Classifying Driver Workload Using Physiological and Driving Performance Data: Two Field Studies

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Motivation

Problem:
Major vehicle crashes involve distracted driving.

Goal:
- Automatically detect driver's cognitive workload (CW) through Machine Learning.
- Evaluate in-vehicle interface performance

Crash by Crash Severity		Overall Crashes	Distraction-Affected Crashes	D-A Crashes Involving Cell Phone Use
2007	Non-Fatal Crashes			
	Injury Crash	1,711,000	309,000 (18%)	17,000 (6%)
	PDO Crash	4,275,000	689,000 (16%)	31,000 (4%)
	Total	**6,024,000**	**1,003,000 (17%)**	**49,000 (5%)**
2008	Non-Fatal Crashes			
	Injury Crash	1,630,000	314,000 (19%)	19,000 (6%)
	PDO Crash	4,146,000	650,000 (16%)	30,000 (5%)
	Total	**5,811,000**	**969,000 (17%)**	**49,000 (5%)**
2009	Non-Fatal Crashes			
	Injury Crash	1,517,000	307,000 (20%)	16,000 (5%)
	PDO Crash	3,957,000	647,000 (16%)	29,000 (5%)
	Total	**5,505,000**	**959,000 (17%)**	**46,000 (5%)**
2010	Non-Fatal Crashes			
	Injury Crash	1,542,000	279,000 (18%)	16,000 (6%)
	PDO Crash	3,847,000	618,000 (16%)	30,000 (5%)
	Total	**5,419,000**	**900,000 (17%)**	**47,000 (5%)**
2011	Non-Fatal Crashes			
	Injury Crash	1,530,000	260,000 (17%)	15,000 (6%)
	PDO Crash	3,778,000	563,000 (15%)	35,000 (6%)
	Total	**5,338,000**	**826,000 (15%)**	**50,000 (6%)**

Motor Vehicle Traffic Crashes and Distraction-Affected Crashes by Year 2011

Introduction

How to achieve Goal

- ❖ Driving is complex activity
- ❖ It imposes varying levels of workload on the driver.

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❖ Understanding cognitive workload: help to reduce accidents.

- **Problem:**

  Understanding of how:

  - evolving in-vehicle interface
  - other device; mobile device, music on radio-box etc.

  affect the driver cognitive load is **extremely difficult task**.

- **Solution:**

  - understand driver's cognitive workload through physiological data.
  - automatic detect elevated cognitive workload using physiology and vehicle data.

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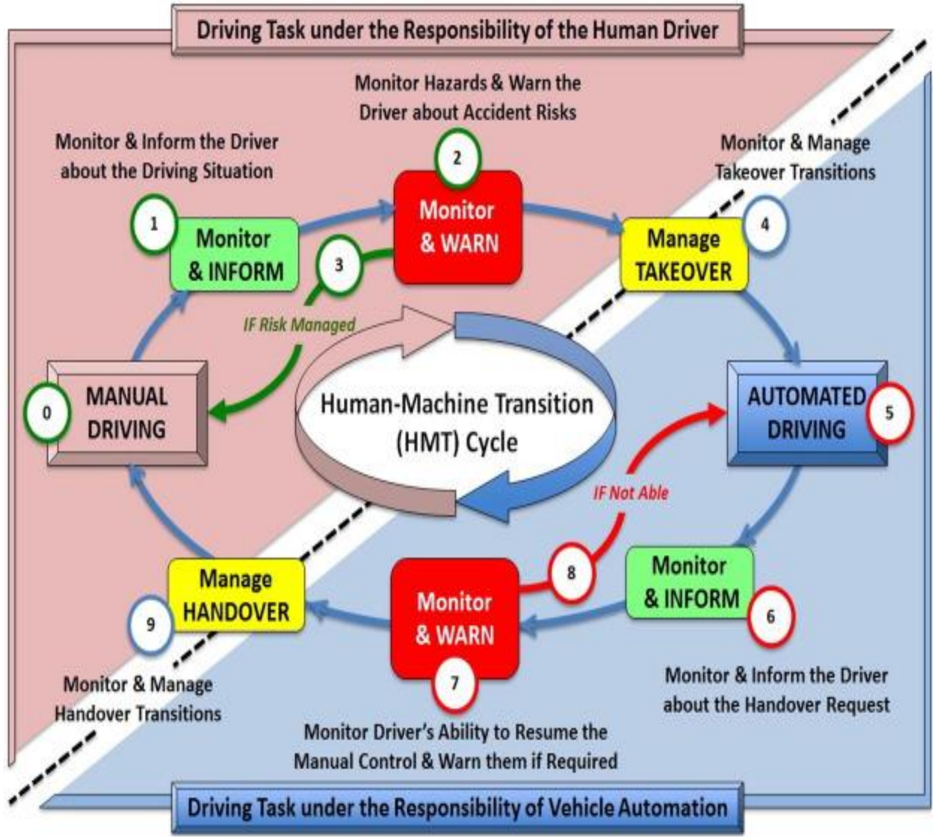
Connection to AHMIAS

