UTDrive: Analysis and Modeling of Driver Behavior

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Project Goals:

- ***Collect multi-modal driving signals*** from a large number of drivers in car environment.
- ***Analyze driving-related activities*** from collected multi-modal signals.
- ***Evaluation driving-related*** distraction and non-distraction.
- ***Design mathematical models*** in three distinct classification tasks.
  - Action classification
  - Driver identification
  - Distraction detection

Project Overview:

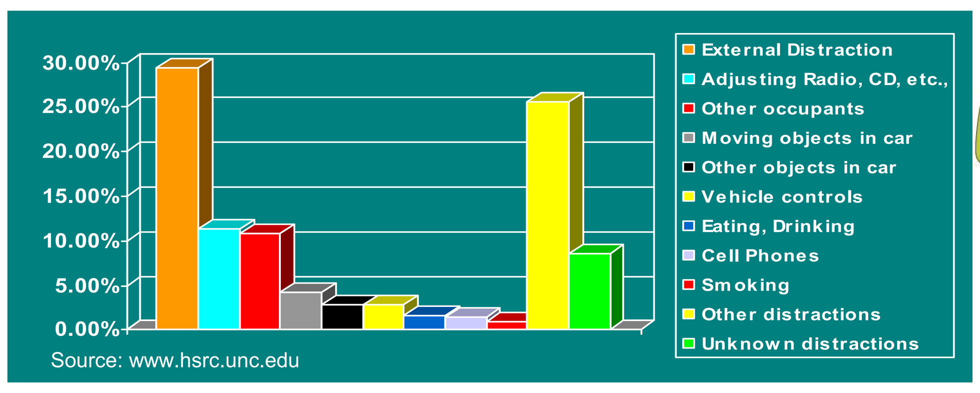
Background

As the number and complexity of in-vehicle technology (information & entertainment systems) increase, drivers will place more emphasis on performing secondary tasks: driver assistance, route navigation, entertainment systems while driving.

"Future design and development will lead to a seamless implementation of hands-free interaction among digital devices within vehicles. In addition, systems will not only meet the wants and needs of drivers but also accommodate their facilities by factoring in the workload context."
Bruce Magladry (Director of Highway Safety Office, U.S. NTSB)

Driver distraction

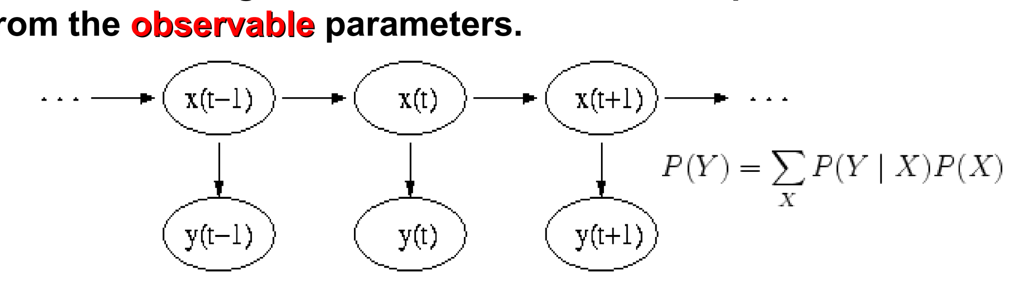
- NHTSA estimates that 20-30% (1.2 million accidents) of all motor vehicle crashes are caused by driver distraction.



