Radar Guided Dynamic Visual Attention for Resource-Efficient RGB Object Detection

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Abstract—An autonomous system’s perception engine must provide an accurate understanding of the environment for it to make decisions. Deep learning based object detection networks experience degradation in the performance and robustness for small and far away objects due to a reduction in object’s feature map as we move to higher layers of the network. In this work, we propose a novel radar-guided spatial attention for RGB images to improve the perception quality of autonomous vehicles operating in a dynamic environment. In particular, our method improves the perception of small and long range objects, which are often not detected by the object detectors in RGB mode. The proposed method consists of two RGB object detectors, namely the Primary detector and a lightweight Secondary detector. The primary detector takes a full RGB image and generates primary detections. Next, the radar proposal framework creates regions of interest (ROIs) for object proposals by projecting the radar point cloud onto the 2D RGB image. These ROIs are cropped and fed to the secondary detector to generate secondary detections which are then fused with the primary detections via non-maximum suppression. This method helps in recovering the small objects by preserving the object’s spatial features through an increase in their receptive field. We evaluate our fusion method on the challenging nuScenes dataset and show that our fusion method with SSD-lite as primary and secondary detector improves the baseline primary yolov3 detector’s recall by 14% while requiring three times fewer computational resources.

Index Terms—Object Detection, Radar, RGB Camera, Sensor Fusion, Autonomous Systems, Deep Learning

I. INTRODUCTION

Object detection is one of the most challenging tasks in autonomous systems. Deep convolutional architectures such as R-CNN [1], Fast R-CNN [2], and Faster RCNN [3] provide very high accurate object detection results. However, due to slow inference time and high memory requirements [4], single stage detectors like SSD [5] and YOLO [6] are used for faster detection often at a slightly lower accuracy. However, single stage RGB detectors suffer from degradation in performance on small object detection task. Object detection becomes very challenging as the object height relative to the image size decreases [7]. In addition to this, these object detectors perform very poorly when they are exposed to novel environments or adverse lighting and weather conditions [8] [9]. These perception failures could be very critical to the autonomous system’s decision making module and may cause catastrophic failures.

To overcome the limitations of RGB camera based perception, modern day autonomous systems are often equipped with multiple perception modalities like cameras, radars, and LiDARs [10] [11]. Using multiple sensors allows the perception engine of the autonomous systems to exploit complementary features provided by different modalities. Automotive radars have been widely used in vehicles for Advanced Driving Assistance Systems (ADAS) [12] as they can detect long range objects and are highly robust to adverse weather and lighting conditions. Hence, a radar could provide valuable information of long range objects that are missed by the RGB detectors.

Although radar could detect objects at long range accurately, processing radar point cloud is a very challenging problem due to the unstructured nature of the data. The radar’s pointcloud is very sparse with inconsistent point density for objects without any labels. Classical methods [13] [14] [15] for fusing camera and radar includes kinetic model based tracking and filter based association algorithms. However, noisy and sparse 3D radar data makes the association problem challenging. Often this process is handcrafted with some heuristic rules to make it work with 2D RGB images. An emergent solution is to use radar point based feature extraction methods. These methods are usually designed for dense LiDAR pointclouds such as PointNet [16] and hence do not have a good performance on sparse and noisy radar data. Other methods include creating a depth map using raw radar data and then fusing the depth map with RGB images [17] [18]. However, many of these methods require two stage detectors [19] making them computationally expensive for resource constrained systems. Even though methods with radar guided feature extraction have better results on small object detection, they are far from real time deployment on robotics systems due to their high computational needs.

This paper introduces a novel fusion method for RGB camera and radar to detect small and far away objects in RGB images with low complexity and memory footprint. The proposed method is designed with a lightweight single stage detector that fuses radar point cloud with RGB images to generate ROIs for object candidates. Radar point cloud contains range, azimuthal and velocity information of objects with high confidence. Each point in the radar pointcloud when projected onto the image plane gives an approximate location of the object in the image. We use radar points to generate...
regions of interests with object candidates. These ROIs are fed to the lightweight detector to generate object detections. This increases the relative size of the object with respect to the ROI image and thereby, reducing the information loss of object features while convolution and pooling operations. The final step includes a fusion of these detections with detections made by passing the full image to another detector using NMS. This way we recover any large objects missed or not fully detected due to cropping of the image. We refer to this network as 'Primary detector' and our lightweight detector as 'Secondary detector'. We evaluate our network on the nuScenes dataset [20] which provides synchronized data from a full autonomous sensor suite including multiple radars and RGB cameras. Our experiments show that the proposed method shows 14% increase in recall for fusion system with and RGB cameras.

