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Forecasting negative effects of monotony and sensation seeking on performance during a vigilance task

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Abstract

The driving task requires sustained attention during prolonged periods and can be performed in highly predictable or repetitive environments. Such conditions could create hypovigilance and impair performance towards critical events. Identifying such impairment in monotonous conditions has been a major subject of research, but no research to date has attempted to predict it in real-time. This pilot study aims to show that performance decrements due to monotonous tasks can be predicted through mathematical modelling, taking into account sensation-seeking levels.

A short vigilance task sensitive to short periods of lapses of vigilance, called Sustained Attention to Response Task, is used to assess participants' performance. The framework for prediction developed on this task could be extended to a monotonous driving task. A Hidden Markov Model (HMM) is proposed to predict participants' lapses in alertness. A driver's vigilance evolution is modelled as a hidden state and is correlated to a surrogate measure: the participant's reaction time.

This experiment shows that the monotony of the task can lead to an important decline in performance in less than five minutes. This impairment can be predicted four minutes in advance with an 86% accuracy using HMMs. This experiment showed that mathematical models such as HMM can efficiently predict hypovigilance through surrogate measures. The presented model could result in the development of an in-vehicle device that detects driver hypovigilance in advance and warns the driver accordingly, thus offering the potential to enhance road safety and prevent road crashes.

Keywords

Monotony, Fatigue, Vigilance, Hidden Markov Models, Sensation seeking

Introduction

Drowsiness at the wheel has been identified globally as a major cause of road crashes. Inattention and fatigue are reported as contributing factors in 6% and 5% of fatal crashes, respectively, in Australia between 1992 and 2006 [1]. It is difficult to reliably measure the influence of such contributing factors so that such estimates are likely to be underestimated. This is supported by the survey conducted by McCartt et al. [2] where 55% of 1000 drivers had reported to have driven while drowsy and 23% had fallen asleep while driving without having a crash.

Boredom, fatigue, monotony and sleep deprivation are factors that induce sleepiness and drowsiness. It results in decreased attention and impaired information processing ability, and impairs decision-making capability. These factors increase crash risk due to driver inability to react to emergency-type situations.

Most research on vigilance-related impairments focuses on sleep-deprived participants. However, there is evidence from crash data and from simulated driving studies that vigilance decrement could occur during daytime, especially on monotonous roads [3]. Driver hypovigilance is often attributed to fatigue, but it can emerge independently of time on task; it is more frequent in monotonous road environments, where task demand and stimulus variability are low and moderate sustained attention [3, 4]. Also, the profile of drivers has an effect on the likelihood of being involved in a crash due to hypovigilance; extraverts and high sensation seekers are at a higher risk [3].

Driver self-assessment questionnaires have been used to evaluate their vigilance state. Such a subjective approach is not applicable on monotonous roads [5], suggesting the need for an objective mathematical model to predict vigilance decrement during driving. The most reliable assessment of vigilance is obtained by electroencephalography (EEG) [6]. However, such a device is too obtrusive to be deployed in vehicles.

Driving performance is impaired during vigilance decrement and surrogate measures from the driver, the car and the environment can be used to assess such impairment. This paper presents a pilot study designed to assess the feasibility of predicting performance decrement during a monotonous task. A low-demand, lab-based vigilance task is used to isolate and simulate impairments due to monotony in a vigilance task. A theoretically sound measure of sustained attention called Sustained Attention to Response Task (SART) is used in a controlled lab-based vigilance task experiment. The SART is a computer-assisted paradigm where participants are asked to respond to non-targets and not respond to targets [7]. Our aim is to predict decline in performance during a short, monotonous vigilance task using surrogate measures (reaction times). Such prediction also takes into account inter-individual differences through sensation seeking levels.

