Biofeedback Arrests Sympathetic and Behavioral Effects in Distracted Driving

Ioannis Pavlidis, *Senior Member, IEEE,* Ashik Khatri, Pradeep Buddharaju, Michael Manser, Robert Wunderlich, Ergun Akleman, and Panagiotis Tsiamyrtzis

Abstract—Operating machinery while distracted is a dangerous behavior, often habitual, which is the source of accidents. Distracted driving in particular has assumed the form of an epidemic, fueled by the ubiquity of smartphone usage and the tendency to slip into absent-mindedness in tedious commutes. Here we show that a method capable of detecting and communicating overarousal trends associated with the onset of distractions, can pull the driver out of a downward psychophysiological spiral. The method is reliable, unobtrusive, and subtle in its intervention - all important characteristics for real-time corrections on human handling of critical machinery. Arousal estimation is performed by a conservative statistical filter acting upon the driver's perinasal perspiration signal, as this is continuously extracted from a thermal imaging feed. Overarousal notices are communicated via a visual indicator placed in the driver's peripheral vision. Using this method, we conducted a parallel group experiment, where a control CL ($n = 23$) and a biofeedback BF ($n = 24$) cohort were distracted mentally and physically while driving, with only the biofeedback group receiving the benefit of overarousal notification. Results show that heeding biofeedback notices, cuts dramatically the time BF subjects are engaged in distractions with respect to the control group, significantly reducing their arousal levels and improving their driving behaviors in the context of a typical commute.

Index Terms—Biofeedback, distracted driving, sympathetic arousal, perspiration, thermal imaging, affective computing, cusum.

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1 INTRODUCTION

DISTRACTIONS account for an increasing number of crashes and fatalities on roadways [1], in aviation [2], [3], and in railways [4], [5], [6], taking the form of an epidemic across the transportation sector. In this research, we focus on driving distractions. In the United States alone, 3,477 people were killed and 391,000 were injured by distracted driving in 2015 [7]. As bad as the official statistics are, the actual problem is likely worse, because esoteric distractions, such as absent-mindedness, are difficult to be accounted for while physical distractions involving electronic devices are likely to be underreported [8]. Studies have also shown that although people feel very unsafe when riding as a passenger with another driver who is physically distracted, they do not believe that their own driving is affected when they use electronic devices [9]. The latter reveals a deep-seated assertive behavioral pattern that is difficult to reverse with policing actions alone. Moreover, such policing actions are not always feasible. This state of affairs identifies a compelling need to develop a method that would act as

both short- and long-term behavioral orthotic. Given that distractions are associated with sympathetic arousal [10], [11], biofeedback has the potential to fulfill such an orthotic role, because it can enhance drivers' self-awareness while keep undermining the misplaced confidence they have on their multitasking abilities.

In this direction, we introduce a contact-free biofeedback method for controlling both esoteric and physical forms of distractions while driving. The method is based on detecting the sympathetic state of the driver through perinasal perspiration. The perinasal perspiration signal is extracted via thermophysiological imagery [12] and is monitored for significant persistent increases through a statistical filter. An over-arousal alert from this filter is communicated to the drivers' peripheral vision as a pink light in the steering wheel emblem (Fig. 1). This serves as feedback to the drivers that are not only distracted (esoterically or physically), but also are exceeding their capacity to drive safely - despite their inflated sense of capability to do so. The suggested action is for drivers to disengage from the stressor and apply mindfulness, to lower their sympathetic signal, thus switching off the pink light.

To test the fitness of biofeedback as a 'on the spot' solution to the problem of distracted driving, we ran a parallel group experiment on a driving environment simulator. One group consisted of control subjects that underwent cognitive and physical distractions while driving without the benefit of any feedback mechanism; the other group were interventional subjects given a physiology-driven overarousal notification in the course of distractions, to which they were asked to respond accordingly. The cognitive and physical distractions were moderate and took place on a $7 - 8$ km roadway section, which is the length of the typical daily

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- *I. Pavlidis and A. Khatri are with the Computational Physiology Lab, University of Houston, Houston, TX, 77204.*
  E-mail: {ipavlidis, arkhatri}@uh.edu
- *P. Buddharaju is with the Computer Science Program, University of Houston-Clear Lake, Houston, TX, 77058.*
  E-mail: Buddharaju@uhcl.edu
- *M. Manser and R. Wunderlich are with the Texas A&M Transportation Institute, Texas A&M University, College Station, TX, 77843.*
  E-mail: {m-manser, r-wunderlich}@tti.tamu.edu
- *E. Akleman is with the Visualization Department, Texas A&M University, College Station, TX, 77843.*
  Email: ergun.akleman@gmail.com
- *P. Tsiamyrtzis is with the Department of Statistics, Athens University of Economics and Business, Athens, 10434, Greece.*
  Email: pt@aueb.gr

Fig. 1: **Experimental setup.** Subject S_{69}^{BF} driving on the simulator while performing mental arithmetic. The biofeedback indicator, located in the steering wheel emblem, is on, suggesting the onset of overarousal.

commute in the United States [13]. The results demonstrated the capacity of biofeedback to arrest driving distractions just as they became sympathetically overbearing and behaviorally dangerous, bringing down arousal levels and improving driving performance in good time.

2 METHODS

2.1 Subjects.

Human subject protocols were approved by the Institutional Review Boards of the Texas A&M University and the University of Houston. The study was conducted according to these approved protocols, using methods that adhered to the relevant guidelines and regulations. We recruited subjects from the Bryan and College Station, TX communities (population about $250, 000$) through email solicitations and flyer postings. Subjects possessed a valid driving license and had normal or corrected to normal vision. We restricted admission to individuals with at least one and a half years of driving experience who were between 18 and 27 years of age (young) or above 55 years of age (old), trying to maintain balances with respect not only to age group but also sex (female vs. male). We excluded subjects on medications affecting their ability to drive safely. A total of $n = 69$ subjects conforming to the inclusion-exclusion criteria volunteered for the study providing informed consent.

Sophisticated software, coordinating the driving simulator with a contact-free biofeedback system, was developed and used for the first time in this experiment. Technical problems afflicted the early phase of the study, until all the bugs were worked out. As a result, recordings for 20 subjects

suffered catastrophic losses. In addition, one subject was not run due to scheduling issues, and one subject opted to stop the study before the completion of the experiment because of motion sickness. Hence, data for only $n = 47$ subjects were largely complete and suitable for consideration.

2.2 Experimental Protocol.

In a high fidelity driving environment simulator manufactured by Realtime Technologies, Inc (Fig. 1), we ran a parallel group experiment, featuring two groups: Control (CL) and Biofeedback (BF). The grouping related to the absence or presence of the biofeedback intervention during distracted driving. Upon signing the consent form, the subjects completed four questionnaires:

Biographic Questionnaire: It identified key facts about the subject, including sex, age, and driving record.

Trait Anxiety Inventory [14]: Long-standing stress might have an effect on sympathetic responses and thus, scoring trait anxiety was of potential interest to this study.

Personality Type A/B: This was a modified version of the Jenkins Activity Survey [15]. Some studies have shown association between type A personalities and specific driving behaviors [16]; thus, scoring of type A/B personalities was also of potential interest to this study.

Attentional Control: Biofeedback involves notification amidst a potentially dangerous situation. Attentional control is known to regulate sympathetic responses in such cases and for this reason we wanted to check for

any biases in the sample using a relevant instrument [17].

Next, the subjects went through the following five experimental sessions:

1: Baseline Session BL: The subjects sat quietly in a dimly lit room, listening to soothing music for 5 min. The purpose of this non-driving baseline session was to bring all subjects to a tonic sympathetic level prior to the start of the experiment.

2: Preparation Drive D_P: The subjects familiarized themselves with the simulator by driving on a 8 km straight section of a four-lane highway at posted speeds; two lanes were dedicated to traffic in each direction, with the subject's car traveling in the right lane (R); the speed limits changed approximately every 3 kilometers (80 km/h $\rightarrow$ 50 km/h $\rightarrow$ 100 km/h) - Appendices/Fig. S1.