Our experiments show that the proposed network is shown in Figure 2. The proposed network consists of two detectors: a primary detector and a secondary detector. The primary detector takes the RGB images and generates detection for the full image. We refer to this network as 'Primary detector' and our lightweight detector. The primary detector takes the RGB images and generates detection for the full image. We refer to this network as 'Primary detector' and our lightweight detector. The primary detector takes the RGB images and generates detection for the full image. We refer to this network as 'Primary detector' and our lightweight detector. The primary detector takes the RGB images and generates detection for the full image. We refer to this network as 'Primary detector' and our lightweight detector. The primary detector takes the RGB images and generates detection for the full image. We refer to this network as 'Primary detector' and our lightweight detector. 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In absence of proposal generators for object regions [7], many works try to divide the image into multiple tiles and pass them through the detector. However, this design may require a large number of regions created randomly in the image to detect all the small objects. This may severely affect the computational efficiency of the network leading to a higher inference time.

Radar’s power of detecting objects at long range could be very helpful in guiding where the object is in the image. Radar detection when mapped to the image gives an approximate location of the object which could be used to create proposals for the object regions. Many of the automotive radars have very sparse data with less than 64 points making them excellent for our purpose. There have been prior works where the radar data is used to guide the proposal generation stage in two stage detectors [25] [26]. Yadav et. al [19] created a network BIRANet which fused radar points with a feature extractor network to guide anchors generation for Faster R-CNN. However, the anchors generated using this method do not increase the receptive field and only act as a proposal generator. Moreover, they require high energy resources and have a longer inference time due to the use of two stage detectors.

| Image size | Recall | GFLOPs |
|------------|--------|--------|
| 256        | 0.29   | 25.1   |
| 416        | 0.42   | 66.4   |
| 512        | 0.45   | 100.5  |
| 640        | 0.49   | 157.1  |
| 1080       | 0.54   | 447.4  |
| 1920       | 0.49   | 1413.9 |

**TABLE I:** Comparison between performance and computation overhead for yolov3 with different input size
Fig. 2: Algorithmic pipeline of Proposed Fusion System

Fig. 3: a.) Yellow points in the image show radar points mapped to the camera image, b.) Radar based proposals generated for secondary detector

to the secondary detector to generate secondary detections. The secondary detections are then merged with the primary detections to generate final detections. The use of radar data ensures that we do not create redundant proposals for detection with no objects. Unlike tiling methods, this method generates proposals in a dynamic fashion. The overall computational cost of the system will depend on the choice of lightweight detectors and the number of radar points. For automotive radars like Aptiv ESR 2.5 [27] that detect less than 64 objects at any timestamp, the maximum computational overload will be 64 times the GFLOPs of the lightweight detector. For a suitable choice of lightweight detector, this could be very well managed by a resource efficient system.

1) Radar Object Proposals: Detected objects by automotive radars are reported as 3D points in bird’s eye view. In addition to position and depth, radars also report the radial velocity of the moving objects. For our method, we parameterize the radar detection as \( D = (x, y, z) \) and treat every detection as stand-alone detection. As a pre-processing step, we perform spatial alignment of radar data into the camera’s coordinate system. The nuScenes dataset provides us with the necessary calibration tools for mapping radar points to the egocentric and camera frame. When mapped onto the camera frame, radar detections point to the detected objects in the frame. Even though not all the objects are detected by radar, detections include most of the objects in long range detected with high confidence. Each radar point in camera frame is parametrized as \( P = (cx, cy) \). We treat this as the approximate location of an object and draw a 2D anchor of predefined size for every point with \( P \) as the center. Figure 3a shows radar points in yellow mapped to the camera frame while ROIs generated using radar points are shown in red boxes in figure 3b.

