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ARTSeg: Employing Attention for Thermal images Semantic Segmentation

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Abstract. The research advancements have made the neural network algorithms deployed in the autonomous vehicle to perceive the surrounding. The standard exteroceptive sensors that are utilized for the perception of the environment are cameras and Lidar. Therefore, the neural network algorithms developed using these exteroceptive sensors have provided the necessary solution for the autonomous vehicle's perception. One major drawback of these exteroceptive sensors is their operability in adverse weather conditions, for instance, low illumination and night conditions. The useability and affordability of thermal cameras in the sensor suite of the autonomous vehicle provide the necessary improvement in the perception of the autonomous vehicle in adverse weather conditions. The semantics of the environment benefits the robust perception, which can be achieved by segmenting different objects in the scene. In this work, we have employed the thermal camera for semantic segmentation. We have designed an attention-based Recurrent Convolution Network (RCNN) encoder-decoder architecture named ARTSeg for thermal semantic segmentation. The main contribution of this work is the design of encoder-decoder architecture, which employ units of RCNN for each encoder and decoder block. Furthermore, additive attention is employed in the decoder module to retain high-resolution features and improve the localization of features. The efficacy of the proposed method is evaluated on the available public dataset, showing better performance with other state-of-the-art methods in mean intersection over union (IoU).

Keywords: Thermal Image · Semantic segmentation · Recurrent Convolution Neural Network · Attention .

1 Introduction

The last three decades have shown significant technological advancements that reflect the development of efficient sensors. The applicability of these sensors in the autonomous vehicle ensures its safe and secure services to the urban envi-

ronment, as indicated by SOTIF-ISO/PAS-21448¹. Keeping safety as a priority in autonomous vehicles, perception of the environment play a critical role along with localization, planning and control module [1] [2] [3]. In the context of perception, the most common exteroceptive sensors that are being deployed are cameras (visible spectrum) and Lidar. The utilization of these sensor modalities provides the necessary perception for the autonomous vehicle. However, these sensors have limitations in adverse weather conditions at night and in low illumination environments. For instance, cameras (visible spectrum) are operated in the visible spectrum domain and provide an in-depth understanding of the environment, but environmental conditions like sun-glare, low illumination affect the camera result, thus yielding low performance in perception algorithms. Lidar, as a surrogate to 2D information from cameras, gives the 3D information about the environment. Lidar provides 3D information of the environment by making a point cloud map by projecting nearly thousands of laser beams to the environment. Besides, Lidar effectiveness in providing the detailed 3D representation of the environment, its expensive cost and limitation in adverse weather conditions are the prime concern of its detriment. On the other hand, thermal cameras, contrary to cameras (visible-spectrum) and Lidar, enable the perception algorithms to be utilized in adverse weather conditions, such as at night or low illumination environmental conditions [4].

Thermal cameras operate in the infrared domain and capture the infrared radiation emitted by the different entities in the environment having the temperature above absolute zero [6]. This property of the thermal camera makes it an optimal solution to be included in the sensor suite of the autonomous vehicle for the perception of the environment in low illumination and night conditions. Furthermore, besides thermal cameras applicability in adverse weather conditions, the affordability of thermal cameras gives the potential to be utilized in different perception tasks for the autonomous vehicle. These perception tasks involve different computer vision applications such as object detection [7] [8], visual tracking [9] and person re-identification [10]. In order to determine the semantics of environment for the scene understanding for the autonomous vehicle, semantic segmentation plays a vital role in the perception of the autonomous vehicle. The capacity of thermal cameras to operate at night and low illumination conditions motivate to use of the thermal camera for semantic segmentation and investigate the semantic segmentation problem using the thermal cameras.

In computer vision, semantic segmentation provides an in-depth understanding of the scene by employing a semantic label to each pixel in the image. Despite traditional machine learning approaches employed to tackle semantic segmentation problems, deep learning approaches gain unprecedented success in semantic segmentation. Most of these deep learning techniques, for instance, convolutional neural networks, are applied using the RGB images for semantic segmentation.

¹ <https://www.daimler.com/innovation/case/autonomous/safety-first-for-automated-driving-2.htm>

Thermal cameras provide the grey-scale image that benefits the neural networks to be employed on thermal images for different computer vision tasks.

