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Tactical Driver Behavior Prediction and Intent Inference: A Review

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Abstract— **Drawing upon fundamental research in human behavior prediction, recently there has been a research focus on how to predict driver behaviors. In this paper we review the field of driver behavior and intent prediction, with a specific focus on tactical maneuvers, as opposed to operational or strategic maneuvers. The aim of a driver behavior prediction system is to forecast the trajectory of the vehicle prior in real-time, which could allow a Driver Assistance System to compensate for dangerous or uncomfortable circumstances. This review provides insights into the scope of the problem, as well as the inputs, algorithms, performance metrics, and shortcomings in the state-of-the-art systems.**

I. INTRODUCTION

The first automobile accident may have occurred as early as 1770, in what were then very slow-moving vehicles. The first recorded *automobile fatality* did not occur until 1869, when a passenger was thrown from a relatively fast steam-powered carriage, as the driver jolted the vehicle around a turn. *Human* error, as opposed to any mechanical factor, has been cited as a primary cause of this accident. Indeed, human error had even been cited in the first railway fatality as early as 1830. [1]

Nearly two centuries later, human errors are still at the foundation of many accidents in every form of transportation, including vehicles, trains, ships, and planes. As technology has evolved, systems have been developed to help mitigate these errors and dangerous situations. In automobiles, safety systems started out from simply requiring brakes to be installed on automobiles, and have evolved into much more advanced technologies in modern Driver Assistance Systems.

However there are still over 30,000 deaths and 1.2 million injuries yearly on roadways in the U.S.; up to 80% of these are due to driver inattention [2], or as a result of unintended maneuvers [3]. This has motivated researchers to develop new ways to assist drivers and prevent dangerous situations.

Drawing upon fundamental research in *human* behavior prediction, recently there has been a focus on how to predict *driver* behaviors. In this paper we review the field of driver behavior and intent prediction. The aim of a driver behavior prediction system is to forecast the trajectory of the vehicle prior in real-time, which could allow a DAS to compensate for dangerous or uncomfortable circumstances. Though we present some opportunities for DAS feedback design, we focus mainly on the research in understanding driving behaviors.

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II. BACKGROUND

For many years research into intelligent systems has been focused on the development of more advanced sensors and networks to perceive, understand, communicate with, and interact with humans and the environment. As these systems have become increasingly adept at performing complex tasks, they have even begun to take control away from humans, in a broad range of arenas from finance to medicine to manufacturing. The resulting increases in safety, productivity, and lifestyle have been a transformative hallmark of the past century.

In certain fields, though, technology continues to lag in its effectiveness at improving the safety and comfort of human agents. Specifically, this includes such tasks as driving, where the human operator continues to play a central role in the task performance. A burgeoning field of research has developed around designs of new generations of intelligent systems to utilize advanced sensing and computational power to assist the humans. Intelligent Driver Assistance Systems (DASs) have the potential to improve safety by observing and interacting with the driver in a way to decrease risky behaviors and maneuvers [4], [5].

For the most part, however, current DASs are insensitive to the state of the driver and whether the driver needs the feedback, potentially annoying the driver to the point of disregarding or disabling the safety device, defeating its purpose. An opportunity for improvement is the utilization of driver information to improve the prediction of the vehicle's upcoming maneuvers. Prior research has shown that data processed from a set of smart cameras focused on the driver can improve maneuver recognition significantly. Cues such as driver head dynamics, eye gaze, hand position, and foot hovering information, have been shown to reveal a driver's intent to change lanes, brake, and turn [6], [7], [8], [9]. This is made possible because of the way that drivers prepare for the maneuvers moments before the start of the maneuver. A driver may check her blind-spot, adjust her speed and grip the steering differently moments prior to performing the maneuvers.

Along with driver pose information gleamed from driver-facing cameras, data from a number of other embedded sensors measuring environmental obstacles can be used to determine future vehicle maneuvers based on driver intentions. The addition of driver pose as a proxy for driver intent allows for considerable disambiguation between potentially dangerous situations and normal driving behavior. This is a very important factor in human assistance systems design, as reducing the false alarm rate is crucial to driver acceptance of the system.