2) Object Detection: The secondary detector is responsible for detecting the objects in the ROIs generated by radar object proposal network. For each radar point, the region bounded by the anchor box is cropped from the image and sent to a lightweight detector. For each image, we generate \( n \) ROIs for secondary detection, where \( n \) is the total number of radar points in the given frame. All the detections for \( n \) ROIs are aggregated with detections by the primary detector generated by passing the full image. Finally, we perform Non-maximum Suppression(NMS) on the aggregated detections to filter out any double detections.
TABLE II: FLOPs of Object Detectors

| Detector   | Image size | GFLOPs |
|------------|------------|--------|
| yolov3-spp | 416        | 66.4   |
|            | 640        | 157    |
|            | 1080       | 447    |
|            | 1900       | 1384.6 |
| tiny-yolov3| 200        | 1.3    |
|            | 300        | 2.9    |
|            | 400        | 5.2    |
|            | 600        | 14.1   |
| SSDlite    | 200        | 0.20   |
|            | 300        | 0.43   |
|            | 400        | 0.74   |

III. EXPERIMENTAL RESULTS

A. Dataset

We test our proposed fusion method on the validation set of the nuScenes [20] dataset that has synchronized data collected from an autonomous vehicle sensor suite of 6 cameras, 5 radars, and 1 lidar, all with a full 360-degree field of view. Since nuScenes has 3D annotations, we first convert these 3D annotations to 2D annotations and merge all relevant classes into 6 classes: car, truck, bus, pedestrian, bicycle, and motorcycle. For our evaluation purposes, we discard highly occluded objects from ground truths annotated in 3D. As shown in figure 4, we observe that many of the far-away objects in the scenes did not have any annotations. This is due to the fact that objects that are not covered with at least one lidar or radar point are discarded by nuScenes even though they were captured by RGB cameras. To overcome this, we annotate a small sample of images manually from the mini-val split of nuScenes. Our dataset contains 396 images and 3777 annotations with annotated classes of: 'cars,' 'pedestrian,' 'truck', 'trailer', 'bus', 'cycle', and 'motorcycle'. The predicted detections are compared against our manually annotated dataset since it has more labels as compared to nuScenes 2D annotations.

B. Object Detection network

We use yolov3-spp, tiny-yolov3 and SSDlite as our primary and secondary object detector for our experiments. It is important to note here that, this approach is applicable to any combination of primary and lightweight secondary detectors to obtain significant detection improvement at low computational power. All the object detectors were trained on the COCO dataset [28] and detection with classes belonging to 'Car', 'Person', 'Bicycle', 'Motorcycle', 'Bus' and 'Truck' considered for evaluation. We compare our fusion system with the detections from the primary detectors. We used PyTorch to implement our system and all the experiments were conducted on a setup with two Nvidia 1080Ti GPUs.

C. Metrics For Evaluation

To compare the detection ability of different object detection systems, we use Recall and the number of False Negatives as our metric. Recall measures the number of correctly detected objects over the number of objects in the ground truth. Following is the equation for Recall:

\[
\text{Recall} = \frac{\text{TruePositives}}{\text{TruePositives} + \text{FalseNegatives}}
\]

(1)

For comparison between different detectors based on the computation overhead, we compute the number of floating operations executed per second. Table II shows the comparison of computational overhead in GFLOPs for yolov3-spp, tiny-yolo and SSDlite. We also compute the total energy consumed per frame for different object detectors. This includes energy consumption for sensor activations, data transfer of captured frames and computational expenses due to object detectors. Based on [30], equations for resource consumption are described below:

\[
\text{Energy} = \alpha + \beta + \gamma \times f_s + \frac{(CL_{pd} + CL_{sd} \times N_{ROIs}) \times fps}{EE_{hw}}
\]

(2)

Here, \(\alpha\), \(\beta\) are the per frame sensor’s data capture energy for RGB cameras and radar respectively while \(\gamma\) is the energy spent on transferring captured frames to the perception engine of the system. \(CL_{pd}\) and \(CL_{sd}\) are the computational overhead of the primary and secondary object detector respectively. \(N_{ROIs}\) represent the number of ROIs created by the radar proposal network per frame that are processed by the secondary detector. \(f_s\) is the combined frame size memory for the radar pointcloud and camera image. We fix the nuScenes frame rate (fps) to 20 for our experiments. UNPU [31] is used as the DNN accelerator to estimate the computational energy required to run the object detector and \(EE_{hw}\) denotes the energy efficiency of our DNN accelerator. For our calculations, we assume that our system has an automotive radar of 77GHz frequency and an RGB monocular camera that are always turned on. Table III shows the values of the variables in equation 2 used for our evaluation.

