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Detection of urban traffic patterns from Floating Car Data (FCD)

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Abstract

Real time data collection in traffic engineering is crucial for better traffic corridor control and management. In the literature, many data collection methods have been used such as; magnetic loops, road tube counters, piezo sensors, radars, Bluetooth etc. to estimate the link occupancy, average speed or density of a corridor. More recently, Floating Car Data (FCD) has become another important traffic data source and has an increasing usage due to its lower cost and higher coverage despite its reliability problems. FCD obtained from GPS equipped vehicles moving in the traffic can provide speed or travel speed data for many segments for even 1-min intervals in real-time. Though not totally diverse providing more than one of the traffic flow parameters, measuring the effectiveness of this extensive data source in detecting some critical urban traffic states is the ultimate goal of this study. As a case study, 1-min interval FCD for an urban arterial in Ankara has been collected during the morning peak hour for 2 months. Average speed values were transformed into a qualitative 4-scale state parameter based on the Level of Service (LOS) definitions for urban roads. Pattern searches over consecutive segment states using different search length (i.e. 2 segments, 3 segments, etc.) showed that FCD is capable to detect recurrent congestion or bottleneck locations, and even have an idea about the length of queue formed before the bottlenecks.

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Keywords: Traffic pattern; Congestion detection; Traffic state estimation; Statistical Analysis

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1. Introduction

Accurate and reliable estimation of the traffic state in urban arterial roads is a crucial part of traffic management and control. Traditionally, a variety of traffic data sources (magnetic loops, road tube counters, radar, Bluetooth) have been used to estimate traffic parameters such as link occupancy, average speed and corridor density. Ultimately, these parameters are combined to estimate traffic state (or characteristics) based on the fundamental relationship between flow, density, and speed. This relationship enables identification of different traffic states (congested, free-flow, etc.) and events (i.e. entering or exiting from a queue/bottleneck, shockwave propagation, etc.).

More recently, another data source, Floating Car Data (FCD), has been increasingly in use. This is mainly due to its lower cost and higher coverage, despite reliability problems. The principle of FCD is to collect real-time traffic data, by locating the vehicle via mobile phones or GPS over the entire road network. Data such as car location, speed and direction of travel are sent anonymously to a central processing center. This information is then processed, in order to derive travel time or average speeds through road segments. If taken from a single probe vehicle, speed and position data can be obtained periodically (e.g.1 or 5 mins) for each road segment (Xu et. al., 2013). However, data from a vehicle fleet is generally preprocessed to obtain segment speed (or travel time) only. As GPS has become increasingly common, it has typically been used to monitor fleet management services (such as taxi drivers, and trucks), with taxi fleets being particularly useful due to their high number and on-board communication systems in urban regions (Leduc, 2008). Traffic data obtained from private vehicles tend to be more suitable for motorways and rural areas.

It is claimed that FCD for Turkey is obtained from 600,000 GPS-equipped vehicles. When the total number of vehicles in Turkey considered, which is around 19 million, this corresponds to an approximately 3% penetration rate. Data from these vehicles provide an opportunity to study FCD with respect to traffic state recognition and congestion detection for urban arterial roads in Turkey, which forms the focus of this study. Traffic patterns are defined following the Level of Service (LOS) definition, based on segment speed on urban arterial roads (HCM, 2010). Complexity and precision of any estimation model depends on the availability of diverse and extensive data. While FCD data is extensive, the extent of its diversity is debatable in terms of being able to estimate more than one traffic flow parameter. Perhaps a more interesting research question is the evaluation of the necessity and cost of estimating more than one traffic flow parameter in urban networks, which requires elaborate data collection or data combination techniques from various traffic data sources. While it is possible and worthwhile to collect data on heavily used intercity corridors via consecutively installed multiple sensors/sources, it is not economically possible to furnish all major roads in a city with sensors, nor computationally simple to rapidly analyse data in urban networks. Therefore, it is necessary to evaluate the power and limits of using FCD alone for detecting urban patterns as a single source, which is the scope of this study. The main contribution of this paper will be to prove the capability of FCD as a rapid evaluation tool for a large amount of data obtained from extensive networks.

