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DOI
10.1109/ITSC.2016.7795658

Publication date
2016

Document Version
Accepted author manuscript

Published in
Proceedings of the IEEE 19th International Conference on Intelligent Transportation Systems, ITSC 2016

Accepted Author Manuscript. Link to published article (IEEE): https://doi.org/10.1109/ITSC.2016.7795658

Author Copy, IEEE ITSC 2016

Drowsiness in Conditional Automation: proneness, diagnosis and driving performance effects

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***Abstract*— Fatigue and drowsiness can play an important role in Conditional Automation (CA), as drowsy drivers may fail to properly recover control.**

In order to provide better insight in the effects of drowsy driving in Take Over Request (TOR), we designed a driving experiment that extends related literature in drowsiness research CA with self-rated subjective drowsiness, and analyze TOR performance adopting methods from recent TOR publications.

Results show that under certain conditions, drivers are very prone to drowsiness. Specifically, in this study the majority of subjects reported a high level of drowsiness before 15 minutes. Furthermore, this self-perceived drowsiness was followed by a decrement in vehicle lateral control during TOR. In this time frame, remaining driving performance and eye-tracking related metrics did not show significant decrements traditionally associated with fatigue and drowsiness, suggesting self-report to be more indicative of drowsiness than eye-based metrics.

I. Introduction

In a near future, automated vehicles are expected on public roads. This expectation is reinforced by technological achievements [1], prototypes [2] and even commercially available cars [3]. As countries such as Germany define roadmaps for operationalizing automation, it becomes evident that humans will still have a relevant role to play. In the different types of automation, according the SAE [4], Conditional Automation (CA) is perhaps the major significant advance because it no longer requires drivers to be vigilant regarding the driving scene or the automation. However, if the system can no longer continue, it can delegate control back to the driver – Take Over Request (TOR).

TOR research addresses driver ability to resume control during vehicle's control transitions [5]. One category of particular interest is the emergency unplanned TOR, where the automation delegates the vehicle control back to the driver in a short time period (typically 3-10 secs) due to unanticipated situations (e.g. road constructions / accidents). If the driver fails to resume control or to resolve the situation in a safe way, the outcome of the event can result in an accident. For this reason, even if these events may be rare, they are a cornerstone for making the CA concept work.

A. Driver State role in TOR

In early CA research, such as [6]–[8], major emphasis is made towards characterizing the time aspects associated with the event. This was expected to help establish a definition for an adequate time window in order to give drivers enough time to handle the situation; the other objective would be to diagnose which aspects contribute more to the performance. Despite setting the frames for analyses of TOR situations, those descriptive models suffer some limitations: limited prediction capability [9], HMI contributions to improve the transition are not always clear [10], [11], and the influence of traffic density on TOR outcomes [12].

In [13] and [14], it is shown that the task drivers were doing previous to the TOR can significantly influence the outcome. In order to the importance of the driver state, more recent TOR schemes such as [15] give as much emphasis on psychological and physiological aspects as to the time and motoric aspects. Examples of psycho-physiological states have been then widely explored such as distraction [16], trust [17], and drowsiness.

B. Drowsy Driving Diagnosis and Effects in CA

Arguably, fatigue and drowsiness effects on TOR have been less explored than other states. This happens perhaps because in early stages of CA, it was not anticipated as a major automation effect [18], [19].

Neubauer and colleagues [20] recognize that automation can decrease workload such that drivers become underloaded (passive fatigue), and therefore increasingly become prone to fatigue. They pointed that increased distress and task disengagement gets high after the use of automation. Another effect found was that the critical event response time also degraded compared to drivers with no automation, in line with [21], specifically in terms of steering response time. Later, in [22] a driving performance effect was found in brake time responses. While the experiments are different in structure and secondary task, both confirm that elicited fatigue contributed to a degraded driving response.

Körber and colleagues [23] designed a driving simulator experiment for eliciting fatigue during automation. To further confirm the effects of fatigue, they used an eye-tracker to detect drowsiness. They showed that blink frequency, and blink duration had significant decrements, while PERCLOS

This work was supported BY THE HF-AUTO: HUMAN FACTORS of Highly Automated Driving (PITN–GA–2013–605817), project funded by the European Commission within the Innovative Training Networks (ITN), a funding scheme under Horizon 2020.

