# Lane Change Maneuver Detection from Probe Vehicle DGPS Data 

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#### Abstract

The impact of lane change maneuvers is fundamental to microscopic traffic flow theory. Due to the difficulty of tracking many vehicles over time and space, most of the published research in this area seeks to find lane change maneuvers visually from wayside cameras. This paper presents a different approach, finding the lane change maneuvers of a probe vehicle itself using Differential Global Positioning System (DGPS) data. We first use multiple probe vehicle trajectories through a study corridor to establish a reference trajectory from the median of all trajectories and this reference trajectory will be used to define the position of the current lane. This approach eliminates the need for high-resolution maps accurate enough to capture the exact position of the individual lanes. Our lane change maneuver detection is then divided into two parts, controlling for the impacts of mandatory lane change maneuvers (MLC) and then for discretionary lane change maneuvers (DLC). MLC are detected by comparing the difference between the mean and median of lateral distance of all trajectories relative to a reference trajectory. After distinguishing all the MLCs, the DLC are found by setting lateral thresholds around the reference trajectory, i.e., when a given trajectory leaves this virtual lane. In the process we control for the impacts of GPS errors, such as multipath, arising from obstructions. DLC are then found by comparing the out-of-thresholdline time and length to a threshold acquired empirically from data.


## I. Introduction

LANE change maneuvering models, together with car following models, are a fundamental component of microscopic traffic flow theory. There have been intensive theoretical and empirical studies to develop macroscopic lane changing models, e.g., [6-8], which focus on the modeling of lane change maneuvers, using simulation and/or experimental data for verification. There are also many practical efforts to develop methods to automatically find lane change maneuvers based on a wayside video stream to detect, track and classify vehicles within the field of view using various image processing algorithms [3-5]. In most cases, when they follow vehicle correctly, these tracking

[^0]algorithms provide the information necessary to deduce the lane change maneuvers. Some have combined both the detection and modeling, e.g., [1] correlates the percentage of vehicles that change lanes and lane-changing frequency with environmental variables, based on empirically measured lane change maneuvers.
Many researchers have considered vehicle mounted im-age-processing systems for safety, driver behavior, or automated highway applications, e.g., [11-14], without considering directly the application to traffic flow theory. Others are starting to use vehicle mounted LIDAR, radar, and image processing to track neighboring vehicles and detect lane change maneuvers, e.g., [2].

This paper also uses vehicle-mounted sensors to detect lane change maneuvers for traffic flow theory development, but we take a different approach. The main contribution of this paper is that the method can rely entirely on the data from a Differential Global Positioning System (DGPS) receiver on the probe vehicle to detect lane change maneuvers by the probe vehicle itself. The approach can either use multiple trajectories through a corridor to deduce the location of the lanes (and thus, when the vehicle changes lanes), or if provided with an accurate geographic information system (GIS), one could find the maneuvers from a single trajectory. Of course the use of probe vehicle GPS data is becoming widespread, e.g., [9-10], use probe vehicle GPS data to estimate link speed and travel time.

Our work provides another way to detect lane change maneuvers, which we plan to use in future studies to better model lane changing properties. The use of multiple trajectories through the corridor could also find application in the Vehicle Infrastructure Integration (VII), which emphasizes the interaction between vehicles and off-road infrastructure to enhance safety. For example, if a small percentage of the fleet were equipped with GPS receivers it should be possible to use the approach presented in this paper to deduce the location of the lanes and then use this knowledge for a GPS based lane departure warning system.

The structure of the paper is organized as follows: Section II explains the details of data collection and the data used in the study. Next, Section III presents our methodology to detect lane change maneuvers, divided into mandatory lane change maneuvers (MLC) and discretionary land change maneuvers (DLC). Finally the paper closes with conclusions in Section IV.

## II. Data Description

The probe vehicle used in this work (Figure 1) is a van equipped with a DGPS receiver and data logging system that measures position and speed every second. For reference and validation purposes, a still camera captures the forward view through the windshield at 1 Hz .

The driver of the probe vehicle is directed to follow a specific route on every tour. The complete route is about 24 km each way and covers sections of three freeways, SR-315, I70 and I-71 in Columbus, Ohio. For most of the route the driver is instructed to stay in the lane second from the center lane. The present study is limited to the eastbound/northbound portion on I-70/71, extending from the central business district (CBD) to a suburb. There are two locations in this study section where the driver has to change lanes (MLC), while they are also allowed to pass slow moving vehicles (DLC) provided they return to the target lane promptly.