This work explores the thermal image segmentation problem by designing a novel encoder-decoder architecture called ARTSeg. The encoder consists of a residual recurrent convolution block accompanied by a max-pooling layer. The encoder outputs a latent representation of features which is fed to the decoder. The decoder incorporates additive attention from the residual connections from the encoder. The ARTSeg is evaluated on a public dataset and compared with state-of-the-art methods. The main contribution of this work are as follows:

1. We have designed a novel encoder-decoder architecture using residual recurrent convolution neural network.
2. We have employed the additive attention mechanism to enhance the localization of encoded features. Further, no post-processing steps are used because of employing the attention for the thermal image segmentation.
3. The proposed method's efficacy is performed on available public dataset shows better performance in term of average accuracy and intersection over union in contrast to state-of-the-art methods.

The rest of the paper is organized as follows: Section 2 explains the related work. The proposed method is described in the Section 3. Section 4 illustrate the experimentation and results for the proposed method. Finally, section 5 concludes the paper.

2 Related Work

The concept of semantic segmentation plays a critical role in the robust perception of the environment for autonomous driving. Deep neural networks, especially convolution neural networks, are mostly used for semantic segmentation using RGB cameras as a sensor modality. The early state-of-the-art method that is employed for the semantic segmentation is Fully Convolutional Network (FCN) proposed by [5]. In FCN, the fully connected layers are replaced with the convolutional layers to output the full resolution maps for the semantic segmentation using the backbone network of VGG16 [23] and GoogleNet [11] architectures, respectively.

In literature, the encoder-decoder architecture is also used for semantic segmentation. In the encoder-decoder architecture, the features are encoded to give the latent representation and then decode to provide the object details and spatial resolution. [22] have proposed the encoder-decoder architecture named SegNet. The encoder network consists of convolutional layers adopted from the VGG16 [23] network to learn the encoded representation followed by batch-normalization, rectified linear unit (ReLU) units and max-pooling layers. The

decoder follows the same encoder architecture for upsampling the encoded features for semantic segmentation. Similarly, using the encoder-decoder architecture, the encoder of the network is improved by using image pyramids [28] [29], conditional random fields [28], spatial pyramid pooling [28] and atrous convolution [30] [31]. There is a trade-off between accuracy and speed; in literature, some research is focused on improving the inference speed using the encoder-decoder architecture; for instance, [13] have proposed the encoder-decoder architecture ENet that is optimized for the fast inference speed for semantic segmentation. In order to retain the feature generalization, skip connections have been introduced for the semantic segmentation as proposed by UNet [12].

Besides, using the single sensor modality, for instance, RGB images, in literature, the fusion of thermal and visible-spectrum RGB domain is also investigated for semantic segmentation. [15] have proposed FuseNet for the semantic segmentation by incorporating the fusion of visible-spectrum RGB domain with the thermal domain. Similarly, MFNet [19] and RTFNet [21] networks follows the encoder-decoder architecture for the semantic segmentation using the fusion of RGB and thermal data. [20] have proposed the FuseSeg using the Bayesian fusion theory for the semantic segmentation using both RGB and thermal data. In addition to the fusion techniques, some research is focused on multi-spectral domain adaptation [32] [33] [34].

In contrast to the literature review, we have designed a novel encoder-decoder architecture using the residual recurrent convolution layers followed by an attention mechanism to retain the feature generalization for semantic segmentation. We have explicitly used the thermal data for the semantic segmentation without employing the fusion or domain adaption techniques in this work.

3 Methods

This section presents the proposed method for the thermal image segmentation, as illustrated in Fig.1. The proposed method is composed of encoder-decoder architecture. The encoder module of the proposed method contains the residual recurrent convolution block (RRCNN) followed by the max-pooling layer. The residual recurrent convolutional block is comprised of recurrent convolutional layers and skip connection from the encoder to decoder module. The encoder module of the architecture receives the thermal image as input and generates the encoded feature representation for the input image. Suppose x_l represent the input image at the l layer of the residual recurrent convolutional block, and a pixel is located at (u, v) at the input image on the p feature map of the recurrent convolution layer, then the output o_{uvp} is expressed in Eq.1.

$$o_{uvp}^l = (w_p^f)^T * x_l^f(u, v)(t) + (w_p^r)^T * x_l^r(u, v)(t - 1) + b_p, \quad (1)$$

