Demo: Continuous Diver Monitoring and real-time inference of Dangerous Driving

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***Abstract*—In recent years, the detection of dangerous driving has been a matter of great importance. However, finding a practical yet minimally intrusive solution has proven to be challenging, as current technologies heavily rely on visual features or physical proximity. To address this issue, we leverage mmWave radar exclusively to identify dangerous driving behaviors. By analyzing unique patterns of range-doppler caused by nine typical dangerous driving actions, we present a demonstration of our method called *mmDrive* . This approach collects real-time mmWave data and utilizes a CNN classifier to detect instances of dangerous driving and classify the specific action among the nine categories. Through extensive experiments involving five volunteer drivers in real driving conditions, we have observed that our system can differentiate between dangerous driving actions with an average accuracy of $97\%(\pm 2\%)$.**

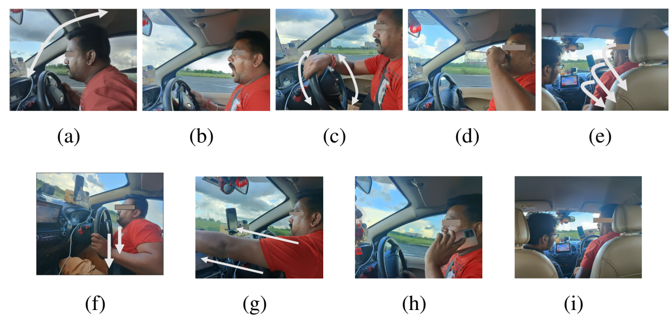


Fig. 1. Dangerous driving activities – (a) Nodding, (b) Yawning, (c) Steering anomaly, (d) Drinking, (e) Talking to the rear passenger, (f) Picking a drop, (g) Fetching from the dash, (h) Using mobile, (i) Talking sideways

I. Overview

According to the World Health Organization (WHO), approximately 1.2 million people die each year worldwide as a result of road accidents, with dangerous driving being a major contributor, accounting for around 45% of these incidents. Although significant technological advancements have been made in monitoring dangerous driving in real-time, current vision-based methods face challenges regarding privacy concerns, particularly in public and shared vehicles. Moreover, the accuracy of detection is influenced by various factors like lighting conditions and camera orientation. Similarly, wearable-based approaches are difficult to apply universally since the characteristics observed in one age group may not seamlessly apply to another age group. Additionally, ensuring that drivers consistently use the necessary wearable devices is not a simple task.

The rise of 5G technology, which is built upon mmWave communication, has brought about a significant shift in the paradigm. With the integration of mmWave hardware into a wide range of devices, this technology has become pervasive. A mmWave radar, capable of measuring various parameters like distance and velocity, has been utilized to address diverse problems such as human activity recognition, gesture recognition, vital sign detection, and even voice reconstruction, all involving estimation of positioning and movement. In this demonstration, we utilize a Frequency-modulated continuous-wave (FMCW) mmWave radar to monitor dangerous driving behaviors from the perspective of the driver. When distracted driving is detected, immediate actions can be taken using our approach, such as warning the driver or notifying nearby vehicles with appropriate messages.

Advantages over Existing Approaches: Utilizing mmWave sensing for monitoring dangerous driving offers several advantages over existing approaches, including the following: (i) Direct Monitoring: mmWave sensing enables direct monitoring of a driver's movements, unlike existing methods that rely on indirect observations such as vehicle states and kinematics. (ii) Privacy-Friendly: Unlike cameras, mmWave sensing minimizes privacy invasion as it doesn't capture visual features of the environment. (iii) Device-Free: Unlike wearables, mmWave sensing doesn't require the driver to wear or carry any additional device. It measures passively, allowing the driver to move freely without any restrictions. (iv) Micro-Movement Detection: mmWave sensing can detect subtle movements like yawning, which is crucial for determining a driver's sleepy state. Despite these advantages, there are still challenges that our proposed method needs to overcome in order to be practically viable.

Challenges: Monitoring activities within a moving vehicle using a mmWave radar presents several challenges that need to be addressed for an effective system: (i) Noisy Environment: The interior of a car is a noisy environment where various movements from objects inside the car and external factors like road and traffic conditions can directly impact mmWave signals. (ii) Multiple Passengers: Cars can have multiple passengers, but it is essential to focus on monitoring the specific movements of the driver to detect dangerous driving scenarios. Therefore, separating the driver's movements from others is crucial to ensure accurate monitoring of dangerous driving behaviors.

