# Sensor-Based Assessment of the In-Situ Quality of Human Computer Interaction in the Cars

FINAL RESEARCH REPORT

SeungJun Kim (PI) and Anind K. Dey (Co-PI).

**The problem**

Human attention is a finite resource. When interrupted while performing a task, this resource is split between two interactive tasks. People have to decide whether the benefits from the interruptive interaction will be enough to offset the loss of attention from the ongoing task.

The issue of dealing with self-interruptions and external interruptions is particularly critical in driving situations. In general, interruptions result in a time lag before users resume their primary task, increase mental workload, and thus decrease primary task performance. Therefore, being able to identify when a driver is interruptible is critical for building systems that can mediate these interruptions.

Related note – Studies in Interruption domain offer important insights for designing human-centered interruptions; however, they have mostly explored static, on-screen tasks mediated with conventional computers or mobile devices (e.g., the impact of call notifications for smartphone users). Little research has been conducted to replicate existing findings or approaches for delivering interruptions in situations in which users cannot fully divert their attention from the primary task (e.g., driving cars) and in which interruption timings can critically impact the user experience.

**Approach**

In order to identify situations in which drivers enter either low or high cognitive load states during naturalistic dring (i.e., opportune moments for driver interruption – e.g., more interruptible states vs. less interruptible states), we have examined a broad range of sensor data streams to understand real-time driver/driving states (e.g., motion capture, peripheral interaction monitoring, psycho-physiological responses, etc.), and presented a model-based driver/driving assessment by using machine learning technology.

**Methodology**

We conducted a human-subject experiment in the field.

We recruited 25 drivers (age $M$=32.0, $SD$=14.3, age range: 19 – 69, gender: 14 female and 11 male) as our study participants. We plugged an on-board diagnostics (OBD) device in their cars, and they were asked to wear five body-worn sensor devices: four accelerometer sensors for capturing body motion and one chest belt sensor for tracking physiological responses. We installed two smartphones in each car - one on the front windshield and the other on the head-rest of the passenger seat.

Study performed two sessions of naturalistic field driving. In the 1st driving session, drivers used any route that they prefer to get to a destination. In the 2nd session, they used a GPS system, and followed a fixed route. By doing so, we tried to have drivers exposed to similar configuration of roads and similar demands of interruptive interaction, with the GPS system. See Figure 1.

We installed the devices in driver's cars and helped them wear a physiological sensor,

time-synched devices and collected baseline data, and had drivers complete a pre-questionnaire, perform the driving task, and complete a post-task questionnaire and interview.



Route 1 – approx. 14.7 mile
(approx. 43m 59.2s)

(a) Any preferred or familiar route to a shopping mall.



Route 2 – approx. 4.8 mile
(approx. 33m 18.3s)

(b) A fixed route suggested by GPS to get a sports stadium.

**Figure 1.** Routes in the two driving sessions with sensors.

Data gathered

In total, we had 100 basic features and 52 derived features (OBD: 72, YEI: 40, BH: 40) and 5 manually annotated features related to traffic from videos (one car driving state and four traffic states around the vehicle – front, right, left, and oncoming. After time syncing the sensors, all sensor data were aggregated, and their means ($\mu$) and standard deviations ($\sigma$) were calculated for every 1-second segment as statistical features.

Details are as follows:

*An OBD device* provided information about the status of the vehicle (sampled at 1Hz) including longitude, latitude, altitude, car speed, engine RPM, throttle position, and fuel flow rate. The data were transmitted via Bluetooth to the smartphone responsible for

recording traffic video. From the OBD data we derived road curvedness by tracking variations of longitude and latitude coordinates, centrifugal forces by combining car speed and curvedness information, types and gradient of road slope by using the 1st derivative of altitude data.

*Four YEI 3-Space devices* were used, placed on each of the drivers' wrists, on the front of the head, and top of the foot. The devices collected information about the drivers' motions using a tri-axial gyroscope, a tri-axial accelerometer, and compass sensors, all at 4-5 Hz. The sensor data was transmitted via Bluetooth to the other smartphone. From the YEI data, we derived motion information on how much each monitored body part moved from the baseline position.