This field is heavily influenced by research into driver modeling, which is broad in scope and seeks to characterize all aspects of human drivers, from cognition to operations. Several good reviews of driver modeling research can be found in recent literature [10], [11], [12]. Here we focus on those studies that attempt to understand any and all of those components necessary to identify and *predict* specific patterns of behaviors.

III. Modeling and Understanding Driver Behaviors

A. Intentionality and Awareness

To predict the trajectory behavior of a driver, we must first ask whether the behavior is intended or unintended. An unintended behavior may be difficult to predict well before-hand, as in these cases the driver loses control of the situation at some point. Recent events related to "pedal misapplications" have led to the exploration of some potential causes of unintended behaviors, in which the driver commits to a particular intentional action, but nevertheless performs a different action. Some other commonly cited causes for unintentional behaviors include distractions and workload [2], multi-tasking [13], and fatigue [14], among others. As we discuss later, these factors may also create variations in at different times in fully executed patterns of intentional behaviors.

Though there may be motivators and early indicators of an upcoming intentional maneuver, a driver may also decide to abort the maneuver at any time. This may be due to the appearance of inhibitors, or events in the driving scene which cause the driver to change their plans. In such cases, there may be little way to verify whether the original intent ever existed. This issue is usually dealt with in the literature by only training systems on fully completed intentional behaviors; however in real-world performance, aborted intents may contribute to false alarms in systems.

In Table I, we show how the detection of an intent, or lack thereof, can help to disambiguate between safe maneuvers, aborted maneuvers, and dangerous situations. If an intended maneuver is successfully carried out, then the situation may be safe. As discussed above, intended maneuvers may be aborted, which indicates that the driver has changed plans. When no intent is detected, yet a maneuver occurs, the situation may be more dangerous as the driver may be unaware of potential inhibitors.

The lack of awareness is a key contributor to accidents, and is sometimes classified as "inattention". For example, a driver may notice the leading vehicle stopping suddenly, and to avoid a collision the driver may swerve into an adjacent lane. This may result in an inadvertent collision with a vehicle in the adjacent lane, of which the ego-vehicle driver was unaware. As another example, the driver may be drowsy or distracted, and drift into the adjacent lane with similarly dangerous outcomes. In such cases, by detecting the start of a maneuver with no prior intent, an advanced DAS might be able to more rapidly react to or prepare for the subsequent dangerous maneuver.

TABLE I

Potential Outcomes of Intent Predictions

	Maneuver Completed	No Maneuver Completed
Intent Predicted	Safe Maneuver	Aborted Maneuver
No Intent Predicted	Dangerous Maneuver or Unaware Driver	Safe Situation

B. Motivations

The motivations for any particular driving maneuver can be understood from a driver's desire for (a) *safe* (no accidents) and (b) *comfortable* (e.g. not too slow, not too close) guidance to (c)*a destination*, given the dynamics of the vehicle (model), driver (style), and environment (other vehicles and obstacles, weather).

For the purposes of this review, we will define a situation as an interaction of any of the three components, the driver, vehicle, and environment. There is certainly feedback amongst these components. We can thus explore how planned maneuvers develop with these driver-centric interactions in mind, along each of the time-scales below.

C. Time-scale

Intentional maneuvers may be planned on operational, tactical, or strategic timescales. These timescales have been proposed by prior researchers [10], [12] in driver modeling. The operational, or critical, timescale, on the order of hundreds of milliseconds, is the shortest possible timescale for human interaction. Tactical, or short-term, timescales are on the order of seconds, and encompass many successive critical operations. Finally, the strategic, or long-term, group is associated with minutes or hours of prior planning.

These timescales are widely used in the driver modeling literature [10], [12], where most driver models tend to focus solely on the critical, operational aspect of driving. Very detailed models of operational behaviors have been developed, integrating information about the vehicle and road into understanding how drivers behave [11]. In the following sections we will examine more closely the evolution and motivations of a maneuver on all these time scales.

1) Operational Maneuvers: Operationally-planned intentional maneuvers are a generally a result of a driver's desire to remain safe in following the rules of the road (posted speed limit, road curves, etc), while carefully operating the vehicle within its limits. As mentioned above, many operational models for driver behavior have been proposed, such as [15]; these have been surveyed recently by Macadam [11] and Plochl [12].

