Driver Behavior Analysis for Accidents Prediction

Project report submitted in fulfillment of the requirement for the degree of Bachelor of Technology

In

Computer Science and Engineering/Information Technology

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Candidate's Declaration

I hereby declare that the work presented in this report entitled **"Driver Behavior Analysis for Accidents Prediction"** in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** in **Computer Science and Engineering/Information Technology** submitted in the department of Computer Science & Engineering and Information Technology**,** Jaypee University of Information Technology Waknaghat is an authentic record of my own work carried out over a period from August 2015 to May 2016 under the supervision of **(Dr. Pardeep Kumar)** (**Assistant Professor (Senior Grade**)dept of CSE).

The matter embodied in the report has not been submitted for the award of any other degree or diploma.

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This is to certify that the above statement made by the candidate is true to the best of my knowledge.

(Supervisor Signature)
(Dr. Pardeep Kumar)
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Dated:

ACKNOWLEDGEMENT

It is our privilege to express our sincerest regards to our project coordinator, Dr. Pardeep Kumar, for his valuable inputs, able guidance, encouragement, whole-hearted cooperation and constructive criticism throughout the duration of our project. We deeply express our sincere thanks to him for encouraging and allowing us to present the project on the topic "Driver Behavior Analysis using Prediction Model “at our department premises for the partial fulfillment of the requirements leading to the award of B-Tech degree. We take this opportunity to thank all our lecturers who have directly or indirectly helped our project. We pay our respects and love to our parents and all other family members and friends for their love and encouragement throughout our career. Last but not the least we express our thanks to our friends for their cooperation and support.

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ABSTRACT

Road accidents are a human tragedy. They involve high human suffering and monetary costs in terms of untimely deaths, injuries and loss of potential income. Although we have undertaken many initiatives and are implementing various road safety improvement program the overall situation as revealed by data is far from satisfactory. During the calendar year 2010, there were close to 5 lakh road accidents in India, which resulted in more than 1.3 lakh persons. These numbers translate intone road accident every minute, and one road accident death every 4 minutes. Unfortunately, more than half the victims are in the economically active age group of 25-65 years. The loss of the main bread winner can be catastrophic. Road traffic accidents are amenable to remedial action. Many a countries have curbed the menace of road accidents by adopting a multipronged approach to road safety that encompasses broad range of measures, such as, traffic management, design and quality of road infrastructure, application of intelligent transport system, safer vehicles, law enforcement, effective and quick accident response and care etc. The Government alone cannot tackle road safety problems. There is a need for active involvement of all stake- holders to promote policy reform and implementation of road safety measures. Addressing road safety is comprehensive manner underscores the need to involve multiple agencies and sectors like health, transport and police. The present study provides the magnitude and various dimensions of road accident in India. The analysis on road accidents in this study will help to create awareness, guidelines and assist in informed decision making on road safety.

Our effort to improvise the road accidents prevention techniques, various algorithms involving data mining and databases have been used keeping in mind the better future of public.

CHAPTER-1

INTRODUCTION

1.1 Introduction:-

Careless driving is among the more common violations given out by police, but in many cases there is some confusion as to what careless driving actually is. This is because there is a lot of room for interpretation on the part of police when it comes to determining what determines as careless driving. When driving on the road, a driver has to be away of many different things. The drive has to be aware of the road, his driving skills, other driver's skills and weather conditions. Therefore, the driver’s attention is already spread thin when there are other distractions that he or she can avoid.

One of the worst distractions that a driver can avoid is the act of looking at phone. The use of a cell phone while driving is illegal; however, many people still engage in this intentional diversion.

One aspect of driving that careless drivers heed no attention frequently is the safe driving speed of a particular area. Most of the areas display speed limits higher than the standard speed limit of the area making it life threatening. However, many careless drivers will speed in those areas thinking that the posted speed was immaterial to them. This can be the cause of accidents that result in serious injury or even fatalities, especially if there is a bend involved where the driver’s view is not really that well.

Unlike a speeding ticket, which is easily measurable using radar, careless driving violations can be given out in a variety of situations where the officer feels a driver was not using the care and attention to the road needed to drive safely. In essence, reckless drivers put themselves and others at death risk. As such, reckless driving offenders are punished by fines, jail time, and/or driver’s license suspension or revocation.

1.1.1 Defining Careless Driving:-

The Highway Traffic Act of Ontario defines careless driving as driving “a vehicle or street car on a highway without due care and attention or without reasonable consideration for other persons using the highway.”

There is a great deal of interpretation on the part of the police officer giving the violation. That officer must determine that the driver was not obeying the level of safety measures of their surroundings that is required for safe driving. This can apply in many situations, whether or not an accident occurs. Careless driving charges are common in the case of accidents where one driver caused the crash due to not obeying rules and regulations. Police can also hand out a charges if they witness a driver performing an action on the road that shows negligence and could potentially cause an accident or death.

Because careless driving has so much room for interpretation in the definition and relies on the officer’s judgment, it is a charge that many people consider fighting in court.

Reckless driving is often defined as" A mental state in which the driver displays a meaningless disregard for the rules of the road; the driver misjudges common driving procedures, often causing accidents and other damages". Reckless driving has been studied by psychologists who found that reckless drivers score high in risk-taking personality traits. However, no one cause can be assigned to this state.

Courts and juries have found defendants guilty of reckless driving when any or some of the following behaviors were proved by the prosecution:

- Driving in excess of the speed limit, in a dangerous way;
- Passing red lights or stop signs, in circumstances that endanger others;
- Failure to yield a right-of-way;
- Failure to give electronic signals, or to keep a lookout (such as while texting, talking on the phone, or fiddling with electronic music controls);
- Not having proper street lights;

However, a mere error of judgment, without more (such as passing a stopped car and colliding with an oncoming but hard-to-see car) usually will not amount to reckless driving and the same is true for skidding.

Defendants have found that the lack of any injury or damage to persons or property does not rule out a certainty for reckless driving, nor will a last-minute attempt to avoid the same.

There are some states, such as Virginia, where mental state is not considered, but rather a set of more than a dozen specific violations can be deemed reckless. Excessive speed by itself is sufficient for a reckless driving conviction in some jurisdictions (e.g., Virginia).

1.1.2 DRIVING IN INDIA:-

At the beginning when the number of vehicle was very low on the roads of our country there were no serious needs for traffic rules and regulations. But when mass production of vehicles began and the roads flooded with different kind and class of vehicles the Government felt the need for a system to control the vehicular traffic.

In the year 1914 the first legislation as "Indian Motor Vehicle Act 1914" was passed in our country to regulate the motor vehicles and as well as other road users. Since then the traffic pressure on the roads of our country increased and at the same time to control the unprecedented growth in the number of motor vehicles, the first Motor Vehicle Act 1914 which was in later years known as "The motor Vehicle Act 1988" was amended and revised several times by the Government of India. Traffic rules and regulations are devised to assure the smooth flowing of motor vehicles in the road. Moreover, traffic rules and regulation are not only for the driver of the vehicles but at the same times these rules are meant for the pedestrians, cyclist, motor-cyclist and other road users. The thorough knowledge of traffic rules/regulations, traffic signs and markings are very essential for the drivers and road users. The proper knowledge of these rules can reduce the number of accident and thus can establish a healthy and organized traffic system in our country.

India is generally considered to be one of the most dangerous countries in the world where driving is risky. In 2007, more than 130,000 people died on the roads in India – more than anywhere else in the world, though the number needs to be weighed against the large population of the country. A driving license is required to drive in India on right side where, like the United Kingdom, the traffic drives on the left side of the road. The wide variety of methods of transportation, and what is often portrayed as a common disregard for the rules of the road, contributes to the losses.

1.1.3 RULES OF THE ROAD:-

The 30 brief rules are:-

- Keep **Left:** Drive as close to the left side of the road and allow all traffic going in the opposite direction to pass on the right hand side.
- Turning **Left:** When needing to turn onto a road on the left, stay close to the left side of the road and after making the turn continue on the left side of the road. (Do not cut across lanes from the right side of the road and then turn left).
- Turning **Right:** When turning onto a road on the right side, first approach the center of the road as safely as possible and then turn to the right and stay on the left side of the road.
- Passing: If there is a need to pass traffic proceeding in the same direction, always pass/overtake them on their right side. The only exception to this would be the case where a vehicle that is trying to turn to the right (and has indicated their intention to turn right) is occupying the center lane and therefore requires passing them on the left side.
- Passing **Prohibited**: Overtaking/passing a vehicle proceeding in the same direction is prohibited in the following scenarios:

1. The passing/overtaking would cause inconvenience or danger to any vehicle proceeding in any direction.
2. On bends/curves in the road or on hills or there are other obstructions present that prevents a clear view of the road ahead.
3. If the driver behind the current vehicle has already started to overtake the vehicle
4. The driver of the vehicle in front has not yet signaled that he may be overtaken. (***Please Note***: The solid lines painted on the middle of the road indicate passing is prohibited for as long as the line is a solid line- you will notice them on bridges, curves and where visibility of the road ahead is not present. Overtaking when safe to do so is allowed when the line changes to a dashed line.)

• When **being Passed/Overtaken by another vehicle:** The driver should not speed up or do anything to prevent the other vehicle from passing.
• Intersections**:** Drivers should slow down when approaching road corners, intersections, junctions or pedestrian crossings and not enter until sure that such an entry will not endanger the safety of pedestrians or people in other vehicles there.
• Right **of Way:** When entering an intersection that is not regulated by a traffic signal or by a traffic policeman and which is an entry onto a main road, the driver of the vehicle is to give right of way to the vehicles already proceeding on that road. In all other cases the driver is to give way to traffic approaching from his right hand side and only then proceed.
• Emergency **Vehicles:** Fire Service Vehicles and Ambulances are to be allowed free passage and drivers of all other vehicles should move their vehicles to the side of the road to do so.
• Pedestrians**:** Pedestrians have the right of way at uncontrolled pedestrian crossings.
• “**U” Turns:** “U” turns may be done only when

1. Not explicitly prohibited by a sign
2. Only after indicating the turn is being planned either through a hand signal or through the vehicle indicators
3. After checking the mirrors to make sure there is no traffic from behind
4. Checking the road to make sure that there is no other traffic and it is safe to do so.

• Required **Signals:** These are really hand signals are mentioned in point 13 of the rules of the road. Very few people actually know the hand signs and use them. It is good to learn them and be prepared to use them if you have any issue with your indicator lights or with your brake lights. The hand signs for the following should be followed if the vehicle brake/indicator lights do not work:

1. When the vehicle is about to slow down
2. When the vehicle is about to stop
3. When the vehicle is about to turn to the right side or pass a vehicle on the right
4. When the vehicle is about to turn to the left
5. When indicating that it is safe for the vehicle behind to pass

- Indicators**:** The signals indicated in regulation #13 can be simplified by the use of mechanical or electrical devices (indicators).
- Parking**:** When parking the vehicle make sure that it does not cause any danger, obstruction or inconvenience for other road users.
- Registration**:** Loads or goods should not be kept on the vehicle in a manner that obstructs visibility, the headlamps/tail lamps or the registration number of the vehicle. If any obstruction of the registration is done a duplicate is to be kept in a visible spot.
- One **Way Roads:** On designated "One Way" roads drive only in the direction indicated on the road signs. Do not drive the vehicle in reverse into a "One way" street.
- Stop **Lines:** At road intersections, pedestrian crossings and stop signs make sure that the vehicle is fully behind the stop lines painted on the road. The driver has to drive taking into account this requirement of stopping before the stop line when required by a stop light or sign or by a police officer.
- Towing**: No** vehicles may be towed behind another motor vehicle. The only exceptions are

1. Mechanically disabled vehicles
2. Incompletely assembled vehicles
3. Registered trailers and sidecars
4. The above may be towed only for the purpose of delivery or to the nearest garage or service station.