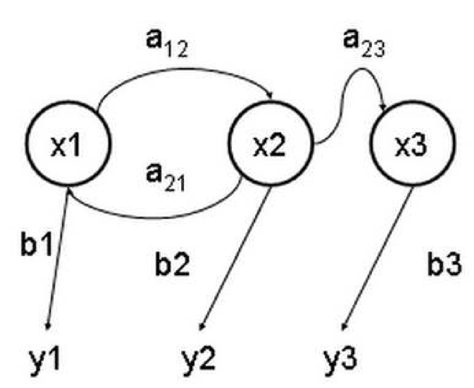
- Average American spends more than 300 hrs in the car every year, and estimates the number of people using cell phones while driving vary 50-73%.
- Estimates are that 60% of cell phone calls initiated in 2000 originated in car environments

Hidden Markov Model (HMM)

is a **statistical model** in which the system being modeled is assumed to be a **Markov process** with unknown parameters, and the challenge is to determine the hidden parameters from the **observable** parameters.



$$P(Y) = \sum_X P(Y \mid X)P(X)$$



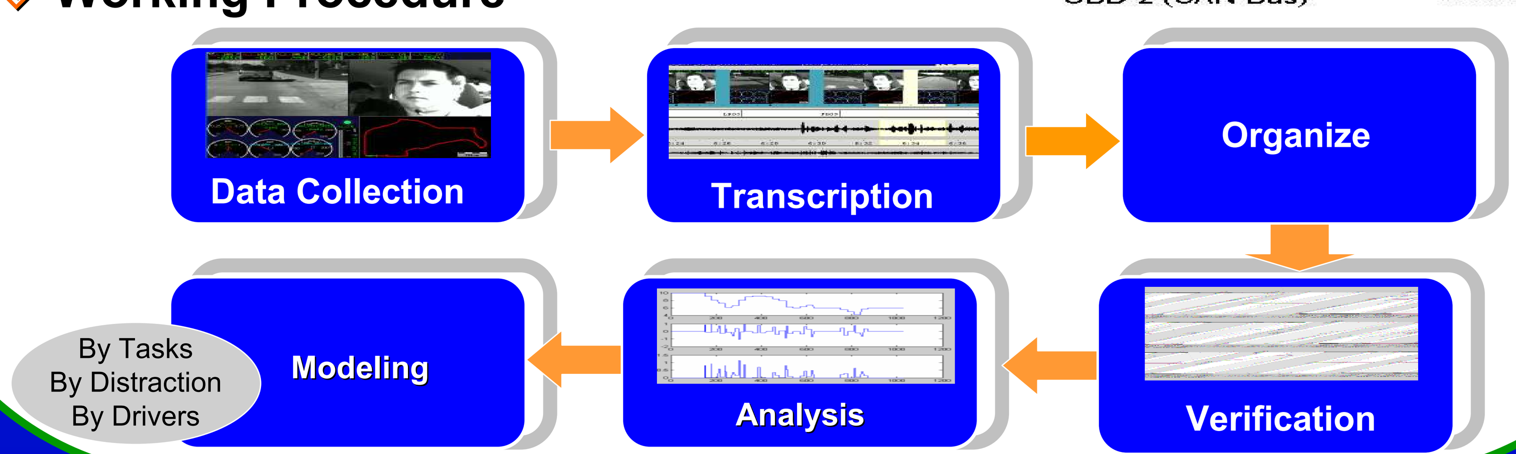
State transitions in a hidden Markov model
x — hidden states
y — observable outputs
a — transition probabilities
b — output probabilities

The value of the hidden variable $x(t)$ (at time t) *only* depends on the value of the hidden variable $x(t-1)$ (at time $t-1$). This is called the Markov property. Similarly, the value of the observed variable $y(t)$ only depends on the value of the hidden variable $x(t)$ (both at time t).