In addition, drivers wore *a BioHarness (BH) chest belt* that collected drivers' physiological data including electrocardiogram, heart rate, respiration rate, body orientation and activity at 20Hz sampling rate. From the BH data, we quantified levels and duration of breathing-in, breathing-out, and holding-breath states.

Analyses performed

We included the data from our 15 drivers in our final analysis, after filtering out errorneous or missing sensor data. Then, we examined how driver and driving states differ across the following five driving state classes:

- `STEERING_ONLY` - moments when both hands were on the wheel.

- `ONE_HAND_DRIVE_ WITH_NO_PI` - moments when one of the driver's hands was off the steering wheel but that hand was not performing any specific activity.

- `DRIVING_I` - activities that are quite central to the primary driving task (e.g., changing grip positions, operating levers for blinkers or wipers, switches for opening side windows).

- `PI` - activities that are not directly central to the primary task (e.g., eating food, manipulating the air conditioner or car radio, talking on the phone).

- `NO_HAND_DRIVE` - moments when both hands were off the steering wheel and not performing any peripheral activity.

*Statistical analysis*. For analyzing the continuous measures (e.g., car speed), we conducted a univariate ANOVA by using a general linear model and then used either Tukey HSD or Games-Howell as post-hoc tests after checking the homogeneity of variances (i.e., Levene Statistic), where $\eta p2$ was examined as effect size. For ordinal measures (e.g., human-annotated data or fixed level data), we conducted the Kruskal Wallis Test followed by Mann-Whitney U test as post-hoc, where *r* was examined as effect size. In the analysis of Likert-scale rating data, Friedman tests and a Wilcoxon Signed Rank post-hoc test were conducted.

*Machine-learning analsyis*. For a binary classification problem (i.e., driver interruptibility, `INTERRUPTIBILE` vs. `LESS_INTERRUPTIBILE`), we used a random forest classifier, which runs efficiently on large databases such as our sensor data. We also handled unbalanced classes using stratified 10-fold cross validation where each fold contains

approximately the same percentage of samples from each target class as the complete set, and then applied different sample weights based on the ratio of samples that belong to each class. We automated this procedure for each driver and for each fold.

**Findings**

- Statistical implications from the 22 of driver activities that had a total duration of at least 90 seconds summed across multiple instances (See Table 1). For examples:

  o For most of the driving time, drivers used both their hands (48.0%) or one hand (22.8%) for controlling the vehicle without any peripheral interaction

  o Although drivers did not actually execute any peripheral activity, one handed driving is a distinct state from using both hands for steering. Similarly, there was no discernible distinction in durations between one handed and no-handed driving.

  o Driver activities that corresponded to the driving task (e.g., turning on blinkers) were completed in 2.4 seconds on average, while peripheral interactions lasted for 10.6 seconds.