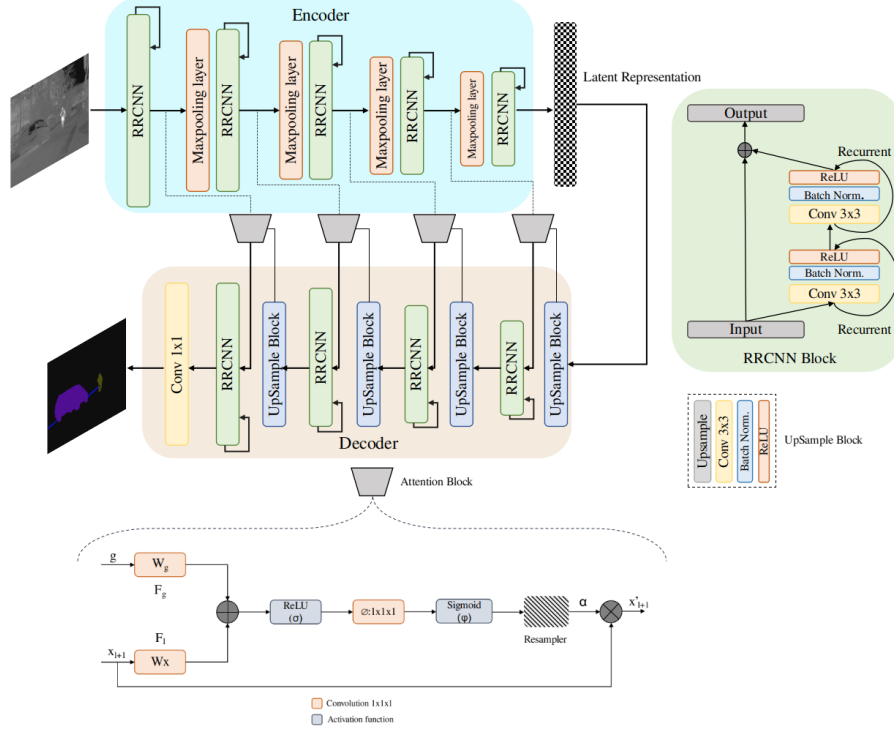


Fig. 1: The overall framework of ARTSeg Network consisting on encoder-decoder.

where w_p^f and w_p^r are the weights of convolutional and recurrent convolutional layer respectively and b_p is the bias of the network. The inputs to the convolution and l^{th} layer recurrent convolutional layer are represented as $x_t^f(u, v)(t)$ and $x_t^r(u, v)(t-1)$ respectively. In Fig.1 the recurrent convolution layer are represented in the RRCNN block with the “arrow” indicating the recurrence. The output of the recurrent convolutional layer is batch-normalized and fed to the rectified linear activation function (ReLU) as shown in Eq.2.

$$\mathfrak{F}(\mathbf{x}_1, \mathbf{w}_l) = f(o_{uvp}^l(t)) = \max(0, o_{uvp}^l(t)), \quad (2)$$

$\mathfrak{F}(\mathbf{x}_1, \mathbf{w}_l)$ represents the outcome of the activation function from the l^{th} layer recurrent convolutional network. This is summed with the input x_l in residual to give us the output of RRCNN block as expressed as Eq.3.

$$x_{l+1} = x_l + \mathfrak{F}(\mathbf{x}_1, \mathbf{w}_l), \quad (3)$$

where x_{l+1} represent the outcome from the RRCNN block.

The decoder module follows the same architecture of the encoder module with the addition of Upsample block and additive attention in the skip connections. The decoder includes the same RRCNN block as encoder module but in that case the RRCNN module is used for the upsampling of the encoded features. Fig.1 shows the decoder module with attention block. The output of the attention is calculated by the element-wise multiplication of attention coefficient and input feature maps from as shown in Eq.4.

$$x'_{l+1} = x_{l+1} \cdot \alpha, \quad (4)$$

The term g represent the vector taken from the lowest layer of the network. The purpose of the attention module is to focus on the salient region for the thermal image segmentation. Mathematically, the attention of the network is given by Eq.5. The detailed architecture is presented in Table-1.

$$\begin{aligned} s_{att}^l &= \phi^T(\sigma(W_x^T x_{l+1}^i + W_g^T g^i + b_g)) + b_\phi, \\ \alpha^l &= \varphi(s_{att}^l(x_{l+1}^i, g^i; \Theta_{att})), \end{aligned} \quad (5)$$