In this study, based only on FCD-dependent travel time (hence speed), information was archived both quantitatively and qualitatively in the form of a "state" parameter. In the absence of density and flow values, the state was defined as a function of a decrease in the average speed compared to free-flow values, which did not exist. The scope of the study included detection of critical patterns such as recurrent congestion, bottleneck release locations, and segments suffering queueing in their upstream, etc. The structure of the paper is as follows: a brief literature review regarding traffic state estimation from FCD is presented in Section 2, followed by methodology in Section 3, overall results in Section 4, and conclusions and further recommendations in Section 5.

2. Literature Review

2.1. Characterization of traffic state

Traffic state characterization studies in the literature can be generally gathered into three categories: i) determination of the average speed, ii) detection of congestion/bottleneck locations, and iii) determination of traffic flow parameters. Average speed estimation studies, which is a first step in the characterization of traffic state, is generally conducted in order to analyze speed profiles of the selected corridor, to examine sudden changes amongst consecutive segments, and to explore the statistical distribution of speeds for each road segment (Quayle et al., 2010; Pan et al., 2011; Shoufeng et al., 2013, Wang et al., 2014). This will later be used to identify the recurrent/nonrecurrent congestion locations or detection of the bottleneck locations, which also have been the focus of many studies (Xu et al., 2013; Li et al., 2012; Reinthaler et al., 2010).

Particularly for the determination of the relationship between traffic flow parameters, two of the three parameters (speed, density and flow) must be known, in order to explain the relationships between them. These kinds of studies involve either data collection and implementation of well-known traffic flow models to best fit the data (Zhao et al., 2009; Anuar et al., 2015), or developing mathematical models to derive fundamental diagrams (Celikoglu and Silgu, 2015; Celikoglu, 2013; Celikoglu, 2014). For such studies, Celikoglu (2013, 2014) obtained traffic data from the Remote Traffic Microwave Sensor Data (RTMS), including volume and speed data taken every 3 minutes. LOS-based classification was proposed for the derivation of a traffic flow fundamental diagram. Traffic data were obtained from the RTMS, including speed and volume parameters. Density was used as an input parameter, and a neural network-based model was proposed for the classification of traffic patterns, with flow rate values with respect to speed for each LOS being obtained. In a follow-up study, Celikoglu and Silgu (2015) performed a multivariate clustering method for the classification of traffic patterns in the same corridor.

2.2. Traffic state estimation using FCD

Traffic state estimation studies for urban arterial roads are generally focused on either exclusively using FCD data, or combining such data with other data sources (such as the RTMS, inductive loops, video cameras, Automated Vehicle İdentification systems etc.) to estimate traffic state. As an example of the latter, Zhao et al. (2009) analyzed traffic flow characteristics on ring road expressways in Beijing using FCD and RTMS data. Average speeds were obtained from both data types, whilst volumes were accessed from RTMS data only. Data were combined, in order to derive the flow-speed relationship in the fundamental diagram. A regression analysis was performed for both RTMS and FCD average speeds, and showed that RTMS speed values were generally 6% higher than FCD speed values. Chase et al. (2012) evaluated the reported speeds obtained from 3 different kinds of traffic data: i) FCD was obtained from Inrix with 5-minute aggregation. Travel time, speed, average speed and reference speed data were obtained; ii) Microwave radar sensors with 5-min aggregation speed data. Volume and occupancy values were collected from the same corridor for the same study period; iii) Radar sensors, for which only speed values were obtained. Speed profiles showed that all data types had a similar pattern. Speed differences obtained from Inrix and microwave radar sensor data were compared and differences were found normally distributed. For the traffic state evaluation, Inrix speed data and microwave radar sensor data were combined to investigate speed-flow relationships. Similar to these studies, Anuar et al. (2015) used FCD and loop detectors to derive the relationship between flow and speed, and stated the model most closely describing this relationship was Van Aerde's fundamental diagram. Haghani (2010) compared the average speed of road segments obtained from FCD and Bluetooth data. Statistical evaluation was performed for 4 speed categories: i) below 30mph, ii) 30-45 mph, iii) 45 and 60 mph, and iv) speed above 60 mph. Bluetooth mean speeds were not found to be significantly different from the FCD speeds for each speed category.