- Noise: Drivers should not

1. Sound the horn more than necessary for safety. Continuously and unnecessary sounding of the horn is illegal.
2. Sound the horn In designated silent zones (for e.g. such as hospital zones)
3. Use multi-toned horns that are harsh, shrill, loud or alarming
4. Use cut outs for the exhausts
5. Drive vehicles that create a lot of noise when in motion
6. Drive vehicles without proper mufflers causing a loud sound

- Traffic **Lights & Signs:** Obey the traffic signal lights , the instructions given by the traffic policemen or by designated/authorized people in charge of regulating traffic
- Following **Distance:** Keep sufficient distance behind the vehicle in front to allow distance to stop if the vehicle in front has to stop suddenly.
- Right **of Way on mountain roads/ steep roads:** Where the width of the road is not sufficient for vehicles to pass each other safely, the vehicle going downhill has to stop to the side of the road and allow the vehicles going uphill to pass.
- Obstruction **of Control:** The driver of the vehicle should not allow a person to sit, stand or place anything that obstructs his control of the vehicle.
- Passing **Pedestrians:** When passing a procession, meeting, troops or police on the march or road repair workmen do not drive faster than 25 kilometers per hour.

• Tractor **& Goods Carriages:** Drivers of tractors are not permitted to carry passengers on the tractor. Drivers of good carriages should not allow more persons than listed on the vehicle registration to travel in the cabin or take passengers for hire or reward.

• Loading**:** Vehicles should not be loaded in such a way that causes danger to other road users. Load carrying vehicles should not have anything extending outside the vehicle towards the front, rear, sides and should also follow allowed maximum height restrictions.

• Dangerous **Materials:** Other than the fuel and lubricant necessary for vehicle operation, no explosive, inflammable or other dangerous substance should be carried on any public transport vehicle.

• Driving **in reverse:** The driver should not drive the vehicle in reverse without first making sure that doing so would not cause any danger or inconvenience to any person on the road.

• Documents **to be carried/produced on demand:** The person driving the vehicle is to always carry the following documents:

1. Driving License
2. Certificate of registration of the vehicle
3. Certificate of taxation
4. Certificate of insurance
5. For transport vehicles the following additional documents are required
    1. The permit
    2. Fitness certificate
6. These documents are to be produced on demand by any Police officer in Uniform, Officers of the Motor Vehicles Department in Uniform or by any officer authorized by the Government. If the driver does not have the documents in his/her possession he should produce attested copies in person or through registered post to the officer who demanded it within 15 days.

Additionally, the national upper speed limit is 100 kilometres per hour (62 mph) for cars, 80 kilometres per hour (50 mph) for motorcycles, and varies for other categories of vehicle. Until 2014, there was no national upper speed limit for cars in India, as local police set the limits in their own areas. Local governments are still encouraged to set specific limits within their own jurisdiction.

As with the United Kingdom, traffic drives on the left side of the road in India. To acquire a driving licence a person has to be at least 18 years old. Driving under the influence the limit in India is 0.03% blood alcohol content is punished heavily, a first offence could result in a ₹10,000 fine and or a prison sentence of up to six months. A seatbelt must be worn when driving in cities.

1.1.4 DANGERS:-

India is traditionally held to have some of the most dangerous driving in the world. In 2007, Indian roads were the deadliest in the world; more than 130,000 died on them (11.21 deaths per 100,000 people), although 85% of these deaths were to pedestrians or cyclists. A 2014 article published by *Reuters* described a driving test in Delhi, which lasted less than two minutes, and involved one examiner testing ten people at the same time.

Peter Foster, a journalist for *The Daily Telegraph*, recounted that in his experience" fellow drivers paid little heed to the rules of the road, and did anything they could do avoid queuing; succeeding in blocking up more of the road".

1.1.5 GLOBAL SURVEY:-

According to the World Health Organization, road traffic injuries caused an estimated 1.24 million deaths worldwide in the year 2010, slightly down from 1.26 million in 2000. That is one person is killed every 25 seconds. Only 28 countries, representing 449 million people (7% of the world's population), have adequate laws that address all five risk factors (speed, drink–driving, helmets, seat-belts and child restraints). Over a third of road traffic deaths in low- and middle-income countries are among pedestrians and cyclists. However, less than 35% of low- and middle-income countries have policies in place to protect these road users.

Eighty per cent of road traffic deaths occur in middle-income countries, which account for 72% of the world's population, but only 52% of the world's registered vehicles. This indicates that these countries bear a disproportionately high burden of road traffic deaths relative to their level of motorization.

There are large disparities in road traffic death rates between regions. The risk of dying as a result of a road traffic injury is highest in the African Region (24.1 per 100 000 population), and lowest in the European Region (10.3 per 100 000).

Half of the world's road traffic deaths occur among motorcyclists (23%), pedestrians (22%) and cyclists (5%) – i.e. "vulnerable road users" – with 31% of deaths among car occupants and the remaining 19% among unspecified road users.

Adults aged between 15 and 44 years account for 59% of global road traffic deaths. 77% road deaths are among men.

The total fatalities figures comes from the WHO report (table A2, column *point estimate*, pp. 242–255) and are often an adjusted number of road traffic fatalities in order to reflect the different reporting and counting methods among the many countries (e.g. *"a death after how many days since accident event is still counted as a road fatality?"* (by standard adjusted to a 30 days period), or "to compensate for underreporting in some countries", see WHO report pp. 48–51).

1.2 Problem Statement:-

Driver Behavior Analysis for Accidents Prediction (based on Data Mining)

1.3 Objective:-

Traffic accident happened every day. In order to decrease the number of traffic accident and the losses caused by the traffic accident our government have a lot of policy, but these policies are focus on the entire citizen. But now we think the policy have to focus on the certain group ,the group who have high rate in traffic accident, to let the policy have more significant effect.

1.4 **Methodology:-**

Active safety is seen as the feasible solution necessary to lessen vehicle accidents. This approach addresses the problem using system engineering methodology by incorporating all technological solutions related to vehicle, road structure, traffic management and driver assistance monitoring systems.
Vehicle, driver and environment are perceived as the three main workings mechanisms of the system. There is a wide range of systems developed to increase safety of vehicles themselves by making them more steady and reliable. However, a large portion of improbability exists in any driving scenario because of the long term as well as instant ability of the driver, changing environment and their interaction. Therefore, the complete solution for reduction of road accidents is only possible by making the vehicles 'aware' of the driving context (environment, route and manoeuvre type) and the driver status (distracted, neutral, aggressive, drowsy etc.). This can be achieved by analysing driver behavior signals including driver inputs (i.e., steering wheel angle, steering velocity, brake/gas pedal pressures), vehicle responses to driver inputs (i.e., vehicle speed, acceleration and position), and driver biometric signals (i.e., eye gaze, eye closure, heart rate).

"Driver behavior analysis is an interdisciplinary research field where exploratory statistics, stochastic modeling, signal processing, control theory, human factors and artificial intelligence methods are used by researchers to model certain aspects of driver behavior in a mathematical scheme". One emerging trend has been to borrow techniques based on **Hidden Markov Models (HMM)** from the speech processing and language technology field and apply this to driver behavior modeling for route recognition, driver identification, and distraction detection in an analogy with speech recognition, speaker identification, and stress detection in speech. HMMs which have already been established in speech processing, and are applied in several pattern recognition areas such as place learning and recognition for mobile robots , signature recognition and human action learning (intent and skills) for teleportation of robots .

In order to represent both the stochastic and dynamic-continuous properties of human behavior in driving, dynamic models using Kalman filters to estimate the vehicle outputs from driver inputs are employed by feeding their prediction errors into HMMs. Benefits of using HMMs with a dynamical scheme to predict the driver actions within the first 2 sec of an action sequence have been shown in . Driving events were recognized by HMMs in with a recognition rate of 93.8% using only vehicle speed and acceleration as raw data.

1.5 Organization:-

In this we will go through various stages- firstly the literature part will there which will include various research papers, secondly system development part which will include series of developing the solution, thirdly the performance analysis will be there.

Lastly conclusion will be added and results are analyzed.

CHAPTER-2

LITRATURE SURVEY

Road and vehicle technology is improving all the time. The best motorways nowadays have variable speed limits, warning and traffic information signs, multicolored cats eyes, SOS phone boxes every few hundred meters, congestion monitoring and digital speed cameras. In-vehicle technologies are being developed to make driving easier and safer, there are many different types, most are not in the remit of this project to describe but a few are worth considering due to their geographical nature (geographically). Features that reduce the complexity of the driving task (including automatic gears, windscreen wipers, climate controls, headlights etc.); features that detect and report mechanical faults; and improvements in basic features like power steering and anti-skid breaks are almost totally irrelevant here. Monitoring systems that record in cab conditions and to some extent driver behavior are similarly irrelevant here. Speed delimiters that prevent vehicles being driven above certain speeds and information systems that aid in navigation and provide details of the road ahead are more relevant. But perhaps the most relevant in-vehicle technologies are those which continually record and process the location, velocity and accelerations, along with other details of the vehicle. These are like a sophisticated Black Box Recorder (BBR) but are perhaps better referred to as Real Time Communicable Kinematic Geographical Positioning Transit Information System Onboard Processing Nodes. However, because that is such a mouthful, in this Section I shall refer to them simply as Onboard Information Processors (OIP).

OIP data could be very useful for accident investigations and could be key to complete accident prevention. In the near future it is conceivable that traditional BBR on all vehicles linked via wireless communication with Transport Information Systems (TIS) and linked to other in-vehicle driver support systems could either inform drivers about the road ahead and immediate dangers or even automate the driving task under certain emergency conditions, and that each vehicle is fitted with such an OIP as a mandatory requirement. The contribution of onboard recording systems to road safety accident and analysis was reviewed in Lehmann and Reynolds 1999. The paper details experiences gained with onboard computers for accident reconstruction and accident analysis with reference to a case study for accident prevention by an operator of school bus fleets in the United States of America (USA). As might be expected there was an observed reduction in the number of accidents involving buses fitted with onboard recorders, and it was found that where accidents did occur the onboard recorders usually helped reconstruction and analysis, in particular the reconciling of conflicting reports from eye witnesses. The paper also detailed an in car BBR that measured the kinematics of the vehicle, and the use of controls (breaks, steering, indications etc**.).**

Developments in remote sensing technology, increases in sensor coverage, and developments in image processing offer great promise in automating kinematics data extraction. In particular, these developments could aid in the identification and tracking of non-vehicle objects in the immediate road environment that do not contain OIP. There has been a growing appreciation, recognition and outlining of the potential importance of remote sensing and image processing in road accident and safety research; see Chin and Quek 1997, others refs... Linked with TIS, GPS, GIS and wireless communication systems, Sensing Processing and Real-time Communication (SPARC) offers an means to avoid motorway multiple pile-ups and much more. The process of fitting vehicles with OIP and installing infrastructure for SPARC has only recently begun in developed countries for transport applications. It is perhaps to be expected that this technology has been used for some time by the various military although this information is sure to be classified and top secret. However, it would seem sensible to install something along these lines for the emergency services. At least I am expecting and hoping that in the next few years, accidents at traffic light controlled junctions (involving emergency vehicles) will become a thing of the past (under normal circumstances). There is a lot in that expectation, not least the fact that from 1992 to 1999 there have been a total of X fatalities, Y serious injuries, and Z slight injuries in Great Britain at traffic light controlled junctions when they have been fully operational (no road-works etc) (Can I get figures for accidents involving emergency service vehicle?). In emergency circumstances speed is of the essence and it can be trebly tragic if emergency vehicles on route are involved in accidents.

