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DeepTake Summary
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Problem and Solution and Insights:

With the booming autonomous vehicle (AV) industry, users are able to spend less and less of their attention on the road and more on non-driving related tasks (NDRTs). However, there currently exists no AV system that allows the vehicle to maintain control of all driving-related activites 100% of the time. Wether it be for safety reasons or for legal reasons, the AV must return control to the driver every so often. For example, if driving conditions worsen to the point that the AV is not confident that it will be able to protect the driver better than him/herself, the human driver will need to take control.

Pakdamanian et. al. realized that the manner at which the action of the AV passing control back to the human driver (takeover) is performed is extremely important in terms of the driver's safety. Certain aspects of the driver's state at the time of the takeover have a large impact on how smoothly the takeover goes. The factors that determine takeover quality include the driver's cognitive load, emotions, and trust. Such factors are subjective in nature and cannot be easily determined by objective measurements. Objective measures that DeepTake focuses on that can be taken to determine subjective observations on the driver include eye movement, heart rate, and galvanic skin response (GSR), all of which play a key role in determining the fitness of the driver to retake control of the vehicle. Other objective measurements taken into account are a pre-driving survey of the driver, and vehicle data such as lane distances, the distance to a potential hazard, steering wheel angle, velocity, and the angles of the throttle and the brake. All of this data is periodically fed into a deep neural network (DNN) built by the DeepTake researchers to determine takeover intention (wether or not the driver will takeover control), takeover time (the time it would take the driver to takeover control), and takeover quality (the confidence that the DeepTake system has that the driver will takeover smoothly).

The researchers tested their system on a driving simulator. There were 20 participants (11 female, 9 male) in the study who either have normal vision or were able to have normal vision via correction. All of the participants were from the same university. 3 participants' data was not used because it was of poor quality. They were places in 1 of 5 driving scenarios which all involved driving on a 4-way highway. Their eye movement, heart rate, and GSR was tracked throughout each trial and fed into the DNN for training and testing purposes. Throughout each trial, the participant participated in some sort of NDRT, either conversation with a passenger, using a cellphone, reading articles, or solving arithmetic problems.

After all of the data was collected from each trial, the researchers had roughly two million observations to train their model with. The next step in the process was comparing DeepTake with existing deep-learning models which perform similar functions. There were 6 competitors: Logistic Regression, Gradient Boosting, Random Forest, Bayesian Network, Adaptive Boosting (Adaboost), and Regularized Greedy Forest (RGF), and DeepTake outperformed them all.

Strengths and Weaknesses:

The research done by Pakdamanian et. al. is sound for the most part. They certainly identified an interesting problem, came up with an effective solution, and presented their findings in a logical and intuitive manner that is easily understood by a broad audience. There are, however, many limitations in their work cause by a narrow participant selection pool. There were too few participants, the age range of the participants is too acute as all users were between 18 and 30, all of the participants were from the same geographic area, race was not a factor, and all participants were required to have normal vision. All of these factors limited diversity in the dataset, likely hampering the breadth of users that would benefit from the software.