DISTRACT: Driver Inattention State Transition Recognition Using Attention-Based Convolutional Transformers

Dey, Ronit (School: North Carolina School of Science and Mathematics)

Distracted driving represents an escalating public safety crisis, with its role in motor vehicle collisions and resulting fatalities steadily increasing. Despite advances in distracted driving classification (DDC) systems, current approaches remain limited to detecting distraction. They fail to model or quantify a driver's attention over time, a key limitation preventing adaptive safety systems. In response, this study introduces the DISTRACT model. This comprehensive model combines advanced computer vision with human attention dynamics to enable real-time quantification of driver attention. DISTRACT integrates three key components. First, it features a hybrid Convolutional Neural Network (CNN)-Vision Transformer (ViT) image classification model that classifies nine distinct driver states with exceptional accuracy, achieving an F1-Score of 95.51%. Next, those classifications are converted into probabilities and smoothed using a Simple Moving Average (SMA) to identify transitions between normal driving and distraction. The time-series analysis exhibited just a 10.78% average error in estimating distraction length. Lastly, a severity quantification function translates the distraction duration into a 0-1 severity score. This function was derived from empirical crash risk data, reflecting the exponential increase in crash risk associated with prolonged lengths of distraction. Integrating the DISTRACT model's severity score into ADAS could allow vehicle safety systems to proactively adapt to driver attention levels rather than react to emergencies, marking a new paradigm in intelligent driver monitoring. By transforming the DISTRACT model from concept to reality, we can pioneer intelligent and adaptive vehicular safety systems that save countless lives.

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