Recently the UK Government tendered research into in-vehicle technology that made an evaluation of devices that can inform drivers or monitor driver behavior, including BBR and vehicle collision avoidance systems. This research involved a trial with Royal Mail vehicles that resulted in a reduction in accident rates for vehicles installed with on-board recorders.[1] This was similar to the aforementioned study for school bus fleets in the USA (Lehmann and Reynolds 1999). Research commissioned by the Health and Safety Executive found that a third of serious road accidents involve someone driving in the course of their job.

2.1 RESEARCH PAPER 1

Driver behavior analysis and route recognition by
Hidden Markov Models

CONFERENCE PAPER · OCTOBER 2008

2.1.1 Abstract

In this investigation, driver behavior signals are modeled using Hidden Markov Models (HMM) in two different and complementary approaches. The first approach considers isolated maneuver recognition with model concatenation to construct a generic route (bottom-to-top), whereas the second approach models the entire route as a 'phrase' and refines the HMM to discover maneuvers and parses the route using finer discovered maneuvers (top-to-bottom). By applying these two approaches, a hierarchical framework to model driver behavior signals is proposed. It is believed that using the proposed approach, driver identification and distraction detection problems can be addressed in a more systematic and mathematically sound manner. We believe that this framework and the initial results will encourage more investigations into driver behavior signal analysis and related safety systems employing a partitioned sub-module strategy.

2.1.2 INTRODUCTION

Active safety is seen as the viable solution necessary to reduce vehicle accidents. This approach addresses the problem using system engineering methodology by incorporating all technological solutions related to vehicle, road structure, traffic management and driver assistance/monitoring systems. Vehicle, driver and environment are perceived as the three main components of the system. There is a wide range of systems developed to increase safety of vehicles themselves by making them more stable and reliable. However, a large portion of uncertainty exists in any driving scenario because of the long term as well as instantaneous ability of the driver, changing environment and their interaction. Therefore, the complete solution for reduction of road accidents is only possible by making the vehicles 'aware' of the driving context (environment, route and maneuver type) and the driver status (distracted, neutral, aggressive, drowsy etc.). This can be achieved by analyzing driver behavior signals including driver inputs (i.e., steering wheel angle, steering velocity, brake/gas pedal pressures), vehicle responses to driver inputs (i.e., vehicle speed, acceleration and position), and driver biometric signals (i.e., eye gaze, eye closure, heart rate).

Driver behavior analysis is an interdisciplinary research field where exploratory statistics, stochastic modeling, signal processing, control theory, human factors and artificial intelligence methods are used by researchers to model certain aspects of driver behavior in a mathematical scheme.

One emerging trend has been to borrow techniques based on Hidden Markov Models (HMM) from the speech processing and language technology field and apply this to driver behavior modeling for route recognition, driver identification, and distraction detection in an analogy with speech recognition, speaker identification, and stress detection in speech. HMMs which have already been established in speech processing, and are applied in several pattern recognition areas such as place learning and recognition for mobile robots , signature recognition and human action learning (intent and skills) for teleportation of robots . In order to represent both the stochastic and dynamic-continuous properties of human behavior in driving, dynamic models using Kalman filters to estimate the vehicle outputs from driver inputs are employed by feeding their prediction errors into HMMs.

Benefits of using HMMs with a dynamical scheme to predict the driver actions within the first 2 sec of an action sequence. Driving events were recognized by HMMs with a recognition rate of 93.8% using only vehicle speed and acceleration as raw data.

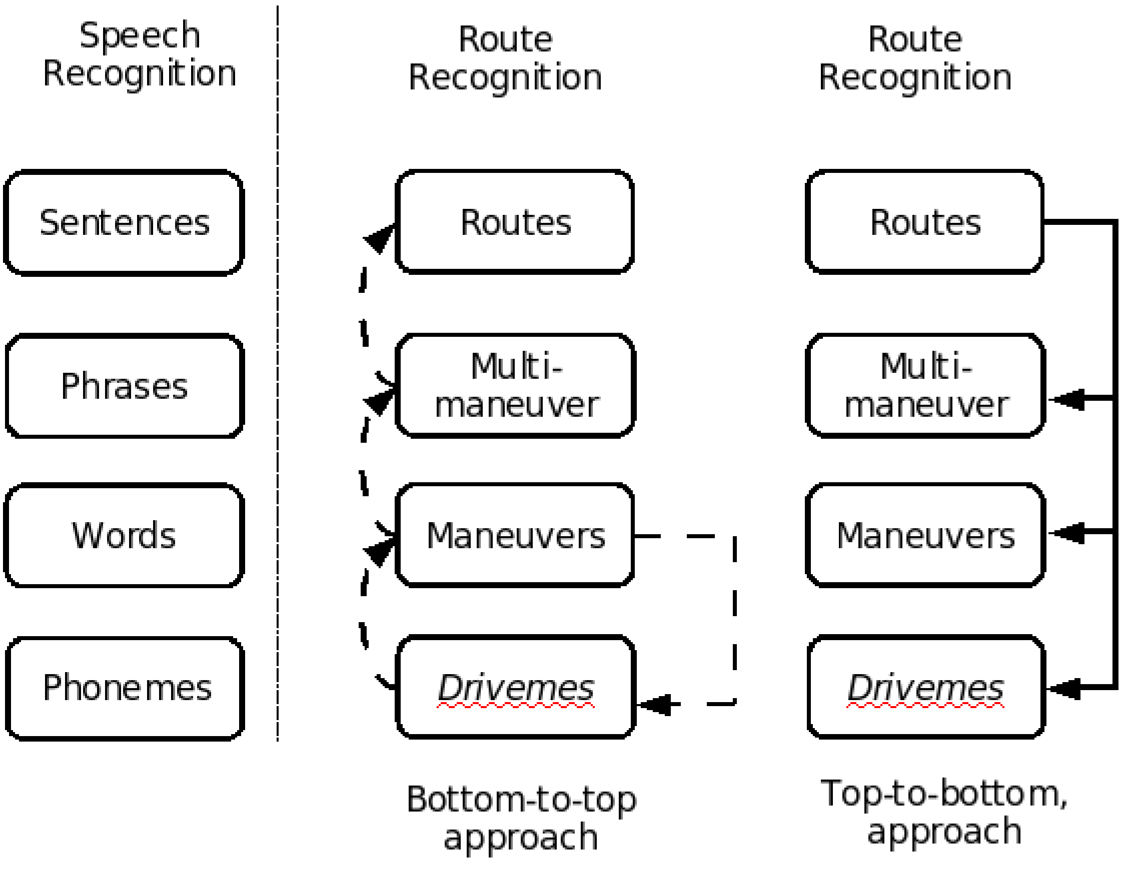

Fig 1- Different approaches

Following this work, a bottom to top approach drawing an analogy from speech systems was suggested in. Using only steering wheel angle, headway, speed and acceleration values they were able to model most of the maneuvers, discovering the construction sub-units of maneuvers, so called 'drivemes'. In addition to these encouraging results, HMMs proved to be an efficient method even in complex intersection scenarios. A single HMM was used to identify the vehicles in conflict with other vehicles in a limited intersection route with appropriate measurements of dynamics of ego-vehicle and surrounding vehicles. This represents the opposite approach in driver behavior signal modeling as it starts from the top (the route) with a single HMM, and parses down the individual meaningful parts (i.e., maneuvers, states) clustering and separating the initial HMM structure. As a result of this approach, they identified three main clusters to represent the driver behavior in intersections, contributing to the understanding of driver behaviors. Moreover, the level of skill or performance of the driver can also be assessed by an HMM incorporating an ANN or similar classification tool to help capture the dynamics of the signals.

2.1.4 Hidden Markov Models

The foundation of HMM is a stochastic Markov process consisting of a number of states with corresponding transitions. At discrete time intervals, the Markov process moves from one state to another according to a set of transition probabilities. State changes in the Markov process are hidden from the user.

The vehicle is equipped to perform multi-modal data collection with signal channels including:

- Videos: driver and the road
- Microphone array and close microphone to record driver speech
- Distance sensor using laser
- GPS for position measurement
- CAN-Bus: vehicle speed, steering wheel angle, brake/gas
- Gas/Brake pedal pressure sensors

The driving scenarios include two different routes: residential and commercial areas including right turn, left turn, lane change, cruise and car following segments. Each route is driven by each driver twice: neutral and distracted. In this present investigation, only CAN-Bus signals are used since they are readily available in the vehicle and offer a low-cost solution for vehicle/driver modeling. However, in further studies, other sensors will be fused to obtain more comprehensive results.

2.2 RESEARCH PAPER 2

Modeling Pipeline Driving Behaviors-Hidden Markov Model Approach

Xi Zou and David M. Levinson

2.2.1 ABSTRACT

Driving behaviors at intersections are complex. At intersections, drivers face more traffic events than elsewhere and are thus exposed to more potential errors with safety consequences. Drivers make real-time responses in a stochastic manner. This study used hidden Markov models (HMMs) to model the driving behavior of through-going vehicles on major roads at intersections. Observed vehicle movement data were used to estimate the model. A single HMM was used to cluster movements when vehicles were close to the intersection. The estimated clustered HMMs could more accurately predict vehicle movements compared with traditional car-following models.

2.2.2 INTRODUCTION

Driving behavior is complex in terms of the amount of information being processed, the number of involved parties, and the chances of being affected by human errors. A driver has to perceive the status of his own and adjacent vehicles, road geometry and surface conditions, traffic control facilities and traffic signs, and even weather and lighting conditions. Further, driving is a process of correction. Drivers have to redress their own errors efficiently and recognize and respond to other drivers' errors. Their capability of addressing errors in driving varies across the population, changes over time, and depends on the temporal, physical, and psychological conditions. All these factors make driving behaviors stochastic rather than deterministic.

However, this important aspect has not been well addressed to date in modeling driving behaviors. Driving models are many. Each is used for a different purpose, and each has specific limitations. Control models are widely used in traffic simulation, which includes car-following models, lane changing models, and emergency maneuver models. These models are designed to emulate highway vehicle movement and always oversimplify intersection maneuvers. Driver models developed in psychological research concentrate on drivers' perceptions and operational tasks. For the purposes of driver education and suggesting methods of collision avoidance, these models usually provide qualitative descriptions of driver behavior and are hardly strict in predicting driver maneuvers at intersections. Since Pipes proposed a linear car-following model, there have been many improvements, including Chandler et al.'s and Gazis et al.'s improved Pipes model, Tyler's optimal control model, Newell's desired speed and shifted trajectory model, and Gipps's psychodynamic car-following model. Other microscopic driving models include the cellular automaton model, the cell transmission model, and the intelligent driver model, among others.

