Deep Dive into Gradients: Better Optimization for 3D Object Detection with Gradient-Corrected IoU Supervision

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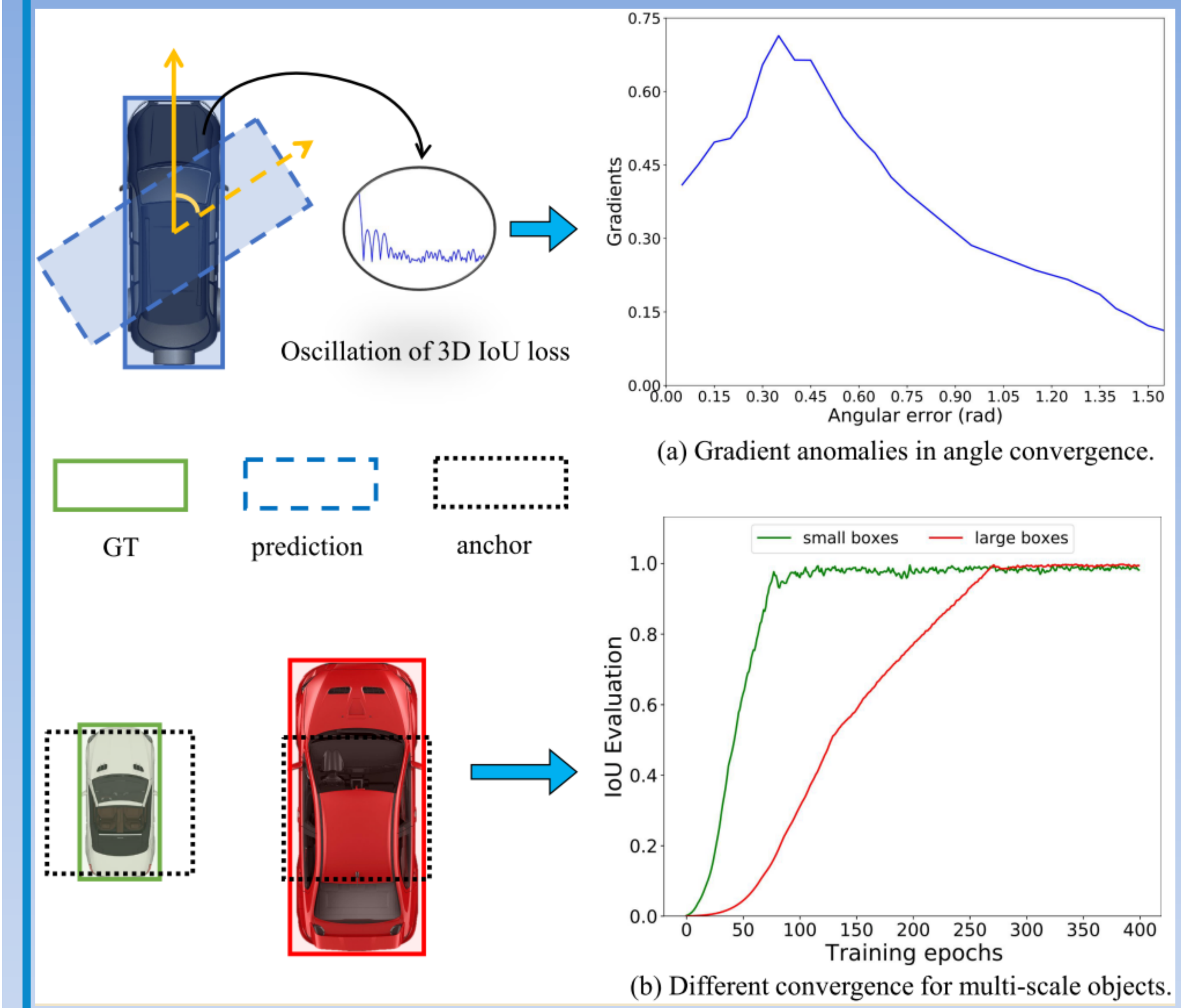
Observation