In the absence of additional data sources, in the discussion of the use of extensive FCD data to detect congestion, Xu et al. (2013) highlighted the issues when dealing with the enormous historical data set when endeavoring to find meaningful traffic and congestion patterns. They obtained FCD from 12,000 GPS-equipped taxi fleets in Wuhan city, China. They proposed a statistical method for data analysis (data cube management). Li et al. (2012) used 3 months of historical FCD to examine variabilities in average speeds, and attempted to determine congestion locations depending on sudden decreases in average speeds in consecutive road segments. Fabritiis et al. (2008) proposed a neural network-based model to estimate average speed through the sections, and to determine congestion locations of the two selected corridors. Kong et al. (2015) developed a fuzzy comprehensive evaluation method for identifying congestion locations for every 5 minutes. In contrast to these studies, Adu-Gyamfi and Sharma (2015) explored the reliability of probe speed data for detecting congestion trends. The study focused on pattern recognition and time series data analysis to identify similarities with probe-based speed data. Reinthaler et al. (2010) used FCD from both taxi fleets and public transport in the German city of Dusseldorf. Public transportation-based data was found to provide more accurate results for speed and travel time values. Furthermore, they developed a model to integrate these two data sources for estimating traffic states and to identify the most congested locations.

3. Methodology

The method used in this study includes utilization of raw FCD data (with 1-minute measurements) which is basically processed to obtain LOS-based traffic states (from 1 to 4) as shown in Figure 1. Using the predetermined urban traffic pattern definitions, a simple pattern search algorithm is run to detect urban traffic patterns with their locations and observed frequencies. This search can be done using 2 (or more) consecutive segment search (2CSS, 3CSS, etc.) version of the algorithm, which only requires appropriate pattern definitions as an input. A key issue in this algorithm is the definitions of "traffic state" and its process from segment speed values. It is proposed to use HCM-based urban LOS intervals, as it solely depends on average speed value. Second issue is the definition of critical patterns for urban traffic, which has to be defined based on the traffic states, as well. These will be discussed in the following subsections.