2.2.3 HIDDEN MARKOV DRIVING MODEL:

A driver model relates the driver's behavior to his perception, physical and psychological conditions, driving experience, and preferences under traffic conditions. Driver behavior is affected by many internal and external factors. At intersections drivers perceive information from their own vehicles, other vehicles on the road, traffic facilities, and the environment and generate responses through a decision making process that is hardly tractable. Vehicle dynamics vary from one vehicle to another. Drivers' understanding of their own vehicles and traffic environment varies also. These factors make the combination of driver and vehicle complex and hard to predict, even when the knowledge of vehicle and driver history is abundant. The uncertainty, deviation, and inconsistency may seem to dominate the output. While difficult, predicting driver–vehicle behavior is possible.
Vehicles have physical limitations in making maneuvers. Drivers also possess psychological and physiological limitations.

Drivers' preferences under certain traffic circumstances are fairly consistent. Their skills and habits are observable or derivable from their previous behavior. Driver behaviors at or near intersections are complex. In this study, only conflicts related to crossing and left-turn traffic will be studied. Right-turn, U-turn, and lane-changing behaviors are not considered. Traditional intersection safety studies for left-turn and crossing traffic concentrate on gap acceptance of drivers. An implicit assumption is used: drivers will be safe if they accept a gap that is long enough for their crossings. But the reality is more complicated. Many accidents happen after vehicles on a minor road have fully stopped and accepted a gap. One can argue that this is because the drivers accepted a bad gap. But even if a gap is big, if the crossing vehicle is slow, there is still a chance for a crash. Many factors, such as driver hesitation, or insufficient acceleration, failure to consider vehicle length, overestimating the vehicle's accelerating capability, long driver response time (especially with elderly drivers), underestimating vehicle load, or unrecognizable road surface conditions, may cause unexpected conflicts that may be avoided under average traffic conditions (average vehicle, average driver, and an ordinary road surface that help to generate the critical gap). Despite these uncertainties, there are relatively few road crashes compared with the number of opportunities for crashes. This is because drivers adjust their behavior after they recognize their initial failure in perception and action. Their adjustments may not be another one-shot decision. Instead, the adjustment is a sequence of behaviors until the conflict is over. All these behaviors are chosen from a finite set of driver behaviors. These adjustments can be modeled as Markov chains.

Recognizing driver–vehicle behaviors as stochastic processes helps us understand the odds in traffic safety. A Markov chain or process is a sequence of stochastic events or states. These events or states belong to a set with a finite number of elements. The probability of an event or state presenting at a moment depends only on the immediately previous event or state. A HMM represents a Markov process whose states are not directly observable. The state of the observed sequence is associated with the hidden states by a set of probability distributions. The use of HMMs in sign language recognition (*20*), shows their potential in modeling resemble and distinct behaviors in other areas. This analysis assumes that, in a certain population, driver behavior is statistically consistent when facing certain level of conflicts. For instance, a portion of drivers will accept a specific gap at intersections, and a portion of drivers will accelerate their vehicles at a certain rate with a limited deviation after they accept a gap. On the basis of this assumption, HMMs are expected to capture the common driver behavior from several recorded sequences of vehicle movement.

2.3 RESEARCH PAPER 3

A Driver Behavior Recognition Method Based on a Driver Model Framework

Nobuyuki Kuge, Tomohiro Yamamura and Osamu Shimoyama

2.3.1 ABSTRACT

A method for detecting drivers' intentions is essential to facilitate operating mode transitions between driver and driver assistance systems. We propose a driver behavior recognition method using Hidden Markov Models (HMMs) to characterize and detect driving maneuvers and place it in the framework of a cognitive model of human behavior. HMM-based steering behavior models for emergency and normal lane changes as well as for lane keeping were developed using a moving base driving simulator. Analysis of these models after training and recognition tests showed that driver behavior modeling and recognition of different types of lane changes is possible using HMMs.

2.3.2 INTRODUCTION

Vigorous efforts are under way today to research and develop partially or fully automated driver assistance systems, such as those for headway distance control or lane keeping control, which make use of Intelligent Transportation System (ITS) technologies. In developing these systems, it is important to adopt approaches aimed at improving the performance of the whole driver vehicle cooperative system by regarding driving as interaction between the driver and the vehicle.

Achieving smooth control mode transitions from automated to manual operation is one issue of human machine interaction in these systems. Such transitions can be divided into instances of forced return to the manual mode when the system encounters non supported situations or when it fails and instances initiated spontaneously by a driver. In the latter cases, it is important not to automatically interfere with driver induced evasive maneuvers in emergency situations and also to avoid feelings of incongruity in ordinary driving.

Accordingly, establishing a technique for detecting the driver's intentions or for recognizing driver behavior is imperative to facilitate smooth and appropriate control mode transitions. The development of effective driver behavior recognition methods requires a thorough understanding of driver behavior and the construction of a model capable of explaining and reproducing drivers'
behavioral characteristics. Among various driving actions, this study focused on lane change maneuvers. Some methods have been developed previously to estimate a driver's lane change intention, for example, by making a comparison with the maximum steering angle during ordinary lane keeping, or by using the vehicle's yaw angle relative to the traffic lane and steering data .However, these methods are not human model-based. We focus on information processing models of human driver behavior generation and utilize them to adopt a model based approach in the development of a lane change detection and recognition model. The primary components are skilled low level maneuvers whose initiation is managed by higher level decision making components. Development, analysis, and application of this model using a driving simulator are described in this paper.

DRIVER BEHAVIOR RECOGNITION BASED ON DRIVER MODEL

COGNITIVE APPROACH

The cognitive process underlying human actions has been researched extensively over the years. One of the most famous approaches to modeling human-machine interaction concerns the model proposed by Rasmussen. In Rasmussen's model, information processing is divided into three hierarchically organized levels based on demand complexity: knowledge base, rule base, and skill base. In the driving context, an identical classification is possible. Michon showed the thought that the organizational structure well suited for driver modeling contains a strategic, a tactical and an operational level which roughly correspond to the knowledge, rule, and skill division in Rasmussen's model. Boer et al. proposed an integrated driver model (IDM) which borrows from Rasmussen's and Michon's model and incorporates the concept of the dynamic aspects of driver behavior as well as an important role of driver needs.

2.4 RESEARCH PAPER 4

Modeling and prediction of driver behavior by foot gesture analysis

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2.4.1 ABSTRACT

Understanding driver behavior is an essential component in human-centric Intelligent Driver Assistance Systems. Specifically, driver foot behavior is an important factor in controlling the vehicle, though there has been very few research studies on analyzing foot behavior. While embedded pedal sensors may reveal some information about driver foot behavior, using vision-based foot behavior analysis has additional advantages. The foot movement before and after a pedal press can provide valuable information for better semantic understanding of driver behaviors, states, and styles. They can also be used to gain a time advantage in predicting a pedal press before it actually happens, which is very important for providing proper assistance to driver in time critical (e.g. safety related) situations. In this paper, we propose and develop a new vision based framework for driver foot behavior analysis using optical flow based foot tracking and a Hidden Markov Model (HMM) based technique to characterize the temporal foot behavior. In our experiment with a real-world driving test bed, we also use our trained HMM foot behavior model for prediction of brake and acceleration pedal presses. The experimental results over different subjects provided high accuracy (_94% on average) for both foot behavior state inference and pedal press prediction. By 133 ms before the actual press, _74% of the pedal presses was predicted correctly. This shows the promise of applying this approach for real-world driver assistance systems.

2.4.2 INTRODUCTION

Human behavior analysis from vision input is a challenging but attractive research area with lots of promising applications, such as image and scene understanding, advanced human computer interaction, intelligent environment, driver assistance systems, video surveillance, video indexing and retrieval. In general, human behavior can be analyzed at several levels of resolution such as full body level, upper body, lower body, hand, head . There are trade-offs between achieving detailed information of human behavior at different levels, and the efficiency as well as robustness of the algorithm. Therefore research studies typically focus on behavior analysis at one level depending on applications. In this paper, we focus on driver foot behavior analysis with applications to Intelligent Driver Assistance.

It should be mentioned that an effective driver assistance system needs to be human-centric, and take into account information about all three main components (i.e. environment, vehicle, and driver) interacting in a holistic manner. Among those, driver foot behavior is an important source of information that has a strong impact on vehicle control.

One problem of recent interest to the automotive safety community is that of ‘‘pedal misapplication’’, in which the driver accidentally presses the wrong pedal. Several recent unintended acceleration-related accidents in the US could have been a result of this pedal misapplication phenomenon. Incidents related to pedal misapplication have been observed for many years, and the investigation into Toyota’s recent ‘‘sudden unintended accelerations’’ has led to a renewed interest in avoiding such incidents. We propose that understanding the driver foot behavior could help to predict and mitigate this kind of problem.

To our knowledge, there are very few research studies in foot gesture and behavior analysis; for example, Choi and Ricci developed a foot-mounted device which can recognize walking gestures. In the domain of driver assistance, some studies related to analyzing driver foot behavior have been published. Park and Sheridan used pressure-based sensors in a driving simulator to show that driver leg motion can help to improve the performance of Antilock Brake System (ABS). Tanaka analyzed a mechanical model of driver foot and pedal which has potential for having better pedal design and layout.

HMM-based foot behavior model

By observing the driver foot movement, we see that the foot motion can be divided into the following semantic states:

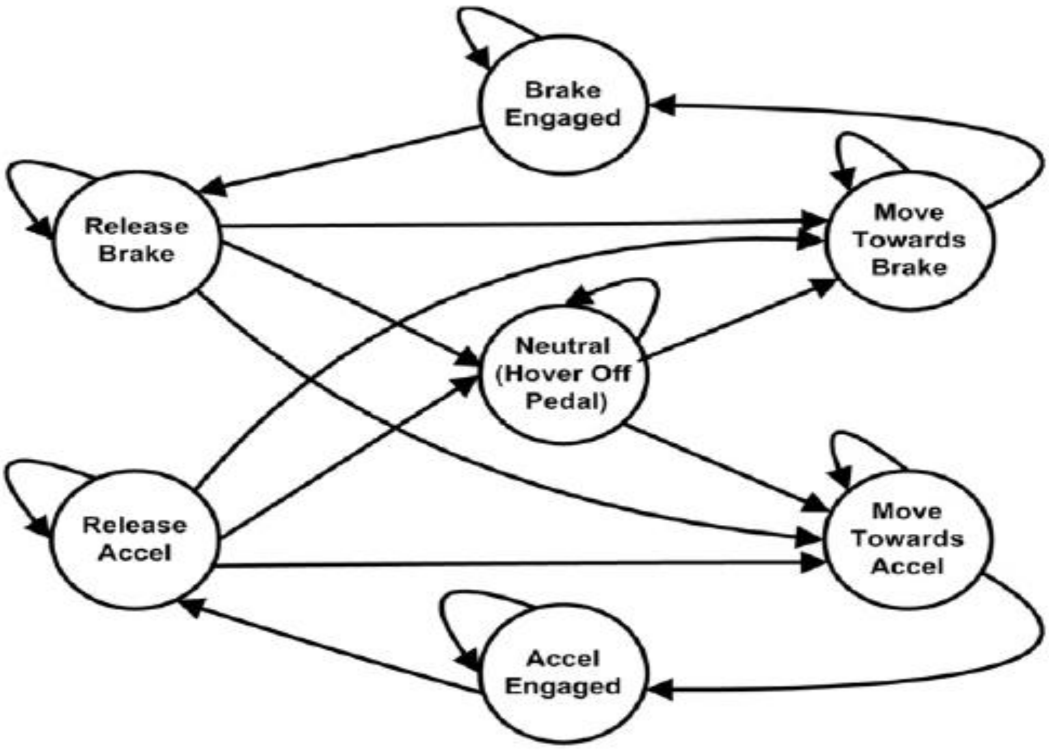


Fig 2: predicts the idea of how seven states are modeled by foot behavior HMM state

1. Neutral (hover off pedal).
2. Moving towards brake pedal.
3. Moving towards acceleration pedal.
4. Engaging brake pedal.
5. Engaging acceleration pedal.
6. Release from brake pedal.

