City versus Highway Driver Arousal State Analysis for Stress Level Assessment

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Résumé. Suite à une urbanisation croissante et un progrès technologique avancé, la conduite dans les milieux urbains devient une tâche compliquée qui nécessite un niveau élevé de vigilance. Ainsi, la charge mentale des conducteurs doit être optimale afin de pouvoir gérer des situations critiques dans ces conditions de conduite. Afin d'étudier les performances des conducteurs, la plupart des études antérieures se basaient sur des mesures subjectives. Récemment, le développement de nouveaux capteurs non intrusifs et mobiles, permet le suivi de l'état affectif d'une personne en enregistrant ses données physiologiques en temps réel. Cette étude s'intéresse à l'utilisation de ces capteurs afin d'étudier le changement du comportement cognitif des conducteurs selon les différents espaces urbains. Ceci permettra, en perspectives, de modéliser la variation de la charge mentale selon la complexité de l'environnement. Notre approche commence par une extraction de plusieurs descripteurs à partir de l'activité électrodermale (AED) de dix expériences de conduite passant par trois zones urbaines : zone de repos, ville et autoroute. On propose dans cette étude d'introduire l'indice de Hurst de l'AED comme descripteur, en plus des réponses "startles" caractérisant les réactions électrodermales (RED). Une méthode statistique de classification basée sur les forêts aléatoires est utilisée afin d'ordonner et de sélectionner les descripteurs. Les résultats préliminaires de cette étude confirment qu'en moyenne, la conduite en ville invoque un niveau d'éveil élevé (RED) et une AED correspondante plus irrégulière que celles associées aux zones de repos et d'autoroutes. Cette étude peut servir dans l'évaluation de l'état du conducteur, en particulier dans le cas des voitures autonomes où le problème du bien-être et de sécurité est crucial.

Mots-clés. Activité électrodermale (AED), indice de Hurst, Espaces Urbains, Forêts aléatoires.

Abstract. With the increasing urbanization and technological advances, urban driving is bound to be a complex task that requires higher levels of alertness. Thus, the driver's mental workload should be optimal in order to manage critical situations in such challenging driving conditions. Past studies relied on driver's performances used subjective measures. The new wearable and non-intrusive sensor technology, is not only providing real-time physiological monitoring, but also is enriching the tools for human affective and cognitive states tracking. This study focuses on a driver's physiological changes using portable sensors in different urban routes. Specifically, the Electro-Dermal Activity (EDA) of ten driving experiments in three types of routes are considered: rest area, city, and highway driving. We consider the Hurst exponent (H) as a new feature of the EDA signal, in addition to the 'startle' responses characterizing the electrodermal reactions (EDR). A statistical classification method based on 'Random Forest' provides an order of relevance in routes classification complexity. The preliminary results of this study confirm that on average, city driving invokes highest level arousal (EDR) and the corresponding EDA is more complex, compared with that of highway driving and rest period. Such analysis may help in the driver's state assessment especially in the case of autonomous vehicle where the driver's comfort and safety issues are crucial. Ultimately, we seek to develop a model for mental workload variability in different driving environment complexity.

Keywords. Electrodermal Activity (EDA), Startles, Hurst exponent, Urban spaces, Random Forest