CAN-Bus & Signals

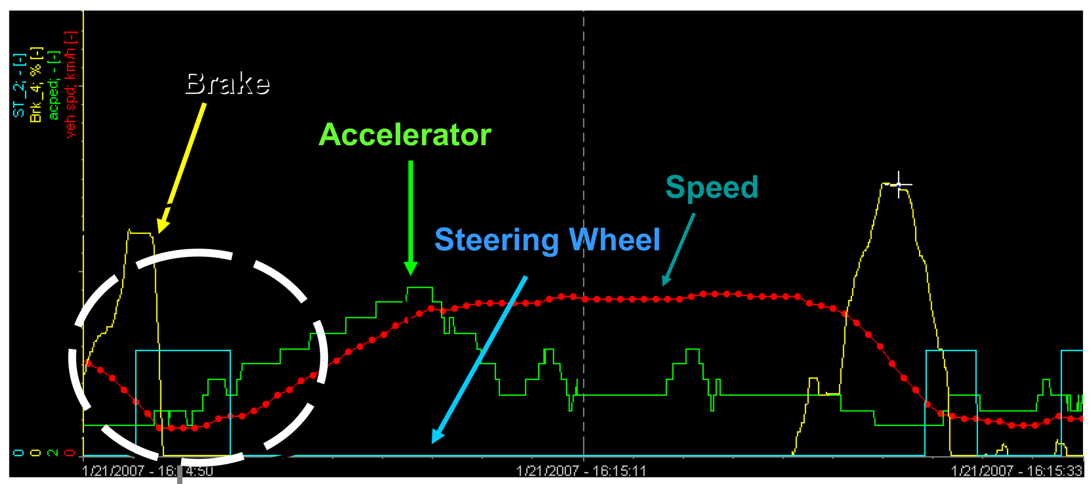
- Acceleration signal
- Brake pedal signal
- Steering signal
- Video signal
- Audio signal
- GPS signal

Working Procedure

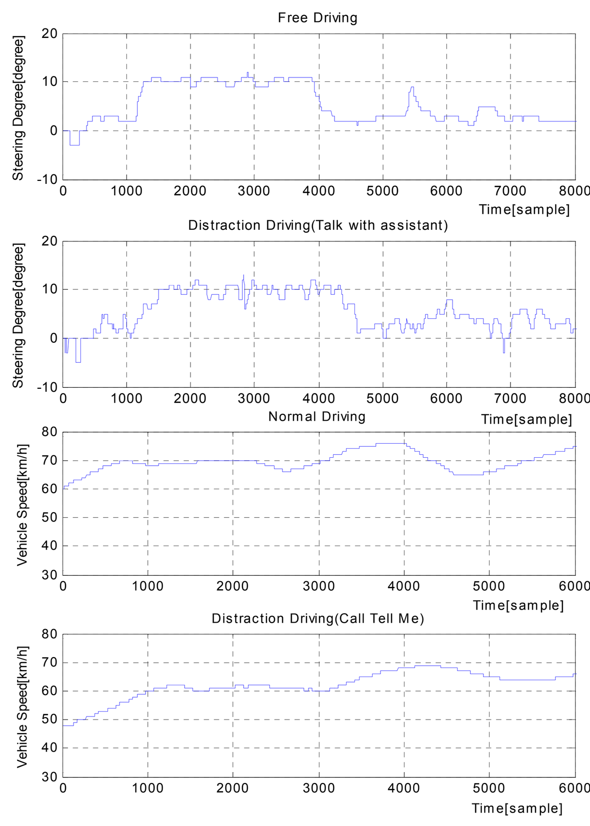


Project Results:

Analysis



i. **Driver hits brake & begins turning steering wheel**
ii. **While speed drops to the lowest point (in middle of turn), driver engages the accelerator.**
iii. **Once desired speed is obtained, driver periodically uses accelerator to maintain overall vehicle speed.**



Window size 300
Normalized variance = 0.2729

Normalized variance = 0.8178
Larger variance
Call Tell Me gave driver distraction

Mean speed = 69.9116[km/h]