Abnormal gradient

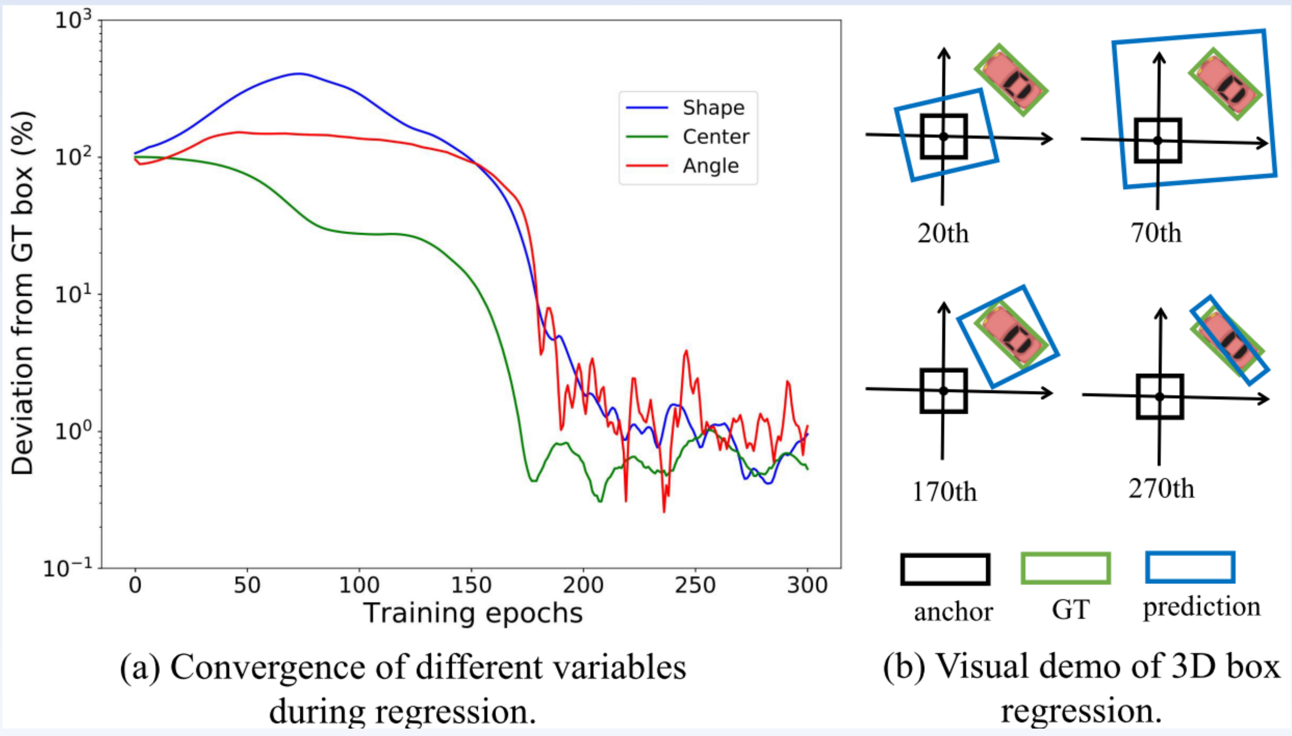


(a) Gradient anomalies in angle convergence.

(b) Different convergence for multi-scale objects.

- 3D IoU loss suffers from abnormal gradient changes during training.
- Firstly, it produces small gradients for large targets.
- Secondly, IoU loss performs differently for objects with different scales.