1 INTRODUCTION

Stress arises when the responses capabilities of a person to master the environmental demands are not sufficient [1]. It is defined as the unique set of responses (intellectual, emotional and physiological) to a stimulus[2]. Stress among drivers varies with driver's own susceptibility to stress, his/her reaction to the environment (road condition, weather, temporal factors, etc.). Moreover, the driver's mental workload increases with events in reaction to surrounding traffic and necessary manoeuvres to reach an objective (i.e. destination). In addition, tasks such using mobile devices (cell phones, tablets, GPS, etc.), eating, drinking and talking with passengers while driving require an increased level of awareness and can increase the stress level [3]. While driving, the emotional factors are key elements in decision making and therefore to improve safety and comfort [4] An automatic recognition of the driver's cognitive and emotional states aim to assist the driver in performing primary, secondary and tertiary driving tasks where primary driving tasks include steering, braking, accelerating, correct lane choosing, etc. Secondary tasks refer to an activity such as manipulating gearbox, windscreen wipers, turn signal are considered as tasks related to safety, while tertiary driving tasks (such as activating and regulating the air conditioner, seat heater, radio and mobile devices such as cell phones, tablets, GPS, etc. use) mainly refer to the driver's comfort [5]. Over the years, various tools and methods were proposed for driver's alertness levels. The development of eye movement monitors, gaze detectors, speech technologies were among several human-machine interactions assessment tools. Nowadays, information from the driver's voice, face, physiological signals and contextual state can be captured and processed in order to improve ways of Human-Computer Interaction [6]. Physiological signals captured using non-invasive and non-intrusive sensors offer particular advantages in that regard, as they can determine a driver's affective state in real-world situations. Metrics derived from these signals have been used in several fields such as simulation of flights for pilots [7], normal daily commute in the city and highway [9] and real-world driving in rural roads [8].

In a pioneering study, [9] pointed out that features extracted from Electrodermal Reaction (EDR) statistic features extracted from the Electrodermal Activity (EDA) were most closely correlated with driver's stress level.

This paper offers a new objective analysis on the EDA data based on the work of [10] where we examine the complexity of the routes and the induced EDA levels, and compare its relevance with that of EDR features. The protocol and the data collected were detailed in a previous work [11]. First, we characterize the electrodermal activity with features qualified classically as the most accurate descriptors in stress determination. The contribution of this paper consists of considering the auto-correlation patterns of the EDA signal as a new feature. The fractal approach as a complexity indicator of the EDA signal offers a first EDA complexity analysis [12]. A classification based on random forest [13] clearly suggests the reliability of the fractal analysis in correctly ordering the drivers arousal state and the driving routes.