Background

Monotony, vigilance and performance

Vigilance is defined as the ability to sustain attention to a task for a period of time [8]. Vigilance fluctuates and is an issue in terms of road safety when decreasing. This particularly applies to monotonous environments where driving is largely reduced to a visual vigilance task (lane-keeping task). Vigilance tasks are the paradigm used to study sustained attention and its vigilance decrement. Vigilance can be classified to define whether an individual is able to perform a task with the expected performance. Duta et al. [9] developed such a classification from the classification of the sleep-wake continuum obtained with an EEG [10]:

- Alert: corresponds to responsive participant, capable of performing a task with full to acceptable performance
- Hypovigilant: corresponds to the participant no longer able to perform a task at an acceptable level of performance
- Sleeping participant
- Unknown.

Vigilance level is often assessed automatically by an algorithm through the estimated performance (from 0 to 1) of a vigilance task (particularly with neural networks). In this case, results from the model can be used to classify the vigilance level by using the following method [9]:

- Alert: 0.7-1
- Intermediate: 0.3-0.7
- Hypovigilant: 0-0.3.

Hypovigilance can be assessed through psychomotor tests (for instance, by reaction time tests), since a reduction of performance in such tests is interpreted as a sign of decrease in vigilance [11]. A loss of performance usually implies that the individual suffers from a decreased ability to maintain vigilance. Such psychomotor tests are expected to perform particularly well as an index of vigilance in monotonous contexts. When the task is monotonous, responses are automated, leading to short reaction times and poor performance [12]; and such responses are direct consequences of a decline in vigilance. This is supported by the fact that performance during a sustained attention task is correlated to changes in the EEG power spectrum at several frequencies (relatively variable between subjects but stable within subjects) [13].

Factors that have an effect on vigilance can be divided into two categories: endogenous and exogenous factors. Endogenous factors are associated with long-term fluctuation of alertness that emanates from within the organism, whereas exogenous factors are linked to the task itself or the interaction between the driver and the outside environment.

Among the endogenous factors are physical and mental fatigue, sleep deprivation and task duration. Personality dimension (age, gender, mood and particularly sensation-seeking level), time of day (circadian rhythms), caffeine and other stimulants, and cognitive task demands are also endogenous factors [11].

Exogenous factors include complexity and monotony of the task, and environmental factors such as noise, ambient temperature, and frequency and variation of stimulation [10]. This is particularly the case when driving on a highly predictable highway where, because of lack of stimuli (or repetitive ones), the driver pays less attention to the road situation [14]. These numerous factors result in complex and strongly interrelated phenomena regulating vigilance. The impacts of the different factors leading to changes in vigilance performance are not of the same order. Stressors such as heat, noise and circadian effects are of low impact on the performance compared to fatigue, monotony and/or boredom [15].

Each individual has their personal optimal level of stimulation and arousal required to perform well. This can be measured through the Sensation-Seeking Scale. Sensation seekers are people who need varied, novel and complex sensations and experiences to maintain alertness. They require greater arousal than non-sensation seekers to perform well [16].

The profile of drivers more likely to be involved in fatigue-related crashes was determined in a simulator experiment [3]. In this experiment, the impact of the driver's personality on decline in vigilance was studied. Sensation-seeking drivers are able to take physical and social risks to achieve varied, complex sensations and experiences. This factor can be more or less developed, but it leads to risk-taking driving and negative reactions to monotonous driving. High sensation seekers experience vigilance decrement faster than any other group [17].

In this experiment an adaptation of the vigilance task SART is used where participants are asked to respond to non-targets and not respond to targets. In such an experiment the vigilance as assessed by performance has been shown to depend on the level of monotony and is correlated to reaction times (RTs) [18, 19]. The SART was chosen since performance during this continuous task correlates significantly with everyday life attention failures [20]. The authors are aware of the research debate related to the validity of the SART as a vigilance proxy [21]. However, this study makes the assumption that the SART induces hypovigilance.

Such a vigilance task is used in this paper to show the feasibility of forecasting vigilance decrement using surrogate measures. This study uses reaction times and error measurements obtained from a SART experiment to validate a framework that predicts vigilance decrement before it occurs. Such a framework can be extended to a monotonous driving task using EEG measurements as a vigilance-level reference and various surrogate measures from in-vehicle sensors [19, 22]. Larue et al. [23] have shown on a driving simulator experiment that speed, lateral position of the vehicle and physiological measurements – such as heart rate variability, blink frequency and electrodermal activity – are potential surrogate measures of driving performance impairment during monotonous driving.