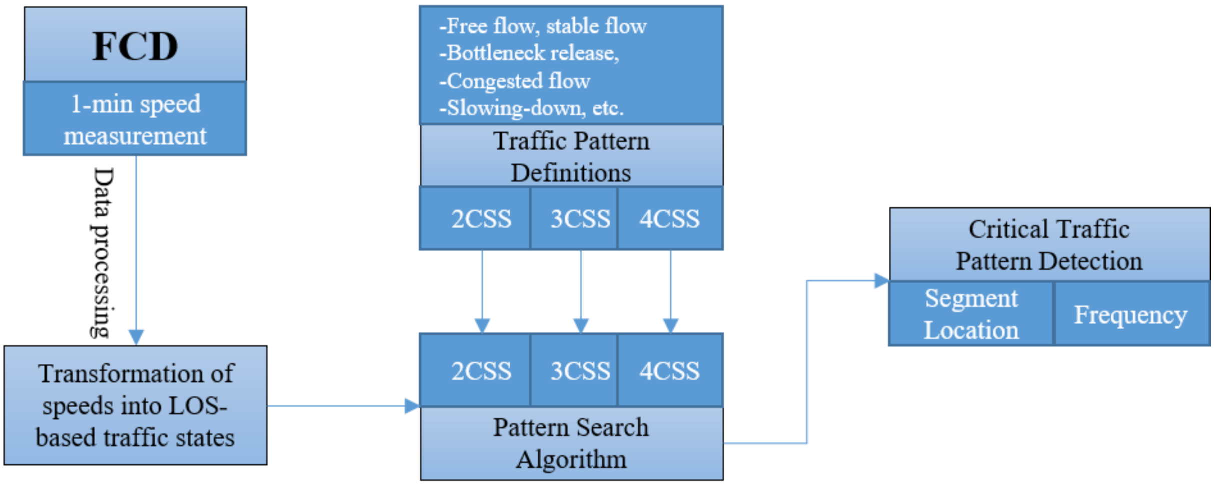


Fig.1. Framework of the proposed methodology

3.1. LOS and state definitions for urban corridors

LOS is a quantitative measure representing quality of service (HCM, 2010). Generally, 6 different LOS states are defined for different road types, where LOS A represents the best operating condition and LOS F the worst. HCM (2010) defined LOS for urban roads as "the reductions in travel speed as a percentage of the free-flow speed of the corridor". Table 1 shows speed thresholds and corresponding LOS values based on HCM (2010) for the 50km/hr and 90km/hr free-flow speeds. In Turkey, urban arterial roads have a legal speed limit of 50 km/hr, which can be increased up to 70 km/hr or even 82 km/hr (by a 10% tolerance margin before a penalty is issued, which corresponds to 90 km/hr in practice) by local government. Assuming a 90 km/hr free-flow on the study corridor, LOS A and LOS B states corresponded to speed intervals of "90km/hr - 77 km/hr" and "77 km/hr - 60 km/hr". Speed intervals for LOS C and LOS D correspond to "45km/hr – 60km/hr" and "36km/hr – 45km/hr". Finally, a segment speed less than 27km/hr was the worst case, resulting in LOS F.

Traffic patterns are defined following the LOS definition, based on segment speed on urban arterial roads in HCM (2010), as discussed previously. Speed information from FCD is converted to a qualitative "state" parameter (Table 1), in order to detect critical patterns such as locations facing recurrent congestion, bottleneck release locations etc. As the speed limit of the study corridor was registered as 70 km/hr, which was the limit of the recent increase to 82 km/hr (and 90 km/hr in practice for a speeding penalty) by the municipality, speed data obtained was truncated at 70 km/hr. Due to this truncation, LOS A and LOS B were defined as a joint state (termed State 1) of "free-flowing conditions" for average speeds of more than 60 km/hr. In accordance with the classification by HCM, a stable flow state is State 2. LOS D, which represents those conditions "approaching unstable flow", correspond to State 3 in this study. Unstable flow conditions (LOS E and F) are represented in one single state, State 4, with speeds less than 36 km/hr.

Table 1. Average speed and corresponding LOS values for the urban roads based on (HCM, 2010).

LOS	**Travel Speed as a Percentage of Base Free-flow Speed**	**Travel Speed Intervals (km/hr) for speed limits of**		**Assumed Traffic State**
		50 km/hr	**90 km/hr**	
A	>85	>42.5	>76.5	1
B	67-85	33.5<V<42.5	60.3<V<76.5	
C	50-67	25<V<33.5	45<V<60.3	2
D	40-50	20<V<25	36<V<45	3
E	30-40	15<V<20	27<V<36	4
F	<30	<15	<27	

3.2. Critical pattern search

After transforming average speeds into predefined states, a series of search algorithms were developed to detect critical patterns in the urban traffic. Based on the number of segments used in each search, “2 Consecutive Segment Search (2CSS)”, “3 Consecutive Segment Search (3CSS)” and “4 Consecutive Segment Search (4CSS)” options were used in this study. In these searches, the traffic state in each segment was compared against the traffic state of the following segment(s), in order to acquire different patterns such as bottleneck release, persistent congestion, etc. At the final stage, all segments were evaluated to detect the frequency and start point of the predefined critical patterns in the extensive FCD archive of the corridor.

Assuming 4 states, as illustrated in Table 1, it is possible to define up to 16 different situations in 2CSS, while more complex patterns can be defined in 3CSS and 4CSS. Some of these situations can be further grouped together to simplify the analysis and focus on the critical patterns. These patterns assumed for this study for 2CSS and 3CSS are shown in Table 2, and explained below:

- **Free-flow:** This condition is represented by a strictly 1-1 state for the 2CSS. However, more situations are simplified as “free-flow conditions” in 3CSS and 4CSS, as shown in Table 2.
- **Stable flow:** This pattern represents LOS C conditions for the proposed study.
- **Transition between free-flow and stable flow:** This pattern represents transitions between states 1 and 2.
- **Approaching unstable flow:** This pattern represents state 3 conditions.
- **Entering congestion:** This is the case when sudden reductions in speed were observed. For example, for 2CSS, state 1 to state 4 or state 2 to state 4 conditions were gathered under this category.
- **Congested flow:** This condition is the congested regime that can occur under state 4 (LOS F).
- **Transition between stable and unstable flow:** This pattern represents transitions between states 2 (LOS C) and 3 (LOS D).
- **Transition between unstable flow and congestion:** This pattern represents the transitions between states 3 (LOS D) and 4 (LOS E/F).
- **Speeding-up:** States “3-2-1” and “4-3-2” patterns can be considered as the speed-up condition for the 3CSS method.
- **Slowing-down:** States “1-2-3” and “2-3-4” patterns can be considered as the slow-down condition for the 3CSS search.
- **Slowing-down rapidly:** This is the case when sudden decreases in speed were observed. For example, for 2CSS search “state 1” to “state 3” or for the 3CS search states “2-1-3”, “1-1-3” can be considered as fulfilling this pattern (see Table 2 for all possibilities).
- **Bottleneck release:** The sudden increase in speed is considered as the bottleneck release point. We assumed these as involving any changes from state 3 to state 1; state 4 to state 1 or state 2. Furthermore, we noted possible queue lengths before the bottleneck release locations for further research, as illustrated in Table 2.

In 4CSS, 256 possible situations were initially analyzed to search for given critical patterns in Table 2. However, further patterns were defined such as bottlenecks with queue lengths in more than 2 segments etc., although these definitions are not presented here due to page limits.

Table 2. Critical traffic pattern definitions and its frequencies for the 2CSS and 3CSS for the study corridor

Patterns	2CSS	Frequency	3CSS	Frequency
Free-flow	1-1	78763	1-1-1; 1-1-2 ; 2-1-1	82117
Stable flow	2-2	22000	1-2-2; 2-2-1; 2-2-2; 2-2-3; 3-2-2	25496
Transition between free-flow and stable flow	1-2,2-1	11929	2-1-2; 1-2-1	2986
Approaching Unstable Flow	3-3	2065	3-3-2; 3-3-3; 3-3-4; 2-3-3; 4-3-3	2869
Entering congestion	2-4,1-4	1786	2-2-4; 1-4-3; 1-4-4; 2-1-4 ; 1-2-4; 1-1-4 ; 2-4-3; 2-4-4 ; 3-2-4	2888
Congested flow	4-4	2349	3-4-4; 4-4-3; 4-4-4	2026
Transition between stable and unstable flow	2-3,3-2	3162	2-3-2; 3-2-3	558
Transition between unstable and congestion	3-4, 4-3	1941	3-4-3; 4-3-4	272
Speeding-up	-	-	3-2-1; 4-3-2	792
Slowing-down	-	-	2-3-4; 1-2-3	693
Slowing-down rapidly	1-3	494	2-1-3; 1-1-3;1-3-2; 1-3-3 ; 1-3-4;	865
Bottleneck Release				
Queue length ≥1	3-1, 4-1, 4-2	1994	3-1-1; 3-1-2; 4-2-1; 4-2-2; 4-2-3; 4-1-1 ; 4-1-2	1981
Queue length ≥2	-	-	3-4-1; 3-4-2 ; 3-3-1; 4-4-1 ; 4-4-2; 4-3-1	1149
Queue length=1	-	-	1-3-1; 1-4-1 ; 1-4-2; 2-3-1 ; 2-4-1; 2-4-2	845

4. Numerical Results

In this section, to better illustrate the proposed methodology, numerical results are presented over an urban corridor in Ankara, where FCD was available.

4.1. Study corridor and FCD data

The case study includes a 4.5 km corridor on Dumlupınar Boulevard (from Hacettepe University interchange to Middle East Technical University entrance), which is a major arterial road in the form of a multilane urban highway corridor (4 lanes in each direction) in Ankara, Turkey (Figure 2). The study corridor consists of 134 segments in one direction, and the study period was from December, 2015 to February, 2016 for the morning peak-hour period (between 07:30-09:00). FCD data in this study is provided by a Belgium-based traffic information provider, which delivers real-time average speed data in 1-minute periods for small road segments of lengths shorter than 50m. It produces average speed data for road segments, however these results are truncated for the road speed limits. The study area includes one section with an electronic speed enforcement point (spot speed enforcement located around road Segment ID 27), 3 major grade-separated interchanges (Hacettepe, Bilkent and Middle East Technical University (METU)), and a major bus stop near METU interchange (Segment ID 116), as shown in Figure 2.