- Poorly designed in-vehicle user interfaces can lead to:
  - distraction
  - risky driving
- **Adaptive human interface can optimize user experience and safety during driving.**

Find a way to increase classification accuracy

automatically identifying the elevated cognitive workload levels in drivers.

evaluate/enhance the **interface interaction ability to be more adaptive**

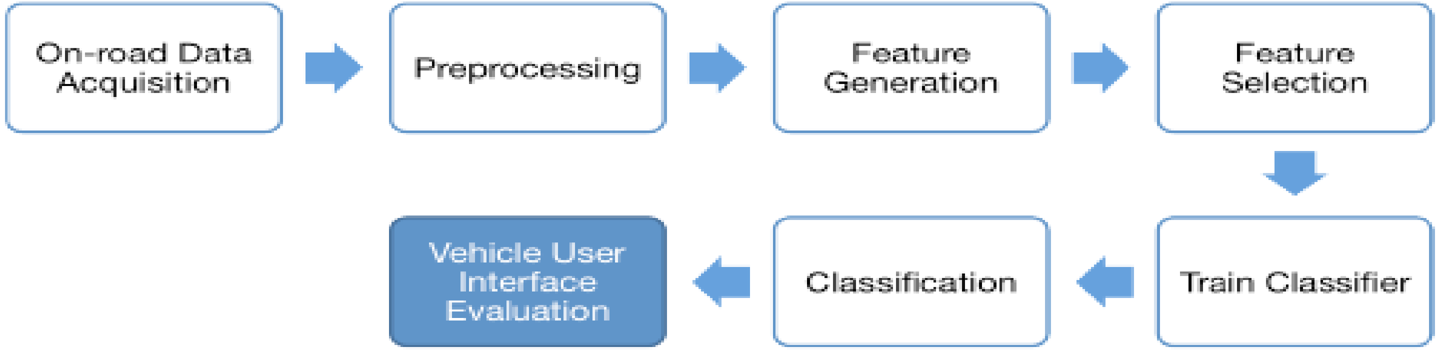


Automatically detect cognitive workload and transfer of control of autonomous vehicles

Approach

Classifying driver data for UI evaluation

- Approach to evaluate/improve interface performance to automatically detect cognitive workload through Machine Learning.



Steps required for on-road cognitive state classification for vehicle user interface evaluation

On-road data acquisition

Two types of data: Physiological data (HR, SCL) and Vehicle data (Vehicle speed and Steering wheel angle).

- Heart rate(HR) and Skin conductance level (SCL): measure cognitive/mental load of drivers.

- Vehicle speed and Steering wheel angle: measure driving performances.

- Why HR
  - easy to use.
  - Give information about autonomic nervous system.
- Why SCL
  - Very sensitive to arousal (flight-or-fight) and mental workload.