Mathematical model for prediction

Vigilance decrement can manifest quite early on [24] and change quite abruptly during monotonous vigilance tasks. This can be well described by discrete modelling. Performance, defined as the accuracy of target detection, is categorised as presented before. We aim to predict this performance through surrogate variables that are correlated to the ability to sustain attention.

Research has shown that such performance models must be able to deal with inter-individual differences to be implemented reliably in operational settings. Bayesian forecasting is widely used to overcome this limitation. Indeed such models can handle these differences even when prediction is applied to individuals not studied beforehand [25]. Among Bayesian models, Hidden Markov Models (HMMs) have been used to model numbers of real-life problems, such as driver manoeuvre recognition [26]. Larue et al. [19] have also shown that Bayesian models provide better estimates of performance from surrogate measures during the SART as compared to neural networks and Generalised Linear Mixed Models. HMMs combine independence assumptions making the model numerically computable with field knowledge that vigilance decrement is the cause of reaction-time variations [27].

A Hidden Markov Model is designed to model a sequence of T observations data (at time $t=1,2,\ldots T$), which is the consequence of an unobserved (hidden) variable [28]. Here the unobserved variable is the vigilance level Vig_t at time t. This variable is the cause of other random variables, the surrogate measure RT_t at time t in this study as suggested by previous research done by Larue and colleagues [19]. These variables must have the following conditional independence properties for each time t [29]:

- given Vig_{t-1}, the sequences $\{Vig_{t:T}, RT_{t:T}\}$ and $\{Vig_{1:t-2}, RT_{1:t-1}\}$ are independent, where the notation $A_{a:b}$=(30) is used (Markov property of order one)
- given Vig_t, RT_t is independent of the sequence $\{Vig_{-t}, RT_{-t}\}$, where the notation $A_{-t}=\{A_1,\ldots, A_{t-1},A_{t+1},\ldots, A_T\}$ is used.

In the case of a Hidden Markov Model with discrete states and discrete observation sequences, the model is completely characterised in terms of [28, 31]:

- number of states in the model, say N. Here the random variable Vig_t takes its values in the set $S=\{$*alert, intermediate, hypovigilant*$\}$ so that $N=3$
- number of distinct observation symbols per state. Here it is the reaction times values once categorised
- transition probability matrix giving the probability to go from the state S_i at time t to the state S_j at time $t+1$
- observation symbol probability distribution
- initial state distribution.

The training of the HMM is done through Bayesian learning from the given hidden and observation sequences. If the hidden state is not available during training, the Baum-Welch algorithm (adaptation of the EM-algorithm applied to HMM training) can be used. Then the model can be used for prediction (see Figure 1). The Viterbi algorithm is used to infer the value of the vigilance state given the reaction times [28]. This algorithm determines the states sequence, respecting the transition probabilities, that is the most likely to occur with the model used. Then predicting the next vigilance state can be done using the transition probability matrix.

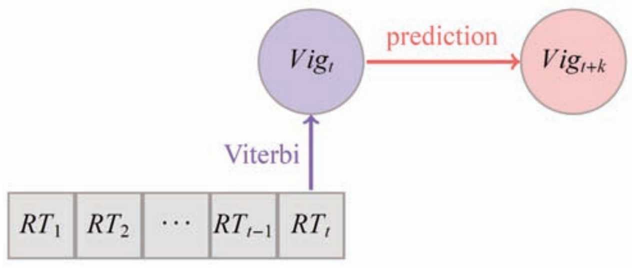

Figure 1. Prediction methodology with HMMs

Method

Participants

Forty students of the Queensland University of Technology (QUT), 8 males and 32 females (mean age = 22.6 years, SD = 9.2), volunteered to participate in this study. All subjects provided written consent for this study, which was approved by the QUT ethics committee. Students undertaking the first year psychology subject received course credit for their participation.