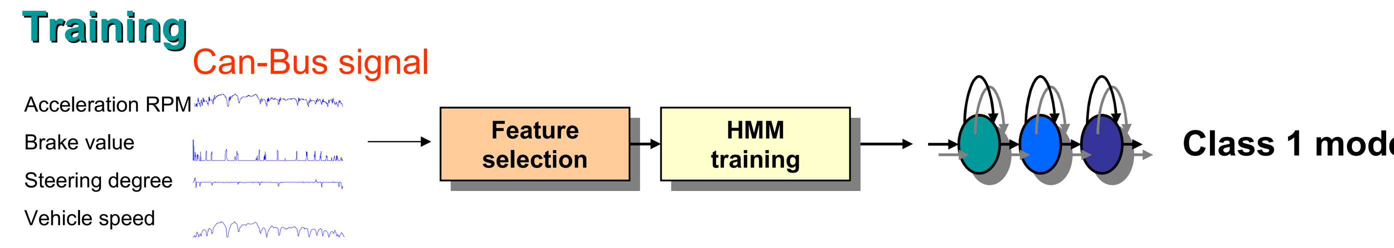
Mean speed = 63.9199[km/h]

Same road condition
Same traffic condition
Same route
But different mean speed
=>Driver focuses on Distraction Task vs. Driving Activity

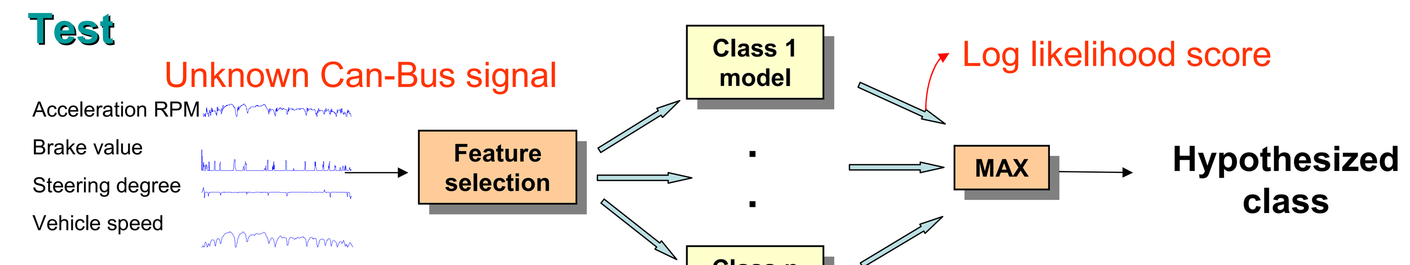
Modeling

- **Action Classification** : 6 classes : Turn-right, Turn-left, Line-change-right, Line-change-left, Stop, Free-driving
- **Driver Identification** : 8 classes : driver1, driver2, ...,drvier8
- **Distraction Detection** : 2 classes : normal driving or distracted driving

Training



Test



Performance

Activity	TR	TL	LR	LL	ST	FR
Accuracy(%)	87.99	100	52	44.44	85.18	68.80

Driving condition	Distraction	Non-Distraction
Accuracy(%)	70.00	65.15

Driver	#1	#2	#3	#4	#5
Accuracy(%)	60.71	41.38	19.44	25.58	22.22

->Average accuracy more than 70% represent that driver-behavior (driving activities) can be modelled & detected using HMM classification methods

Project Conclusions/Outcomes:

- **Impact**
  - Project Results will help develop a framework for effective models of driving behavior for safe driving. Smart vehicles will predict driver behavior that causes driving performance to deteriorate (e.g., under-distraction, drowsiness) and alert the driver (or the other drivers on the road) to avoid crashes.
- **Outcomes**
  - Austin, TX Univ. of Texas System Tech Transfer Conference
  - Submitted paper to the INTERSPEECH 2007
  - Preparing paper for IEEE DSP in Cars/In-Vehicle Workshop
- Conclusion& Future Research Directions
- Effective driver behavior model

  Generate/explain driver's behavior characteristics & Predict driver's "next move"
  Monitor/identify driving behavior (e.g., sleepy)
  Recognize driver ⇨ adjust systems to support driver, increase safety and security
  Make Recommendations on Driver Distractions which impact driving performance