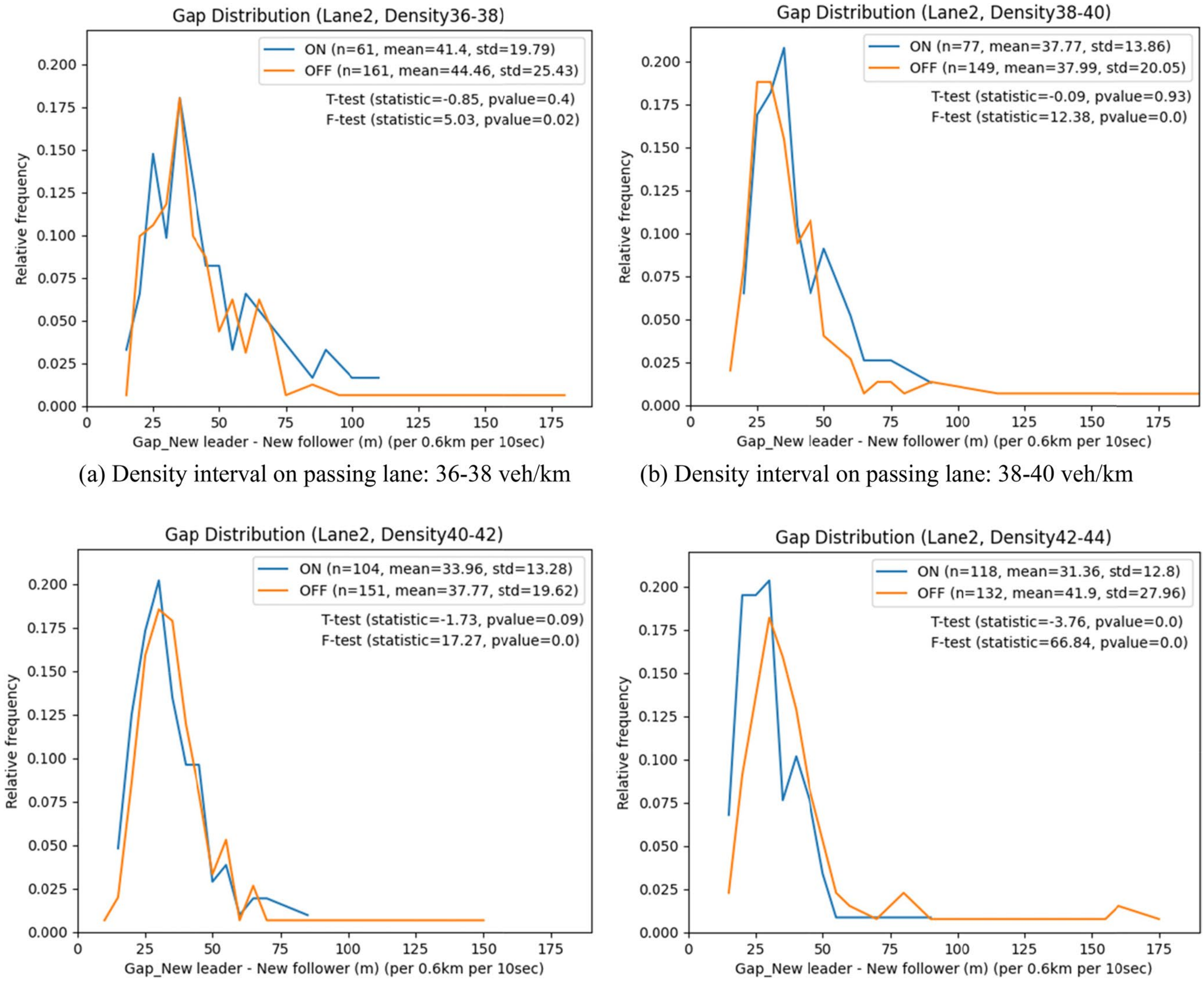
Fig. 18 Number of lane changes per vehicle speed difference

Table 4 Distribution of the headway gap between new leader and new follower in the passing lane when lane change occurs

Density on passing lane (veh/km)	With MLGS			Without MLGS			T-test (P value)	F-test (P value)
	Number of data	Mean value (m)	Standard deviation (m)	Number of data	Mean value (m)	Standard deviation (m)		
36-38	61	41.40	19.79	161	44.46	25.43	0.40	0.02*
38-40	77	37.77	13.86	149	37.99	20.05	0.93	>0.01*
40-42	104	33.96	13.28	151	37.77	19.62	0.09	>0.01*
42-44	118	31.36	12.8	132	41.90	27.96	>0.01*	>0.01*

lanes) is higher under MLGS operation than without it, and lane change frequency tends to increase with greater speed differences between lanes. This pattern suggests that the MLGS may encourage lane changes from the driving lane to the passing lane, potentially reducing disturbances in the driving lane where inflow from entrance ramps is high.

Additionally, lane changes were observed under MLGS operation even at minimal speed differences between lanes, suggesting that other factors may motivate these lane changes. This could include an expectation of speed recovery downstream, among other possible influences, which warrants further investigation in future research.



(a) Density interval on passing lane: 36-38 veh/km

(b) Density interval on passing lane: 38-40 veh/km

(c) Density interval on passing lane: 40-42 veh/km

(d) Density interval on passing lane: 42-44 veh/km

Fig. 19 Distribution of the headway gap between new leader and new follower in the passing lane when lane change occurs

Based on these findings, we suggest that MLGS can be utilized indirectly for lane-change management. Specifically, the MLGS may encourage lane changes by promoting speed homogenization in the passing lane and creating speed differences with the driving lane. This implies that lane-changing behavior can be managed by strategically placing MLGS installations in sections where lane changes are encouraged. Conversely, if the goal is to reduce lane changes, installing MLGS in a different, yet unknown, way that minimizes speed differences between lanes could be effective.

The research hence also revealed topics for further study. Further investigation is needed to understand the reasons or other motivations behind lane changes occurring at small speed differences under MLGS operation, and to consider about the disruptive impact for traffic flow by lane changes. Additionally, the results of this study did not consider the impact of the lighting speed or the differences between the lighting speed and vehicle speed, which may also influence lane-changing behavior. Future work can also focus on suggesting effective MLGS operation methods for efficient lane-change management, including installing the system on the most effective sections and optimizing the control of lighting speeds.

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wish to thank Hanshin Expressway Co.

Data Availability The data that supports the findings of this study are available in Zen Traffic Data at https://zen-traffic-data net, reference. These data are available for research and development organizations to contribute to the development of basic research, technology and services that will make road traffic more safe, secure and comfortable for the next generation.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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