Experimental design

Two 5-minute adaptations of a continuous sustained attention to response task (SART) [7] were run on an IBM-compatible computer using E-Prime. The conditions varied in terms of task monotony, with two different settings for target appearance: probability 0.11 (low target probability) and probability 0.5 (high target probability). The first probability creates a monotonous condition where a response can be predicted and leads to automatic responses. The second probability, with a markedly higher stimulation, is a non-monotonous condition and results in a non-automatic response mode associated with lower response predictability [4].

Experimental conditions

This experiment was designed by Michael and Meuter [4]. Two hundred twenty-five single digits (ranging from 1 to 9, height of 29mm) were displayed randomly for 250ms in the middle of a computer screen. An inter-stimulus interval of 1150ms was used with a mask (height 29mm) consisting of an 'X'. The chosen target stimulus was the display of the number 3. When a stimulus different from the target stimulus was displayed, the participant was asked to press the spacebar as fast as possible, and when the target number was displayed, action required was to withhold the response (that is to say, not press the spacebar).

Procedure

Participants were tested individually in a quiet room, between 9am and 3pm, in a session lasting approximately 45 minutes. They were randomly assigned to two groups, each of which performed five short vigilance tasks, as follows. Each participant performed a monotonous then a non-monotonous task, followed by one of various types of monotonous tasks (this task formed part of a larger study and will not be further described here). Finally, there was a repetition of the monotonous and non-monotonous tasks, participants of the second group performing this sequence in a counterbalanced order with time.

Prior to each condition, participants received written instructions on the computer screen. The instructions asked them to respond as quickly as possible to all stimuli, and this with the highest accuracy possible. On completion, participants filled out short questionnaires: the Sensation Seeking Scale - Form V (SSS), the General Health Questionnaire (GH-28) to screen and eliminate participants for psychiatric morbidity (found to impair performance using the SART) and a general background questionnaire (control sleep pattern and caffeine consumption).

Data analysis

The software Matlab version 7.4.0.287 was used to analyse data. Responses to target are used to assess vigilance fluctuations. They are converted into error rates in fixed time windows (also referred to as performance measure in this paper), defined as the fraction of targets not detected by the subject (i.e., lapses) within a fixed window. Due to the small number of targets in the monotonous setting, a window size of 45 stimuli (targets and non-targets) was chosen to obtain an average number of five targets in the window in the monotonous setting. This window size corresponds to approximately one minute.

The window size was chosen to be the same for the non-monotonous task. Pearson's linear correlation coefficient between the reaction times of two consecutive time windows is computed. The same coefficient is also computed for performance. This enables us to test whether assumptions required during HMM modelling are reasonable. Performance is then divided into states as described in the 'Vigilance' section. The predictor reaction time is computed as the mean response time to non-targets. Reaction times are normalised per participant and then categorised.

The sensation-seeking level of the participant is categorised into one of the following classes: low (less than one standard deviation (SD) in the available participants sample), normal (within one SD) or high (greater than one SD) [16].

Six different HMMs are fitted to take into account the impact of the monotony of the task (monotonous or not) and the sensation-seeking scale (low, medium and high level). Vigilance states and reaction times are known when the model is trained. That way, computing the joint distribution is only a matter of counting the different transitions from the different performance states and the probability of observation of the different reaction times for each vigilance state (Bayesian learning) [32].

A stratified 10-fold cross-validation is performed to assess the robustness of the modelling. In this technique, data are divided into 10 folds. The model is trained on nine and tested on the remaining one. This is repeated so that each fold is used as a test sample [33]. A stratified cross-validation was used to avoid putting high and low sensation seekers in the same fold.

The most probable performance state sequence at time t using the reaction times data until time t is computed with the Viterbi algorithm. This gives the probable vigilance state at this time. Future vigilance states are then inferred up to four minutes in advance using the transition probability matrix. The model's accuracy is evaluated through the capacity to detect hypovigilance occurrences reliably. Therefore sensitivity and specificity are reported. Sensitivity measures the proportion of actual hypovigilance states that are correctly identified as such, while specificity measures the proportion of non-hypovigilant states that are correctly detected. Their mean is also provided.