3-5: Drives Each drive was uniquely characterized by a distraction or absence thereof, featuring the same non-challenging driving conditions. We randomized the order of the two distracted driving sessions. This distraction assumed the form of a secondary activity that was forced during the middle phase of the drive. All drives were on the same 11 km section of a four-lane highway with posted speed limit of 70 km/h; two lanes were dedicated to traffic in each direction, with the subject's car traveling in the right lane (R). The drives featured traffic only on the oncoming lanes. Importantly, the drives consisted of three segments, called phases, delineated by mile markers: **Phase** $P_1 \sim 1.20$ km; **Phase** $P_2 \sim 7.25$ km; **Phase** $P_3 \sim 2.55$ km. In more detail, the drives were as follows:

- **Drive with No Distractions $D_\varnothing$:** Subjects concentrated on the driving task only - Appendices/Fig. S2. This meant to serve as the driving baseline, against which the effects of the planted distractions could be gauged.
- **Drive with Cognitive Distractions D_C:** Subjects were driving under a cognitive distraction - Appendices/Fig. S3. Upon entering P_2, the experimenter asked the subjects to sequentially subtract the number 13 from 1,022, requesting them to start over each time they made an error. Upon exiting P_2, the experimenter asked the subjects to stop the sequential subtraction. In the BF group, if the subjects received biofeedback notification, they were advised to stop subtracting, irrespective of whether the end of P_2 was reached or not.
- **Drive with Sensorimotor Distractions D_M:** Subjects were driving under a sensorimotor distraction - Appendices/Fig. S3. Upon entering P_2, the experimenter asked the subjects to text back words, sent one by one to the subjects' smartphones. Upon exiting P_2, the experimenter asked the subjects to stop texting. In the BF group, if the subjects received biofeedback notification, they were advised to stop texting, irrespective of whether the end of P_2 was reached or not.

There was a 2 min break between the drives. During each break, subjects were completing the NASA Task Load Index (TLX) for the preceding drive. NASA-TLX is a subjective workload assessment tool that complements the objective assessment of task-induced sympathetic arousal, captured via thermal imaging. NASA-TLX features a multi-dimensional rating procedure that derives an overall workload score based on a weighted average of ratings on six sub-scales. These sub-scales include Mental Demand, Physical Demand, Temporal Demand, Own Performance, Effort, and Frustration [18].

2.3 Design of Biofeedback Indicator.

A critical design consideration for the intervention was the placement and color of the biofeedback indicator. We chose to put the indicator in the steering wheel emblem, a position falling in the driver's peripheral visual field; thus, its status change would be perceptible but minimally distracting. We also chose the indicator's LED color to be pink. According to standard ergonomic principles the red color is reserved for communicating potentially dangerous state [19], [20]. Choosing a light shade of red, we were still in compliance with standard ergonomic guidelines, but refraining from instilling a sense of panic. To ascertain the goodness of our usability choices, we included three relevant questions in the post-study survey:

- **Noticeability:** Did you notice when the biofeedback indicator light turned on?
- **Color:** How do you feel about the biofeedback indicator light color?
- **Location:** Do you think the biofeedback indicator light is in a good location?

The BF driver responses were overwhelmingly positive in all three questions - 93.31%, 95.83%, and 87.5%, correspondingly ($p < 0.001$, proportions test in all cases) - Fig. 2.
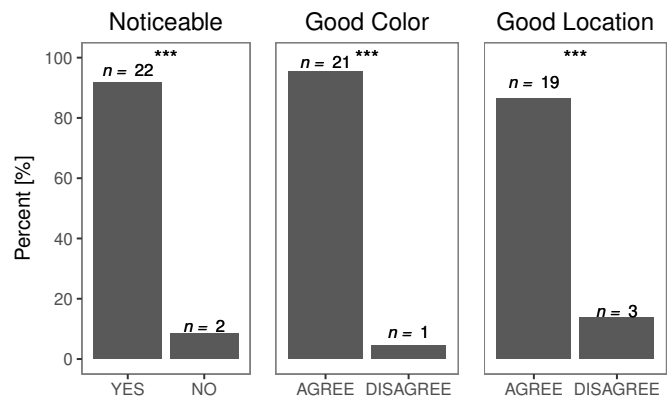

Fig. 2: **Usability results for the biofeedback indicator based on the survey responses of the BF cohort at the end of the experiment. For the color and location questions two subjects did not answer, and their inputs were treated as missing values.**

2.4 Data Acquisition.

During the baseline session and all the subsequent drives, we continuously imaged the subject's face with a thermal camera. We used the Tau 640 thermal camera (FLIR Commercial Systems, Goleta, CA); it features a small size

$(44 \times 44 \times 30$ mm$)$, and adequate thermal $(< 50$ mK$)$ and spatial resolution $(640 \times 512$ pixels$)$. These thermal imaging sequences were subjected to algorithmic processing for the real-time extraction of the perinasal perspiration signal. At the same time, we programmed the simulator to save a record of the evolving driving parameters. These parameters included speed, steering angle, and lane position. The maximum value of the lane position signal in each drive defined the tendency to veer off the road.

2.5   Data Quality.

To carry out the pre-planned hypothesis tests, we measured four variables (distracted segment of P_2, mean perinasal perspiration, mean absolute steering angle, and maximum lane departure) in three drives ($D_\varnothing$, D_C, D_M) for $n = 47$ subjects. Hence, the total number of measurements should have been $4 \times 3 \times 47 = 564$. However, only 534 measurements were usable. The remaining 30 measurements were marred by technical problems and experimenter errors. The missing data is a very small portion of the total dataset ($\sim 5.32\%$), and represent a typical loss in such a complex multimodal study. In addition, due to the conservative nature of the biofeedback algorithm, the biofeedback indicator either came on at the end of phase P_2 or did not come at all in five cases in the D_C drive and in another five cases in the D_M drive. For these cases, we were not able to test any biofeedback effects in the commuting itinerary under consideration. Altogether, we were able to run the full set of tests on 29 subjects; 8 subjects missed participation in at least one test due to a missing piece of data; and, 10 subjects missed participation in half of the tests due to biofeedback non-responsiveness in one of the two distracted drives. In Table 1a, the n numbers for each group are given explicitly. In Table 1b, the n numbers, which can be easily deduced from the (d.f.) numbers, indicate the fully paired subject measurements available in each case.

2.6   Thermal Imaging Algorithms.

Algorithmic processing of the thermal imagery yielded a signal that quantified perinasal perspiration. The algorithm included a virtual tissue tracker that kept track of the region of interest, despite the subject's small motions. This ensured that the physiological signal extractor operated on consistent and valid sets of data over the clip's timeline.

Tissue Tracking: We used the tissue tracker reported in Zhou *et al.* [21] On the initial frame, the user initiates the tracking algorithm by selecting the upper orbicularis oris portion of the perinasal region. The tracker estimates the best matching block in every next frame of the thermal clip via spatio-temporal smoothing (Fig. 3). A morphology-based algorithm was applied on the evolving region of interest to compute the perspiration signal. Any high-frequency noise in this signal was suppressed by a Fast Fourier Transformation (FFT) filter. The tracker, which underwent extensive validation [21], is robust to physiological and position perturbations, because its statistical methodology adapts to temporal and spatial changes taking place in the region of interest.

In the current dataset, the tracker weathered significant thermophysiological changes precipitated from stressful stimuli. The image sequence for subject S_2^{BF} depicted in Fig. 3 gives a glimpse of the tracking performance. There, not only the perspiration pattern in the region of interest fluctuates widely, but also the nasal tip where the tracker anchors, almost disappears due to drastic changes in the breathing function. Despite this highly dynamic situation, the tracker (red rectangle) maintains its grip on the region of interest throughout the session.