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[24] did not. Further research, in [25], showed that even if subjects are prone to boredom, there was no significant effect in event detection for relatively long trips (25 min).

In [12] Jamson et al. study the voluntary non-driving task uptake as a means to divert drivers away supervision monotony. They report that through PERLCOS they were able to detect a significant difference between manual and automation driving. No critical events were tested.

Addressing specifically drowsiness signs, Miller et al. [26] defines drowsiness indicators in terms of manual eye-closure for 5 seconds or yawning events. Results show that these events happen significant more when the driver needs to be in a supervision mode instead of being engaged with multimedia non-driving tasks.

The current status of drowsiness effects associated with CA is far from a consensus that allows a clear strategy for exploiting the knowledge to build effective driver state monitoring systems. Non-repeatable effects in driving performance and eye behavior are evident, insufficient experiment details are reported, and a lack of similar replicable conditions make it hard to identify possible causes of differing effects between studies.

C. *Study's purpose*

The aim of this study is to clarify the effects of drowsiness in TOR. As previous works showed somehow contradictory results, we intend to contribute by improving drowsiness monitoring, and by better detailing the handling of the driving event.

In order to provide more insight in the drowsiness aspect, we complement eye based measurements with specific instructions, and by adding the subjective drowsiness self-assessment during the experiment.

As for the driving performance analysis, inspired in the good tradition of TOR analysis established by [27], we defined several objective metrics that help interpret the driving performance.

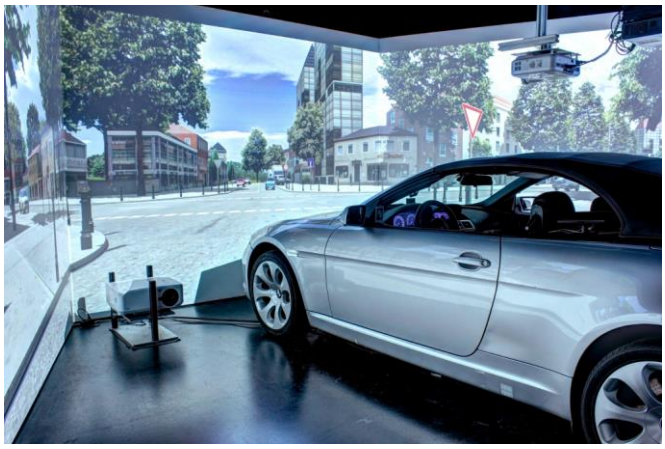

Figure 1. The high fidelity driving simulator used for the experiment.

Finally, and regarding our expectations concerning the outcome of this study, we expect to find negative effects of drowsiness in driving performance, and likewise no positive effects. It is also our expectation that this work will be relevant for the TOR analysis community with the addition of drowsiness driving state; fatigue and drowsiness communities should also be interested in this work, as more studies with more details are needed to clarify this field; and the driver state monitoring community can profit from in depth human factor research.

II. Method

A. *Apparatus*

The study was conducted in the installations of the Institute of Ergonomics from the Technical University of Munich. A fixed high fidelity driving simulator, composed of a BMW Series 6 vehicle and around 180° degrees of vision, as showed in Figure 1. Inside the vehicle participants had a the Stanford Sleepiness Scale (SSS) [28] table positioned in the central console, and a number pad in the arm support. The simulation software was SILAB 4 version.

B. *Groups and Instructions*

The experiment followed a between design approach, where volunteers were assigned to one and only one group: Reference Group and Drowsy Group. In the first group participants experience the scenario in fit condition, while the second group is in a state of induced drowsiness.

1) *All groups instructions*

All participants, regardless of group, had to perform a monitoring task. The instruction was to be vigilant concerning any traffic event happening in the driving scenario. Monitoring the road at all the time was mandatory, and distraction with objects inside/outside of the simulator was prohibited.

Feet position was delimited by a mark in the bottom of the vehicle, and hands must be positioned over the lap. This was instructed to ensure the posture consistency, while not engaged with the vehicle controls.