Table 1: The detailed architecture of the proposed ARTSeg

	Layer	Output size
	Input data	
Encoder	RRCNN-1 block	32*256*256
	Max pooling	32*128*128
	RRCNN-2 block	64*128*128
	Max pooling	64*64*64
	RRCNN-3 block	128*64*64
	Max pooling	128*32*32
	RRCNN-4 block	256*32*32
	Max pooling	256*8*8
	RRCNN-5 block	256*8*8
Decoder	Up-Block	128*32*32
	Attention Module	256*32*32
	RRCNN-4 block	128*32*32
	Up-Block	128*64*64
	Attention Module	256*64*64
	RRCNN-3 block	128*64*64
	Up-Block	64*128*128
	Attention Module	128*128*128
	RRCNN-2 block	64*128*128
	Up-Block	32*256*256
	Attention Module	64*256*256
RRCNN-1 Block	32*256*256	
Output	Conv 1X1	5*256*256

where σ and φ represent ReLU and sigmoid activation function respectively. The W_x and W_g shows the linear transformation for the attention network. In addition, the Upsample block includes an upsampling layer followed by convolutional layer, batch normalization and the ReLU activation unit. The semantic segmentation output is obtained by placing the final convolution layer of kernel size 1×1 at the final RRCNN block in the decoder layer.

4 Experimentation and Results

This section explains the experimentation and results of the proposed method. The performance of the proposed method is evaluated on the available public dataset [19]. The efficacy of the proposed method is compared with the state-of-the-art methods for thermal image semantic segmentation. For the evaluation, we have adopted the standard metrics: Average class Accuracy and mean Intersection over Union (IOU). The following section discusses the details of experimentation and results.

4.1 Thermal Semantic Segmentation Dataset

We have utilized the available public dataset for thermal image segmentation provided by [19]. The dataset is comprised of thermal and visible-spectrum RGB images. The dataset is collected using the InfRec R500 thermal camera, which simultaneously captures the thermal spectrum and visible spectrum images. The range of the thermal spectrum for collecting the images is $814\mu m$, giving the images of resolution 480×640 . The field of view of the visible-spectrum image and the thermal image is not identical. The visible spectrum images have a horizontal field of view of 100° ; besides, the thermal spectrum images have a horizontal field of view of 32° . In order to align the thermal and RGB spectrum images, the RGB images are cropped and resized. The dataset provides the semantic labels for the urban environment and is classified into nine classes: bicycle, person, car, curve, car_stop, color_cone, guardrail, and background. The dataset has 1569 images pairs of RGB and thermal altogether. There are 820 image pairs recorded during the daytime and 749 recorded at nighttime. The

Table 2: The number of images in training and testing split of the dataset.

Dataset	Training set	Testing set
Day & Night time	784	393
Day Time	-	205
Night Time	-	188

Table 3: Comparison of the evaluation results of ARTSeg with other state-of-the-art methods on the test set consisting of Day and Night time images. The Class Accuracy (%), Avg.Acc (%) and *IOU* (%) are the evaluation metrics. ”-” indicates that the value is not available.

Model	Background	Car	Pedestrian	Bike	Curve	Car stop	Guardrail	Color cone	Bump	Avg.Acc	<i>IOU</i>
SegNet [19]	96.90	83.30	72.10	76.80	58.30	31.90	0.00	0.00	63.90	53.70	58.30
SegNet_4ch [19]	96.10	89.00	82.30	0.00	61.40	21.70	0.00	0.00	86.70	48.60	50.40
ENet [19]	88.50	58.60	42.70	24.70	30.10	18.10	0.30	45.80	23.00	37.00	44.90
MFNet [19]	96.80	82.90	85.20	74.20	61.50	27.30	0.00	60.70	43.30	59.10	64.90
FuseSeg [20]	-	93.10	81.40	78.50	68.40	29.10	63.70	55.80	66.64	70.60	54.50
RTFNet [21]	-	93.00	79.30	76.80	60.70	38.50	0.00	45.50	74.70	63.10	53.20
ARTSeg (Our)	97.10	94.76	86.66	79.20	71.25	49.69	65.21	58.11	64.28	74.03	68.80

dataset is split into the training set and testing set. The testing set is further split into the daytime set and nighttime set. The percentage of images in each set are shown in Table 2.