D. Hyperparameter Study

Our proposed algorithm’s performance depends on the choice of ROI size of the proposal and input image size for the lightweight detector since these determine the effective receptive field of the objects in ROIs. A large ROI proposal will decrease the effective stimuli of the object thereby leading to a missed detection while a small ROI may crop some pixels of the object necessary for the detection. The receptive field

TABLE III: Value Table.

| Name      | Value          |
|-----------|----------------|
| \(\alpha\) | 20mJ/frame     |
| \(\beta\) | 0.92J/frame    |
| \(\gamma\) | 3.9mJ/Mb       |
| \(f_s\)  | 3.08 TOPS/W    |
| fps       | 20             |
| EE_{hw}   | 3.08 TOPS/W    |

\(\alpha\) Values adapted from [29].

\(\beta\) Values calculated from Delphi ESR-2.5 datasheet [27] with max frame-rate=13fps.
Fig. 5: ROIs size vs Recall comparison with yolov3-spp as primary detector and tiny-yolov3 as secondary detector

Fig. 6: Multiple detection for small ROI sizes not removed after NMS

decrease in the recall if we increase the image size beyond 300. Increasing the input size for the secondary detector with small input ROIs will increase the upscaling of the ROI before it is processed by the object detector and lead to an increase in noisy detections. The memory footprint of the network increases as the input size is increased. Based on the recall numbers and GFLOPs for the network, we choose an image size of 300 for the secondary detector. For all our further experiments, we fix the input image size of the secondary detector to 300 and the ROI size to 240.

E. Evaluation

1) Experiments with different detectors: Table V shows the performance of the fusion algorithm using different primary and secondary object detectors. The table shows the Average Recall (AR), Average Precision (AP), False Negatives, Total Energy consumption per frame and average GFLOPs per frame for the object detection task with an IoU of 0.4. The image sizes for the primary detector and the secondary detector are kept to 416 and 300 respectively with an ROI size of 240. According to Table V, we get the highest recall for the system with yolov3-spp as both primary and secondary detector, however, it requires memory of 1791.4 GFLOPs per frame which is very high for a system with limited

| Mode                  | P det.(im sz) | Sec det. | Recall | Precision | False Negatives | TE(J) | GFLOPs/frame |
|-----------------------|---------------|----------|--------|-----------|-----------------|-------|-------------|
| Fusion yolov3-spp(416)| SSDlite       | 0.51     | 0.67   | 1851      | 1.32            | 87.9  |
| Fusion SSDlite(416)   | SSDlite       | 0.48     | 0.69   | 1978      | 1.10            | 22.3  |

Base Network

| Mode                  | P det.(im sz) | Sec det. | Recall | Precision | False Negatives | TE(J) | GFLOPs/frame |
|-----------------------|---------------|----------|--------|-----------|-----------------|-------|-------------|
| Base yolov3-spp(416)  | SSDlite       | 0.42     | 0.92   | 2205      | 1.24            | 66.4  |
| Base yolov3-spp(1080) | SSDlite       | 0.53     | 0.93   | 1769      | 2.48            | 447.4 |

Prior Work

| Mode                  | P det.(im sz) | Sec det. | Recall | Precision | False Negatives | TE(J) | GFLOPs/frame |
|-----------------------|---------------|----------|--------|-----------|-----------------|-------|-------------|
| Fusion BIRANet-FFPN   | 0.53          | 0.73     | 1762   | 1.71      | 207             |       |             |

Pdet=Primary detector, Secdet=Secondary detector, imsz=Input image size for detector, Recall=Recall, Precision=Precision, FN=Fast Negatives, TE=Avg. Energy(J) per frame, GF= avg GFLOPs/frame
computational resources. Fusion networks with tiny-yolov3 and SSDlite have similar performance in terms of average recall, however there is a big difference between their memory requirements. Network with yolov3 as primary and tiny-yolov3 as secondary detector requires more than twice the memory that the fusion system of yolov3 and SSDlite as primary and secondary detector respectively. Hence, we choose SSD-lite as our secondary detector due to its low complexity and memory footprint. For SSDlite systems, yolov3 as the primary detector has the best recall however it requires nearly four times more computational power than the framework with SSDlite as the primary detector. In a system with very low computational power, a framework with SSDlite as both primary and secondary detector could be chosen over the yolov3-SSDlite framework with a slight decrease in detection accuracy. The framework with SSDlite as the primary detector will be referred to as ‘SSDlite-SSDlite’ while the framework with yolov3 as the primary detector will be ‘yolov3-SSDlite.’