Preliminary



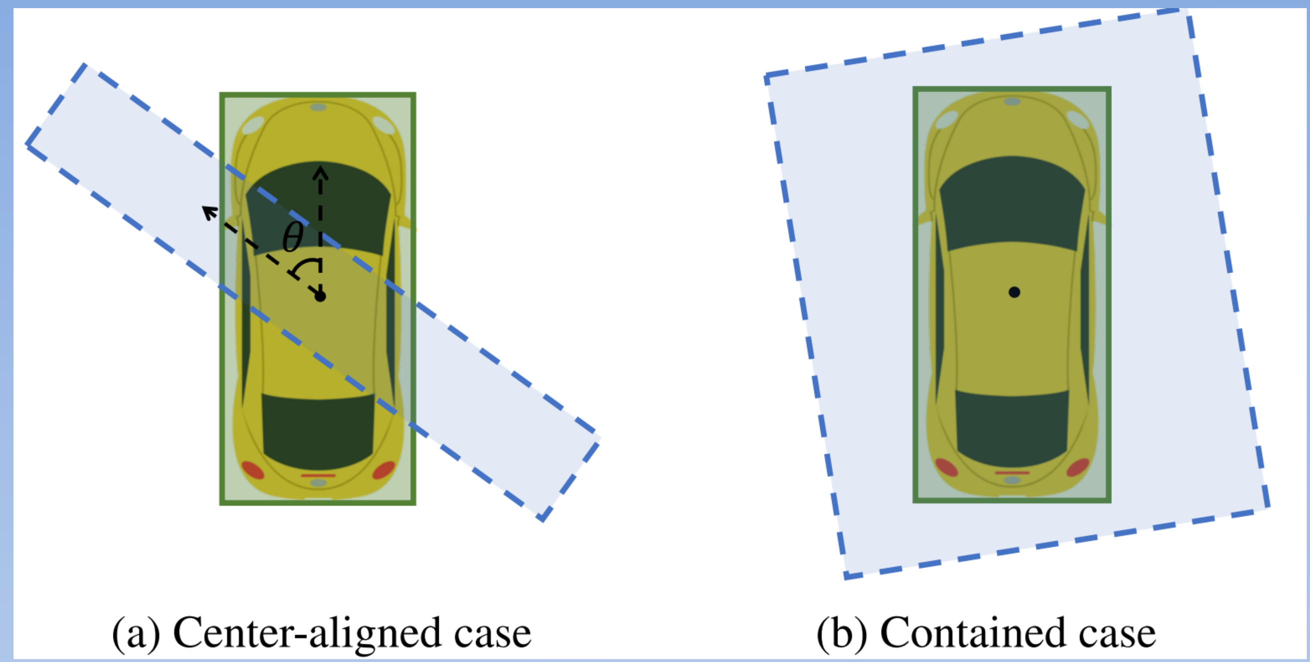
(a) Convergence of different variables during regression.

(b) Visual demo of 3D box regression.

Center points are easy to be regressed. Therefore, we only pay attention to the optimization of shape and angle as follows.

Analysis and Proof

Special cases



(a) Center-aligned case

(b) Contained case

Mathematical proof

With the following geometric relationship:

$$\begin{cases} I = \dfrac{h_t h_p l}{sin\theta}, \\ U = w_t h_t l_t + w_p h_p l_p - I, \end{cases}$$

The gradients of 3D IoU loss can be obtained:

$$\frac{\partial IoU}{\partial x} = \frac{\partial(\frac{I}{U})}{\partial x} = (\frac{\partial I}{\partial x} \cdot U - \frac{\partial U}{\partial x} \cdot I)/U^2,$$

$$\frac{\partial \boldsymbol{L}_{IoU}}{\partial \theta} = \text{IoU}(1+\text{IoU}) \cdot \cot\theta$$

$$\begin{cases} \dfrac{\partial \boldsymbol{L}_{IoU}}{\partial h_p} = -\text{IoU} \cdot \dfrac{V_t}{U h_p}, \\ \dfrac{\partial \boldsymbol{L}_{IoU}}{\partial w_p} = \text{IoU} \cdot \dfrac{h_p l_p}{U}. \\ \dfrac{\partial \boldsymbol{L}_{IoU}}{\partial l_p} = \begin{cases} \text{IoU} \cdot \dfrac{V_t}{U l_p}, & l = l_p, \\ -\text{IoU} \cdot \dfrac{w_p h_p}{U}, & l = l_t, \end{cases} \end{cases}$$

The above derivation justifies our observations. Therefore, existing 3D IoU losses need to be optimized to achieve better performance.