4.2 Training details

The proposed method ArtSeg is implemented using Pytorch deep learning library. In training the proposed method, no pre-processing step is performed on the input images. The proposed network ArtSeg is trained from scratch in an end-to-end manner and does not employ any pre-trained weights. The network is trained for a total of 500 epochs on Nvidia RTX 3090 having 24GB memory. The cross-entropy loss function is used for training the network given by Eq.6.

$$Loss = -\frac{1}{M} \sum_M \sum_C^{j=1, c=1} S_{c,j} \ln(\hat{S}_{c,j}) \quad (6)$$

where M is the total number of pixels in the ground truth label image, C is the number of classes, in this case, 9. $S_{c,j}$ denotes the ground truth class label of each pixel, and $\hat{S}_{c,j}$ denotes the predicted class of each pixel. We have used Adam optimizer for training the ARTSeg network with the weight decay of 1×10^{-4} ; epsilon of 1×10^{-8} and learning rate of 5×10^{-4} . The learning rate schedule policy given by the Eq.7 is used to update the learning rate.

$$LR = LR_{initial} \times \left(\frac{1 - epoch}{epochs_{total}}\right)^p, \quad (7)$$

The p is set to 0.9. The network is trained for 100 epochs. All the parameter values are chosen empirically through grid search. These parameters are kept constant in all the experiments. Moreover, training data is augmented using the flip technique.

4.3 Evaluation metrics

In order to evaluate the performance of the proposed network, two evaluation metrics are selected. The Average class Accuracy and Mean Intersection over Union (IOU). The Average class Accuracy is expressed as

$$Avg.Acc = \frac{1}{N} \sum_{i=1}^N \frac{TP_i}{TP_i + FN_i}, \quad (8)$$

where N is number of classes. TP is true positive rate ($TP_i = \sum_{M=1}^{m=1} p_{ii}^m$) and FN is false negative rate ($FN_i = \sum_{M=1}^{m=1} \sum_{j=1, j \neq i}^N p_{ij}^m$). The IOU is expressed as

$$IOU = \frac{1}{N} \sum_{i=1}^N \frac{TP_i}{TP_i + FN_i + FP_i}, \quad (9)$$

here FP is define as false positive rate ($FP_i = \sum_{M=1}^{m=1} \sum_{j=1, j \neq i}^N p_{ji}^m$). The p_{ii} corresponds to the correct number of pixels classified for class i having the same class i in the frame m , whereas p_{ji} represents the number incorrectly classified pixel of class j as class i in the frame m . Similarly, the number of incorrectly classified pixel of class i as class j is represented by p_{ij} in the frame m .

4.4 Results

The thermal image semantic segmentation dataset is benchmarked on existing techniques, including MFRNet [19], FuseSeg [20], SegNet [22] and RTFNet [21]. Image segmentation using thermal images is an emerging research direction in contrast to RGB image segmentation; given this, a few techniques have been employed in the literature for thermal image segmentation. The MFRNet, FuseSeg and RTFNet have fused the information from the visible spectrum and thermal

Table 4: Quantitative analysis of ARTSeg with other state-of-the-art methods for day time and night time test set. The evaluation is performed using Avg.acc (%) and IOU (%) metrics.

Methods	Day Time		Night Time	
	Avg.Acc(%)	IOU(%)	Avg.Acc(%)	IOU(%)
SegNet [19]	46.10	48.80	54.00	55.20
SegNet_4ch [19]	50.50	51.10	50.50	51.10
MFNet [19]	47.70	57.40	63.50	62.10
FuseSeg [20]	62.10	47.80	67.30	54.60
RTFNet [21]	60.00	45.80	60.70	54.80
ARTSeg (Our)	65.58	64.08	70.85	65.56