Perinasal Signal Extraction: A key method of this study was the extraction of the perinasal perspiration signal from the thermal imagery; this was the sympathetic indicator used. Figure 3 shows the thermal signature of perspiration spots on the perinasal area of a subject in moments of low and high excitation. In facial thermal imagery, activated perspiration pores appear as small 'cold' (dark) spots, amidst substantial background clutter. The latter is the thermo-physiological manifestation of the metabolic processes in the surrounding tissue. We quantified this spatial frequency pattern by extracting an energy signal $\mathbf{E}(k, j, i)$, indicative of perspiration activity in the perinasal area of subject k, for session j, and phase i. We computed this signal by applying the clinically validated morphological method reported by Shastri *et al.* [12]

2.7   Biofeedback Algorithm.

If the physiological variable is sampled at a rate higher than 1 measurement per second, then we take the mean of all measurements each second of the evolving timeline. This is sufficient temporal resolution for tracking sympathetic arousal via peripheral physiological indicators. Indeed, these indicators are either adrenergic or cholinergic in nature, with the latter being the most sensitive. Even cholinergic indicators of arousal, however, have time constants ranging between 2 to 5 seconds [22]. Hence, a sampling rate of 1 measurement per second can capture all sympathetic phenomena manifesting peripherally in a subject. As most physiological sensors sample at a higher rate, averaging the measurements at the 1 second level, provides the extra benefit of smoothing out high frequency noise. For cholinergic signals, such as EDA and perinasal perspiration, which are characterized by large ranges, a logarithmic transformation is suggested on the averaging process, to bring the distribution close to normality:

$$\mathbf{E}(i) = ln \left(\frac{x_1 + x_2 + ... + x_m}{m} \right), \qquad (1)$$

where $\mathbf{E}(i)$ is the computed value of the sympathetic signal, on the i-th second during the observational period, and $x_i, i = 1, 2, ..., m$ are the sympathetic measurements within the i-th second.

The biofeedback algorithm should be capable of detecting drifts from sympathetic conditions obtained near the beginning of the drive, assuming the subject was not distracted during that period. We view this as a quality control problem and we use a method based on the self-starting cusum [23] to address it. The algorithm's computational

TABLE 1. **Information about the four main variables of analysis. a,** Descriptive statistics and tests regarding the length of the distracted segment in phase P_2 of D_C and D_M. **b,** Descriptive statistics and tests regarding the mean perinasal perspiration, the mean absolute steering, and the maximum departure off the road in D_C and D_M.

a

	Variable	Subjects				Statistic(d.f.)†	p value
	Between	CL		BF			
		n	Mean (SD)	n	Mean (SD)		
Drive D_C	L_{P_2}	22	7.54 (0.79)	18	1.93 (1.20)	$t(28.39)=17.07$	0.0000
Drive D_M	L_{P_2}	21	7.27 (0.41)	18	2.78 (1.70)	$t(18.69)=10.98$	0.0000

†*Welch two sample t-test not assuming equal variances.*

b

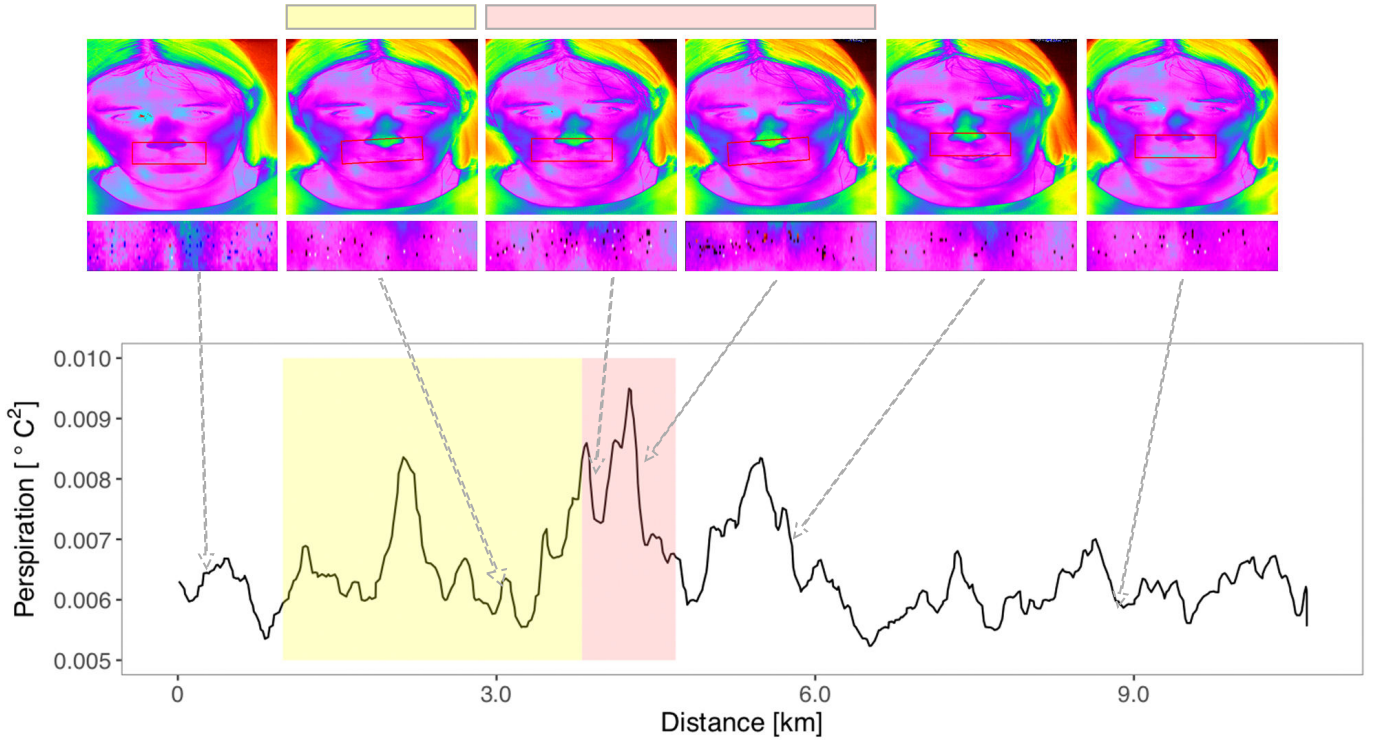|	Variable	Subjects					
	Within	CL			BF		
		Mean (SD)	Statistic(d.f.)	p value	Mean (SD)	Statistic(d.f.)	p value
D_C	$\Delta\ln(\overline{\mathbf{E}})$	0.12 (0.12)	$t(18)=4.23$	0.0005	0.06 (0.15)	$t(17)=1.57$	0.1352
D_C	$\Delta\ln(|\overline{\mathbf{ST}}|)$	0.21 (0.42)	$t(18)=2.11$	0.0495	0.09 (0.60)	$t(17)=0.64$	0.5325
D_C	ΔX_R	0.16 (0.24)	$t(18)=2.87$	0.0101	-0.02 (0.46)	$t(17)=-0.19$	0.8487
D_M	$\Delta\ln(\overline{\mathbf{E}})$	0.09 (0.08)	$t(17)=5.12$	0.0000	0.06 (0.11)	$t(17)=2.27$	0.0365
D_M	$\Delta\ln(|\overline{\mathbf{ST}}|)$	0.89 (0.39)	$t(17)=9.77$	0.0000	0.29 (0.45)	$t(17)=2.69$	0.0155
D_M	ΔX_R	-0.27 (0.39)	$t(17)=-2.90$	0.0010	-0.14 (0.41)	$t(17)=-1.39$	0.1828

Fig. 3: **Extraction of sympathetic responses.** Motion tracking [21] of the perinasal region of interest or ROI (red rectangle) from where the perspiration signal is extracted during the course of drive D_C for subject S_2^{BF}. The thermal facial snapshots are accompanied by the zoomed-in perinasal ROIs, where black dots manifest active perspiration pores detected by the algorithm [12]. This algorithm turns the spatial perspiration pattern into a signal by applying a morphological filter. Elevations in the signal correspond to densification of active perspiration pores, characterizing overarousal bouts. The yellow background indicates the period of the cognitive distraction, which led to signal elevation, triggering the biofeedback indicator (pink background). The driver responded by disengaging from the cognitive stressor, leading eventually to signal reduction.

machinery depends on point estimates of the sympathetic signal's running mean $\overline{\mathbf{E}}(n)$ and variance $\sigma^2_{\overline{\mathbf{E}}(n)}$, which are determined iteratively:

$$\overline{\mathbf{E}}(n) = \overline{\mathbf{E}}(n-1) + \frac{\mathbf{E}(n) - \overline{\mathbf{E}}(n-1)}{n} \quad \text{with} \quad (2)$$

$$\overline{\mathbf{E}}(0) \equiv \mathbf{E}(0)$$

$$\sigma^2_{\overline{\mathbf{E}}(n)} = \frac{S_n}{n-1} \quad \text{with} \quad (3)$$

$$S_0 \equiv 0 \ \text{ and } \ S_n = S_{n-1} + \frac{(n-1)[\mathbf{E}(n) - \overline{\mathbf{E}}(n-1)]^2}{n}$$

As new sympathetic measurements are acquired in each time step, they are standardized in the form of the random variable Y_n (line 7 in Algorithm 1). Then, the cumulative distribution function (CDF) probability of Y_n is sought using the t statistic (line 8 in Algorithm 1); the inverse of this CDF points to the deviation from the mean in a Normal standard distribution. The latter represents the deviation estimate of the sympathetic state for the current time step. The k and h are cusum design parameters aiming to detect a persistent increase of one standard deviation with the false alarm rate being approximately 5%. To be on the conservative side, this estimate is filtered by subtracting $k = 0.5$ deviations, before it is added to the running cusum. If at some time step, the cusum exceeds approximately $h = 5$ deviations, then the biofeedback indicator is turned on (Fig. 4), and the cusum process starts afresh on the negative side, proceeding in an antisymmetric manner (lines 16-20 in Algorithm 1).