Results

The correlation between two consecutive performance measures (rate of accurate target detection in a time window) was $\rho=0.70$ while the correlation between the mean reaction time of two consecutive time windows was $\rho=0.18$. This shows that vigilance evolution is progressive and depends on the previous state. Particularly, there is no need to use a Markov property of order higher than one. Such observation was not true in the case of reaction times. Reaction times are not equivalent to the performance level though they depend on it (a reaction time value does not correspond to a specific vigilance state). This supports the choice of HMMs, their assumptions being compatible with the data.

The non-monotonous setting of the SART did not create hypovigilance, with only two occurrences appearing when considering all the participants. However, the monotonous setting resulted in a total of 104 occurrences of hypovigilance when considering all the participants (out of 200 measurements). Therefore, there was no need to detect hypovigilance on the non-monotonous setting, and only results on the monotonous setting were further analysed.

Reaction times (continuous values) were categorised in order to be used in the HMM. Various numbers of categories were investigated in order to optimise the model's accuracy. For each number of categories N, the range of reaction time values was divided into N intervals of fixed width.

$\left(width = \dfrac{RT_{\max} - RT_{\min}}{N} \right)$ Best results in terms of prediction were obtained for 19 categories. The values of the transition probabilities for the corresponding HMM are shown in Table 1 for each level of sensation seeking.

Table 1. HMM transition probabilities (in percentage) for the monotonous setting

	Low SS†			Medium SS			High SS		
↗	alert‡	inter‡	hypo‡	alert	inter	hypo	alert	inter	hypo
alert	74	19	7	< 1	61	39	2	72	26
inter	20	40	40	18	39	42	19	52	30
hypo	6	24	70	3	31	66	< 1	22	78

Column: vigilance state at time t; Row: vigilance state at time $t+1$
† SS Sensation Seeker
‡ states: alert, intermediate (inter) and hypovigilant (hypo)

In this monotonous setting, only low sensation-seeking participants may stay in the alert state. However, each participant – independently of their sensation-seeking level – is highly likely (66% for medium sensation seekers) to stay in the hypovigilance state once they reach it. This is also apparent from Figure 2, which provides a graphical representation of the transition probabilities between the different vigilance states from time t to time $t+1$. This figure provides information on the likely vigilance state at the next time step, knowing the current vigilance state. The width of the different arrows is proportional to the probability of a transition. Figure 2a shows these transitions for the non-monotonous setting for medium and high sensation seekers. Probability transitions used to make this diagram for the non-monotonous setting are not provided in this paper but can be found in Larue et al. [19]. Figure 2b presents such transitions for the monotonous setting for medium and high sensation seekers.

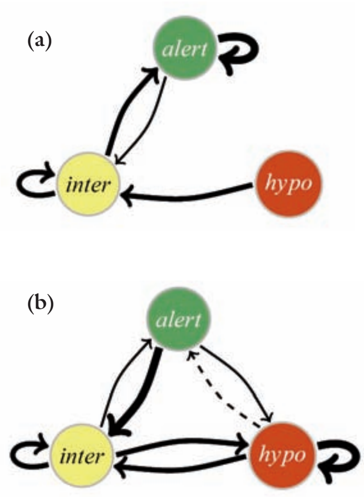

Figure 2. Transition between vigilance states for the (a) non-monotonous setting and (b) monotonous setting (arrow width is used to highlight the likelihood of transition)

The trained HMM has been used to make predictions using reaction times until time t up to four minutes in advance (as presented in Figure 1). The accuracy of these predictions is reported in Table 2. The prediction of vigilance at time t has a mean value of 80.0% (73.1% and 86.9% for sensitivity and specificity, respectively). This mean increases as prediction steps increase up to four minutes *(t+4)*, reaching 88.0% (100.0% and 75.9% for sensitivity and specificity, respectively). This increase is due to an increase in sensitivity (while specificity decreases) and results from the high likelihood of finishing the experiment in the hypovigilant state.