2) *Drowsy Group specificities*

During the recruiting process, and the experiment participants assigned to the Drowsy Group were selected/instructed to comply with requirements detailed in Table 1. The other distinct instruction for the Drowsy group is the need to do an additional task: drowsiness self-report. The frequency of such report is not fixed, rather the participant is instructed to just report whenever assess his/her drowsiness progressed using a number pad. The motivation for this freedom to report, was to avoid inclining participants to report increasingly high levels when regularly pressured to self-evaluate because they know they are participating in a drowsy experiment. Another motivation was to minimize the stimuli during the experiment.

C. *Training*

All participants followed the same training procedure. This consisted of manually driving around 10 minutes on a highway. Then the interaction to intentionally start or interrupt the automation was trained, and finally a TOR sound was issued and the driver recovered control.

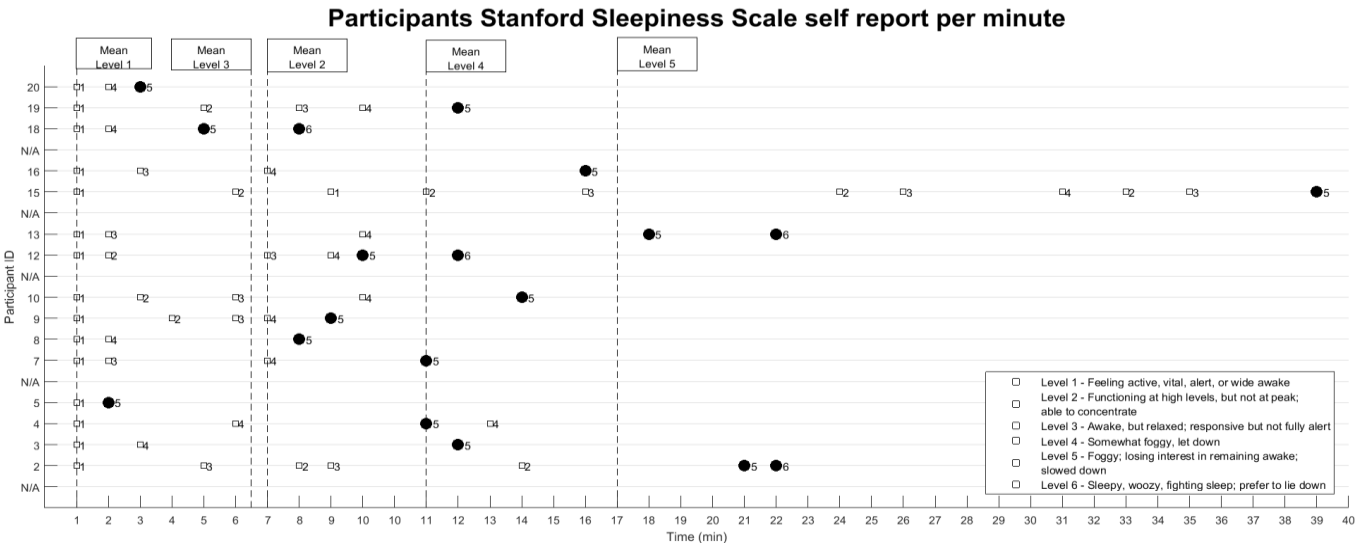

Figure 2. Self-experience subjective drowsiness reported over time per participant. Vertical lines represent the mean values. The filled black dots represent reports above or equal to 5, which trigger the TOR event; empty fill square represent lower levels of drowsiness. N/A are participant excluded.

TABLE I. REQUIREMENTS FOR THE DROWSY GROUP

Experiment Phase	Designation	Requirement
Before	Time of the Day	Experiment only between 14h and 16h.
	Sleep Disorder	Acknowledgement of having sleep disorders are not eligible.
	Sleep Quality	Report of experienced bad sleep quality in last 2 days are not eligible.
	Eating Behaviour	Participants must have had lunch. However no coffee or energy drink allowed that day.
	Physiologic Needs	Participants were required to go to the bathroom just before the start.
During	External Devices	Devices such as watches, and electronic devices are removed from the participant.
After	Transport	Participants must not drive vehicles after the experiment. Public transportation payed if needed for the return.

D. Scenario

During all course length, elements that can stimulate drivers were removed, i.e. other vehicles, trees, billboards, and changes in background.

The course can be divided in two phases, the Pre-TOR area and the TOR area.

1) Pre-TOR area

Before the TOR, participants experienced a long straight highway with a very smooth elevation. Albeit the map's layout is the same for both groups, the length of this area is different.