It is suggested to not activate the biofeedback algorithm exactly at the start of each drive, in order to avoid transient effects. A buffer window of 20 s appears to work well in this respect. In case the biofeedback indicator stays on for long periods of time, suggesting that the subject's high arousal levels do not drop, it is recommended that the algorithm is overruled and the indicator is turned off, as it is likely becoming annoying and counterproductive. A window of 45 s for continuous activation appears to work well; almost all S^{BF} subjects in our study managed to control their arousal effects within this time window.

2.8 Statistical Analysis.

We applied statistics using the freeware program R, version 3.4.3 (http://www.r-project.org). We performed the pre-planned hypothesis tests against a two-tail alternative, setting levels of significance at $\alpha = 0.0125$ designated by $\star$, or $\alpha = 0.01$ designated by $\star\star$, or $\alpha = 0.001$ designated by $\star\star\star$. The $\alpha = 0.0125$ is Bonferroni-corrected for $\mathcal{C} = 4$ comparisons, referring to the four variables we used to characterize drivers, that is, distracted segment of P_2, mean perinasal perspiration, mean absolute steering angle, and maximum lane departure off the road.

3 RESULTS

We performed the analysis on $n = 23$ controls and $n = 24$ subjects that received biofeedback treatment. Both the Control (CL) and Biofeedback (BF) group were balanced in terms of sex and age (Table 2a). The experiment included three drives:

Algorithm 1 Biofeedback Algorithm

1: **procedure** SWITCH ON AND OFF THE BIOFEEDBACK INDICATOR
2:    $n = C_0^+ = C_0^- = 0$
3:    $k = 0.5; h^+ = 5.07; h^- = -5.07$
4: *loop*:
5:    $n \leftarrow n + 1$
6:    *Acquire the next sympathetic measurement and compute*:
7:    $Y_n \leftarrow \left[\mathbf{E}(n) - \overline{\mathbf{E}}(n-1)\right] \bigg/ \left[\sqrt{\sigma^2_{\overline{\mathbf{E}}(n-1)}}\right]$
8:    $CDF_n \leftarrow \Pr\left(t < Y_n \sqrt{\frac{n-1}{n}}\right)$
9:    $U_n = \Phi^{-1}(CDF_n)$
10:    **if** the biofeedback indicator is OFF **then**
11:      $C_n^+ = \max\left[0, U_n - k + C_{n-1}^+\right]$
12:      **if** $C_n^+ > h^+$ **then**
13:        $n = 0$
14:        switch biofeedback indicator ON
15:    **goto** *loop*
16:    **if** the biofeedback indicator is ON **then**
17:      $C_n^- = \min\{0, U_n + k + C_{n-1}^-\}$
18:      **if** $C_n^- < h^-$ **then**
19:        $n = 0$
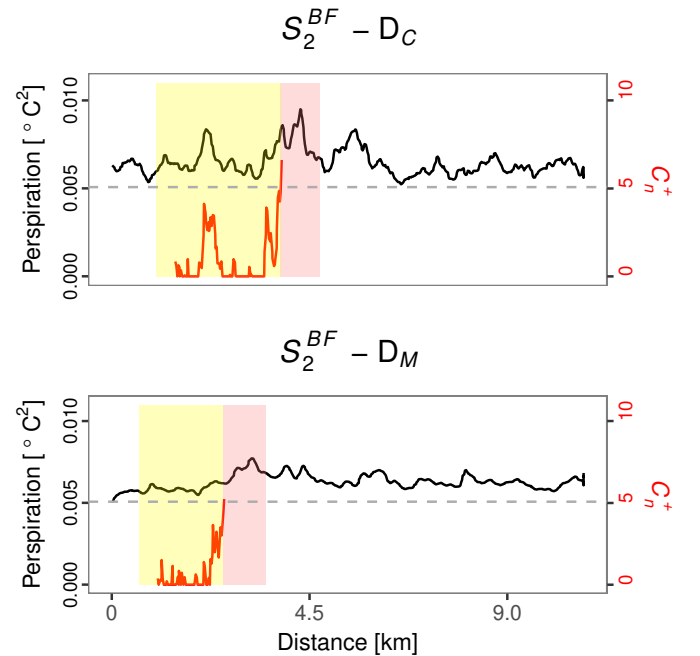20:   switch biofeedback indicator OFF
21:    **goto** *loop*

Fig. 4: **Decision making of the biofeedback method.** The self-starting cusum algorithm at work in drives D_C and D_M of subject S_2^{BF}. The black curve in each panel is the perinasal perspiration signal, while the red curve depicts the evolution of the cusum parameter C_n^+. Once this parameter crosses the 5 deviations threshold, the biofeedback indicator comes on (pink background period), prompting the driver to disengage from the distraction; evidently, the perspiration signal starts decreasing as a result.

TABLE 2. **Information about the subject profiles. a,** Demographic values along with the associated tests for the CL and BF groups. **b,** Descriptive statistics and tests regarding the psychometric measures obtained from the CL and BF groups.

a

Measure	Subjects		Statistic(d.f.)	p value
	CL	BF		
Sex Ratio (Male:Female)	12:11	11:13	$\chi^2(1) = 0.02$	0.8864
Age Group Ratio (Young:Old)	11:12	13:11	$\chi^2(1) = 0.02$	0.8864

b

Measure	Subjects				Statistic(d.f.)†	p value
	CL		BF			
	n	**Mean (SD)**	n	**Mean (SD)**		
TAI	23	33.57 (10.55)	24	31.21 (10.02)	$t(44.60) = 0.78$	0.4368
Type A/B	23	217.87 (32.32)	24	215.92 (33.71)	$t(45.00) = 0.20$	0.8402
Attn. Control	23	56.78 (12.40)	24	58.17 (8.05)	$t(37.51) = 0.45$	0.6541

†*Welch two sample t-test not assuming equal variances.*

1) A drive where subjects drove without any distractions ($D_\varnothing$).
2) A drive with cognitive distractions (D_C), where subjects performed a mental arithmetic task while driving. Mental arithmetic is a well-known type of cognitive stressor [24], which acts as proxy for absent-mindedness in this experiment.
3) A drive with sensorimotor distractions (D_M), where subjects texted while driving. Texting is the most widespread form of physical distraction [25], taxing both the sensory (eyes) and motor (hands) systems of drivers [10].

All three drives featured identical layout, traffic, and weather conditions to control confounding factors. Consequently, any significant persistent elevation of a subject's sympathetic level within or across drives was attributable solely to the distractive tasks. The $D_\varnothing$ drive was first, serving as the driving baseline. The order of the distracted drives D_C and D_M was randomized to ameliorate bias. Control subjects did not get any feedback during distractions.

As this was a behavioral experiment, certain personality traits could have biased the results. These traits included: (a) Anxiety disposition, which is known to affect sympathetic responses, and is measured via the Trait Anxiety Inventory (TAI) [14]; it takes values in the range $[20, 80]$. (b) A vs. B personality, which is known to affect driving style [16], and is measured via a variant of the Personality Type A/B [15] questionnaire; it takes values in the range $[35, 380]$. (c) Attentional control, which is known to bias attention favoring 'threatening' information, such as the notification issued by the biofeedback system; it is measured via the Attentional Control [17] questionnaire that takes values in the range $[20, 80]$. The key concern was the distributions of these traits in the two experimental groups. In this respect, we found no significant differences between the CL and BF cohorts when we tested for the TAI, the Personality Type A/B, and the Attentional Control scores (t-test, $p > 0.05$ for all cases). The descriptive statistics for all three traits were also in non-extreme subranges and consistent with normal personality characteristics (Table 2b).