**Table 1.** Frequecy and duration of 22 top-ranked driver activities.

| Driver activities | Occurrence | | Duration (sec) | | Duration (sec / occurrence) |
| --- | --- | --- | --- | --- | --- |
| | / subject | / 10-min drive | / subject | / 10-min drive | *M* (*SD*) |
| **ONE_HAND_DRIVE** | **57.1** | **6.9** | **15.4** | **117.0** | **17.0 (26)** |
| GEAR_SHIFT | **37.1** | **4.5** | 2.7 | **19.0** | 4.2 (6.7) |
| TOUCHING_SELF (e.g., face) | **24.5** | **3.0** | 7.6 | **28.5** | 9.7 (21.5) |
| **REST_OFF_WHEEL** | **20.6** | **2.5** | **14.7** | **37.2** | **15.0 (14.1)** |
| L_BLINKER | **15.7** | **1.9** | 3.9 | 8.6 | 4.6 (16.8) |
| R_BLINKER | 14 | 1.7 | 4.4 | 9.4 | 5.6 (22) |
| CAR_RADIO | 9.2 | 1.1 | 5.9 | 9.5 | 8.6 (16.7) |
| R_GRIP_CHANGE | 8 | 1.0 | 2.9 | 6.3 | 6.6 (12.5) |
| HEAD_ TURNING_WAY_LEFT | 7.3 | 0.9 | 4.2 | 4.8 | 5.5 (12.1) |
| **CELLPHONE** | **6.7** | **0.8** | **13.5** | **17.6** | **21.7 (26.9)** |
| L_GRIP_CHANGE | 6.7 | 0.8 | 1.8 | 2.0 | 2.5 (3.1) |
| HEAD_TURNING_WAY_RIGHT | 5.7 | 0.7 | 2.6 | 1.9 | 2.8 (2.7) |
| GPS_PORTABLE | 4.5 | 0.5 | **14.3** | 6.5 | 12.1 (13.5) |
| AC_CONTROL_SWITCHES | 3.1 | 0.4 | 1.8 | 1.0 | 2.5 (1.5) |
| BOTH_HANDS_OFF_DRIVE | 2.3 | 0.3 | 2.2 | 3.0 | 11.0 (11) |
| **FOOD_OR_DRINK** | **2.6** | **0.3** | **11.6** | 5.9 | **18.8 (16.6)** |
| OTHERS_MISCELLANEOUS (e.g., shouting outside) | 2.7 | 0.3 | 6.5 | 3.3 | 9.9 (10.7) |
| OTHERS_MUSIC | 2.7 | 0.3 | 1.4 | 5.2 | 16.2 (15.3) |
| **SMOKING** | **1.9** | **0.2** | 1.2 | 4.3 | **18.3 (41.8)** |
| WIPER_WASHER | 1.7 | 0.2 | 2.9 | 1.6 | 7.5 (12.5) |
| AC_AIR_VENTS | 1.1 | 0.1 | 3.5 | 1.5 | 11.7 (19.2) |
| OTHERS_DANCE | 0.1 | 0.0 | 0.7 | 0.2 | 11.0 (8.5) |
| Total | 235.3 | 28.3 | 5.7 | 13.4 | **10.4** (19.7) |

- Sensor-based implications related to driver interruptibility. For examples:

  o Drivers significantly regulated car speed while performing peripheral activities or taking both hands off the steering wheel.

  o Drivers tend to drive at more consistent speeds during PI (47.8%) or NO_HAND_DRIVE (73.7%) states than in the ONE_HAND_DRIVE_WITH_NO_PI state (24.6%). These findings implied that driving status for the PI or

`NO_HAND_DRIVE` states are most similar. See Figure 2.

- o Driver physiological states for the `PI` and `NO_HAND_DRIVE` states are most similar to the resting states. We confirmed that from our analysis of physiological states, driving states and road conditions, drivers are more interruptible than in the remaining states.

- o Interruptibility while one-handed driving without any peripheral interactions is still unclear since driver physiological states are similar to the two interruptible states and the baseline (i.e., no driving), but the driving states and road conditions differed significantly.

- o Regarding driver interruptibility, we found that the five interaction states can be combined as follows:

  - • `PI` = `NO_HAND_DRIVE` (= REST without driving) → `INTERRUPTIBLE`

  - • `DRIVING_I` = `STEERING_ONLY` → `LESS_INTERRUPTIBLE`

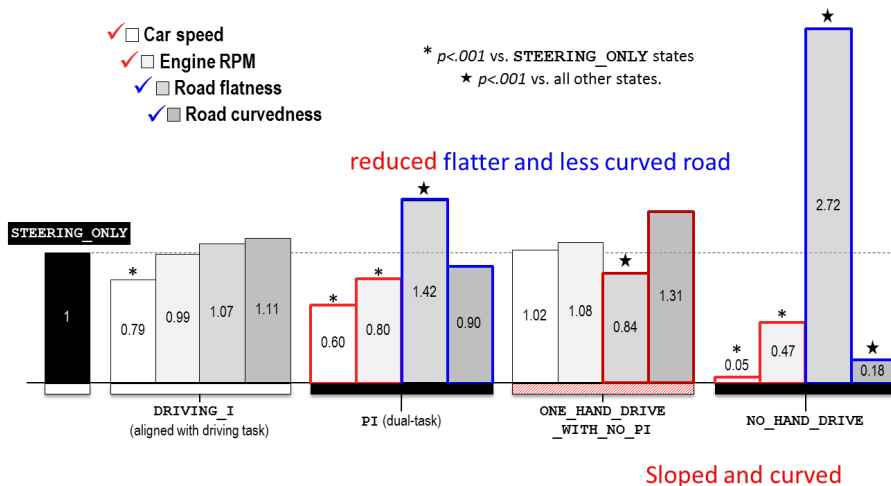  - • `ONE_HAND_DRIVE_WITH_NO_PI` (as not clearly interruptible) → `LESS_INTERRUPTIBLE`