In the reference group the Pre-TOR area is calibrated to last the exact duration of 3 minutes. This is decided to reduce the exposition of this group to a monotonous scenario, therefore keeping them fit.

Drowsy group participants experience this segment as an infinite straight, with no specific time duration. The strategy is to keep participants reporting their subjective drowsiness level until it reaches a high level. The 5th level from the SSS was set as the threshold for considering the driver was drowsy. Once 5 or higher level is reported the TOR area can be queued in.

2) TOR area

The TOR scenario consists of an obstacle, in the same lane as the ego vehicle, that triggers a TOR with a Time to Collision (TTC) of approximately 5 seconds. The TOR was indicated with a tone of 680Hz with 28% amplitude, and immediately deactivated longitudinal and lateral automation. Since there are no other vehicles in the highway, there are two types of maneuvers that can be performed: evasive and stop.

Since participants are not performing any high demanding task apart from being vigilant, in the 5 seconds time window drivers are expected to regain control, develop and implement a strategy for handling the situation.

The experiment is designed such that when participants reach this situation, the major difference between the two groups is that in one group drivers are drowsy while others not.

III. RESULTS

During this section it is established for the purpose of statistical tests that alpha = 0.05 as the significance level.

A. Sample

In total we collected 31 eligible participants. For the reference condition a total of 16 subjects participated with mean age of 23.23 and a standard deviation of 1.95 years old. Concerning drowsy conditions, sample size is 15 with a mean age of 26.45 and standard deviation 7.49.

All participants were at least 18 years, and had a valid driving license at the experiment time and had normal or corrected to normal vision. The participation in the experiment was voluntary, without monetary compensation.

B. *Self-Reported Subjective Drowsiness*

Figure 2 presents the results for the self-report drowsiness. By plotting individual self-reports against time, it helps clarify how drowsiness is perceived at the individual level, in terms of evolution, but also how different this progress can be between individuals.

With drowsiness level 5 defined as the threshold for the TOR, results show the time to reach level 5 was M = 13.33s and SD = 9.26s. This shows how fast perceived drowsiness evolves. A second lesson is the high variation, indicating major inter individual differences between participants, undertaking the experiment in the same conditions.

C. *Eye Behavior Analysis*

We proceed our analysis by analyzing the eye-tracker data, with the objective of obtaining evidence of eye-behavior effects. Using FaceLab 5.1 data for blink frequency, duration and PERCLOS, we select the period just before the TOR, which represents the mean value from the last 3 minutes. The results are summarized in Table 2.

TABLE II. EYE BEHAVIOUR DIFFERENCE BETWEEN CONDITIONS.

Feature	**Reference**		**Drowsy**		**Two-Tail t-Test equal variance**	
	M	SD	M	SD	T(30)	p
Blink Frequency	0,39	0,06	0,40	0,07	0,14	0,89
Blink Duration	0,16	0,005	0,17	0,005	1,05	0,30
PERCLOS	0,03	0,01	0,05	0,02	0,67	0,51

As none of the metrics had a significant difference, we conclude that there was no effect in eye-behavior caused by drowsiness in this study.

D. *Driving Performance Effects*

In terms of collisions, in both conditions, no participant crashed. The intervention time and the minimum time to collision (minTTC) are defined in [27]. The Intervention time and minTTC are helpful to understand how fast drivers intervene after the TOR starts; and how close they were to colliding with the obstacle, respectively. The results are plotted in Figure 3.

Intervention time in the reference condition is characterized by M = 1.81s, SD = 0.72s, and Med = 1.75s. As for the drowsy condition, the values are M = 1.87s, SD = 0.89s, and Med=1.82s. A student t-test resulted in a non-significant difference, t(30)=-0.37, p= 0.71.

Following similar analysis for the minTTC, there was no significant difference between reference condition (M= 1.87s, SD= 0.89s) and drowsy condition (M= 2.46s, SD=1.10s) with t(30)= -1.68, p=0.10.

Therefore, in this study, and following a similar analysis as TOR research, drowsiness did not significantly affected the temporal aspects.

Using the maximum (absolute) acceleration during the TOR can discriminate between good and bad takeovers, as it is often interpreted that high de/accelerations mean extreme measures and loss of control.