3.1 Analytic Framework

Each of the $D_\varnothing$, D_C, and D_M drives consisted of three phases: P_1, P_2, and P_3, separated by mile markers. In the $D_\varnothing$ drive no distraction was applied in any of the phases. In the D_C and D_M drives cognitive and sensorimotor distractions, respectively, took place in P_2. There was an important difference, however, between the CL and BF cohorts. In the CL subjects, the distractions lasted for the entire phase P_2 of the D_C and D_M drives, with the onset and offset being triggered by mile markers. In the BF cohort, when the subjects' sympathetic arousal levels exhibited a persistent significant increase, a pink LED in the steering wheel emblem was illuminated. Upon seen this indicator, BF subjects disengaged from the secondary activity and concentrated back on driving, thus cutting short the duration of distractions during phase P_2. Note that the phase P_2 was the largest segment of the drives, and was designed to be the length of the typical U.S. commute ($7 - 8$ km) [13] to have practical relevance. The phases P_1 and P_3 were short initial and finishing segments ($\sim 1 - 2$ km each) meant to isolate phase P_2 from confounding start-up and finish-up effects [10].

We focused on phase P_2 in all the drives, where we investigated the effect of cognitive and sensorimotor distractions on sympathetic arousal and driving behavior. Sympathetic arousal was tracked via the perinasal perspiration signal **E**. Driving behavior was tracked via the steering signal **ST** and the maximum lane departure to the right X_R, off the paved road. The former is linked to arousal triggered motor reactions, while the latter manifests the end effect, that is, the tendency to veer off the road.

We were interested to confirm if full engagement with the distracting stressors in control subjects $\mathcal{S}_i^{CL}$ had a significant adverse effect with respect to arousal levels and driving behaviors (HYPOTHESIS SET H1) - a result first reported by Pavlidis *et al.* [10] In contradistinction, we were interested to test if timely disengagement from the distracting stressors in biofeedback subjects $\mathcal{S}_i^{BF}$ had a significant ameliorating effect with respect to arousal levels and driving behaviors (HYPOTHESIS SET H2). As subjects are individuals with different sympathetic and behavioral characteristics, the only meaningful way to test these sets of

hypotheses was by considering intra-individual paired differences, where the drive $D_\varnothing$ served as the driving baseline.

3.2 Experimental Validity.

We opted for a highly automated biofeedback application, not only because anything else would have been impractical, but also because it would have introduced non-systematic biases due to intra- and inter-operator variability. Before proceeding with the analysis of the results, we needed to verify that:

(1) **The designed distractions and biofeedback were perceived as effective.** To ascertain that the experiment's distracted drives were perceived as challenging and the biofeedback as having an ameliorating effect, we asked subjects to complete the NASA Task Load Index (TLX) after each drive. The NASA TLX measures subjective workload assessment on machine operators. It draws on six sub-scales TLX_s: Mental Demand (TLX_{MD}), Physical Demand (TLX_{PD}), Temporal Demand (TLX_{TD}), Performance (TLX_P), Effort (TLX_E), and Frustration (TLX_F).

We ran a mixed effects model to examine the dependence of each sub-scale TLX_s on fixed effects, defined by the experimental condition ($G_j \equiv G_{CL}$ or G_{BF}) and the type of drive ($D_i \equiv D_\varnothing$ or D_C or D_M); we kept as references the control group G_{CL} and the drive with no distractions $D_\varnothing$, respectively:

$$TLX_s \sim 1 + G_j + D_i + 1|S_k, \qquad (4)$$

where S_k stands for subjects, acting as random effects. The model indicated that the experimental condition had a significant effect on the Mental Demand and Effort sub-scales ($p < 0.05$ for TLX_{MD}, TLX_E in G_{BF} vs. G_{CL}). Specifically, the BF subjects had significantly lower scores in these two sub-scales with respect to CL subjects. The model also indicated that the type of drive had a significant effect, that is, the distracted drives D_C and D_M with cognitive and sensorimotor stressors, respectively, had significantly higher scores with respect to $D_\varnothing$ in all NASA TLX sub-scales ($p < 0.001$ for all TLX_s in D_C vs. $D_\varnothing$ and D_M vs. $D_\varnothing$).

These results suggest that subjects perceived drives with cognitive or sensorimotor distractions as challenging across the sub-scales of a validated instrument, [18] thus, confirming the effectiveness of the study's design regarding these two stressors. The fact that BF subjects perceived that they expended significantly less effort (mental and otherwise) with respect to CL subjects, gives a first indication of the effectiveness of the biofeedback intervention.

(2) **The biofeedback system was responsive.** The biofeedback system was conservatively responsive to both types of driving distractions, activating shortly after the application of the stressor in $n = 18$ cases in drive D_C and in $n = 18$ cases in drive D_M. All subsequent analysis with respect to the BF group is based on these usable cases. Interestingly, for the 10 cases the biofeedback algorithm did not raise a flag (five in D_C and five in D_M), we found that the mean perinasal perspiration was higher with respect to the $D_\varnothing$ drive, if an extreme outlier was excluded ($p = 0.012$, paired t-test). The low significance, however, of the sympathetic elevation justifies the non-interventional stance of the biofeedback algorithm, highlighting its reliability. Interestingly, the mean absolute steering and maximum departure off the road for these cases were not significantly different than the subjects' performance in $D_\varnothing$ ($p > 0.05$, paired t-tests in both cases) - Appendices/Fig. S4. This suggests that the absence of strong overarousal was accompanied by the absence of behavioral deterioration during distracted driving.

(3) **The biofeedback system's responsiveness was non-biased.** We wanted to ascertain if the prior driving record of subjects played any role in the onset and offset of the biofeedback indicator - an important consideration for the universal applicability of the method. In this respect, we identified three covariates of interest that were relevant and quantifiable: (a) the subjects' level of habitual texting while driving; (b) the subjects' profile of lawful driving behavior; and, (c) the subjects' crash history. We coded habitual texting while driving in four levels: $1 \equiv$ no texting; $2 \equiv$ texting in less than 25% of the drives; $3 \equiv$ texting 50% - 75% of the drives; $4 \equiv$ texting in more than 75% of the drives. We coded the profile of lawful driving behavior in two levels: $0 \equiv$ no tickets; $1 \equiv$ one or more tickets. We coded crash history in two levels: $0 \equiv$ no crashes; $1 \equiv$ one or more crashes. We found no significant differences in the onset and offset times of the biofeedback indicator in the D_C and D_M drives with respect to all three prior driving record covariates ($p > 0.05$, analysis of variance for all cases with respect to habitual texting; t-test for all cases with respect to tickets and crashes). This indirectly suggests that habitual texting while driving, tendency for risky driving, and traumatic driving experiences do not significantly alter biofeedback responses.

3.3 Analysis of Length of Distractions.

A key question was if biofeedback activation drastically reduced the planned subject engagement with the distracting stressors. Figure 5a shows the segments of phase P_2 during which the subjects were distracted in the CL and BF groups. There were significant L_{P_2} segment differences between the two groups in each type of distracted drive ($p < 0.001$, t-test in all cases). It took on average 1.93 km in D_C and 2.78 km in D_M for the biofeedback system to flag distractions (Table 1a). Hence, the BF subjects were distracted on average in just 26.62% and 38.34% of the originally planned 7.25 km in D_C and D_M, respectively - a fairly effective curtailing of distractions in the context of this typical commuting itinerary.