2.5 SCENARIO IN INDIA

The table below shows data for India. These data show that the total number of vehicles increased from 37 million in 1997 to 73 million in 2004. This represents an annual average growth rate of about 11% for cars and motorized two-wheelers and 7% for trucks and buses. However, these numbers are probably overestimates as personal vehicle owners register their vehicles and pay the road tax once when they buy the vehicle and are not required to pay an annual tax. Because of this, a large number of vehicles remain on the official record even when they are not in use any more. Recent estimates suggest that the actual number of vehicles in use may be about 60-70% of the official .The sales figures also show an average annual increase of 10-12% per year.

Table 1. : Motor vehicle registration in India

Year	MTW*	Cars/Jeeps	Trucks	Buses	Others**	Total
1997	25,729 (69)***	4,672 (13)	2,343 (6)	484 (1.1)	4,104 (11)	37,332 (100)
2004	51,922 (71)	9,451 (13)	3,749 (5)	768 (1.3)	6,828 (09)	72,718 (100)
Growth/year (%)	10.6	10.6	6.9	6.8	7.5	10.0

Table2: Vehicle sales in India

Year	Motorized two-wheelers	Three-wheelers	Cars	Commercial vehicles	Total
1997	2,885,004 (79)	216,729 (06)	396,450 (11)	169,937 (5)	3,668,120 (100)
2007	7,416,191 (78)	380,663 (04)	1,273,893 (13)	479,593 (5)	9,550,340 (100)
Growth/year (%)	10	6	12	11	10

Source: society of Indian Automobile Manufacturers, Delhi

The total number of fatalities increased at an average rate of about 4% per year in the period 1997-2003 and the rate has increased to 8% per year since then. The number of fatalities per million populations remained around 79-83 in the period 1997-2003 and has since increased to 101. Traffic fatalities per unit population has been taken as an indicator of the health burden of road traffic crashes on society at the city, regional, or national level. At the individual level, what is of consequence is the risk of injury per trip, and the total number of trips is proportionate to the population. Therefore, traffic fatalities per unit population can be taken as a rough indicator of risk faced by individuals. The risk of being involved in a fatal road traffic crash has obviously been increasing for Indian citizens over the past few years. While some of this increase can be attributed to increase in the number of motor vehicles per capita in India, however, increasing vehicle ownership need not result in increased fatality rates if adequate safety measures are implemented.

Table 3: Road traffic fatalities in India

Year	Fatalities	Population (million)	Fatalities/million persons
1997	77,000	955	81
1998	79,900	971	82
1999	82,000	987	83
2000	78,900	1,002	79
2001	80,900	1,027	79
2002	84,059	1,051	80
2003	84,430	1,068	79
2004	91,376	1,086	84
2005	98,254	1,103	89
2006	105,725	1,120	94
2007	114,590	1,136	101

Source: National Crime Records Bureau, Delhi

2.5.1 CRASH PATTERNS

Details of traffic crashes are not available at the national level. While the official road traffic fatality data may be close to the actual number, the injury data are gross underestimates[5]. In this report only fatality data are used for analysis as non-fatal data may suffer from many biases.

2.5.1.1 Road user category

Official road traffic crash data do not include fatalities by road user category in India. Such data are only available from a few cities and research studies done on selected locations on rural highways. These data show that car occupants were a small proportion of the total fatalities, 3% in Delhi and 15% on rural highways. Vulnerable road users (pedestrians, bicyclists, and motorized two-wheeler riders) accounted for 84% of deaths in Delhi and 67% on highways. This pattern is very different from that obtained in all high-income countries. The low proportion of car occupants can be explained by the low level of car ownership at 7 per 100 persons as compared to more than 50 per 100 persons in most high income countries. At present levels of growth in vehicle ownership in India, vulnerable road users are likely to remain the dominant mode for the next few decades. The incidence of road traffic fatalities can only be controlled in the coming years if road safety policies put a special focus on the safety of vulnerable road users.

Table 4: Traffic fatalities by category of road user in Delhi and selected locations on national highways

	Location (%)	
Type of road user	Delhi 2001-2005	Highways* 1999
Truck	2	14
Bus	5	3
Car	3	15
Three-wheeled scooter taxi	3	–
Motorized two-wheeler	21	24
Human and animal powered vehicle	3	1
Bicycle	10	11
Pedestrian	53	32
Total	100	100

*

The data are for 11 selected locations, and thus might not be representative for the entire country. (Tractor fatalities are not included.

2.5.1.2 Age and gender

In 2007, only 15% of the victims were females. This is partly because of the low representation of women in the Indian workforce and exposure on roads. Children aged 14 years and younger comprise only 6% of the fatalities, though their share in the population is 32%. The proportion of fatalities in the age groups 15-29 and greater than 60 years is similar to their representation in the population, but the middle-age groups 30-44 and 45-59 are over represented by about 70%. The low representation of children (2 fatalities per 100,000 persons) is curious because a significant number of children walk and bicycle to school unescorted, both in urban and rural areas. Though the exposure numbers for India are not available, children's presence on the road unsupervised is not insignificant. The reasons for the low involvement rate of children needs to be investigated.

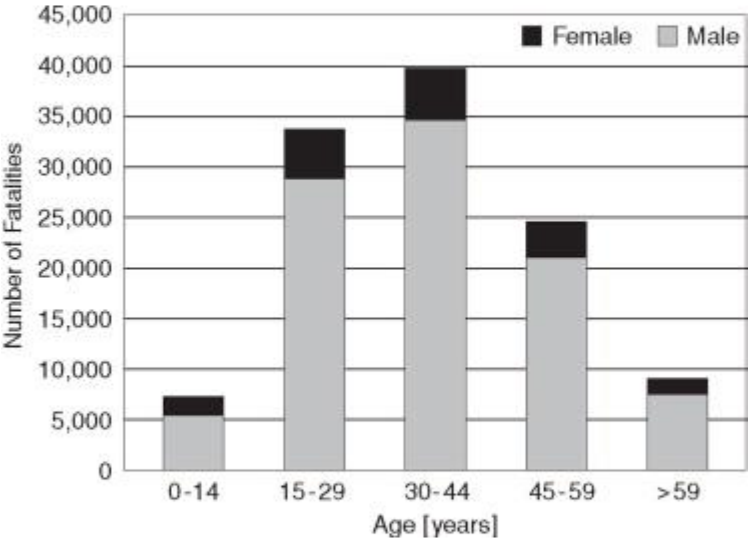


Fig 3: Traffic fatalities by age and gender, India 2007

2.5.1.3 Time of day

In the period 09:00 to 21:00 the proportions remain high and similar both in the large cities and elsewhere. In the late night hours (21:00-24:00) traffic volumes are much lower than the peak day time rates[1] but the fatality rates do not reflect this. In the early morning hours (00:00-06:00) the proportions are much lower in the large cities, but relatively higher in the rest of the country. It is possible that since the rest of the country includes national highways, the commercial goods traffic on those highways may account for this. In the absence of more detailed epidemiological data we can only surmise that the high rates at night could be due to higher speeds of vehicles when traffic volumes are lower and/or higher frequency of driving under the influence of alcohol. Evidence for increased use of alcohol comes from a hospital study in Delhi where 29% of the riders of motorized two-wheelers admitted to alcohol consumption before the crash[7]. In Bangalore, a hospital-based study showed that alcohol was involved in 22% of nighttime crashes, and that 35% of randomly checked drivers on the road at night were under the influence of alcohol[5].

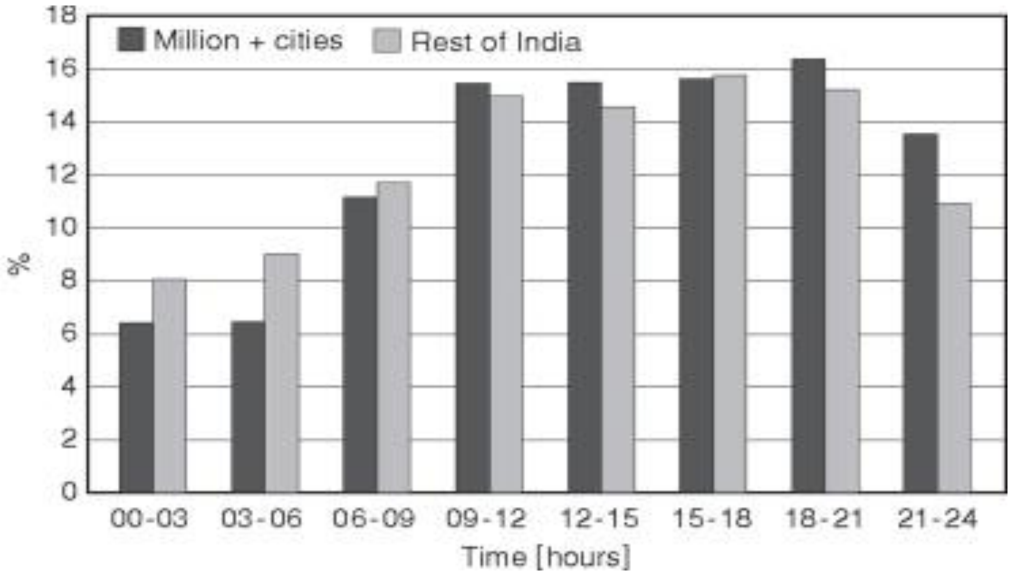


Fig 4: Road traffic accident proportions (%) by time of day in 35 cities with more than 1 million population and those in the rest of India in 2007

Delhi had the highest number of fatalities in 2007 (1,789) with a rate of 140 per million population. The lowest rate was in Kolkata (35) and the highest in Agra (386), with an overall average of 122 fatalities per million persons for all these cities. The probability of pedestrian death is estimated at less than 10% at impact speeds of 30 km/h and greater than 80% at 50 km/h, and the relationship between increase in fatalities and increase in impact velocities is governed by a power of four. Small increases in urban speeds can increase death rates dramatically.

