PHYSICS INFORMED SYNTHETIC IMAGE GENERATION FOR DEEP LEARNING

FIGURE 2

FIGURE 4

FIGURE 8: The virtual environment.

in the image and can be saved as json les. All the images were

FIGURE 11: Mask R-CNN architecture.

Pyramid Network (FPN) [48] is used as the neck, along with the stage, the model learns task-speci c knowledge on how the defects look in the real layup, which includes additional noise originating from lighting conditions, robot actuation, occlusions, etc.

Another way to mitigate the gap between the real and synof 0.9 and weight decay of 1e4 to optimize our model. The learning rate is 2e 3. A step learning rate scheduler is employed, hence in the 8th and 11th epochs, the learning rate will be scaled down by 0:1:

	Test mAP					Train mAP							
	Def.	Pre.	Und.	Avg.	Gain	Def.	Pre.	Und.	Avg.	Gain	Mem.	Inf.	Train.

(a)

(b)

(c)

(d)

We also elaborated on the challenges encountered while implementing the synthetic image generation framework for a process such as composite prepreg layup. A detailed CGI procedure for generating a precise and realistic texture of the composite sheet is prescribed. We have investigated different modeling variants and presented an ablation study to identify the best modeling and training methodology. The 2-Stage training process with our hybrid dataset using the mask R-CNN architecture helped us achieve 0.98 mAP on our test dataset. The entire image generation pipeline and model training can be accomplished within a short time enabling fast deployment.

We have also analyzed the failure cases of our model and recommended potential techniques to improve the performance. The developed model can then be deployed online in a production setting to detect defects during a composite layup process. Such a robust defect detection method can aid in the adaptive control of robots, and signi cantly reduce defect introduction, boosting the overall process quality.

There are several fronts in which this work can be extended to further improve defect detection capabilities using deep learning. We will discuss them in detail here.

Synthetic Image Generation: The idea of combining physics based simulation and advanced CGI to generate synthetic data can be further extended such that independent generative models can be implemented to achieve the proposed capabilities. Although GANs in its conventional form cannot be directly used for this application, we can use ensemble of networks where multiple networks can be deployed. We can have subgroups of networks capturing the physics of the sheet as well as the sheet's texture and physical appearance. Such a physics aware generative model can further improve the photo-realism of the synthetic data without incurring extremely high computational cost. Ideas from physics sware image restoration can be utilized to achieve this capability [59].

Data Preparation: Currently, since the training process is completely supervised, data preparation becomes a strenuous task. For scalability of deep learning models, self-supervision is 18 9r8-352.99Cervision ribThere signi calon pgroces-
(e)-215.004 (self-superv(zed)F)14.499 (image)suss ribmodL[(this)-284.002 (appliL[(t 1005 (v60[(t 10-)]TJ61 9.)-27s)15.0Inspi999 (c

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