Other instances of operationally-planned intentional maneuvers include unsafe situations, and may involve sudden braking or swerving to avoid any danger. The targeted execution of critically-planned maneuvers is usually in the steering and pedal actuators, where the driver has direct operational control.

Several studies monitor and detail the operational actions of drivers in these critical situations [16], [17], [18], some with an eye toward prediction [19], [20], [21], [22] and taking corrective actions in case of emergencies [23], [24]. Due to the proliferation of good surveys and literature on operational maneuvers [10], [11], [12], we instead focus more on tactical maneuvers below.

2) Tactical Maneuvers: Tactically-planned intentional maneuvers include a coherent set of operations intended to fulfill a short-term goal. In this study we classify maneuvers such as turns, lane changes, and stops, as tactically-planned.

The time between the plan and the full execution of the tactical maneuver is on the order of multiple seconds. Thus tactical plans are of particular interest, as in these cases the driver still has time to react to feedback from an assistance system.

These are motivated by an impending uncomfortable or unsafe situation, or by the desire to follow a specific route. A driver may change lanes because the leading vehicles in the current lane are slowing down, or because a desired exit is coming up soon.

A driver may be motivated to perform a tactical maneuver, but typically prior to engagement, the driver will search for inhibitors which will affect the safety of the maneuver. These inhibitors, such as pedestrians in a crosswalk, or vehicles in the adjacent lane, may cause the tactical maneuver to be delayed, altered, or in some cases aborted all together. As discussed above, drivers who plan a tactical maneuver but are **unaware** of any inhibitors may be at risk for a dangerous situation.

3) Strategic Maneuvers: Finally, strategically-planned intentional maneuvers are motivated by the destination goals of the driver, and sometimes by comfort as well (e.g., fastest route, no tolls). Given the starting point, the target space of strategic planning is the desired destination and route of the driver. The route plan gives away important details as to the planned trajectory of the driver.

A number of studies target the route or destination of the driver, and generally include GPS and Map data as inputs [25], [26], [27], [28], [29], [30], [31]. One issue with these studies is the lack of a common evaluation metric; given that they are evaluated in their own manners it is difficult to compare performance. Ultimately, however, these studies could be used as inputs to tactic and operation prediction models [32]. Due to space constraints, the focus of this survey will remain on tactical maneuver predictions.

IV. Tactical Maneuver Prediction

Once started, tactical maneuvers are defined by a series or group of operational maneuvers. For example, intersection turns or lane changes are defined by a series of pedal presses and steering adjustments. The detection of a tactical plan is most reliably made by the recognition of the start of a specific series of operations. However by detecting proxies to the driver's intents, the tactical plan can be detected prior to the start of the maneuver.

There have been several research thrusts into modeling of driver tactics [43], [44], [45], [46], [47], or in historical analysis of drives to segment individual tactics [48], [49], [50], [51], [52], [53], [54], [55], [56], [57]. These models and algorithms focus on identifying maneuvers after the completion of the maneuver.

In the case of predictive models, we can separate out two broad categories of studies. In the first case, are those which target the prediction of single tactics, shown in Table II. Targets include lane changes, turns, or stopping maneuvers. Within these studies, Table II further subdivides the targets into Brake maneuvers, Turn maneuvers, and Lane Change maneuvers. Another category is shown in Table III, including those studies focused on multi-target prediction of driver behavior. This includes models which predict whether the driver is one of many different states, including various combinations of the single-target maneuvers.

Below we discuss several important characteristics of these studies.

A. Inputs

The inputs to the models generally include vehicle data, as well as some measure of the surround. Vehicle data is generally collected from the Controller Area Network, or **CAN** bus. Signals typically collected from the CAN include steering wheel angle, pedal position, and turn signal state, among others.

Several sensor systems may provide a sense of the surrounding environment. These may include a **Lane** position sensor, which gives off information regarding the lateral lane position and deviation. An **ACC**(Adaptive Cruise Control) radar determines the distance to a leading vehicle, and an **SWA**(Side Warning Assist) radar system detects vehicles in the blind spot. Certain SWA systems provide a full 360° view of the surround, and are labeled as **SWA+**. Finally, **GPS** systems provide a coarse localization of the ego-vehicle.