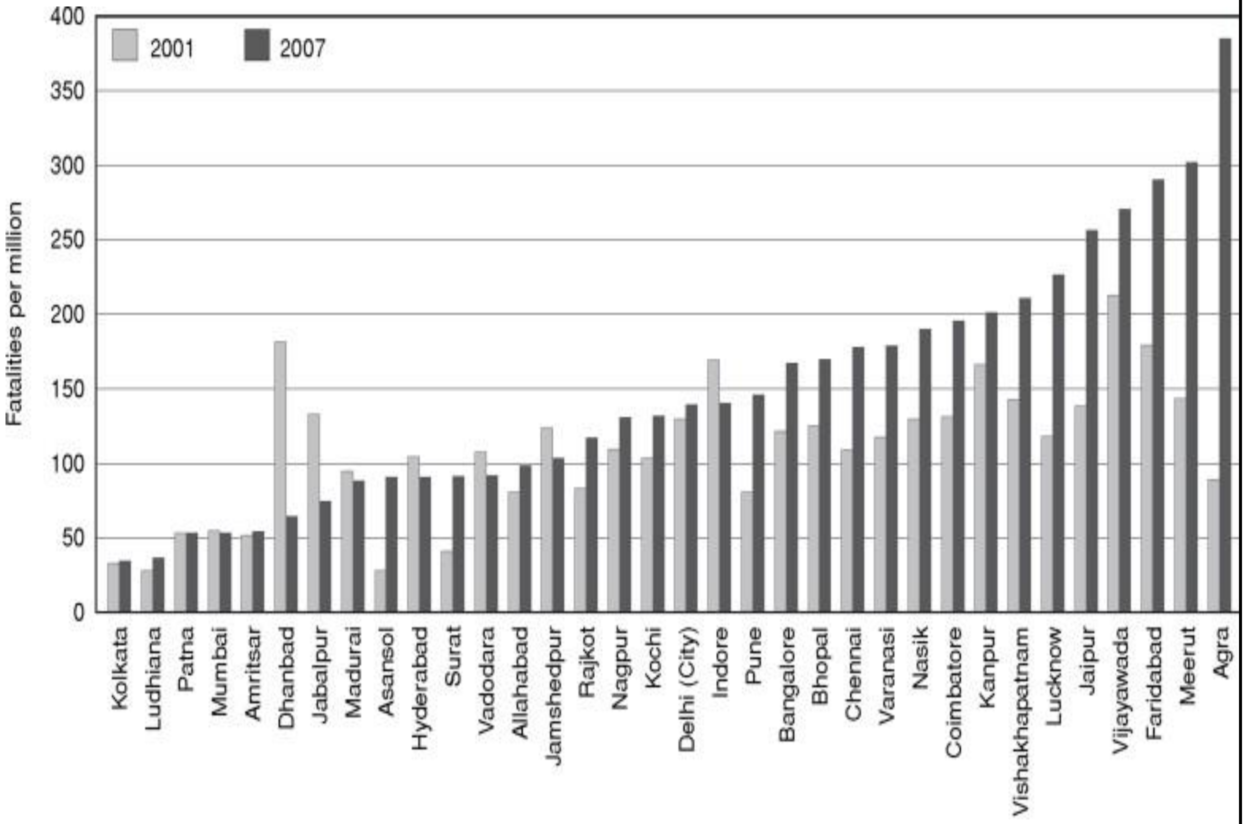


Fig 5. Traffic fatality rates in cities with populations of at least one million, 2001 and 2007

2.5.2. Fatalities on rural highways

Detailed data are not available at the national or state level for crashes on national highways. A study collected data on modal shares, vehicle speeds, and traffic crashes on selected locations on national and state highways around the country in the late 1990s. The study reported that trucks were the striking party in 65% of fatal crashes. Other studies report that majority of the crashes involved buses, 25% of the victims were pedestrians, rear-end crashes comprised 40% of total crashes and that crashes were increasing at a rate of 3.9% per year. A study of road traffic crashes on a National Highway in the southern state of Kerala reported that heavy vehicles had a high involvement, and pedestrians and cyclists were 28% of the victims. The most important finding of this study is that the fatality rate per volume is more than three times higher on the four-lane section than on two-lane sections. The construction of four-lane divided highways (without access control) does not seem to have reduced fatality rates, and vulnerable road users still account for a large proportion of fatalities. There is a clear case for redesign of intercity roads with separation of slow and fast modes. The need of road users on local short distance trips will have to be accounted for. Solutions for many of these issues are not readily available and research studies are necessary for the evolution of new designs.

CONCLUSION ON THE BASIS OF LITRATURE REVIEW:-

Road traffic fatalities have been increasing at about 8% annually for the last ten years and show no signs of decreasing. Two modeling exercises have attempted to predict the time period when we might expect fatality rates to start to decline in a range of countries. Cropper and Kopits predicted that fatalities in India would reach a total of about 198,000 before starting to decline in 2042 and Koornstra predicted an earlier date of 2030 for the peak traffic fatalities in India. If we assume that the present growth rate of 8% per year declines in a linear manner to 0% by 2030, then we can expect about 260,000 fatalities by 2030. Neither of these projected dates (2042 and 2030) can be accepted as road safety goals for the country.

An earlier report co-authored by the present author has a more detailed analysis of the road traffic situation in India and possible countermeasures. In summary, road safety policies in India must focus on the following issues to reduce the incidence of road traffic injuries: pedestrians and other non-motorist in urban areas; pedestrians, other non-motorists, and slow vehicles on highways; motorcycles and small cars in urban areas; over-involvement of trucks and buses; night-time driving; and wrong-way drivers on divided highways. There is an urgent need to revamp police data collecting procedures so that necessary information is available for scientific analysis. India specific countermeasures will be possible through continuous monitoring and research, which will require the establishment of road safety research centers in academic institutions and a National Road Safety Board that could help move toward a safer future as outlined above.

CHAPTER-3

SYSTEM DEVELOPMENT

DEVELOPMENT OF THE HMM-BASED RECOGNITION MODEL

3.1 Development tool

Using the measured driver behavior data, an HMM consisting of three recognition categories—emergency lane change (LCE), ordinary lane change (LCN), and lane keeping (LKN)--was developed. For the two types of lane change situations, data were extracted in the period between command presentation and the first peak of the steering angle.

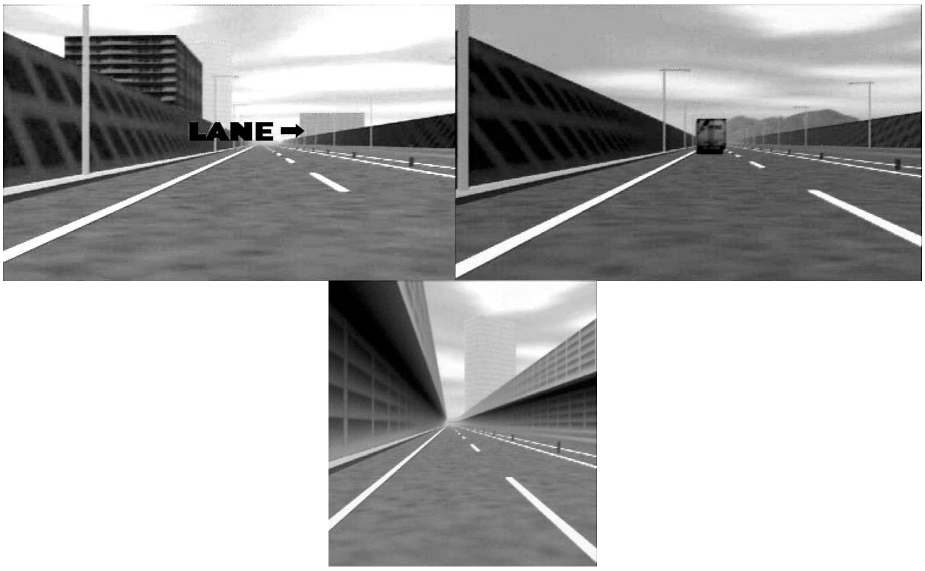


Fig 6- Lane Demonstrations

For lane keeping, data were extracted for a five-second interval from the original data measured with the driving simulator.

3.1.1 Definition of HMM grammar

A unique grammar concept was introduced for model development that differs from the general approach for three reasons. Firstly, it would be irrational to have the same HMM structure (i.e. same number of states and same set of transitions between them) because of large differences with respect to number of clearly identifiable stages in the action profile for each of the three maneuvers (e.g. the characteristic steering profile of a lane change does naturally not appear in lane keeping).

Secondly, the emergency lane change would involve a large steering angle change whereas
an ordinary lane change would involve little change. To improve specificity lane change
of the recognition model, these two manifestations of the same maneuver should be characterized separately.

Thirdly, it was necessary to have a model that could perform continuous recognition, as will be explained later. The adopted approach is one in which a basis sub-HMM is used as a building block for a more complex model. In the lane change situations in this experiment, the reaction time domain continued until a subject initiated a steering maneuver after command presentation. In the model, that time period was assumed to be the same as for lane keeping.

3.1.2 Structure of HMM

Three sub-HMMs were used for both LCN and LCE. Each sub-HMM consisted of three states with a left-to-right configuration which did not allow for skipping of states or backward state transition. The steering angle, steering angle velocity, and steering force were used for the observation data sequence. Different subsets of these three measurements were used to identify the three maneuver models.

3.1.3 Training of the HMM

The HMM was trained to estimate the parameters *ak* (*i*) and *bk Y* and to maximize Pr ($Y|\lambda$), where λ is the parameter vector. Parameter estimation was completed in three stages.

First, an initial set of parameter values was obtained from the training data based on a more or less arbitrary segmentation of the data (i.e. collecting statistics of the measurements in each state as represented by the segments). That was followed by repeated use of Viterbi alignment to re-segment the training data. The Viterbi algorithm can be viewed as a special form of the forward-backward algorithm where only the maximum path of transitions through the states at each time step is taken instead of all paths. This optimization reduces the computational load and additionally allows the recovery of the most likely state sequences. The most likely state sequence determines the new segmentation of the observation sequence, and the parameters of each state are re-estimated according to this new segmentation.

Second, a Baum-Welch re-estimation of individual HMMs was performed using the training set. Here, the probability of being in each state in each time frame is calculated using the forward-backward algorithm. A new estimate for the respective output probability can be assigned. Since either the forward or backward algorithm can be used to evaluate the posterior probability with respect to the previous estimation, this technique can be used iteratively to converge the model to some error criterion. Third, parameter re-estimation was performed using an embedded training version of the Baum-Welch algorithm.

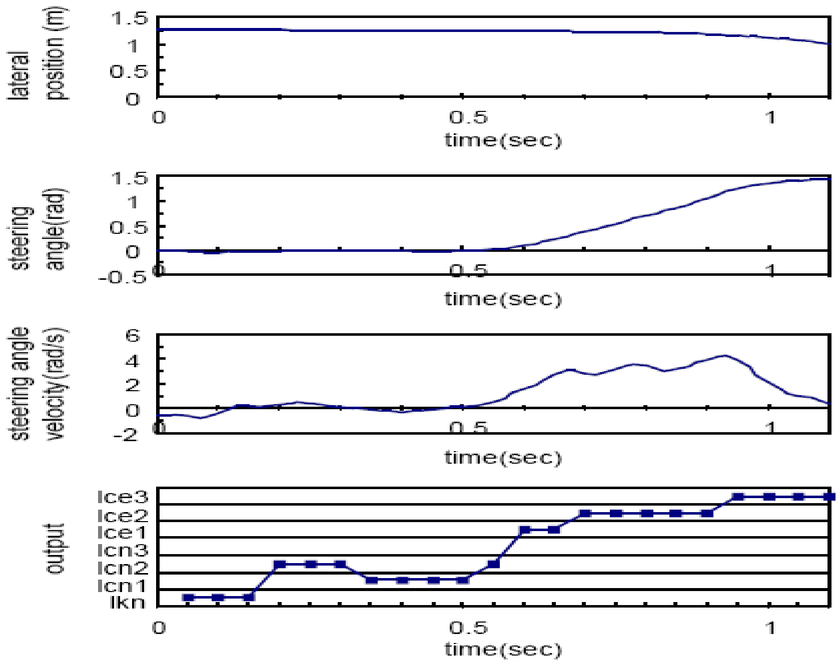
In this case, all model parameters were simultaneously re-estimated from an un-segmented training data. Further details about these procedures can be found. Probability of the HMM developed in this study is given in the form of a Gaussian distribution. The change in the average values of the output distribution accompanying state transitions was used to study the performance of the HMM in lane changes. The model examined was the one that provided the best recognition results for both the steering angle and steering angle velocity.

