Combining contextual and neurophysiological information for predicting driver's turning intent

Alexander Trende[1], Anirudh Unni[2], Martin Fränzle[1,2], Jochem W. Rieger[2]
[1]OFFIS – Institute for Information Technology
[2]University of Oldenburg

Introduction and Goal

Turning through oncoming traffic at unsignalized intersections can lead to safety-critical situations contributing to 7.4% of all non-severe vehicle crashes [Harding, 2014]. An important reason for these crashes are human errors in the form of incorrect estimation of the gap size with respect to the oncoming vehicle. Human intention prediction could help reduce the frequency of these safety-critical situations by predicting dangerous turning manoeuvres in advance. Turning behaviour at intersections has been investigated and modelled by several researchers over the past decades (e.g. [Ragland, 2006][Yan, 2007]). Though most research focused on demographic and contextual information, like the gap size in the stream of oncoming vehicles as predictors for the turning intention, [Damm, 2019] presented a case study for how the combination of neurophysiological sensors and contextual information could be used to predict and reflect in low-level control the human's turning intention to improve safety of turning manoeuvres. The aim of the current study was to enhance the accuracy of the underlying intention prediction beyond that first case-study. It addresses more thoroughly the creation of a turning intention model based on the combination of neurophysiological whole-head fNIRS brain activation measurements and contextual information about the traffic situation recorded during a driving simulator study. We show how the inclusion of fNIRS measurements can increase the performance of such a model in comparison to a context-only intention prediction model.

Methods and Data Analyses

We presented the participants of the driving simulator study with a cover story that they are driving in a time-critical situation through urban traffic. On their way through the simulated scenario, participants were repeatedly confronted with left-lane merging situations at unsignalized intersections where theyhad to wait and then decide when to make a turn through an oncoming stream of vehicles. The data used for the modelling procedure was the context information about the traffic situation recorded at these intersections along with whole-head fNIRS brain activation. During cross validation a principal component analysis was performed on the training set of the fNIRS data. The first principal component (PC1) has been shown to be linked to motion artifacts [Brigadoi et al., 2014], and was removed from further analysis. The PC explained on average 38% +- 20% of the variance in the respective data sets. We used a discrete Bayesian network to model the turning intention. Bayesian networks have been used widely in the modelling of brain activation measurements (e.g. [Burge, 2009][Yang, 2010][He, 2016]). A Bayesian network represents the joint probability distribution of its variables by an easy-to-understand graph structure. The Bayesian network fitted for the turning intention prediction consists of ten variables (s. Fig. 1). The seven principal components (PC2-PC8) of the brain activation measurements which explain most variance were used as variables in the network. The seven PCs together explained on average 32% +- 16% of the variance. As contextual information, the gap sizes between consecutive cars and the number of cars already having been waited for were included. The tenth variable represents the merging intention. We used uniform discretization to discretize all variables into four groups except for the already binary turning intention variable. We calculated the accuracy and area-under-curve to evaluate the model. We fitted one model for each of the study participants and a 5-fold cross-validation was performed. We compare these performance metrics with respect to three different sets of evidences which are available for the inference. The three evidence sets are fNIRS-only, context-only, and a model with both.

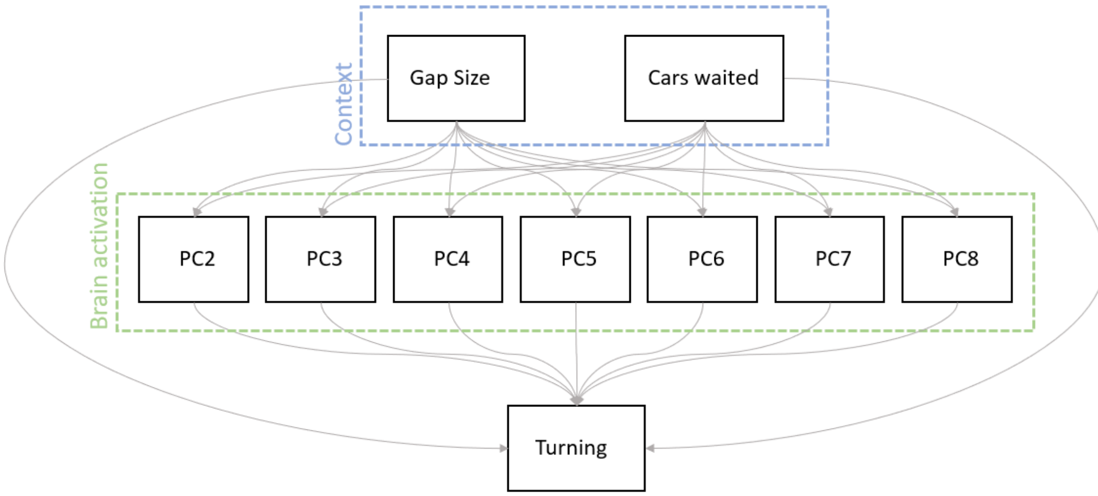

Figure 1. Structure of the Bayesian network for turning intention prediction. The variables can be separated into context (blue box) and brain activation (green box) related groups.