**Figure 2.** Driving states and road conditions, revealed in sensor data streams.

- • Sensors can discriminate driver interruptibility, even in naturalistic driving situations, every second, at 94.9% accuracy (See Figure 3). The Lowest was almost 90%, among the individual models; however, we also found individual difference in hit rates and false discovery rates.
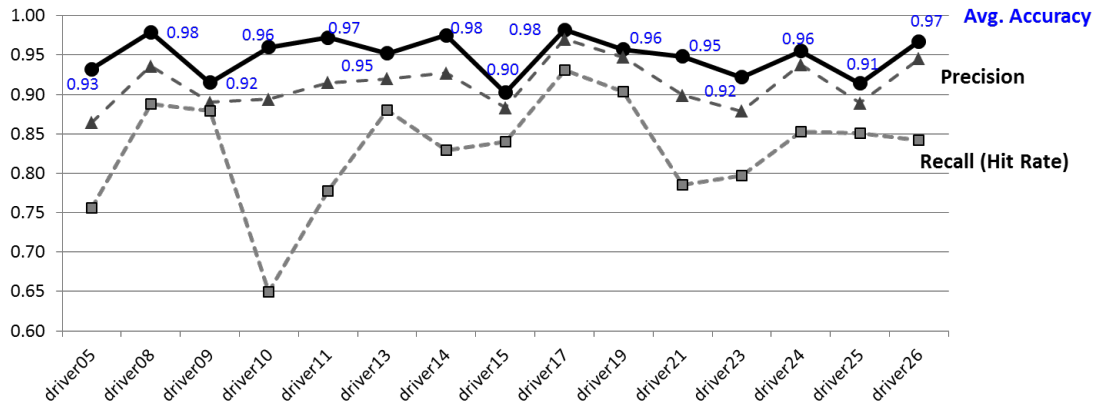
**Figure 3.** The classification performance of individual models.

## Conclusions

<u>Results achieved</u> - In this UTC project, we successfully developed the technology of *near* real-time detection of driver interruptibility based on a range of sensor data streams. We used instances of drivers engaged in peripheral interactions as moments of ground truth for their split attention while managing interruptions. As a result, we demonstrated that sensor data could build a machine learning classifier to determine driver interruptibility every second with almost 95% accuracy. We also successfully identified sensor features that best explained the states where drivers performed peripheral interactions, which contributed to the high performance of our system.

Based on our findings, we continue the project by appling this technology to improve the intelligence of in-car cyber-physical systems that mediate when drivers use technology to self-interrupt and when drivers are interrupted externally by technology. We are refining our key technology to create sensor-based models that retain information about the real-time mechanisms whereby drivers' perceived value of the presented information interacts with the nature of the information and the attributes of the sensor-detected interruptible moments. As the delivery, we plan to develop a workload manager that mediates interruptions in cars, thereby increasing driver appreciation of the quality of presented information

**Recommendations** - next steps developed as a result of the project

- Collect additional data to confirm that the results generalize across a wider driving population and work to build models and apply features that more consistently perform across drivers and for the nuances of specific drivers.

- Investigate how to mediate interruptions to drivers, with the obatined accurate classifier and easy-to-deploy system. Specifically, push interruptions at different timings to assess the real-world impact of being able to detect interruptible moments while driving, as another field study. Design these interruptions to differ in terms of their temporal urgency, relevance to the driving tasks, and overall importance.

- Develop generalized guidelines for designing intelligent interruption systems for drivers. Use the improved models and understanding to identify the attributes of opportune

moments detected (e.g., expected duration, expected level of driver engagement).

- Apply the key technology to identify breakpoint moments for prompting drivers to safely participate in experience sampling while driving, which will support others doing driving-related research in naturalistic driving situations.

**Note**: This report summarizes the descriptions in one of the UTC project outcomes - Kim, S., Chun, J., and Dey, A. K. (2015). Sensors Know When to Interrupt You In the Car: Detecting Driver Interruptibility Through Monitoring of Peripheral Interactions. Proc. SIGCHI Conf. Human Factors in Computing Systems (CHI '15). ACM, Seoul, Korea, Apr 2015.