It is seen that the change in the steering data in the transition of the LCE sub-HMMs corresponded well to the typical change in steering action. This indicates that the HMM fully learned the characteristics of an emergency lane change. On the other hand, for LCN, although the average of the steering angle velocity of S3 was smaller than that of state S2, the steering angle increased with the progress of the lane change. Furthermore, the minimum absolute average values of the steering angle and steering angle velocity of each state in LKN was less than 0.003 rad and 0.008 rad/s respectively. In summary, it can be considered that HMMs learn well the characteristics of a temporal change in the steering pattern in a lane change, indicating they that can be used to build a driver behavior recognition model.

3.1.4 Continuous recognition of lane change

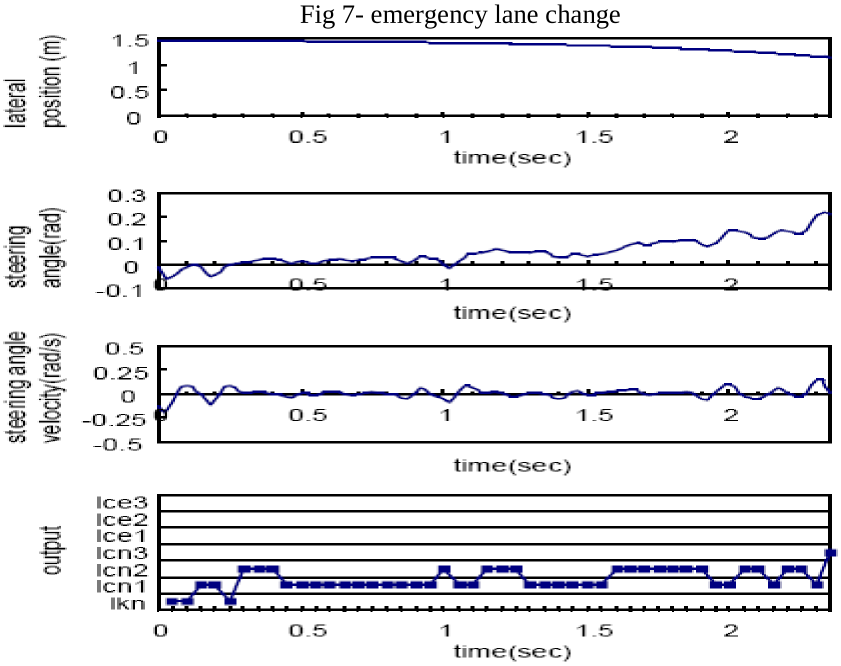
The recognition method in the previous section generated a single output for each set of data containing a time interval between command presentation and the execution of a steering maneuver for changing lanes. However, in order to recognize a lane change at an early stage when a driver support system is operating, it is necessary to generate output continuously. Using a revised version of the recognition method, the possibility of operating the recognition system continuously was examined and the characteristics of driver behavior were also analyzed based on the recognition results.

3.1.5 CONTINUOUS RECOGNITION OF LANE CHANGES



(a) LCE

Fig 7- emergency lane change



(b) LCN

Fig 8- another example of ordinary lane change

3.2 Sensor and data acquisition

To provide a basis for our experiments, data acquisition hardware and software were developed. The accelerometers are set to measure longitudinal and lateral vehicle acceleration. We use Analog Devices ADXL05 accelerometers and micro-machined uniaxial sensors with a movable beam(often used as air-bag sensors). Two gyroscopes are mounted to measure the horizontal rotation (left and right vehicle turns) and the changes in road slope. Gyroscopes and accelerometers are mounted on a separate sensor board that could be easily fixed to the car interior. Sensors provide analog output digitized by an eight-channel, 12-bit data acquisition card mounted inside a desktop personal computer (PC) modified to work in a car.
A GPS receiver is used as a velocity sensor to avoid otherwise necessary changes to the vehicle electronics (as we used a private car for experiments). A Trimble Placer 400 GPS receive is connected to the PC through a serial connection. Positions provided by the GPS receiver are also collected to serve as a reference during data analysis but are not used for driving event recognition.

Following our goal to implement the simplest possible system, we decided not to use gyroscope data for the HMM experiments. Gyroscopes are not often used in vehicle electronics and are much more expensive than accelerometers. As will be proved later, we found speed and acceleration data sufficient for

- The driving event recognition.
- Multi-modal
- Data collection with signal channels including:
- Videos: driver and the road
- Microphone array and close microphone to record driver speech
- Distance sensor using laser
- GPS for position measurement
- CAN-Bus: vehicle speed, steering wheel angle, brake/gas
- Gas/Brake pedal pressure sensors

3.3 Measurements

Subjects were asked to drive in the left lane (slower traffic lane in Japan) of two lanes of traffic at a constant speed of approximately 80 kmph (50 mph). Driver behavior data were measured in the following situations.

- o Ordinary lane change: When a text message indicating a lane change was superimposed on the screen showing the forward road view, a subject changed to the right lane in the same way as in ordinary driving.

- o Emergency lane change: A large truck was suddenly presented as an obstacle in front of a subject without any prior warning. Upon seeing it, the subject executed an evasive steering maneuver. The position of the parked truck was set at a forward distance equal to the vehicle speed times

2.5 seconds. Subjects did not know in advance when the obstacle would be presented. They were instructed to change to the right lane immediately upon discovering the truck so as to avoid it.

- Lane keeping: While a subject stayed in the same lane on a straight segment, data were arbitrarily measured by the operator. During the lane keeping task, data were measured over particular time intervals whose lengths correspond to those of a lane change. The order in which the tasks were executed was randomized. Ten subjects (five males and five females) who had a driving license participated in the experiment.

The participants were in their 20s and 30s. Six runs were executed for each condition per subject.

3.3.1 MEASUREMENT OF DATA

Apparatus
A driving simulator capable of simulating a motorway traffic environment was used to measure driver behavior data. An image of the road ahead was generated by computer graphics and projected on a large field of view, 120 degrees in the horizontal by 30 degrees in the vertical.

3.4 Algorithms involved

Notational conventions
T = length of the sequence of observations (training set)
N = number of states (we either know or guess this number)
M = number of possible observations (from the training set)
Omega_X = {q_1,...q_N} (finite set of possible states)
Omega_O = {v_1,...,v_M} (finite set of possible observations)
X_t random variable denoting the state at time t (state variable)
O_t random variable denoting the observation at time t (output variable)
sigma = o_1,...,o_T (sequence of actual observations)

Distributional parameters
A = {a_ij} s.t. a_ij = Pr(X_t+1 = q_j |X_t = q_i) (transition probabilities)
B = {b_i} s.t. b_i(k) = Pr(O_t = v_k | X_t = q_i t) (observation probabilities)
pi = {pi_i} s.t. pi_i = Pr(X_0 = q_i) (initial state distribution)

Definitions
A **hidden Markov model** (HMM) is a five-tuple (Omega_X,Omega_O,A,B,pi).
Let lambda = {A,B,pi} denote the parameters for a given HMM with fixed Omega_X and Omega_O.

Problems
1. Find Pr(sigma|lambda): the probability of the observations given the model.
2. Find the most likely state trajectory given the model and observations.
3. Adjust lambda = {A,B,pi} to maximize Pr(sigma|lambda).

Motivation

A discrete-time, discrete-space dynamical system governed by a Markov chain emits a sequence of observable outputs: one output (observation) for each state in a trajectory of such states. From the observable sequence of outputs, infer the most likely dynamical system. The result is a model for the underlying process. Alternatively, given a sequence of outputs, infer the most likely sequence of states. We might also use the model to predict the next observation or more generally a continuation of the sequence of observations.

Hidden Markov models are used in speech recognition. Suppose that we have a set W of words and a separate training set for each word. Build an HMM for each word using the associated training set. Let lambda_w denote the HMM parameters associated with the word w. When presented with a sequence of observations sigma, choose the word with the most likely model, i.e.,

w* = arg max_{w in W} Pr(sigma|lambda_w)

3.4.1 VARIOUS DESIGN ALGORITHM

3.4.1.1 FORWARD-BACKWARD ALGORITHM

Preliminaries

Define the alpha values as follows,

alpha_t(i) = Pr(O_1=o_1,...,O_t=o_t, X_t = q_i | lambda)

Note that,

alpha_T(i) = Pr(O_1=o_1,...,O_T=o_T, X_T = q_i | lambda = Pr(sigma, X_T = q_i | lambda)

The alpha values enable us to solve Problem 1 since, marginalizing, we obtain:-

Pr(sigma|lambda) = sum_i=1^N Pr(o_1,...,o_T, X_T = q_i | lambda) = sum_i=1^N alpha_T(i)

Define the beta values as follows :-

beta_t(i) = Pr(O_t+1=o_t+1,...,O_T=o_T | X_t = q_i, lambda)

We will need the beta values later in the Baum-Welch algorithm.

Algorithmic Details

1. Compute the forward (alpha) values:
   a. alpha_1(i) = pi_i b_i(o_1)
   b. alpha_t+1(j) = [sum_i=1^N alpha_t(i) a_ij] b_j(o_t+1)
2. Computing the backward (beta) values:
   a. beta_T(i) = 1
   b. beta_t(i) = sum_j=1^N a_ij b_j(o_t+1) beta_t+1(j)

3.4.1.2 VITERBI ALGORIHM

Intuition

Compute the most likely trajectory starting with the empty output sequence; use this result to compute the most likely trajectory with an output sequence of length one; recurs until you have the most likely trajectory for the entire sequence of outputs.

Algorithmic Details

1. *Initialization:*

    For 1 <= i <= N,

    a. delta_1(i) = pi b_i(o_1)

    b. Phi_1(i) = 0

2. *Recursion:*

    For 2 <= t <= T, 1 <= j <= N,

    a. delta_t(j) = max_i [delta_t-1(i)a_ij]b_j(o_t)

    b. Phi_t(j) = argmax_i [delta_t-1(i)a_ij]

3. *Termination:*

    a. p* = max_i [delta_T(i)]

    b. i*_T = argmax_i [delta_T(i)]

4. *Reconstruction:*

    For t = t-1,t-2,...,1,

    i*_t = Phi_t+1(i*_t+1)

    The resulting trajectory, i*_1,...,i*_T, solves Problem 2.