Results

We fitted one model for each of the 12 participants of the driving simulator study. Fig. 2 shows the accuracies (left) and area-under-curve (right) values for the three different evidence sets. The mean accuracies for the three models were 59%, 70% and 81% and the area-under-curve was 0.61, 0.78 and 0.89, respectively. The model combining both fNIRS and context evidences performed best in both respects. The model using only context evidence shows a very high variance indicating a variability of subjective preferences regarding preferred gap sizes for turning maneuvers.

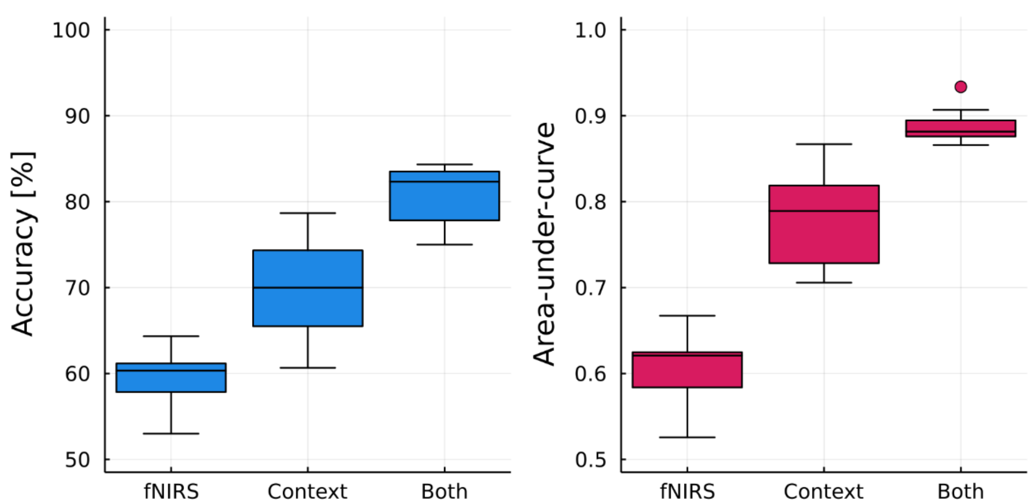

Figure 2. One model for each of the 12 participants was fitted. The resulting distributions of accuracies (left) and area-under-curve values (right) for the turning intention prediction models are displayed as boxplots.

Discussion and Conclusion

Our results show that the inclusion of brain activation measurements can help to improve the turning intention prediction by 11% with respect to the median accuracy of a simple context-based model, effectively reducing the error rate by a third. This result could be further investigated by performing a feature importance analysis, such as permutation feature importance or SHAP (SHapley Additive exPlanations**)**. Such an approach could show the importance and influence of each variable to the model's output in more detail. In further work, we want to investigate which brain areas contribute most to the prediction using above mentioned feature importance analysis. Bayesian networks can be used to sample data and thus simulate data given a specific set of evidence. We want to harness this approach to have a more detailed look into safety-critical, rare cases for traffic manoeuvres like the turning manoeuvres investigated in this study. A possible safety gain provided by such a turning intention prediction could also be calculated as suggested in [Damm, 2019].

References:

Brigadoi, S., Ceccherini, L., Cutini, S., Scarpa, F., Scatturin, P., Selb, J., ... & Cooper, R. J. (2014). Motion artifacts in functional near-infrared spectroscopy: a comparison of motion correction techniques applied to real cognitive data. *Neuroimage*, *85*, 181-191.

Burge, J., Lane, T., Link, H., Qiu, S., & Clark, V. P. (2009). *Discrete dynamic Bayesian network analysis of fMRI data* (Vol. 30, No. 1, pp. 122-137). Hoboken: Wiley Subscription Services, Inc., A Wiley Company.

Damm, W., Fränzle, M., Lüdtke, A., Rieger, J. W., Trende, A., & Unni, A. (2019, June). Integrating neurophysiological sensors and driver models for safe and performant automated vehicle control in mixed traffic. In *2019 IEEE Intelligent Vehicles Symposium (IV)* (pp. 82-89). IEEE.

Harding, J., et al. (2014). *Vehicle-to-vehicle communications: readiness of V2V technology for application* (No. DOT HS 812 014). United States. National Highway Traffic Safety Administration.

He, L., Liu, B., Hu, D., Wen, Y., Wan, M., & Long, J. (2016). Motor imagery EEG signals analysis based on Bayesian network with Gaussian distribution. *Neurocomputing*, *188*, 217-224.

Ragland, D. R., Arroyo, S., Shladover, S. E., Misener, J. A., & Chan, C. Y. (2006). Gap acceptance for vehicles turning left across on-coming traffic: implications for intersection decision support design.

Yan, X., Radwan, E., & Guo, D. (2007). Effects of major-road vehicle speed and driver age and gender on left-turn gap acceptance. *Accident Analysis & Prevention*, *39*(4), 843-852.

Yang, G., Lin, Y., & Bhattacharya, P. (2010). A driver fatigue recognition model based on information fusion and dynamic Bayesian network. *Information Sciences*, *180*(10), 1942-1954.