Table 2. Predictions accuracy (in percentage) for the monotonous setting for different time steps (up to 4 minutes in advance)

	Sensitivity†	Specificity‡	Mean*
at current time t	73.1	86.9	80.0
at time t + 1minute	88.5	76.0	82.3
at time t + 2minutes	95.5	72.3	83.9
at time t + 3minutes	97.9	73.5	85.7
at time t + 4minutes	100	75.9	88.0

† related to type II errors
‡ related to type I errors
* Mean between sensitivity and specificity

Discussion

The state of low performance to targets is observed half of the time in the monotonous setting and almost never in the non-monotonous scenario. Therefore, this short vigilance task shows that the monotonous setting of the task can lead to hypovigilance, while such vigilance impairment is not observed in the non-monotonous setting. Furthermore, once the hypovigilance state is reached, it is very difficult to go back to better performance (as can be seen by the low transition probabilities on Table 1 and Figure 2).

Sensation-seeking level changes the way participants cope with the monotonous setting. High and medium sensation seekers are not able to maintain high vigilance, whereas low sensation seekers can. Also high and medium sensation seekers tend to have an immediate and fast decrease in vigilance, going from an alert to a hypovigilant state directly with 39% and 26% probability, respectively. By contrast, vigilance decrement for low sensation seekers is less abrupt and goes through the intermediate vigilance level (7% probability to go straight from the alert state to the hypovigilant state). These results on sensation-seeking levels impacting on vigilance decrement are in line with previous research conducted on a driving simulator by Thiffault and Bergeron [3] where steering wheel movements were used as a measure of driving performance.

The vigilance decrement can be accurately detected and predicted up to four minutes in advance through surrogate measures (here reaction times) using HMMs, with a mean around 80%. Although the increase in the accuracy as the prediction step increases is counterintuitive, it can be explained in this experiment. Independently of the sensation-seeking level, participants are highly likely to finish the experiment in the hypovigilant state when the setting is monotonous. Therefore, it is easier to predict the vigilance state closer to the end of the experiment, which results in better predictions.

Limitations

Models were trained according to the Sensation Seeking Scale level, so that a population modelling approach has been used in this study. Adapting models to each participant should improve these results. Also, the sample of participants is heavily biased by age, gender and possibly intellectual capacity compared to the wider population, due to the sampling population being university students. Nevertheless, generalisation of the results found in this pilot study seems reasonable due to the simplicity of the task involved.

Conclusion

We show on a short vigilance task that monotony can quickly lead to critical vigilance impairment. Such impairment depends importantly on the sensation-seeking level of the participant and is detected through task performance. In view of predicting hypovigilance during driving, this vigilance decrement has to be detected through surrogate measures. Indeed, the most reliable and most often used method to assess vigilance is electroencephalography, which cannot be implemented in a real car.

This experiment shows that the vigilance decrement can be predicted using reaction times as surrogate measures with 80% to 86% accuracy and up to four minutes in advance. Such results support the idea of using HMMs to predict hypovigilance during driving using surrogate measures. Different measures, such as lane-keeping, steering wheel movements or eye-tracking performance, have been shown in the literature to be altered when driver vigilance is impaired. Such further research could be implemented in an in-vehicle device to predict driver vigilance decrement and therefore prevent crashes.

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Motorcycling in South Australia

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The Centre for Automotive Safety Research has released the report, *Motorcycling in South Australia: Knowledge gaps for research*, by MRJ Baldock and TP Hutchinson. It is available in full text online at http://casr.adelaide.edu.au/publications/list/?id=1184, or in hard copy from CASR.

The aim of this report is to provide an overview of knowledge regarding motorcycling that can be applied to South Australia. To this end, recent relevant literature published prior to 2010 was reviewed. Areas of interest include the number of motorcyclists, the motorcycles they ride, riding exposure, motorcycle crashes, motorcycling injuries, attitudes, training and countermeasures. The report is not an exhaustive examination of these issues, but a general overview allowing for identification of knowledge gaps in South Australia that would be suitable for research. An analysis of the costs of motorcycle crashes in South Australia is provided in an appendix.