The DGPS device used in this work is a Trimble AG132 GPS receiver with Omnistar VBS corrections. It is an L1 only (single frequency) receiver with 12 channels. Omnistar VBS corrections are processed in real time. The antenna is a magnetic mount antenna fixed on the roof of the probe vehicle. The accuracy is reported to be less than 1 m radius for $95 \%$ of the time [16]. The 1 Hz DGPS data includes the following information: timestamp (sec after midnight), latitude (degrees), longitude (degrees), velocity ( $\mathrm{m} / \mathrm{sec}$ ), heading (radians), differential status, and altitude (m).

This study uses 23 tours through the corridor recorded between June 29, 2005 and November 30, 2005. Two out of the 23 tours are in the rain and other tours are in clear or overcast weather. Each tour includes two round trips, i.e., the analysis can use up to 46 trajectories at a given location along the route. Here the trajectory is in fact the time series of latitude and longitude measurements, which indicate the


Fig. 1. Probe vehicle. DGPS antenna is fixed at the top of the van.
position of the probe vehicle. Ideally these position measurements from DGPS should be accurate. However, the probe vehicle passes through many obstructions including so-called urban canyons and underpasses that degrade or impede operation. The route passes under many bridges, including one 100 m long underpass. The greatest problems arise from multipath, where the DGPS receiver may not be able to deduce the fact that an error occurred and the measured position is inaccurate. We have to differentiate between the noise arising from these obstructions and true deviations due to lane change maneuvers.

## III. Methodology

## A. Establishing a Reference Trajectory

Given many noisy individual trajectories of the probe vehicle passing through the corridor, we first find a reference trajectory to establish where the route is. Most of the time, trajectories should fall within the vicinity of this reference trajectory, since the driver is instructed to stay in the second lane from center, with deviations arising from lane change maneuvers or GPS errors.

First, an arbitrary trajectory T1 is chosen and used to define a curvilinear coordinate system, with x-coordinate correspond to the lateral distance (across the road), and $y$ coordinate correspond to the longitudinal distance (along the road). Thus, points on T 1 will be in the format of $(0, \mathrm{y})$. Then we resample all the other trajectories at every $y$ coordinate along T1, and map them into this coordinate system. The reference trajectory at each point along T1 is then defined as the median of the lateral distances of all trajectories at each given y.

The median, rather than the arithmetic mean, is used because the median is less sensitive to outliers in the dataset. So if the probe vehicle changes its lane occasionally, while keeping the current lane most of the time on the route, the median will not be affected by DLC while the mean would yield a reference trajectory that includes the impacts of every DLC.

Ultimately this reference trajectory is used to find when a given trajectory deviates from it due to DLCs. We use the large number of trajectories to reduce significantly the impacts of transient GPS errors and DLC. If one has another source to gather a reference trajectory, e.g., accurate center line position through a GIS, the task of finding the reference trajectory could be different. In such a case one could potentially find the lane change maneuvers from a single probe vehicle trajectory, without this extra step of finding the median over many trajectories. However, our proposed method to find reference trajectory is convenient and inexpensive. It eliminates the need for high-resolution maps accurate enough to capture the exact position of the individual lanes.


Fig. 2. The lateral distance of all 46 trajectories and their mean with respect to reference trajectory

## B. Finding Mandatory Lane Change Maneuvers

Mandatory lane change maneuvers occur when the probe vehicle has to shift lanes, e.g., due to geometric features or the need to reach an exit ramp. Across several trajectories through the section the distribution of MLCs begins over a small length of road rather than at a single longitudinal distance, i.e., a range of y coordinates. Consider a MLC observed across many trajectories. One of the trajectories will begin the MLC further upstream than the others. Moving downstream, more and more of the trajectories will begin the maneuver until the last trajectory changes lanes. Within this longitudinal window, the lateral position distribution will become more diffuse, becoming bimodal (peaking in the center of both lanes) if the window is much longer than the distance it normally takes to complete the maneuver. As one progresses through this window, more and more trajectories will fall on the side of the median in the direction of the MLC until the median jumps over to the other lane and the remaining trajectories now become prominent on the opposite side of the median until reaching the end of the window. Within the window these MLC will disrupt the reference trajectory since it uses the median lateral position. Fortunately, the MLC will have a different impact on the mean of lateral position, rather than changing abruptly, it will gradually shift along the length of the window. Thus, the difference between the mean and median can be used to find locations of MLCs. This difference will shift first in the direction of a MLC and then once the median shifts lanes, the difference will jump at the same location to the opposite side of the reference trajectory, i.e., the median. In other words, a MLC will result in two pulses in the mean of lateral distance relative to the reference trajectory, e.g., if a MLC is to the right-hand side, the first pulse will be to the right followed immediately by one to the left.