3.4 Analysis of Control Subjects' Responses.

The control arm of the experiment was meant to reproduce the results reported by Pavlidis et al. [10], where cognitive and sensorimotor distractions during driving led to elevated sympathetic arousal accompanied by oscillatory handling of the steering wheel. This subconscious oscillatory handling was apparently controlled by an autonomic conflict
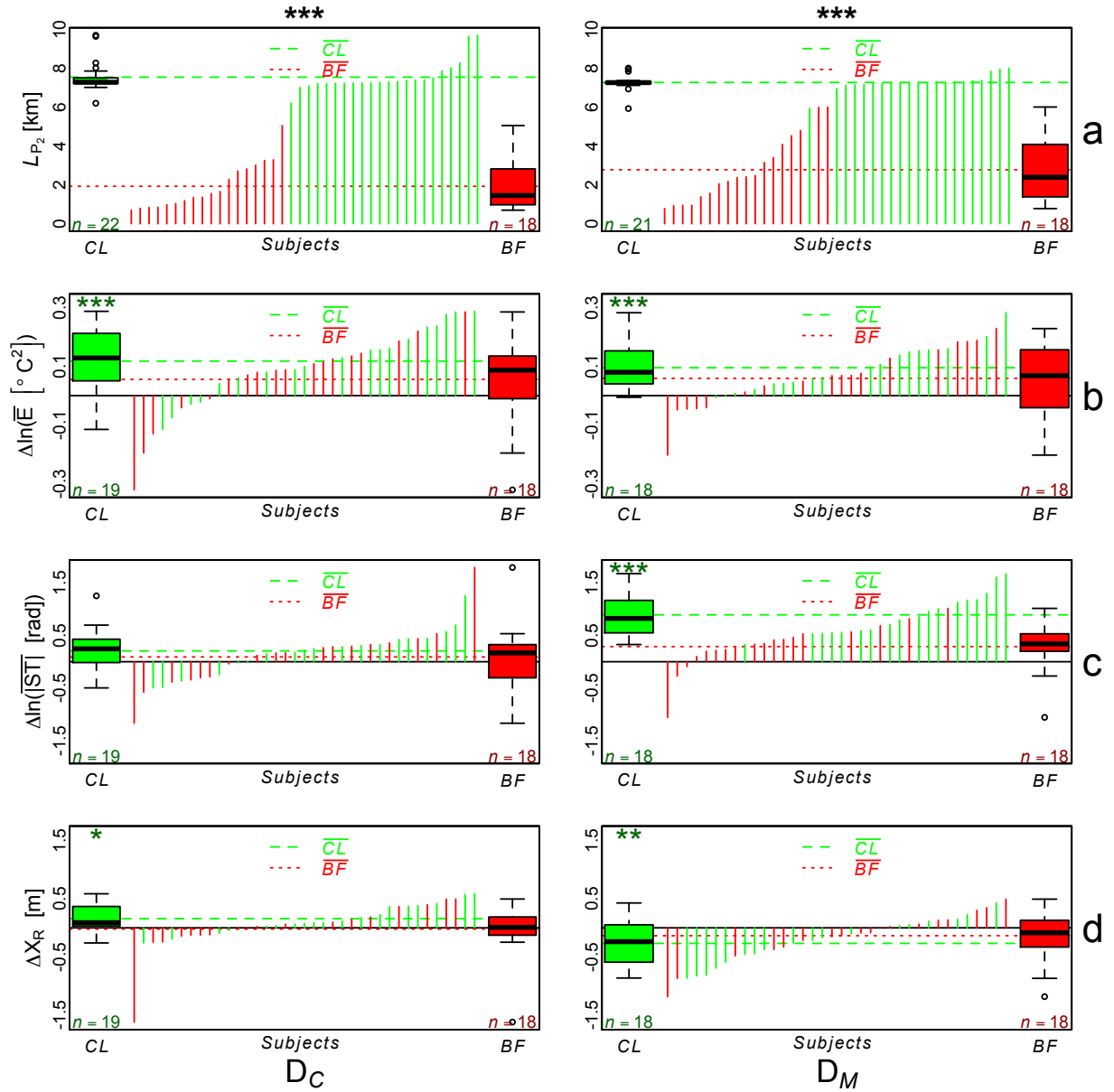
Fig. 5: **Behavioral and sympathetic effects on the two experimental groups. a,** Distributions of the length of distractions in phase P_2 of the D_C and D_M drives. **b-d,** Distributions of within-subject differences of mean perinasal perspiration $\Delta \ln(\overline{\mathbf{E}})$, mean absolute steering $\Delta \ln(\overline{|\mathbf{ST}|})$, and maximum departure off the road ΔX_R in drives D_C and D_M with respect to drive $D_\varnothing$. Results for the CL and BF cohorts are presented in juxtaposition. Stars indicate significance for the corresponding between-groups t-tests (row a) or within-group paired t-tests (rows b-d).

resolution center in the brain - likely the anterior cingulate cortex (ACG). In the case of cognitive distractions, the oscillatory handling had near perfect symmetry, manifesting optimal containment of 'fight or flight' effects by instant counterbalancing of tremors. In the case of sensorimotor distractions, this symmetry was marred by momentary failures, because the eye and hand resources used by ACG were occasionally diverted to the texting task, rendering instant counterbalancing impossible. As a result, the cars were sometimes veering off the lane - an outright dangerous driving pattern. Such lane departures were not observed under cognitive distractions, but the drivers' state remained potentially dangerous, due to the oscillatory handling of the

steering wheel.

Accordingly, for the control subjects $\mathcal{S}_i^{CL}$ in this study, we computed the distributions of paired differences between the distracted drive $D.$ ($\cdot \in \{C, M\}$) and the drive $D_\varnothing$, regarding the sympathetic and behavioral variables of interest.

- Mean perinasal perspiration (Eq. 5) - proxy for sympathetic changes, manifesting driver overloading due to multitasking:

$$\Delta \ln(\overline{\mathbf{E}}(\mathcal{S}_i^{CL}, \cdot, P_2)) = \ln(\overline{\mathbf{E}}(\mathcal{S}_i^{CL}, D., P_2) \, [^\circ C^2])$$
$$- \ln(\overline{\mathbf{E}}(\mathcal{S}_i^{CL}, D_\varnothing, P_2) \, [^\circ C^2]) \quad (5)$$

- Mean absolute steering angle (Eq. 6) - proxy for steering changes, manifesting oscillatory handling of the steering wheel due to 'fight or flight' musculoskeletal effects:

$$\Delta \ln(\overline{|\mathbf{ST}(\mathcal{S}_i^{CL}, \cdot, \mathrm{P}_2)|}) = \ln(\overline{|\mathbf{ST}(\mathcal{S}_i^{CL}, \mathrm{D}., \mathrm{P}_2)|} \, [\mathrm{rad}])$$
$$- \ln(\overline{|\mathbf{ST}(\mathcal{S}_i^{CL}, \mathrm{D}_\varnothing, \mathrm{P}_2)|} \, [\mathrm{rad}])$$
(6)

- Maximum lane departures off the road (Eq. 7) - proxy for driving changes, manifesting instantaneous failure of the anterior cingulate cortex (ACC) to tightly control oscillatory steering:

$$\Delta X_R(\mathcal{S}_i^{CL}, \cdot, \mathrm{P}_2) = X_R(\mathcal{S}_i^{CL}, \mathrm{D}., \mathrm{P}_2) \, [\mathrm{m}]$$
$$- X_R(\mathcal{S}_i^{CL}, \mathrm{D}_\varnothing, \mathrm{P}_2) \, [\mathrm{m}]$$
(7)

Results from Eqs. (5), (6), and (7) with $\cdot \equiv C$ suggest that cognitive distractions on CL subjects produced the following effects with respect to the drive $\mathrm{D}_\varnothing$ (Figure 5 and Table 1b):

- Significant increase in the subjects' mean sympathetic arousal ($p \leq 0.001$, paired t-test). This result is consistent with prior reports in the literature [10], [11], indicating that the cognitive distractions used in this experiment resulted in overarousal, and at least in this respect were effective.
- No significant increase in mean steering tremors ($p > 0.0125$, paired t-test). This result differs from what is reported by Pavlidis et al. [10]. Despite significant sympathetic loading from cognitive distractions, no oscillatory handling of the steering wheel took place in our sample. The discrepancy between the two experimental outcomes suggests the existence of an overarousal threshold for 'fight or flight' tremors. We speculate that the 'lighter' cognitive stressor we used in this study did not spur enough overarousal to exceed this threshold. Specifically, instead of a series of mental arithmetic and analytic questions [10], [11], we asked the subjects to keep subtracting 13, starting from 1022, while driving. This mode of mental arithmetic was easier to administer experimentally, but apparently was not strong enough to produce the full range of anticipated effects.
- Significant reduction with respect to maximum off the road departures ($p \leq 0.0125$, paired t-test). This paradoxical result is consistent with prior reports in the literature [10], indicating the tendency of drivers to follow straighter trajectories under the tight control exercised by ACG during esoteric distractions, where the hand-eye coordination is flawless.