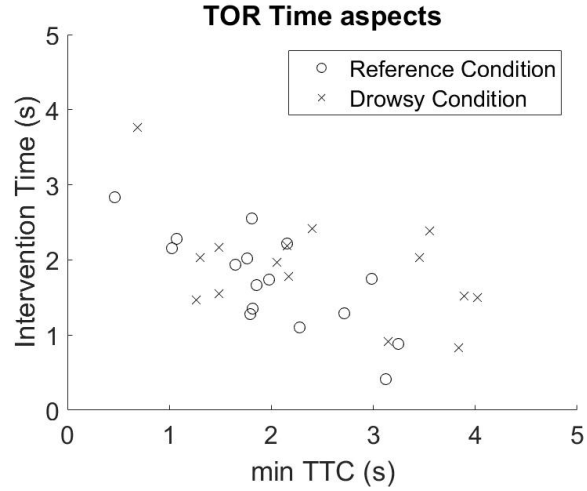

Figure 3. Intervention Time and minimum TTC. The temporal aspects associated with response to the event, and danger of collision.

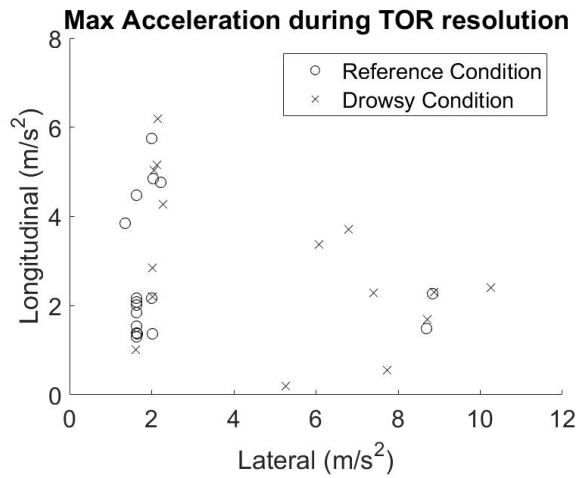

Figure 4. Maximum acceleration. Circles represent the reference condition, and X the drowsy condition. Lateral acceleration was significantly higher for drowsy condition subjects.

In longitudinal acceleration, there was no effect of drowsiness with the reference condition (M= 2.63s, SD= 1.48s) and the drowsy condition (M= 2.88s, SD= 1.74s) scoring t(30)= -0.45, p= 0.66. Lateral acceleration showed a significant effect of drowsiness, where reference condition (M= 2.58s, SD= 2.34s) and (M= 5.03s, SD= 3.12) tested significant with t(30)= -2.53, p=0.02.

The data evidences that drowsy condition had more extreme lateral accelerations, which in practice translated to stronger jerks in the steering wheel when compared with the reference group. This becomes evident in Figure 4, with the right side of the plot being populated by a cluster mainly composed by drowsy participants.

The final qualitative measurement we assess is mirror checking, and can be useful to assess if drivers perform good or bad maneuvers for the right or wrong reasons by checking if subjects consult the mirrors before intervening. The results

are presented in Figure 5.Testing if the frequencies are different, the results are $\chi^2(3) = 8$, p = 0.24. Therefore, we have no evidence that drowsiness significantly affected mirror checking despite the slightly lower score for the reference group.

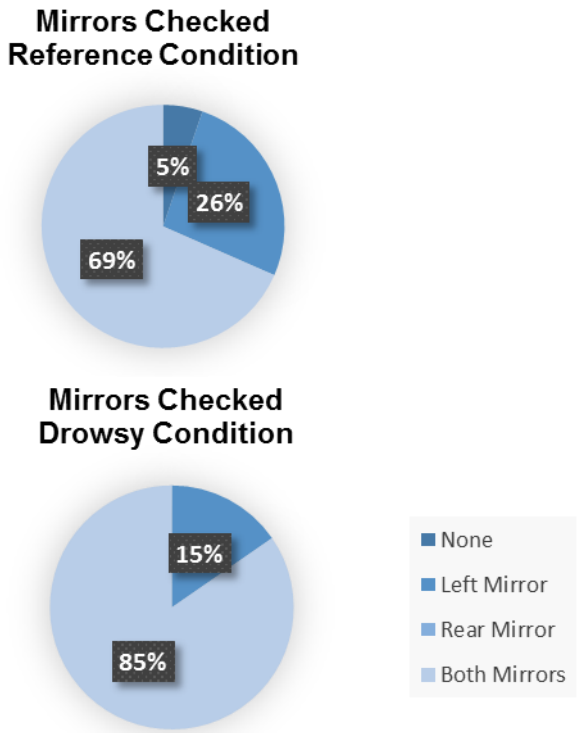

Figure 5. Mirror checkings during TOR. Checking the mirrors before interve is interpreted as a good practice. No signigicant difference between the two conditions.

