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Robust Multiview Multimodal Driver Monitoring System Using Masked Multi-Head Self-Attention

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Outline

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Introduction

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Modern *driver monitoring systems* (DMSs) in Level-2+ self-driving-enabled cars aim to enhance safety by estimating drivers' readiness levels for driving and enabling safe control handovers when necessary.

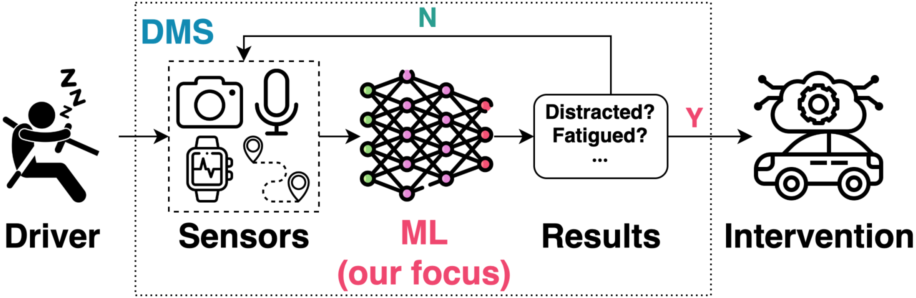

Fig. 1: A simplified illustration of a DMS.

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These systems usually rely various sensors, which may be deployed at different in-car locations, to comprehensively monitor drivers' states, e.g.,

- **RGB**: optical details.
- **Depth**: 3D information.
- **Infrared**: thermal information.
- **ECG**: heart rates.
- **Audio**: speech and sound.

Hence, modern DMSs are *multimodal* (and *multiview*).

Our work specifically focuses on *driver action recognition*, which involves classifying drivers' actions into *normal driving* and several *non-driving-related activities* (NDRAs), e.g., texting and drinking.

(a) Top IR **(b)** Top Depth **(c)** Front IR **(d)** Front Depth

Fig. 2: Sample frames from the DAD dataset [1].

Our contributions in this paper are as follows:

1. We propose a novel robust *multiview multimodal* DMS for driver action recognition that leverages feature-level fusion through masked *multi-head self-attention* (**MHSA**).
2. We manually annotated the anomalies in DAD dataset with 9 fine-grained classes of non-driving-related activities (NDRAs).
3. We conduct extensive experiments on the DAD dataset to compare different fusion strategies, assess the significance of individual views/modalities, and evaluate the efficacy of patch masking in enhancing MHSA's robustness against view/modality collapses. Results show that our MHSA-based DMS achieves state-of-the-art performance with an AUC-ROC score of 97.0%.

Related Work

- AUC-DD [2] is the first public dataset for DMSs. It was collected using an RGB camera from a single side view and thus have some limitations.

Fig. 3: A sample from the AUC-DD dataset [2] illustrating that RGB is not robust to illumination changes.

Related Work
Driver Monitoring Datasets

- Later databases [1], [3]–[5] have incorporated additional views and modalities to address these issues.
  - For example, top and front views have also been introduced to capture the driver's hand and head movements amongst other movements.
  - Regarding modalities, IR and depth have also become popular, as they can provide thermally based features and geometry information, which are complementary to the optical details from RGB.
- Among these datasets, we benchmark our models on DAD [1], the only one designed for SAE L2+ with open-set recognition: its test set contains extra classes of NDRAs in addition to those in the training split.

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Various multiview multimodal DMSs have also been proposed with different emphases:

- Kopuklu *et al.* [1] proposed a novel learning framework based on contrastive learning.
- Ortega *et al.* [4] and Su *et al.* [6] proposed to leverage Conv-LSTM structures.
- Only Shan *et al* [7] proposed a feature-level modality fusion method, but it has several drawback:
    - Features are pooled before fusion, which leads to the loss of semantic information.
    - Its fusion module has the additional task of handling the temporal dimension.