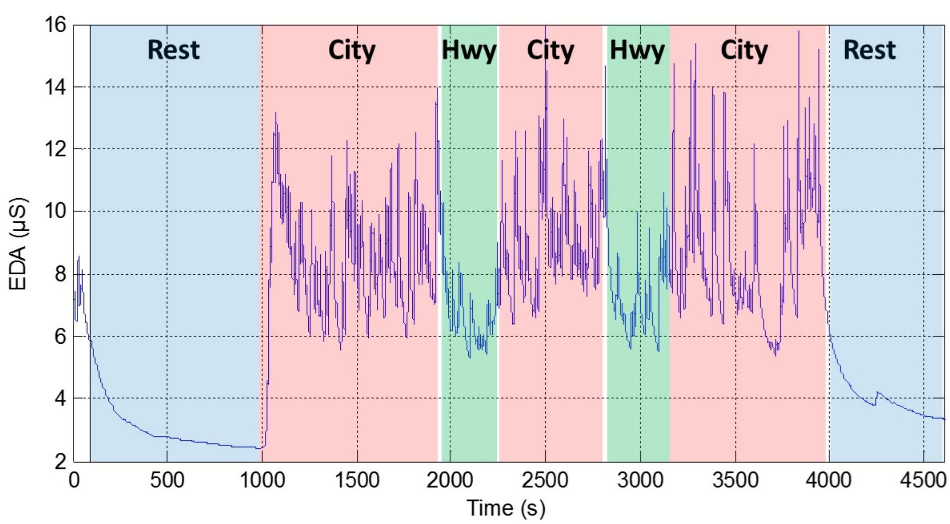

Figure 1: The raw EDA signal of participant 3-drive N2

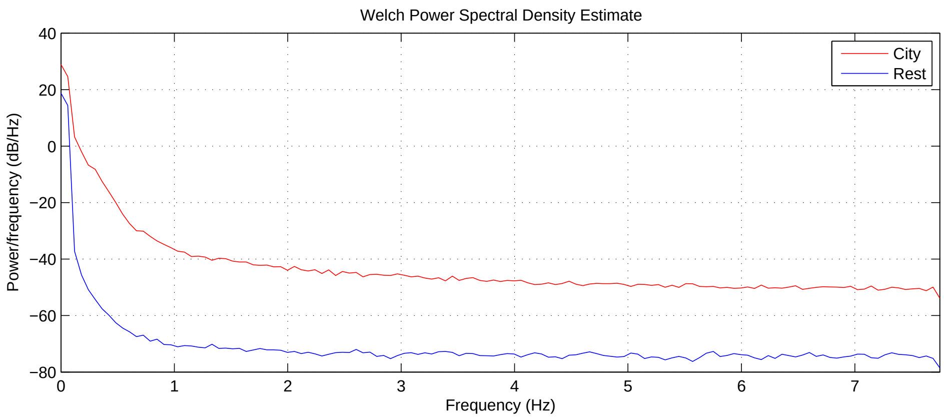

Figure 2: The power spectral Density of the City and the rest driving period of the participant 3-drive N2

References

[1] Mc Grat3h, J.E., 1970. A conceptual formulation for research on stress. Social and Psychological Factors in Stress, 10, 10-21.

[2] Orris, P., Hartman, E.D., Strauss, P., Anderson, J. R., Collins, J., Knopp, C., Xu, Y., and Melius, J., 1997. Stress among package truck drivers. American Journal of Industrial Medicine, 31, 202-210.

[3] Sharma, Anuj, Velipasalar, Senem, Singh, Sanjay M.D.; Engel, Dave B.S.; and Gyawali, Sunil Ph.D., 2012. Effect of Freeway Level of Service and Driver Education on Truck Driver Stress - Phase 1. Final Reports & Technical Briefs from Mid-America Transportation Center. Paper 43.

[4] Eyben F., Wöllmer M., Poitschke T., Schuller B., Blaschke C., Färber B., Nguyen-Thien N. 2010. Emotion on the road: necessity, acceptance, and feasibility of affective computing in the car. Adv.Hum-Comp.Int., 1-17.

[5] Bubb, H. 2003. Fahrerassistenz primar ein Beitrag zum Komfort oder fur die Sicherheit? VDI Berichte, no. 1768, pp. 25–44, 2003

[6] Batliner, A., Burkhardt, F., Van Ballegooy M., Noth, E., 2006. A taxonomy of applications that utilize emotional awareness, in Proceedings of the 1st International Language Technologies Conference (IS-LTC '06), pp. 246–250, Ljubljana, Slovenia.

[7] Skinner M.J. & Simpson P.A., 2002. Workload Issues in Military Tactical Airlift. The International Journal of Aviation Psychology, 12:1, 79-93

[8] Helander, M., 1978. Applicability of drivers' electrodermal response to the design of the traffic environment. Journal of Applied Psychology, Vol 63(4), Aug 1978, 481-488

[9] Healey, J., Picard, R.W., 2005. Detecting Stress During Real-World Driving Tasks Using Physiological Sensors, IEEE Trans. on Intelligent Transportation Systems, Volume 6, No. 2, June 2005, pp. 156-166.

[10] Healey, J, 2000. Wearable and automotive systems for affect recognition from physiology, Ph.D. dissertation, MIT.

[11] El Haouij, N., Ghozi, R., Poggi, J-M., Ghalila, S. and Jaidane, M., 2015. Feature extraction and selection of electrodermal reaction towards stress level recognition: two real-world driving experiences, 47èmes Journées de Statistique de la SFdS (JdS), Lille, 1-5 juin, available on http://papersjds15.sfds.asso.fr/submission_183.pdf

[12] Bardet, J-M., Lang, G., Oppenheim, G., Philippe A., Taqqu M.S. and Stoev S., 2003, Semi-parametric estimation of the long-range dependence parameter: a survey, in Theory and applications of long range dependence, Birkhaüser, Eds Taqqu M.S., Oppenheim G., Doukhan P.

[13] Breiman, L., 2001. Random forests. Machine learning, 45(1), 5-32.