Recording of physiology during on-road driving. Electrocardiogram (top right) and skin conductance (bottom right) sensor placement are shown

Vehicle data: measured during primary task

Physiological data: measured during secondary task

How to induce cognitive load on drivers using secondary task

What is Secondary task?

- an audio presentation – verbal response delayed digit recall task.
- Perform in the form of **"n-back task"**.

What is n-back task?

- 0-back: same digit
- 1-back: digit 1-item back
- 2-back: digit 2-item back

Auditory stimuli	Stimulus	9	3	7	1	8	0	2	4	6	5
Verbal responses	Response	.	.	9	3	7	1	8	0	2	4

2-back secondary task performed during on-road driving

How does n-back task work?

- 0-9 digits appears randomly with 2.5 second's gap.
- After each digit, driver needs to say the digit out loud in n-back task sequence manner.

Data Pre-processing

- **For HR:**

- In EKG signals QRS segments of heartbeat contains sharp spikes.
- EKG signal contain artifices and anomalies while data acquisition.
- QRS detection algorithm used to identify heart beats in the signal.

- **For SCL:**

- Wavelet transform used to remove high frequency noise from skin conductance recordings.

- **For driving performance:**

- Steering wheel angle (gap) measure the stability of control while distraction with the help of steering wheel reversal rates.

- After preprocessing, signals were resampled to 10 Hz.

Implementation

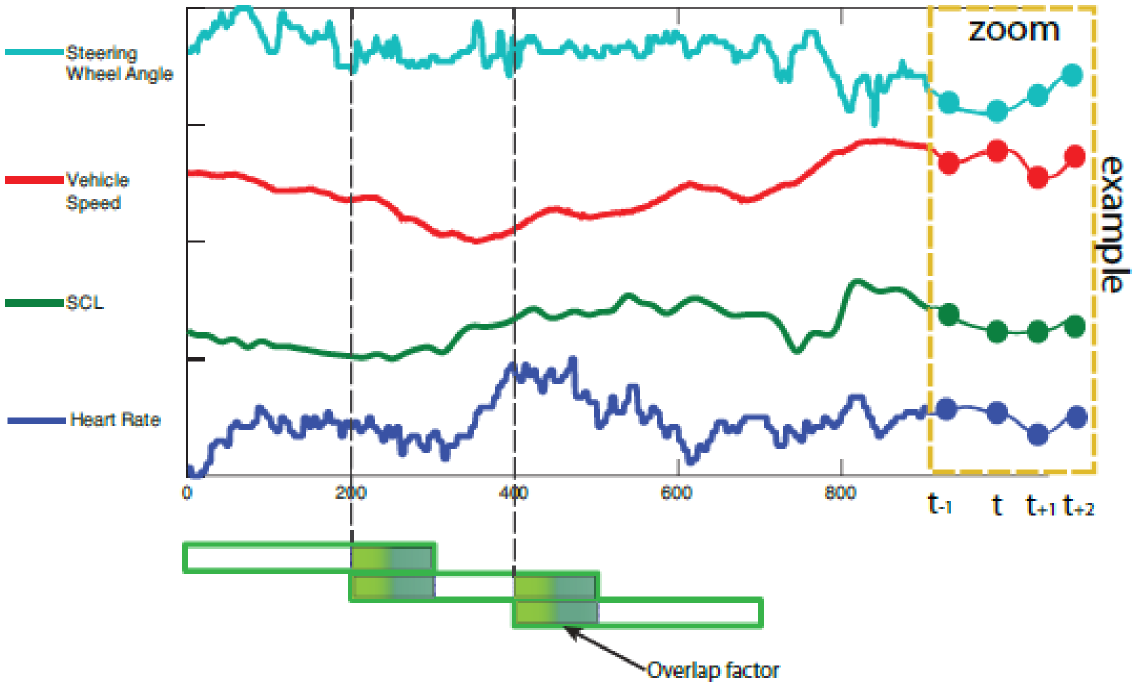
Supervised approach

Features: heart rate (HR), skin conductance level (SCL), vehicle speed and steering wheel angle

Labels:

- **Elevated CW:** n-back cognitive demand task period(secondary task)
- **Normal CW:** driving only periods (primary task)

Hyper Parameters: window size and overlap factor.