Figure 2a shows the lateral distance of all 46 trajectories with respect to reference trajectory, and the mean of the lateral distances is shown in Figure 2b.
Around longitudinal distance 4.3 km there is a MLC to the right (in this case due to the drivers' instructions) shown in Figure 3. Figure 3a shows the lateral distance of all trajectories with respect to the reference trajectory. Figure 3b shows the mean of lateral distances relative to the reference trajectory, and the two pulses are evident. Figure 3a and 3b are obtained by zooming in from Figure 2a and 2b.
Figure 3 c is an idealized schematic of the trajectories relative to the reference trajectory. Since most individual trajectories do not change lanes at the exact location that the reference trajectory changes lanes, these individual trajectories

(a) Lateral distance of all trajectories with respect to reference trajectory

(b) Mean of lateral distances

(c) Idealized schematic of trajectories with respect to reference trajectory

(d) Reference trajectory with respect to real road

(e) All trajectories with respect to real road

Fig. 3. Mandatory lane change around longitudinal distance 4.3 km .
will appear as if they changed lanes in the opposite direction in this plot, i.e., the given trajectory will pass through AB or $C D$ and the phantom shift reflects the change in the reference trajectory. A few trajectories will complete the MLC around the same location the reference trajectory shifts lanes and these trajectories will roughly pass through AD in the figure.

After adding 3.6 m (the lane width) in lateral distance to the trajectories passing through CD (superimposing them on AB ), to capture the impact of the MLC on the reference trajectory, the mean lateral position across all of the trajectories passing through CD (after shifting 3.6 m ) or AB is subtracted from the reference trajectory. Figure 3d shows the results, i.e., how the reference trajectory changes lanes relative to the roadway. We then add Figure 3a and 3d to get the distribution of trajectories with respect to roadway, shown in Figure 3e. Each trajectory now exhibits a single MLC to the right without any of the phantom lane change maneuvers due to the reference trajectory changing lanes.

After subtracting out the shift in the reference trajectory, the MLC can be found using the techniques presented in the next section to find DLC. Figure 4 shows three sample trajectories from Figure 3a and 3e, the first and second columns show respectively the corresponding plots before and
 vidual trajectories with respect to reference trajectory, and (b), (d), (f) after correcting for the fact that reference trajectory changes lanes. (a), (b) show an MLC upstream of the reference trajectory shift. (c), (d) show an MLC close to the location of the reference trajectory shift. (e), (f) show an MLC downstream of the reference trajectory shift.
after correcting the reference trajectory. The first row is a MLC upstream of the reference trajectory shift, the second row is a MLC close to the location of the reference trajectory shift, and the third row is a MLC downstream of the reference trajectory shift.

## C. Finding Discretionary Lane Change Maneuvers

In this data set the DLCs arise from overtaking. Each overtaking maneuver is comprised of two successive DLCs. This section first seeks to find the overtaking maneuvers then extract the two DLCs from each overtaking. In the event that the driver failed to return to the target lane the single DLC would simply appear as a very long overtaking maneuver and could still be detected by this method.

During an overtaking the probe vehicle will have to travel in the adjacent lane for some distance (usually to the lefthand side in this data set), so we calculate the lateral distances of every individual trajectory to the reference trajectory, e.g., as shown in Figures 3e. During a DLC, the probe vehicle should be offset laterally by a lane width, which is roughly 3.6 m . To find these departures we set two threshold curves laterally at half of the lane width on both sides, i.e., 1.8 m and -1.8 m defining the range of lane.