To adequately measure driver intention, we note that there are several single-target studies that incorporate measurements of driver behaviors [8], [35], [9], [7], [42]. Sensor systems generally include camera-based systems to detect **Head**, **Eye**, **Foot**, or **Hand** positions. These studies include more information useful for driver intent inference by detecting preparatory behavior, and tend to outperform the studies which attempt to predict maneuvers with no direct measurement of the driver behavior. Several of the multi-target studies [58], [59] also include explicit information of driver behavior, and by directly inferring driver intent demonstrate better performance, earlier before the maneuver.

B. Algorithms

Single-target algorithms tend to make use of both discriminative algorithms, such as Support Vector Machines or Relevance Vector Machines, as well as generative methods, such as Bayesian Nets or Hidden Markov Models. Multi-target algorithms tend to exclusively rely on generative models, such as Hidden Markov Models, especially since they are better suited to multi-target inference. In both cases,

TABLE II

SELECTED STUDIES IN SINGLE-TARGET DRIVER TACTIC PREDICTION (SHORT-TERM)

Paper	Target	Inputs	Algorithm	Loc	Dat	Num	TPR	FPR	Time
[33]	S	CAN, ECG	DBN + HMM	S	I	5	-	-	-2.6
[34]	S	CAN	HMM, SLDS	R	N	1	-	-	-
[8]	B	CAN, ACC, Foot, Head	RVM	R	N	28	80	20	-1
[35]	TR, TL, LK	CAN, GPS, Head	Conceptual Fuzzy Sets	R	-	7	89.7	-	0
[9]	TR, TL, LK	CAN, Head, Hands	RVM	R	N	1	76	20	0**
[36]	LC, LK	CAN, Lane	Markov chain, Kinematics model	R	I	1	-	-	0
[7]	LC, LK	CAN, ACC, Head, Lane	RVM	R	N	3	90	4	-2.5
[37]	LC, LK, dLC	CAN	HMM	S	I	10	100	-	0
[38], [39]	LC, LK	CAN, ACC, Lane, SWA+	Clustering	R	N	9	77	5	+1
[40]	LC, LK	CAN, SWA+	Dynamic belief networks	-	-	-	-	-	-1.5
[41]	LC, LK	CAN, Lane	RNN, FFNN, SVM	S	N	10	100	10	-1.5
[42]	LC, LK	CAN, ACC, Lane, Head, SWA	RVM	R	N	15	70	0.2*	-2.5

Targets: (S)stop, (B)brake, (TR)turn right, (TL)turn left, (LC)lane change, (dLC)dangerous lane change, (LK)lane keep.
Inputs: (CAN)vehicle params, (GPS)location, (ECG)heart rate monitor, (ACC)forward-radar, (SWA)side-radar, (SWA+)surround-radar, (Head,Hands,Lane)positions.
Algorithms: (DBN)Dynamic Bayesian Networks, (RVM)Relevance Vector Machine, (HMM)Hidden Markov Model, (SLDS)Switching Linear Dynamic System, (RNN, FFNN)Recurring / Feed-forward Neural Net.
Loc: Location - Real-world or Simulator.
Dat: Data Collection - Naturalistic or Instructed.
Num: Number of Subjects.
TPR: True Positive Rate., *FPR*: False Positive Rate. (percentages)
Time: Time (seconds) from prediction to maneuver (negative=before, positive=after start of maneuver).
* - reported in false positives per second.
** - time before entering intersection, not before maneuver.

the models are trained using examples from experimental data collections, as described below.

C. Location, Data, and Number of Subjects

The location of the data collection for these studies was either collected in a Simulator or using a Real vehicle. Simulator studies have the advantage of control over many different variables, such as traffic conditions, weather, and distractions, and are easily repeatable. However simulator performance does not always translate well to on-road performance [60], so many of the studies use a vehicle testbed to collect on-road data.