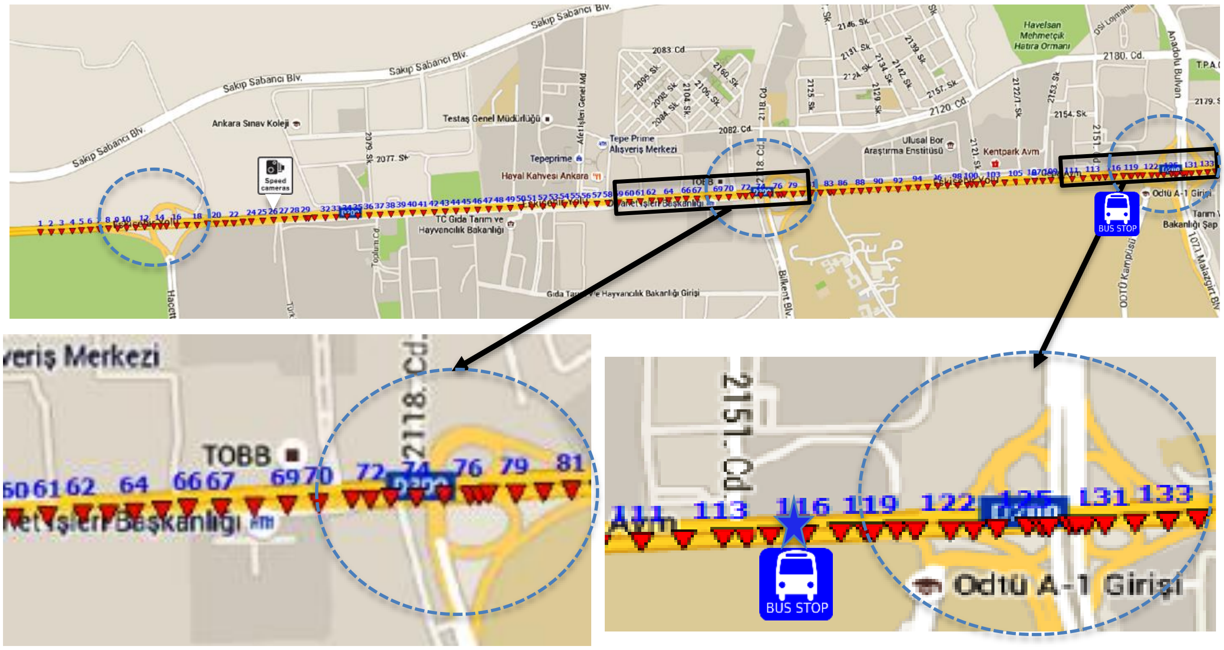


Fig.2. a) The study corridor and the locations of the 134 road segments and close-up view of b) Bilkent interchange and c) METU Interchange (Google maps, 2016)

4.2. Free-flow frequencies versus critical patterns along the corridor

Free-flow frequencies along the study corridor showed very similar patterns for the 2CSS, 3CSS and 4CSS methods. The free-flow profile of the selected corridor for 2SCC is illustrated in Figure 3. Higher free-flow frequencies shown in Figure 3a designate segments that do not face many critical patterns and mostly involve LOS A, whereas low frequencies of free-flow cases indicate potential critical patterns that should be analyzed in more detail. These critical locations are observed at major interchanges, and before speed enforcement and bus stop locations, as expected. Whilst travel speeds are observed at a value much lower than free-flow levels at the Hacettepe interchange, this is most likely the impact of slowing down prior to electronic enforcement measures, located immediately after, at Segment 27. Traffic conditions at the Bilkent interchange improve along the segments within the interchange, whilst the main problems are observed in the upstream segments. Similarly, traffic is mostly free-flowing at the METU interchange, while severe congestion is observed at the segments immediately prior to the bus stop close to this interchange.