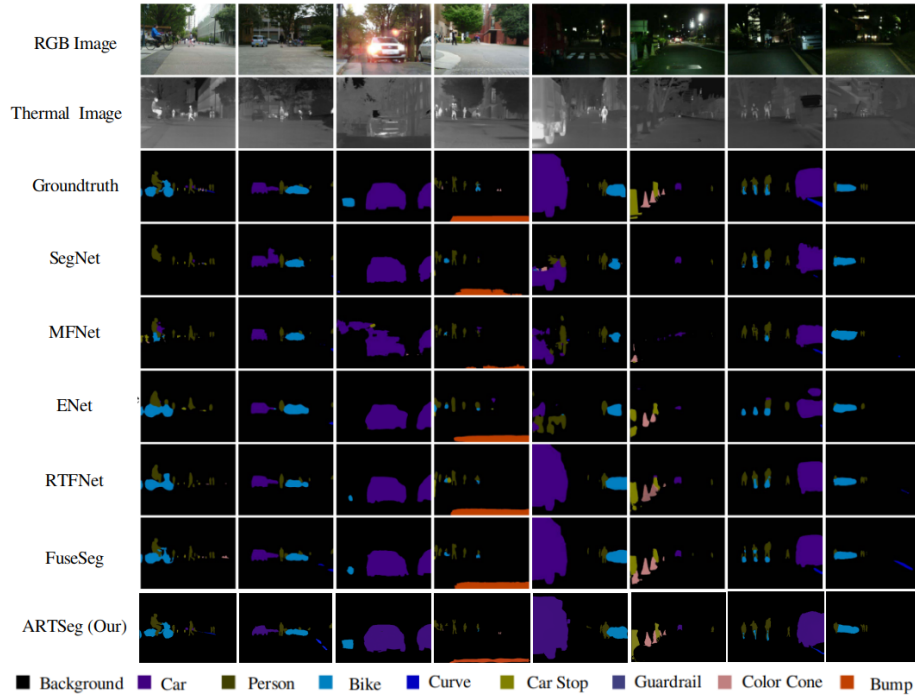


Fig. 2: The qualitative comparison between ARTSeg and other state-of-the-art methods for semantic segmentation on thermal image dataset.

spectrum images. However, SegNet uses only thermal images for predicting semantic segmentation. The proposed network ARTSeg is trained on only thermal images. The evaluation of ARTSeg in comparison to the algorithms as mentioned earlier is shown in Table 3. The Table shows the Accuracy measure of each class and Avg.Acc and *IOU* over all classes for both day and night time. However, Table 4 shows the evaluation of the methods for daytime and nighttime separately for all classes. ARTSeg has outperformed all existing methods and achieved an improvement 3.43% in Avg.Acc and 3.9% in *IOU* scores in comparison to FuseSeg. Fig.2 manifests the qualitative results of the proposed ARTSeg algorithm with other methods. In addition, we have also investigated the effect of using different backbone networks to extract the features for the encoder of ARTSeg network.

We utilize six different backbone network including VGG16 [23], ResNet-18 [24], ResNet-50 [24], MobileNetV2 [25], ShuffleNet [26] and DenseNet [27]. The thermal image is input to the backbone network, and the encoded features are obtained are then passed to the decoder module. The backbone networks are trained with pre-trained weights. The Table 5 shows the quantitative results

Table 5: Quantitive analysis of ARTSeg with different backbone networks. The evaluation is performed using Avg.acc (%) and *IOU* (%) metrics on day and night time test set.

Methods	DayTime		NightTime	
	Avg.Acc(%)	<i>IOU</i> (%)	Avg.Acc(%)	<i>IOU</i> (%)
ARTSeg-VGG16	54.21	46.80	59.12	48.20
ARTSeg-ResNet-18	57.50	47.60	61.89	51.10
ARTSeg-ResNet-50	63.25	55.40	65.50	57.23
ARTSeg-MobileNetv2	59.45	49.89	60.10	50.80
ARTSeg-DenseNet	58.41	49.50	59.45	49.34
ARTSeg-ShuffleNet	62.58	58.18	66.85	59.56
ARTSeg (Our)	65.58	64.08	70.85	65.56

with the backbone networks. The results using different backbone networks in the encoder module do not show any significant improvement compared to ARTSeg.

5 Conclusion

In this research article, we proposed ARTSeg, a novel encoder-decoder architecture for thermal image semantic segmentation. The ARTSeg introduces residual recurrent convolution block in the encoder, followed by a decoder that utilizes additive attention in skip connection to refine full resolution detection. The ARTSeg is evaluated on the public dataset in terms of Avg.Acc and *IOU*. In comparison to other state-of-the-art methods, ARTSeg has a higher Avg.Acc (74.03%) and *IOU* (68.80%).

The use of the thermal camera in the autonomous driving stack to understand surroundings is beneficial in low illumination conditions. For future work, we aim to fuse information from the thermal camera and Lidar to improve the perception of the autonomous vehicle.

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