Sequential sensor data can be broken into fixed length windows (green bars at bottom), which slide across the data. Within each window, we can calculate average, standard deviation, etc. The size of the window and the amount of overlap will affect the analysis.

Implementation: Experiment 1: Automatic classification of elevated workload in individual drivers

- 20 subjects

Classification results

	All Features		Heart Rate	
	Mean	S.D.	Mean	S.D.
Decision Tree	75.0	10.8	72.8	12.8
Logistic Regression	75.5	10.9	73.9	11.3
Multilayer Perceptron	75.7	10.9	74.0	12.4
Naïve Bayes	75.0	12.5	74.1	11.8
Nearest Neighbor	69.4	11.6	71.5	10.3

Mean and standard deviation for classification of elevated cognitive load from normal driving across 13 subjects using all features (20 subjects for heart rate only)

Goal:

- collect individual's physiological and vehicle data.
- build individual models to account for individual differences between drivers.

Result discussion

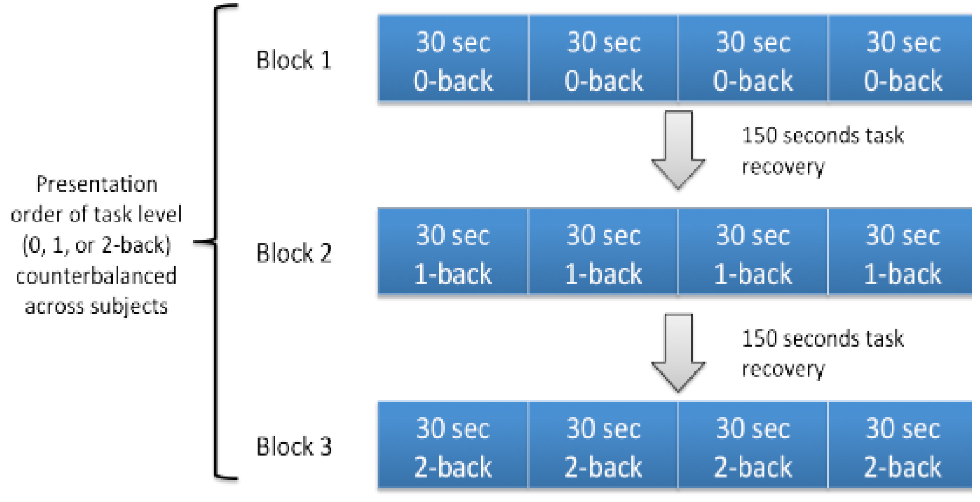
- 24 observations for 48 minutes.
- Training done on 43 minutes (90% of data), which is not ideal training time for real world dataset
- **Not ideal to build individual classifiers.**

Implementation: Experiment 2: Establishing methods across individuals

- ➢ 99 subjects

- ➢ **Experiment 1 Drawback:** bad performance even though built individual classifier.

- ➢ **Goal:**
    - find common features and algorithms that reliably can classify cognitive load automatically across individuals and build one classifier only for all participants.