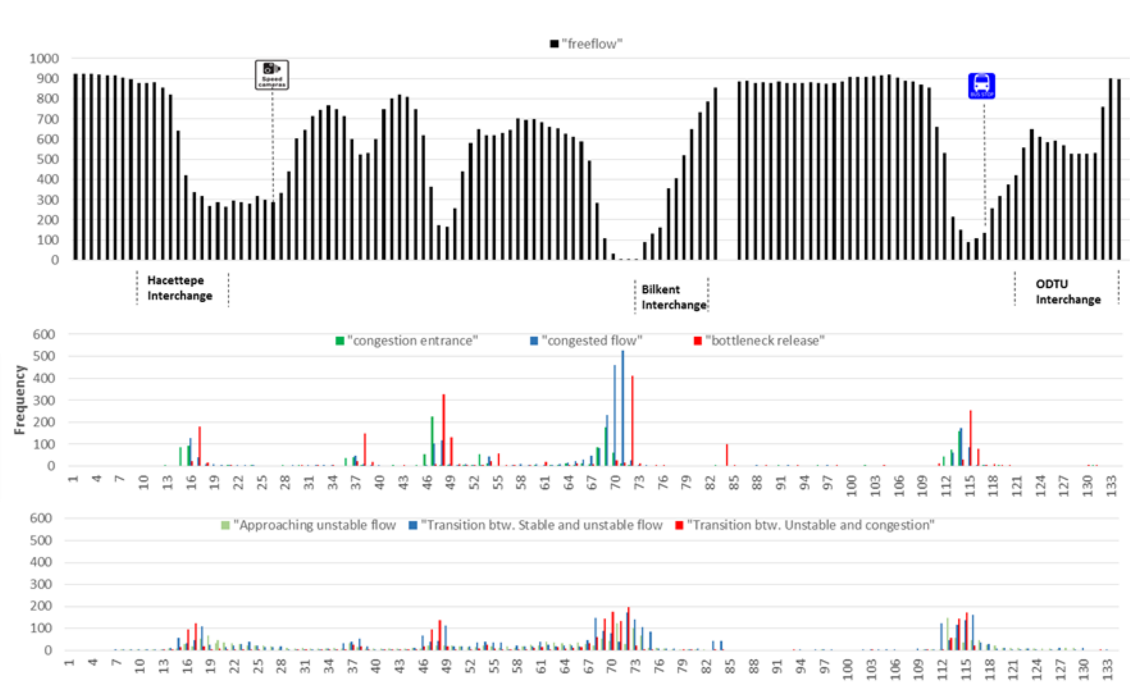
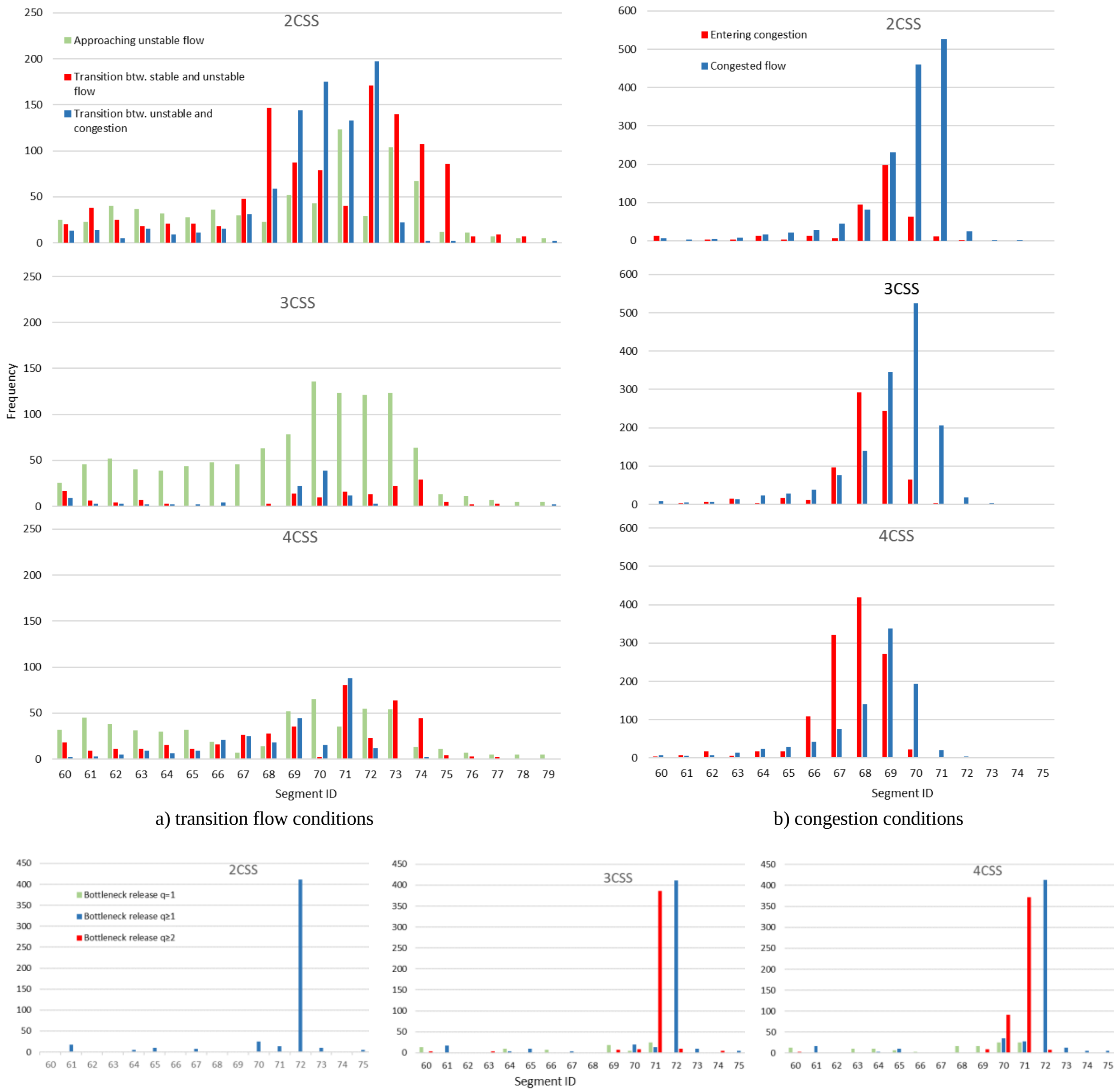