Results from Eqs. (5), (6), and (7) with $\cdot \equiv M$ suggest that sensorimotor distractions on CL subjects produced the following effects with respect to the drive $\mathrm{D}_\varnothing$ (Figure 5 and Table 1b):

- Significant increase in the subjects' mean sympathetic arousal ($p \leq 0.001$, paired t-test).
- Significant increase in mean steering tremors ($p \leq 0.001$, paired t-test).
- Significant increase in maximum off the road departures ($p \leq 0.01$, paired t-test).

These results are consistent with prior reports in the literature [10], [11], suggesting that sensorimotor distractions produced overarousal, which was accompanied by intensely oscillatory handling of the steering wheel, and significant tendencies to veer off the road.

3.5 Analysis of Biofeedback Subjects' Responses.

The interventional arm of the experiment meant to test if heeding to biofeedback alerts significantly ameliorated sympathetic and behavioral effects in the context of a typical commute. Accordingly, for the usable $\mathcal{S}_i^{BF}$ cases, we computed the distributions of paired differences between the distracted drive D. ($\cdot \in \{C, M\}$) and the drive $\mathrm{D}_\varnothing$, regarding the sympathetic and behavioral variables of interest.

- Mean perinasal perspiration (Eq. 8) - proxy for sympathetic changes, manifesting the presence or absence of overloading:

$$\Delta \ln(\overline{\mathbf{E}}(\mathcal{S}_i^{BF}, \cdot, \mathrm{P}_2)) = \ln(\overline{\mathbf{E}}(\mathcal{S}_i^{BF}, \mathrm{D}., \mathrm{P}_2) \, [^\circ\mathbf{C}^2])$$
$$- \ln(\overline{\mathbf{E}}(\mathcal{S}_i^{BF}, \mathrm{D}_\varnothing, \mathrm{P}_2) \, [^\circ\mathbf{C}^2]) \quad (8)$$

- Mean absolute steering angle (Eq. 9) - proxy for steering changes, manifesting the presence or absence of oscillatory handling of the steering wheel:

$$\Delta \ln(\overline{|\mathbf{ST}(\mathcal{S}_i^{BF}, \cdot, \mathrm{P}_2)|}) = \ln(\overline{|\mathbf{ST}(\mathcal{S}_i^{BF}, \mathrm{D}., \mathrm{P}_2)|} \, [\mathrm{rad}])$$
$$- \ln(\overline{|\mathbf{ST}(\mathcal{S}_i^{BF}, \mathrm{D}_\varnothing, \mathrm{P}_2)|} \, [\mathrm{rad}])$$
(9)

- Maximum lane departures off the road (Eq. 10) - proxy for driving changes, manifesting the presence or absence of tendencies to veer off the road:

$$\Delta X_R(\mathcal{S}_i^{BF}, \cdot, \mathrm{P}_2) = X_R(\mathcal{S}_i^{BF}, \mathrm{D}., \mathrm{P}_2) \, [\mathrm{m}]$$
$$- X_R(\mathcal{S}_i^{BF}, \mathrm{D}_\varnothing, \mathrm{P}_2) \, [\mathrm{m}] \quad (10)$$

Results from Eqs. (8), (9), and (10) with $\cdot \equiv C$ suggest that cognitive distractions on BF subjects produced with respect to drive $\mathrm{D}_\varnothing$ (Figure 5 and Table 1b):

- No significant increase in the subjects' mean sympathetic arousal ($p > 0.0125$, paired t-test).
- No significant increase in mean steering tremors ($p > 0.0125$, paired t-test).
- No significant increase in maximum off the road departures ($p > 0.0125$, paired t-test).

These results indicate that the biofeedback intervention in the course of cognitive distractions successfully arrested sympathetic arousal effects in the typical commute programmed in the simulator.

Results from Eqs. (8), (9), and (10) with $\cdot \equiv M$ suggest that sensorimotor distractions on BF subjects produced with respect to drive $\mathrm{D}_\varnothing$ (Figure 5 and Table 1b):

- No significant increase in the subjects' mean sympathetic arousal ($p > 0.0125$, paired t-test).
- No significant increase in mean steering tremors ($p > 0.0125$, paired t-test).
- No significant increase in maximum off the road departures ($p > 0.0125$, paired t-test).

These results indicate that the biofeedback intervention in the course of sensorimotor distractions successfully arrested both sympathetic arousal and negative behavioral effects in the typical commute programmed in the simulator.

3.6   Age and Gender Considerations.

Age and gender are important covariates in driving studies; thus, the question is if they affected results in the current study.

Age factor. People drive from their late teens all the way into their 70s. Hence, the entire span of adult ages is represented in the driving population. In the present study, there are four key variables: (a) one variable of physiological nature (i.e., perinasal perspiration $\mathbf{E}$), and (b) three variables that track driving behaviors (i.e., length of distractions L_{P_2}, steering $\mathbf{ST}$, and maximum lane departure X_R). As aspects of physiology and driving behaviors tend to change through adulthood, we thought of concentrating our sample to the two ends of the adult age spectrum, that is, young adults (20.92 ± 1.67 years) and older individuals (65.3 ± 5.31 years). If there were no significant differences between these two extreme age groups, chances are that there would be no significant differences with respect to intermediate ages either. This sampling strategy allowed us to gather enough subjects within each age group to perform equality of means tests in all scenarios defined by the study design.

Figure S5 shows how the experimental results presented in Fig. 5 look like, when each subject group is split into two subgroups: Young $.Y$ and Old $.O$; thus, $CL.Y$ and $CL.O$ are the young and old subgroups of] the Control group CL, while $BF.Y$ and $BF.O$ are the young and old subgroups of the Biofeedback group BF, respectively. All the mean equality tests between the $.Y$ and $.O$ age subgroups in the 16 cases shown in Fig. S5 yield insignificant results ($p > 0.0167$, t-test for all cases). Note that even if we do not adopt the corrected $\alpha = 0.0167$ that we set as the standard for this study, and we go with the typical $\alpha = 0.05$, only in two cases appears to be marginal significance: (a) Steering ($\mathbf{ST}$) in drive D_M for Biofeedback (BF), where $p = 0.03$ and, (b) length of distractions (L_{P_2}) in drive D_M for Control (CL), where $p = 0.02$. Hence, by and large, age did not affect results with respect to any of the variables of interest, and given that the age grouping was extreme, it is not expected to affect any intermediate grouping in future sampling.

Gender factor. Figure S6 shows how the experimental results presented in Fig. 5 look like, when we account for gender. Each subject group is split into two subgroups: $.F$ (for Female) and $.M$ (for Male); thus, $CL.F$ and $CL.M$ are the female and male subgroups of the Control group CL, while $BF.F$ and $BF.M$ are the female and male subgroups of the Biofeedback group BF, respectively. All the mean equality tests between the female and male subgroups in the 16 cases shown in Fig. S6 yield insignificant results ($p > 0.05$, t-test for all cases). Hence, gender did not have any effect on the physiological or behavioral variables of this study.

4   DISCUSSION

The findings of this study have interventional and methodological implications for managing distracted driving - a ubiquitous negative human behavior. They also stand to benefit investigations of distractions in the broader context of human-machine interactions.

The control arm of the study largely reproduced the results reported by Pavlidis et al. [10] regarding the sympathetic elevation and the ominous or outright dangerous behavioral modification incurred by cognitive and physical distractions (HYPOTHESIS SET H1). In a novel contribution, the interventional arm of the study demonstrated that heeding overarousal notifications to disengage from ongoing distractions, helps maintaining the drivers' sympathetic and performance levels at a safe equilibrium in the context of typical commuting distances (HYPOTHESIS SET H2).

The present study marks a move towards subject-centered triggers in managing multitasking behaviors during critical human-machine operations. This is a radical departure from existing device-centered triggers, such as the auto-locking of smartphones, once their bluetooth connection senses that the vehicle's engine is on. Drivers can always override such triggered locks or ignore alerts if they feel confident to multitask at will. In this respect, device-centered triggers have an inherent disadvantage, because they are generic and 'mechanical' implementations of the law. For instance, smartphone locking activates before any actual driving takes place, reinforcing a low opinion about its operational significance.