3.4.1.3 BAUM-WELCH ALGORITHM

Intuition

Suppose that the outputs (observations) are in a 1-1 correspondence with the states so that

N = M, varphi(q_i) = v_i and b_i(j) = 1 for j = i and 0 for j != i. Now the Markov process is not hidden at all and the HMM is just a Markov chain. To estimate the lambda parameters for this Markov chain it is enough just to calculate the appropriate frequencies from the observed sequence of outputs. These frequencies constitute sufficient statistics for the underlying distributions.

In the more general case, we can't observe the states directly so we can't calculate the required frequencies.

Instead of calculating the required frequencies directly from the observed outputs, we iteratively estimated the parameters. We start by choosing arbitrary values for the parameters (just make sure that the values satisfy the requirements for probability distributions).

We then compute the expected frequencies given the model and the observations. The expected frequencies are obtained by weighting the observed transitions by the probabilities specified in the current model. The expected frequencies so obtained are then substituted for the old parameters and we iterate until there is no improvement.

On each iteration we improve the probability of O being observed from the model until some limiting probability is reached. This iterative procedure is guaranteed to converge on a local maximum of the cross entropy (Kullback-Leibler) performance measure.

Preliminaries

The probability of a trajectory being in state q(i) at time t and making the transition to q(j) at (t+1) given the observation sequence and model.

xi_t(i,j) = Pr(X_t = q(i), X_t+1 = q_j | sigma, lambda)

We compute these probabilities using the forward backward variables

alpha_t(i) a_ij(o_t+1) beta_t+1(j) xi_t(i,j) = Pr(O | lambda)

The probability of being in q(i)at t given the observation sequence and model.

gamma_t(i) = Pr(X_t = q(i) | sigma, lambda)

Which we obtain by marginalization.

gamma_t(i) = sum_j xi_t(i,j)

Note that

sum_t=1^T gamma_t(i) = expected number of transitions from q(i)

sum_t=1^T xi_t(i,j) = expected number of transitions from q(i) to q(j)

Algorithmic Details

1. Choose the initial parameters, lambda = {A, B, pi}, arbitrarily.
2. Restimate the parameters.
   a. bar{pi}_i = gamma_t(i)

        sum_t=1^T-1 xi_t(i,j)
   b. bar{a}_ij = ------------------------
      sum_t=1^T-1 gamma_t(i)
      sum_t=1^T-1 gamma_t(j) 1_{o_t = k}
   c. bar{b}_j(k) = ------------------------------------
       sum_t=1^T-1 gamma_t(j)
      where 1_{o_t = k} = 1 if o_t = k and 0 otherwise.
3. Let bar{A} = {bar{a}_ij}, bar{B} = {bar{b}_i(k)}, and bar{pi} = {{bar{pi}_i}.
4. Set bar{lambda} to be {bar{A}, bar{B}, bar{pi}}.
5. If lambda = bar{lambda} then quit, else set lambda to be bar{lambda} and return to Step 2.

3.5 Experimental results and analysis

Since the proposed post-processing framework can automatically label the data, the HMM parameters can be learned specifically for different subjects for better performance. Therefore in above section, we have analyzed the behavior state estimation to show performance of the proposed framework.
We also test a subject-wise cross-validation procedure to illustrate the benefit of the proposed framework in adapting the learned model to different subjects and situations.

CHAPTER 4

PERFORMANCE ANALYSIS

4.1 PROJECTS OVERALL OUTLINE

GANTT CHART

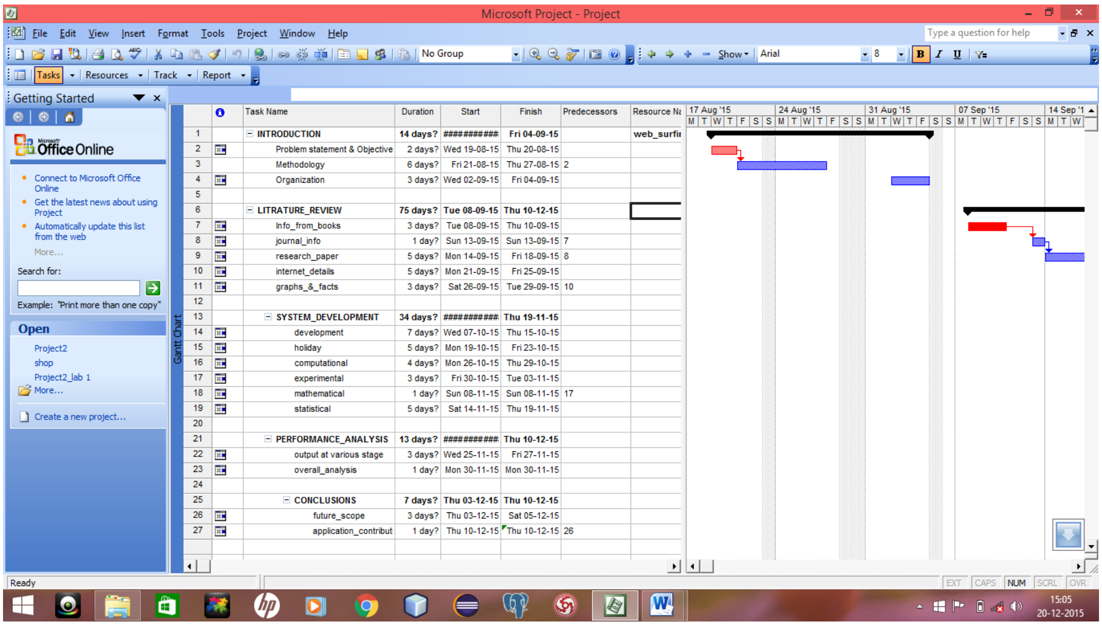


Fig. 9

NETWORK DIAGRAM

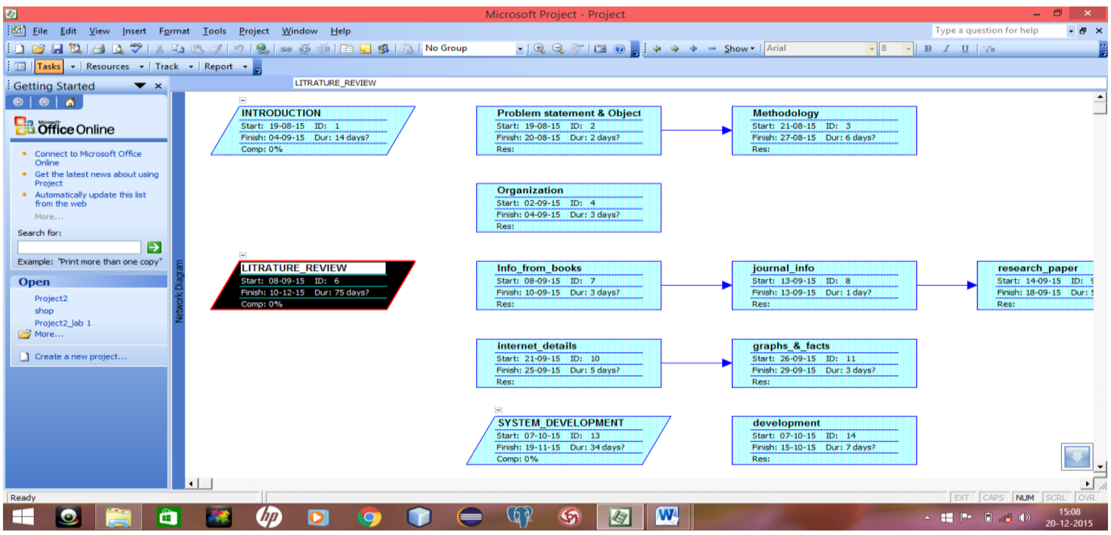


Fig. 10

RESOURCE GRAPH

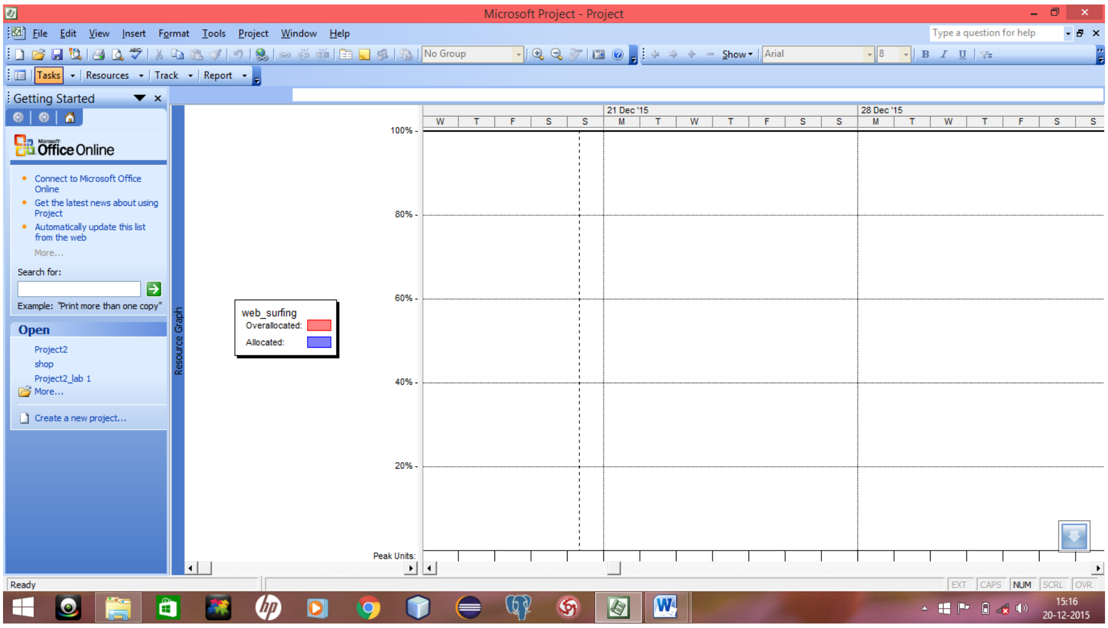


Fig. 11

In this investigation, using only three CAN-Bus signals (i.e., vehicle speed, steering wheel angle and brake force) three different maneuvers (left turn, right turn and lane change) were recognized.

CHAPTER 5

CONCLUSION

The study contributes to driver behavior signal processing area in two ways. First, it proposes a hierarchical way of formulating the maneuvers and combining them for the route models.

Second, it proposes a plausible solution to maneuver recognition and driver distraction detection problems. We believe that this study will open the ways to construct systems analyzing driver behavior based on time windows as small as 2 seconds. There is also possibility of using such a system to activate certain controllers in a safer way in intelligent vehicles provided that this system's output (maneuver context and distraction) is used for decision making.

Using driver behavior data measured with a driving simulator, an HMM-based driver sbehavior recognition model in lane changes was developed that takes into account the characteristics of the driver model within the driver model framework, and its fundamental performance was analyzed. Primary conclusions are as follows.

1) The results suggest that HMMs can be used to model driver behavior and build a system for recognizing driver behavior in lane changes. Further, HMMs have the potential to detect a lane change in the very early stage of steering.

2) An analysis conducted with the HMM-based model indicated the formulary and importance of context in driver behavior. A modeling approach for improving early recognition of lane changes was also found.

3) To apply HMM-based driver behavior recognition to driver assistance systems, it will be necessary to develop general models and assure robustness corresponding to actual driving situations, in addition to improving recognition performance by resolving the above mentioned issues.

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