IV. Discussion

A. *Drowsiness in Conditional Automation*

Drowsiness seems to have an important role to play, perhaps more relevant than previously anticipated. In this study, we explored the concept of passive fatigue [29], where prolonged exertion of a task [30] in a monotonous environment can be elicit fatigue and drowsiness.

In order to exploit this situation, we setup drowsy condition participants to have pre-conditions (see section II.B.2) and place them in monotonous highway traffic. As data shows, most subjects experience subjective drowsiness in less than 15 minutes. Albeit works such as [22], [26] suggest that performing engaging non-driving tasks can counter this effect, there is still no large scale experiment or high number of experiments confirming the validity.

Driving CA with the pre-conditions as the drowsy group, and having a segment of 15 minutes' monotonous road segment in a long trip, can arguably occur sufficient times during a year to be worth our attention towards this topic.

B. *Relevance of Drowsiness effects on Performance*

Assuming the difference between intervention time and response time (i.e. time to reach the vehicle's controls) is neglectable, then this study contrasts with the increment of time from the studies [21], [22], and [29]. Two main reasons can contribute to this disparity: experiment time and pre-warning. One important difference between experiments is the time drivers are experiencing the drowsy condition, where this study is roundabout 15 minutes, others are 50 min [29], 35 min [31] and 45 minutes. The second difference is that critical events in this study are preceded by an auditory warning, which can improve the reaction time compared to subjects that are required to identify the situations.

In this study we had evidence that subjective drowsiness can be used to predict decrement in lateral control. Effects on lateral control are also reported in [31], and [29]. Albeit metrics are different, with other authors relying in SDLP, there is a common denominator that lateral control has potential to be affected. Yet, in [29] the SDLP is lower than the other groups (on manual driving after critical event), while in [31] it was higher. Since SDLP can be interpreted both ways, it is not clear how it affects drivers, just the changing effect seems to be consistent.

Considering eye-based metrics used for drowsiness detection [24] and their potential capabilities for CA [32], the results do not support their use, at least for such short time. However, as showed by the works of [23], [12], and [24] eye behavior of each individual seems to significantly differ; not even metrics like PERCLOS hold in all studies; this may happen due to the wrong premise that eye-behavior alone captures drowsiness effects. As Philips and colleagues noticed [30], it is possible to have "normal" eye-behavior even when experiencing major drowsiness.

The individual differences were quite noticeable also in terms of facial and motion behavior, as some participants would nod or yawn making it evident they were experiencing drowsiness. This individual behavior and the expansion of sensory data to motion and facial behavior looks likean interesting source of information for complementing eye behavior [33],[34] and [35].

C. *Study Limitations*

It should be mentioned that this study was done with a relatively small sample, and it is not representative of the full driver population.

Due to technical limitation it was not possible to objectively check all pre-conditions (i.e. energy drinks, or sleep quality the night before) for admitting a subject into the drowsy group. This control was made by only questioning the subject.

V. Conclusion & Future work

In this study we provide evidence on driving performance effects caused by a drowsy state using a driving experiment design similar to TOR research, allowing us to compare the effects of this state with other driver states.

By adding the self-report mechanism for subjects to report their perceived drowsiness, this study showed that human self-assessment may outperform eye-based assessment.

For future research, the focus will be twofold: 1) extend the time of the experiment to be equivalent to related literature and; 2) explore diagnosis models focused on the intra and inter-individual eye, motion and facial differences when drowsy.

ACKNOWLEDGMENT

Honorable mention to Yan, Chan and Li who supported in this research implementation.

Mention also to the technical support from Christoph Rommerskirchen. Matt Sassman for paper reviewing and proving valuable recommendations.

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