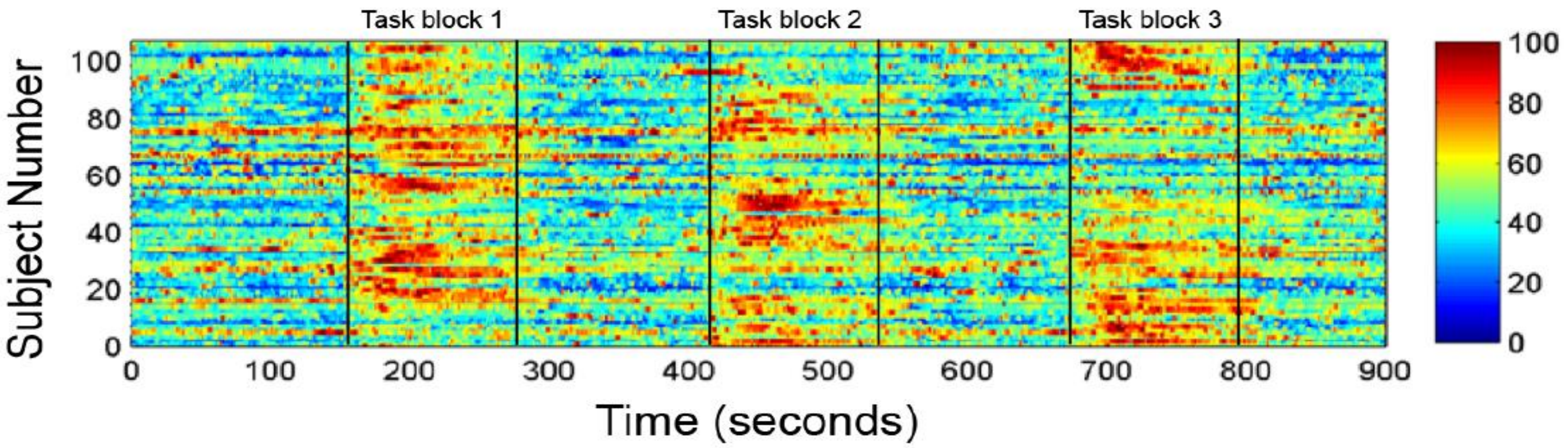
Protocol Procedure for Experiment 2.

➢Exploratory Analysis :

- Heart rate and skin conductance level sensitive to changes in cognitive workload.
- Figure shows that while giving metal load in each task block, we get Red spikes.