Fig.3. Critical traffic patterns for the study corridor obtained from 2CSS.

4.3. Critical patterns at Bilkent Interchange

A more focused analysis of the non-free flow conditions at and around the Bilkent Interchange reveals further details regarding the capabilities of the pattern search algorithm and the FCD. Figure 4a shows the frequencies of different transition flow patterns observed at the interchange segments, whereas Figure 4b displays the extent and location of congestion observed before the interchange. As expected, a bottleneck release is observed at Segment 71 and/or 72, which is expected to have 3 segment long queues in the upstream. As can be seen from the results of different search length algorithms, searches using only 2 consecutive segments are simple and rapid, but are not significantly illustrative of the spatial distribution. On the other hand, critical patterns searched with 3 or 4-segment algorithms reveal more information about the length of the congestion, as seen in Figure 4.



a) transition flow conditions

b) congestion conditions

c) Bottleneck release conditions

Fig. 4. The comparisons of the critical traffic patterns around the Bilkent interchange obtained from 2CSS, 3CSS and 4CSS method.

5. Conclusion

These results indicate that even though only one parameter (average travel speed from FCD) is used, it is still possible to detect critical patterns along urban roads, if data is continuous and extensive. Critical patterns able to be detected include persistent congestion due to interchanges, speed enforcement points, bus stops etc. Furthermore, bottleneck release points, as well as the length of queue formation in their upstream segments, can be easily identified. Use of 2CSS can increase the detection rate, but reveal less information about the spatial extent of the pattern. Conversely, the use of longer segment chains (as in 3CSS and 4CSS) in the analysis allows one to identify more complex patterns. The real power of the methodology is its flexibility when used for large-scale analyses; many urban corridors can be easily assessed retrospectively as well as in real-time. Observing pattern variations over time can reveal more information about the time-varying state of traffic at a given location, or on a network level. This methodology can be used alone, or in combination with other traffic data sources.

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