We identify three actions related to driver fatigue/drowsiness (nodding, yawning, steering anomaly) and six actions indicating driver distraction (drinking/eating, turning back, picking up/dropping objects, fetching forward, speaking on mobile, turning heads to talk to passengers). These nine actions (shown in Fig. 1) are considered potentially dangerous and should be avoided while driving. Using a commercially available FMCW mmWave radar, we analyze signal features such as range doppler, range profile, and noise profile to distinguish these activities from regular driving actions. In Fig. 2, we show the variation in the range-doppler data across these 9 dangerous activities. For the classification of these activities, we have developed a Fused-CNN-based driver behavior model for this purpose. To replicate our findings, we have made our implementation and a subset of our dataset available as open-source on GitHub[1]. Through extensive deployment and field experimentation, we collected 20 hours of driving data from 5 users using three different vehicles (two sedans and one SUV).

II. System Design

The proposed method, *mmDrive* , utilizes a combination of FMCW mmWave radar measurements and IMU sensor data to monitor and classify dangerous driving behaviors. The processing steps involved in the formulation of *mmDrive* include pre-processing and a classification pipeline. In the pre-processing step, feature frames are concatenated to capture the temporal variations, and a min-max scaler is applied to normalize the features. The classification pipeline incorporates a Fused-CNN architecture (shown in Fig. 3) that extracts features from range-doppler, range profile, and noise profile information. The extracted features are then passed through the FE Network to obtain embeddings, and subsequent classifiers, namely the Dangerous Driving Behaviors (DDB) Classifier and Dangerous vs. Normal Driving (DVN) Classifier, are used to classify different driving actions. Lazy inferencing is implemented to optimize computational resources by selectively querying the DDB Classifier based on the output of the DVN Classifier. The proposed method has been evaluated using a dataset collected from driving experiments with multiple users and vehicles. . An elaborate description of the technique is included in [1].

III. Conclusion

In this demonstration, we emphasize the importance of selecting appropriate features from the measurements of a single commercially available mmWave FMCW radar. The hardware setup of *mmDrive* is shown in Fig. 4(a). Our solution is compact, pervasive, and privacy-preserving, as it operates entirely on the device without relying on external systems. As shown in Fig. 4(b), the accuracy of *mmDrive* in detecting critical driver activities associated with dangerous driving scenarios is demonstrated to be greater than 95%. We conduct extensive evaluations of *mmDrive* in various real-world environments. The positive results obtained from these evaluations strongly indicate that *mmDrive* has the potential to save lives and contribute to on-road safety in diverse situations.

[1]https://github.com/arghasen10/mmdrive.git

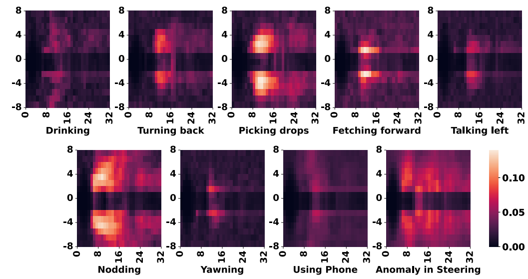


Fig. 2. Range-doppler heatmaps for driving actions

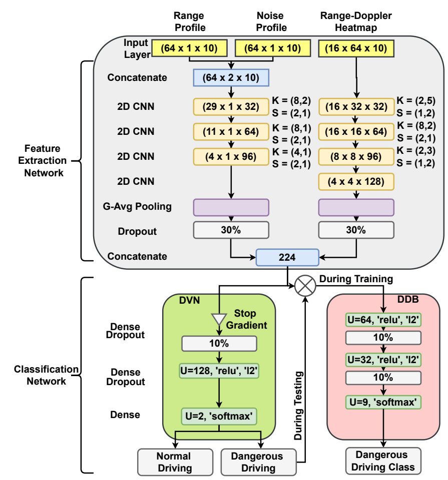
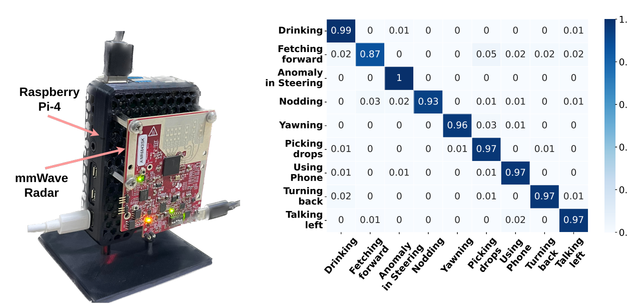


Fig. 3. Fused-CNN Model Architecture

References

[1] A. Sen, A. Mandal, P. Karmakar, A. Das, and S. Chakraborty, "mmdrive: mmwave sensing for live monitoring and on-device inference of dangerous driving," in *2023 IEEE PerCom*, 2023, pp. 2–11.



(a) (b)

Fig. 4. (a) *mmDrive* Setup, (b) Confusion matrix for all the dangerous driving behaviors using the proposed Fused-CNN classifier