Methodology

Gradient correction for angles

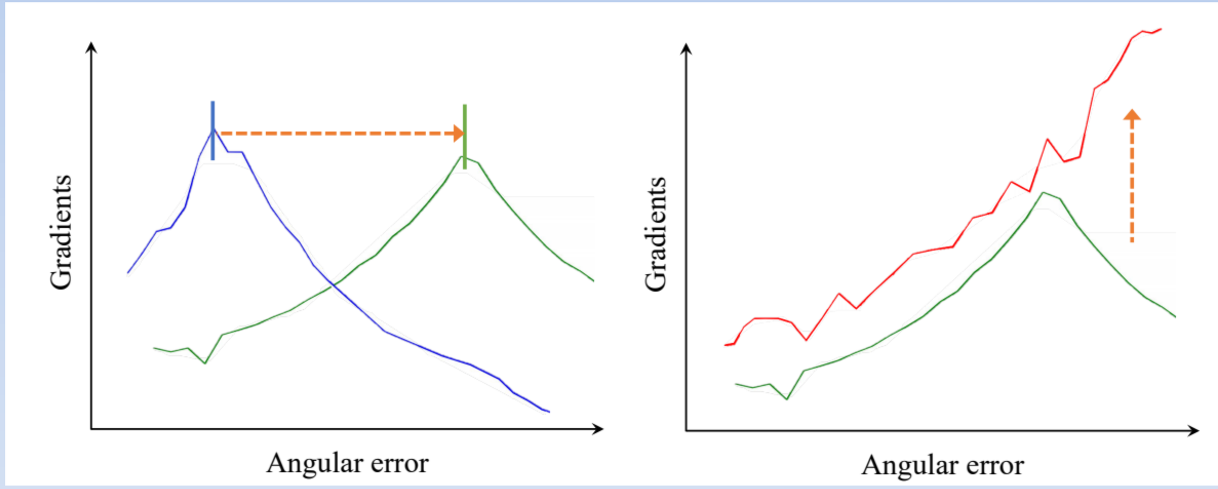
The corrected gradients of 3D IoU loss should solve the following issues:
- Abnormal gradient growth as angle converges
- When the angular error is large, small gradient is not conducive to the angle convergence.

Paradigm of GCIoU is as follows:

$$\boldsymbol{L}_{GCIoU} = -ln(\text{IoU}) \cdot f(\theta) + g(\theta)$$

Specifically, the modules are well-designed:

$$\boldsymbol{L}_{GCIoU} = -ln(\text{IoU}) \cdot e^{\theta^\alpha} + \tan\theta$$



Gradient correction for scales

Scale correction is performed directly during optimization process as follows:

$$s_{t+1} = s_t - \eta \cdot \frac{\partial \boldsymbol{L}_{GCIoU}}{\partial s} \cdot \text{U}^{\frac{2}{3}}$$

Experiments

Component-wise ablation

	GC $f(\theta)$	GC $g(\theta)$	GR	Car (IoU=0.7) Easy	Moderate	Hard
1				88.61	78.12	77.27
2	✓			89.21	78.56	78.22
3		✓		88.98	78.53	77.75
4	✓	✓		89.54	78.81	78.39
5			✓	89.16	78.54	78.01
6	✓	✓	✓	**89.85**	**80.03**	**78.66**

Ablations about modules

	$P(\theta)$	α	Car (IoU=0.7) Easy	Moderate	Hard
-ln(IoU)	0	—	88.61	78.12	77.27
GCIoU	$\alpha\theta$	1	88.86	78.19	77.22
		2	89.06	78.29	77.50
		3	89.19	78.43	77.62
	θ^α	1	89.38	78.62	77.52
		2	**89.54**	**78.81**	**78.39**
		3	89.15	78.33	77.41
		5	87.26	77.35	75.89

	$g(\theta)$	Car (IoU=0.7) Easy	Moderate	Hard
-ln(IoU)	—	88.61	78.12	77.27
GCIoU	θ	88.69	78.23	77.32
	$\tan\theta$	88.86	78.36	76.91
	$e^\theta - 1$	**88.98**	**78.53**	**77.75**

Source Code

Our code is available at https://github.com/ming71/GCIoU-loss

Detections