2) Comparison with baselines: In Table VI, we compare the performance of our SSDlite fusion systems with two single yolov3-spp networks operating at input image sizes of 416 and 1080. The yolov3 network with an input size of 1080 has a bigger receptive field for small objects and hence scores better recall than its counterpart with an input size of 416. Our both fusion systems (yolov3-SSDlite and SSDlite-SSDlite) outperform the baseline yolov3 with an input size of 416 with an improvement of 21% and 14% in the recall respectively. The single yolov3 detector with an input size of 1080 performs slightly better than our fusion systems however requires nearly 5 and 20 times more resources than our yolov3-SSDlite and SSDlite-SSDlite fusion systems respectively. This demonstrates the high performance of our fusion systems while having very low memory requirements.

We also evaluated BIRANet [19] on our dataset and observed only 4% and 10% increase in recall compared to our SSDlite-SSDlite and yolov3-SSDlite fusion systems respectively even though it uses high performing Faster R-CNN with a feature pyramid network for detection. The memory requirements for BIRANet are also very high compared to our fusion systems, requiring almost 9 times computational memory compared to our SSDlite-SSDlite fusion system. We also plot per frame recall for BIRANet, baseline yolov3 with 1080 input size and yolov3-SSDlite fusion system in figure 7. We observe that our fusion system has very similar recall as compared to other analyzed networks over the sequence. Thus our system is most suitable for deployment in real world resource efficient systems with the promise of better performance at low memory consumption.

Figure 8 shows the variation of memory requirements with the RGB frames for our fusion system with yolov3 and SSDlite. Unlike the tiling methods where a fixed number of proposals are created, our fusion system’s number of proposals depend on detection made by radars. Hence the computational requirements change dynamically depending on the radar detections. This behavior is captured in figure 8. This ensures that the energy consumption is kept low for the dynamic scenes with very few objects in the frame.

The effect of object size on the detection performance of our system is analysed in figure 9. The y-axis in the figure represents the number of true positives and the x-axis represents the area of the detected true positive objects. We use SSDlite as the secondary detector and yolov3-spp as the primary detector with other parameters as mentioned above. In general, the performance of the fusion system and baseline are comparable for large objects. However, we see a significant increase in true positives with an area less than 1000 pixel x pixel for our fusion system as compared to the baseline primary detector.

Figure 10 shows the qualitative results of our fusion system with yolov3 as the primary detector and SSDlite as the secondary detector. The results support that our method performs very good in detecting small objects as well as the objects in low lightening or contrast regions. The image in the fourth row belongs to a dark sequence in nuScenes and our detectors have never seen night time sequences during training making object detection harder.

IV. CONCLUSION

Deep convolutional network based object detectors often fail in detecting small objects when operating at a fixed size input. The lack of distinctive semantic features for the object and the mixing of background features when passed through the convolution network makes the small object detection problem
very challenging. In this work, we have shown how radar could be used to create object proposals which when passed through a lightweight detector could help in the detection of small objects missed by the RGB detector. The proposed architecture uses a primary and a lightweight detector with low computational overhead to detect objects. The radar pointcloud is used to generate object proposal regions and these proposals are fed into the secondary detector to generate secondary detections. Detections generated with the primary detector with the full image as input are fused with the secondary detections via NMS. Our proposed fusion algorithm has the merits of high performance at longer distances, low computational requirements, high reliability and robustness. Experiments on our annotated dataset show that our proposed SSDlite-SSDlite fusion method outperforms baseline primary yolov3 detector with a 14% increase in recall while having a very small computational overhead of 22.3 GFLOPs as opposed to the baseline’s 66.4 GFLOPS.

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Fig. 10: Qualitative results of our fusion algorithm

(a) Detections by Fusion method

(b) Detections by Primary Detector