The value of individualized expert advice on effective prevention, and potentially on rule adherence and behavioral modification is well documented in the literature [26], [27]. What we propose here is anchored in this framework. For the purposes of our study, we could have tested the concept without a biofeedback algorithm, by having an expert monitoring the driver's sympathetic signal, and activating the overarousal indicator when s/he deemed that there was a significant and persistent increase. Due to the highly quantitative nature of the information, however, we were concerned about intra- and inter-operator consistency, given also the real-time pressure for expert decisions. For this reason we opted to employ the self-starting cusum algorithm [23] - a robust statistical filter for detecting significant persistent shifts.

Although it was not a central consideration in the present study, the issue of a biofeedback system that could be used in actual vehicles naturally enters into the discussion. This was a controlled experiment, where we kept all possible confounding factors at bay, including traffic conditions and weather, so that we can easily account for the true effects of the planted distractions. How then could the biofeedback method work in the real world, where traffic and weather, two factors that contribute to sympathetic arousal, change frequently? Indeed, the method's algorithm detects persistent overarousal, which is successfully associated with distractions only when all environmental factors are properly controlled. In realistic conditions environmental factors cannot be controlled, but can be accounted for in a mixed model that has to be incorporated into the biofeedback algorithm. This is technically feasible, given the availability of real-time GPS, weather, and traffic data in the computers of modern cars, as well as the fact that human commuting patterns have the characteristics of Lévy flights [28] (i.e., they are space-limited and recurring), allowing the

estimation of long term averages.

Outside the specific characteristics of the ultimate app that will bring the findings of this study into practice, two key characteristics of the methodological framework we propose are unobtrusiveness and comprehensive coverage of distractions. Unobtrusiveness is quintessential, as the variable upon which the method operates is of sympathetic nature, and thus likely to be confounded if it is extracted via obtrusive sensing means. Importantly, the method should be capable of detecting both physical and esoteric distractions. Sympathetic methods can accomplish this, because both types of distractions have sympathetic effects. In contradistinction, observational methods, such as eye-tracking, can detect physical distractions, but not cognitive distractions, because the latter lack observational signatures.

One could argue that in the ~ 2 highway kilometers that takes the biofeedback method to intervene in the course of a distraction, bad things could happen. That may be true, but it should be noted that this was a simulation experiment with moderate distracting stressors. Stronger stressors (e.g., mixed physical and cognitive distractions) in real conditions will likely produce persistent overarousal, prompting biofeedback intervention, much faster. Irrespectively, the most important point here is the behavioral implication of the method as it stands - when the 'pink' light turns on, this indicates with high degree of statistical certainty that the subject started exceeding his/her physiological and technical capacity to drive safely. This was sobering to the S^{BF} subjects in the experiment per the exit interviews, and we believe it will be sobering to the general population, should a system adhering to the tested principles is made robust enough to enter into practice.

Relevant to this discussion is the fact that in the few cases the biofeedback algorithm did not raise a flag, the subjects experienced overarousal, but of low significance, and without manifesting any adverse behavioral effects. This is an intriguing phenomenon that is under explored in the present study. It reinforces a radical rethinking of sanctioning distractions on an individualized basis, where biofeedback systems would play an indispensable role. While it is evident that the great majority people who drive while distracted are a danger to themselves and others, there may be a minority of individuals who sometimes drive while distracted without any loss of operational efficiency. Future studies with larger subject numbers would be able to answer this and other questions.

Interestingly, we found no significant age or gender effects. At first glance, the absence of age effects is somewhat surprising. One should note, however, that these results apply for the typical driving commute application targeted in the present study. Different and more exotic applications (e.g., driving for hours under extreme weather conditions in difficult terrain) may reveal more substantial differences between age groups. Such applications, however, were well outside the scope of this research.

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Ioannis Pavlidis (S'85-M'87-SM'00) received his B.E. degree in Electrical Engineering from Democritus University of Thrace, Xanthi, Greece, in 1987, his first M.S. degree in Robotics from the University of London, London, U.K., in 1989, and a second M.S. and a Ph.D. degree in Computer Science from the University of Minnesota, in 1995 and 1996, respectively. He is currently the Eckhard-Pfeiffer Professor of Computer Science and the Director of the Computational Physiology Laboratory, in the University of Houston. His research has been supported by multiple sources including the National Science Foundation, the Department of Defense, and corporations. He is the author of many scientific articles on computational physiology and affective computing. Dr. Pavlidis is well-known for his work on facial signs of stress, which first appeared in *Nature* and *Lancet*.

Ashik Khatri Ashik Khatri is a Ph.D. candidate at the Computational Physiology Laboratory of the University of Houston. He obtained his B.S. and M.S. degrees in Computer Science from the University of Houston in 2013 and 2015, respectively. He worked as intern at the NASA Johnson Space Center in 2015-2017. Mr. Khatri's research interests are in affective computing, data science, and software engineering. His work has appeared in numerous *ACM CHI* publications.

Pradeep Buddharaju Pradeep Buddharaju received his B.S. degree in Computer Science from J.N.T.U. in Hyderabad, India in 2002. Then, he obtained his M.S. and Ph.D. degrees in Computer Science from the University of Houston in 2005 and 2007, respectively. Dr. Buddharaju's research interests are in computational physiology, affective computing, and software engineering. He published extensively in *ACM CHI*, and he is a pioneer of physiological face recognition (*IEEE PAMI*, 2007). Dr. Buddharaju is currently an Associate Professor of Computer Science at the University of Houston - Clear Lake.

Mike Manser Mike Manser is a Senior Research Scientist and Human Factors Program Manager in the Center for Transportation Safety (CTS) at the Texas A&M Transportation Institute. His work examines the behavioral, cognitive, and perceptual driver-related factors that contribute to transportation safety, mobility, and efficiency with a specific focus on the interaction between drivers, vehicles, and infrastructure-based technology. He has more than 19 years of professional experience in the area of transportation human factors research. He holds a Ph.D. from the University of Minnesota, is active with the Human and Ergonomics Society and the Transportation Research Board, and has written book chapters and professional journal articles within the domain of human factors and transportation.

Robert Wunderlich Robert Wunderlich is Director of the Center for Transportation Safety at the Texas A&M Transportation Institute. The center's work is focused on developing safer roadways and safer drivers through research and outreach programs funded at nearly $5 million each year. Mr. Wunderlich is responsible for leading the various research programs for the center, which was established by the Texas Legislature in 2001. He has 35 years of experience in transportation safety and engineering in the municipal, private sector and research fields, and is dedicated to enhancing the capacity of transportation professionals to improve traffic safety. He is a past international president of the Institute of Transportation Engineers (ITE) and was named the Transportation Engineer of the Year by the Texas District of ITE in 2007. He received his B.S. and M.S. degrees in civil engineering from the University of Tennessee and is a licensed professional engineer in Texas.

Ergun Akleman Ergun Akleman received his B.S. in Electronic Engineering from Istanbul University in 1981, and his M.S. and Ph.D. degrees in Electrical and Computer Engineering from the Georgia Tech University in 1986 and 1992, respectively. He is currently a Professor at the Visualization Department of the Texas A&M University. Dr. Akleman's research interests are interdisciplinary, and are motivated by aesthetic concerns. He published extensively in the areas of shape modeling, image synthesis, artistic depiction, image based lighting, texture, and computer aided caricature. He is also a professional cartoonist, illustrator and caricaturist who has published more than 500 cartoons, illustrations and caricatures.

Panagiotis Tsiamyrtzis Panagiotis Tsiamyrtzis received his B.S. degree in Mathematics from the Aristotle University of Thessaloniki, Greece. He obtained his M.S. and Ph.D. degrees in Statistics from the University of Minnesota, where he served as a visiting faculty member in the School of Statistics in Fall 2000. In 2004, he joined the Department of Statistics, Athens University of Economics and Business, where he is currently Associate Professor. His research interests include statistical aspects of computer vision problems, statistical process control, and applications of Bayesian statistics. He was the recipient of the Best Student Paper Award and Best Contributed Paper in the 2000 Joint Statistical Meetings of the Risk Analysis Section of the American Statistical Association. He also received the Best Talk Award in the 2007 Annual Conference of the European Network for Business and Industrial Statistics.