Method

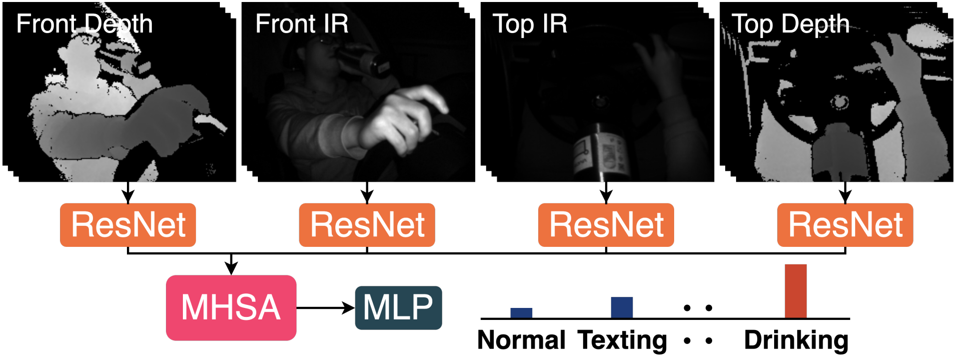


Fig. 4: An overview of our proposed DMS.

Method

Overview

1. We first use R3D-18 [8] to extract spatiotemporal features from the input multiview multimodal videos.
2. We the feed the feature maps to our masked multi-head self-attention module to interact and fuse the features.
3. We also used the supervised contrastive learning based on MoCo [9] to facilitate training.
4. The classifier is co-trained under the supervision of the cross-entropy loss.

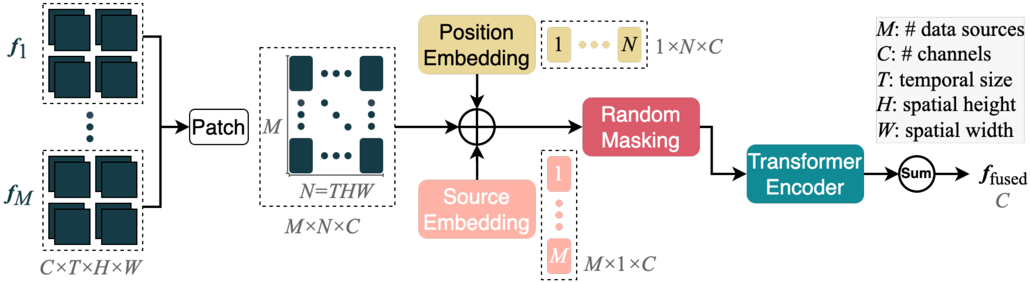
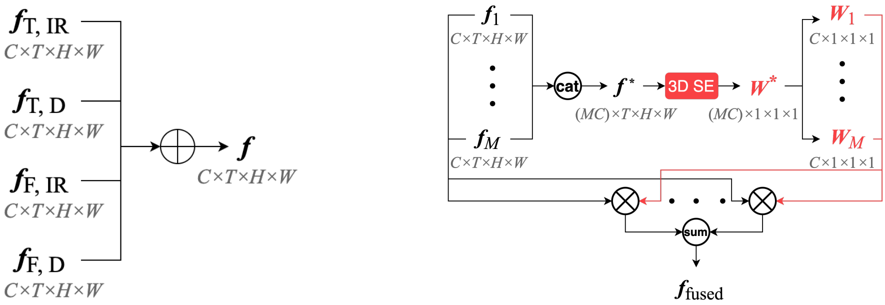


Fig. 5: The architecture of our masked multi-head self-attention module.

Method

Other Fusion Methods



(a) Sum. **(b)** SE.

Fig. 6: The architectures of the other fusion methods.

Experiments

Experiments

Detecting NDRAs

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Sources	Decision [1]	Sum	Conv	SE	AFF	MHSA (our)
Top (D)	91.3	**92.9**				
Top (IR)	88.0	**91.3**				
Top (D+IR)	91.7	91.7	92.2	92.3	92.5	**92.9**
Front (D)	90.0	**91.7**				
Front (IR)	87.0	**90.2**				
Front (D+IR)	92.0	92.7	92.9	92.9	**93.1**	**93.1**
Top+Front (D)	96.1	94.8	05.8	05.9	96.5	**96.7**
Top+Front (IR)	93.1	94.5	94.6	94.9	95.0	**95.7**
Top+Front (D+IR)	96.6	96.3	96.2	96.4	96.7	**97.0**

Table 1: The AUC-ROC scores of different fusion methods on the NDRAs detection task on DAD. **D** and **IR** denote the depth and infrared modalities, respectively. The best scores for each view and modality are in **bold**.