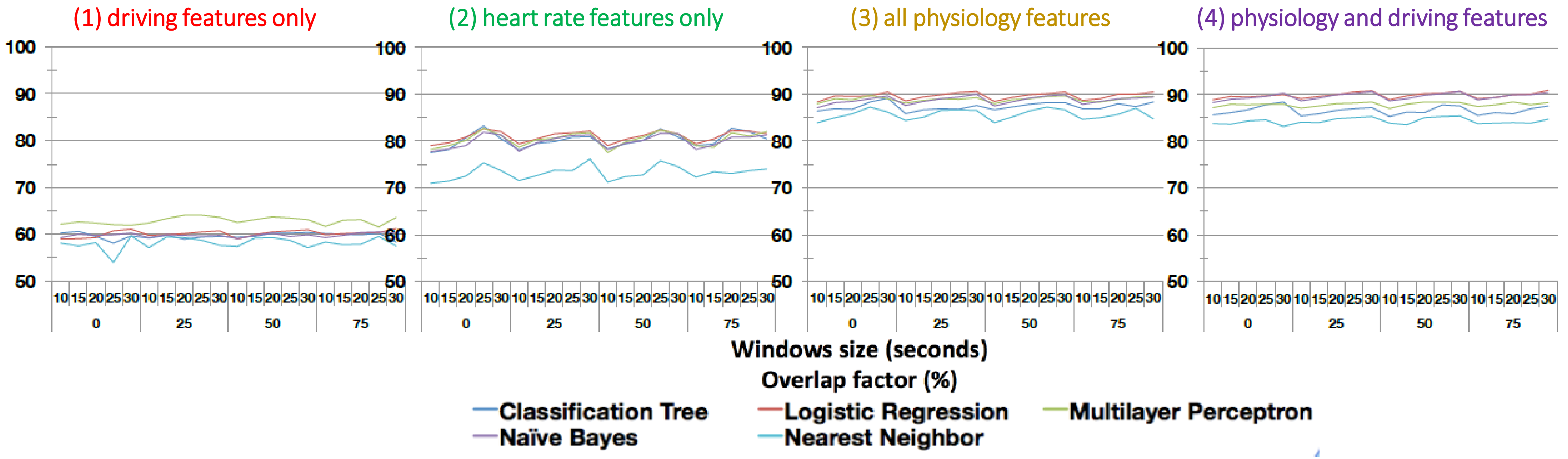
Red indicates maximum heart rate

Blue indicates minimum heart rate



Results and Evaluation

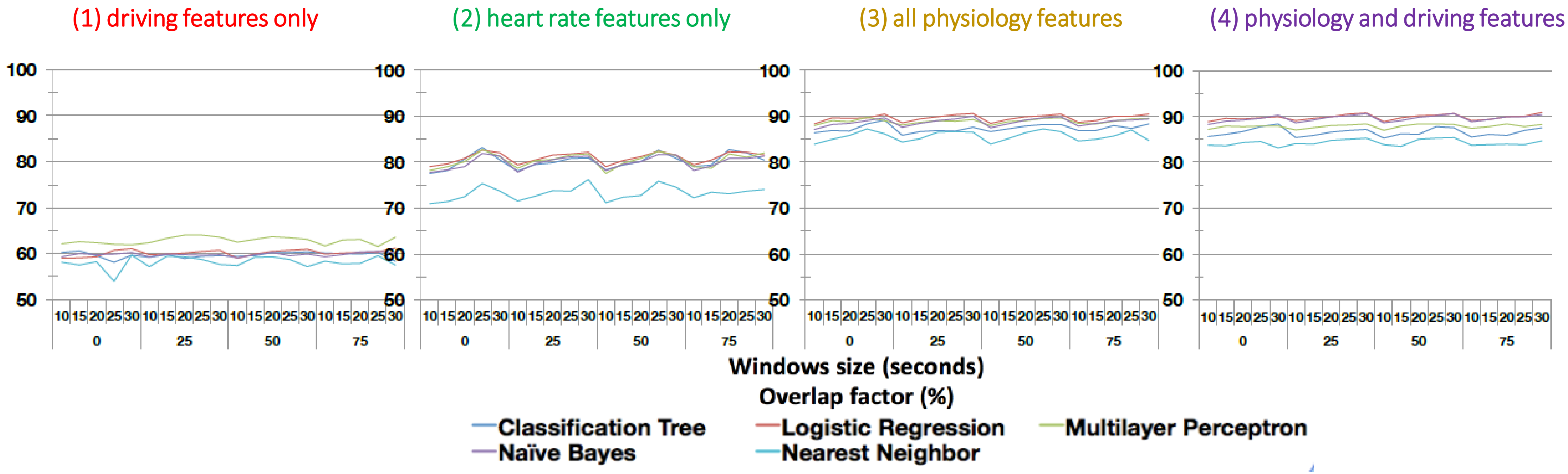
➢ Classification Results



Classification accuracy (from left to right) using

➢Result Analysis:

- **Hyper Parameters:**
  - increase windows size improved classification accuracy in all cases, except in first case
  - overlap factor doesn't have a significant impact on the classification accuracy.
- Nearest neighbor performed worst, while the other classifiers had similar performance.
- The best performance was found in 3 and 4 using physiological data.



Conclusion

Summary:

1) Physiological data improves performance in order to automatically detect elevated cognitive workload.

2) Classification accuracy depends on
   - Learning algorithm
   - Training data
   - Sliding window size
   - Feature type

3) Feature selection is the key for any machine learning algorithms.

4) High accuracy can lead to:
   - better recognition of elevated cognitive load periods
   - can improve adaptive human interface.
   - can help in transfer of control to adaptive interfaces.

Discussion and Future work

Discussion:

To develop an automatic cognitive workload classifier to evaluate interfaces in real-world driving:

- window size, classification accuracy and training data matters.
- Trade off between window size and classifier accuracy.
- Heart rate feature is a very powerful feature into this.

Future Work:

- With additional measures:
  - more sensitive physiological performance.
  - other driving performance (velocity and both large and short steering wheel reversals)

There are chances to get similar or improved results.

- Train the algorithm on bigger dataset.
- Also include 0-back and 1-back to evaluate physiological measures with demand levels change.
- Choose other classification algorithms.

Thank you!

Open for question

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