But not all of the lateral deviations beyond the threshold are due to DLCs, some disturbances come from GPS errors due to obstructions. Most of these GPS positioning errors are large in magnitude but short in duration, e.g., while reacquiring a lock on the satellites during one or two samples after emerging from an underpass. Such short transient errors can be quickly filtered out using a moving median on the time series lateral distance from the reference trajectory. In contrast, a real overtaking maneuver will usually take many seconds. We find whenever the lateral position of a trajectory is beyond the threshold of the lane and calculate both the out-of-threshold-line time and length (longitudinal distance).
The still camera imagery was used to verify the source of all departures from the lane, allowing us to differentiate between an overtaking and a disturbance. Figure 5 shows the cumulative distribution function (CDF) of the out-of-threshold-line time and length. Based on the manual verification, the data set has 30 actual overtaking maneuvers and 57 disturbances. Most of the overtaking maneuvers can be differentiated from the disturbances simply from a minimum out-of-threshold-line time or length. No overtaking is missed if the time threshold is set to 10 seconds, or length threshold is set to 300 m , but there are two GPS errors that are erroneously accepted as DLC by this simple filter. These errors are due to the combination of a loss of GPS data and roadway geometry, as shown in Figure 6. When the road bends the loss of GPS data for several samples will result in the straight line approximation having a large lateral deviation from the reference trajectory.
For reference, Figure 7 shows the location of all of the ob-
served overtaking maneuvers and disturbances from the 46 trajectories relative to the reference trajectory. Most, but not all, of the disturbances correspond to locations where the route passes through underpasses.
After finding the overtaking maneuvers we extract the two DLCs from each overtaking. The criterion to find the starting and ending points is based on the time series derivative

(b)

Fig. 5. CDF of the out-of-threshold-line statistics. (a) time, (b) length.


Fig. 6. An example showing how a GPS error is mislabeled as an overtaking maneuver, the straight line is due to the loss of GPS data points.


Fig. 7. Locations where (a) overtaking maneuvers, and (b) disturbances occur, shown as stars superimposed on the reference trajectory.
of the lateral position. Consider the first DLC of any overtaking, i.e., leaving the lane of the reference trajectory. Before and after the DLC, the rate of change in the lateral position is small. In contrast, during the DLC, there will be a large rate of change in the lateral position, as illustrated in Figure 8 . We constrain the starting and ending points, requiring the former to be within $1 / 4$ of a lane width $(0.9 \mathrm{~m})$ to be in the current lane and the latter beyond $3 / 4$ of a lane width $(2.7 \mathrm{~m})$ to be in the adjacent lane (as indicated on the figure). The DLC is then defined as the portion of the trajectory that the lateral position rate of change is at least $0.3 \mathrm{~m} / \mathrm{s}$. The DLCs are then segmented out of the overtaking maneuvers, as illustrated in Figure 8. Most of the DLCs occurred at free flow speeds, it is likely that this simple lateral rate criterion will have to be modified to accommodate DLCs during congestion and this point is the subject of on-going research.

Figure 9 shows the relationship between the length and time of the overtaking maneuvers. A linear relationship fits the data points well because most of the observed maneuvers


Fig. 8. Find the starting and ending point of the two DLCs of each overtaking. The circles denote the starting and ending points of the exiting DLC, and the starts denote those of the returning DLC.
happened in free flow traffic. The slope of the line is 28.6 meter $/ \mathrm{sec}$ ( 64 mph ), the average speed across all of the overtaking maneuvers.


Fig. 9. Relationship between the length and time from observed overtaking maneuvers. The slope of the line is 28.6 meter $/ \mathrm{sec}$ (64mph).

## IV. CONCLUSIONS

This study develops a methodology for detecting lane change maneuvers of a probe vehicle strictly from DGPS data. The first step is to establish a reference trajectory, in this case it is the median lateral position across many trajectories, though if another source is available that could be used instead and enable detection from just a single trip through the corridor.

The second step is to find MLCs from the mean of lateral distances across all the trajectories. The mean will show two opposite pulses wherever there is MLC, and it will be almost zero the rest of the time. Then we find and eliminate the effect of the lane change of the reference trajectory, and use the trajectories with respect to real road to find all the individual MLCs.

Next, the detection of DLC is based on finding overtaking maneuvers. We compare the lateral distance of a given trajectory to the reference trajectory. Whenever this difference exceeds a pre-defined threshold it is a candidate for an overtaking maneuver. Then we calculate the length and time of the out-of-threshold-line to discard most of the false positives arising from GPS errors. After finding all the overtaking maneuvers we extract the two DLCs from every overtaking.

Some work remains, our lane change maneuver detection algorithm is restricted to the probe vehicle itself. Now that we are able to track the lane of the probe vehicle, the detection of the lane change maneuvers by other vehicles will require additional sensors that can accurately measure the position of vehicles around the probe vehicle, e.g., [15]. However, the methodology would fit well into a VII framework, whereby many different GPS equipped vehicles pass
through a corridor and can provide the data necessary to construct reference trajectories. This latter scenario would eliminate the need for labor-intensive GIS data reduction and could accommodate any shift in lanes, e.g., short term due to a snowstorm or longer term due to road maintenance.

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