The data collection itself may have been either Naturalistic or Instructed. With Naturalistic data collection, generally the driver (subject) is told to drive as they normally would over a potentially prescribed route, without knowledge of the direct goals of the study. Though this allows the collection of natural data that would be useful for realistic DAS design, the number of examples collected is not always a large amount. Instructed data collection, where a moderator tells the subject when to perform specific maneuvers, allows for a set number of examples to be collected, but potentially modifies the way the subject drives compared to natural settings.

These studies also vary in the number of subjects used in data collection. While several studies rely on just one subject [34], [9], [36], the numbers range up from there, with an average of 19 subjects per study. Ideally to prove generality, a model should be based on data from at least 100 subjects [61] or more.

D. Performance

To measure performance prediction, generally some measure of True and False Positive Rates (TPR/FPR) is used. These numbers represent the overall proportion of target examples that were correctly predicted (TPR), and the proportion of non-target examples that were incorrectly predicted as targets (FPR). Though we report single pairs of TPR/FPR performance, a more accurate comparison between classifiers would show their performance curve along a range of thresholds, with a Receiver Operating Characteristic (ROC) curve. Not all studies report performance this way, so such a comparison is beyond the scope of this review.

It is also important to keep in mind the time-lag of the prediction, when comparing these numbers. As the time gets closer to the maneuver, prediction performance generally increases. Certain studies are tuned to predict the maneuver just before it occurs [35], [36], [37], [61], whereas others are tuned to predict at certain times, e.g. 1.5 or 2.5 seconds prior

TABLE III

SELECTED STUDIES IN SHORT-TERM MULTI-TARGET DRIVER TACTIC PREDICTION (SHORT-TERM)

Paper	Target	Inputs	Algorithm	Loc	Dat	Num	TPR	FPR	Time
[62]	A, B, LK, LCL, LCR	CAN, ACC, Lane	Dynamic belief networks	-	-	-	-	-	-
[63]	TR, TL, TU, RO, B	CAN	HMM	R	I	20	-	-	-
[61]	NS	GPS	Markov	R	N	100	90	-	0
[58]	P, TR, TL, LCL, LCR, ST, S	CAN, Eye, Lane	HMM and CHMM	R	N	70	66.5	-	-1
[59]	FL, FC, P	CAN, ACC, Eye, Lane, SWA+	PWARX, Clustering, Grammatical Inference	S	N	5	70	-	-2.5
[64]	LCL, LCR, TL, TR, LK	CAN, GPS, Map*	HMM	R	N	NR	69.6	14.2	+2

Targets: (A)accelerate, (S)stop, (B)brake, (TR)turn right, (TL)turn left, (TU)u-turn, (LCL)lane change left, (LCL)lane change right, (LK)lane keep, (RO)roundabout, (NS)next segment in map, (P)passing, (ST)start, (FL)follow-long, (FC)follow-close, .

Inputs: (CAN)vehicle params, (GPS)location, (ECG)heart rate monitor, (ACC)forward-radar, (SWA)side-radar, (SWA+)surround-radar, (Head,Hands,Lane)positions.

Algorithms: (DBN)Dynamic Bayesian Networks, (RVM)Relevance Vector Machine, (HMM)Hidden Markov Model, (SLDS)Switching Linear Dynamic System, (RNN, FFNN)Recurring / Feed-forward Neural Net.

Loc: Location - Real-world or Simulator.

Dat: Data Collection - Naturalistic or Instructed.

Num: Number of Subjects.

TPR: True Positive Rate, *FPR*: False Positive Rate. (percentages)

Time: Time (seconds) from prediction to maneuver (negative=before, positive=after start of maneuver).

* - Advanced map marked with lanes and intersections.

to the maneuver. Many of the methodologies report tuning for multiple decision times (e.g., [8], [42]), where only one performance time is reported here.

As described above, the studies that incorporate measures of driver behavior perform better, and earlier, at predicting driver behaviors. These studies demonstrate the value of incorporating direct measurements of driver behavior, and thereby direct inference of intent, into the prediction of tactically-planned maneuvers. The measurement of behavior allows for the detection of behaviors associated with planning for the maneuver - behaviors such as visual search and preparatory hand or foot movements.

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