Experiments

Classifiying Drivers' Actions

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Source	Decision	Sum	Conv	SE	AFF	MHSA (ours)
Top (D)	84.3					
Top (IR)	83.7					
Top (D+IR)	84.5	85.0	85.4	85.4	85.4	**85.7**
Front (D)	87.7					
Front (IR)	83.7					
Front (D+IR)	87.9	87.7	88.1	88.2	88.5	**88.7**
Top+Front (D)	90.7	90.1	90.4	90.5	90.6	**90.9**
Top+Front (IR)	88.4	89.9	90.2	90.2	90.4	**90.6**
Top+Front (D+IR)	90.9	90.8	91.2	91.4	91.5	**91.6**

Table 2: The mAP scores for multi-classification of drivers' activities on DAD.

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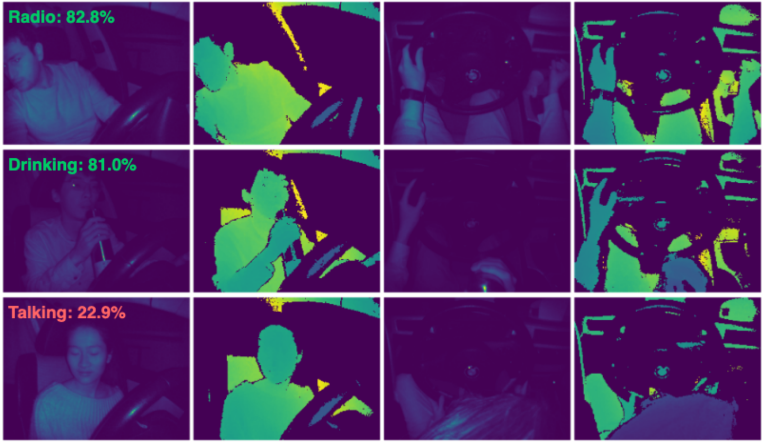
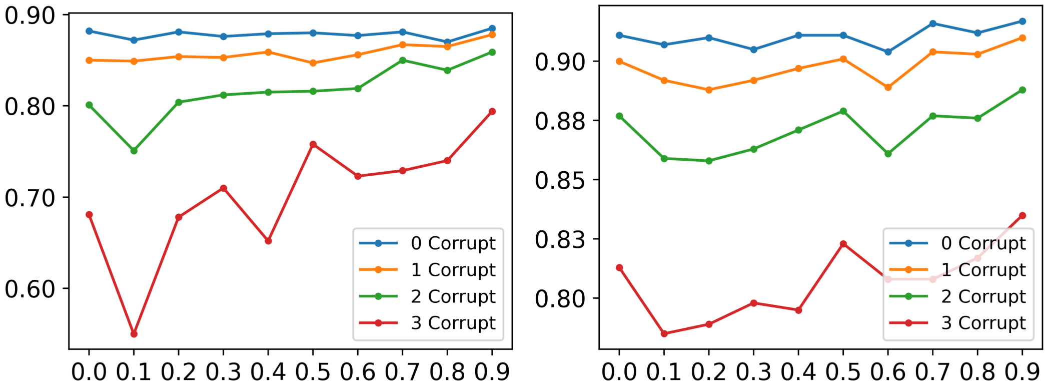


Fig. 7: Visualisation of the middle frames of four test samples from DAD.

Experiments

Robustness against Modality/View Collapses



(a) Mult. Acc. **(b)** Mult. mAP

Fig. 8: Masked training improves MHSA's robustness against corrupt views/modalities.

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Thanks!

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